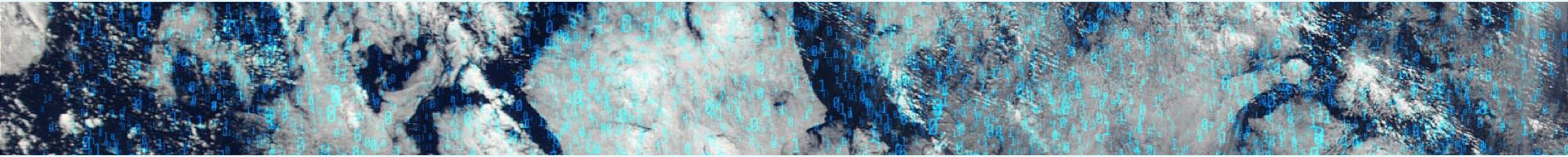

Reconstructing Aerosol Vertical Profiles with Aggregate Output Learning

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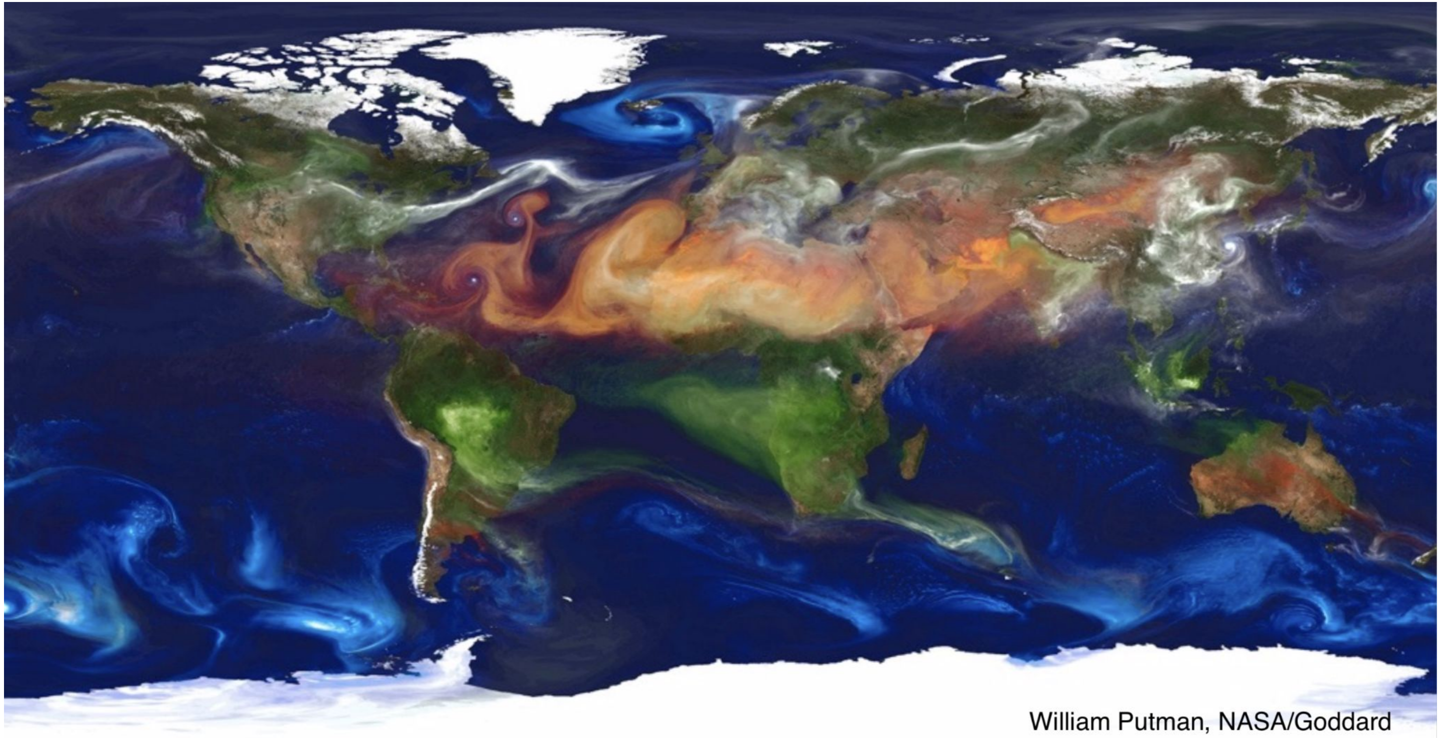
Motivation



GEOS-5 10km resolution
Red: Dust Blue: Sea Salt Green: Smoke White: Sulfate

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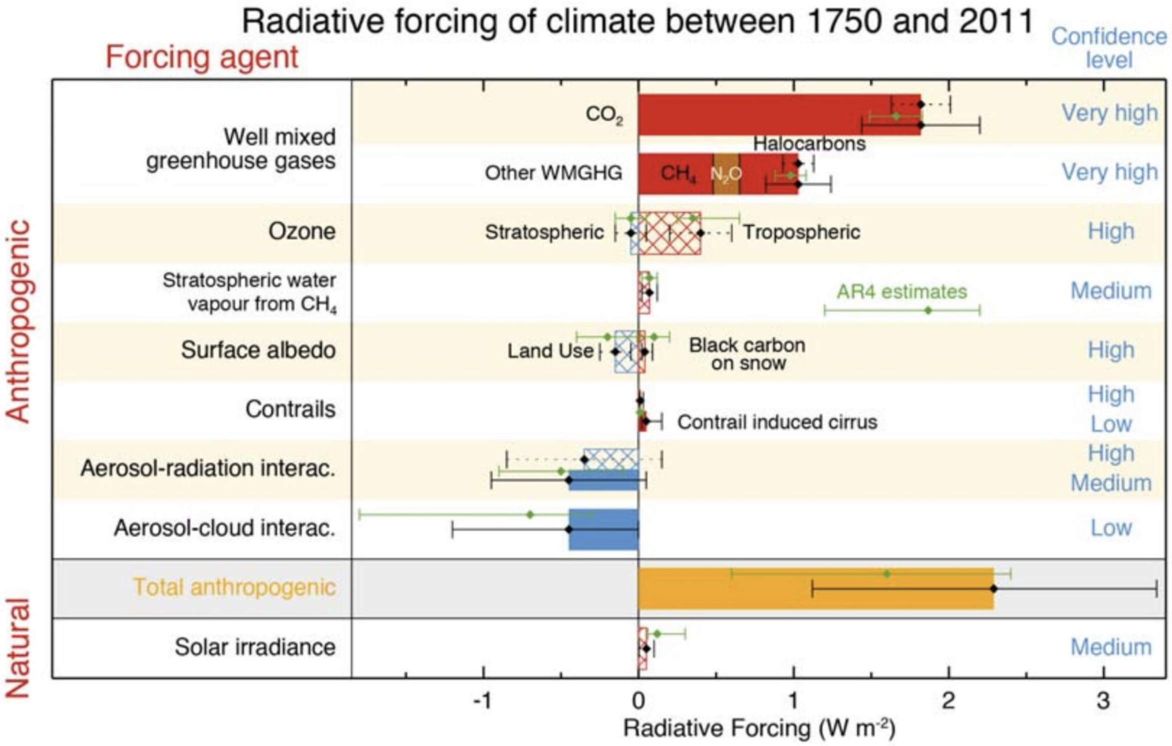
Motivation



IPCC 2013

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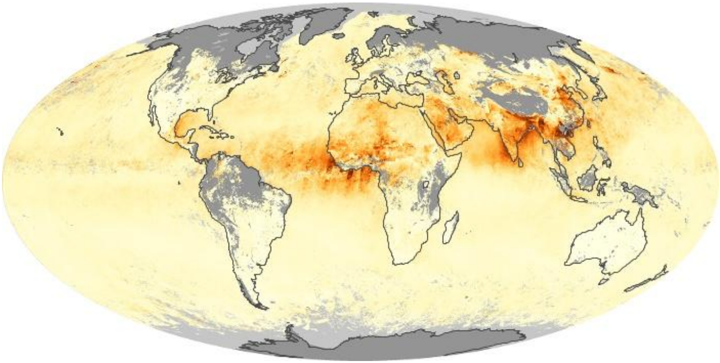
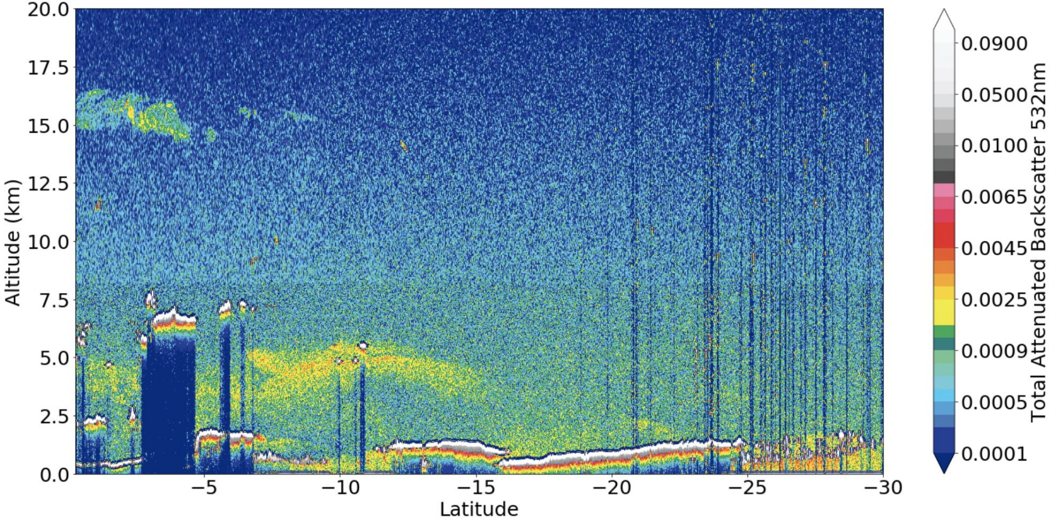
Motivation

2D proxies (vertically aggregated data) often insufficient to understand aerosol distribution

e.g. aerosol optical depth from satellites $\mathrm{AOD} = \int_0^H b_{\mathrm{ext}}(h)\mathrm{d}h$



MODIS AOD



CALIOP lidar vertical profile (‘scene’)

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Problem Statement

General setup:

- Collection of bagged observations: $\{\{x_j^{(i)}\}_{i=1}^{H}, y_j, z_j\}_{j=1}^{n}$
- Function to disaggregate: $f : \mathbb{R}^{d_x} \to \mathbb{R}$
- Aggregation operator over column height: $\mathrm{Agg}_j : f \mapsto \int_{j^{\mathrm{th}}\mathrm{column}} f(x)\,\mathrm{d}h(x)$
- Aggregate observation model:

$$z_j = \mathrm{Agg}_j(f) + \varepsilon_j$$

Specific problem to develop a proof of concept for the methodology:

Reconstruct vertical profiles of sulfate concentrations from aggregated column mass density + chemical and meterological covariates

$$\sigma_{\mathrm{SO}_4} = \int_0^H [\mathrm{SO}_4](h)\mathrm{d}h$$

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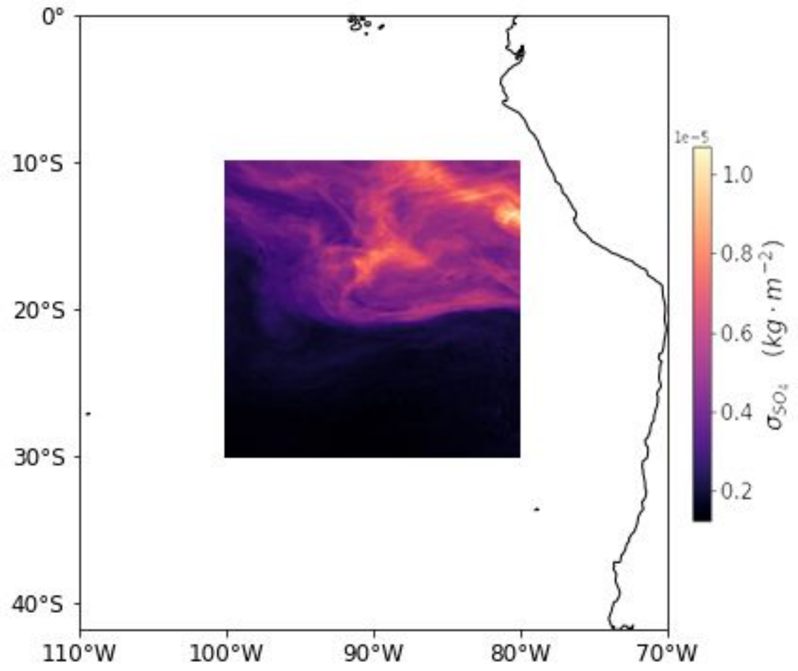
Dataset

NASA's GEOS-5 Nature Run output used as dataset basis.

	Name	Notation	Units
2D	SO_4 column density	σ_{SO_4}	$kg \cdot m^{-2}$
	Liquid water path	LWP	$kg \cdot m^{-2}$
3D	SO_4 mass mixing ratio	r_{SO_4}	$kg \cdot kg^{-1}$
	SO_2 mass mixing ratio	r_{SO_2}	$kg \cdot kg^{-1}$
	Relative Humidity	RH	1
	Air temperature	T	K
	Vertical velocity	w	$m \cdot s^{-1}$
	Cloud liquid water	q	$kg \cdot kg^{-1}$
	Moist air density	ρ	$kg \cdot m^{-3}$

Table 1. Dataset variables, "2D" corresponds to variables indexed by time, latitude and longitude while "3D" corresponds to variables that also have a height dimension.



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Initial Solutions - Baseline 1

Input 3D covariates : $x = (\text{latitude}, \text{longitude}, \text{altitude}, r_{\text{SO}_2}, \text{RH}, T, w, q)$

Objective : $$\min_f \sum_{i=1}^{n} \left(\sigma_{\text{SO}_4\, i} - \int_{\text{i}^{\text{th}}\ \text{column}} f(x) \mathrm{d}h(x) \right)^2$$

Hypothesis : $f(x) = \beta^\top x$

Solution : Closed form ridge regressor of column-aggregate inputs against AOD

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Initial Solutions - Baseline 2

Input 3D covariates : $x = (\text{latitude}, \text{longitude}, \text{altitude}, r_{\mathrm{SO}_2}, \mathrm{RH}, T, w, q)$

Input 2D covariates : $y = (\text{latitude}, \text{longitude}, \sigma_{\mathrm{SO}_4}, \mathrm{LWP})$

Step 1 : Fit $g : y_i \mapsto \int_{\mathrm{i^{th}\ column}} f(x) \mathrm{d}h(x)$

Step 2 : $\min_f \sum_{i=1}^{n} (\sigma_{\mathrm{SO}_4\ i} - g(y_i))^2$

Hypothesis : $f(x) = \beta^\top x$ $\quad$ $g(y) = \gamma^\top y$

Solution : Closed form two-stage ridge regressor

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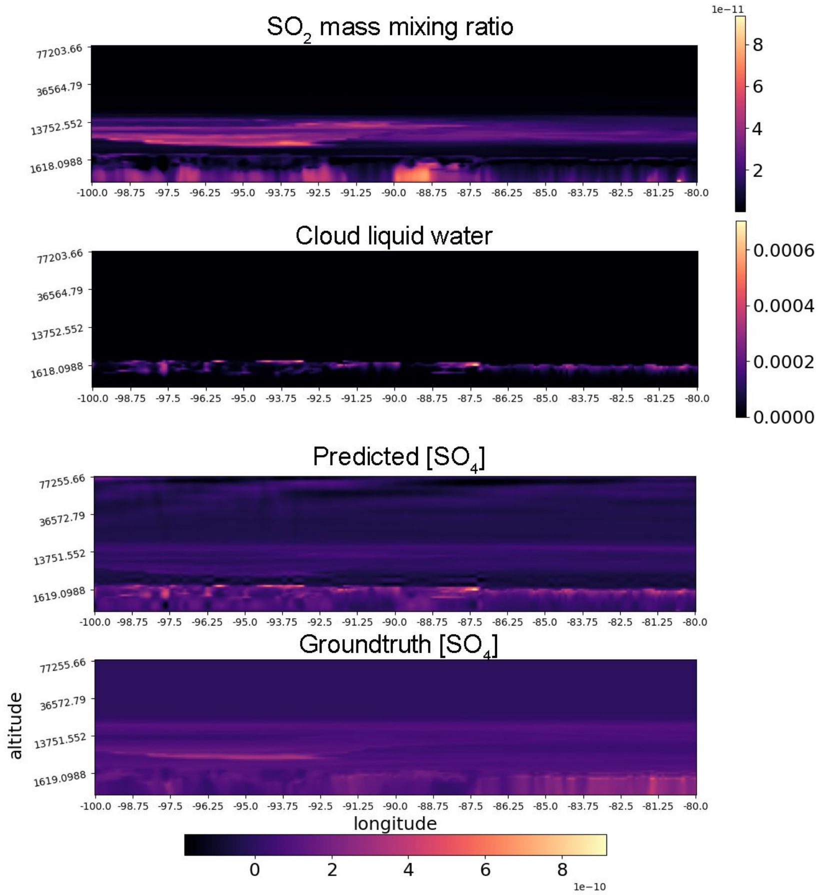
Experiments

		RIDGE	TWO-STAGE
	RMSE (10^{-6})	3.47	3.52
2D	MAE (10^{-6})	3.39	3.39
	Corr. (%)	93.5	87.5
	RMSE (10^{-10})	2.71	2.50
3D	MAE (10^{-10})	1.07	1.10
	Corr. (%)	62.5	63.9

Table 2. Evaluation scores on vertical profile reconstruction; "2D" refers to evaluation against aggregate σ_{SO_4} targets used for training; "3D" refers to evaluation against vertical groundtruth



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Discussion & future work

- Two-stage regression shows a slight increase in performance over simple kernel ridge regression with metrics used
- Unclear why the influence of SO2 profiles (important sulfate precursor gas) on predictions varies in experiments
- Metrics more suited to the problem should be developed
- Next step: use specialised aerosol models with lidar simulator and develop kernel-based model to tackle the AOD disaggregation problem:

Reconstruct vertical profiles $b_{\text{ext}}(h)$ from aggregated observations of the AOD and chemistry + meterological covariates

Code and data available at:
https://github.com/shahineb/aerosols-vertical-profiles

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