

Information synthesis from literature sources

Bayesian analysis of a simulated patient dataset, using prior information from normal volunteers and from another patient group

In-Sun Knutsson, Leon Aarons⁽¹⁾, Sophie Callies⁽²⁾

(1) School of Pharmacy, University of Manchester, UK

(2) Eli Lilly, UK

Outline

- **Information synthesis from literature sources**
 - *WHY*
 - To address important aspects of drugs' PK (& PD)
 - A single source of info. often *cannot* achieve this
 - *HOW*
 - Bayesian approach (using WinBUGS)
- **Bayesian analysis & reporting**
 - Subjectivity : *Subjectivity is not a weakness*
 - *Important !!!*
 - *Good coverage* of realistic prior believes
 - *Purpose* of an analysis

Good Bayesian analysis

(mixed effects modelling perspective)

- Good frequentist approach *plus*
- Accurate prior elicitation from credible sources
- Exchangeability of priors & datasets
 - Similarity of important quantities
- Realistic sensitivity analyses

Case study

Fluconazole (anti-fungal): primarily renally cleared

Prior – PK studies

Toon et al. (UK, 1990)

Shiba et al. (Japan, 1990)

Berl et al. (US, 1995)

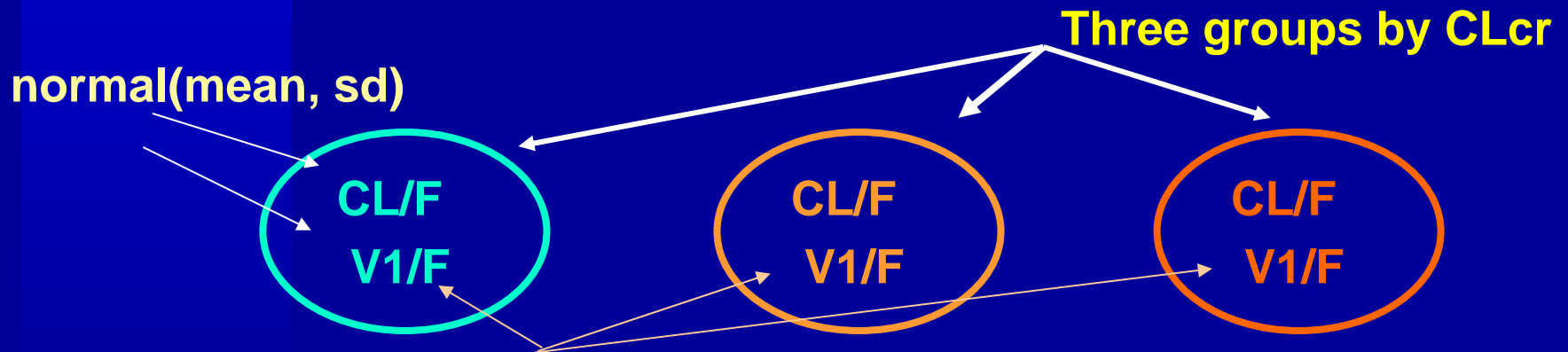
Data (simulated) – HIV, AIDS PK

McLachlan et al. (Australia, 1996)

Toon *et al.*

(UK, 1990)

- **Parallel; Single 50 mg oral dose**
- **Four groups of 5 by CLcr (Male/Female: 8/12)**
 - **> 70 ml/min**
 - **20 – 70 ml/min**
 - **< 20 ml/min; haemodialysis**
- **Densely sampled**
- **Summary info:**
 - Mean + SD of observations (a plot)
 - Mean + SD of estimated CL/F and V1/kg/F per each renal group



$$V1/F = V1/kg/F \times \text{weight (mixture, } p = 0.4)$$

$$\begin{aligned} \text{male} &= \text{Norm}(78, 10) \\ \text{female} &= \text{Norm}(62, 10) \end{aligned}$$

- ***From another source***

- Fixed proportional intra. subject variability
- Fixed mean + variability of K_a

Model 2 CL/F (model 1)

Mean trend
 Pro: accurate

Con: extrapolation
 - Identified through simulations

$$CL/F = 0.24 + 0.01 * CL_{cr}$$

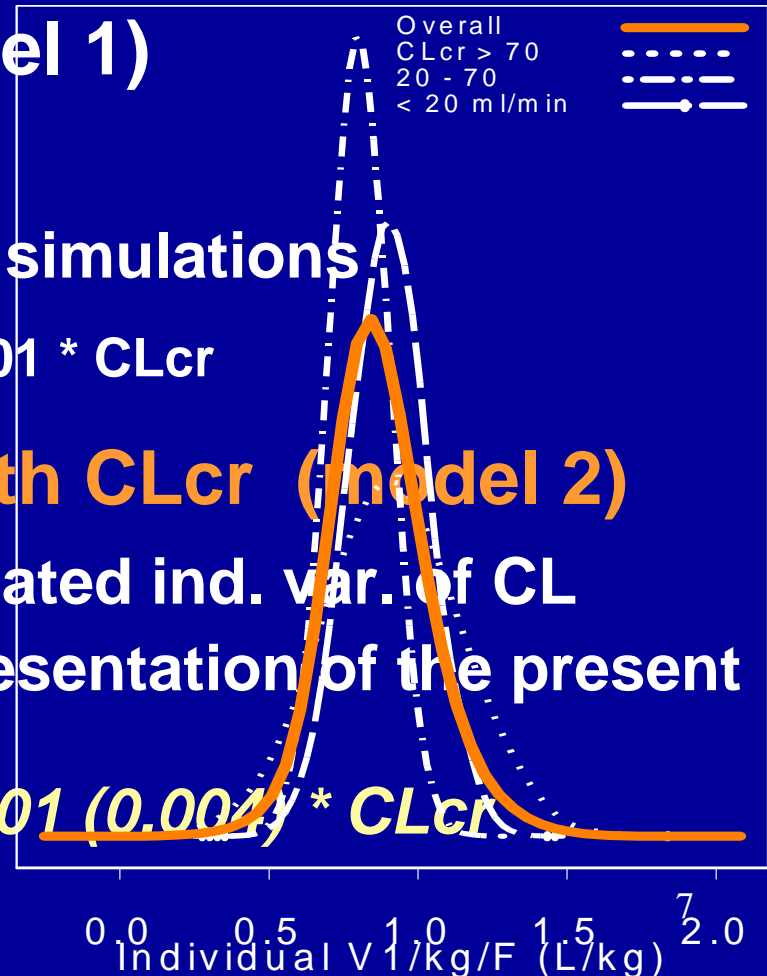
Univariate normal for CL with CLcr (model 2)

Pro: extrapolation
 - Considering estimated ind. var. of CL

Con: a lesser quality representation of the present
 - in Toon's dataset

$$CL/F = 0.24 (SD: 0.02) + 0.01 (0.004) * CL_{cr}$$

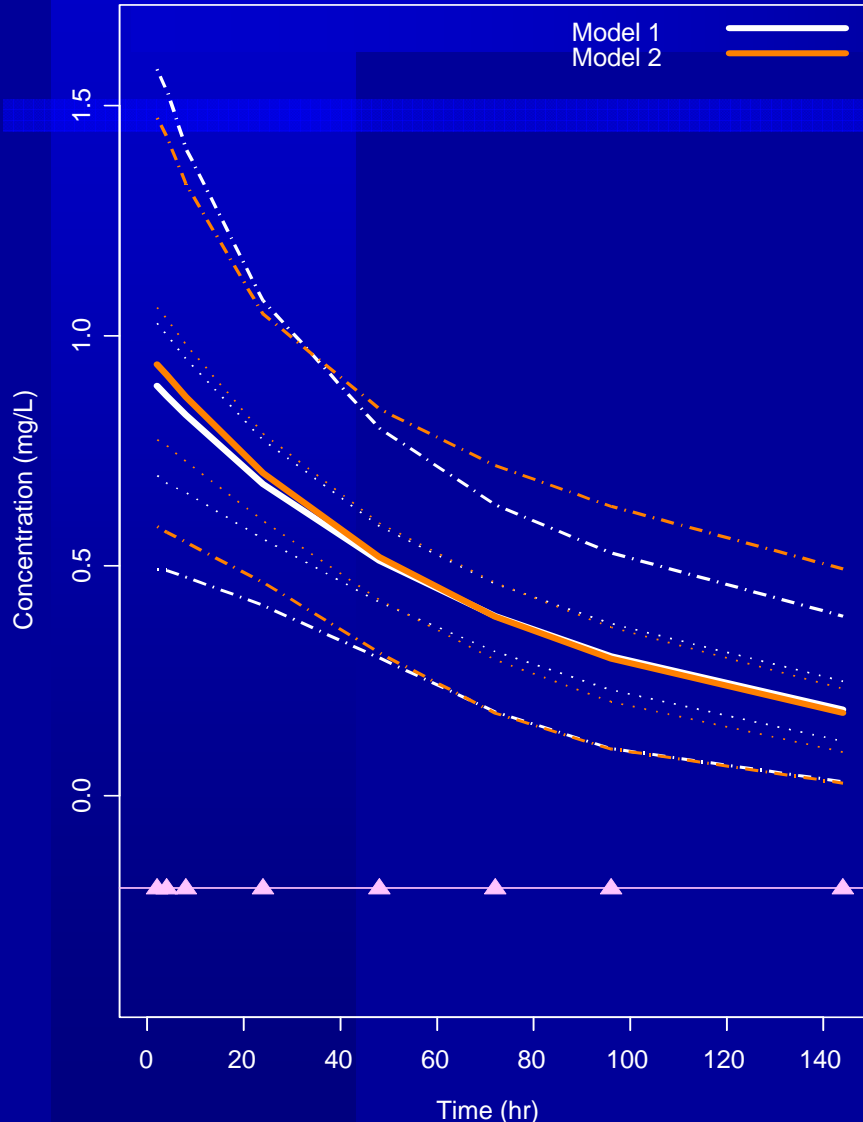
Individual CL/F (L/hr)³



Individual V1/kg/F (L/kg)^{2.0}

Model 2 vs. Model 1: 95 % credible plasma conc. intervals

20 ml/min \leq CLcr \leq 70 ml/min



- **Comparison:**

Model 2 vs. Model 1

- **Similarity:**

Box's generalised significant test

$$2 \text{ Min}(P(y_{\text{obs}} < y_{\text{pred}}), 1 - P(y_{\text{obs}} < y_{\text{pred}})) \approx \text{two sided } p\text{-value}$$

- *For individual points*

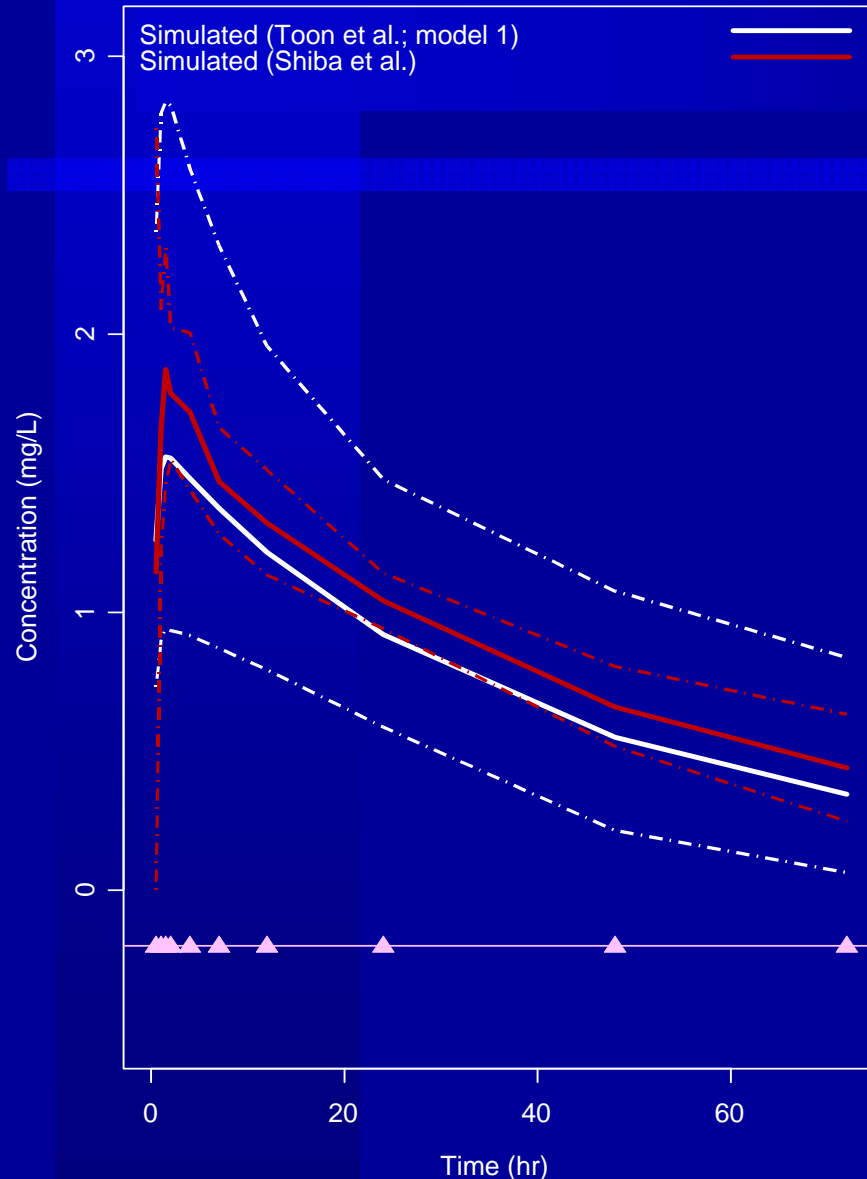
- *Overall stat. = 0.95*

Shiba *et al.* (Japan, 1990)

- **Crossover study**
- **Single 25/ 50/ 100 mg oral dose (& some IV)**
- **8 healthy male volunteers**
- **Densely sampled**
- **Summary info:**
 - Mean + SD of observations (*a table*)
 - Mean + SD of estimated CL/F and V1/F per each dosing group
 - Weight info.

Toon's model 1 vs. Shiba's data summary (95 % intervals)

100 mg



- **Comparison:**

Simulations from Toon's model 1
(CL_{cr} > 70ml/min)

vs.

Simulations from Shiba's data
summary
(normal volunteers)

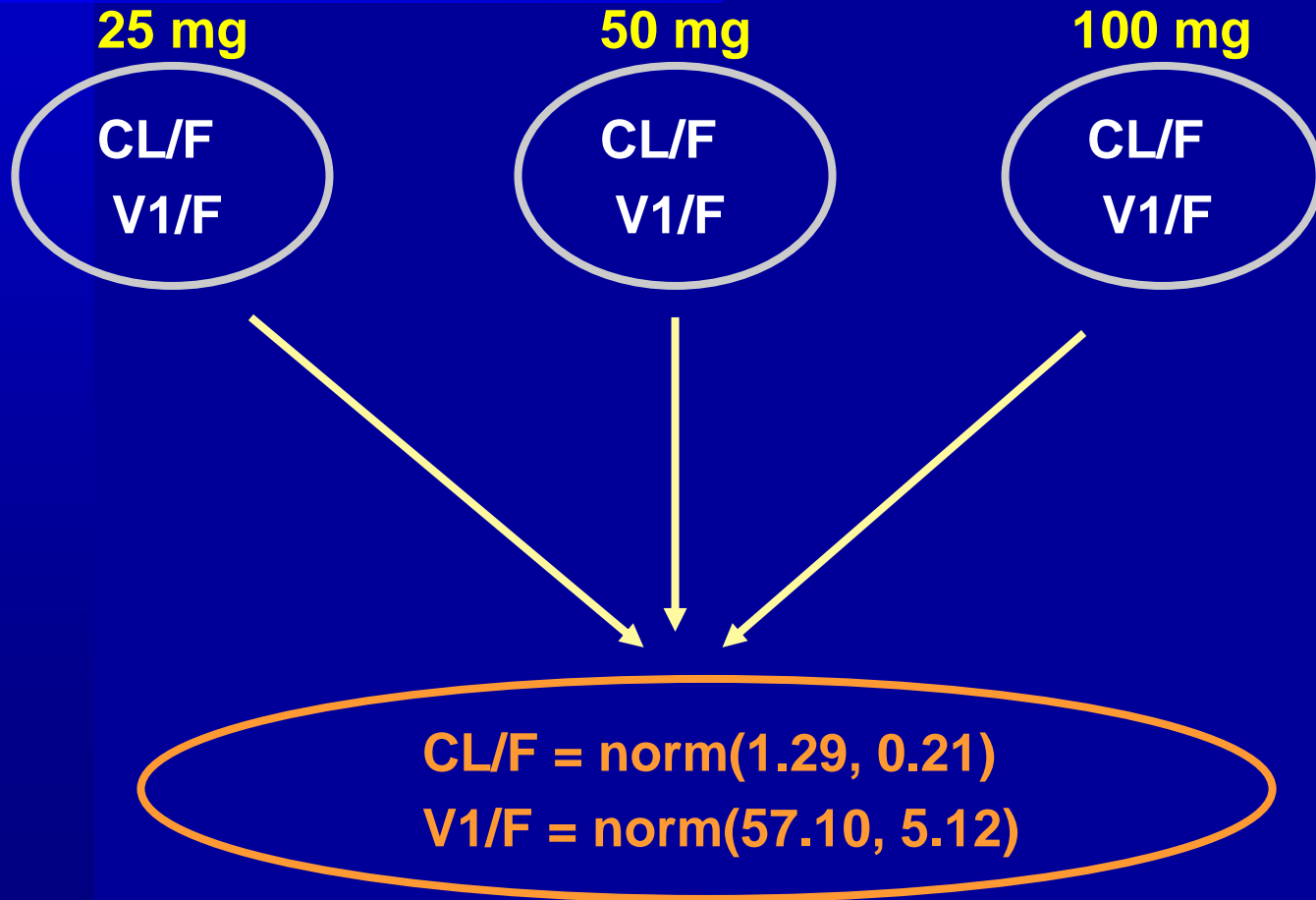
- **Similarity (*exchangeability*)**

- *For individual points*

- *Overall Box's stat. = 0.71*

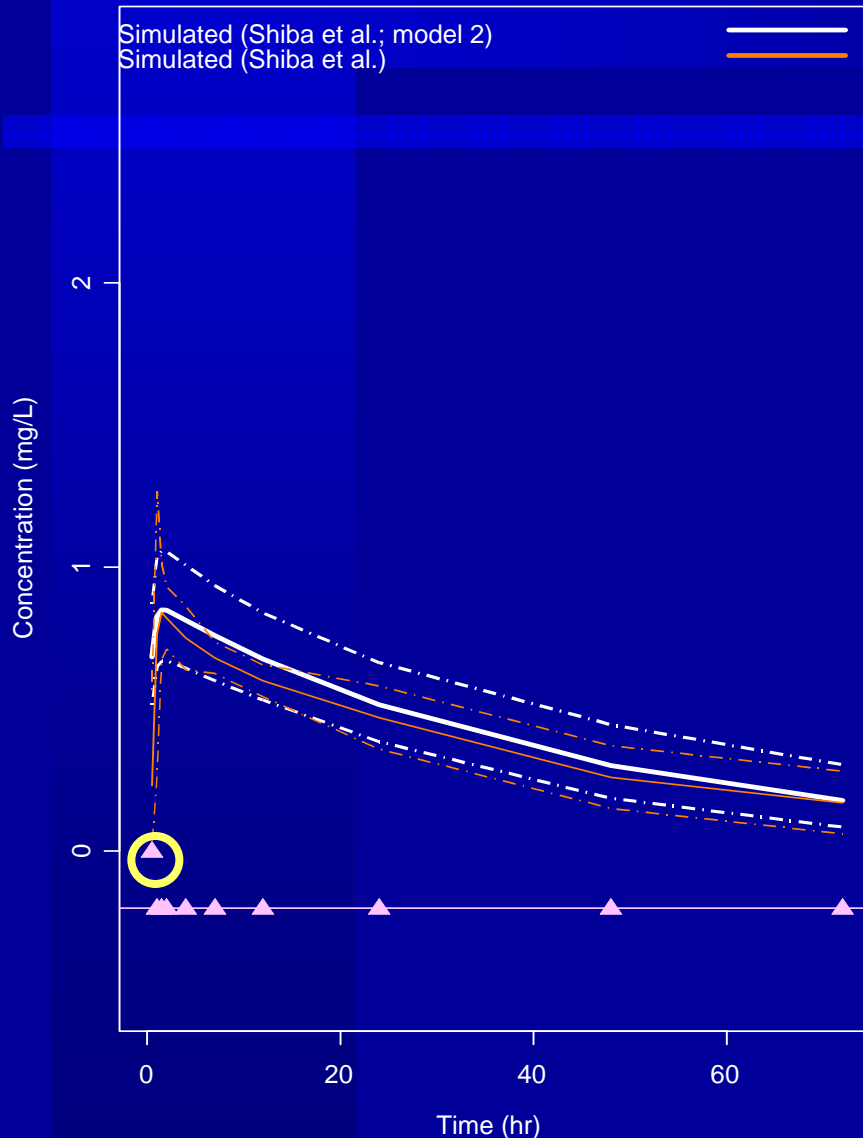
Shiba *et al.*

model 2



Shiba's *model 2* vs. Shiba's data summary (95 % intervals)

50 mg



- **Comparison:**

Simulations from Shiba's model 2
vs.
Simulations from Shiba's data summary

- **Similarity**

- *For individual points*

- **Overall Box's stat. = 0.96**

Berl *et al.* (Australia, 1995)

- Multiple daily dose study
- Four groups of 10 by CLcr (*mainly male*)
 - > 50 ml/min (*in reality* > 70 \equiv Toon's); (400, 200)
 - 20-50 ml/min (loading/maintenance: 200, 100)
 - < 20 ml/min (100, 50); haemodialysis
- Densely sampled
- Summary info
 - Mean + SD of observations (plots)

Berl *et al.*

- Berl's vs. Toon's: exchangeable
- Can Berl's results be composed as a parametric prior?
 - CL/F (mean, sd), V1/F (mean, sd) cannot be obtained solely from Berl's article
 - Model to mimic Berl's results – too many assumptions
 - Still provides important information

Case study

Fluconazole (anti-fungal)

Objectives

- 1, To find out whether PK (non HIV, AIDS; *prior*) \approx PK (HIV, AIDS; *McLachlan*)?
- 2, If PK (*prior*) \approx PK (*McLachlan*), what are the consequences of *likely prior believes + McLachlan's*?

Toon et al. (UK, 1990)

Shiba et al. (Japan, 1990)

Berl et al. (US, 1995)

parametric priors

semi-parametric prior

+

McLachlan et al. (1996)

McLachlan *et al.*

(1996)

Objectives

- 1, Pop. PK in HIV and AIDS
- 2, Dosing recommendation

Study 1

19 volunteers simulated
cross-over based on Study 1
Densely sampled
Up to 3 oral dose levels + IV

Study 2

100 subjects
Steady State
3 observations per subject
50 subjects with CD4 > 200
50 subjects with CD4 < 200
800 mg oral doses

Sim. Data generation

- 2 simulated datasets

- **Model 1**: No covariate, study 1 structure
≡ McLachlan's results (P-Pharm)

- **Model 2**:

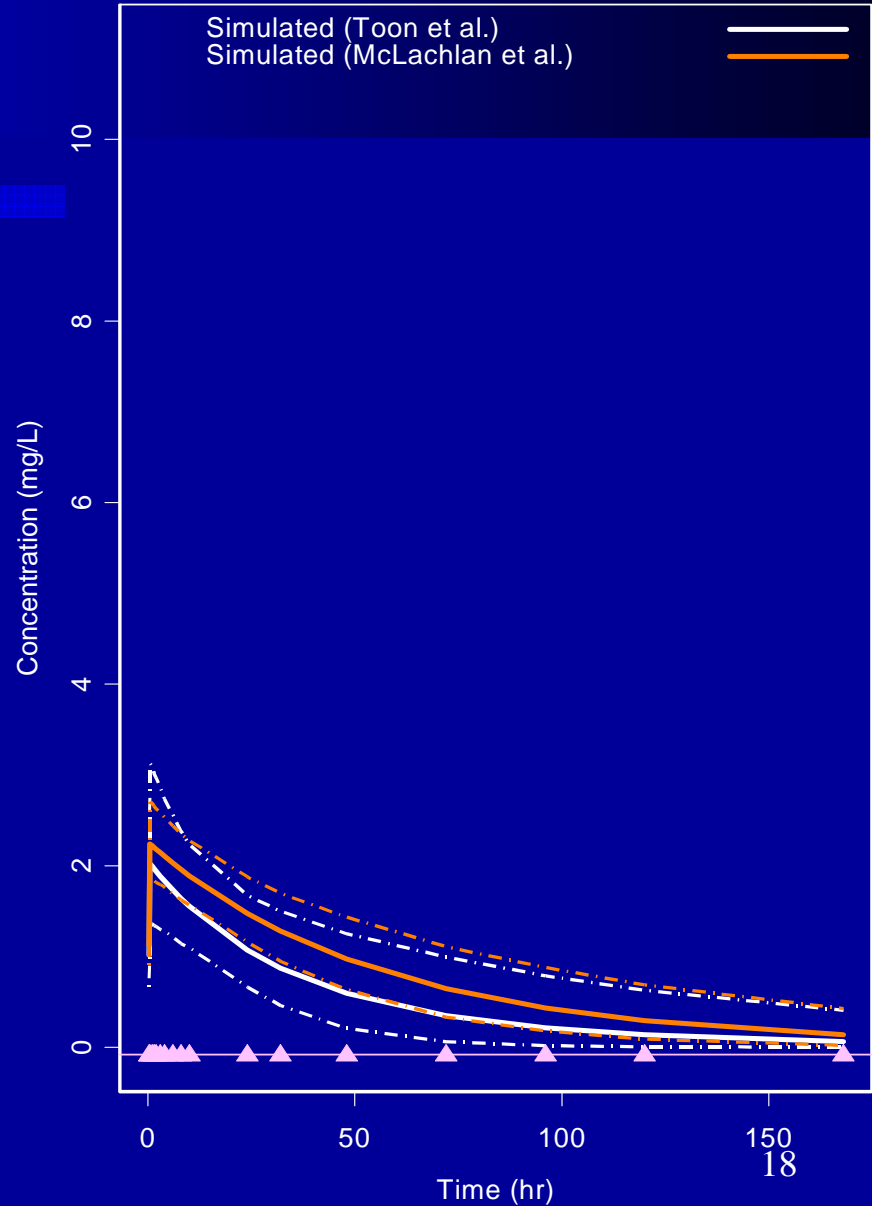
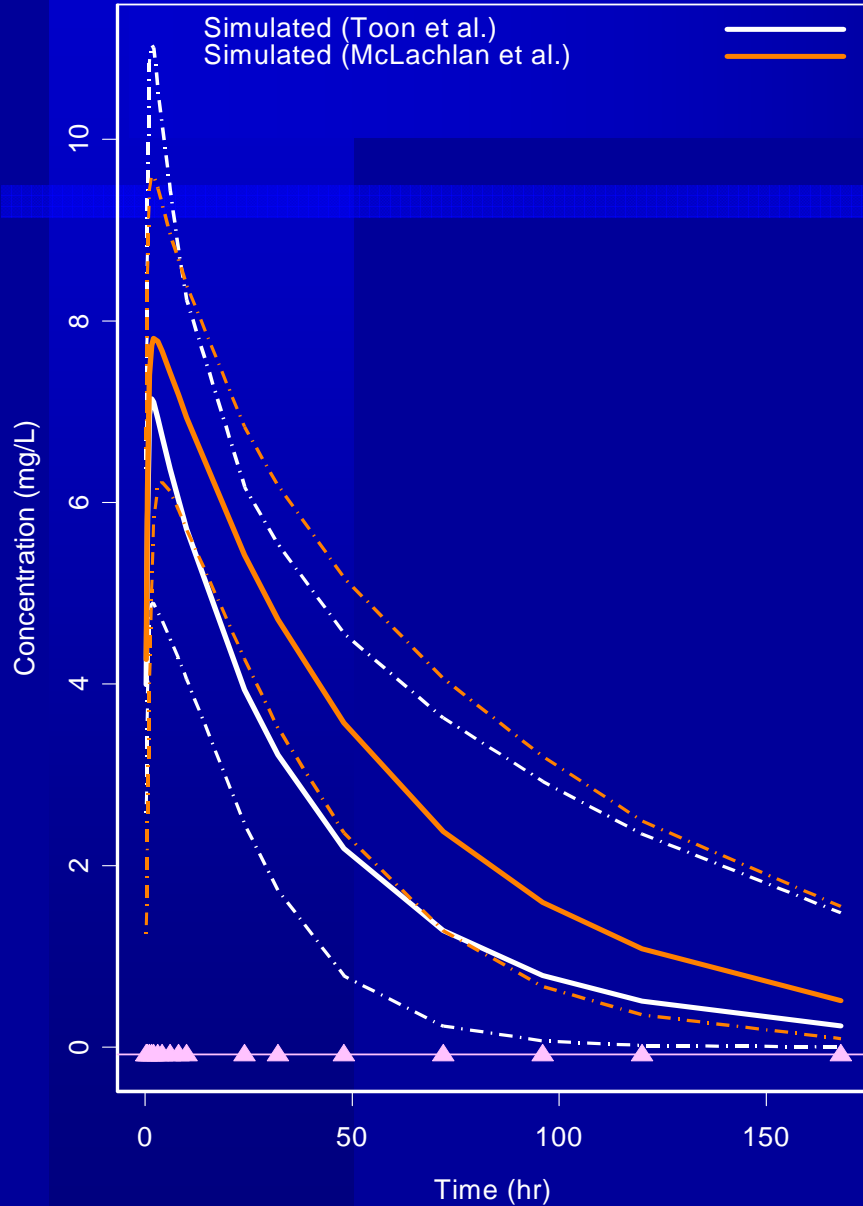
- CL vs. additive **CL_{cr}**, study 1 structure

- ≈ McLachlan's results (P-Pharm)

Model 1 simulations vs. Toon's model 1: exchangeable (Box: 0.41)

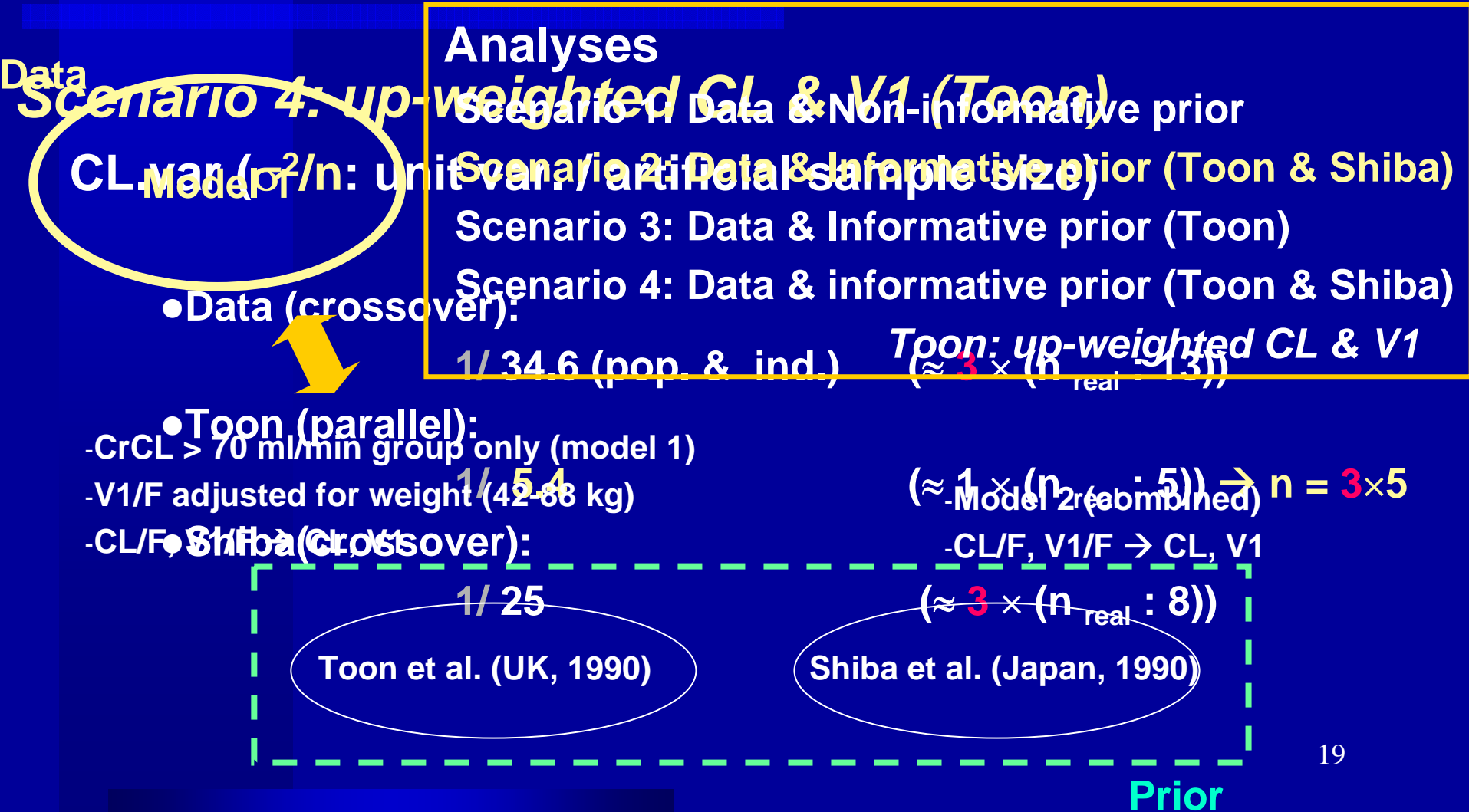
400 mg Oral

100 mg IV



Prior adjustment

model 1



Results

model 1

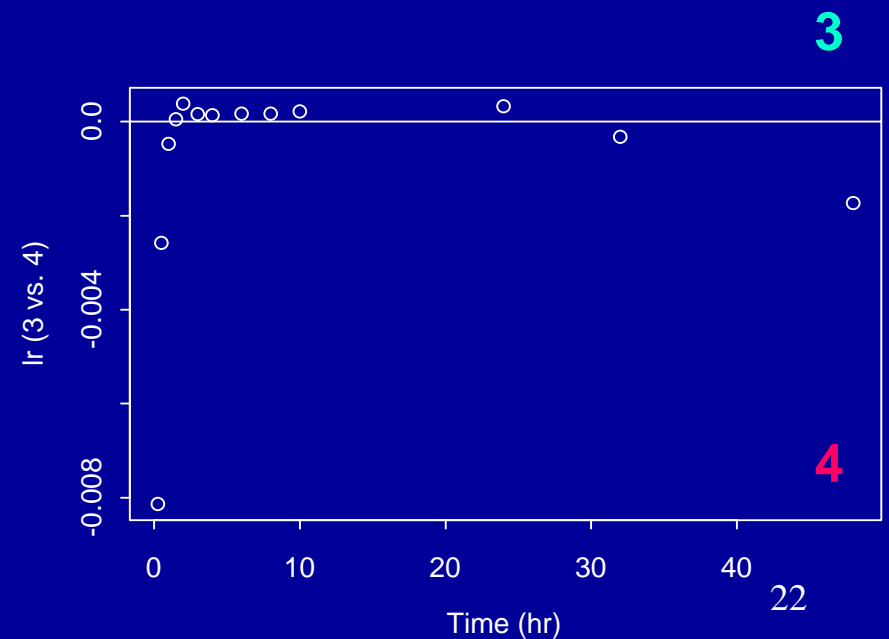
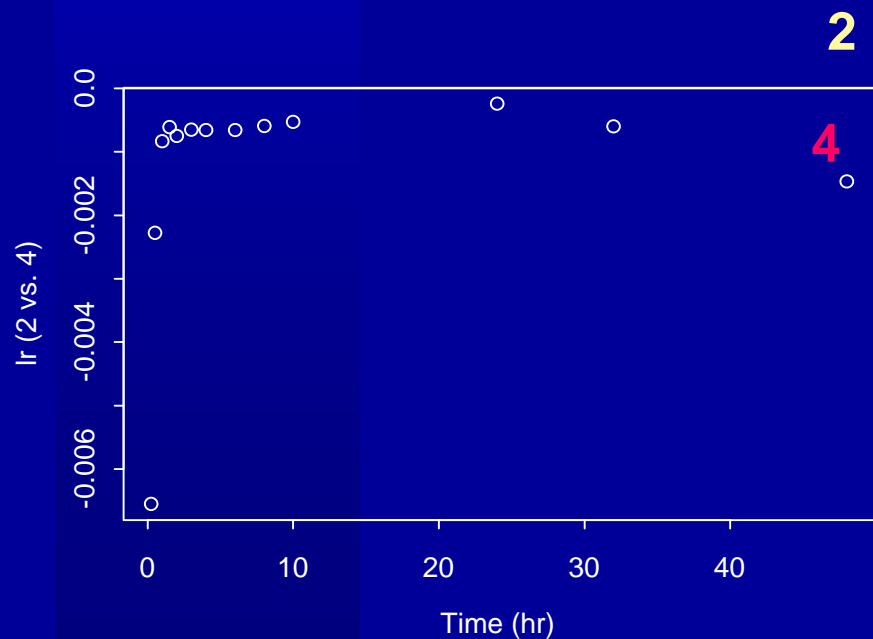
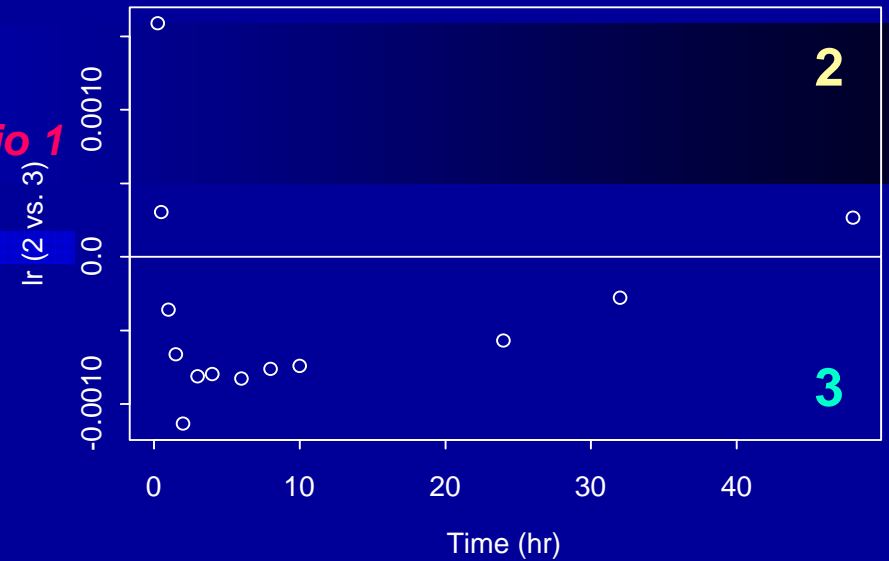
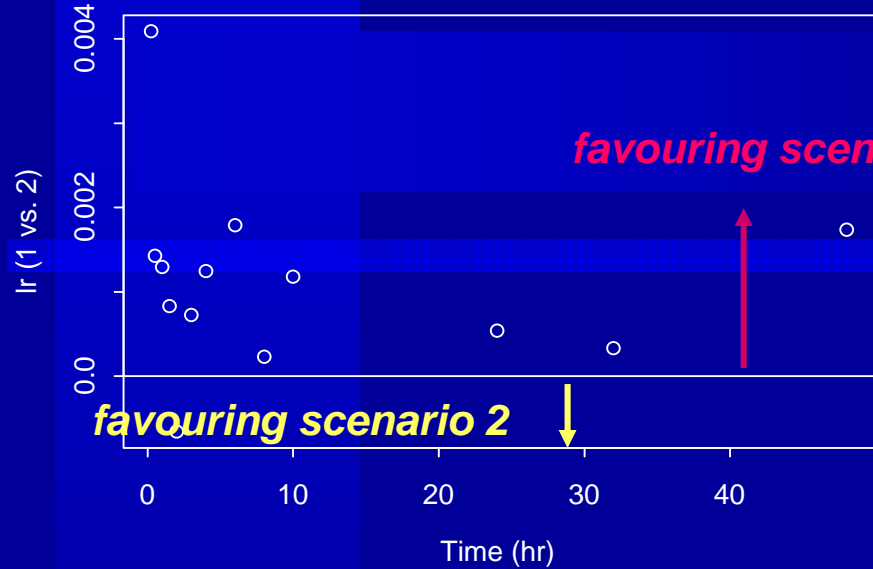
	Sce.1 Non- informative	Sce.2 Informative (Toon & Shiba)	Sce.3 Informative (Toon)	Sce.4 Informative (up-weighted Toon)
PPC (χ^2)	0.5	0.51	0.51	0.5
F	0.91 (0.01)	0.91 (0.01)	0.91 (0.01)	0.91 (0.01)
CL (L/hr)	0.93 (0.05)	0.96 (0.06)	0.97 (0.06)	0.95 (0.04)
V1 (L)	44.11 (0.92)	46.11 (1.55)	46.41 (1.79)	45.28 (1.17)
Ka – Ke (1/hr)	3.21 (0.40)	3.22 (0.41)	3.21 (0.40)	3.22 (0.39)

Results

model 1

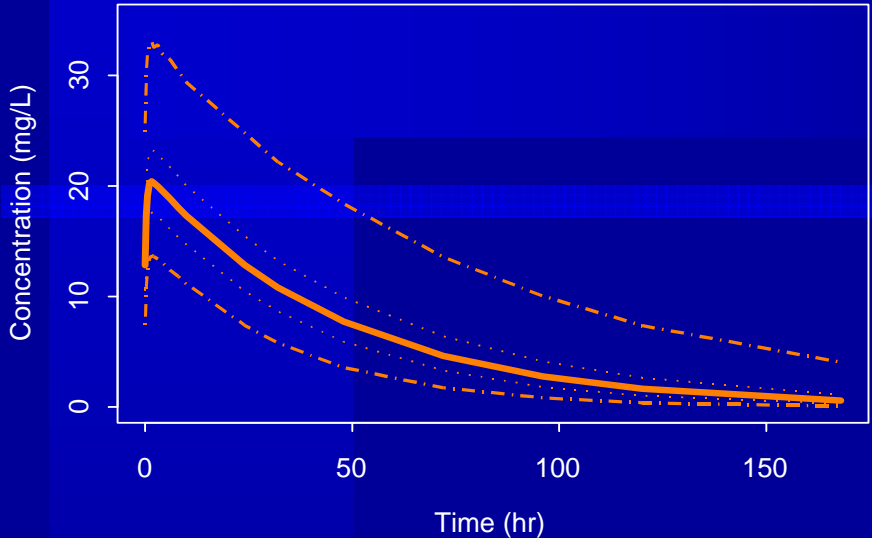
Ind.SD	Sce.1 Non- informative	Sce.2 Informative (Toon & Shiba)	Sce.3 Informative (Toon)	Sce.4 Informative (up-weighted Toon)
F	0.03 (0.02)	0.04 (0.01)	0.04 (0.01)	0.04 (0.01)
CL (L/hr)	0.19 (0.05)	0.22 (0.04)	0.24 (0.05)	0.15 (0.02)
V1 (L)	2.94 (0.80)	6.12 (0.81)	7.50 (1.22)	4.29 (0.40)
Ka – Ke (1/hr)	1.32 (0.36)	1.33 (0.37)	1.32 (0.36)	1.32 (0.36)
Resid.SD	0.11 (0.00)	0.11 (0.00)	0.11 (0.00)	0.11 (0.00)

Ir_i vs. $k = \log_{10} CPO_i - \log_{10} CPO_k$ (CPO = conditional predictive ordinates)

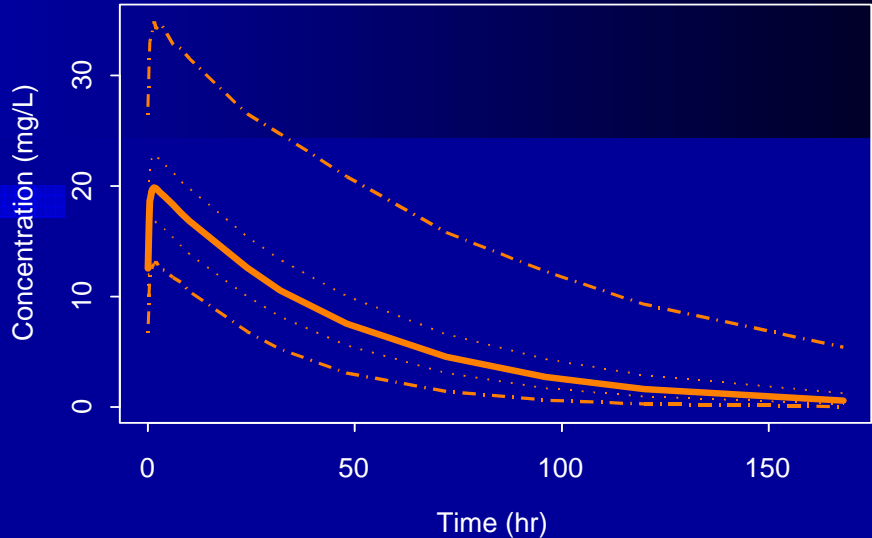


Predictions (95% credible intervals; after the last steady-state dose)

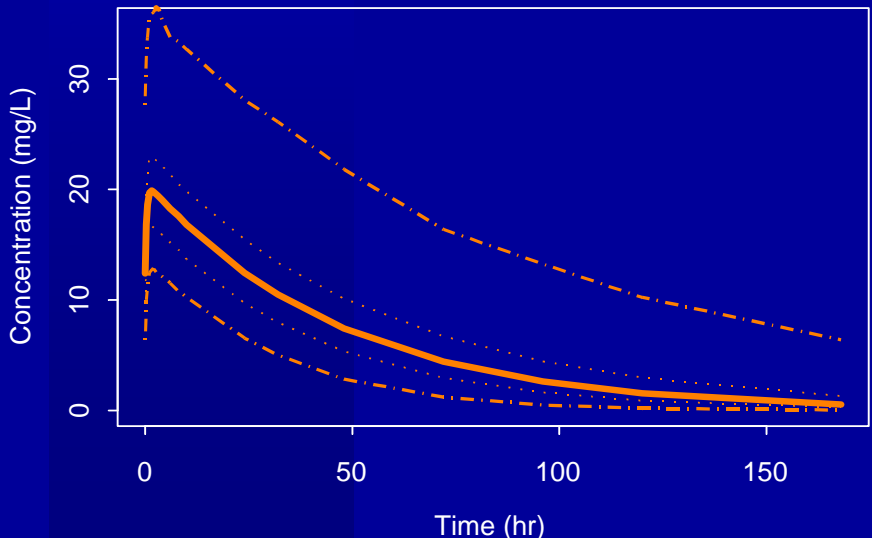
400 mg oral; **scenario 1**



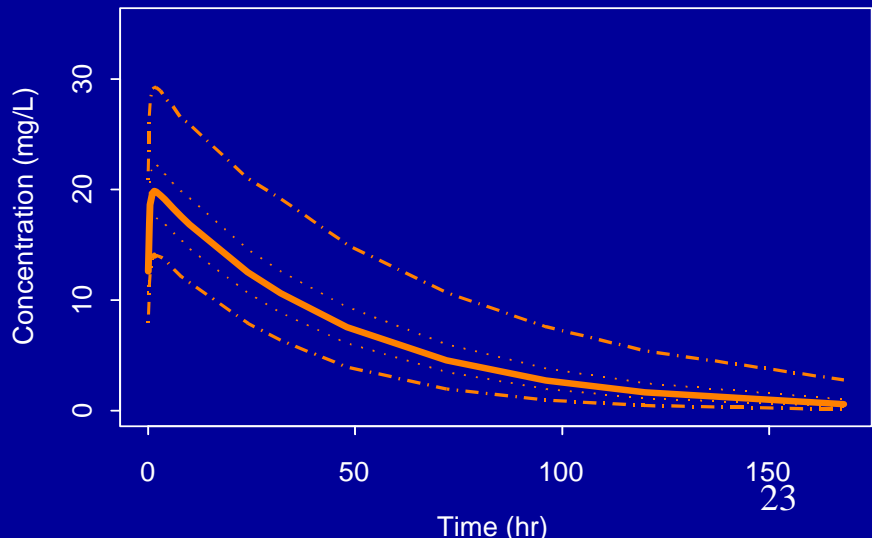
400 mg oral; **scenario 2**



400 mg oral; **scenario 3**



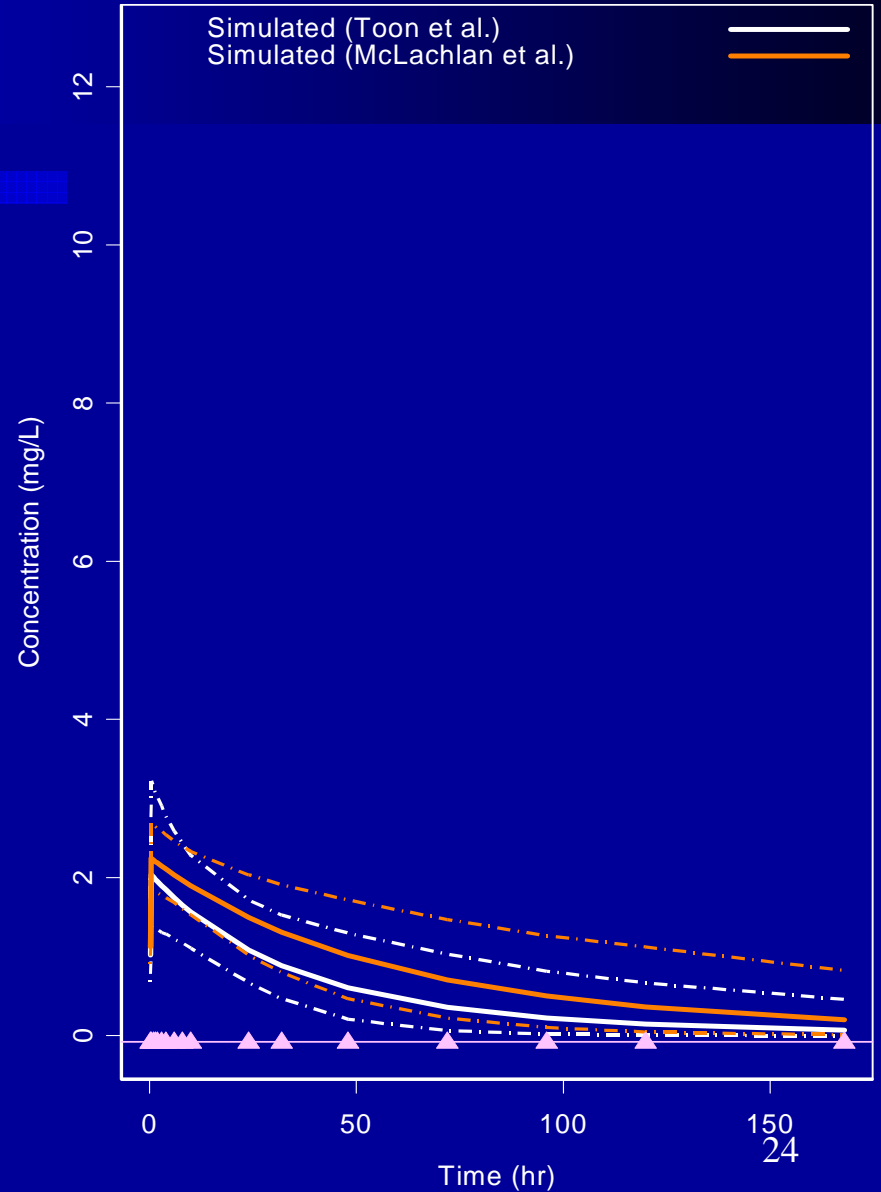
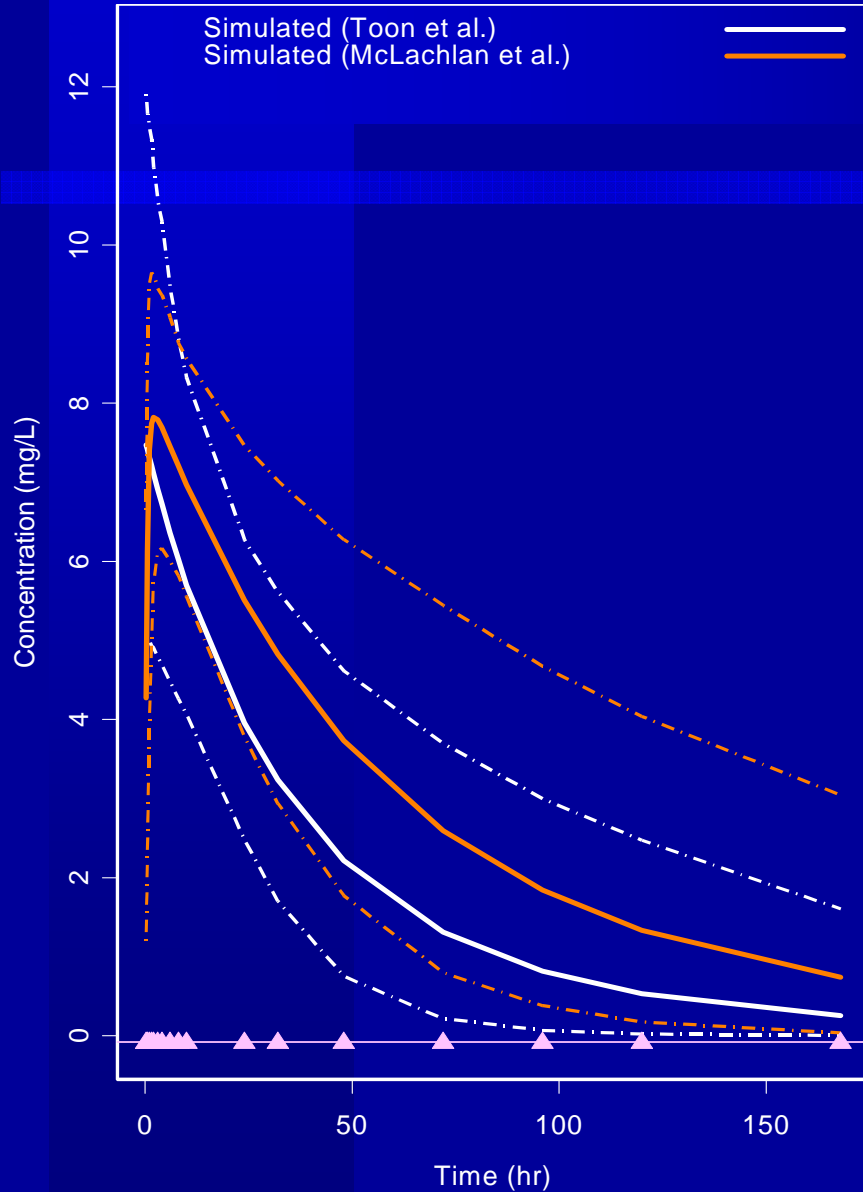
400 mg oral; **scenario 4**



Model 2 simulations vs. Toon's model 1: exchangeable (Box: 0.48)

400 mg Oral

100 mg IV



Prior adjustment

model 2

$$CL_i = \text{baseline} * CLcr_i$$

Data

Scenario 3: up-weighted base SD for CL & V1 - Informative prior

Model 2

CL (σ^2/n : unit var. / additional sample size)

• Data, base (CLcr > 80 ml/min): up-weighted base SD for CL, & V1

• Toon, base:

• Data, slope:

• Toon, slope:

Scenario 2: Data & Informative prior (Toon & Shiba)

Scenario 1: Data & Informative prior (Toon)

Scenario 4: Data & informative prior (Toon)

$m = 10.5$
 $m = 13$

$n = 69.5$

up-weighted base SD for CL, & V1
($\approx 1 \times m_{\text{real}}$)
($\approx 5 \times m_{\text{real}}$)

changed Pop. var. : Ind. var. ratio; Pop. ↑

Scenario 4: up-weighted base SD for CL, & V1 - Combined (model 2)

Pop. var. increased by 2 fold → Ind. var. reduced accordingly
Toon et al. (UK, 1990) → Shiba et al. (Japan, 1990)

Prior

Conclusion

- **Bayesian approach for information synthesis**
 - **Why synthesising information?**
 - A single source of information is often not enough
 - **Why Bayesian?**
 - Through a prior, one's belief can be elicited in a open quantitative manner
- **Key issues:**
 - **Clear, logical elicitation of prior information**
 - **Good coverage of likely prior believes**