

Paracelsus, Dose, and the Importance of Exposure in Translating Toxicology into Public Health Risk

John Wambaugh

*Center for Computational Toxicology and Exposure
Office of Research and Development
U.S. Environmental Protection Agency*



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

US EPA Office of Research and Development

- The Office of Research and Development (ORD) is the scientific research arm of EPA
 - 543 peer-reviewed journal articles in 2019
- Research is conducted by ORD's four national centers, and three offices organized to address:
 - Public health and env. assessment; comp. tox. and exposure; env. measurement and modeling; and env. solutions and emergency response.
- 13 facilities across the United States
- Research conducted by a combination of Federal scientists (including uniformed members of the **Public Health Service**); contract researchers; and postdoctoral, graduate student, and post-baccalaureate trainees



ORD Facility in
Research Triangle Park, NC

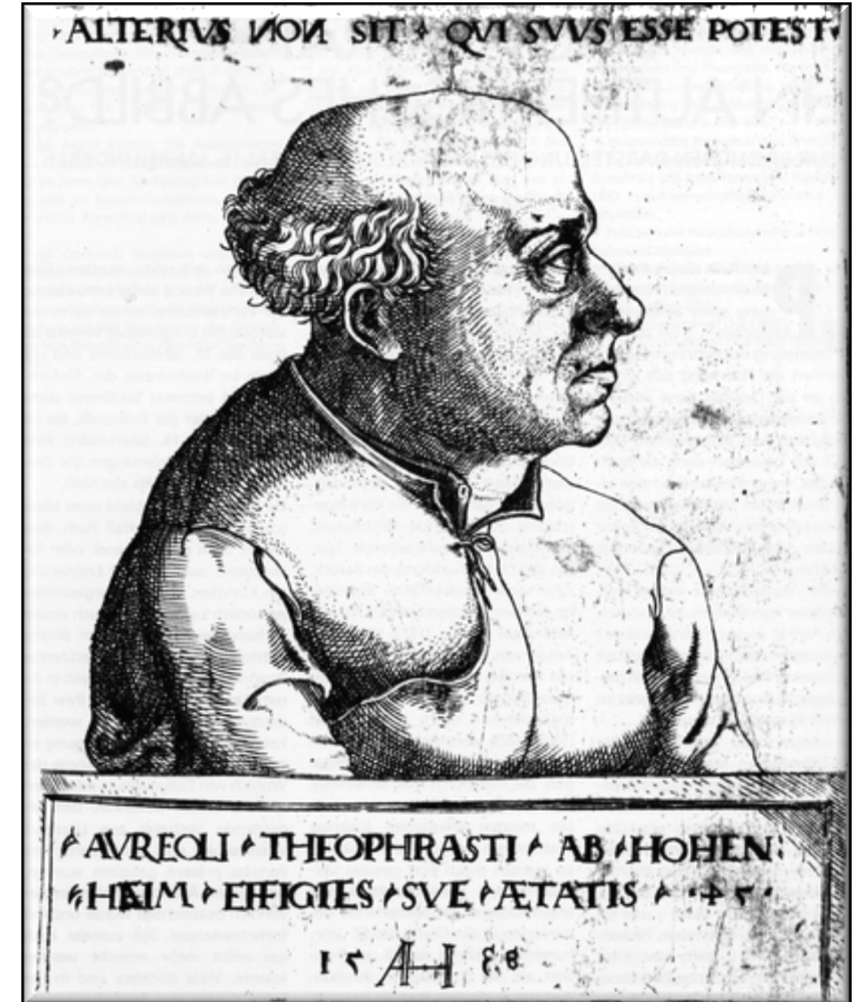
Paracelsus

“What is there that is not poison? All things are poison and nothing is without poison. Solely the dose determines that a thing is not a poison” — Paracelsus (1493-1541)

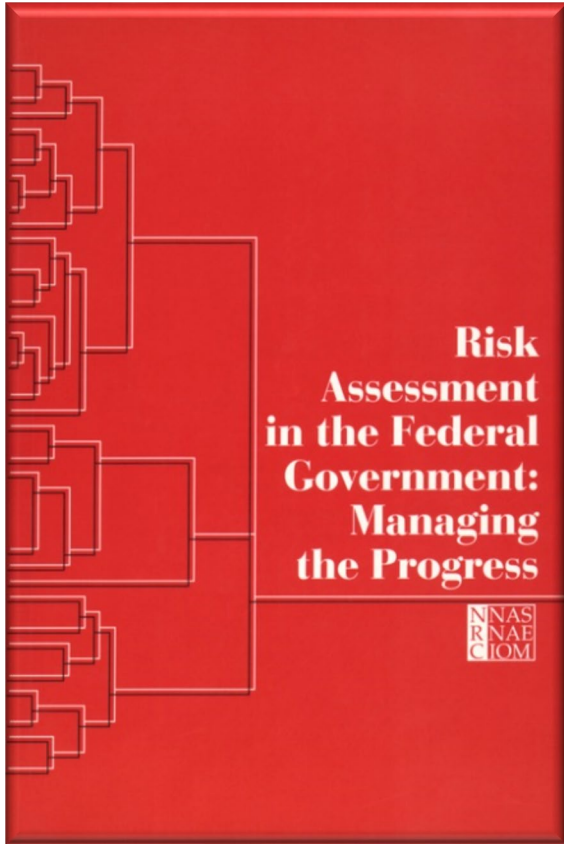
Complications (adapted from Grandjean, 2016):

- Many thousands of chemicals in the environment
- Developmental windows of susceptibility
- Confounding benefits (nutrition vs. toxicity)
- Genetic variability in susceptibility
- Variability in exposure (occupational, heavy users)

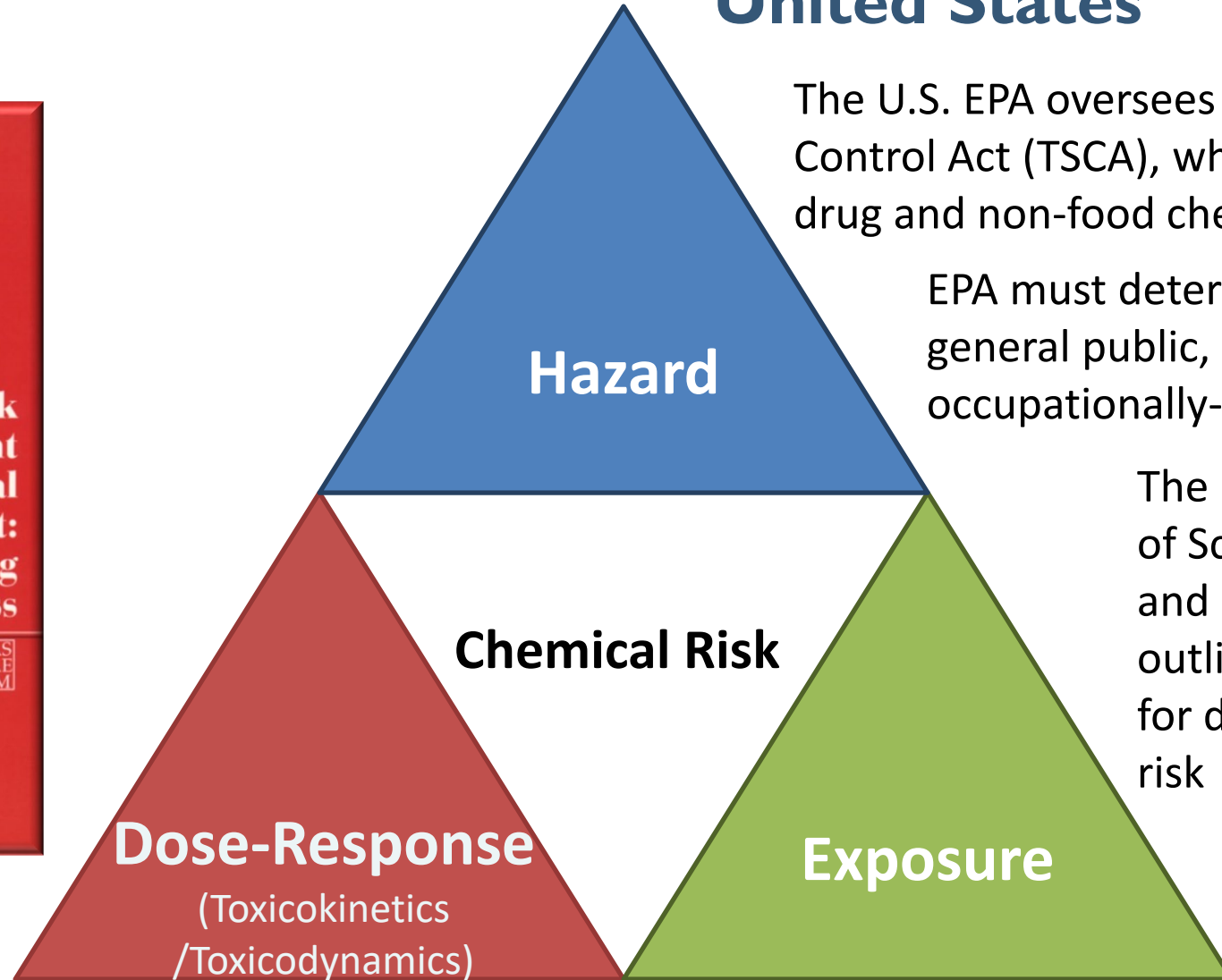
“From a public health viewpoint, toxicology needs to provide better guidance on decision-making under ever-present uncertainty” — Grandjean (2016)



Three Components for Chemical Risk in the United States



NRC (1983)



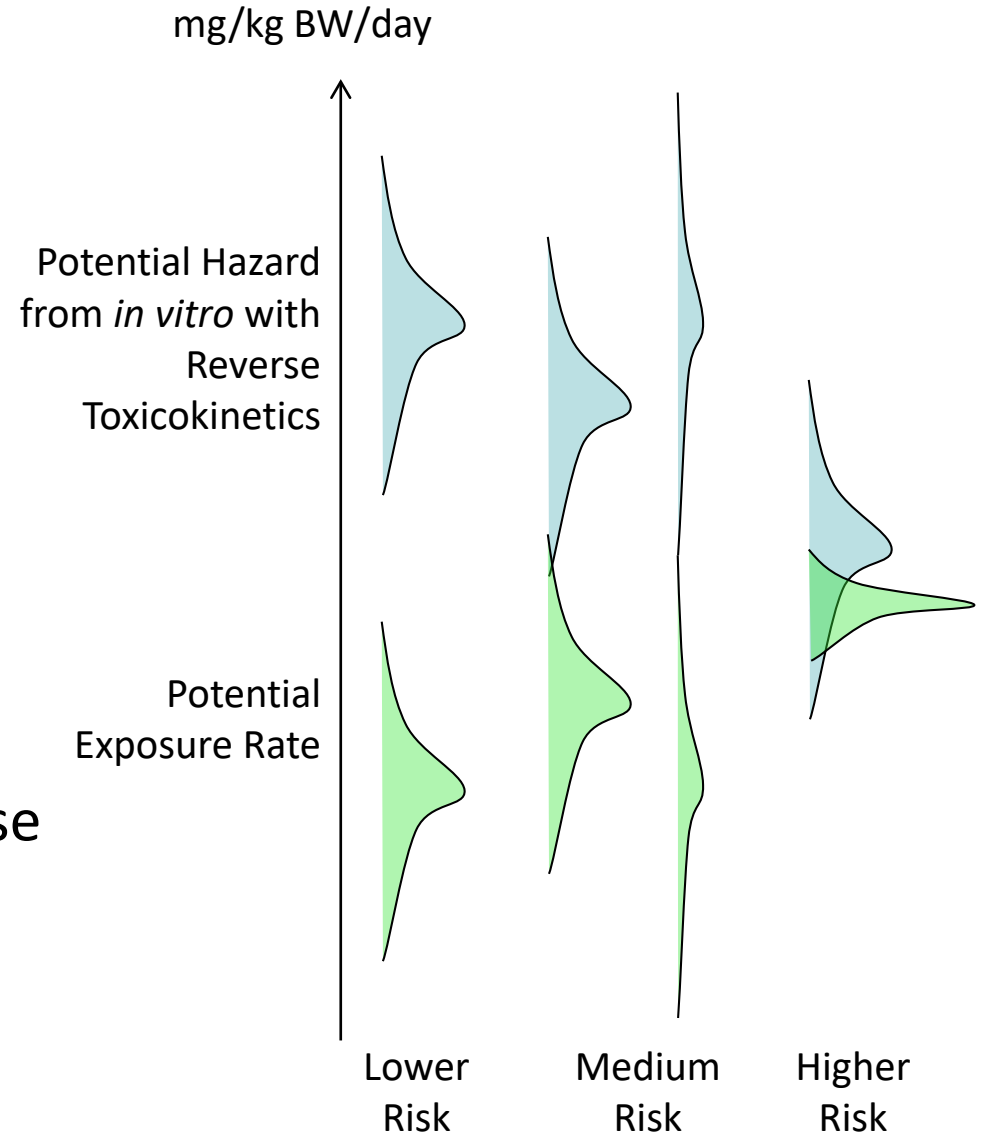
The U.S. EPA oversees the U.S. Toxic Substances Control Act (TSCA), which regulates most non-drug and non-food chemicals

EPA must determine risk to the general public, sensitive, and occupationally-exposed populations

The U.S. National Academy of Sciences, Engineering and Medicine (1983) outlined three components for determining chemical risk

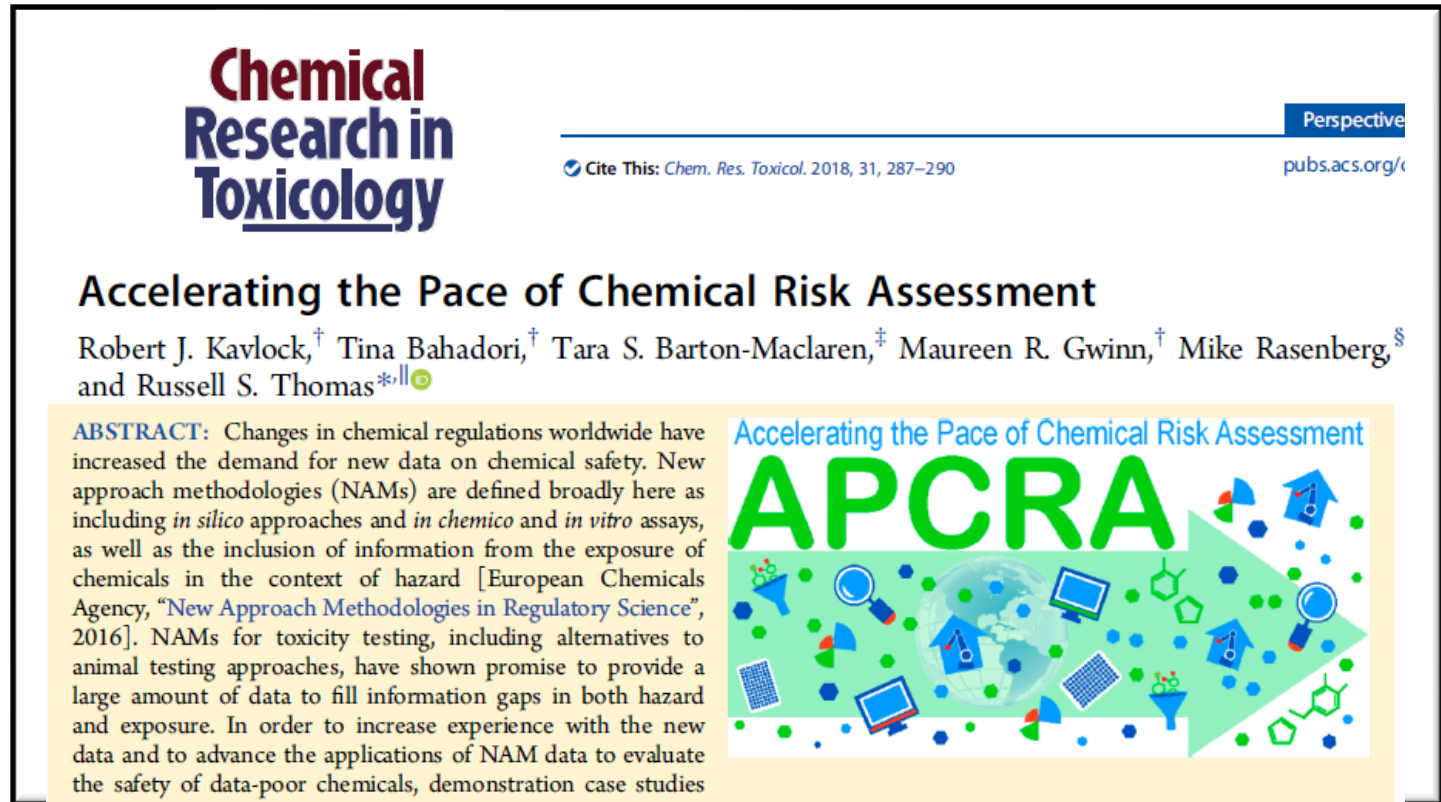
Decision-Making Under Ever-Present Uncertainty

- There are roughly 10,000 TSCA-relevant chemicals in commerce
 - Traditional methods are too resource-intensive to address all of these
- Therefore, high throughput risk prioritization needs:
 1. High throughput hazard characterization (Dix et al., 2007, Collins et al., 2008)
 2. High throughput exposure forecasts (Wambaugh et al., 2013, 2014; Ring et al., 2019)
 3. High throughput toxicokinetics (i.e., dose-response relationship) linking hazard and exposure (Wetmore et al., 2012, 2015)



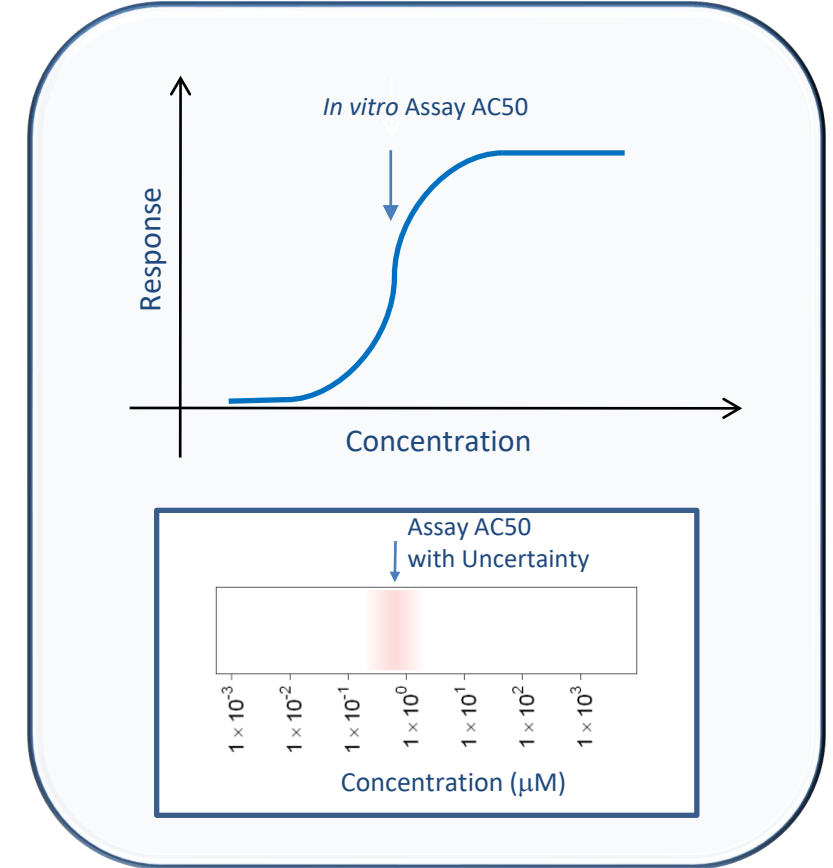
New Approach Methodologies (NAMs)

- NAMs include:
 - High throughput screening (ToxCast)
 - High throughput exposure estimates (ExpoCast)
 - High throughput toxicokinetics (HTTK)
- TSCA was updated in 2016 to allow more rapid evaluation of chemicals
- TSCA Proof of concept: Examine ~200 chemicals with ToxCast, ExpoCast and HTTK
 - Toxicokinetics was rate limiting factor on number of chemicals in study
 - *“A Proof-of-Concept Case Study Integrating Publicly Available Information to Screen Candidates for Chemical Prioritization under TSCA”*

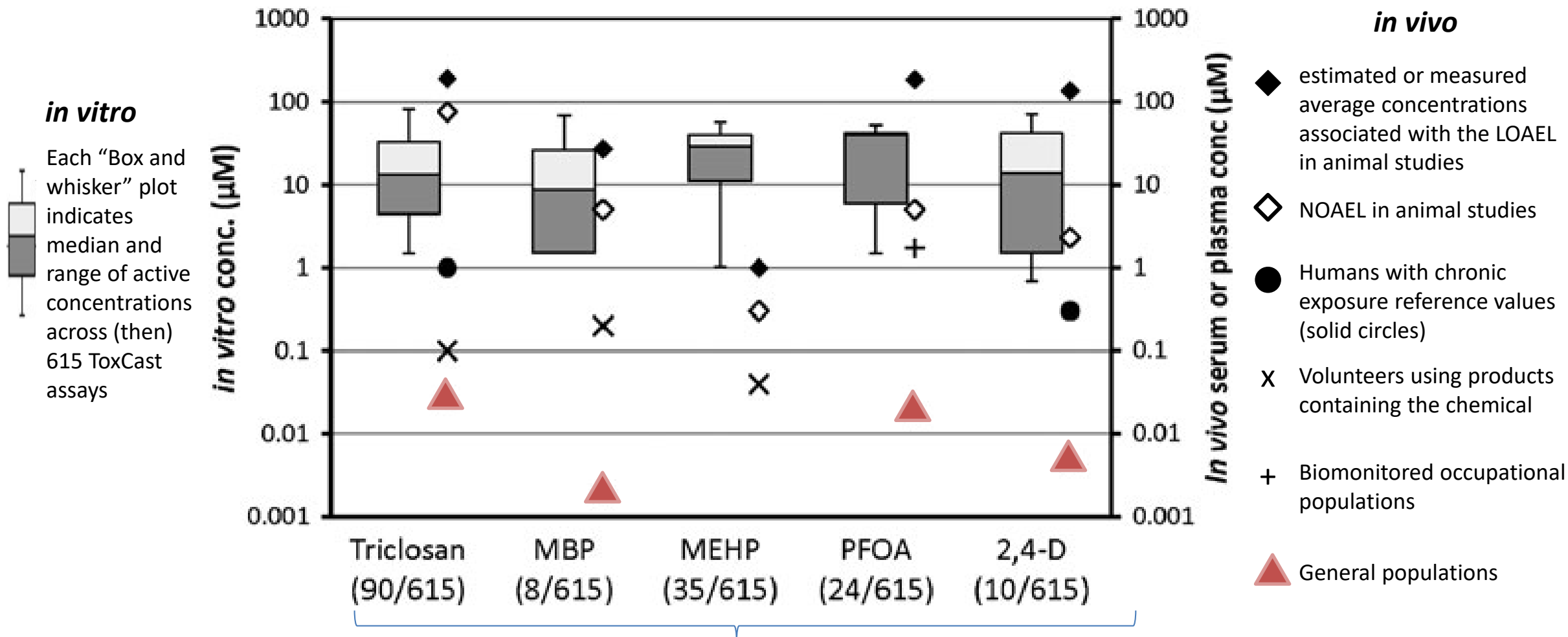


High-Throughput Bioactivity Screening Projects

- High throughput screening (HTS) for *in vitro* bioactivity potentially allows characterization of thousands of chemicals for which no other testing has occurred
- **Tox21:** Examining >8,000 chemicals using ~50 assays intended to identify interactions with biological pathways (Schmidt, 2009)
- **ToxCast:** For a subset (>2000) of Tox21 chemicals ran >1100 additional assays (Kavlock *et al.*, 2012)
- Most assays conducted in dose-response format (identify 50% activity concentration – AC_{50} – and efficacy if data described by a Hill function, Filer *et al.*, 2016)
- All data are public: <http://comptox.epa.gov/dashboard/>



The Margin Between Exposure and Hazard

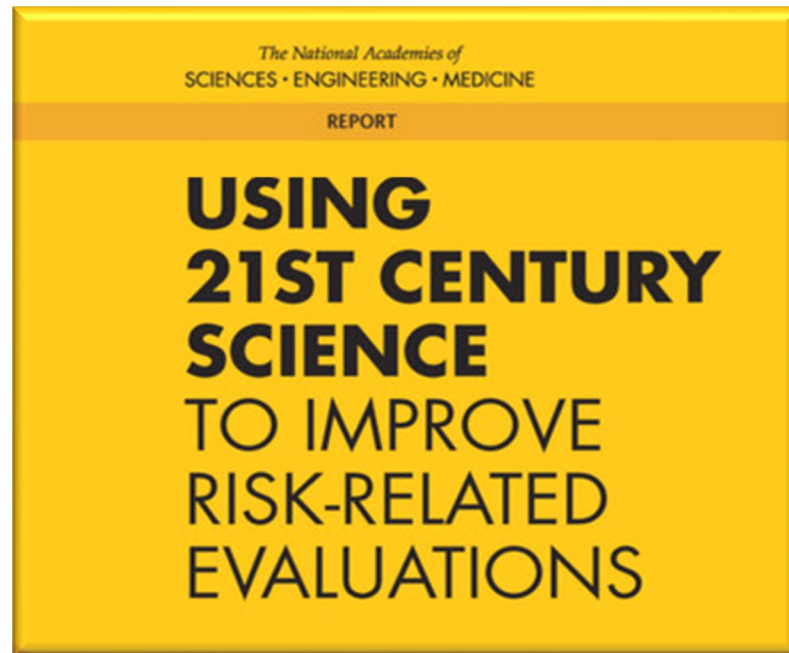


This study was limited to five chemicals by general population data on exposure

Aylward and Hays (2011)



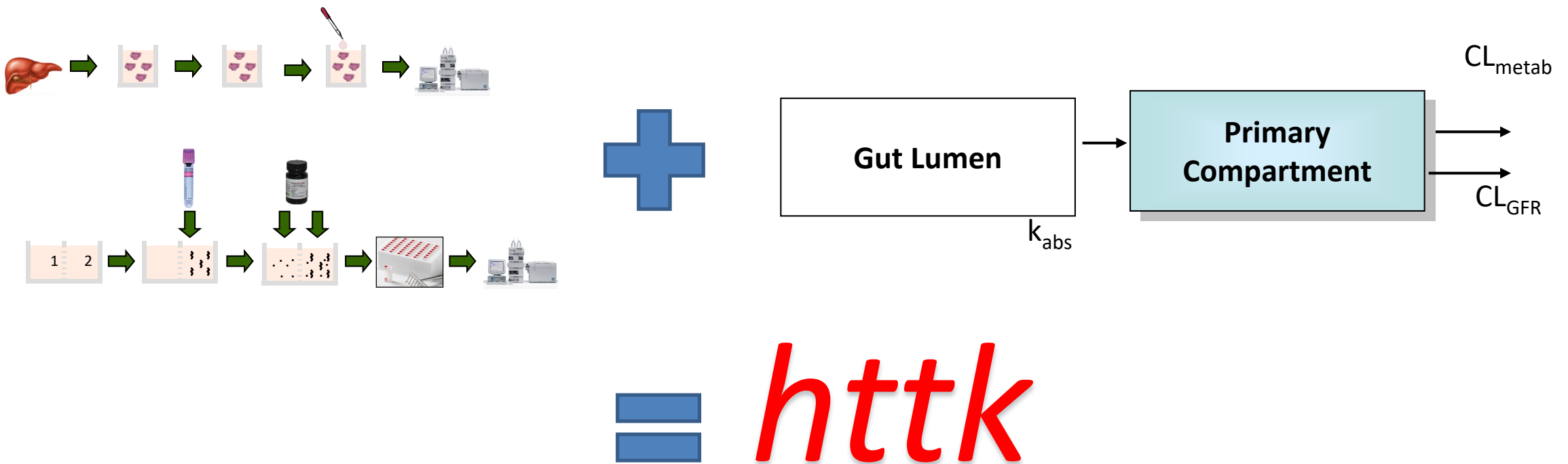
*“NAMs were taken in a broad context to **include in silico approaches**, in chemico and in vitro assays, as **well as the inclusion of information from the exposure of chemicals** in the context of hazard assessment”*



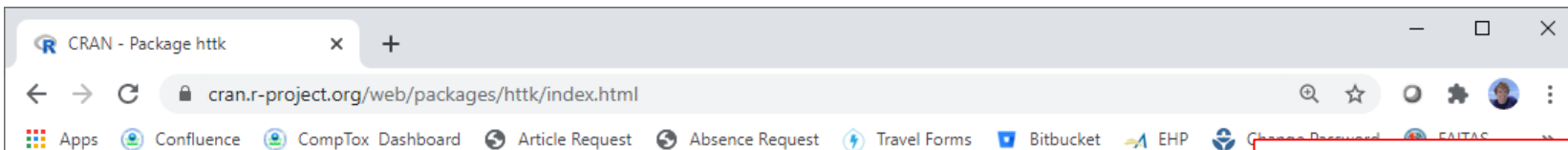
*“...the committee sees the potential for the application of **computational exposure science** to be highly valuable and credible for comparison and priority-setting among chemicals in a risk-based context.”*

NAMs for Toxicokinetics: HTTK

***In vitro* toxicokinetic data + generic toxicokinetic model
= high(er) throughput toxicokinetics**










<https://CRAN.R-project.org/package=httk>



httk: High-Throughput Toxicokinetics

Generic models and chemical-specific data for simulation and statistical analysis of chemical toxicokinetics Pearce et al. (2017) <[doi:10.18637/jss.v079.i04](https://doi.org/10.18637/jss.v079.i04)>. Chemical-specific in vitro data have been obtained from experiments. Both physiologically-based ("PBTK") and empirical (for example, one compartment) "TK" models are parameterized with the data provided for thousands of chemicals, multiple exposure routes, and various species of systems of ordinary differential equations which are solved using compiled (C-based) code for speed. A Monte Carlo simulation is included, which allows for simulating human biological variability (Ring et al., 2017 <[doi:10.1016/j.envint.2017.05.011](https://doi.org/10.1016/j.envint.2017.05.011)>), propagating parameter uncertainty. Calibrated methods are included for predicting tissue:plasma partition coefficients and in vivo extrapolation ("IVIVE") of low-dose toxicokinetics (also known as "RTK")

downloads 1071/month

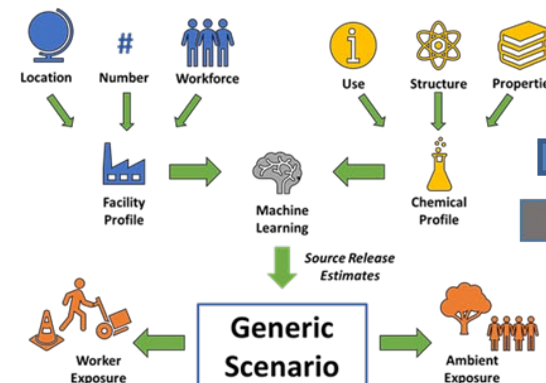
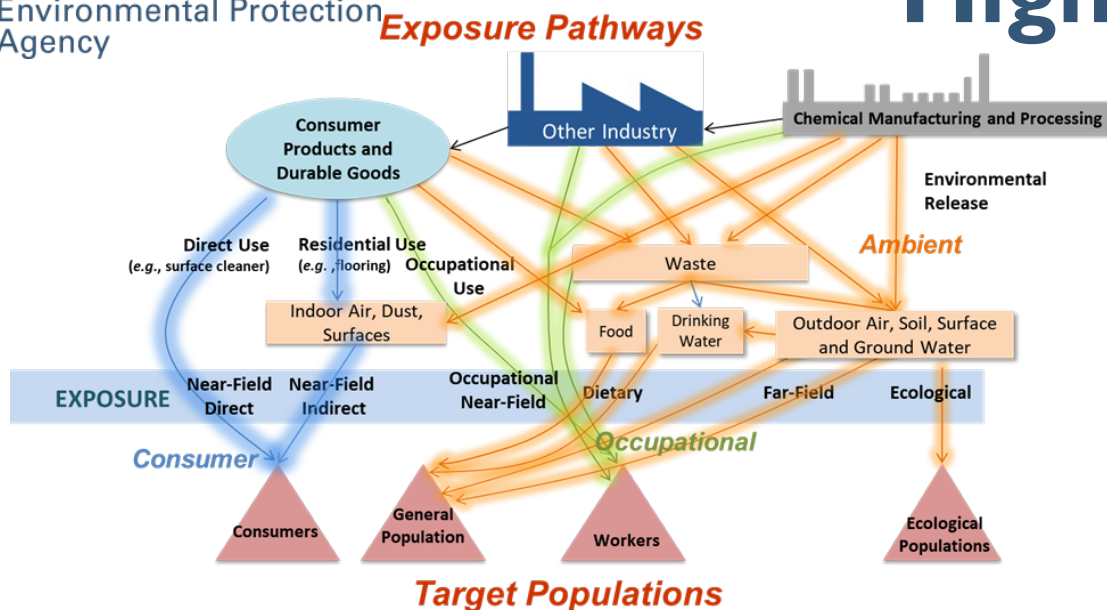
Version: 2.0.3
Depends: R (≥ 2.10)
Imports: [deSolve](#), [msm](#), [data.table](#), [survey](#), [mvtnorm](#), [truncnorm](#), stats, graphics, utils, [magrittr](#), [ggplot2](#), [knitr](#), [rmarkdown](#), [R.rsp](#), [GGally](#), [gplots](#), [scales](#), [EnvStats](#), [MASS](#), [RColorBrewer](#), [classInt](#), [ks](#), [stringr](#), [reshape](#), [reshape2](#), [gdata](#), [viridis](#), [CensRegMod](#), [gmodels](#), [colorspace](#), [dplyr](#), [forcats](#), [smatr](#), [gtools](#), [gridExtra](#)
Published: 2020-09-25
Author: John Wambaugh  [aut, cre], Robert Pearce  [aut], Caroline Ring  [aut], Greg Sfeir [aut], Matt Linakis  [aut], Jimena Davis [ctb], James Sluka  [ctb], Nisha Siwetmore  [ctb], Woodrow Setzer  [ctb]
Maintainer: John Wambaugh <wambaugh.john@epa.gov>
BugReports: <https://github.com/USEPA/CompTox-ExpoCast-httk>

R package "httk"

- Open source, transparent, and peer-reviewed tools and data for **high throughput toxicokinetics (httk)**
- Available publicly for free statistical software R
- Allows *in vitro-in vivo* extrapolation (IVIVE) and physiologically-based toxicokinetics (PBTK)
- Human-specific data for >1000 chemicals
- Oral, intravenous, and inhalation exposure routes
- Described in Pearce et al. (2017)

NAMs for Exposure: High Throughput Models

*Occupational
for example:
ChemSteer*



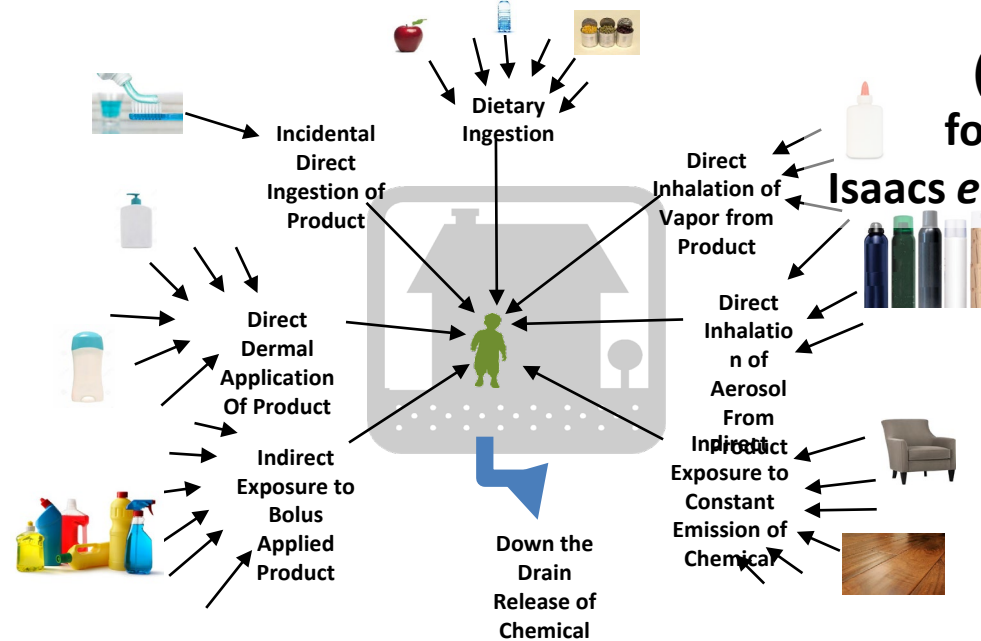
```
from . import checks
from . import exposures

class dermal_model(object):
    """
    A Python class for creating a dermal exposure model from ChemSteer.
    """
    def __init__(self, ED=1, Hwexp=1, H5=1, EY=40, BM=70, ATC=70, AT=40):
        """
        Attributes:
            route : string, declares model route to be dermal.
            ED : integer, days exposed per year; 0 < ED < 365 (default: 1 days/site-yr)
            Hwexp : integer, number of workers exposed while performing the activity
                   (default: 1 workers/site)
        """
```

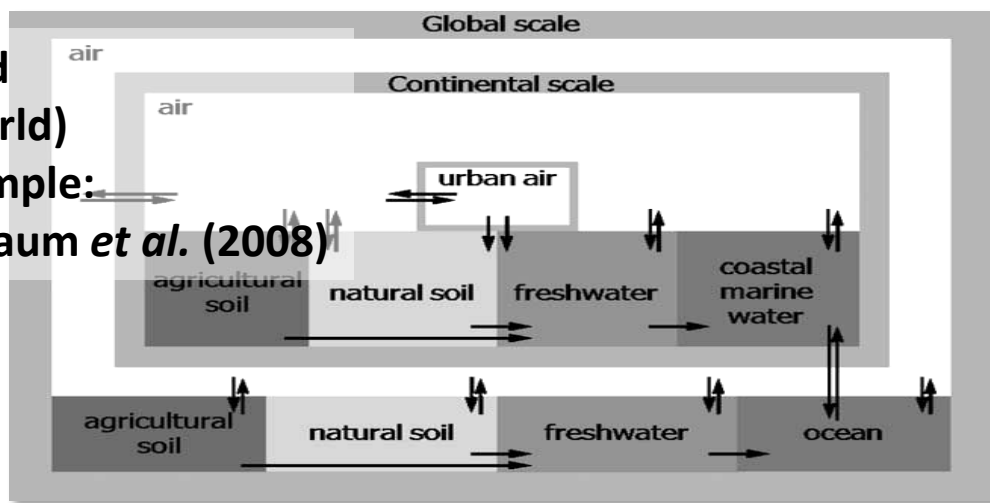
High-throughput implementation of EPA occupational models will enable rapid predictions for workers exposure

Meyer et al. (2018)

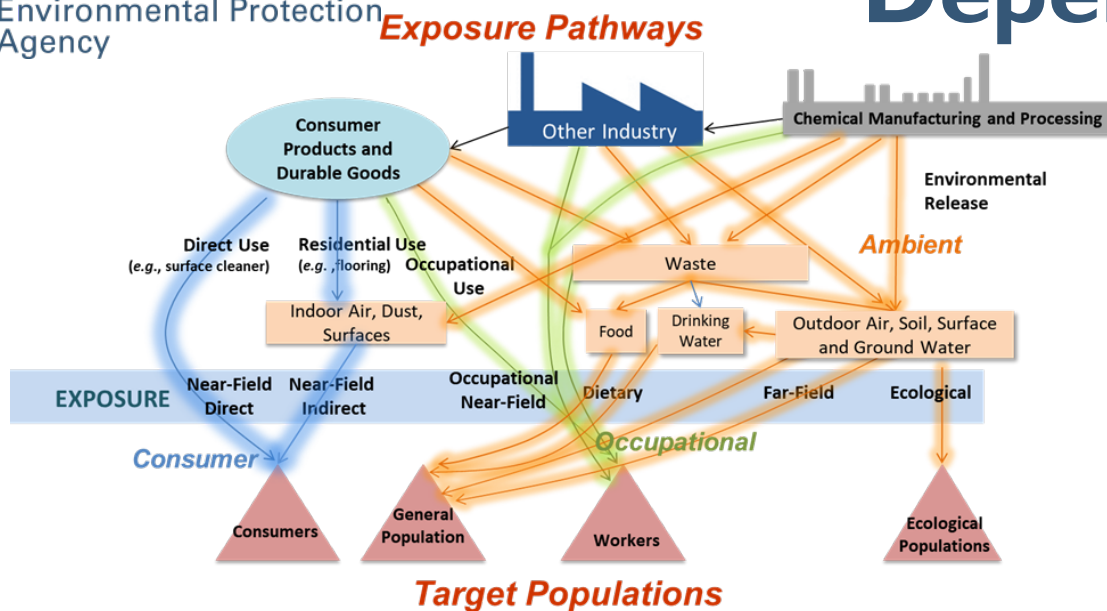
**Near-field
(the home)
for example:
Isaacs et al. (2014)**



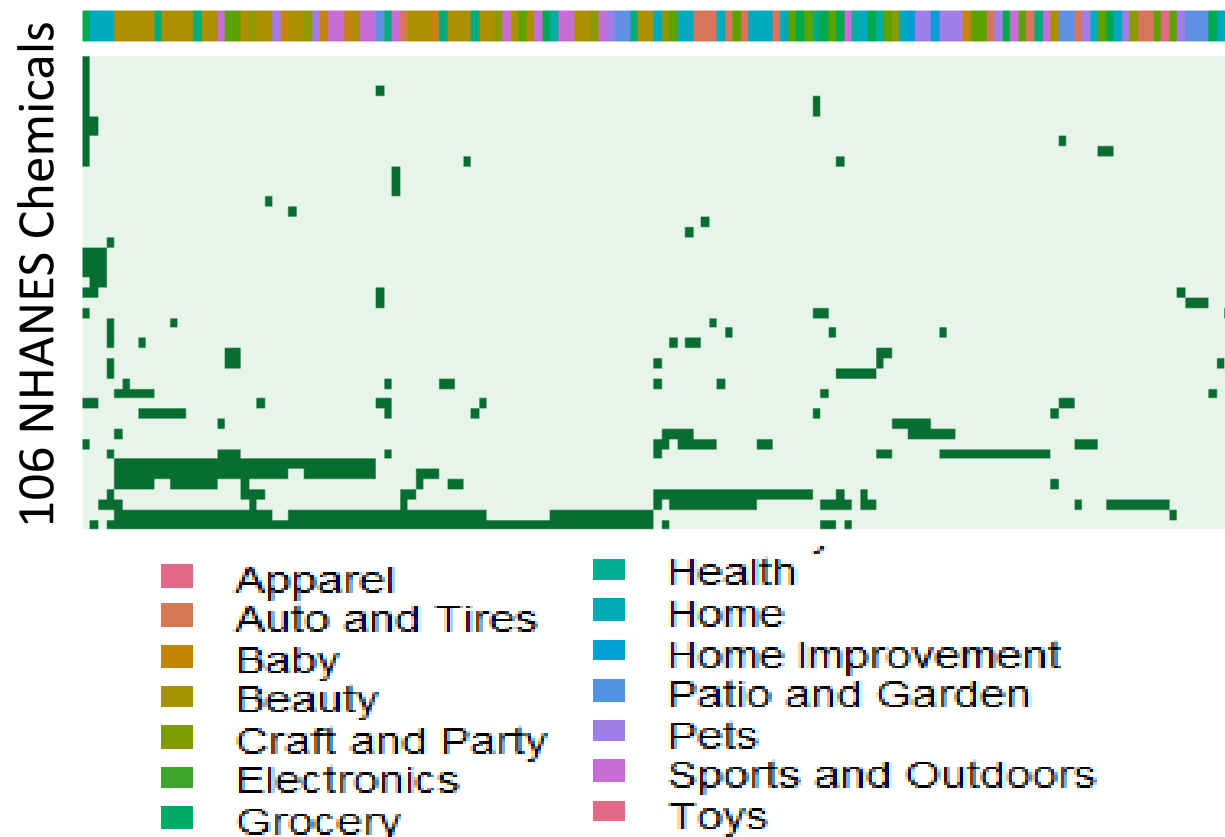
**Far-field
(the world)
for example:
Rosenbaum et al. (2008)**



Selecting the Appropriate Model Depends on Chemical Use



Occurrence of Chemicals in Retail Products
>2000 chemicals with Material Safety Data Sheets
Goldsmith *et al.*, 2014



- Different chemicals are involved in different exposure pathways
- Some pathways have much higher average exposures!
- Near field sources have been known to be important at least since 1987 – see Wallace, *et al.*

How Can we Know Chemical Use?

Chemical Property NAMs

SCIENTIFIC DATA

OPEN **Data Descriptor: The Chemical and Products Database, a resource for exposure-relevant data on chemicals in consumer products**

Received: 16 October 2017
Accepted: 30 April 2018
Published: 10 July 2018

Kathie L. Dionisio¹, Katherine Phillips¹, Paul S. Price¹, Christopher M. Grulke², Anthony Williams², Derya Biryol^{1,3}, Tao Hong⁴ & Kristin K. Isaacs¹

Contents lists available at ScienceDirect

Food and Chemical Toxicology

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

Development of a consumer product ingredient database for chemical exposure screening and prioritization

M.-R. Goldsmith^{a,*}, C.M. Grulke^a, R.D. Brooks^b, T.R. Transue^c, Y.M. Tan^a, A. Frame^{a,c}, P.P. Egeghy^a, R. Edwards^d, D.T. Chang^a, R. Tornero-Velez^a, K. Isaacs^a, A. Wang^{a,c}, J. Johnson^a, K. Holm^a, M. Reich^f, J. Mitchell^g, D.A. Vallero^a, L. Phillips^a, M. Phillips^a, J.F. Wambaugh^a, R.S. Judson^a, T.J. Buckley^a, C.C. Dary^a

MSDS Data

Occurrence and quantitative chemical composition

Green Chemistry

PAPER

High-throughput screening of chemicals as functional substitutes using structure-based classification models[†]

Katherine A. Phillips,^{a,c} John F. Wambaugh,^b Christopher M. Grulke,^b Kathie L. Dionisio^c and Kristin K. Isaacs^c

Functional Use Data

The roles that chemicals serve in products

CPCat

CPDat



Ingredient Lists

Occurrence data

Measured Data

Environmental Science & Technology

Suspect Screening Analysis of Chemicals in Consumer Products

Katherine A. Phillips,[†] Alice Yau,[‡] Kristin A. Favela,[‡] Kristin K. Isaacs,[‡] Andrew McEachran,^{§,||} Christopher Grulke,^{||} Ann M. Richard,^{||} Antony J. Williams,^{||} Jon R. Sobus,[†] Russell S. Thomas,^{||} and John F. Wambaugh^{*,||}

Measurement of chemicals in consumer products

Broad "index" of chemical uses

Contents lists available at ScienceDirect

Toxicology Reports

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

Exploring consumer exposure pathways and patterns of use for chemicals in the environment

Kathie L. Dionisio^a, Alicia M. Frame^{b,1}, Michael-Rock Goldsmith^{a,2}, John F. Wambaugh^b, Alan Liddell^{c,3}, Tommy Cathey^d, Doris Smith^b, James Vail^b, Alexi S. Ernstoff^e, Peter Fantke^e, Olivier Jolliet^f

Journal of Exposure Science and Environmental Epidemiology (2018) 28, 216–222
© 2018 Nature America, Inc., part of Springer Nature. All rights reserved 1559-0631/18
www.nature.com/jes

ORIGINAL ARTICLE

Consumer product chemical weight fractions from ingredient lists

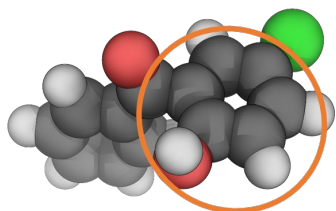
Kristin K. Isaacs¹, Katherine A. Phillips¹, Derya Biryol^{1,2}, Kathie L. Dionisio¹ and Paul S. Price¹

Machine Learning NAMs for Exposure

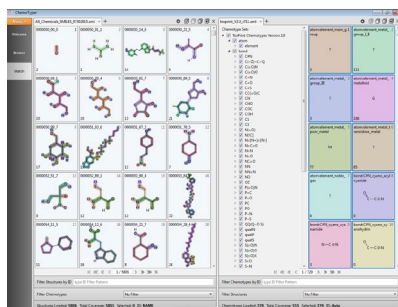
Use Database (FUSE)



“...machine learning can be thought of as inferring plausible models to explain observed data.” Gharamani (2015)



Chemical Structure and
Property Descriptors



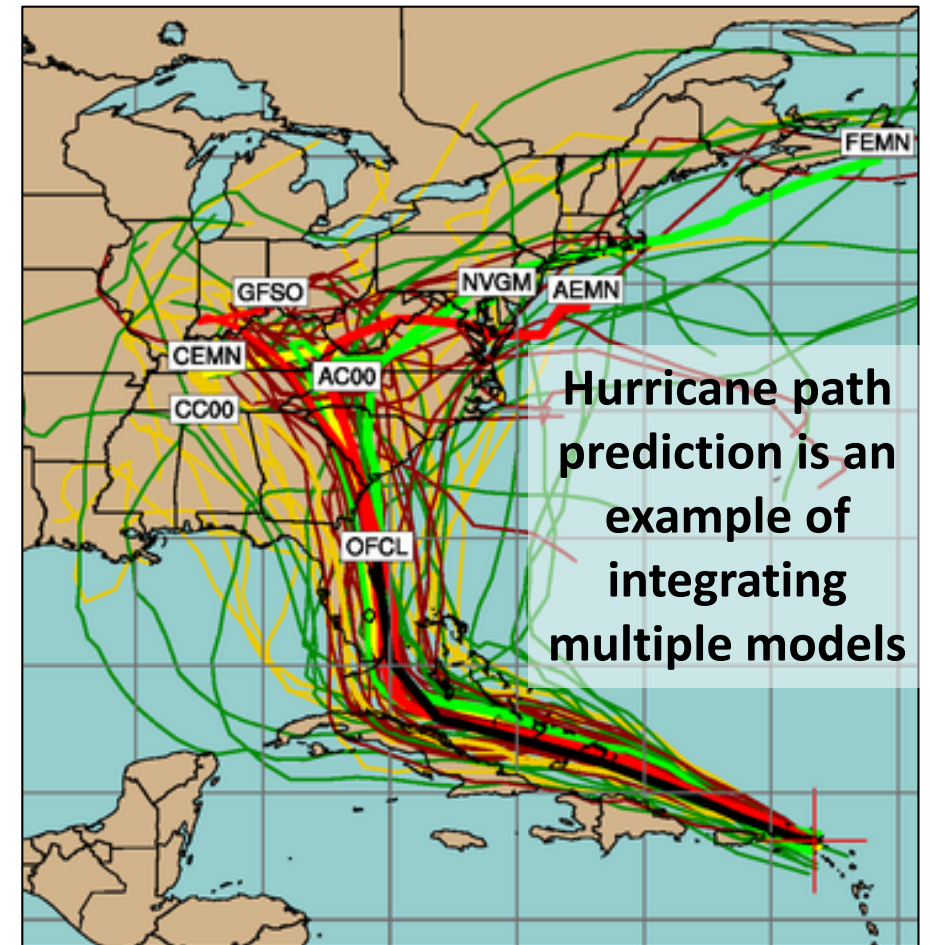
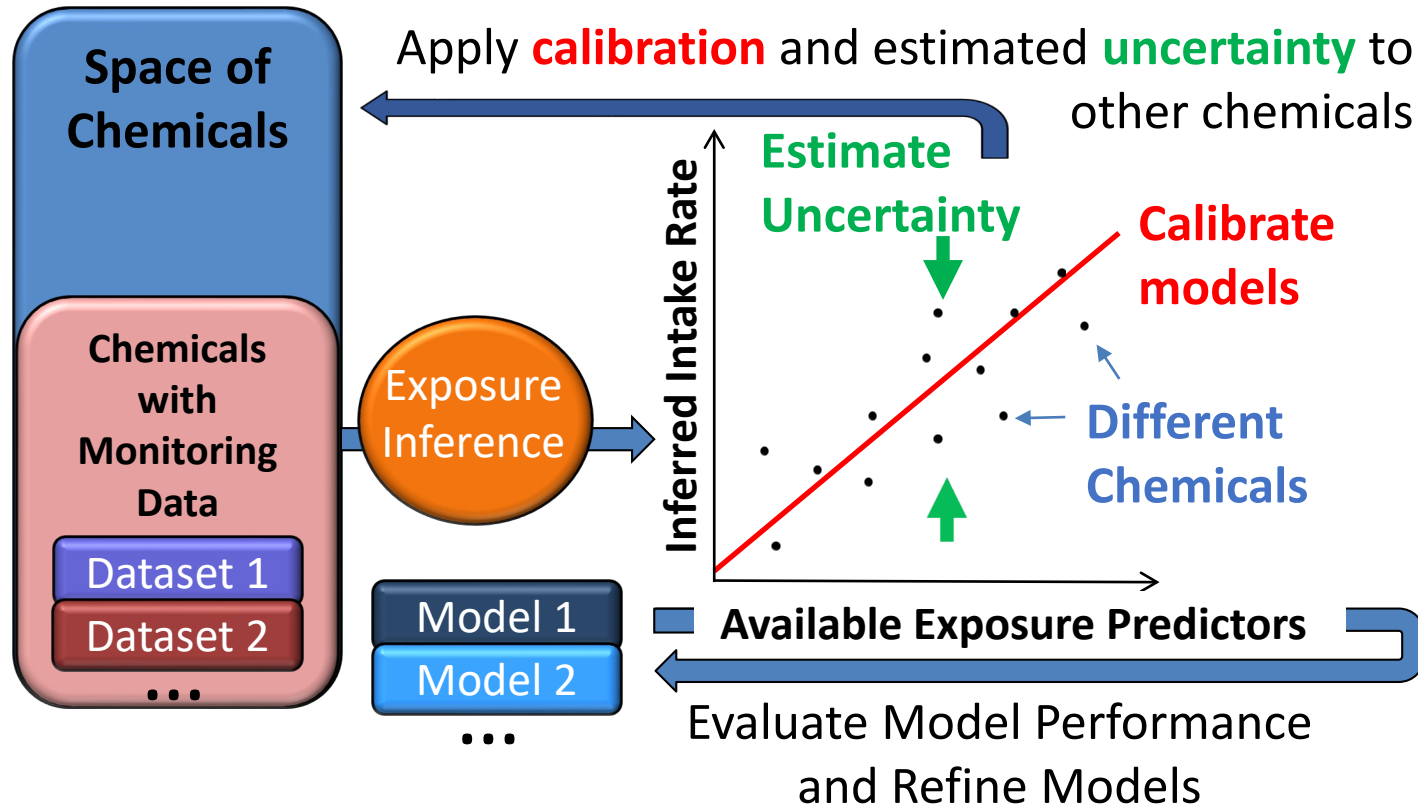
Prediction of
Of Potential
Alternatives from
Chemical Libraries

Machine Learning Based Classification Models
(Random Forest, Breiman, 2001)

Phillips *et al.* (2017)

Evaluation NAMs for Exposure: The SEEM Framework

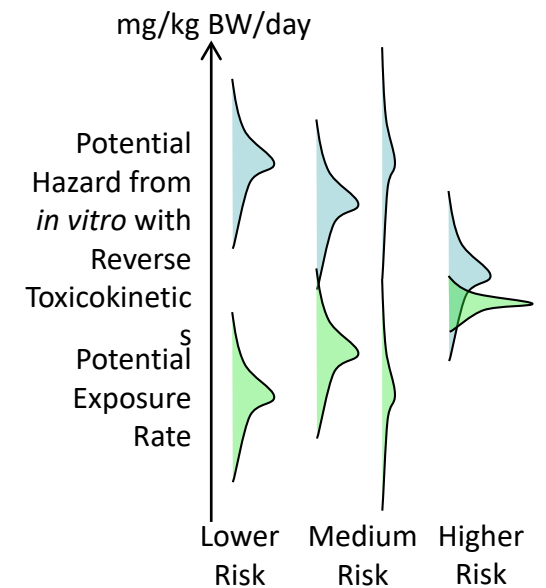
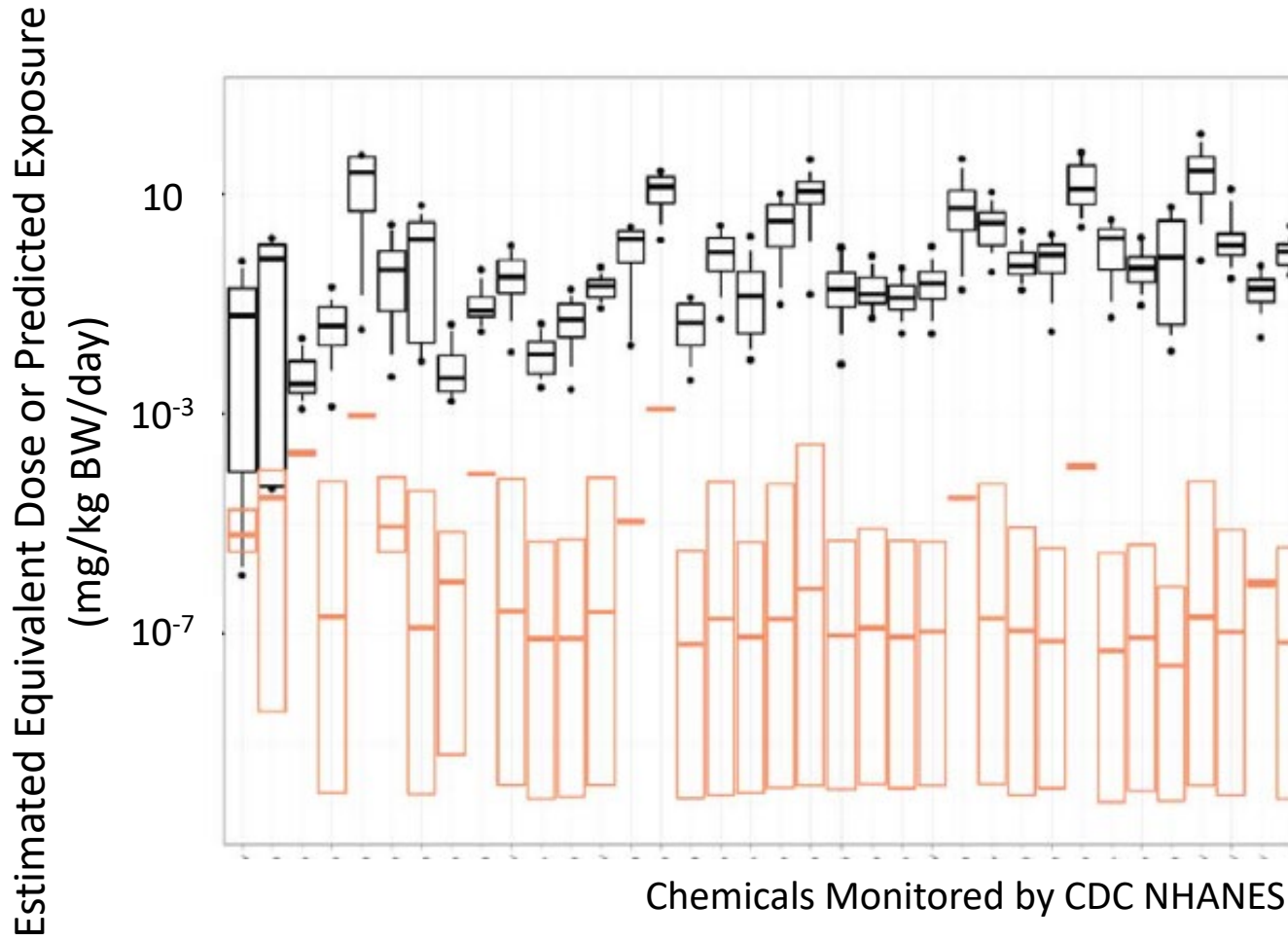
- We use Bayesian methods to incorporate multiple models into consensus predictions for 1000s of chemicals within the **Systematic Empirical Evaluation of Models (SEEM)** (Wambaugh et al., 2013, 2014; Ring et al., 2018)



Chemical Prioritization NAMs

High throughput *in vitro* screening can estimate doses needed to cause bioactivity (for example, Wetmore et al., 2015)

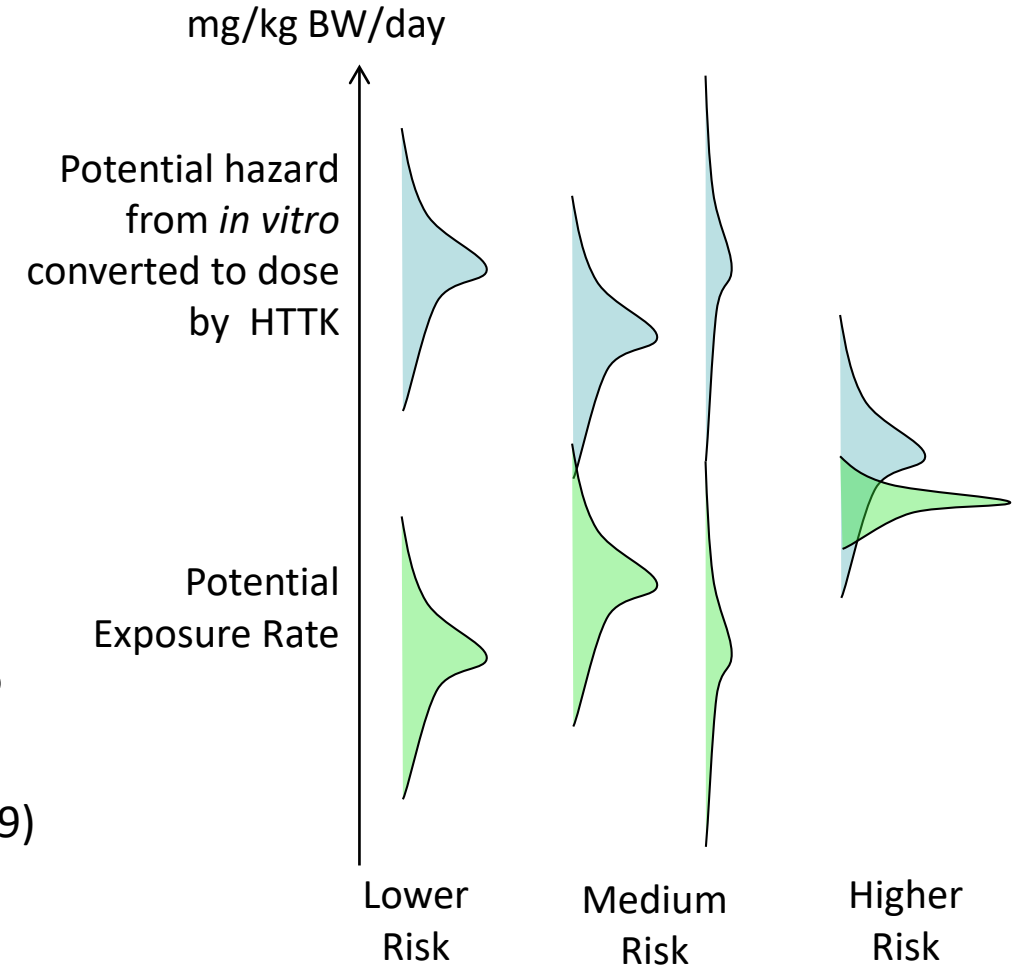
Exposure intake rates can be inferred from biomarkers (for example, Ring et al., 2018)



Ring et al. (2017)

Summary

- We must consider **exposure** to identify chemical risk – for example, windows of developmental susceptibility and occupational exposure
- In the U.S. **both** the toxic potency (**hazard**) and the magnitude of the **exposure** is needed to calculate risk
 - There are thousands of chemicals in commerce and the environment without these data
- **New approach methodologies (NAMs)** are being developed to prioritize these existing and new chemicals for testing
 - These NAMs include TK and exposure (Wambaugh et al., 2019)
- If the **uncertainty** in these tools is **properly evaluated and quantified**, we can inform public health decision making



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



ExpoCast Project (Exposure Forecasting)

Center for Computational Toxicology and Exposure

Linda Adams	Mike Hughes
Lucas Albrecht	Victoria Hull*
Matthew Boyce*	Kristin Isaacs
Miyuki Breen*	Richard Judson
Alex Chao	Jen Korol-Bexell*
Daniel Dawson*	Anna Kreutz*
Mike Devito	Charles Lowe*
Christopher Eklund	Katherine Phillips
Peter Egeghy	Paul Price
Marina Evans	Tom Purucker
Alex Fisher*	Ann Richard
Rocky Goldsmith	Caroline Ring
Louis Groff*	Risa Sayre*
Chris Grulke	Mark Sfeir*
Colin Guider*	Marci Smeltz*

Jon Sobus
Zach Stanfield*
Mike Tornero-Velez
Rusty Thomas
Elin Ulrich
Dan Vallero
Barbara Wetmore
John Wambaugh
Antony Williams

CEMM

Hongwan Li
Xiaoyu Liu
Seth Newton
Mark Strynar

Collaborators

Arnot Research and Consulting
Jon Arnot
Johnny Westgate
Integrated Laboratory Systems
Kamel Mansouri
Xiaoqing Chang
Shannon Bell
National Toxicology Program
Steve Ferguson
Nisha Sipes
Ramboll
Harvey Clewell
Silent Spring Institute
Robin Dodson
Simulations Plus
Michael Lawless
Southwest Research Institute
Alice Yau
Kristin Favela
Summit Toxicology
Lesla Aylward
Technical University of Denmark
Peter Fantke
Unilever
Beate Nicol
Cecilie Rendal
Ian Sorrell
United States Air Force
Heather Pangburn
Matt Linakis
University of California, Davis
Deborah Bennett
University of Michigan
Olivier Jolliet
University of Texas, Arlington
Hyeong-Moo Shin

*Trainees

References

Annot, Jon A., et al. "Screening level risk assessment model for chemical fate and effects in the environment." *Environmental science & technology* 40.7 (2006): 2316-2323.

Aylward, Lesa L., and Sean M. Hays. "Consideration of dosimetry in evaluation of ToxCast™ data." *Journal of Applied Toxicology* 31.8 (2011): 741-751.

Collins FS, Gray GM, Bucher JR. Transforming environmental health protection. *Science*. 2008;319:906–907.

Dionisio, Kathie L., et al. "Exploring consumer exposure pathways and patterns of use for chemicals in the environment." *Toxicology reports* 2 (2015): 228-237.

Dionisio, Kathie L., et al. "The Chemical and Products Database, a resource for exposure-relevant data on chemicals in consumer products." *Scientific data* 5 (2018): 180125.

Dix David, et al. "The ToxCast program for prioritizing toxicity testing of environmental chemicals." *Toxicol Sci*. 2007;95:5–12

European Chemicals Agency (ECHA). "New Approach Methodologies in Regulatory Science." *Proceedings of a Scientific Workshop*. 2016.

Filer, Dayne L., et al. "tcpl: the ToxCast pipeline for high-throughput screening data." *Bioinformatics* 33.4 (2016): 618-620.

Goldsmith, M-R., et al. "Development of a consumer product ingredient database for chemical exposure screening and prioritization." *Food and chemical toxicology* 65 (2014): 269-279.

Ghahramani, Zoubin. "Probabilistic machine learning and artificial intelligence." *Nature* 521.7553 (2015): 452-459.

Grandjean, Philippe. "Paracelsus revisited: the dose concept in a complex world." *Basic & clinical pharmacology & toxicology* 119.2 (2016): 126-132.

Isaacs, Kristin K., et al. "SHEDS-HT: an integrated probabilistic exposure model for prioritizing exposures to chemicals with near-field and dietary sources." *Environmental science & technology* 48.21 (2014): 12750-12759.

Isaacs, Kristin K., et al. "Consumer product chemical weight fractions from ingredient lists." *Journal of Exposure Science and Environmental Epidemiology* 28.3 (2018): 216.

Kavlock, Robert, et al. "Update on EPA's ToxCast program: providing high throughput decision support tools for chemical risk management." *Chemical research in toxicology* 25.7 (2012): 1287-1302.

Kavlock, R. J., et al. (2018). Accelerating the pace of chemical risk assessment. *Chemical research in toxicology*, 31(5), 287-290

National Research Council. (1983). *Risk Assessment in the Federal Government: Managing the Process* Working Papers. National Academies Press.

National Academies of Sciences, Engineering, and Medicine. (2017). *Using 21st century science to improve risk-related evaluations*. National Academies Press.

Pearce, Robert, et al. "httk: R Package for High-Throughput Toxicokinetics." *Journal of Statistical Software*, 2017

Phillips, Katherine A., et al. "High-throughput screening of chemicals as functional substitutes using structure-based classification models." *Green Chemistry* 19.4 (2017): 1063-1074.

Phillips, Katherine A., et al. "Suspect screening analysis of chemicals in consumer products." *Environmental science & technology* 52.5 (2018): 3125-3135.

Ring, Caroline L., et al. "Identifying populations sensitive to environmental chemicals by simulating toxicokinetic variability." *Environment International* 106 (2017): 105-118.

Ring, Caroline L., et al. "Consensus modeling of median chemical intake for the US population based on predictions of exposure pathways." *Environmental science & technology* 53.2 (2018): 719-732.

Rosenbaum, Ralph K., et al. "USEtox—the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment." *The International Journal of Life Cycle Assessment* 13.7 (2008): 532.

Schmidt, Charles W. "TOX 21: new dimensions of toxicity testing." *Environmental health perspectives* 117.8 (2009): A348.

US Congress. "Frank R. Lautenberg Chemical Safety for the 21st Century Act." (2016).

U.S. E.P.A. (2018) "A Working Approach for Identifying Potential Candidate Chemicals for Prioritization." <https://www.epa.gov/assessing-and-managing-chemicals-under-tsca/identifying-existing-chemicals-prioritization-under-tsca>

Wallace, Lance A., et al. "The TEAM study: personal exposures to toxic substances in air, drinking water, and breath of 400 residents of New Jersey, North Carolina, and North Dakota." *Environmental research* 43.2 (1987): 290-307.

Wambaugh, John F., et al. "High-throughput models for exposure-based chemical prioritization in the ExpoCast project." *Environmental science & technology* 47.15 (2013): 8479-848.

Wambaugh, John F., et al. "High Throughput Heuristics for Prioritizing Human Exposure to Environmental Chemicals." *Environmental science & technology* (2014).

Wambaugh, John F., (2019). New approach methodologies for exposure science. *Current Opinion in Toxicology*, 15, 76-92. of dosimetry, exposure and high-throughput screening data in chemical toxicity assessment." *Tox. Sciences* (2012)

Wetmore, Barbara A., et al. "Incorporating high-throughput exposure predictions with dosimetry-adjusted in vitro bioactivity to inform chemical toxicity testing." *Toxicological Sciences* 148.1 (2015): 121-136.