Cost-Efficient Spatial Prediction of Groundwater PFAS Risk Reveals Exposure Hotspots in New Hampshire

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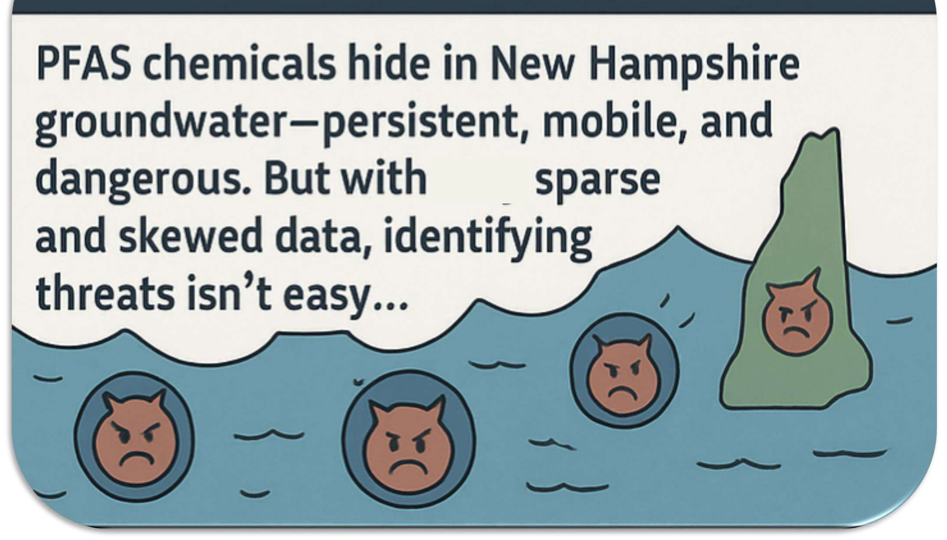
THE PROBLEM

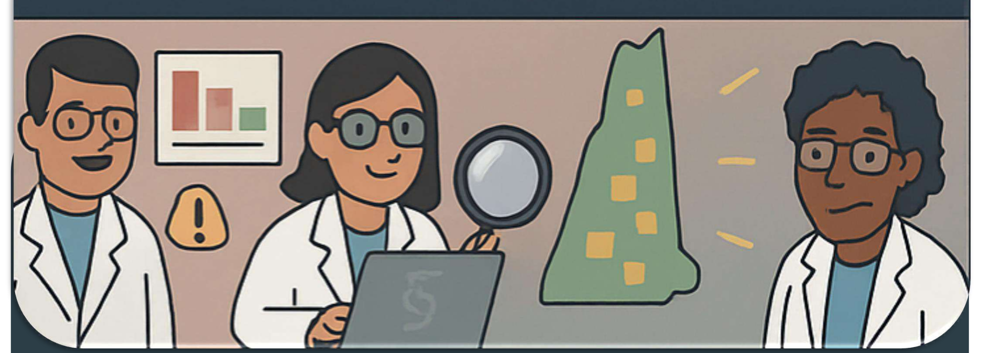


PFAS chemicals hide in New Hampshire groundwater—persistent, mobile, and dangerous. But with sparse and skewed data, identifying threats isn't easy...

THE CHALLENGE

Monitoring data is limited, unevenly distributed, and influenced by both industry and environment. Traditional models fall short.

THE SOLUTION



We built a statewide model with smart resampling, boosting prediction, improving spatial generalization, and making monitoring fairer and more cost-effective.

OUR IMPACT

Our method targets hotspots, supports equity-aware action, and helps guide decisions that protect the most vulnerable.

Background

PFAS are highly persistent, mobile and toxic chemicals that accumulate in groundwater and drinking-water wells across New Hampshire. Despite compound-specific MCLs for PFOA, PFOS, PFHxS and PFNA, monitoring data are sparse, biased toward non-detects, and influenced by a mix of industrial sources and environmental controls. This hampers effective compliance, risk prioritization and protection of vulnerable communities.

Aims & Methods

Development and evaluation of a statewide PFAS risk-mapping framework for New Hampshire groundwater, combining a 1-km geospatial database, compound-specific random forest classification models, and a novel grid-wise resampling strategy, with SHAP-based interpretation and overlays with CDC Social Vulnerability Index data to identify equity-sensitive high-risk hotspots.

Results

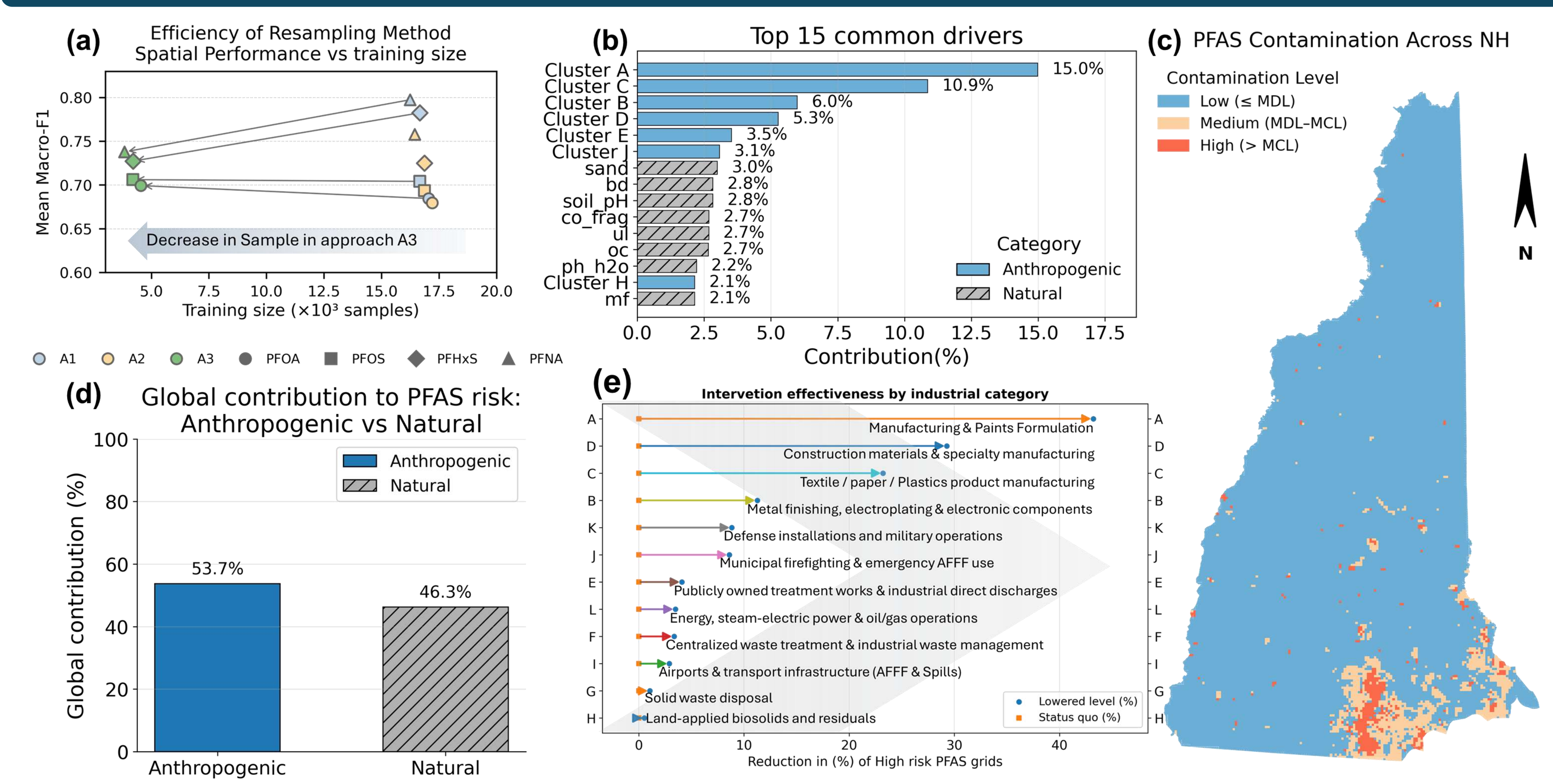
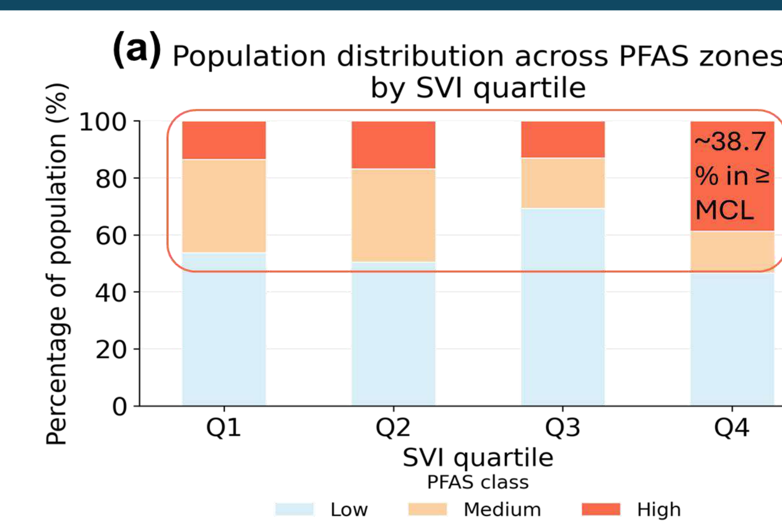


Figure 1 (a) Novel Grid-wise resampling (A3) maintains macro-F1 with far fewer samples, **(b)** Top 15 contamination predictors, **(c)** PFAS contamination across NH **(d)** SHAP results show anthropogenic drivers dominate over natural controls, **(e)** scenario plus map panels highlight which industrial clusters and locations offer the greatest potential for reducing high-risk PFAS grids.



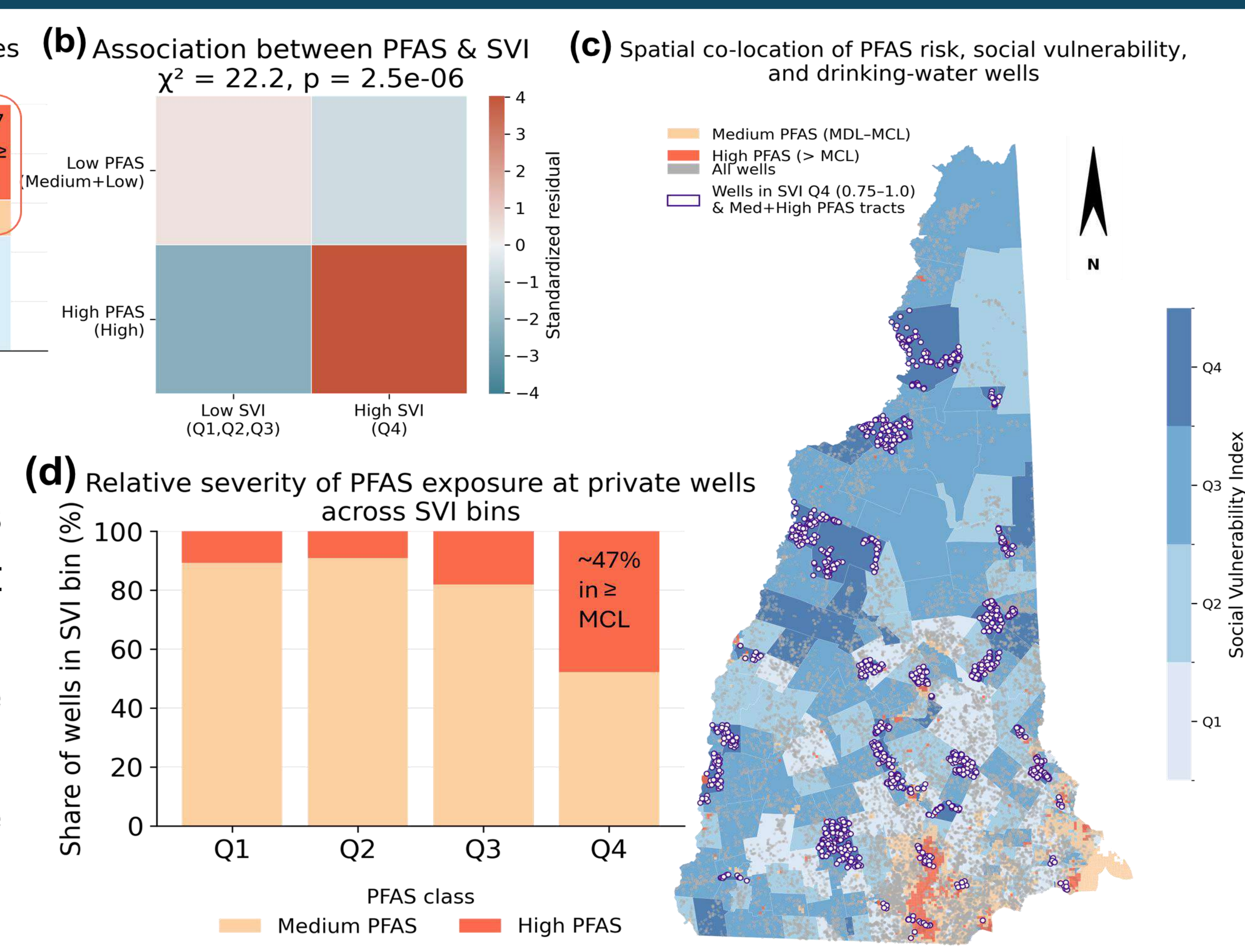


Figure 2 (a, b, d) Stacked bars and the 2×2 association heat map show that higher-SVI tracts host a disproportionate share of ≥MCL PFAS cells and private wells, **(c)** vulnerable communities, modeled PFAS, and private-well use overlap.

Conclusion

1. Our grid-wise resampling with one-third of the available data kept PFAS risk predictions within 10–15% of full-data performance across compounds.
2. Coupled with SHAP and SVI overlays, this research framework pinpoints industrial drivers and equity-sensitive hotspots for targeted monitoring and source control.

References

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