U-Net For Learning And Inference Of Dense Representation Of Multiple Air Pollutants From Satellite Imagery

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TomTom

Motivation

New research linking pollution to COVID-19: lethality rate and as a transmission vector

→Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., and Dominici, F. (2020) *Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study.* medRxiv.
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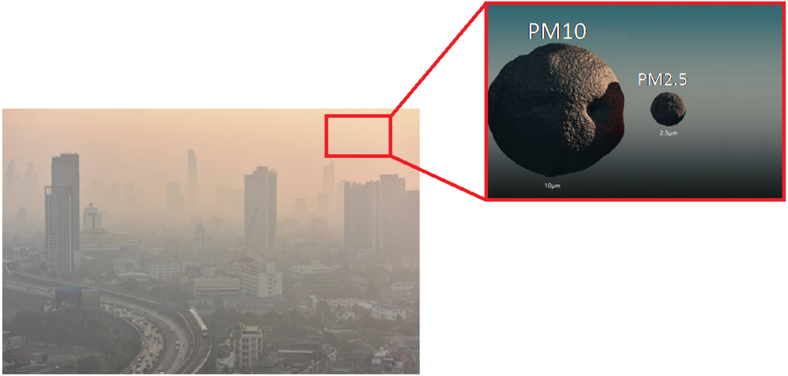

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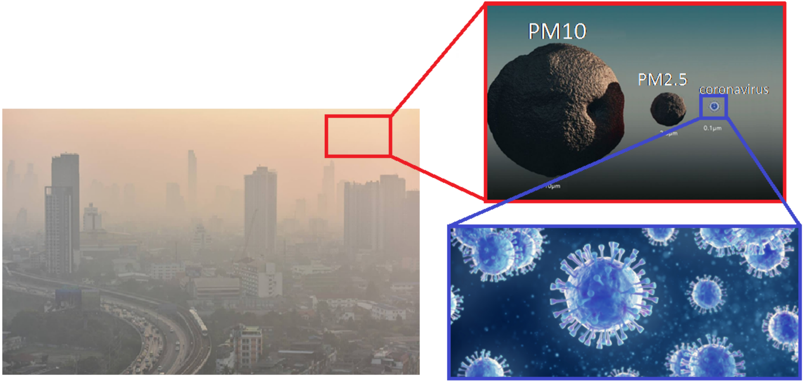

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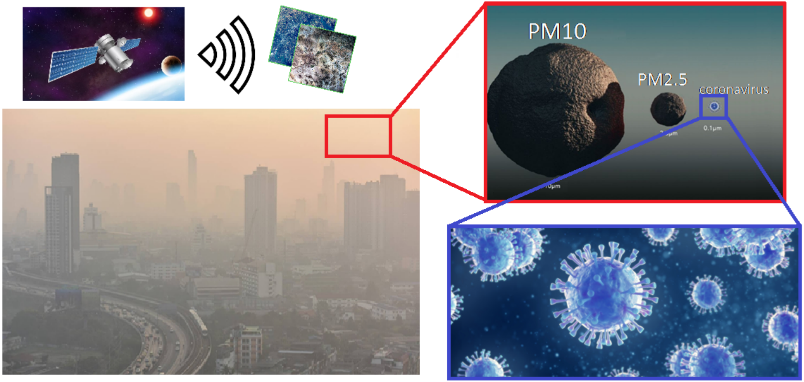
⇒ **Goal:** Machine learning to estimate air pollution concentrations at fine scale using satellite imagery



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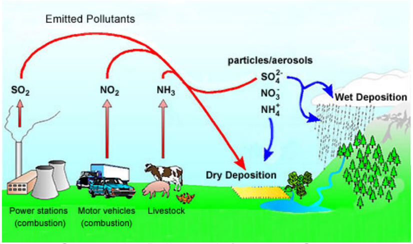
Air pollution – From primary air pollutants to aerosols



Source: Air Pollution Information System

Primary pollutants (ground emissions):

- Nitrogen oxides – NO_x
- Sulphur oxides – SOx
- Volatile organic compounds – VOC

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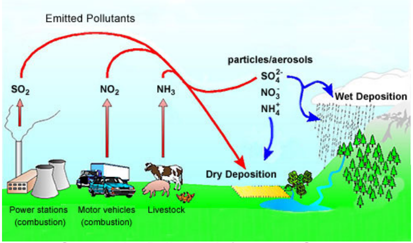

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Primary pollutants (ground emissions):

- Nitrogen oxides – NO_x
- Sulphur oxides – SOx
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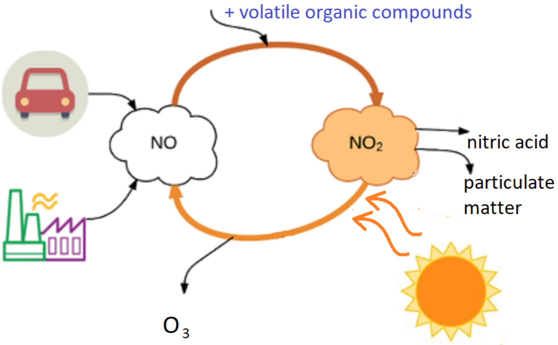
Secondary pollutants (form in atmosphere):

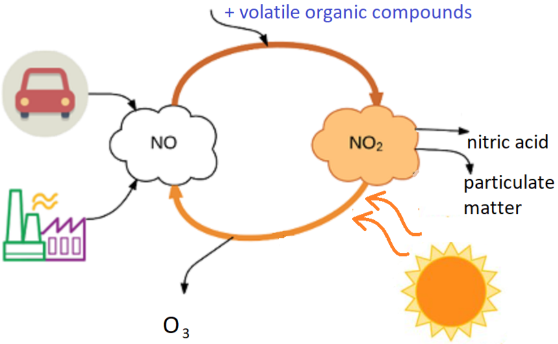
- React with each other
- Can travel long distances as aerosols
- Eventually return to the surface as wet or dry deposition

Air pollution – Nitrogen cycle in atmosphere



Source: World Air Quality Index

Air pollution – Nitrogen cycle in atmosphere



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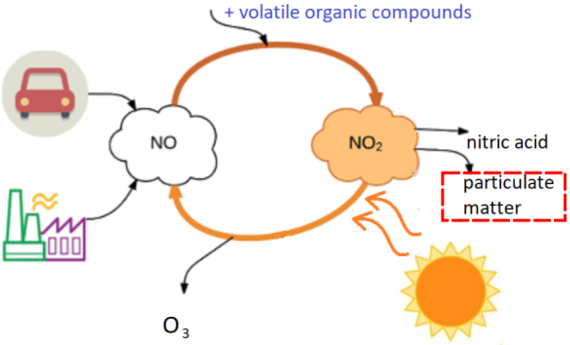
- Nitric acid and ammonia react to form NH_4^+, NH_3^-

Air pollution – Nitrogen cycle in atmosphere



Source: World Air Quality Index

- Nitric acid and ammonia react to form NH_4^+, NH_3^-
- Result: **aerosol** ammonium nitrate **contribute** to **particulate matter**

Air pollution – Consequences

…include the following:

- NO_2 linked to respiratory problems in humans
- Nitric acid formation leads to acid rain
- Affects visibility by altering the way light is absorbed and scattered in the atmosphere
- Some constituents of the ambient PM mixture promote climate warming (e.g., black carbon) or cooling influence (e.g., nitrate and sulfate)
- Adversely affect ecosystems, including plants, soil and water through deposition of PM and its subsequent uptake by plants or its deposition into water, affecting water quality/clarity

Worldwide monitoring of air pollution

- Dedicated measurement stations for NO_x, SO_x, O_3, PM
- More than 30,000 stations in the World (source: World Air Quality Index)

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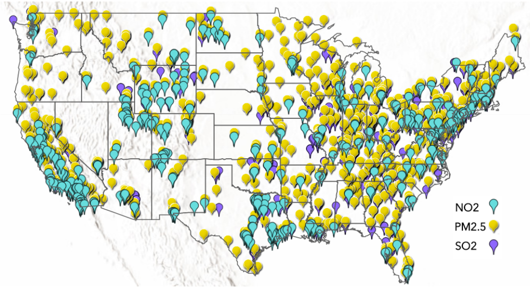
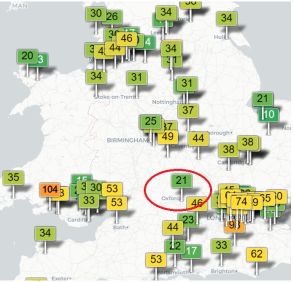
- Low spatial resolution



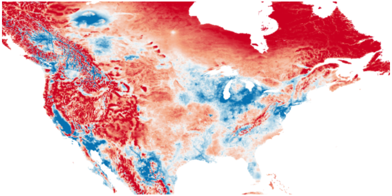
Unites States - locations of pollution sensors (epa.gov)

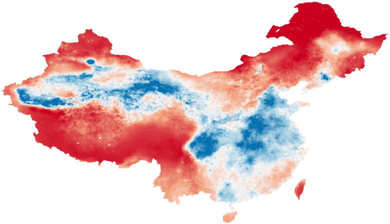


Daily pollution values in UK (waqi.info)

Pollution data – Ground-truth

- Pollution database: (Aaron van Donkelaar et al., 2019) monthly estimates of $PM_{2.5}$ for North America and China, from 2001-2017 at 0.01° resolution (no further updates)





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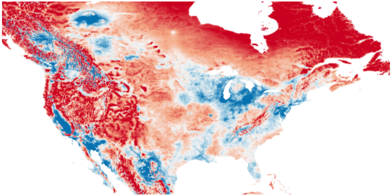
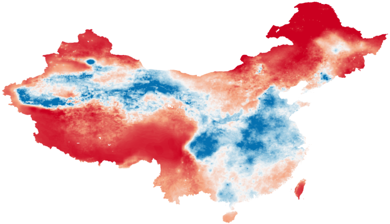

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- Partial masses of component pollutants $(NO_3^-, NH_4^+, \ldots)$

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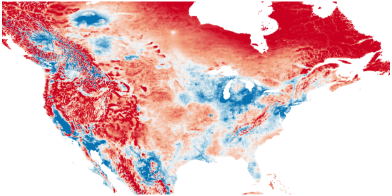
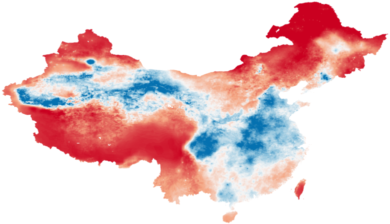

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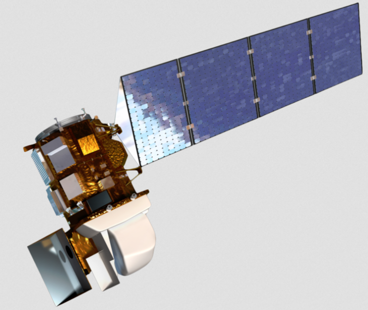
$\Rightarrow$ **Goal:** learn from this historical pollution data to predict new pollutant concentrations at fine scale

Multispectral satellite imagery - Landsat 8

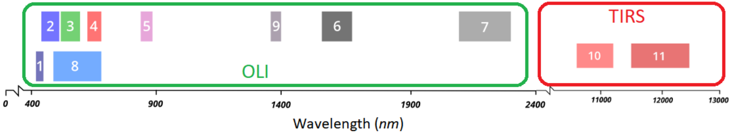
Landsat series: longest continuous satellite mission in operation (since 1972)



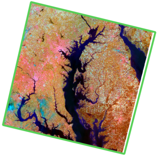
Source: US Geological Survey

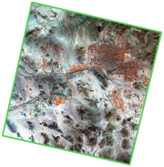
- Carries two independent optical instruments
  - Operational Land Imager
  - Thermal Infrared Sensor
- Worldwide coverage with 16 day revisit period
  - 2 images per month
- Ground sampling distance: 30 m (OLI) and 100 m (TIRS)

Multispectral satellite imagery - Landsat 8

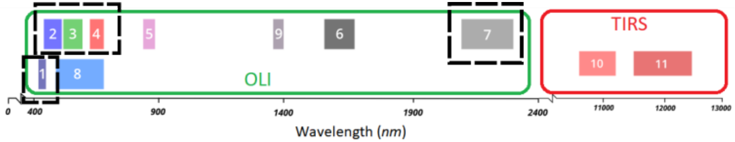


- Covers various parts of the electromagnetic spectrum from violets to thermal infrared with 11 spectral bands
- Publicly available from US Geological Survey
  - Mirrors hosted by Google/Amazon (for bulk download)





Multispectral satellite imagery – Pollution



Aerosol optical depth (AOD): measures attenuation of light rays passing through atmosphere

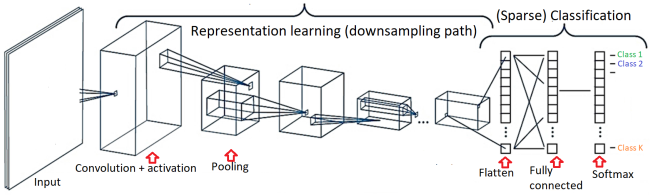
- Proxy for $PM_{2.5}$ content (light scattering on aerosol)
- Explicit estimation methods based on deep blue (#1), blue (#2), red (#4) bands
- Bands #3 and #7 have also been linked to PM levels

→Vermote, E., Justice, C., Claverie, M., Franch, B. (2016) *Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product.* *Remote Sens. Env.*
→Zhang, B.; Zhang, M.; Kang, J.; Hong, D.; Xu, J.; Zhu, X. (2019) *Estimation of PM_x Concentrations from Landsat 8 OLI Images Based on a Multilayer Perceptron Neural Network.* *Remote Sens.*

Fully Convolutional Networks (FCNs)

Classic Convolutional Neural Networks

- Sparse representation learning (size independent)
- Classification with Fully Connected Layers (size-bound)



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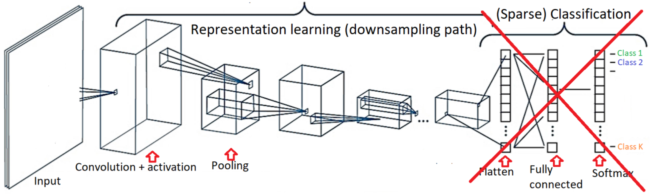
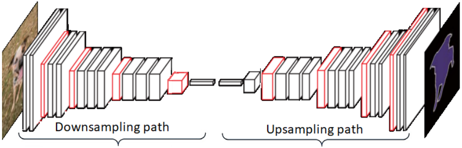
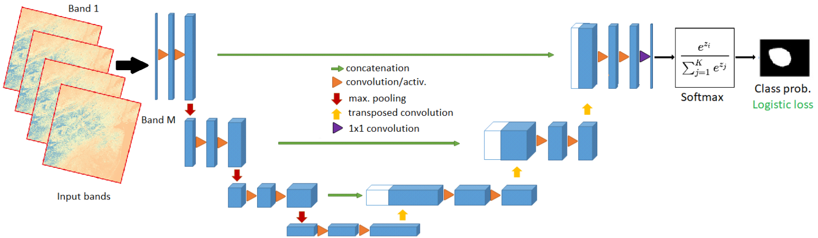


Fully Convolutional Networks

- Only size-independent operations
- Dense (per-pixel) predictions (non-sparse)



U-Net: a state-of-the-art Fully Convolutional Neural Networks



- Introduced by Ronneberger et al. (2015) in the context of classification
- To alleviate loss of detail, includes high-resolution original feature maps in upsampling

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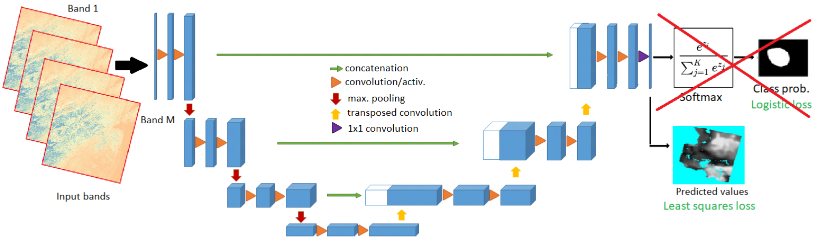
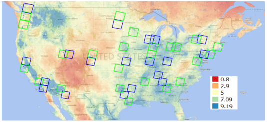
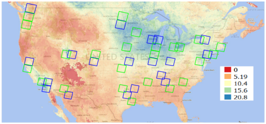


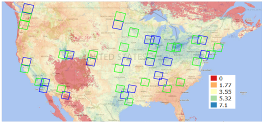
- Introduced by Ronneberger et al. (2015) in the context of classification
- To alleviate loss of detail, includes high-resolution original feature maps in upsampling
- We remove softmax layer and trained with least-squares loss directly on the 1x1 convolution output (final layer)



$PM_{2.5}$



NO_3



NH_4

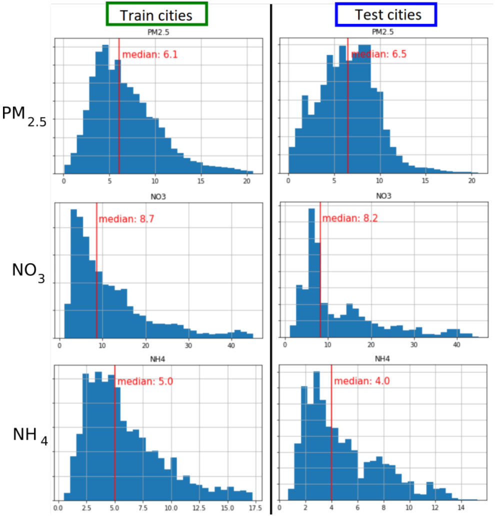
Satellite data:

- $N = 114$ Landsat images from $2013 - 2017$ →24 training cities
  - Additional $N_T = 24$ images from 20 test cities
- Locations of US cities chosen to reasonably represent the diverse US geography
- Rectangles indicate bounding boxes of the Landsat images' locations:
  green boxes = training and validation, blue boxes = testing

Pollution data:

- Pollutant concentration maps and regions defining training and testing data
- Background: average concentrations of $PM_{2.5}$, NO_3 , NH_4 in 2017 $[\mu g/m^3]$

Experiments – Setting

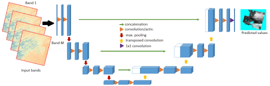


Data properties:

- Eliminated outliers beyond 1st and 99th quantile
- Training and testing cities show similar medians and distributions

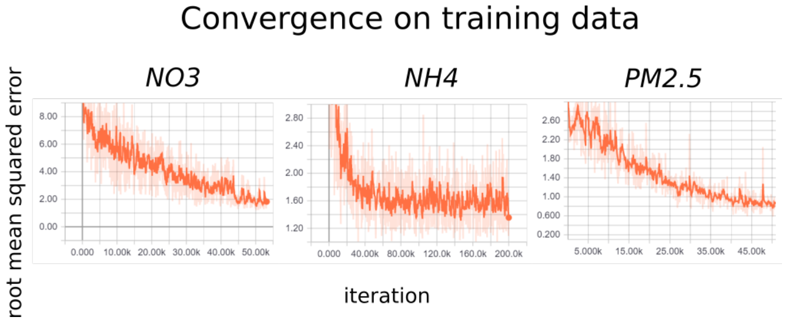
Experiments – Setting

U-net set-up:



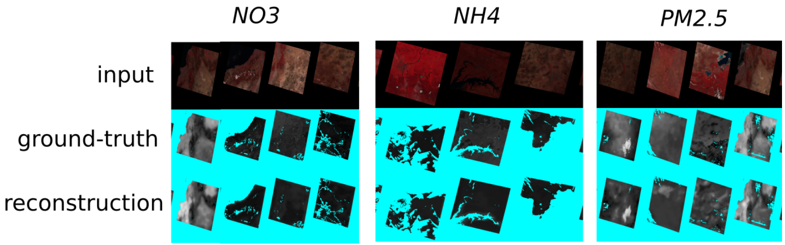
- Optimization: network trained separately for each pollutant – $PM_{2.5}$, NO_3 , NH_4 – by optimizing with ADAM over 500 epochs w. minibatch size of 15 and 100 internal iterations
- Parameterization: dropout ratio $= 0.5$, learning rate $= 0.00005$
- Structure: 3 layers, 32 feature maps at top level
- Input: 10/11 Landsat bands (high-resolution panchromatic dropped), 200x200 tiles
  - Save download time (4x size), no new information

Experiments — 1. Sanity check with ground-truth



- Trained on 93 of 114 images from training cities
- Shown: Convergence of U-net performance to low predictive error indicated by root mean squared error loss function (y-axis) on training set NO_3, NH_4, and $PM_{2.5}$ over iterations (x-axis)

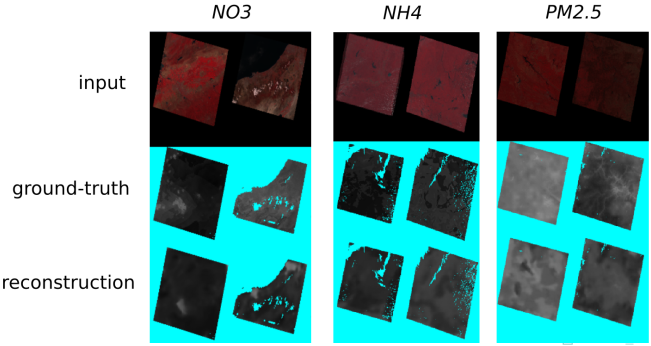
Experiments — 2. Generalize to temporally novel data



- Goal: Test on 23 previously unseen images from training cities
- Results: Mean absolute deviations: $NO_3 = 4.75$, $NH_4 = 2.24$, and $PM_{2.5} = 2.23\ \mu g/m^3$
- Shown: Ex. of pollutant concentrations predicted by the U-Net for new temporal data at locations used during training for all pollutants

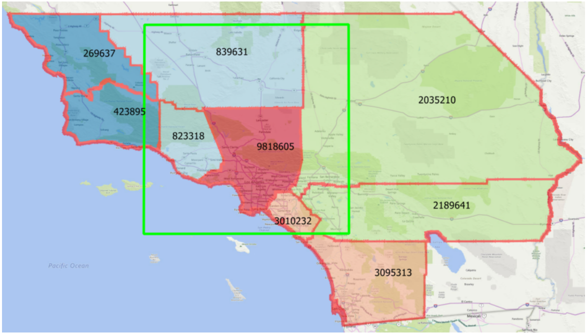
Experiments – 3. Cities with similar pollution profile

- Goal: Evaluate performance of predicting pollutant concentrations at cities not seen during training
- Results: Mean absolute deviations: $NO_3 = 2.46$, $NH_4 = 4.07$, $PM_{2.5} = 2.27\ \mu g/m^3$
- Shown: Ex. of predicted concentrations of 20 unseen cities

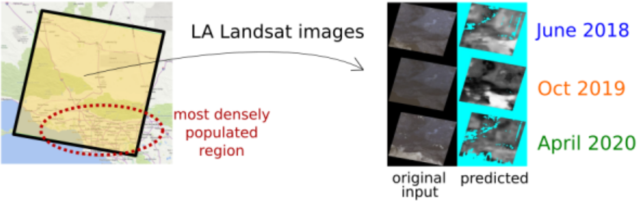


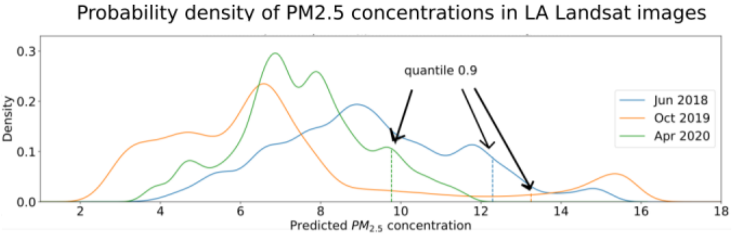
Experiments – 4. Predicting $PM_{2.5}$ for *COVID-19*

- Goal: Predict $PM_{2.5}$ concentration structure around Los Angeles before/during *COVID-19* lockdown and analyze shift in concentration distributions – years 2018-2020
- **No ground-truth** $PM_{2.5}$ concentrations for *time or city*



Experiments – 4. Predicting $PM_{2.5}$ for *COVID-19*





Shown: Landsat images w. predicted $PM_{2.5}$ concentration maps and density of predicted $PM_{2.5}$ concentrations for before/during *COVID-19* outbreak

→ Densely populated LA has high $PM_{2.5}$ concentrations – maps capture this

Summary

To **summer**-ize...

- U-net adapted to perform dense regression to learn three pollutants: NO_3 , NH_4 , and $PM_{2.5}$ from publicly available satellite imagery
- Shows generalization capabilities in both temporal and spatial domains on US cities and to data without *any* ground-truth
- Potential predictive benefits regarding *COVID-19* by inferring $PM_{2.5}$ concentrations, movement, and structure

Future/current:

- Multi-task learning - train a single network to predict multiple pollutants simultaneously
- Integrate ground measurement stations
- Large-scale experiments

Thanks!

Thanks for your attention! Questions?
Feedback or suggestions?