Spatially optimal targeting of interventions to reduce air pollution

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Motivation

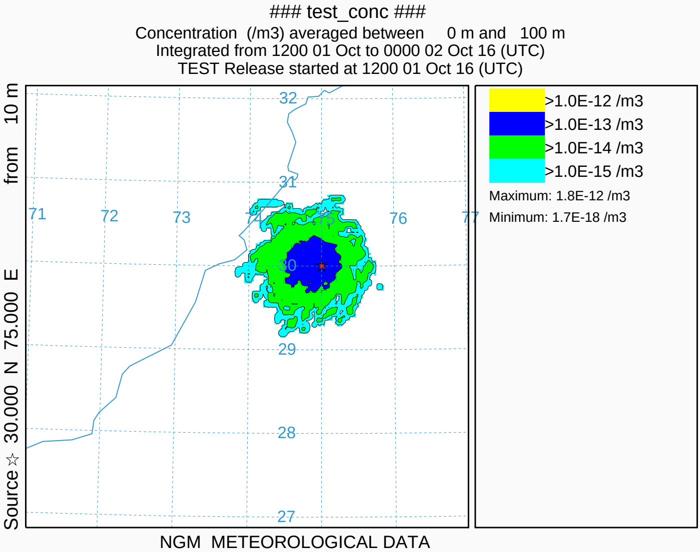
- Air pollution (PM2.5, PM10) shown to have adverse effects on health (Deryugina et al., 2019), productivity (Chang et al., 2016), and academic achievement (Gilraine and Zheng, 2022)
- Crop residue burning is an important contributor air pollution in Indian cities during the late fall (Liu et al., 2018)
- Various interventions proposed to reduce residue burning such as conditional payments to farmers
- 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

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
  - Average over 8 days after release


test_conc
Concentration (/m3) averaged between 0 m and 100 m
Integrated from 1200 01 Oct to 0000 02 Oct 16 (UTC)
TEST Release started at 1200 01 Oct 16 (UTC)
Source ☆ 30.000 N 75.000 E from 10 m
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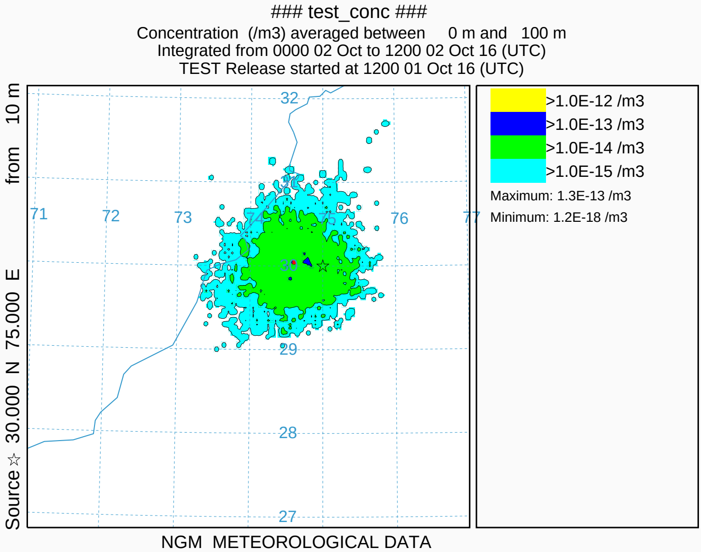
>1.0E-12 /m3
>1.0E-13 /m3
>1.0E-14 /m3
>1.0E-15 /m3
Maximum: 1.8E-12 /m3
Minimum: 1.7E-18 /m3
NGM METEOROLOGICAL DATA



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>1.0E-12 /m3
>1.0E-13 /m3
>1.0E-14 /m3
>1.0E-15 /m3
Maximum: 1.3E-13 /m3
Minimum: 1.2E-18 /m3
NGM METEOROLOGICAL DATA

test_conc
Concentration (/m3) averaged between 0 m and 100 m
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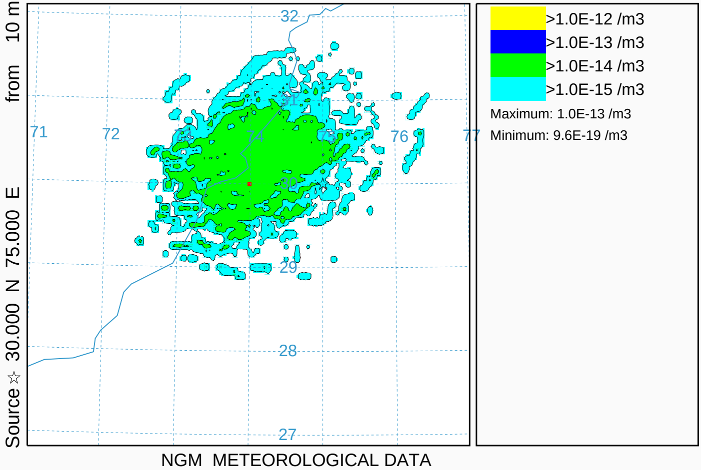
TEST Release started at 1200 01 Oct 16 (UTC)

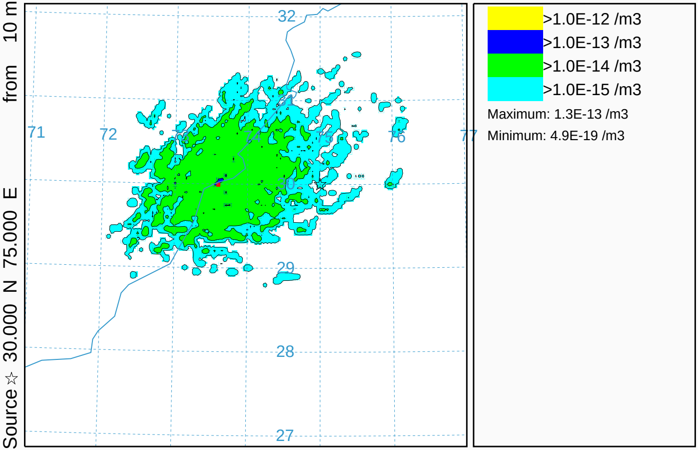


test_conc

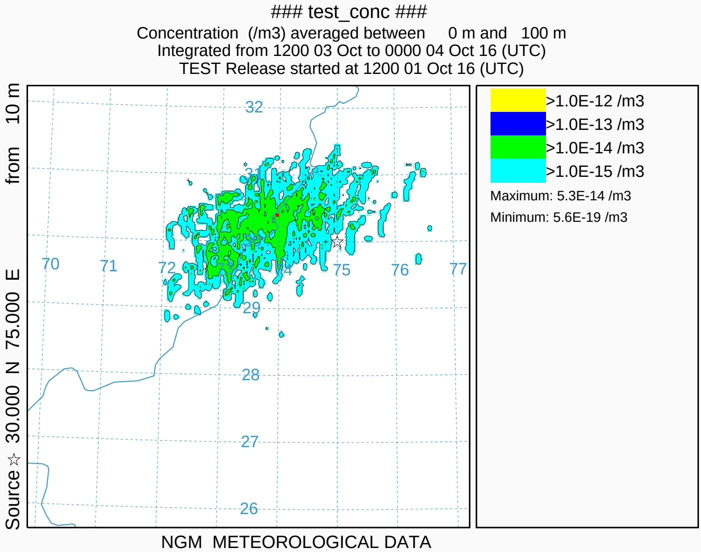
Concentration (/m3) averaged between 0 m and 100 m

Integrated from 0000 03 Oct to 1200 03 Oct 16 (UTC)

TEST Release started at 1200 01 Oct 16 (UTC)



NGM METEOROLOGICAL DATA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>1.0E-14 /m3
>1.0E-15 /m3
Maximum: 5.3E-14 /m3
Minimum: 5.6E-19 /m3
NGM METEOROLOGICAL DATA

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 in i
- $L_j = f(P_j)$ ... loss (harm) to a single person from being exposed to air pollution in j
- N_j ... total population in j
- $TL = \sum_j L_j \cdot N_j$ ... total population-weighted loss caused by air pollution across all locations

Measuring the impact

- The impact of small change 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 $f(P_j) = a + b \cdot P_j$, this simplifies to

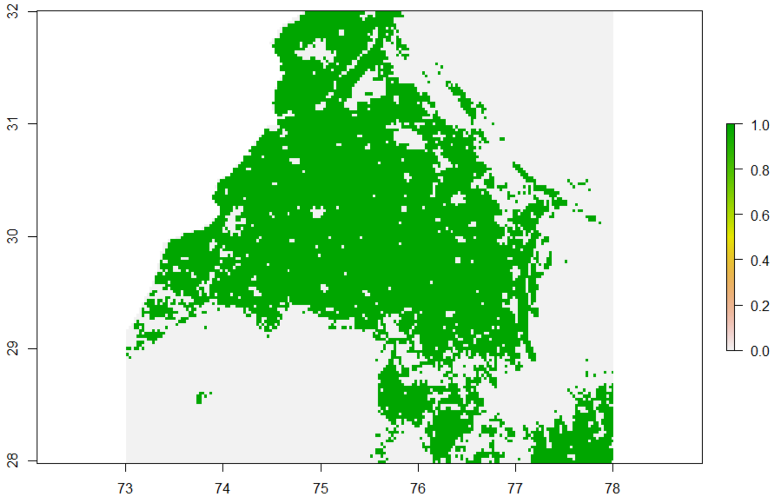
$$\frac{\partial TL}{\partial E_i} = b \sum_j SRM_{ij} N_j := b \cdot \alpha_j$$

- Clearly, it is optimal to target locations with the highest $\frac{\partial TL}{\partial E_i}$ since that will lead to greatest reductions in loss
- In case of linear $f(P_j)$, this means locations with highest α_j
    - Some evidence to support linear effect of PM2.5 concentrations on infant mortality (Heft-Neal et al., 2020)

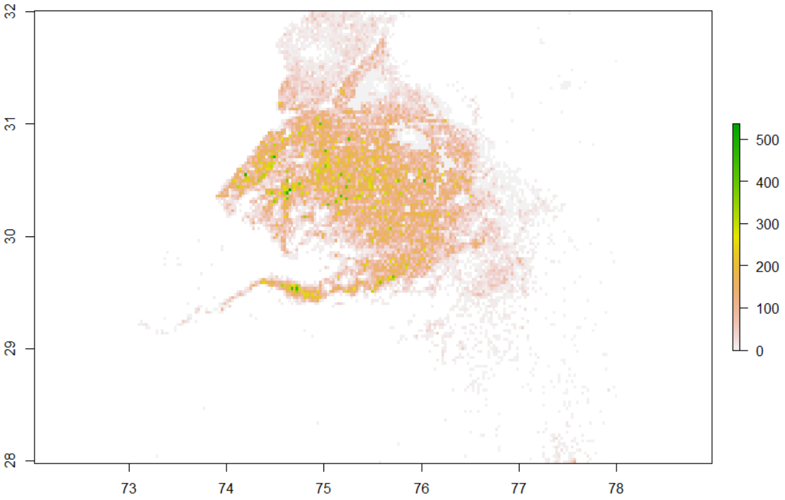
Preliminary results

- I focus on North-west of India where the air pollution is very severe and crop residue burning is common
- I run simulations based on weather data for the beginning of October for 10 different years
- Regular grid of 121 source location
  - α_j computed for each location separately, then interpolated across across them on a finer grid
  - Further, I restricted the locations to those with likely winter cropping (per Jain et al., 2016 data) and with the total fire radiating power of at least 5 (using VIIRS fire data)

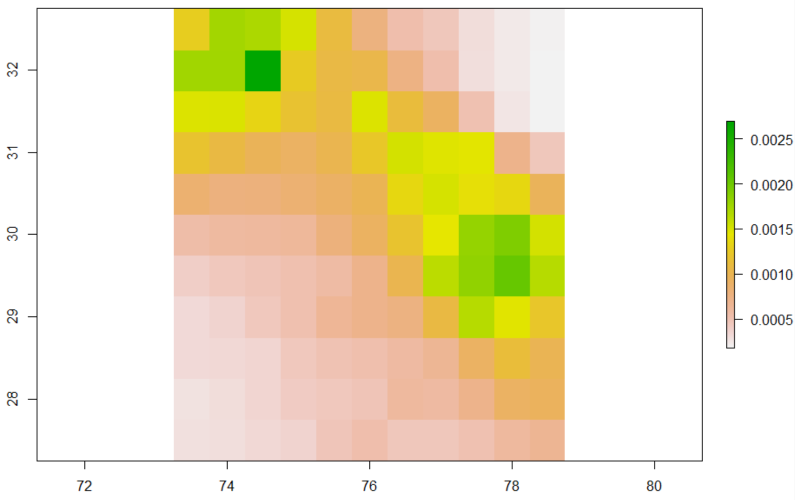
Winter cropped area



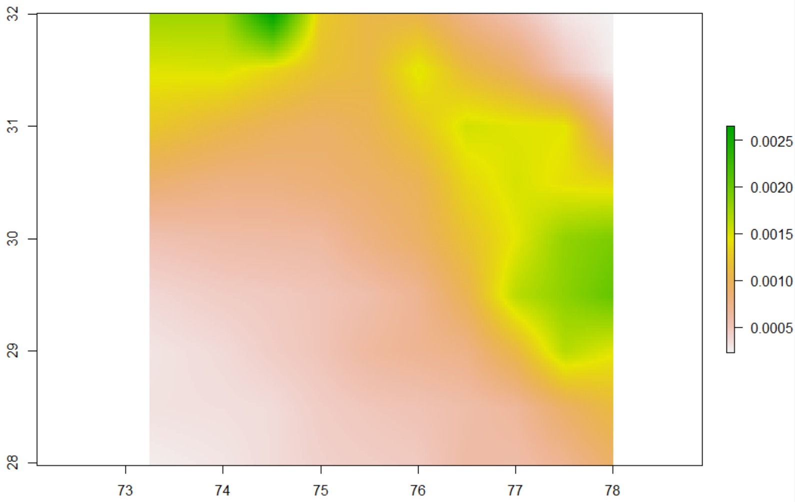
Total fire radiation power - October 2019



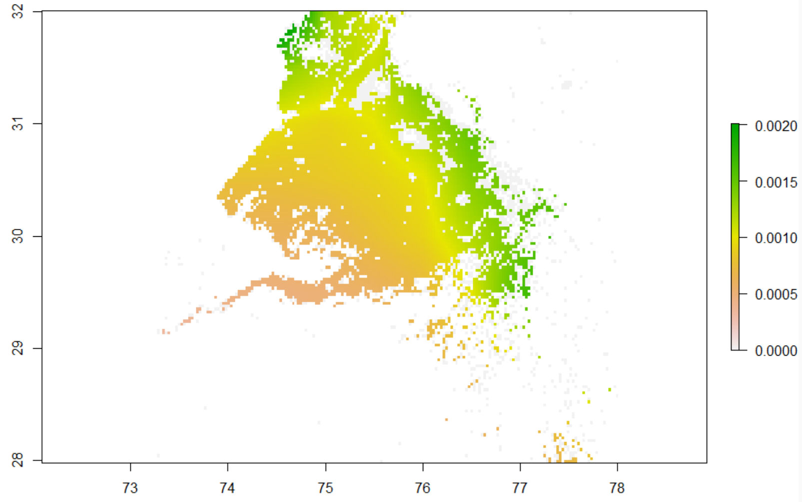
α_j in space



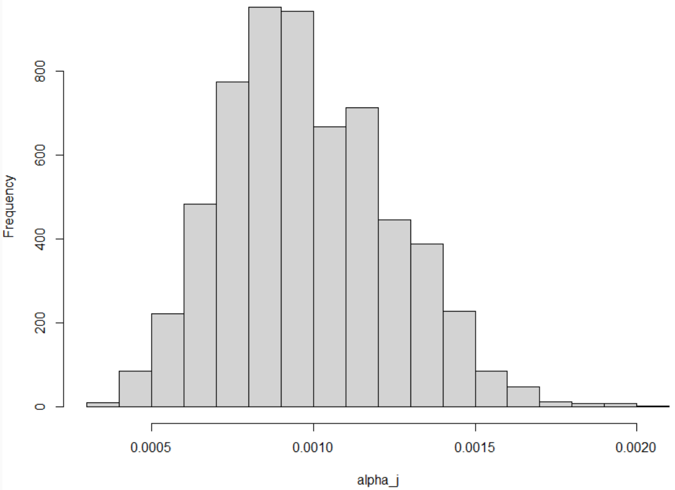
α_j - interpolated



α_j - interpolated - only crop residue burning locations



α_j - histogram



Conclusion

- The very preliminary results suggest that might be larger gains from optimal spatial targeting of interventions to reduce air pollution
- This is especially case for small-scale projects
  - Assuming linear loss and spatially uniform costs, targeting 10% crop-residue burning locations with the highest α_j results in around 55% greater reduction in loss compared to targeting 10% location with mean α_j
- More work to do on the cost side

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Thank you for your attention.