

# Decision making in Next Generation Risk Assessment (NGRA)

30/05/2022



Unilever

# Learning objectives

- Give an overview of next generation risk assessment.
- Awareness of different computational approaches that are used (e.g., Bayesian inference, dose response models etc), illustrated with examples taken from case studies.
- Understand how to get started using computational approaches to analyse data (including open access tools and other resources).

# About me

- Degree in Mathematics from the University of Edinburgh
- PhD in Applied Mathematics from the University of Nottingham
- Postdocs in Germany at the University of Freiburg and the University of Heidelberg
- Joined Unilever in 2014, hired as a mathematical modeller
- Science leader in Computational Toxicology



# Web Resource

Unilever's Safety and Environmental Assurance Centre's Website  
for what we are discussing today:

[www.TT21C.org](http://www.TT21C.org)

# Ensuring Safe Ingredients for Foods, Drinks, Homecare and Cosmetic Products

## Risk Based Approach:

Considers both the hazard and the exposure to evaluate the risk

Can we safely use % of ingredient in product?

For **consumers; workers;**  
the **environment**



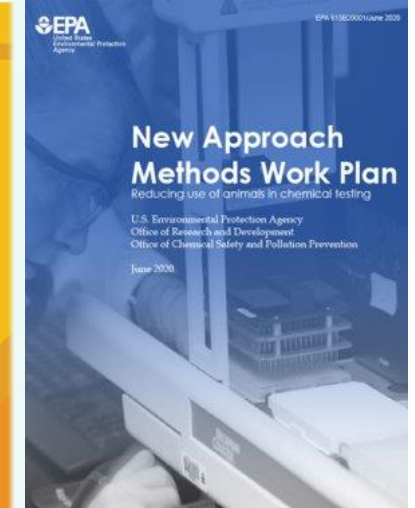
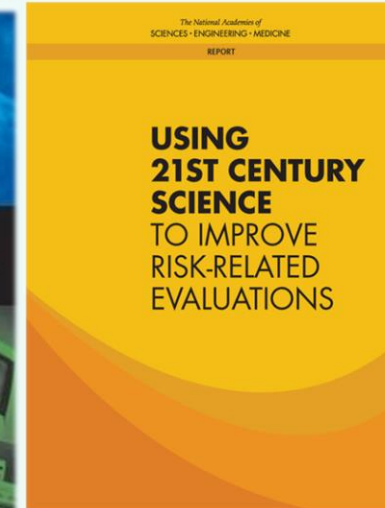
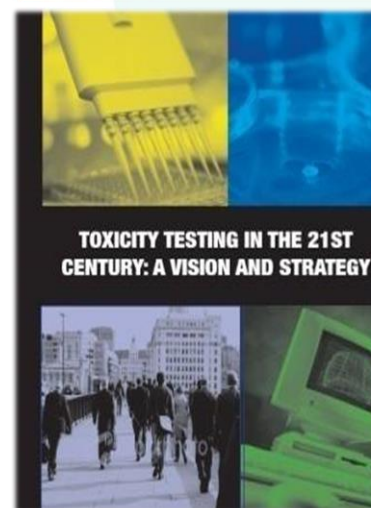
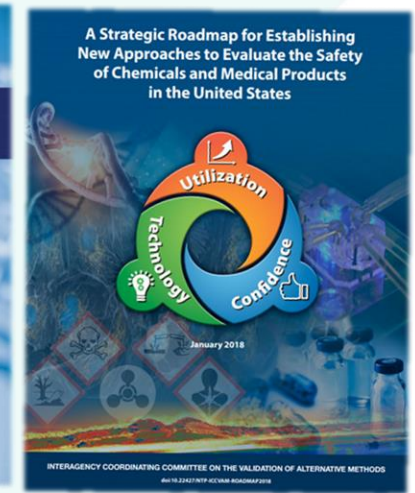
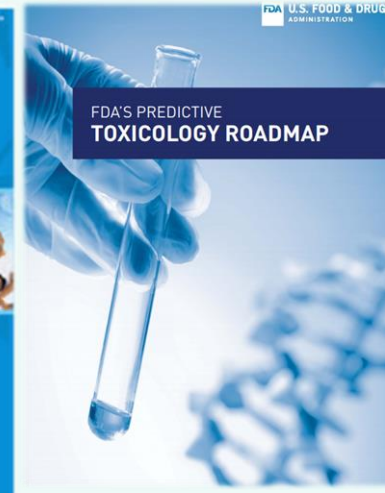


# Next Generation Risk Assessment (NGRA)

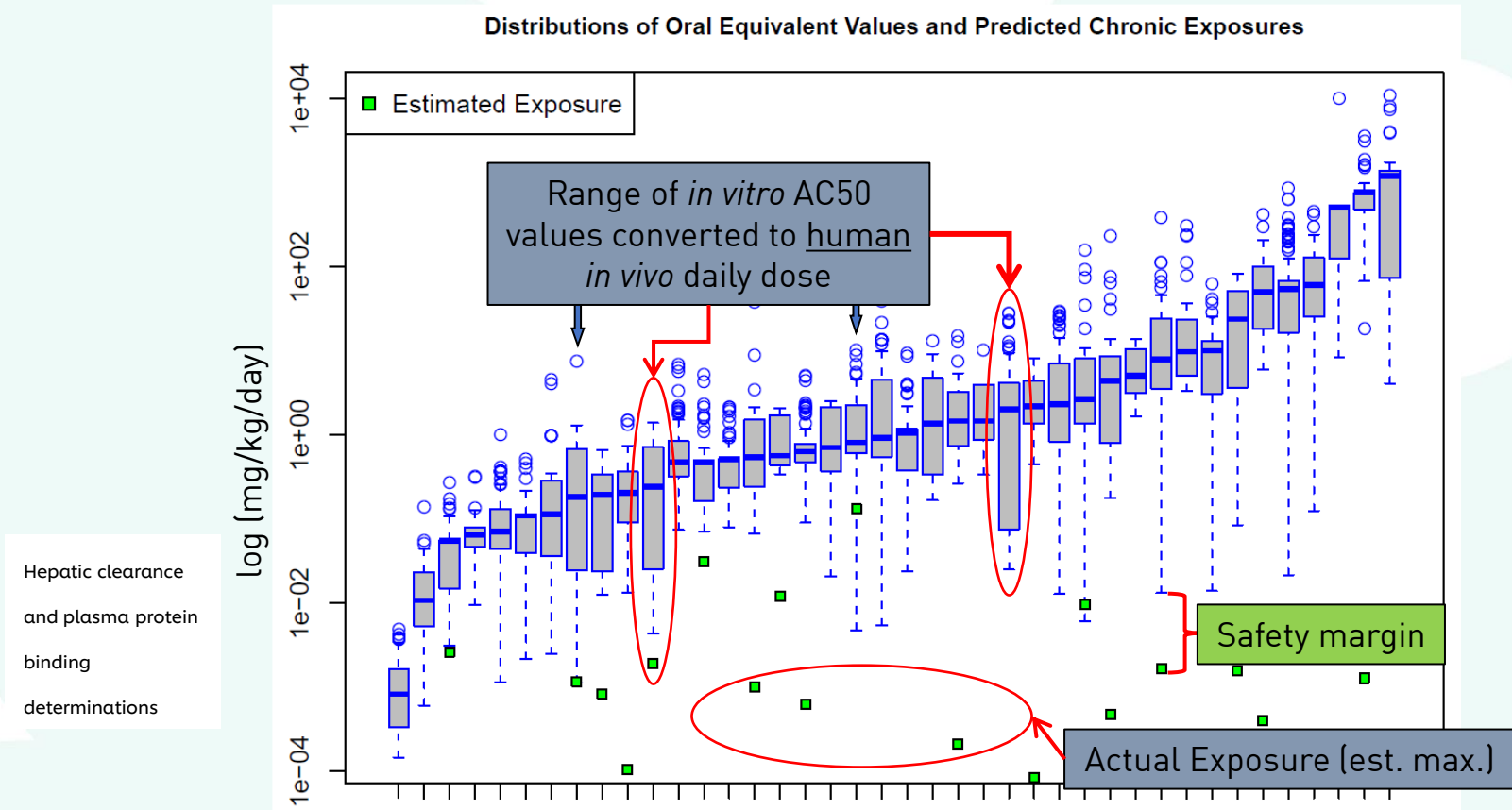
NGRA is defined as ***an exposure-led, hypothesis-driven*** risk assessment approach that ***integrates New Approach Methodologies (NAMs)*** to assure ***safety without the use of animal testing***



Safety without animal testing



# In Vitro Bioactivity vs Bioavailability



“Protection not Prediction”



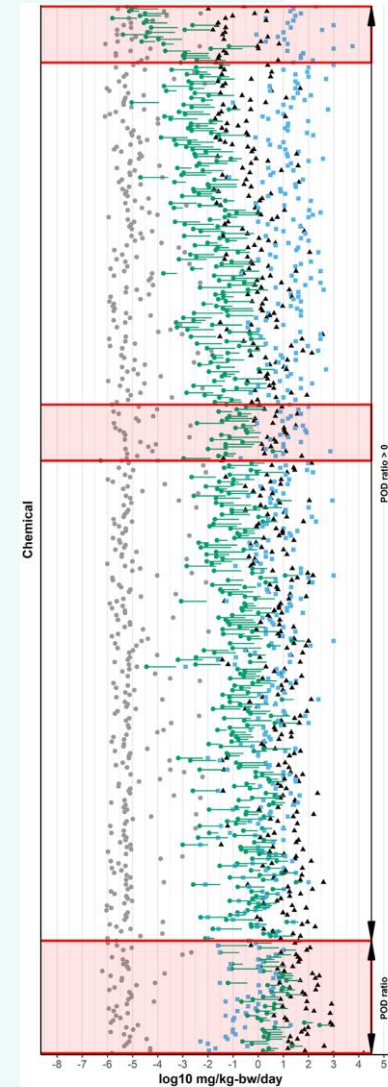
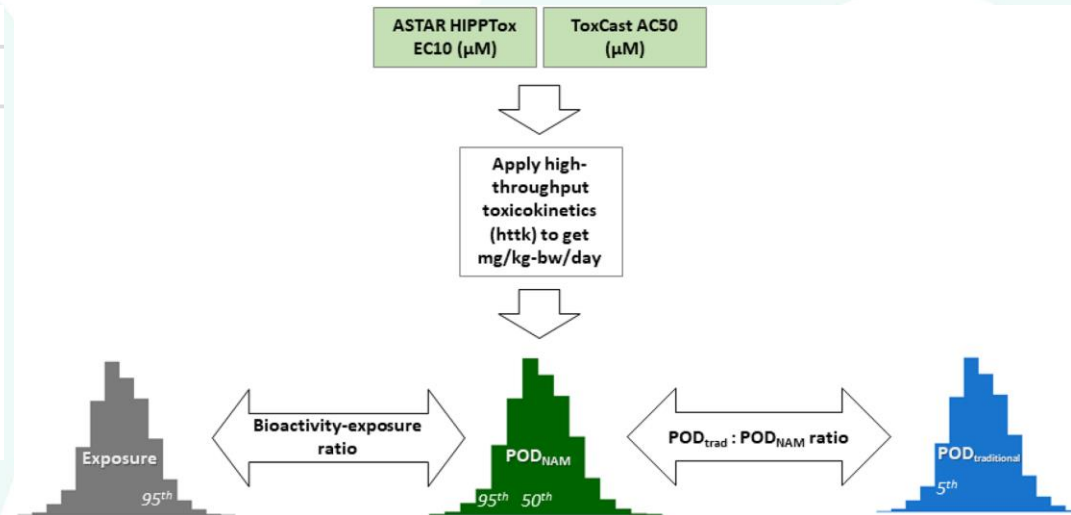
Slide from Dr Rusty Thomas, EPA, with thanks

# Integration of exposure and bioactivity for decision-making – Example from the *Accelerating the Pace of Chemical Risk Assessment (APCRA)* initiative

OXFORD SOT Society of Toxicology academic.oup.com/toxsci Tox Spotlight article  
 TOXICOLOGICAL SCIENCES, 173(1), 2020, 202–225  
 doi: 10.1093/toxsci/kfz201  
 Advance Access Publication Date: September 18, 2019  
 Research Article

## Utility of *In Vitro* Bioactivity as a Lower Bound Estimate of *In Vivo* Adverse Effect Levels and in Risk-Based Prioritization

Katie Paul Friedman <sup>1</sup>,<sup>\*</sup> Matthew Gagne,<sup>†</sup> Lit-Hsin Loo,<sup>‡</sup> Panagiotis Karamertzanis,<sup>§</sup> Tatiana Netzeva,<sup>§</sup> Tomasz Sobanski,<sup>§</sup> Jill A. Franzosa,<sup>¶</sup> Ann M. Richard,<sup>\*</sup> Ryan R. Lougee,<sup>||</sup> Andrea Gissi,<sup>§</sup> Jia-Ying Joey Lee,<sup>‡</sup> Michelle Angrish,<sup>|||</sup> Jean Lou Dome,<sup>|||</sup> Stiven Foster,<sup>#</sup> Kathleen Raffaele,<sup>#</sup> Tina Bahadori,<sup>||</sup> Maureen R. Gwinn,<sup>\*</sup> Jason Lambert,<sup>\*</sup> Maurice Whelan,<sup>\*\*</sup> Mike Rasenberg,<sup>§</sup> Tara Barton-Maclaren,<sup>†</sup> and Russell S. Thomas <sup>1</sup>,<sup>\*</sup>



• ExpoCast • POD-NAM • max AED • POD-traditional

- Of the 448 substances, 89% had a  $POD_{NAM,95}$  that was less than the traditional  $POD$  ( $POD_{traditional}$ ) value.
- Bioactivity:exposure ratios (BERs), useful for identification of substances with potential priority, demonstrated that high-throughput exposure predictions were greater than the  $POD_{NAM,95}$  for 11 substances.

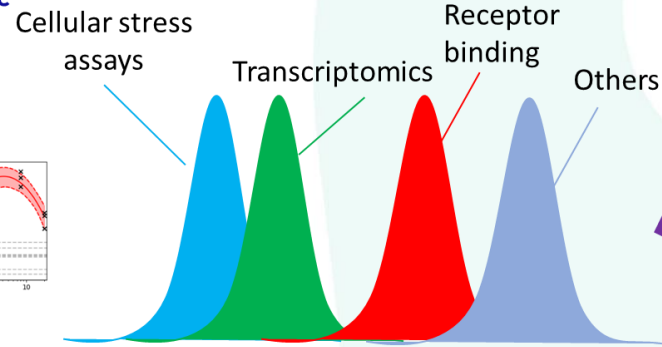
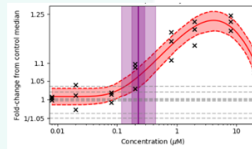


# Integration of exposure and bioactivity for decision-making – The assessment is designed to prevent harm

**Hazard identification and characterisation of ingredients**



Point of departure derived from concentration-response data



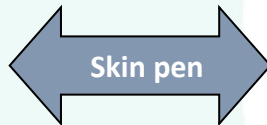
**Risk Assessment**

Calculation of Bioactivity Exposure Ratio (BER)

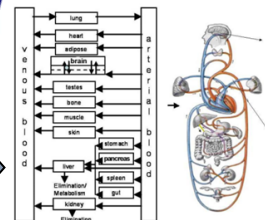


The BER/MoE is defined as the ratio of the PoD and the relevant exposure estimate

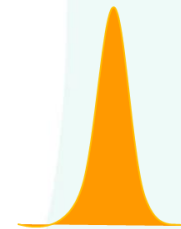
**Consumer Exposure characterisation**



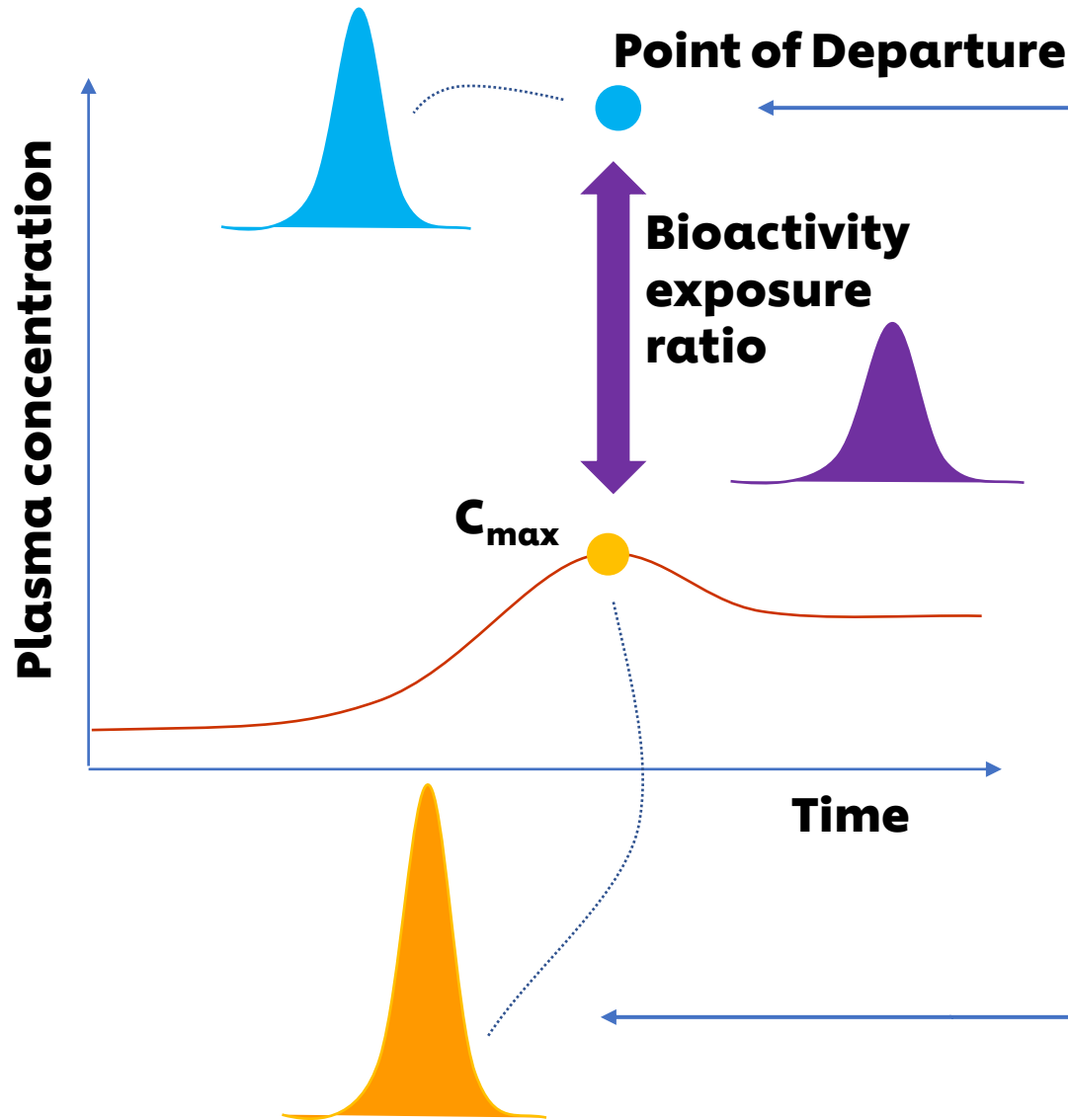
Exposure models (PBK, free/total concentration)



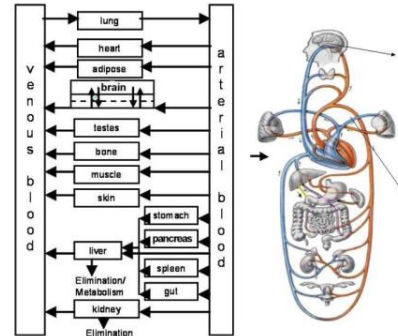
Exposure estimation: Plasma  $C_{max}$



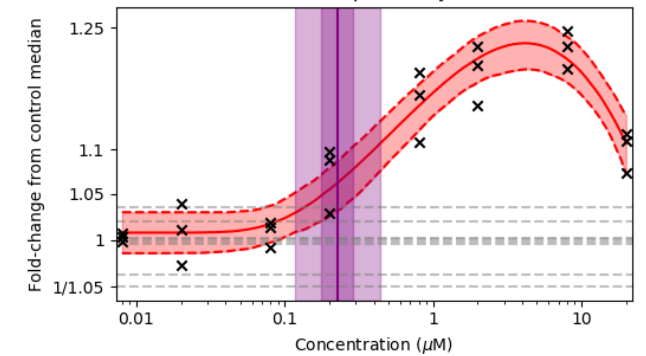
# Bioactivity Exposure Ratio



Exposure models  
(PBK, free/total  
concentration)



NAM\* Point of departure  
derived from *in vitro*  
concentration-response



# Integration of exposure and bioactivity for decision-making – Case studies

## NAMs to support hypothetical read-across NGRA case studies (e.g. caffeine and parabens)

Regulatory Toxicology and Pharmacology 123 (2021) 104931

Contents lists available at ScienceDirect

**Regulatory Toxicology and Pharmacology**


journal homepage: [www.elsevier.com/locate/yrtph](http://www.elsevier.com/locate/yrtph)

**New framework for a non-animal approach adequately assures the safety of cosmetic ingredients – A case study on caffeine**

Dagmar Bury<sup>a</sup>, Camilla Alexander-White<sup>b</sup>, Harvey J. Clewell III<sup>c</sup>, Mark Cronin<sup>d</sup>, Bertrand Desprez<sup>e</sup>, Ann Detroyer<sup>f</sup>, Alina Efremenko<sup>g</sup>, James Firman<sup>d</sup>, Eric Hack<sup>g</sup>, Nicola





 **OECD**  
Organisation for Economic Co-operation and Development

ENV/JM/MONO(2020)16

Unclassified English - Or. English  
24 September 2020

ENVIRONMENT DIRECTORATE  
JOINT MEETING OF THE CHEMICALS COMMITTEE AND THE WORKING PARTY ON CHEMICALS, PESTICIDES AND BIOTECHNOLOGY

Cancels & replaces the same document of 23 September 2020

Case Study on use of an Integrated Approach to Testing and Assessment (IATA) and New Approach Methods to Inform a Theoretical Read-Across for Dermal Exposure to Propylparaben from Cosmetics

Series on Testing and Assessment  
No. 320

## NAMs applied in an *ab initio* hypothetical/NGRA case study

OXFORD **SOT** Society of Toxicology  
academic.oup.com/toxsci

TOXICOLOGICAL SCIENCES, 176(1), 2020, 236–252  
doi: 10.1093/toxsci/ktaa048  
Advance Access Publication Date: April 10, 2020  
Research article

**A Next-Generation Risk Assessment Case Study for Coumarin in Cosmetic Products**

Maria T. Baltazar,<sup>1</sup> Sophie Cable, Paul L. Carmichael, Richard Cubberley, Tom Cull, Mona Delagrange, Matthew P. Dent, Sarah Hatherell, Jade Houghton, Predrag Kukic, Hequn Li, Mi-Young Lee, Sophie Malcomber, Alistair M. Middleton, Thomas E. Moxon, Alexis V. Nathanail, Beate Nicol, Ruth Pendlington, Georgia Reynolds, Joe Reynolds, Andrew White, and Carl Westmoreland

Unilever Safety and Environmental Assurance Centre, Colworth Science Park, Sharnbrook, Bedfordshire MK44 1LQ, UK

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## NAMs applied in real-life chemical safety assessments

APPLIED IN VITRO TOXICOLOGY  
Volume 7, Number 2, 2021  
© Mary Ann Liebert, Inc.  
DOI: 10.1089/aivt.2021.0005

**Use of the MucilAir Airway Assay, a New Approach Methodology, for Evaluating the Safety and Inhalation Risk of Agrochemicals**

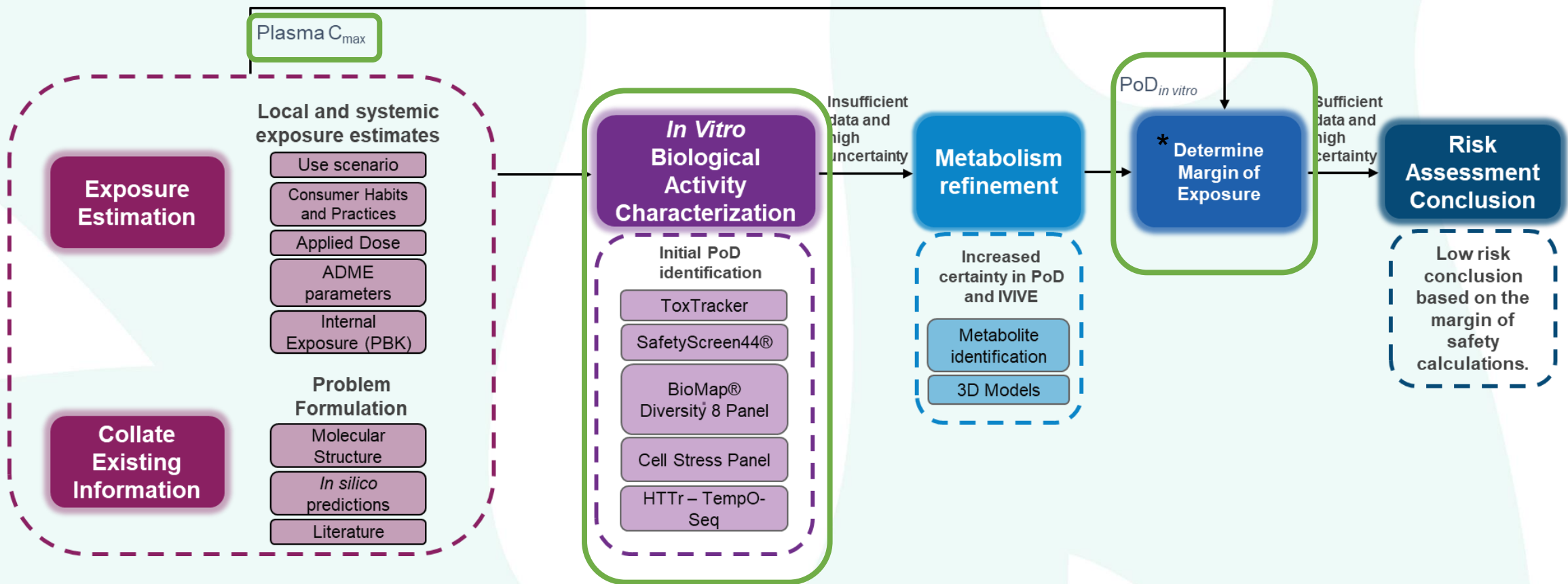
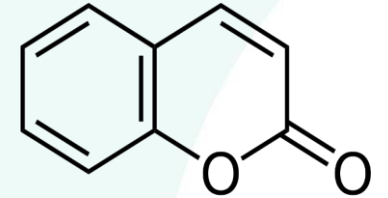
Marie McGee Hargrove,<sup>1,1</sup> Bob Parr-Dobrzanski,<sup>2</sup> Lei Li,<sup>3</sup> Samuel Constant,<sup>4</sup> Joanne Wallace,<sup>5</sup> Paul Hinderliter,<sup>1,\*</sup> Douglas C. Wolf,<sup>1</sup> and Alex Charlton<sup>2</sup>



<https://www.regulations.gov/document/EPA-HQ-OPP-2011-0840-0080>

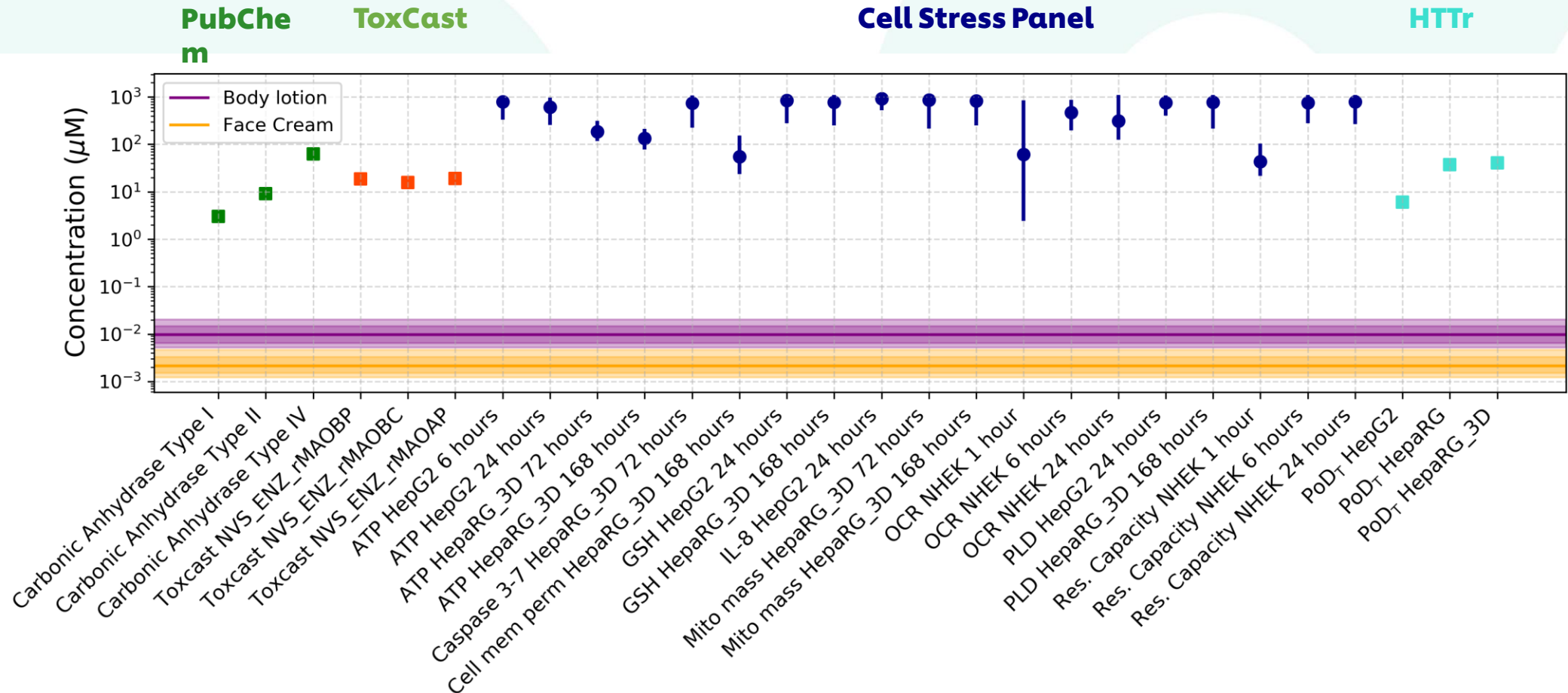
# Example how to integrate NAMs for a NGRA: coumarin case study

## 0.1% COUMARIN IN FACE CREAM AND BODY LOTION (NEW FRAGRANCE)





# Exposure and PoD are plotted and used to derive a Bioactivity-Exposure Ratio (MoE/BER)



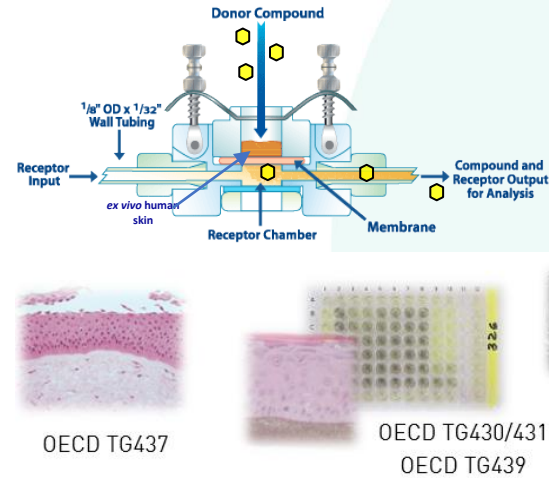
- **The 5th percentile of the BER distribution ranged between 158 and 96738**



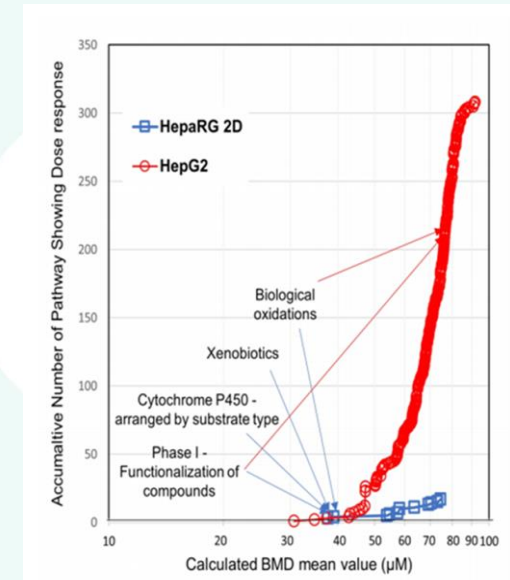
# Next Generation Risk Assessment is highly interdisciplinary



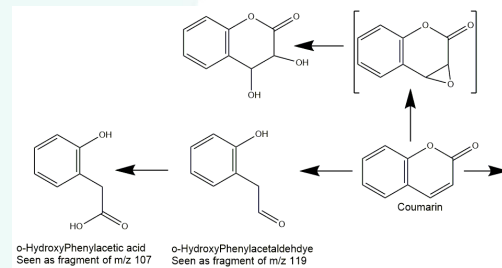
Risk assessment



Biology



Bioinformatics



Chemistry

$$y_t = \underbrace{\begin{bmatrix} w_{g,1}^{(1)} & \dots & w_{g,1}^{(m)} \\ \vdots & & \vdots \\ w_{g,n_y}^{(1)} & \dots & w_{g,n_y}^{(m)} \end{bmatrix}}_C \underbrace{\begin{bmatrix} \phi_g^{(1)}(x_t, u_t) \\ \vdots \\ \phi_g^{(m)}(x_t, u_t) \end{bmatrix}}_{\bar{\varphi}_g(x_t, u_t)} + e_t.$$

Mathematical and statistical modelling

# Back to the toolbox

### PBK models

### Free concentration

### Conc. Resp. models

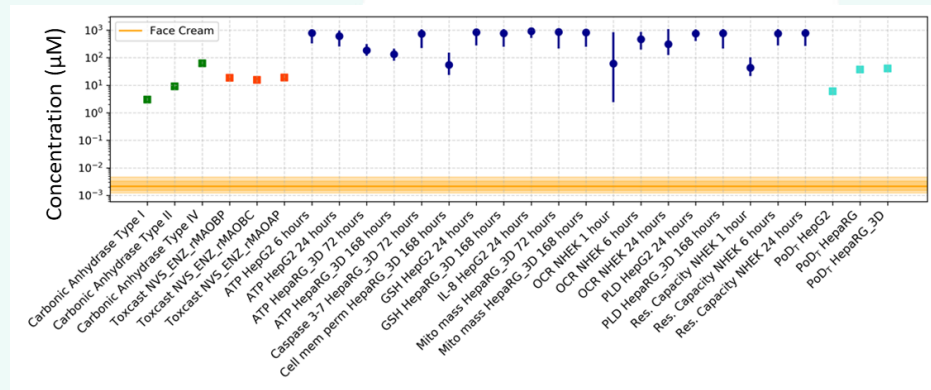
### HTTr

### CSP

### IPP



## Bioactivity exposure ratio



Inform safety decision

HTTr: High-throughput transcriptomics

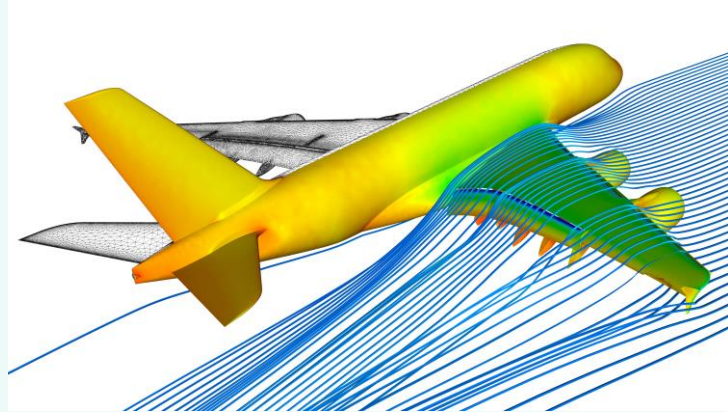
CSP: Cell Stress Panel

IPP: In vitro pharmacological profiling



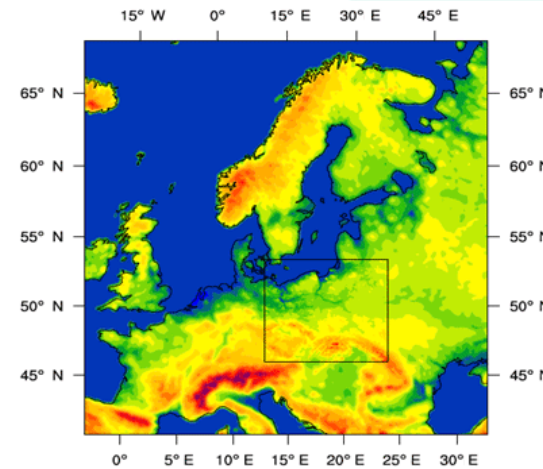
# Computational models and their impact on everyday life

Air transport



dlr.de

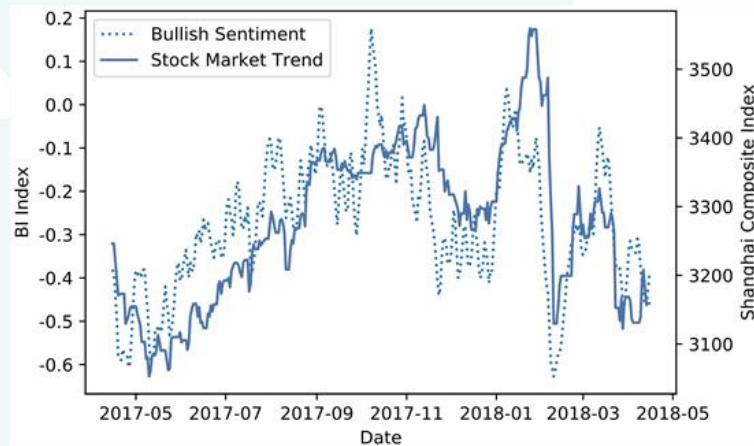
Weather forecast



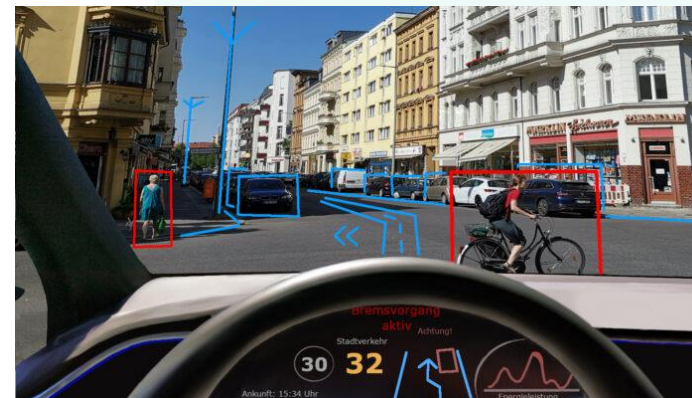
Satnav



Stock market



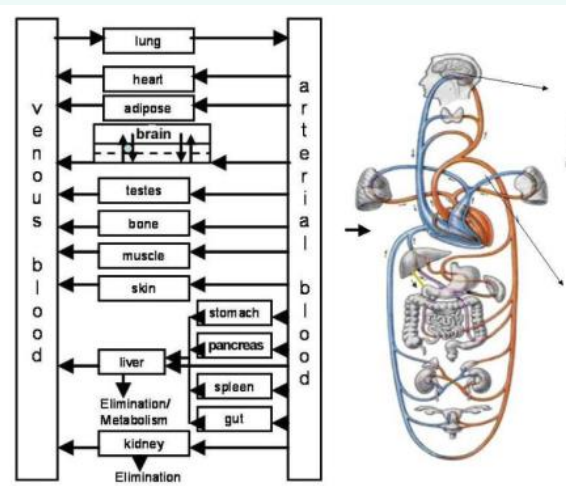
Self driving cars



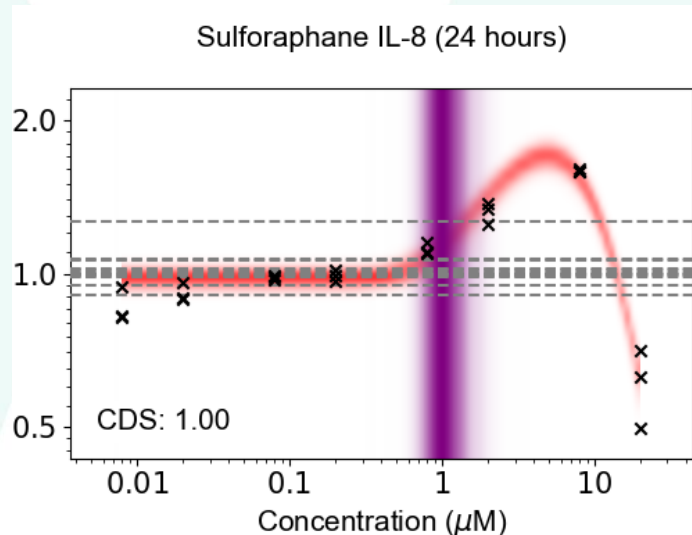
digitalgyan.org

# Different types of computational approaches used in NGRA

## Physiologically-based kinetic (PBK) modelling



## Dose response modelling

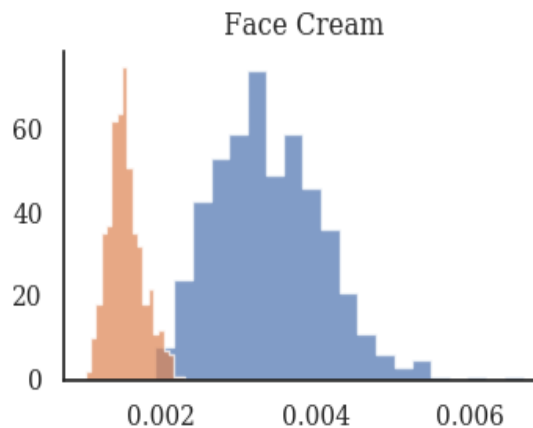


## In silico tools

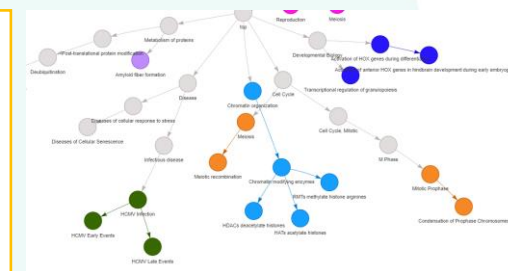
The screenshot shows the ToxTree software interface. The main window displays the chemical structure of Sulforaphane IL-8 and its hazard classification. The classification is based on Cramer rules and is categorized as High (Class III). The interface includes a menu bar, a toolbar, and a main display area with a structure diagram and a list of Cramer rules.

ToxTree

## Statistical models of uncertainty and variability



## Bioinformatics tools for analysing omics data



# Dose response models

# The cell stress panel

Intended to cover off non-specific modes of action that lead to cell stress or mitochondrial toxicity

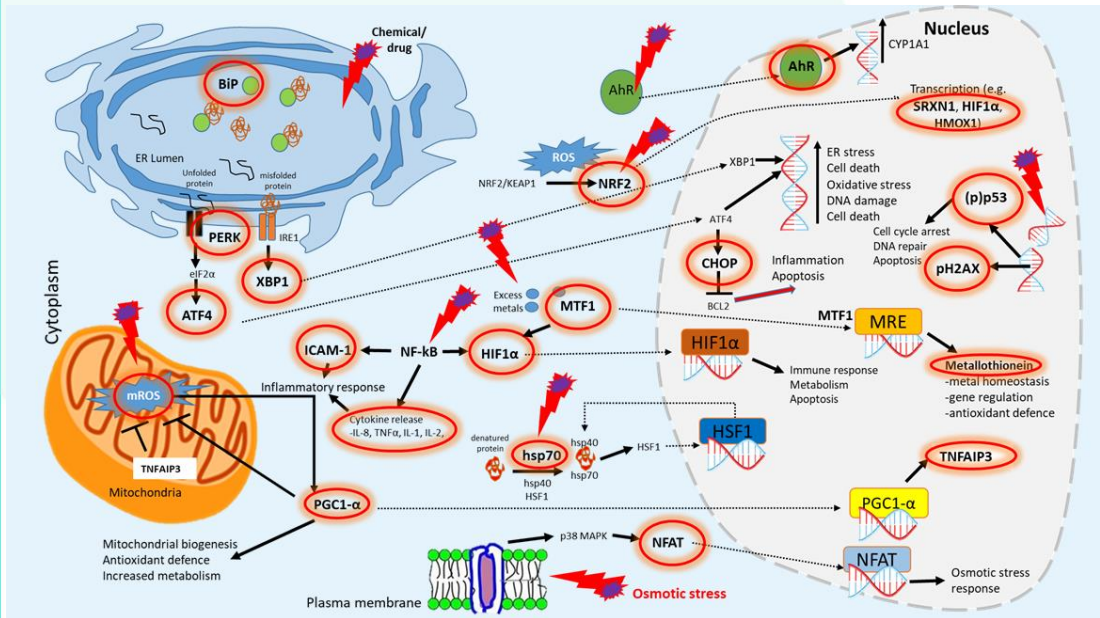


Image kindly provided by Paul Walker (Cyprotex)



TOXICOLOGICAL SCIENCES, 2020, 1-23

doi: 10.1093/toxsci/kfaa054  
Advance Access Publication Date: May 6, 2020  
Research article

## Identifying and Characterizing Stress Pathways of Concern for Consumer Safety in Next-Generation Risk Assessment

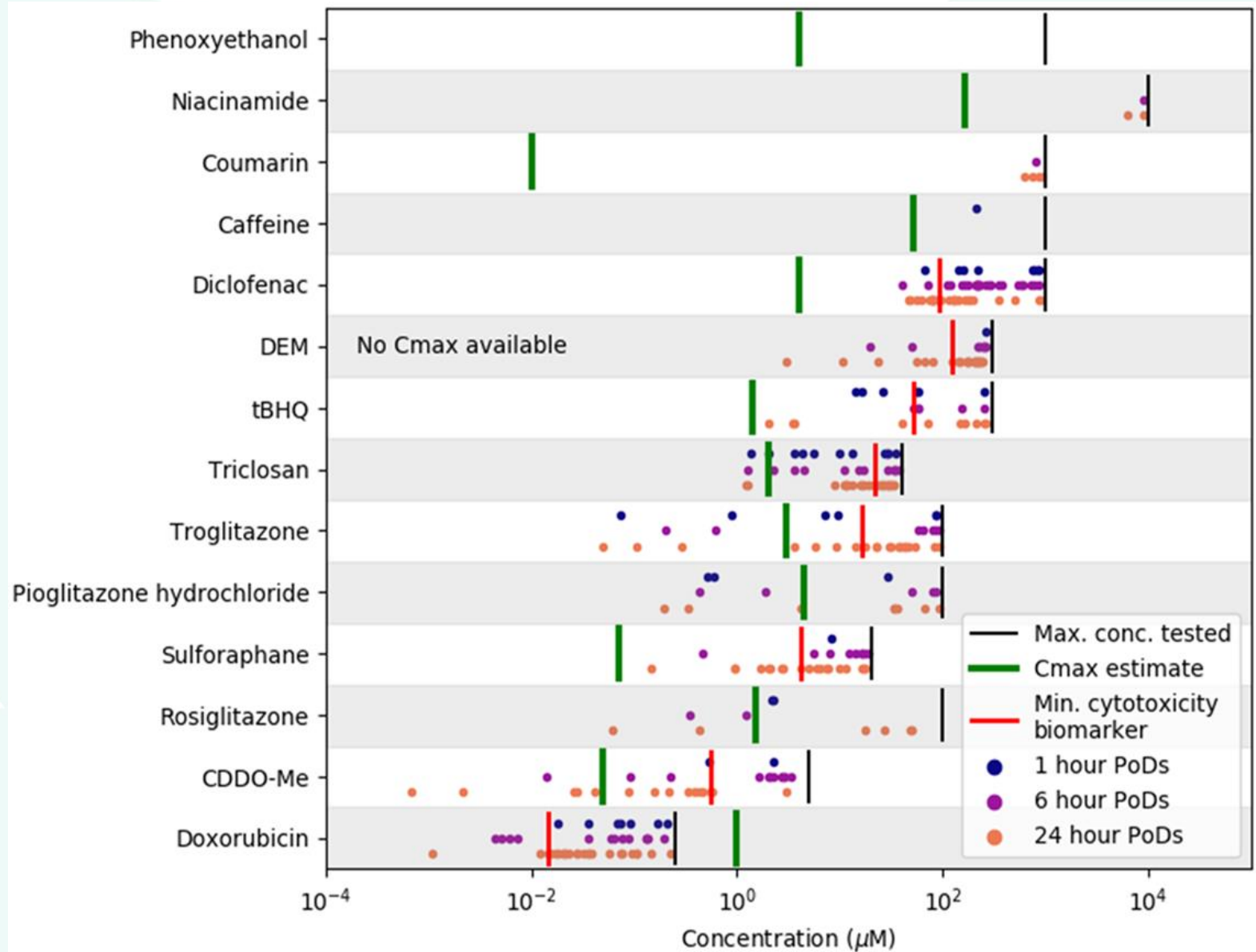
Sarah Hatherell,\* Maria T. Baltazar,\* Joe Reynolds,\* Paul L. Carmichael,\* Matthew Dent,\* Hequn Li,\* Stephanie Ryder,<sup>†</sup> Andrew White,\* Paul Walker ,<sup>†</sup> and Alistair M. Middleton\*<sup>1</sup>

\*Unilever Safety and Environmental Assurance Centre. Colworth Science Park. Sharnbrook. Bedfordshire

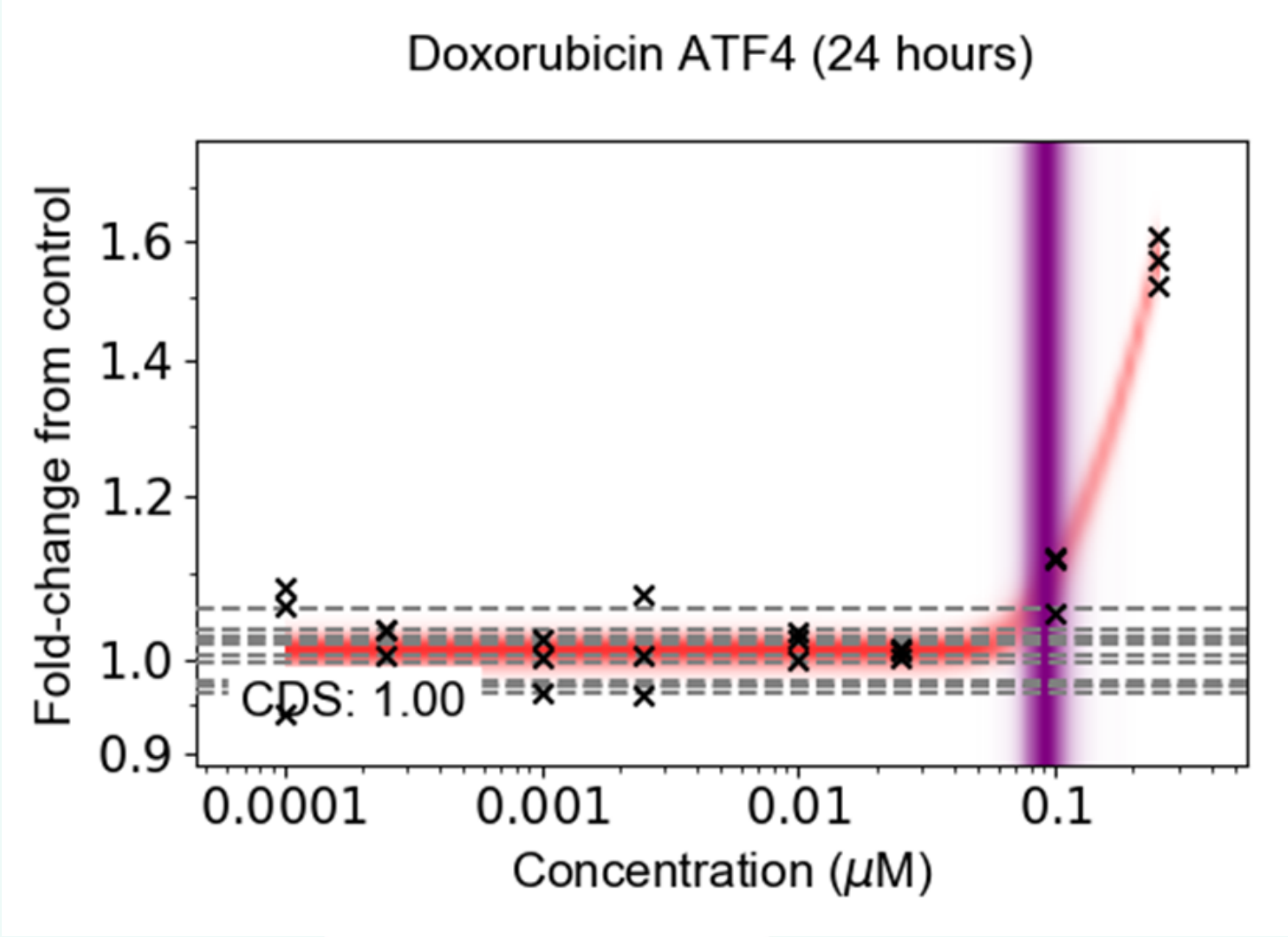
**36 biomarkers identified that were representative of key stress pathways, mitochondrial toxicity and cell health.**

**Cell stress biomarkers predominantly measured using high content imaging. Includes Extracellular Flux assay to measure mitochondrial function.**





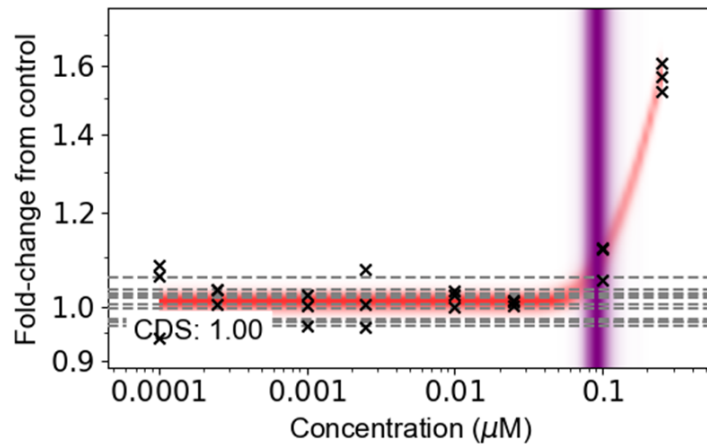
# Dose response analysis and estimating PODs



# Dose response analysis and estimating PODs

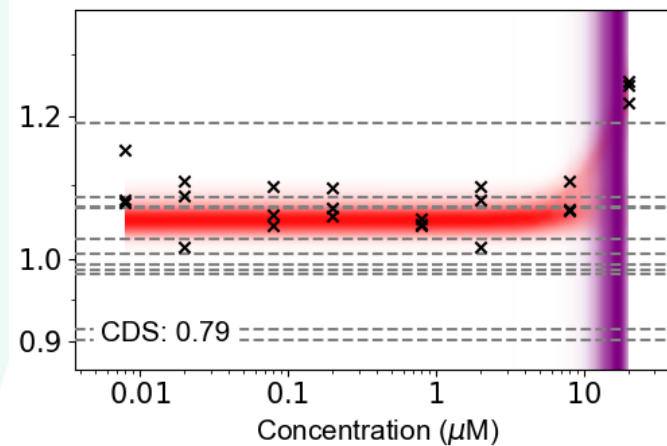
## Clear effect

Doxorubicin ATF4 (24 hours)



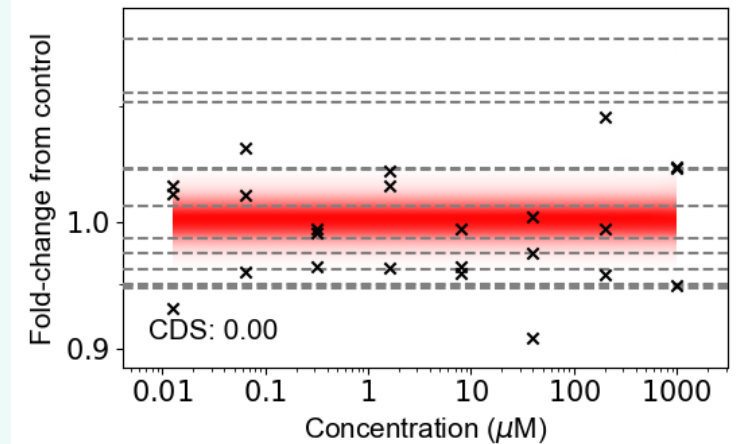
## Is there an effect here?

Sulforaphane DNA struct (24 hours)



## No effect

Caffeine ROS (24 hours)



- Broadly, there are two approaches to doing this – **parametric** and **non-parametric**
- We will focus on the **parametric** approach

# Principles of model development and the wet-dry cycle

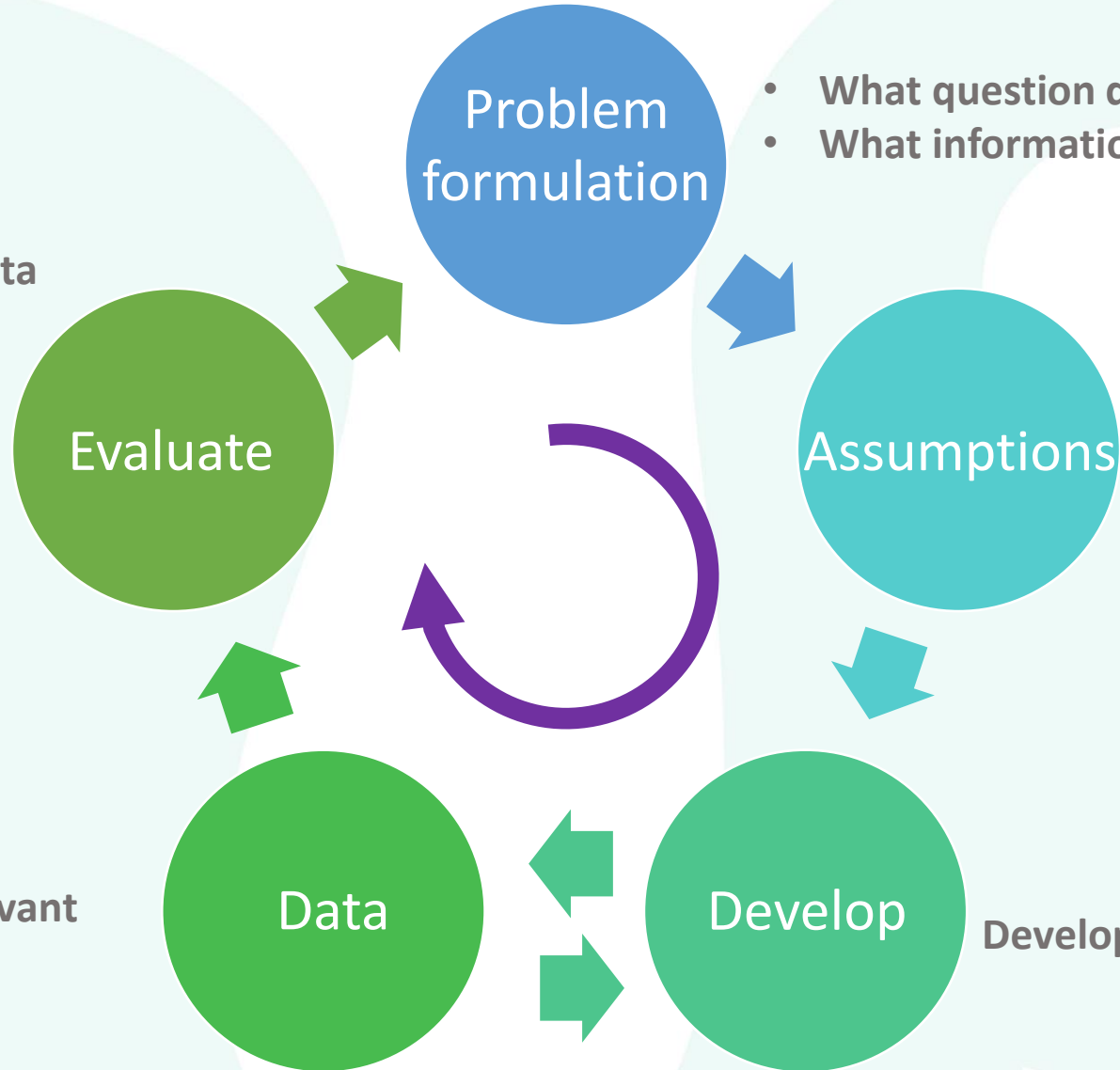
How does the model perform?  
Does it describe the data well?

- What question do you want to answer?
- What information do you have available?

Define model assumptions

Develop and implement the model

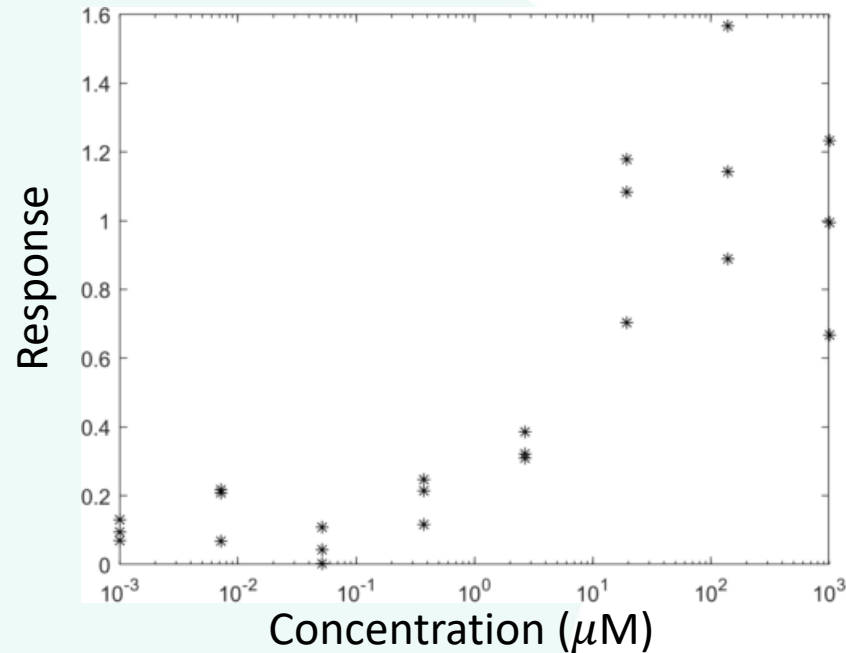
Generate/curate relevant data



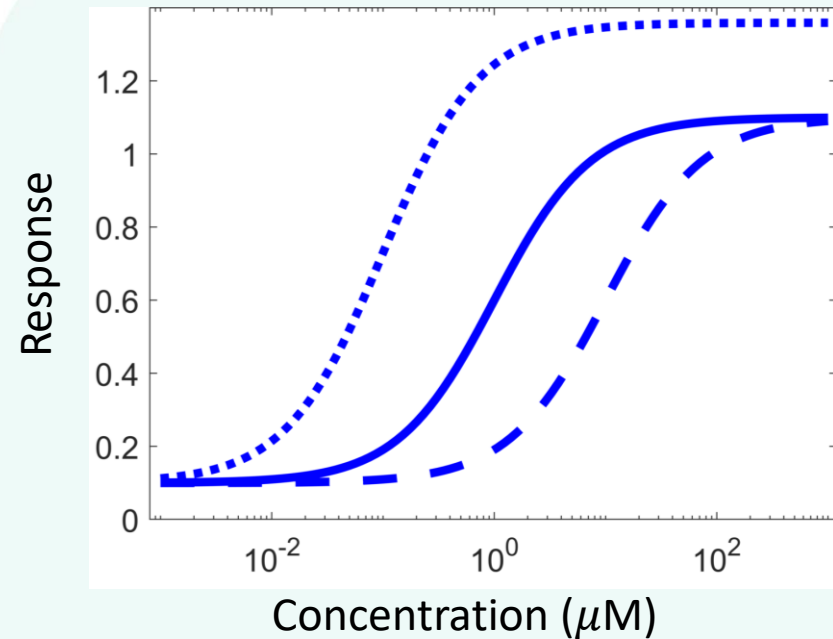


# Developing a dose response model

## Example dose response data



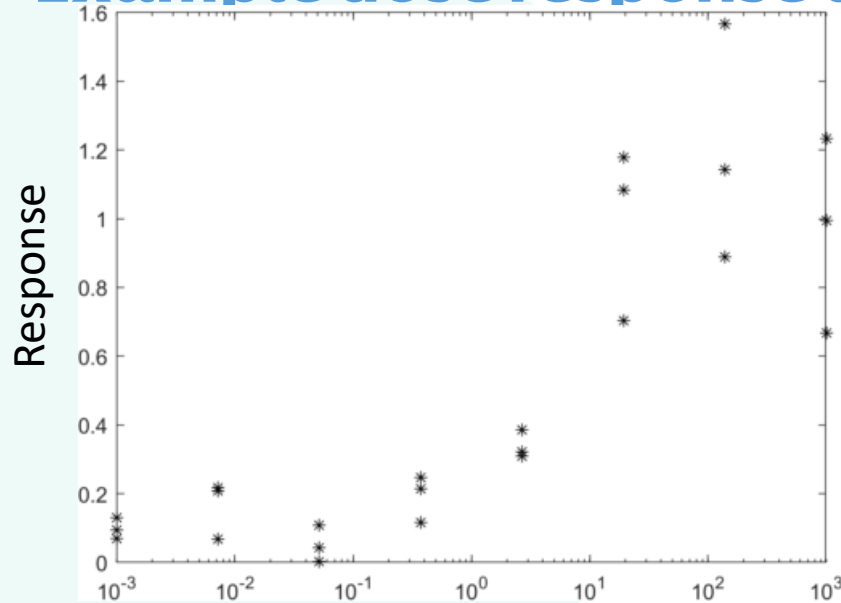
## Hill function



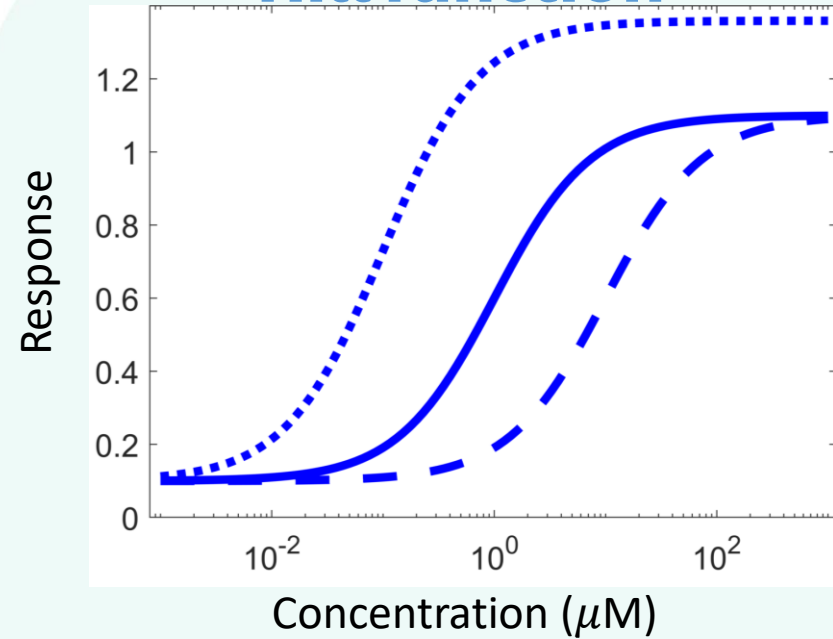
- **Problem:** We want to know:
  - Does the chemical have an effect on our biomarker
  - At what concentration does this occur?
  - We want to quantify the uncertainty in these.
- **Assumption:** There is an increase in our biomarker, which can be captured using a Hill function.

# Back to the dose response example

## Example dose response data



## Hill function

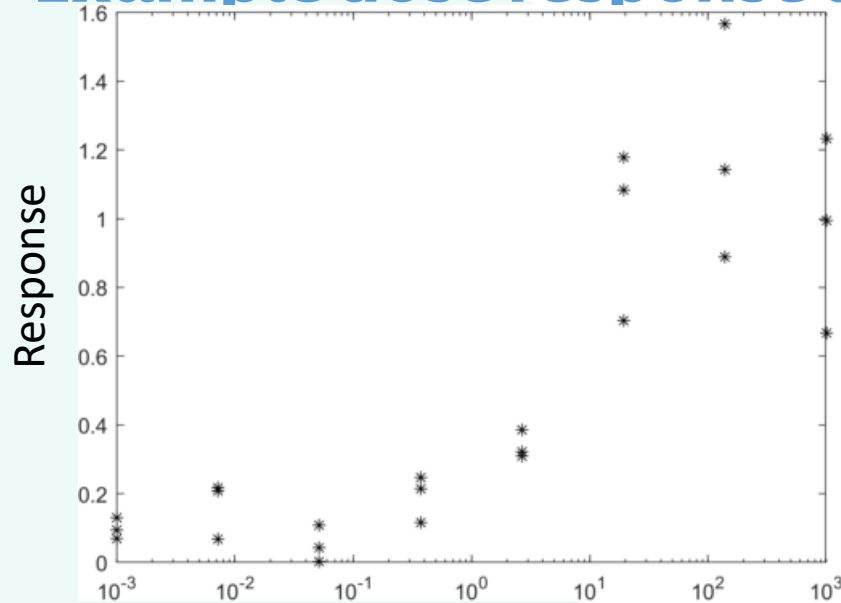


## Develop

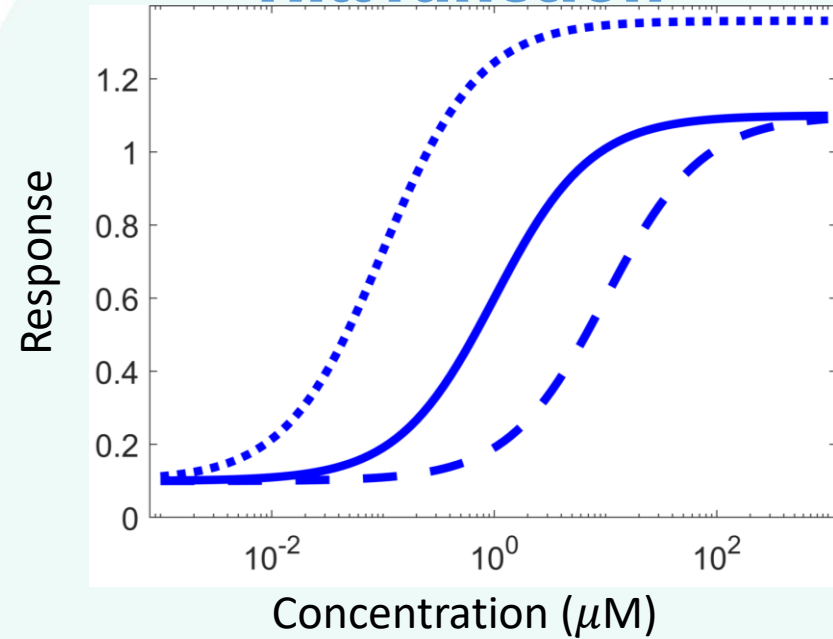
- Main building blocks of the model:
  - Measured data = Mean Response + Observational Noise
  - $y = f(x|C, \theta, V_{max}) + \eta$
- $y$  and  $x$  are the observations and concentrations respectively.
- Assume  $\eta$  is normally distributed with standard deviation  $\sigma$

# Using Bayesian models to quantify uncertainty

## Example dose response data



## Hill function



## Develop

- Hill equation:

$$f(x|C, \theta, V_{max}) = V_{max} \frac{x}{x + \theta} + C$$

- (full Hill equation has exponent on  $x$  and  $\theta$  to obtain sharper curves)

# Bayesian statistics – what and why

## Bayesian probability:

- Probability reflects the **plausibility** or **belief** in some event being true.
- Provides framework for updating plausibility based on available data.
- For example, can talk about the **probability of a hypothesis being true**, or a parameter taking on a certain value.
- Key terms: credible interval, priors, posterior

## Frequentist probability

- What people are normally taught in school
- Basis for **p-values** and **hypothesis testing**
- Probability reflects the relative frequency at which an event occurs in many over many repeated trials.
- Only really relevant when dealing with **well-defined random experiments**
- Can't use it to talk about the probability of a 'parameter taking a certain value' or a 'hypothesis being true'.



Thomas Bayes, 1701-1761

# Bayesian statistics – what and why

## Bayesian interpretation of probability

- Probability quantifies the plausibility of some event.
- **Bayes' theorem:**

The diagram illustrates Bayes' theorem with three blue boxes: 'Posterior' on the left, 'Likelihood' in the middle, and 'Prior' on the right. An arrow points from 'Posterior' to the left side of the equation. An arrow points from 'Likelihood' to the numerator of the fraction. Another arrow points from 'Prior' to the numerator of the fraction. The equation is: 
$$P(X|D) = \frac{P(D|X)P(X)}{P(D)}$$

- Here, D is the data and X is random variable
- E.g.,  $X = V_{\max}$  parameter, D – experimental observations
- The key things are the likelihood, the prior and the posterior:
  - **Posterior:** probability that  $V_{\max}$  takes a certain value
  - **Likelihood:** probability of the data, given  $V_{\max}$
  - **Prior:** probability reflecting initial assumptions  $V_{\max}$

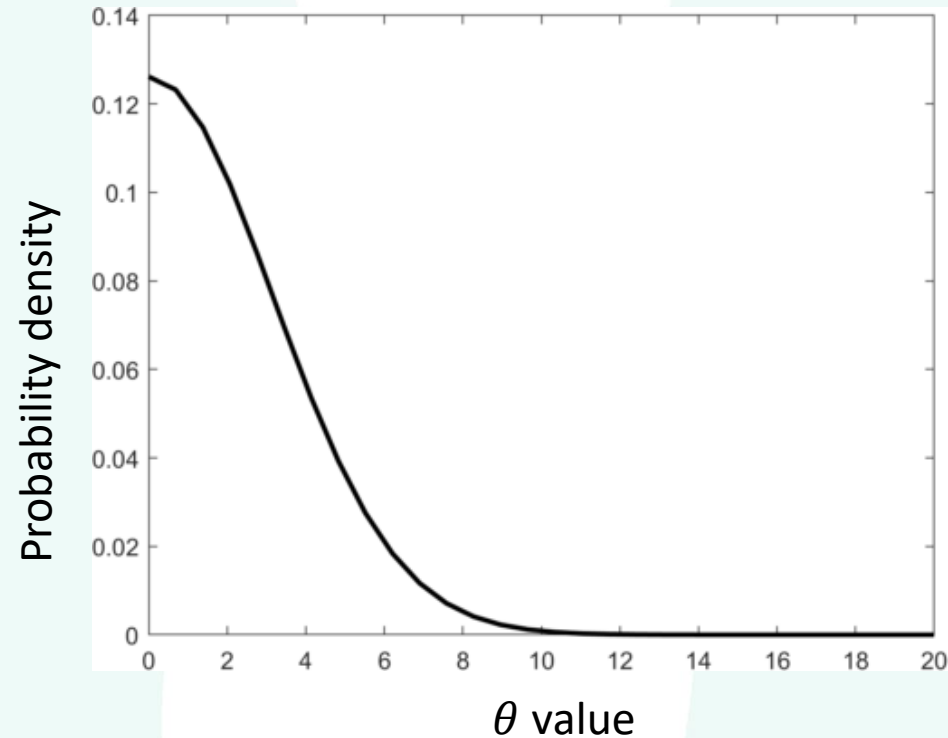


# Example of a prior

## Develop

- Have parameters  $\theta$ ,  $C$ ,  $V_{max}$  and  $\sigma$  – need to be learned from the data

Prior for  $\theta$  (threshold value)

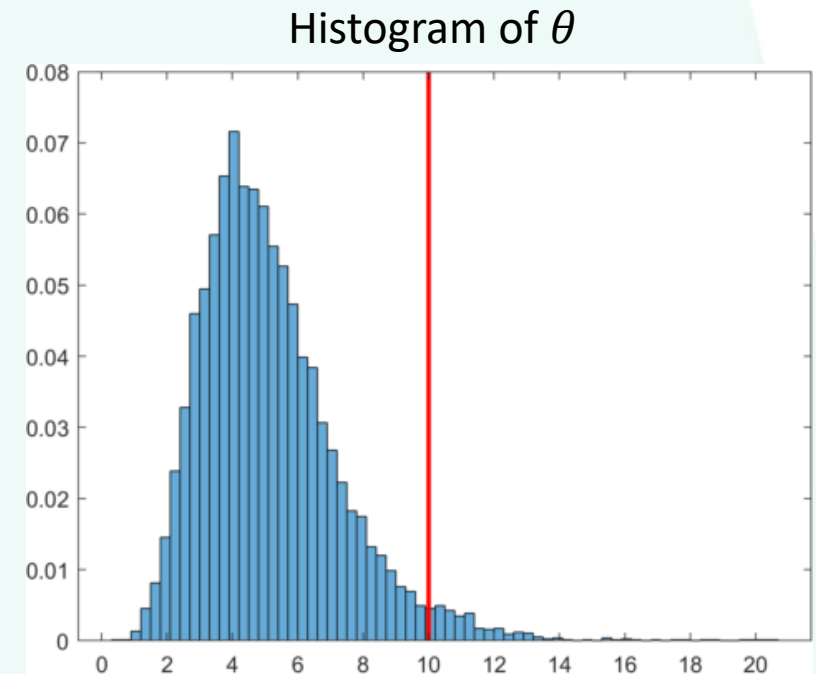
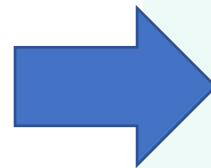
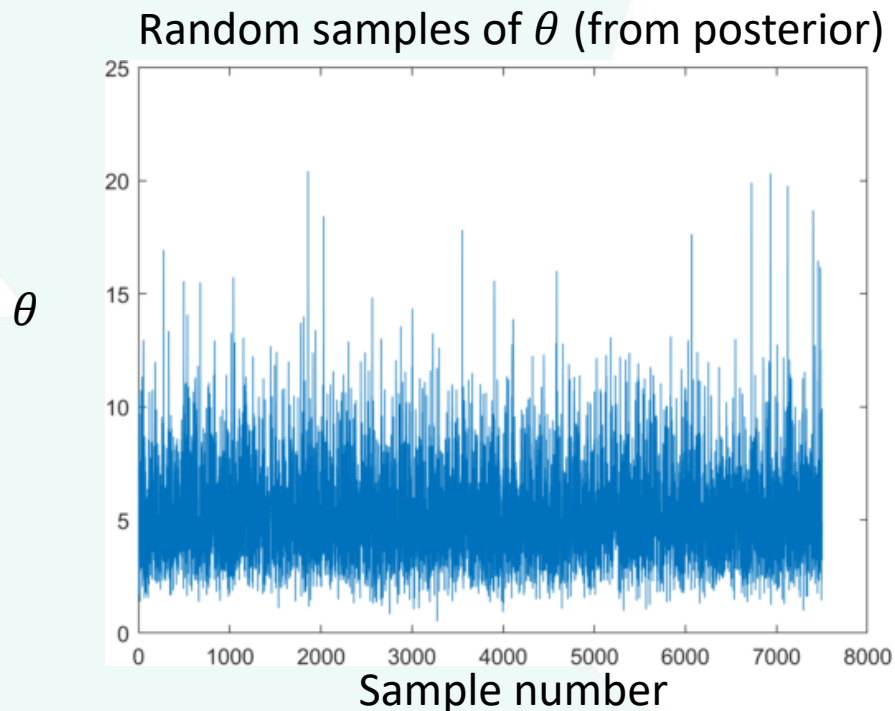


## Data

- Typically you only have the measured values that you are fitting to, but you could incorporate prior knowledge (e.g. biologically plausible values) into the prior.

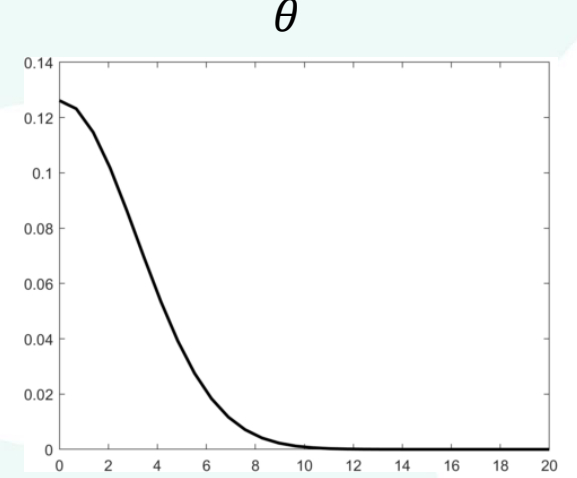
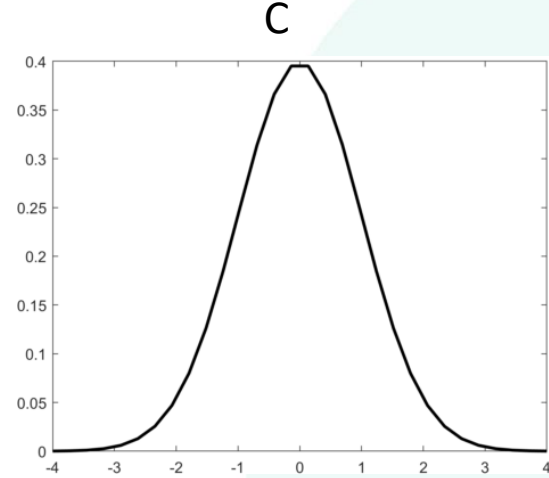
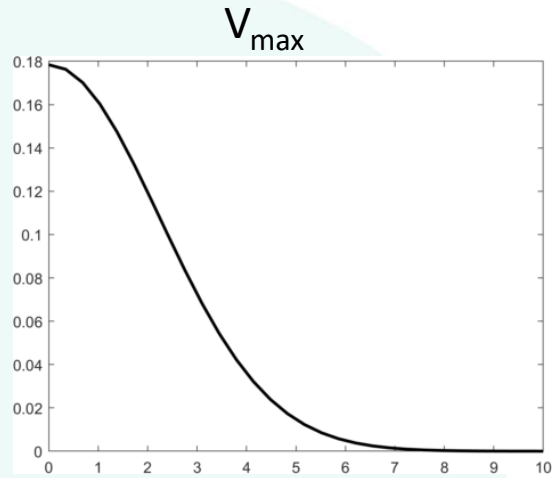
# Learning parameters from the data

- One things that's important to know about Bayesian statistics is that for most problems, it is impossible to get an exact solution to the posterior.
- Resort to using methods like **Markov Chain Monte Carlo (MCMC)** to take random samples from the distribution.

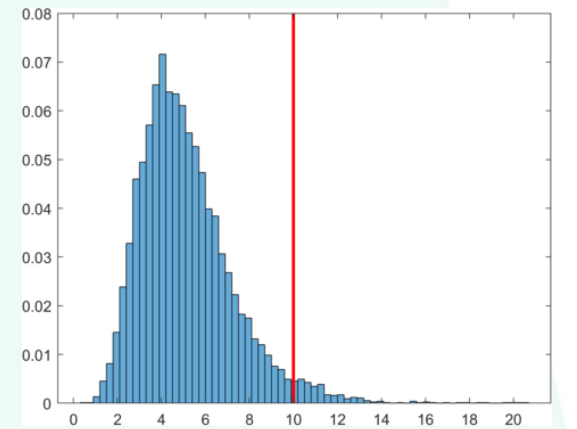
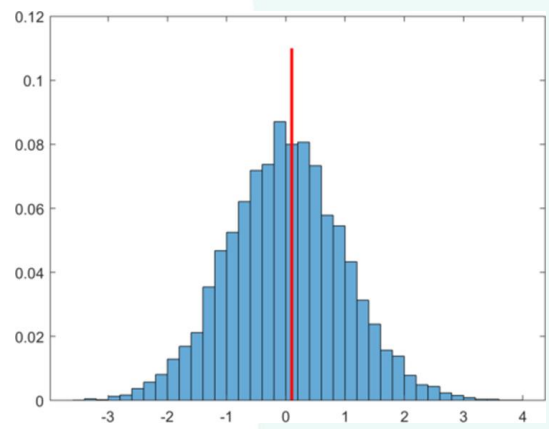
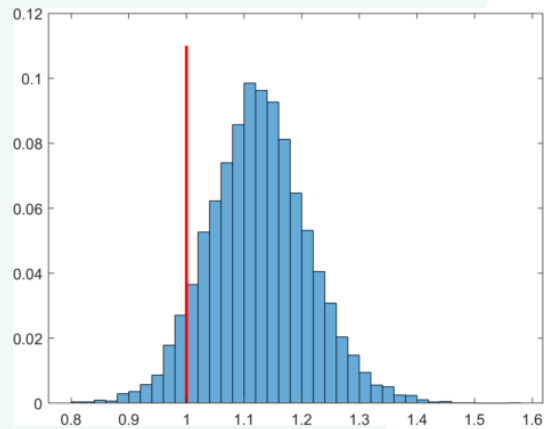


# Learning parameters from the data: prior vs posterior

Prior

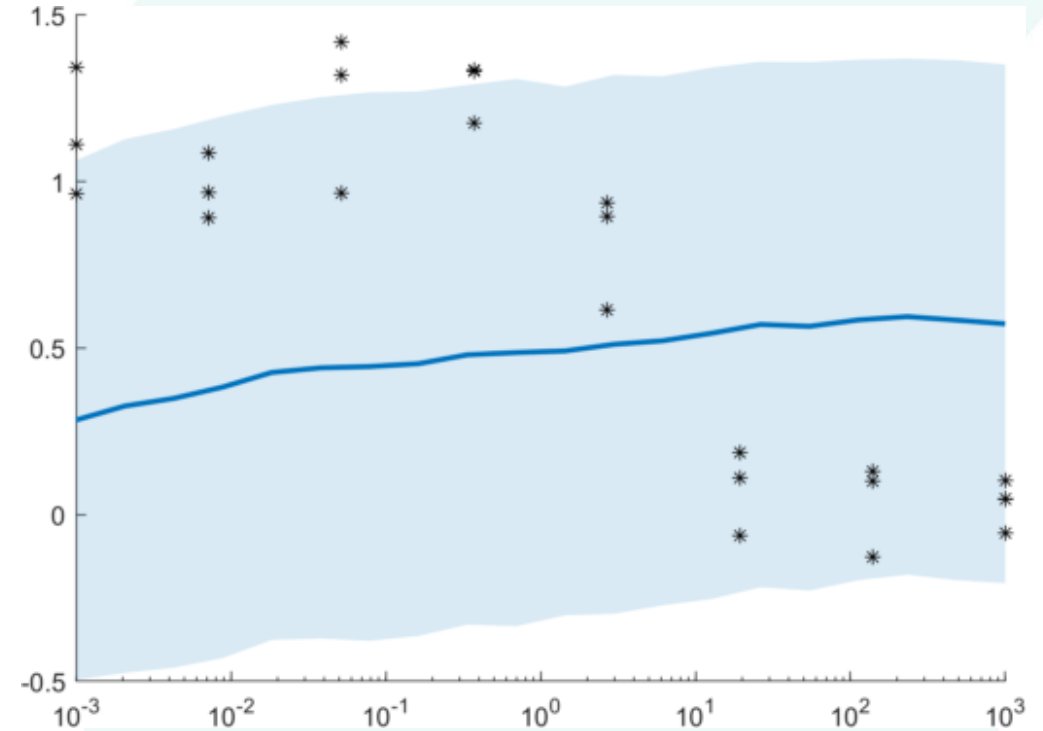
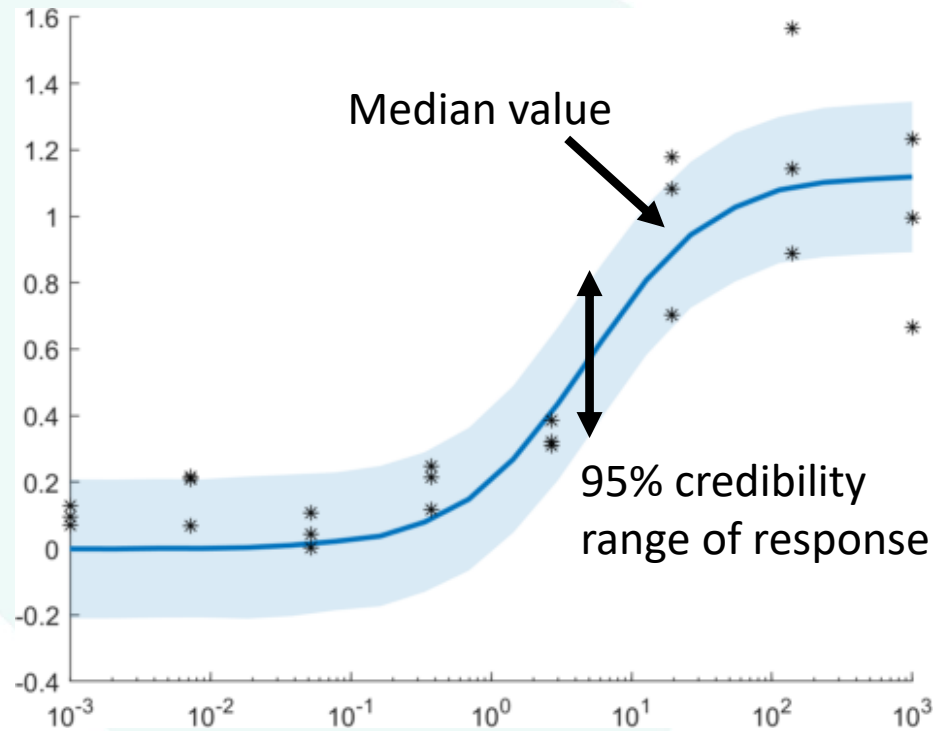


Posterior



Red horizontal line indicates the 'true' value

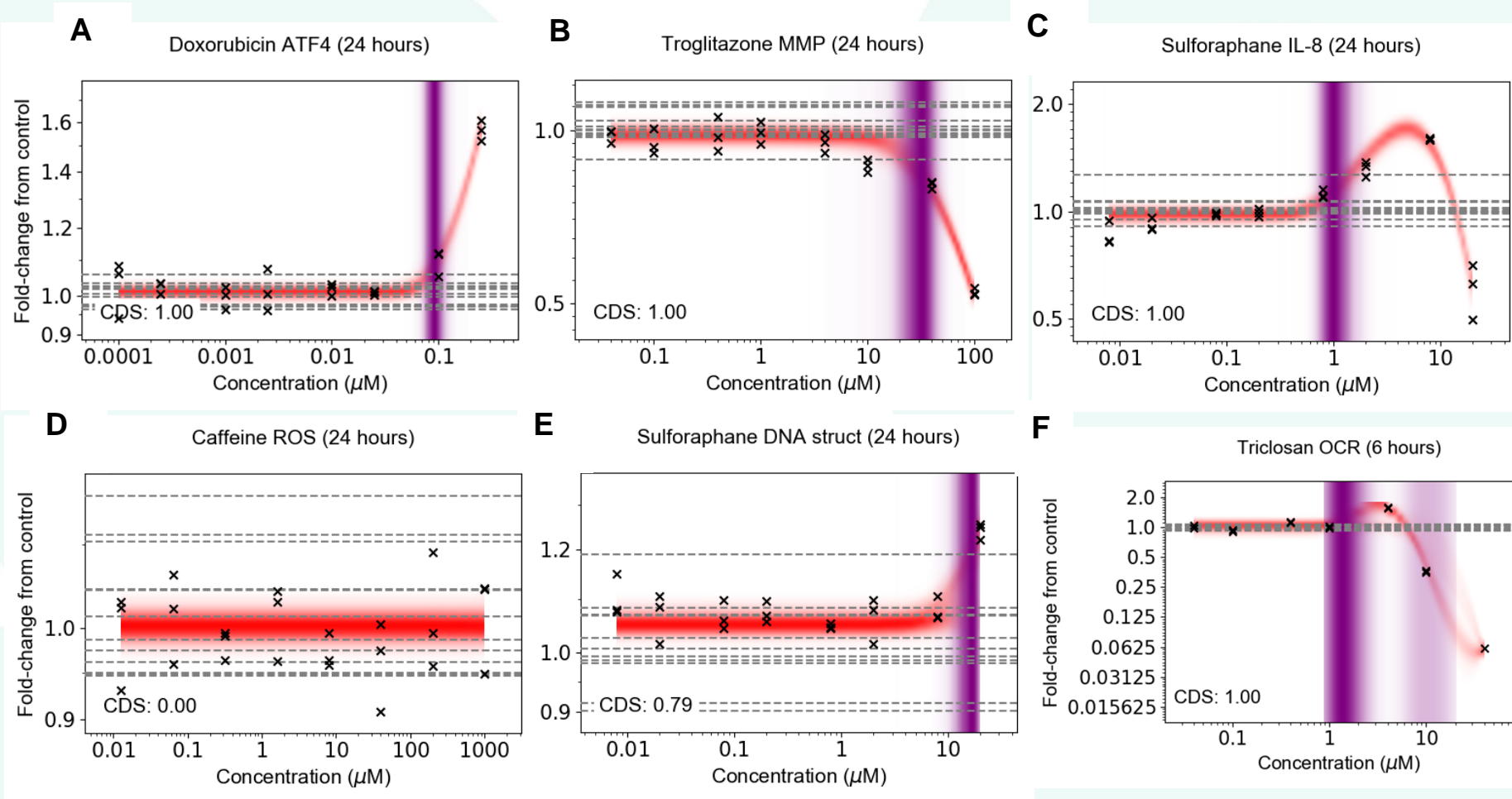
# Evaluating the dose response model



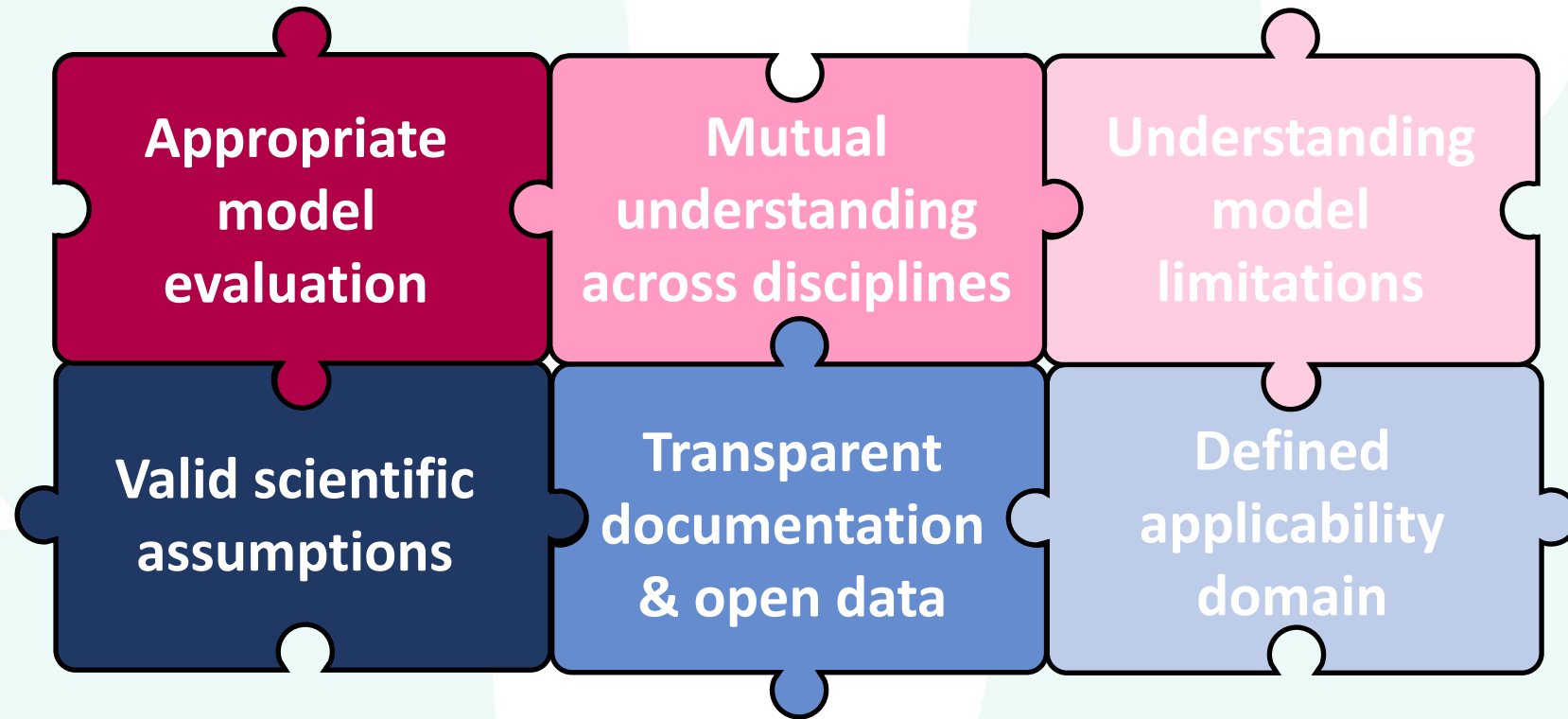
- Bayesian models can be evaluated by comparing the predictive distributions to the training data
- When using parametric models is to fit data to multiple models and decide which one is best
- Sometimes you can miss effects, not because there is no effect, but because the model does a poor job of describing the data



# Back to the cell stress panel



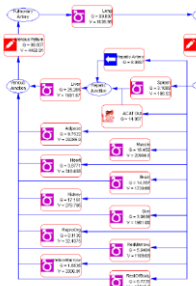
# Challenges in the acceptance of using computational approaches in NGRA



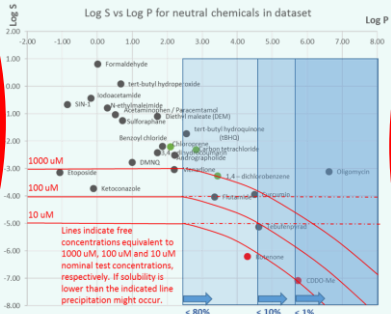
# Evaluating a toolbox of NAMs

# Back to the toolbox

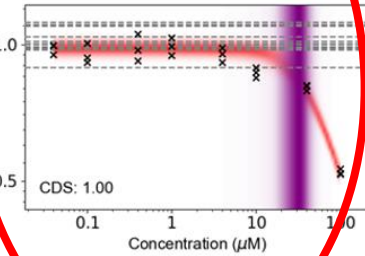
## PBK models



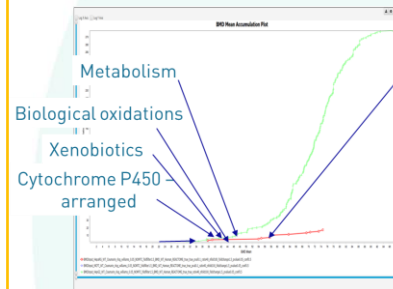
## Free concentration



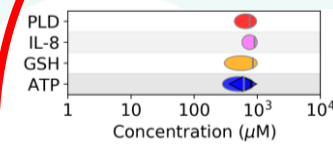
## Conc. Resp. models



## HTTr



## CSP

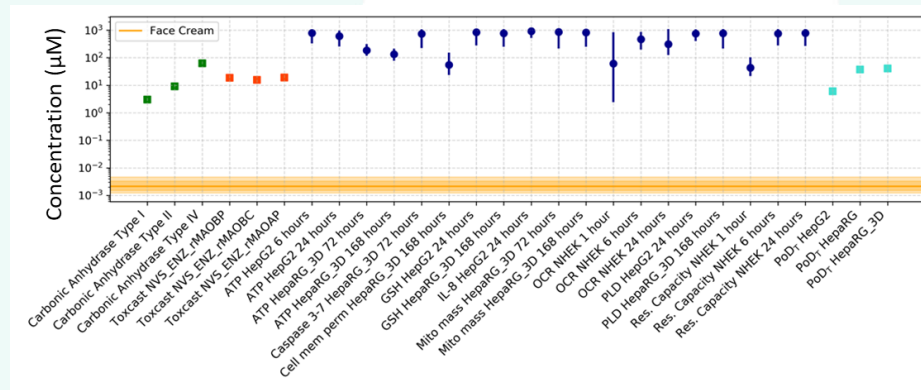


## IPP

Target	IC50 (uM)	IC90 (uM)	IC95 (uM)	IC99 (uM)
MAO-A	0.001	0.001	0.001	0.001
MAO-B	0.001	0.001	0.001	0.001
COMT	0.001	0.001	0.001	0.001
ADAMTS-1	0.001	0.001	0.001	0.001
ADAMTS-2	0.001	0.001	0.001	0.001
ADAMTS-3	0.001	0.001	0.001	0.001
ADAMTS-4	0.001	0.001	0.001	0.001
ADAMTS-5	0.001	0.001	0.001	0.001
ADAMTS-6	0.001	0.001	0.001	0.001
ADAMTS-7	0.001	0.001	0.001	0.001
ADAMTS-8	0.001	0.001	0.001	0.001
ADAMTS-9	0.001	0.001	0.001	0.001
ADAMTS-10	0.001	0.001	0.001	0.001
ADAMTS-11	0.001	0.001	0.001	0.001
ADAMTS-12	0.001	0.001	0.001	0.001
ADAMTS-13	0.001	0.001	0.001	0.001
ADAMTS-14	0.001	0.001	0.001	0.001
ADAMTS-15	0.001	0.001	0.001	0.001
ADAMTS-16	0.001	0.001	0.001	0.001
ADAMTS-17	0.001	0.001	0.001	0.001
ADAMTS-18	0.001	0.001	0.001	0.001
ADAMTS-19	0.001	0.001	0.001	0.001
ADAMTS-20	0.001	0.001	0.001	0.001
ADAMTS-21	0.001	0.001	0.001	0.001
ADAMTS-22	0.001	0.001	0.001	0.001
ADAMTS-23	0.001	0.001	0.001	0.001
ADAMTS-24	0.001	0.001	0.001	0.001
ADAMTS-25	0.001	0.001	0.001	0.001
ADAMTS-26	0.001	0.001	0.001	0.001
ADAMTS-27	0.001	0.001	0.001	0.001
ADAMTS-28	0.001	0.001	0.001	0.001
ADAMTS-29	0.001	0.001	0.001	0.001
ADAMTS-30	0.001	0.001	0.001	0.001
ADAMTS-31	0.001	0.001	0.001	0.001
ADAMTS-32	0.001	0.001	0.001	0.001
ADAMTS-33	0.001	0.001	0.001	0.001
ADAMTS-34	0.001	0.001	0.001	0.001
ADAMTS-35	0.001	0.001	0.001	0.001
ADAMTS-36	0.001	0.001	0.001	0.001
ADAMTS-37	0.001	0.001	0.001	0.001
ADAMTS-38	0.001	0.001	0.001	0.001
ADAMTS-39	0.001	0.001	0.001	0.001
ADAMTS-40	0.001	0.001	0.001	0.001
ADAMTS-41	0.001	0.001	0.001	0.001
ADAMTS-42	0.001	0.001	0.001	0.001
ADAMTS-43	0.001	0.001	0.001	0.001
ADAMTS-44	0.001	0.001	0.001	0.001
ADAMTS-45	0.001	0.001	0.001	0.001
ADAMTS-46	0.001	0.001	0.001	0.001
ADAMTS-47	0.001	0.001	0.001	0.001
ADAMTS-48	0.001	0.001	0.001	0.001
ADAMTS-49	0.001	0.001	0.001	0.001
ADAMTS-50	0.001	0.001	0.001	0.001

- All binding and enzymatic assay results were negative at 10 uM, including COX-1 and COX-2
- Highest inhibition (22%) was for MAO-A

## Bioactivity exposure ratio



Inform safety decision

HTTr: High-throughput transcriptomics

CSP: Cell Stress Panel

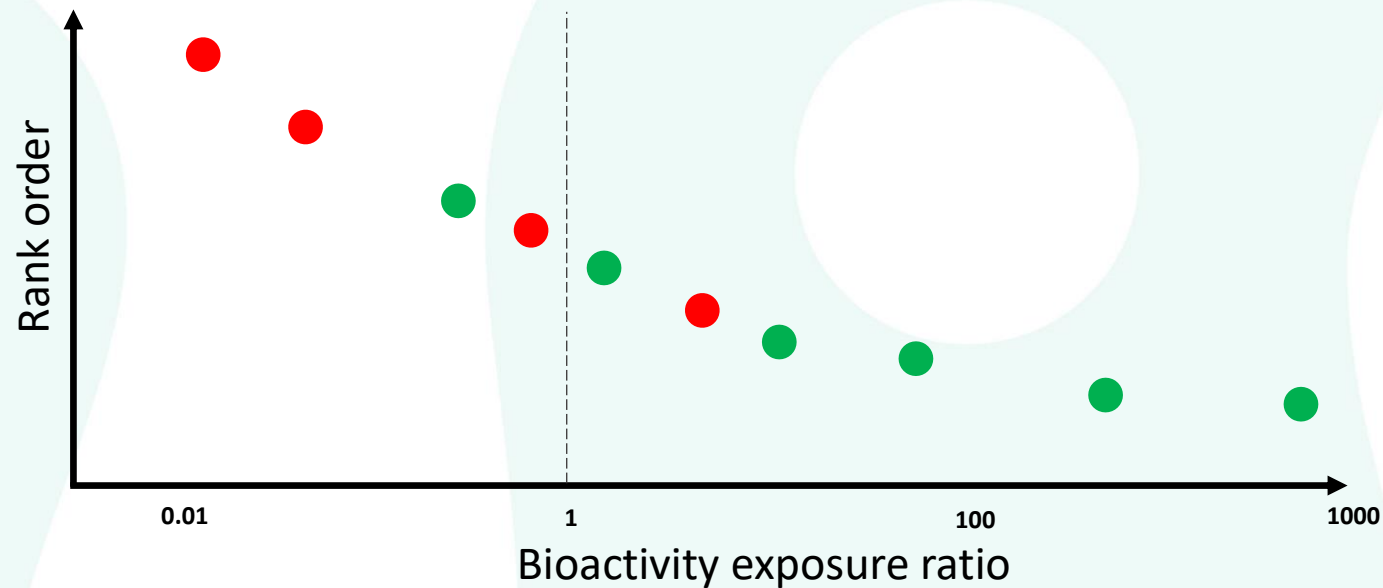
IPP: In vitro pharmacological profiling



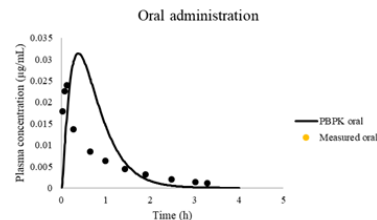
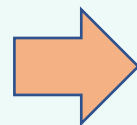
# An evaluation strategy for the toolbox

## Chemical exposures scenarios

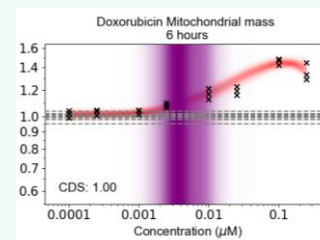
- 'Low' risk (from consumer goods perspective) – e.g. foods, cosmetics
- 'High' risk (from consumer goods perspective) – e.g. drugs



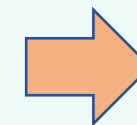
Define typical use-case scenarios benchmark chemical-exposures; Mixture of High and low risk



PBK models of systemic exposure

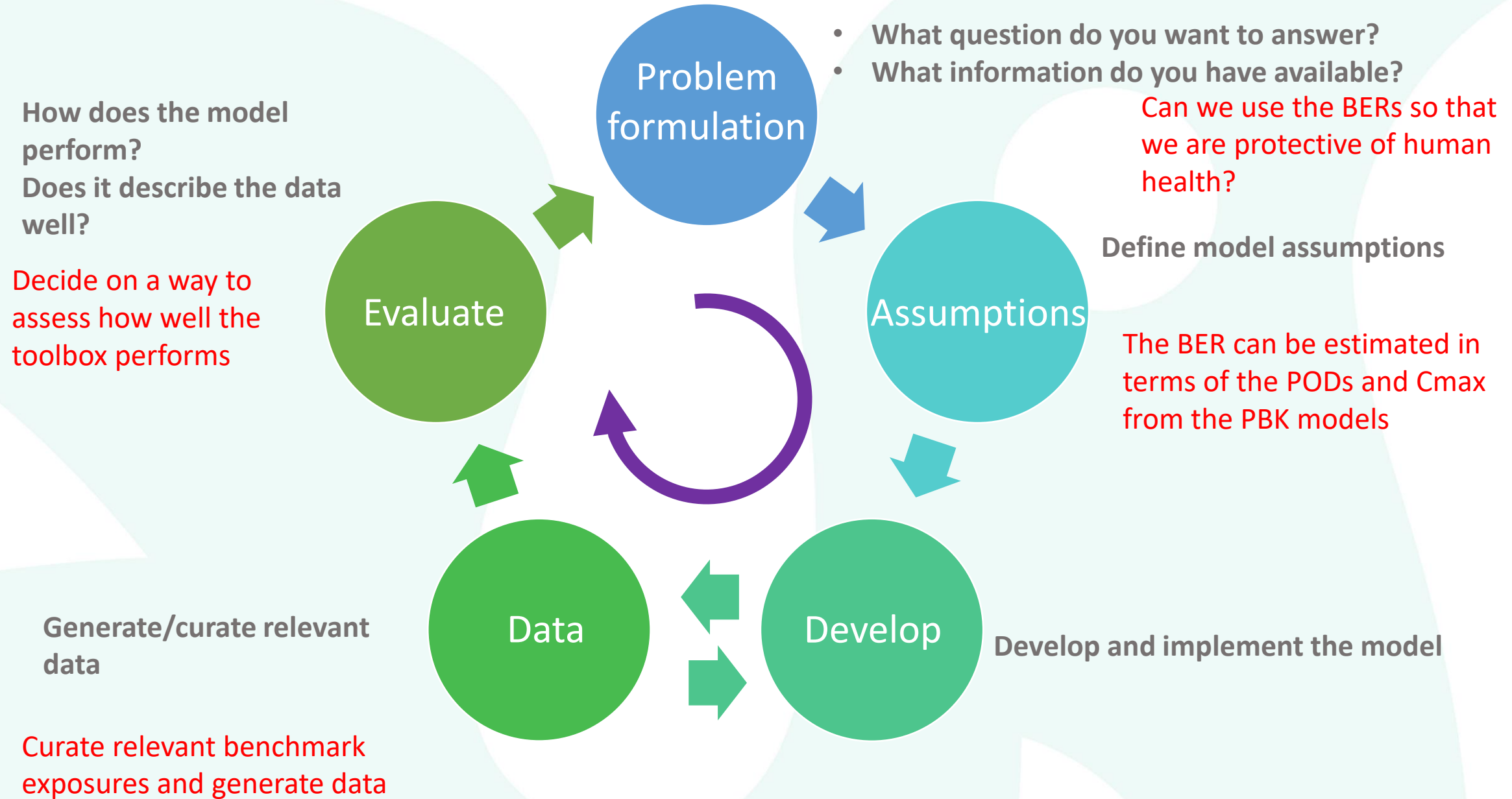


In-vitro cell assays, estimate PoDs



Calculate the bioactivity exposure ratio

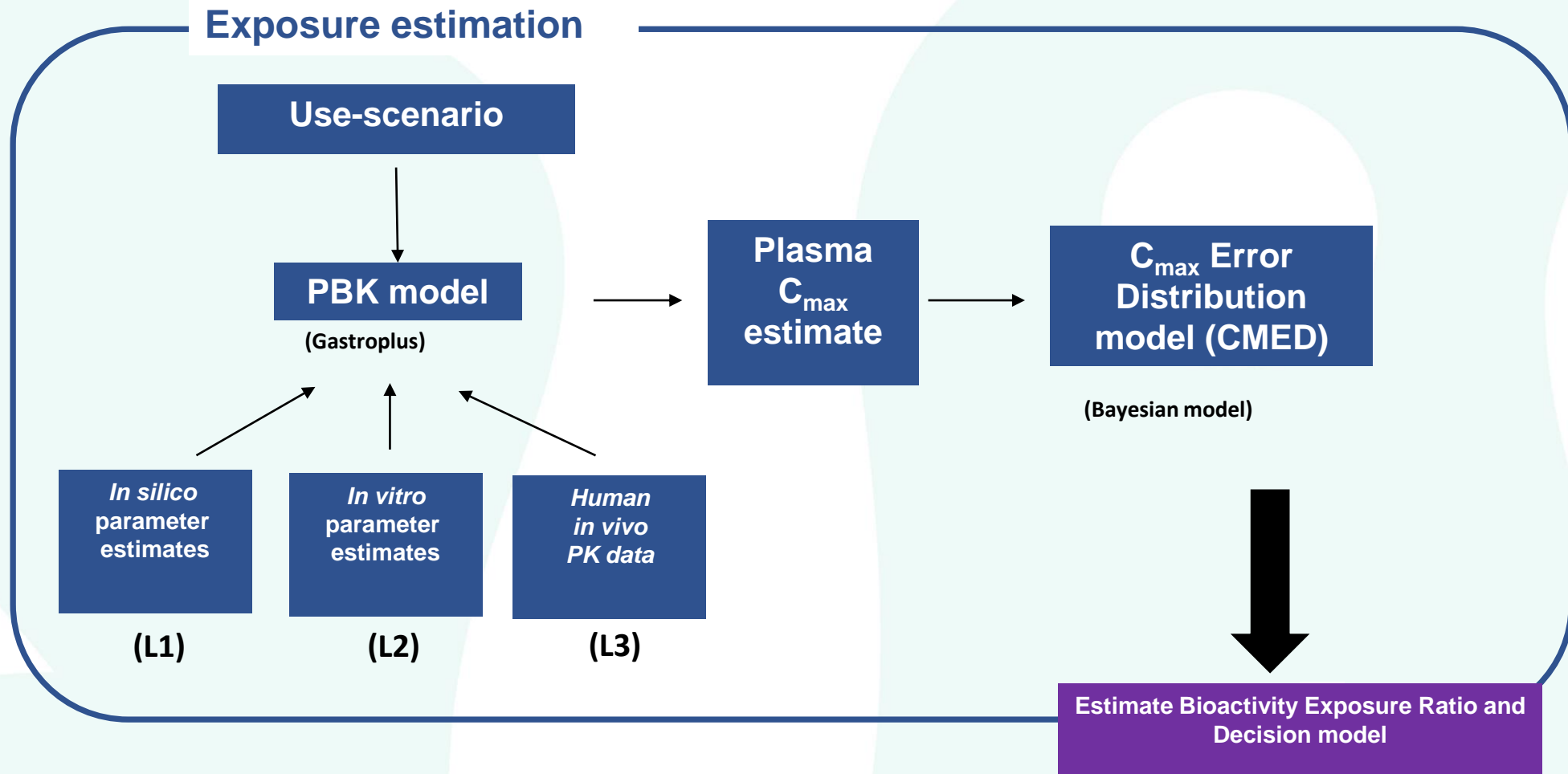
# Thinking about it in terms of model development



# Identifying suitable benchmarks for the evaluation

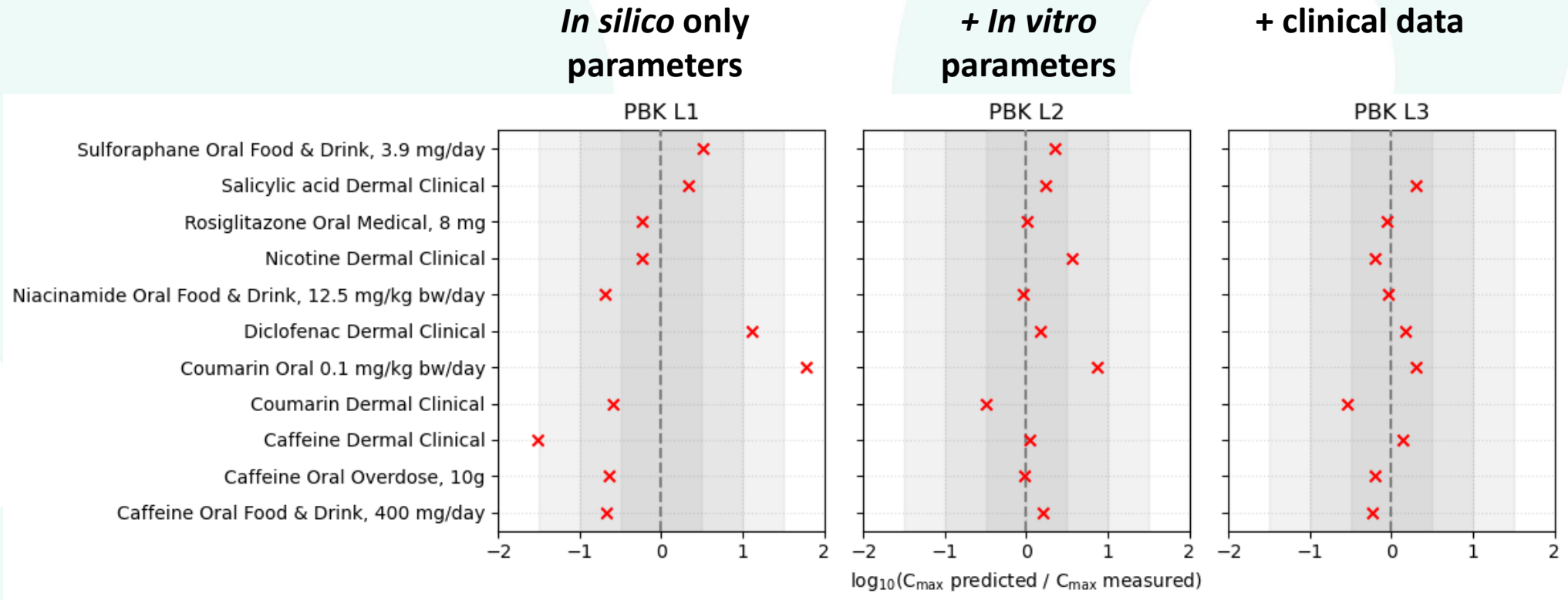
Chemical	Exposure scenario	Risk classification
<b>Oxybenzone</b>	<b>2 scenarios:</b> 0.5%; 2% sunscreen	Low risk
<b>Caffeine</b>	<b>2 scenarios:</b> 0.2% shampoo & coffee oral consumption 50 mg	Low risk
<b>Caffeine</b>	10g – fatal case reports	High risk
<b>Coumarin</b>	<b>3 scenarios:</b> 4 mg/d oral consumption; 1.6% body lotion (dermal); TDI 0.1 mg/kg oral	Low risk
<b>Coumarin</b>	400 mg/kg clinical trial ~ 14 months	High risk
<b>Hexylresorcinol</b>	<b>3 scenarios:</b> Food residues (3.3 ug/kg); 0.4% face cream; throat lozenge 2.4 mg	Low risk
<b>BHT</b>	Body lotion 0.5%	Low risk
<b>Sulforaphane</b>	<b>2 scenarios:</b> Tablet 60 mg/day; food 4.1-9.2 mg/day	Low risk
<b>Niacinamide</b>	<b>4 scenarios:</b> oral 12.5-22 mg/kg; dermal 3% body lotion and 0.1 % hair condition	Low risk
<b>Thalidomide</b>	<b>3 scenarios:</b> oral tablet 50 mg, 100 mg, 400 mg	High risk
<b>Doxorubicin</b>	75 mg/m <sup>2</sup> IV bolus 10 min; 21 days cycles; 8 cycles	High risk
<b>Rosiglitazone</b>	8 mg oral tablet	High risk
<b>Valproic Acid (VPA)</b>	<b>2 scenarios:</b> oral tablet 1000 mg & > 60 mg/kg	High risk
<b>Paraquat</b>	Accidental ingestion 35 mg/kg	High risk

# Using PBK models to predict C<sub>max</sub>



- Used a (**bottom-up**) PBK model to predict C<sub>max</sub> under different parameterisations
- Used a (**top down**) Bayesian statistical model to quantify the potential error in the est

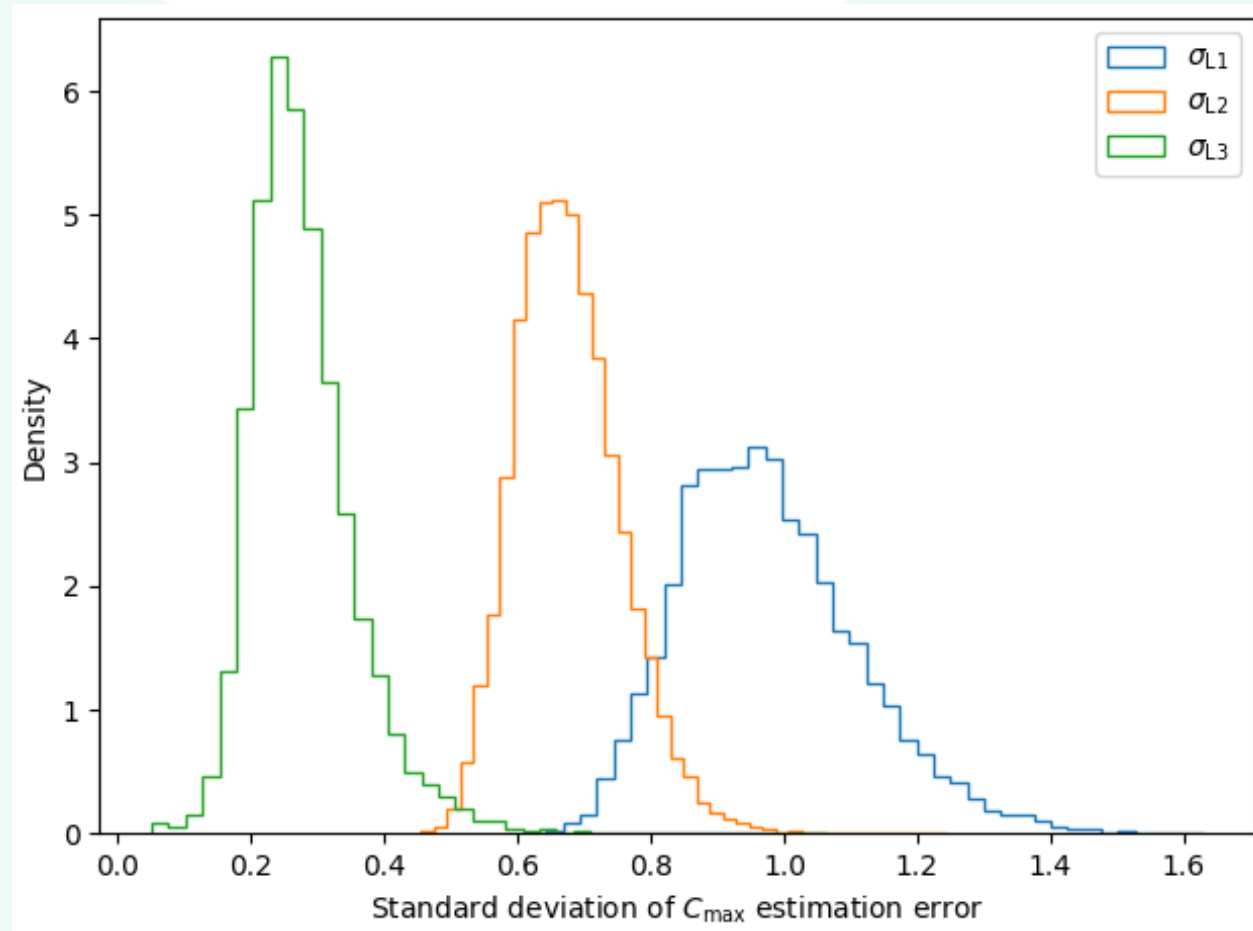
# Quantifying the error in the C<sub>max</sub> estimates



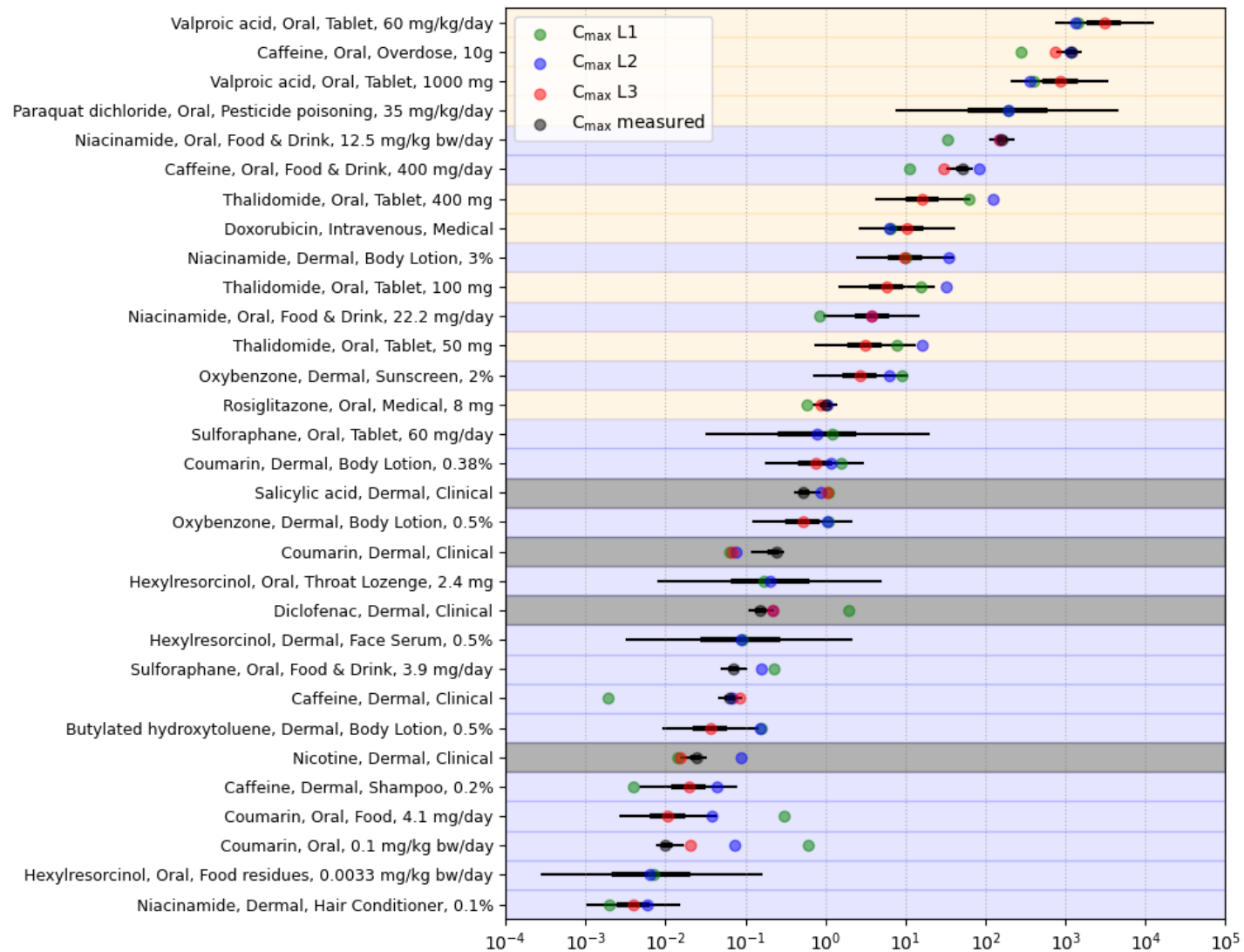
- The PBK prediction error decreases as we go through the different parameterisation levels
- This is an empirical observation



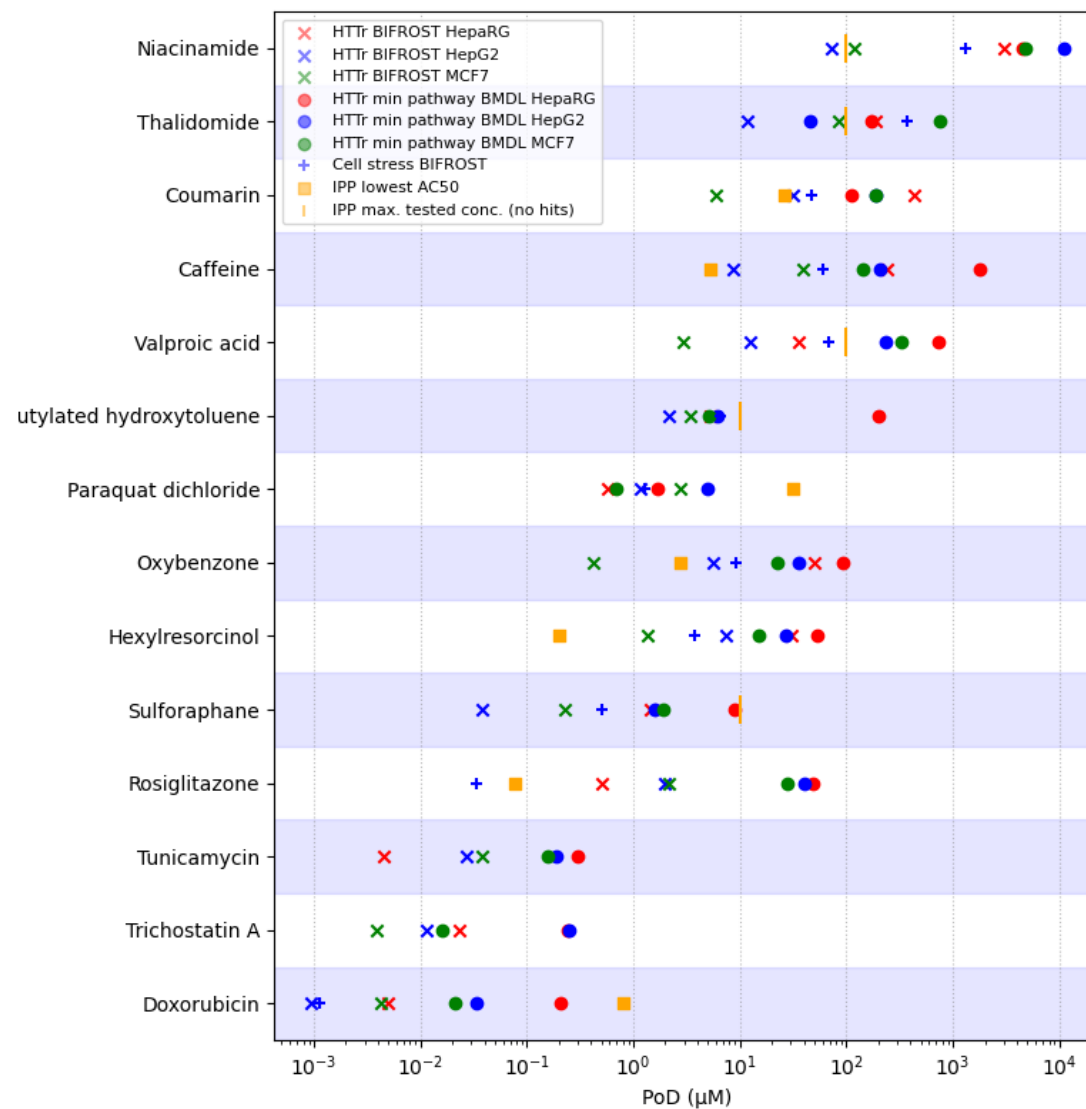
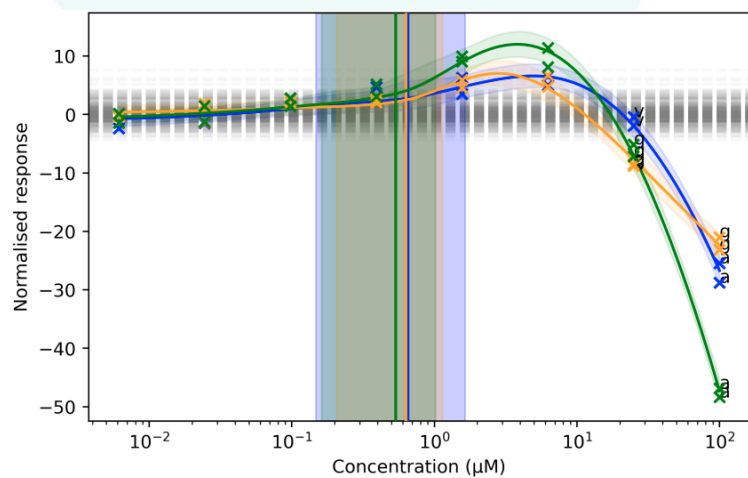
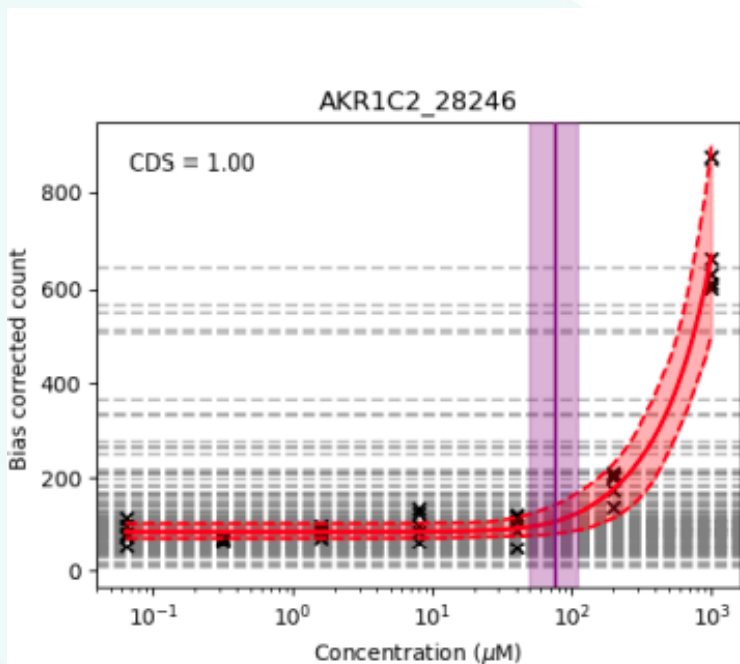
# Using a Bayesian model to learn the PBK $C_{\max}$ prediction error



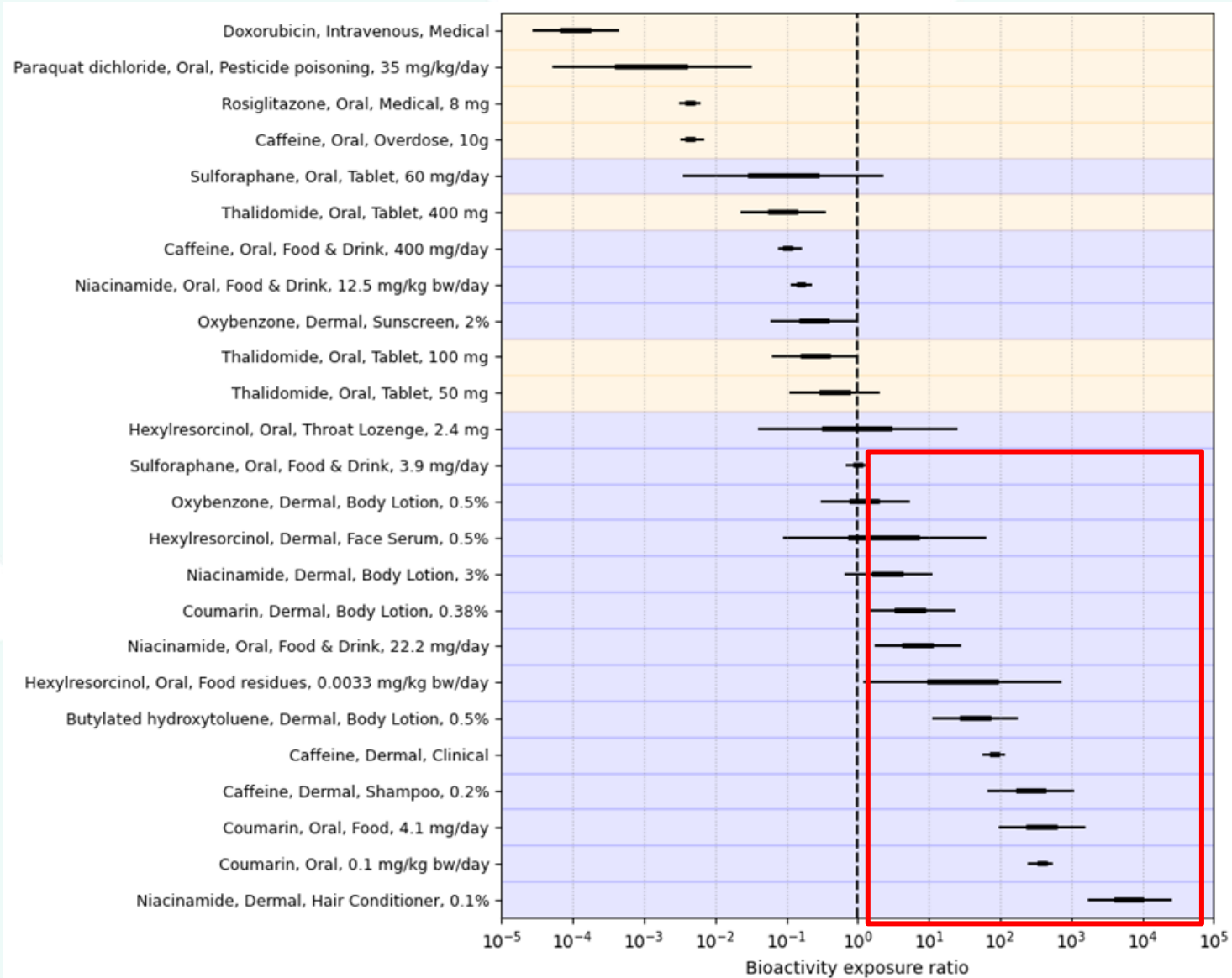
# Using PBK models to predict Cmax



# PODS from the bioactivity platforms



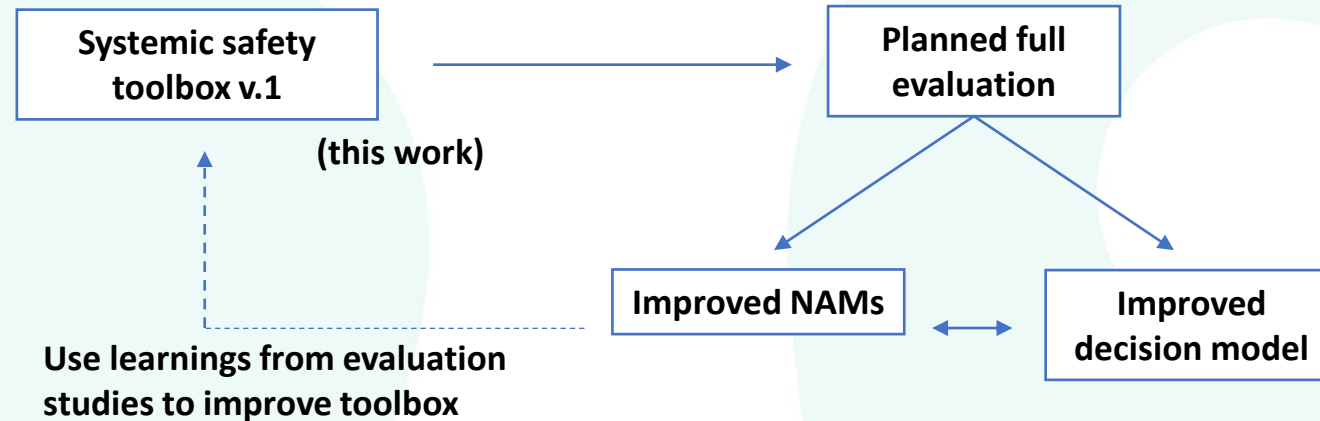
# Initial results indicate the toolbox is protective



- Blue: low risk chemical-exposure scenario
- Yellow: high risk chemical-exposure scenario

- Protectiveness: 100%
- Utility: 62%

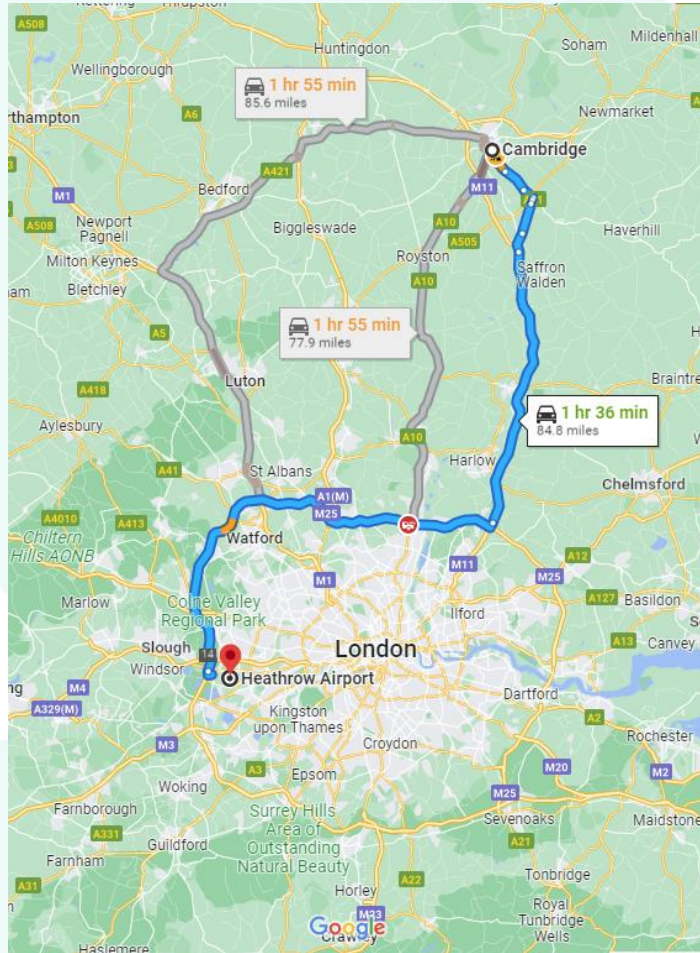
# Next step for the toolbox – the full evaluation



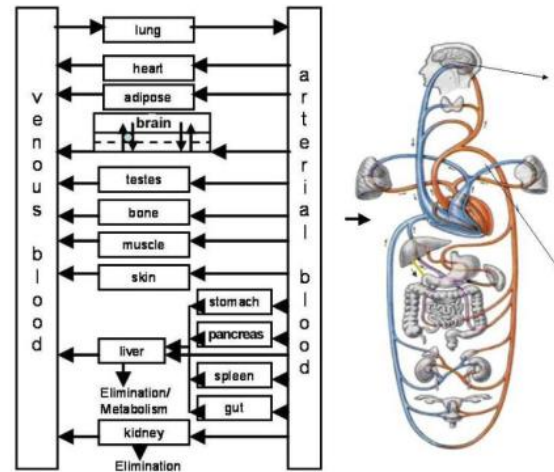
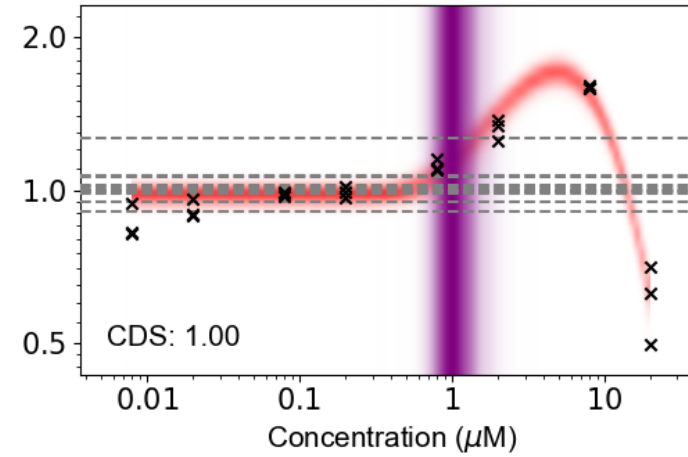
- Planning to extend evaluation to ~40 chemicals with ~60 associated **high risk** and **low risk** exposure scenarios.
- Also in collaboration with US-EPA, expanding range of NAMs
- Adopt **iterative approach** to evaluating and then identifying potential improvements to the toolbox.
- Use of concepts from used model evaluation and development should help build confidence in the approach.



# Thinking about the future...



Sulfuraphane IL-8 (24 hours)



Toxic Hazard by Cramer rules	
Estimate	
Low (Class I)	
Intermediate (Class II)	
<b>High (Class III)</b>	

ToxTree

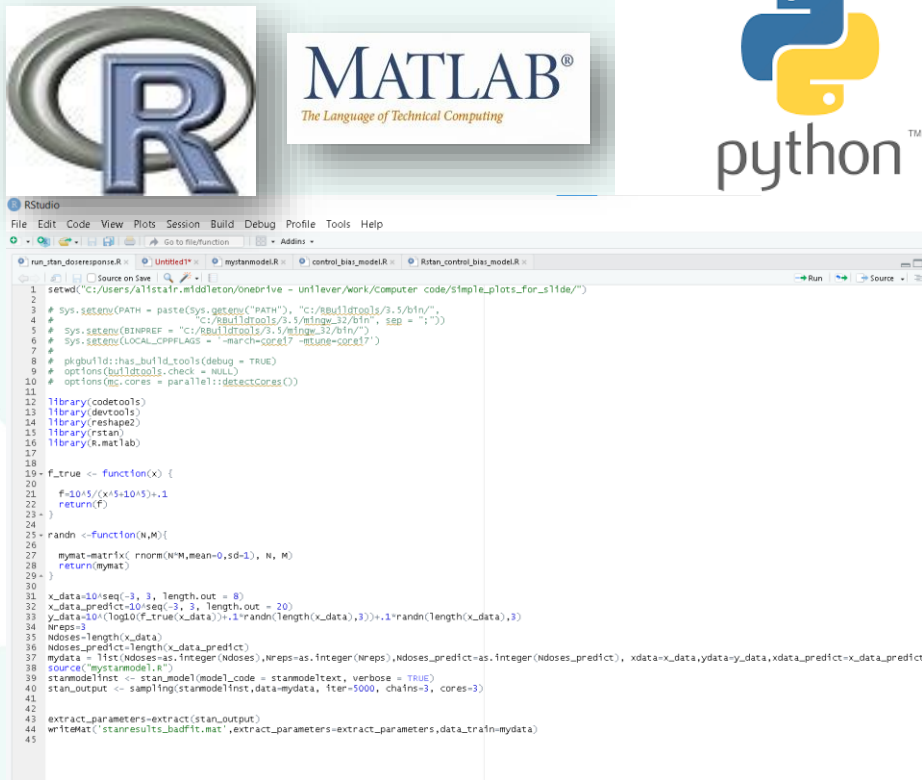
Gastroplus

# Getting started with computational approaches...

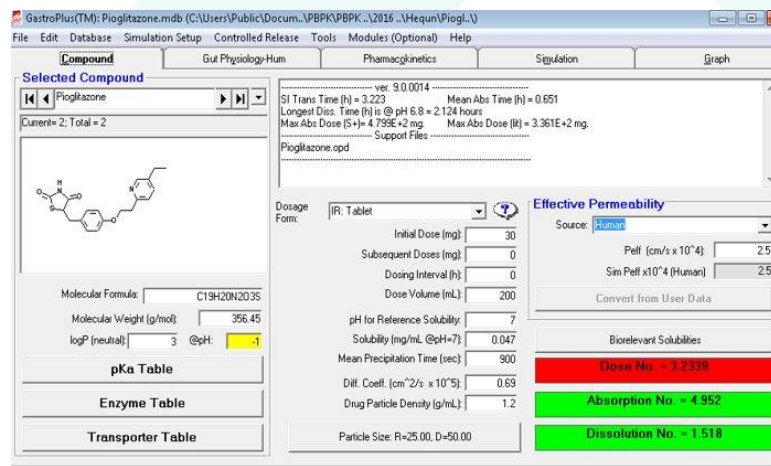
# Learning to code vs using existing tools

Programming

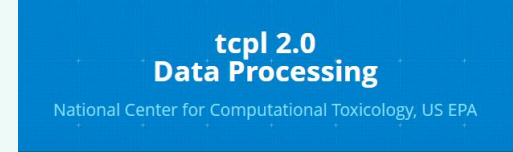
Graphical user interfaces



PBK software



Dose response software



[https://cran.r-project.org/web/packages/tcpl/vignettes/Data\\_processing.html](https://cran.r-project.org/web/packages/tcpl/vignettes/Data_processing.html)



<https://benchmarkdose.com/>



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Bowes *et al.*, (2012) Reducing safety-related drug attrition: the use of in vitro pharmacological profiling *Nat Rev Drug Discov* 11(12):909-22 <https://doi.org/10.1038/nrd3845>

Dent *et al.*, (2018) Principles underpinning the use of new methodologies in the risk assessment of cosmetic ingredients *Comp Tox* 7: 20-26 <https://doi.org/10.1016/j.comtox.2018.06.001>

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Rajagopal *et al.*, (2022). Beyond AOPs: A Mechanistic Evaluation of NAMs in DART Testing. *Frontiers in toxicology*, 4. <https://doi.org/10.3389%2Fftox.2022.838466>

Li *et al.*, (2022) PBK modelling of topical application and characterisation of the uncertainty of C<sub>max</sub> estimate: A case study approach, *Toxicology and Applied Pharmacology*, Vol 442(1) <https://doi.org/10.1016/j.taap.2022.115992>