Spatially optimal targeting of interventions to reduce air pollution

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Motivation

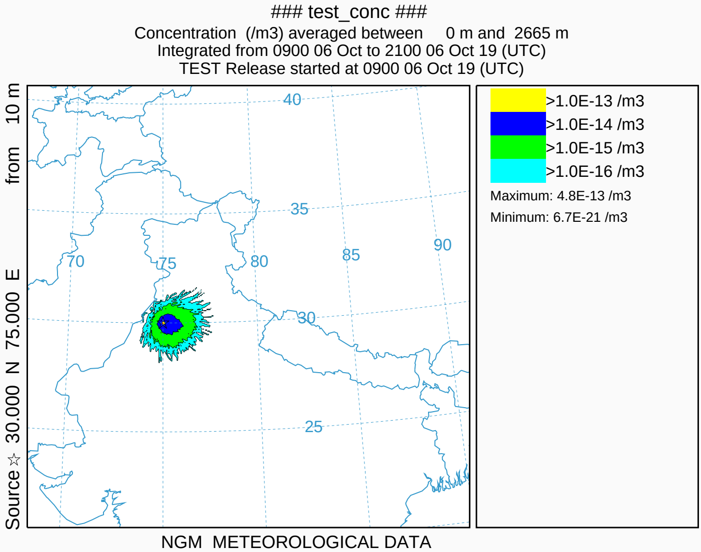
- Air pollution shown to have adverse effects on health (Deryugina et al., 2019), productivity (Chang et al., 2016), and academic achievement (Gilraine and Zheng, 2022)
- Biomass fires make up 15.4 % of PM infant deaths at 285 the country level annd this share has been on the rise globally (2004 to 2018) (Pullabhotla et al., 2022)
- Conditional payments to farmers proposed to reduce residue burning (Jayachandran et al., 2019)
- This paper: Given limited resourced, 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)
Source ☆ 30.000 N 75.000 E from 10 m
40
35
30
25
70
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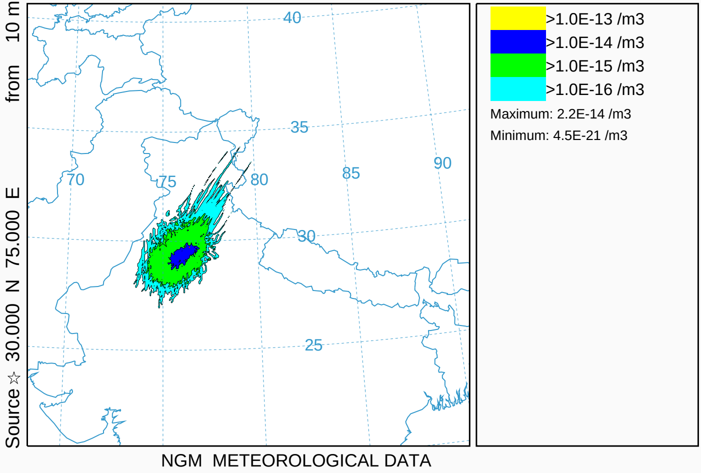
85
90
>1.0E-13 /m3
>1.0E-14 /m3
>1.0E-15 /m3
>1.0E-16 /m3
Maximum: 4.8E-13 /m3
Minimum: 6.7E-21 /m3
NGM METEOROLOGICAL DATA

test_conc

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



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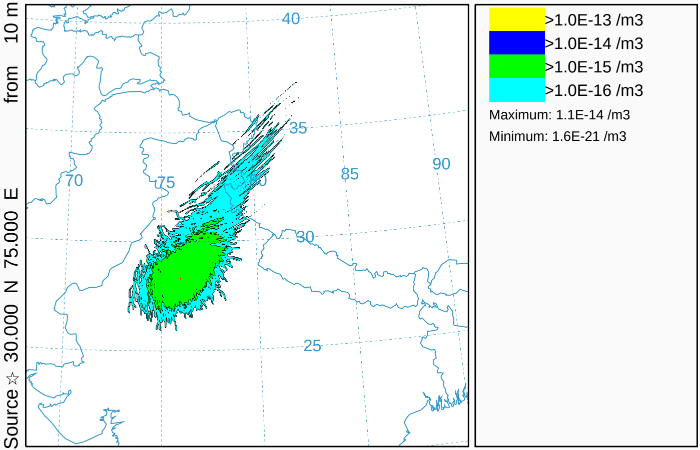

NGM METEOROLOGICAL DATA

test_conc

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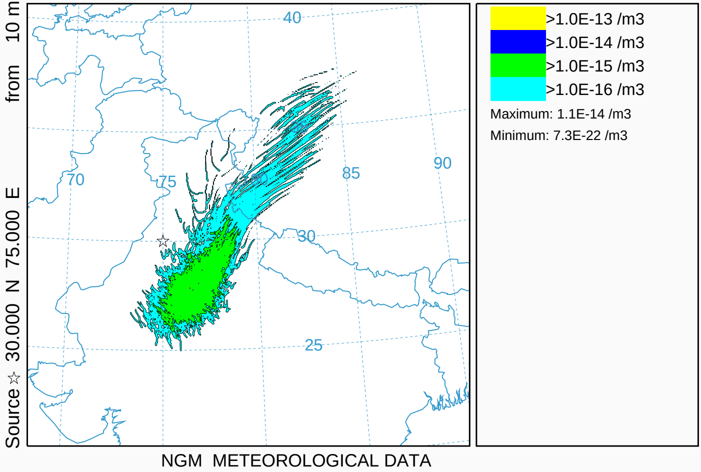


Measuring the impact - definitions

- 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 i
- $L_j = f(P_j)$ ... 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

$$\min_{s_i \in \{\bar{s}_1, \ldots, \bar{s}_J\}} \mathsf{TL} = \min_{s_i \in \{\bar{s}_1, \ldots, \bar{s}_J\}} \sum_j L_j N_j, \tag{1}$$

subject to budget constraint

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

the equation for enrollment rate into the program

$$r_i = \omega^B b(s = 0, x_i) + \omega^N \left(1 - b(s = 0, x_i)\right), \tag{3}$$

the pollution loss function

$$L_j = f(P_j) = f(p_j^b + p_j^0), \tag{4}$$

source-receptor matrix decomposition of air pollution

$$p_j^b = \sum_i SRM_{ij} E_i, \tag{5}$$

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

$$E_i = \phi b(s_i, x_i) \cdot l_i, \tag{6}$$

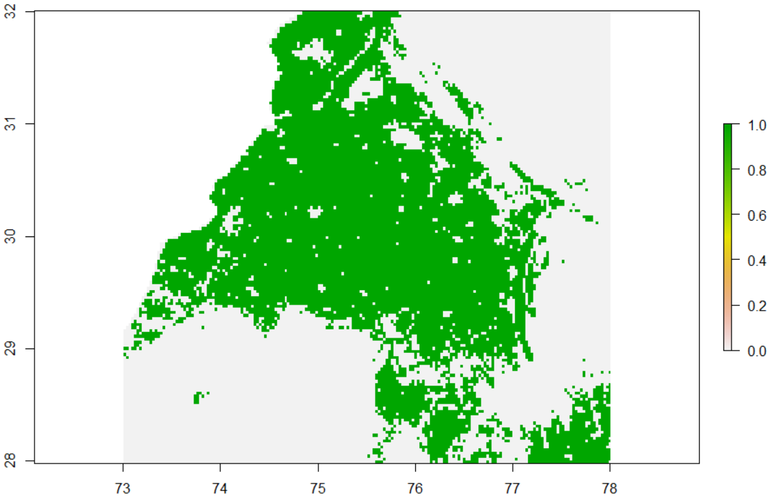
and the predicted share of land burned given the conditional payment amount (s_i) and the covariates (x_i)

$$b(s_i, x_i) = \frac{\exp\left(\hat{\beta} s_i + x_i' \hat{\gamma}\right)}{1 + \exp\left(\hat{\beta} s_i + x_i' \hat{\gamma}\right)}. \tag{7}$$

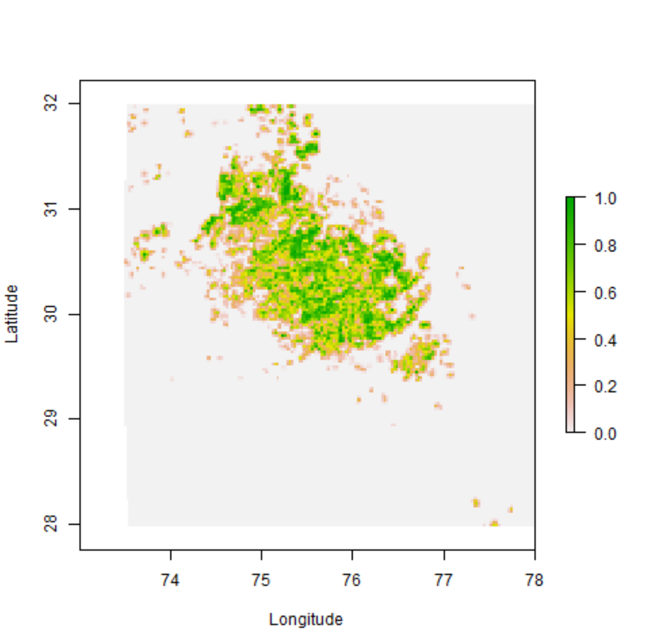
Preliminary results

- 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 121 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*

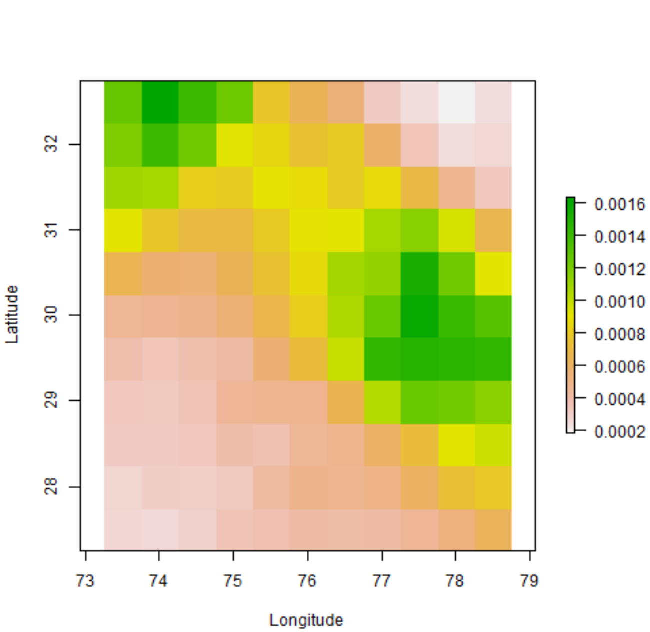
Winter cropped area



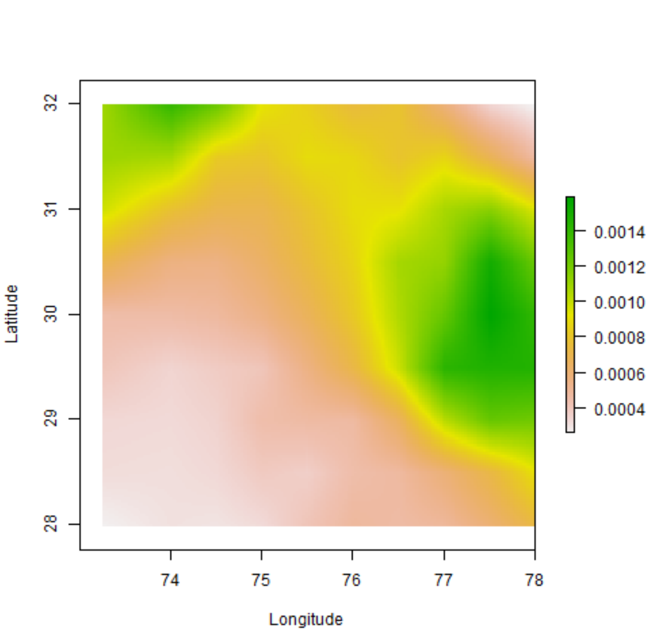
Burned cropped area share



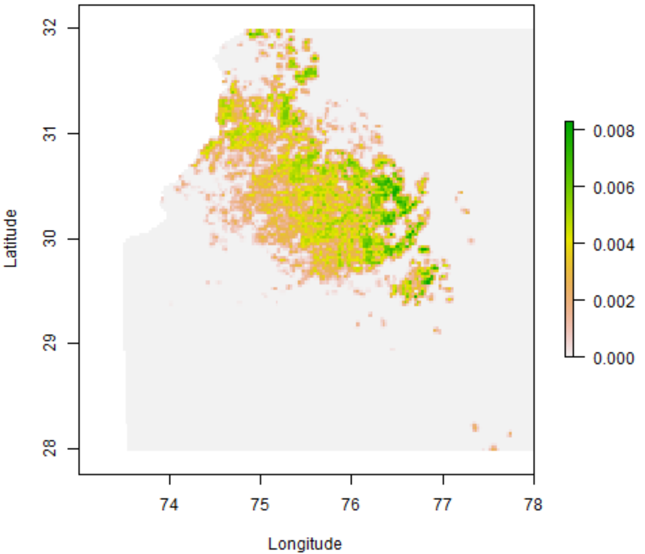
Source impacts (α_j) by location



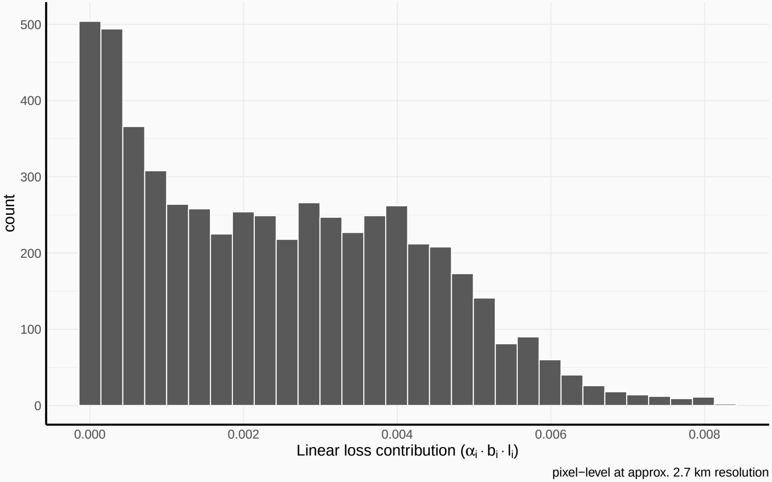
Source impacts (α_j) - interpolated



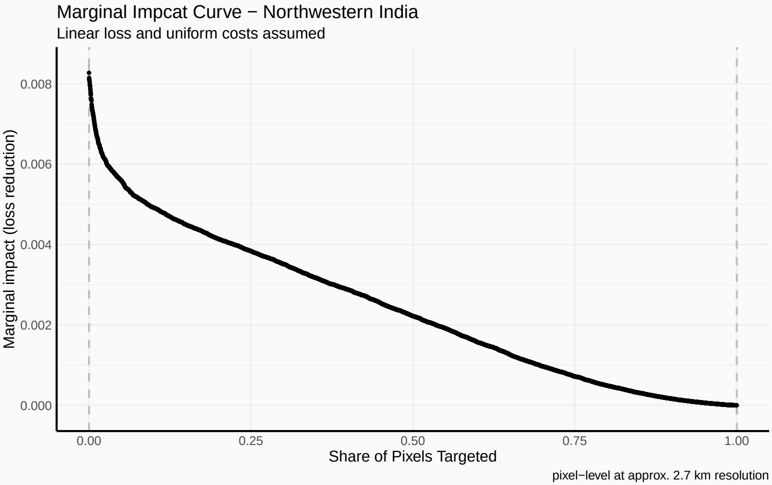
Linear loss contributions of pixels



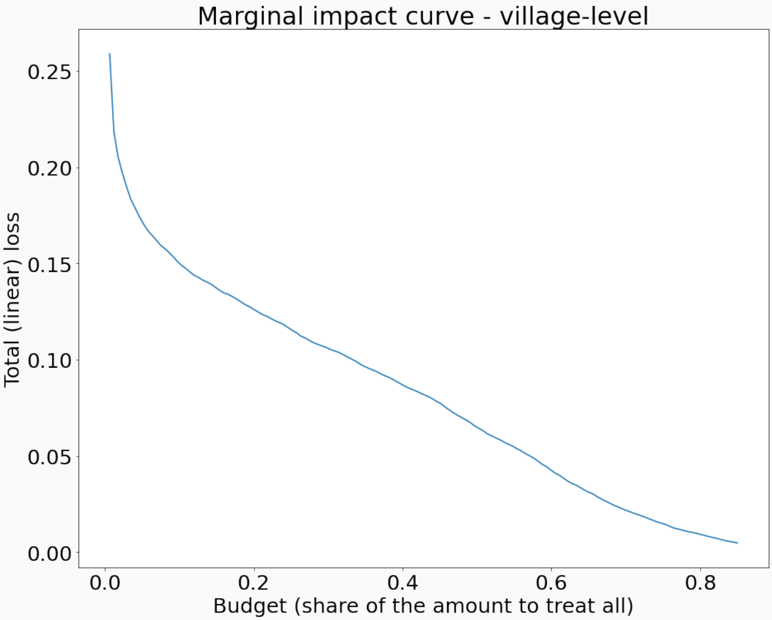
Linear loss contributions of pixels - histogram



Marginal impact curve - pixel-level



Marginal impact curve - village-level



Conclusion

- The very preliminary results suggest that 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

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Thank you for your attention.