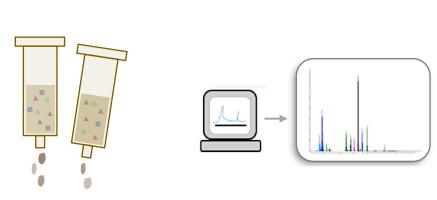
Towards Quantification Without Standards: Impacts of Environmental Matrices on the Solubilities and Ionization Efficiencies of Per- and Polyfluoroalkyl Substances (PFAS)

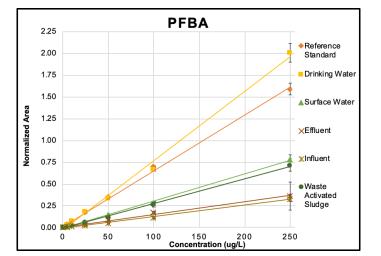
### **KC Donnelly Fellowship**

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- 3. Office of Research and Development, United States Environmental Protection Agency

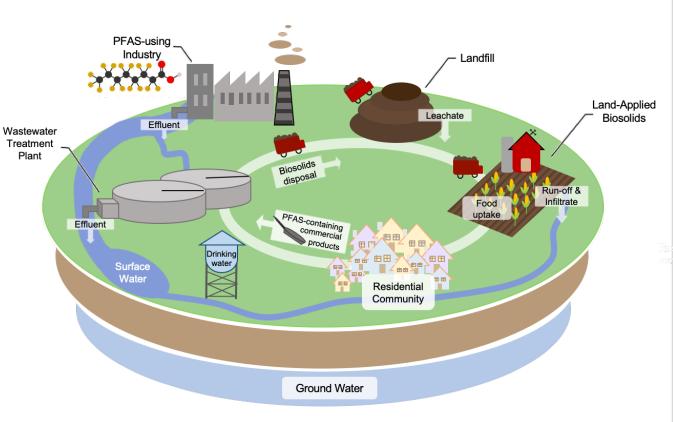






# Background: Studying PFAS in the Environment

- Per- and polyfluoroalkyl substances (PFAS) have been detected on every continent in surface,<sup>1,2</sup> drinking,<sup>1,2</sup> wastewater and biosolids <sup>3</sup>
- Liquid chromatography mass spectrometry (LC-MS) is often used for PFAS targeted identification & quantification<sup>1-3</sup>
- Non-targeted analysis has identified several new PFAS for which reference standards are not available and therefore can not be directly quantified <sup>4</sup>



#### How can we quantify PFAS without reference standards?

- 1. Kurwadkar, S., et al. Science of The Total Environment, 2022.
- 2. Vento, S.D., et al., Atmospheric Pollution Research, 2012.
- 3. Venkatesan, A.K., et al. Journal of Hazardous Materials. 2014.
- 4. Nakayama, S, F. et al. Trends in Analytical Chemistry

#### 1. Groff, L.C., et al. Analytical and Bioanalytical Chemistry. 2022

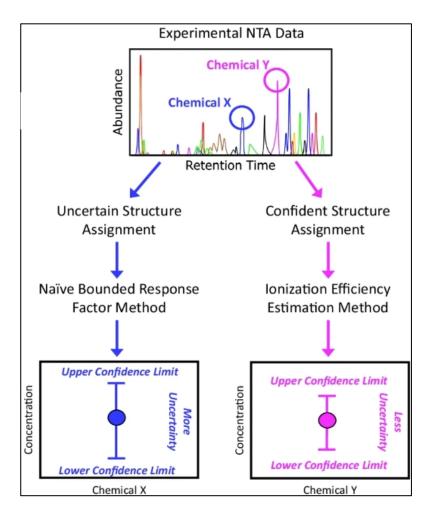
## Background: Current inverse prediction models

- Inverse prediction models were used to quantify organic contaminants without reference standards in solvent
- Naïve bounded response factor (RF) bootstrap method:
  - All chemical RFs from training set used to bound the concentration estimate of an unknown
  - No assumptions about chemical structure
  - High uncertainty due to models generic nature

### Ionization efficiency estimation method:

- Considers SMILES structures, analytical solvents, and analyte retention times
- Lower overall uncertainty than bootstrap RF method but more error than ideal inverse predictions

### → But matrix effects & solubility were not considered



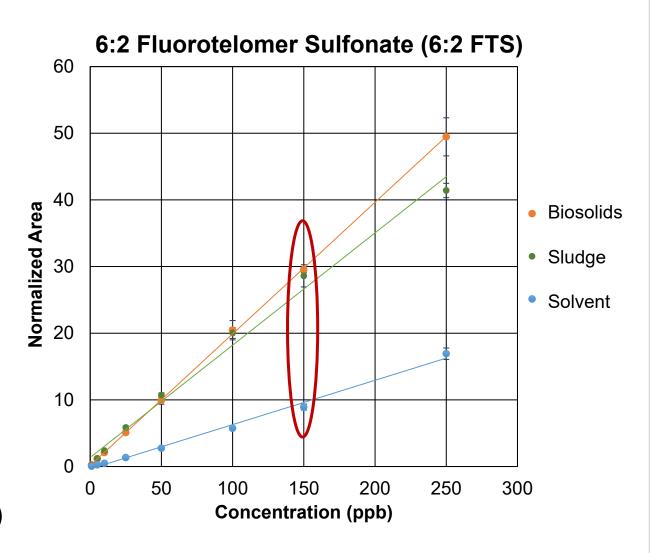
## Background: Matrix effects on response factor

Targeted analyses use calibration curves to calculate analyte response factor (RF) and quantify detections

 $(RF) = \frac{Analyte Area}{Concentration}$ 

- Assumed to be consistent across linear dynamic range
- Can be affected by matrix coextracted ions Ex. RF is 3x higher in sludge & biosolids than solvent (150 ppb)

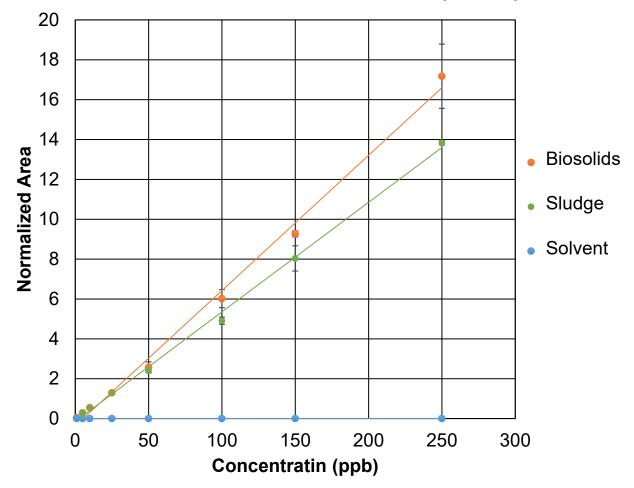
→ Hypothesis 1: Coextracted matrix influences the RF of PFAS in LC-MS analyses using electrospray ionization (ESI)



## Background: Solubility effects on response factor

- No signal for FOSA in solvent (95% water, 5% acetonitrile)
- Aqueous solubility (OPERA<sup>1</sup> calculated) for FOSA = 7.81 x 10<sup>-7</sup> mol / L
- FOSA in sludge and biosolids samples had good signal and peak shape
  - Matrix can increase non-polar characteristics of water<sup>2</sup> and improve PFAS solubility in matrix extracts
- → Hypothesis 2: Variation in analyte solubility causes low observed RFs for some PFAS in aqueous solvent and can also vary between matrix coextracts

#### Perfluorooctane Sulfonamide (FOSA)



1. USEPA Comptox Dashboard, OPERA predicted properties. 2022

2. Renner, R. KOW controversy. ES&T 2002

### **Project Goals:**

→Develop a technique for inverse quantification predictions for PFAS without reference standards that can correct for sample matrix & resuspension solvent

<u> Tasks:</u>

→ (1) Evaluate the effects of matrix and solvents on analyte RF
(2) Calculate inverse estimation error for each analyte with optimal techniques:
*i.e. Matrix-matched calibration curves*

(3) Calculate inverse estimation error with naïve conditions with no assumptions about physico-chemical properties

i.e. naïve bounded RF method

(4) Optimize an inverse error estimation method that considers matrix & solvent effects

(5) Validate the optimized method through bootstrapping and cross-validation

## Analytes & sample matrices

**Training analytes:** Isotopically labelled PFAS standards including - carboxylates (10), sulfonates (3), fluorotelomer sulfonates (3), and sulfonamides (3)

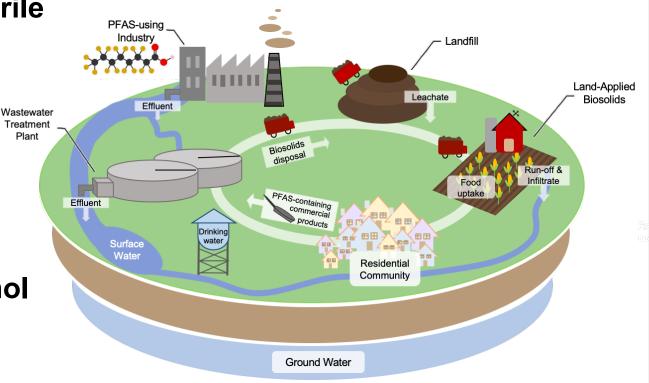
Linear range: 0.5 – 250 ppb

### 95% 5mM ammonium acetate, 5% Acetonitrile

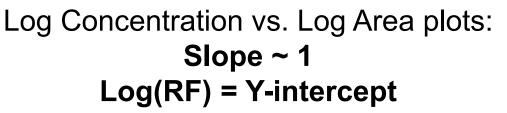
- Reference standard
- Drinking water (500 mL)
- Surface water (500 mL)
- Secondary effluent (100 mL)
- Raw influent (100 mL)
- Waste activated sludge (250 mg)

### 25% 5mM ammonium acetate, 75% Methanol

- Reference standard
- Drinking water (500 mL)
- Waste activated sludge (250 mg)



## Matrix & solubility effects on RF

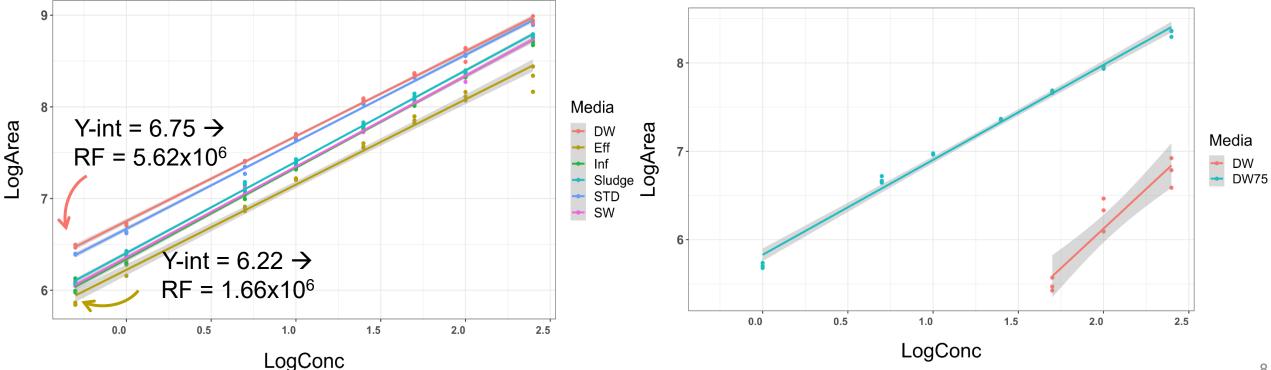


 $\rightarrow$  Matrix coextracts are shown to affect RF

The linear range of some analytes & matrices have only 3 calibration points & slopes ≠ 1

→ Analyte solubility in aqueous solvent is poor for certain analytes

N-Me-FOSAA



#### <u>PFHxA</u>

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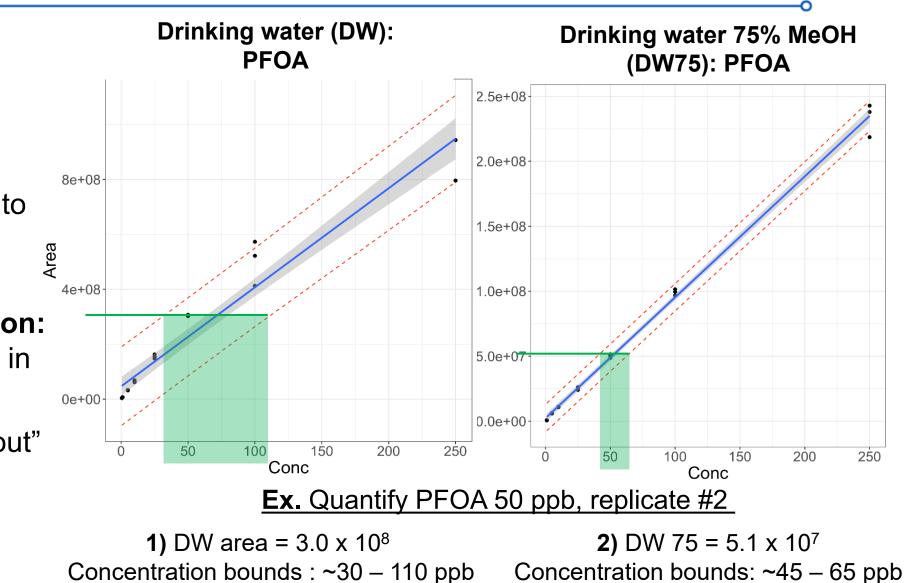
(5) Validate the optimized method through bootstrapping and cross-validation

# Inverse predictions: Ideal conditions

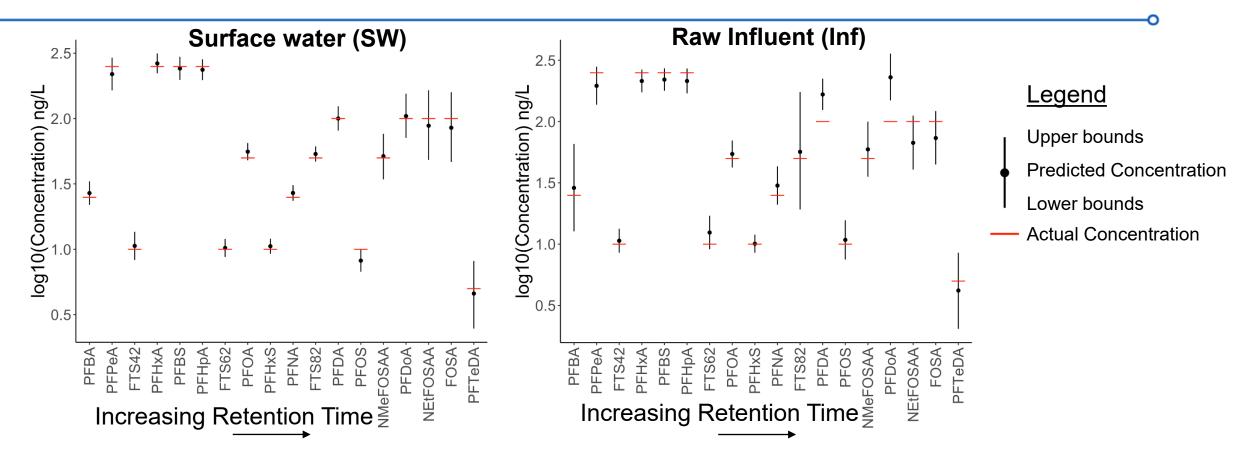
# Matrix-matched calibration curves:

- Ideal quantification technique
- Benchmark for error to compare other techniques
- "Leave-one-out" validation: All but 1 injection included in calibration curve

Concentration of the "left out" injection is calculated to determine uncertainty

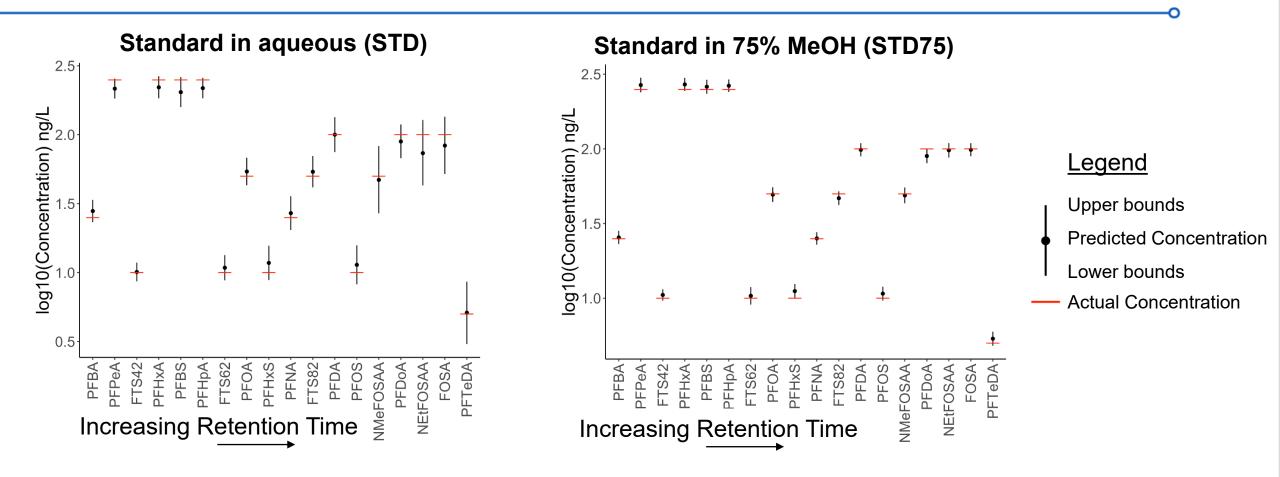


### Matrix effects on inverse estimation error



- Complex matrices (e.g., Inf) often had higher error intervals vs. cleaner matrices (e.g., SW)
- Long chain and sulfonamide PFAS often had larger intervals vs. shorter chain analytes

### Solubility effects on inverse estimation error



- More error in aqueous standard than in 75% MeOH standard
- Uncertainty in the aqueous standard increases with retention time
- 75% MeOH standard had smaller and more stable error overall

### **Project Goals:**

→Develop a technique for inverse quantification predictions for PFAS without reference standards that can correct for sample matrix & resuspension solvent

### <u> Tasks:</u>

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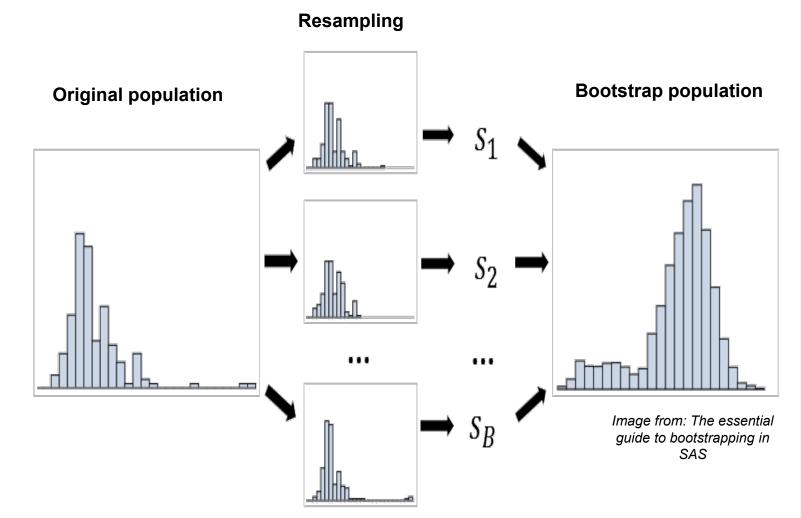
(4) Optimize an inverse error estimation method that considers matrix & solvent effects

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## Naïve bounded RF predictions

#### Naïve bootstrap predictions:

- Predict concentrations for unknown PFAS using other 18 PFAS as surrogates for RF
- RF bootstrap distribution quantiles can be used to bound uncertainty in the predictions
  - 97.5  $\rightarrow$  upper uncertainty bound
  - 2.5  $\rightarrow$  lower uncertainty bound
  - Median  $\rightarrow$  best estimate



## Benchmark vs. naïve inverse estimations

- Naïve bootstrap RF predictions had a higher uncertainty fold-range than the targeted calibration inverse predictions
- Simpler/aqueous matrices including the standard had a higher uncertainty range than the 75% MeOH resuspension or complex matrices (i.e. Sludge)

	Percent Exceedance		<b>Uncertainty Fold-Range</b>	
	Calibration Curve	Naïve Bounded RF	Calibration Curve	Naïve Bounded RF
Aqueous resuspension				
Standard	3.1%	19.7%	1.9	68.2
Drinking Water	5.3%	21.5%	2.0	54.8
Surface Water	5.6%	20.0%	1.8	77.1
Secondary Effluent	5.7%	13.1%	2.6	27.9
Raw Influent	5.7%	12.1%	2.6	11.9
Sludge	5.6%	11.4%	1.9	12.2
75% Methanol resuspension				
Standard	4.7%	13.7%	1.2	5.2
Drinking Water	5.5%	16.9%	2.8	14.4
Sludge	4.2%	10.9%	1.5	9.1

# Conclusions

# Future work

- Matrix effects and solubility effects impacted the observed RFs for PFAS
- Analytes with a retention time > 21 minutes had poor solubility in aqueous solvents
  - Artificially low RF in aqueous solvent causing wide RF distributions
  - Naïve bootstrapping had highest error in simple, aqueous samples (drinking water, surface water, standard)
- Naïve bootstrap predictions had higher uncertainties compared to inverse calibration predictions

- Test expert surrogate inverse prediction to bootstrap RF distributions based on chemically specific surrogates (n=3)
- Develop an inverse prediction technique for PFAS which considers matrix and solubility effects
  - Apply a mixed model with predicted ionization efficiencies to a training set in sample matrix
  - Include variable to correct RF for solubility limitation for late eluting analytes
- Validate the optimized method through bootstrapping and cross-validation

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