

## **Handling data below the quantification limit in viral kinetic modelling for model evaluation and prediction of treatment outcome**

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# Outline

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- ▶ **Context**
- ▶ **Objectives**
- ▶ **3 projects**
  - ▶ **Methods**
  - ▶ **Results**
- ▶ **Conclusions & Perspectives**

# Context: Viral kinetic (VK) models

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## ▶ VK models

- ▶ Better understanding of viral lifecycle (HCV, HIV) and mechanism of action of antiviral agents<sup>(1,2)</sup>
- ▶ Improvement of the understanding of viral kinetics by including pharmacokinetic (PK) information <sup>(3,4)</sup>

## ▶ New effective anti-HCV treatments

- ▶ Direct acting antivirals: telaprevir, boceprevir, sofosbuvir, daclatasvir,...
- ▶ Host-targeting antivirals: alisporivir (Novartis)
- ▶ Viral loads below the quantification limit (BQL) are indicators of treatment effectiveness

⇒ BQL data very frequent with new effective treatments

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▶ 3 <sup>(1)</sup> Neumann et al, Science (1998)

<sup>(2)</sup> Guedj et al, PNAS (2013)

<sup>(3)</sup> Shudo et al, J Viral Hepat (2010)

<sup>(4)</sup> Talal et al, Hepatol (2006)

# Context: Handling of BQL data

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- ▶ **Estimation of population parameters**
  - ▶ Omitting BQL data often result in biased estimates<sup>(1-3)</sup>
  - ▶ Likelihood-based approaches (SAEM, M3 method in NONMEM, etc.) provide better parameter estimates <sup>(1-3)</sup>
- ▶ **Model evaluation**
  - ▶ Most evaluation methods omit or impute BQL data at the limit of quantification (LOQ) even though they were handled in estimation step
    - ⇒ Trends in diagnostic graphs
    - ⇒ Confuse model evaluation/selection
- ▶ **Individual parameter estimation**
  - ▶ Impact of handling BQL data is not yet studied

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▶ 4 <sup>(1)</sup> Samson et al, Comput Stat Data An (2006)  
<sup>(2)</sup> Bergstrand et al, AAPS J (2009)

<sup>(3)</sup> Yang et al, Pharm Stat (2010)

# Objectives

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- ▶ Extend prediction discrepancies (pd) and normalized prediction distribution errors (npde), to handle BQL data
- ▶ Build a PK-VK model for virologic response to alisporivir (ALV) and pegylated interferon (peg-IFN). Evaluate this PK-VK model with these metrics
- ▶ Evaluate the impact of BQL data, design and *a priori* information on individual parameter estimates and prediction of treatment outcome

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## Project I

Extend prediction discrepancies (pd) and  
normalized prediction distribution errors (npde)  
to take into account BQL data

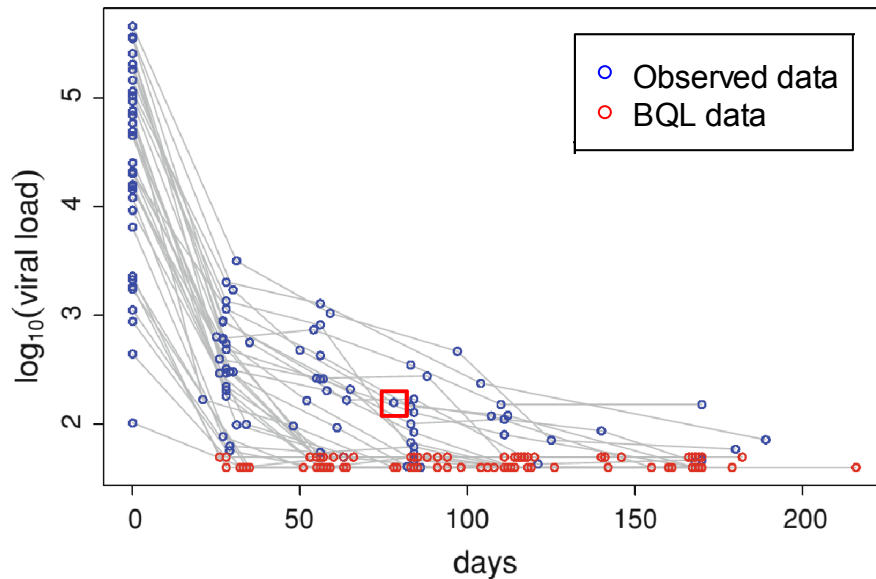
J Pharmacokinet Pharmacodyn (2012) 39:499–518  
DOI 10.1007/s10928-012-9264-2

ORIGINAL PAPER

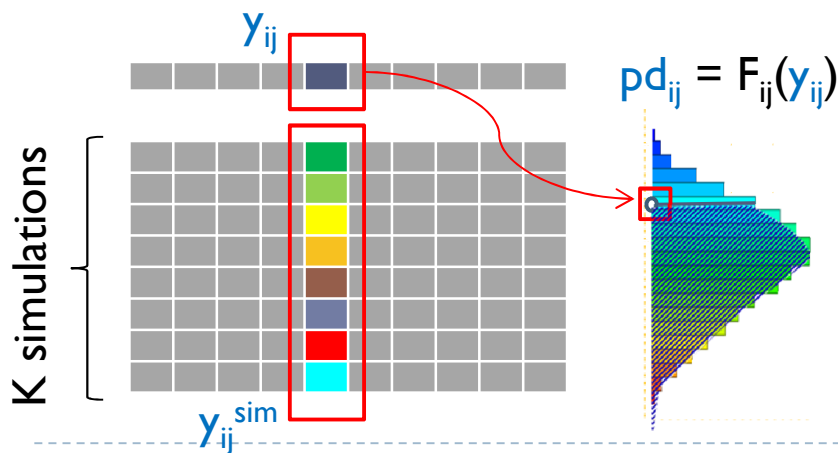
**Extension of NPDE for evaluation of nonlinear mixed effect  
models in presence of data below the quantification limit  
with applications to HIV dynamic model**

Thi Huyen Tram Nguyen · Emmanuelle Comets ·  
France Mentré

# Methods: $pd$ and $npde$ for observed data



- ▶  $F_{ij}$ 
  - ▶ Cumulative distribution function predicted by the model
  - ▶ Obtained by K Monte Carlo simulation
- ▶  $pd_{ij} = F_{ij}(y_{ij})^{(1)}$
- ▶  $npde$ : normalized decorrelated  $pd^{(2)}$

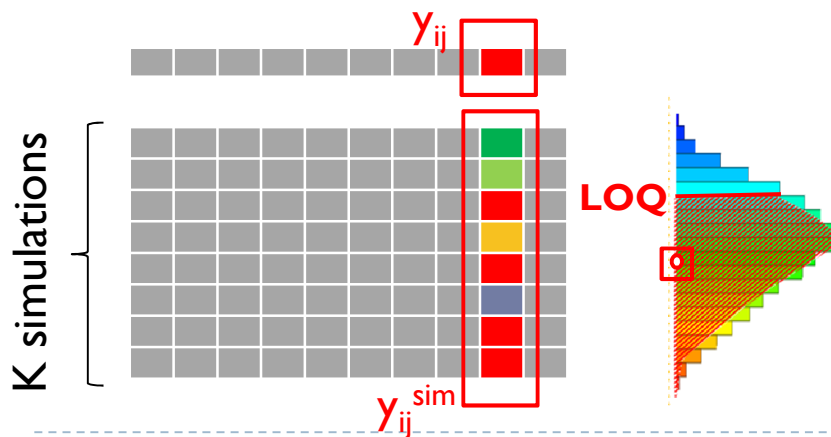
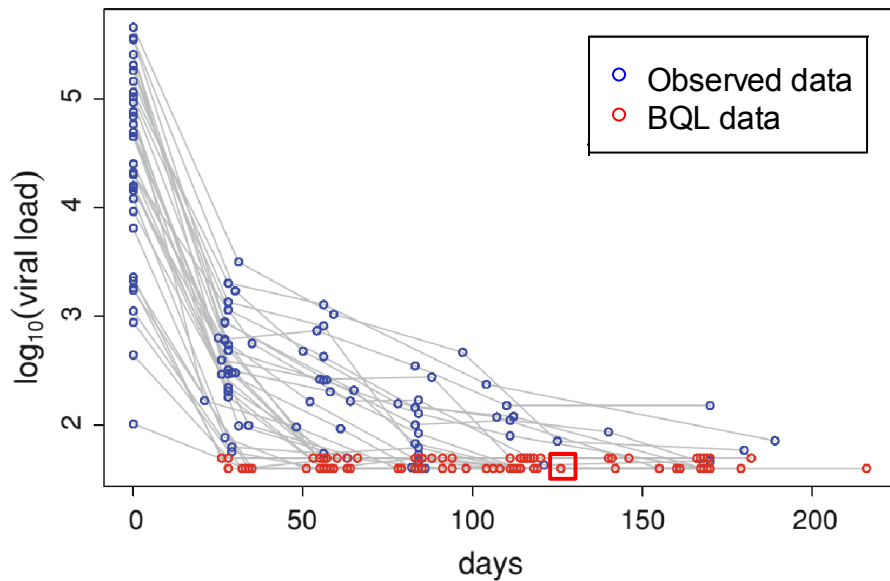


- ▶ If the model is true (hypothesis  $H_0$ ):
  - $pd_{ij} \sim U[0, 1]$
  - $npde_{ij} \sim N(0, 1)$

(1) Mentré et al, J Pharmacokinet Pharmacodyn (2000)

(2) Brendel et al, Pharm Res (2006)

# Methods: $pd$ and $npde$ for BQL data



- ▶  $pd_{ij}$  for a BQL observation  $y_{ij}$ 
  - ▶  $F_{ij}(LOQ)$ : probability of being under  $LOQ$
  - ▶  $pd_{ij}$  is randomly chosen in  $U[0, F_{ij}(LOQ)]$
  
- ▶  $npde_{ij}$  for a BQL observation  $y_{ij}$ 
  - ▶ Impute observed and simulated BQL data
  - ▶ Calculate  $npde_{ij}$  from imputed data



# Methods: Simulation study

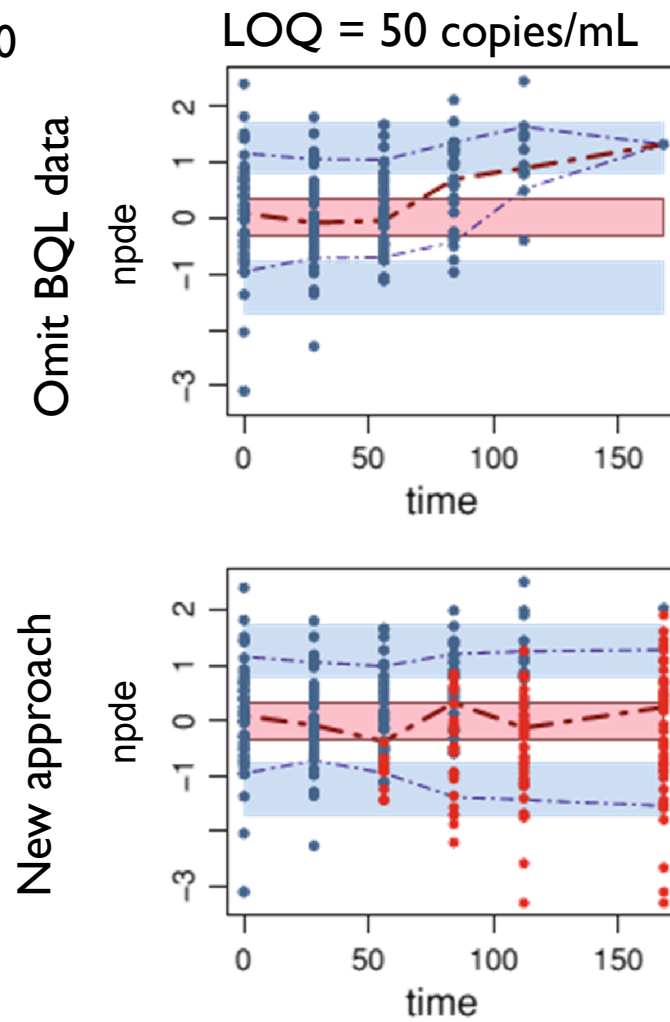
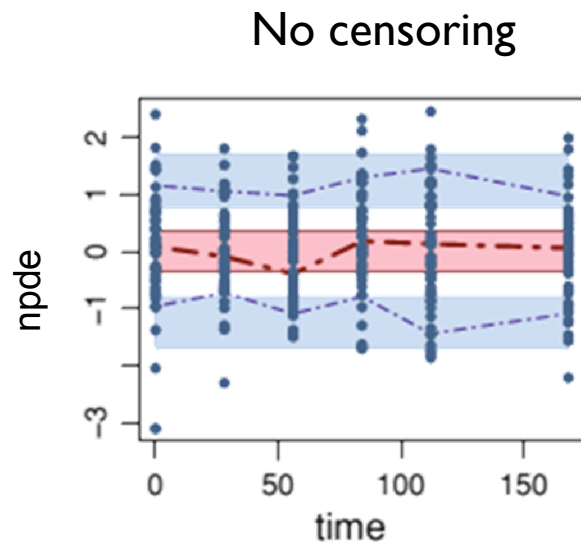
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- ▶ Results under  $H_0$  are presented
- ▶ Model: inspired from a model built for real data<sup>(1)</sup>
  - ▶ Observed dataset
  - ▶ Monte Carlo samples to approximate  $F_{ij}$
- ▶ 2 censoring levels: LOQ = 0 (no censoring), 50 copies/mL
- ▶ Evaluation of new metrics
  - ▶ Graphical evaluation
  - ▶ Type I error of the global test<sup>(1)</sup> to test if  $npde \sim N(0,1)$

(Powers also evaluated but results not shown)

# Results

## ► Graphical evaluation under $H_0$



# Results

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## ▶ Type I errors\*

No censoring	LOQ = 50 copies/mL	
5.4	Omit BQL data	46.9
	New approach	6.2

\*Type I errors evaluated on 1000 datasets

Prediction interval for 5%: [3.6 – 6.4]

# Results

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- ▶ New pd, npde and other graphical improvements were implemented in the package npde 2.0 for R

[www.npde.biostat.fr](http://www.npde.biostat.fr)

[cran.r-project.org/web/packages/npde](http://cran.r-project.org/web/packages/npde)

## Package ‘npde’

August 29, 2013

**Type** Package

**Title** Normalised prediction distribution errors for nonlinear mixed-effect models

**Version** 2.0

**Date** 2012-08-15

**Author** Emmanuelle Comets, Karl Brendel, Thi Huyen Tram Nguyen, France Mentre.

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## Project 2

PK-VK model to characterize virologic response to alisporivir (ALV) and pegylated interferon (peg-IFN)

**A pharmacokinetic – viral kinetic model describes the effect of alisporivir monotherapy or in combination with peg-IFN on hepatitis C virologic response**

Thi Huyen Tram Nguyen<sup>1,2</sup>, France Mentré<sup>1,2</sup>, Micha Levi<sup>3</sup>, Jing Yu<sup>4</sup>, Jérémie Guedj<sup>1,2</sup>

(Submitted)

# Methods

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- ▶ Alisporivir (Novartis):
  - ▶ Cyclophillin inhibitor
  - ▶ Currently in phase 3
- ▶ Study DEB025-A2203<sup>(1)</sup>
  - ▶ Phase 2a clinical study: 4-week treatment & 3-week wash-out
  - ▶ 90 naïve patients
    - ▶ Infected with various HCV genotypes (GT)
    - ▶ Randomized into 5 treatment arms
- ▶ Data
  - ▶ PK concentrations of ALV, peg-IFN
  - ▶ Viral load data

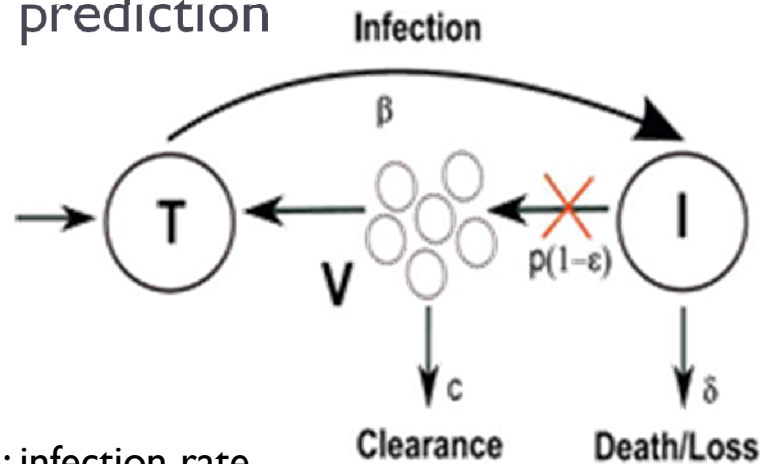
5 treatment arms

ALV Dose (mg)	Peg-IFN (µg)
200	180
600	180
1000	180
1000	0
0	180

# Methods

## ► Modeling strategy

- Build PK models for ALV and peg-IFN
- Build viral kinetic model<sup>(1)</sup> by incorporating individual PK prediction



$\beta$ : infection rate  
 $p$ : production rate per infected cell  
 $c$ : clearance rate of free virus  
 $\delta$ : loss rate of infected cells  
 $\varepsilon$ : treatment effectiveness

$$\frac{dT}{dt} = \beta VT - \delta I$$

$$\frac{dV}{dt} = (1 - \varepsilon)pI - cV$$

$$\varepsilon_{ALV}(t) = \frac{C_{ALV}(t)}{IC50_{ALV} + C_{ALV}(t)}$$

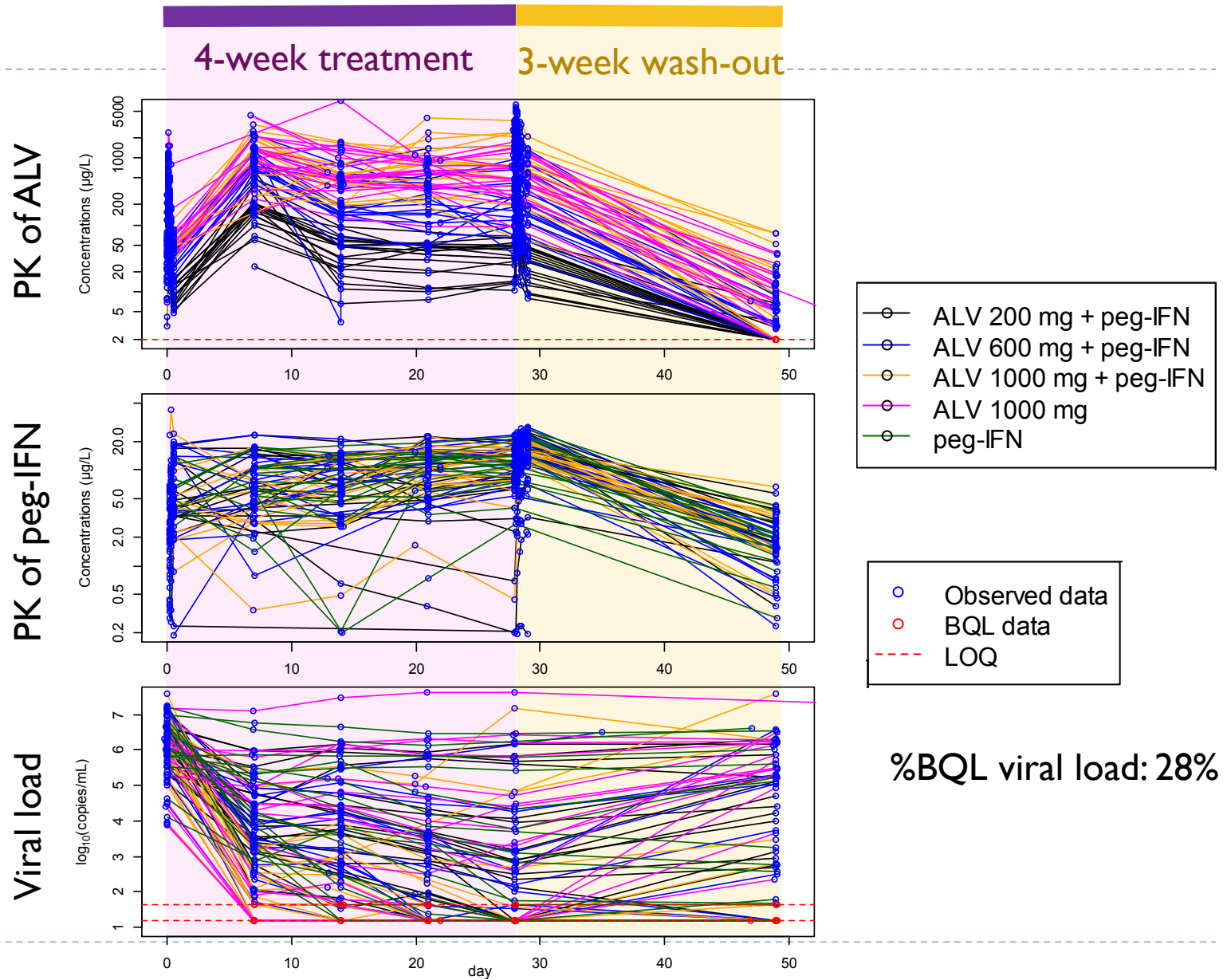
$$\varepsilon_{peg}(t) = \frac{C_{peg}(t)}{IC50_{peg} + C_{peg}(t)}$$

$$\varepsilon = 1 - (1 - \varepsilon_{peg})(1 - \varepsilon_{ALV})$$

## ► Parameter estimation: SAEM (MONOLIX 4.2)

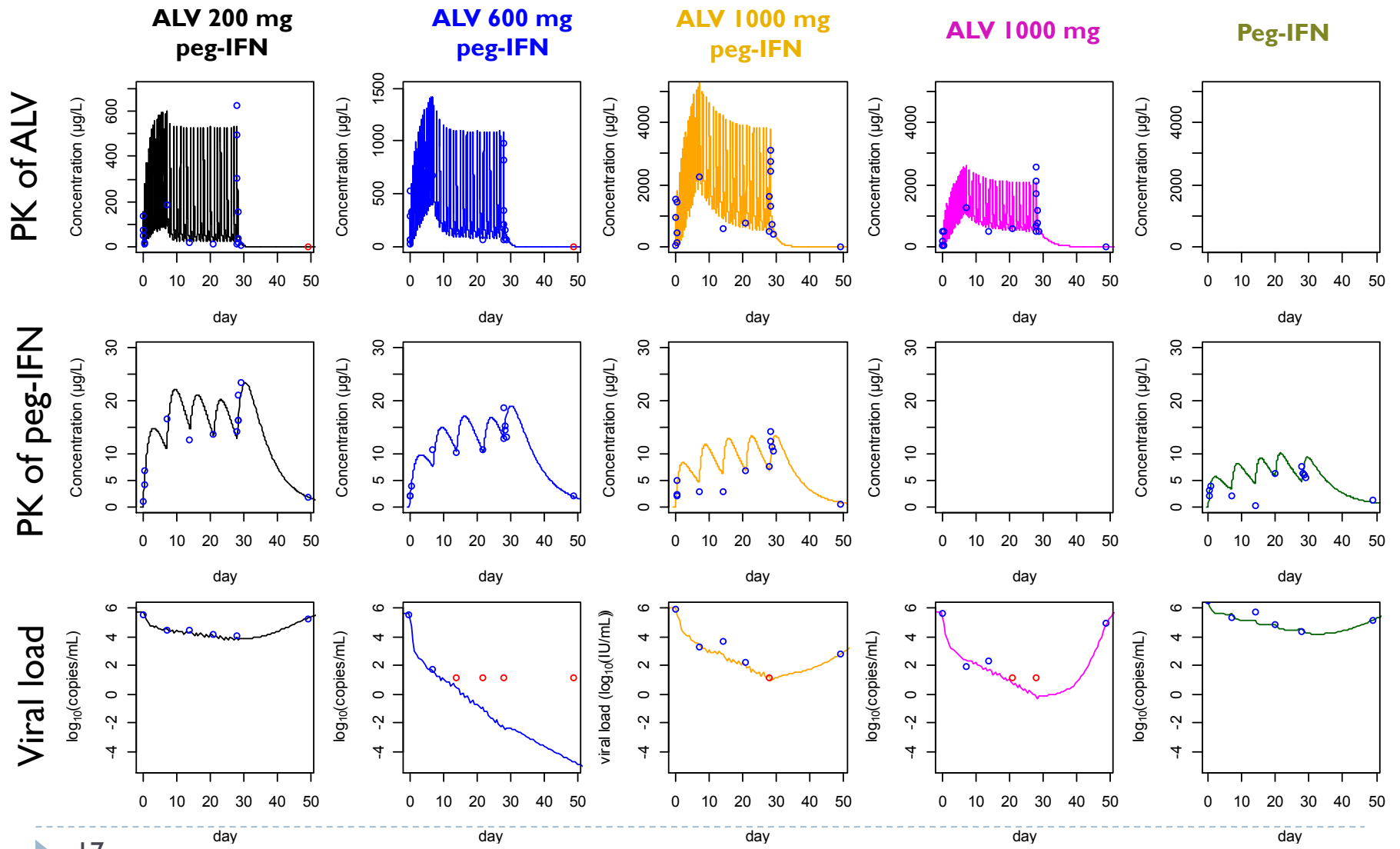
► 15 <sup>(1)</sup> Neumann et al, Science (1998)

# Results: Spaghetti plots



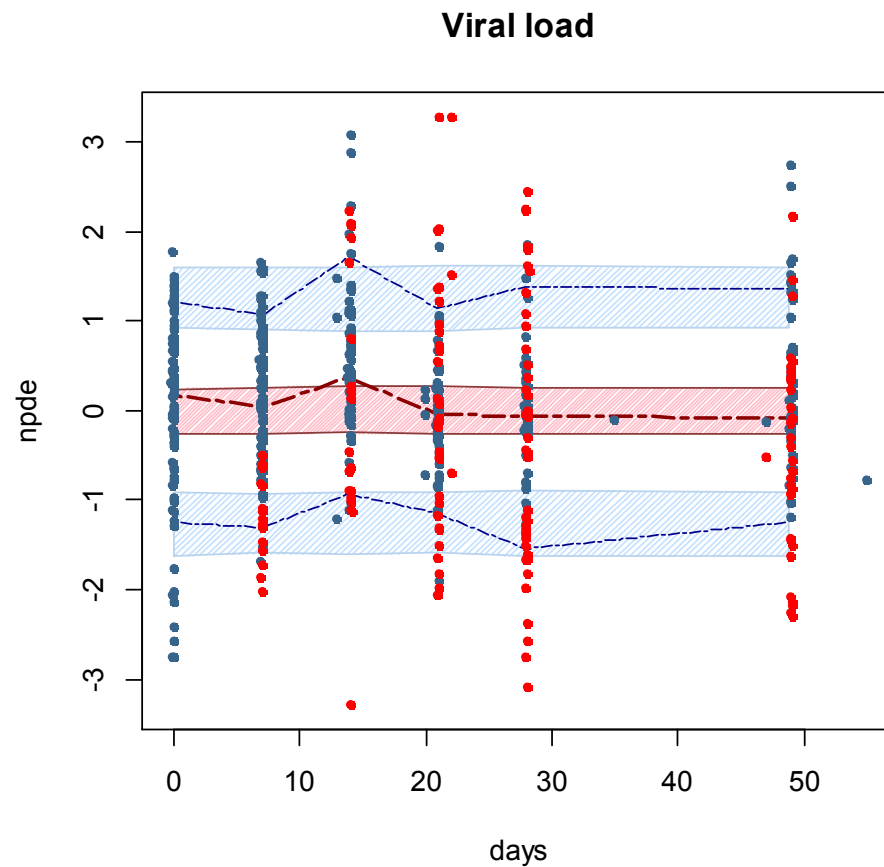


# Results: Individual fits



# Results

- ▶ Scatterplot of npde vs time for final PK-VK model



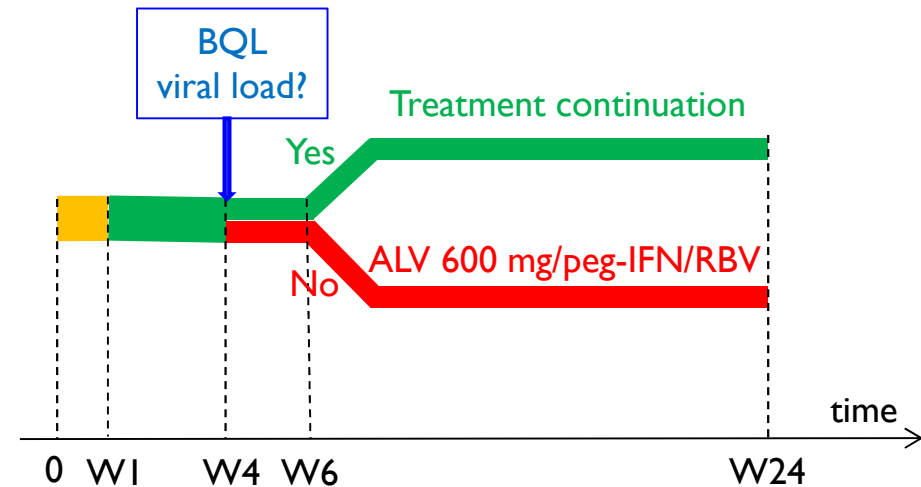
⇒ PK-VK model is adequate to describe viral kinetics in the 203 study

⇒ Will it be able to predict virologic response in another study?

# External validation - Simulation

## ▶ VITAL-I study (phase 2b)

- ▶ Different dosing regimens and different combinations of ALV
  - ▶ ALV 600 mg/Ribavirin (RBV)
  - ▶ ALV 800 mg/Ribavirin
  - ▶ ALV 600 mg/peg-IFN
- ▶ Complex design: response-guided therapy



## ▶ Compare model predictions and virologic response of VITAL-I study

- ▶ Sustained virologic response (SVR): undetectable viral load 24 weeks after stop of treatment
- ▶ Prediction of SVR: SVR achieved if the “cure boundary” is reached during treatment ( $< I$  predicted infected cell in the whole body fluids)<sup>(1,2)</sup>

# External validation - Results

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Treatment arms	% BQL data at week 4		% BQL data at week 12		% SVR	
	Observed	Predicted*	Observed	Predicted*	Observed	Predicted*
ALV 600 mg/RBV (N=77)	37.0	44.0 (33.8 – 51.9)	99.0	92.9 (88.3 - 96.8)	91	91.7 (85.7 – 96.1)
ALV 800 mg/RBV (N=80)	42.0	46.8 (36.3 – 58.4)	98.0	93.6 (88.1 – 97.5)	91	92.6 (86.3 – 97.5)
ALV 600 mg/peg-IFN (N=35)	85.0	87.2 (74.3 – 95.8)	96.0	96.2 (89.9 - 100.0)	91	94.9 (87.1 – 100.0)

\*Median (95% prediction interval obtained from 100 simulations)

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## Project 3

Impact of BQL data, design and  
*a priori* information of population parameters  
on individual parameter estimates and  
prediction of treatment outcome

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© 2013 ASCPT All rights reserved 2163-8306/12  
www.nature.com/psp

ORIGINAL ARTICLE

**Influence of *a priori* Information, Designs, and Undetectable Data on Individual Parameters Estimation and Prediction of Hepatitis C Treatment Outcome**

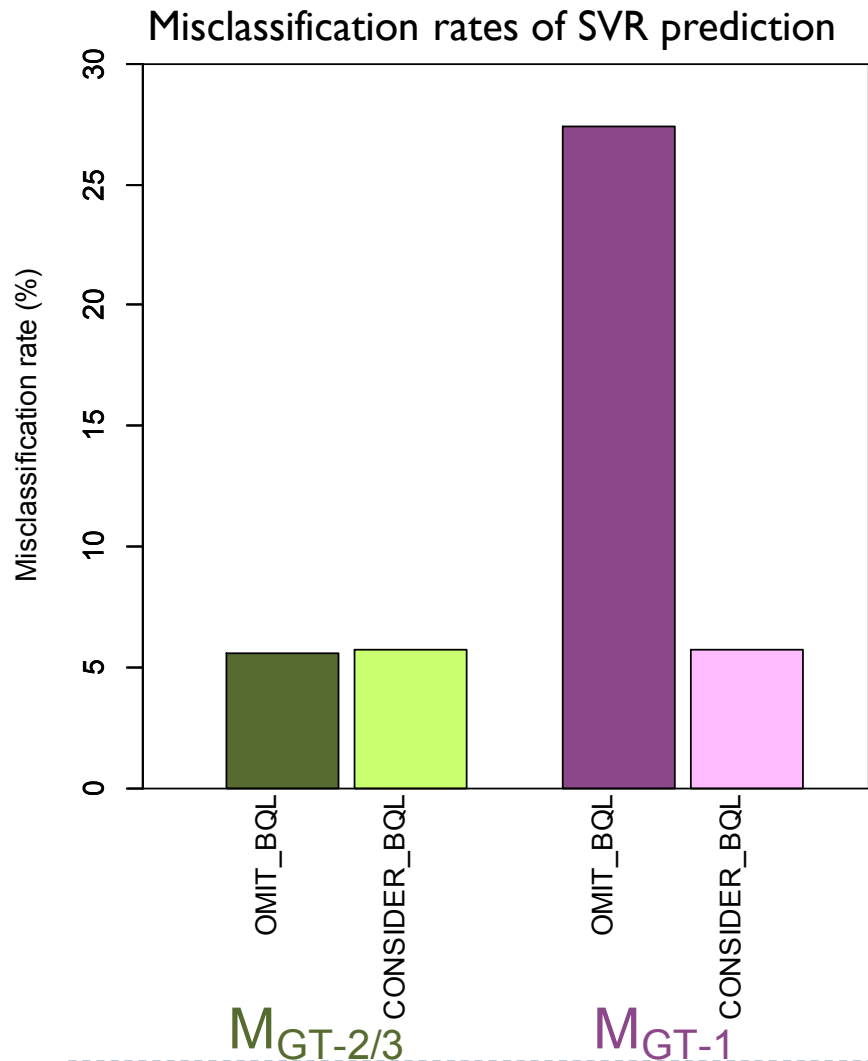
THT Nguyen,<sup>1,2</sup> J Guedj,<sup>1,2</sup> J Yu,<sup>3</sup> M Levi<sup>4</sup> and F Mentré<sup>1,5</sup>

# Methods: Simulation study

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- ▶ Data simulation
  - ▶ Virologic response in 1000 patients using typical parameters found in HCV GT-2/3 patients receiving peg-IFN/RBV for 24 weeks<sup>(1)</sup>
- ▶ Individual parameter estimation & SVR prediction
  - ▶ Bayesian approach
  - ▶ *A priori* information
    - ▶ True model ( $M_{GT-2/3}$ )
    - ▶ False model ( $M_{GT-1}$ ): typical viral kinetic parameters of HCV GT-1 patients<sup>(2)</sup>
  - ▶ Design: Day 0, Week 1, Week 2, Week 4 (influence of design not shown)
  - ▶ Methods for handling BQL data
    - ▶ OMIT\_BQL: omitting all BQL data
    - ▶ CONSIDER\_BQL: taking into account BQL data
  - ▶ Comparison of predicted and simulated SVR for each patient

# Results



- ▶ Good prediction with the true model  $M_{GT-2/3}$  regardless of methods for handling BQL data
- ▶ Good prediction with the false model  $M_{GT-1}$  if BQL data correctly handled

# Conclusions

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- ▶ Extended pd/npde for handling BQL data show better behaviors than naïve evaluation methods
- ▶ These metrics were implemented in npde 2.0
- ▶ The new metrics were used to evaluate a model of HCV kinetics during a short term treatment with alisporivir
- ▶ This model provided good predictions for both early viral kinetics and treatment outcome in a subsequent phase 2 study
- ▶ Bayesian estimation of individual parameters could provide good prediction of treatment outcome from only few early responses if BQL data are correctly handled



# Perspectives

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- ▶ Extension of other evaluation metrics to handle BQL data
- ▶ Comparison with other approaches that handle BQL data (e.g., IPRED method in MONOLIX)
- ▶ Prediction of individual treatment outcome with uncertainty using *a posteriori* distribution of individual parameters
- ▶ Optimal design which accounts for BQL data to obtain precise individual estimation/prediction
- ▶ Evaluation of viral kinetic prediction for HCV treatment individualization

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# Thank you for your attention!

## Acknowledgements



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- ▶ HCV clinical team