

Paediatric trial design optimization using prior knowledge in combination with modelling & simulations

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UCL



β -thalassemia

Rare hereditary blood disorder

- reduced Hb level in RBC
- reduced RBC production
- anemia

1/100,000 per year

Frequent RBC transfusions

→ **Iron overload**

→ Iron chelators



DEEP project

DEEP-2 study



**DEFERIPRONE
EVALUATION IN
PAEDIATRICS**

– Efficacy study

To **assess non-inferiority** of deferiprone (DFP) compared to deferasirox (DFX) in paediatric patients (1 month – 18 years)

- Primary endpoint: change in serum ferritin from baseline after 1 year

– PK sub-study (at the end of the 1 year efficacy study)

To **characterize DFX exposure** in paediatric patients (1 year - 18 years)

Knowledge gaps

DEEP-2 PK sub-study

To **characterize DFX exposure** in paediatric patients



A popPK model for DFX is needed

Issues

- ✓ very sparse PK data
- ✓ few subjects

Knowledge gaps

DEEP-2 PK sub-study

To **characterize DFX exposure** in paediatric patients



A popPK model for DFX is needed

Issues

- ✓ very sparse PK data
- ✓ few subjects

Objective n° 1

Evaluate to what extent the use of

prior knowledge (adult PK data)

+

allometry (and maturation)

can support **the analysis of very sparse PK data**

Knowledge gaps

DEEP-2 PK sub-study

To **characterize DFX exposure** in paediatric patients



A popPK model for DFX is needed

Issues

- ✓ very sparse PK data
- ✓ few subjects

Objective n° 2

Evaluate to what extent the use of

prior knowledge (adult PK data)

+

ED-optimization methods

can support **the design of future paediatric PK studies with chelating agents**

Knowledge gaps

DEEP-2 efficacy study

To **assess non-inferiority** of DFP compared to DFX in 1 year



Issues

- ✓ Time to response set to 1 year by empiricism
- ✓ Some patients may be treated with suboptimal doses for a long period

Knowledge gaps

DEEP-2 efficacy study

To **assess non-inferiority** of DFP compared to DFX in 1 year



Issues

- ✓ Time to response set to 1 year by empiricism
- ✓ Some patients may be treated with suboptimal doses for a long period

Objective n° 3

Evaluate to what extent the use of

prior knowledge
(adult/pediatric efficacy data)

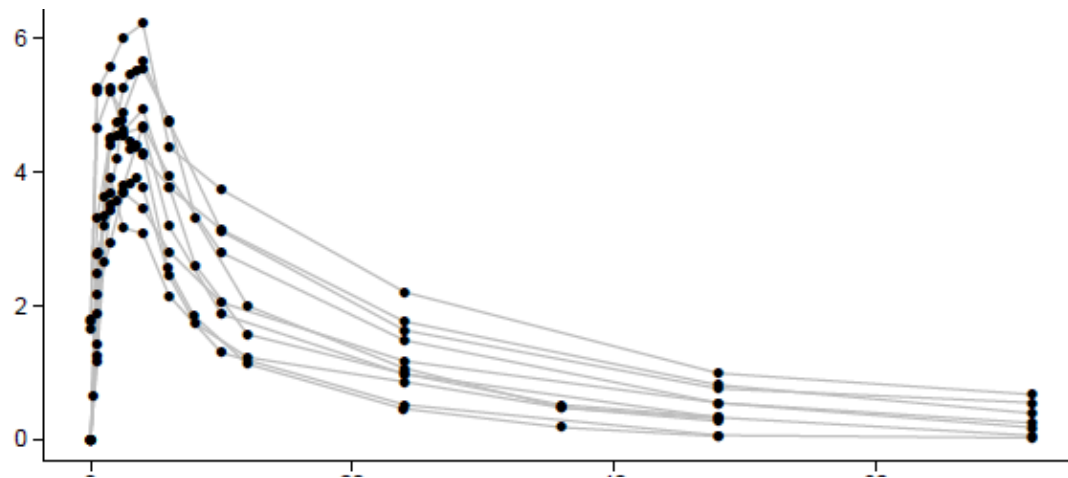
+

drug-disease models

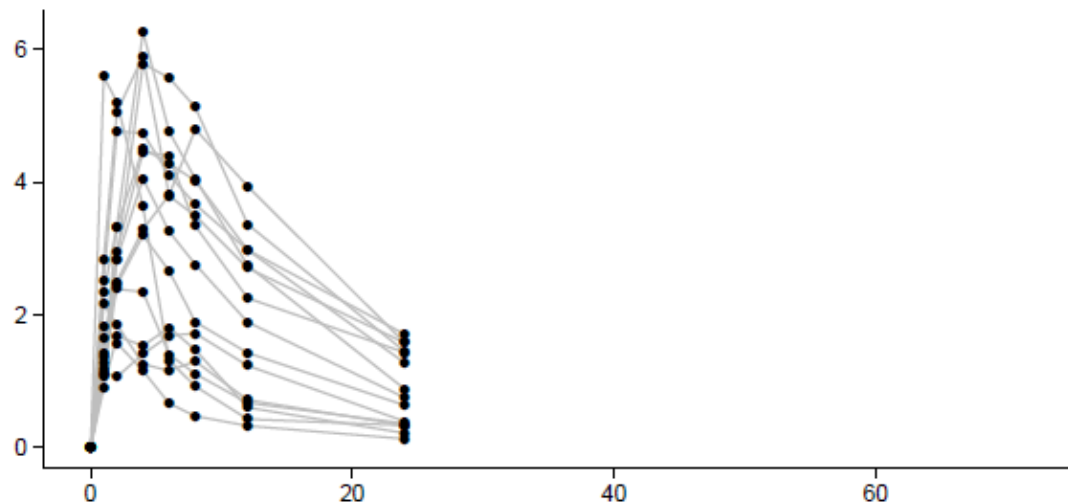
allows **prediction of clinical response** earlier than 12 months as well as **optimization of drug therapy**

Population DFX PK model

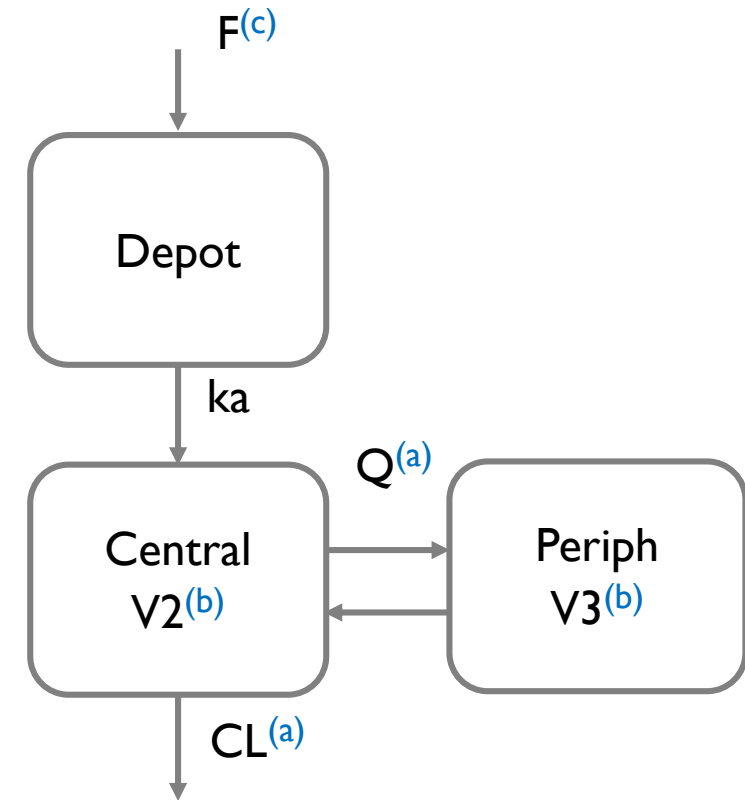
Mean data from several PK studies



Individual data from a single PK study



Time after dose [hours]

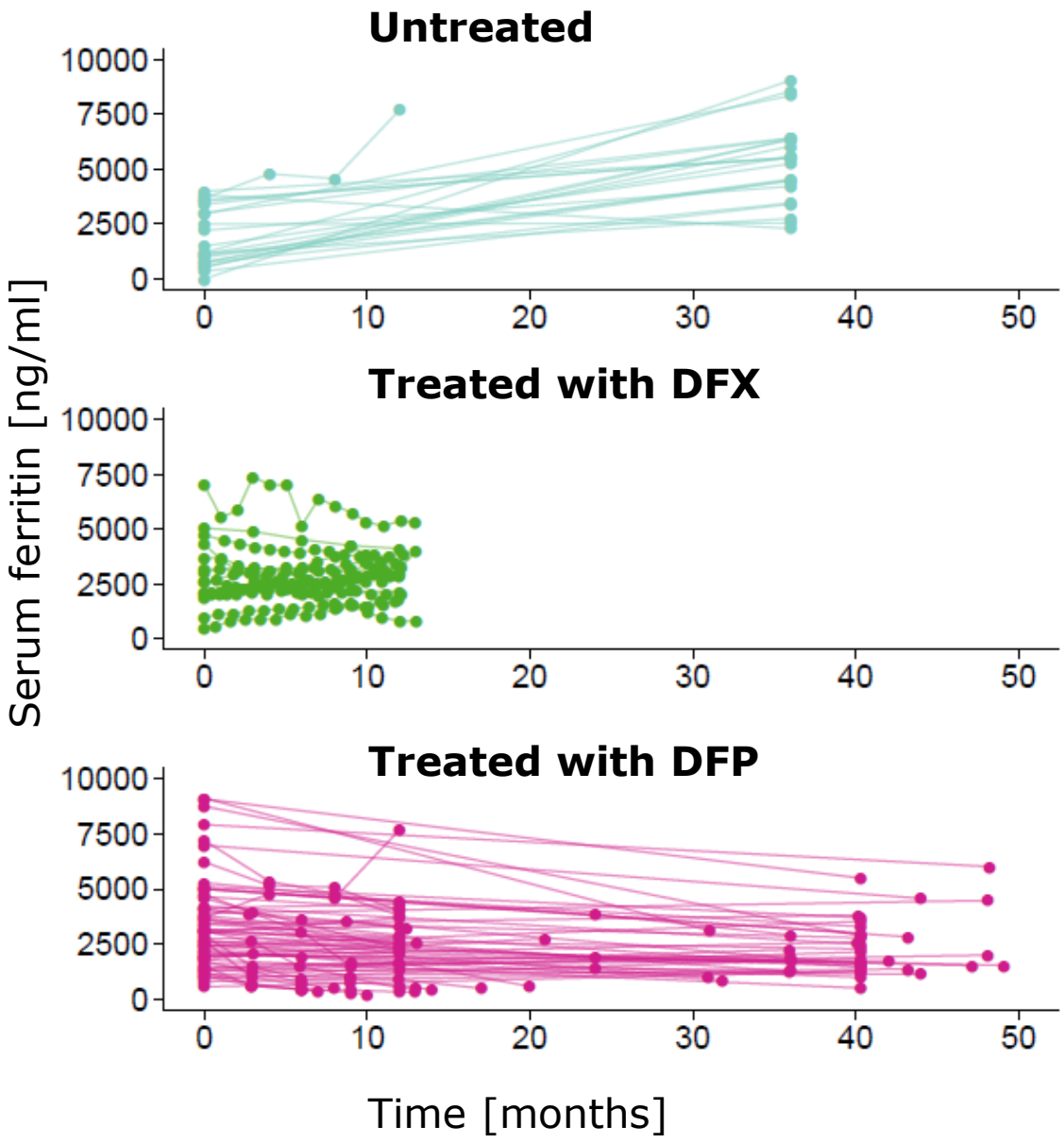


(a) $PAR = POP_PAR \cdot (WEIGHT/70)^{0.75}$

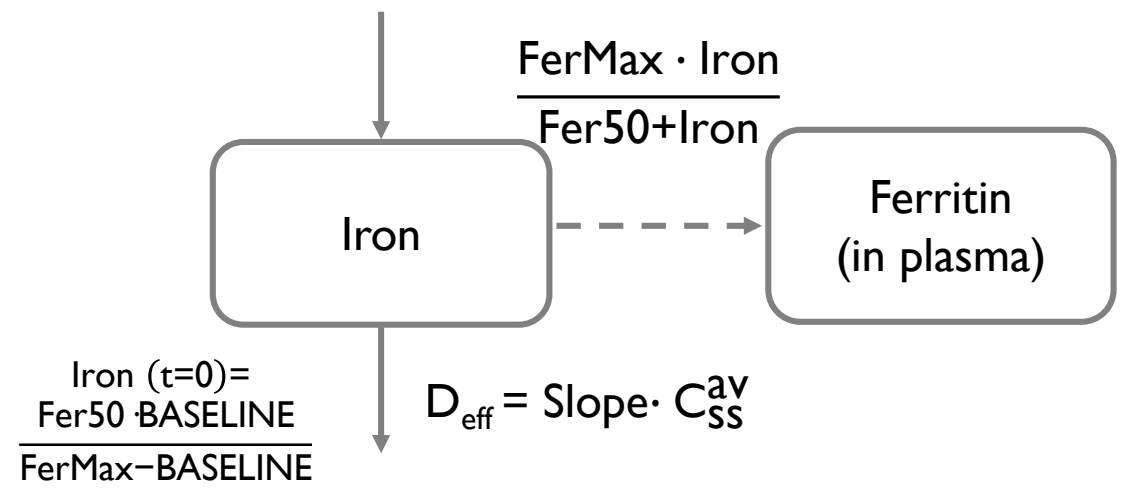
(b) $PAR = POP_PAR \cdot (WEIGHT/70)^1$

(c) Fixed to the value reported in Sechaud *et al.* J Clin Pharmacol, 48(8), 2008

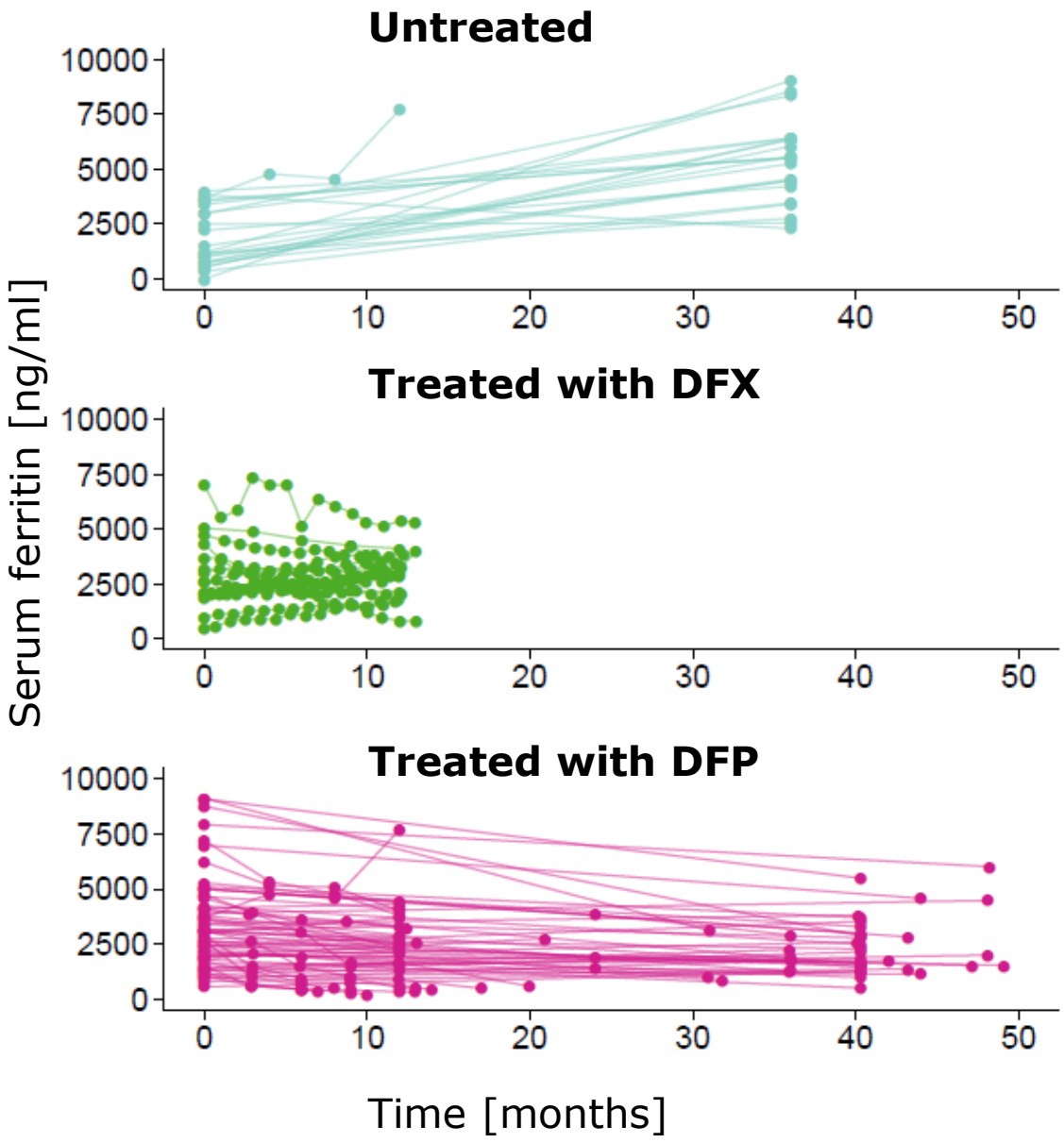
Population drug-disease model for iron overload



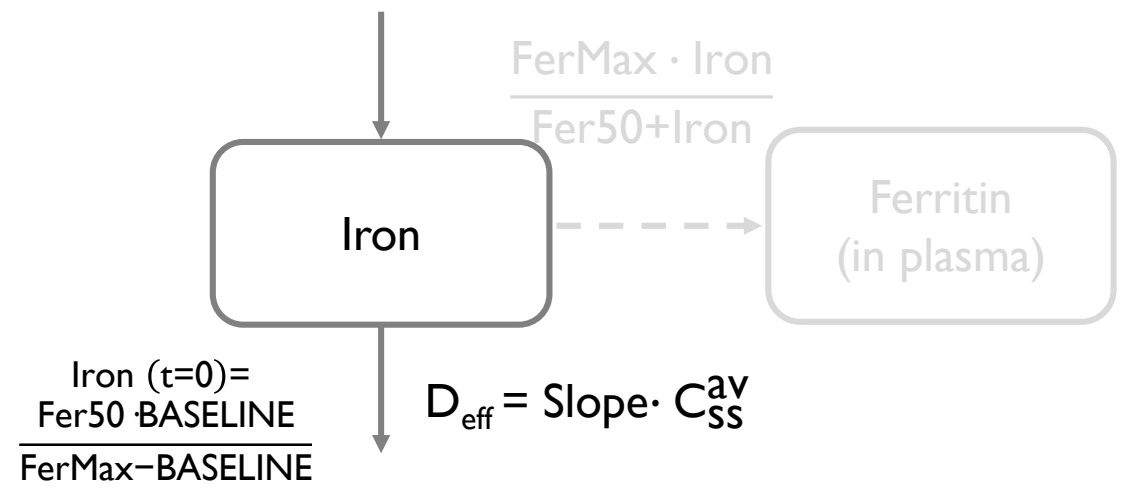
Transfusional iron input
 (mg iron/kg/month)
 [= 1.6 · BLOODCONS (ml RBC/kg/month)]



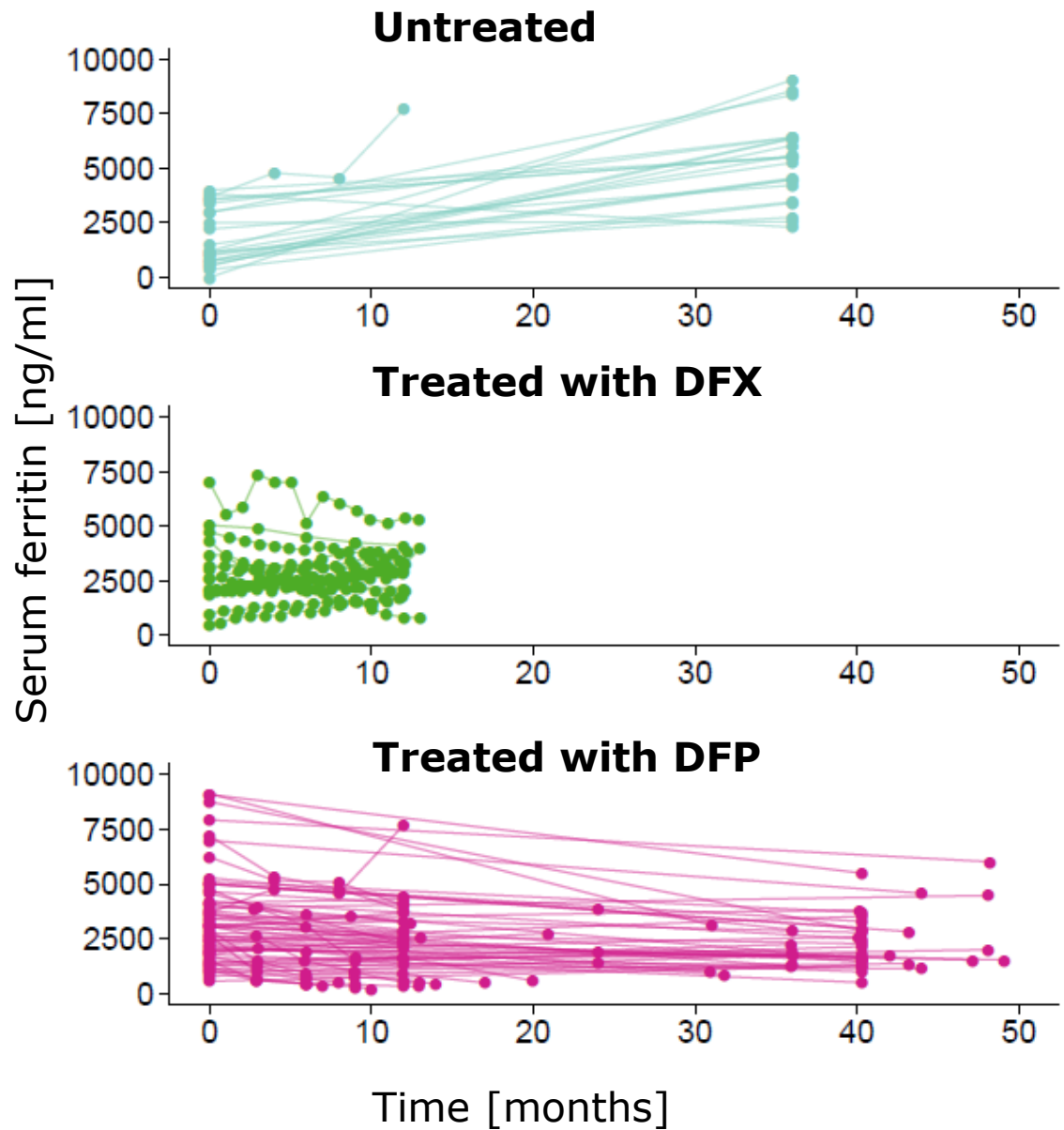
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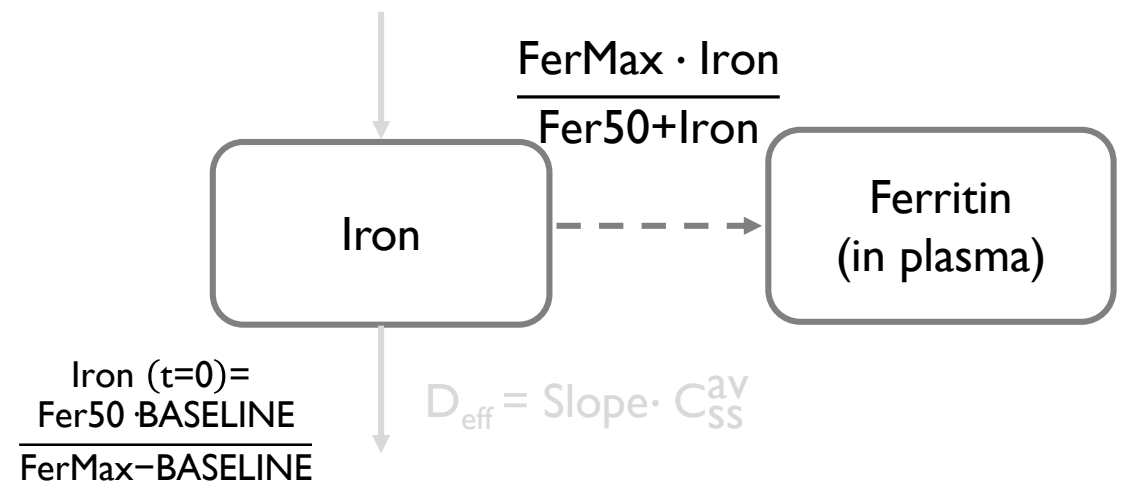
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Population drug-disease model for iron overload



Transfusional iron input
 (mg iron/kg/month)
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Objective n° 1

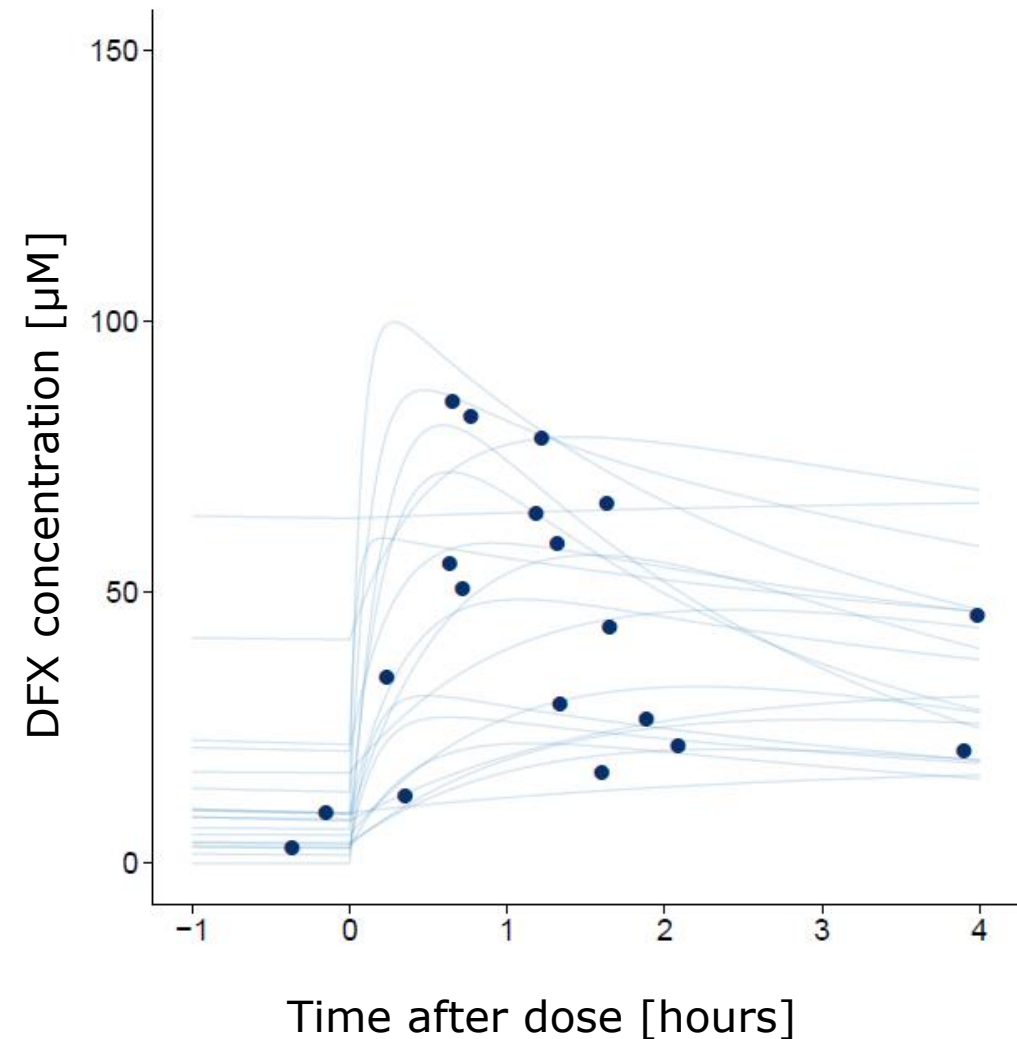
Understanding the impact of prior knowledge on sparse PK sampling

DEEP-2 PK sub-study

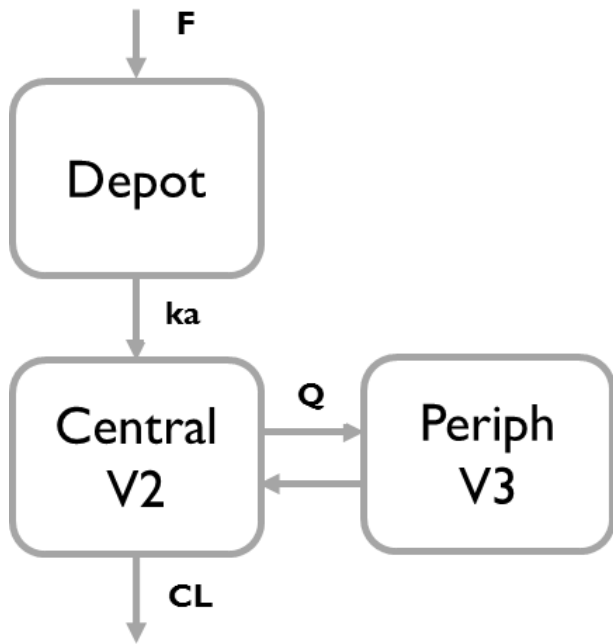
Protocol and sampling schedule

- 19 subjects
 - 1 year - 18 years
 - Affected by heamoglobinopathies
- 1 PK blood sample for each patient

Sampling times (minutes)									
PreDose	T1	T2	T3	T4	T5	T6	T7	T8	T9
-15	15	30	45	60	75	90	105	120	240



I. Simulation of paediatric PK profiles from 1 h pre-dose to 4 hrs post-dose

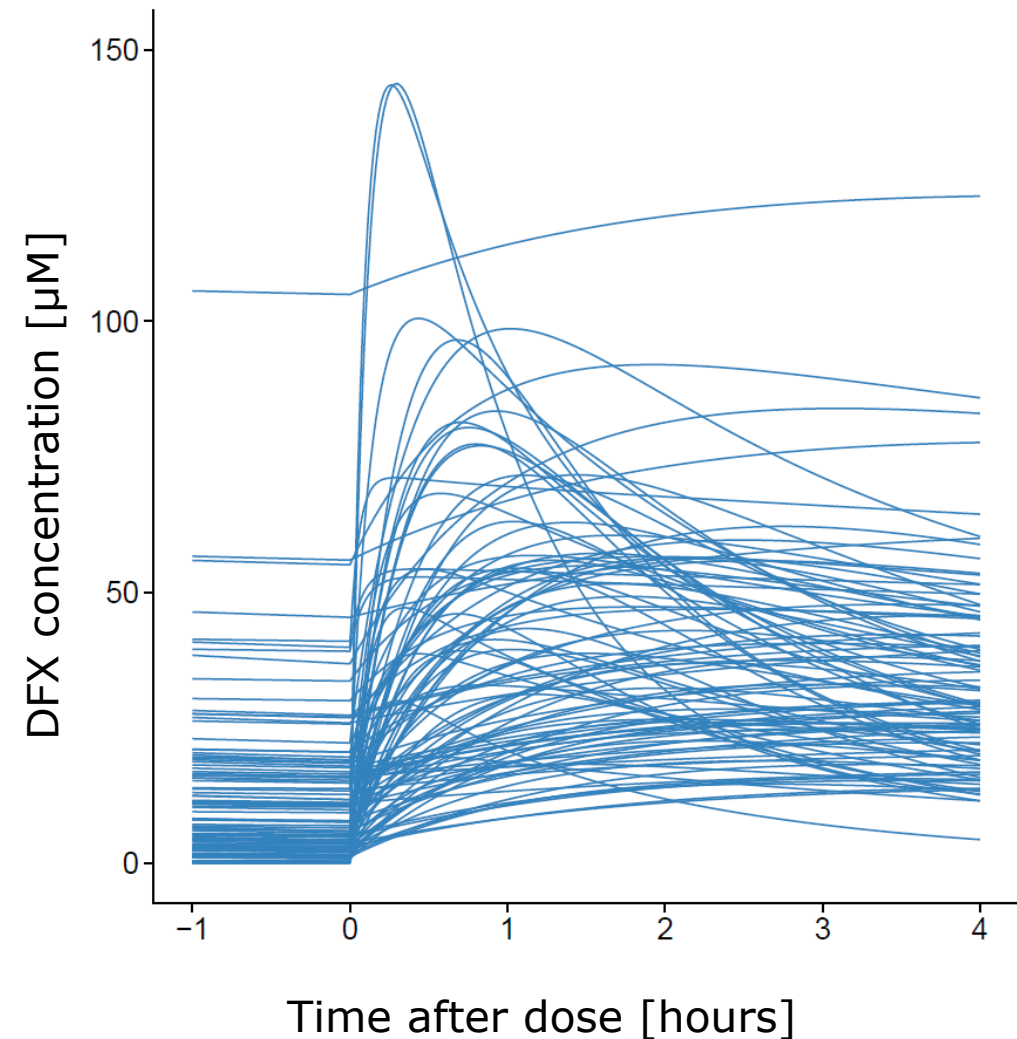


+ DFX dose 20 mg/kg (at SS)

+ DEEP-2 study patients
covariates

- $\text{Weight} = f(\text{PMA}, \text{Sex})^2$
PMA: 1 – 18 years
1:1 sex ratio

²Sumpter *et al.* Paediatr Anaesth, 21(3), 2011



I. Simulation of paediatric PK profiles

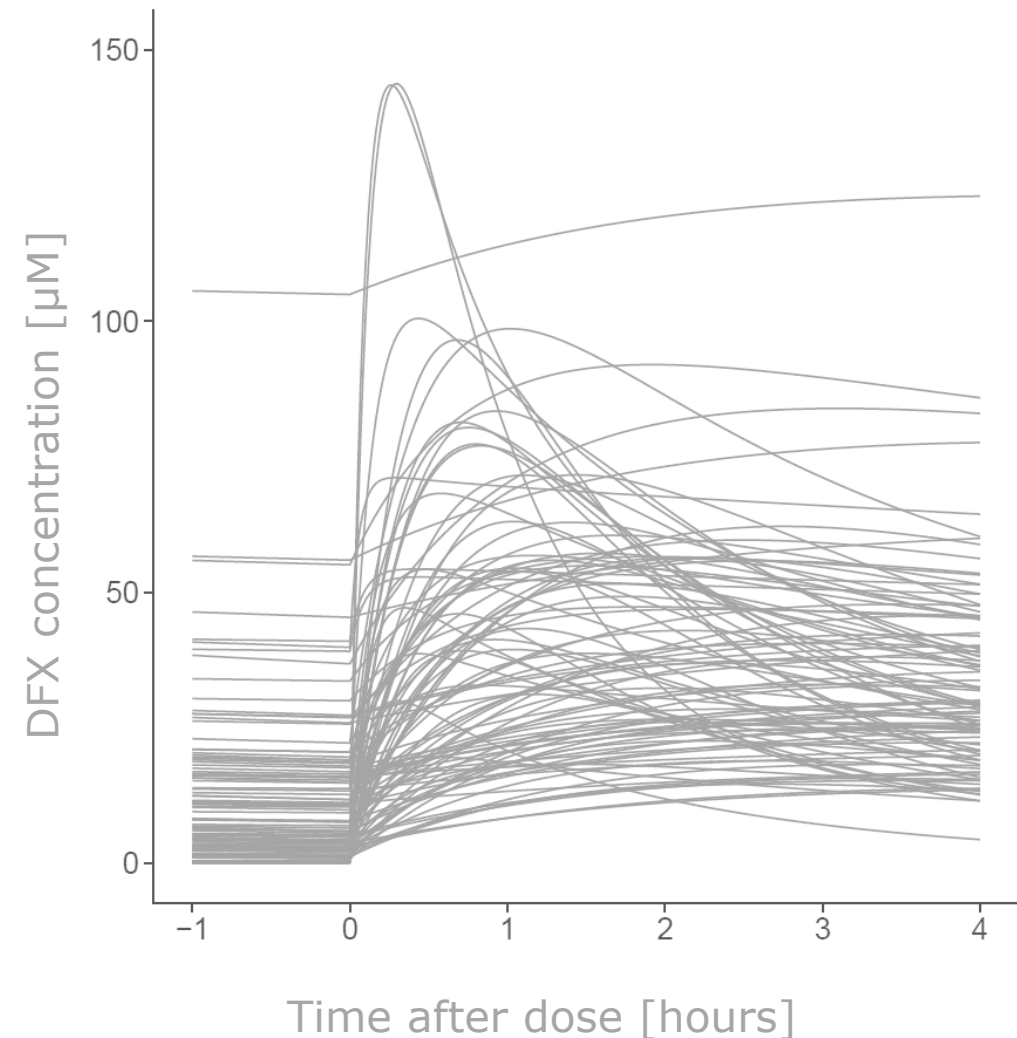
from 1 hr pre-dose to 4 hrs post-dose

Scenario 1

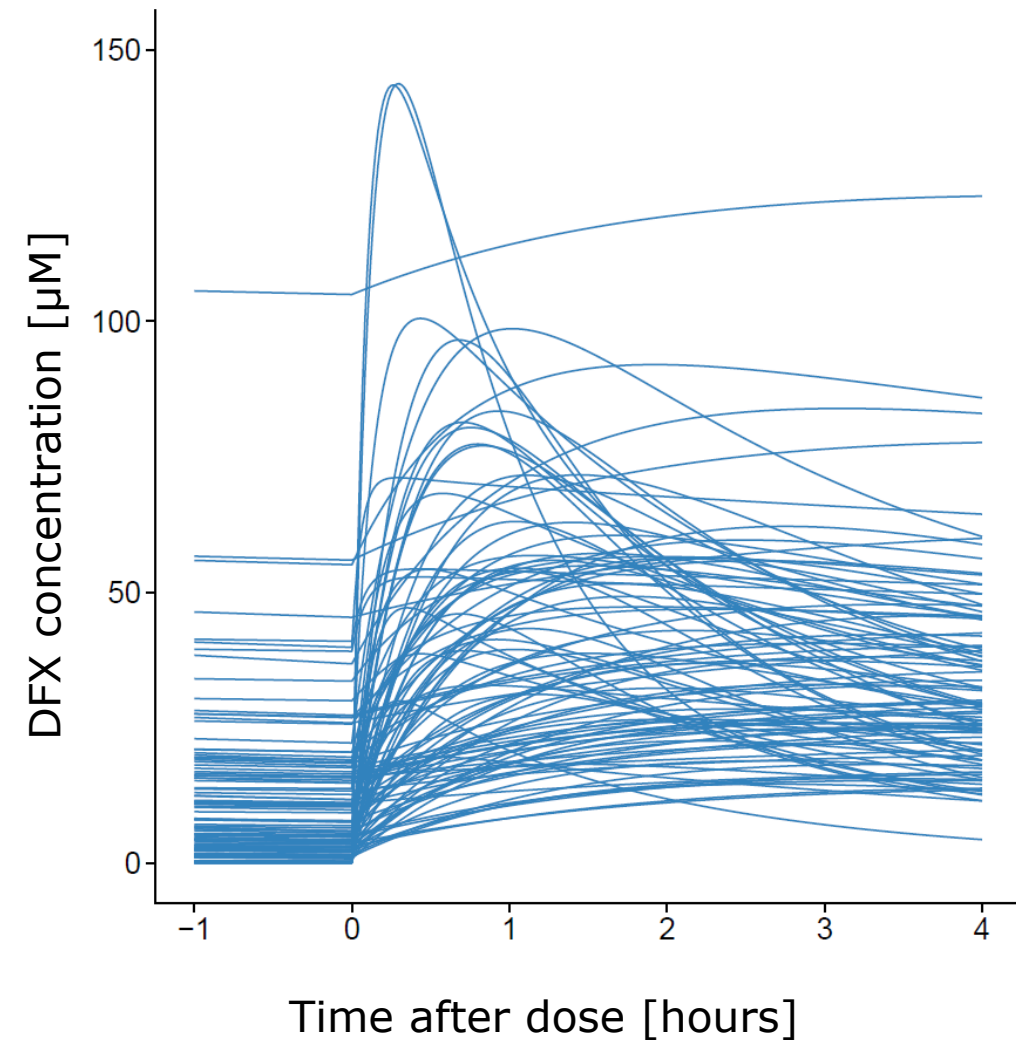
- Parameters allometrically scaled

Scenario 2 (with sub-scenarios)

- Different model parameters *or*
- Different allometric exponent



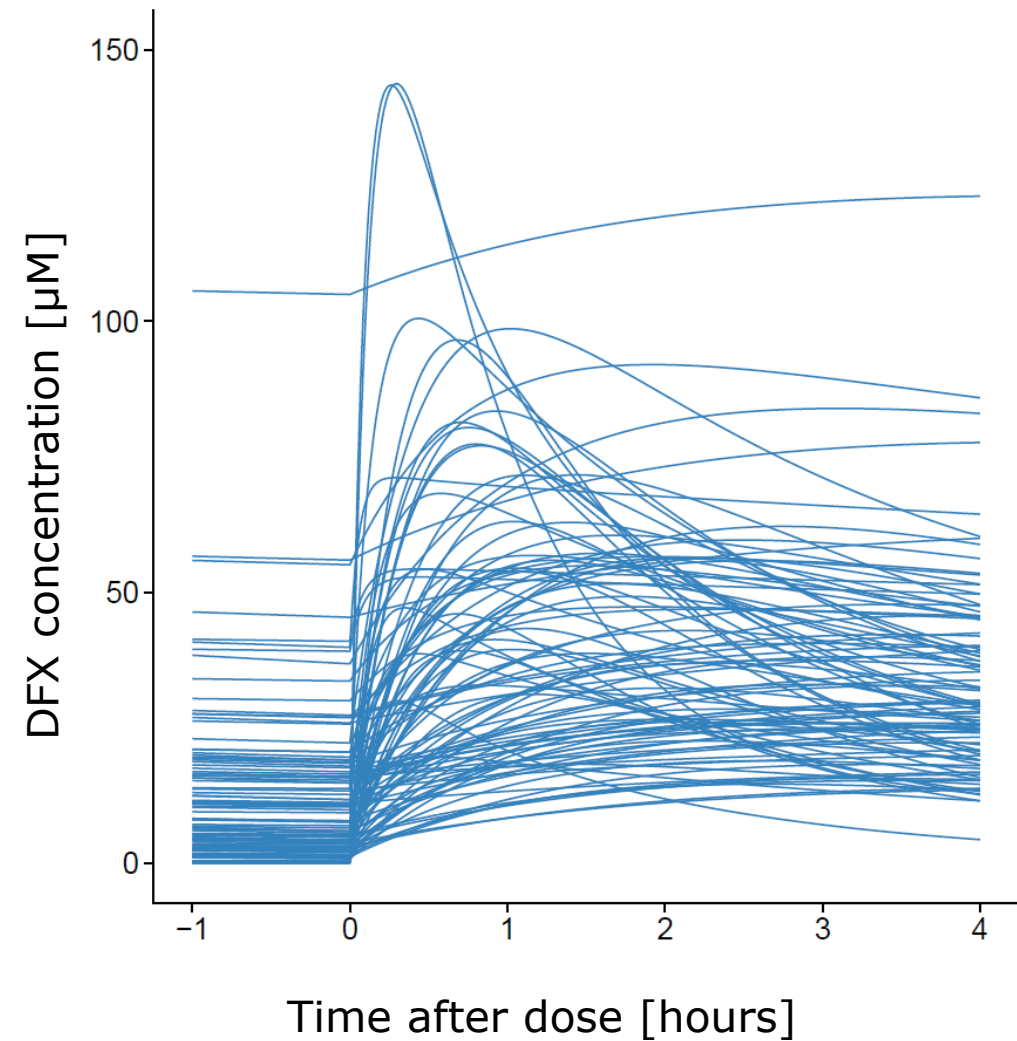
2. Simulation-estimation of PK sub-study with original protocol



2. Simulation-estimation of PK sub-study with original protocol

Extract

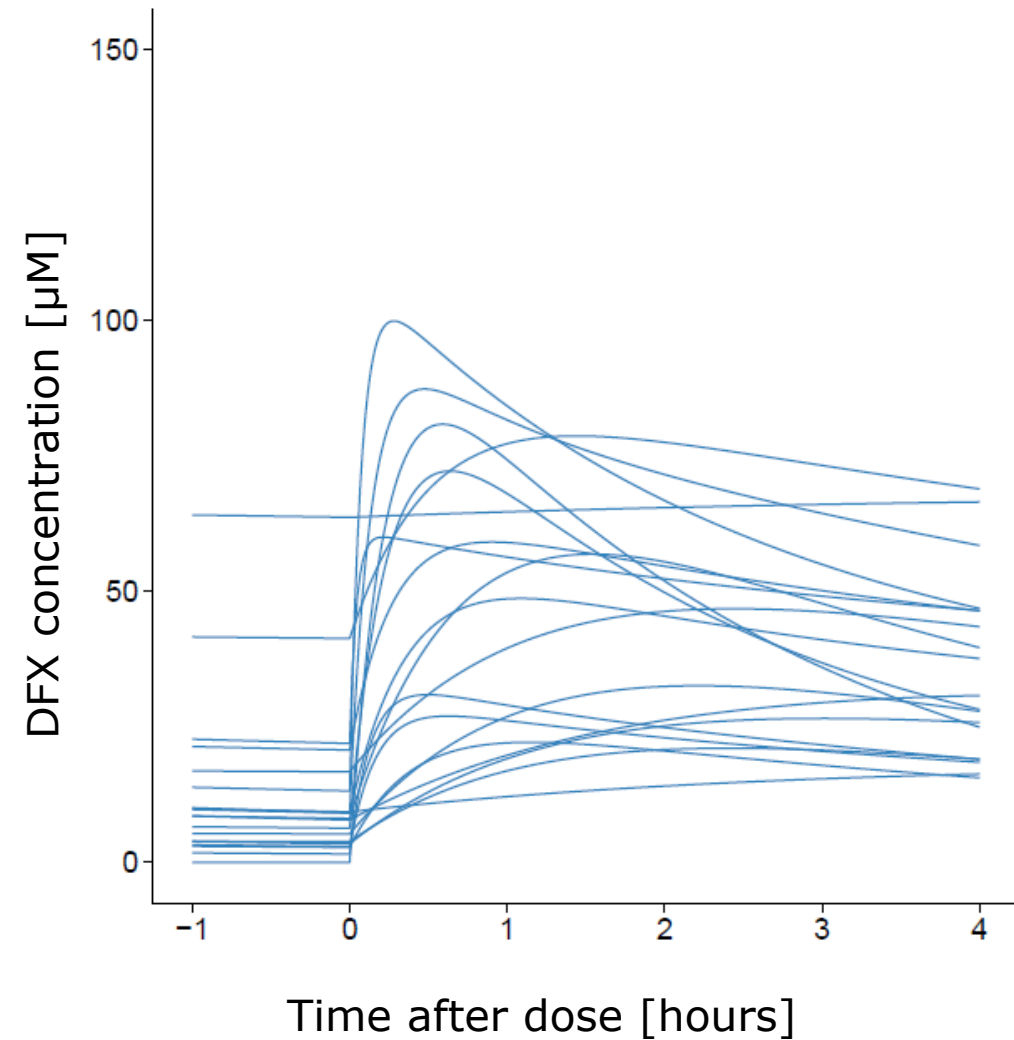
- 19 subjects
- 1 sample/subj



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Extract

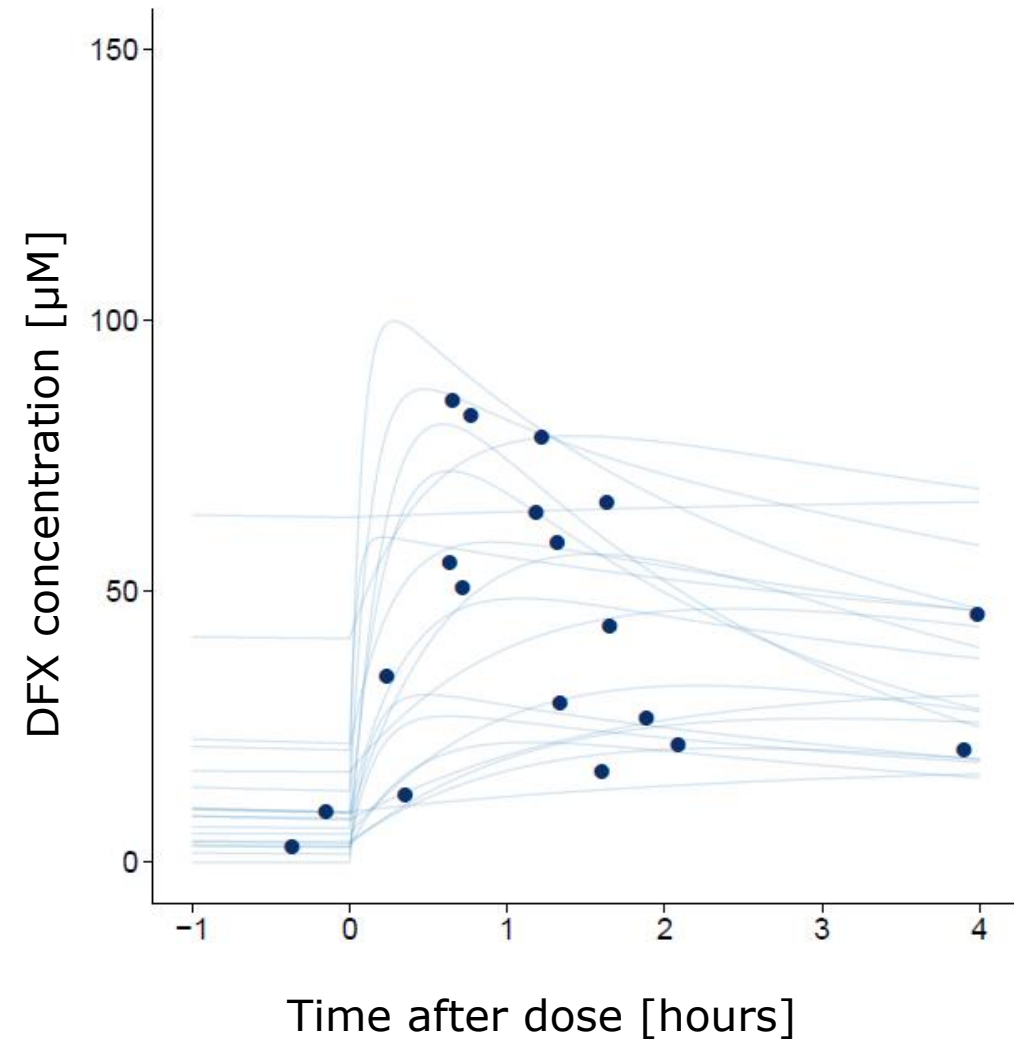
- 19 subjects
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2. Simulation-estimation of PK sub-study with original protocol

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- 19 subjects
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2. Simulation-estimation of PK sub-study with original protocol

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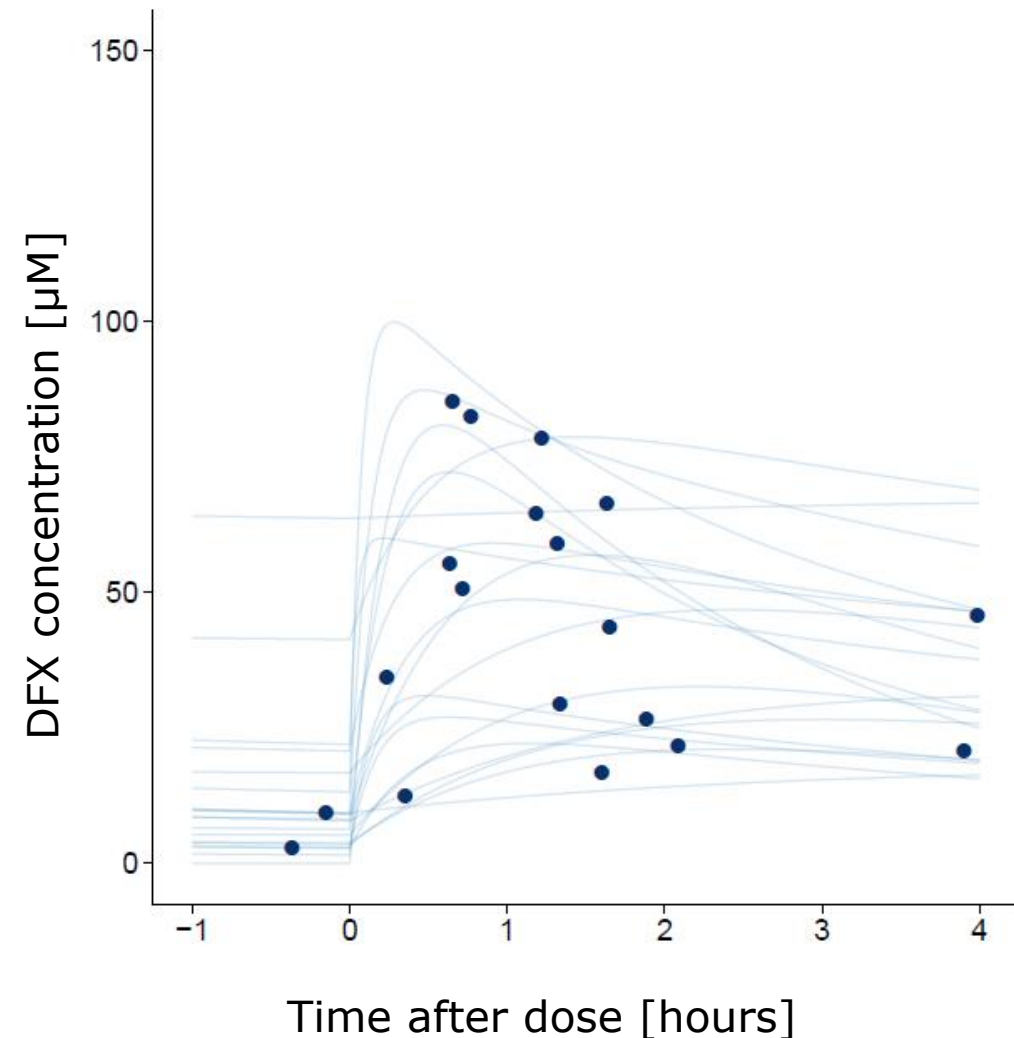
- 19 subjects
- 1 sample/subj

Estimate popPK model

- Typical values of CL, V2, V3, Q and ka
- IIV of CL, V2, V3 and ka

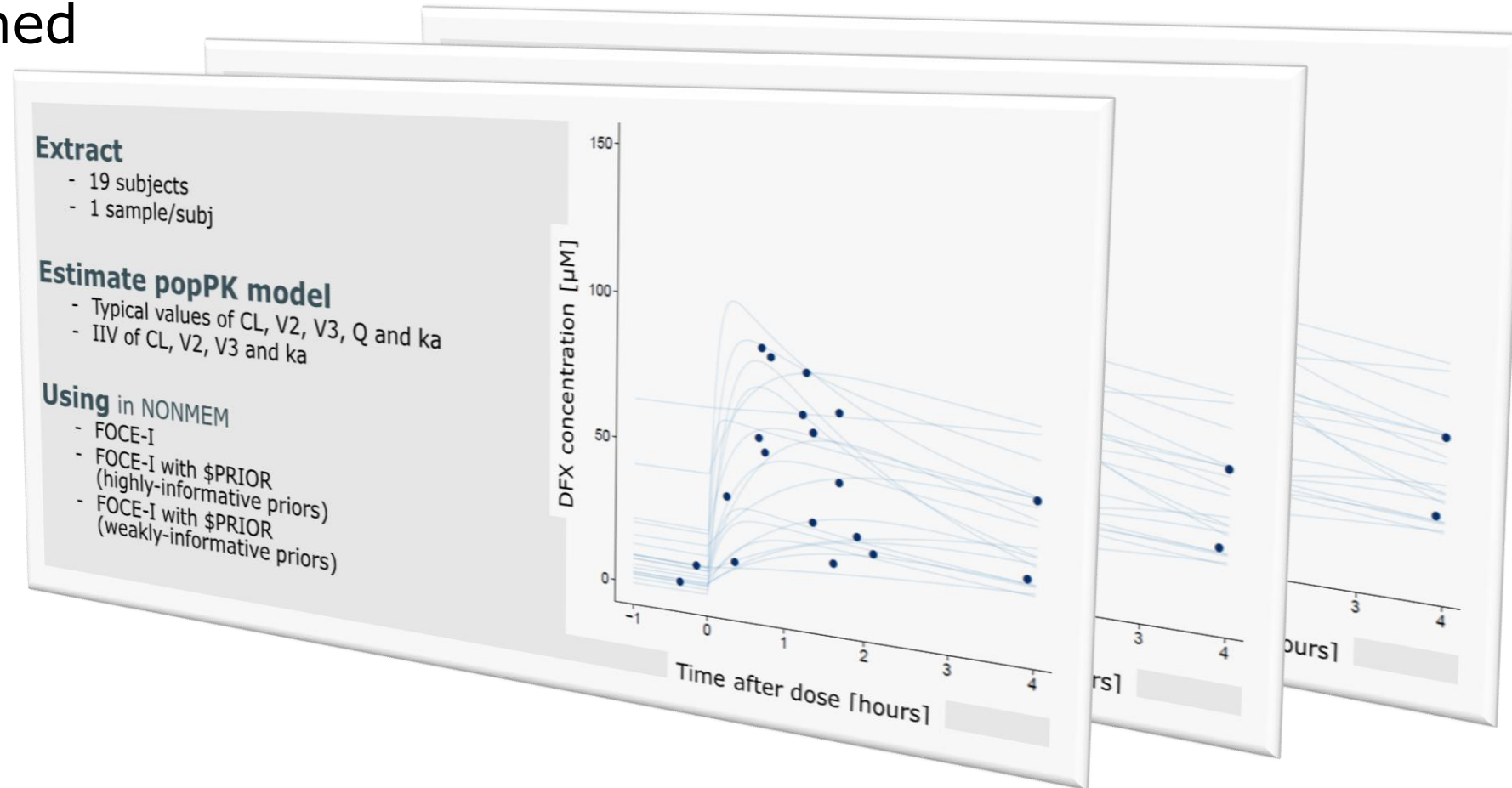
Using in NONMEM

- FOCE-I
- FOCE-I with \$PRIOR (highly-informative priors)
- FOCE-I with \$PRIOR (weakly-informative priors)



2. Simulation-estimation of PK sub-study with original protocol

Repeat until 100 successful runs are obtained



Results

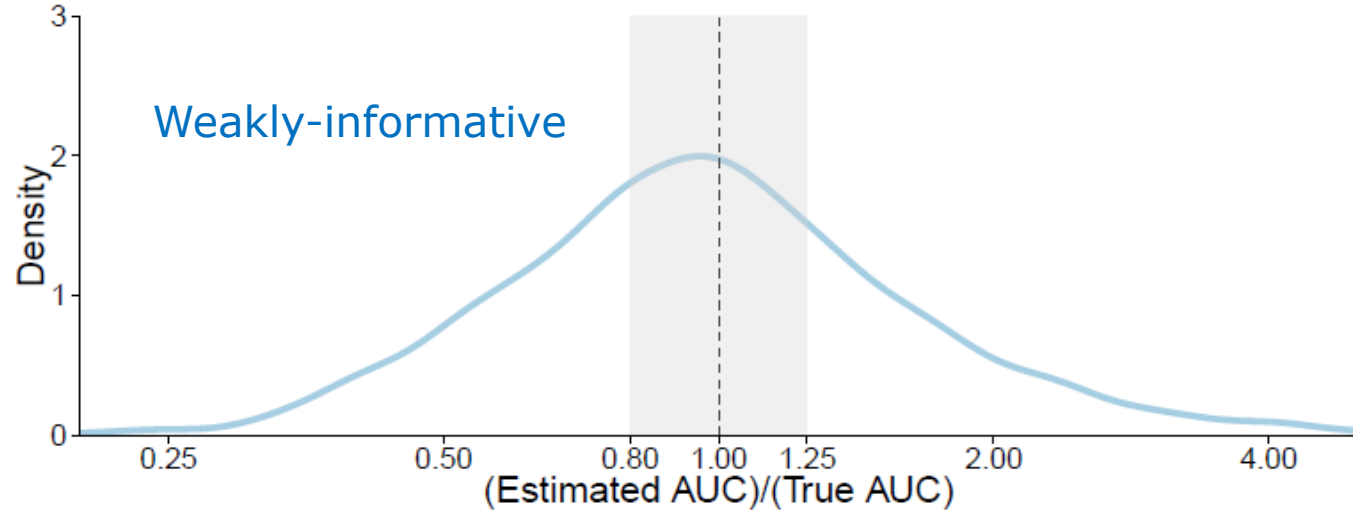
Comparison: No priors vs Priors

Type of sampling	N° of samples/subj	Scenario	Priors	Probability of successful run (%)
Protocol sampling	1	Scenario 1: only allometric scaling	Weakly-informative	56.50
			Highly-Informative	75.19
			No priors	12.22

$$\text{Probability of successful run (\%)} = \frac{100}{\text{n° of runs necessary to obtain 100 successful runs}} \cdot 100$$

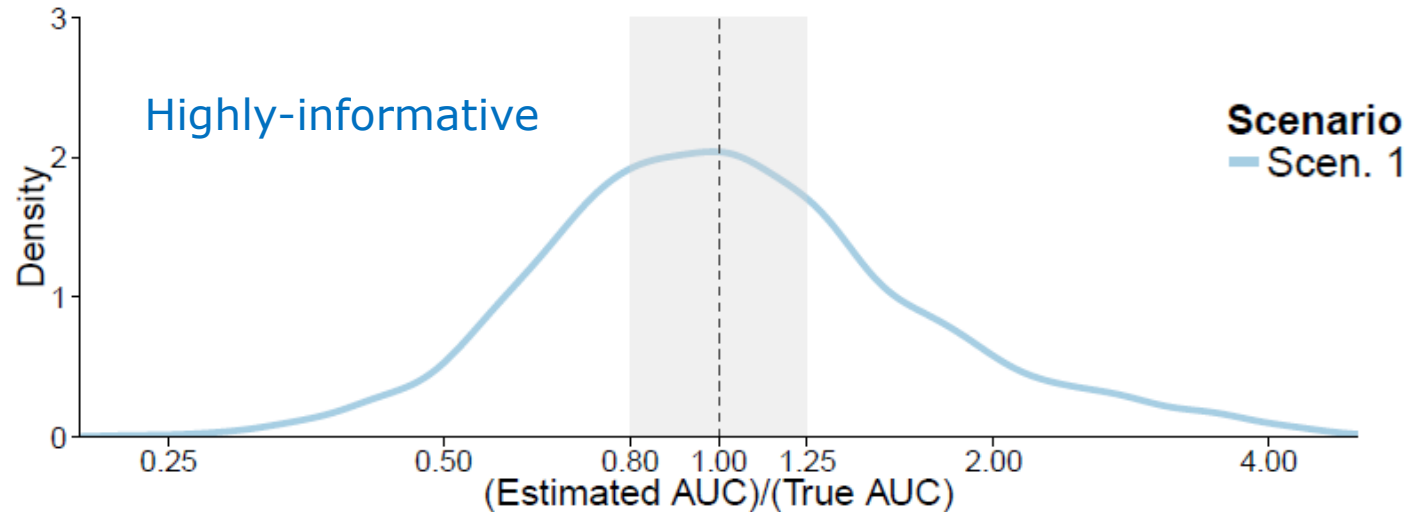
Results

Comparison: Weakly-informative vs Highly-informative priors



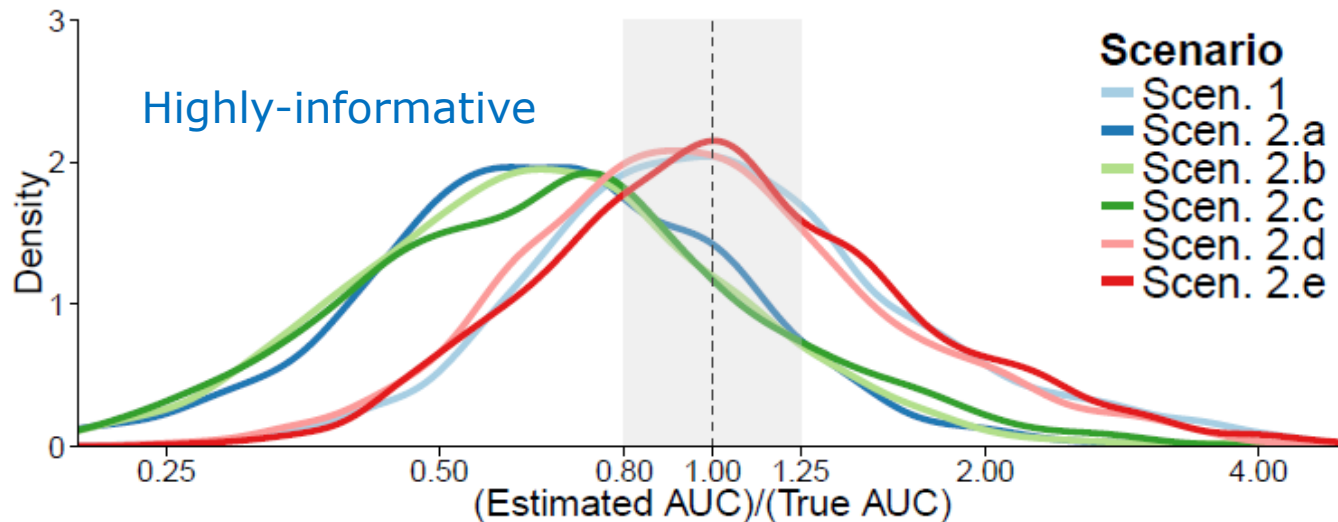
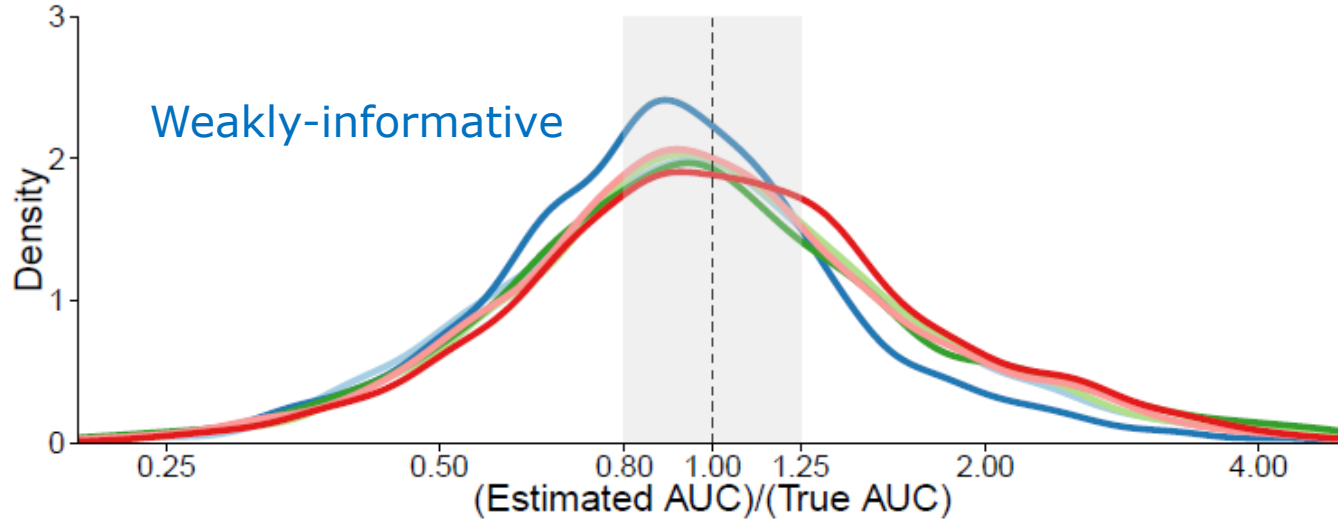
Scenario 1

- Parameters allometrically scaled



Results

Comparison: Weakly-informative vs Highly-informative priors



Scenario 1

- Parameters allometrically scaled

Scenario 2

- a) $CL = CL_{\text{adult}}/2$
- b) $CL = CL_{\text{adult}}/2, V2 = V2_{\text{adult}}/2$
- c) $CL = CL_{\text{adult}}/2, V2 = V2_{\text{adult}}/2, Q = Q_{\text{adult}}/2, V3 = V3_{\text{adult}}/2$
- d) All. exp. $CL/Q = 0.85$
- e) All. exp. $CL/Q = 2/3$

Objective n°2

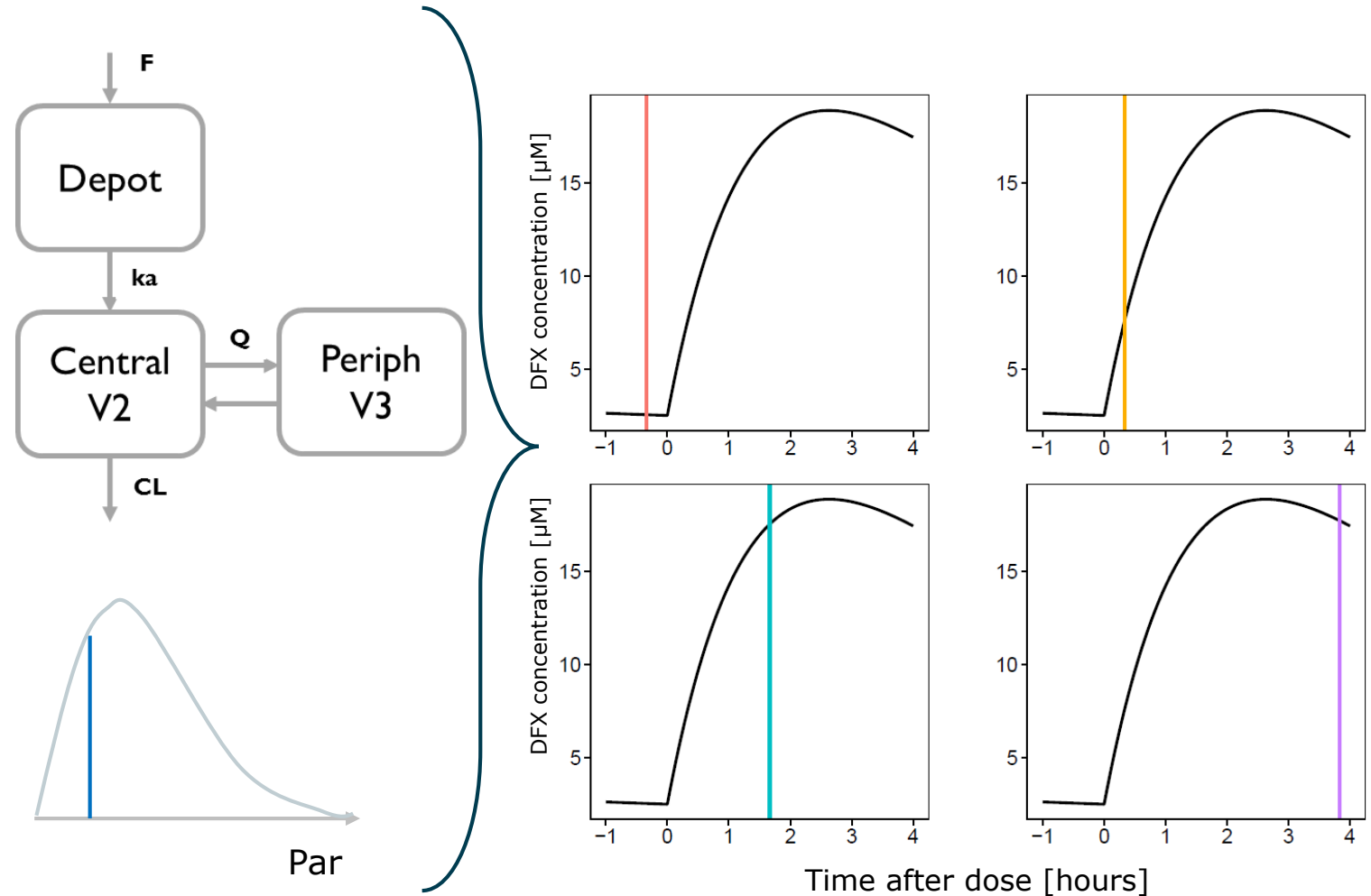
Optimization of sparse PK sampling times

I. Optimization of PK sampling schedule in PopED

ED-optimization

Uncertainties on model parameters

- Line Search method
- 19 subjects (according to current practice)
- 1 sample/subj between 1 h pre-dose to 4 hrs post-dose
- 4 designs

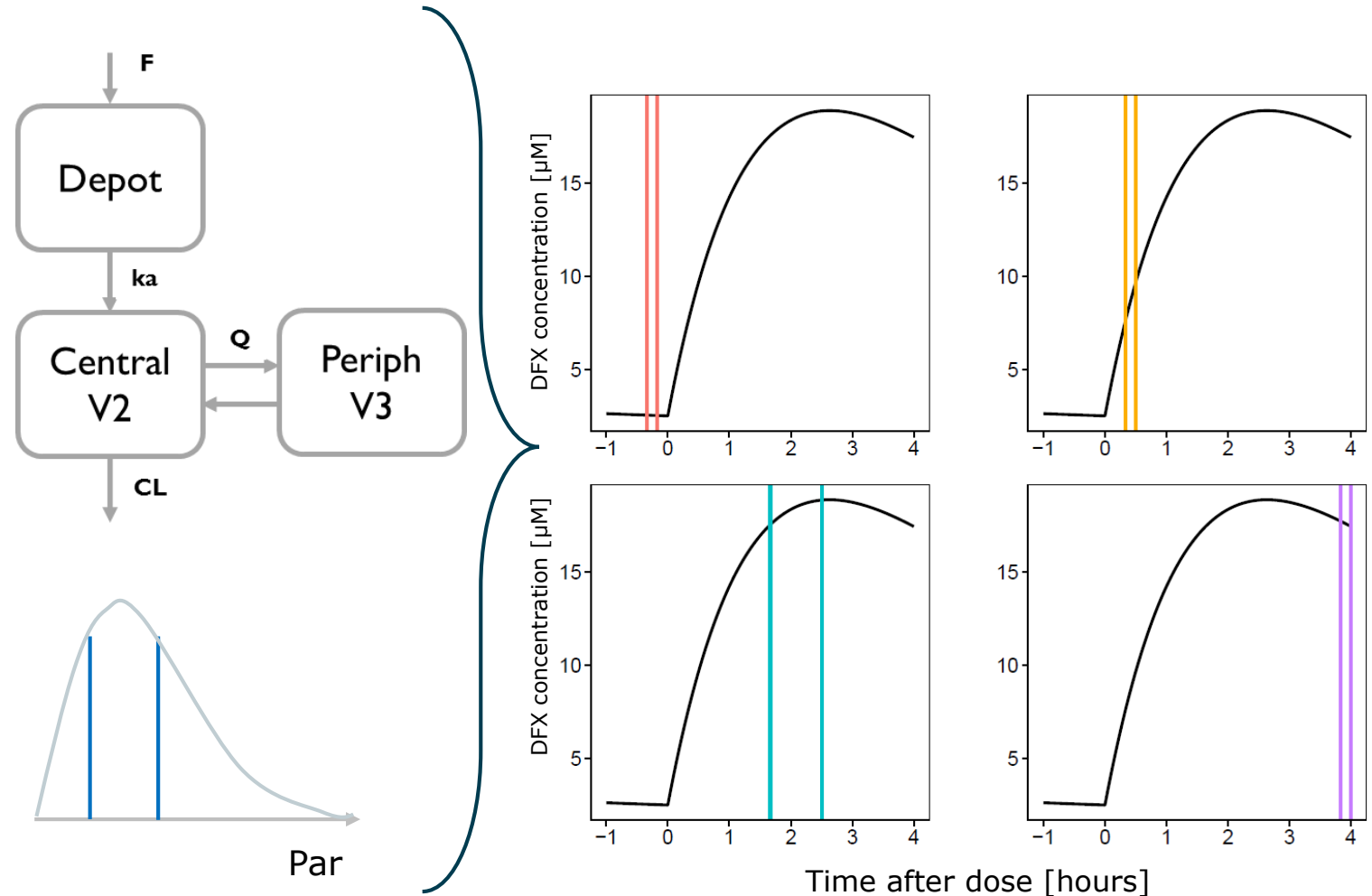


I. Optimization of PK sampling schedule in PopED

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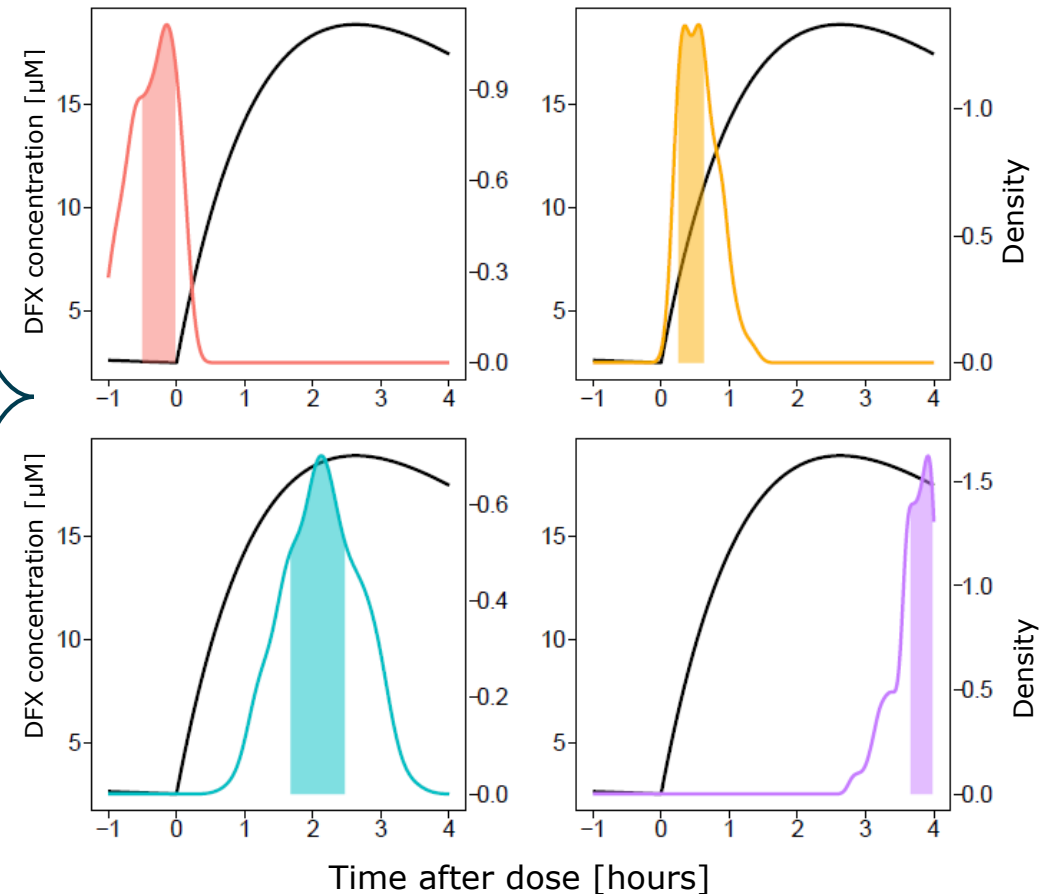
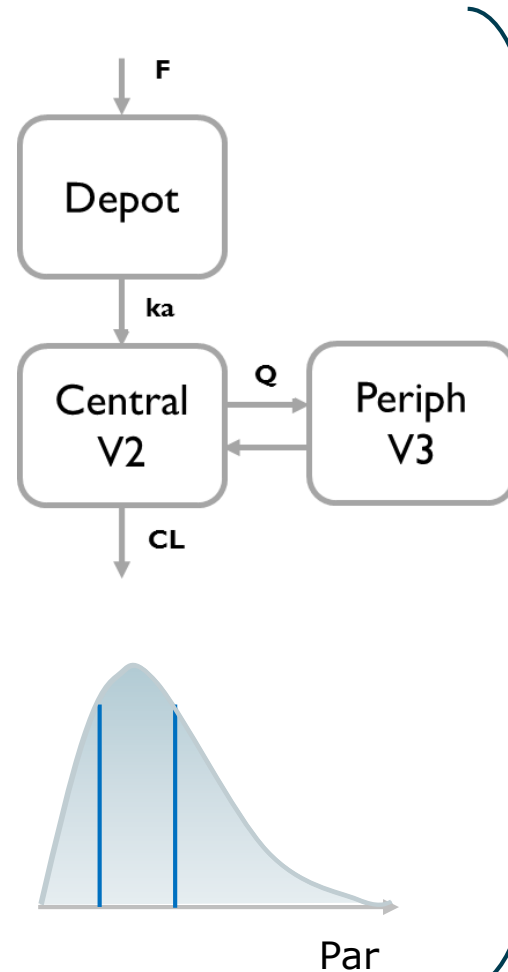


I. Optimization of PK sampling schedule in PopED

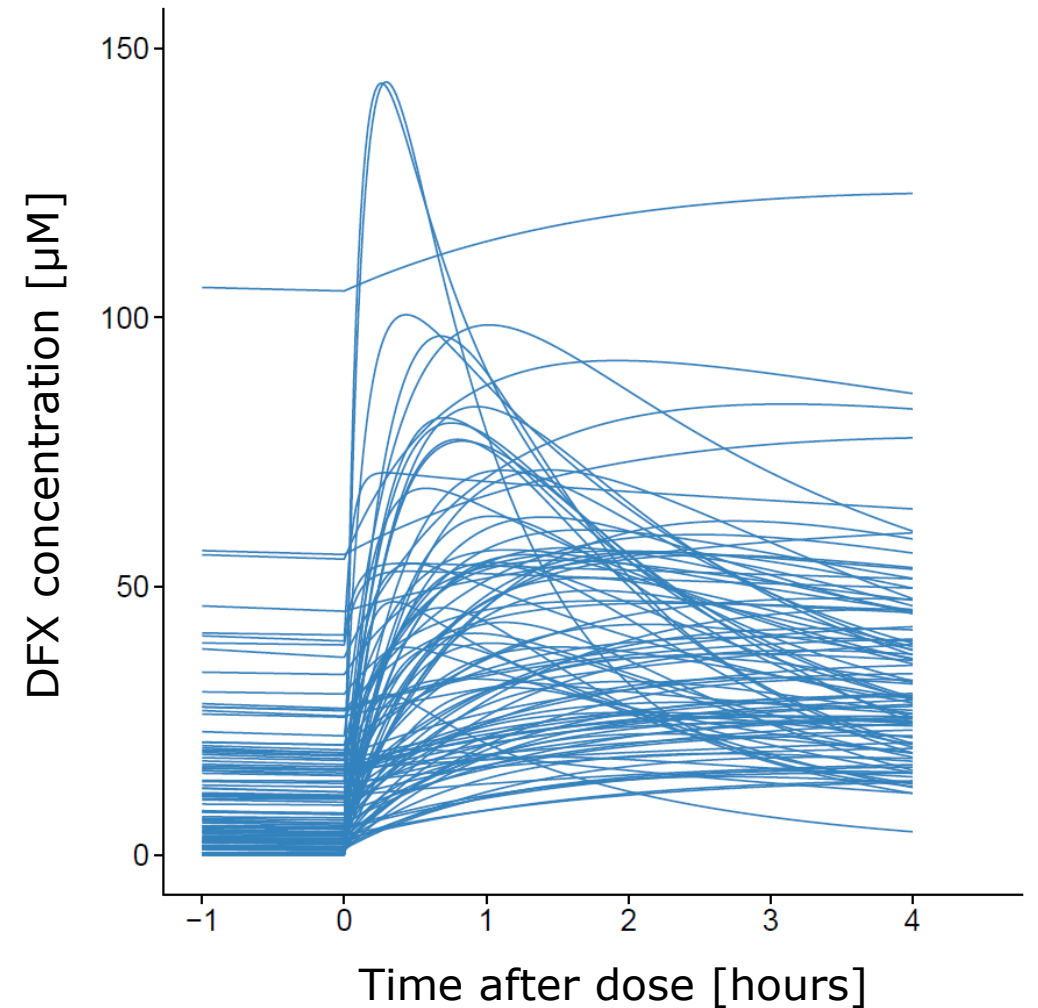
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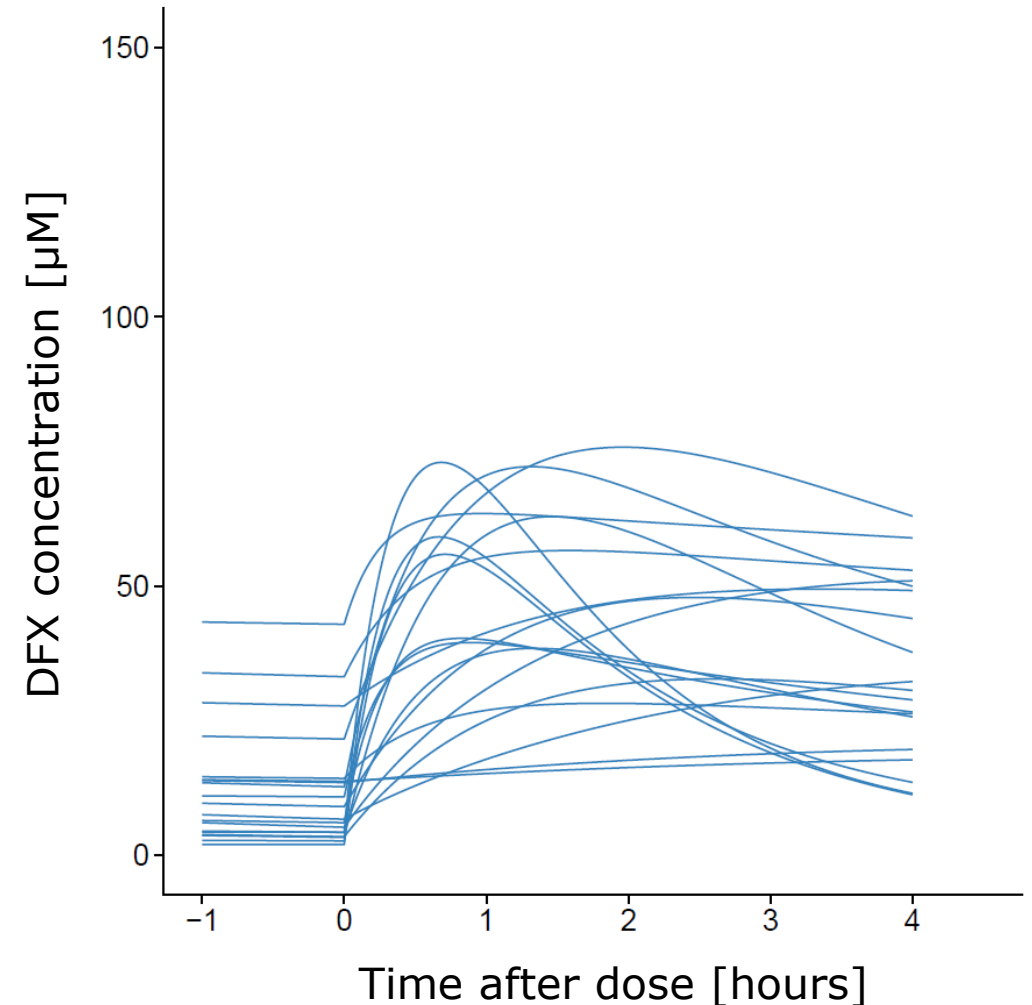
2. Simulation-estimation of PK sub-study with an optimized sampling scheme



2. Simulation-estimation of PK sub-study with an optimized sampling scheme

Extract

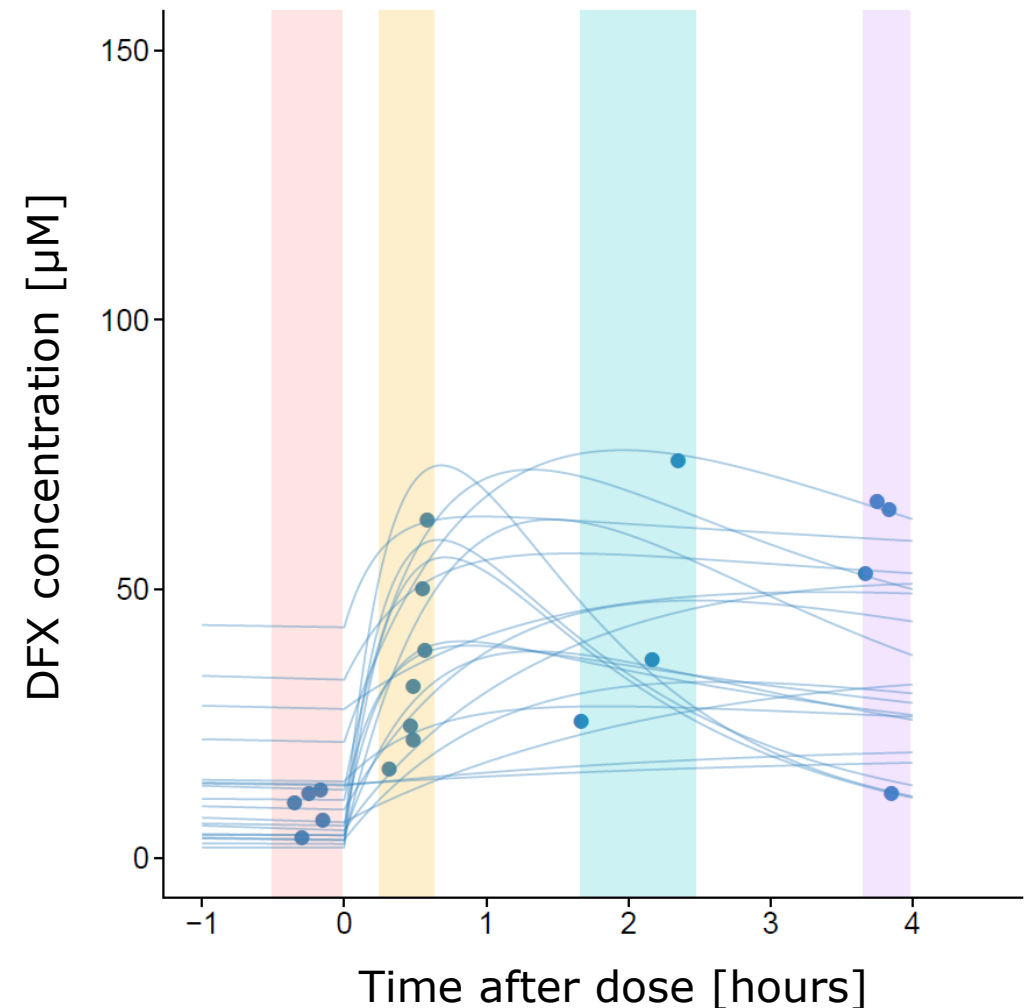
- 19 subjects
- **1 optimized sample per subject**



2. Simulation-estimation of PK sub-study with an optimized sampling scheme

Extract

- 19 subjects
- **1 optimized sample per subject**



2. Simulation-estimation of PK sub-study with an optimized sampling scheme

Extract

- 19 subjects
- **1 optimized sample per subject**

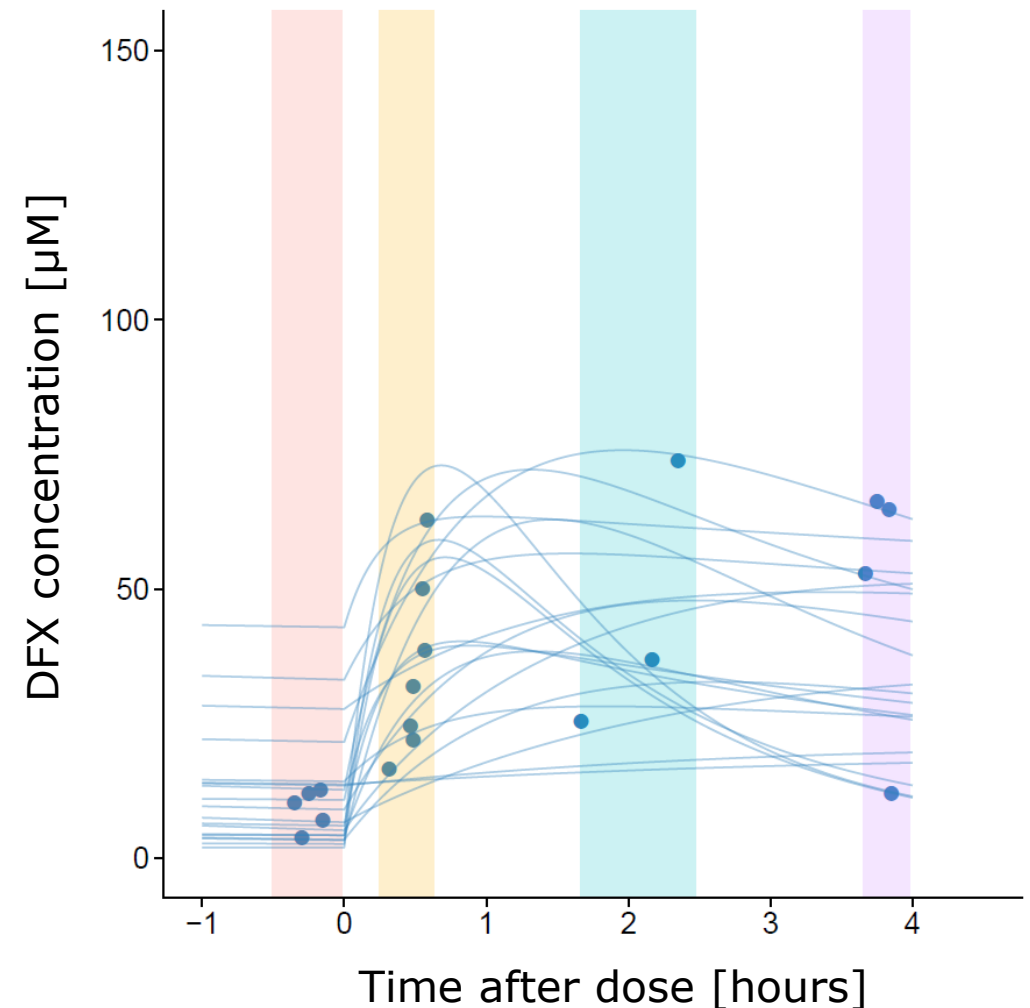
Estimate popPK model

- Typical values of CL, V2, V3, Q and ka
- IIV of CL, V2, V3 and ka

Using in NONMEM

- FOCE-I with \$PRIOR
(weakly-informative priors)

Only Scenario 1 (parameters allometrically scaled)



2. Simulation-estimation of PK sub-study with an optimized sampling scheme

Extract

- 19 subjects
- **2/3/4 optimized samples per subject**

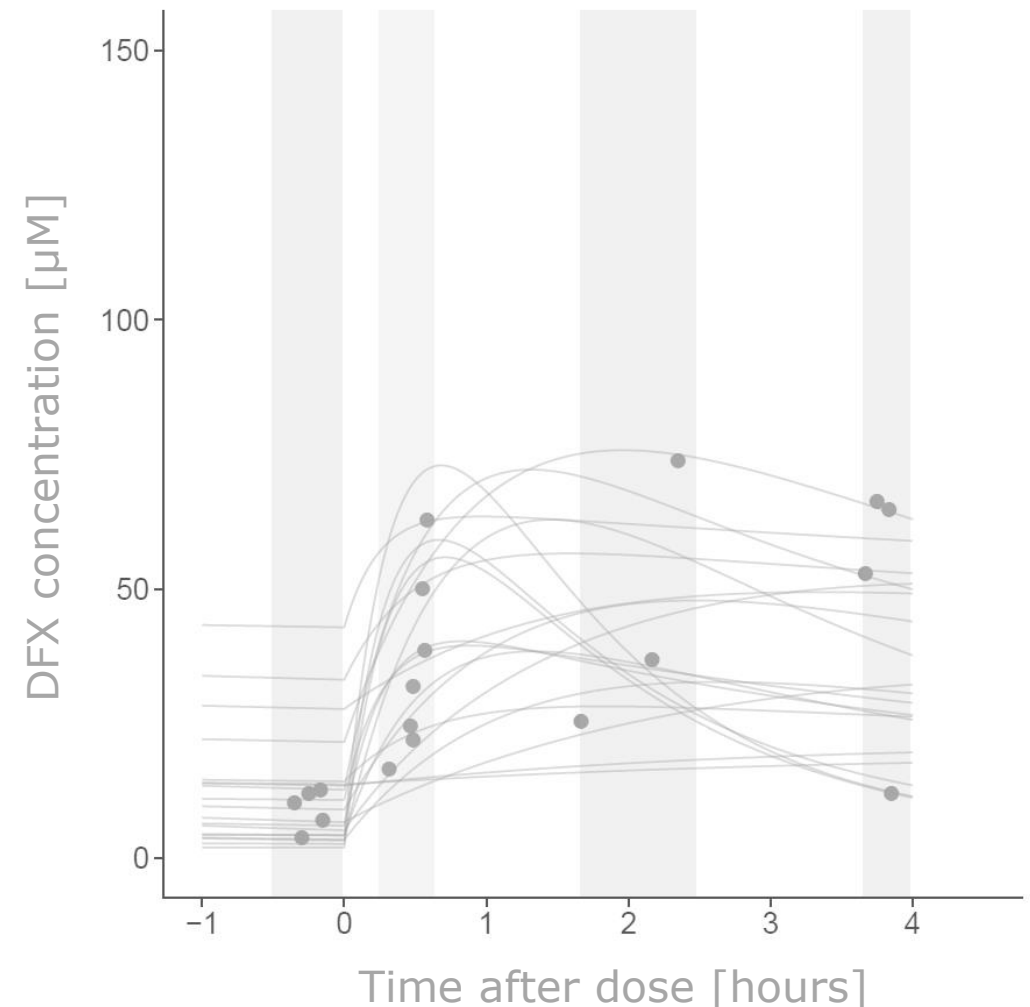
Estimate popPK model

- Typical values of CL, V2, V3, Q and ka
- IIV of CL, V2, V3 and ka

Using in NONMEM

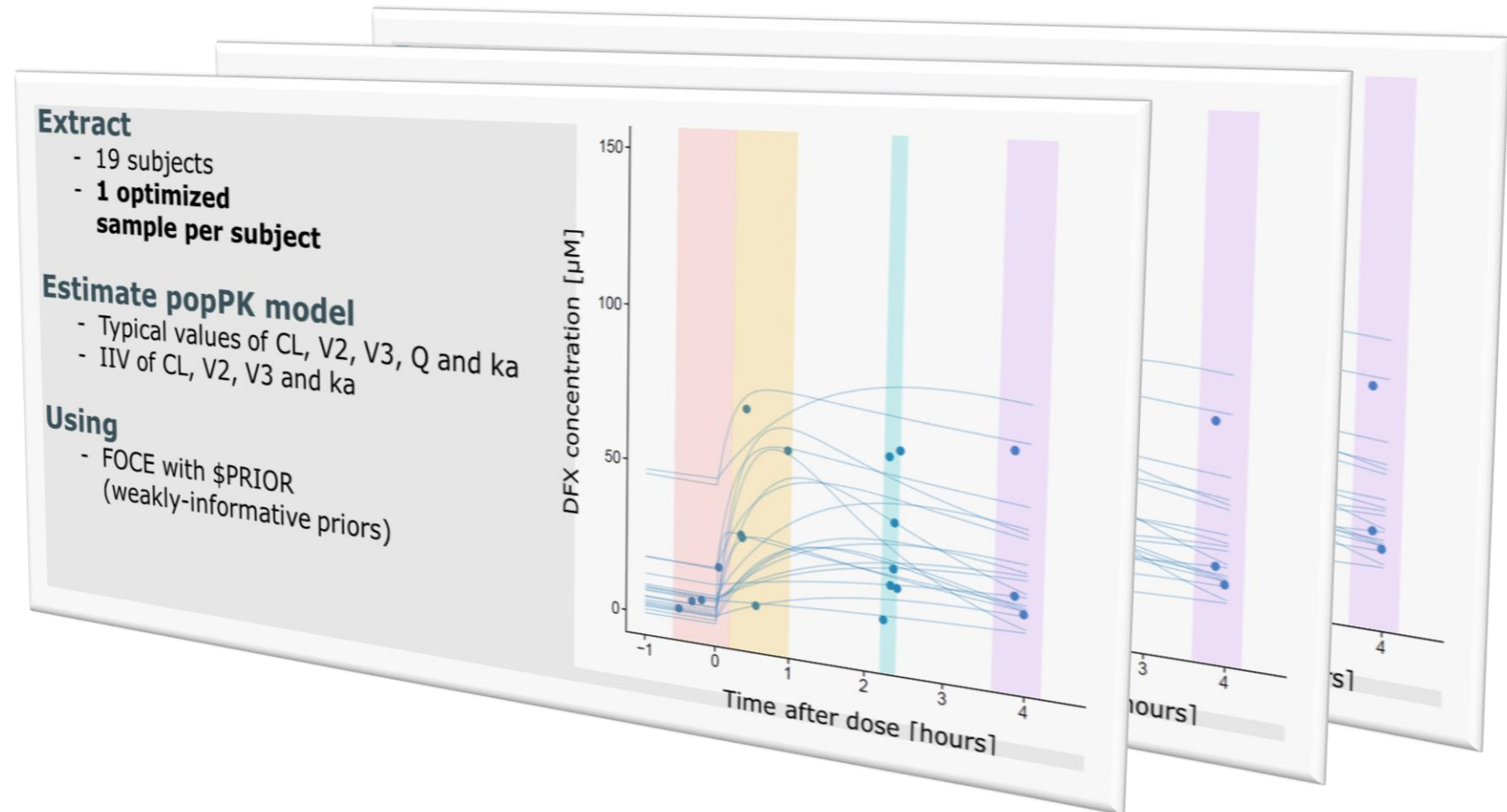
- FOCE-I with \$PRIOR
(weakly-informative priors)

Only Scenario 1 (parameters allometrically scaled)



2. Simulation-estimation of PK sub-study with an optimized sampling scheme

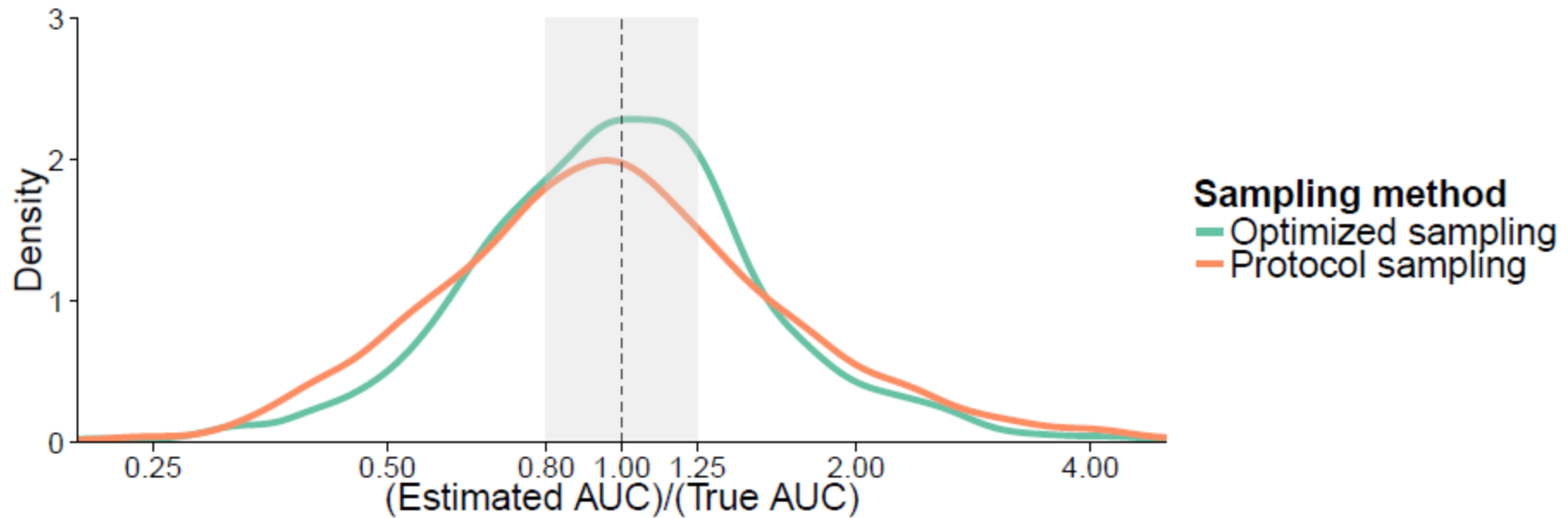
Repeat until 100 successful runs are obtained



Results

Comparison: protocol sampling vs optimized sampling (1 sample/subj)

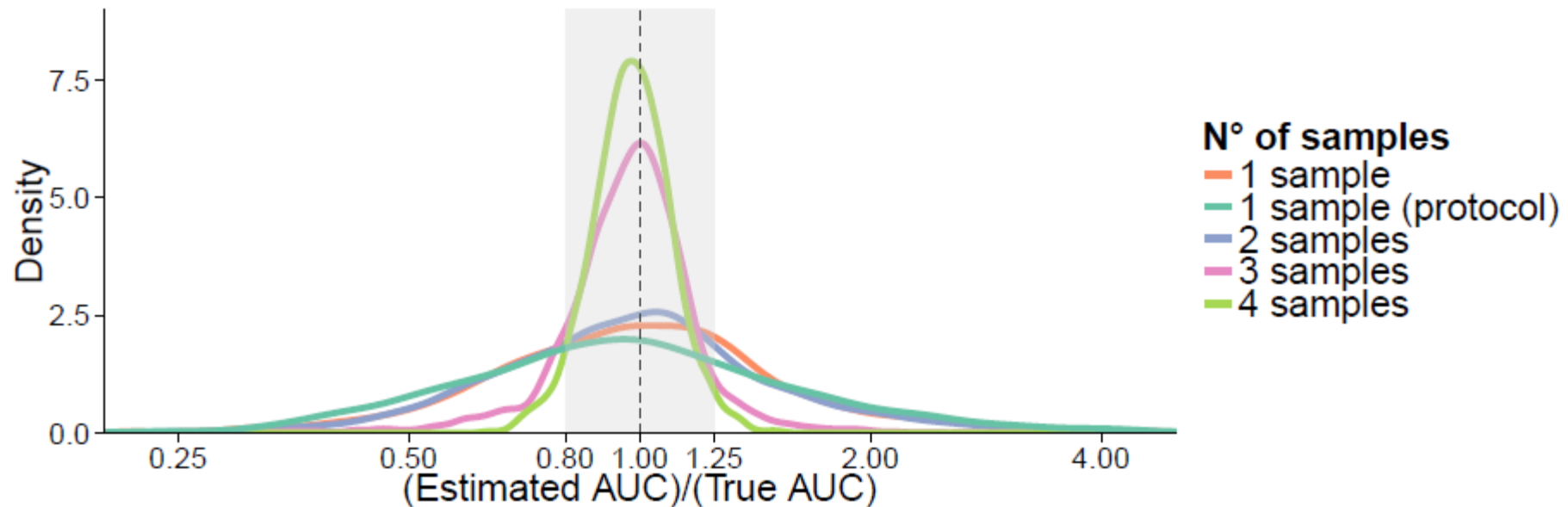
Type of sampling	N° of samples/subj	Probability of successful run (%)	Probability (%) of ratios between [0.8 ; 1.25]
Protocol sampling	1	56.50	37
Optimized sampling		51.28	42



Results

Comparison: 1 optimized sample/subj vs N optimized samples/subj (N=2,3,4)

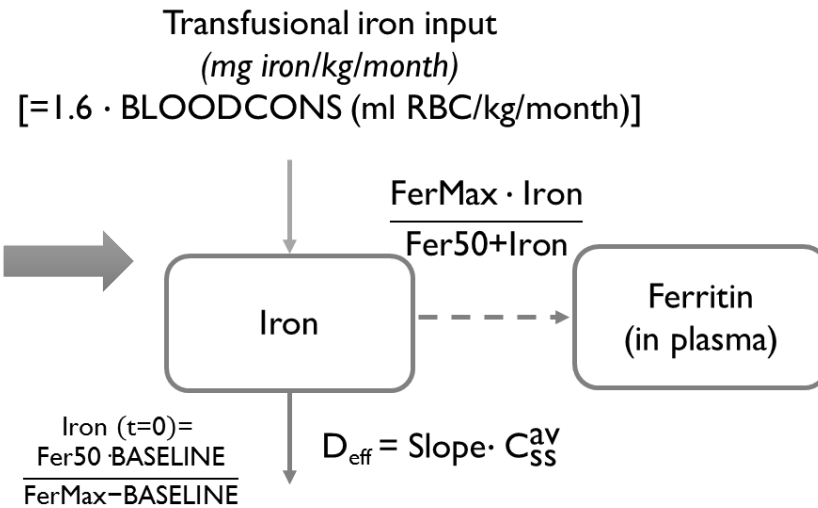
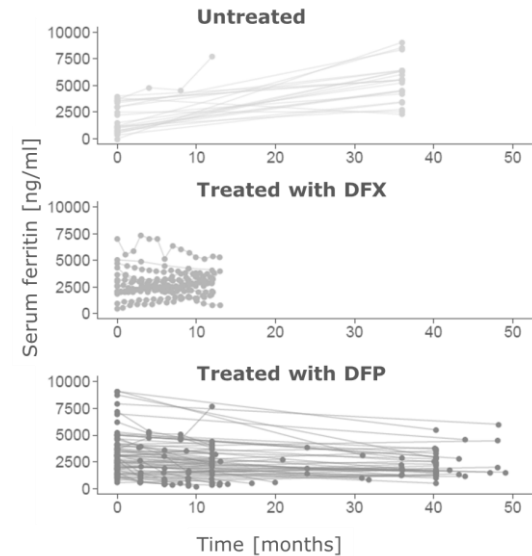
Type of sampling	N° of samples/subj	Probability of successful run (%)	Probability (%) of ratios between [0.8 ; 1.25]
Optimized sampling	1	51.28	42
	2	89.96	46
	3	92.59	82
	4	94.34	93



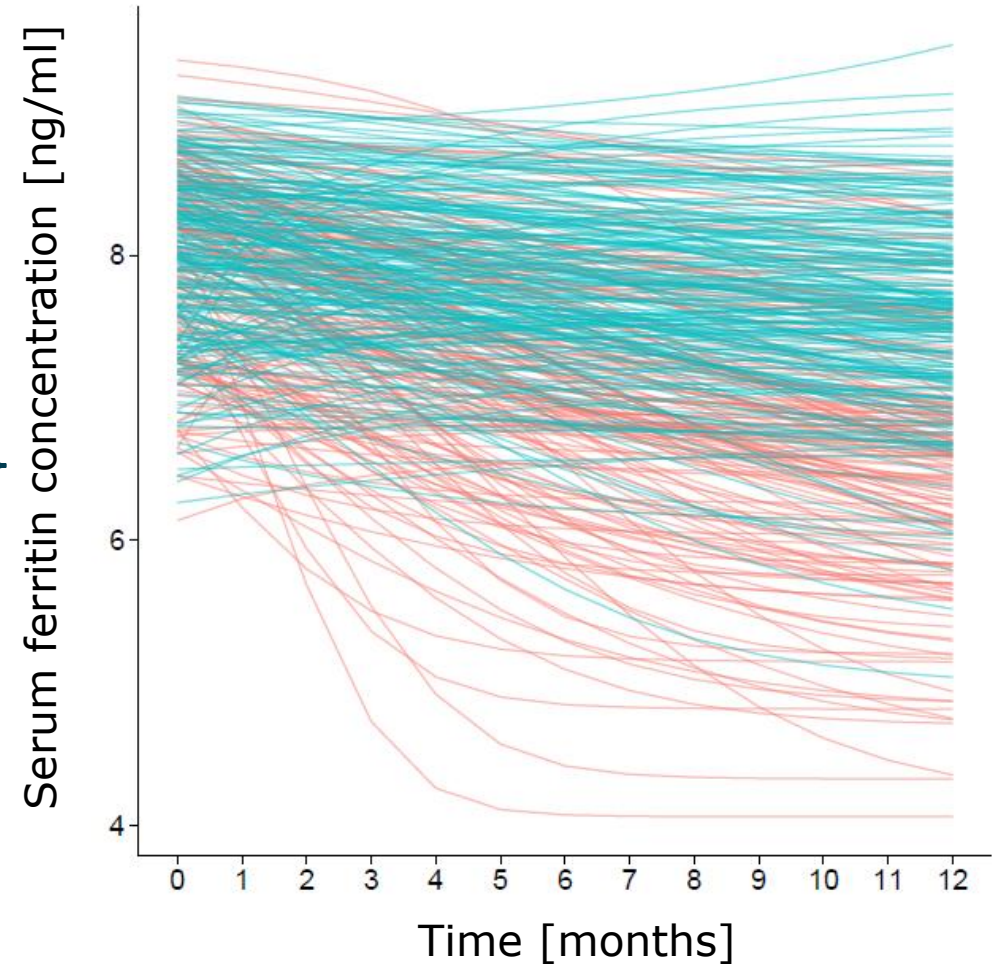
Objective n°3

Efficacy study earlier predicting
treatment response

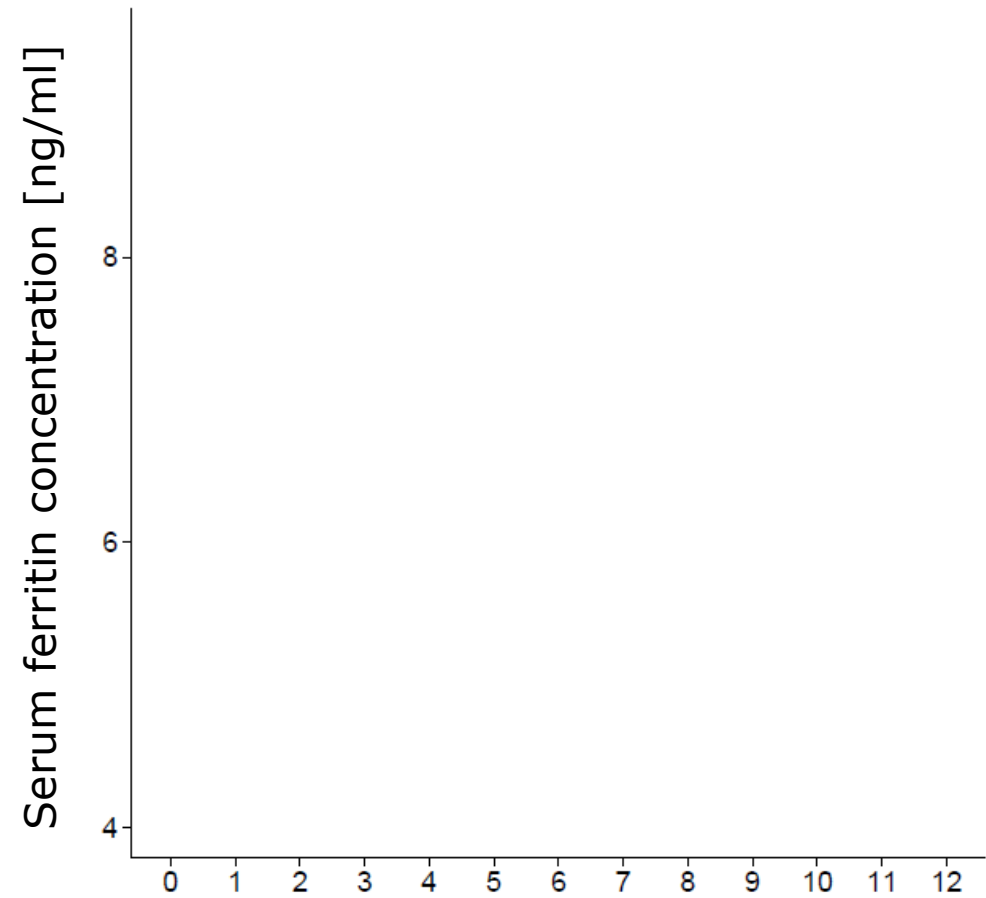
I. Simulation of serum ferritin profiles from 0 to 12 months



- + **Dose DFX:** 20-40 mg/kg/day
- + **Dose DFP:** 75-100 mg/kg/day
- + DEEP-2 study patients covariates
 - BLOODCONS: 150-200 ml/kg/year
 - BASELINE: 800-6000 ng/ml
 - Weight

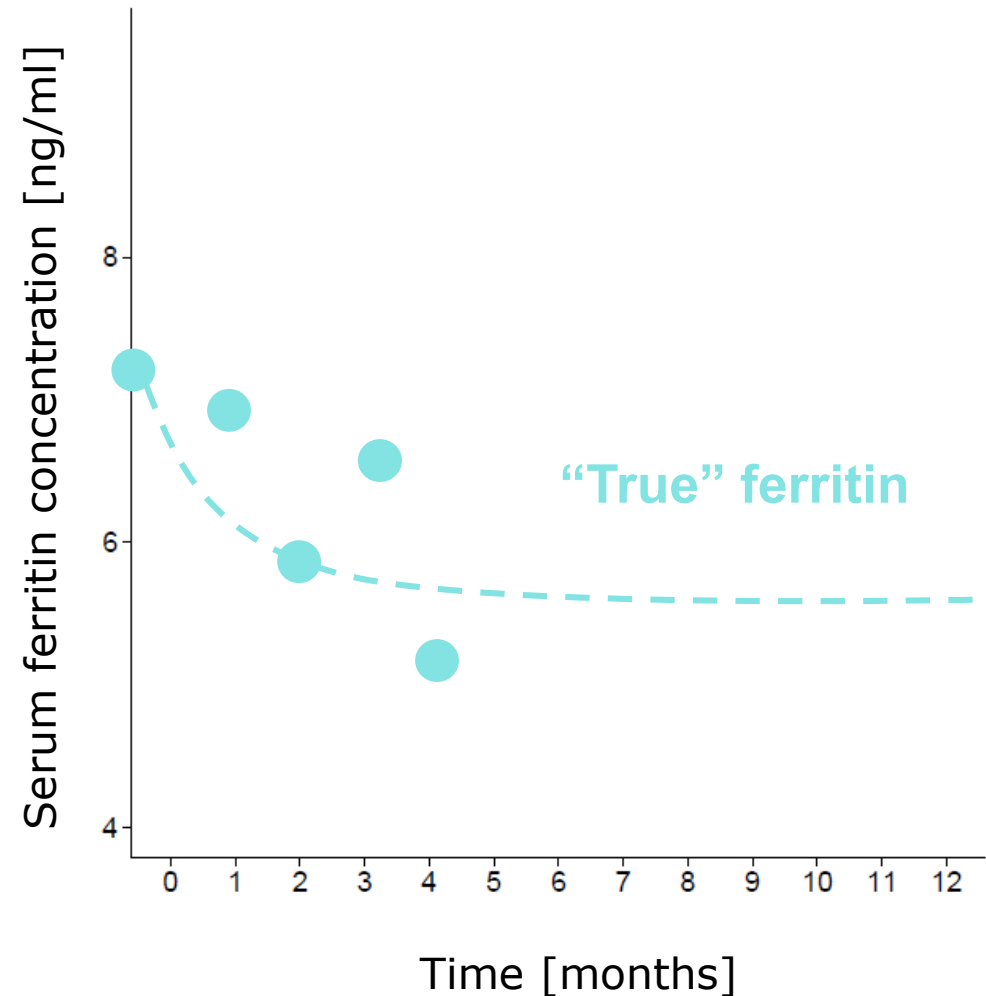


2. Prediction of ferritin response at 12 months after different treatment durations (from 1 to 11 months)



2. Prediction of ferritin response at 12 months after different treatment durations (from 1 to 11 months)

Extract for each subj
- **1 sample/month**
until the end of the treatment



2. Prediction of ferritin response at 12 months

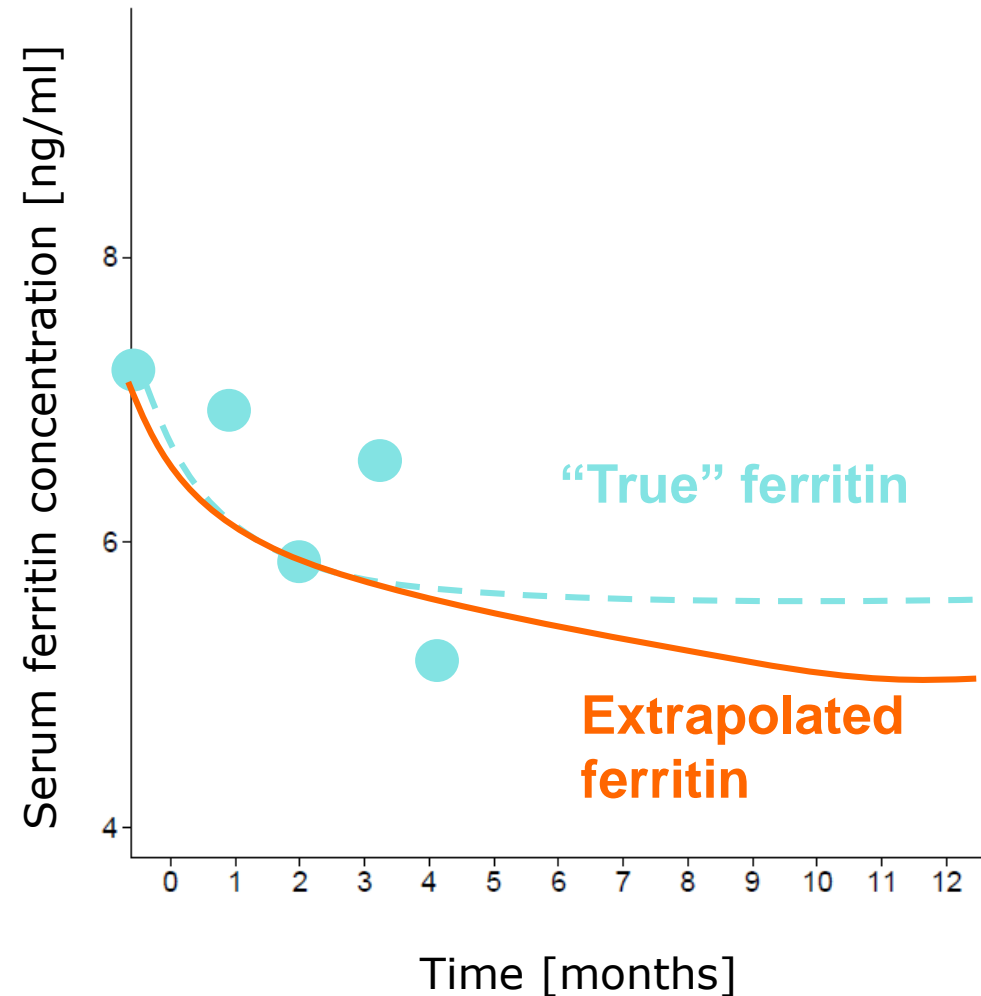
after different treatment durations (from 1 to 11 months)

Extract for each subj

- **1 sample/month**
until the end of the treatment

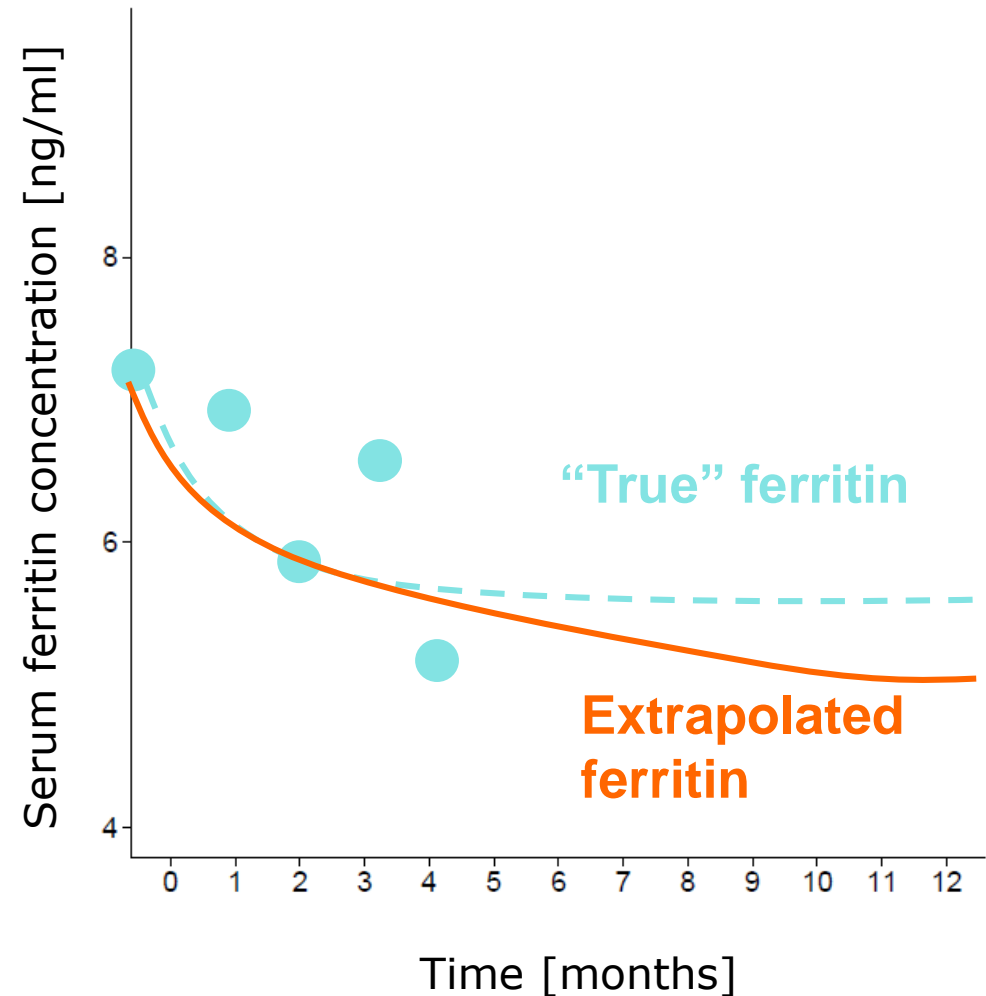
**Post-hoc estimation of
popPK-PD model**

Extrapolate at 12 months



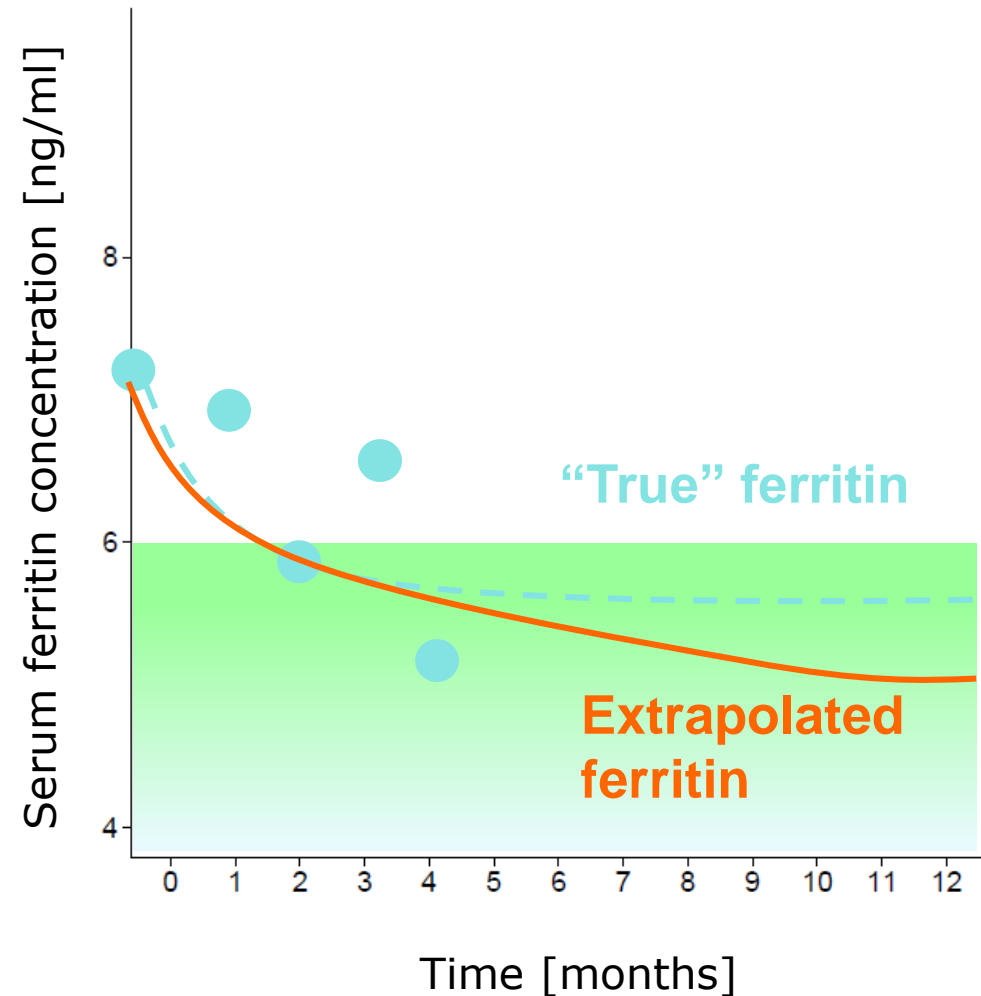
3. Classify patients according to their true and extrapolated values and the criteria specified in the protocol

PREDICTED	ACTUAL	
	Success (+)	Not success (-)
Success (+)	TP	FP
Not success (-)	FN	TN



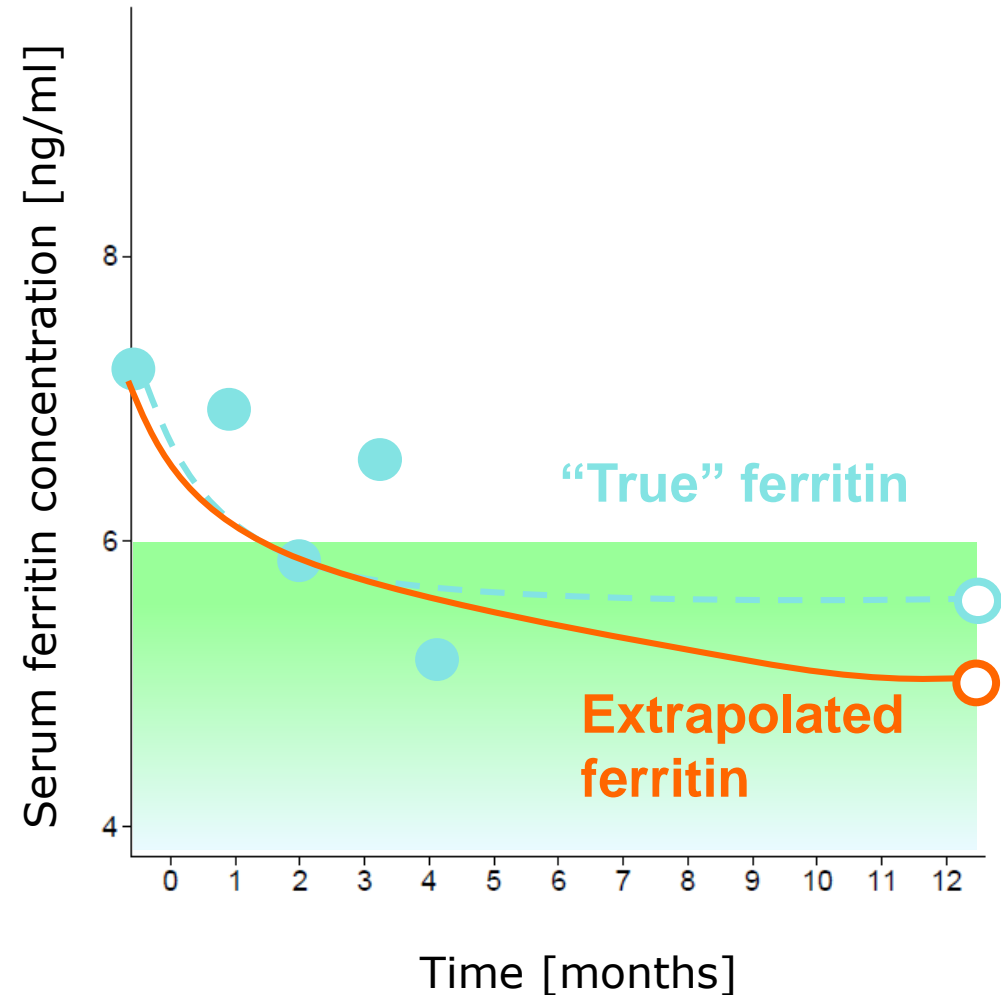
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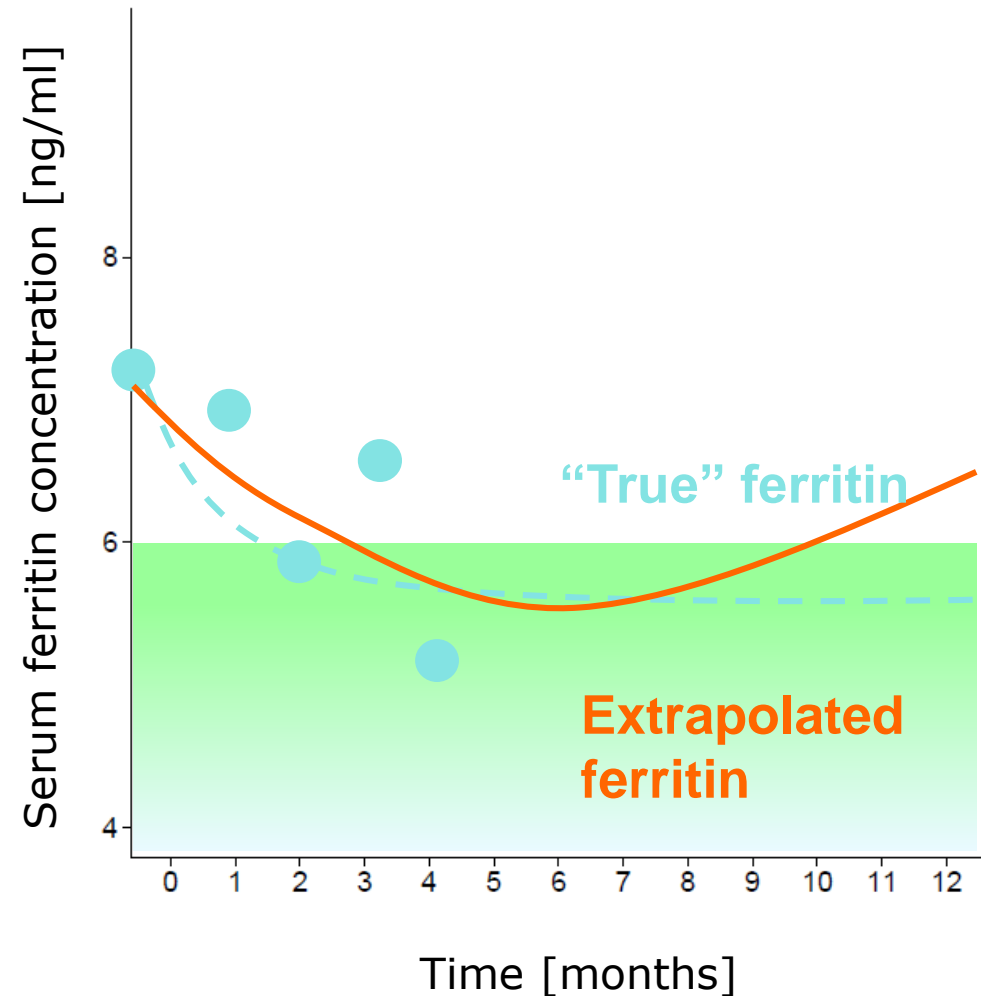
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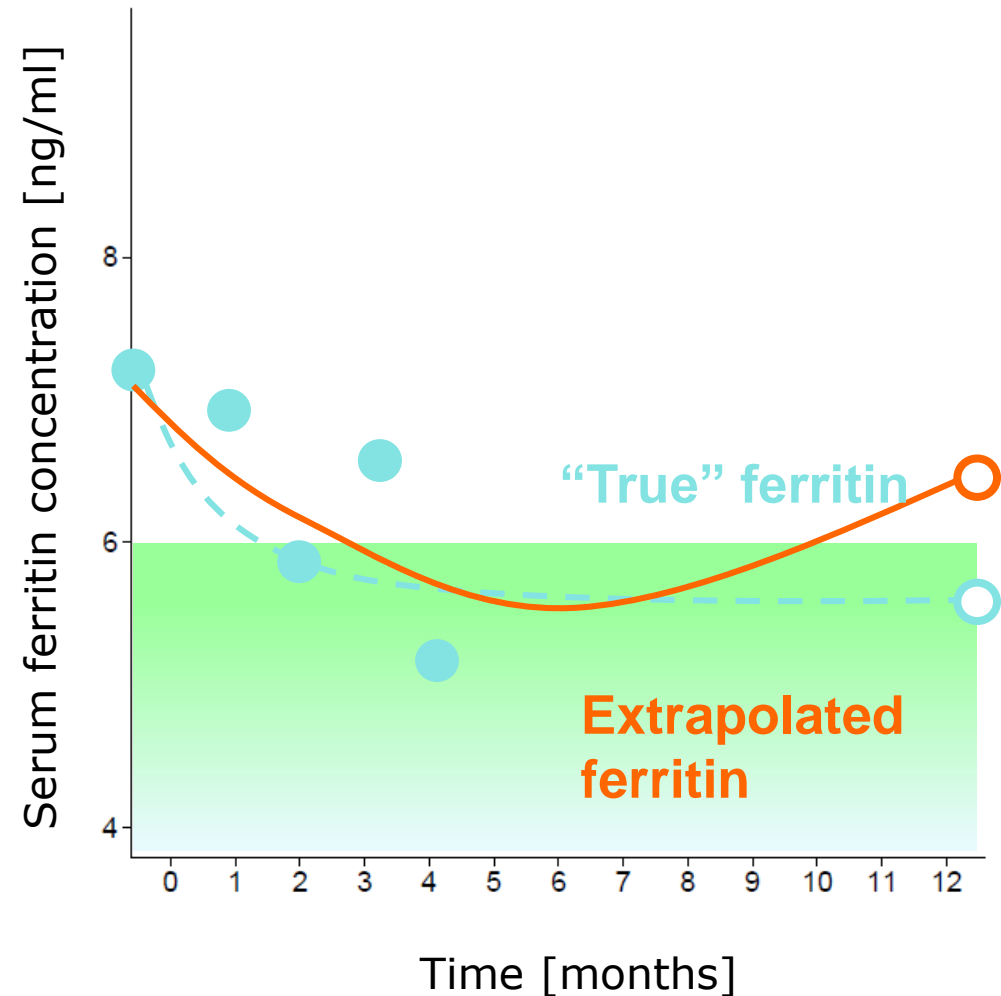
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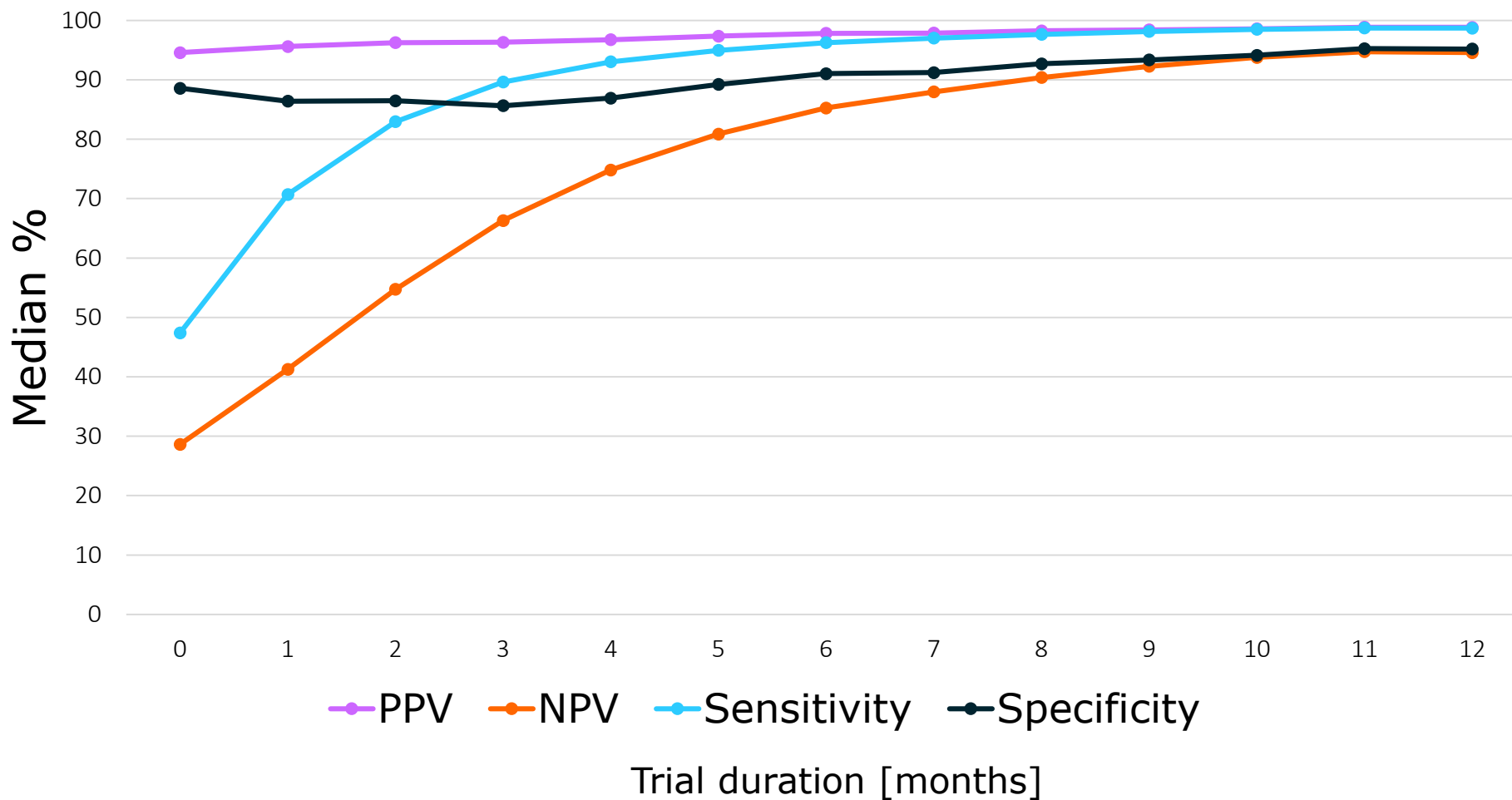
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Results

Extrapolated efficacy outcome vs true efficacy outcome



$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

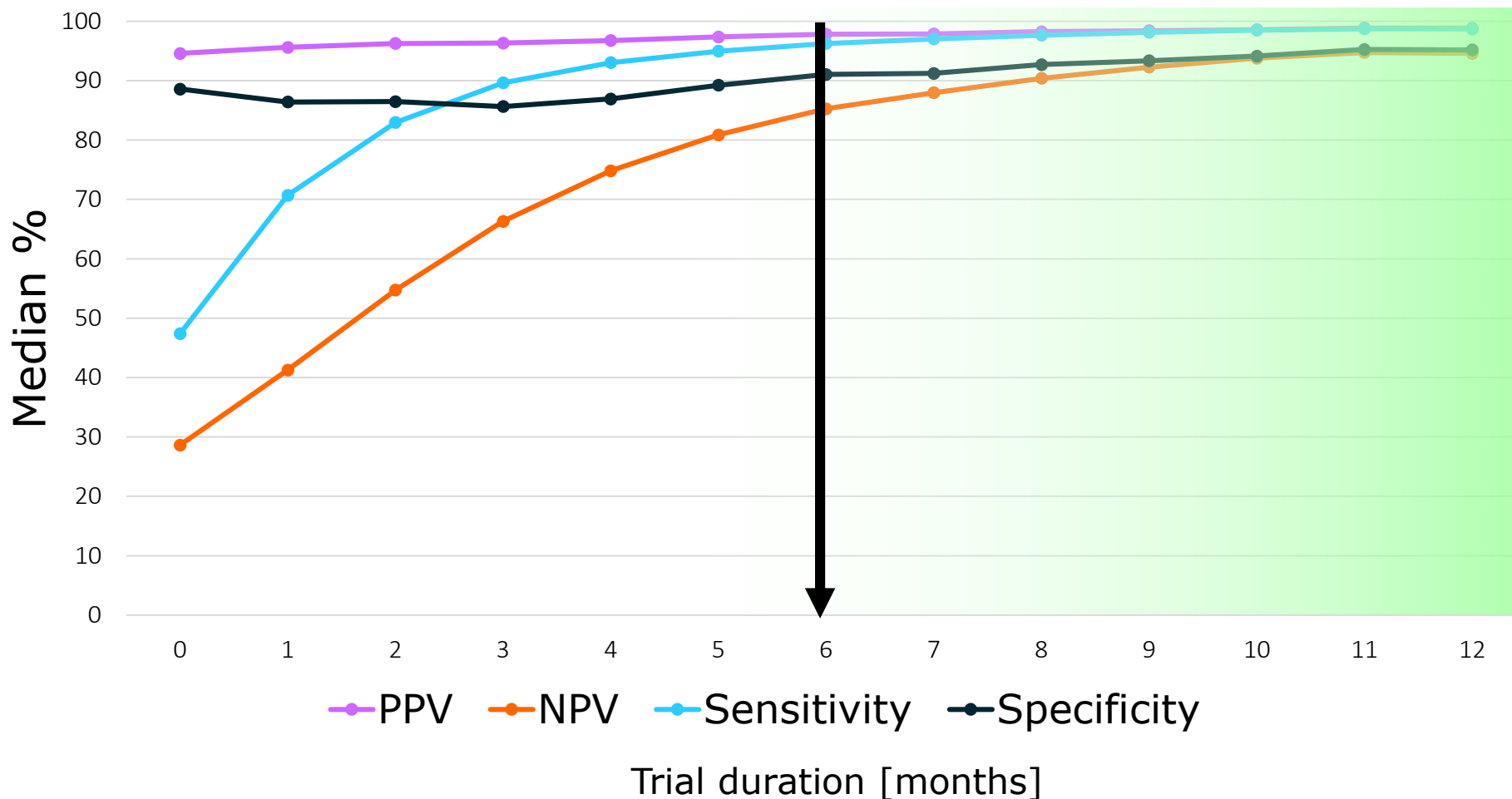
$$\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Results

Extrapolated efficacy outcome vs true efficacy outcome



$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

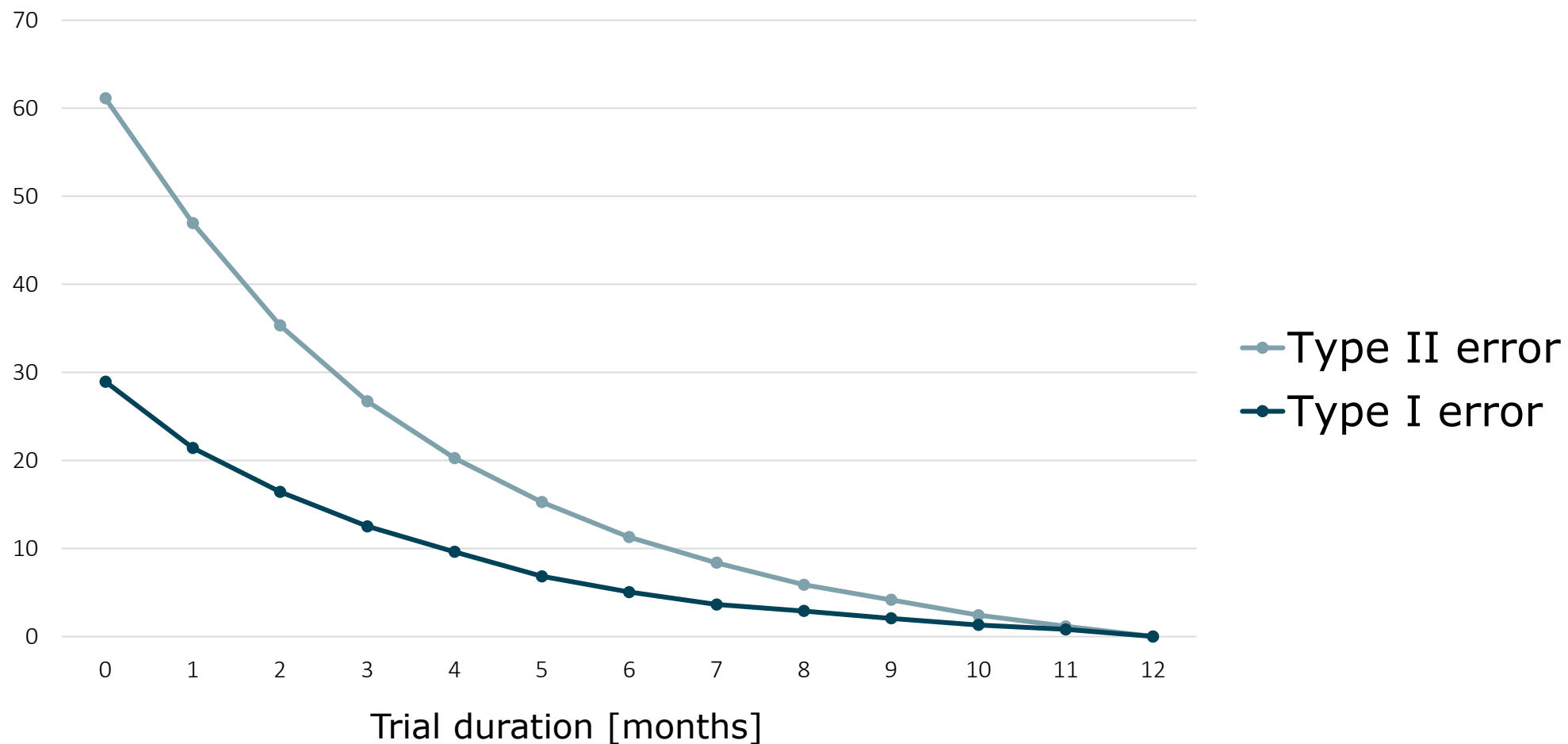
$$\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

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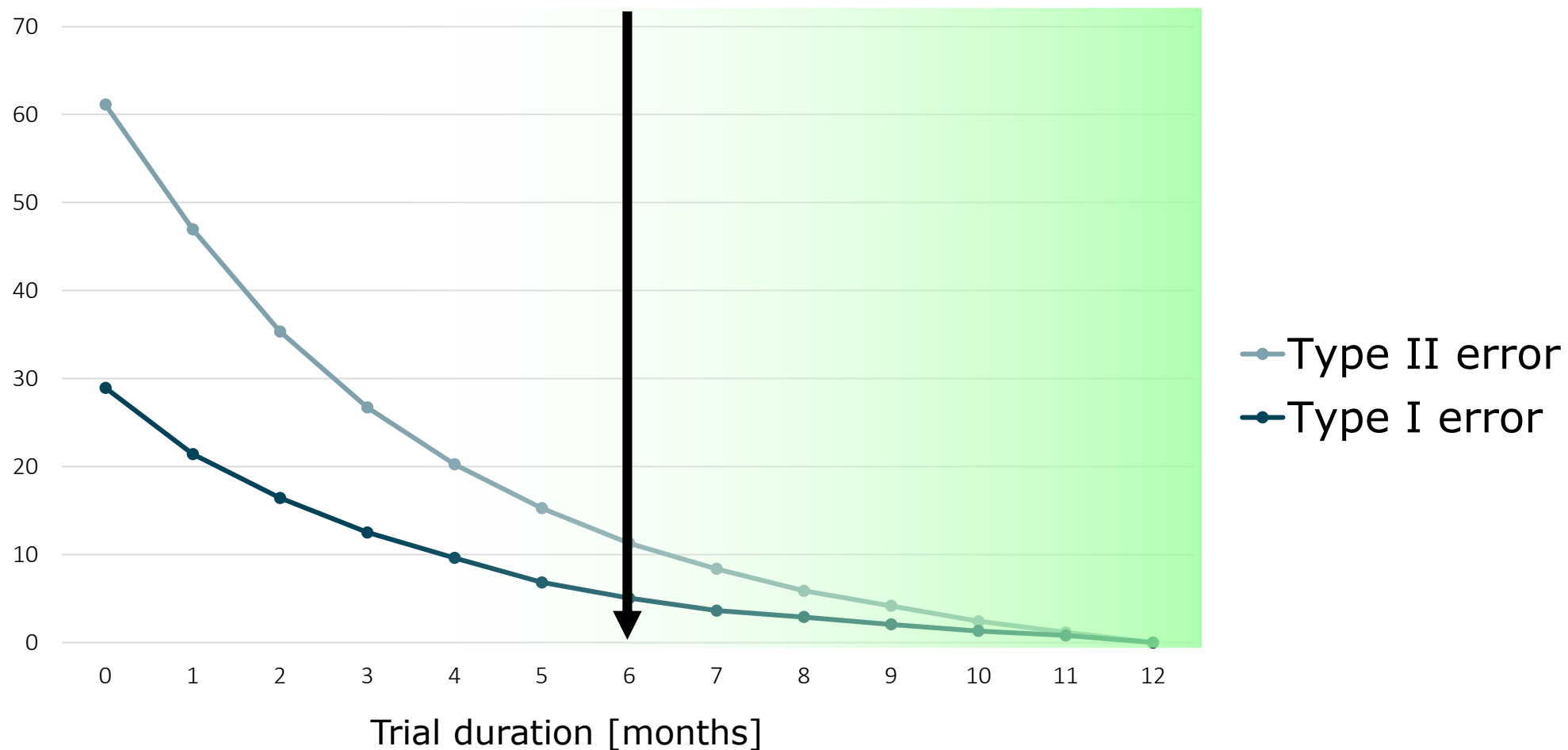
Results

True efficacy outcome at the end of the treatment vs true efficacy outcome at 12 months



Results

True efficacy outcome at the end of the treatment vs true efficacy outcome at 12 months



Summary

- Priors increases dramatically the probability of successful convergence of the FOCE-I method
- One sample per subject, even if optimized, leads to a 60% chance of over/underestimating the exposure
- Increasing the number of samples from 1 to 3 shrinks this probability to less than 10%
- The use of a model-based meta-analytical approach leads to predictive performances (e.g., PPV) at 6 months that are not significantly different from those at 1 year, suggesting the possibility of shorter trial duration

Acknowledgments

**Laboratory for Bioinformatics,
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Biology**
at University of Pavia

**Clinical Pharmacology and Therapeutics
group**
at UCL School of Pharmacy

DEEP project

Contact:

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