Revisiting and updating chemical groupings with new approach methodologies

US EPA in collaboration with Health Canada, Environment Climate Change Canada

^{*}The views expressed in this presentation do not represent US EPA policy or endorsement. Mention of trade names of commercial products should not be interpreted as an endorsement.

Team Members

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Overview

A chemical category is a group of chemicals whose physicochemical and human health and/or ecotoxicological properties and/or environmental fate properties are likely to be similar or follow a regular pattern, usually as a result of structural similarity. - OECD

- Applications of chemical categorization include first tier assessment efforts and read across from structurally similar analogs:
 - Toxic Substances Control Act (TSCA) New Chemical Program Chemical Categories (NCC; US EPA)
 - ECOSAR (focus of presented work)

US EPA ECOSAR Chemical Classifications

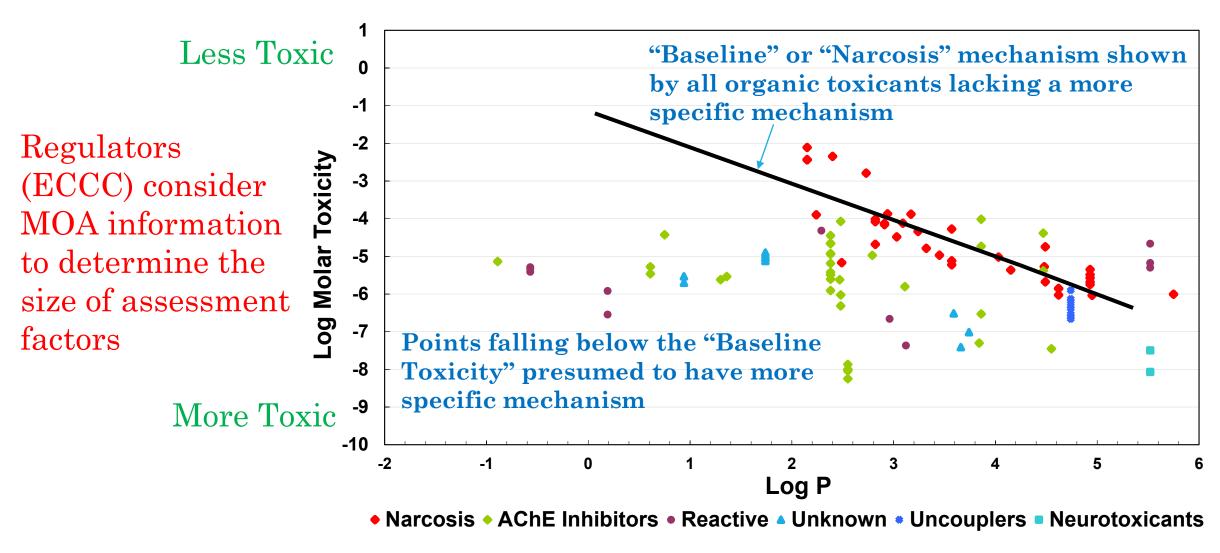


- Class-based SAR to predict aquatic toxicity
- Classification scheme identifies excess toxicity
- Estimates acute and chronic toxicity based on accumulated data and past decisional precedents

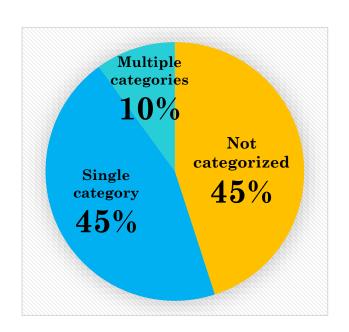
 $\begin{array}{ll} \underline{\text{Acute Effects:}} & \underline{\text{Chronic Effects:}} \\ \text{Fish 96-hr LC}_{50} & \text{Fish ChV} \\ \text{Daphnid 48-hr EC}_{50} & \text{Daphnid ChV} \\ \text{Algae 72/96-hr EC}_{50} & \text{Algae ChV} \\ \end{array}$

• Profiler in OECD QSAR Toolbox

Narcosis vs. specific-acting toxicity MOA



Potential approach for updating chemical categories



- Almost half of all New Chemical inventories across regulatory jurisdictions cannot be categorized using NCC or ECOSAR
- Some fall into multiple categories

How to update?

- Incorporate New Approach Methodologies (NAMs) -i.e., ToxCast and Tox21 biological activity information
- Apply cheminformatic approaches

General approach

Training set chemicals

- Well-defined MOA (narcosis vs. specific-acting)
- NAM data in vitro toxicity data
- in vivo toxicity data
- Representative of chemicals of interest for prediction

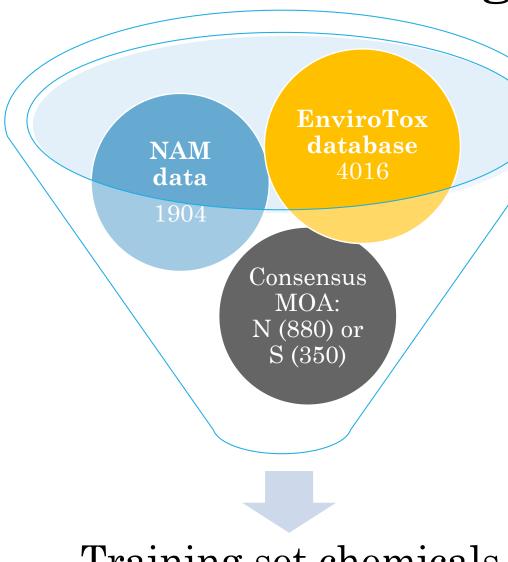
Characterize training set

- 1. ECOSAR classes
- 2. NCC
- 3. Chemotype fingerprints (ToxPrints)

Model

- NAM data, chemotypes and combination of both
- Evaluate different machine learning algorithms

Training set chemicals



Training set chemicals

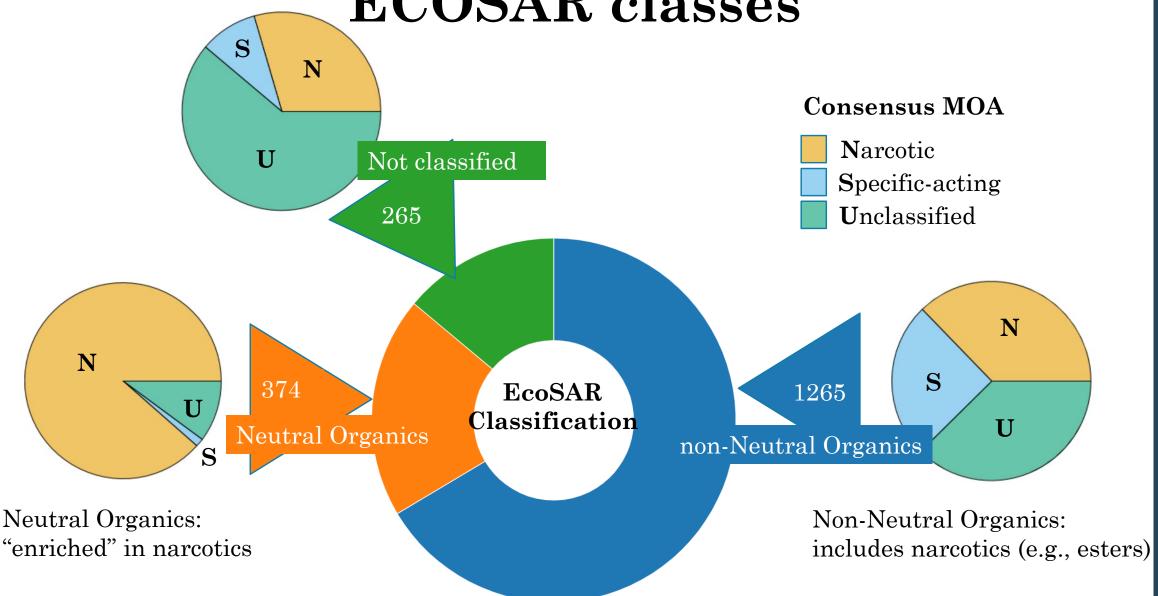
- 1. Chemicals with *in vivo* eco-data from the EnviroTox¹ database 4016
- 2. Sub-selection for chemicals with NAM data (ToxCast and Tox21) 1904
- 3. MOA predictions based on 4 publicly-available classification models
 - VERHAAR, ASTER, OASIS, TEST
 - Each predicts Narcotic, Specific-Acting or Unclassified

Consensus MOA with confidence scores²

Examples:	Results:
NNNN = N, score =3	880 Narcotic
NNSN = N, score= 2 SUSS = S, score= 2	350 Specific-acting
NUNS = U, $score = 0$	674 Unclassified

¹Health and Environmental Sciences Institute (HESI). 2019. EnviroTox Database & Tools. Version 1.1.0 Available: http://www.envirotoxdatabase.org/

Characterize training set chemicals: ECOSAR classes

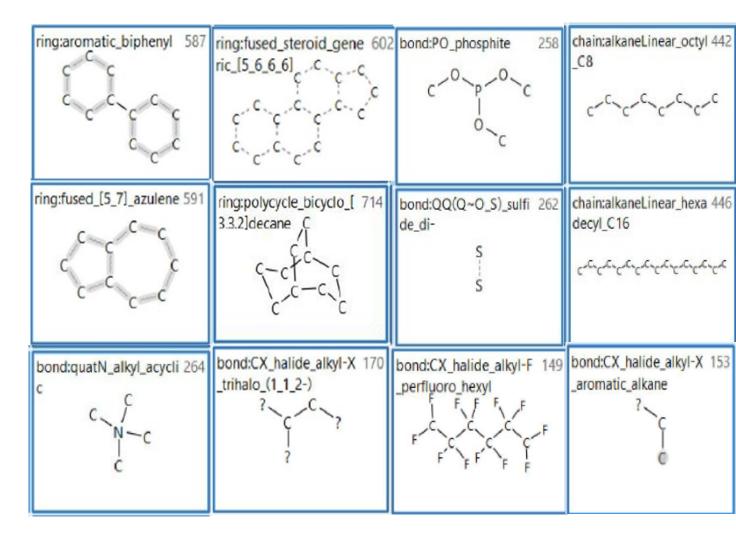


Characterize Training Set Chemicals: ToxPrints

- Pull in chemotype information for our chemicals via ToxPrints
 - Publicly available tool
 - EPA Comptox Chemicals Dashboard

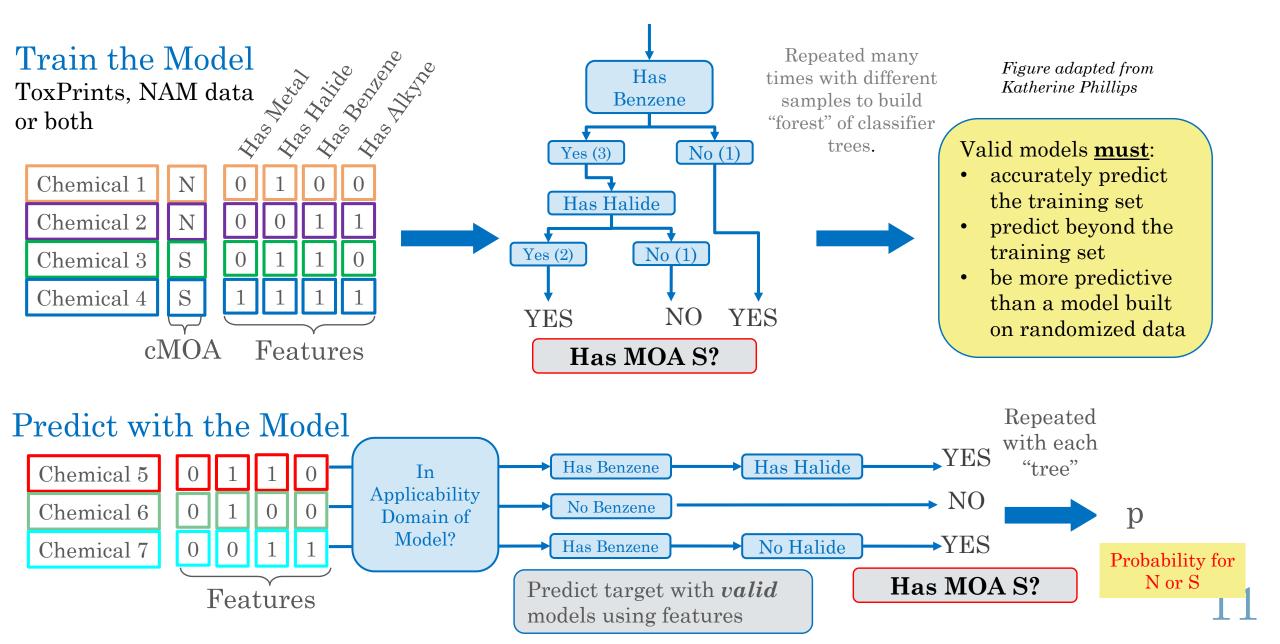
ToxPrints:

- √ 729 chemical features
- ✓ Chemically interpretable
- ✓ Coverage of diverse chemistry
- ✓ Includes scaffolds, functional groups, chains, rings, bonding patterns, atom-types



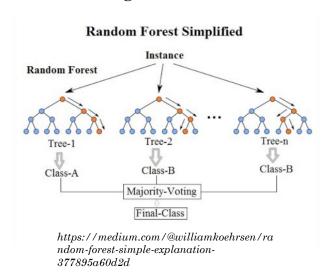
Yang et al. J. Chem. Inf. Model. 2015. Richard et al., Chem. Res. Toxicol. 2016, 29(8) 1225 – 1251; Strickland et al., Arch Toxicol. 2018 92(1) 487 – 500; Wang et al., Environment International 2019, 126 377 – 386

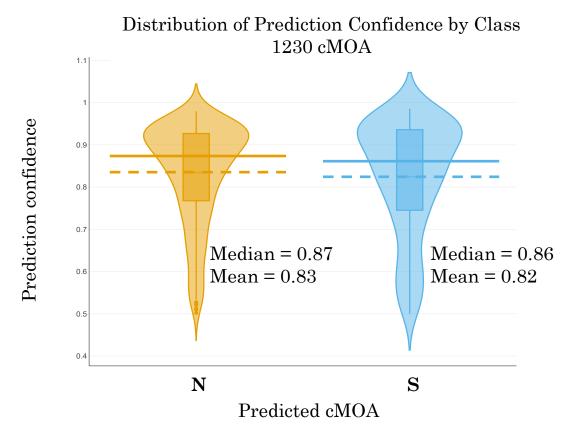
Classification model development



Preliminary results

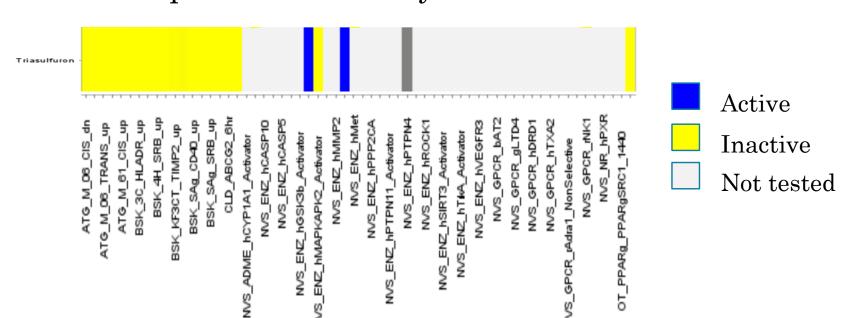
- Random Forest provided the best model results:
 - Trained on a "balanced" down-sampled subset (675 cMOA N+S)
 - Training Out-of-Bag (OOB) error rate = 10.2%
 - Total Accuracy on the full N+S data set = 94.5% (1230 cMOA N+S)
 - 68 chemicals misclassified:
 - 11 F_{pos}{predicted S}
 - 57 F_{neg}{predicted N}

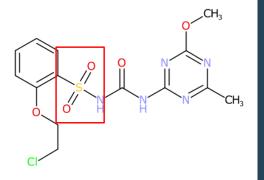




Example: Differences in model prediction vs. cMOA: Triasulfuron

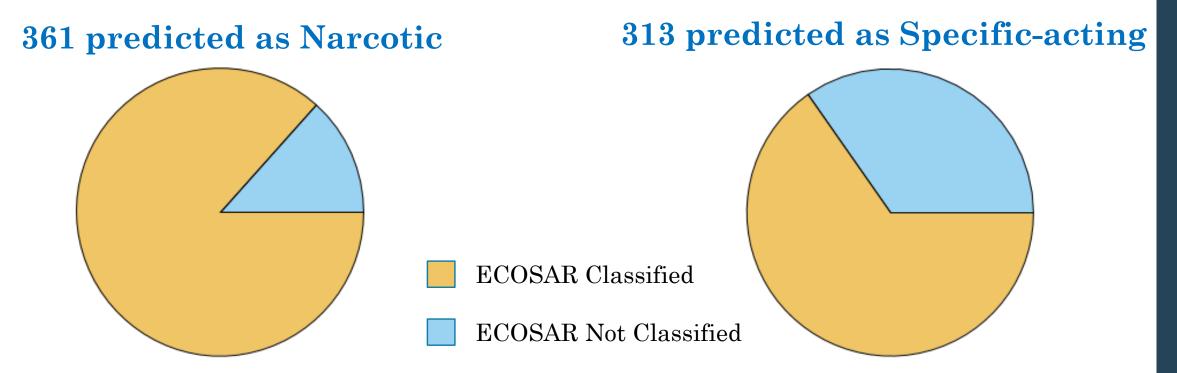
- N-sulfonylurea herbicide
- Model prediction: Specific-acting
- EnviroTox consensus MOA: Narcotic
- ECOSAR classification: Sulfonyl Urea
- S(=O)_sulfonyl ToxPrint is enriched in the specific-acting MOA space and 47 assays



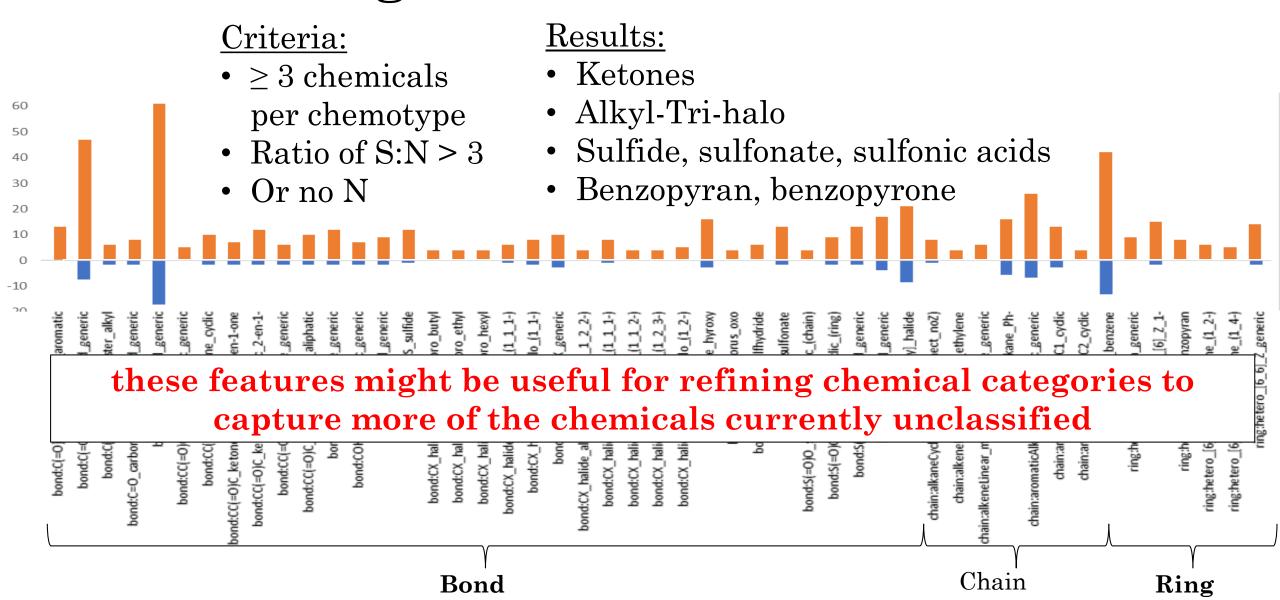


Predicted MOAs of the Unclassified set

- 674 chemicals in the EnviroTox dataset that had low confidence or ambiguous consensus
- Applied model to the Unclassified set and compared predictions to ECOSAR classification



Unclassified chemicals, predicted Specific-Acting: Enriched ToxPrints



Summary

- Identified relevant NAM information to develop a classification model for specific-acting MOAs
- Explored differences in predicted and consensus MOA via chemotype enrichments
- Used model to inform ECOSAR unclassified chemicals
 - Majority of unclassified chemicals were predicted to have a specific acting MOA
 - Identified primary chemotypes for specific acting MOAs

Next steps/ongoing work

- Leverage more invitroDB chemicals beyond the 1905 EnviroTox chemicals
 - Generated KNIME workflow for the consensus MOA calls
 - Greater coverage of the NAM assay space
 - >7000 chemicals with MOA calls
 - Integration of HTS and transcription assay data
- Use methods to inform classification models for TSCA (New Chemical Categories)
- Use chemotype enrichments to identify potential bioassays with bioactivity