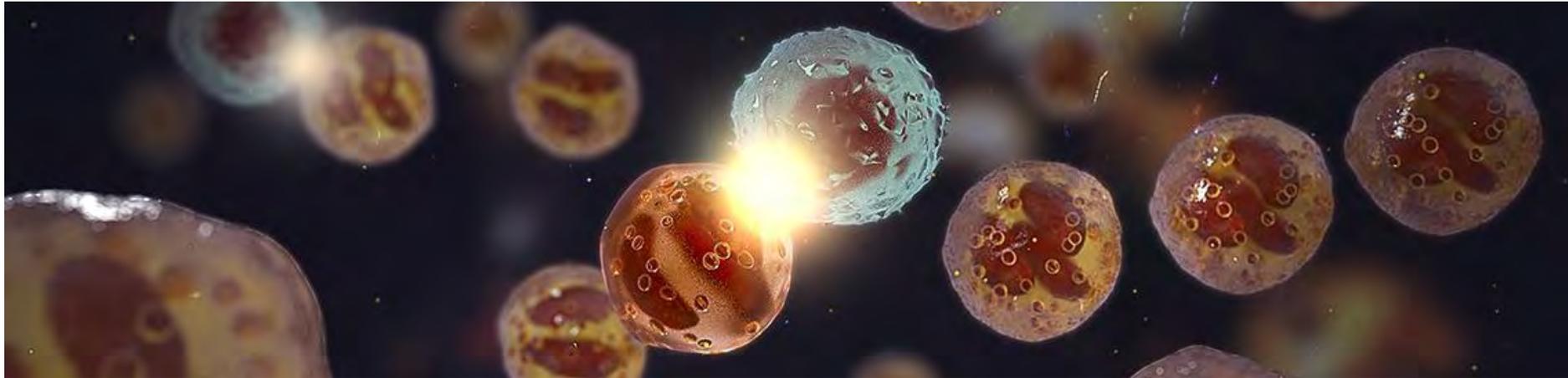


# Quantifying and Communicating Uncertainty in Human PK and Dose Prediction

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# Introduction

- In drug discovery, prospective prediction of human pharmacokinetics facilitates the differentiation of possible clinical candidates and is a key step in the prediction of efficacious clinical dose, optimal dosing regimen and therapeutic index.
- Of similar importance to the prediction of point estimates for each human PK parameter, is the accurate quantitation and communication of the *uncertainty* in the point estimates.
- This presentation describes a 'Monte-Carlo' based approach to estimating prediction intervals for both primary PK parameters (such as Cl and  $V_{ss}$ ) and key secondary parameters such as  $C_{max}$ , half-life & clinical dose.



# Presentation Overview

- Introduction to sources of uncertainty (as applied to prediction of human PK and 'efficacious' clinical dose)
- Overview of reference datasets and process used to characterize the uncertainty associated with our standard PK parameter prediction tools/approaches
- 'Monte-Carlo' process used to combine the uncertainty in the individual predicted PK parameters to compute uncertainty in dose
- Example: drug discovery project used to illustrate the process of quantifying and communicating the uncertainty in PK and dose prediction





..I hate all this  
uncertainty!



# Key sources of uncertainty in PK & dose prediction.

## Model

- **Model uncertainty** reflects the predictive accuracy of a particular model.

## Parameter

- **Parameter uncertainty** reflects uncertainty in the 'true' values of the mathematical model input parameters.

## Translation

- **Translation uncertainty** reflects uncertainty in the translation from animal to man, or from one patient group to another.

## Scenario

- **Scenario uncertainty** may reflect uncertainty in how the compound is to be administered or the efficacious target exposure.

## Population

- **Population uncertainty** reflects uncertainty around the target population or the prevalence of a particular mutation.

The challenge is to recognise, quantify and communicate the implications of these sources of uncertainty in predictions



# Examples of PK parameter prediction models - Clearance

## Hepatocyte $Cl_{int}$ based IVIVE

$Cl_{int}$  estimates from human hepatocyte incubations are scaled to a liver (metabolic)  $Cl_{int}$  according to:

$$\text{Scaled liver } Cl_{int} = Cl_{int,hep} * SF * fu_{blood} / fu_{inc}$$

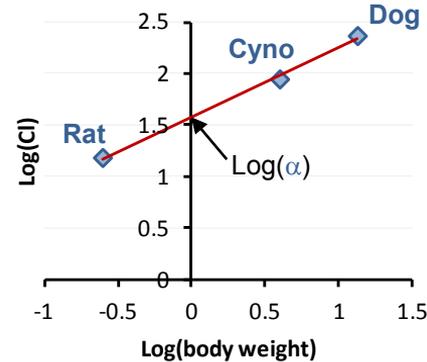
Where  $SF$  represents the product of hepatocellularity ( $10^6$  cells/ $g_{liver}$ ) and liver weight ( $g_{liver}/kg_{body\ weight}$ ).

Scaled liver  $Cl_{int}$  is then converted to a 'Predicted hepatic metabolic  $Cl_{int, in vivo}$ ' using established regression line (to correct for the general systematic under-prediction of direct IVIVE).

Input parameters are therefore human hepatocyte  $Cl_{int}$ ,  $fu_p$ , blood:plasma ratio &  $fu_{inc}$

Sohlenius-Sternbeck, A; Jones, C; Ferguson, D; Middleton, BJ; Projean, D; Floby, E; Bylund, J; Afzelius, A. Practical use of the regression offset approach for the prediction of in-vivo intrinsic clearance from hepatocytes. Xenobiotica 42(9): 841-843 (2012)

## $fu_p$ Corrected intercept method (FCIM)



Starts with a simple allometric plot....

$$Cl = \alpha * \text{BodyWeight}^b$$

This method predicts clearance from the equation below:

$$\text{Human Cl} = 33.35 * (\alpha / Rfu_p)^{0.77}$$

(Where  $Rfu_p$  is the ratio of  $fu_p$  in rat to  $fu_p$  in man.)

Input parameters are therefore plasma Cl in preclinical species &  $fu_p$  in rat and man.

Tang H, Mayersohn M. A novel model for prediction of human drug clearance by allometric scaling. Drug Metab Dispos 2005;33: 1297-1303



# Example of PK parameter prediction models - $V_{ss}$

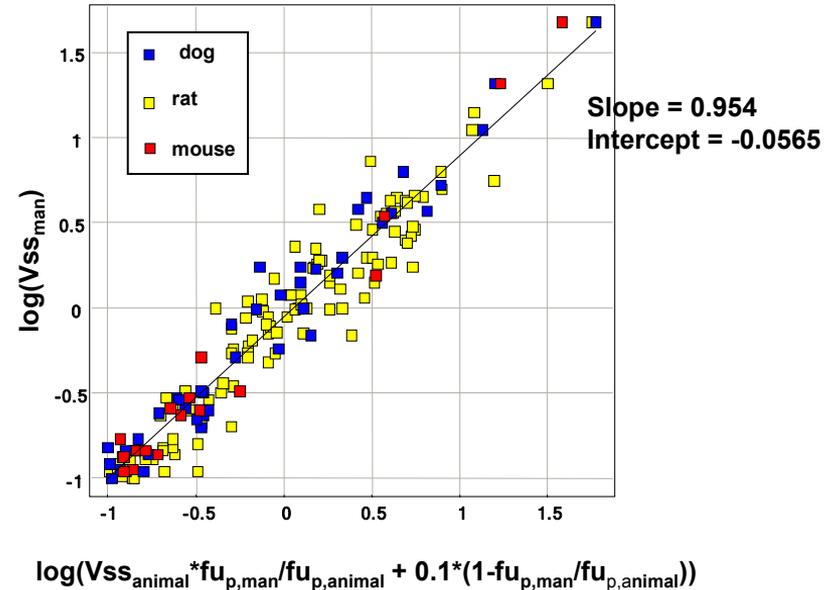
## 'McGinnity 2007' $V_{ss}$ prediction

Assumes tissue binding ( $f_{u,t}$ ) is equivalent in animals and humans and that the lower limit of  $V_{ss}$  = distribution volume of albumin = 0.1 l/kg

$$V_{ss,man} = \frac{f_{u,p,man}}{f_{u,p,animal}} V_{ss,animal} + 0.1 \left( 1 - \frac{f_{u,p,man}}{f_{u,p,animal}} \right)$$

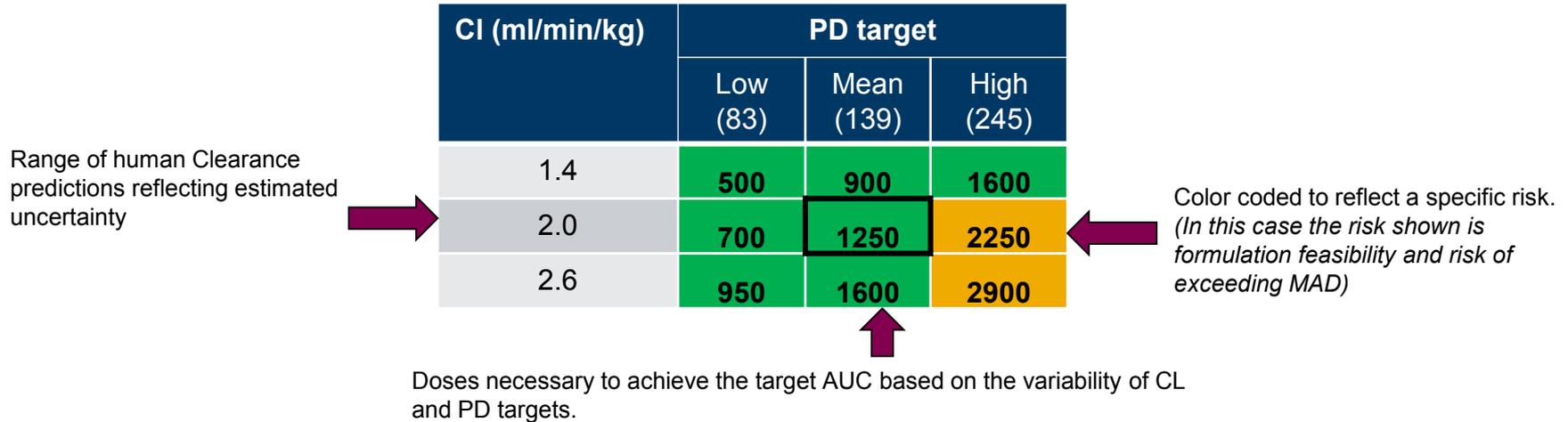
Small regression correction is applied to the prediction from each species and the geometric mean of the prediction from each species is obtained.

Input parameters are therefore plasma  $V_{ss}$  in preclinical species &  $f_{u,p}$  in preclinical species and man.



# Typical 'Dose Nomogram'....

Target exposure uncertainty: low, average and high (in this example numbers refer to AUCu/potency)



- Main weakness of this approach is that it doesn't usually express the likelihood of the various scenarios described.
- Only deals with 2 dimensions of uncertainty...which may not be sufficient.



# Datasets used to assess the uncertainty associated with individual PK parameter estimation methods

- Lombardo et al. 2013 dataset<sup>1</sup> (~400 compounds; human, rat, dog and monkey PK;  $Cl$ ,  $V_{ss}$ ,  $fu_p$ )
  - Øie-tozer  $V_{ss}$  (*rat only, dog only, rat & dog average  $fu_p$* )
  - McGinnity  $V_{ss}$  (*rat only, dog only, rat & dog geomean  $V_{ss}$  prediction*)
  - FCIM  $Cl^*$  (*rat only fixed exponent; rat and dog*)
- Astrazeneca internal  $V_{ss}$  dataset (~110 compounds; human, rat & dog  $V_{ss}$  &  $fu_p$ )
  - McGinnity  $V_{ss}$  (*rat only, dog only, rat & dog geomean  $V_{ss}$  prediction*)
- Paine 2011 renal clearance database<sup>2</sup> (35 compounds)
  - Renal  $Cl^*$  correlation method (*rat correlation, dog correlation*)
- Astrazeneca internal Human heps & human Mics test set compounds
  - IVIVE derived hepatic  $Cl^*$  from human heps and human Mics

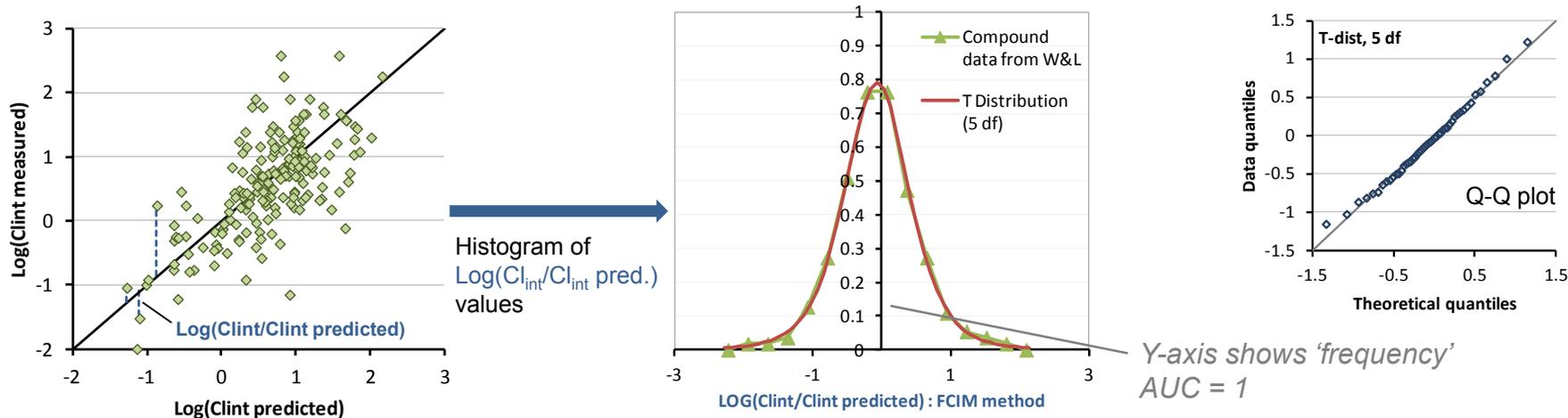
1. Lombardo F. et al. Comprehensive assessment of human pharmacokinetic prediction based on in vivo animal pharmacokinetic data, part 2: clearance. J. Clin. Pharmacol. 53(2):178-191 (2013)

2. Paine, SW et al. Prediction of human renal clearance from preclinical species for a diverse set of drugs that exhibit both active secretion and net reabsorption. Drug Metab. Dispos. 39(6):1008-13 (2011)



# Assessing uncertainty distributions...

- The distribution of  $\text{LOG}(\text{measured parameter}/\text{predicted parameter})$  was used to assess the predictive accuracy for each method when applied to the relevant test set(s)



- Example shown is the result of applying the FCIM to the W&L dataset. Green triangles derived from a histogram of the data (using  $0.5\sigma$  bin width). Red line is the equation for T-distribution (5 df; Std dev = 0.48)
- The uncertainty distributions for each PK prediction method are generally best described by either a Normal or T-distribution (*example Q-Q plot shown*)
- Each distribution is characterized by type (Normal or T), number of df (if required), bias & standard deviation and used as an estimate of the prediction error distribution associated with that method.

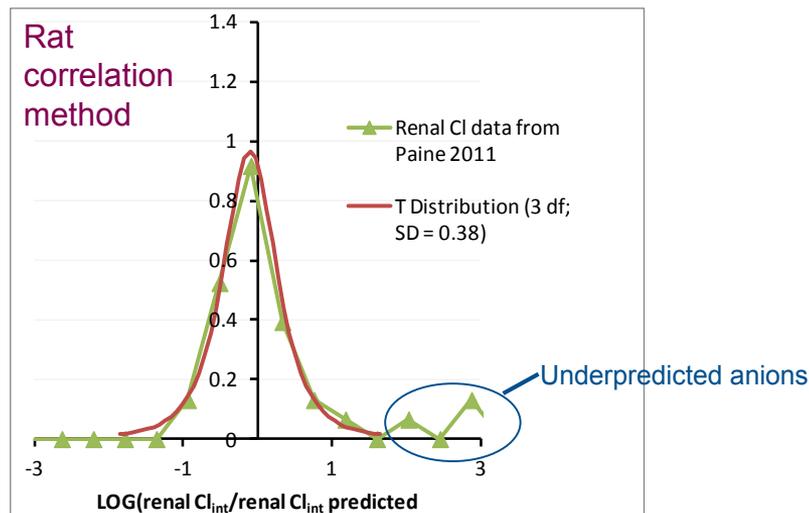
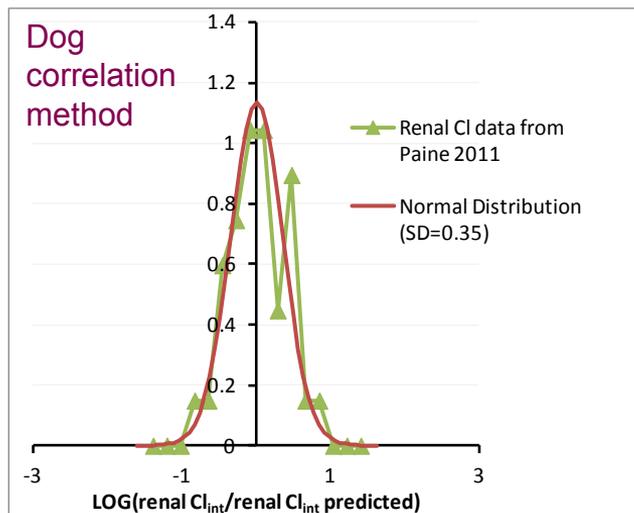


# Renal CI correlation method – use of Renal 'CI<sub>int</sub>'

Normally this method is based upon the assumption that renal CI in man can be predicted from renal CI in animals by correcting for interspecies differences in  $f_{u,p}$  and KBF.

$$\text{Renal CI}_{\text{human}} = \text{Renal CI}_{\text{dog}} * (f_{u,p,\text{human}}/f_{u,p,\text{dog}}) * (\text{KBF}_{\text{human}}/\text{KBF}_{\text{dog}})$$

However, for the purposes of uncertainty assessment, it is simpler to convert to a 'renal CI<sub>int</sub>'  $[ \text{KBF} * \text{CI}_{\text{renal}} / (\text{KBF} - \text{CI}_{\text{renal}}) ]$ .



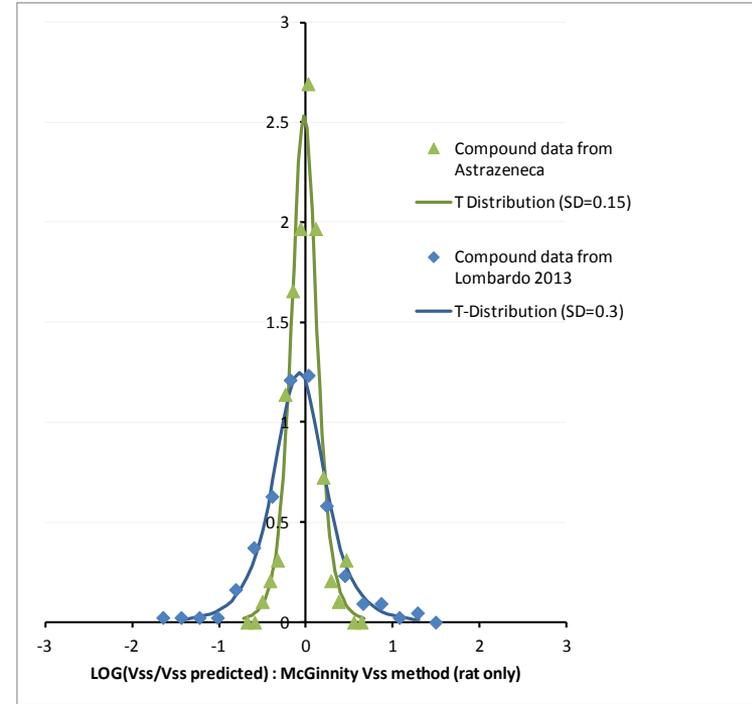
Assessing predictive accuracy in terms of CI<sub>int</sub> prevents the prediction of possible 'true' values of CI<sub>renal</sub> that exceed KBF.



# Overall uncertainty in PK parameter prediction results from combination of input parameter and model uncertainty

## Example McGinnity $V_{ss}$ Method

- The distribution of  $\text{LOG}(V_{ss}/V_{ss \text{ predicted}})$  appears to vary depending upon which reference set is used. The apparent larger uncertainty with the W&L dataset probably arises from incorporation of poorly defined PK datasets and inter-lab differences in determination of  $f_{up}$  for different species.
- Realistic assessment of the overall uncertainty associated with a particular method requires that the reference data set, used to probe the accuracy of method, is of similar 'quality' to that available for the test compound.



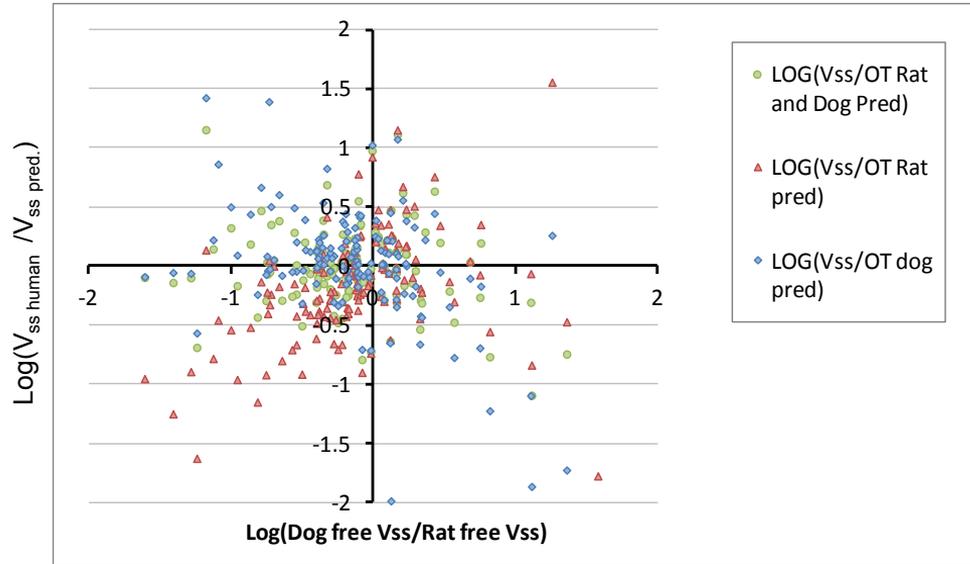
# Human PK parameter prediction methods: Distributions

		Log(measured/predicted)				
	Method	Parameter assessed	Distribution shape	Std Dev ( $\sigma$ )	Bias	Dataset
Hepatic CL	Hep $Cl_{int}$ IVIVE	<i>in-vivo</i> $Cl_{int}$	Normal	0.4	0	AZ
	Mic $Cl_{int}$ IVIVE	<i>in-vivo</i> $Cl_{int}$	Normal	0.46	0	AZ
	FCIM ( <i>based on <u>rat</u> PK only</i> )	<i>in-vivo</i> $Cl_{int}$	T-Dist. (5 df)	0.48	-0.066	Lombardo 2013
	FCIM ( <i>based on <u>rat and dog</u> PK</i> )	<i>in-vivo</i> $Cl_{int}$	T-Dist. (5 df)	0.38	-0.085	Lombardo 2013
Renal CL	Renal CL correlation method - <i>dog</i>	Renal ' $Cl_{int}$ '	Normal	0.35	0.0133	Paine 2011
	Renal CL correlation method - <i>rat</i>	Renal ' $Cl_{int}$ '	T-Dist. (3 df)	0.38	-0.092	Paine 2011
$V_{ss}$	$\emptyset$ ie-tozer $V_{ss}$ ( <i>rat only</i> )	$V_{ss}$	T-Dist. (4 df)	0.3	-0.14	Lombardo 2013
	$\emptyset$ ie-tozer $V_{ss}$ ( <i>dog only</i> )	$V_{ss}$	T-Dist. (4 df)	0.3	0.05	Lombardo 2013
	$\emptyset$ ie-tozer $V_{ss}$ ( <i>rat and dog</i> )	$V_{ss}$	T-Dist. (4 df)	0.25	-0.032	Lombardo 2013
	McGinnity $V_{ss}$ ( <i>rat only</i> )	$V_{ss}$	T-Dist. (5 df)	0.15	-0.02	AZ
	McGinnity $V_{ss}$ ( <i>dog only</i> )	$V_{ss}$	T-Dist. (5 df)	0.11	0.042	AZ
	McGinnity $V_{ss}$ ( <i>rat and dog</i> )	$V_{ss}$	T-Dist. (5 df)	0.075	0.016	AZ



# Correlation of residual distribution with compound properties..

Example:

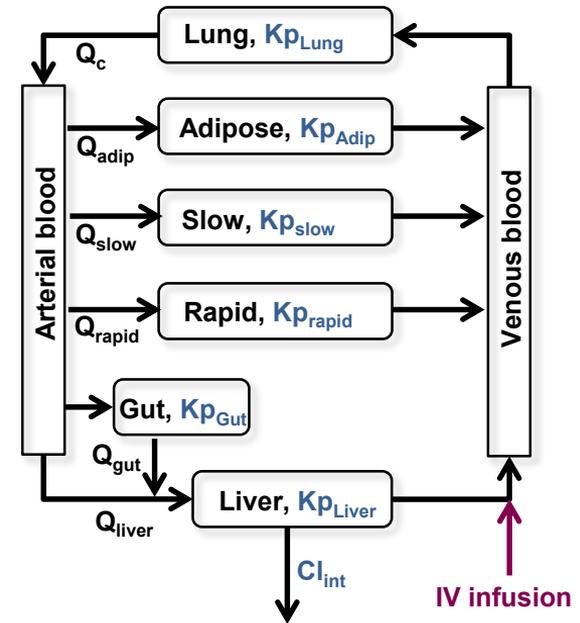


- Standard deviation of residual distribution appears to be correlated to fold-difference in free Vss between dog and rat (i.e. greater uncertainty in human Vss prediction when rat and dog free Vss don't 'agree')
- May be appropriate to take these sort of observations into account when estimating the uncertainty distribution for a new compound.



# Dealing with PBPK models?

- More challenging to establish uncertainty distributions for PBPK models as there are multiple tissue Kp values that contribute to  $V_{ss}$  and the overall 'shape' of the concentration time profile
  - Requires analysis of full concentration vs time profiles in each test sets.....and how to quantify accuracy of 'shape' prediction?
- However, because PBPK models are based on similar assumptions (equivalent tissue binding across species) and input data as other  $V_{ss}$  prediction methods (e.g. McGinnity & Øie-Tozer) the distribution of  $\text{Log}(V_{ss}/V_{ss \text{ pred}})$  should be similar
  - This is supported by a PhRMA assessment that demonstrated similar predictive accuracy when comparing Arundel PBPK with other  $V_{ss}$  prediction methods\*
- Application of PBPK models requires point estimates of human tissue:blood partition coefficients. Simplest approach is to assume equal predictive error ( $\log(Kp/Kp_{\text{predicted}})$ ) for all tissues when dealing with  $V_{ss}$  prediction.
- Dealing with uncertainty at the Kp level (rather than  $V_{ss}$ ) prevents the generation of non-physiologically possible 'true' values of  $V_{ss}$  for low  $V_{ss}$  compounds.

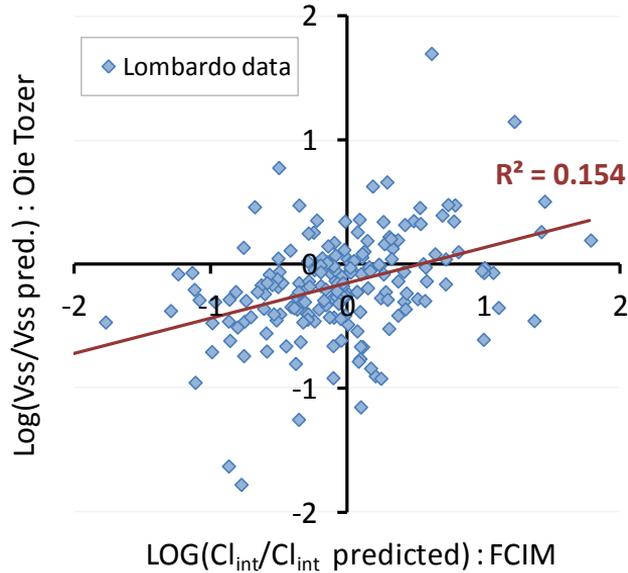


\*Jones, RD et al. PhRMA CPCDC initiative on predictive models of human pharmacokinetics, part 2: Comparative assessment of prediction methods of human volume of distribution. J. Pharm. Sci. 100(10): 4074-89 (2011)



# Correlation

- The correlation between 'residuals' [i.e.  $\text{Log}(\text{measured}/\text{predicted})$ ] for different methods was also assessed (for the range of PK parameter prediction models)



- In the example shown both FCIM  $Cl_{int}$  and McGinnity  $V_{ss}$  rely upon the ratio of  $f_{u,p, human} / f_{u,p, rat}$ . Results is a slight correlation between method residuals.

Generally there was low correlation between the residuals for  $V_{ss}$  and  $Cl$  prediction methods



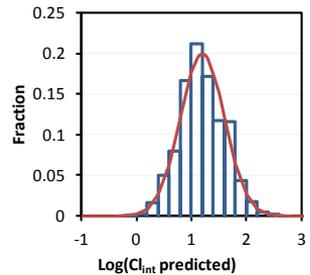
# Combining uncertainty distributions in a Monte-carlo approach...

- **Key assumption:** for a new test compound, the distribution of *possible* 'true' values (for a given human parameter) relative to the point estimate prediction, will be equivalent to the corresponding distribution of (*known*) true values relative to the single point 'predictions' for the established set of reference compounds. *[Note: there will be only one actual true population mean value..]*
- **Step 1:** Derive the point estimate prediction for each relevant PK parameter
- **Step 2:** Generating lists of *possible* 'true' values distributed around the point estimate predictions.
- **Step 3:** Randomly sample a single *possible* true value for each primary parameter (e.g. hepatic CI,  $V_{ss}$ , renal CI..) from the respective distributions and then calculate/estimate a single value for each secondary parameter (such as  $T_{1/2}$ ,  $C_{max}$ , Dose..) .
- Step 3 is repeated a large number of times (say 1000...) to give a distribution of possible true values for each secondary parameter of interest.

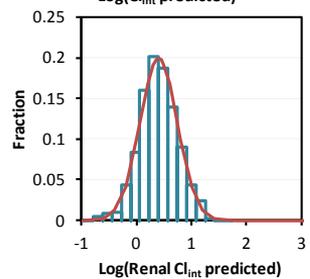


# Schematic of process used to estimate prediction intervals

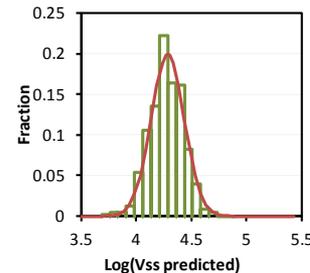
Hepatic CI = 10 mL.min<sup>-1</sup>.kg<sup>-1</sup>



Renal CI = 2.2 mL.min<sup>-1</sup>.kg<sup>-1</sup>



Vss = 19 L.kg<sup>-1</sup>



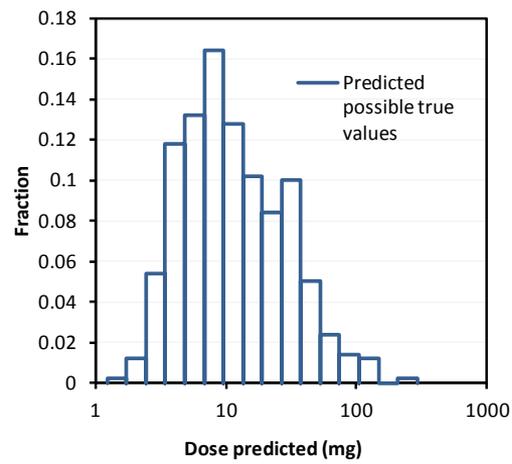
random selection

random selection

random selection



*Can also include distribution of possible true values for PD/efficacy model parameters*



***Distribution of possible values of dose***

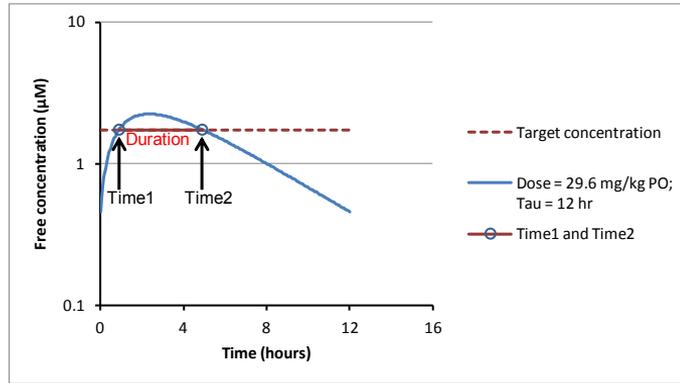
***Point estimate predictions***

***Distributions of possible 'true' values of primary parameters***



# Monte-carlo dose prediction – process for ‘closed form’ dose equations

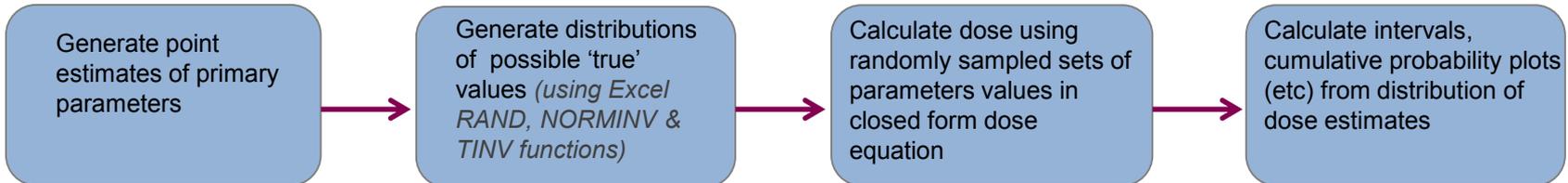
Example: one compartment PK; first order absorption; aiming to maintain free concentration above target for specified time at steady state



$$\text{Time1} = \frac{\text{Ln} \left[ \frac{(1 - e^{-K_a \cdot \text{Dur}})}{(1 - e^{-K_a \cdot \text{tau}})} * \frac{(1 - e^{-K_e \cdot \text{tau}})}{(1 - e^{-K_e \cdot \text{Dur}})} \right]}{K_a - K_e}$$

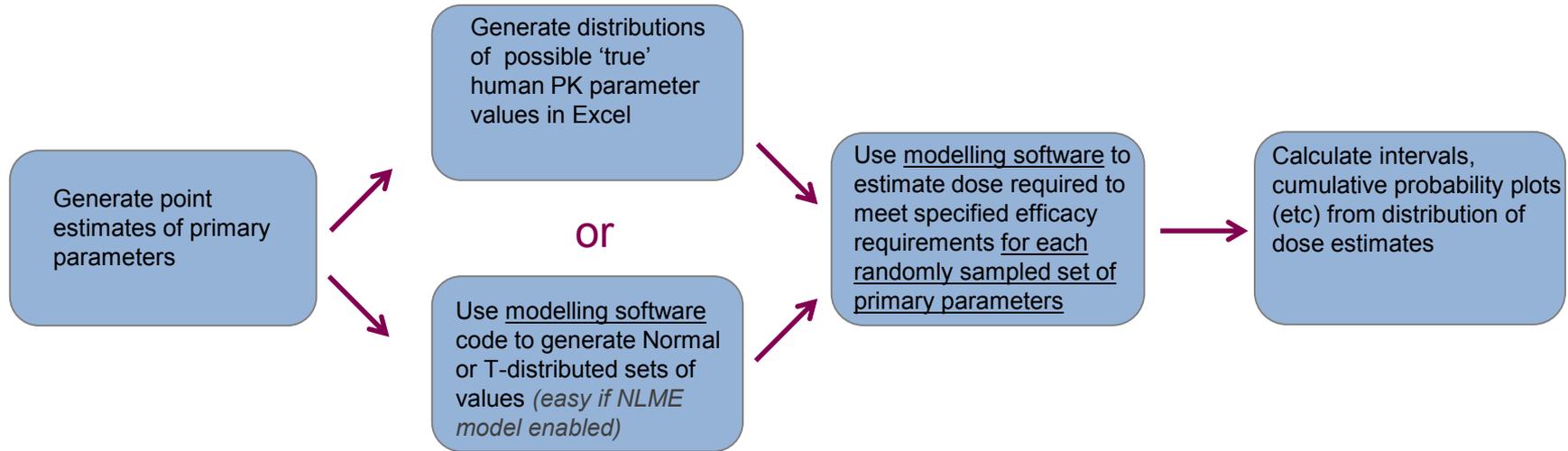
$$\text{Dose} = \frac{\text{Target free conc} * V_{ss} * (K_e - K_a)}{f_{u_{\text{blood}}} * K_a * F * \left[ \frac{e^{-K_a \cdot \text{Time1}}}{(1 - e^{-K_a \cdot \text{tau}})} - \frac{e^{-K_e \cdot \text{Time1}}}{(1 - e^{-K_e \cdot \text{tau}})} \right]}$$

Entire process readily accomplished in Excel



# Monte-carlo dose prediction – process for differential equation based dose prediction

Requires the use of model fitting software....but is the same as point estimate dose prediction (just repeated ~1000 times)



The 'difficult' part of the process is making qualified prior estimates of uncertainty distributions



## Example: AZ Drug discovery project

- Oral delivery (once a day)
- Multi-exponential plasma kinetics with both hepatic and renal Cl.
- Aiming to achieve free plasma concentration that equals the free 'IC<sub>50</sub>' at 12 hours.

Note: this is simple example to illustrate concepts



# PK parameter prediction methods employed

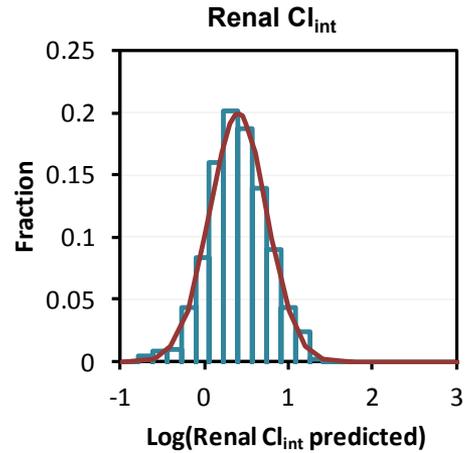
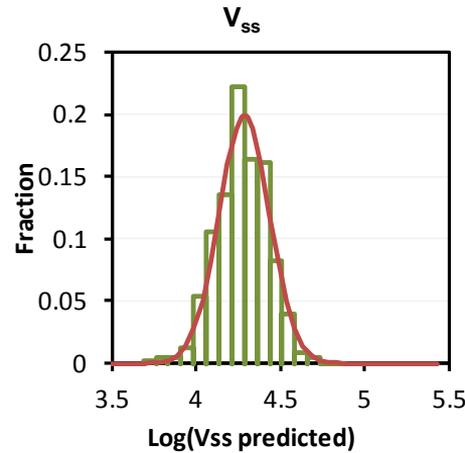
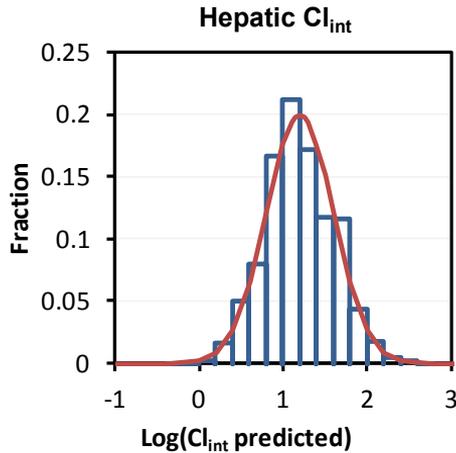
- Hepatic Clearance – estimated from  $Cl_{int}$  in hepatocytes using standard IVIVE approach. Predicted *in-vivo* hepatic clearance (10 ml/min/kg) was converted to *in-vivo* hepatic  $Cl_{int}$  by application of reverse WSM
- Renal Clearance – estimated from dog renal clearance using the ‘Dog renal  $Cl_{int}$  correlation method’. Predicted renal  $Cl = 2.2$  ml/min/kg.
- Distribution - Arundel PBPK\* approach applied using rat as primary species to derive tissue  $K_p$  values. Predicted  $V_{ss} = 19.3$  l/kg.
- $f_{abs}$  assumed to be 1 (based on high permeability and high  $f_{abs}$  in all pre-clinical species)
- $K_a$  assumed to be  $3.5 \text{ hr}^{-1}$  (GI prediction software)

\*Arundel, PA (AstraZeneca UK). A multi-compartment model generally applicable to physiologically-based pharmacokinetics. Poster session presented at: 3rd IFAC Symposium on Modeling and Control in Biomedical Systems; 1997 March 23-26; University of Warwick



# Distributions of possible 'true' values for primary PK parameters..

- Model was written in Phoenix WinNonlin® to generate 500 sets of values for hepatic  $Cl_{int}$ , renal  $Cl_{int}$  & tissue  $K_p$ s distributed around the point estimates. (Note:  $V_{ss}$  values were then derived as a function of  $K_p$  values)
- For each parameter the generated distribution of possible 'true' values was assessed to ensure that it was consistent with the expected shape (based on the assumed distribution of prediction errors).

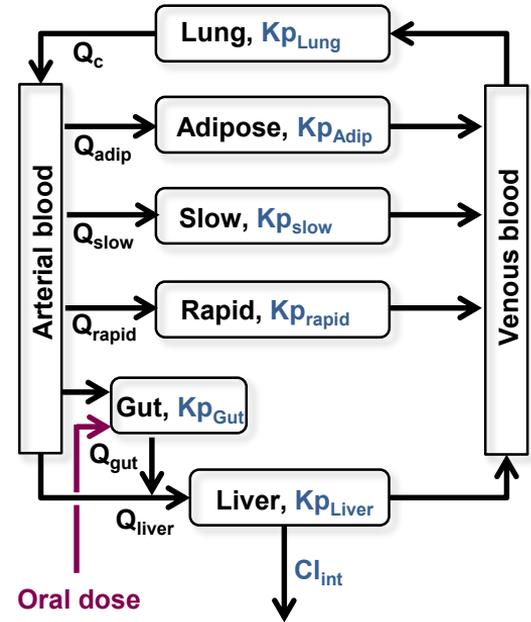
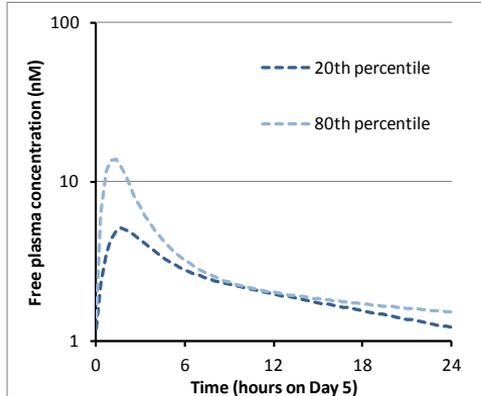


- Monte Carlo approach was used to randomly sample possible 'true' values from each parameter distribution - to create sets of possible primary parameter values....

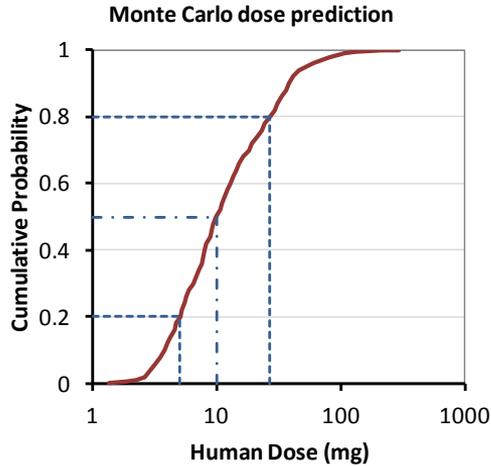


# Monte Carlo analysis –using Arundel PBPK model

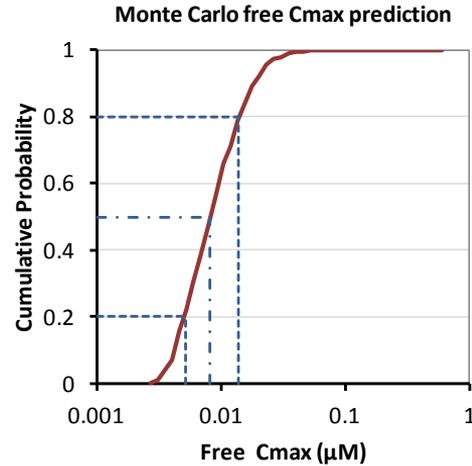
- PBPK model was written in Phoenix WinNonlin®
- Target (free) plasma concentration was set at 2 nM at 12 hours post dose on Day5. (*Note: uncertainty in target concentration was not considered*)
- 500 sets of possible 'true' PK parameter values were randomly sampled from the assumed distributions
- For each randomly sampled set of possible 'true' PK parameter values the oral dose was optimized such that the target free plasma concentration was attained



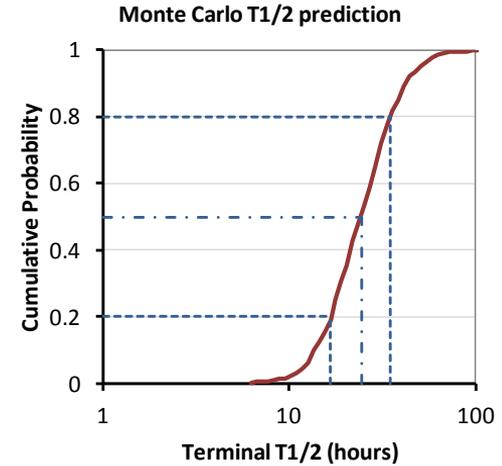
# Monte Carlo – Cumulative probability curves



20% probability  $\leq$  5 mg  
50% probability  $\leq$  10 mg  
80% probability  $\leq$  27 mg



20% probability  $\leq$  5.1 nM  
50% probability  $\leq$  8.2 nM  
80% probability  $\leq$  13.9 nM



20% probability  $\leq$  17 hour  
50% probability  $\leq$  25 hours  
80% probability  $\leq$  35 hours

- These plots allow the impact of uncertainty in predicted PK to be quantified in terms of 'risk' to the project.....
- Example – quantify the probability that the required dose will exceed the estimated maximum absorbable dose
- Example – quantify the probability that the free C<sub>max</sub> will exceed a threshold associated with secondary pharmacology or safety signals.



# Conclusions/Comments

- Process described is a relatively simple approach for combining uncertainty in multiple predicted primary parameters to estimate uncertainty in key secondary parameters.
- Assessing the impact of uncertainty in PK prediction on key project 'risks' provides clarity for decision making.
- Work remains to be done to further refine our understanding of how certain observations impact the likely 'uncertainty' in PK prediction'. E.g.
  - *If rat & dog have the same unbound  $V_{ss}$  how much does that reduce the uncertainty in human  $V_{ss}$  prediction?*
  - *To what extent does the accuracy of rat and dog Cl prediction by hepatocyte  $Cl_{int}$  IVIVE impact the uncertainty in human Cl predictions by hepatocyte  $Cl_{int}$  IVIVE?*
- Need to continually track the accuracy of human PK prediction as clinical data on new candidate drugs becomes available. Ensure the predictive performance is in line with expectations.



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- Peter Gennemark



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