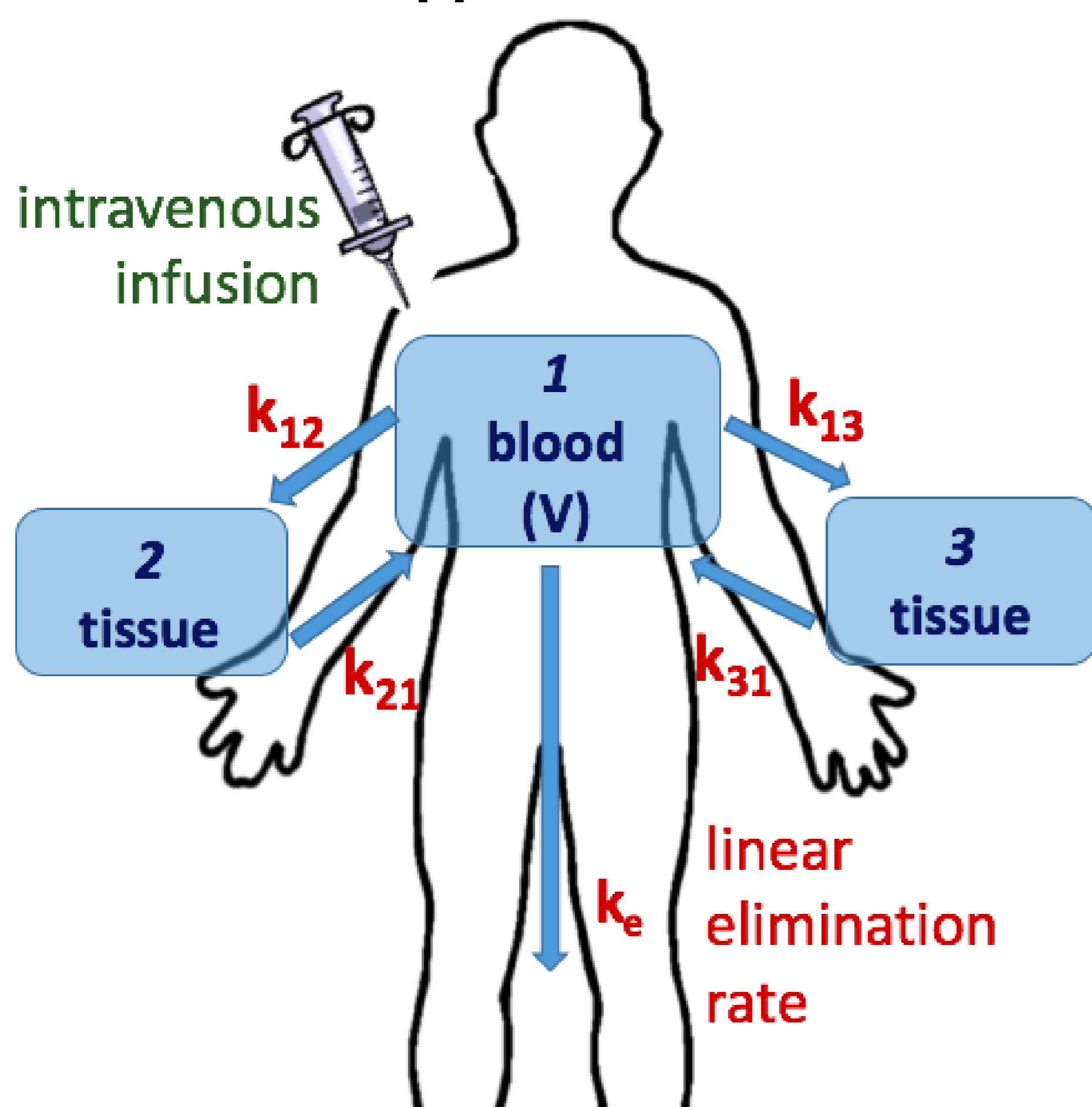


INTRODUCTION

The aim of this work was to model in-vivo pharmacokinetic (PK) data using a three-compartment model with first-order elimination. The parameters of the compartmental model were estimated by non-linear mixed models in R and MONOLIX. The fit of the resulting models was compared to the individual intravenous (IV) infusion data.

METHODS

- To examine the drug's PK, the mean and individual plasma concentration time profile after intravenous infusion has been measured in each of 18 subjects at 20 time points.
- Each infusion lasted 15min and contained 300 µg (=0.3 mg).
- PK processes can be simplified and visualized as compartmental models [3]:



- Mathematically, pharmacokinetic models are characterized by *non-linear models*,

$$y_{ij} = f(t_{ij}; \phi_{ij}, c_{ij}) + e_{ij}, \quad e_{ij} \sim \mathcal{N}(0, \sigma^2)$$

$$i = 1, \dots, M, \quad j = 1, \dots, n_i$$

- The function f can be defined as the solution to a system of:

ordinary differential equations (ODE's)

$$\frac{dA_1(t)}{dt} = \text{absorption} - \text{elimination}$$

$$= k_{21}A_2(t) + k_{31}A_3(t) - [k_{12}A_1(t) + k_{13}A_1(t) + k_e A_1(t)]$$

$$\frac{dA_2(t)}{dt} = k_{12}A_1(t) + k_{32}A_3(t) - [k_{21}A_2(t) + k_{23}A_2(t)]$$

$$\frac{dA_3(t)}{dt} = k_{13}A_1(t) + k_{23}A_2(t) - [k_{31}A_3(t) + k_{32}A_3(t)]$$

- To predict the drug concentration C in the blood for any time t , the amount of drug (A) in the blood has to be divided by the *apparent volume of distribution* (V) of the blood:

$$C_1(t) = A_1(t)/V_1$$

- Data not only from one subject, but from a whole sample of 18 subjects
- Parameters are different for each subject i , thus, are the sums of population (fixed) effects and individual (random) effects [2]:

$$V_i = \beta_V + b_{V,i}, \quad b_{V,i} \sim \mathcal{N}(0, \sigma_b^2)$$

⇒ **Non-linear mixed effects** modelling

- The fixed effects model was determined using nonlinear least-squares estimation in R (functions `nls()` and `optim()` (Gauss-Newton algorithm)).
- The random effects model was computed in
 - the experimental R-package 'nlmixr' [4], applying the functions `nlme_lin_cmpt()` and `nlme_ode()`,
 - the frequentist estimation procedure of MONOLIX [1].

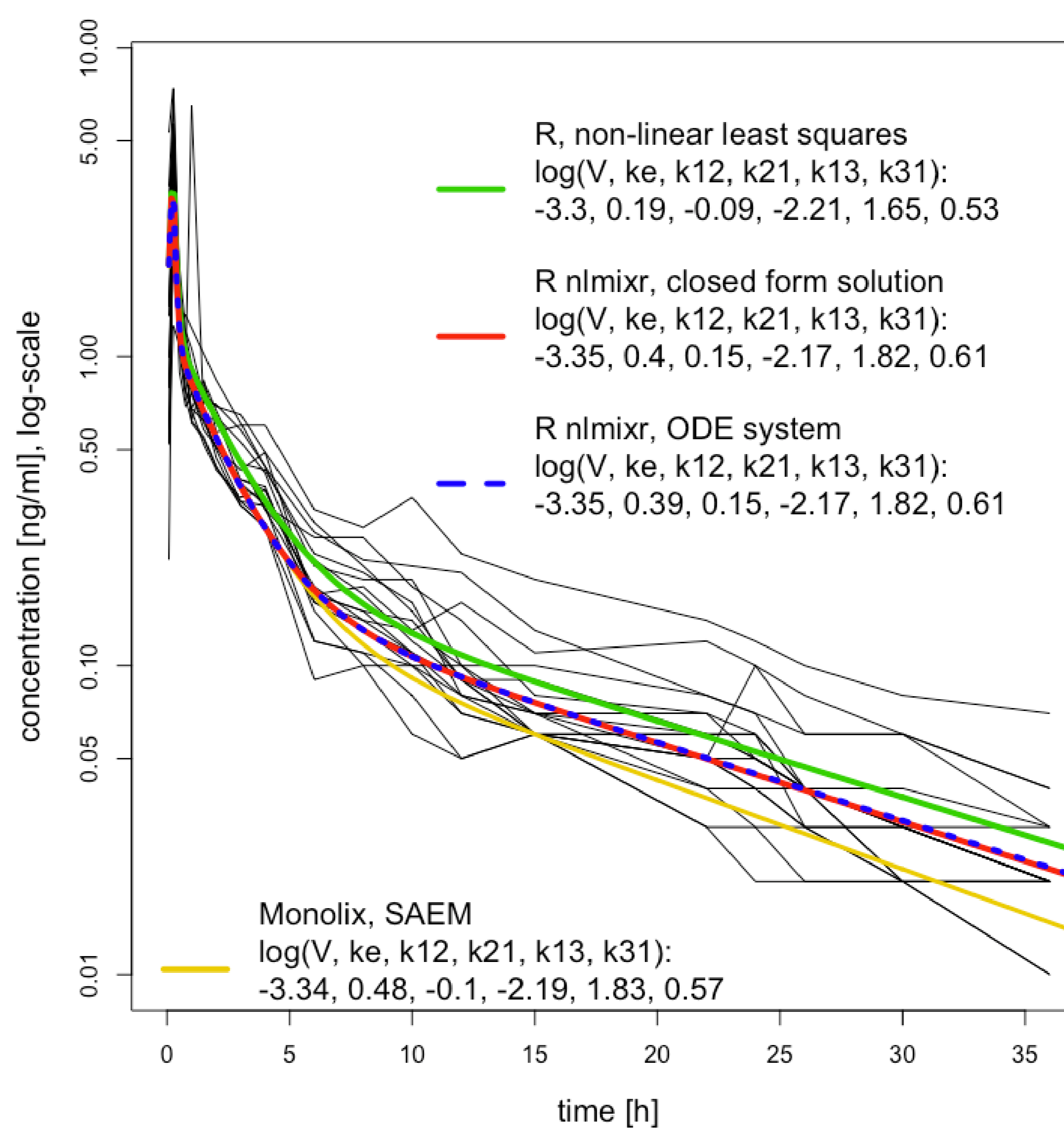
NLMIXR CODE

```
#1) NLME_LIN_CMPT (closed form solution)
specs.1 <- list(fixed = 1V+1KE+1K12+1K21+1K13+1K31 ~ 1, random = 1V~1|ID, start = c(...))
Mixr.1 <- nlme_lin_cmpt(data, par_model=specs.1, ncmt=3, oral=F, infusion=TRUE, parameterization=2, control = ...)
```

```
#2) NLME_ODE (ODE system)
ode <- " d/dt(centr) = K21*periph+K31*periph2-K12*centr-K13*centr-KE*centr;
d/dt(periph) =-K21*periph+K12*centr;
d/dt(periph2)=-K31*periph2+K13*centr; "
mypar <- function(1V, 1KE, 1K12, 1K21, 1K13, 1K31)
{ V = exp(1V); KE = exp(1KE); K12= exp(1K12); K21 = exp(1K21); K13= exp(1K13); K31 = exp(1K31) }
specs.ODE1 <- list(fixed = 1V+1KE+1K12+1K21+1K13+1K31 ~ 1, random = 1V~1|ID, start = c(...))
MixrODE.1 <- nlme_ode(data, model=ode, par_model=specs.ODE1, par_trans=mypar, response="centr", control = ...,
response.scaler="V")
```

RESULTS

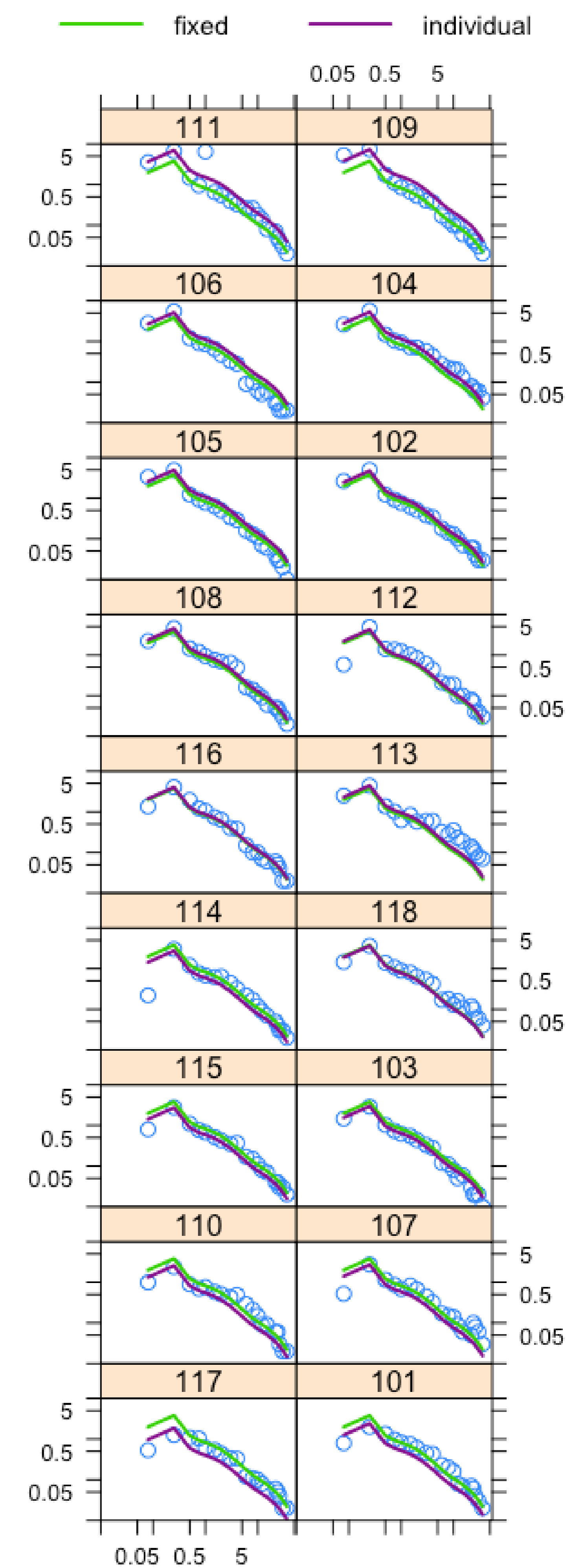
For reasons of convergence and lower AIC, only the random effect for V has been included. The result of the fixed effects model served as initial values for the mixed effects models.



	R			Monolix
	NLS	NLME LIN_CMPT	NLME ODE	SAEM
$\log(V)$ FE	-3.30 (0.10)	-3.34 (0.11)	-3.34 (0.11)	-3.34
RE	-	SD: 0.375	SD: 0.375	SD: 0.389
$\log(ke)$	0.19 (0.45)	0.40 (0.29)	0.39 (0.20)	0.48
$\log(k12)$	-0.09 (0.74)	0.15 (0.44)	0.15 (0.45)	-0.10
$\log(k21)$	-2.21 (1.74)	-2.17 (1.05)	-2.17 (0.93)	-2.19
$\log(k13)$	1.65 (0.23)	1.82 (0.15)	1.82 (0.15)	1.83
$\log(k31)$	0.53 (0.32)	0.61 (0.20)	0.61 (0.16)	0.57

	R		Monolix
	NLME LIN_CMPT	NLME ODE	SAEM
AIC	373.21	373.21	373.49
BIC	403.89	403.89	380.62
logLik	-178.60	-178.60	-178.75

Note: In the individual plots the time-axis has been log-scaled for improved visibility.
SD: standard deviation. Table: values in brackets are standard errors.



DISCUSSION

As can be seen in the left graph, the estimated PK parameters - by R as well as by MONOLIX - lie very close together, fit the individual concentration curves well and make biologically sense. The random effects models are preferred over the NLS-estimation as they incorporate also the individual effects. The parameters estimated in R fit the observed data better based on visual inspection of the individual profiles.

REFERENCES

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- [4] W. Wang. *nlmixr: an r package for fitting pk and pkpd models*. <https://github.com/nlmixrdevelopment/nlmixr/blob/master/inst/nlmixr-intro.pdf>, 2016. [Online; accessed 20-February-2017].