

Open Dumps and the Global Trade in Garbage

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NBER SI - Development

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Motivation: Dumps

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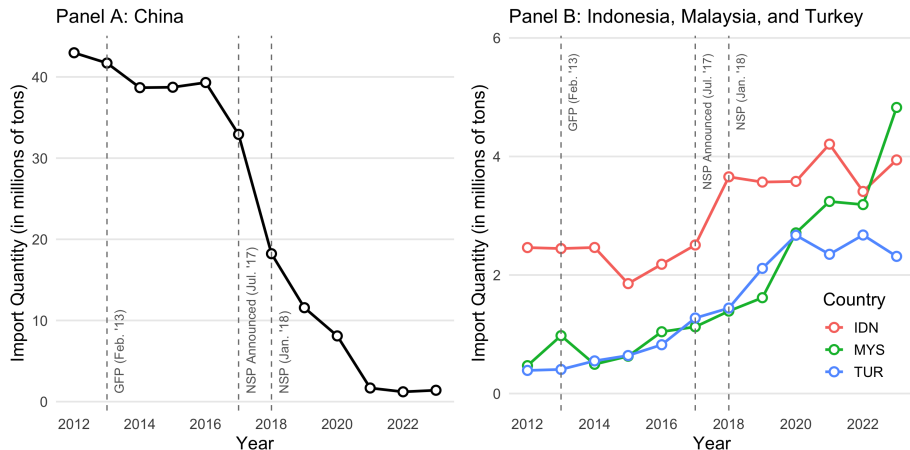
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 - “Data should be considered with a degree of caution due to ... estimates made without basis” (Kaza et al. 2018)
- **Trade:** $\approx$ half of plastic waste collected for recycling is traded internationally
 - “no quantitative estimates exist of the proportion of material exported for recycling that is ultimately discarded as waste” (Law et al. 2020)



Motivation: Trade and the China Waste Ban

In 2018, China's National Sword Policy banned imports of several types of waste materials



Ongoing discussions to restrict trade in plastic waste under the Basel Convention

This Paper: Data on Dumps

- **How do we find them?** Satellite data, ML, and sampling methods:
 - Start with totally unrepresentative, crowdsourced training data
 - Train an ML model that is **Totally wRong...Although Somewhat Helpful** (TRASH!)
 - Use *active learning* methods to create **globally-representative time-series of dumps**
 - Case Studies: Java, SE Brazil, California — attempt to find the universe of dumps

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- **Welfare and Trade:** China's waste import ban as a natural experiment
 - Indonesia waste imports generate $\approx$ \$13k in CS/life lost
 - No detectable impact on pollution in California

Data: Training Data Collection



Crowdsourced Data Collection:

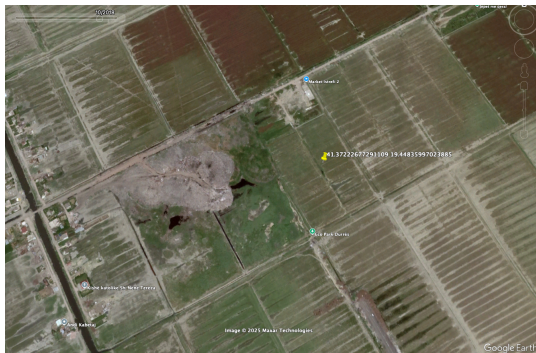
- Partnership with NGOs, researchers, and activists; set up Atlas of Plastic Waste portal www.ban.org
- 270 unique open-air waste sites across 24 countries

Other Data Sources: D-waste, Earthrise, Greenpeace

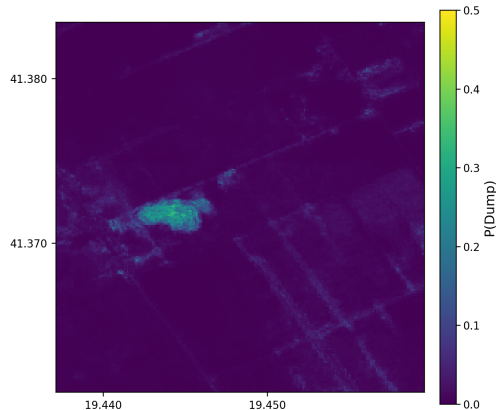
- $\approx$ 2,000 additional sites from 80+ countries

Satellite Data and ML: Sample Dump, Durrës, Albania

High Resolution Imagery (for verifications)



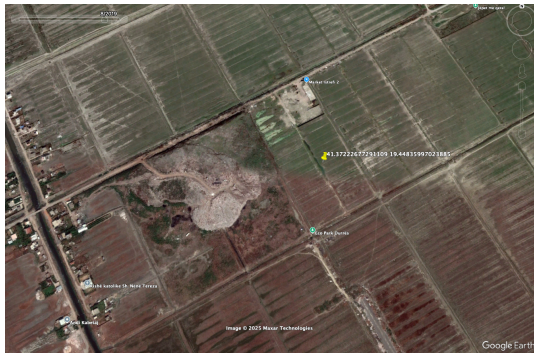
Sentinel 1 and 2 (model predictions)



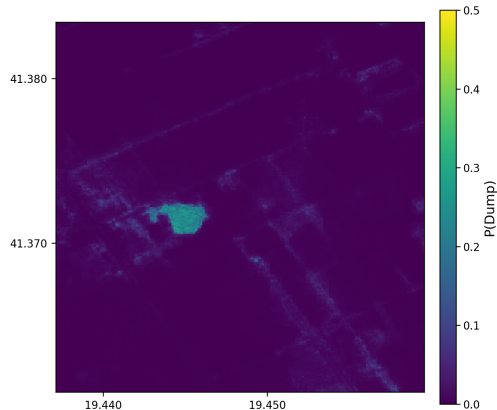
2018

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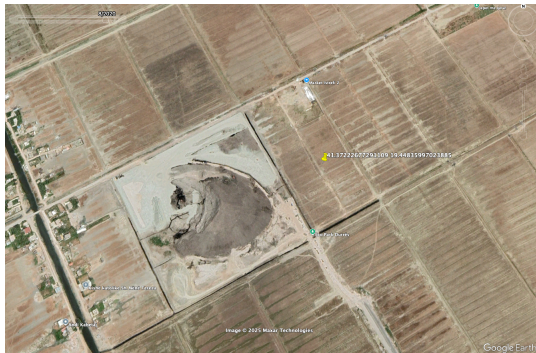


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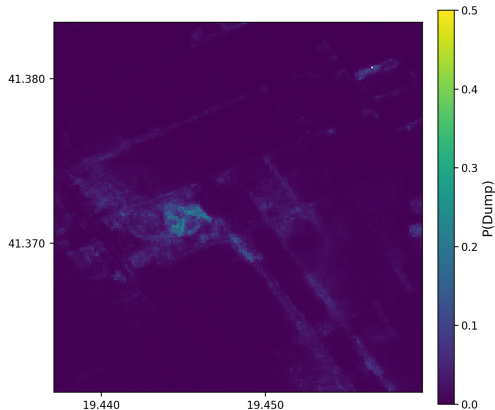


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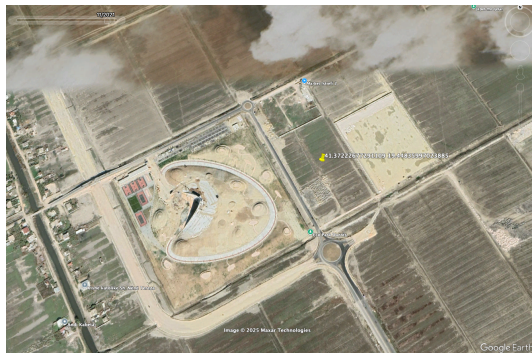


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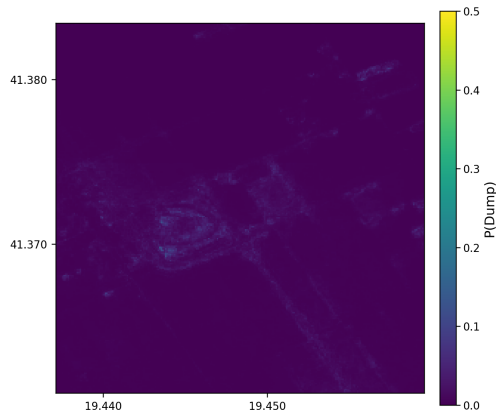


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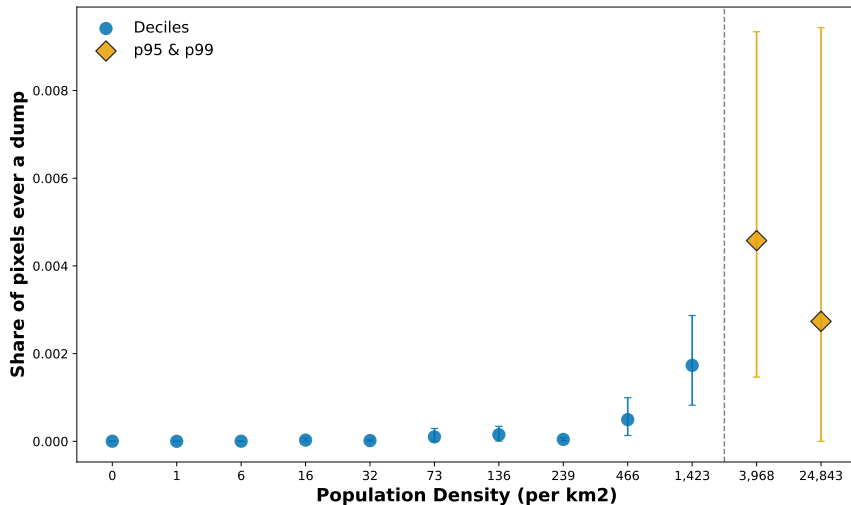
Satellite Data and ML: Active Sampling

- Gradient-boosted tree model trained on Sentinel features and derived indices
 - AUC: 0.977, Balanced Accuracy: 95% out of sample
- Hopelessly biased, rare positives exacerbate issues
 - If dumps make up 0.1% of landcover, and accuracy varies by 0.05% between periods/countries, we could find a 50% change in dumps when no change has occurred.

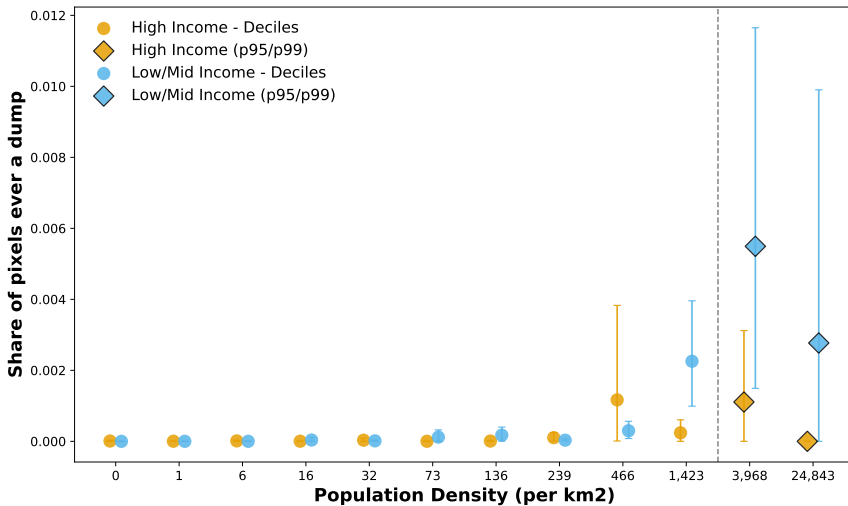
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- Do not use ML predictions as the answer, use them to decide **where to look**
 - Expert interpretation of high-resolution imagery: gold-standard data but expensive
 - Sample more where the model is uncertain → more precise estimates for the same sampling budget
 - Estimates unbiased even when model is miscalibrated (but precision may suffer)
 - See paper for details

Global Descriptives: Dumps vs Population Density

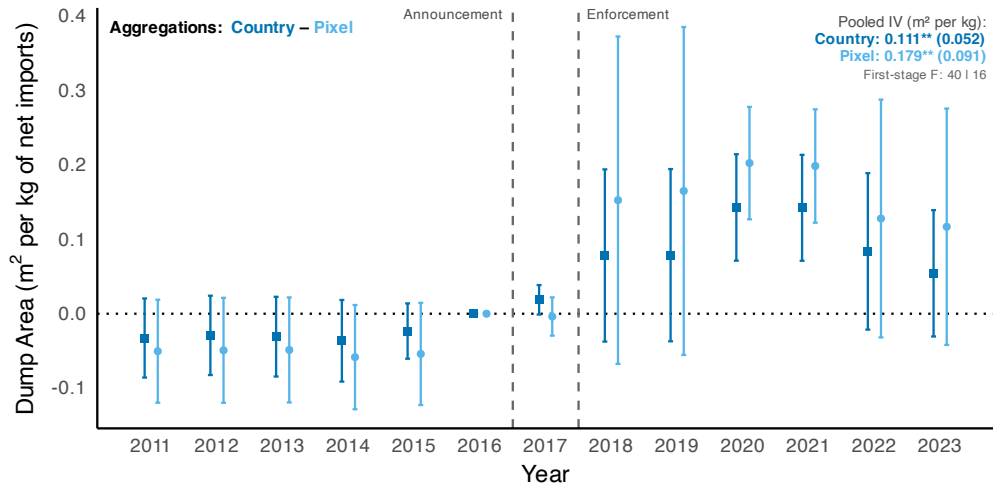


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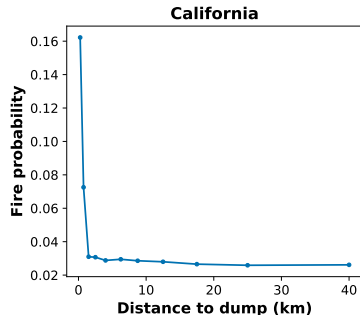
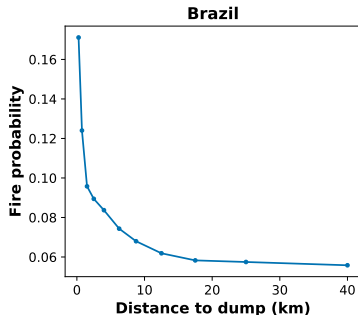
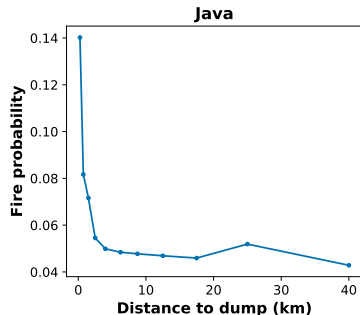
Global Event Study: Do waste imports end up in open-dumps?

Waste Imports-Dump Elasticity: China waste ban shift-share IV for imports



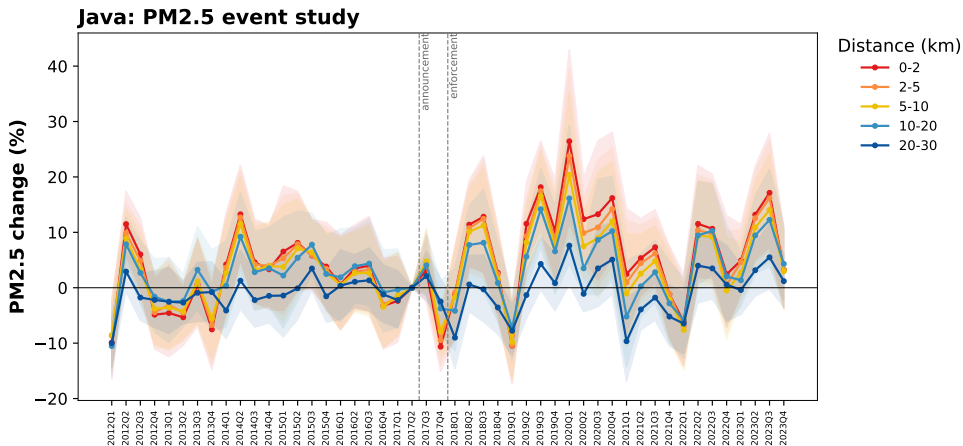
Case Studies: Garbage Fires

In Java, SE Brazil, and California, we attempt to find the universe of dumps to compare with administrative data on landfills



Probability of a fire detection, by distance to the nearest dump

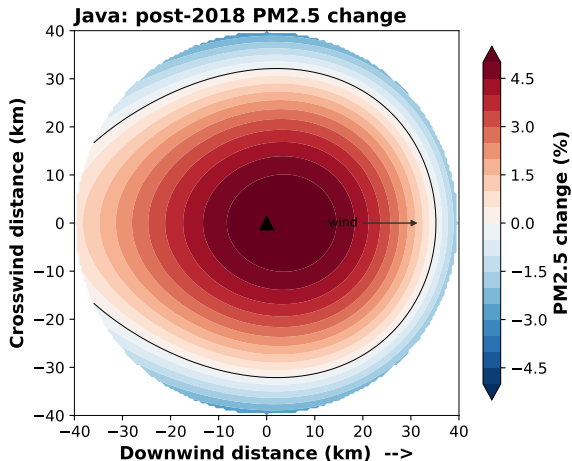
Case Studies: Near-Far Event Study Java (PM_{2.5})



Increases in PM_{2.5} close to dumps after 2018 waste import shock

Case Studies: Near-Far Event Study Java (PM_{2.5})

- Overlay the plumes on dumps and nearby populations, apply a dose-response function (Burnett et al. 2018)
- Caveats: no migration response/defensive actions, average plumes over time/space



Estimated plume change Pre-Post Waste Ban

Takeaways: Waste Imports and Welfare in Indonesia

Costs: 4,381 deaths/year in Java alone from diverted waste imports (CI: [1,836, 7,295])

- No increase in pollution near California dumps from reduced exports

Benefits: Increased supply of scrap generates \$32-69 M/year in consumer surplus

Preliminary central estimate: \$12,672 in Indonesian benefits per premature death

- \$7,000 to \$38,000 depending on assumptions

Takeaways: Pollution haven hypothesis on a global scale

- More polluting disposal technology, dense nearby populations, low value materials

Methods: Data collection on novel outcomes

- Active sampling methods useful when ground-truth data is expensive to collect

Thank you!

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