Learning Global Variations in Outdoor PM₂₅ Concentrations with Satellite Images

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Introduction

- Fine particulate matter (PM $_{25}$) kills millions annually with economic impacts measured in billions of dollars
- Cost-effective methods for estimating air pollution are needed to support pollution mitigation and health research
- Traditional geostatistical models for predicting exposures rely on detailed geographic information (e.g. traffic, land use) that are not always available
- Alternatively, this geographic information can be captured through satellite imagery

Methods

 20,000 annual average measurements among 6000 global sites (spanning 2010-2016) were compiled from the WHO and grouped into ~156 x 156km geohash cells

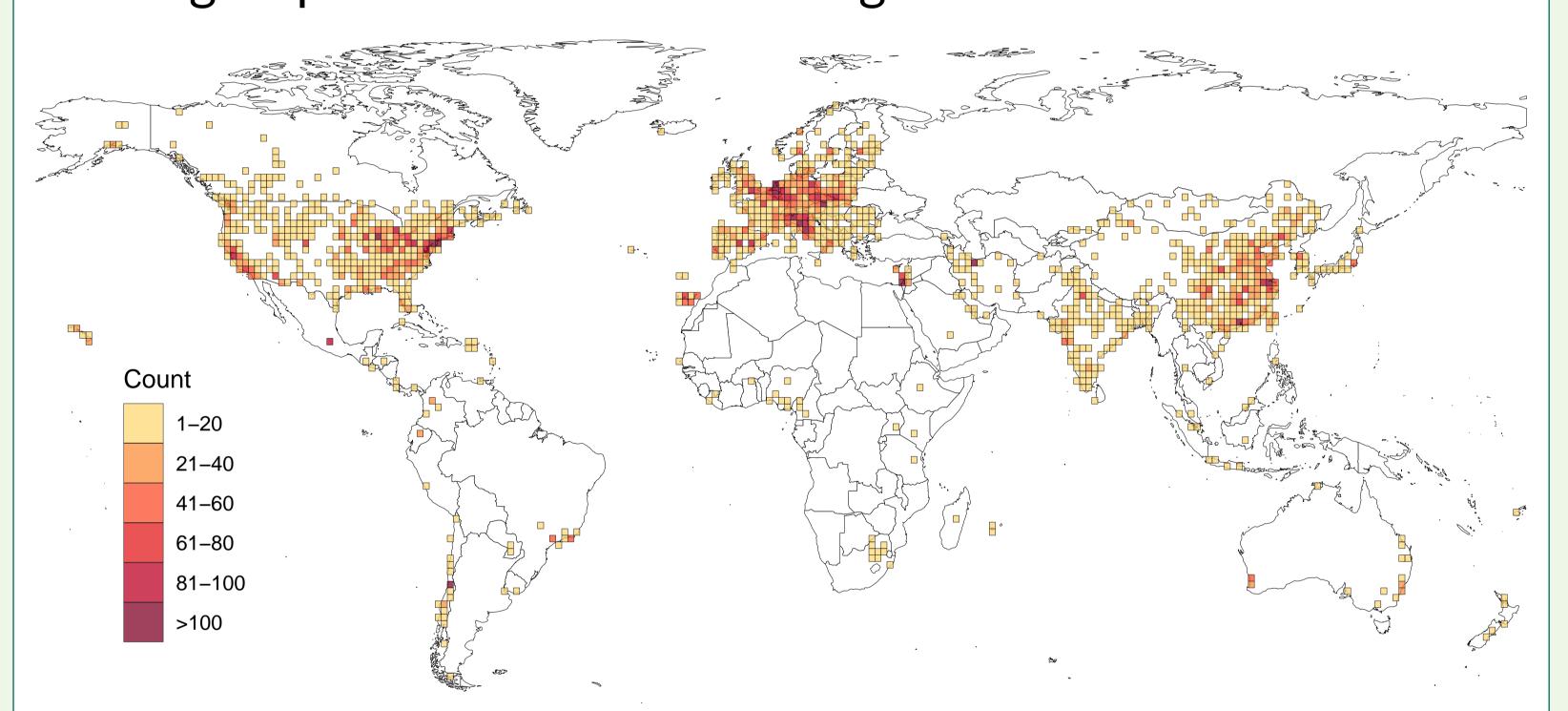


Figure 1: Locations of global PM_{2.5} monitoring sites grouped into 1200 geohash cells.

 Zoom level 13 to 16 satellite images centred on measurement sites were downloaded from Google static maps



Figure 2: From left to right, respectively: zoom level 13 (10 x 10km) through 16 (1.5 x 1.5km)

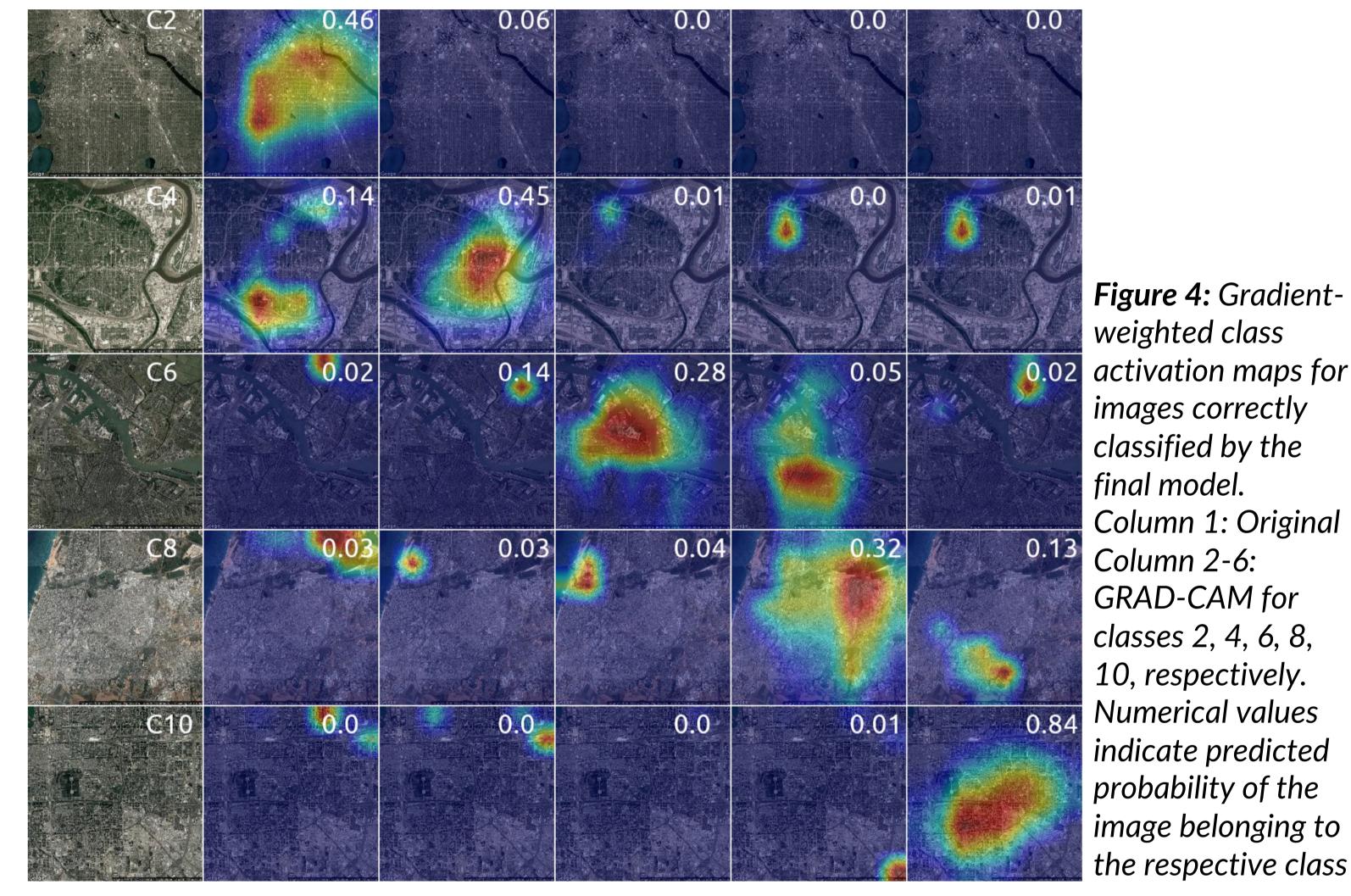
- Data were randomly split into disjoint training (80%), validation (10%), and test sets (10%) by geohash cells
- Categorical (10 balanced classes split evenly by deciles of PM_{2.5} distribution) and continuous models were developed
- Optimal configuration consisted of zoom level 13 images and an Xception base initialized with ImageNet weights
- Model performance was compared to "gold standard" DIMAQ geostatistical model from the Global Burden of Disease Study

Results Test set SD: $23.82 \mu g/m^3$ Classification accuracy: 33.7% Regression RMSE: 13.01 μg/m³ One-off classification accuracy: 65.7% 0 0 0 0.01 0.11 0.53 0.34 C8 | 0.16 | 0.01 | 0 | 0.01 | 0.07 | 0.01 | 0.23 | 0.21 | 0.18 | 0.12 C7 | 0.19 | 0.1 | 0.03 | 0.09 | 0.08 | 0.05 | 0.19 | 0.14 | 0.06 | 0.07 C4 | 0.05 | 0.18 | 0.3 | 0.21 | 0.08 | 0.08 | 0.02 | 0.03 | 0.01 | 0.04 Other C3 | 0.09 | 0.26 | 0.38 | 0.15 | 0.03 | 0.04 | 0.01 | 0.01 | 0 | 0.03

Figure 3: Measured versus predicted PM_{2.5} concentrations (C1: low; C10: high) in the test set

C2 | 0.13 | 0.31 | 0.4 | 0.07 | 0.02 | 0.01 | 0.02 | 0.02 | 0 | 0.02

C1 0.41 0.31 0.15 0.02 0.01 0 0.04 0 0.02 0.04



weighted class activation maps for images correctly classified by the final model. Column 1: Original Column 2-6: **GRAD-CAM** for classes 2, 4, 6, 8, 10, respectively. Numerical values indicate predicted probability of the image belonging to the respective class

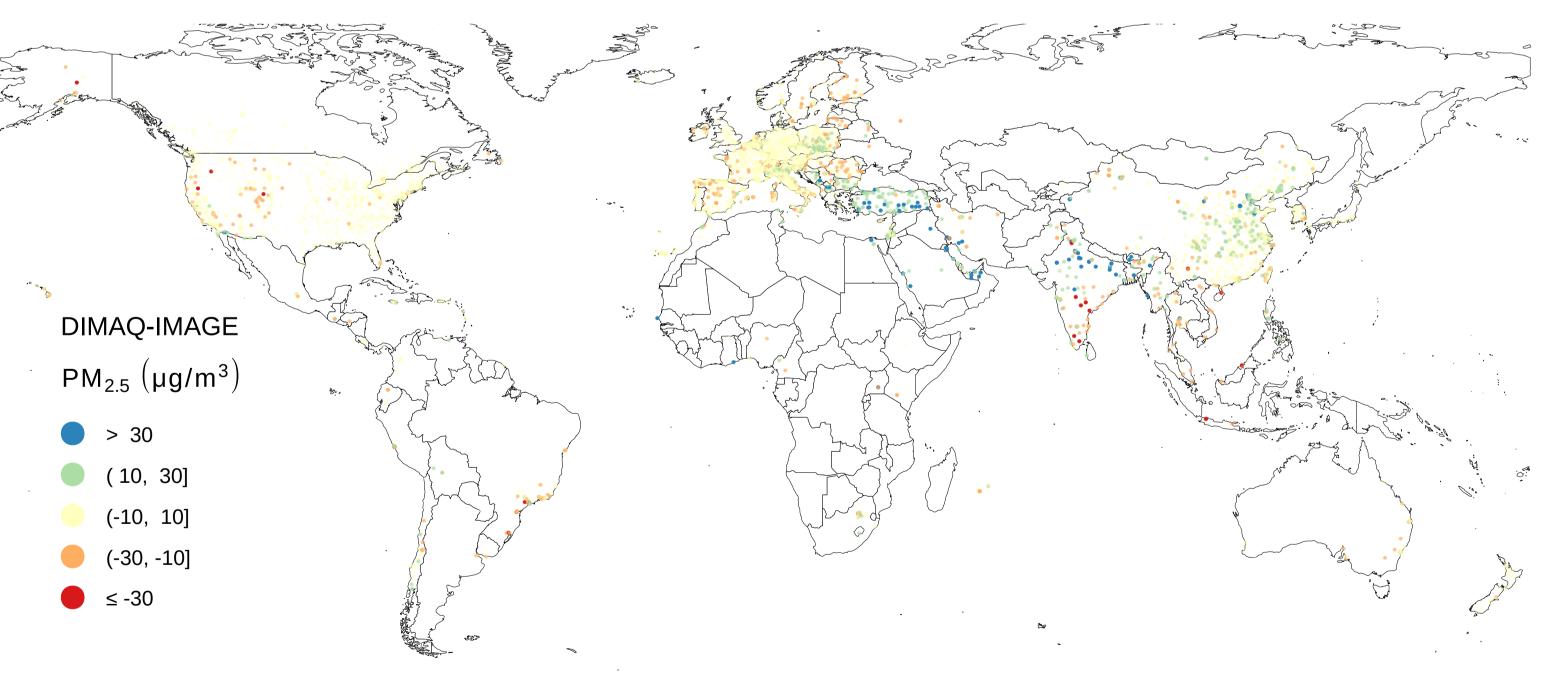


Figure 5: Difference in predicted PM_{2.5} between the IMAGE-PM_{2.5} and DIMAQ models

Discussion

- The IMAGE-PM_{2.5} model offers a fast cost-effective method for estimating global variations in annual average PM_{2.5}
- Model could be improved with timestamped hi-res imagery
- Satellite images could serve as a predictor for other exposures



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References

Shaddick, G., Thomas, M. L., Green, A., Brauer, M., Donkelaar, A., Burnett, R., Chang, H. H., Cohen, A., Dingenen, R. V., Dora, C., et al. Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. Journal of the Royal Statistical Society: Series C (Applied Statistics), 2018





