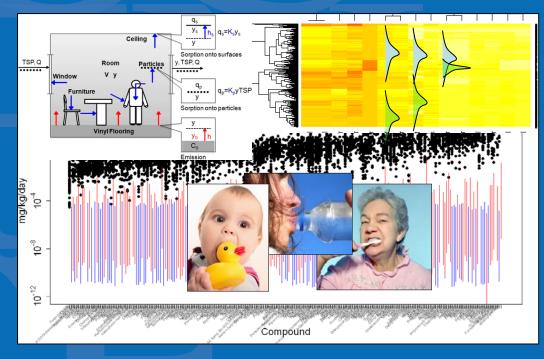


ExpoCast Framework for Rapid Exposure Forecasts

John Wambaugh U.S. EPA, Office of Research and Development



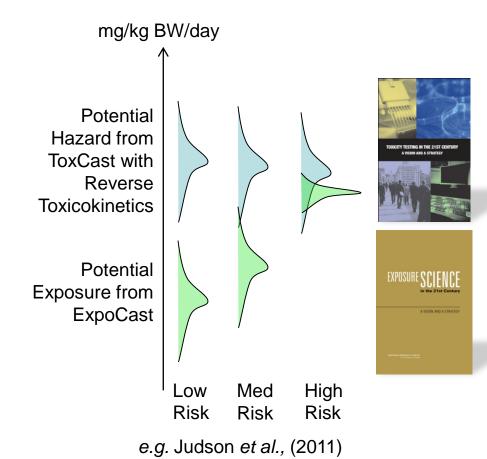
International Society for Exposure Science Annual Meeting
October 14, 2014
Cincinnati, OH

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



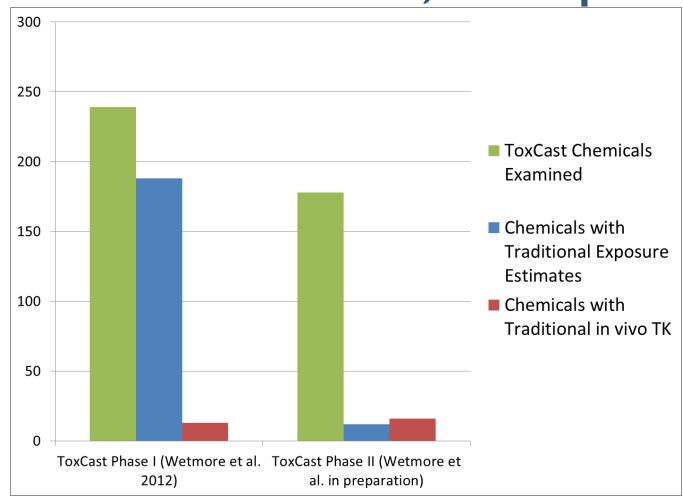
Risk Prioritization Requires Exposure

- Tox21/ToxCast: Examining thousands of chemicals using high throughput screening assays to identify in vitro concentrations that perturb biological pathways (Schmidt, 2009)
- In Wetmore et al. (2012), High throughput toxicokinetic in vitro methods are used to approximately convert in vitro bioactive concentrations (μM) into daily doses needed to produce similar levels in a human (mg/kg BW/day)
- These doses can then be directly compared with exposure rates,
 where available





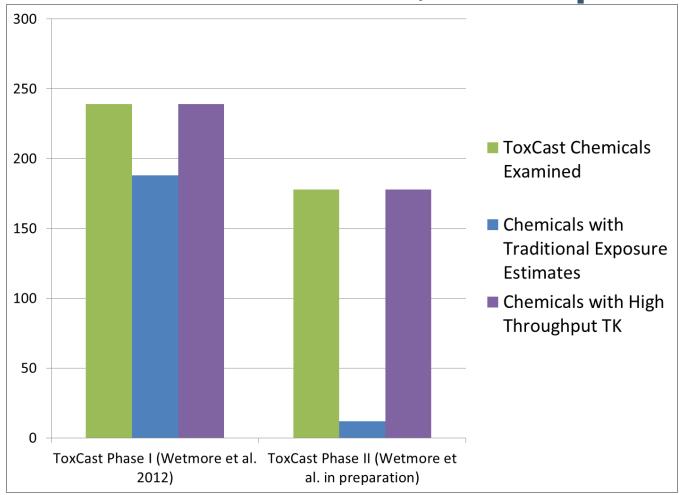
In Vitro Bioactivity, In Vivo Toxicokinetics, and Exposure



 Studies like Wetmore et al. (2012),addressed the need for toxicokinetic data



In Vitro Bioactivity, In Vitro Toxicokinetics, and Exposure



 As in Egeghy et al. (2012), there is a paucity of data for providing context to HTS data

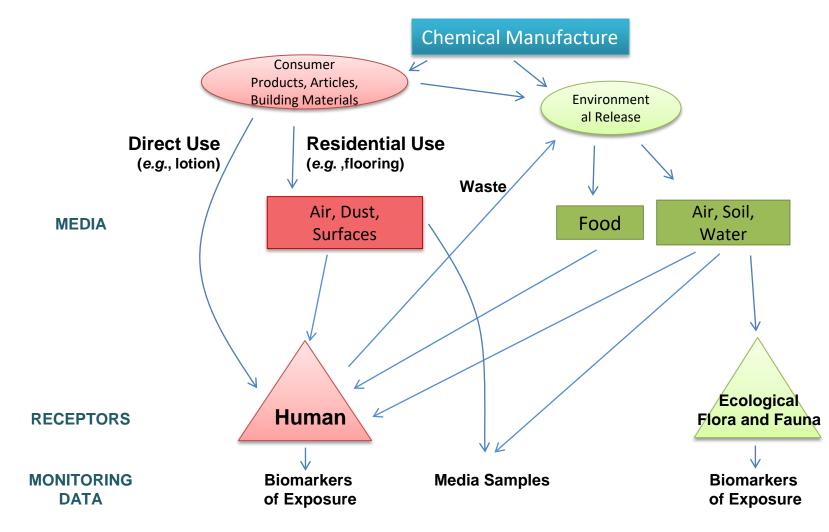


Goals for High Throughput Exposure

- Incorporate multiple models into consensus predictions for 1000s of chemicals
- Evaluate/calibrate predictions with available measurement data across many chemical classes
- Empirically estimate uncertainty in predictions

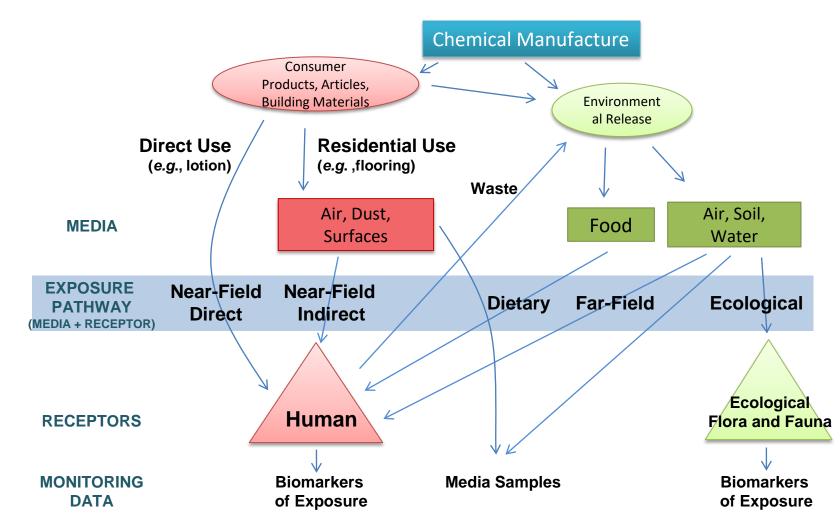


Exposure Space



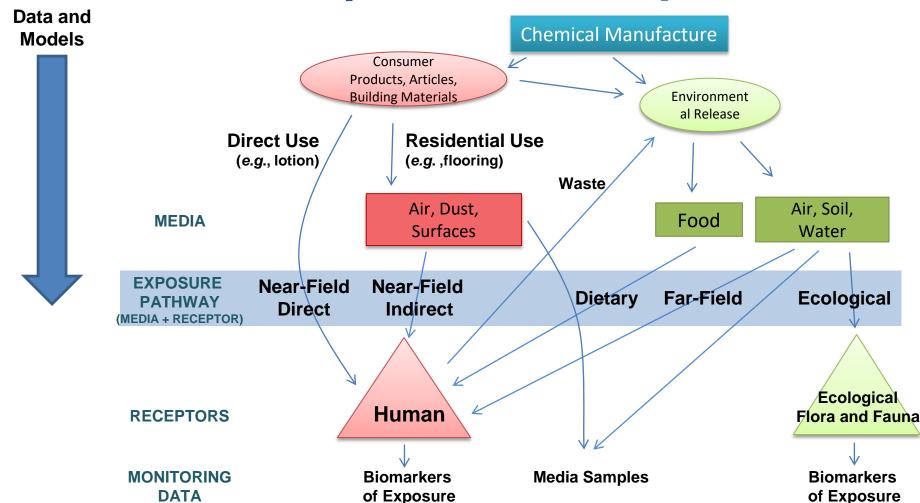


Exposure Pathways



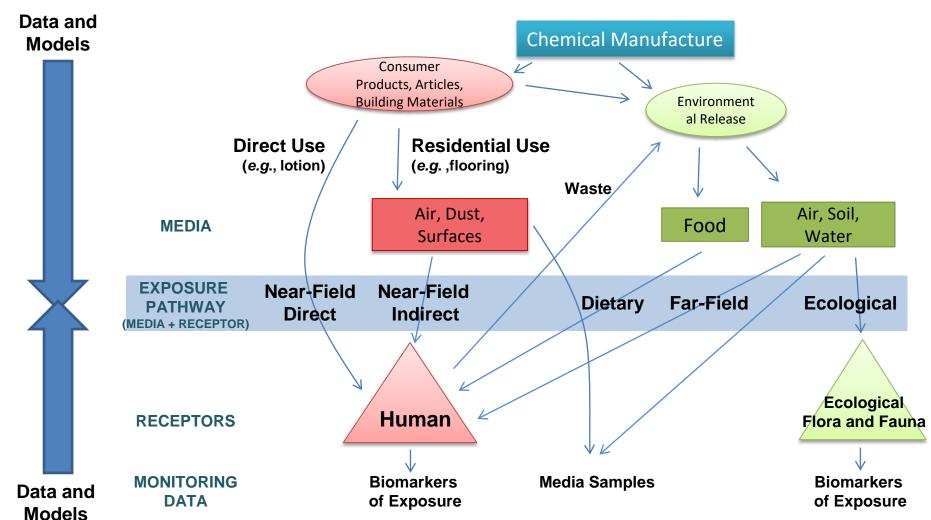


Forward Modeling of Exposure Pathways



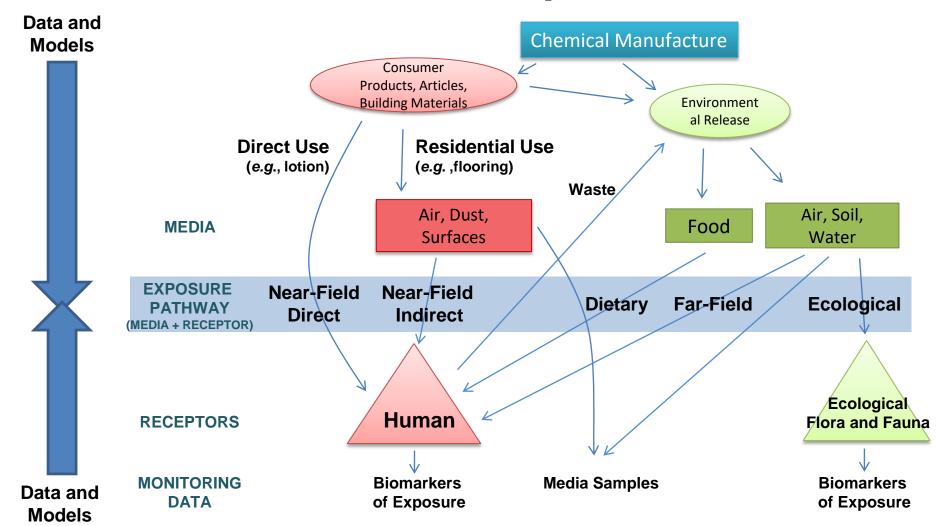


Inference of Exposure Pathways



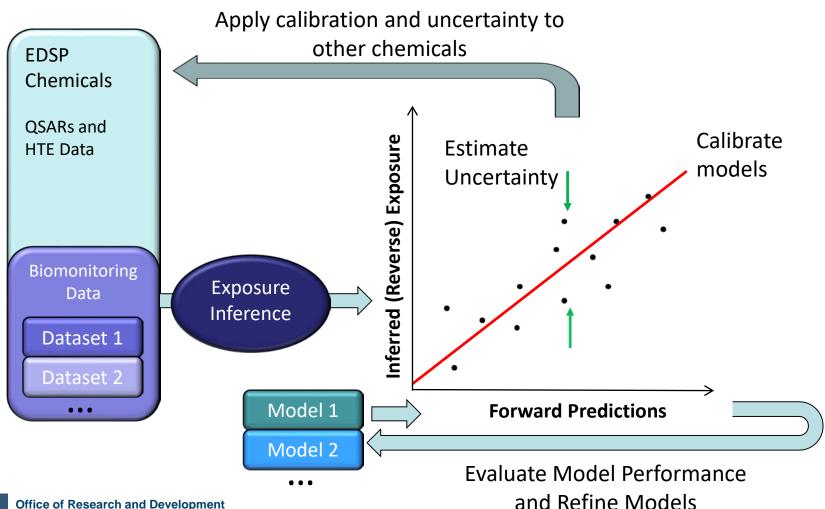


Evaluation of Forward Predictions United States Environmental Protection with Inferred Exposure Agency





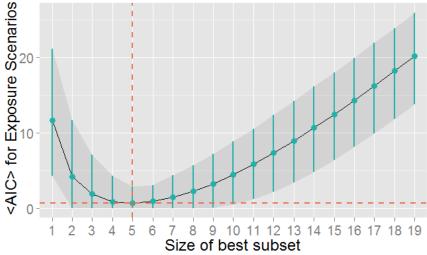
Systematic Empirical Evaluation of Models

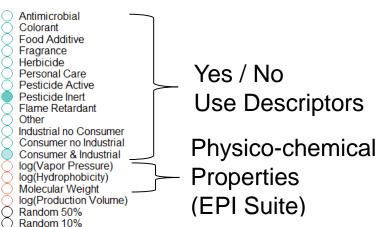




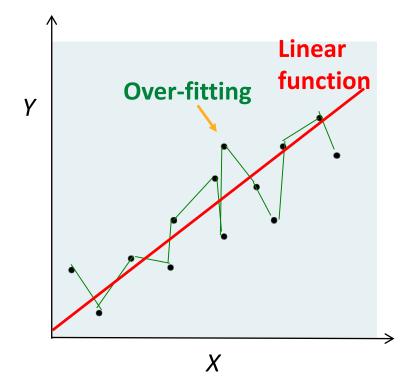
High Throughput Descriptors

for Exposure



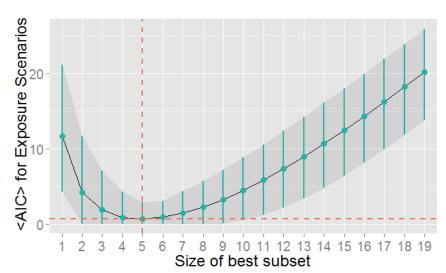


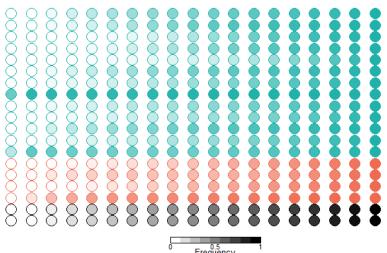
 The average relative AIC (smaller is better) for models made with different numbers of parameters for explaining 1500 different combinations of chemical exposures





Not All Descriptors Are Useful



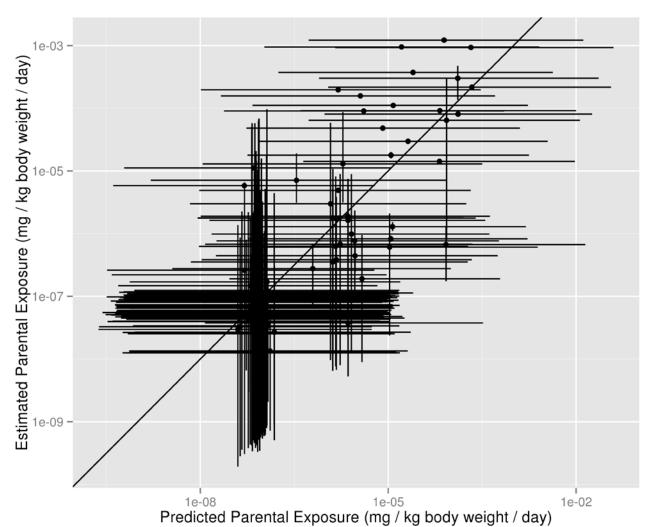


Antimicrobial Colorant Food Additive Fragrance Herbicide Personal Care Pesticide Active Pesticide Inert Flame Retardant Industrial no Consumer Consumer no Industrial Consumer & Industrial log(Vapor Pressure) log(Hydrophobicity) Molecular Weight log(Production Volume) Random 50% Random 10%

- The average relative AIC (smaller is better) for models made with different numbers of parameters for explaining 1500 different combinations of chemical exposures
- The predictors involved in the optimal model with higher frequencies are represented by darker circles, and those with lower frequencies by lighter circles
- As a sanity check, two random variables generated from binomial distribution with probability 50% and 10% of obtaining 1, are not selected as optimal descriptors in the five factor model

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Predicting NHANES exposure rates



R² ≈ 0.5 indicates that we can predict 50% of the chemical to chemical variability in mean NHANES exposure rates

Same five predictors work for all NHANES demographic groups analyzed – stratified by age, sex, and bodymass index

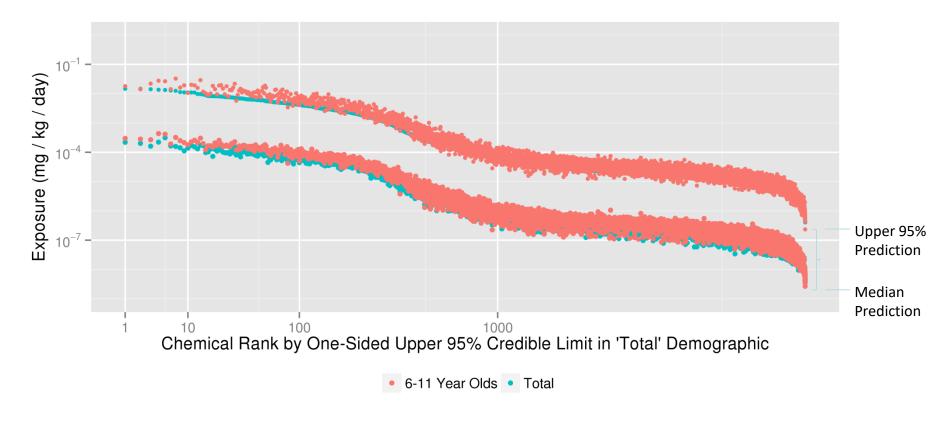


High-throughput exposure heuristics

		Number of Chemicals	
Heuristic	Description	Inferred NHANES Chemical Exposures (106)	Full Chemical Library (7784)
ACToR "Consumer use & Chemical/Industrial Process use"	Chemical substances in consumer products (e.g., toys, personal care products, clothes, furniture, and home-care products) that are also used in industrial manufacturing processes. Does not include food or pharmaceuticals.	37	683
ACToR "Chemical/Industrial Process use with no Consumer use"	Chemical substances and products in industrial manufacturing processes that are not used in consumer products. Does not include food or pharmaceuticals	14	282
ACToR UseDB "Pesticide Inert use"	Secondary (<i>i.e.</i> , non-active) ingredients in a pesticide which serve a purpose other than repelling pests. Pesticide use of these ingredients is known due to more stringent reporting standards for pesticide ingredients, but many of these chemicals appear to be also used in consumer products	16	816
ACToR "Pesticide Active use"	Active ingredients in products designed to prevent, destroy, repel, or reduce pests (<i>e.g.</i> , insect repellants, weed killers, and disinfectants).	76	877
TSCA IUR 2006 Total Production Volume	Sum total (kg/year) of production of the chemical from all sites that produced the chemical in quantities of 25,000 pounds or more per year. If information for a chemical is not available, it is assumed to be produced at <25,000 pounds per year.	106	7784



Calibrated Exposure Predictions for 7968 Chemicals





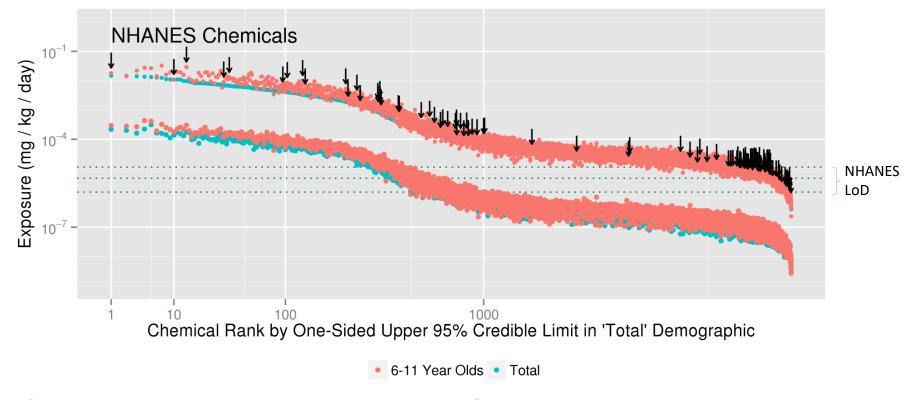
Calibrated Exposure Predictions for 7968 Chemicals



- We focus on the median and upper 95% predictions because the lower 95% is below the NHANES limits of detection (LoD)
- Dotted lines indicate 25%, median, and 75% of the LoD distribution



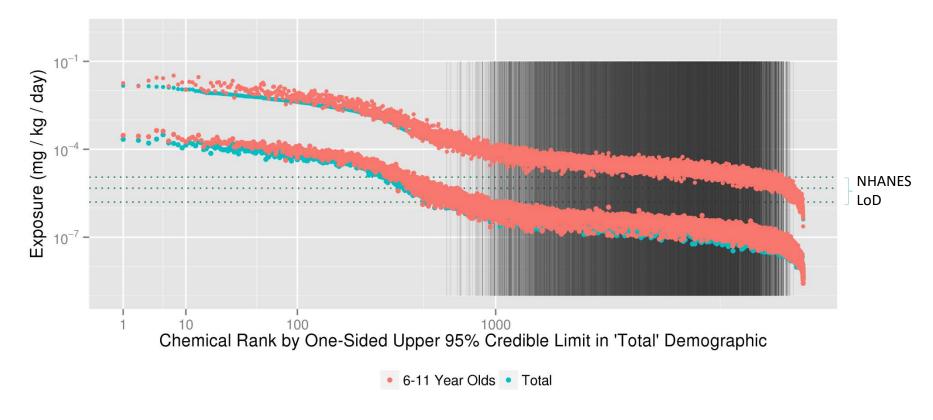
Calibrated Exposure Predictions for 7968 Chemicals



- Chemicals currently monitored by NHANES are distributed throughput the predictions
- Chemicals with the first and ninth highest 95% limit are monitored by NHANES



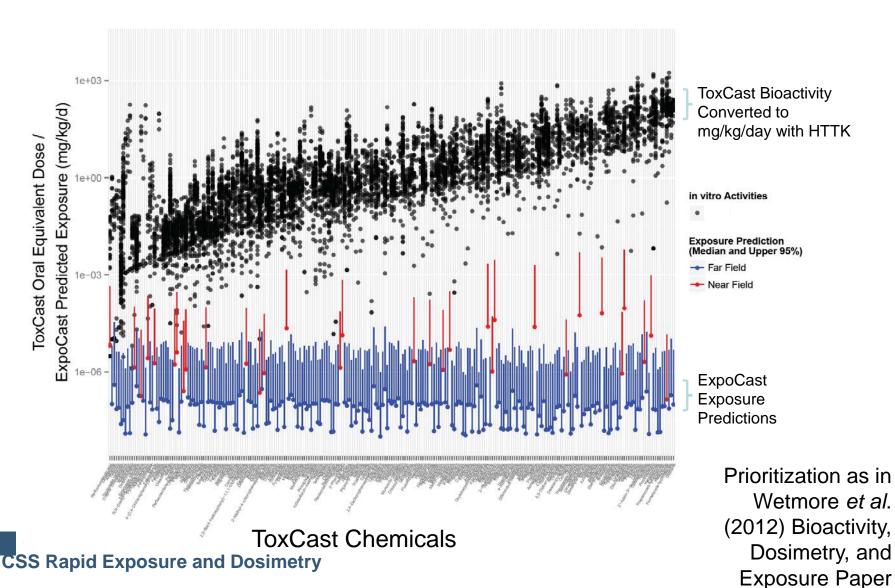
Calibrated Exposure Predictions for 7968 Chemicals



 The grey stripes indicate the 4182 chemicals with no use indicated by ACToR UseDB for any of the four use category heuristics



High Throughput Risk Prioritization



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Conclusions

- We identify those HTE factors that correlate with the NHANES data and estimate uncertainty
- The calibrated meta-model can estimate relative levels of chemical exposures for 7968 chemicals
 - This includes thousands of chemicals with no other data on human exposure
 - Same factors are predictive (R² ~ 0.5) across demographics characterized by NHANES
- Different demographics have different mean (overall) exposures:
 - There are demographic-specific aspects not currently described by available HTE factors
- Upcoming analysis:
 - Replace heuristics with calibrations of new mechanistic HT models for exposure from consumer use and indoor environment (e.g., SHEDS-HT)
 - Develop new data sources with additional chemical descriptors (e.g., CPcatDB)
 - Should help decrease uncertainties and increase confidence in extrapolation



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