

New Tricks with High Throughput Toxicokinetics

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Introduction

- Toxicokinetics (TK) provides a bridge between HTS and HTE by predicting tissue concentrations due to exposure
 - Traditional TK methods are resource intensive
- Relatively high throughput TK (HTTK) methods have been used by the pharmaceutical industry to determine range of efficacious doses and to prospectively evaluate success of planned clinical trials (Jamei, et al., 2009; Wang, 2010)
 - A key application of HTTK has been "reverse dosimetry" (also called Reverse TK or RTK)
 - RTK can approximately convert in vitro HTS results to daily doses needed to produce similar levels in a human for comparison to exposure data (Wetmore, et al., 2012)
- R is a free, open source programming language and software environment for statistical computing and graphics
 - R "packages" add special functionality and data for statistical analysis
- New R package "httk" freely available on CRAN allows RTK and other statistical analyses of 543 chemicals (more coming)



Why Build Another PBTK Tool?

	SimCYP	ADMET Predictor / GastroPlus	MEGen	httk	
Maker	SimCYP Consortium / Certara	Simulations Plus	UK Health and Safety Laboratory (Loizou)	US EPA	
Availability	License, but inexpensive for research	License, but inexpensive for research	Free: http://xnet.hsl.gov.uk/mege n	Free: CRAN Repository	
Population Variability Monte Carlo	Yes	No	No	Yes	
Batch Mode	Yes	Yes	No	Yes	
Physiological Data	Yes	Yes	Yes	Yes	
Chemical-Specific Data Library	Clinical Drugs	No	No	Pharma and ToxCast Compounds: 443 PBTK, +100 steady-state only	
Export Function	No	No	Matlab and AcslX	SBML and Jarnac	
R Integration	No	No	No	Yes	
Easy Reverse Dosimetry	Yes	Yes	No	Yes	
Future Proof XML	No	No	Yes	No	

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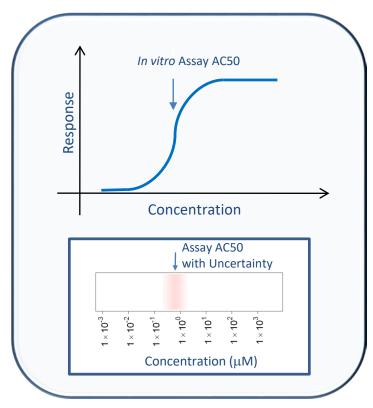
We want to do a statistical analysis (using R) for as many chemicals as possible



High-Throughput Bioactivity

- Tox21: Examining >10,000 chemicals using ~50 assays intended to identify interactions with biological pathways (Schmidt, 2009)
- ToxCast: For a subset (>1000) of Tox21 chemicals ran >500 additional assays (Judson et al., 2010)
- Most assays conducted in doseresponse format (identify 50% activity concentration – AC50 – and efficacy if data described by a Hill function)
- All data is public: http://actor.epa.gov/







In vitro Bioactivity, HTTK, and in Vivo Toxic Doses

Comparison of HTTK predicted oral equivalent doses (box and whisker plots in mg/kg/day) with doses for no effect and low effect groups in animal studies

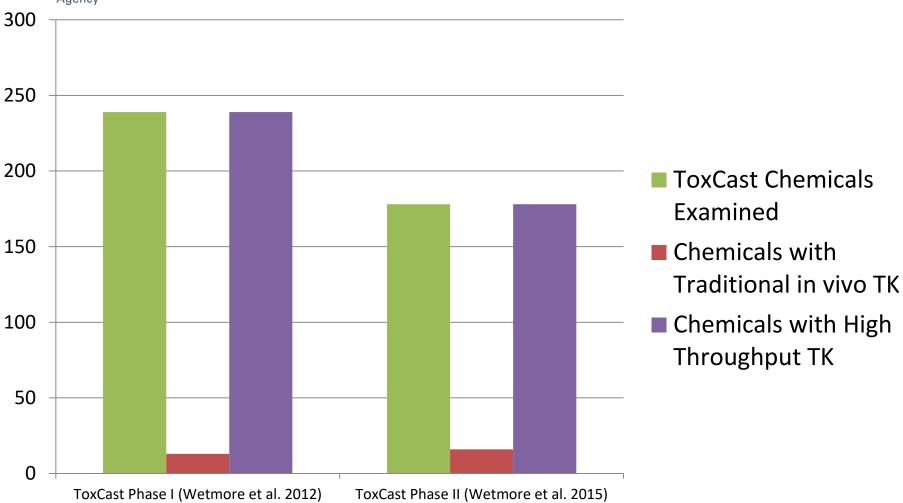
- Lowest Observed Effect Level
- [△] No Observed Effect Level (NEL)
- ▼ NEL/100

from food residues are indicated by vertical red lines. All values are in mg/kg/day.

Judson et al. (2011)



The Need for *In Vitro*Toxicokinetics



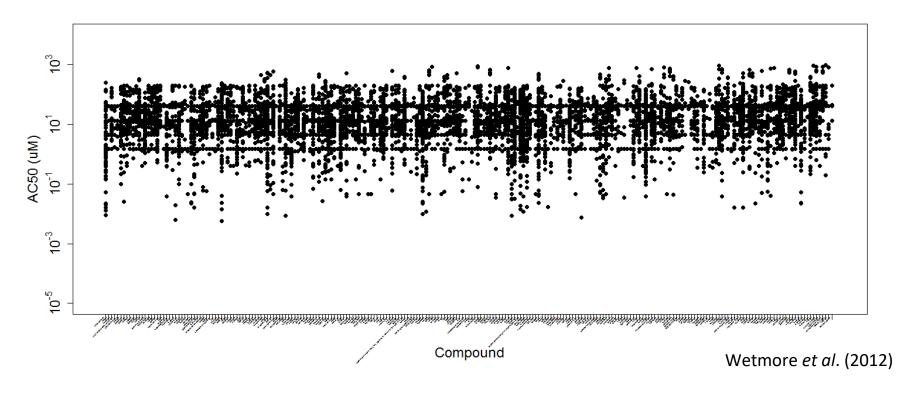
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 Studies like Wetmore et al. (2012),addressed the need for TK data using in vitro methods



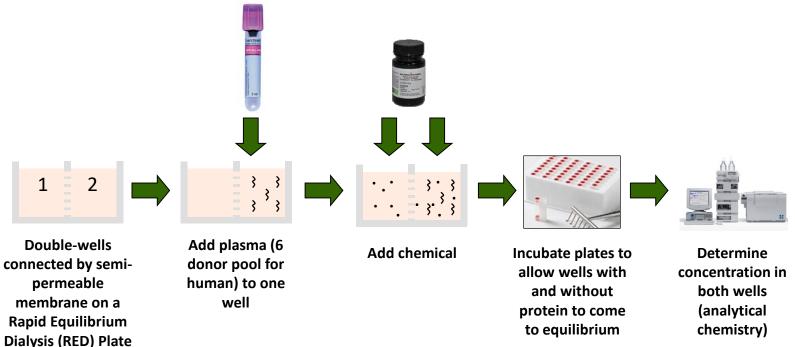
ToxCast *in vitro* Bioactive Concentrations



- One point for each chemical-in vitro assay combination with a systematic (Hill function) concentration response curve
- How can we use toxicokinetics to convert these to human doses?



Plasma Protein Binding (Fraction Unbound in Plasma)



$$F_{ub,p} = \frac{C_{well1}}{C_{well2}}$$

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 Data on ToxCast chemicals initially collected at Hamner Institutes

Published:

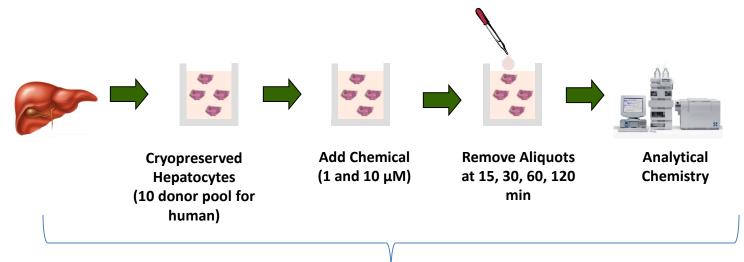
- Rotroff et al. (2010) Pilot study using 38 Phase I ToxCast chemicals
- Wetmore et al. (2012) Remainder of easily analyzed Phase I chemicals
- Wetmore et al. (2013) Rat TK for 50 ToxCast/ToxRefDB compounds
- Wetmore et al. (2015) ~200 ToxCast Phase II chemicals

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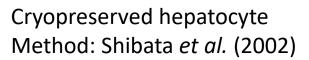
RED Method: Waters et al. (2008)

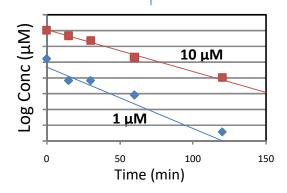


Intrinsic Hepatic Clearance



The rate of disappearance of parent compound (slope of line) is the **hepatic clearance** (µL/min/10⁶ hepatocytes)





We perform the assay at 1 and 10 µM to check for saturation of metabolizing enzymes.

- Data on ToxCast chemicals initially collected at Hamner Institutes Published:
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High Throughput Toxicokinetics (HTTK)

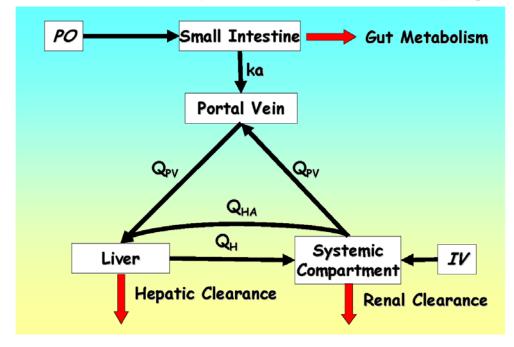
Jamei et al. (2009)

Minimal Model: Lumped Single Distribution Volume

SIM#CYP

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- In vitro plasma protein binding and metabolic clearance assays allow approximate hepatic and renal clearances to be calculated
- At steady state this allows conversion from concentration to administered dose
- 100% bioavailability assumed



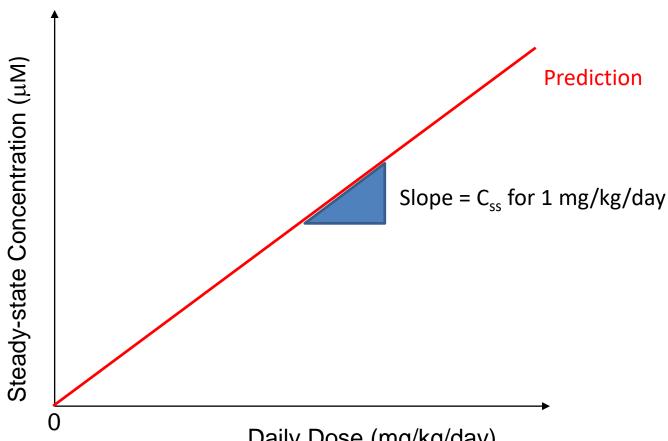
$$C_{ss} = \frac{\text{oral dose rate}}{\left(\text{GFR} * F_{ub}\right) + \left(Q_1 * F_{ub} * \frac{Cl_{int}}{Q_1 + F_{ub} * Cl_{int}}\right)}$$

Oral dose in (mg/kg/day)

Sum of hepatic and renal clearance (mg/kg/day)



Steady-State is Linear with Dose



$$C_{ss} = \frac{\text{oral dose rate}}{\left(\text{GFR * F}_{ub}\right) + \left(Q_1 * F_{ub} * \frac{Cl_{int}}{Q_1 + F_{ub} * Cl_{int}}\right)}$$

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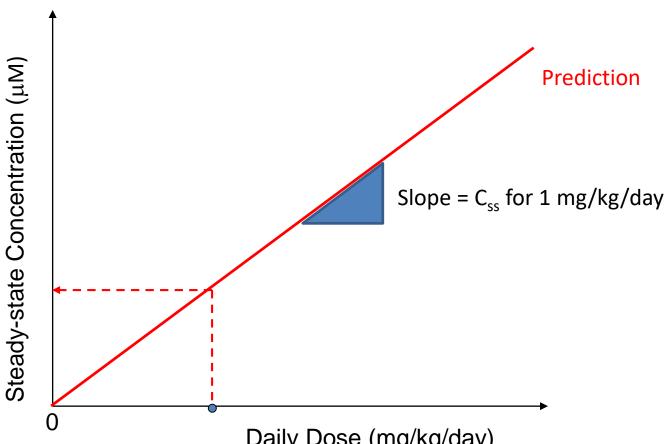
Wetmore *et al.* (2012)

Daily Dose (mg/kg/day)

Can calculate predicted steady-state concentration (C_{ss}) for a 1 mg/kg/day dose and multiply to get concentrations for other doses



Steady-State is Linear with Dose



$$C_{ss} = \frac{\text{oral dose rate}}{\left(\text{GFR * F}_{ub}\right) + \left(Q_1 * F_{ub} * \frac{Cl_{int}}{Q_1 + F_{ub} * Cl_{int}}\right)}$$

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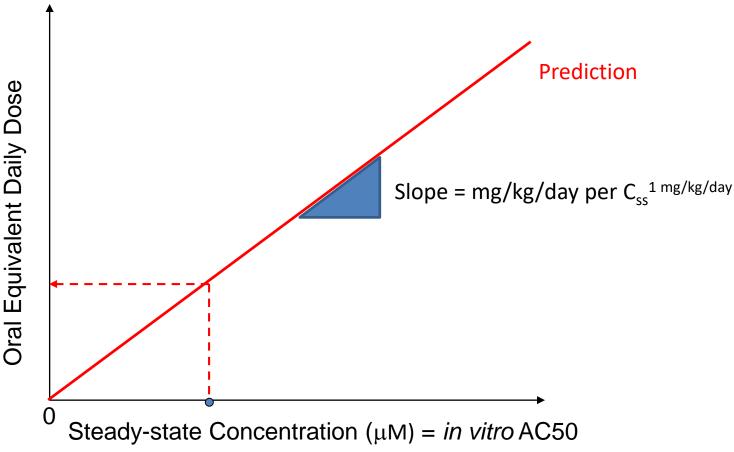
Wetmore *et al.* (2012)

Daily Dose (mg/kg/day)

Can calculate predicted steady-state concentration (C_{ss}) for a 1 mg/kg/day dose and multiply to get concentrations for other doses



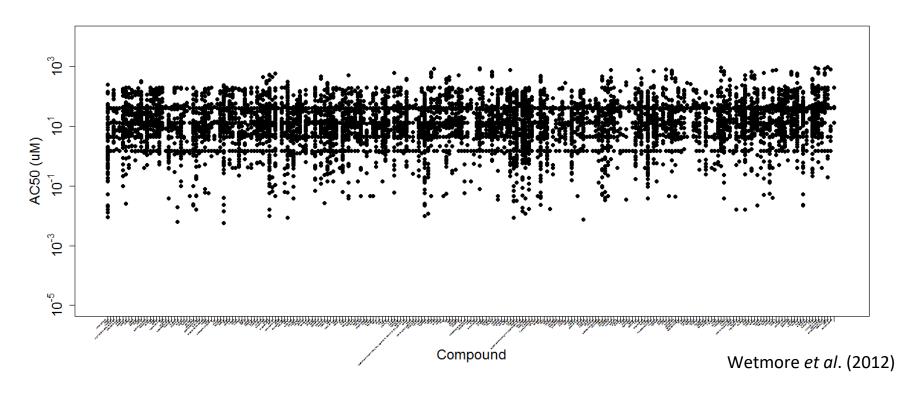
HTTK Allows Steady-State *In Vitro- In Vivo* Extrapolation (IVIVE)



- Swap the axes (this is the "reverse" part of reverse dosimetry)
- Can divide bioactive concentration by C_{ss} for for a 1 mg/kg/day dose to get oral equivalent dose



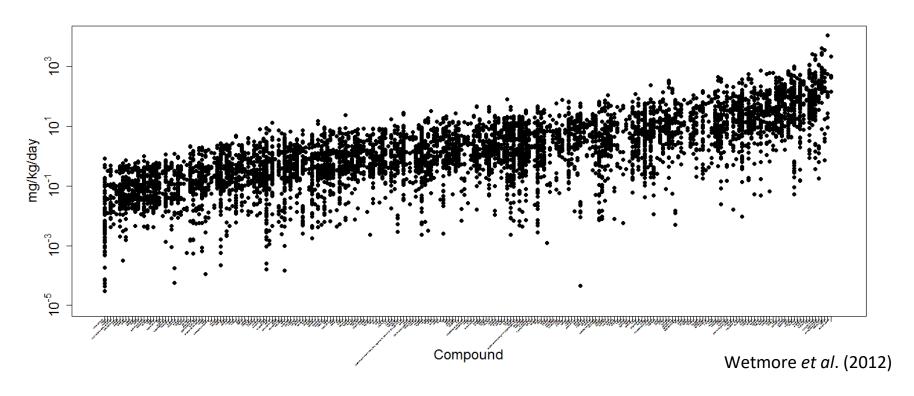
ToxCast *in vitro* Bioactive Concentrations



 It appears harder to prioritize on bioactive in vitro concentration without in vivo context



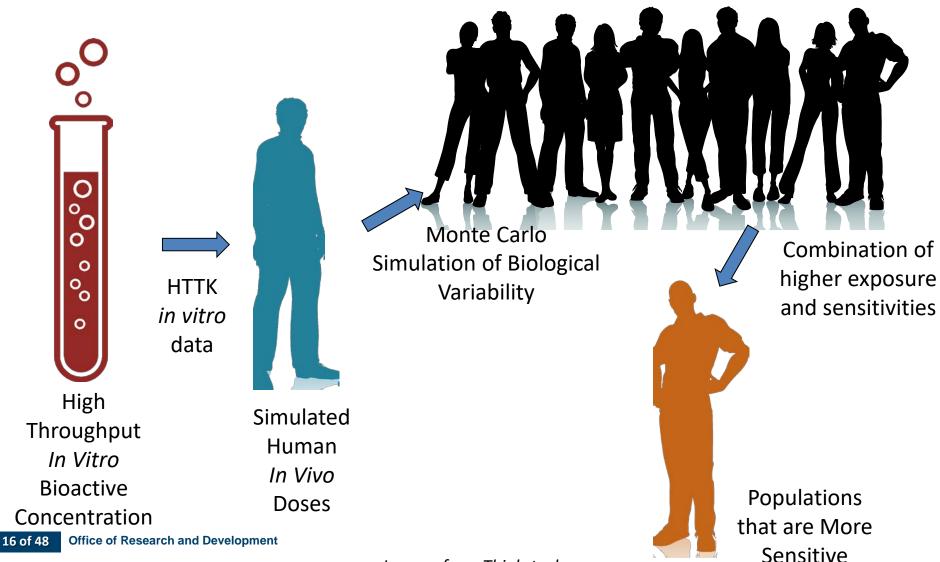
HTTK Oral Equivalents



 Translation from in vitro to steady-state oral equivalent doses allow greater discrimination between effective chemical potencies



Reverse Dosimetry with HTTK



Images from Thinkstock



Variability in this Steady-State TK Model

Jamei et al. (2009)

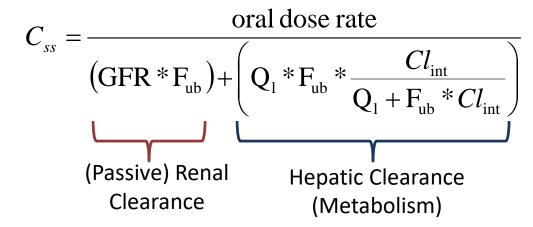
Minimal Model: Lumped Single Distribution Volume

Small Intestine

Gut Metabolism

Renal Clearance

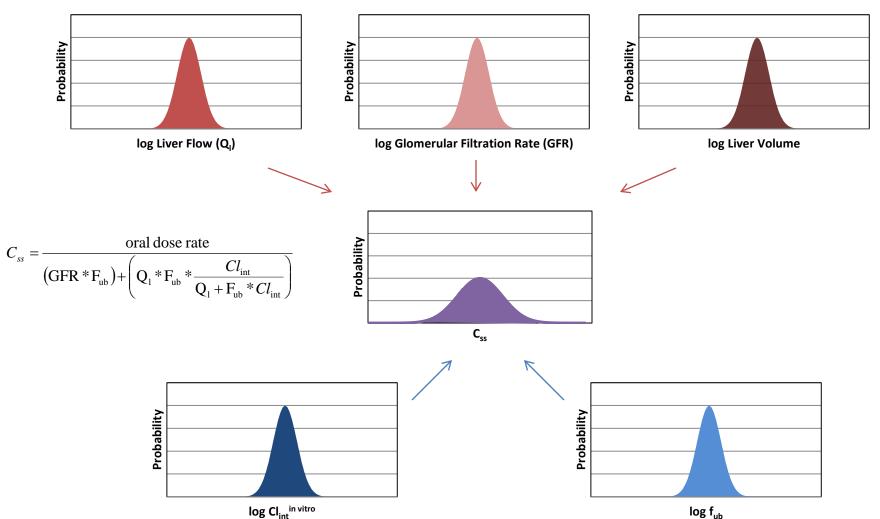
Renal Clearance



- In vitro clearance (μL/min/10⁶ hepatocytes) is scaled to a whole organ clearance using the density of hepatocytes per gram of liver and the volume of the liver (which varies between individuals)
- Glomerular filtration rate (GFR) and blood flow to the liver (Q_I) both vary from individual to individual
- Further assume that measured HTTK parameters have 30% coefficient of variation

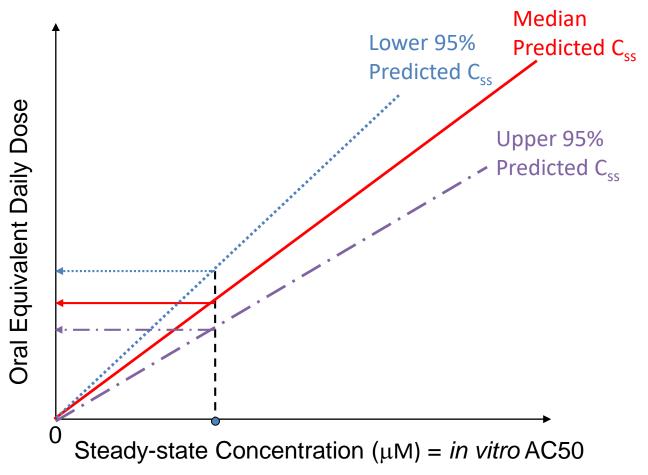


Monte Carlo (MC) Approach to Variability: SimCYP (Pharma) Approach





Steady-State In Vitro-In Vivo Extrapolation (IVIVE)



The higher the predicted C_{ss} , the lower the oral equivalent dose, so the upper 95% predicted C_{ss} from the MC has a lower oral equivalent dose



Application to High Throughput Risk Prioritization

Prioritization as in Wetmore *et al.* (2012) Bioactivity, Dosimetry, and Exposure Paper

> ToxCast-derived **Receptor Bioactivity** Converted to mg/kg/day with HTTK

ExpoCast Exposure **Predictions**

Near Field Far Field

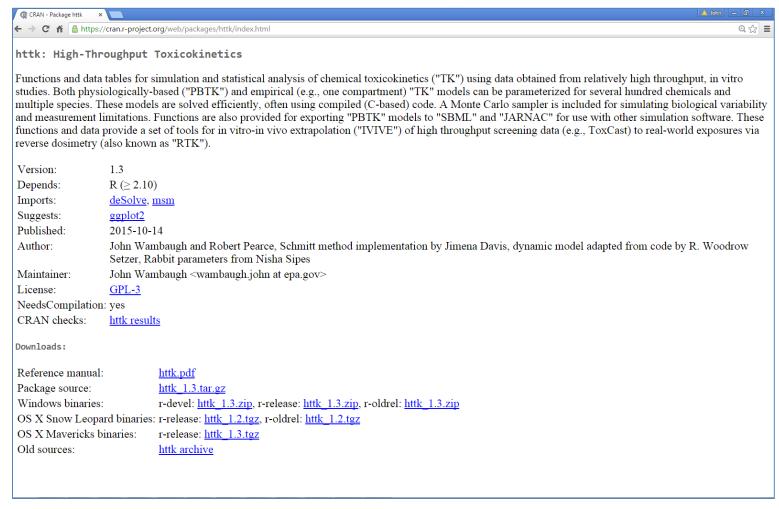
ToxCast Chemicals

December, 2014 Panel:

"Scientific Issues Associated with Integrated Endocrine Bioactivity and Exposure-Based Prioritization and Screening"



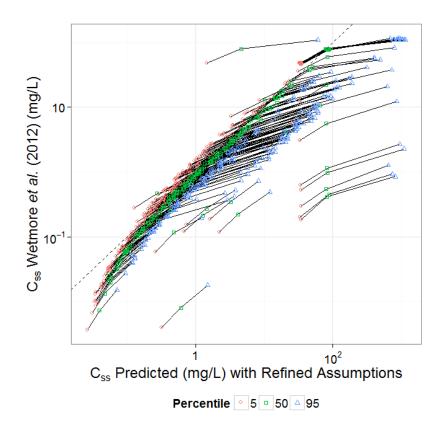
Steady State Concentrations with httk R Package





Comparison Between httk and

SimCYP

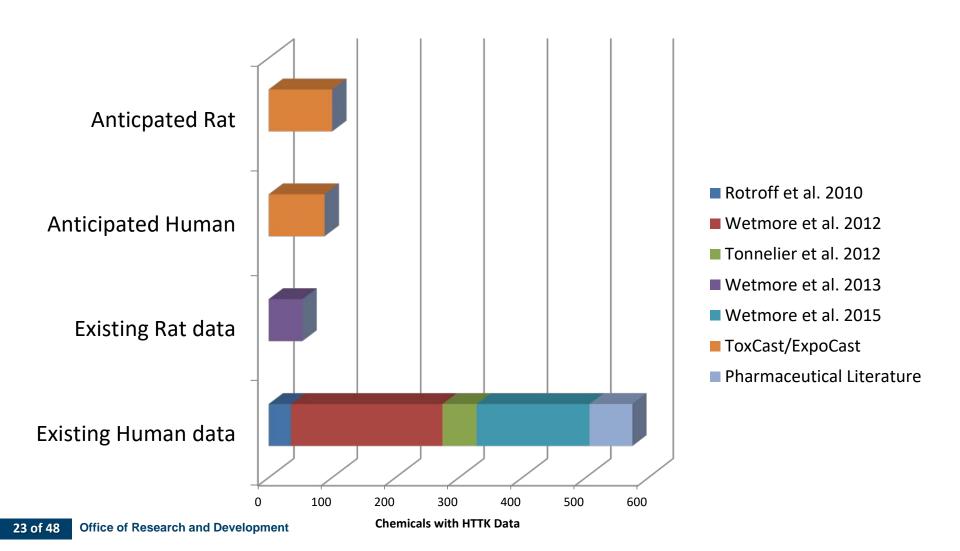


- In the Rotroff et al. (2010) and Wetmore et al. (2010) papers SimCYP was used to predict distributions of C_{ss} from *in vitro* data
 - We show that our new we can reproduce the results from those publications for most chemicals using our implementation of Monte Carlo.
- Any one chemical's median and quantiles are connected by a dotted line.
- Hepatic clearance assays with p-values < 0.05 are considered "good".

The RED assay for measuring protein binding fails in some cases because the amount of free chemical is below the limit of detection. For those chemicals a default value of 0.5% free was used. We have replaced the default value with random draws from a uniform distribution from 0 to 1%.

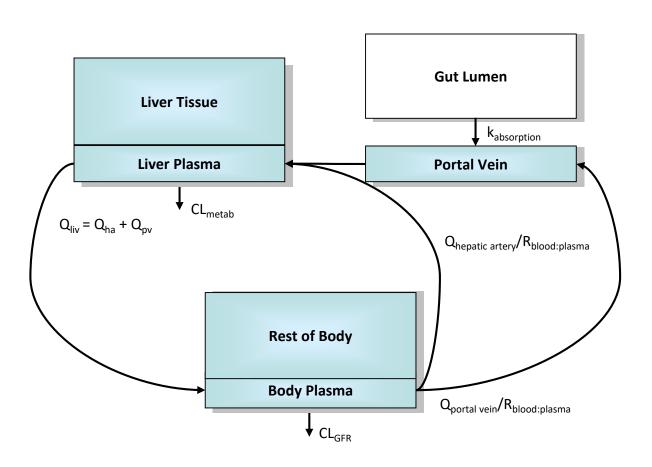


Chemicals with HTTK Data





Three Compartment (SimCYP) Model



nmental Protection **Inhaled Gas Lung Tissue** Q_{cardiac} **Lung Blood Kidney Tissue** Q_{GFR} $\boldsymbol{Q}_{\text{kidney}}$ **Kidney Blood Gut Lumen Arterial Blood** Venous Blood **Gut Blood Liver Tissue** $\mathbf{Q}_{\text{metab}}$ **Liver Blood Rest of Body** \mathbf{Q}_{rest} **Body Blood**

A General Physiologically-based Pharmacokinetic (PBPK) Model

Some tissues (e.g. arterial blood) are simple compartments, while others (e.g. kidney) are compound compartments consisting of separate blood and tissue sections with constant partitioning (i.e., tissue specific partition coefficients)

Exposures are absorbed from reservoirs (gut lumen)

Some specific tissues (lung, kidney, gut, and liver) are modeled explicitly, others (e.g. fat, brain, bones) are lumped into the "Rest of Body" compartment.

Blood flows move the chemical throughout the body. The total blood flow to all tissues equals the cardiac output.

The only ways chemicals "leaves" the body are through metabolism (change into a metabolite) in the liver or excretion by glomerular filtration into the proximal tubules of the kidney (which filter into the lumen of the kidney).

Physiological Data



	A ~ ~ ~ ~									
	Volume (L/kg)				Blood Flow (ml/min/kg)					
Tissue	Mouse	Rat	Dog	Human	Rabbit	Mouse	Rat	Dog	Human	Rabbit
Adipose	0.07	0.07	0.05	0.21	0.05	10.80	1.60	3.50	3.71	12.80
Bone	0.05	0.04	0.04	0.07	0.04	23.31	36.11	1.30	3.36	36.11
Brain	0.02	0.01	0.01	0.02	0.01	13.20	5.20	4.50	10.00	5.20
Gut	0.04	0.03	0.04	0.02	0.05	72.50	39.20	23.00	16.43	44.40
Heart	0.00	0.00	0.01	0.00	0.00	14.00	15.60	5.40	3.43	6.40
Kidneys	0.02	0.01	0.01	0.00	0.01	65.00	36.80	21.60	17.71	32.00
Liver	0.05	0.03	0.03	0.02	0.04	90.00	47.20	30.90	20.71	70.80
Lung	0.01	0.00	0.01	0.01	0.01	2.00	6.22	10.56	2.00	6.22
Muscle	0.37	0.39	0.44	0.38	0.54	45.50	30.00	25.00	10.71	62.00
Skin	0.15	0.17	0.17	0.03	0.04	20.50	23.20	10.00	4.29	23.20
Spleen	0.00	0.00	0.00	0.00	0.00	5.50	4.07	1.65	1.10	3.60
Rest	0.03	0.05	0.00	0.05	0.03	110.19	90.00	5.59	2.97	90.00

Volumes and flows from Schmitt (2008) + Nisha Sipes (Rabbit)

Other parameters from Davies and Morris (1993) + Nisha Sipes (Rabbit)

	Units	Mouse	Rat	Dog	Human	Rabbit
Total Body Water	ml/kg	725.00	668.00	603.60	600.00	716
Plasma Volume	ml/kg	50.00	31.20	51.50	42.86	44
Cardiac Output	ml/min/kg	400.00	296.00	120.00	80.00	212
Average BW	kg	0.02	0.25	10.00	70.00	2.5
Total Plasma Protein	g/ml	0.06	0.07	0.09	0.07	0.057
Plasma albumin	g/ml	0.03	0.03	0.03	0.04	0.0387
Plasma a-1-AGP	g/ml	0.01	0.02	0.00	0.00	0.0013
Hematocrit	fraction	0.45	0.46	0.42	0.44	0.36
Urine	ml/min/kg	0.035	0.139	0.021	0.014	0.0417
Bile	ml/min/kg	0.069	0.063	0.008	0.003	0.0833
GFR	ml/min/kg	14.0	5.2	6.1	1.8	3.12



Schmitt (2008) Tissue Composition Data

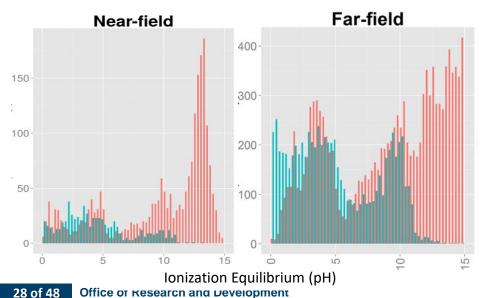
	Fraction of total volumea		Fraction of cell volume ^b			Fraction of total lipid			
Tissue	Cells	Interstitium	Water	Lipid	Protein	Neutral Lipid ^c	Neutral Phospholipid ^c	Acidic Phospholipid ^c	рН ^d
Adipose	0.86	0.14	0.03	0.92	0.06	1	0.0022	0.0006	7.10
Bone	0.9	0.1	0.26	0.02	0.21	0.85	0.11	0.04	7.00
Brain	1	0.004	0.79	0.11	0.08	0.39	0.48	0.13	7.10
Gut	0.9	0.096	0.78	0.07	0.15	0.69	0.26	0.05	7.00
Heart	0.86	0.14	0.7	0.11	0.19	0.48	0.43	0.09	7.10
Kidneys	0.78	0.22	0.73	0.06	0.21	0.26	0.61	0.13	7.22
Liver	0.82	0.18	0.68	0.08	0.21	0.29	0.59	0.11	7.23
Lung	0.5	0.5	0.74	0.04	0.11	0.51	0.38	0.11	6.60
Muscle	0.88	0.12	0.76	0.01	0.19	0.49	0.42	0.09	6.81
Skin	0.69	0.31	0.47	0.14	0.41	0.9	0.08	0.02	7.00
Spleen	0.79	0.21	0.75	0.02	0.23	0.3	0.54	0.15	7.00
Red blood cells	1	_	0.63	0.01	0.33	0.3	0.59	0.1	7.20

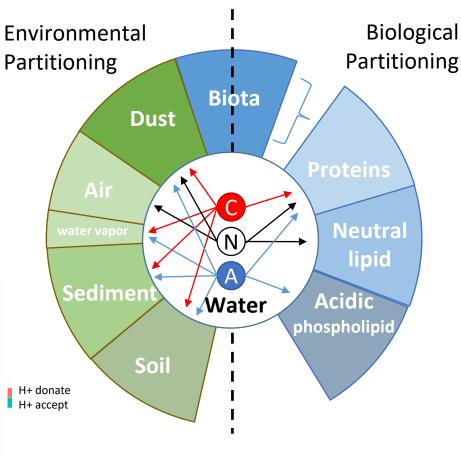
- **a** Values taken from (Kawai et al., 1994). Original values given as fraction of total organ volume were rescaled to tissue volume by subtracting vascular volume
- **b** Values taken from (ICRP, 1975). Original values given as fraction of total tissue mass were rescaled to cellular volume as follows: Water fraction of total tissue reduced by interstitial volume and subsequently all values normalized by cellular fraction.
- c Data taken from (Rodgers et al., 2005a).
- **d** Values taken from ([Waddell and Bates, 1969], [Malan et al., 1985], [Wood and Schaefer, 1978], [Schanker and Less, 1977], [Harrison and Walker, 1979] and [Civelek et al., 1996]). Mean values were calculated when more than one value was found for the same tissue.
- e Data taken from (Gomez et al., 2002).



Prediction of Ionization

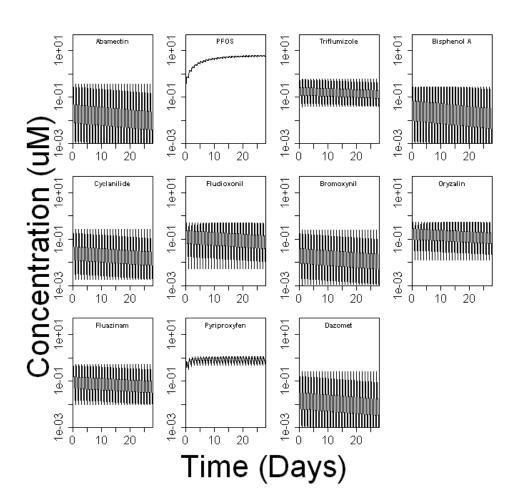
- Neutral and ionized species of the same molecule will partition differently into environmental and biological media
- Better models are needed for predicting pKa at different pH for chemicals







Predicted PK Metrics

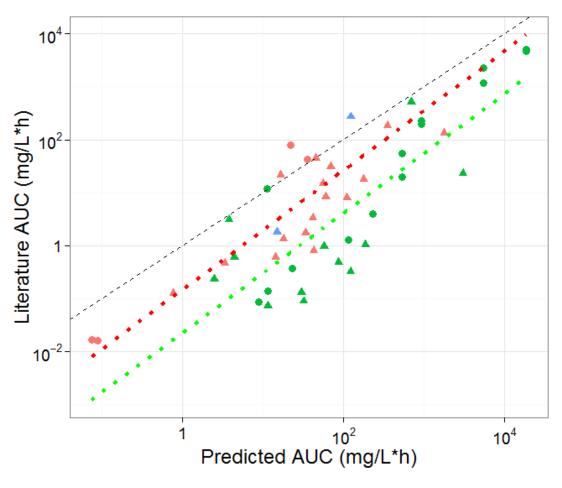


Example at left: Human hepatic concentration of various chemicals as a function of 28 daily doses (10 mg/kg/day)

Can predict mean and peak concentration and time integrated area under the curve (AUC) for various tissues



Evaluating HTPBPK Predictions from In Vitro Data



- HTPBPK predictions for the AUC (time integrated plasma concentration or Area Under the Curve)
- in vivo measurements from the literature for various treatments (dose and route) of rat.
- Predictions are generally conservative – i.e., predicted AUC higher than measured
- Oral dose AUC ~6.4x higher than intravenous dose AUC

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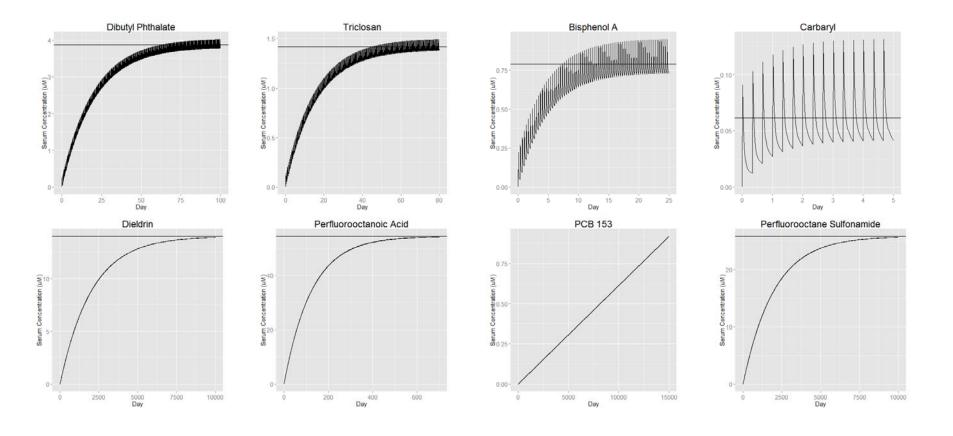
calc_stats Examples

library(httk)

```
#A Function to get PK summary statistics from the PBPK model: help(calc_stats)
# 28 day human study (20 mg/kg/day) for Abamectin: calc_stats(days=28,chem.name="bisphenol a", dose=20)
# Units default to μM but can use mg/L: calc_stats(days=28,chem.name="bisphenol a", dose=20,output.units="mg/L")
# Same study in a mouse: calc_stats(days=28,chem.name="bisphenol a", dose=20,species="mouse")
```

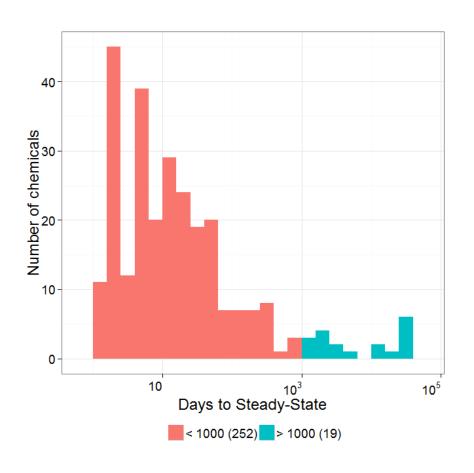


PBPK Simulated Approach to Steady-State





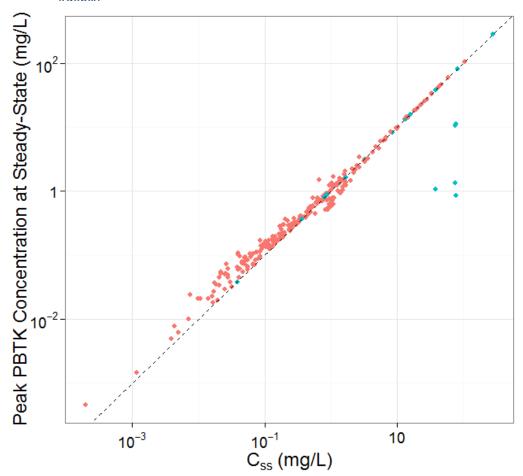
Evaluation of Steady-State Predictions



- Using HTPBTK model and assuming three daily doses (every eight hours)
- This allows us to evaluate the plausibility of the steady-state dosing assumption.
- We find that the majority of chemicals reach steady state in a few weeks
- A second population of chemicals never reach steady state.



Peak Concentration vs. C_{ss}



Peak serum concentrations from the HTPBPK model are compared against the steadystate concentration predicted by the three compartment model for a constant infusion exposure (as in Wetmore et al. 2012)

The dashed, identity (1:1) line indicates that for most compounds the peak concentrations are very similar to C_{ss} .



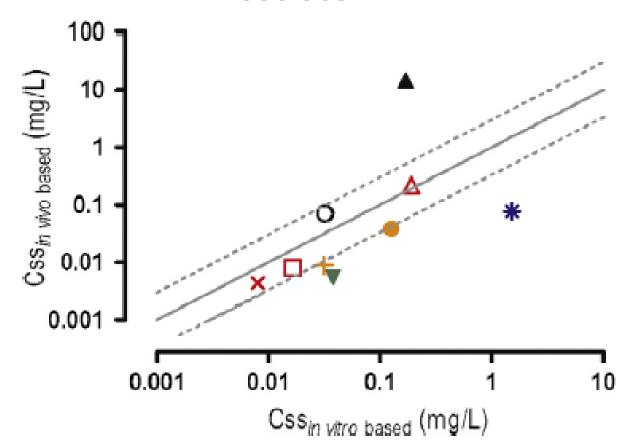
In vivo Predictive Ability and Domain of Applicability

- In drug development, HTTK methods estimate therapeutic doses for clinical studies – predicted concentrations are typically on the order of values measured in clinical trials (Wang, 2010)
- For environmental compounds, there will be no clinical trials
- Uncertainty must be well characterized ideally with rigorous statistical methodology
 - We will use direct comparison to in vivo data in order to get an empirical estimate of our uncertainty
 - Any approximations, omissions, or mistakes should work to increase the estimated uncertainty when evaluated systematically across chemicals



Characterizing Uncertainty in HTTK

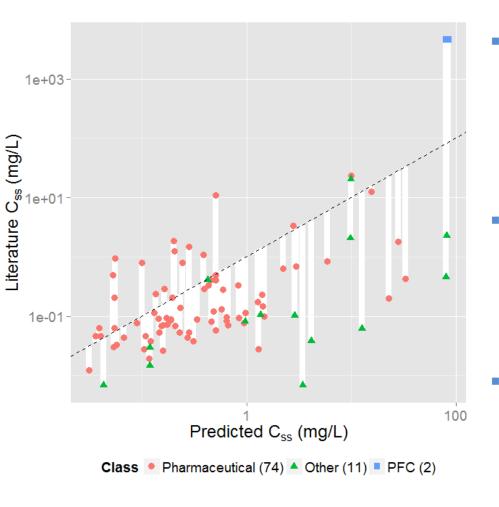
Yoon et al. (2014): Manual curation of chemical specific PK models allowed direct evaluation of HTTK IVIVE predictions



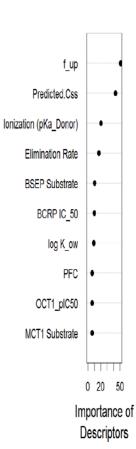
Wang (2010): In vitro predictions typically within a factor of three for pharmaceuticals



Using in vivo Data to Evaluate RTK



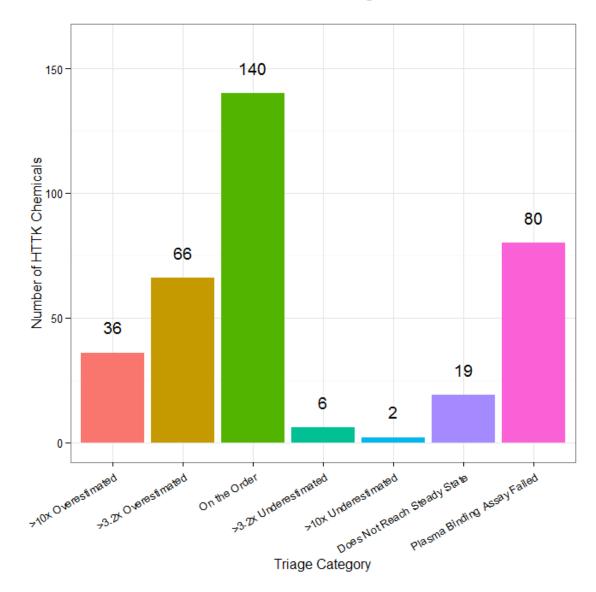
- When we compare the C_{ss} predicted from in vitro HTTK with in vivo C_{ss} values determined from the literature we find limited correlation ($R^2 \sim 0.34$)
- The dashed line indicates the identity (perfect predictor) line:
 - Over-predict for 65
 - Under-predict for 22
 - The white lines indicate the discrepancy between measured and predicted values (the residual)





- Through comparison to in vivo data, a crossvalidated (random forest) predictor of success or failure of HTTK has been constructed
- Add categories for chemicals that do not reach steady-state or for which plasma binding assay fails
- All chemicals can be placed into one of seven confidence categories

Toxicokinetic Triage





Calibrated Exposure Predictions for 7968 Chemicals

R² ≈ 0.5 indicates that we can predict 50% of the chemical to chemical variability in **geometric mean NHANES exposure rates** (this does not cover highly exposed individuals)

Same five predictors work for all NHANES demographic groups analyzed – stratified by age, sex, and body-mass index:

- Industrial and Consumer use
- Pesticide Inert
- Pesticide Active
- Industrial but no Consumer use
- Production Volume



Application to High Throughput Risk Prioritization

Prioritization as in Wetmore *et al.* (2012) Bioactivity, Dosimetry, and Exposure Paper

> ToxCast-derived **Receptor Bioactivity** Converted to mg/kg/day with HTTK

ExpoCast Exposure **Predictions**

Near Field Far Field

ToxCast Chemicals

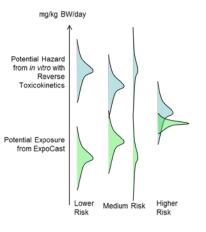
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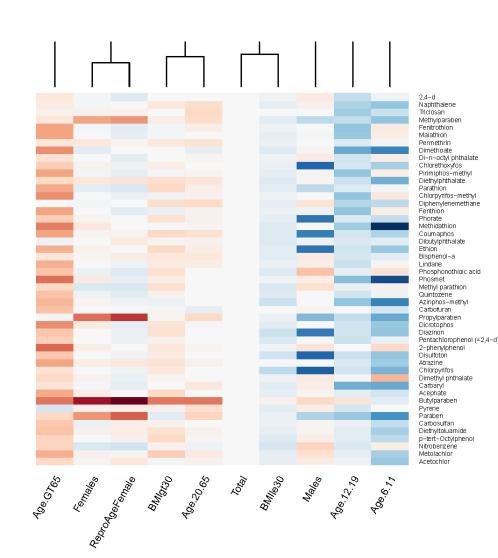


Life-stage and Demographic Specific Predictions

- Wambaugh *et al.* (2014) predictions of exposure rate for various demographic groups
- New version of httk R package (Ring et al., in preparation) allows prediction of parameters based on actual NHANES biometrics

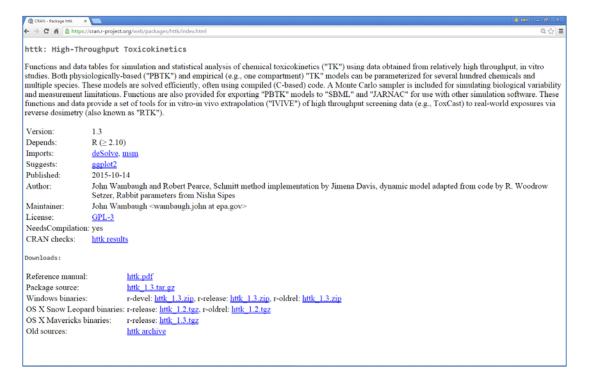


Change in Risk





httk R Package



Ongoing refinements:
High log P, better
treatment of ionization
(eventual Pearce et al.
manuscript)

"httk" R Package
543 Chemicals to date
Lead programmer Robert Pearce
Wambaugh et al. (2015), Pearce et al. submitted



Version history for the "httk" R Package

The publicly available R package contains code and data that has been part of peer-reviewed publications

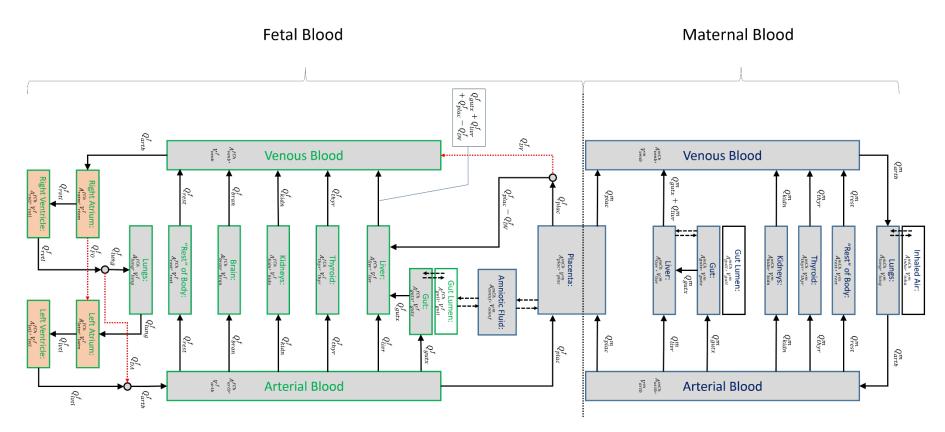
- Version 1.1 accompanied "Toxicokinetic Triage for Environmental Chemicals" Wambaugh et al. (2015) Tox. Sci.
- Version 1.2 accompanied "httk: R Package for High-Throughput Toxicokinetics" Pearce et al., submitted to Journal of Statistical Software
- Version 1.3 accompanied "Incorporating High-Throughput Exposure Predictions with Dosimetry-Adjusted *In Vitro* Bioactivity to Inform Chemical Toxicity Testing" Wetmore et al., (2015) Tox. Sci.
- Version 1.4 is in development to accompany Ring et al., in preparation

We maintain internal versions containing data and code that has yet to be peer reviewed.

Lead programmer Robert Pearce



Gestational Version of PBTK model Under Development

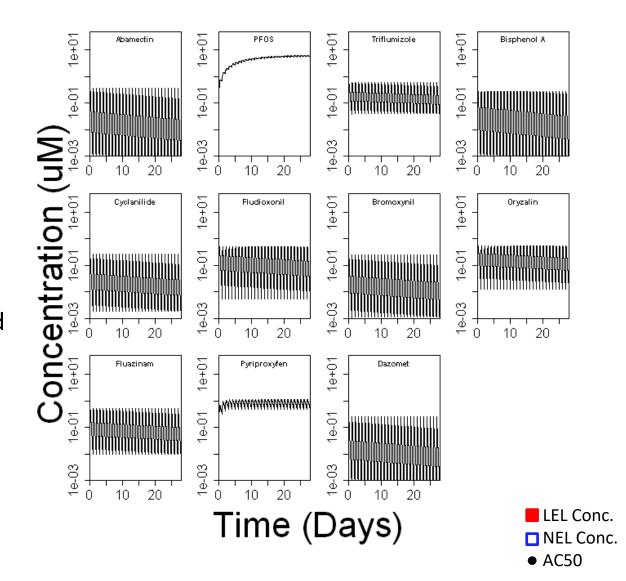


Dustin Kapraun, Eric Watt, and Robert Pearce of NCCT are developing a model for the httk package that allows fetal tissue concentration predictions for 443 chemicals



HTPBTK Predicted Metrics

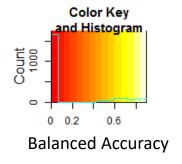
- With HTPBTK we can predict the concentration time course for various tissues
- For now, we identify mean serum concentration for no effect level (NEL) and low effect level (LEL) treatments
- Look for coincident gene expression changes

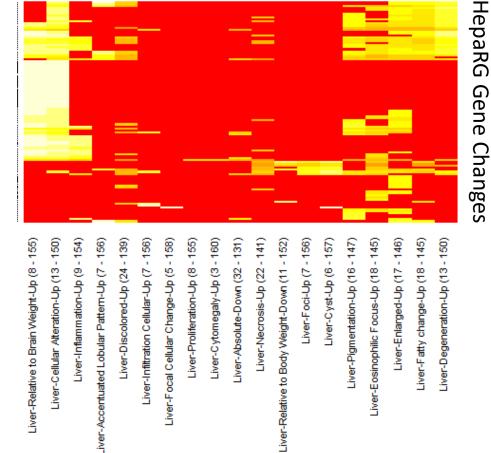


United States Environmental Protection Agency

 We get higher balanced accuracies than ToxCast Phase I using the results of the HepaRG assay and nonsteady-state PK (from the "httk" R package

Correlating HepaRG with Toxicity



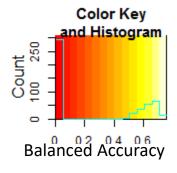


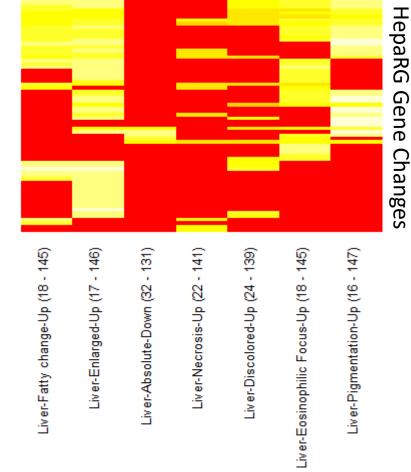
ToxRef Liver Phenotypes (# Pos - # Neg Chems)

United States Environmental Protection Agency

- We get higher balanced accuracies than ToxCast Phase I using the results of the HepaRG assay and nonsteady-state PK (from the "httk" R package
- Here we subset for just those effects with more than 15 positive chemicals
- Highest balanced accuracy is 0.76

Correlating HepaRG with Toxicity







Summary

- Toxicokinetics (TK) provides a bridge between HTS and HTE by predicting tissue concentrations due to exposure
- HTTK methods developed for pharmaceuticals have been adapted to environmental testing
- A primary application of HTTK is "Reverse Dosimetry" or RTK
 - Can infer daily doses that produce plasma concentrations equivalent to the bioactive concentrations, but:
- We must consider domain of applicability
 - Collected new PK data from in vivo studies (EPA/NHEERL and Research Triangle Institute)
 - Organizing data from larger, systematic studies (e.g., National Toxicology Program) into computable format
- New R package "httk" freely available on CRAN allows statistical analyses
 - Analysis has been submitted



Chemical Safety for Sustainability (CSS) Rapid Exposure and Dosimetry (RED) Project

NCCT

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The views expressed in this presentation are those of the author and do not necessarily reflect the views or policies of the U.S. EPA