Geospatial Surveillance of EPA-Regulated PFAS in Florida Waters to Assess Drinking-Water Source Vulnerability

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Background

- Per- and polyfluoroalkyl substances (PFAS) are a group of synthetic "forever" chemicals characterized by their environmental persistence.
- Major anthropogenic sources include municipal wastewater treatment plants, airports, military installations, and industrial manufacturing.
- Increasing evidence links exposure to adverse human and ecological health effects.
- Previous studies have examined PFAS distribution in certain media in Florida, but a unified, statewide geospatial assessment remains lacking.

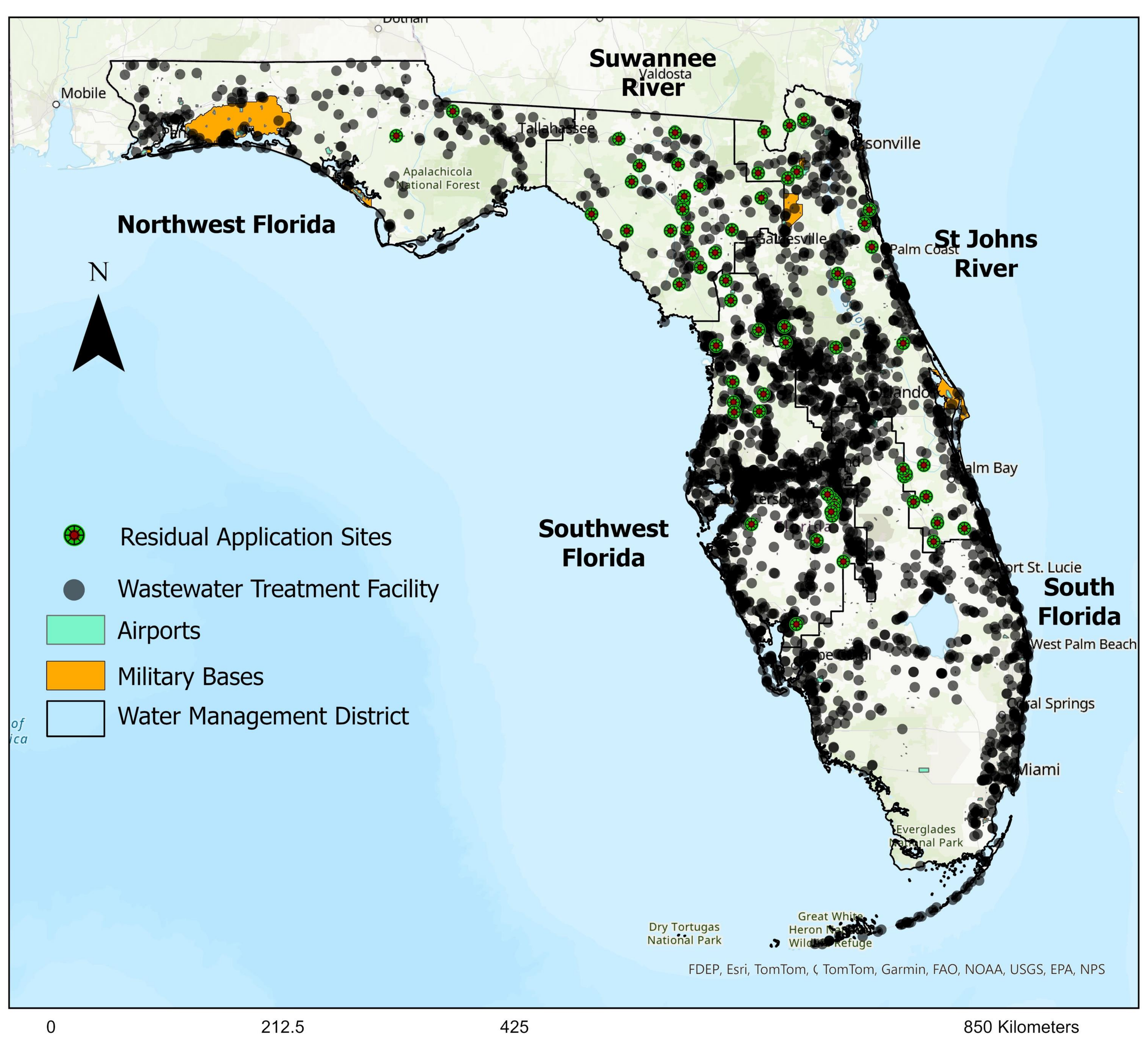

Figure 1. Potential sources of PFAS across the state of Florida.

Objectives

- Map statewide distribution patterns of six priority compounds for which the United States Environmental Protection Agency (USEPA) established drinking water standards.
- Identify watersheds and public water systems potentially vulnerable to upstream contamination.
- Attribute sources of PFAS contamination.

Research Method

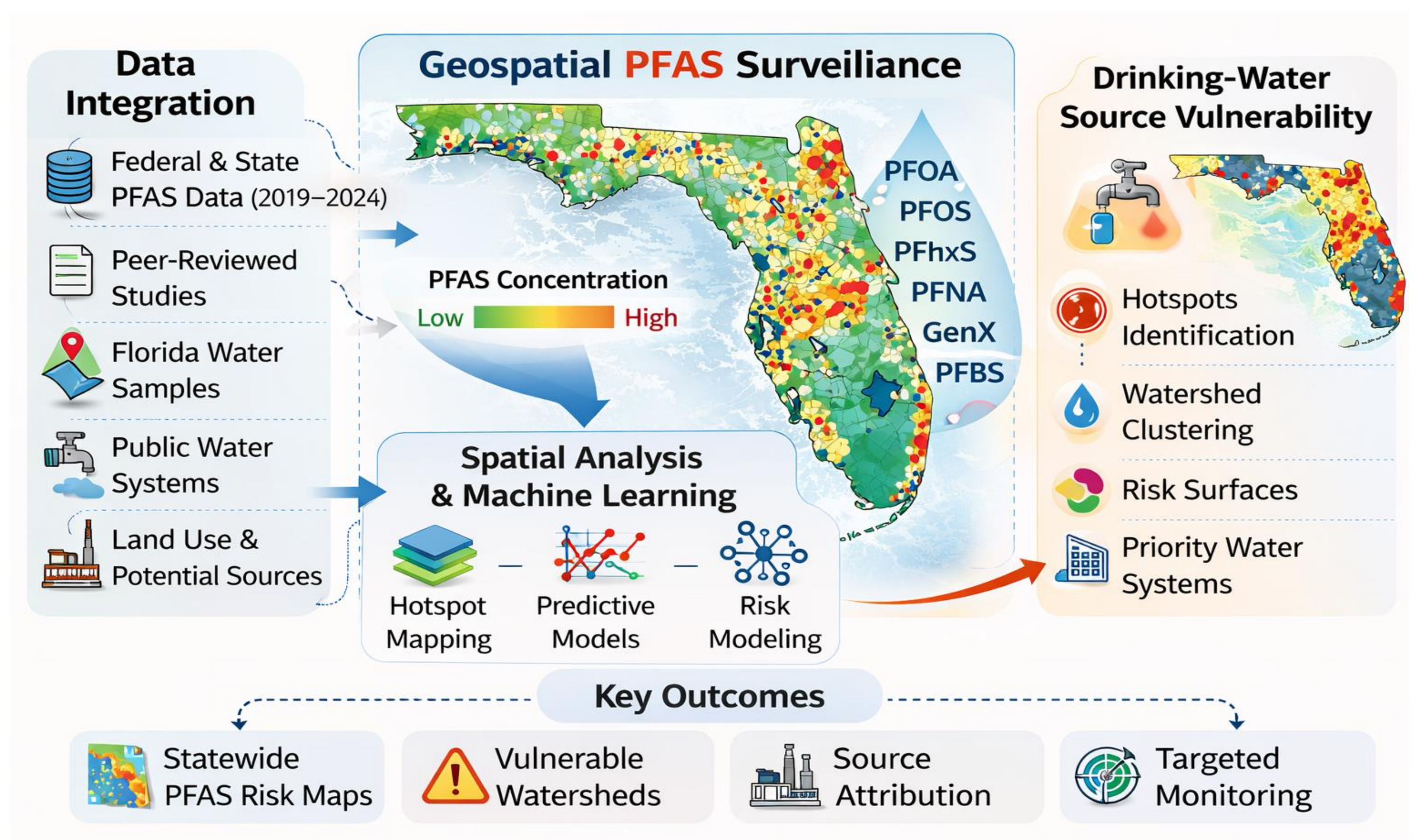

Figure 2. Flow chart describing the methods and outcomes of the project.

- PFAS sampling data were compiled from publicly available sources, including the EPA, the Florida Department of Environmental Protection (FDEP), and peer-reviewed studies into a unified canonical dataset.
- The dataset was subset to the six PFAS compounds regulated under USEPA drinking water standards: PFOA, PFOS, PFHxS, PFNA, HFPO-DA (GenX), and PFBS.
- Sample coordinates and concentrations were plugged into a geographic information system (ArcGIS) to map and predict the geospatial distribution of each compound using inverse distance weighting.
- Concentrations are evaluated relative to EPA health-based benchmarks.

Table 1. Descriptive statistics of PFOA and PFOS concentrations (ng/L) in groundwater (GW) and surface water (SW) samples across Florida, including non-detect frequencies.

Chemical	Media	N	Mean (ng/L)	Median (ng/L)	Max	Std. Dev	ND, MRL, LOQ
PFOA	GW	2440	1.07	0	39.2	3.08	2110 (86.48%)
PFOA	SW	2292	3.99	2.91	81.16	4.5	295 (12.87%)
PFOA	Overall	4732	2.48	0	81.16	4.11	2405 (50.82%)
PFOS	GW	2497	3.53	0	1135.22	9.35	1917 (76.77%)
PFOS	SW	1472	7.77	1.84	652.79	32.39	280 (19.02%)
PFOS	Overall	3969	5.1	0	1135.22	21.17	2197 (55.35%)

•IDW Interpolation: Spatial prediction of PFAS concentrations was performed using Inverse Distance Weighted (IDW) interpolation-

$$(x_0) = \frac{\sum_{i=1}^{n} \frac{z(x_i)}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}}$$

•Risk Modeling: Relative contamination risk was estimated using

$$R = \frac{C}{C_{ref}}$$

to identify PFAS hotspot regions and potential exposure risks.

Results & Conclusion

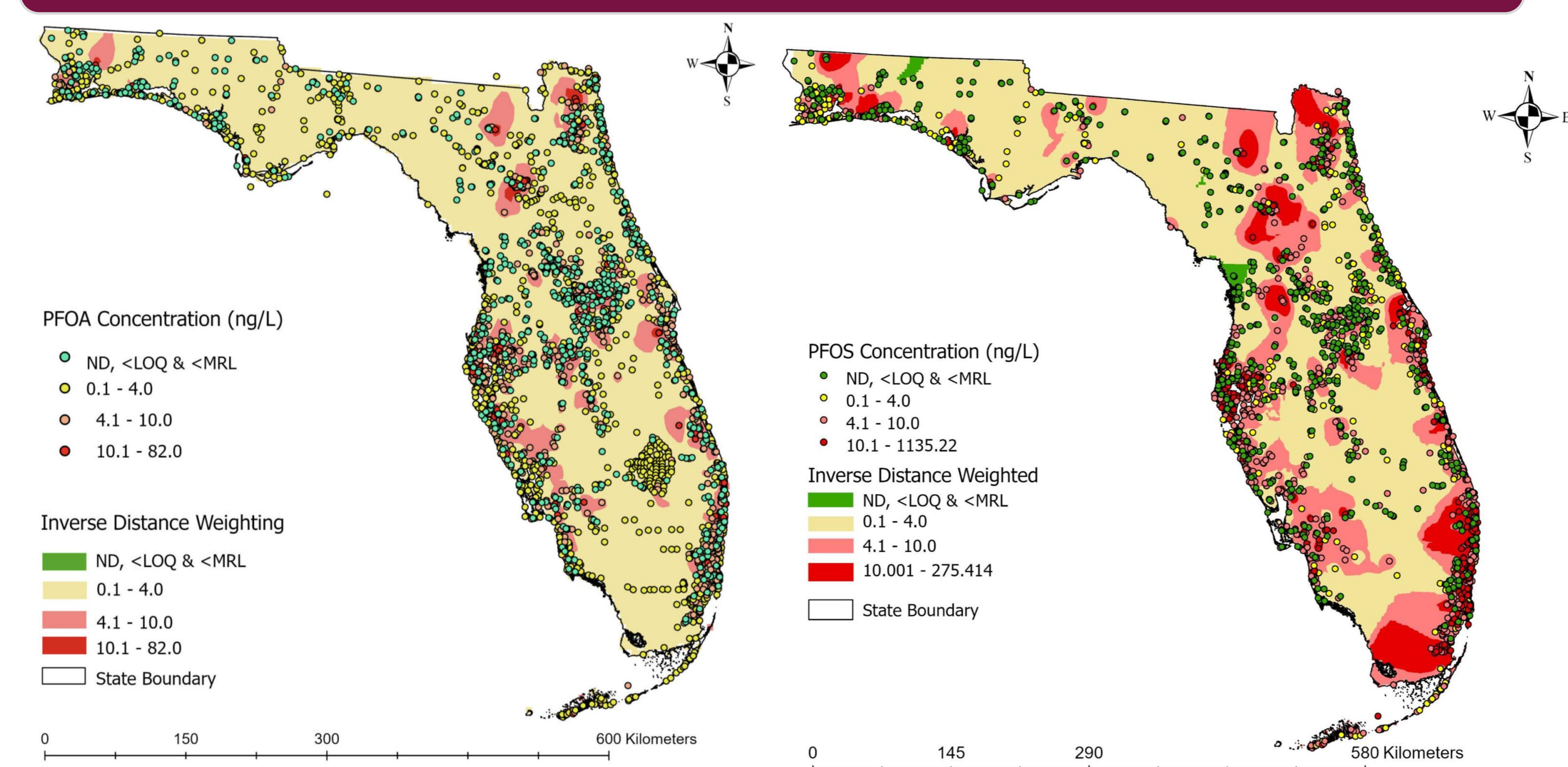

Figure 3. Maps of the distribution of PFOA & PFOS across the state of Florida.

- Research is ongoing but demonstrates the first comprehensive approach to monitoring the distribution of PFAS across Florida.
- Results can be used to inform source-water protection to target monitoring strategies where water systems are predicted to be vulnerable to contamination.
- Strengths: A variety of sources were used to collect a significant amount of data.
- Limitations: Measurement variability/inconsistency among different sources.
- Future steps include continuing to map each of the six priority PFAS compounds (PFOA and PFOS are completed) relative to EPA benchmarks to identify hotspots and sources.

Further Research

- Further research should:
  - Use spatiotemporal machine learning for PFAS detection/exceedance prediction and generate uncertainty maps.
  - Predict drinking-water source vulnerability using machine learning models (logistic regression, Random Forest, XGBoost, and spatial blocks).
  - Identify and map likely PFAS sources using GIS proximity analysis, PFAS fingerprinting, and explainable machine learning.
  - Implement deep learning forecast scenarios.
  - Assess correlations between PFAS levels and sources.

Acknowledgments And References

Thank you to Shahin Alam for being a wonderful mentor and assisting me throughout this process. Thank you to FSU UROP for supporting the Project.