*From Space to Place: Advancing Environmental Health with Remote Earth Observations*

# Uncertainty Quantification for Satellite
# and Environmental Health Applications


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# High-level overview of methods used to quantify uncertaint quality measurements using satellite data

I will focus on statistical and machine learning methods:

1. Is uncertainty modeled/estimated internally, or after the fact?
2. Are uncertainty estimates evaluated and/or calibrated to different conditions?
3. What metrics are available for downstream health analyses?

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<u>Internally:</u>

- Bayesian statistical models
  - Work directly with probability distributions
  - Explicitly model spatial structure
- Machine learning-based
  - Predict quantiles instead of a single point estimate
  - Repeatedly perturb the model parameters to generate a distribution (“Monte Carlo dropout”)

<u>After the fact:</u>

- Model / interpolate the residuals
  - [Residuals = observations minus model predictions]
- Fit the model many times on resampled data (bootstrap)

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Typically considered best practice

Sometimes combined with modeling the residuals

**After the fact:**

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- Fit the model many times on resampled data (bootstrap)

Traditionally less computationally efficient; some modern adaptations

# How are uncertainty estimates evaluated and/or calibrated?

- For evaluation: are spatial and temporal autocorrelation being accounted for?
  - e.g., spatial and/or temporal cross-validation folds
- Are prediction intervals calibrated? (ideally on held-out data)
  - e.g., does the true exposure fall within a 95% interval 95% of the time?
  - If not, can scale the interval width ("conformal prediction")
- Across conditions of interest?
  - Region / land use type
  - Time period / season / meteorology
  - Pollution concentration
  - Factors affecting satellite retrieval
  - …

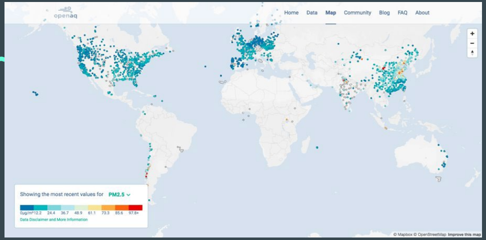
What metrics are available for downstream health analyses?

- Quantile estimates
- Interval width
- …

# Different flavor from my recent work: policy impact evaluat

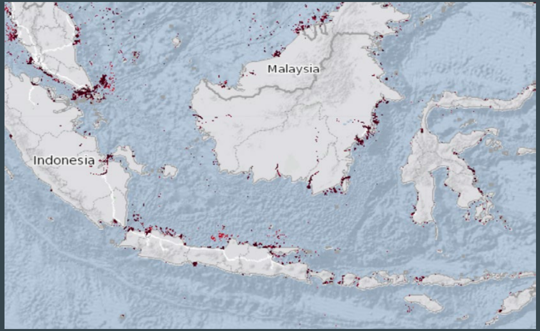
Can credibly estimate a policy effect and its uncertainty over a large region and time period

Even in regions with little to no groundlevel air quality monitoring



By pairing:

- Modern causal inference methods
- Existing satellite-derived air quality datasets
- Complementary remotely-sensed data products which add critical context

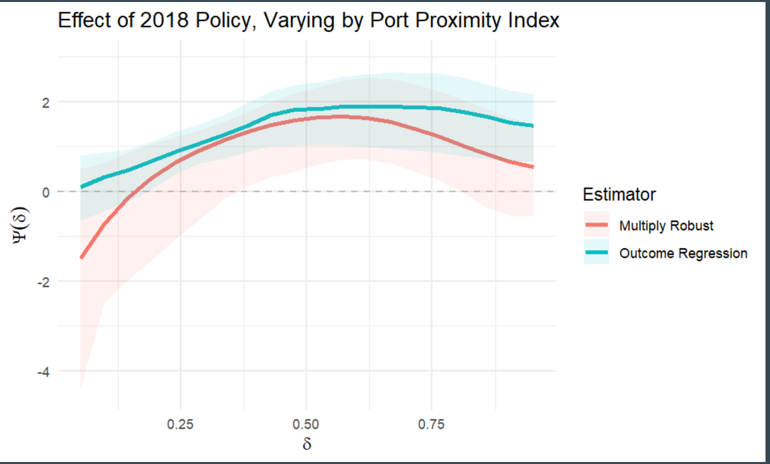



Cargo ship loitering density

Case study: estimating air quality impacts of plastic waste burning in Indonesia, before & after China stopped taking plastic waste exports

# Uncertainty quantification aspects of this work

- "Multiply robust" estimator:
  - Separately models the outcome ($PM_{2.5}$) and exposure using flexible machine learning
    - Cross-fitting
  - Targets confounding with respect to both the time period and the level of port proximity (continuous)
- Accounts for residual spatial correlation through a novel spatial weighted bootstrap



# Thank you!

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# Resources for additional exploration

- [Our 2026 preprint] “A Spatiotemporal, Quasi-experimental Causal Inference Approach to Characterize the Effects of Global Plastic Waste Export and Burning on Air Quality Using Remotely Sensed Data”
- [2026 paper] “Enhancing Estimation of Fine Particulate Matter Chemical Composition Across North America by Including Geophysical A Priori Information in Deep Learning with Uncertainty Quantification”

General:

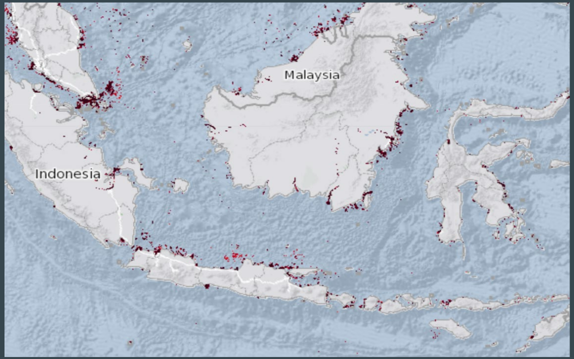
- [2022 short course slides] “Uncertainty quantification in Machine Learning” – *methods overview*
- [2026 paper] “Confidently Uncertain: Validating Satellite ECV Measurement Uncertainty Estimates”
- [2024 paper] “Uncertainty quantification for probabilistic machine learning in earth observation using conformal prediction”
- [2026 paper] “Uncertainty Quantification of Satellite-Based Essential Climate Variables Derived from Deep Learning”

# *Extra slides*

# Triangulating Air Quality Impacts o

# Plastic Waste Burning

- Open burning of plastic wastes is an urgent global health issue
- Case study: in 2018, China stopped importing plastic waste, and other countries such as Indonesia received an influx

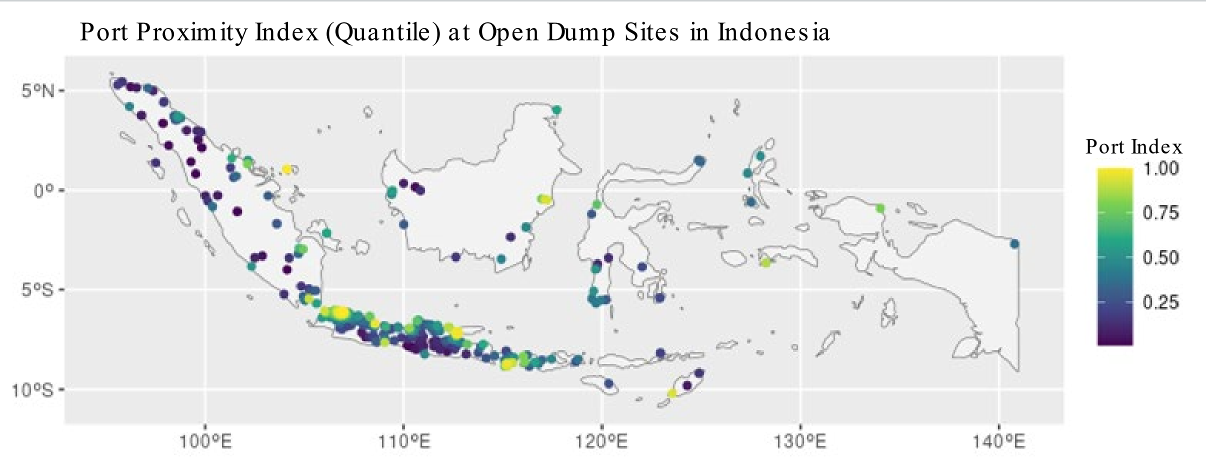



Cargo ship loitering density

Increase up to 1.68 μg/m$^3$ (95% CI = [0.72, 2.48]) at dump sites with medium-high port proximity

- Data:
  - $PM_{2.5}$ estimates (from van Donkelaar et al. 2021)
  - Meteorology from ERA5; active fire points from VIIRS
  - Sites where open dumping has been detected by Global Plastic Watch in satellite imagery
  - Cargo ship signal density (while loitering)
- Statistical method: robust extension of Diff-in-Diff with a continuous exposure
  - Uncertainty quantification accounting for residual spatial correlation
- Results: observed strong evidence that monthly $PM_{2.5}$ increased at Indonesian dump sites in the wake of China's policy change

# Motivation for methodological adaptation




We expect the long-term trend in air pollution at non-dump sites to be *different* than that at dump sites because domestic waste is increasing and nearly half of this is openly burned

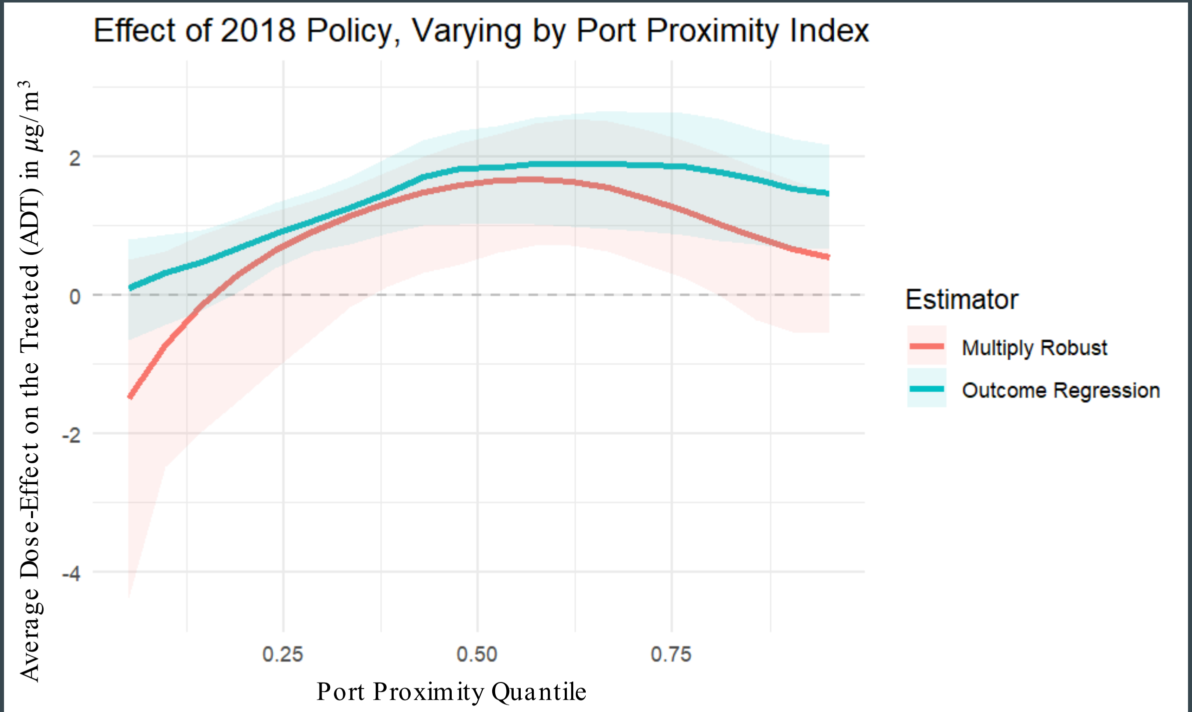
# Adapted cutting-edge quasi-experimental statistical methods

Combined two relevant strains of causal inference:

1. Estimating a heterogeneous pre-post policy effect using distance as an induced continuous exposure – Hettinger et al. (2025)
2. Using pre-intervention years as controls for post-intervention years when the policy is ubiquitous – demonstrated in several recent papers

Also extended Hettinger's weighted bootstrap approach (to obtain 95% CI) to account for residual spatial correlation

# Main results




Interpretation: We observe strong evidence that monthly $PM_{2.5}$ concentrations increased after China's ban took effect (2018-2019) compared to concentrations expected under business-as-usual (2012-2017), with increases as large as 1.68 μg/$m^3$ (95\% CI = [0.72, 2.48]) at dump sites with medium-high port proximity. Interestingly, the effect appears more modest at dump sites with very high port proximity, possibly reflecting smaller increases in dumping/burning where there is more government oversight.