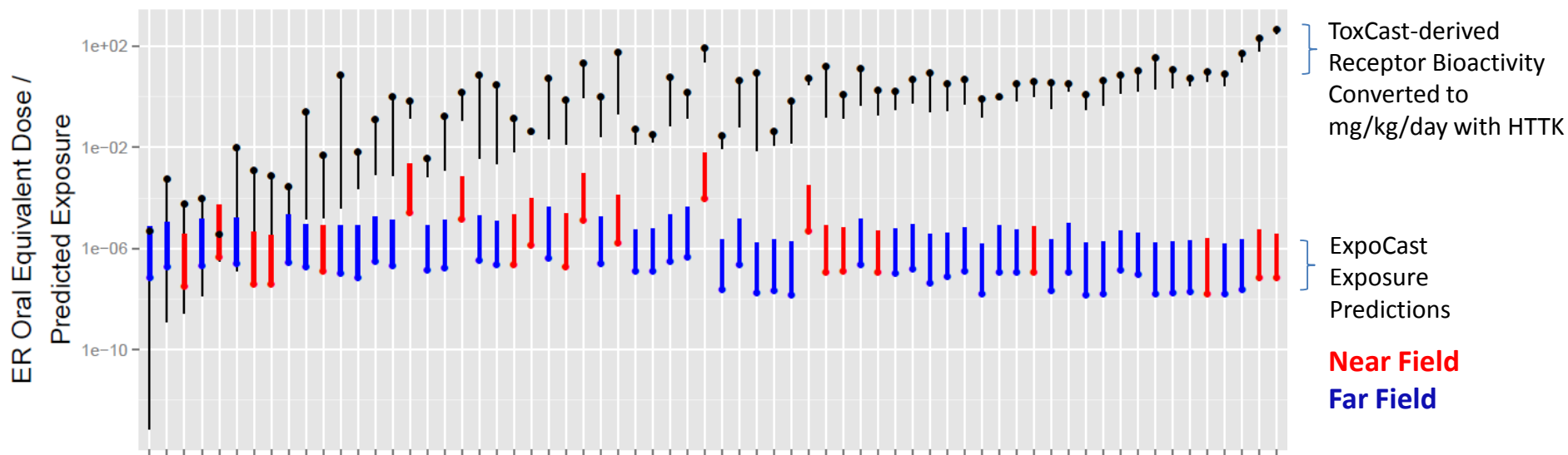


High Throughput Assays for Exposure Science

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

High Throughput Risk Prioritization in Practice



Prioritization as in
Wetmore *et al.* (2015)
Bioactivity, Dosimetry,
and Exposure Paper

ToxCast Chemicals

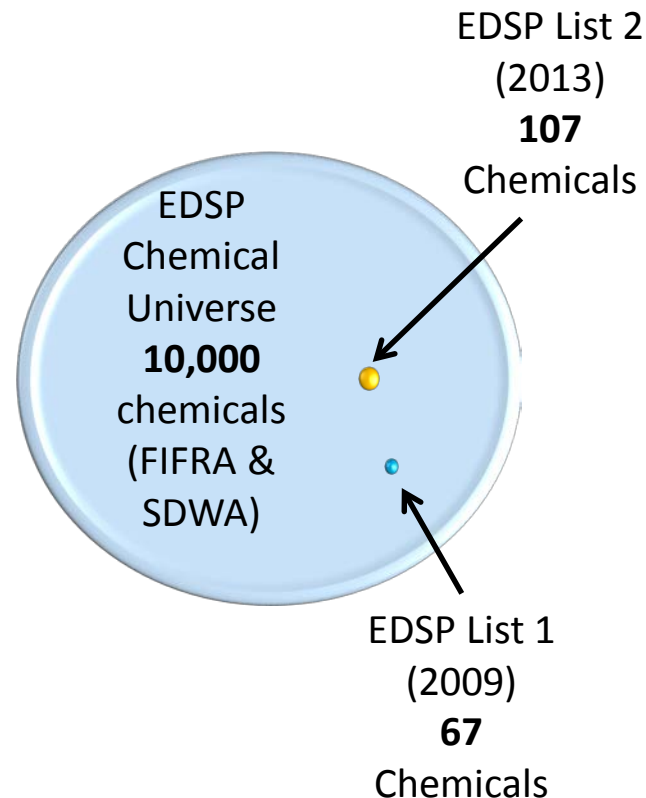
December, 2014 Panel:
“Scientific Issues Associated with Integrated
Endocrine Bioactivity and Exposure-Based
Prioritization and Screening”

Rapid exposure and dosimetry project helps
establish exposure context for ToxCast high
throughput screening

Scale of the Problem

- Park *et al.* (2012): At least 3221 chemicals in humans, many appear to be exogenous

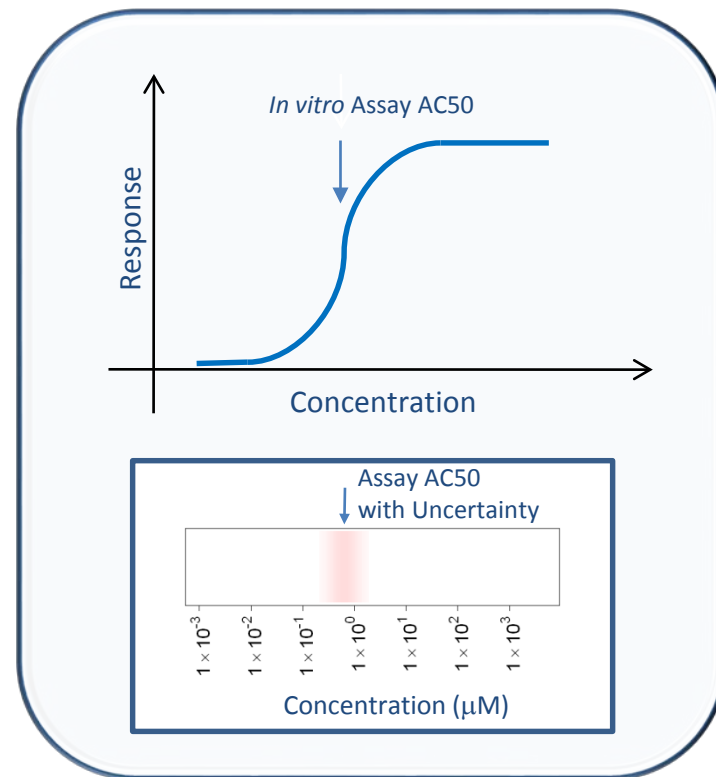
Endocrine Disruptor Screening Program (EDSP) Chemical List	Number of Compounds
Conventional Active Ingredients	838
Antimicrobial Active Ingredients	324
Biological Pesticide Active Ingredients	287
Non Food Use Inert Ingredients	2,211
Food Use Inert Ingredients	1,536
Fragrances used as Inert Ingredients	1,529
Safe Drinking Water Act Chemicals	3,616
TOTAL	10,341



So far 67 chemicals have completed testing and an additional 107 are being tested

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 dose-response format (identify 50% activity concentration – AC50 – and efficacy if data described by a Hill function)
- All data is public: <http://actor.epa.gov/>



High-Throughput Toxicokinetics

CRAN - Package http
https://cran.r-project.org/web/packages/httk/index.html

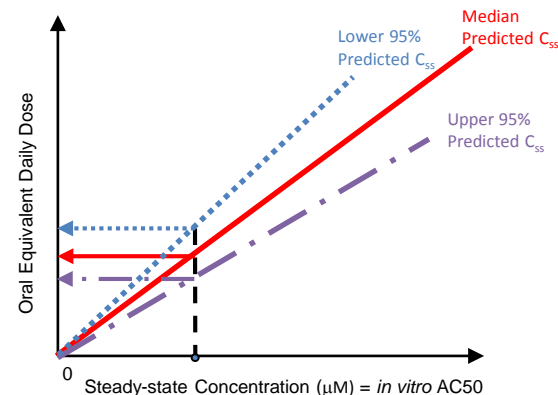
httk: High-Throughput Toxicokinetics

Functions and data tables for simulation and statistical analysis of chemical toxicokinetics ("TK") using data obtained from relatively high throughput, in vitro studies. Both physiologically-based ("PBTK") and empirical (e.g., one compartment) "TK" models can be parameterized for several hundred chemicals and multiple species. These models are solved efficiently, often using compiled (C-based) code. A Monte Carlo sampler is included for simulating biological variability and measurement limitations. Functions are also provided for exporting "PBTK" models to "SBML" and "JARNAC" for use with other simulation software. These functions and data provide a set of tools for in vitro-in vivo extrapolation ("IVIVE") of high throughput screening data (e.g., ToxCast) to real-world exposures via reverse dosimetry (also known as "RTK").

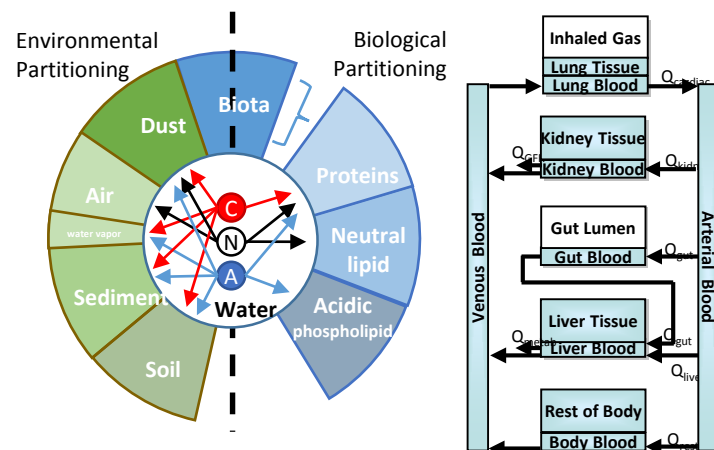
Version: 1.3
Depends: R (≥ 2.10)
Imports: deSolve, msm
Suggests: ggplot2
Published: 2015-10-14
Author: John Wambaugh and Robert Pearce, Schmitt method implementation by Jimena Davis, dynamic model adapted from code by R. Woodrow Setzer, Rabbit parameters from Nisha Sipes
Maintainer: John Wambaugh <wambaugh.john at epa.gov>
License: GPL-3
NeedsCompilation: yes
CRAN checks: [httk results](#)

Downloads:

Reference manual: [httk.pdf](#)
Package source: [httk_1.3.tar.gz](#)
Windows binaries: r-devel: [httk_1.3.zip](#), r-release: [httk_1.3.zip](#), r-oldrel: [httk_1.3.zip](#)
OS X Snow Leopard binaries: r-release: [httk_1.2.tgz](#), r-oldrel: [httk_1.2.tgz](#)
OS X Mavericks binaries: r-release: [httk_1.3.tgz](#)
Old sources: [httk archive](#)

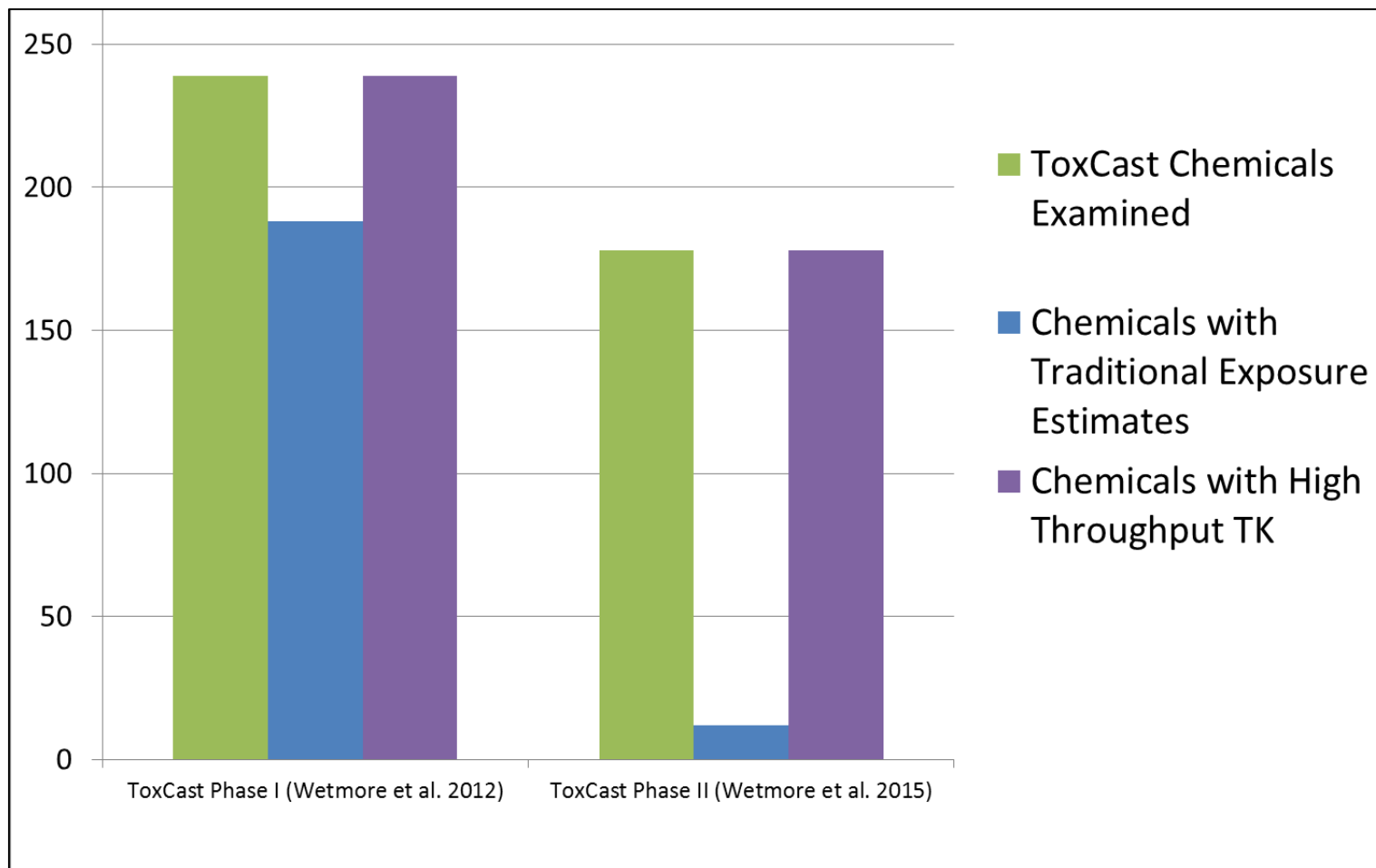


Open source *In Vitro-In Vivo*
Extrapolation and Physiological-
based Toxicokinetics



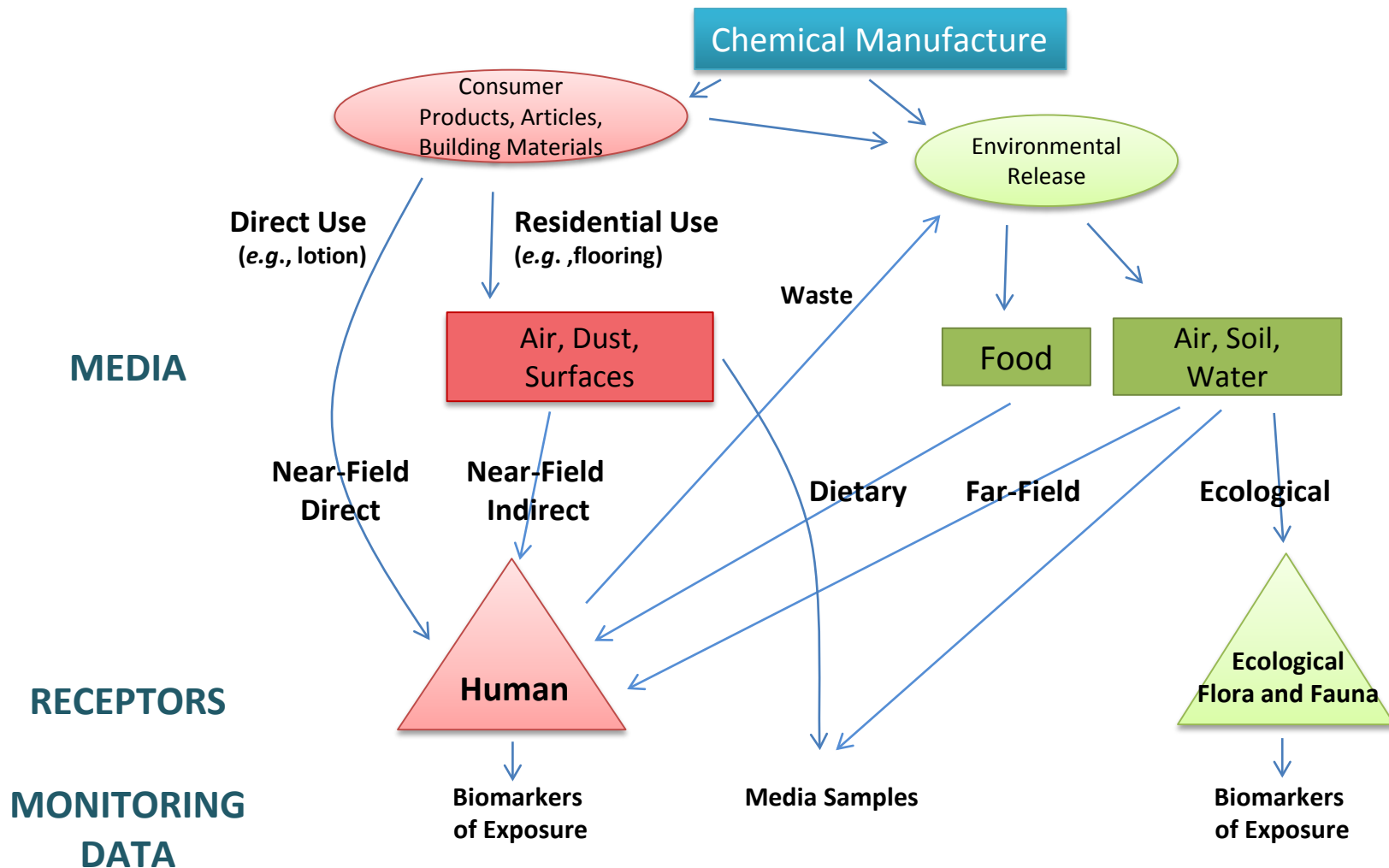
“httk” R Package
543 Chemicals to date
Lead programmer Robert Pearce
Wambaugh *et al.* (2015), Pearce *et al.* submitted

High Throughput Screening (HTS), HT Toxicokinetics (HTTK), and Exposure

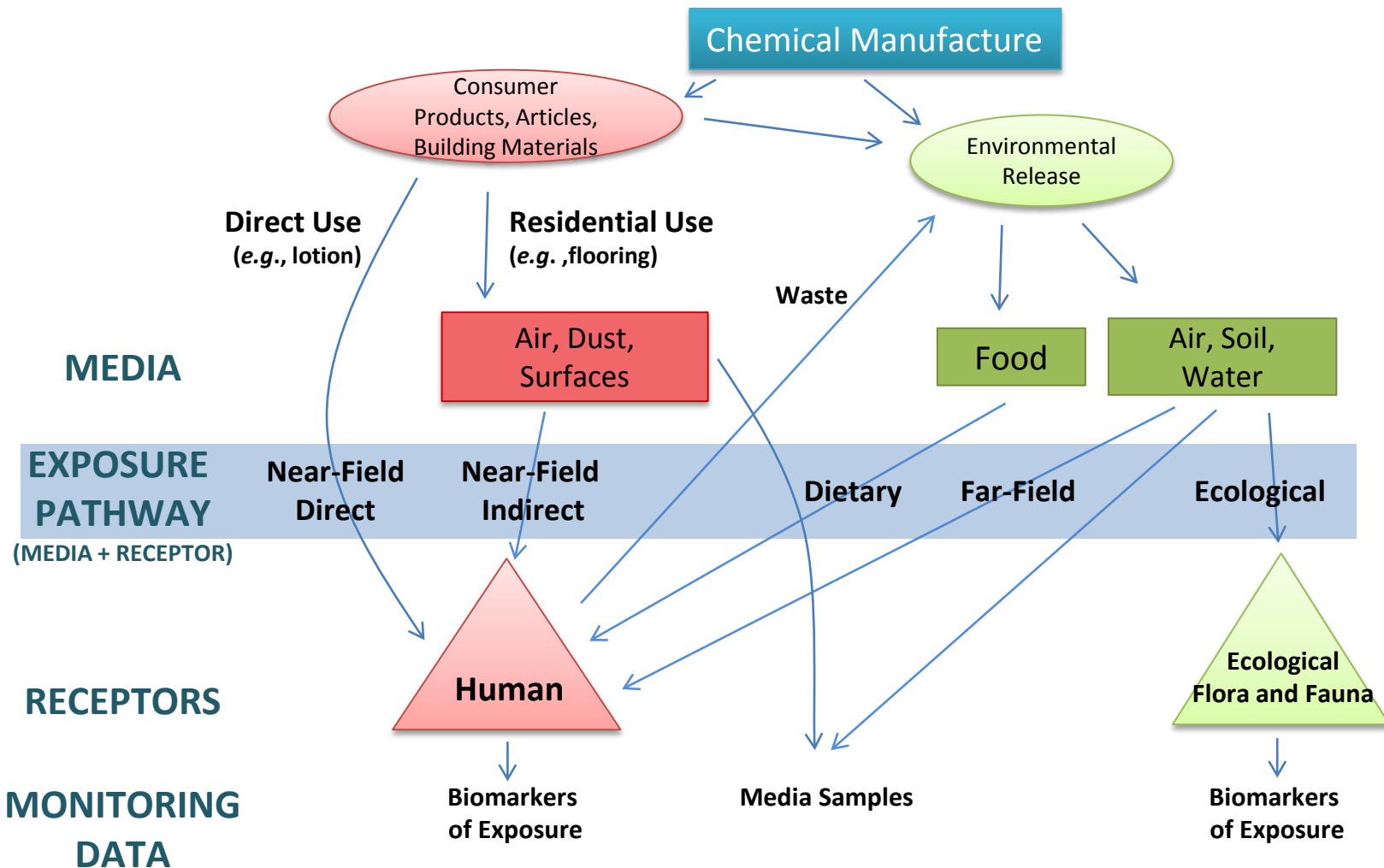


- For non-pesticide chemical space, there is a paucity of data for providing context to HTS data (Egeghy *et al.* (2012))

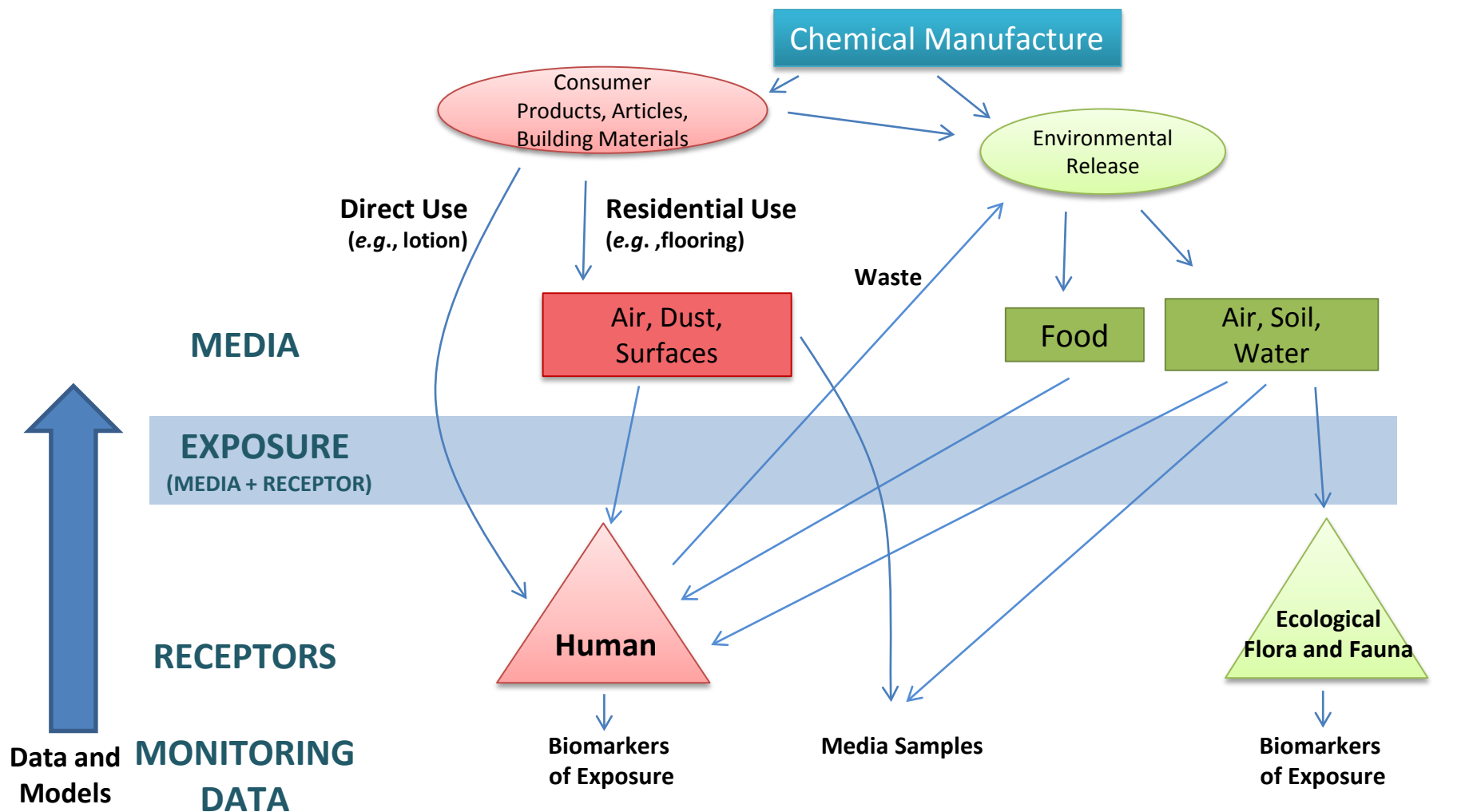
Thinking About Exposure



Exposure Pathways

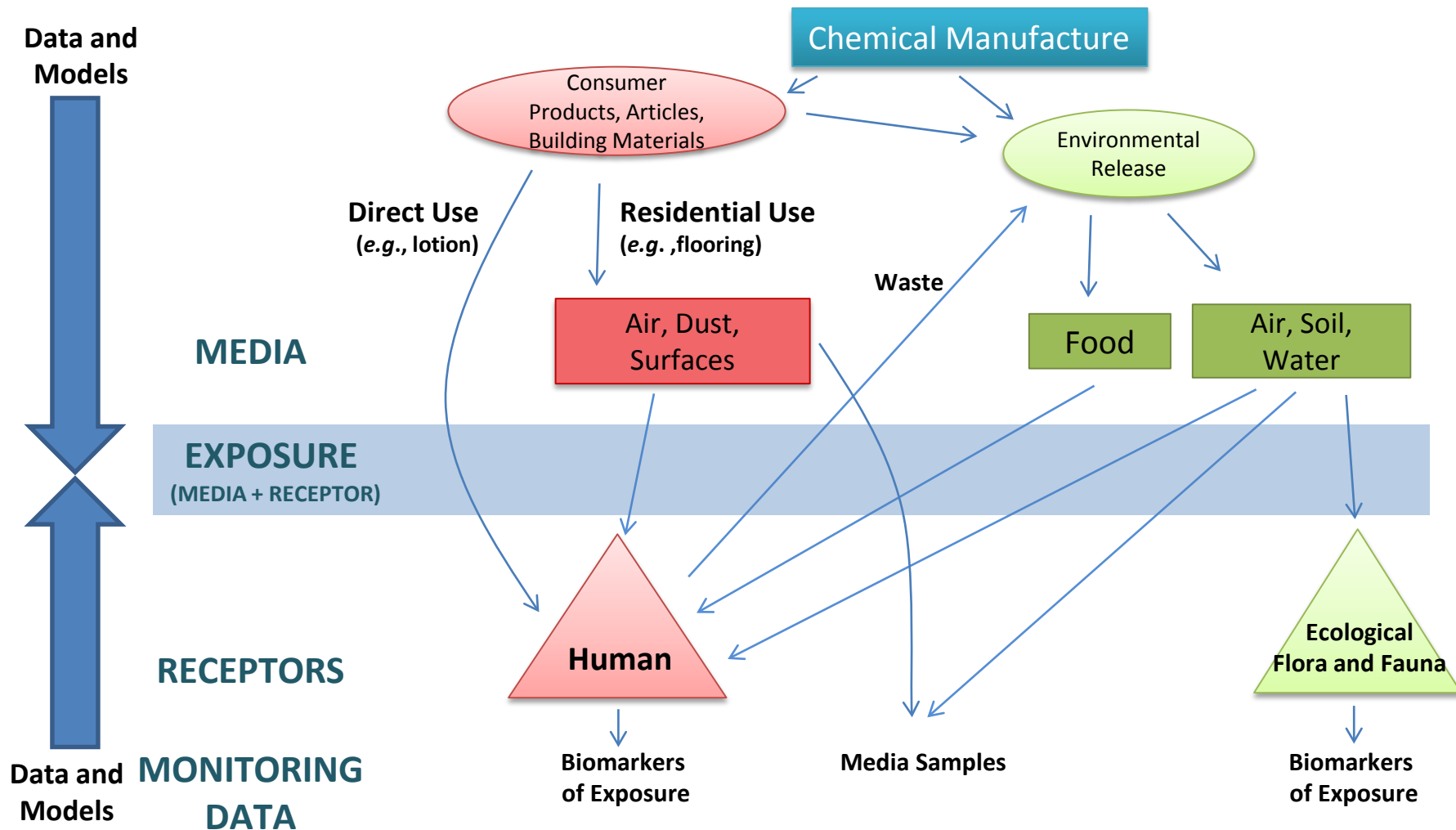


Exposure Monitoring



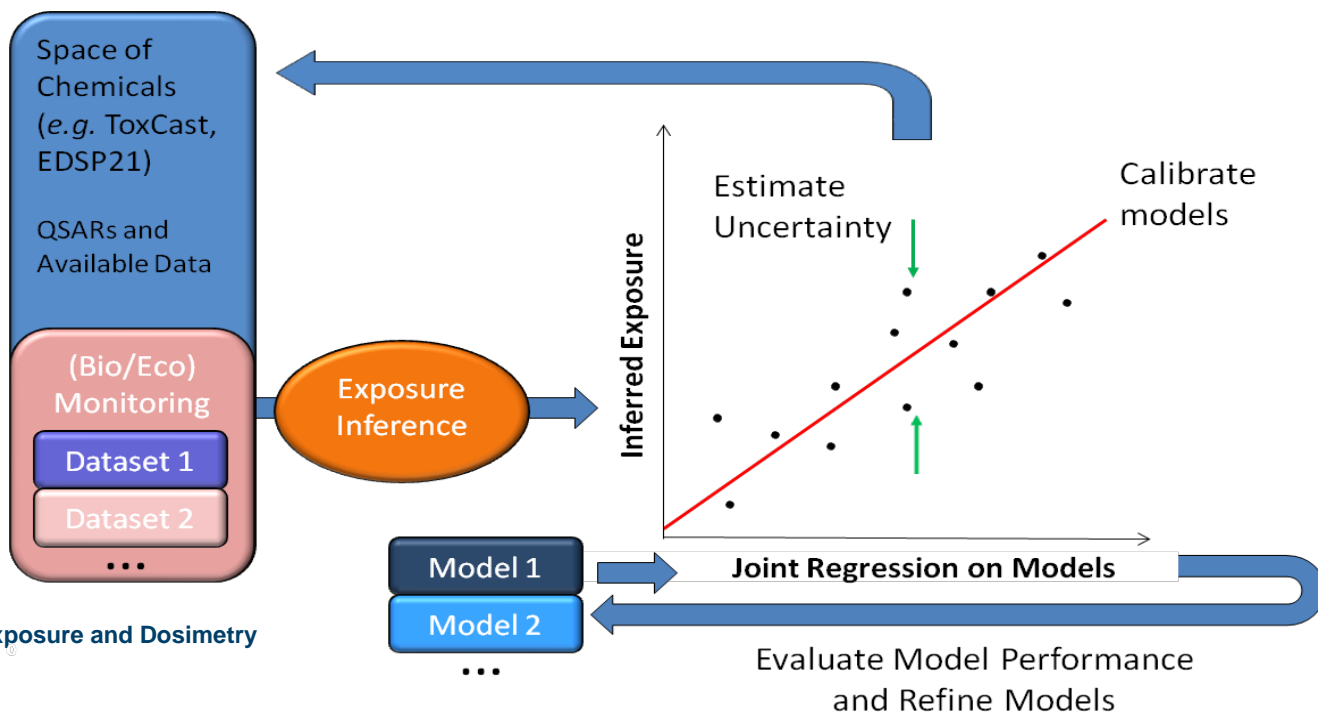
- Centers for Disease Control monitors a few hundred specific chemicals in urine and blood of U.S. citizens

Evaluating Exposure Models

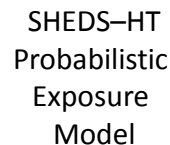
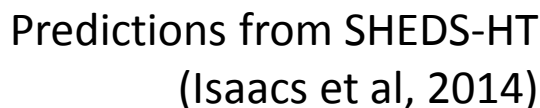


Consensus Exposure Predictions with the SEEM Framework

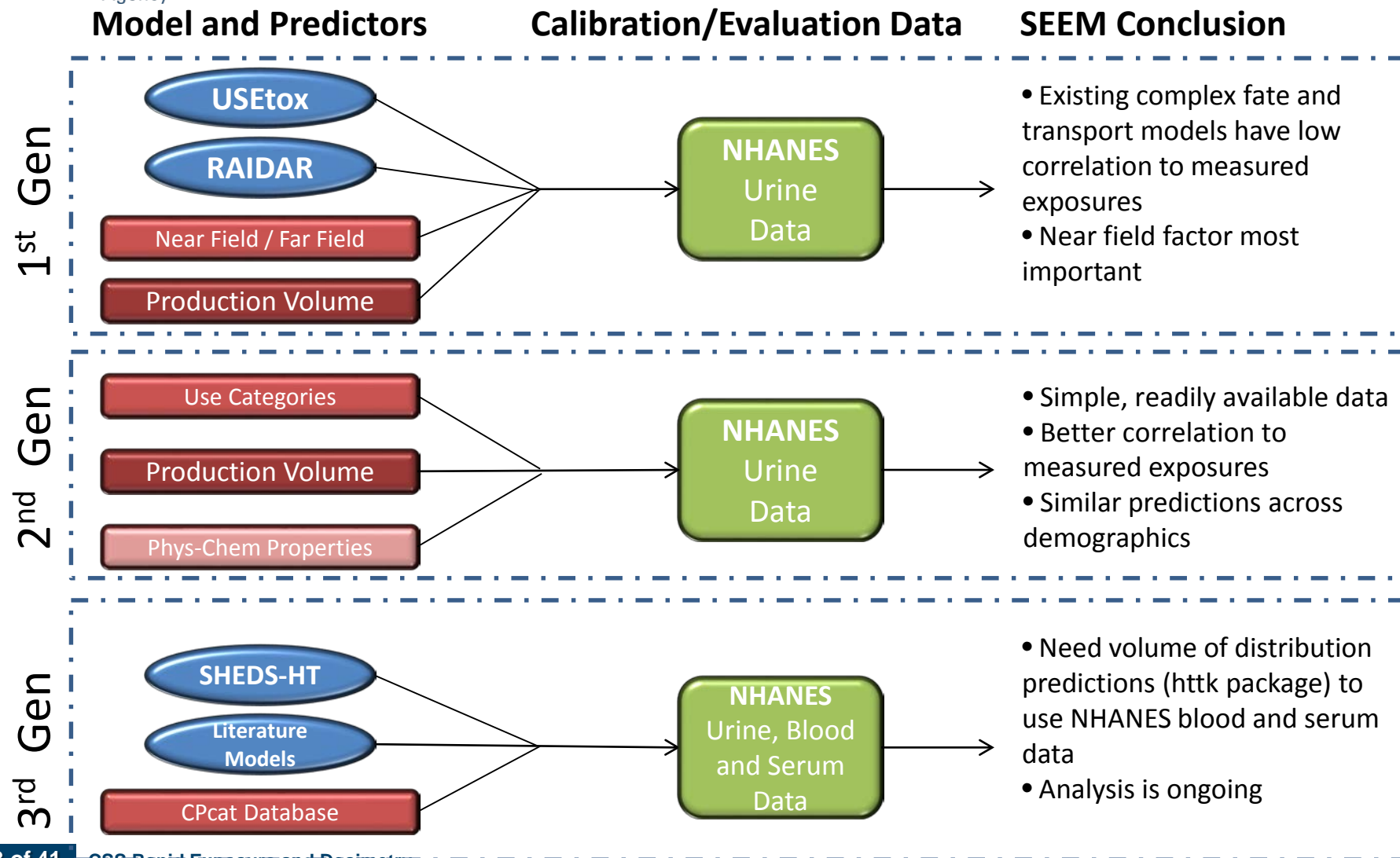
- Incorporate multiple models into consensus predictions for 1000s of chemicals within the **Systematic Empirical Evaluation of Models (SEEM)** framework (Wambaugh et al., 2013, 2014)
- Evaluate/calibrate predictions with available monitoring data across as many chemical classes as possible to allow extrapolation
- Analogous efforts for both human and ecological exposures



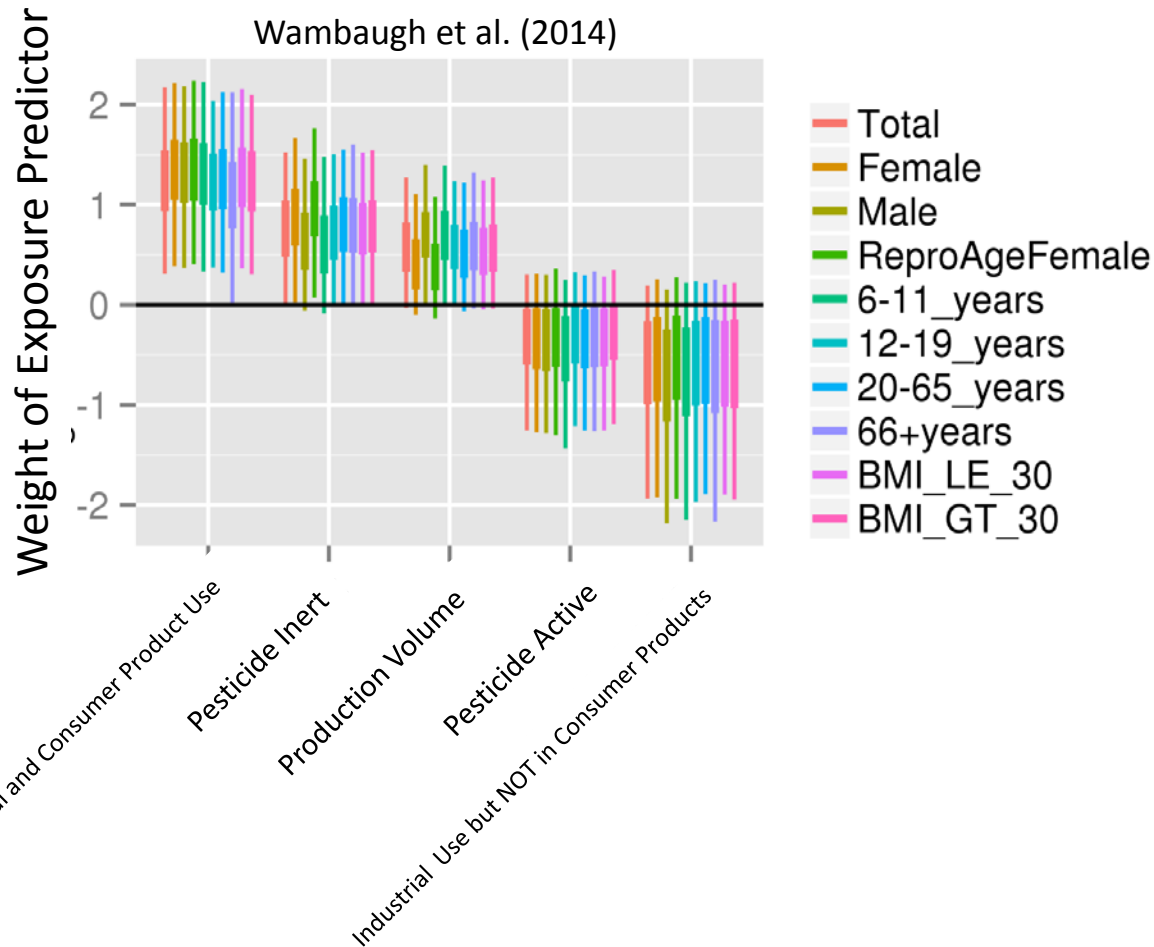
105 NHANES Chemicals



SEEM Evolution



Predicting Exposure



The presence of chemicals in consumer products and elsewhere in the home (“near field” sources) is a key driver of high exposure levels in Centers for Disease Control (CDC) National Health and Nutrition Survey (NHANES) biomonitoring data

Same five predictors work for all groups analyzed :

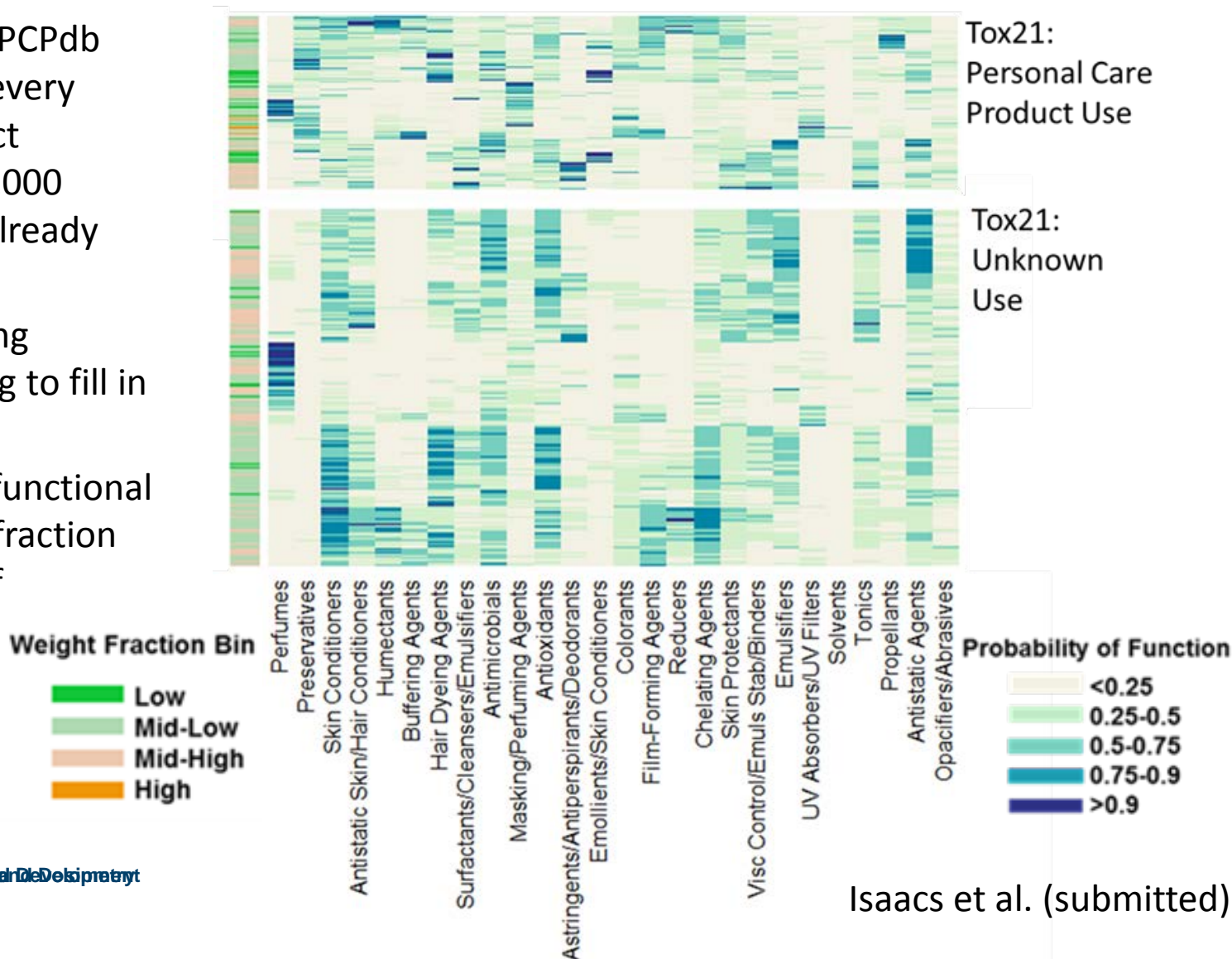
- Industrial and Consumer use
- Pesticide Inert
- Pesticide Active
- Industrial but no Consumer use
- Production Volume

105 NHANES Chemicals



Predicting Chemical Constituents

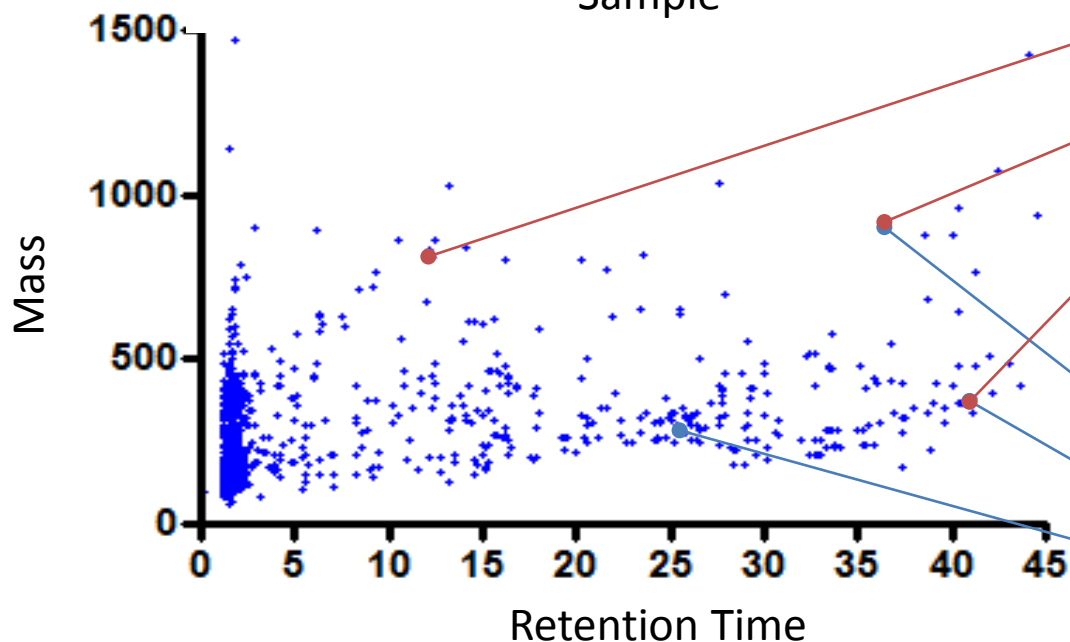
- Unfortunately CPCPdb does not cover every chemical-product combination (~2000 chemicals, but already >8000 in Tox21)
- We are now using machine learning to fill in the rest
- We can predict functional use and weight fraction for thousands of chemicals



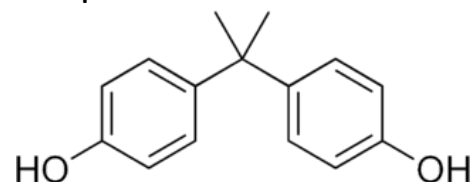
Isaacs et al. (submitted)

Suspect Screening and Non-Targeted Analytical Chemistry

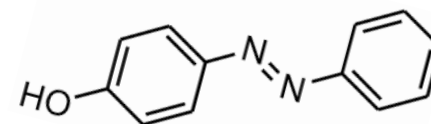
947 Peaks in an American Health Homes Dust Sample



Each peak corresponds to a mass of a chemical or (depending on technique) fragments of that compound



Multiple chemicals can have the same fragments or overall mass



Is chemical A present, chemical B, or both?

Rager, J.E., Strynar, M.J., Liang, S., McMahan, R.L., Richard, A.M., Grulke, C.M., Wambaugh, J.F., Isaacs, K.K., Judson, R., Williams, A.J., Sobus, J.R. "Linking high resolution mass spectrometry data with exposure and toxicity forecasts to advance high-throughput environmental monitoring" *Environment International*, 88, 269-280 (2016).

Pilot Projects to Reduce Uncertainty and Expand Validation Domain

Project	Pilot Project Scope
High throughput chemical property measurement (e.g., log P)	200 chemicals
Determine the chemical constituents of products, materials, articles	20 classes of product, 5 samples each
Determine chemical emission rate from specific products, materials, articles	100 materials
Screening for occurrence of large numbers of chemicals in blood samples	500 individuals

- Expands application domain of physical chemical property computational models
- Better understanding of what chemicals are associated with household products
- Better understanding of chemicals in the indoor environment
- Expands validation domain of human biomonitoring chemicals

Method for Screening Product Compositions

- Southwest Research Institute conducted analytical chemistry screening for large numbers of chemicals in consumer products and articles of commerce
 - Five sample products were arbitrarily selected from -each of twenty different categories
- Products were analyzed using two dimensional gas chromatograph (GC) x GC Time of Flight Mass Spectrometry
 - Chemical presence and approximate quantitation relative to reference chemicals (internal standards) was determined
 - All dilutions and extractions used Dichloromethane (DCM) (*Hexane:Ether was also examined initially, but had a higher background*)
 - Dilution level and processing were tailored to Mass spectra for some each sample; 1x, 10x and/or 100x
- Data processing
- GC features were matched to NIST 07 spectral database for tentative chemical identification
 - Compounds within some chemical classes are very similar, making definitive identifications difficult
 - Some peaks have a large, unresolved region of hydrocarbons in the C17-C32 range
 - Classifications used to manage hydrocarbon regions were ambiguous

Caveats to Non-Targeted Screening

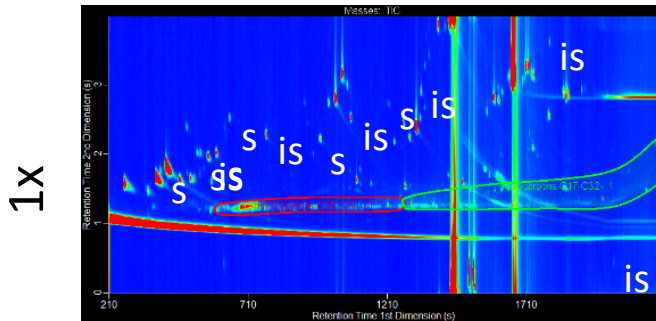
- Chemical presence in an object does not necessarily mean that it is bioavailable
- Samples are being homogenized (e.g., grinding)
- Chemicals are extracted with a solvent (CDM)
- Varying degrees of intimacy of exposure– carpet padding to shampoo to cereal
- Chemical presence in an object does not mean that exposure occurs
- We are not assessing toxicity of chemical exposure here – exposure alone is not risk

Example Chromatograms for Baby Toys

Product 1

Retention Time
Second Dimension (s)

is = internal standard
s = surrogate



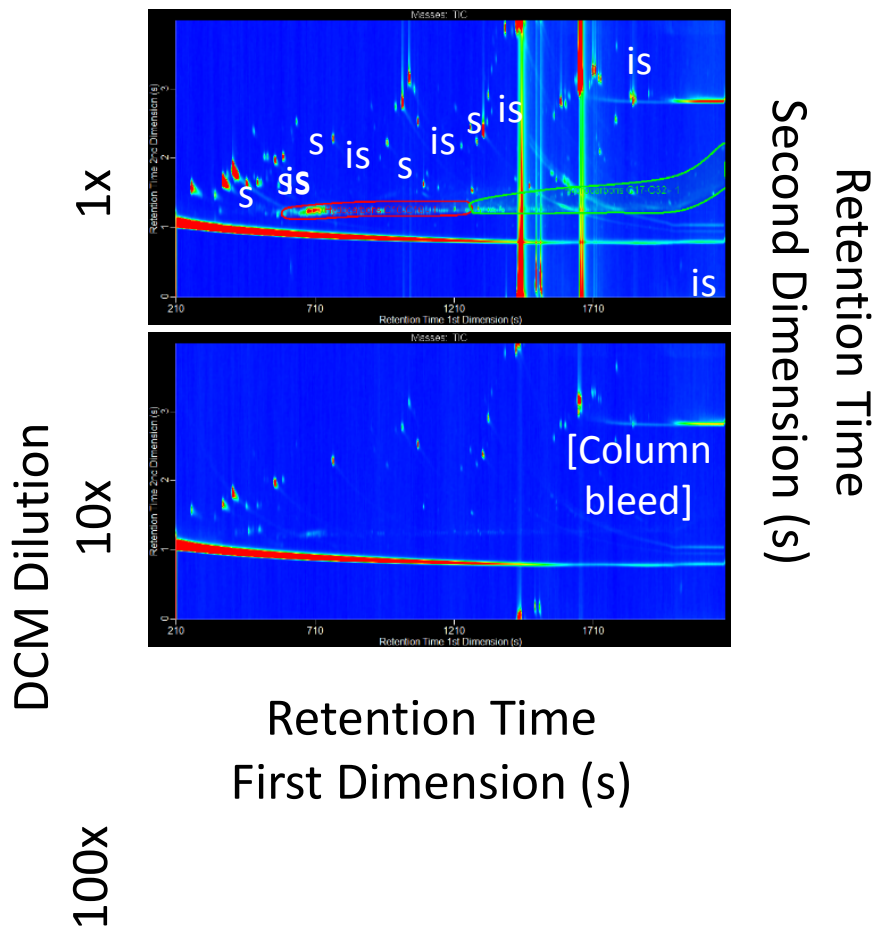
Retention Time
First Dimension (s)

DCM Dilution
10x

100x

Example Chromatograms for Baby Toys

Product 1

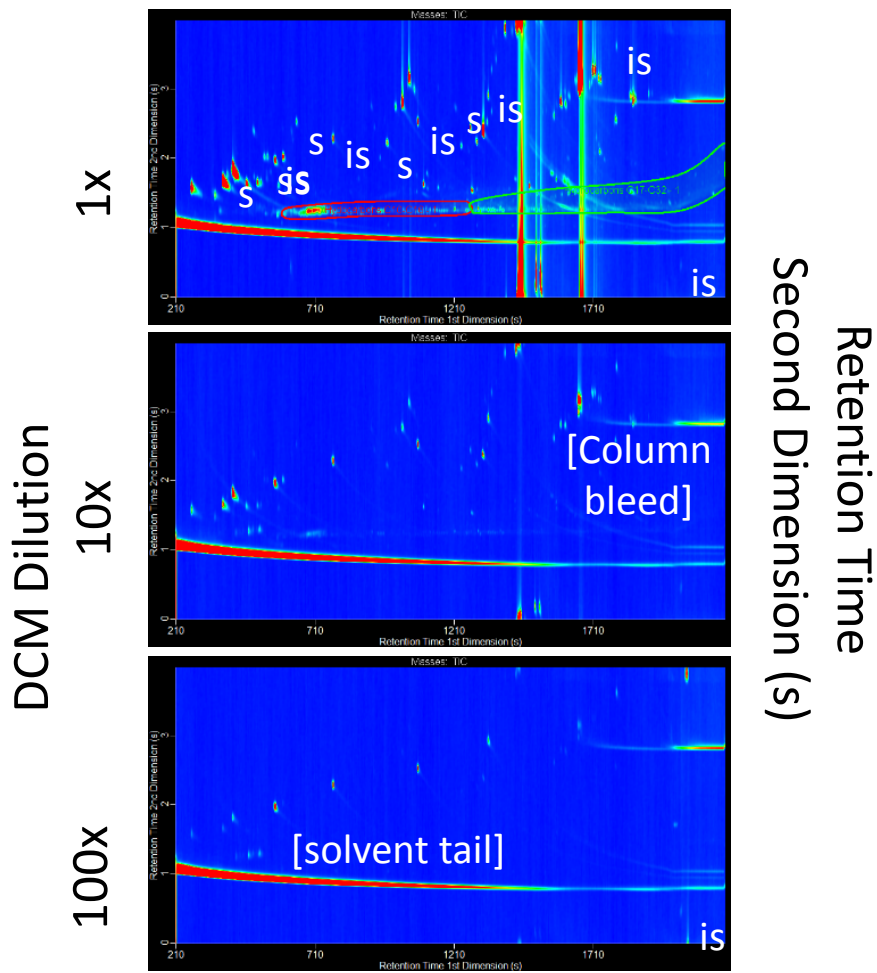


is = internal standard
s = surrogate

Example Chromatograms for Baby Toys

Product 1

is = internal standard
s = surrogate



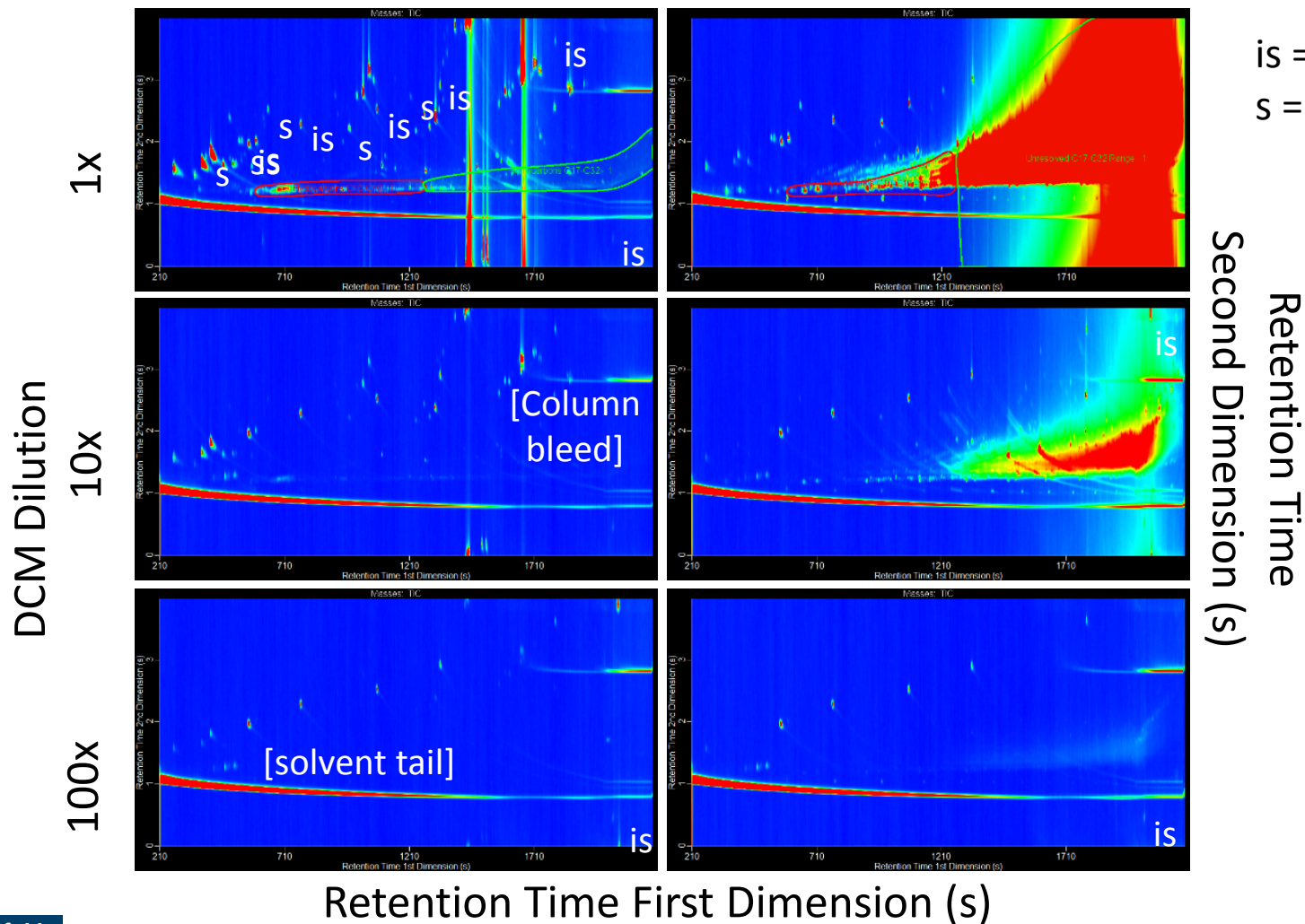
Retention Time First Dimension (s)

Example Chromatograms for Baby Toys

Product 1

Product 2

is = internal standard
s = surrogate



ExpoCast Consumer Product Scan



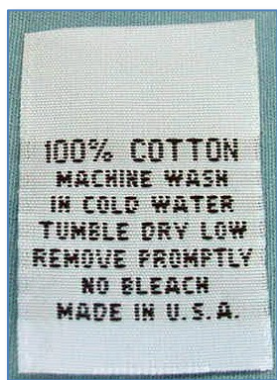
Scanned 5 examples each of 20 class of consumer products

Found 3803 chemical signature across the 100 products

1606 have tentative identifications

41 had confirmed chemical identities

The chemicals found in a cotton shirt



GC-MS with DCM Extraction

- Common Chemical (n>19)
- ToxCast
- Flame Retardant
- Potent ER

Results from Kristen Favela and Alice Yau (SWRI)

ExpoCast Consumer Product Scan

Commonly Found Chemicals

Scanned 5 examples each of 20 class of consumer products

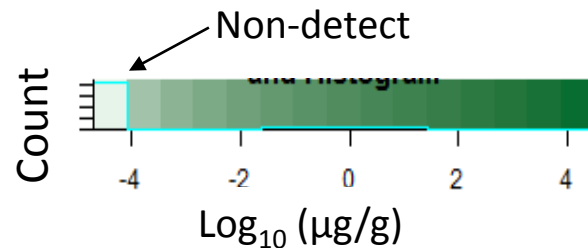
Found 3803 chemical signature across the 100 products

1606 have tentative identifications

41 had confirmed chemical identities

Dark green is a high concentration

Light green is not detected



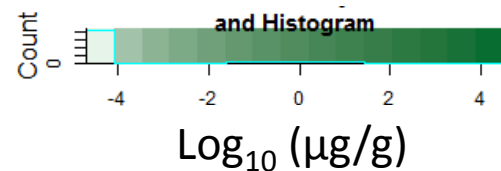
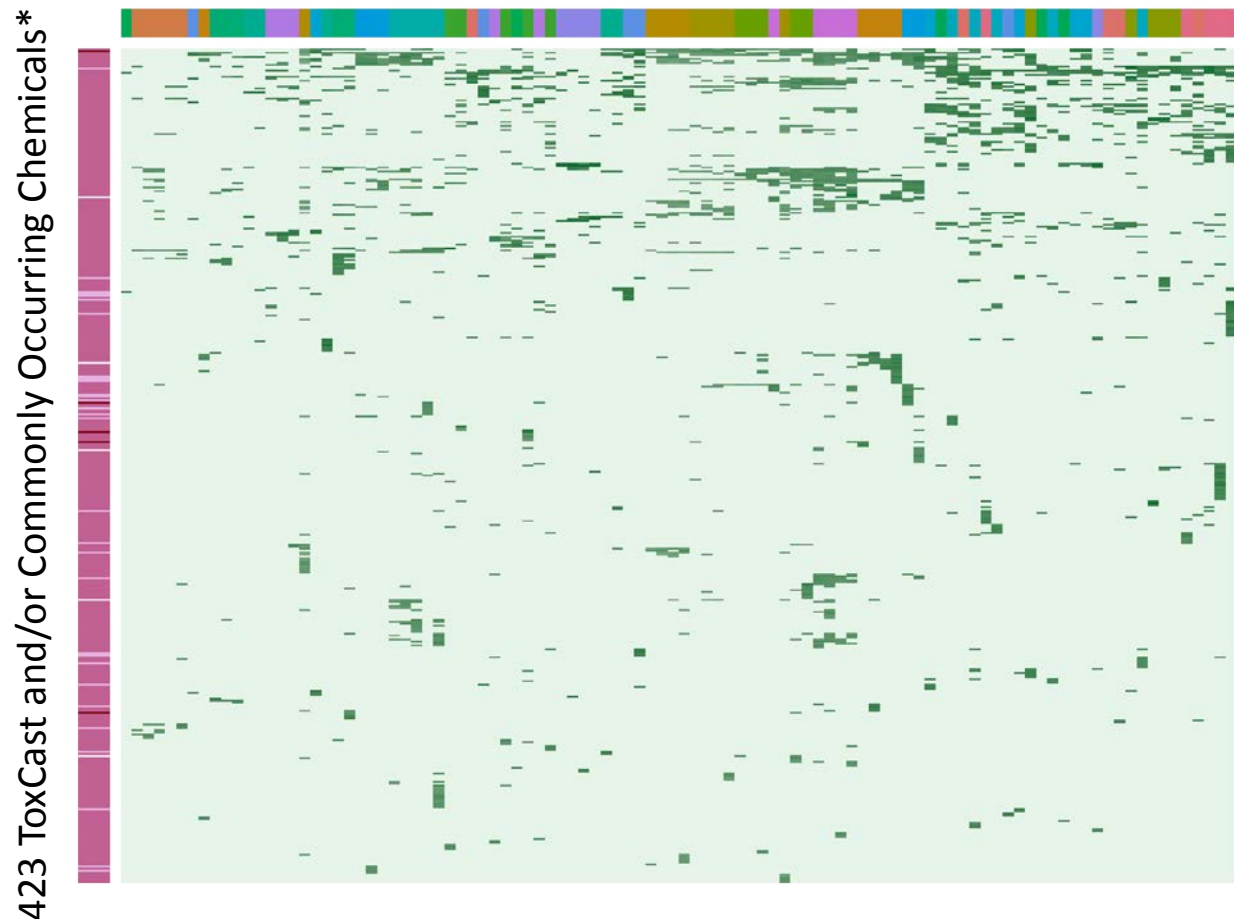
GC-MS with DCM Extraction

- Common Chemical (n>19)
- ToxCast
- Flame Retardant
- Potent ER

Results from Kristen Favela
and Alice Yau (SWRI)

Five arbitrary products in each of twenty categories

100 Consumer Products and Articles of Commerce



- Air freshener
- Baby soap
- Carpet
- Carpet padding
- Cereals
- Cotton clothing
- Deodorant
- Fabric upholstery
- Glass cleaners
- Hand soap
- Indoor house paint
- Lipstick
- Plastic children's toys
- Shampoo
- Shaving cream
- Shower curtain
- Skin lotion
- Sunscreen
- Toothpaste
- Vinyl upholstery

GCXGC-MS with DCM Extraction

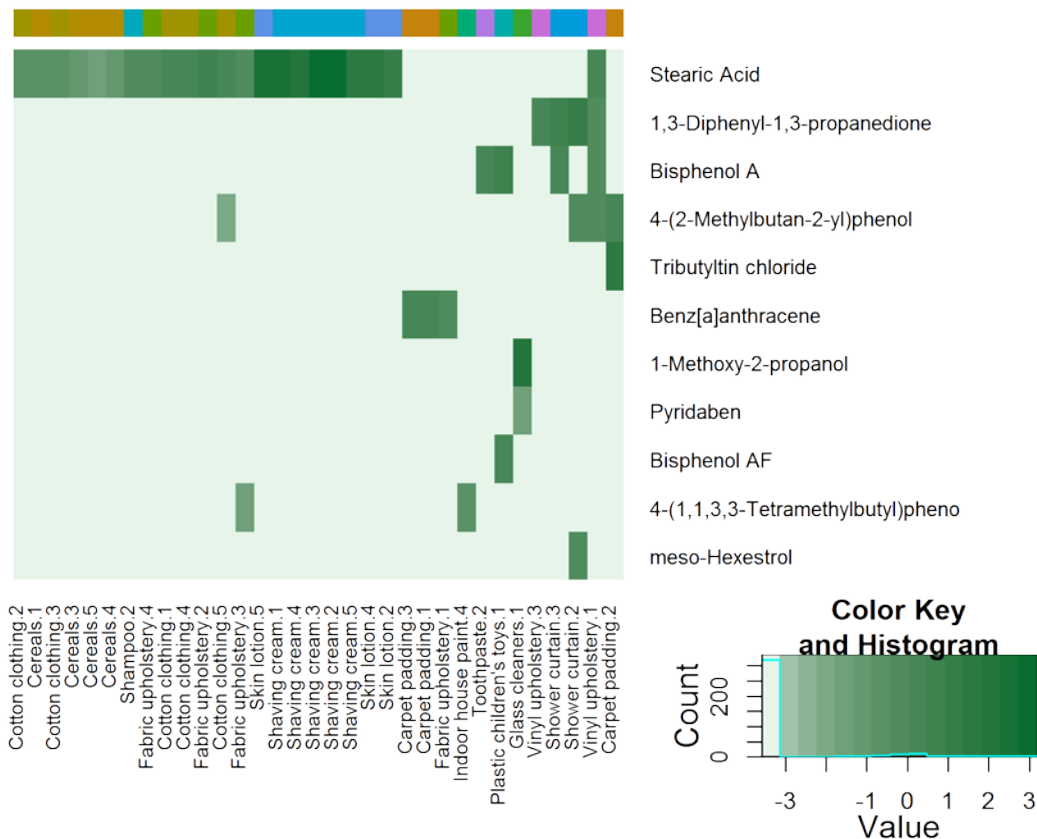
- Common Chemical (n>19)
- ToxCast
- Flame Retardant
- Potent ER

Results from Kristen Favela
and Alice Yau (SWRI)

1606 tentative and confirmed chemical identifications

- 184 of 1797 chemicals with previously known consumer product use (CPCPdb)
- 520 of 8948 Tox21 chemicals
- 393 of 3805 ToxCast chemicals
- 11 of 96 ToxCast ER active chemicals
- 17 of 178 EDSP List 1 and 2 chemicals
- 94 of 1172 ToxRefDB chemicals
- 32 of 452 NHANES chemicals
- 1 of 670 pharmaceuticals (Obach, 2008)
- 9 of 67 flame retardants

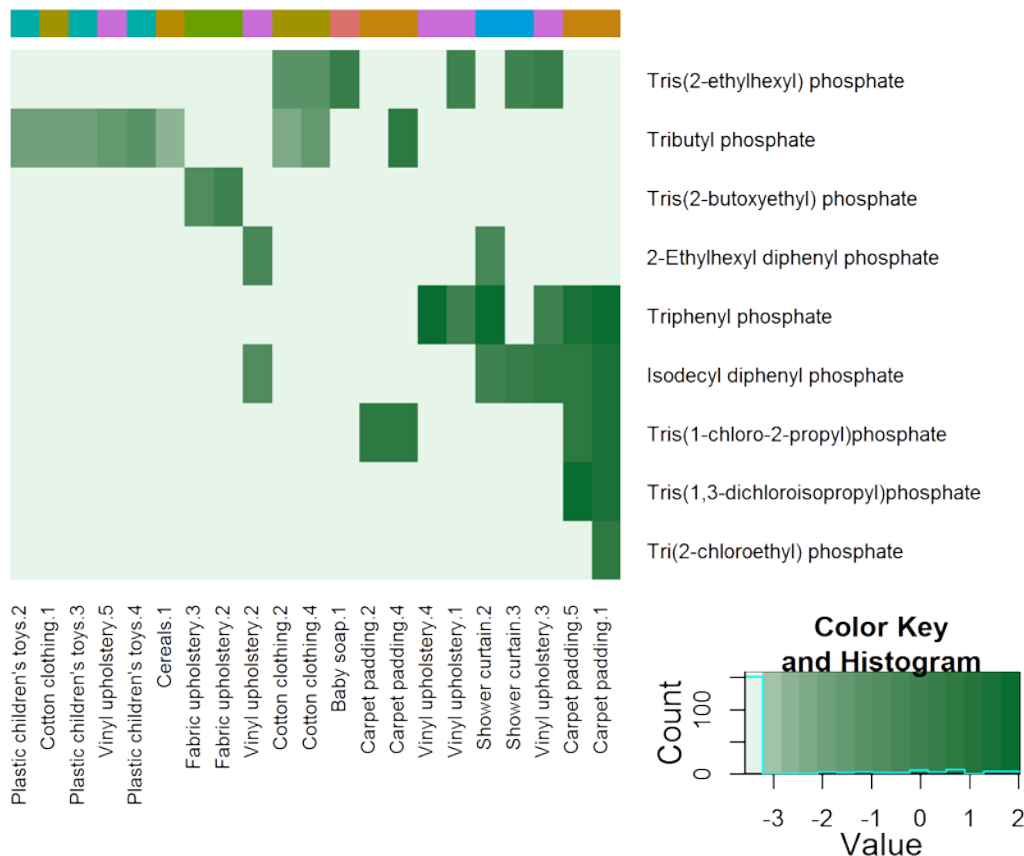
In Vitro Estrogen active chemicals



- Here we examine those chemicals that were among the top 25% most potent ER active chemicals in Judson et al., (2015)
- Stearic acid is a naturally occurring fatty acid known to be used in many detergents, soaps, shampoos, and shaving creams¹⁰ Other estrogen active chemicals were found in articles like shower curtains, upholstery, and carpet padding
- Bisphenol A was found in toothpaste and one children's toy, while a replacement for Bisphenol A, Bisphenol AF, was found in another toy

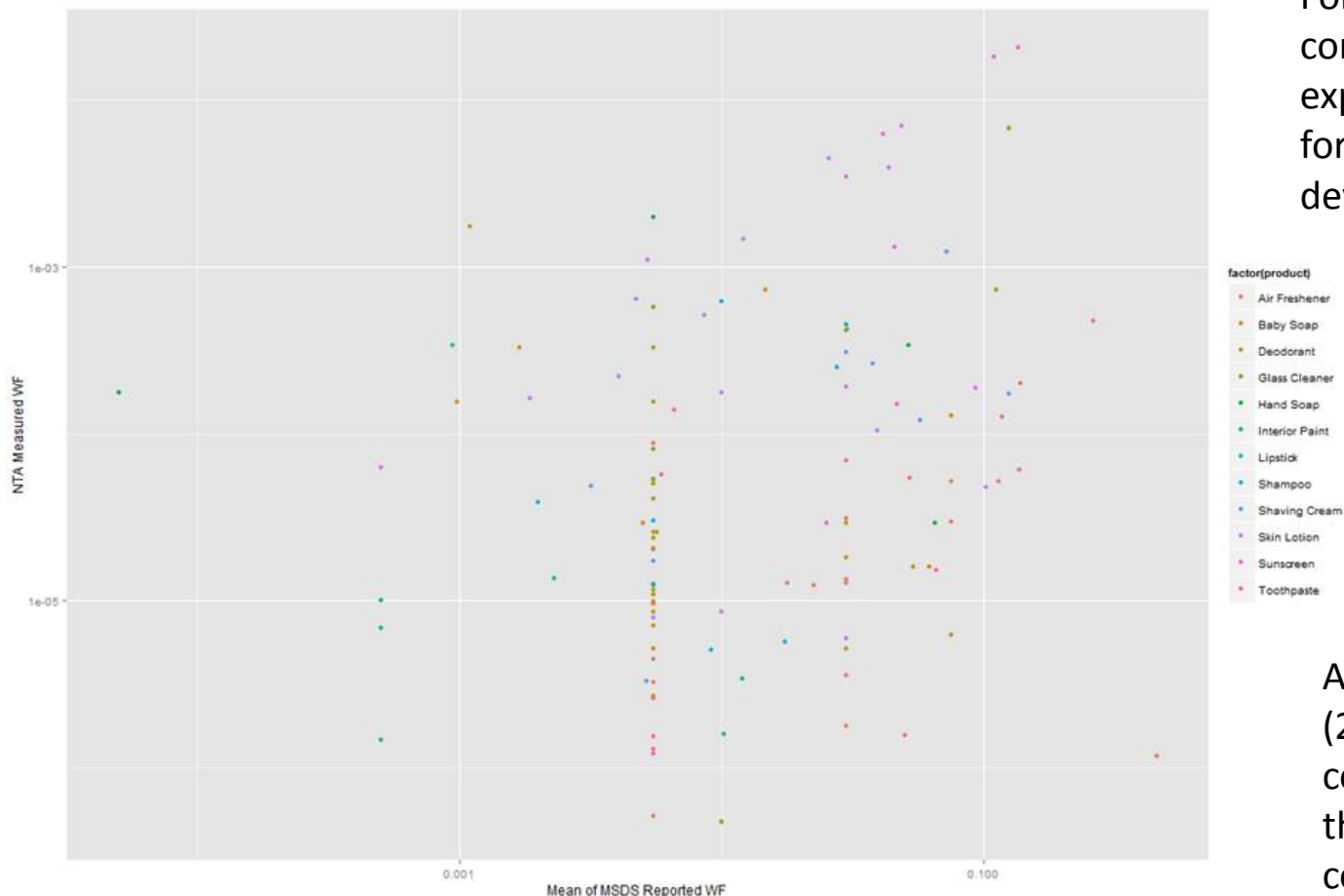
Flame retardant chemicals

- We used ToxCast chemical annotation and public information to identify chemicals that are sometimes used as flame retardants
- Chemicals with flame retardant application were indicated in most fabric and vinyl upholsteries, carpet paddings, cotton clothing, shower curtains, and children's toys, as well as in one hand soap, baby soap, and breakfast cereal* (*likely used as an anti-foaming agent)



Evaluation – Measured Chemical Concentrations vs. Formulation

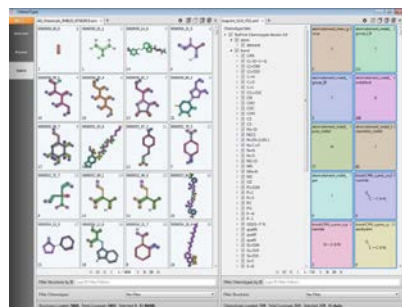
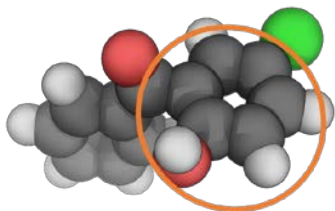
For some chemicals we can compare to concentrations expected in generic formulations that were developed for SHEDS-HT



As seen in Rager et al. (2016), we underestimate concentration of chemicals that occur at high concentrations

Evaluation – Predicting Function in Products Based on Structure

Chemical Structure and Property Descriptors



Use Database (FUSE)



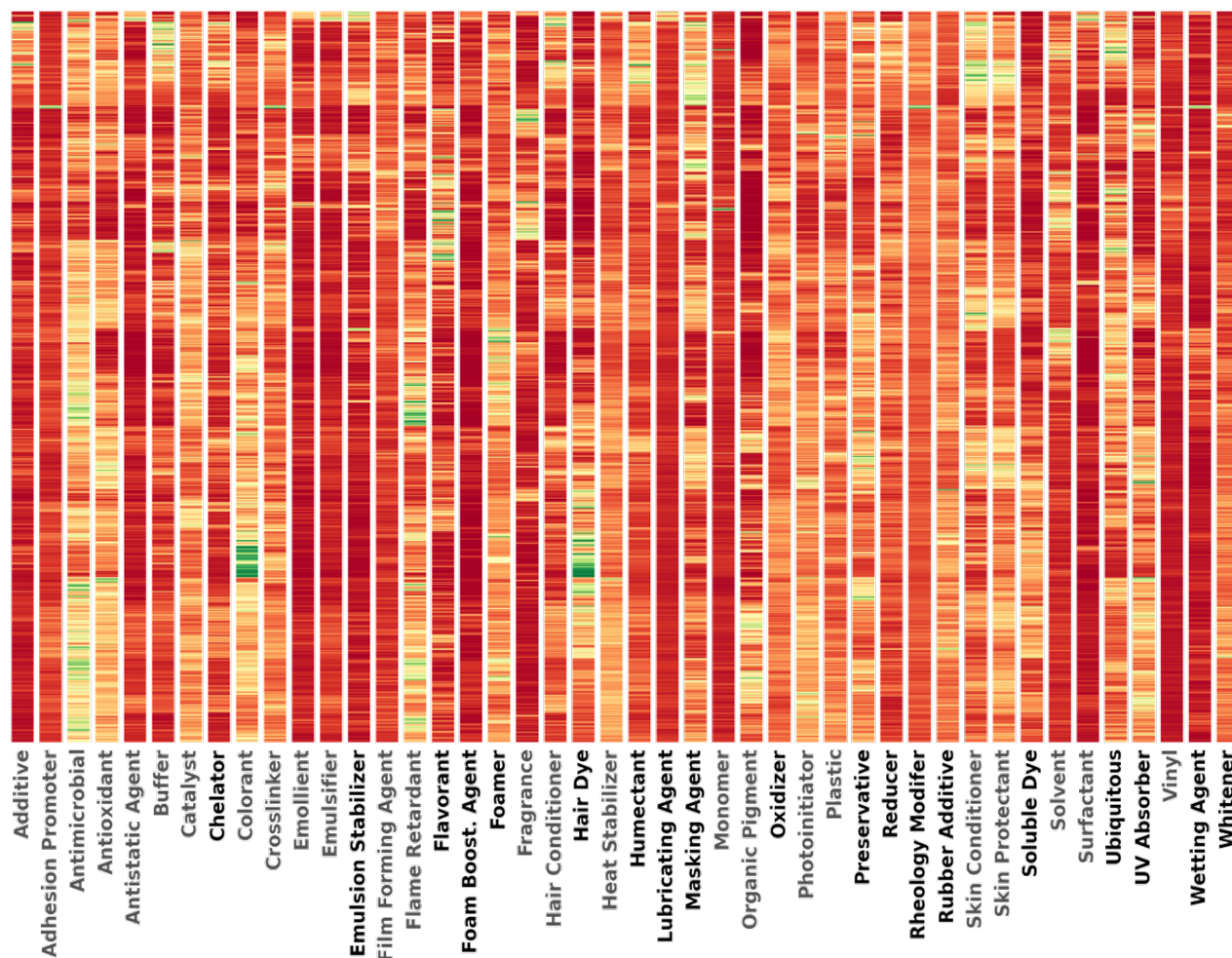
Prediction of
Of Potential
Alternatives
from Chemical
Libraries

Machine-Learning Based
Classification Models

Material from
Katherine Phillips

Screening for Alternatives By Function and Bioactivity

Tox21 Chemicals with
Unknown Functional Use



1.0
0.8
0.6
0.4
0.2
0.0

Probability of
Chemical
Performing
Same
Function

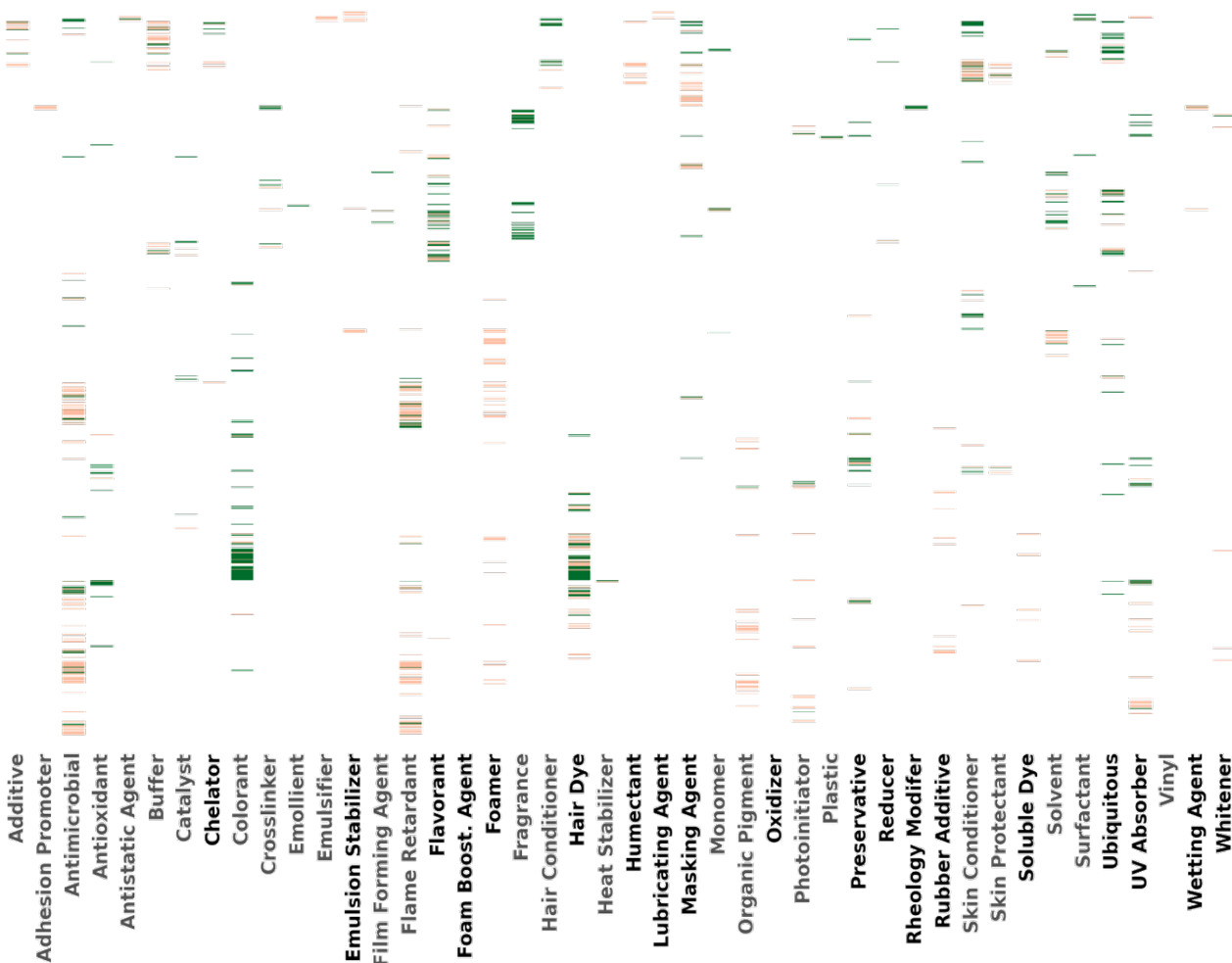
- Unfortunately CPCPdb does not cover every chemical-product combination – using machine learning to fill in the rest

Functional Use

Material from
Katherine Phillips

Screening for Alternatives By Function and Bioactivity

Tox21 Chemicals with
Unknown Functional Use



Lower
Bioactivity
Metric?
Yes
No

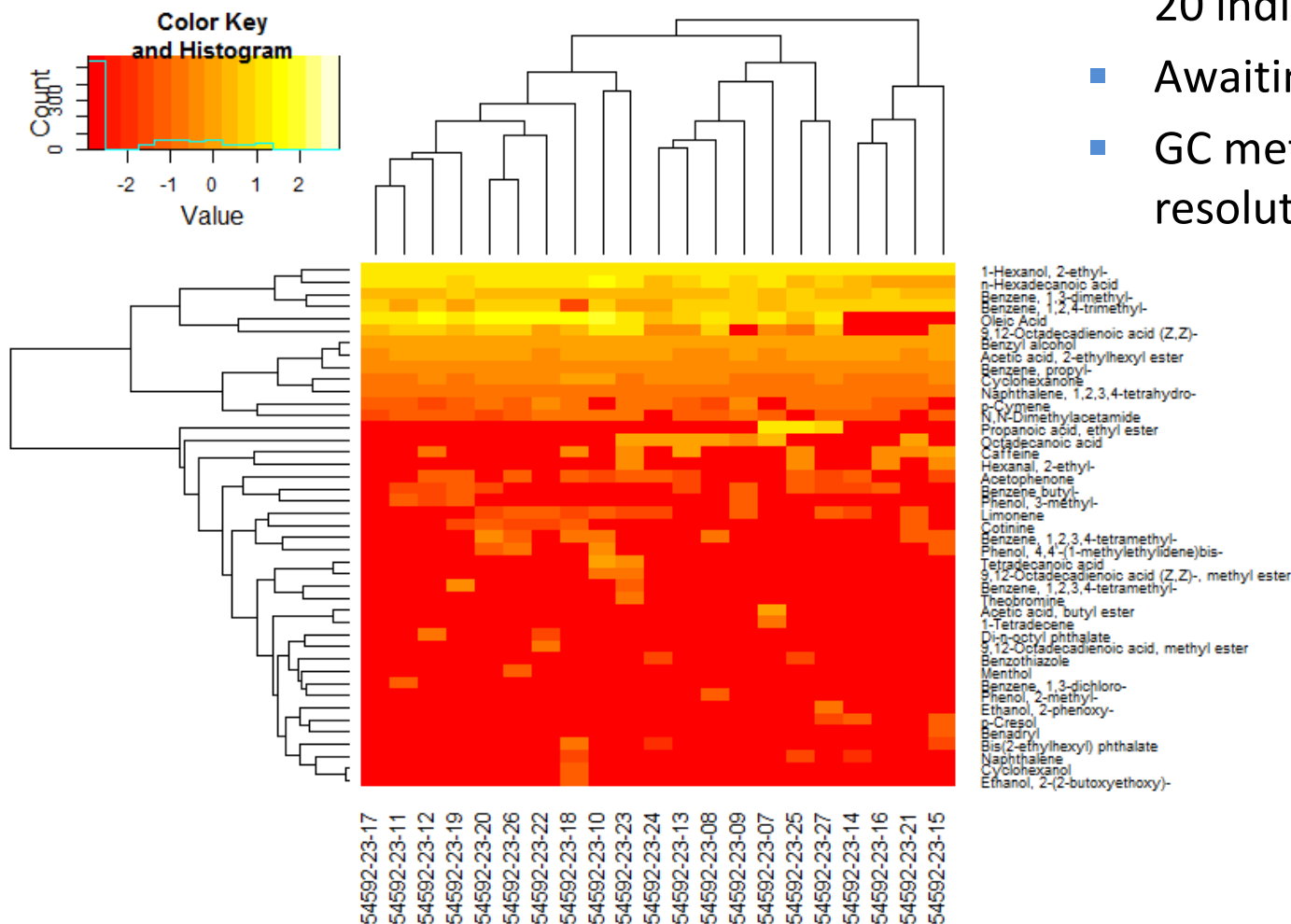
Functional Use

ExpoCast Pilot 4: Biomonitoring

- Screening for occurrence of large numbers of chemicals in sample acquired by contractor (biological media)
- Research Conducted by Battelle Memorial Institute (Anne Gregg)
- Cohort is a mixed gender and race group of adults from Indianapolis
- Sample Screening
 - One extraction method resulting in two aliquots for analysis
 - Two analysis methods GCxGC TOFMS and LC-TOFMS
- In addition to 200 priority ToxCast chemicals, we will look for NHANES chemicals as reference

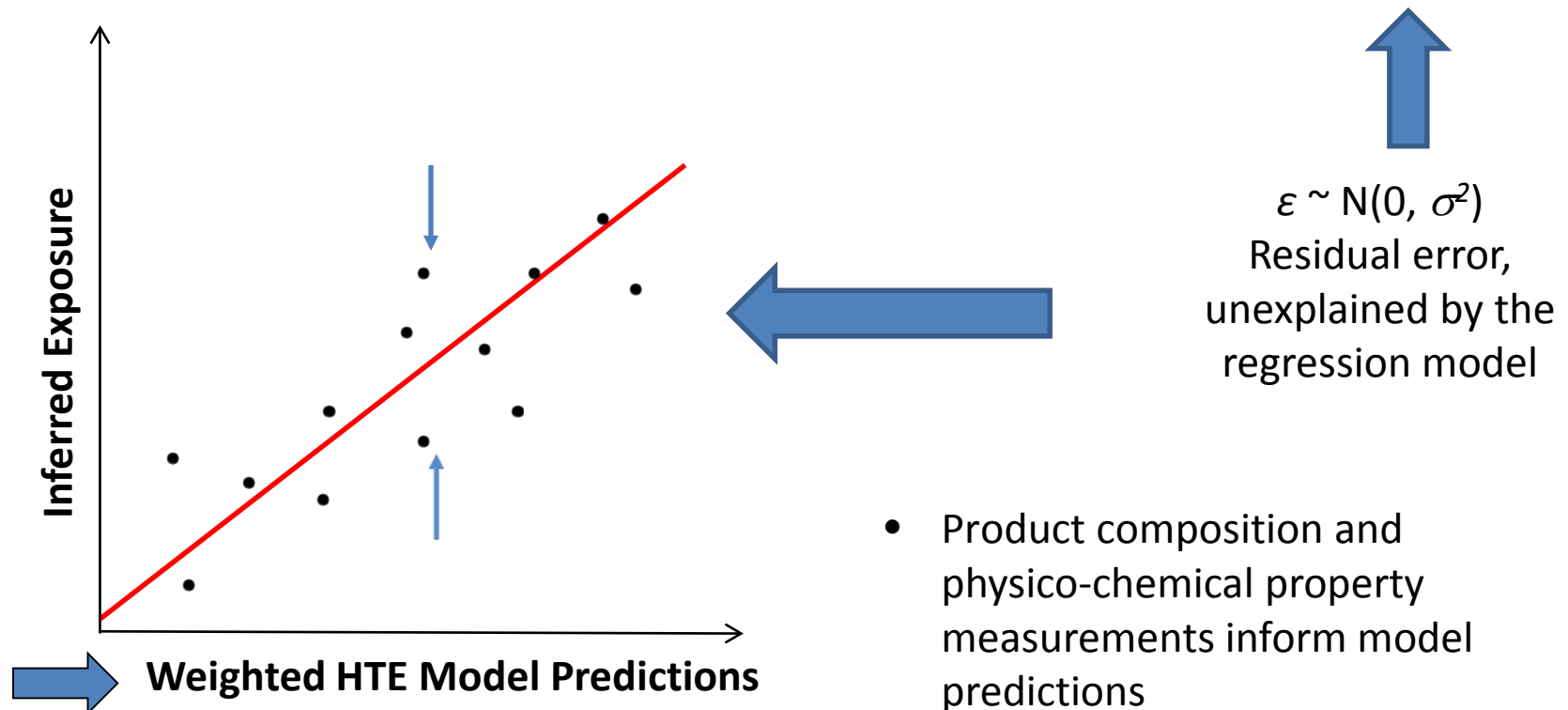
ExpoCast Pilot 4: Biomonitoring

- GCxGC TOFMS data for first 20 individuals
- Awaiting LC-TOFMS
- GC method is not high resolution, but LC method is



SEEM is a Linear Regression

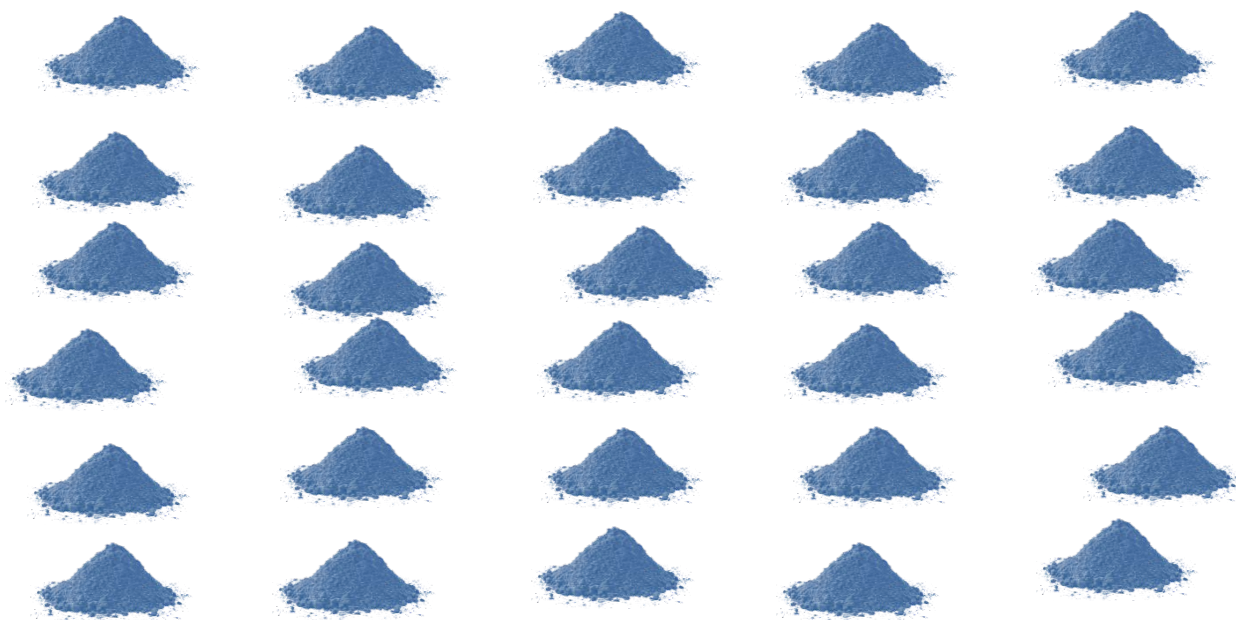
$$\text{Log(Parent Exposure)} = a + m * \log(\text{Model Prediction}) + b * \text{Near Field} + \varepsilon$$



Suspect-Screening Challenge

A “collaborative trial”: What methods are available (“multiple technologies/multiple preparations”)? What is the coverage of chemical universe? Do the methods differ in their coverage?

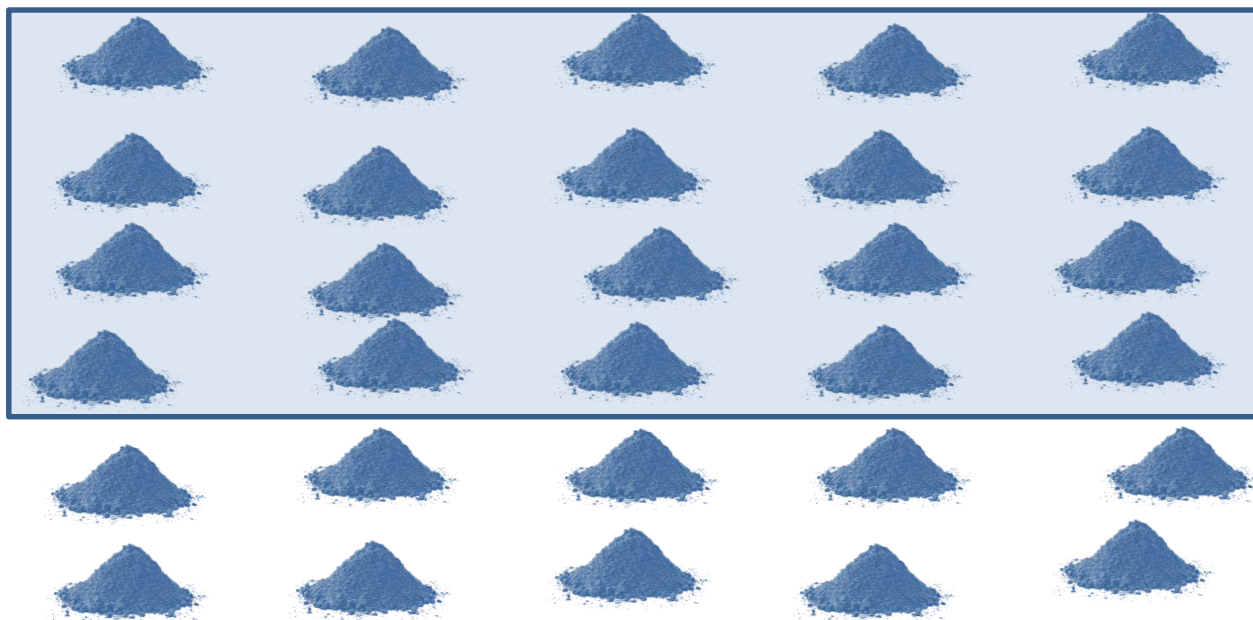
The Chemical Universe



Suspect-Screening Challenge

A “collaborative trial”: What methods are available (“multiple technologies/multiple preparations”)? What is the coverage of chemical universe? Do the methods differ in their coverage?

The Chemical Universe

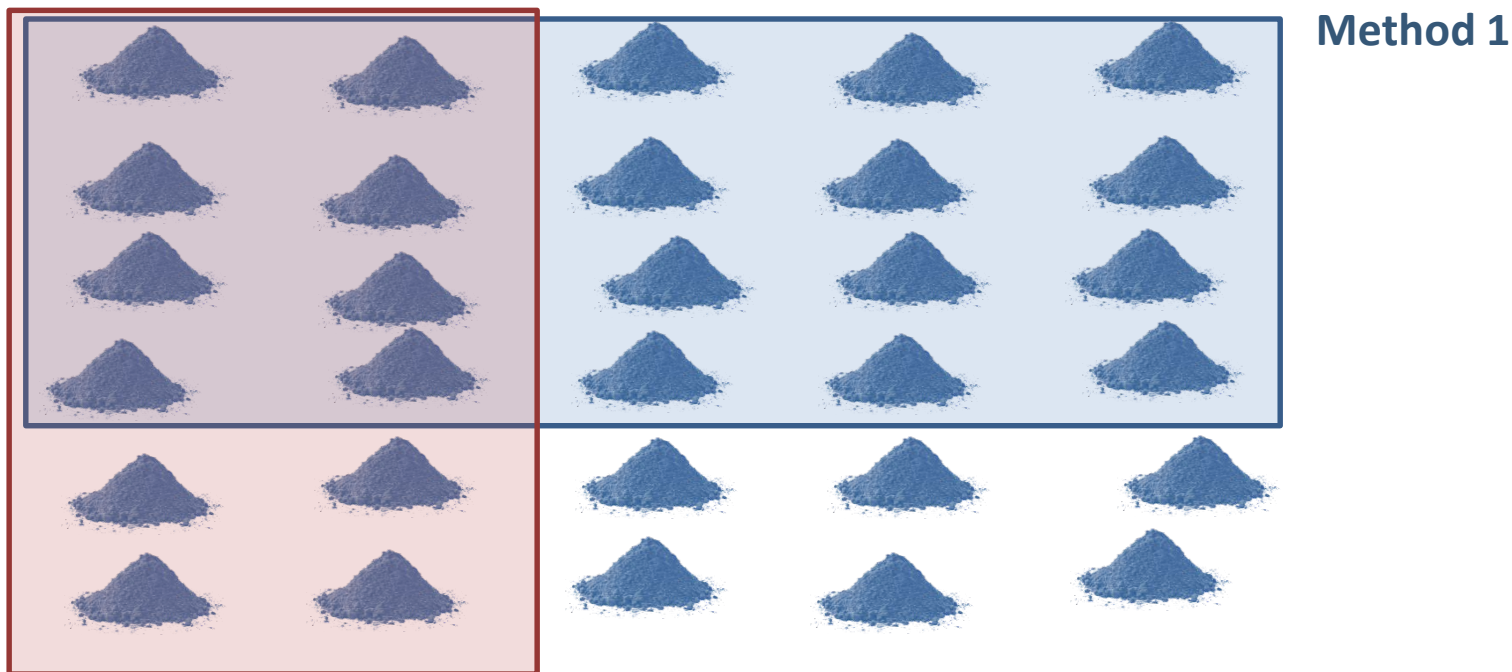


Method 1

Suspect-Screening Challenge

A “collaborative trial”: What methods are available (“multiple technologies/multiple preparations”)? What is the coverage of chemical universe? Do the methods differ in their coverage?

The Chemical Universe

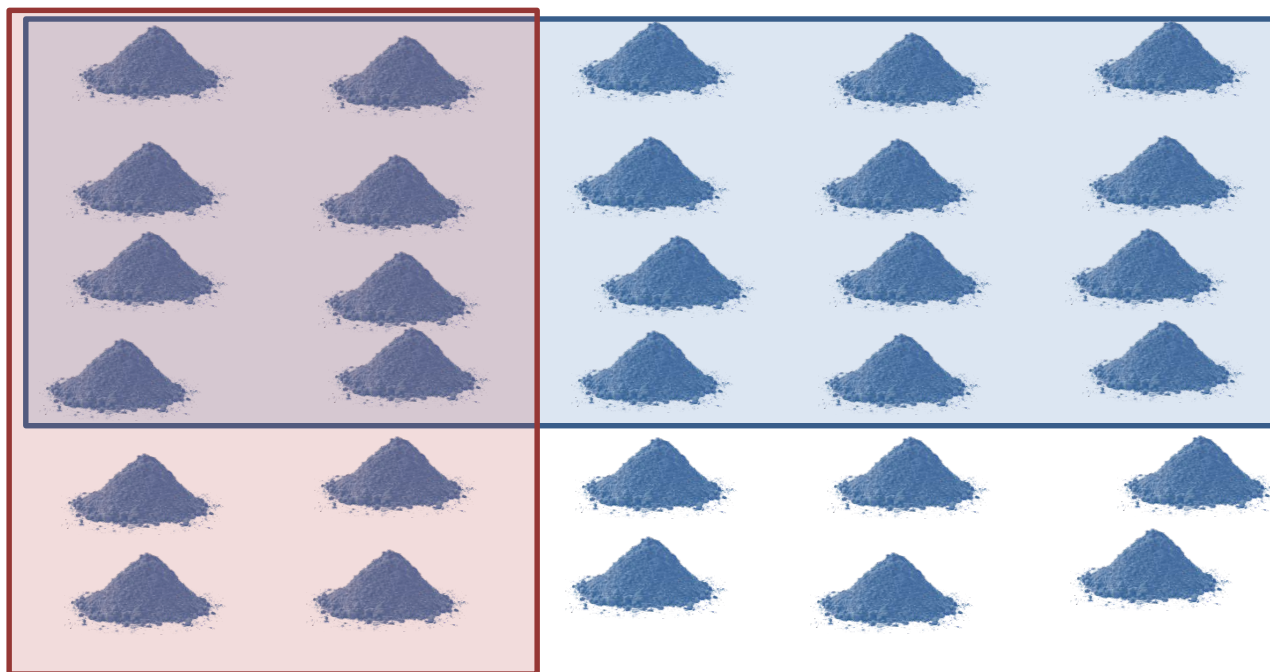


Method 2

Suspect-Screening Challenge

A “collaborative trial”: What methods are available (“multiple technologies/multiple preparations”)? What is the coverage of chemical universe? Do the methods differ in their coverage?

The Chemical Universe



Method 1

EPA has mechanisms to provide reference samples for 1000's of chemicals for cross-lab evaluation

EPA has team devoted to developing and maintaining public databases

Method 2

High Throughput Exposure

- There are low levels of thousands of xenobiotic chemicals present in the metabolome, relating these to exposures and health effects is an important unsolved problem
- Pathways provide a means to address the complexity of exposure as a system
- Can use a combination of forward modeling and reverse inference from biomarkers to predict exposure pathways and rates
 - Broader monitoring data informs evaluation of those predictions
 - Better chemical use data informs models predicting exposure
- Non-targeted and suspect screening provides an important new tool for both evaluating models and broadening applicable chemistries
 - Important limitations must be noted at all times

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

NCCT

Chris Grulke
Richard Judson
Dustin Kapraun*
Robert Pearce*
James Rabinowitz
Ann Richard
Caroline Ring*
Woody Setzer
Rusty Thomas
John Wambaugh
Antony Williams

NRMRL

Yirui Liang*
Xiaoyu Liu

NHEERL

Jane Ellen Simmons
Marina Evans
Mike Hughes

*Trainees

NERL

Craig Barber
Derya Biryol*
Kathie Dionisio
Peter Egeghy
Kim Gaetz
Brandall Ingle*
Kristin Isaacs
Seth Newton
Katherine Phillips
Paul Price
Mark Strynar
Jon Sobus
Mike Tornero-Velez
Elin Ulrich
Dan Vallero

Collaborators

Arnot Research and Consulting

Jon Arnot

Battelle Memorial Institute

Anne Louise Sumner

Anne Gregg

Chemical Computing Group

Rocky Goldsmith

National Institute for Environmental Health Sciences (NIEHS) National Toxicology Program

Mike Devito

Steve Ferguson

Nisha Sipes

Netherlands Organisation for Applied Scientific Research (TNO)

Sieto Bosgra

North Carolina Central University

Chantel Nicolas

Research Triangle Institute

Timothy Fennell

Scitovation

Harvey Clewell

Cory Strope

Barbara Wetmore

Silent Spring Institute

Robin Dodson

Southwest Research Institute

Alice Yau

Kristin Favela

Summit Toxicology

Lesa Aylward

University of California, Davis

Deborah Bennett

Hyeong-Moo Shin

University of Michigan

Olivier Jolliet

University of North Carolina, Chapel Hill

Alex Tropsha