# Probabilistic Points of Departure: A Tiered Approach for Life Cycle Impact Assessment

Workshop: Advancing Quantitative Analysis in Human Health Assessments through Probabilistic Methods 8-Oct-2024

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T i C E R



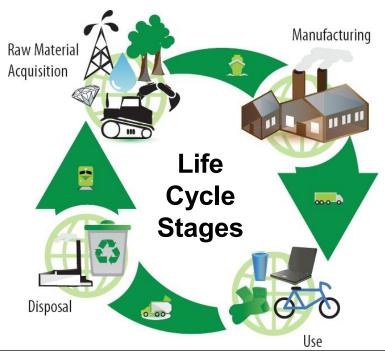


\*Special thanks for providing slides from which this presentation is adapted

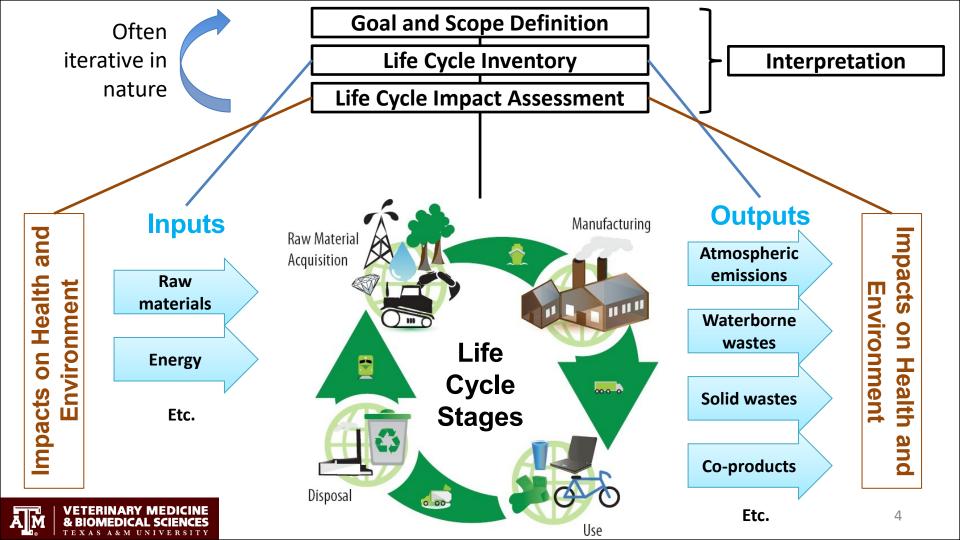
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# What is the Life Cycle?

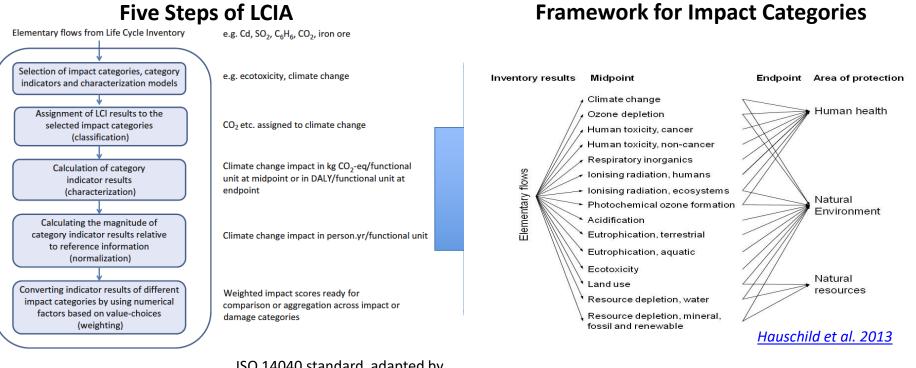
"the major activities in the course of the product's life-span from its manufacture, use, and maintenance, to its final disposal, including the raw material acquisition required to manufacture the product." -<u>EPA 2006 (Life Cycle Assessment: Principles and Practice)</u>







## What does this have to do with Toxicology?





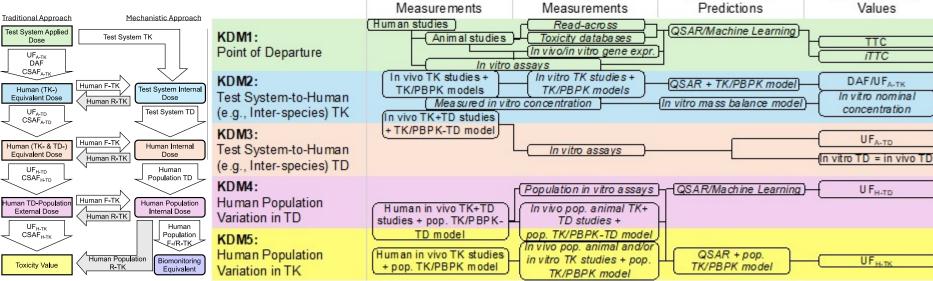
ISO 14040 standard, adapted by Hauschild and Huijbregts (2015) *Life Cycle Impact Assessment*, Ch 1

# Context for this work

- 30,000–100,000 unique chemical substances are commonly used worldwide in various products, processes, or services
- LCIA is a comparative assessment approach that includes characterizing toxicological impacts on human health from all possible chemical exposures associated with the life cycles of those products, processes, or services
- Points of Departure (PODs) are are essential part of characterizing toxicity-related human health impacts in LCA
- Regulatory/authoritative PODs cover a very limited set of chemicals
- Treating "no number" chemicals as non-toxic underestimates impacts, which can bias decision-making



#### Unified Probabilistic Framework for Dose Assessment



Tier 3:

Direct

Generally Increasing Resource Needs ←

Tier 2:

Surrogate

Lu et al. (in press, JTEH-B)



→ Generally Increasing Uncertainty

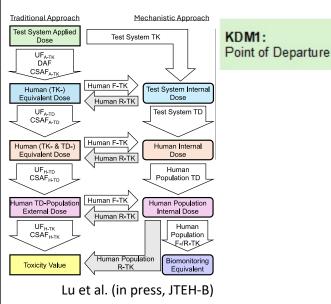
Tier 0:

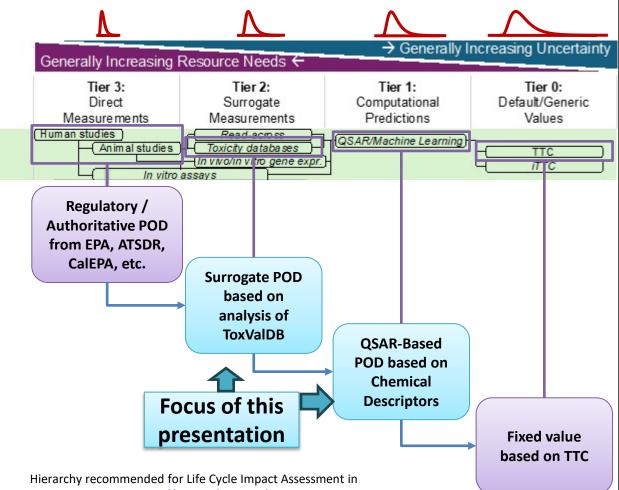
Default/Generic

Tier 1:

Computational

#### Focus on KDM 1: Point of Departure Determination





 VETERINARY MEDICINE

 & BIOMEDICAL SCIENCES

 TEXAS A&M UNIVERSITY

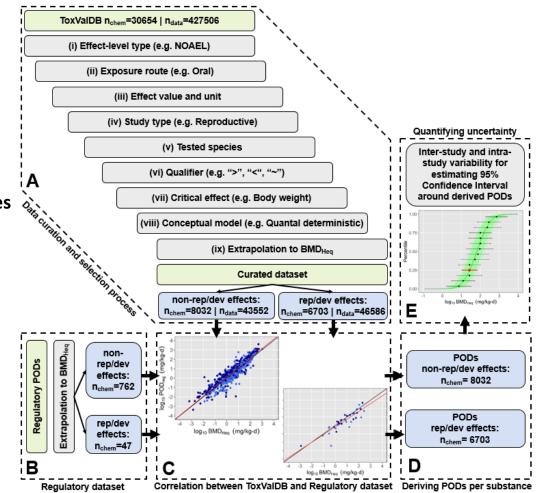
Fantke et al. 2021: <u>https://doi.org/10.1007/s11367-021-01889-y</u>

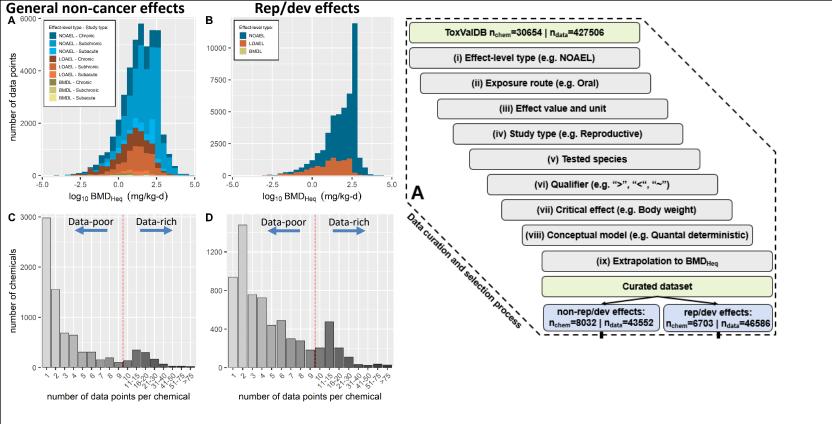
### Surrogate POD based on analysis of ToxValDB

Develop a workflow for deriving PODs <u>with</u> <u>quantified uncertainty</u> for chemical substances <u>with</u> animal toxicology data but <u>without</u> regulatory/authoritative assessments.

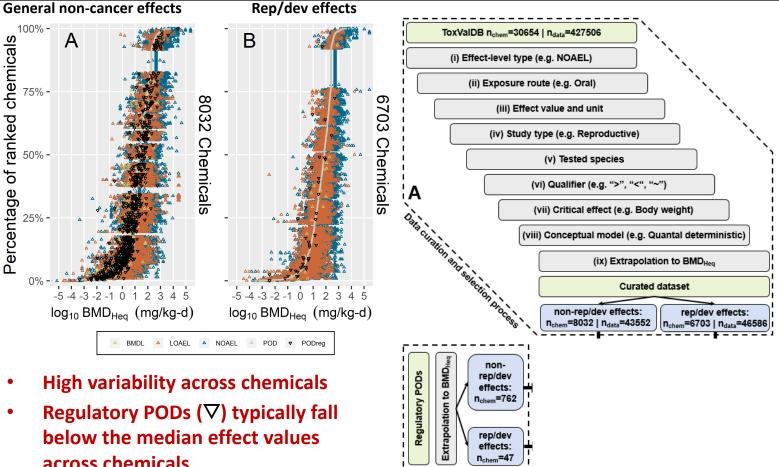
- A: Data curation and selection
- **B-C**: Calibration to overlapping regulatory PODs from authoritative sources
- D: Application to dataset from A
- E: Uncertainty analysis

**Oral PODs:** Aurisano et al. 2023 Inhalation PODs: Aurisano et al. 2024









В

Regulatory dataset

across chemicals



Simple hypothesis: Regulatory PODs can be "modeled" as a "conservative" %ile of the (curated) ToxVaIDB data for each chemical.

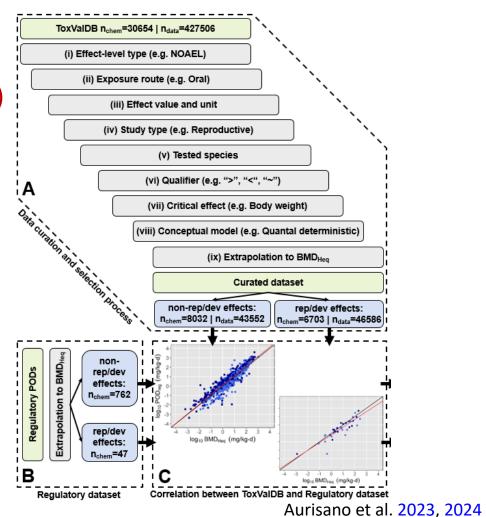
- **Data-rich:** %ile from fitted on a lognormal distribution
- Data-poor: %ile from a fixed log-normal distribution ("avg" data-rich chemical)

#### Results using 25<sup>th</sup> %-ile

- Oral General non-cancer (n=744):
   R<sup>2</sup>=0.85 RSE = 0.46 (log10 units)
- Oral Rep/dev (n=41):

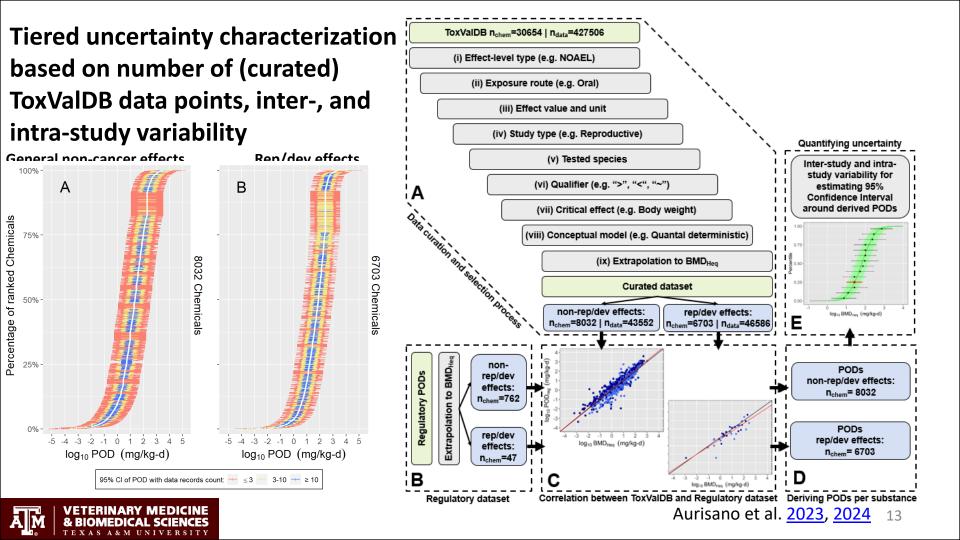
R<sup>2</sup>=0.78 RSE = 0.53 (log10 units)

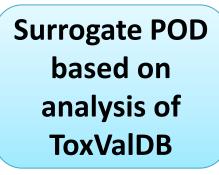
• Inhalation General & Rep/dev (n=174):  $R^2=0.76$  RSE = 0.82 (log10 units)



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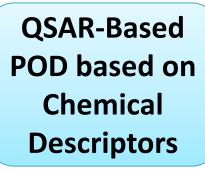


- **Approach:** Expand coverage of chemicals with (non-cancer) toxicity values by
- Created a consistent and curated data set of *in* vivo chronic dose-response toxicity data from EPA ToxValDB
- Developed a statistical approach for calibrating toxicity data against regulatory values
- Quantified uncertainty from inter- and intrastudy variability
- **Results:** Surrogate PODs can be derived using the 25<sup>th</sup> %ile from ToxVaIDB
- Oral PODs expanded by *n* > 10,000
- Inhalation PODs expanded by n > 2,000



#### Limitations

- Tens of thousands of chemicals have no or inadequate data in ToxValDB
- In vivo testing data on these chemicals unlikely to expand substantially in the near future
   Machine Learning to the Rescue?



- Conditional Toxicity Value (CTV) Predictor (2018)
- QSAR built on regulatory toxicity values
- Predicts oral and inhalation (experimental) NOAELs

#### Two-Stage Machine Learning Model (2024)

- QSAR for PODs building on surrogate oral PODs from Aurisano et al. (2023)
- Model for inhalation PODs in development

Both approaches perform better than ToxCast/in vitro NAMs for predicting regulatory PODs



Two-Stage Machine Learning for Human Health Points of Departure



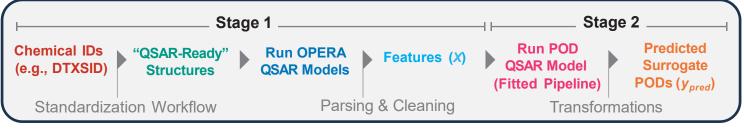
https://wchiu.shinyapps.io/Two-Stage-ML-Results-Browser/

Approach	RMSE	MedAE	R <sup>2</sup>
CTV	N.R.	0.70	0.45
Two-Stage ML			
(general non-			
cancer)	0.69	0.40	0.48
Two-Stage ML			
(repro/dev)	0.58	0.31	0.49
ToxCast+httk			
(general non-			
cancer)	1.87	1.22	<0
ToxCast+httk			
(repro/dev)	1.52	0.84	<0

RMSE: Root-mean-squared-error (log10 units) MedAE: Median absolute error (log10 units) R<sup>2</sup>: Coefficient of determination (<0 means worse that naïve constant model)



### **Conceptual Framework: Two-Stage QSAR Model**

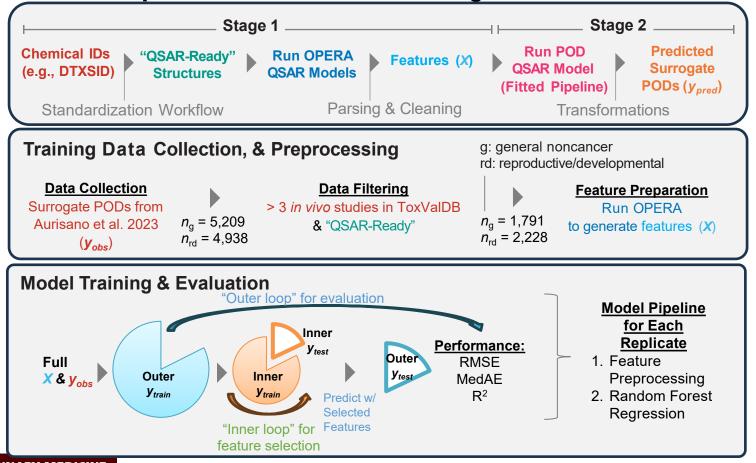


### Why a two-stage model?

- Most chemical descriptors can be hard to interpret by a toxicologist or risk assessor (as opposed to a chemo-informaticist)
- Existing OPERA models provide open-source predictions for *interpretable* physical-chemical-toxicological parameters
- Analogous to a "supervised" neural network with a single intermediate layer composed of interpretable features.



### **Conceptual Framework: Two-Stage QSAR Model**

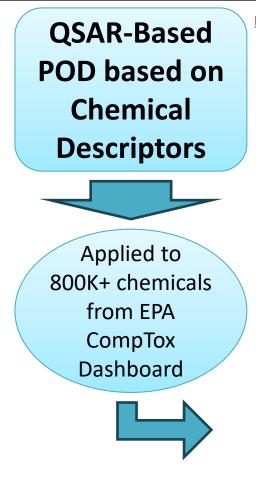


# **Model Evaluation**

**Out-of-Sample (Cross-Validation) Performance** 

#### (B) Cross-Validation Performance (A) Mean Cross-Validation Predictions RMSE: 0.25 RMSE: 0.25 MedAE: 0.14 MedAE: 0.15 With RMSE: 0.67 RMSE: 0.68 Without General Noncancer Fitted log10POD R2: 0.93 R2: 0.93 MedAE: 0.38 MedAE: 0.39 n: 1,791 n: 1,791 General Noncancer Predicted log10POD 0.0 0.5 1.0 R2: 0.50 R2: 0.51 0. 0 n: 1,791 n: 1,791 RMSE 0 0 With -3 -3Without -3 -30.5 0.0 1.0 MedAE -6-6-6-6With Without -6 -30 -6 -3 0 -6 -3 0 3 -6 -30 2 1.0 0.5 0.0 $R^2$ RMSE: 0.23 RMSE: 0.23 Reproductive/Developmental Fitted /og10POD Reproductive/Developmental Predicted log1.pPOD 3 MedAE: 0.12 RMSE: 0.59 RMSE: 0.59 MedAE: 0.11 3 MedAE: 0.30 With MedAE: 0.31 R2: 0.93 R2: 0.93 Without R2: 0.51 R2: 0.51 n: 2,228 n: 2,228 n: 2,228 n: 2,228 0.5 0.0 1.0 0. 0 0 RMSE With -3 -3 -3-3Without 0.5 1.0 0.0 MedAE -6 -6-6-6 With Without -3 -30 -6 -30 -6 -30 -60 -6 ToxValDB Surrogate log10POD ToxVaIDB Surrogate log10POD 1.0 0.5 0.0 ToxVaIDB Surrogate log10POD ToxValDB Surrogate log10POD With Selection With Selection Without Selection $R^2$ Without Selection **Expected performance based on cross-validation results:** Average Error (RMSE): factor of 4~5 • Typical Error (MedAE): factor of 2~2.5 Ā M VETERINARY MEDICINE Explained Variance: ~50% & BIOMEDICAL SCIEN

#### In-Sample Model Fitting

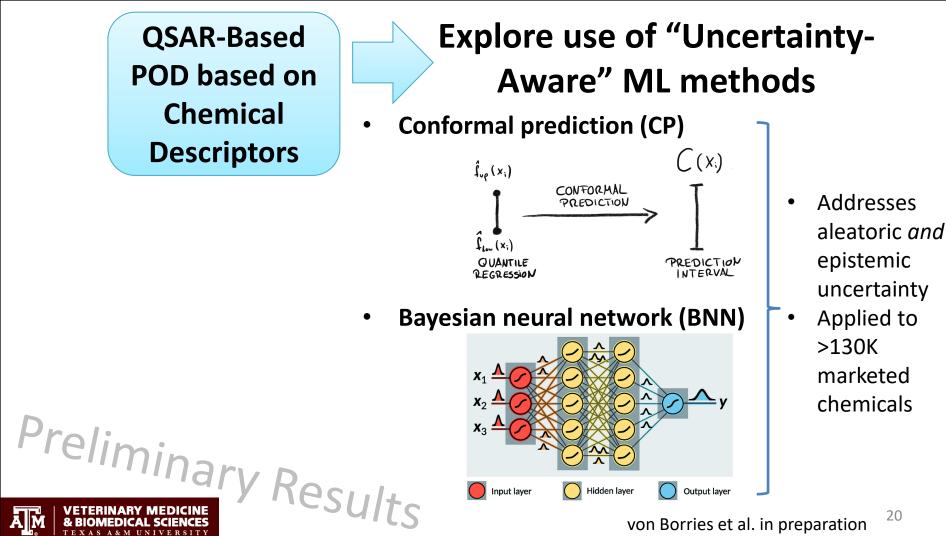


### Limitations

- Same uncertainty estimate for every prediction
- Certain classes of chemicals excluded based on OPERA QSAR standardization workflow

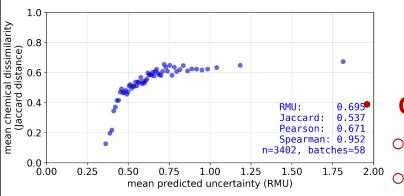


**QSAR-Based** POD based on Chemical **Descriptors** 



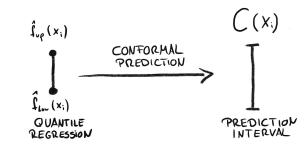


**QSAR-Based** POD based on Chemical **Descriptors** 



### **Explore use of "Uncertainty-**Aware" ML methods

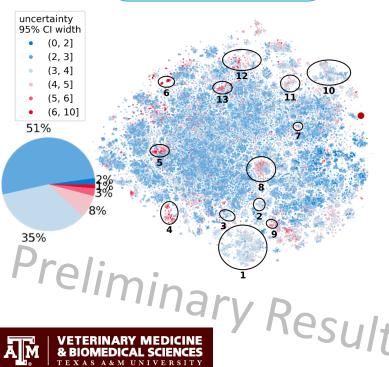
**Conformal prediction (CP)** 



#### **CP models performed better than BNN**

- Good coverage & well-calibrated confidence intervals
- Capture overall heteroscedasticity in prediction errors
- Preliminary Results Higher uncertainty for new chemicals that are unlike training set chemicals

QSAR-Based POD based on Chemical Descriptors



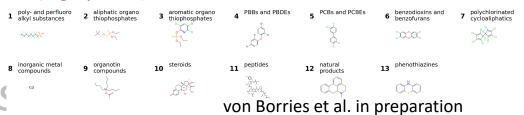
### Explore use of "Uncertainty-Aware" ML methods

- Uncertainty hotspots
  - polychlorinated and polybrominated compounds
  - metals and organometallics
  - alkaloids and phenothiazines
  - Peptides

#### **Drivers of uncertainty**

- low representation in the training data
- low applicability of molecular descriptor developed for small organic molecules

#### (highly toxic) outliers



# Summary: A Tiered Hierarchy of Probabilistic PODs

Regulatory / Authoritative

POD from EPA.

ATSDR, CalEPA,

etc.

Surrogate POD based on

analysis of

**ToxValDB** 

**QSAR-Based** 

POD based on Chemical

Descriptors

Fixed value based on TTC

- LCIA requires PODs for tens-hundreds of thousands of chemicals for characterizing human health impacts of product, process, or service life cycles
- Regulatory/authoritative PODs cover a very limited set of chemicals
- Two classes approaches can fill these data gaps while also quantifying their uncertainty with varying degrees of sophistication
- **Key limitation:** Calibrated to existing regulatory PODs, which are largely based on experimental animal studies.
- Counterfactual: If we were to have new regulatory/authoritative assessments based on animal studies in the absence of any human data, we would make decisions based on them!

