Using machine learning to identify clouds polluted by anthropogenic aerosols in NASA satellite images

Clouds polluted by anthropogenic aerosols, i.e. microscopic solid and liquid air pollution particles, at anthropogenic aerosol point sources (Fig 1) help to better understand anthropogenic impacts on Earth's climate (Toll et al., 2019). However, visual/manual identification of polluted cloud tracks is time-consuming. Machine learning has been used to identify clouds polluted by shipping emissions (Yuan et al., 2019; Yuan et al., 2022; Watson-Parris et al., 2022).

We would like to use machine learning to build a large dataset of clouds polluted by industrial aerosols. The images are available through NASA GIBS
https://www.earthdata.nasa.gov/eosdis/science-system-description/eosdis-components/gibs
https://go.nasa.gov/492aCpG

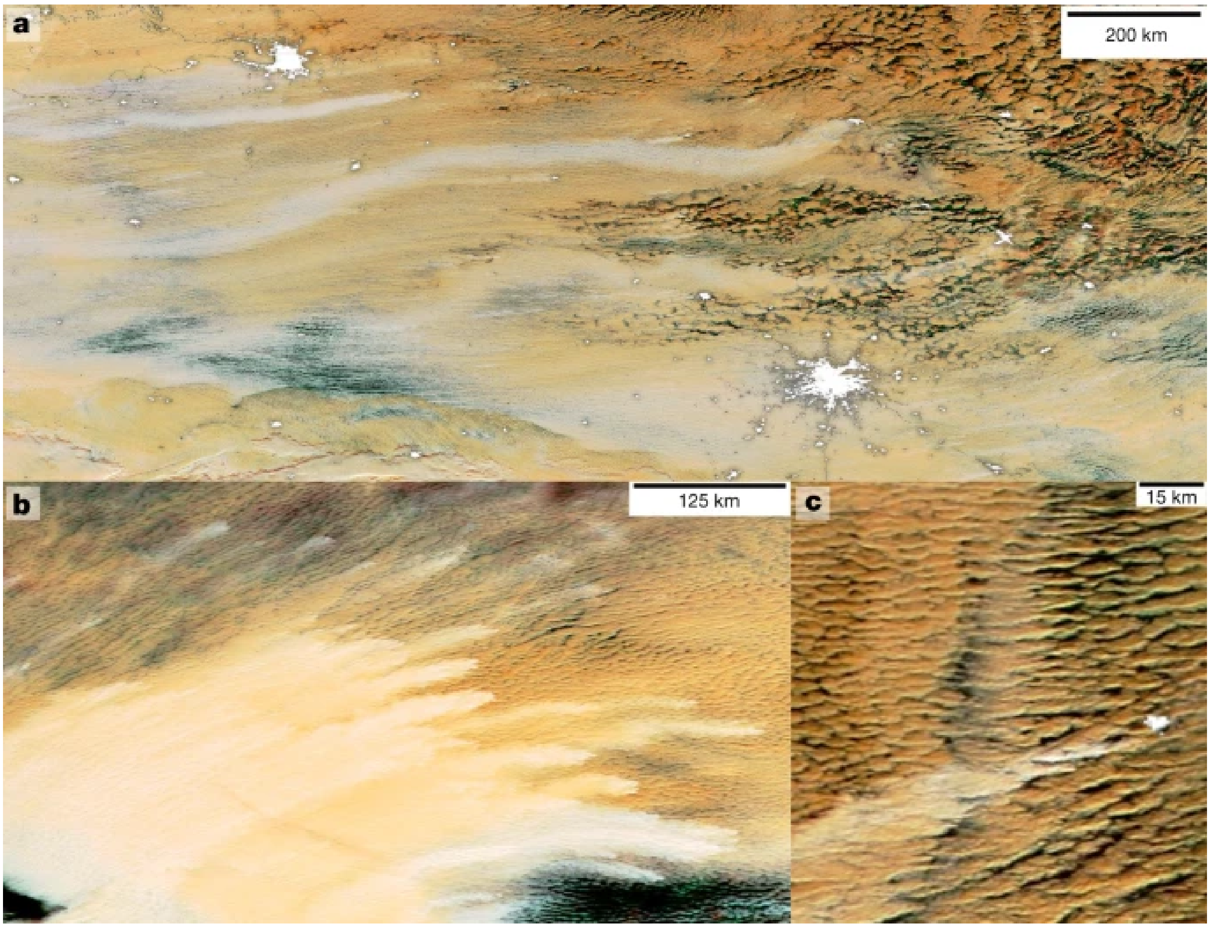

Fig 1. MODIS daytime near-infrared composite satellite images of pollution tracks. Polluted clouds are shown in grey-white colours and unpolluted clouds in yellow-brown colours. a, Polluted clouds downwind of the megacity of Moscow, Russia, and nearby cities and industries on 11 October 2016. The night lights of Moscow (bottom right), Saint Petersburg (top left) and other smaller settlements and industries are overlaid in white. b, Pollution tracks

caused by fires in Siberia, Russia, on 8 October 2016. c, Pollution track originating from nickel smelting and refining industry in Thompson, Manitoba, Canada, on 19 October 2012. The night lights of Thompson are overlaid in white at the origin of the track. We note that the map scales are different in each panel.
https://www.nature.com/articles/s41586-019-1423-9/figures/1

References

Toll, V., Christensen, M., Quaas, J., & Bellouin, N. (2019). Weak average liquid-cloud-water response to anthropogenic aerosols. *Nature*, *572*(7767), 51-55.

Yuan, T., Wang, C., Song, H., Platnick, S., Meyer, K., & Oreopoulos, L. (2019). Automatically finding ship tracks to enable large-scale analysis of aerosol-cloud interactions. *Geophysical Research Letters*, *46*(13), 7726-7733.

Yuan, T., Song, H., Wood, R., Wang, C., Oreopoulos, L., Platnick, S. E., ... & Wilcox, E. (2022). Global reduction in ship-tracks from sulfur regulations for shipping fuel. *Science Advances*, *8*(29), eabn7988.

Watson-Parris, D., Christensen, M. W., Laurenson, A., Clewley, D., Gryspeerdt, E., & Stier, P. (2022). Shipping regulations lead to large reduction in cloud perturbations. *Proceedings of the National Academy of Sciences*, *119*(41), e2206885119.

Datasets

HAND-LOGGED INDUSTRIAL POLLUTION TRACKS
https://researchdata.reading.ac.uk/208/

SHIP TRACKS
This file includes date, time, mean latitude, and mean longitude of every ship-tracks in years 2003-2020
https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/JII4DN

Machine learning training data, inference output and all analysis data have been made available as follows:
•The raw machine learning output, including segmentation masks: https://doi.org/10.5285/0d88dc06fd514e8199cdd653f00a7be0 (28)
•The derived data: https://doi.org/10.5281/zenodo.7038703 (29)
•Machine learning training data: https://doi.org/10.5281/zenodo.7038715 (20)
•The machine learning algorithm and associated code: https://doi.org/10.5281/zenodo.7038855 (21).

ML for identification of interesting features in NASA GIBS images
https://nasa-gibs.github.io/gibs-api-docs/python-usage/
https://www.earthdata.nasa.gov/learn/articles/spaceml
https://spaceml.org/repo/project/605b7b751644770011e850c3