

Advances in EPA's Rapid Exposure and Dosimetry Project

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Interagency Alternatives Assessment Webinar

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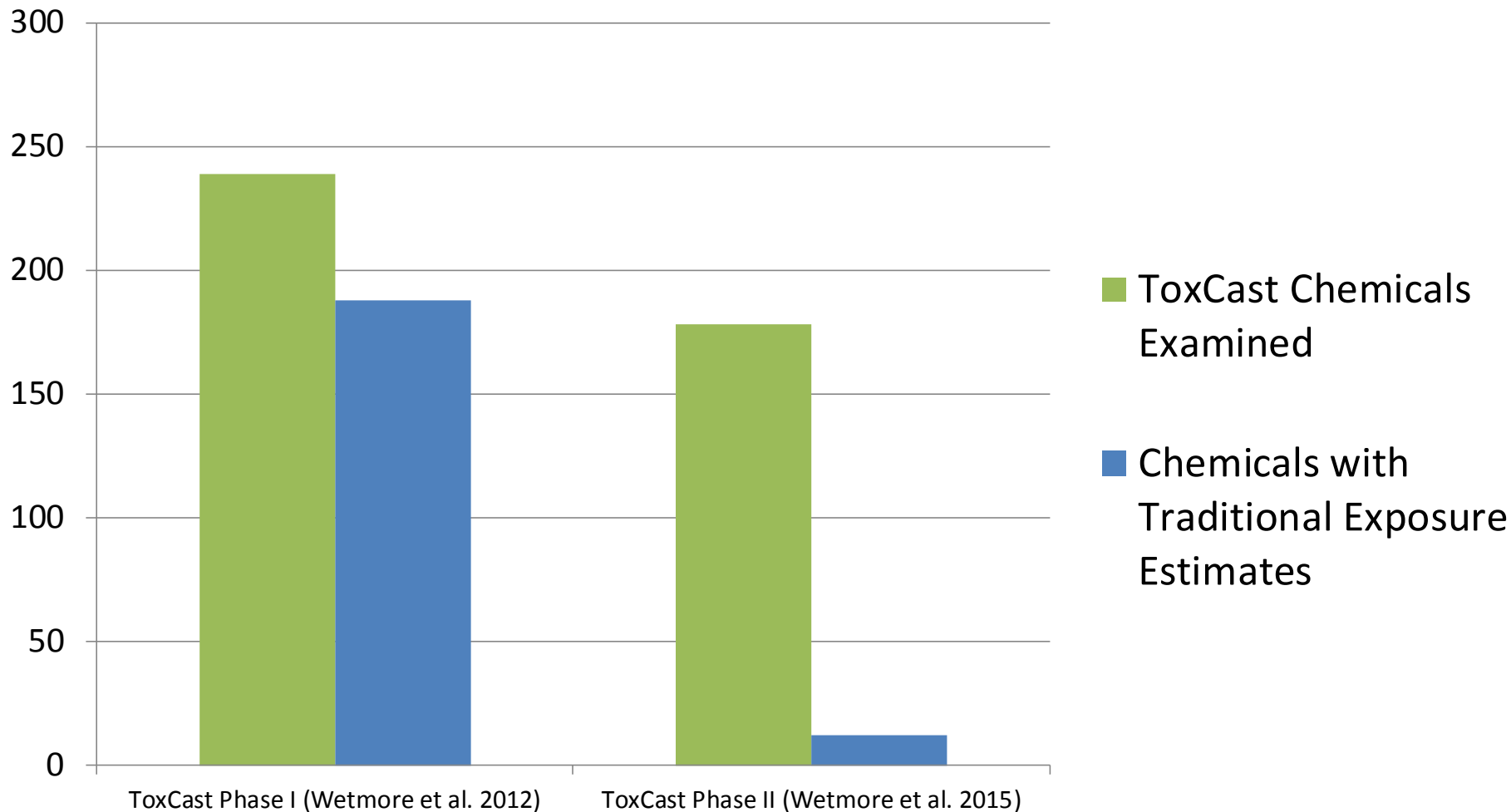
Introduction

The timely characterization of the human and ecological risk posed by thousands of existing and emerging commercial chemicals is a critical challenge facing EPA in its mission to protect public health and the environment



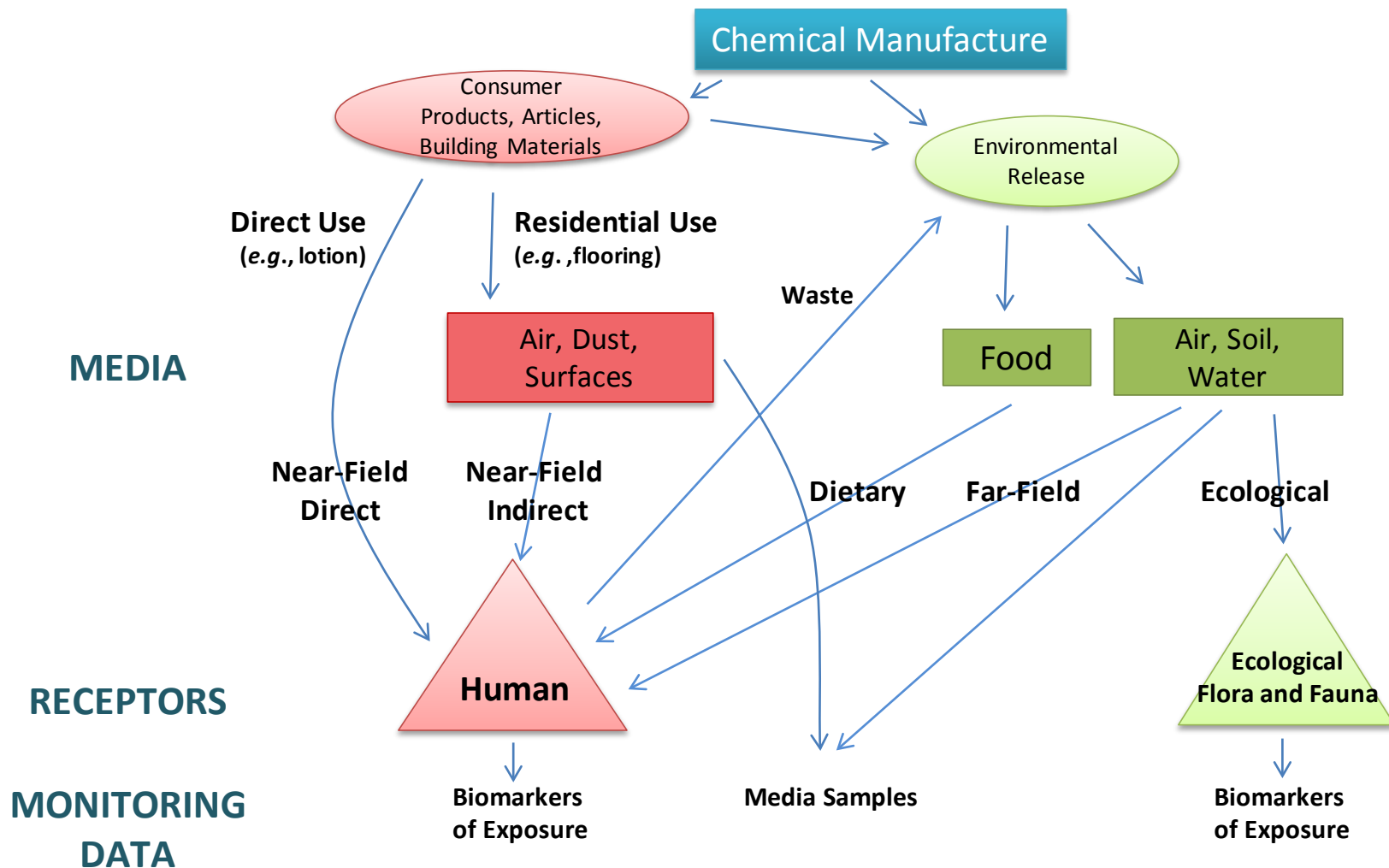
November 29, 2014

Available Data for Exposure Estimations

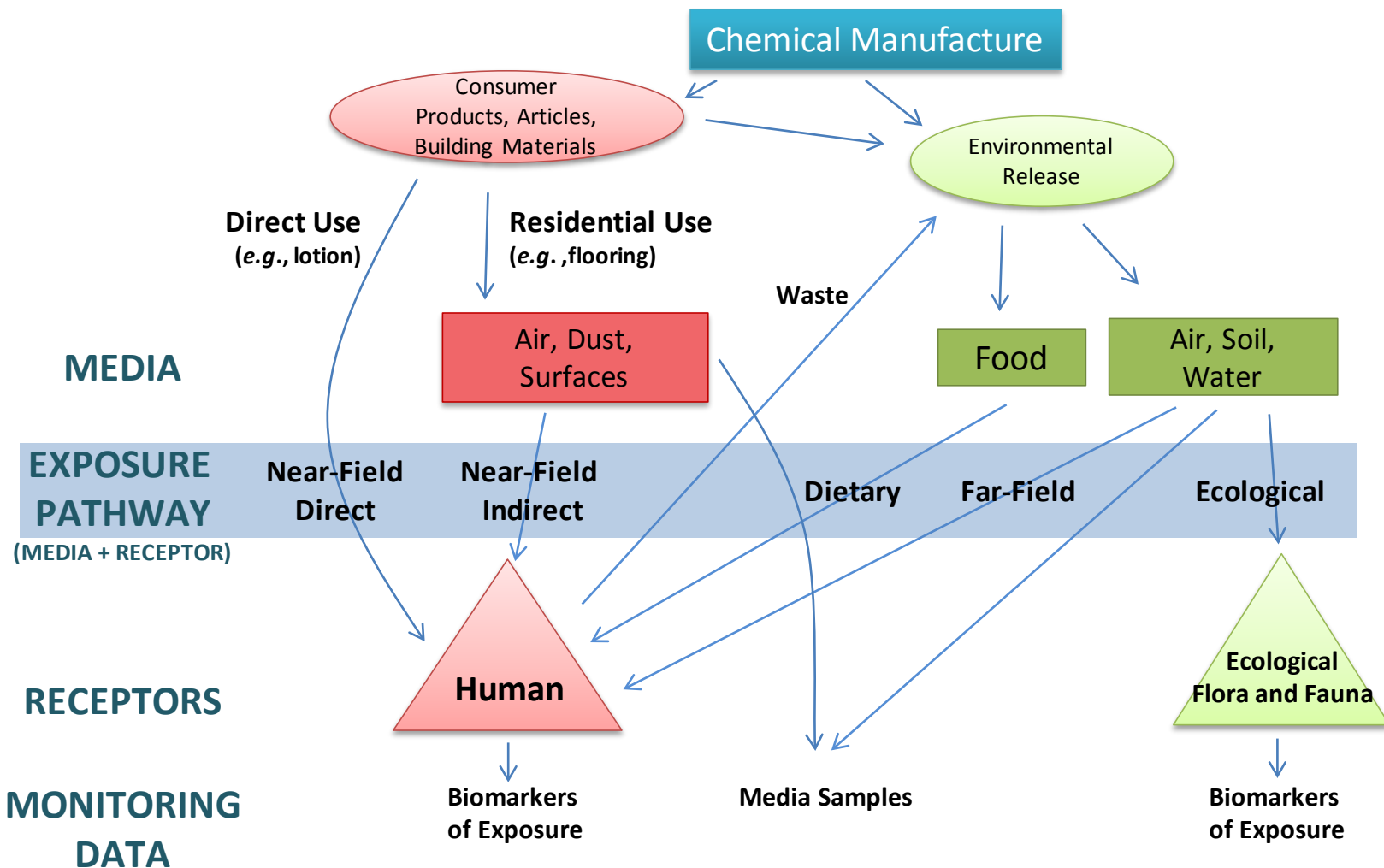


- Egeghy et al. (2012) – Most chemicals lack exposure data

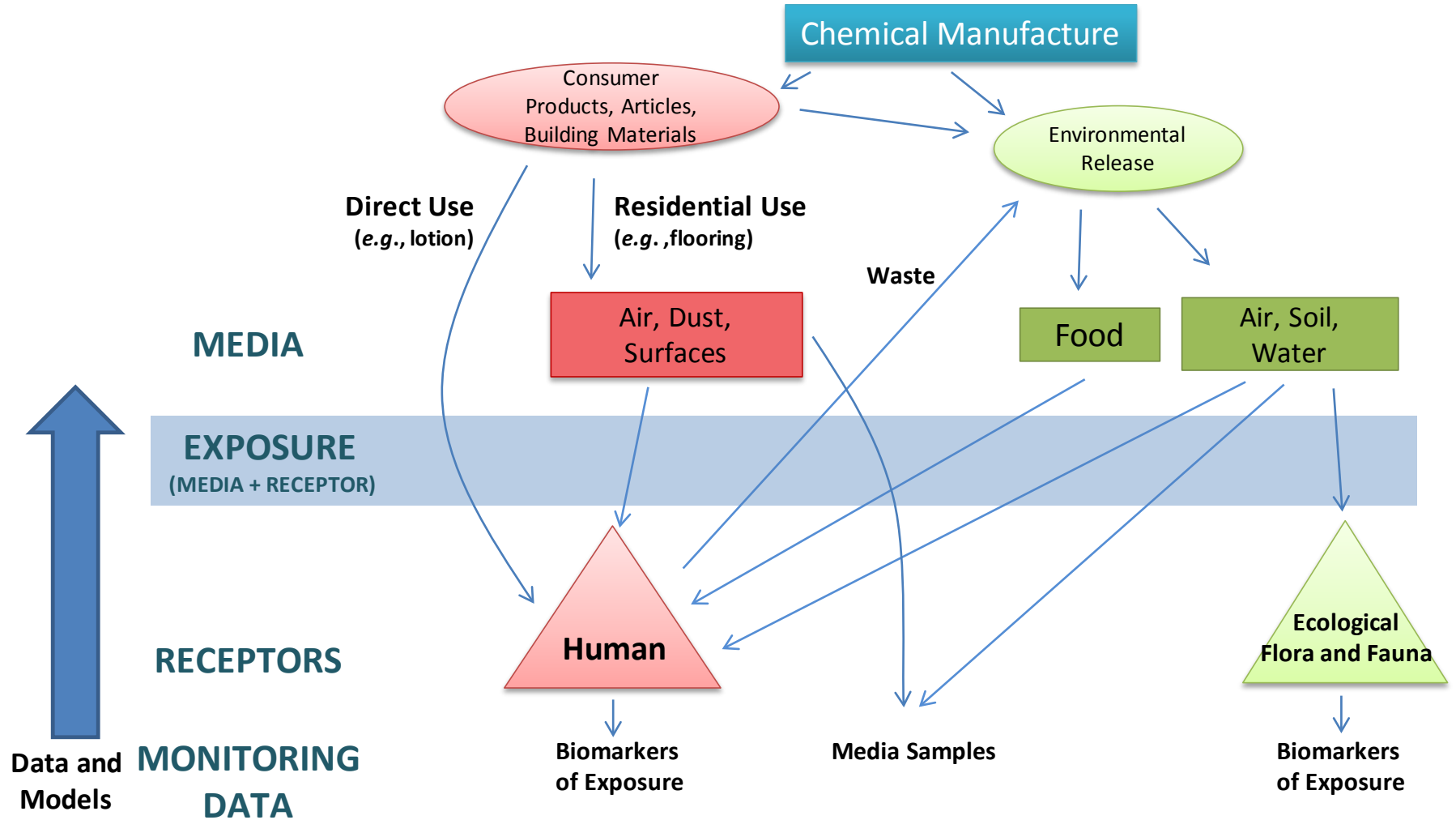
Thinking About Exposure



Exposure Pathways

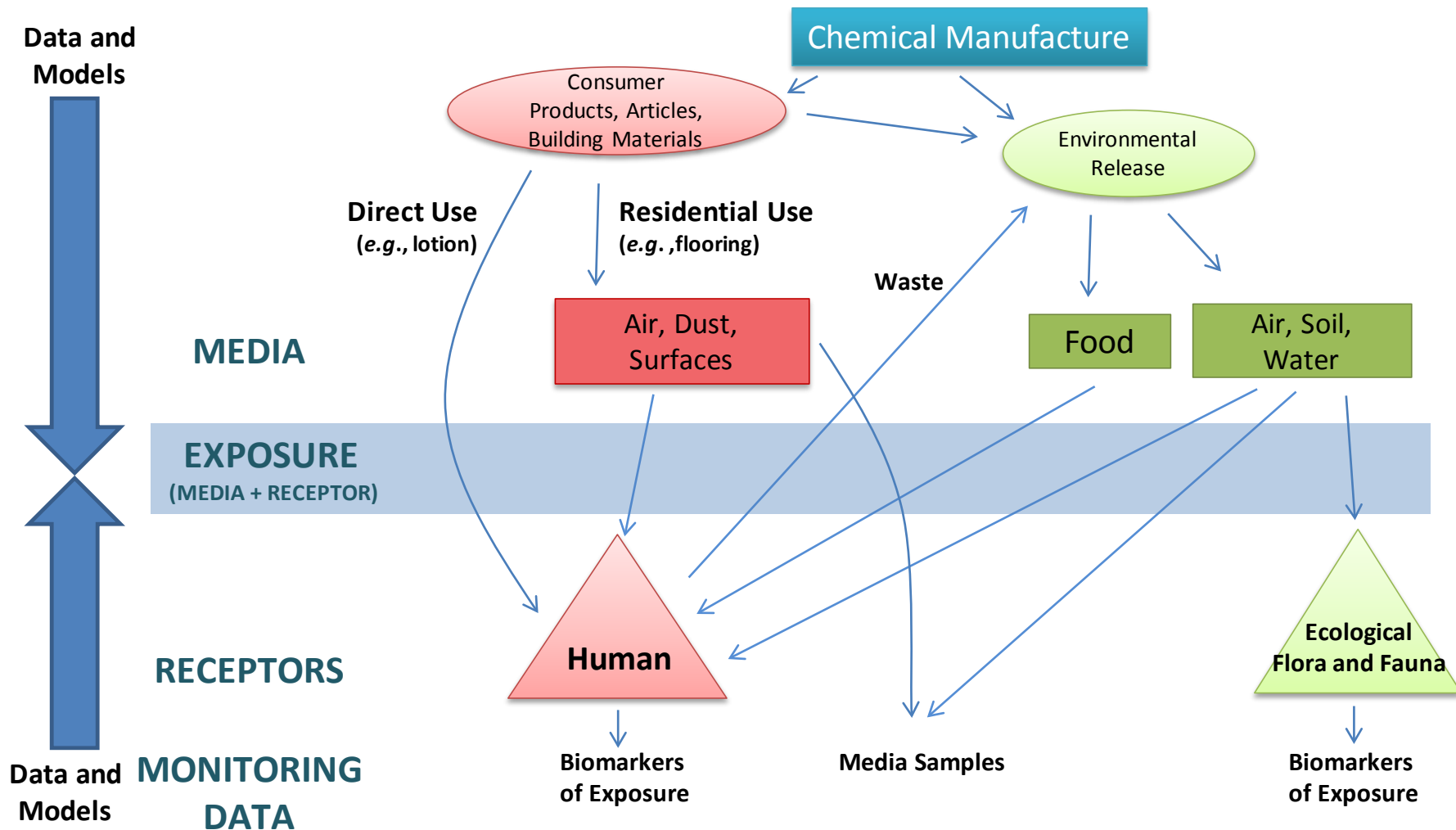


Exposure Monitoring

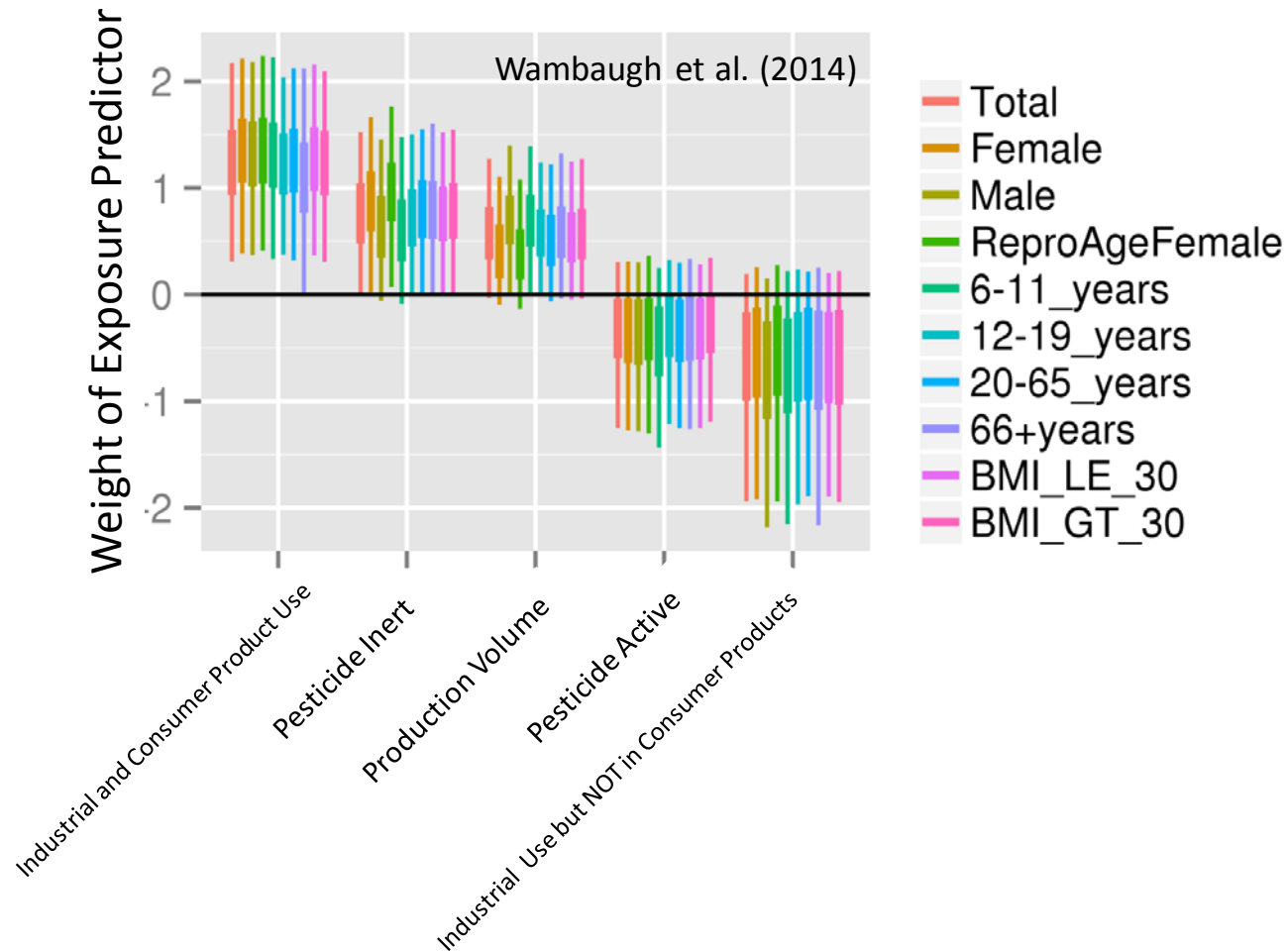


- Centers for Disease Control monitors a few hundred specific chemicals in urine and blood of U.S. citizens

Evaluating Exposure Models



Predicting Exposure



We incorporate multiple computer models into consensus predictions for 1000s of chemicals

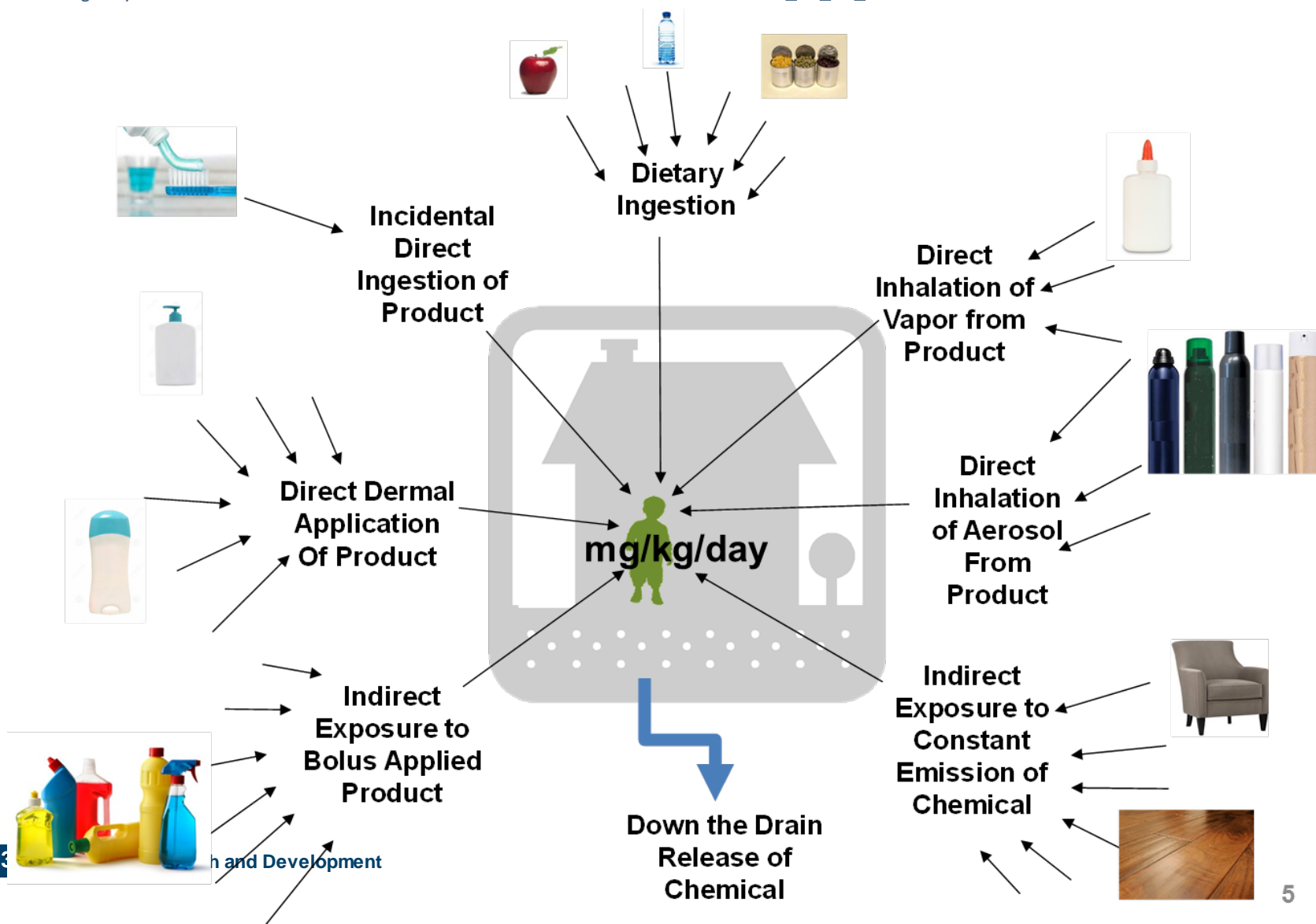
Same five predictors work for all NHANES demographic groups analyzed – stratified by age, sex, and body-mass index:

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

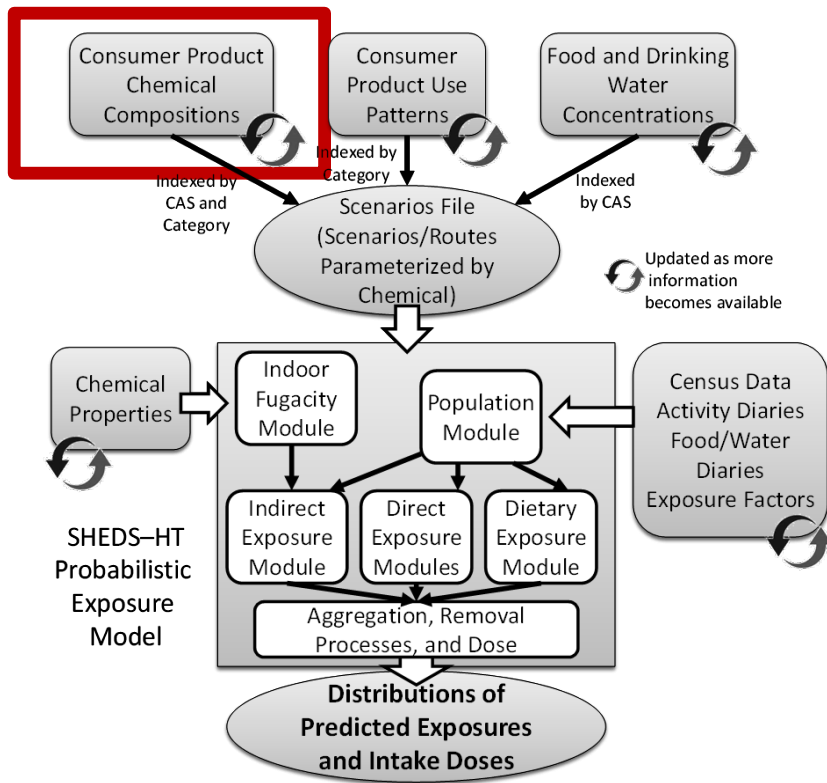
105 NHANES Chemicals



Advancing Near-Field Models: SHEDS- HT



Advancing Near-Field Models: SHEDS-HT

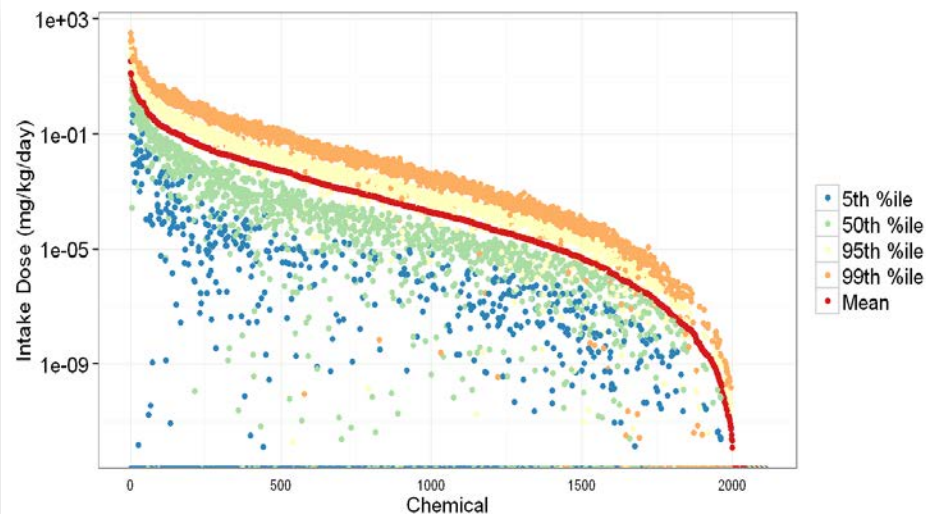


**Environmental
Science & Technology**

Article
pubs.acs.org/est

SHEDS-HT: An Integrated Probabilistic Exposure Model for Prioritizing Exposures to Chemicals with Near-Field and Dietary Sources

Kristin K. Isaacs,^{*,†} W. Graham Glen,[‡] Peter Egeghy,[†] Michael-Rock Goldsmith,^{§,○} Luther Smith,[‡] Daniel Vallero,[†] Raina Brooks,^{||} Christopher M. Grulke,^{⊥,○} and Haluk Özkaynak[‡]



USE: What chemicals are in consumer products and articles?

FUNCTION: Why are they there?

COMPOSITION: At what weight fractions are they present?

- Chemical and Product Categories Database (CPCat)
 - Cross-lab effort
 - Effort to curate data and harmonize use categories across many different public data sources
 - Chemical to use-category linkages
 - Publically available: <http://actor.epa.gov/cpcat>

Chemical and Product Categories Database (CPCat)

- Information on the use of 40,000 unique chemicals Chemical and Product Categories Database (CPCat)
- Curated across many different public data sources
- Indexed by a set of 800 harmonized *terms* describing how chemicals are used
- Terms are combined into *cassettes* to provide refined categories of chemicals with potential uses

Publically available:

<http://actor.epa.gov/cpcat>

Original data source	Class of categories	Original categories	CPCat cassettes	Chemicals
ACToR Data Sets and Lists	General-use	131	173	35,838
ACToR UseDB	General-use	15	15	31,622
CDR 2012:				
Consumer	General-use	34	36	3,321
Industrial Function	Functional-use	34	27	5,023
Industrial Sector	Industrial sector-use	42	43	5,226
DfE	Functional-use	11	9	444
Dow	Functional-use	19	18	104
DrugBank	Therapeutic-use	582	460	1,754
2006 IUR	General-use	19	24	1,152
Keml	Functional-use	61	31	876
NICNAS	General-use	17	17	177
Retail Product Categories	Product-use	359	191	2,778
SPIN:				
detpcat	General-use	781	284	6,491
Industrial Sector	Industrial sector-use	580	221	4,603
NACE	Industrial sector-use	57	52	7,745
UC62	General-use	61	59	9,059
Toxome	Functional-use	16	16	442

- 14 of 30 Office of Research and Development

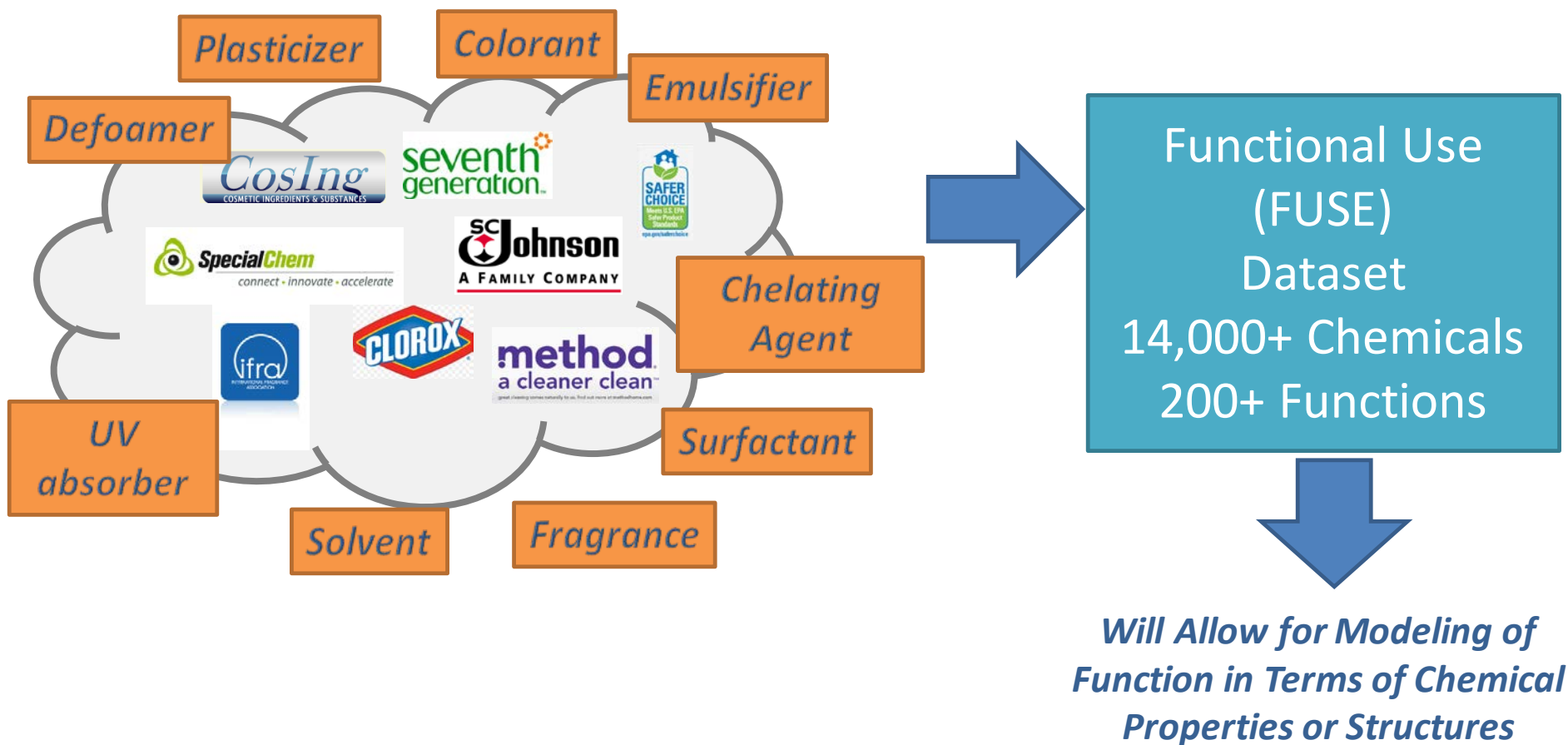


What Do We Do When We Don't Know How a Chemical is Used?

- Unfortunately we are lacking specific use information for 1000s of known chemicals
- Including a large part of the Tox21 library
- How might we go about predicting chemical use and ultimate exposure potential?
- *Function* may be key
- Use machine learning to fill in data gaps



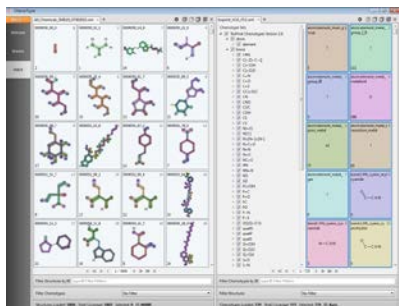
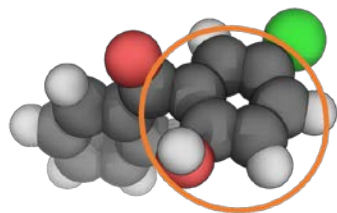
Expanding the Use Information in CPCat to Include Chemical Functional Use



Predicting Function Based on Properties and Structure

Chemical Structure and Property Descriptors

Use Database (FUSE)



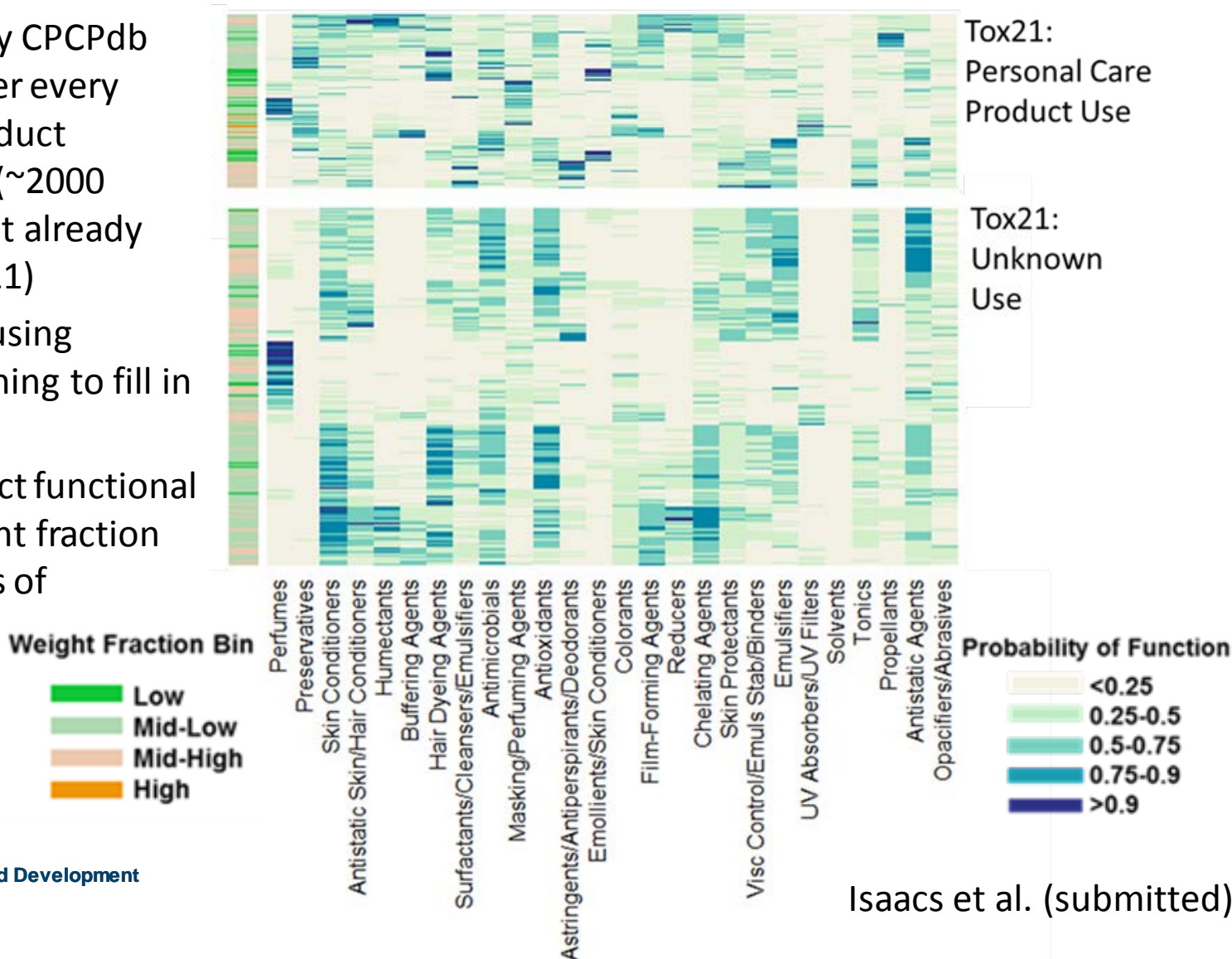
**Prediction of
Of Potential
Function
from Chemical
Libraries**

**Machine-Learning Based
Classification Models**

**Material from
Katherine Phillips**

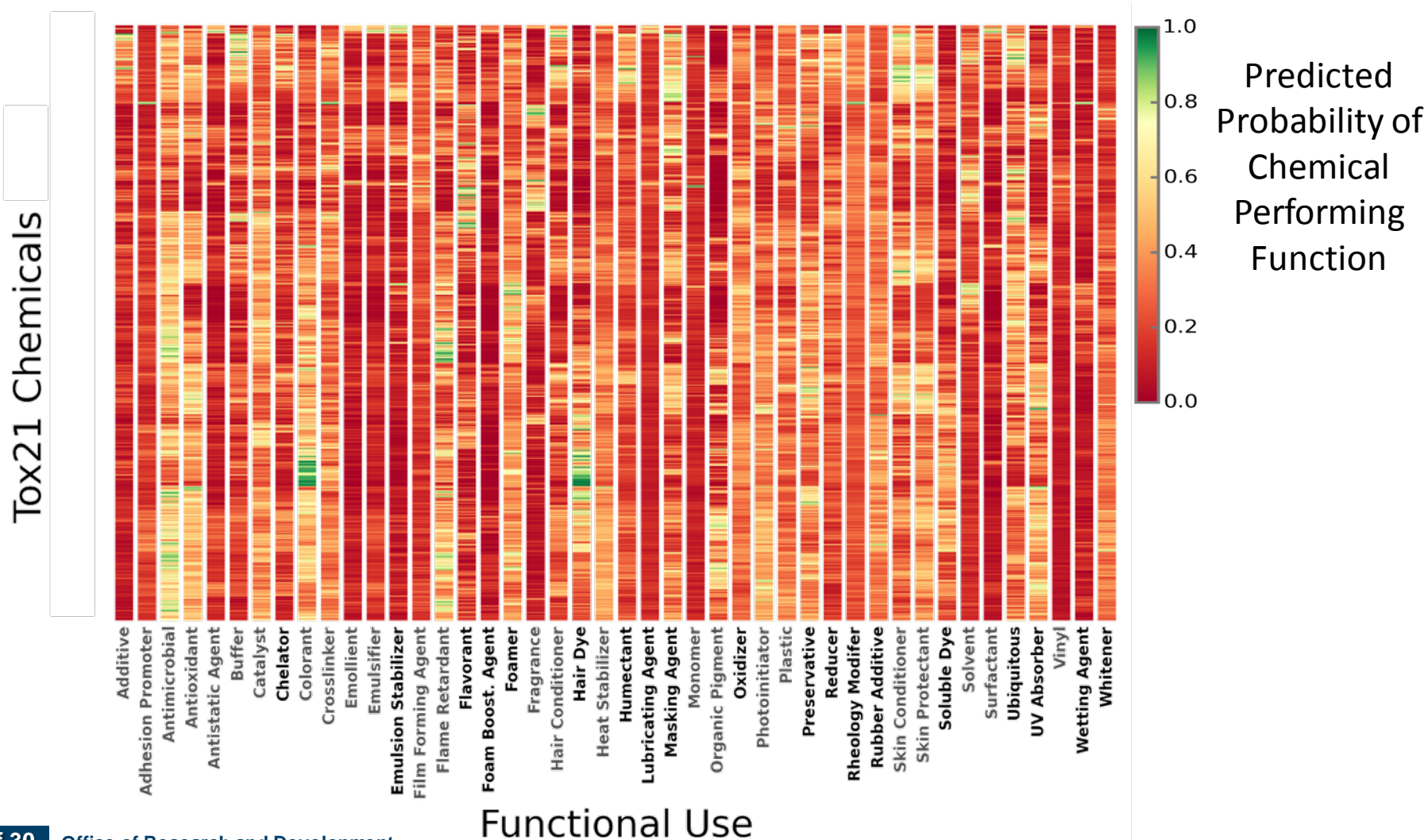
Predicting Chemical Constituents

- 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



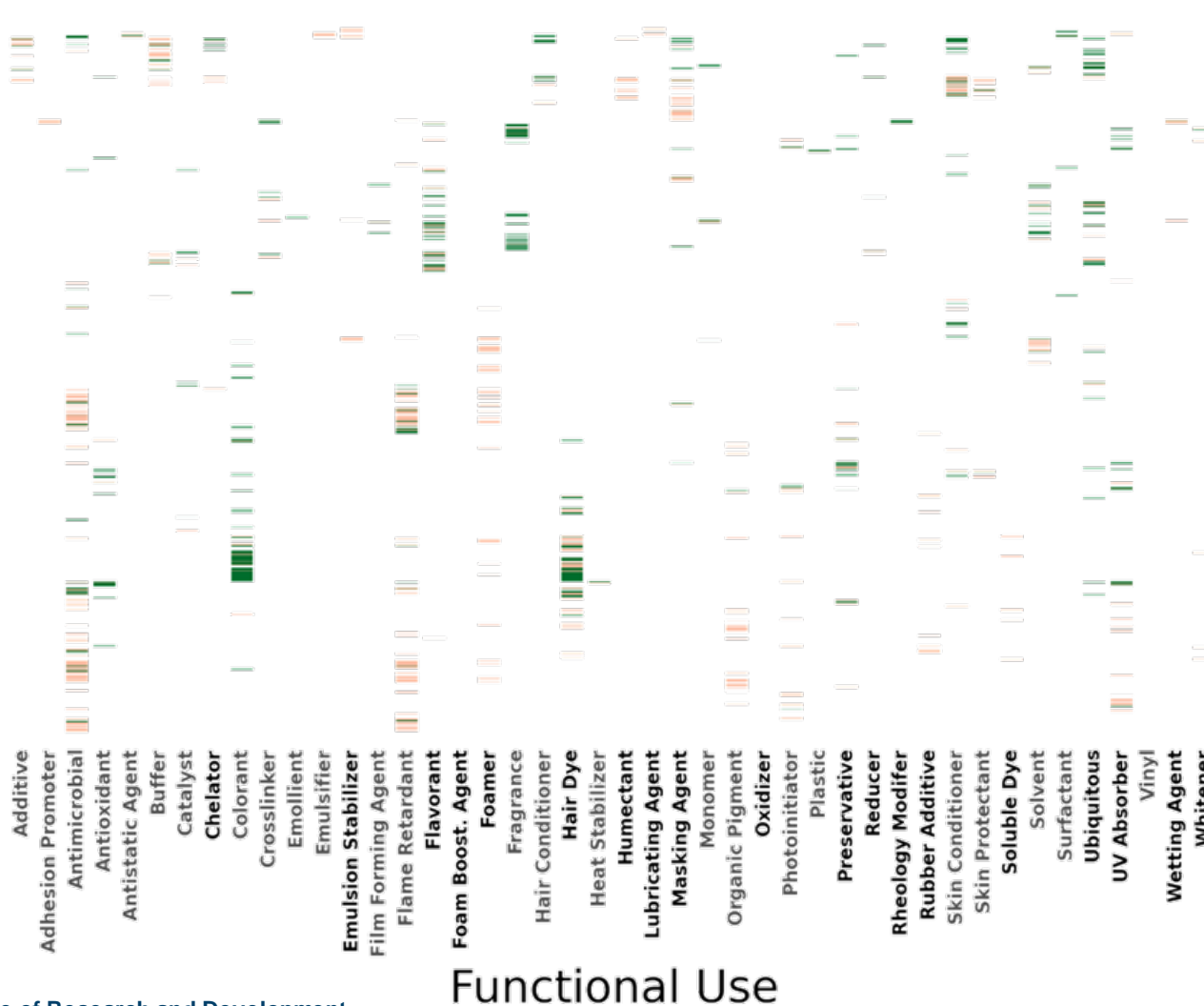
Isaacs et al. (submitted)

Screening for Potential Alternatives By Function and Bioactivity



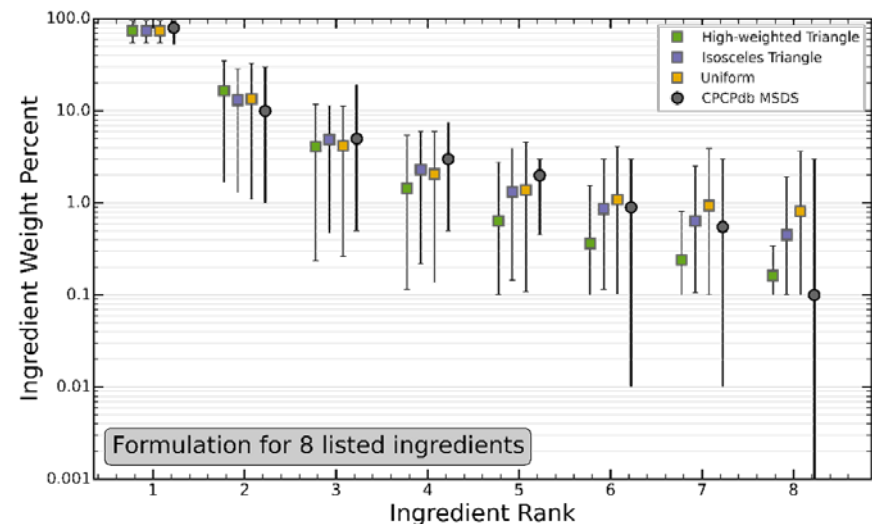
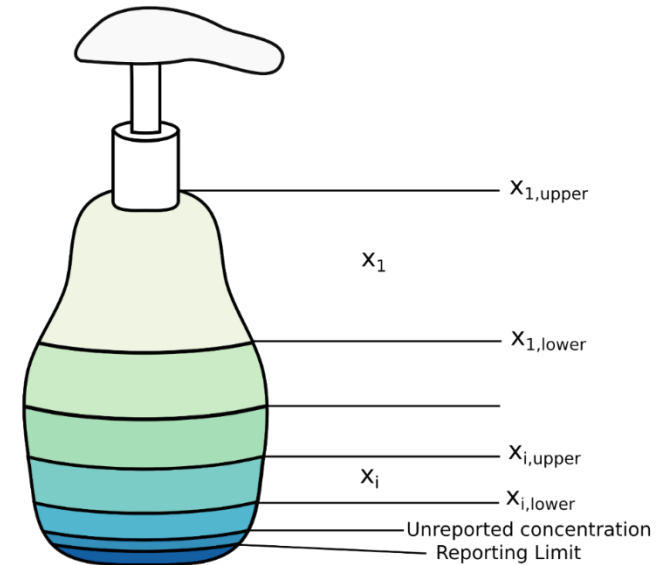
Screening for Alternatives By Function and Bioactivity

Tox21 Chemicals



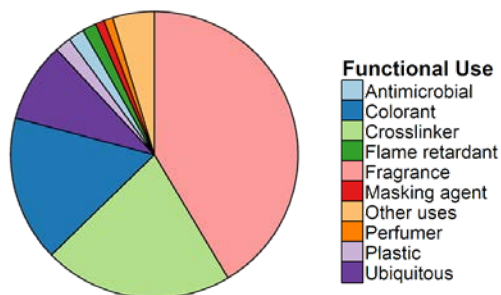
Predicted Concentrations from Ingredient Lists

- When a list of ingredients
 - Is presented in descending order by weight fraction
 - Includes all ingredients above a cut off weight fraction
- The weight fraction of a chemical is constrained by:
 - The rank of the chemical in the list
 - The length of the list
 - The cut off for reporting

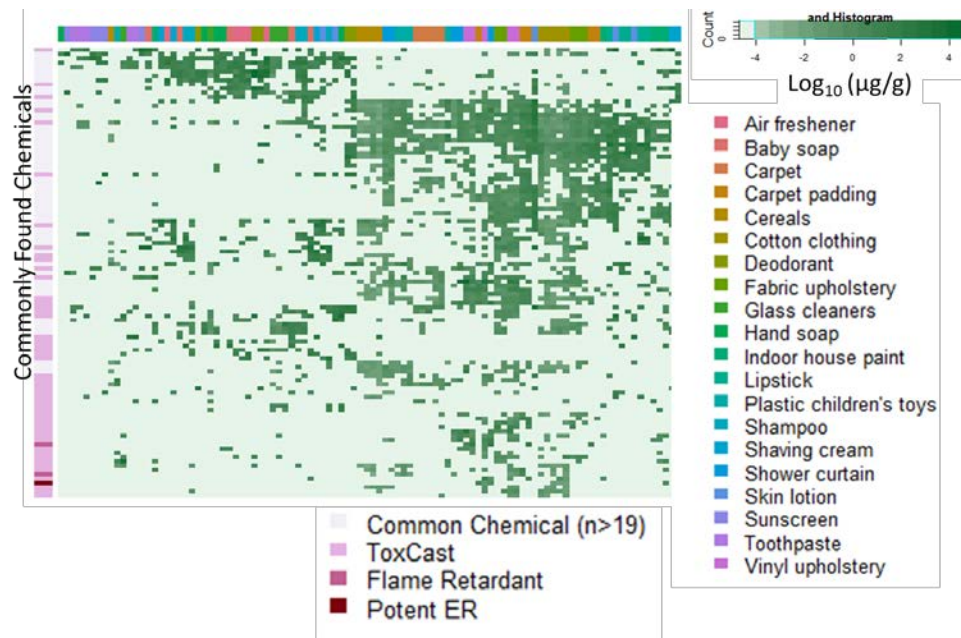
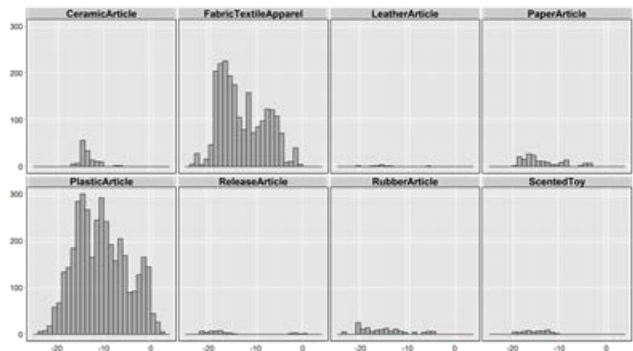


Moving Forward from Formulations to Articles

Danish EPA Surveys on Chemicals in Consumer Products



Log(Concentration) distributions



ExpoCast/RED HT Measurement
Contract

Material from John Wambaugh, Alice
Yau (SWRI) and Katherine Phillips

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

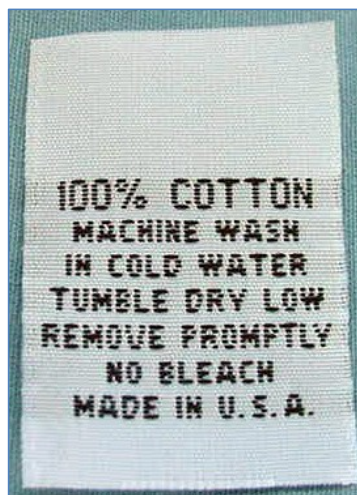
ExpoCast Consumer Product Scan

Commonly Found Chemicals

Scanned 5 examples each of 20 class of consumer products

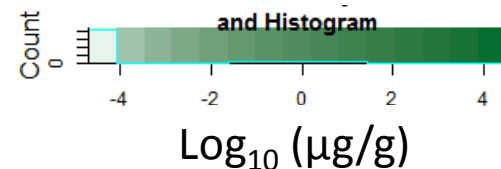
Found >3500 chemicals in total across the 100 products

The chemicals found in a cotton shirt



GC-MS with DCM Extraction

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



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

Results from Alice Yau (SWRI)

ExpoCast Consumer Product Scan

Commonly Found Chemicals

Scanned 5 examples each of 20 class of consumer products

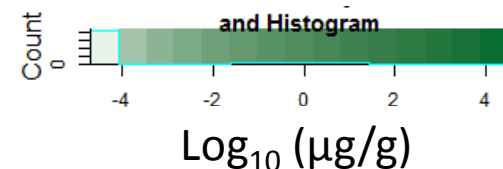
Found >3500 chemicals in total across the 100 products

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



- 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

Results from Alice Yau (SWRI)

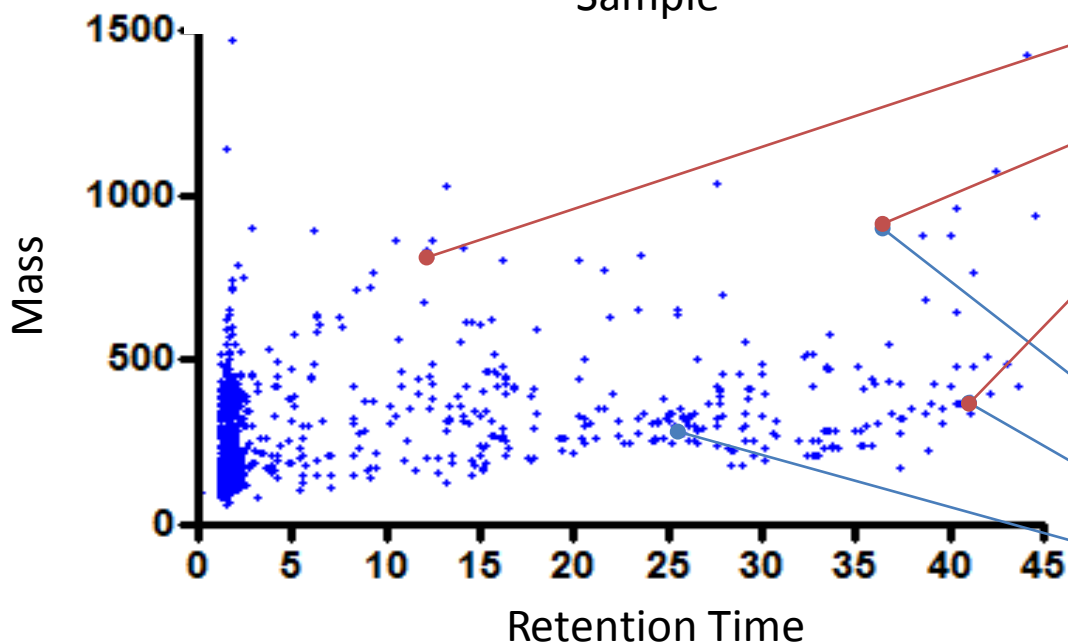
ExpoCast Consumer Product Scan



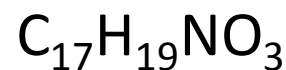
Results from Alice Yau (SWRI)

Suspect Screening and Non-Targeted Analytical Chemistry

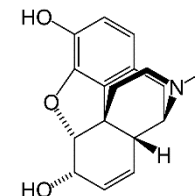
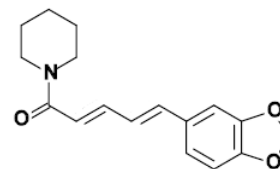
947 Peaks in an American Health Homes Dust
Sample



Each peak corresponds to a
chemical with an accurate mass
and predicted formula:



Multiple chemicals can have the
same mass and formula:



Is chemical A present,
chemical B, or both?

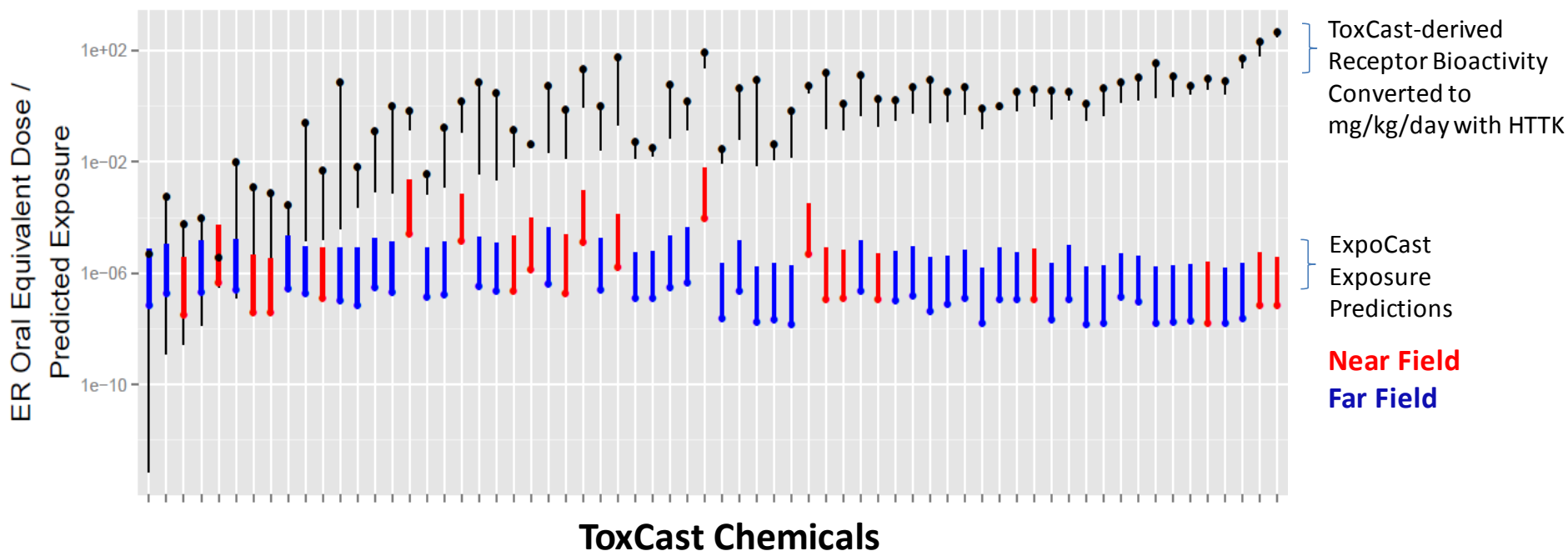
We are now expanding our identity libraries using reference samples of ToxCast chemicals

Applying Non-Targeted Screening

- ExpoCast consumer product scanning and blood sample monitoring
- EPA is also analyzing house dust from American homes – can identify 50% of the mass but only 2% of the chemicals Rager et al., Environment International (In Press)
- EPA is coordinating a comparison of the abilities of leading academic, government, and industry non-targeted screening groups to assess strengths and weaknesses



High Throughput Risk Prioritization in Practice



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

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

DOCKET NUMBER:
EPA-HQ-OPP-2014-0614

Conclusion

- We would like to know more about the risk posed by thousands of chemicals in the environment – which are most worthy of further study?
 - Exposure provides real world context to hazards indicated by high-throughput bioactivity screening

- Using **high throughput exposure** approaches we can make coarse predictions of exposure
 - We are actively refining and better validating these predictions with new models and data
 - In some cases, upper confidence limit on current predictions is already many times lower than predicted hazard

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



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

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