

Introduction

- Physiologically based pharmacokinetic (PBPK) models rely on chemicalspecific parameters to predict internal concentrations or generate in vitro to in vivo extrapolation (IVIVE) estimates.
- Input parameters can be empirically measured or estimated through in silico approaches such as quantitative structure-activity relationship (QSAR) models.
- Uncertainty and variability are inherent in both empirical and *in silico* parameters, as experimental variability (e.g. interlaboratory effects) impacts empirical measures as well as in silico predictions trained with empirical data.
- This uncertainty in input parameters propagates through PBPK calculations to result in uncertainty in model predictions.
- This study evaluated how parameter uncertainty impacts PBPK predictions using the OPEn quantitative structure-activity/property Relationship App (OPERA v2.7), which provides QSAR parameter predictions as well as estimates of uncertainty in the form of a range around each prediction value.

Methods



Case

Three pes

 In vitro bio Pesticide

(+)-trans-P ("Permethri Carabyl

Captan

Results

(Mµ) ntration Conce Plasma (Mµ)



10

Time (h)

15



ncentration

Co

a

Integrating Parameter Uncertainty in PBPK Modeling

David Hines¹, Jaleh Abedini¹, Dave Allen¹, Nicole Kleinstreuer², Kamel Mansouri² ¹Inotiv, Research Triangle Park, NC, USA; ²NIH/NIEHS/DNTP/NICEATM, Research Triangle Park, NC, USA

Stud	ly				
دا دا	Permethrin 51877-74-8	Ca 63	rbaryl 8-25-2	Captan 133-06-2	
ticides we bactivity da	are selected that represent ata used for IVIVE (AC50 Intrinsic Clearance*	nted diversity in structu) values) were obtaine Fraction Unbound	ire and entire QS d from ICE. pKa	AR prediction range (see	e table below). Log Henry's Law
ermethrin n")	68.39 [57.83 : 87.59]	0.01 [0.01 : 0.01]		6.49 [6.46 : 6.54]	-7.6 [-9.5 : -5.7]
	27.27 [26.17 : 28.37]	0.69 [0.67 : 0.69]	8.1 [7.1 : 9.1] donor	2.35 [2.32 : 2.41]	-7.8 [-8.9 : -6.7]
	0.01 [0.01 : 1.98]	0.08 [0.01 : 0.18]	2.1 [-1.3 : 5.4]	2.80 [2.75 : 2.85]	-5.4 [-6.3 : -4.5]

*QSAR parameters (range). Intrinsic clearance is in units of uL/min/10^6 hepatocytes. The other parameters are unitless

Fig 2: Plasma AUC



Carbaryl Captan

nethrin

Fig 3: IVIVE

Distributions of EAD values based on ICE data. Filled boxes show the effect of input uncertainty.



- Carbaryl had the narrowest range of PBPK results based on QSAR parameter prediction ranges, followed by Permethrin and Captan (Figs 1 and 2).
- Fraction unbound, intrinsic clearance, and logP were the input parameters with the most potential for influence on PBPK model outputs (e.g. Captan).

Parameter/ condition	Biochemical implication	Effect on PBPK plasma prediction	
Fraction 1	High bioavailability in plasma can facilitate rapid clearance	Cmax, AUC	
Intrinsic clearance	High enzymatic activity rapidly clears chemical	Cmax, AUC	
LogP	Highly lipophilic compound accumulates in lipid-rich tissues	Cmax, AUC	

Application of the Cmax range maximum to IVIVE calculations resulted in more conservative EAD estimates informed by QSAR prediction ranges (60.2% lower for Captan; Fig 3).

Take-Home Points

References

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scussion

Quantification of uncertainty in PBPK outputs from input parameter variability an help researchers characterize confidence in model results.

Estimating the variability and uncertainty inherent in empirically measured and SAR predicted parameters, then using the ranges of parameters to generate prediction ranges is a way to describe possible PBPK outcomes based on the est available knowledge.

he case study in this work demonstrates how the QSAR parameter prediction anges generated by OPERA can be used with this approach to characterize he effects of input parameter variability.

The magnitude of input parameter effects can vary with other parameter alues. For example, both Permethrin and Captan have ranges of fraction unbound values near zero, but Captan has substantially higher plasma AUC values due to its lower intrinsic clearance and LogP parameters.

Quantifying how input parameter uncertainty propagates through PBPK models can inform more conservative approaches to applications such as IVIVE.

• Experimental variability results in uncertainty that is inherent in both empirical and in silico predicted PBPK input parameters.

Calculating ranges of PBPK model outputs based on input parameter ranges can characterize the effects of input parameter variability.

Characterization of parameter variability facilitates better informed interpretation of model results.

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