

Spatially optimal targeting of interventions to reduce crop residue burning

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Motivation

- Air pollution shown to have adverse effects on health (Deryugina et al., 2019), productivity (Chang et al., 2016), and academic achievement (Gilraine and Zheng, 2022)
- Biomass fires make up 15.4 % of PM infant deaths at the country level and this share has been on the rise globally (2004 to 2018) (Pullabhotla et al., 2022)
- Conditional payments to farmers proposed to reduce residue burning (Jayachandran et al., 2019)
- **This paper:** Given limited resources, which places should be targeted for interventions to reduce air pollution?

Overview

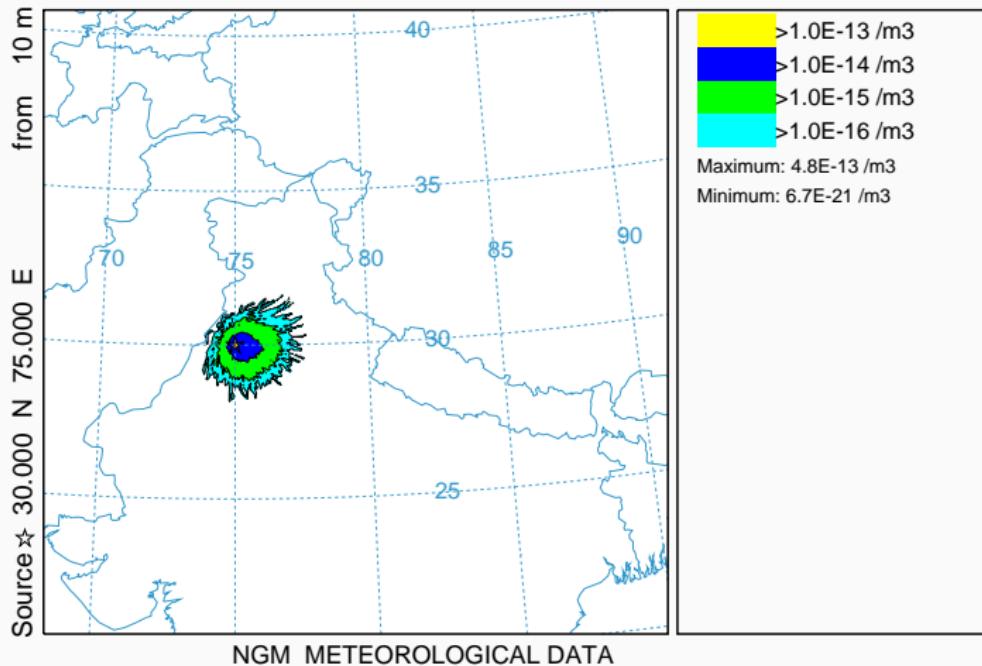
- **Goal:** Target the interventions into places where the greatest impact can be achieved
- Modeling of two main aspects:
 1. Harm
 - On average, how much harm would additional emissions from a given location cause?
 - Depends on the weather patterns (wind direction, strength, etc.) and spatial distribution of the population
 - I will use an air pollution transport model (HYSPLIT) to estimate the overall impact
 2. Costs
 - How much we would have to spend to reduce the pollution in a given location?
 - Need to model the response of farmers to an intervention

Modeling air pollution transport

- HYSPLIT dispersion model
 - Hybrid Single-Particle Lagrangian Integrated Trajectory model
 - One of the most extensively used atmospheric transport and dispersion models in the atmospheric sciences
 - Applications include tracking and forecasting the release of wildfire smoke, wind-blown dust, volcanish ash, and crop residue burning (Stein et al., 2015)
- Main output of interest
 - Source-receptor matrix: SRM_{ij}
 - Fraction of emissions from source i that are transported into j

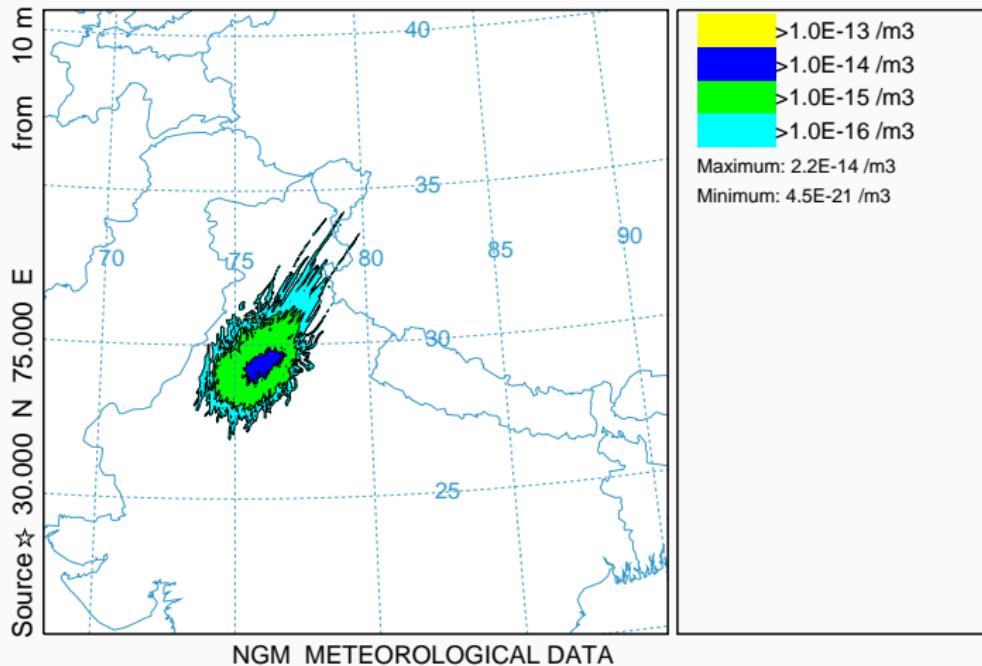
test_conc

Concentration (/m³) averaged between 0 m and 2665 m
Integrated from 0900 06 Oct to 2100 06 Oct 19 (UTC)
TEST Release started at 0900 06 Oct 19 (UTC)



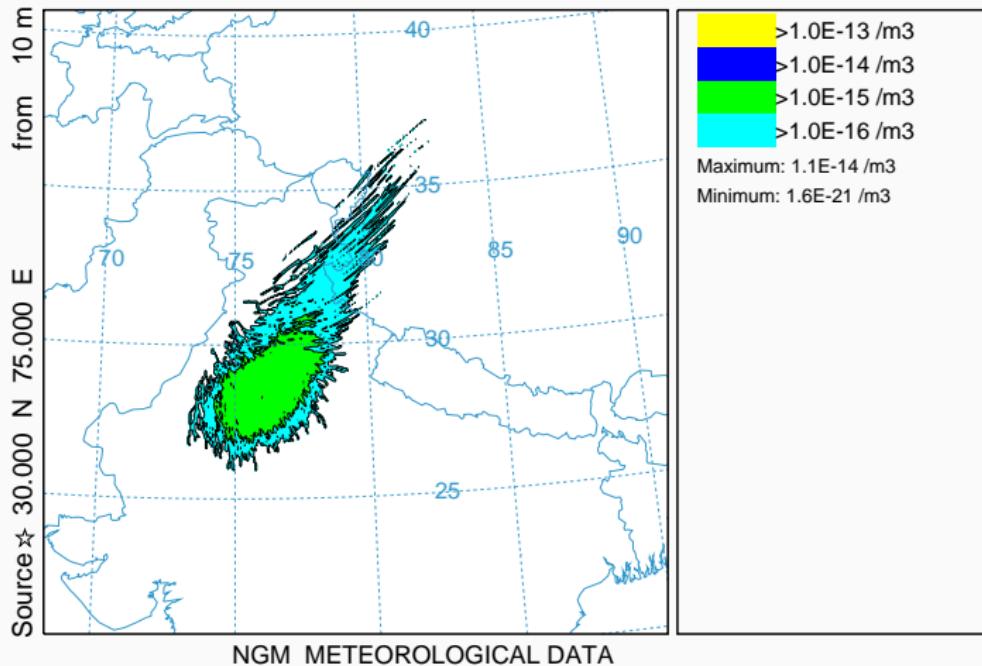
test_conc

Concentration (/m³) averaged between 0 m and 2665 m
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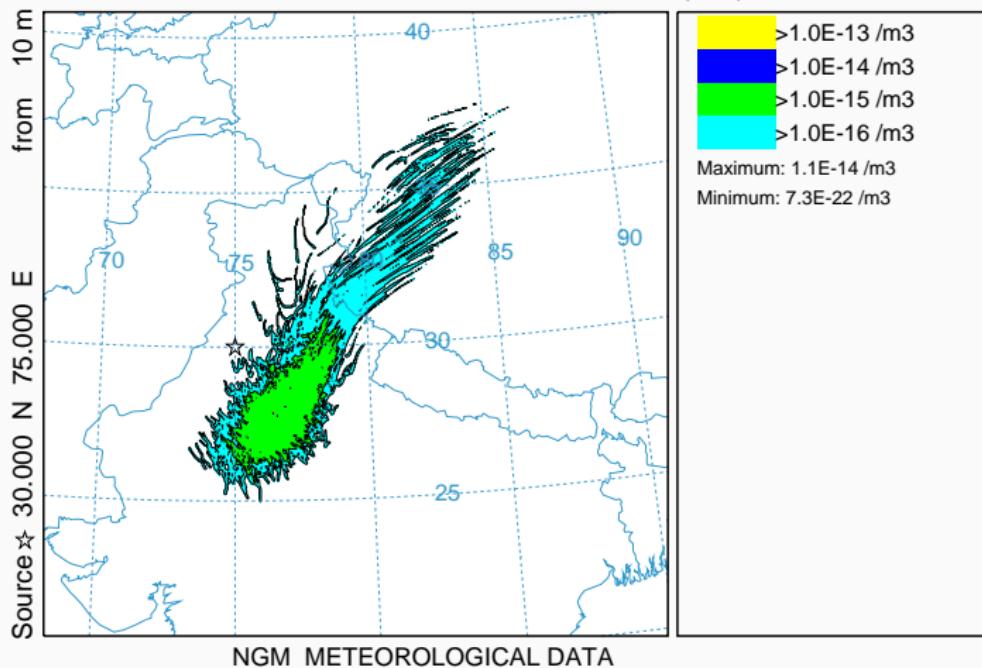
test_conc

Concentration (/m³) averaged between 0 m and 2665 m
Integrated from 0900 07 Oct to 2100 07 Oct 19 (UTC)
TEST Release started at 0900 06 Oct 19 (UTC)



test_conc

Concentration (/m³) averaged between 0 m and 2665 m
Integrated from 2100 07 Oct to 0900 08 Oct 19 (UTC)
TEST Release started at 0900 06 Oct 19 (UTC)



Measuring the impact - definitions

- SRM_{ij} ... fraction of emissions from source i that are transported into j
- E_i ... total air pollution emitted from location i
- $P_j = \sum_i SRM_{ij} E_i$... total air pollution concentration in j
- $L_j = f(P_j)$... per capita loss (harm) of exposure to P_j
- N_j ... total population
- $TL = \sum_j L_j \cdot N_j$... total population-weighted loss caused by air pollution across all locations

Measuring the impact

- The impact of small change in emissions from i on total loss

$$\frac{\partial TL}{\partial E_i} = \sum_j \frac{\partial L_j}{\partial E_i} N_j = \sum_j \frac{\partial f(P_j)}{\partial P_j} \frac{\partial P_j}{\partial E_i} N_j = \sum_j \frac{\partial f(P_j)}{\partial P_j} SRM_{ij} N_j$$

- if $f(P) = \psi_0 + \psi \cdot P$, this simplifies to

$$\frac{\partial TL}{\partial E_i} = \psi \sum_j SRM_{ij} N_j := \psi \cdot \alpha_i$$

- Some evidence to support linear effect of PM2.5 concentrations on infant mortality (Heft-Neal et al., 2018)

Problem formulation I

$$\min_{s_i \in \{\bar{s}_1, \dots, \bar{s}_J\}} \text{TL} = \min_{s_i \in \{\bar{s}_1, \dots, \bar{s}_J\}} \sum_j L_j N_j, \quad (1)$$

subject to budget constraint

$$\sum_i r_i s_i l_i + \mathbb{1}(s_i > 0) F \leq M, \quad (2)$$

the equation for enrollment rate into the program (▶ details)

$$r_i = \omega^B b(s=0, x_i) + \omega^N (1 - b(s=0, x_i)), \quad (3)$$

the pollution loss function

$$L_j = f(P_j) = f(p_j^b + p_j^0), \quad (4)$$

source-receptor matrix decomposition of air pollution

$$p_j^b = \sum_i SRM_{ij} E_i, \quad (5)$$

Problem formulation II

the equation relating the emissions due to crop residue burning (E_i) to the predicted share of land burned ($b_i(s_i, x_i)$) and eligible land area l_i

$$E_i = \phi b(s_i, x_i) \cdot l_i, \quad (6)$$

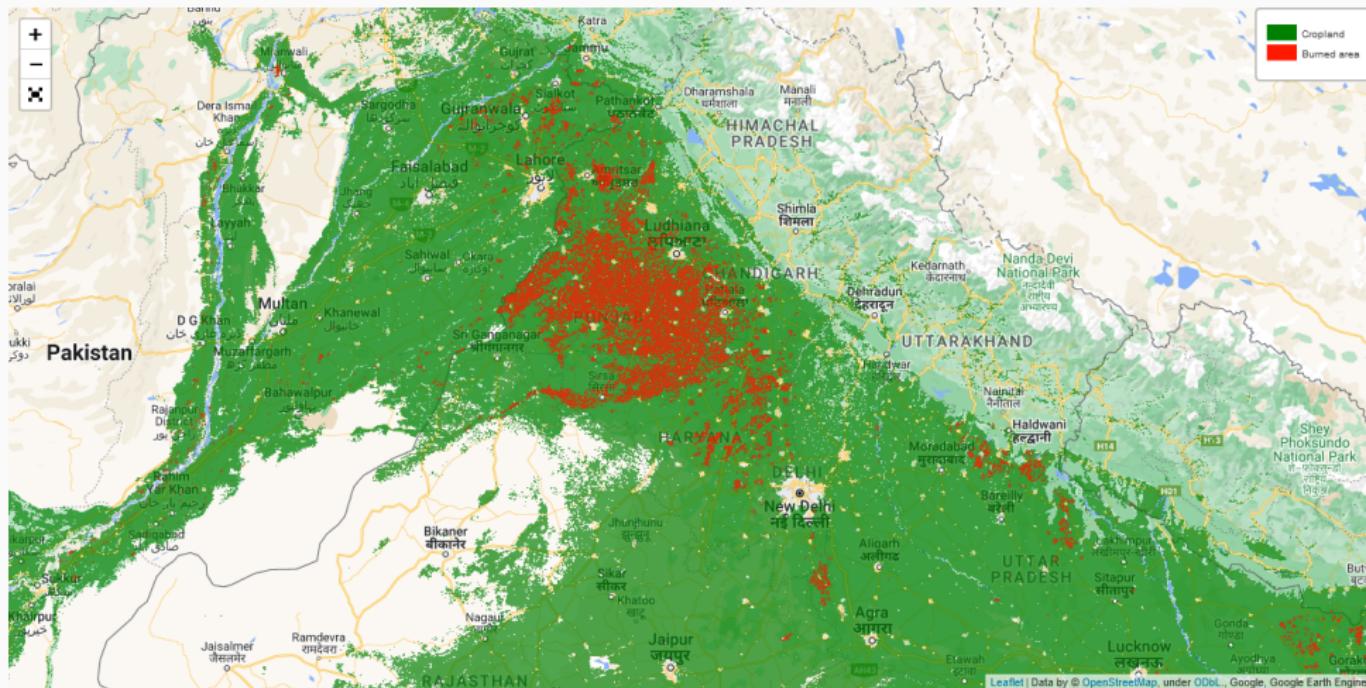
and the predicted share of land burned given the conditional payment amount (s_i) and the covariates (x_i)

$$b(s_i, x_i) = \frac{\exp(\hat{\beta}s_i + x'_i\hat{\gamma})}{1 + \exp(\hat{\beta}s_i + x'_i\hat{\gamma})}. \quad (7)$$

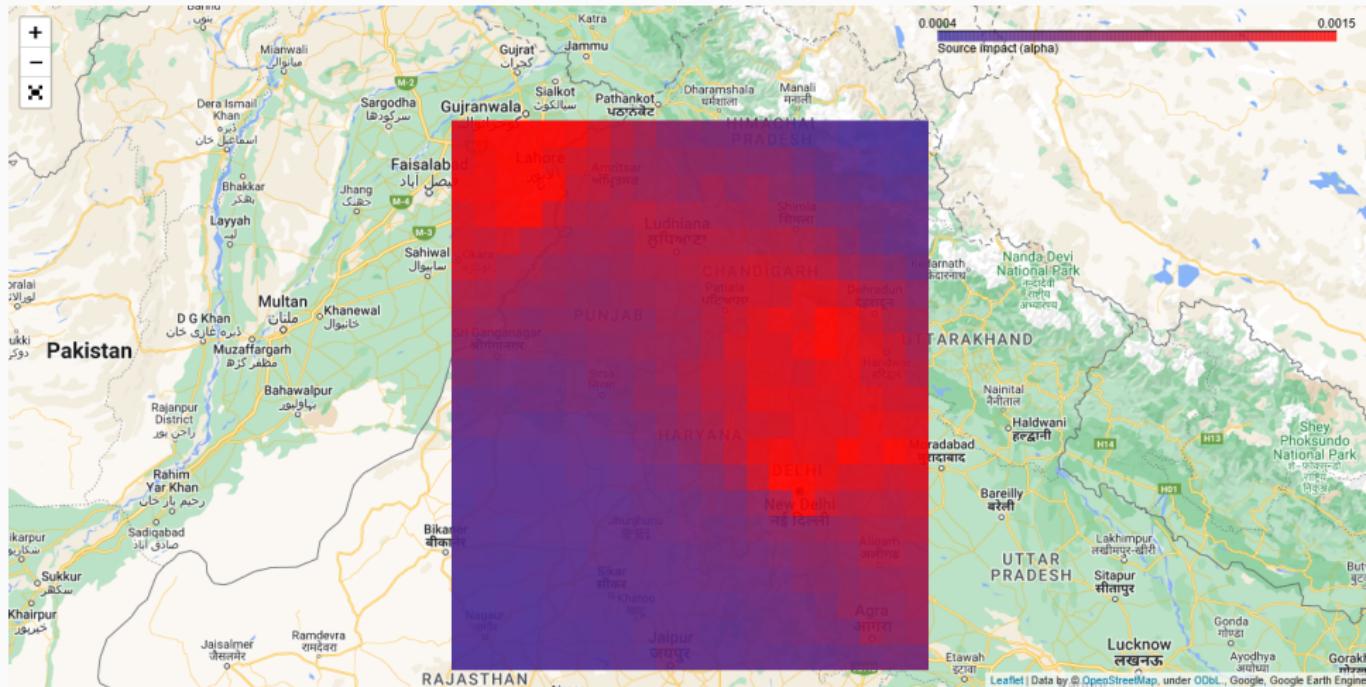
Preliminary results

- I focus on northwestern India where crop residue burning is common
- I run simulations based on October weather data for 40 different emission events
- Regular grid of 441 source location
 - α_j computed for each location separately, then interpolated across them on a finer grid
- MODIS satellite images for land cover and burned area estimates on 500m resolution
- Interactive presentation of the results (Google Earth Engine code editor)
 - [https://code.earthengine.google.com/
84b9d48057c611da316a2f6d64909a94](https://code.earthengine.google.com/84b9d48057c611da316a2f6d64909a94)

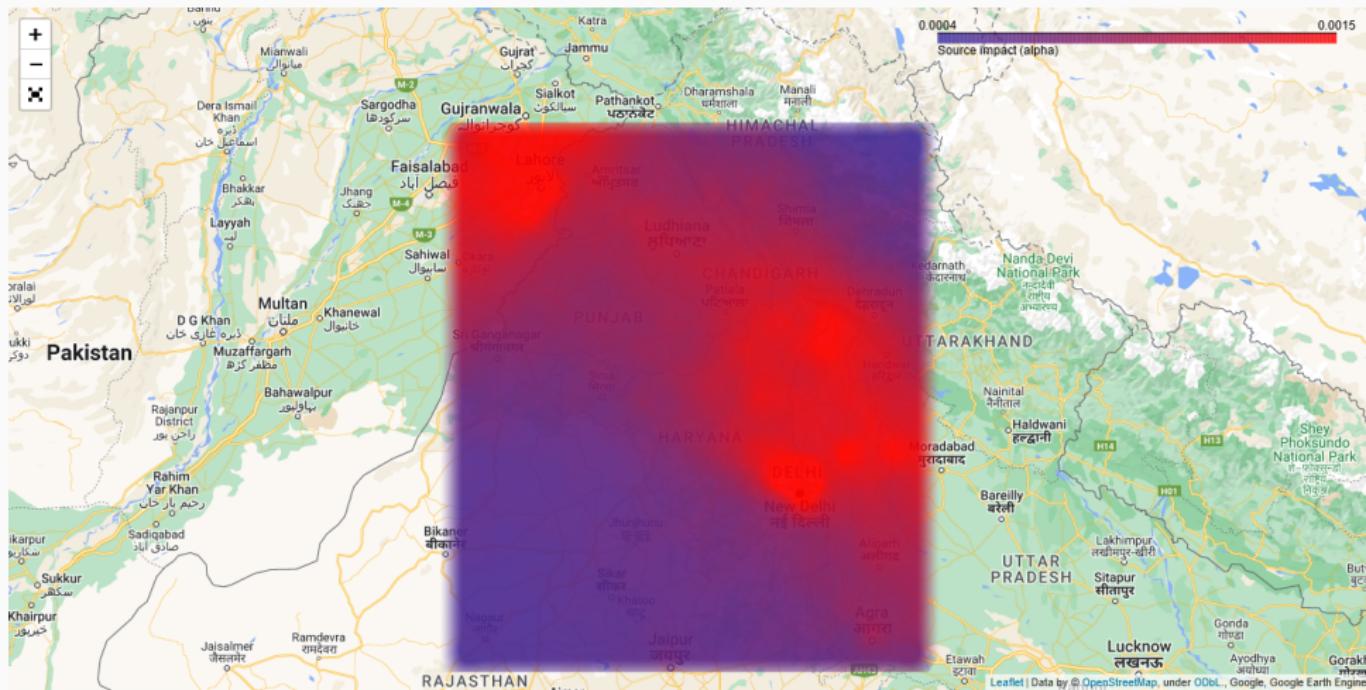
Cropland and burned area



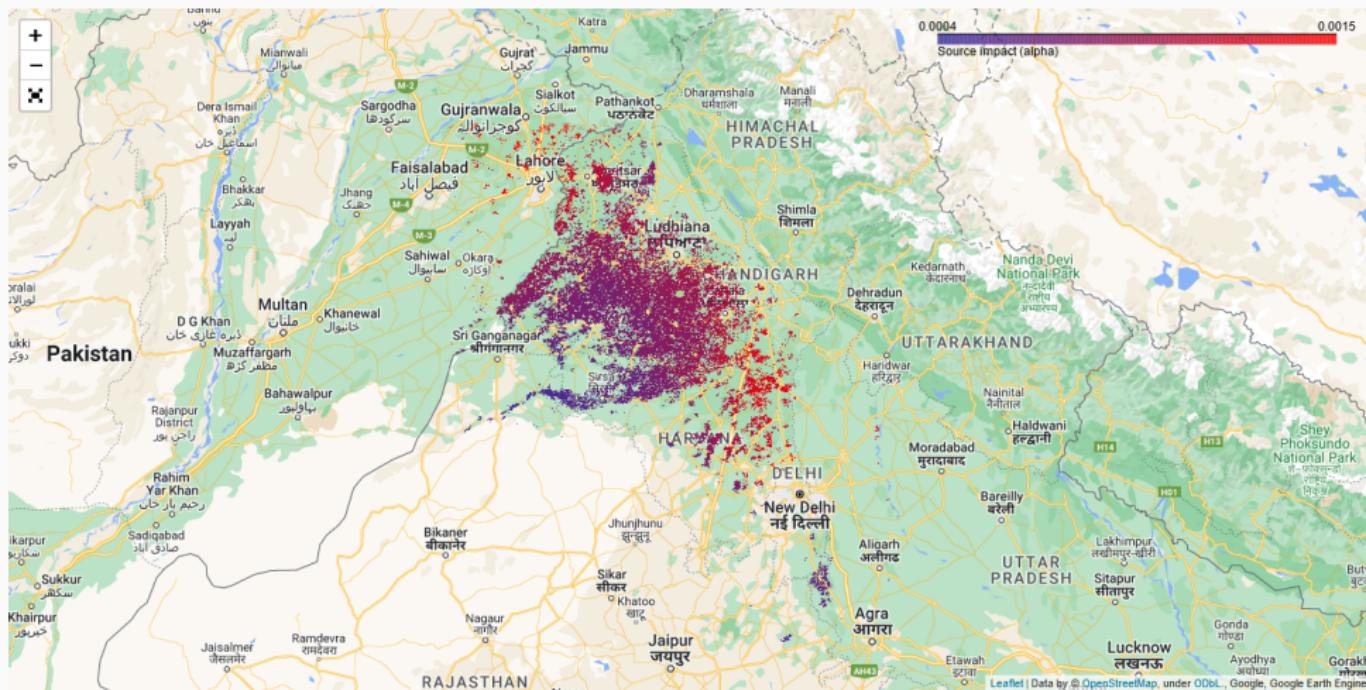
Source impacts (α_j) by location



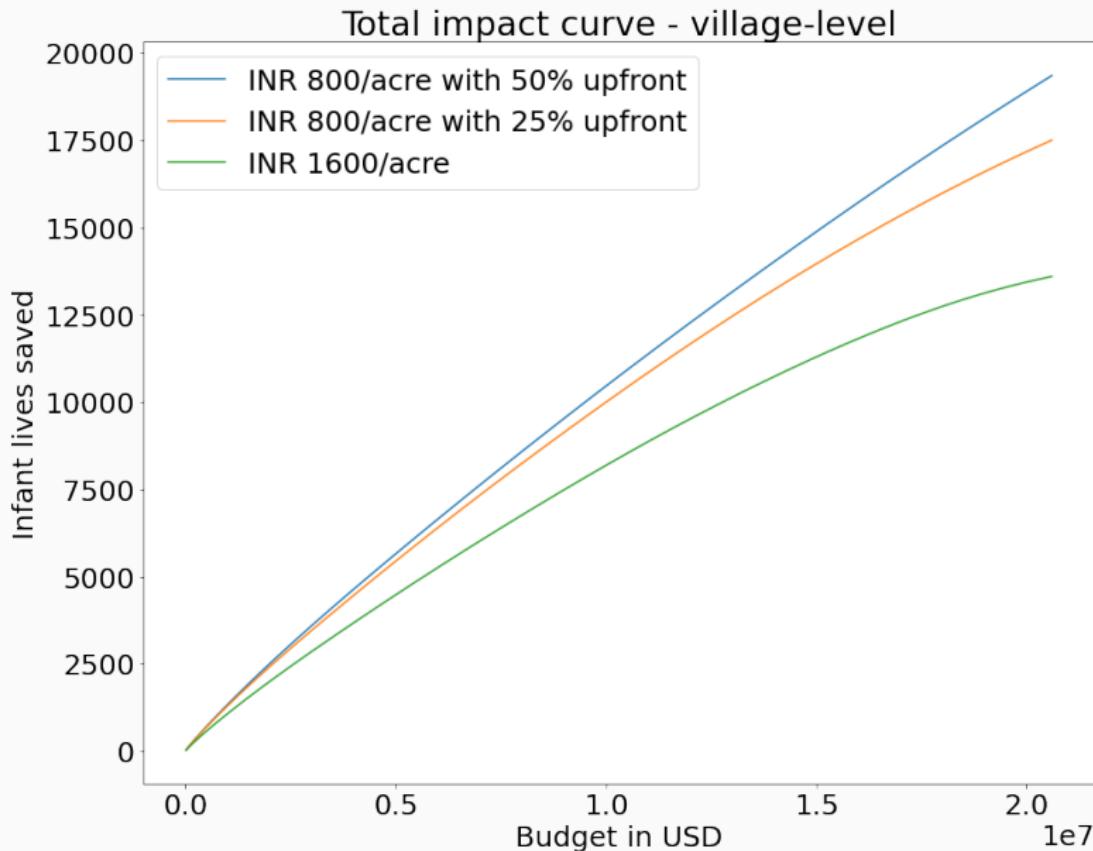
Source impacts (α_j) - interpolated



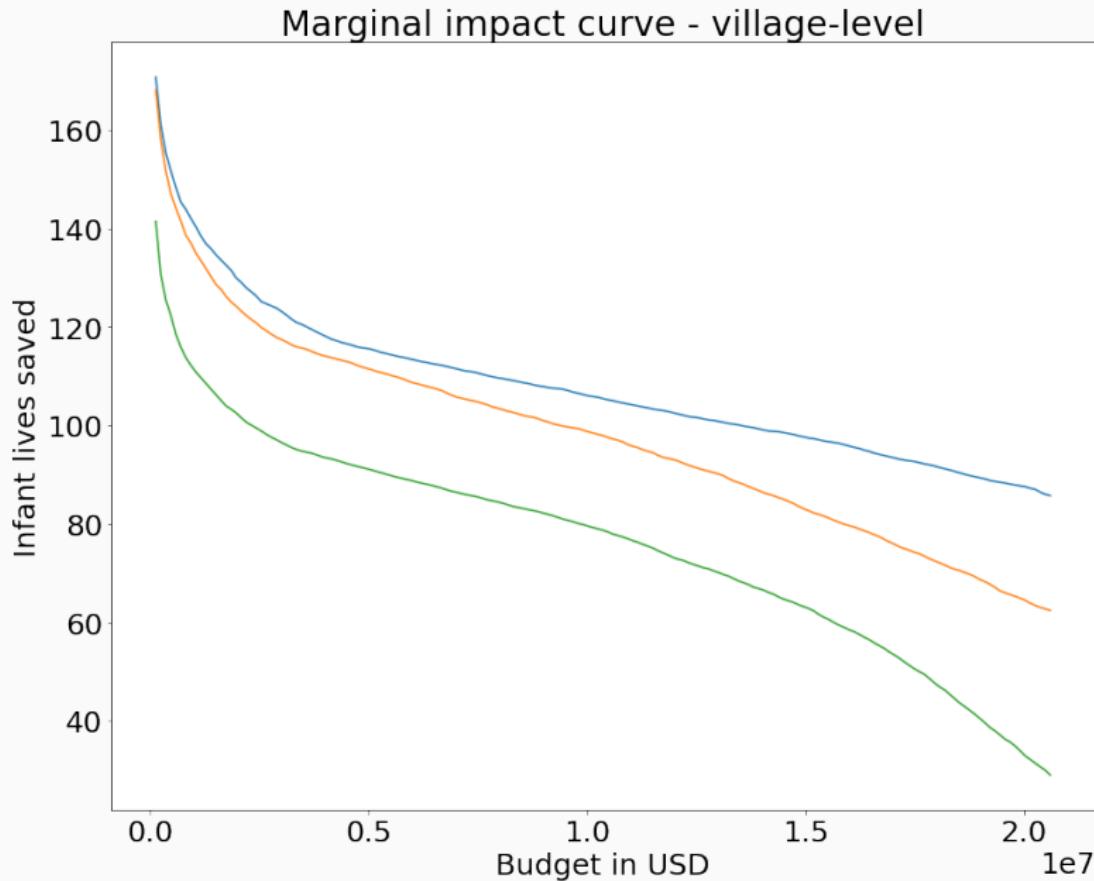
Linear loss contributions of pixels



Total impact curve - village-level



Marginal impact curve - village-level



Conclusion

- The very preliminary results suggest that there might be meaningful gains from optimal spatial targeting of interventions to reduce air pollution
- For linear loss, 25% of pixels contribute 50.8% of the total losses
- Further work
 - Additional regions: Mekong delta, northern China
 - Modelling farmers responses to intervention

References

-  Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell (2016). *The Effect of Pollution on Worker Productivity: Evidence from Call-Center Workers in China*. Working Paper 22328. Series: Working Paper Series. National Bureau of Economic Research. DOI: [10.3386/w22328](https://doi.org/10.3386/w22328).
-  Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif (2019). “The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction”. en. In: *American Economic Review* 109.12, pp. 4178–4219. DOI: [10.1257/aer.20180279](https://doi.org/10.1257/aer.20180279).

-  Gilraine, Michael and Angela Zheng (2022). *Air Pollution and Student Performance in the U.S.* Working Paper 30061. Series: Working Paper Series. National Bureau of Economic Research. doi: [10.3386/w30061](https://doi.org/10.3386/w30061).
-  Heft-Neal, Sam, Jennifer Burney, Eran Bendavid, and Marshall Burke (2018). "Robust relationship between air quality and infant mortality in Africa". en. In: *Nature* 559.7713, pp. 254–258. doi: [10.1038/s41586-018-0263-3](https://doi.org/10.1038/s41586-018-0263-3).
-  Jayachandran, Seema, Namrata Kala, Rohini Pande, Kelsey Jack, and Caitlin Rowe (2019). *Paying Farmers Not to Burn: A Randomized Trial of Payments for Ecosystem Services in India*. en. Tech. rep. doi: [10.1257/rct.4508](https://doi.org/10.1257/rct.4508).
-  Pullabhotla, Hemant Kumar, Mustafa Zahid, Sam Heft-Neal, Vaibhav Rathi, and Marshall Burke (2022). "Global biomass fires and infant mortality". en. In: Publisher: EarthArXiv.

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- Stein, A. F., R. R. Draxler, G. D. Rolph, B. J. B. Stunder, M. D. Cohen, and F. Ngan (2015). "NOAA's HYSPLIT Atmospheric Transport and Dispersion Modeling System". EN. In:
- Bulletin of the American Meteorological Society*
- 96.12. Publisher: American Meteorological Society Section: Bulletin of the American Meteorological Society, pp. 2059–2077. doi:
- [10.1175/BAMS-D-14-00110.1](https://doi.org/10.1175/BAMS-D-14-00110.1)
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Thank you for your attention.