

Progress on Related EPA PFAS Research Activities

OCSPS Stakeholder PFAS Workshop

February 14, 2024

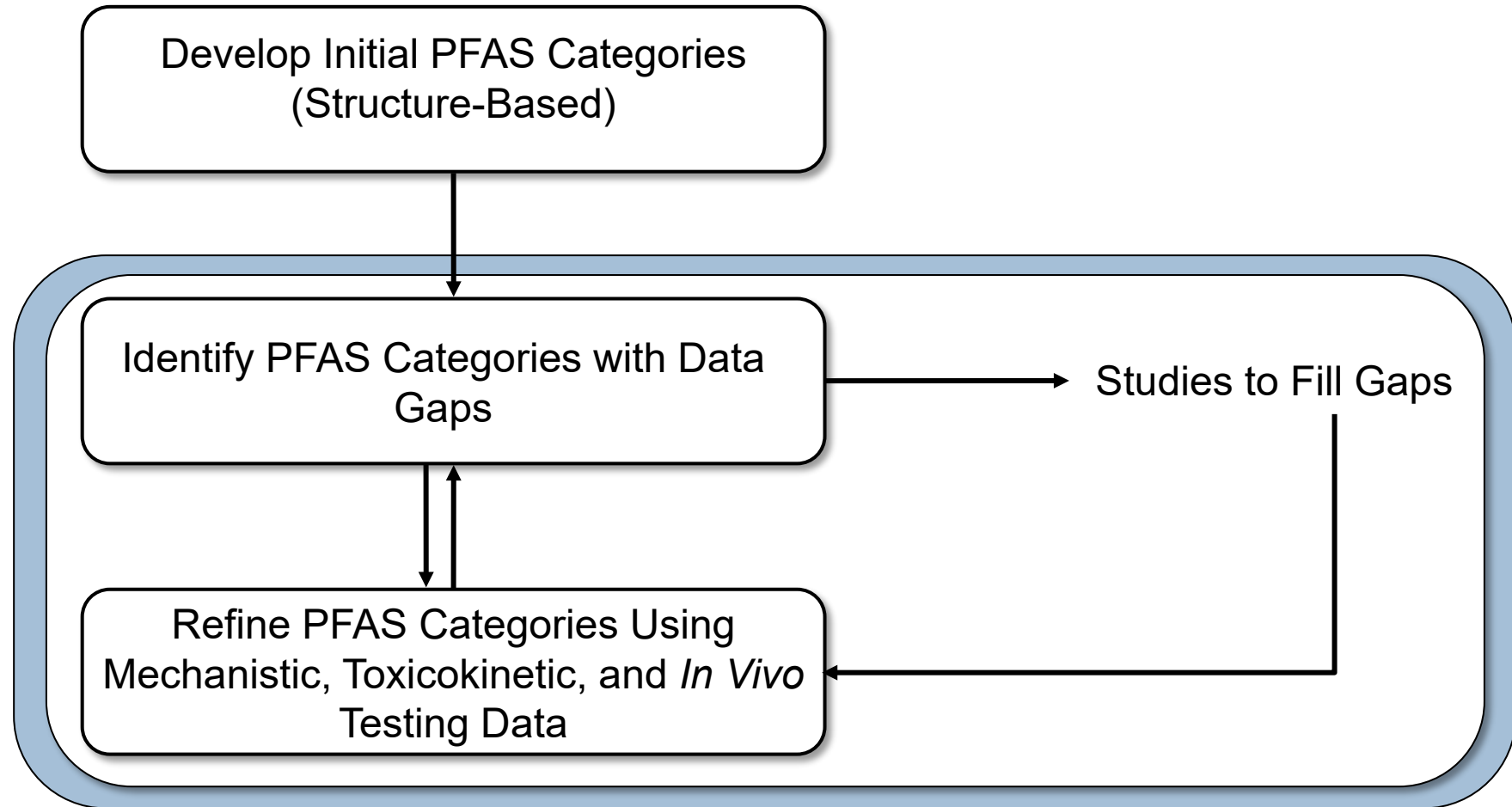
**Rusty Thomas
Center for Computational Toxicology and Exposure
U.S. Environmental Protection Agency**

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

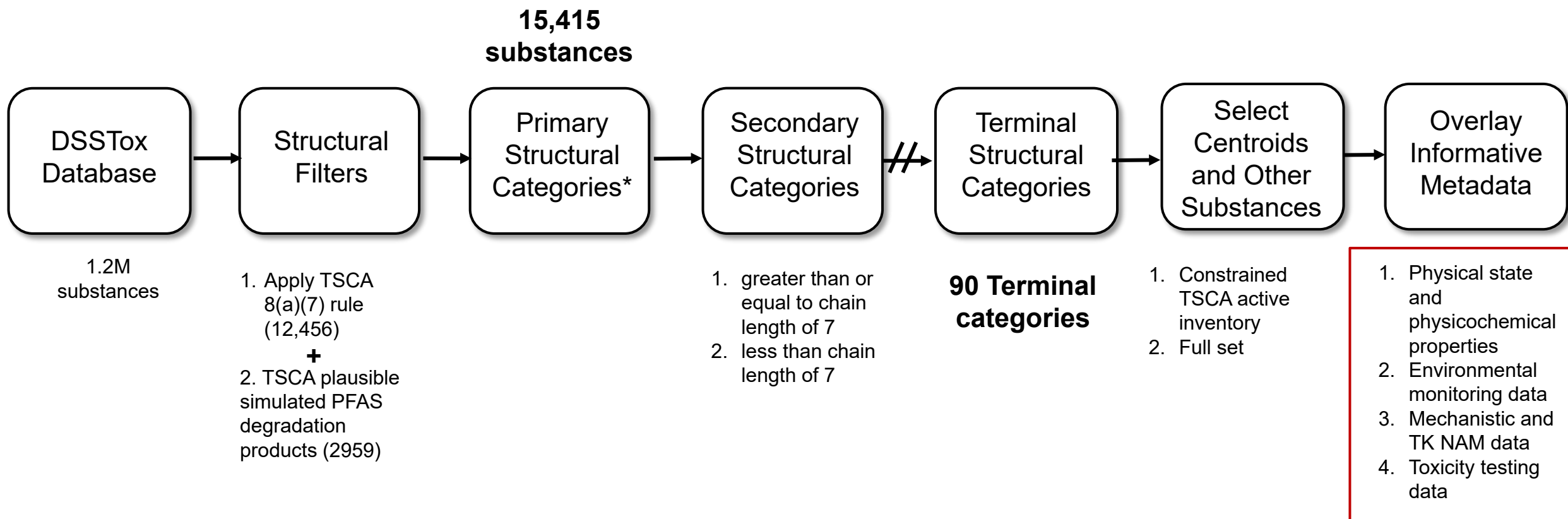
Disclaimer

The views expressed in this presentation are those of the presenter and do not necessarily reflect the views or policies of the U.S. EPA. Some of the results included in this presentation are pre-publication. Do not cite or quote.

A Key Aspect of the PFAS National Testing Strategy is the Iterative Refinement Based on Ongoing Research



Many of These Research Efforts are Intended to Inform and Refine the PFAS Categories



Physical Chemical Properties are Important to Inform Environmental and Exposure Pathways of PFAS

Property	PFAS Experimental Data	All Chemical Experimental Data
HLC	32	1908
VP	101	3440
BP	260	6903
WS	81	9241
LogP	53	14545
MP	195	29052

HLC, Henry's Law Constant; VP, Vapor Pressure; BP, Boiling Point; WS, Water Solubility; LogP, Log Octanol-Water Partition Coefficient; MP, Melting Point

- Multiple research efforts have developed QSAR models to predict physical chemical properties of PFAS (e.g., Bhatarai et al. 2011, Wang et al. 2011, Gramatica et al. 2014, Kim et al. 2015, Lampic et al. 2020, Sosnowska et al. 2023).
- Curated experimental data to inform development of QSAR models have been limited.
- Physical chemical data was compiled from multiple public sources and QCd to the data source.
- Two sets of consensus QSAR models were developed for each of the six physical chemical properties
 - PFAS only model
 - All chemicals model

Progress on the Development of Updated QSAR Models to Predict PFAS Physical Chemical Properties

QSAR Test Set Performance

Property	Trained to All Chemicals		Trained to PFAS	
	R ²	MAE	R ²	MAE
HLC	0.68	1.18	0.85	1.13
VP	0.97	0.55	0.93	0.63
BP	0.88	20.1	0.87	19.4
WS	0.65	0.83	0.57	0.83
LogP	0.59	0.91	0.47	1.07
MP	0.84	40.2	0.77	46.1

HLC, Henry's Law Constant; VP, Vapor Pressure; BP, Boiling Point; WS, Water Solubility; LogP, Log Octanol-Water Partition Coefficient; MP, Melting Point; MAE, Mean Absolute Error

- Consensus QSAR models trained on all chemical classes gave slightly better results for predicting physical chemical properties of PFAS than models trained only on PFAS.
- Model performance for PFAS is similar to CADASTER models, which were trained on PFAS substances.
- Additional QC of experimental data is on-going.
- Results expected to be published in Summer, 2024.

Environmental Monitoring Data are Important to Help Prioritize PFAS Categories for Data Collection

EPA Regional-ORD Appplied Research (ROAR) Project



ORD

Region 3

Region 5

Region 9



- Collaborative project focused on building state capacity to apply Non-Targeted Analysis (NTA) in their management of PFAS and other contaminants of emerging concern.
- Partner States/Regions involved:
 - R3/Maryland – NTA analysis of ~50 drinking water samples collected in relation to industrial release.
 - R5/Minnesota – NTA analysis of ~20 surface and groundwater samples related to two known PFAS point sources.
 - R9/California – NTA analysis of 9 well pilot study to inform large scale study of ~1,000 drinking water supply wells to support source and treatment investigation.
- EPA providing NTA knowledge and tools to standardize data processing and interpretation.
- NTA data will be released through state channels and within associated study time frames.

Mechanistic and Toxicokinetic Data are Intended to Help Refine PFAS Categories and Inform Study Needs

- ~150 PFAS from diverse structural classes were tested in 8 mechanistic and toxicokinetic assay batteries.
- Analytical QC was performed to detect presence and stability of each chemical.

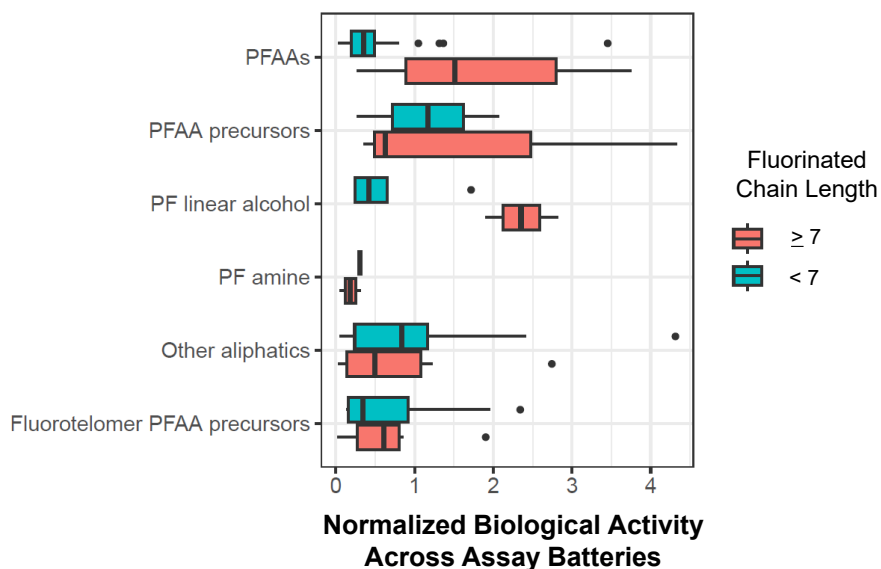
Intended Endpoint	Assay	Purpose
Developmental Toxicity	Zebrafish embryo assay	Assess potential teratogenicity
Immunosuppression	Eurofins BioMAP Diversity PLUS Panel (previously BioSeek) (decreased T-cell proliferation, decreased IgG production and B-cell proliferation, decreased IL-10 production)	Measure potential disease and immune responses in human primary culture and co-culture models
Developmental Neurotoxicity	Microelectrode array assay (rat primary neurons) and High Content Imaging (CD1 and hNP1 cells)	Impacts on development of functional neural networks
Nuclear Receptor and Transcription Factor Activity	Attagene cis- and trans-Factorial assays (HepG2)	Activation of transcription factors involved in critical cell pathways and stress responses
Whole Transcriptome Gene Expression	High-throughput transcriptomic assay (multiple cell types)	Measures changes in important biological pathways
Cellular Phenotypic Response	High-throughput phenotypic profiling (multiple cell types)	Measure changes in cellular organelles and general morphology
Toxicokinetics	Intrinsic hepatic clearance and plasma protein binding	Metabolic breakdown and amount of free chemical in the blood

PFAS Substances Demonstrated Broad Range of Mechanistic and Endpoint-Related Activities

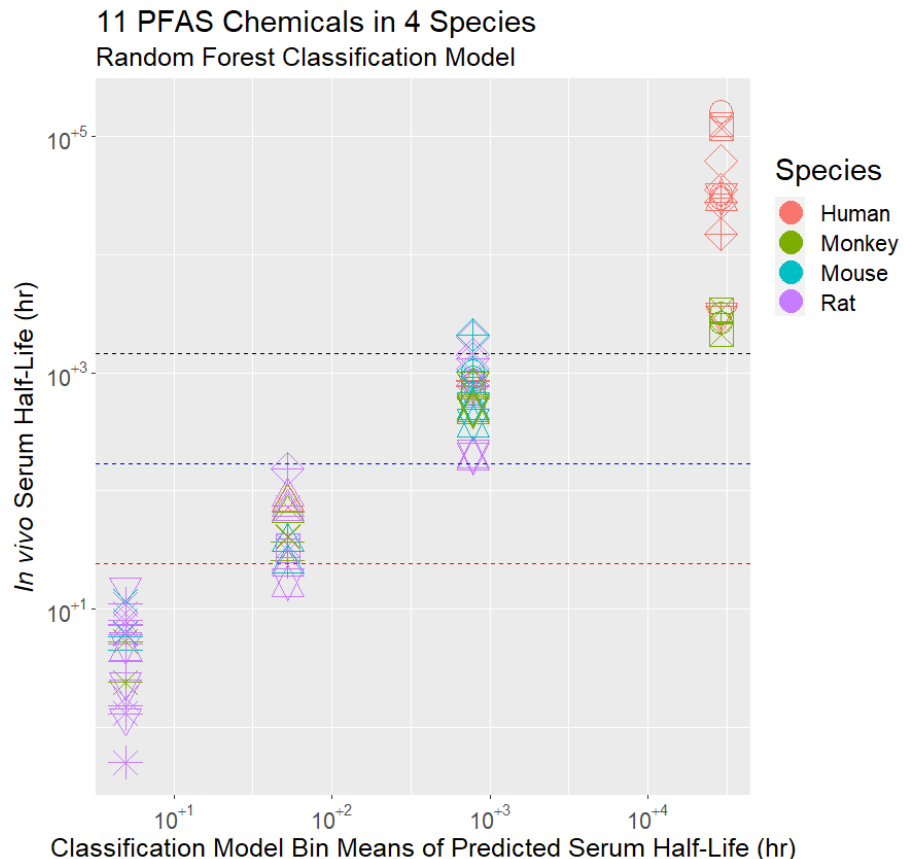
Predictive Performance of Enriched ToxPrints for Mechanistic Endpoints

	Balanced Accuracy	Sensitivity	Specificity
ER Activity	0.67	0.47	0.87
PPAR α Activity	0.78	0.88	0.68
NRF2 Activity	0.82	1	0.64
PXR Activity	0.76	1	0.53
Z-Fish Dev Toxicity	0.66	0.59	0.74
DNT Activity	0.56	0.14	0.98
Immune Activity	0.55	0.1	0.99

- Some PFAS substances showed specific activities towards ER α , PPAR α , PPAR γ , RXR β , PXR, and NRF2 receptors/ transcription factors (Houck et al., 2021).
- PFAS substances containing a perfluorinated carbon chain length ≥ 8 , high C:fluorine ratio, or a carboxylic acid moiety were more likely to be bioactive in the developmental neurotoxicity-related assays (Carstens et al., 2023).
- A subset of PFAS substances demonstrated response profiles consistent with immunosuppression, but there was limited evidence for immunosuppression for PFOA and PFOS in the models employed (Houck et al., 2023).
- Structural alerts represented by enriched ToxPrints show mixed performance for predicting mechanistic activity of untested chemicals.
- Some structural categories show strong biological activity trends with chain length, while others do not.




Toxicokinetic Data are Important for Interpreting Toxicological Responses From Animal Models

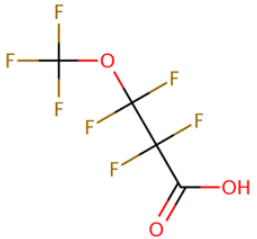


- Cross-species toxicokinetic data are very limited with data available for 11 PFAS in four species (human, rat, monkey, and mice)(Lau et al., 2007, 2012, 2015, and 2021).
- A machine learning model was developed to predict half-lives ($t_{1/2}$) in one of four bins: 0–12 h, >12 h to 1 week, >1 week to 60 days, and >60 days.
- Chemical and physiological descriptors were used as potential predictors of half-life (with surrogates for active transport).
- Model accuracy was 86.4% compared to the no information rate of 27%.
- Additional data have been identified to incorporate into the model.

Novel Toxicity Testing Data May Help Fill Information Gaps and Anchor Data Poor Categories

 EPA External Review Draft

EPA Transcriptomic Assessment Product (ETAP) for
Perfluoro-3-Methoxypropanoic Acid



April 2023

Center for Computational Toxicology and Exposure (CCTE) &
Center for Public Health and Environmental Assessment (CPHEA)
Office of Research and Development
U.S. Environmental Protection Agency

EXAMPLE ASSESSMENT, NOT FOR MAKING PURPOSES

- ORD recently peer reviewed the EPA Transcriptomic Assessment Product (ETAP) designed for developing human health assessments for data poor chemicals in < 9 months.
- The new human health assessment product uses short-term *in vivo* transcriptomic studies to identify a point-of-departure with no coordinated transcriptional changes that would indicate a potential toxicity of concern.
- Transcriptomic reference values are derived using a standardized set of uncertainty factors due to the carefully prescribed design.
- Transcriptomic reference values with traditional reference doses demonstrated similar levels of protection.
- Anticipate releasing ETAP assessments beginning in mid 2024.

Summary

- The EPA National PFAS Testing Strategy was intended to be iteratively updated and refined based on on-going research and data collection activities.
- The on-going research effort includes:
 - Updated models for physical chemical properties to better inform environmental and exposure pathways.
 - Environmental monitoring using non-targeted methods to help prioritize data poor categories.
 - Mechanistic and toxicokinetic data to help refine PFAS categories and inform study needs.
 - Novel toxicity testing and human health assessment approach methods to more rapidly fill information gaps and anchor data poor categories.
- The integration of the PFAS categories and research activities provides a strategic approach to focus data collection activities under TSCA and other authorities.

Acknowledgements

PFAS Physical Chemical Properties Project

Todd Martin
Nathan Charest
Charlie Lowe
Christian Ramsland
Antony Williams

PFAS Mechanistic Characterization Project

Keith Houck
Grace Patlewicz
Ann Richard
Antony Williams
Mahmoud Shobair
Marci Smeltz
Scott Clifton
Barbara Wetmore
Kelly Carstens
Theresa Freudenrich
Kathleen Wallace
Seline Choo
Amy Carpenter
Matthew Henderson
Katie Paul-Friedman
Madison Feshuk
Stephanie Padilla
Logan Everett
Josh Harrill

EPA Transcriptomics Assessment Project

Dan Chang
John Cowden
Sarah Davidson-Fritz
Jeffrey Dean
Mike Devito
Logan Everett
Alison Harrill
Susan Hester
Michael Hughes
Jason Lambert
Lucina Lizarraga
Roman Mezencev
Grace Patlewicz
Kris Thayer
Russell Thomas
Leah Wehmas
Kelsey Vitense
Scott Auerbach (NIEHS)
Warren Casey (NIEHS)

PFAS Cross-Species Toxicokinetics Project

Daniel Dawson
Chris Lau
Prachi Pradeep
Risa Sayre
Richard Judson
Rogelio Tornero-Velez
John Wambaugh

ROAR Non-Targeted Analysis Project

Jackie Bangma
Tim Buckley
Denise MacMillan
James McCord
Jon Sobus
Adam Swank
Heather Whitehead
Antony Williams
Kevin Cofield
Regina Poeske
Erin Newman
Carole Braverman
Matt Small
Sinisa Urban (MD)
Zhao Cao (MD)
Fatima Gowher (MD)
Sadia Muneem (MD)
Wendy Linck (CA)
Erica Kalve (CA)
Andri Dahlmeier (MN)
Stefan Saravia (MN)
Kaila Hanson (MN)
Rosie Rushing (MN)