



Utility of New Approach Methodologies in Deriving Points-of-Departure

Katie Paul Friedman

November 17, 2020

Presented to the OECD Working Party on Hazard Assessment

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



Critical questions for NAMs in safety assessment

- Background
- Part 1: A retrospective case study with the Accelerating the Pace of Chemical Risk Assessment (APCRA)
 - Can NAMs for hazard and toxicokinetics be used to derive a point-of-departure (POD) that is protective of traditional PODs?
 - Can NAMs for hazard, toxicokinetics, and exposure be used to prioritize substances for further consideration?
- Part 2: Work-in-progress for a prospective case study with APCRA using NAMs as they develop in real-time
 - How can NAMs for hazard from Tier 1 (broad-based NAMs) and Tier 2 (targeted high-throughput screening) be combined with toxicokinetics and exposure for prioritization of substances?
- Part 3: Application of hazard-specific NAMs to specific questions about the potential developmental neurotoxicity
 - Can NAMs that recapitulate important aspects of developmental neurobiology be applied for specific hazard and risk questions?



Fit-for-purpose considerations for NAMs in derivation of PODs

- Is the task one that is risk-informed?
 - *Use of a threshold for any bioactivity may be useful.*
 - *Mimics identification of animal-based POD, i.e., a threshold dose at which no effects are anticipated in the animal models employed.*
- Is the task one where specific hazards need to be considered?
 - *Identification of NAMs that are fit-for-purpose regarding the specific hazard may be needed. (how much uncertainty can be tolerated?)*
 - *Consideration of how to identify “selective” bioactivity from specific NAMs, i.e. a “lead” bioactivity that precedes other bioactivity types.*

Considerations by case study

Retrospective
case study

Work in progress: prospective case study

Developmental
neurotoxicity of OPs



Derivation of PODs from NAMs: IVIVE that employs toxicokinetic extrapolation of dose

High-throughput toxicokinetic (HTTK) approaches make it possible to predict doses corresponding to *in vitro* bioactivity for thousands of chemicals.

A subset of the papers describing the development of a high-throughput toxicokinetic approach

2012

Integration of Dosimetry, Exposure, and High-Throughput Screening Data in Chemical Toxicity Assessment

Barbara A. Wetmore,* John F. Wambaugh,† Stephen S. Ferguson,‡ Mark A. S. Kimberly Freeman,§ Harvey J. Clewell, III,* David J. Dix,† Melvin E. Andersen, Richard S. Judson,† Reetu Singh,* Robert J. Kavlock,† Ann M. Richard.

*The Hamner Institutes for Health Sciences, Research Triangle Park, North Carolina 27709-2137; †United States Environmental Protection Agency, Research Triangle Park, North Carolina 27711; ‡National Center for Computational Toxicology, Research Triangle Park, North Carolina 27703; and §Department of Environmental Sciences and Engineering, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina 27599-7550

2017



An Intuitive Approach for Predicting Risk with the Tox21 10k Library

Nisha S. Sipes,*† John F. Wambaugh,‡ Robert Pearce,‡ Jui-Hua Hsieh,§ Andrew J. Shapiro,† Daniel Svoboda,§ Mi

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||National Exposure Research Laboratory, U.S. Environmental Protection Agency, 109 T.W. Alexander Drive, Research Triangle Park, North Carolina 27711, United States



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2014

Incorporating Population Variability and Susceptible Subpopulations into Dosimetry for High-Throughput

FIFRA Scientific Advisory Panel Minutes No. 2014-03

2014

A Set of Scientific Issues Being Considered by the Environmental Protection Agency Regarding New High Throughput Methods to Estimate Chemical Exposure

July 29-30, 2014
FIFRA Scientific Advisory Panel Meeting
Held at the
EPA Conference Center
Arlington, VA

TOXICOLOGICAL SCIENCES, 142(1), 2014, 210-224

doi: 10.1093/toxsci/kfr169
Advance Access Publication Date: August 21, 2014



SOT Society of Toxicology
www.toxsci.oxfordjournals.org

2015

Toxicokinetic Triage for Environmental Chemicals

John F. Wambaugh*,†, Barbara A. Wetmore†, Robert Pearce*, Cory Strope*,†, Rocky Goldsmith§, James P. Sluka||, Alexander Sedych||, Alex Tropsha||, Sieto Bosgra||, Imran Shah*, Richard Judson*, Russell S. Thomas*, R. Woodrow Setzer*

*National Center for Computational Toxicology and †National Research and Development, US EPA, Research Triangle Park, North Carolina 27709-2137; ‡United States Environmental Protection Agency, Research Triangle Park, North Carolina 27711; §Indiana University, Bloomington, Indiana 47405-7105; ||Depar Chemistry, University of North Carolina, Chapel Hill, North C Organisation for Applied Scientific Research (TNO), 3700 AJ Z

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2017

Evaluation and calibration of high-throughput predictions of chemical distribution to tissues

Robert G. Pearce^{1,2} · R. Woodrow Setzer¹ · Jimena L. Davis^{1,3} · John F. Wambaugh¹

TOXICOLOGICAL SCIENCES, 147(1), 2015, 55-67

doi: 10.1093/toxsci/kfv118
Advance Access Publication Date: June 16, 2015
Research Article

2019

Assessing Toxicokinetic Uncertainty and Variability in Risk Prioritization

John F. Wambaugh*,†, Barbara A. Wetmore,† Caroline L. Ring*,†, Chantel I. Nicolas*,†, Robert G. Pearce,† Gregory S. Honda,† Roger Dinallo,† Derek Angus,† Jon Gilbert,† Teresa Sierra,† Akshay Badrinarayanan,† Bradley Snodgrass,† Adam Brockman,† Chris Strock,† R. Woodrow Setzer,† and Russell S. Thomas*

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†Present address: ToxStrategies, Austin, TX 78759.

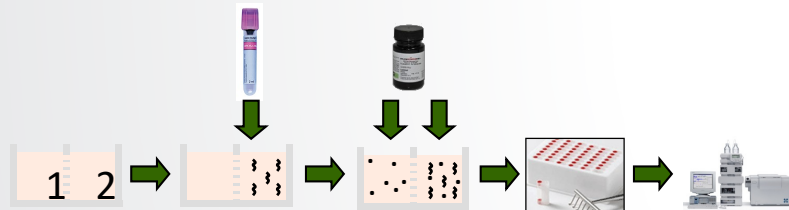
Disclaimer: The views expressed in this publication are those of the authors and do not necessarily represent the views or policies of the U.S. EPA. Reference to commercial products or services does not constitute endorsement.

Reverse dosimetry can be leveraged in IVIVE to estimate the exposure that would produce the plasma concentration corresponding to bioactivity

High throughput toxicokinetics (HTTK)

in vitro data

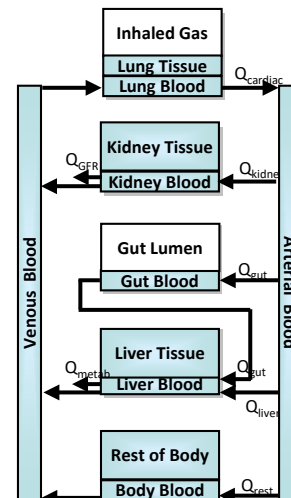
Hepatic clearance from suspended hepatocytes



Plasma protein binding



Generic toxicokinetic models



= *httk*

Some high-level assumptions:

- (1) bioactive nominal *in vitro* assay concentration \sim *in vivo* plasma concentration that would correspond to a similar effect;
- (2) external exposures (in mg/kg/day units) that may have resulted in that plasma concentration can be constructed using estimates of species-specific physiology and Phase I and Phase II enzyme-driven hepatic clearance; and,
- (3) Often, we expect that plasma concentration can be approximated by steady-state kinetics (unless we have enough information to use other dose metrics).



Many works apply HTTK to prioritization and assessment case studies

Chemical
Research in
Toxicology

2011

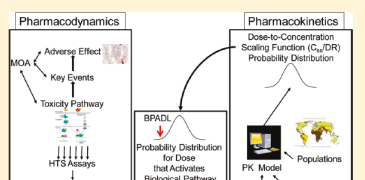
Estimating Toxicity-Related Biological Pathway Altering Doses for High-Throughput Chemical Risk Assessment

Richard S. Judson,^{a,*} Robert J. Kavlock,[†] R. Woodrow Setzer,[†] Elaine A. Cohen Hubal,[†] Matthew T. Martin,[†] Thomas B. Knudsen,[†] Keith A. Houck,[†] Russell S. Thomas,[‡] Barbara A. Wetmore,[§] and David J. Dix[¶]

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[†]The Hamner Institutes for Health Sciences, Research Triangle Park, North Carolina 27709, United States

ABSTRACT: We describe a framework for estimating the human dose at which a chemical significantly alters a biological pathway *in vivo*, making use of *in vitro* assay data and an *in vitro*-derived pharmacokinetic model, coupled with estimates of population variability and uncertainty. The quantity we calculate, the biological pathway altering dose (BPAD), is analogous to current risk assessment metrics in that it combines dose-response data with analysis of uncertainty and population variability to arrive at conservative exposure limits. The analogy is closest when perturbation of a pathway is a key event in the mode of action (MOA) leading to a specified adverse outcome.



Contents lists available at ScienceDirect



2019

Food and Chemical Toxicology

journal homepage: www.elsevier.com/locate/foodchemtox

Profiling 58 compounds including cosmetic-relevant chemicals using ToxRefDB and ToxCast

Ly L. Pham^{a,b}, Lisa Truong^{a,b,c}, Gladys Ouedraogo^d, Sophie Loisel-Joubert^e, Matthew T. Martin^{a,f}, Katie Paul Friedman^{a,*}

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^eL'Oréal Safety

^fCurrently at G

Environment International 137 (2020) 105470

Contents lists available at ScienceDirect

2020

Environment International

journal homepage: www.elsevier.com/locate/envint



High-throughput screening tools facilitate calculation of a combined exposure-bioactivity index for chemicals with endocrine activity

Susanna H. Wegner^{a,b,*}, Caroline L. Pinto^{a,b}, Caroline L. Ring^{a,c}, John F. Wambaugh^c

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TOXICOLOGICAL SCIENCES, 148(1), 2015, 121–136

doi: 10.1093/toxsci/adv171
Advance Access Publication Date: August 6, 2015
Research Article

2015

Incorporating High-Throughput Exposure Predictions With Dosimetry-Adjusted *In Vitro* Bioactivity to Inform Chemical Toxicity Testing

Barbara A. Wetmore,^{a,*} John F. Wambaugh,[†] Brittany Allen,^{*} Stephen S. Ferguson,^{†,‡} Mark A. Sochaski,^{*} R. Woodrow Setzer,[†] Keith A. Houck,[†] Cory L. Strobe,^{*} Katherine Cantwell,^{*} Richard S. Judson,[†] Edward LeCluyse,^{*} Harvey J. Clewell,^{*} Russell S. Thomas,^{a,†,‡} and Melvin E. Andersen^{*}

^aThe Hamner Institutes for Health Sciences, Institute for Chemical Safety Sciences, Research Triangle Park, North Carolina 27709-2137; [†]United States Environmental Protection Agency, Office of Research and Development, National Center for Computational Toxicology, Research Triangle Park, North Carolina 27711; and [‡]Life Technologies, ADME/Tox Division of the Primary and Stem Cell Systems Business Unit, Durham, North Carolina 27703



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2019

TOXICOLOGICAL SCIENCES, 2019, 1–24

doi: 10.1093/toxsci/kfz201
Advance Access Publication Date: September 18, 2019
Research Article

Utility of *In Vitro* Bioactivity as a Lower Bound Estimate of *In Vivo* Adverse Effect Levels and in Risk-Based Prioritization

Katie Paul Friedman^{a,*}, ^{a,1} Matthew Gagne,[†] Lit-Hsin Loo,[†] Panagiotis Karameris,[†] ^{a,2} Thomas S. Thomas,[†] ^{a,3} William A. Anderson,[†] ^{a,4} Ann M. Richa,[†] ^{a,5} PLOS ONE, ^{a,6} Angrish, Bahadori, Rasenber

2020

RESEARCH ARTICLE

Using the concordance of *in vitro* and *in vivo* data to evaluate extrapolation assumptions

Gregory S. Honda^{a,1,2}, Robert G. Pearce^{a,1,2}, Ly L. Pham^{a,1,2}, R. W. Setzer^{a,1}, Barbara A. Wetmore^a, Nisha S. Sipes^{a,†}, Jon Gilbert^a, Briana Franz^{a,‡}, Russell S. Thomas^a, John F. Wambaugh^{a,1}

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Toxicology in Vitro 47 (2018) 213–227

Contents lists available at ScienceDirect

2018

Toxicology in Vitro

journal homepage: www.elsevier.com/locate/toxinvit



Review

In vitro to *in vivo* extrapolation for high throughput prioritization and decision making

Shannon M. Bell^a, Xiaoping Chang^a, John F. Wambaugh^b, David G. Allen^a, Mike Bartels^{c,1}, Kim L.R. Brouwer^d, Warren M. Casey^e, Neepa Choksi^a, Stephen S. Ferguson^f, Grazyna Fraczekiewicz^g, Annie M. Jarabek^b, Alice Ke^b, Annie Lumenⁱ, Scott G. Lynn^j, Alicia Paini^k, Paul S. Price^b, Caroline Ring^{l,2}, Ted W. Simon^m, Nisha S. Sipes^f, Catherine S. Sprankle^a, Judy Strickland^a, John Troutman^a, Barbara A. Wetmore^{a,3}, Nicole C. Kleinstreuer^{a,*}

Toxicology and Applied Pharmacology 387 (2020) 114774

Contents lists available at ScienceDirect

2020

Toxicology and Applied Pharmacology

journal homepage: www.elsevier.com/locate/taap



The role of fit-for-purpose assays within tiered testing approaches: A case study evaluating prioritized estrogen-active compounds in an *in vitro* human uterotrophic assay

Tyler Beames^{a,*}, Marjory Moreau^{a,1}, L. Avery Roberts^b, Kamel Mansouri^b, Saad Haider^a, Marci Smeltz^c, Chantel I. Nicolas^b, Daniel Doheny^b, Martin B. Phillips^a, Miyoung Yoon^{b,2}, Richard A. Becker^c, Patrick D. McMullen^c, Melvin E. Andersen^c, Rebecca A. Clewell^{b,3}, Jessica K. Hartman^{a,4}

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A subset of the papers describing the application of a high-throughput toxicokinetic approach – too many to fit



Part 1: A retrospective case study with the Accelerating the Pace of Chemical Risk Assessment (APCRA)



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TOXICOLOGICAL SCIENCES, 2019, 1–24

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Research Article

Utility of *In Vitro* Bioactivity as a Lower Bound Estimate of *In Vivo* Adverse Effect Levels and in Risk-Based Prioritization

Katie Paul Friedman ,^{*,1} Matthew Gagne,[†] Lit-Hsin Loo,[‡] Panagiotis Karamertzanis,[§] Tatiana Netzeva,[§] Tomasz Sobanski,[§] Jill A. Franzosa,[¶] Ann M. Richard,^{*} Ryan R. Lougee,^{*,||} Andrea Gissi,[§] Jia-Ying Joey Lee,[‡] Michelle Angrish,^{|||} Jean Lou Dorne,^{|||} Stiven Foster,[#] Kathleen Raffaele,[#] Tina Bahadori,^{||} Maureen R. Gwinn,^{*} Jason Lambert,^{*} Maurice Whelan,^{**} Mike Rasenberg,[§] Tara Barton-Maclaren,[†] and Russell S. Thomas ^{*}



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National Institute for Public Health
and the Environment
Ministry of Health, Welfare and Sport



NTP
National Toxicology Program
U.S. Department of Health and Human Services

(APCRA partners for these two case studies)



Why is the retrospective case study important?

- Clear need to demonstrate in practical terms, for as many chemicals as possible, how preliminary screening level risk assessment using a new approach methodologies (NAM) based approach would perform when compared to traditional approaches to deriving points-of-departure (PODs).
- Illustrate the current state-of-the-science.
- Evaluate the specific strengths and weaknesses of rapid, screening level risk assessment using NAMs.
- Approach: Take a retrospective look at the traditional and NAM data for as many chemicals as possible (448 at the time).



See the forest for the trees

The big question:

Can *in vitro* bioactivity be used to derive a conservative point-of-departure (POD) for prioritization and screening level risk assessment?

Case study workflow

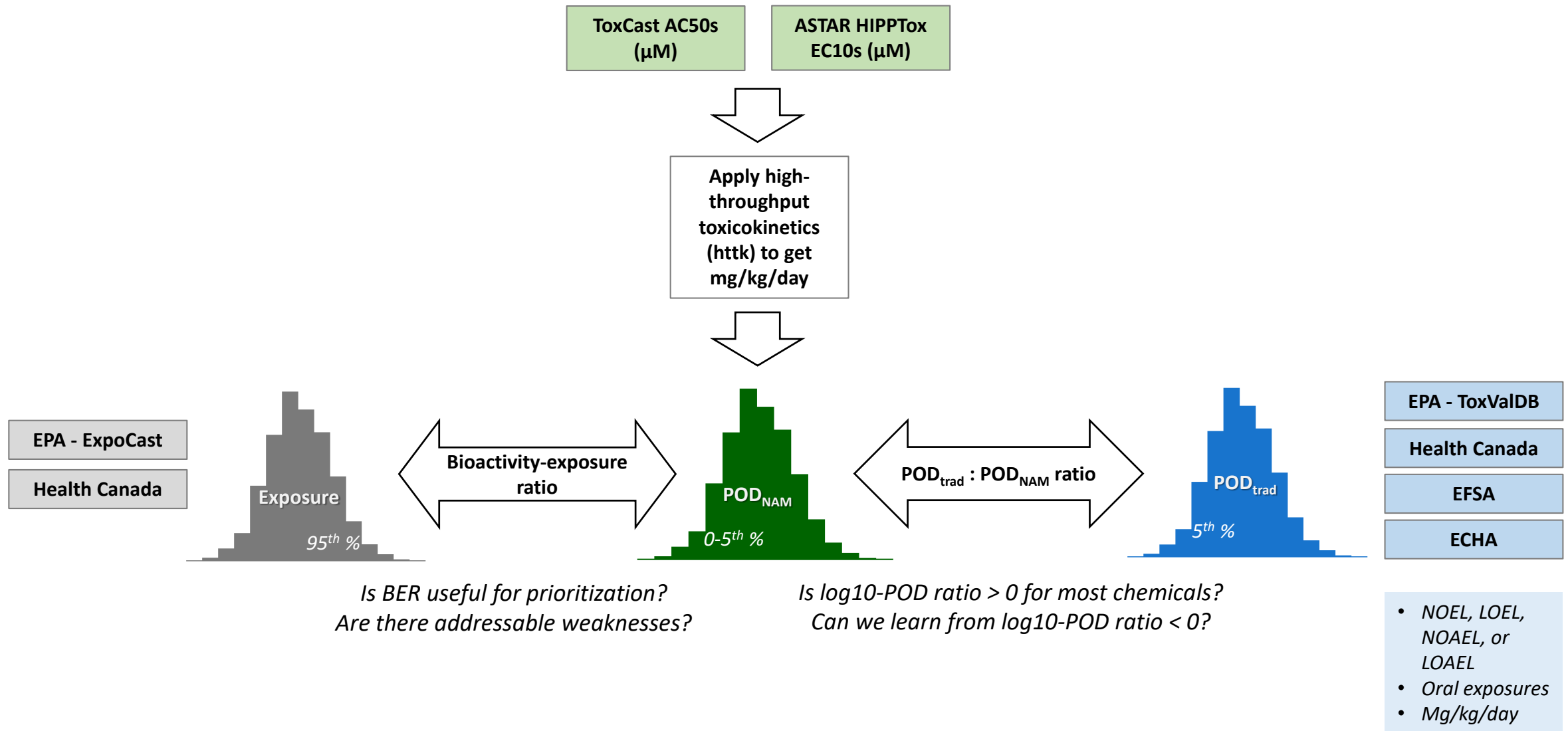
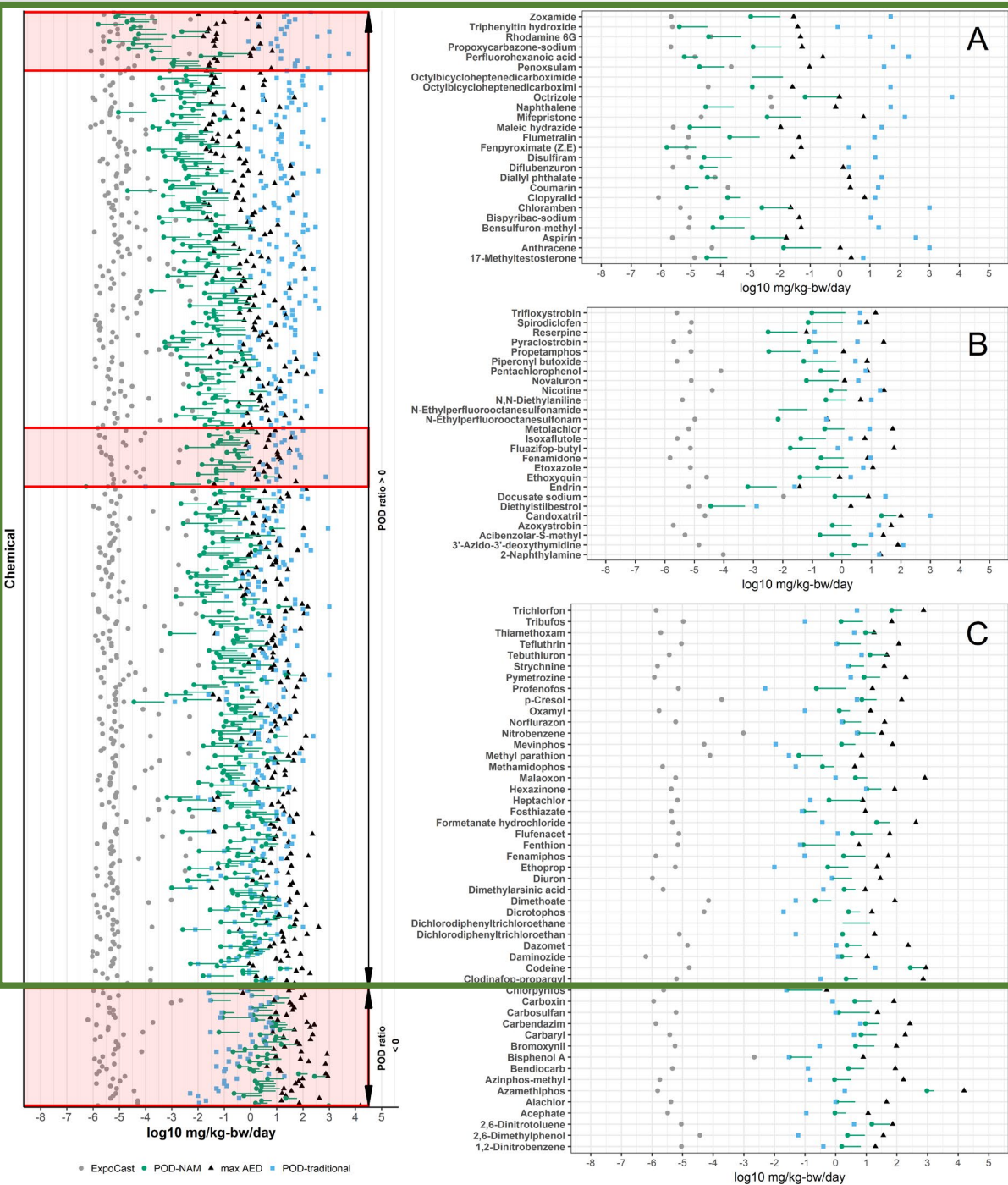


Figure 1, Paul Friedman et al. 2019²⁰

$POD_{NAM} < POD_{traditional}$
(most of the time)

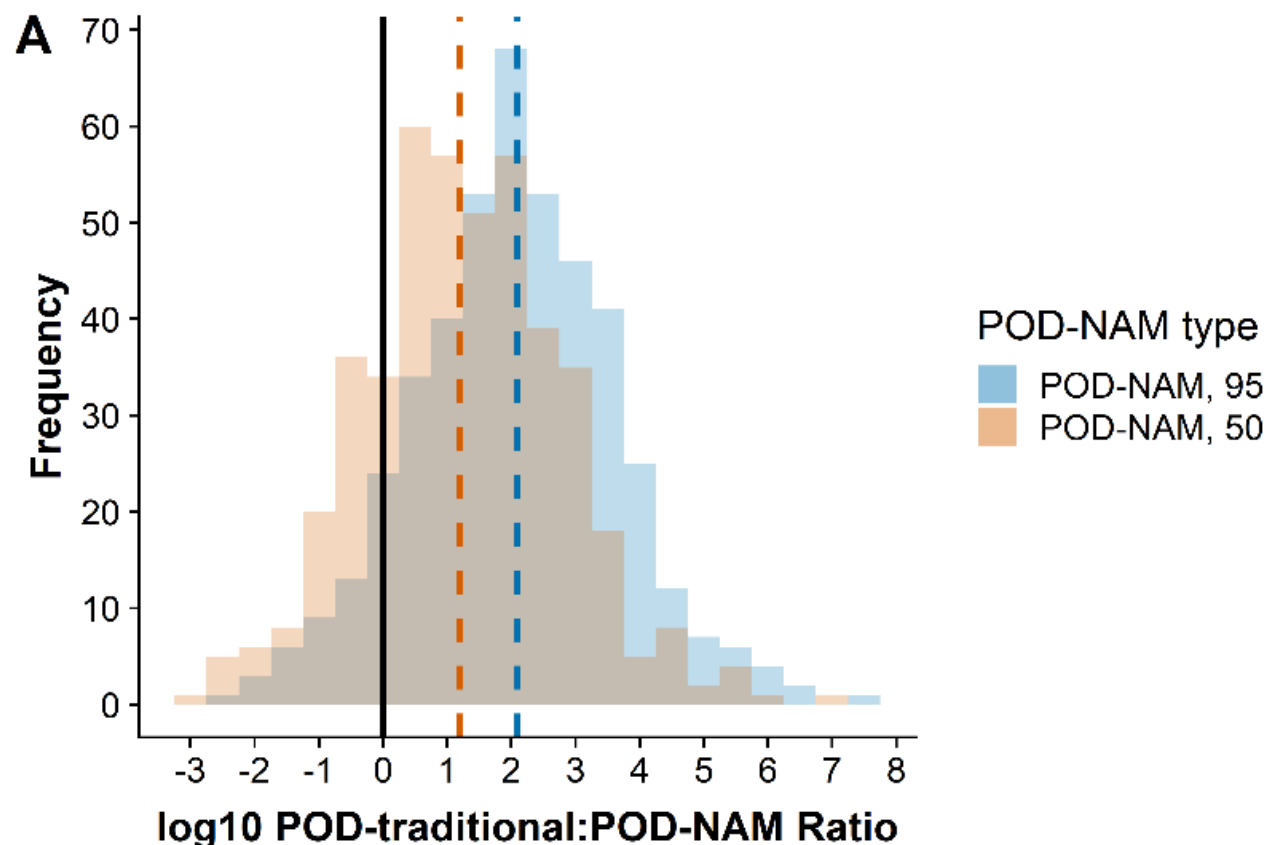
400/448 chemicals =
89% of the time this
naïve approach appears
conservative

48/448 chemicals =
11% where $POD_{NAM} > POD_{traditional}$





The log₁₀-POD ratio distribution shows POD_{NAM} is generally conservative *and adjustable*.



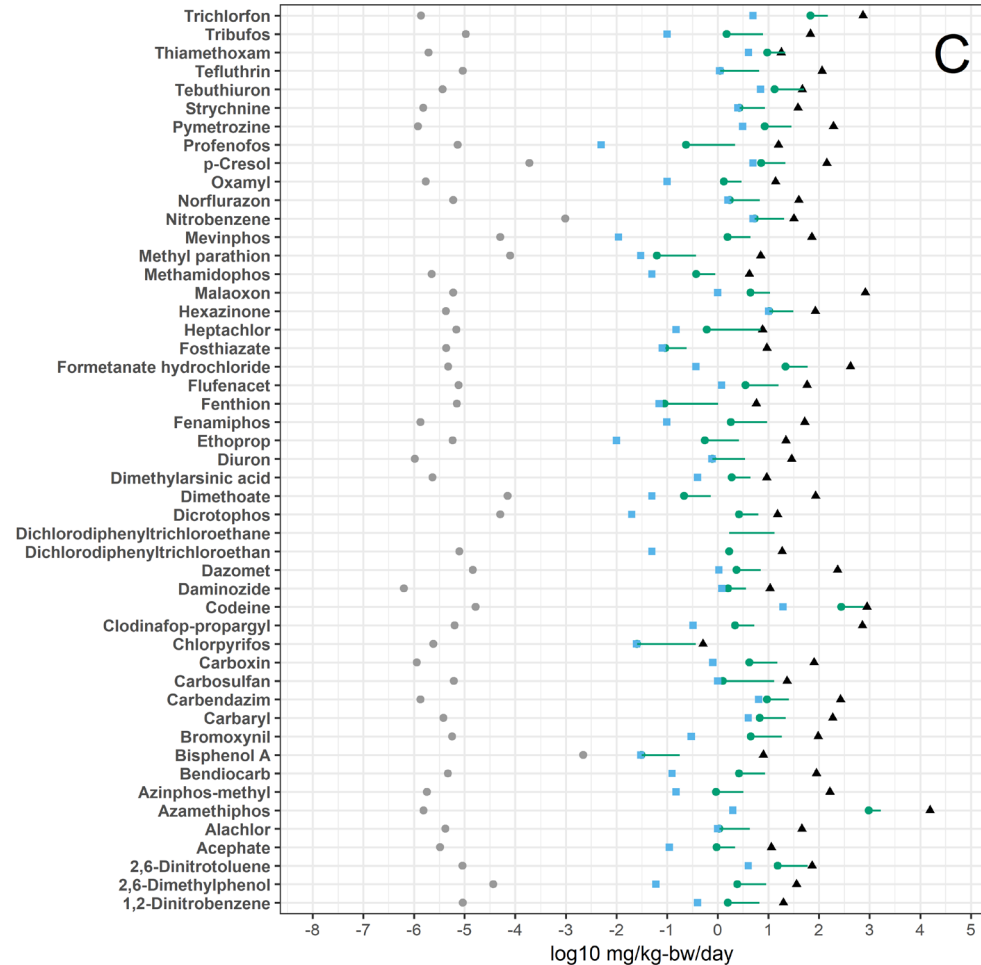
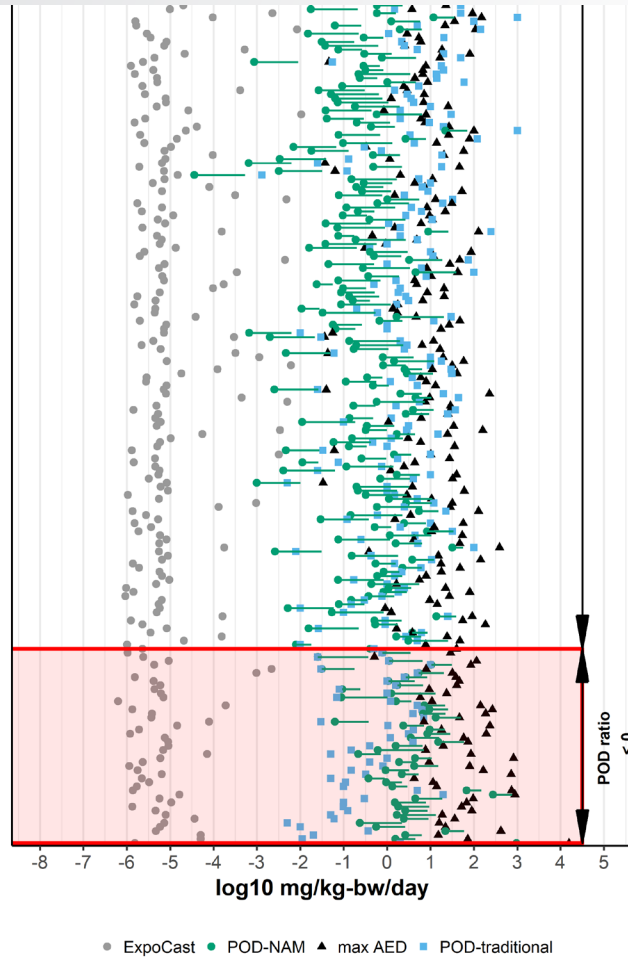
POD_{NAM,95} includes interindividual variability in the in vitro to in vivo extrapolation process to a greater extent and is more often a conservative estimate of POD_{traditional}.

This should trigger thinking regarding uncertainty and uncertainty factors/safety factors. In the NAM-based process, we have quantitatively informed uncertainty that can be included explicitly at multiple steps in the screening assessment process.

- log₁₀POD ratio is illustrated for the POD_{NAM,95} and the POD_{NAM,50}.
- Using the more conservative (i.e., lower) POD_{NAM,95}, 48 of the 448 substances (10.7%) demonstrated a log₁₀POD ratio < 0 (to the left of the solid vertical line), whereas 92 of the 448 substances (20.5%) demonstrated a log₁₀-POD ratio < 0 using the POD_{NAM,50}.
- The medians of the log₁₀-POD ratio distributions are indicated by dashed lines for POD_{NAM,95} and POD_{NAM,50} as 2 and 1.2, respectively.



Are there key drivers of examples where $\text{POD ratio} \leq 0$?



$$\text{POD}_{\text{NAM}} : \text{POD}_{\text{traditional}} \leq 0$$

- Are some *in vivo* toxicity types poorly captured by ToxCast?
- Are some study types enriched in this space, and difficult to predict from bioactivity?





When the \log_{10} POD ratio < 0 , was it driven by a specific study type (as a surrogate for phenotypes)?

Condition	Dev/Repro is min POD	Dev/Repro is not min POD
\log_{10} -POD ratio, 95 < 0	3	45
\log_{10} -POD ratio, 95 > 0	41	359

Condition	Chronic is min POD	Chronic is not min POD
\log_{10} -POD ratio, 95 < 0	28	20
\log_{10} -POD ratio, 95 > 0	244	156



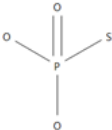
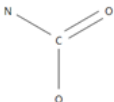


- No.
- *Based on a Fisher's exact test, when \log_{10} POD ratio < 0 , it was not driven by a specific study type.*

Hypothesis	Fisher's exact test results	Caveats
Reproductive and/or developmental studies over-represented when POD ratio ≤ 0 ?	<ul style="list-style-type: none">• No• p-value = 0.98;• odds-ratio = 0.26	Some ambiguity or error expected in assigning study classes; preference given to: DNT, neuro, dev/repro, acute, repeat, chronic (in that order) in the event of a min POD tie
Carcinogenicity or chronic studies over-represented when POD ratio ≤ 0 ?	<ul style="list-style-type: none">• No• p-value = 0.25;• odds-ratio=1.4	



When the \log_{10} POD ratio < 0 , was it driven by a specific chemical features?

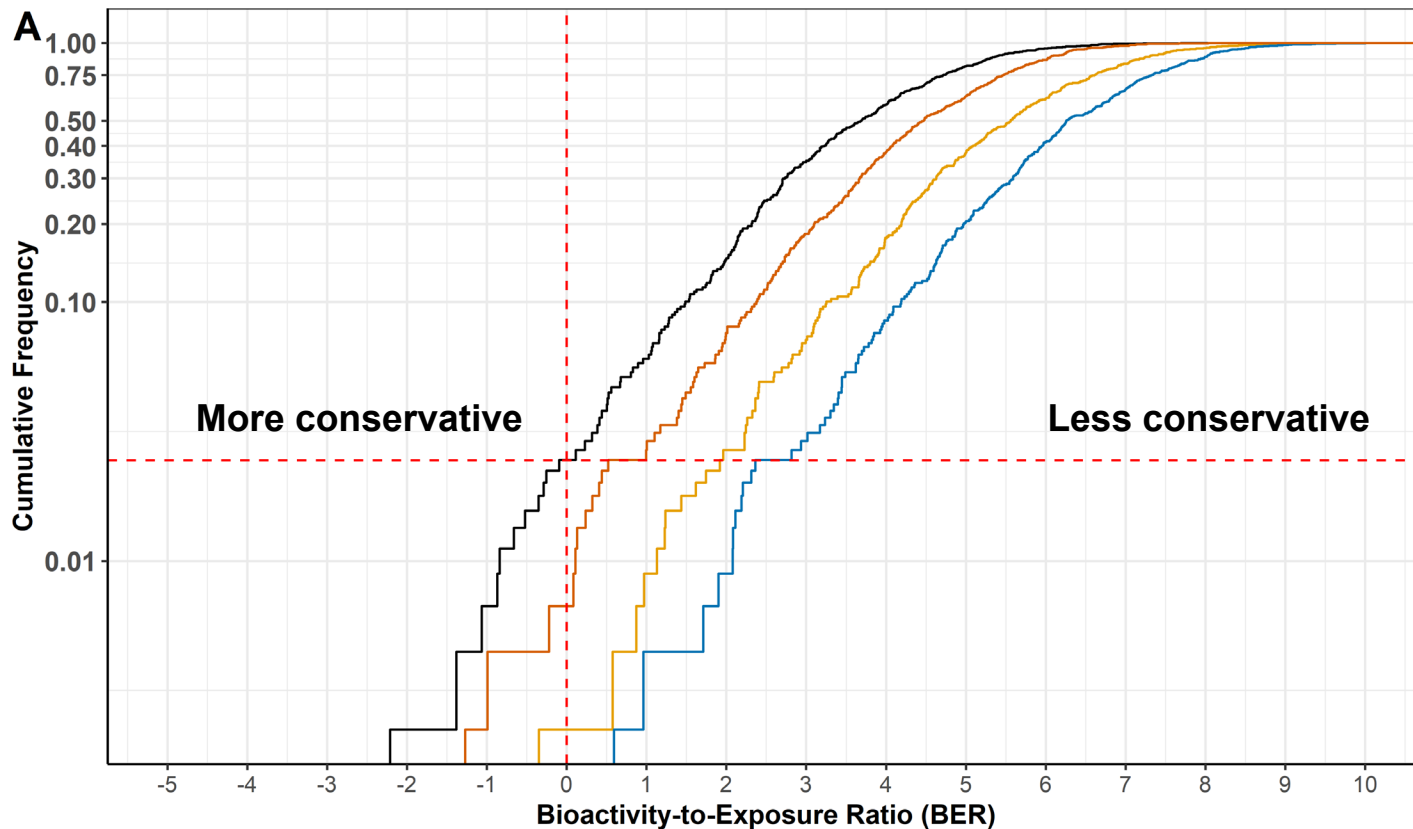
- Yes
- *Based on a Fisher's exact test, chemical features associated with organophosphate pesticides and carbamates are more likely to drive a \log_{10} POD ratio < 0 .*

ChemoType Information		Appearance of the ToxPrint			Metrics			ChemoType Information		Appearance of the ToxPrint			Metrics		
Label	ToxPrint	Total	POD ratio ≤ 0	POD ratio > 0	BA	OR	p-value	Label	ToxPrint	Total	POD ratio ≤ 0	POD ratio > 0	BA	OR	p-value
bond:P=O_phosphorus_oxo		18	12	6	0.62	22	7.4E-09	bond:P~N_generic		5	4	1	0.54	36	0.00055
bond:P=O_phosphate_thio		3	3	0	0.53	NA	0.0012	bond:C(=O)N_carbamate		20	6	14	0.54	3.9	0.014
bond:P~S_generic		27	13	14	0.62	10	3.5E-7	bond:CS_sulfide		53	15	38	0.61	4.3	0.00011

So, we have a sense that a NAM-based POD can be protective of an *in vivo* POD, especially in concert with structure-based strategies like threshold of toxicological concern (TTC). How would prioritization work?



The bioactivity:exposure ratio (BER) provides a way of prioritizing substances for further review.



- Make choices based on tolerable uncertainty (i.e., based on use case).
- BER_{95} used 95th percentile from the credible interval to predict median total US population exposure (ExpoCast SEEM2); BER_{50} the 50th percentile.
- BER_{95} and BER_{50} values were calculated as the “95th%-ile” and “50th%-ile,” using the $POD_{NAM,95}$ and $POD_{NAM,50}$, respectively.

BER_{95} , 95th percentile did not prioritize an unreasonable number of substances; the BER selected reflects the level of conservatism and uncertainty considered within a screening assessment.

Conclusions and limitations

- An approach to using *in vitro* bioactivity data as a POD appears to be a conservative estimate ~ 90% of the time for 448 chemicals.
- POD_{NAM} estimates appear conservative with a margin of ~100-fold.
- POD_{NAM} may provide a refinement of a TTC approach.
- When combined with high-throughput exposure estimates, this approach provides a reasonable basis for risk-based prioritization and screening level risk assessments.
- Specific types of chemicals may be currently outside the domain of applicability due to assay limitations, e.g., organophosphate insecticides: how do we identify these in the future?
- This is the largest retrospective look at this to-date; but what if new chemicals perform differently? What will be the prospective approach?
- Additional research to include expanded and improved high-throughput toxicokinetics and *in vitro* disposition kinetics may help improve POD_{NAM} estimates.





Part 2: Work-in-progress for a prospective case study with APCRA using NAMs as they develop in real-time



Health
Canada

Santé
Canada



(APCRA partners)

The following work is in progress and unpublished

NAMs available for hazard (and toxicokinetics and exposure) are evolving rapidly

Thomas et al. 2019 further evolves a tiered screening strategy that adds in broader biological coverage.

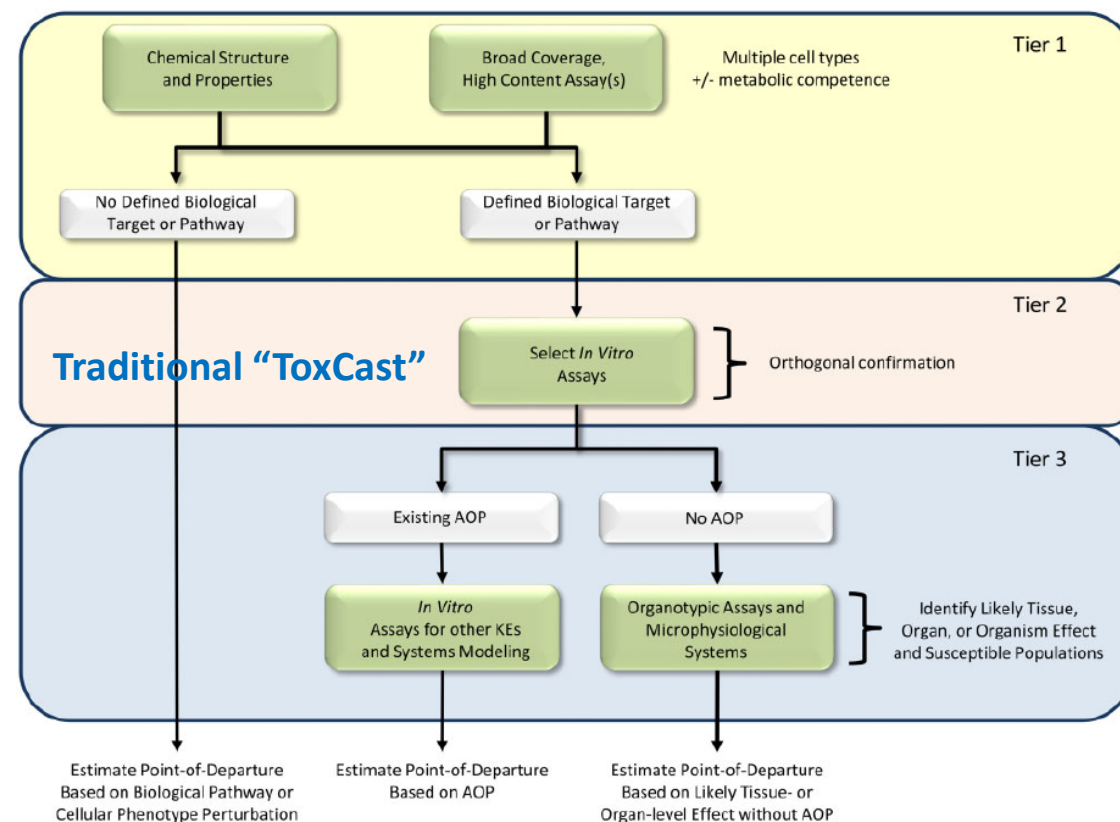
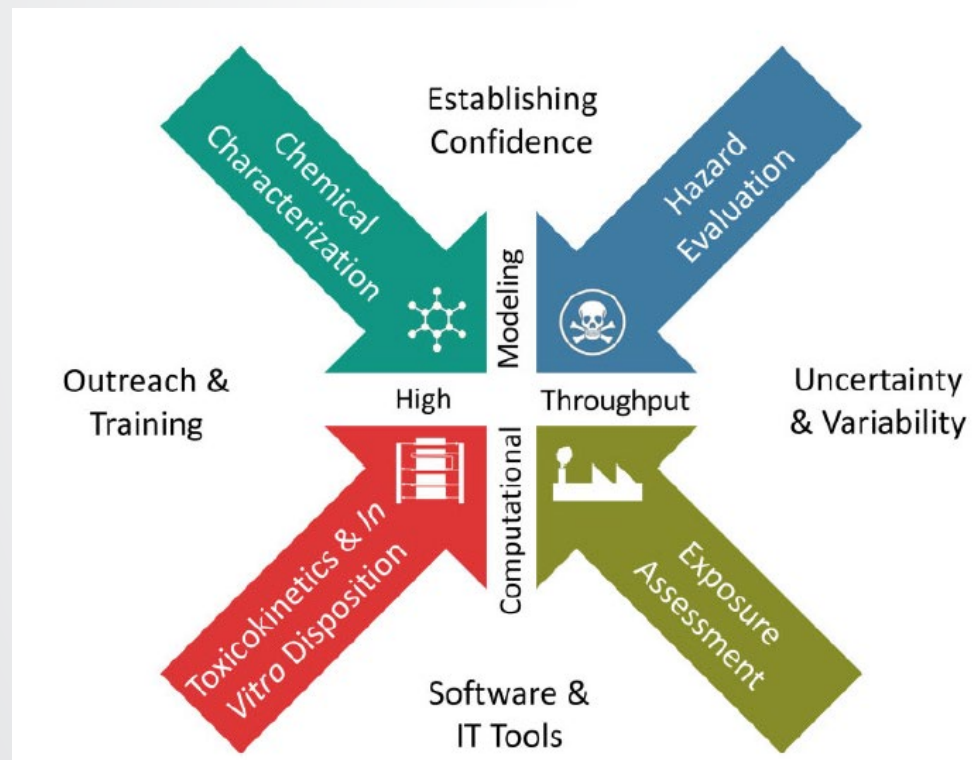


Figure 2. Tiered testing framework for hazard characterization. Tier 1 uses both chemical structure and broad coverage, high content assays across multiple cell types for comprehensively evaluating the potential effects of chemicals and grouping them based on similarity in potential hazards. For chemicals from Tier 1 without a defined biological target / pathway, a quantitative point-of-departure for hazard is estimated based on the absence of biological pathway or cellular phenotype perturbation. Chemicals from Tier 1 with a predicted biological target or pathway are evaluated Tier 2 using targeted follow-up assays. In Tier 3, the likely tissue, organ, or organism-level effects are considered based on either existing adverse outcome pathways (AOP) or more complex culture systems. Quantitative points-of-departure for hazard are estimated based on the AOP or responses in the complex culture system.



Tier 1 becomes a broad-based screening that segues to Tier 2 (targeted screening).

High-throughput phenotypic-profiling

Toxicology and Applied Pharmacology 389 (2020) 114876



Contents lists available at ScienceDirect

Toxicology and Applied Pharmacology

journal homepage: www.elsevier.com/locate/taap



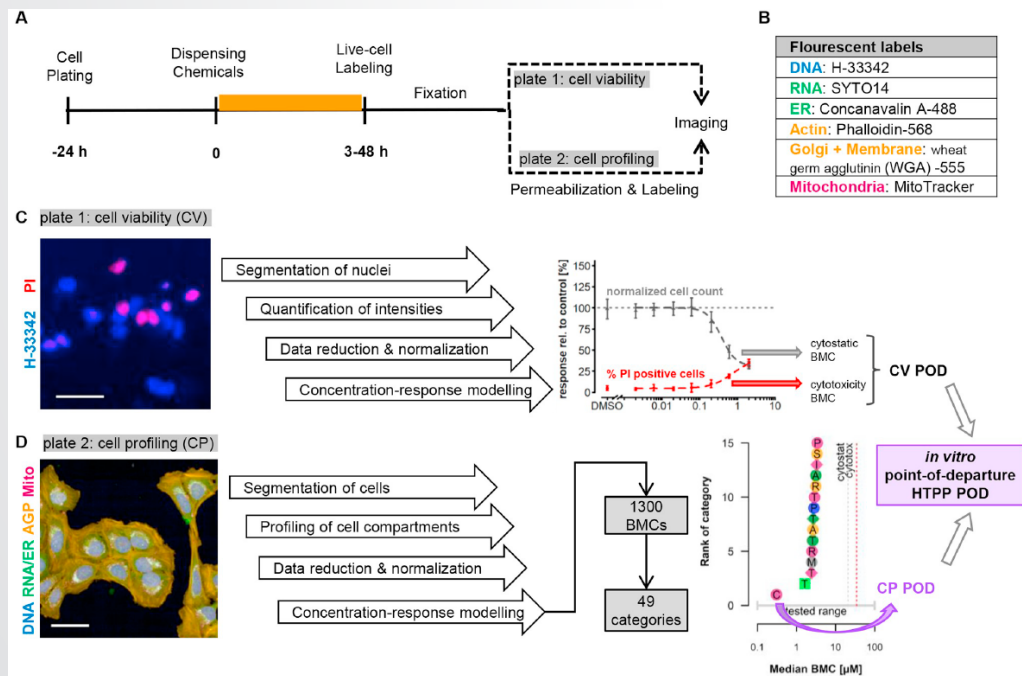
Bioactivity screening of environmental chemicals using imaging-based high-throughput phenotypic profiling

Johanna Nyffeler^{a,b}, Clinton Willis^{a,c}, Ryan Lougee^{a,b}, Ann Richard^a, Katie Paul-Friedman^a, Joshua A. Harrill^{a,*}

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^b Oak Ridge Institute for Science and Education (ORISE), Oak Ridge, TN 37831, United States of America

^c Oak Ridge Associated Universities (ORAU) National Student Services Contractor, Oak Ridge, TN 37831, United States of America



High-throughput transcriptomics

EPA Public Access

Author manuscript

Curr Opin Toxicol. Author manuscript; available in PMC 2020 January 01.

About author manuscripts

Submit a manuscript

Published in final edited form as:

Curr Opin Toxicol. 2019 ; 15: 64–75. doi:10.1016/j.cotox.2019.05.004.

Considerations for Strategic Use of High-Throughput Transcriptomics Chemical Screening Data in Regulatory Decisions

Joshua Harrill¹, Imran Shah¹, R. Woodrow Setzer¹, Derik Haggard², Scott Auerbach³, Richard Judson¹, Russell S. Thomas¹

- High-throughput phenotypic profiling and high-throughput transcriptomics will provide broad screening coverage
- Points-of-departure based on these techniques could then be augmented/refined using targeted screens (e.g., subsets of existing ToxCast assays and new assays to fill gaps)

Question

Can an *in vitro* assay battery be used to derive a (health protective) [point of departure](#) (POD_{NAM}) and qualitative [hazard flags](#) comparable with the outcome from *in vivo* repeat dose toxicity (RDT) studies used in traditional hazard assessment?

Goals

- Identify a portable and scalable combination of NAMs that provides a robust and health protective estimate of the POD for repeat dose toxicities studies and mechanistically-based hazard flags for important health endpoints
 - A number of chemicals overlap with the retrospective case study and can be used to evaluate the POD_{NAM}
- Using the NAM battery, assess a set of chemicals derived from multiple national inventories that have limited/unclear toxicological data and significant potential exposure.
- Inform the further development needs for NAMs:
 - For screening, prioritization, and first tier assessments
 - For conclusive hazard characterization/assessment and risk management
 - To assess chemicals in an international context



APCRA Prospective Case Study Tier 1 Outline

Phase 1: Derivation of POD_{NAM}

Toxicodynamic NAMs

- HTPP
- HTRR
- Targeted assays

Toxicokinetic NAMs

- Assays
- IVIVE modeling
- Disposition modeling

Is there a combination NAMs and a dose metric (C_{ss} , C_{max} , C_{ave}) that provide:

- More robust POD^* for Category 3 substances
- Portable and scalable solution for large numbers of chemicals
- Consider subsets of the NAMs available

**Defined as health protective, but better overall alignment of POD_{NAM} and $POD_{Traditional}$*

No

Flag substances with >1000 days to steady state

Use existing ToxCast and C_{ss} approach to estimate POD_{NAM} for Category 1/2 substances

Yes

Use improved combination of NAMs and dose metric to estimate POD_{NAM} for all substances

Phase 2: BER and Hazard Flag Priority

Flag substances where exposure may be "high" or a driver

$BER < 10,000$

$POD < 1 \text{ mg/kg}$
AND/OR Hazard flags

Substances for further consideration

Are there existing repeat dose toxicity studies?

Yes

Identify existing data gaps for subsequent targeted problem formulation

No

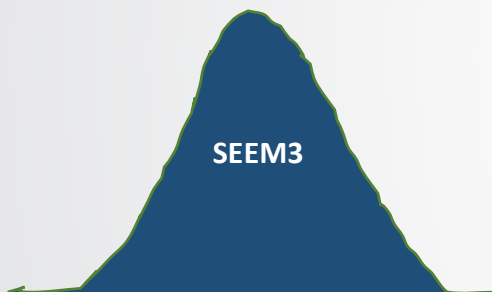
Consider for further in vivo studies (5-day rat or subchronic bioassays)



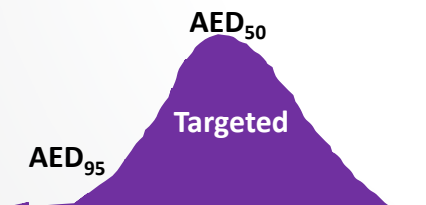
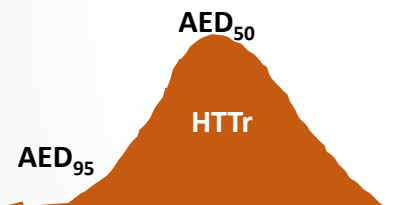
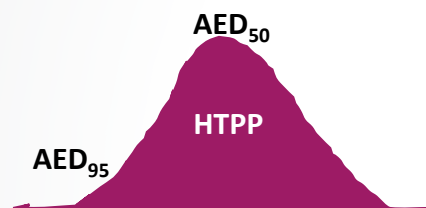
Global BER and hazard flags

Phase 2a: Global Bioactivity: Exposure Ratio and POD_{NAM} Cutoff

SEEM3 exposures estimates



Global POD_{NAM} estimates



* Targeted HTS assay subset

At this point in the analysis, we will look for the potency of bioactivities relevant to typical 90-day studies and potency of bioactivities that may be more targeted (part of considering POD_{NAM} as an alternative for 90-day studies)

Phase 2b: Hazard flagging and selectivity

ER activity: in silico or in vitro

AR activity: in silico or in vitro

Developmental hazard flag

Immune response flag

Acute neurotoxicity flag

* Note that in silico consensus QSAR models are qualitative

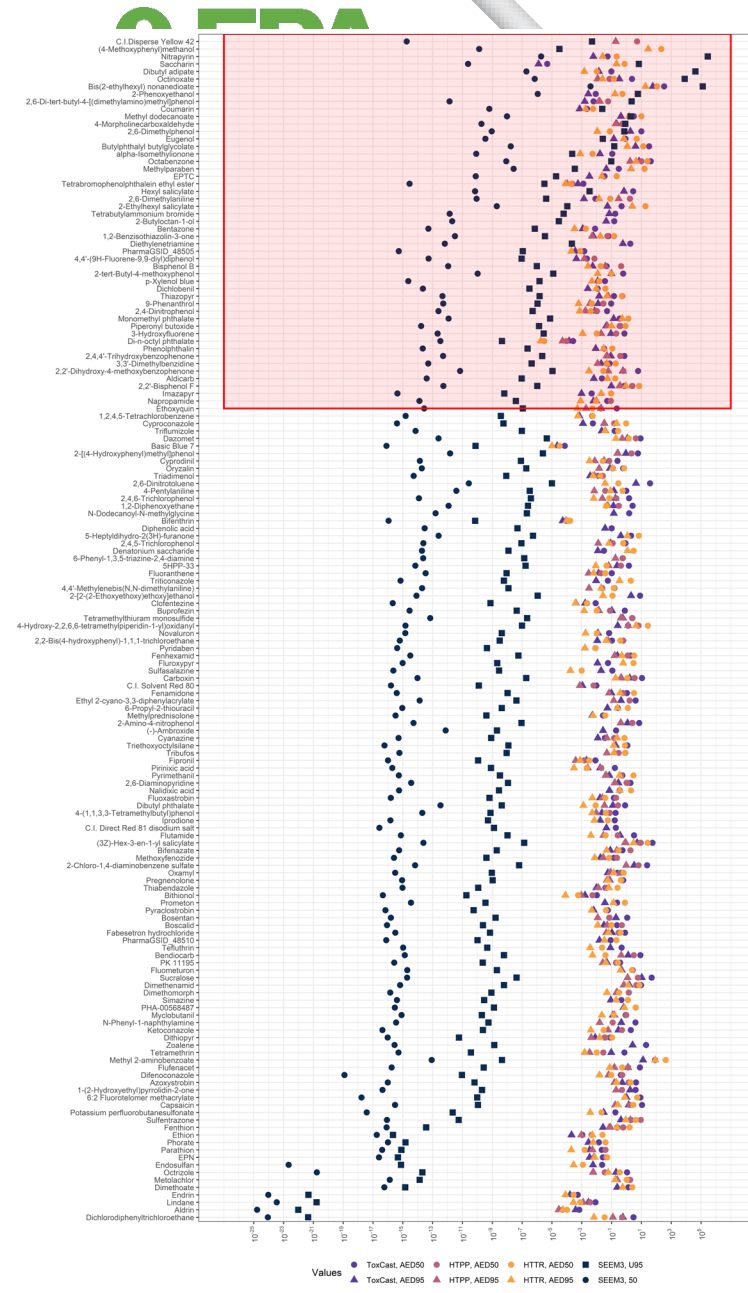


Hazards of interest may not drive minimum POD_{NAM}

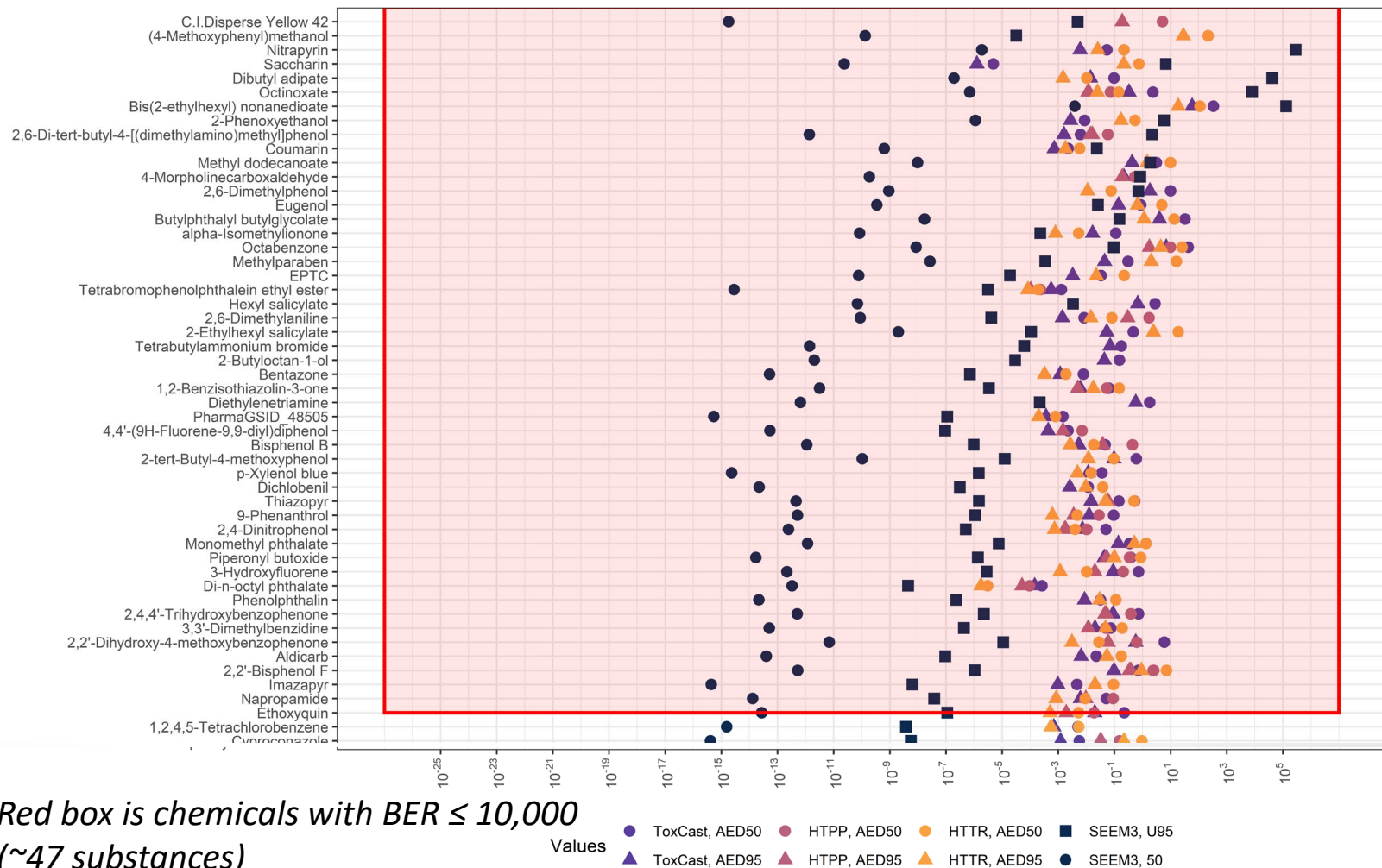
≥ 1 hazards of interest may overlap with a lower bound estimate of POD_{NAM}

Dose or Concentration Units

Draft: using SEEM3 exposure predictions and ToxCast, HTPP, and HTTr PODs



Red box is chemicals with BER $\leq 10,000$
(~47 substances)





Part 3: Application of hazard-specific NAMs to specific questions about the potential developmental neurotoxicity

Agency Issue Paper:

Use of New Approach Methodologies to Derive
Extrapolation Factors and Evaluate Developmental
Neurotoxicity for Human Health Risk Assessment

July 2020

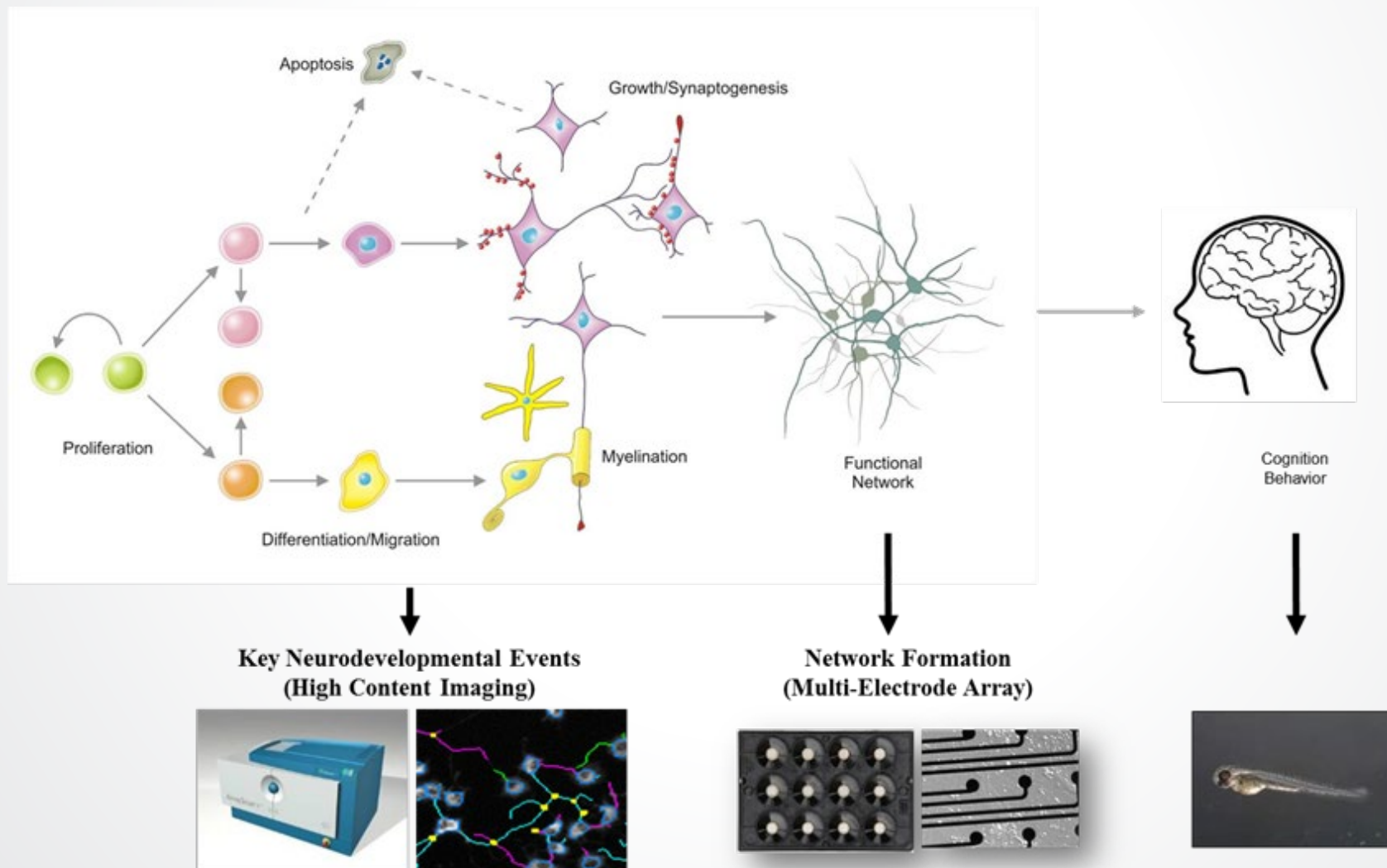
ORD DNT NAMs Team: Josh Harrill, Tim Shafer, Katie Paul Friedman

September 15-18, 2020 Federal Insecticide, Fungicide, and Rodenticide Act
Scientific Advisory Panel met to review this Issue Paper and presentations

<https://beta.regulations.gov/document/EPA-HQ-OPP-2020-0263-0006>

Phenotypic Screening for DNT Hazard

Assays should allow quantitative measurements of key neurodevelopmental events *in vitro*





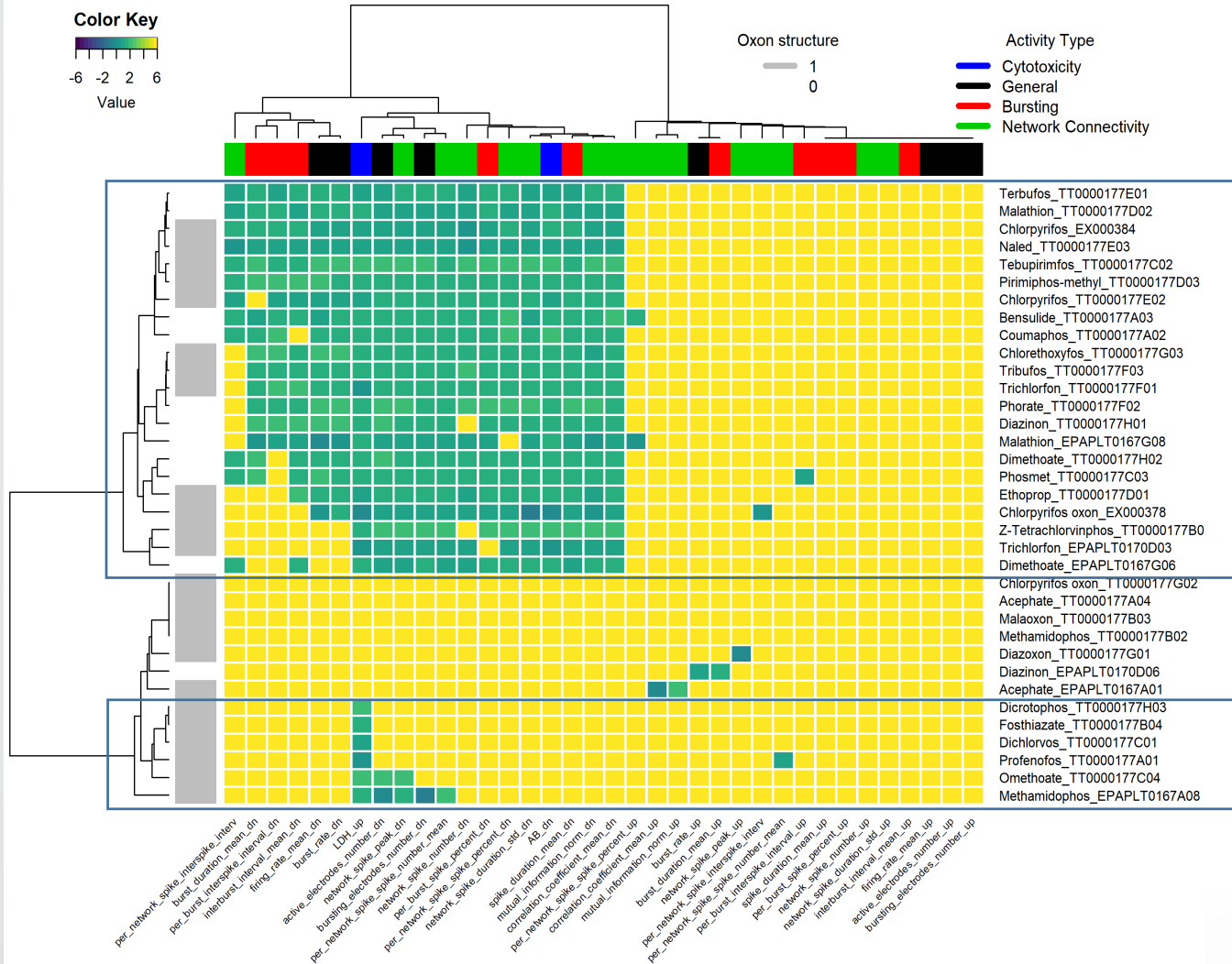
One of several charge questions addressed derivation of PODs

*“In order to compare the relative sensitivity of the MEA NFA and HCI assay results to doses that inhibit acetylcholinesterase in laboratory animals, in vitro to in vivo extrapolation (or IVIVE) approaches were used to approximate NAM administered equivalent doses for a subset of organophosphate pesticides. **Please comment on the strengths and limitations of this comparison and whether there are alternative approaches for this evaluation.**”*

- Underscore the reproducibility of the DNT NAM assays.
- Describe the differential performance of OPs in the DNT NAM assays that are currently available.
- Demonstrate an IVIVE approach to derive doses for comparison to BMD and BMDL values based on rat AChE inhibition.



Like the assay controls, some OPs decrease MEA NFA activity types

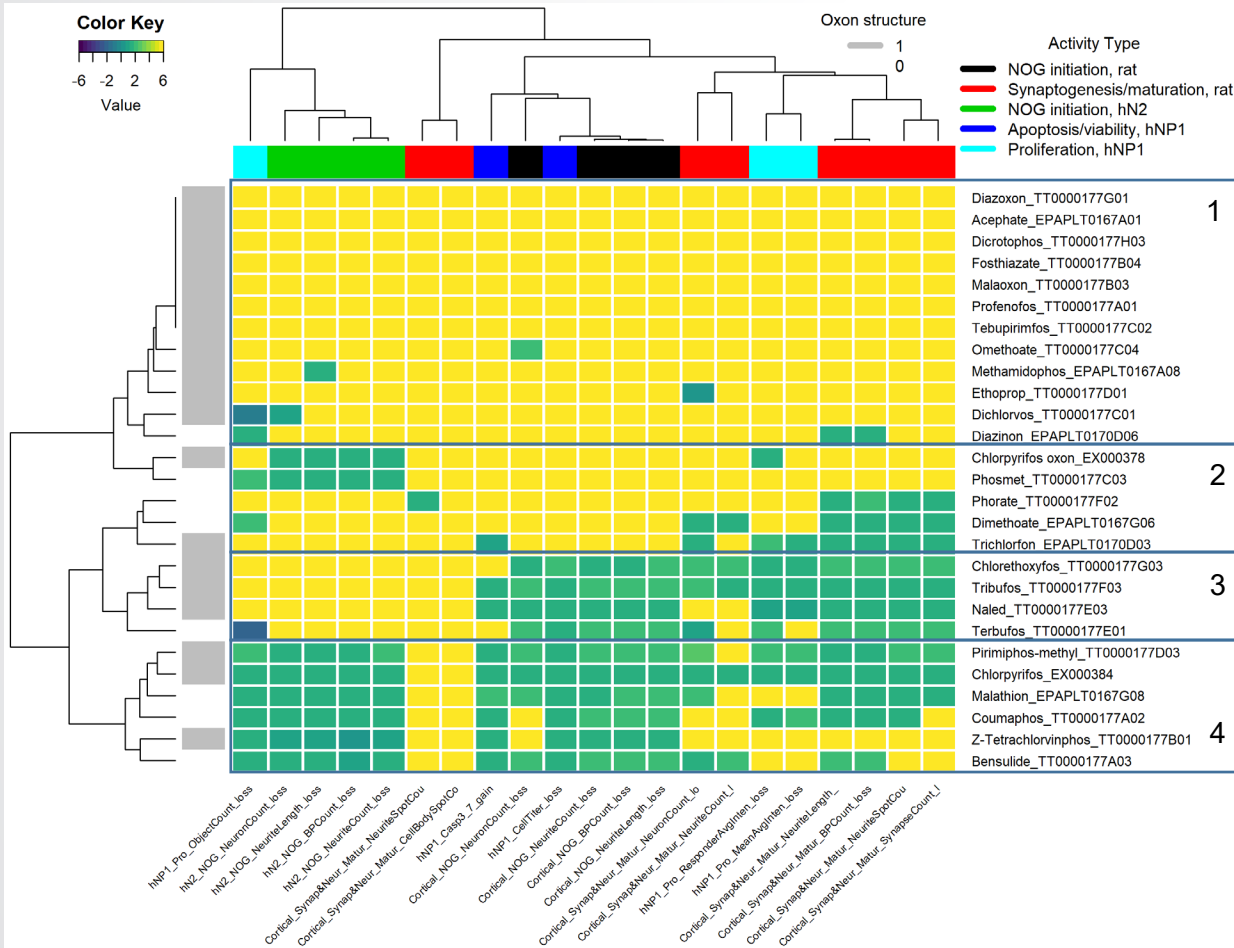


- Top active cluster of OPs contains oxon and non-oxon structures.
- These OPs, like the assay performance controls, appear to generally decrease all activity types and most assay endpoints.
- Cytotoxicity and activity occur within a narrow concentration range.
- Bottom cluster with minimal actives appears somewhat driven by cytotoxicity in the LDH assay.

Conclusion: while not all OPs are active in the MEA NFA, those that are active appear to behave much like the assay performance controls that inhibit NOG and/or synaptogenesis.



OPs demonstrate differential responses in the HCI assays.



- Cluster 1: negative or with effects in 1-3 endpoints.
- Cluster 2: effects on five or more assay endpoints
- Cluster 3: OP samples with effects on all HCI assay activity types except for NOG initiation in hN2 cells
- Cluster 4: widespread effects across activity types

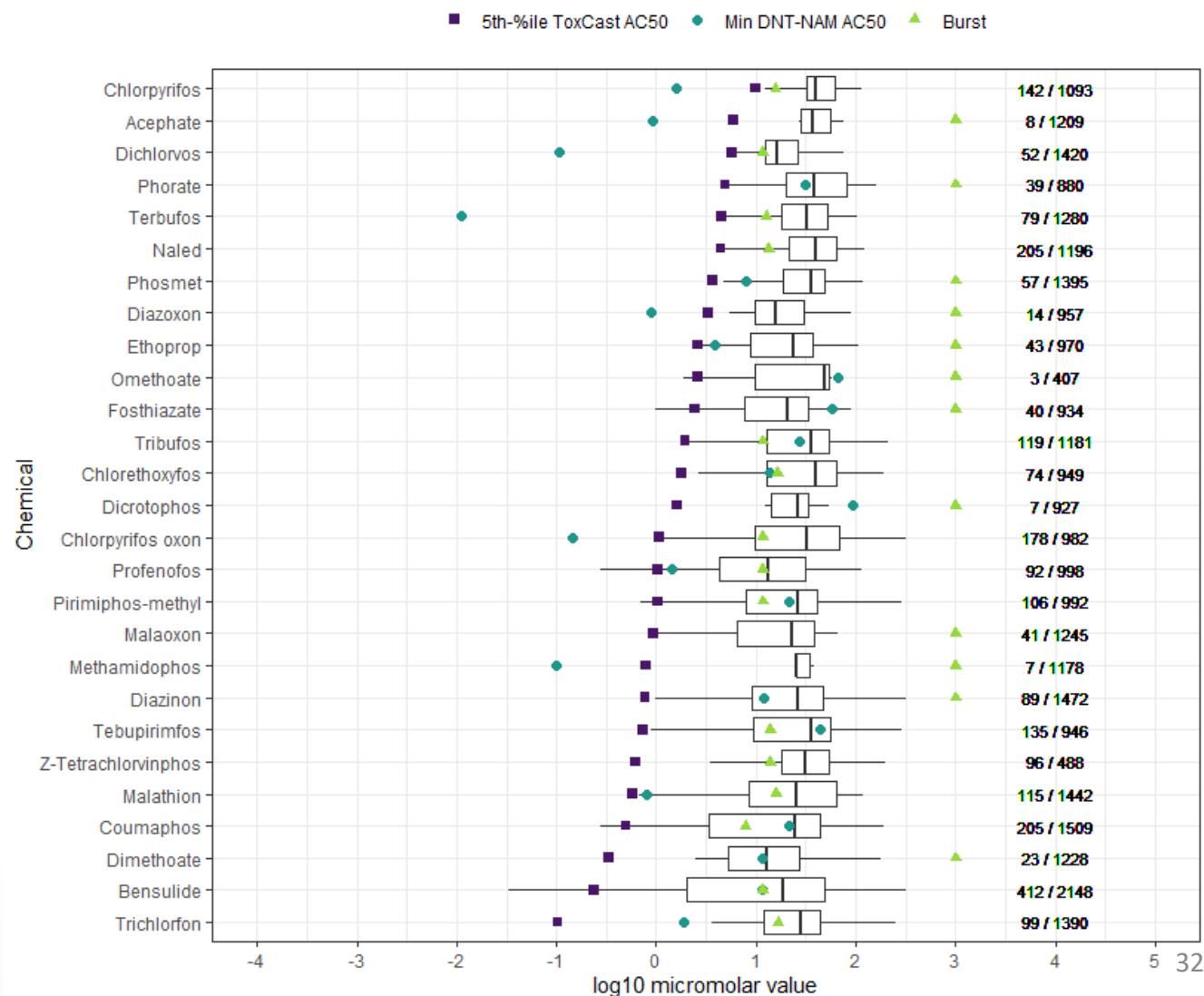


For some OPs, the minimum DNT-NAM AC50 < an estimate of bioactivity from the rest of ToxCast.

DNT-NAM battery may provide a more potent estimate of bioactivity for substances with minimum DNT-NAM AC50 < 5th percentile of filtered ToxCast AC50 values:

- Chlorpyrifos and chlorpyrifos oxon
- Acephate
- Dichlorvos
- Terbufos
- Diazoxon
- Methamidophos

Suggests that the DNT-NAM battery, in covering some new biology not previously in ToxCast, may yield bioactivity threshold concentrations lower than what is already available for some neuroactive substances in ToxCast.





Simplifying assumptions for the HTK approach employed here using htk R package

- 100% bioavailability (all of an oral dose is received by the liver through the portal vein);
- No extrahepatic metabolism: the liver is the only source of chemical clearance from the body by metabolism;
- Hepatic metabolism is first order (proportional to concentration) and does not saturate;
- Renal clearance is proportional to fraction unbound in plasma and glomerular filtration rate (i.e., no active transport); and,
- No biliary excretion or enterohepatic recirculation occurs.

With these assumptions, HTK models have demonstrated reasonable accuracy in predicting relevant TK endpoints, for example plasma concentrations over time (AUC) ($R^2 = 0.62$) and maximum plasma concentrations (C_{max}) ($R^2 = 0.48$) (Wambaugh et al., 2018).

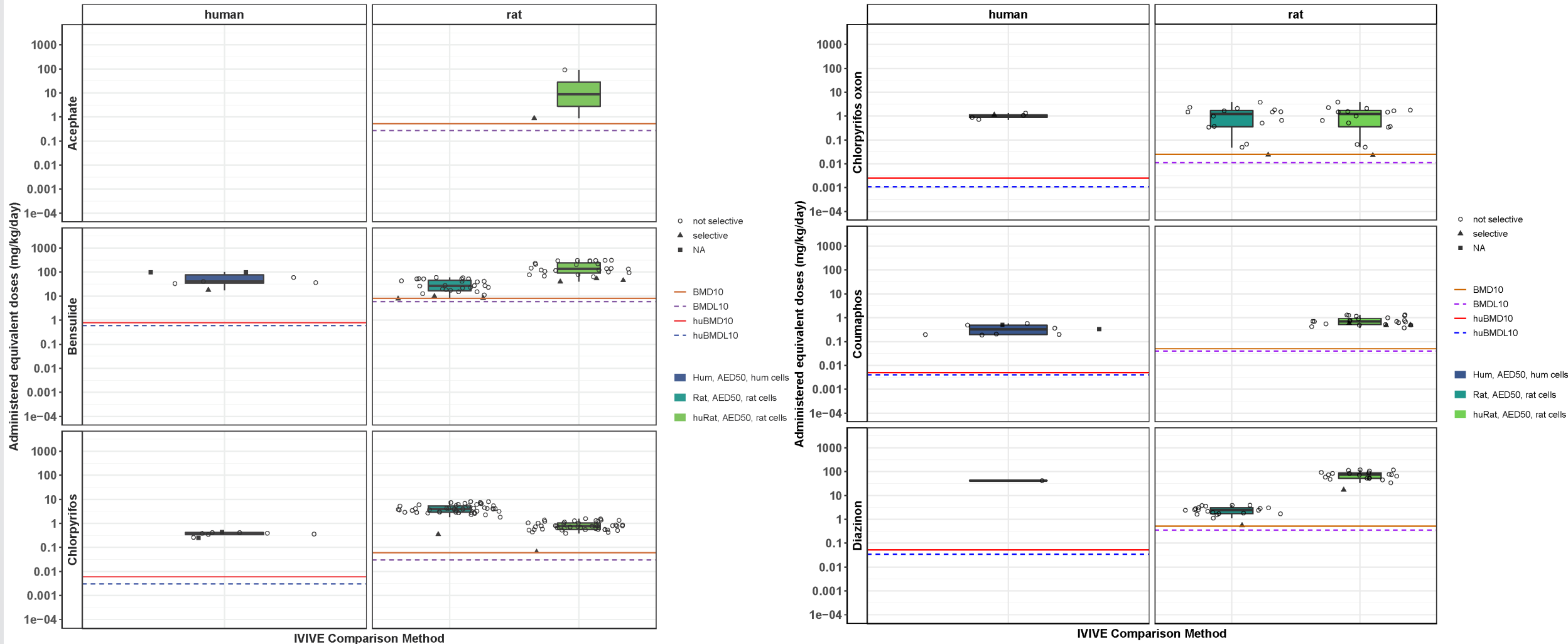
AED values in mg/kg/day units were calculated using the following equation (Eq. 2):

$$Eq.2: AED_{50} \left(\frac{\frac{mg}{kg}}{day} \right) = AC_{50}(\mu M) * \frac{\frac{1 \frac{mg}{kg}}{day}}{C_{ss50}}$$

Where the C_{ss} (steady-state concentration) values for the median individual based on Monte Carlo simulation of species-specific physiological parameters (C_{ss50}) (Pearce et al. 2017) were generated using the 3-compartment steady state model.



Example: AED50 to BMD/BMDL10 comparisons





Overarching conclusions for application of DNT-NAMs

- MEA NFA and HCI assay suite recapitulates key cellular events and processes relevant to DNT, as demonstrated through the use of appropriate assay performance controls;
- the DNT-NAMs presented here represent a major milestone for *in vitro* fit-for-purpose identification of putative DNT-related hazard, though additional methods may be available in the future;
- the MEA NFA and HCI assay suite demonstrates reproducibility in terms of positive responses and potency of these responses;
- the 27 OP chemicals in this set are differentially active in the MEA NFA and HCI assay suite; and,
- application of IVIVE approaches for the *in vitro* bioactivity observed in these DNT-NAMs results in AED₅₀ values that are greater than or in some cases approximate the doses that inhibit AChE *in vivo*.



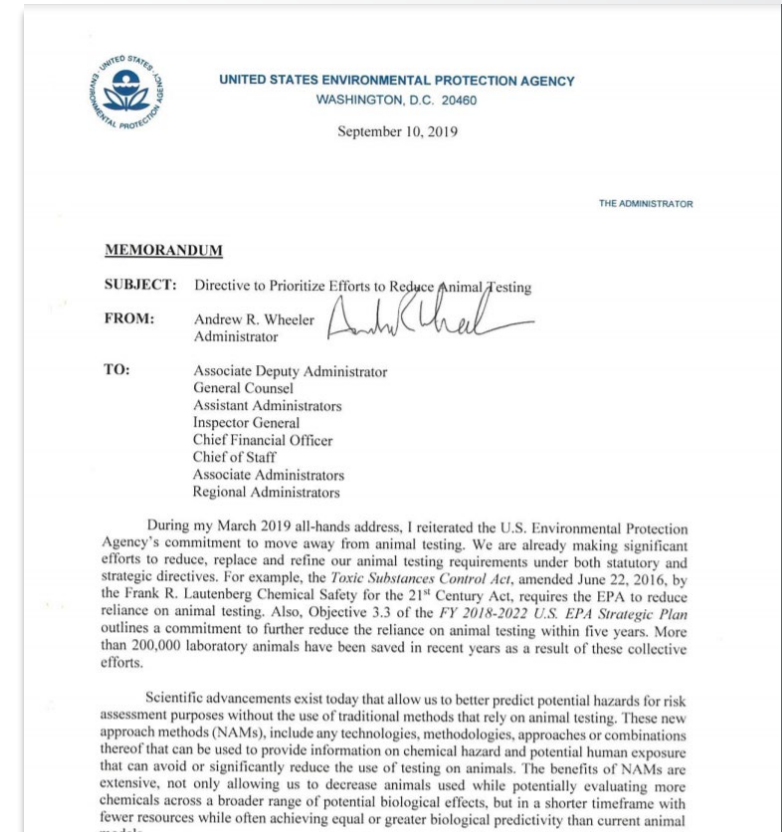
Employing NAMs for derivation of PODs

EPA New Approach Methods Work Plan: Reducing Use of Animals in Chemical Testing

<https://www.epa.gov/chemical-research/epa-new-approach-methods-work-plan-reducing-use-animals-chemical-testing>



- How much uncertainty can be tolerated?
- Can BER be informative for the problem?
- Are there specific hazards of interest?
- How should toxicokinetic modeling be tuned?



<https://www.epa.gov/research/administrator-memo-prioritizing-efforts-reduce-animal-testing-september-10-2019>

There is a lot more work to do, and case studies will help build confidence and identify gaps to fill.



Acknowledgements

Many CCTE collaborators

Many OPP collaborators

Many APCRA partners



EPA
Office of Research and Development
Center for Computational Toxicology & Exposure (CCTE)



Appendix slides



Summary of the AED50 to BMD/BMDL comparison

	Chemicals with AED50 values >>> BMD/BMDL comparator	Chemicals with lowest AED50 within 1 log10 order of magnitude of BMD/BMDL comparator	Chemicals with lowest AED50 approaching BMD/BMDL comparator	Missing in vitro data for comparison
Rat/HuRat	Coumaphos, diazoxon, dicrotophos, ethoprop, fosthiazate, omethoate	acephate, bensulide, chlorpyrifos, chlorpyrifos oxon, diazinon, dimethoate, malathion, methamidophos, and phorate	lower quartile of huRat AED ₅₀ values for <u>dimethoate</u> and <u>methamidophos</u> (these AED ₅₀ values appear to have included selective assay endpoints). The huRat AED ₅₀ value for <u>dichlorvos</u> (only one positive rat assay endpoint) overlaps with the BMDL10 value, and it was not based on selective bioactivity in the DNT-NAM battery. The lowest huRat AED ₅₀ values (selective) for <u>malathion</u> also approach the BMD/BMDL10 values.	Malaoxon was negative in all assays.
Human	bensulide, chlorpyrifos, chlorpyrifos oxon, coumaphos, diazinon, dimethoate, malathion, methamidophos, phosmet, pirimiphos-methyl, tribufos, and trichlorfon		For <u>dichlorvos</u> , only two AED ₅₀ values are available for comparison, and these values are centered around the BMD10/10 and BMDL10/10 values. Neither of these AED ₅₀ values appear selective because the bioactivity was observed in assay endpoints relevant to cell viability. Similarly, for <u>terbufos</u> , only 3 human AED ₅₀ values are available for comparison, and the lowest one of these values approaches the BMD10/10 value. This lowest AED ₅₀ value for terbufos does not appear selective because it is derived from a cell viability related assay endpoint (object count in the HCl hNP1 proliferation assay endpoint).	Acephate, diazoxon, dicrotophos, ethoprop, fosthiazate, omethoate, phorate, profenofos, and tebupirimfos had positive rat assay data but lacked positive responses in the human cell-based assays. Malaoxon was negative in all assays.



Selecting an HTK model: 3 compartment steady state model

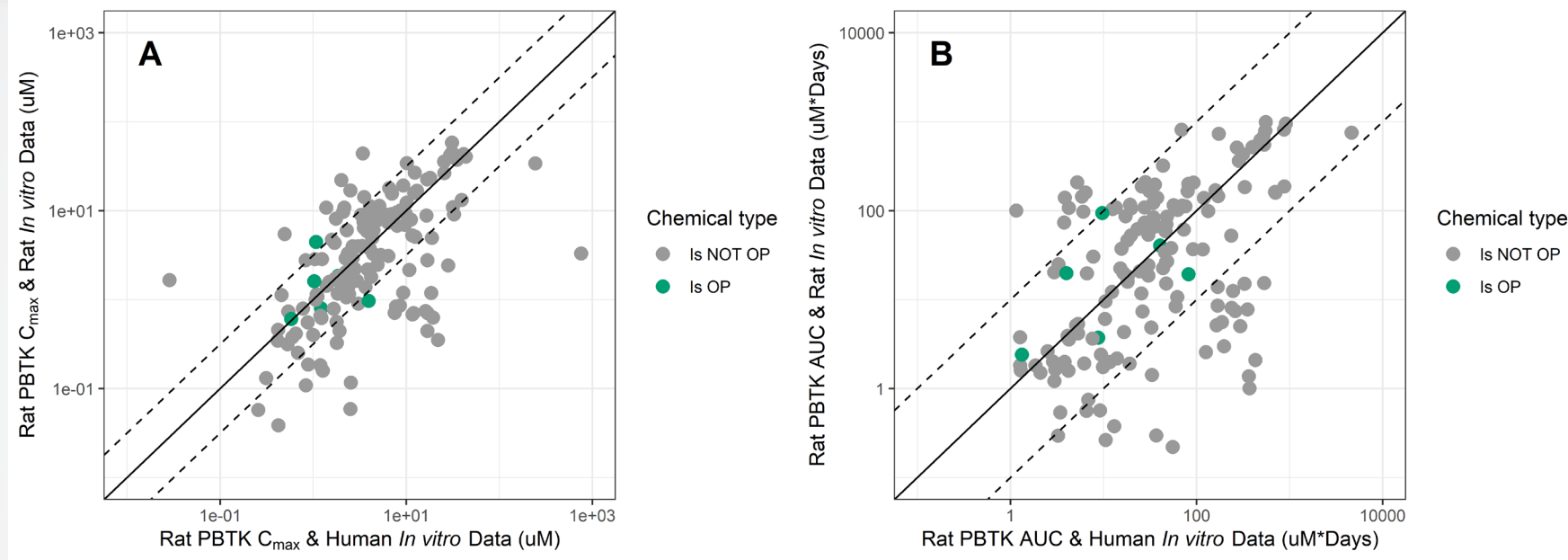
Models:	3-compartment steady state (3compss)	PBTK
Chemical-specific parameters	Clint only	Clint, Fup, logP, pKa
Model inputs	A single oral dose	A single oral dose
Model outputs	Steady-state blood concentrations	Time course of blood concentrations; estimate Cmax, AUC (24 hr), Cmean (AUC/time) from time course simulations
Human interindividual variability	Human physiological parameters (first order hepatic metabolic clearance; plasma protein binding; liver volume, blood flow, and cell density; and glomerular filtration rate) can be varied in a Monte Carlo simulation to estimate the dose required to achieve equivalent blood concentrations for the most to least sensitive individuals. <u>In this Issue Paper, the median individual is used.</u>	
Rat interindividual variability	Rat physiological parameters (rat liver volume and glomerular filtration rate) can be varied in a Monte Carlo simulation to estimate the dose required to achieve equivalent blood concentrations for the most to least sensitive individuals. <u>In this Issue Paper, the median individual is used.</u>	

- Only 6/27 OP insecticides discussed in this Issue Paper have sufficient rat-specific (fraction unbound in plasma and hepatic intrinsic clearance) to inform HTK PBTK models
- Because the fraction unbound in plasma (Fup) assay fails for highly bound chemicals (Wambaugh et al., 2015), the steady state model is advantageous because it can be used with the assumption that plasma protein binding is simply “small,” i.e., typically 0.5% (Wetmore et al., 2012)

To provide the most complete view of a potency comparison between AEDs based on DNT-NAMs and BMD10 and BMDL10 values based on observations of in vivo rat AChE inhibition, and to present an approach that would require the minimum amount of data using the simplest modeling approach, AED values in this Issue Paper were calculated using the 3-compartment steady state model.



To address more of the OPs, we used the “huRat”



Supplemental Appendix Figure 2

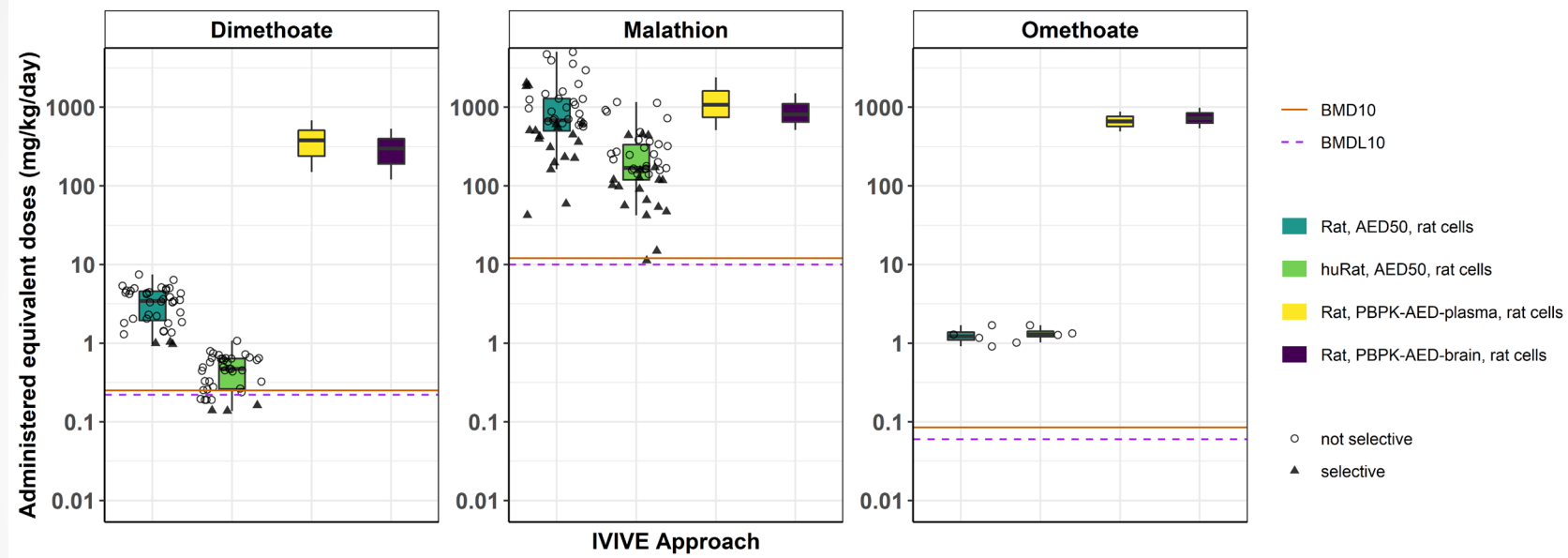
- In the absence of hepatic clearance values from rat hepatocytes, rat liver microsomes, or rat liver Phase I enzymes, would the use of human hepatocyte-derived hepatic clearance values be a reasonable substitute?
- In addition to comparing rat-derived AED_{50} values to BMD10 and BMDL10 values from rat studies, we also compared AED values from the “humanized-rat” or the huRat, which used human H₁TK data in a model parameterized with rat physiology, to BMD10 and BMDL10 values from rat studies.

Comparing HTKK to PBPK-PD models

- Physiologically-based pharmacokinetic (PBPK)-pharmacodynamic (PD) models were available for: dimethoate, omethoate, and malathion *based on a chlorpyrifos model that is no longer available*.
- Though the HTKK model employed and the PBPK-PD models all assumed 100% bioavailability, the HTKK model accounts for hepatic Clint whereas PBPK-PD models incorporate additional metabolism sites in plasma, brain, and kidneys.



HTTK may provide more rapid results that are similar to or more conservative than PBPK-PD models



- Dimethoate and omethoate: PBPK-AED values using plasma and brain AUC were more than two orders of magnitude greater than the HTTK-derived AEDs
- Malathion, the PBPK-AED values were similar to the range of HTTK-derived AED₅₀ values for rat