Predicting environmental health hazards in cities using images

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Urban environmental health: a visual perspective

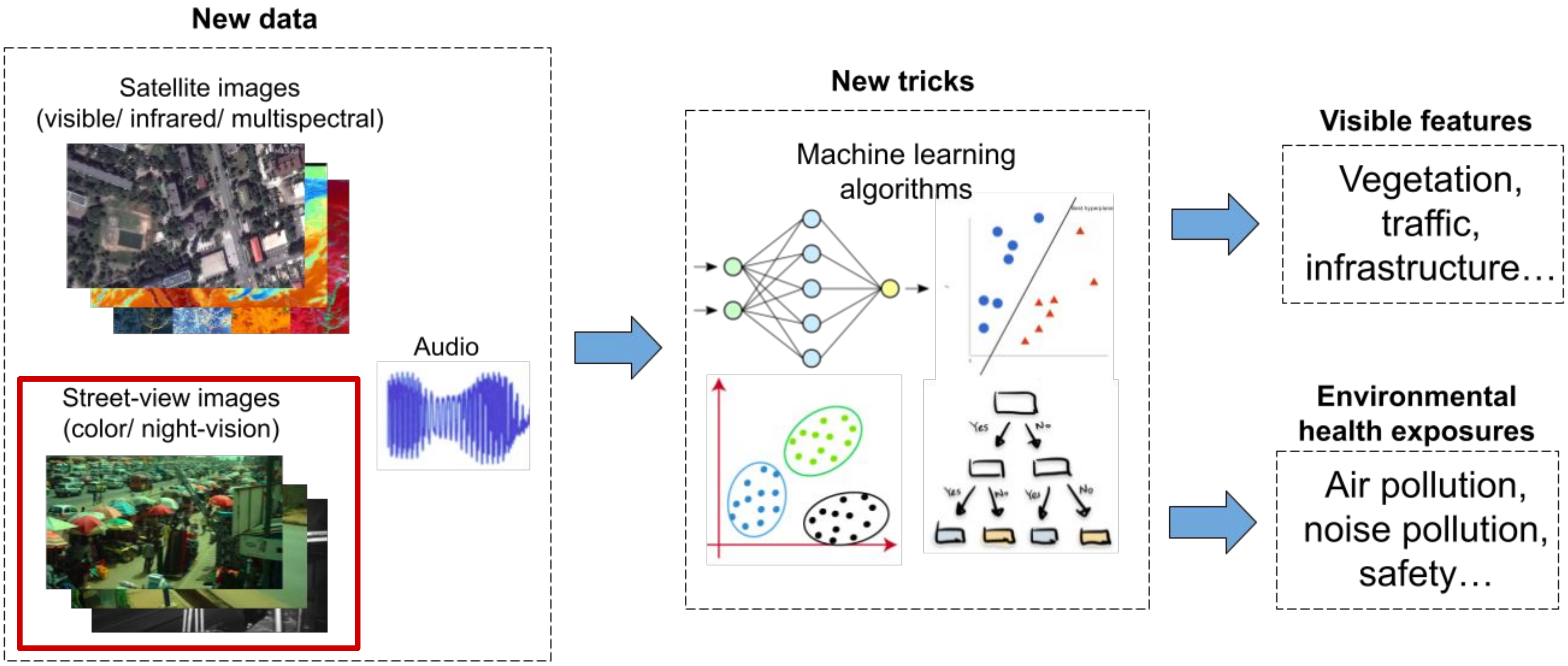
- Many features of environmental health are locally **visible** in nature

Inequality

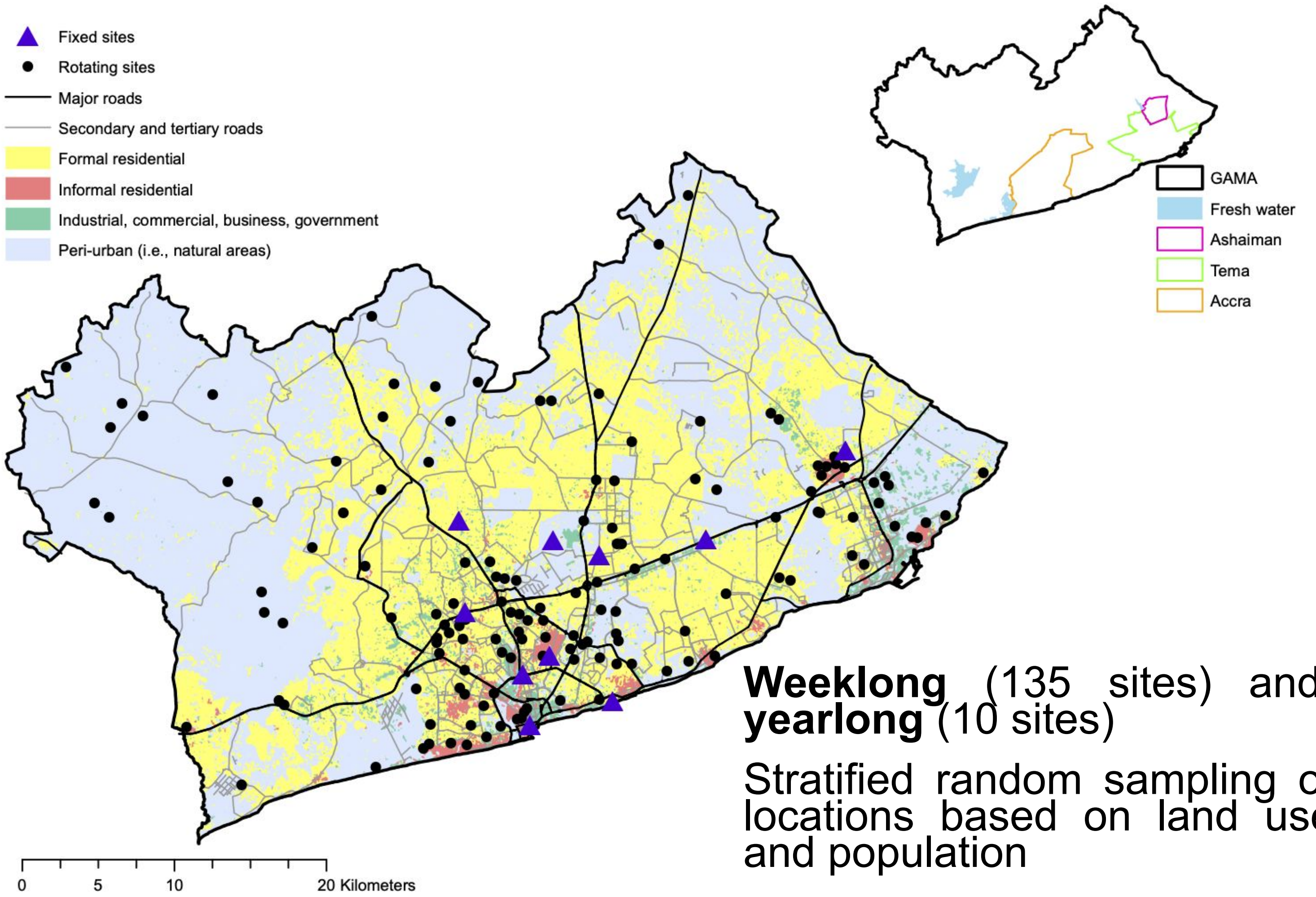
Pollution, walkability, safety

New data; New tricks

- Collecting actual environmental measurements is resource intensive relative to images



Measurement campaign (April 2019 – June 2020)



Weeklong (135 sites) and **yearlong** (10 sites)

Stratified random sampling of locations based on land use and population

Examples of sites

Motorway

Peri-urban greenspace

New Developments

High-density commercial and residential

Adapted from Clark et al. BMJ Open. 2020

Urban data capture

- **Sound levels (noise)**
- **$PM_{2.5}$ and NO_2 (air pollution)**
- **Street-view imagery**
  - **Day and night**
- **Audio**
- Meteorology

scientific reports

OPEN **Space-time characterization of community noise and sound sources in Accra, Ghana**

Sierra N. Clark[1,2], Abosede S. Alli[3], Ricky Nathvani[1,2], Allison Hughes[4], Majid Ezzati[1,2,5,6], Michael Brauer[7], Mireille B. Toledano[1,2,8], Jill Baumgartner[9,10], James E. Bennett[1,2], James Nimo[4], Josephine Bedford Moses[4], Solomon Baah[4], Samuel Agyei-Mensah[11], George Owusu[12], Briony Croft[13] & Raphael E. Arku[3]

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

Spatial-temporal patterns of ambient fine particulate matter ($PM_{2.5}$) and black carbon (BC) pollution in Accra

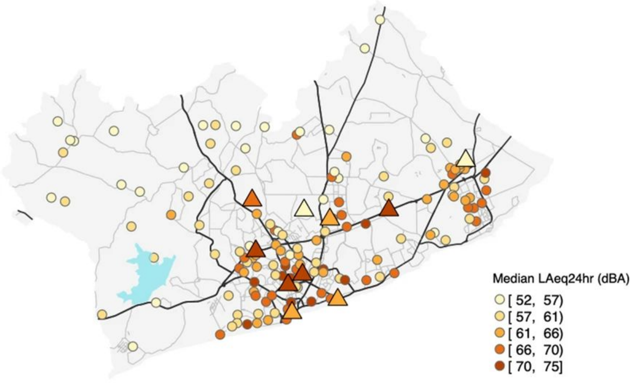
Abosede S Alli[1], Sierra N Clark[2,3], Allison Hughes[4], James Nimo[4], Josephine Bedford-Moses[4], Solomon Baah[4], Jiayuan Wang[1], Jose Vallarino[5], Ernest Agyemang[6], Benjamin Barratt[5,7], Andrew Beddows[5,7], Frank Kelly[5,7], George Owusu[6], Jill Baumgartner[8,9], Michael Brauer[10,11], Majid Ezzati[2,3,12], Samuel Agyei-Mensah[6] and Raphael E Arku[1,*]

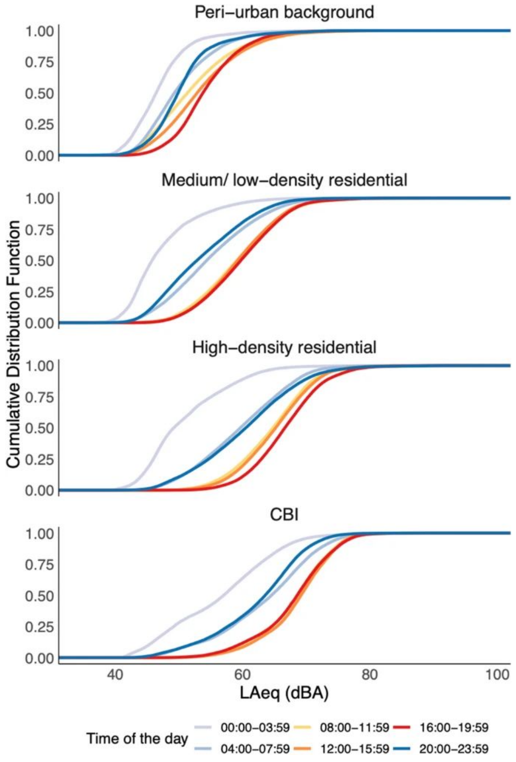
Spatiotemporal variation in noise and air pollution in Accra

Noise

Space-time characterization of community noise and sound sources in

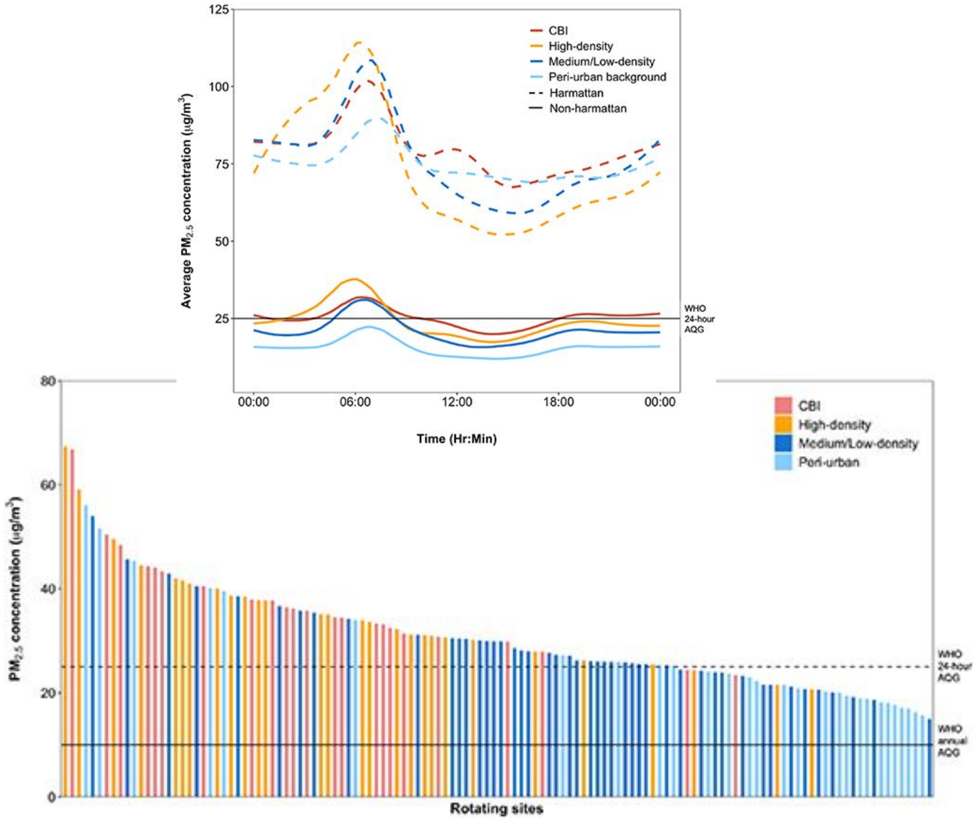
Accra, Ghana - S. N. Clark et al





Air pollution ($PM_{2.5}$)

Spatial-temporal patterns of ambient fine particulate matter ($PM_{2.5}$) and black carbon (BC) pollution in Accra - A. S. Alli et al



Urban activity

Changes in environmental features (traffic-related noise)

Changes in **features** (objects)

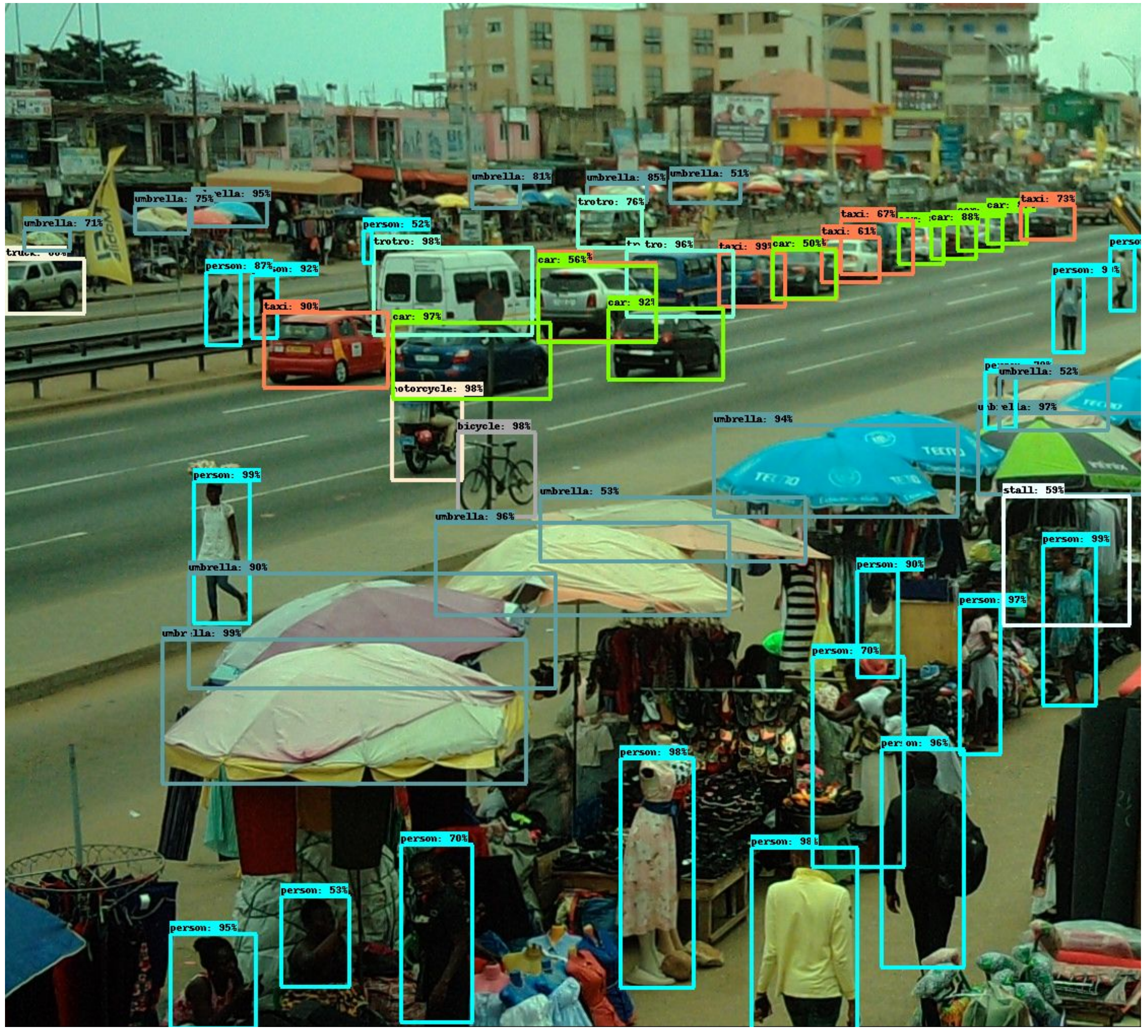
- Identified 238 features relevant to environmental health.

- Shortlisted **20 objects** from frequency, usefulness and uniqueness.

- Final object categories:
  Person, street vendor, car, truck, taxi, market stall, cookstove, loudspeaker, umbrella, cooking bowl, food, motorcycle, bicycle, trash, debris, bus, lorry, van, tro tro and animal.

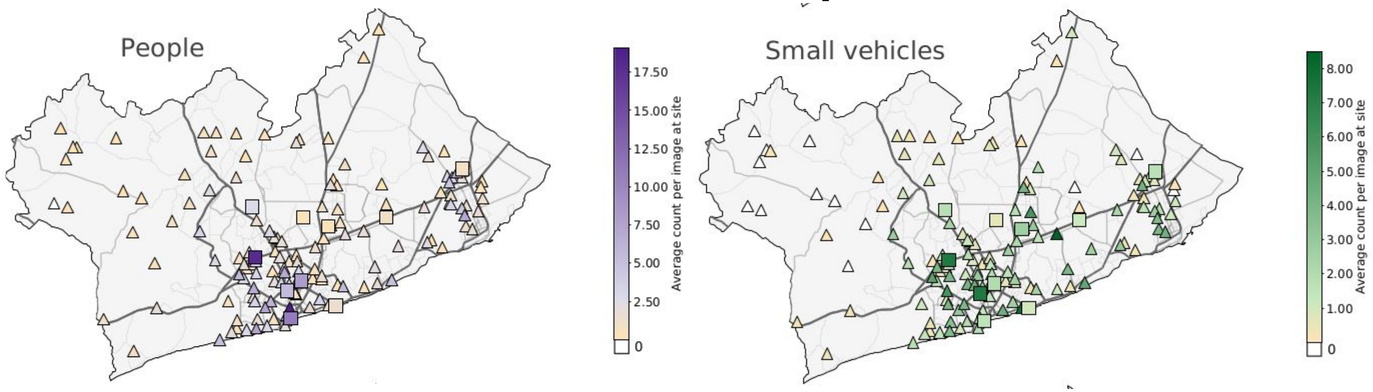
- Label 1,000 sample images → **train CNN** to detect objects in 2.1 million images.

- Environmental change across time and space.



Urban activity and environment in Accra

Trends in space

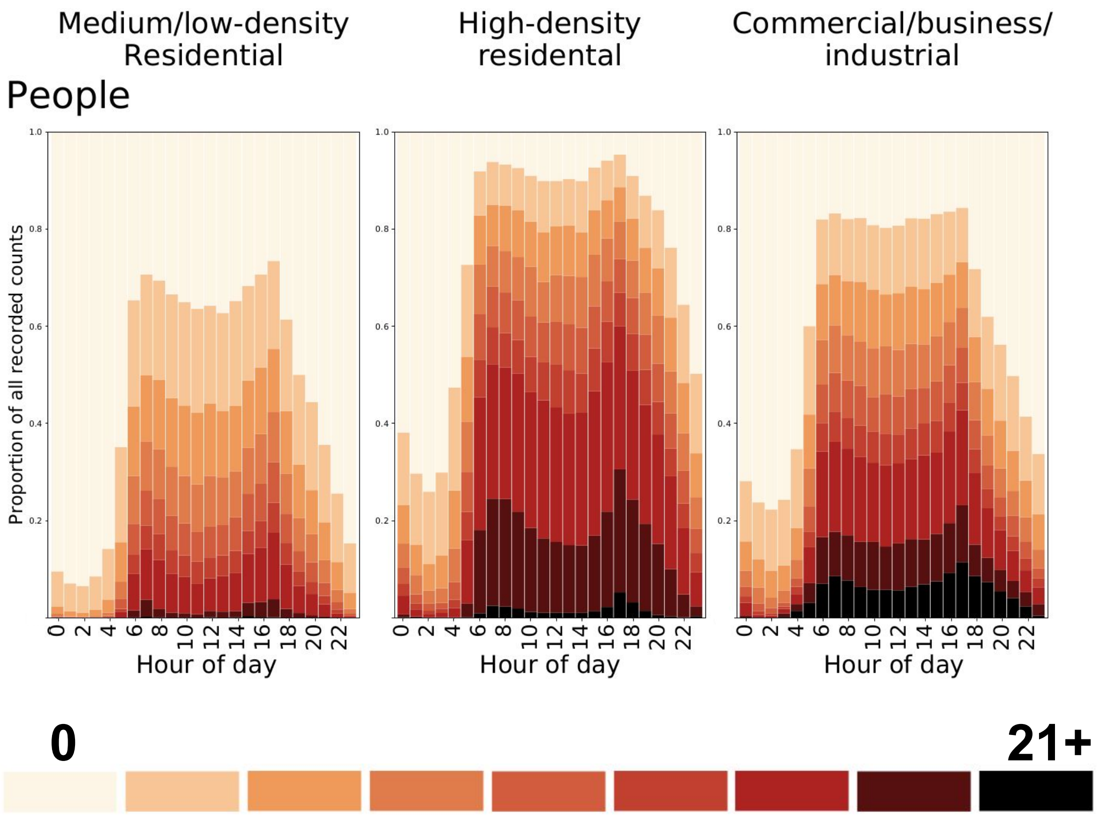


	People	Two wheelers	Small vehicles	Large vehicles	Market-related	Refuse	Animal
People	1.000 (<0.00001)						
Two wheelers	0.405 (<0.00001)	1.000 (<0.00001)					
Small vehicles	0.456 (<0.00001)	0.278 (0.00100)	1.000 (<0.00001)				
Large vehicles	0.705 (<0.00001)	0.203 (0.01400)	0.432 (<0.00001)	1.000 (<0.00001)			
Market-related	0.703 (<0.00001)	0.246 (0.00300)	0.298 (<0.00001)	0.671 (<0.00001)	1.000 (<0.00001)		
Refuse	-0.098 (0.24300)	-0.090 (0.28200)	-0.341 (<0.00001)	-0.069 (0.41100)	-0.123 (0.14100)	1.000 (<0.00001)	
Animal	-0.132 (0.11200)	0.071 (0.39700)	-0.312 (<0.00001)	-0.173 (0.03800)	-0.075 (0.37000)	0.434 (<0.00001)	1.000 (<0.00001)

Positively correlated across city

Negatively correlated across city

Trends in time



Fewer counts of people

More counts of people

Pollution

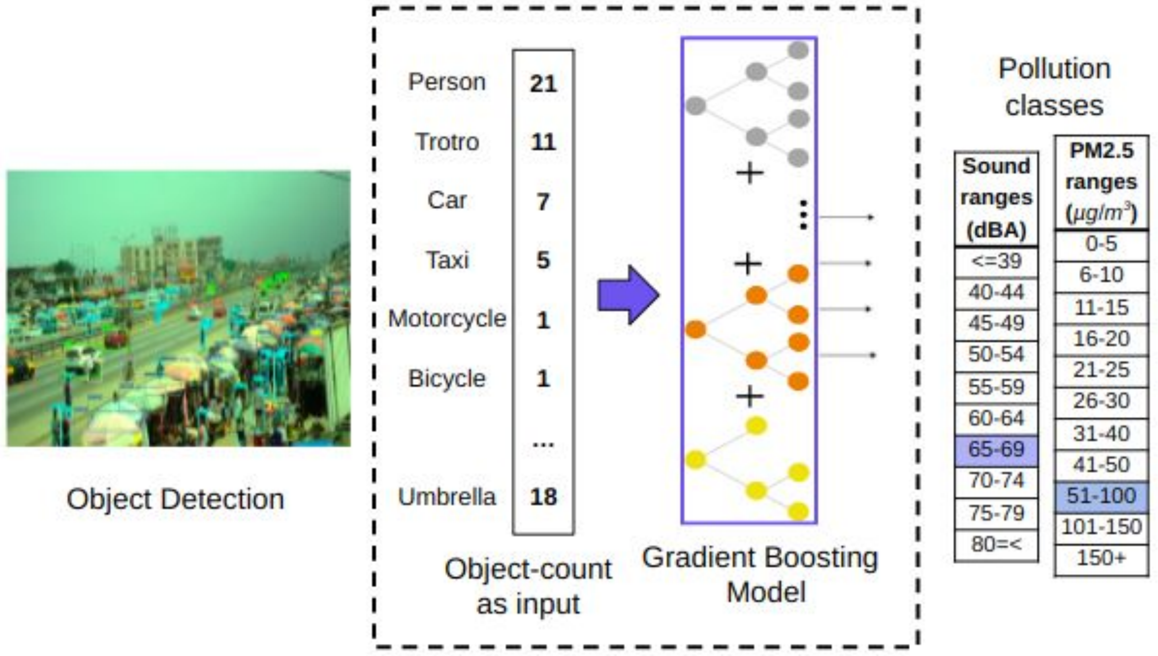
Pollution linked to changes in visibility

Clear: low $PM_{2.5}$

Hazy: high $PM_{2.5}$

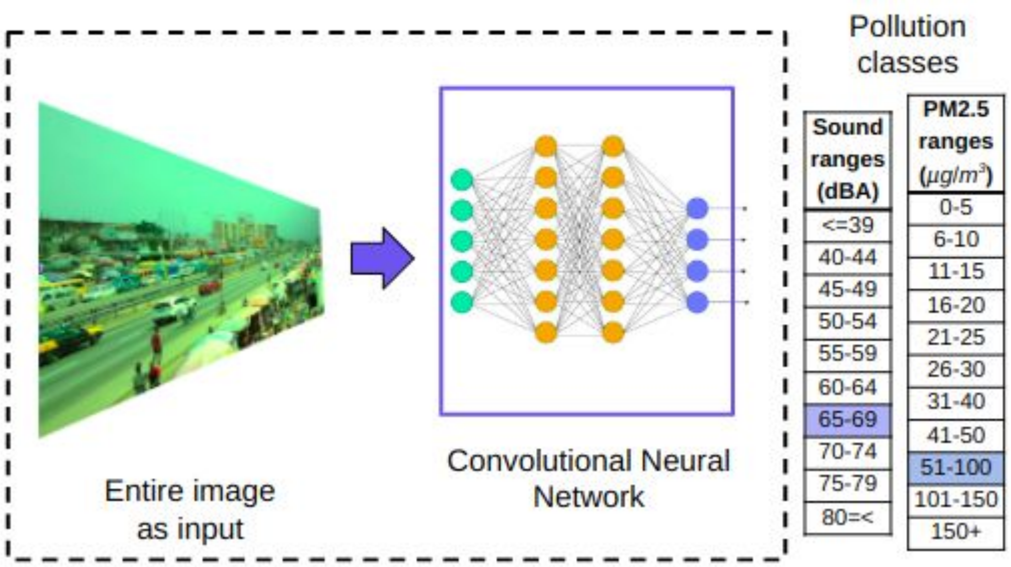
Modeling **noise & air ($PM_{2.5}$)** levels from images

Approach 1: Feature driven



- Features extracted manually
- Subsequently, feature count used for modeling

Approach 2: Outcome driven

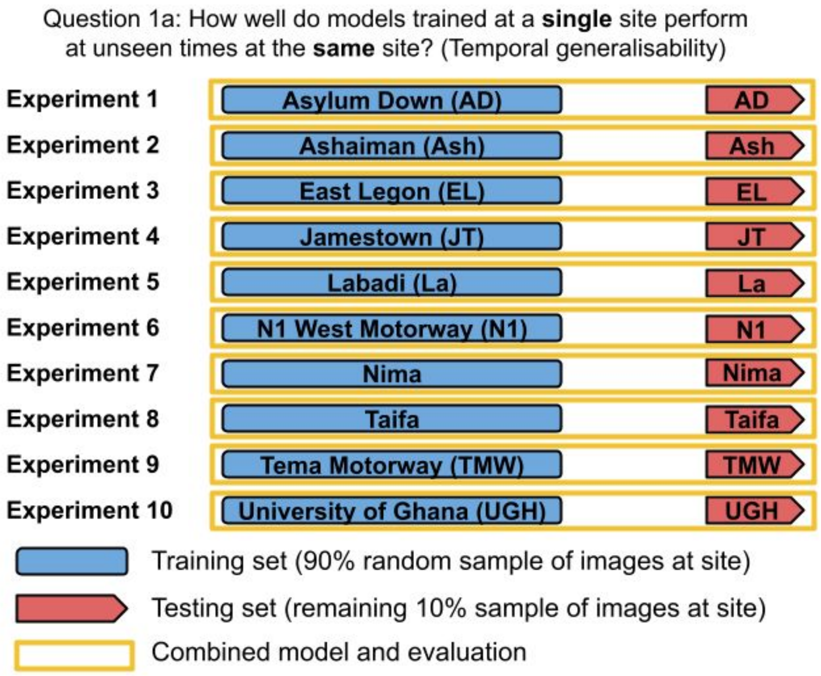


- No prior assumptions made on features
- Entire image used for modeling

How well can such models generalise?

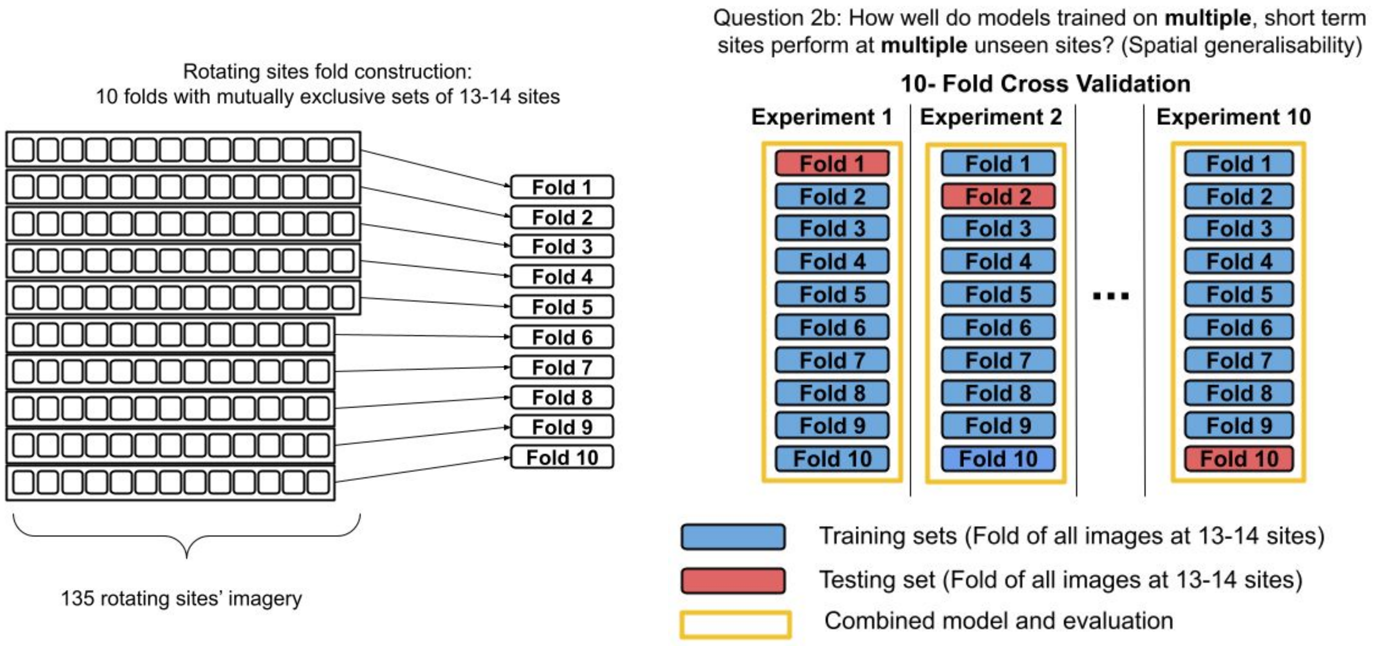
Robustness across time:

Models trained at same location at different **times** - long term sites (~1 year)



Robustness across space:

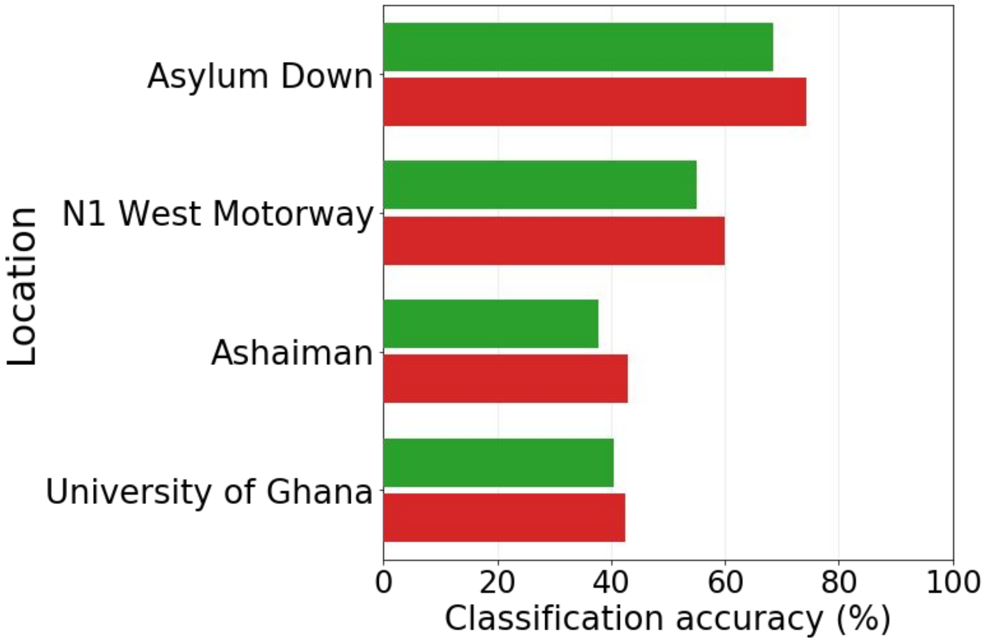
Models trained & evaluated at different **locations** - short term sites (~1 week each)



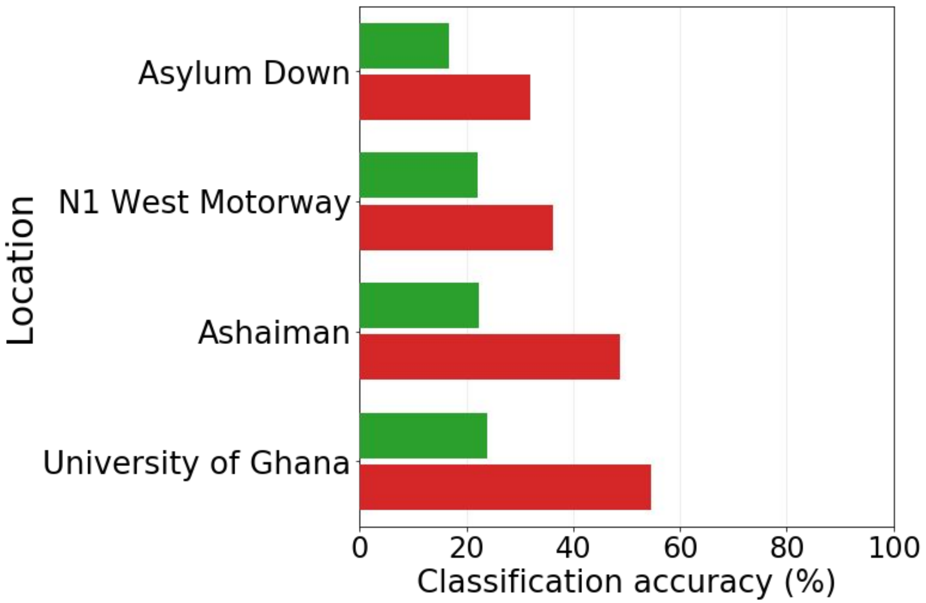
Predicting pollution across **time**

- Outcome driven model is generally **more accurate** than feature driven model
- Locations with predictable noise have **less predictable** air pollution

Noise



Air



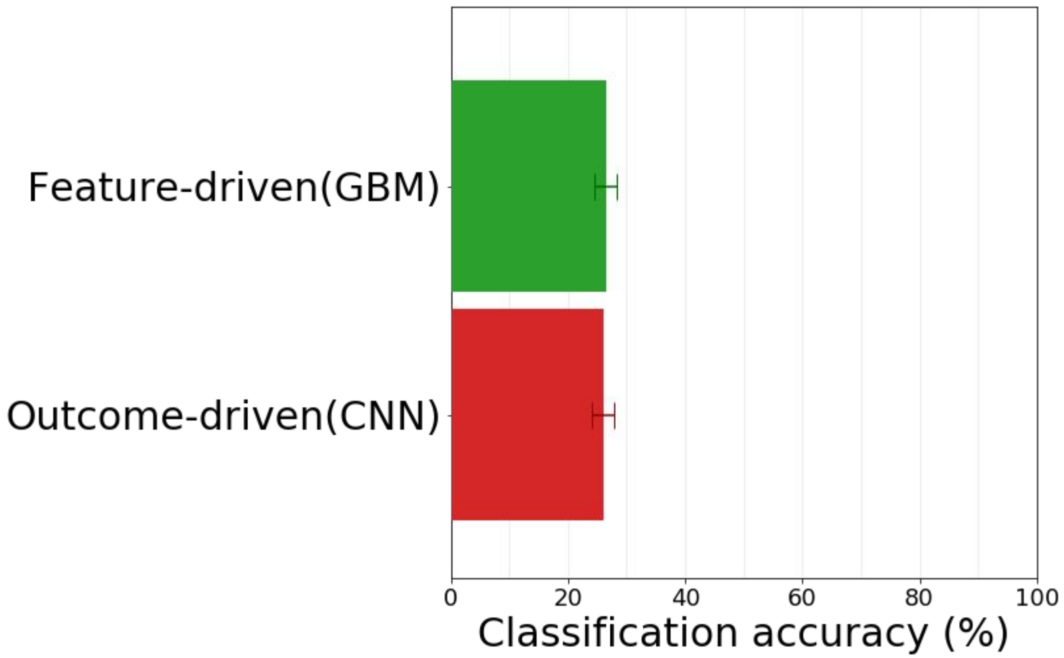
Feature driven (GBM)

Outcome driven (CNN)

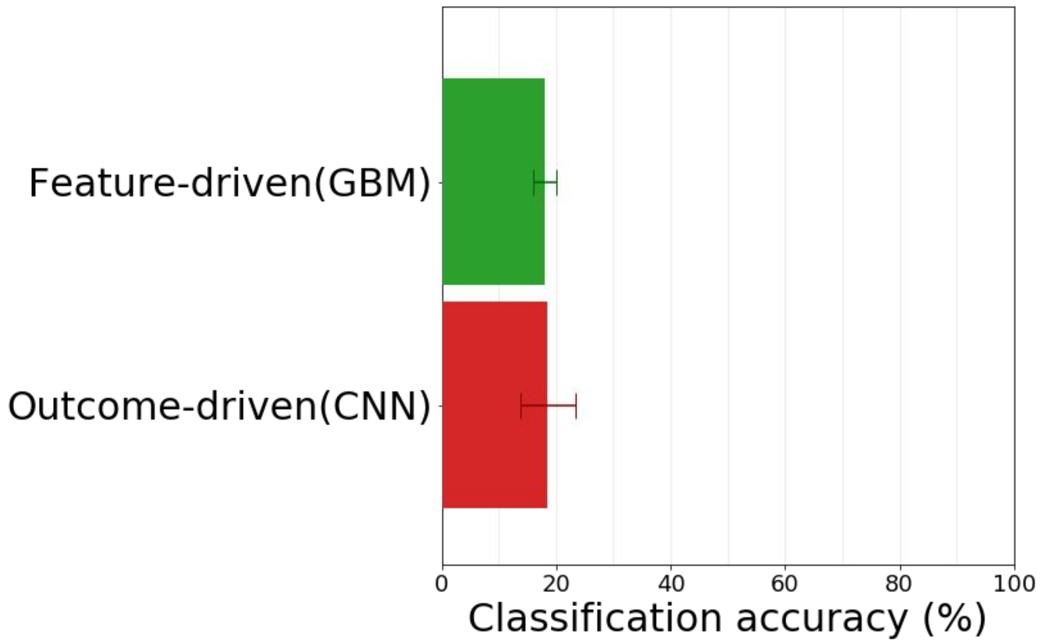
Predicting pollution across **space**

- Modelled from 122 locations and evaluated on 13-14 locations
- Predict in **unseen** locations - much harder! (Both approaches do just as well)

Noise



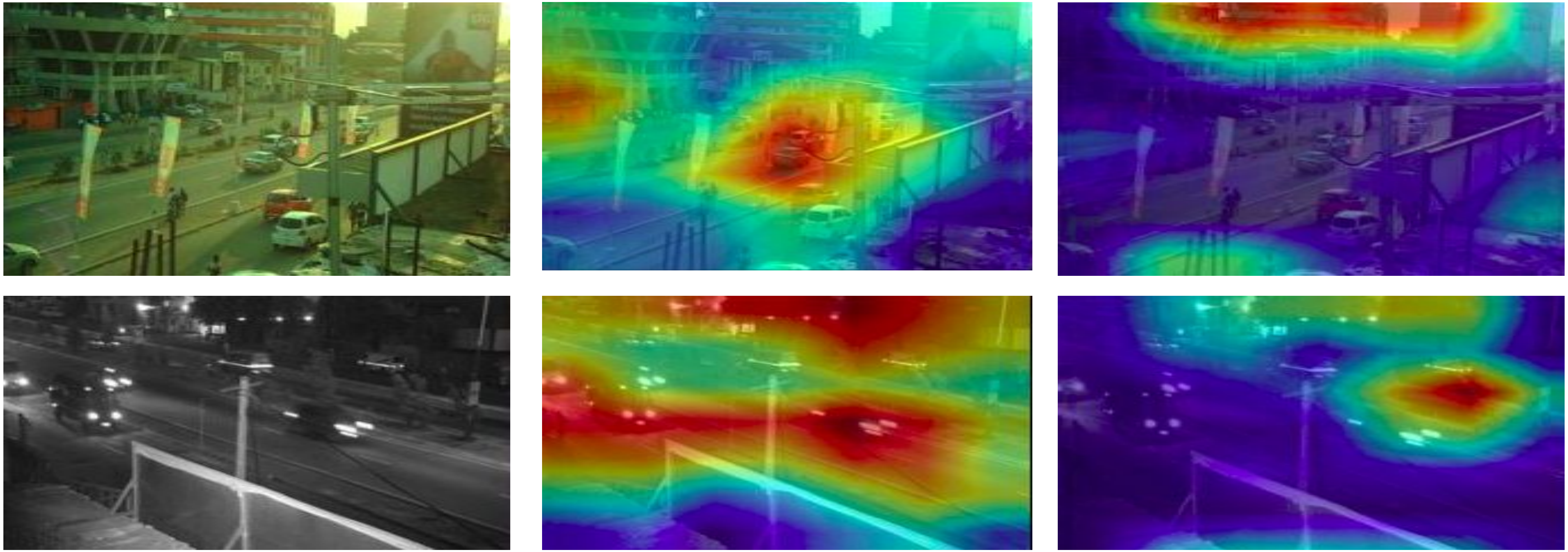
Air



Identifying potential sources and factors

- Noise prediction focuses on specific **features.** e.g. vehicles (also used by **feature-driven** model)
- Air pollution prediction associated with changes in **visibility.** e.g. red skies, haze

Original image | Noise prediction model | Air ($PM_{2.5}$) prediction model



Images for studying urban pollution across space and time

- Images are a rich source of information on urban environmental health

- Advances in computer vision have opened doors
  - Estimating air and noise pollution across space and time.
  - Some promising results for extending reach of estimates **within** cities.

- Many remaining challenges with complex and unstructured data
  - Representative data collection.
  - Generalisation across space and time - new locations and geographics continue to require **in situ monitoring data**.
  - Model transparency and interpretability
    - How reliable are our models?

BACKUP

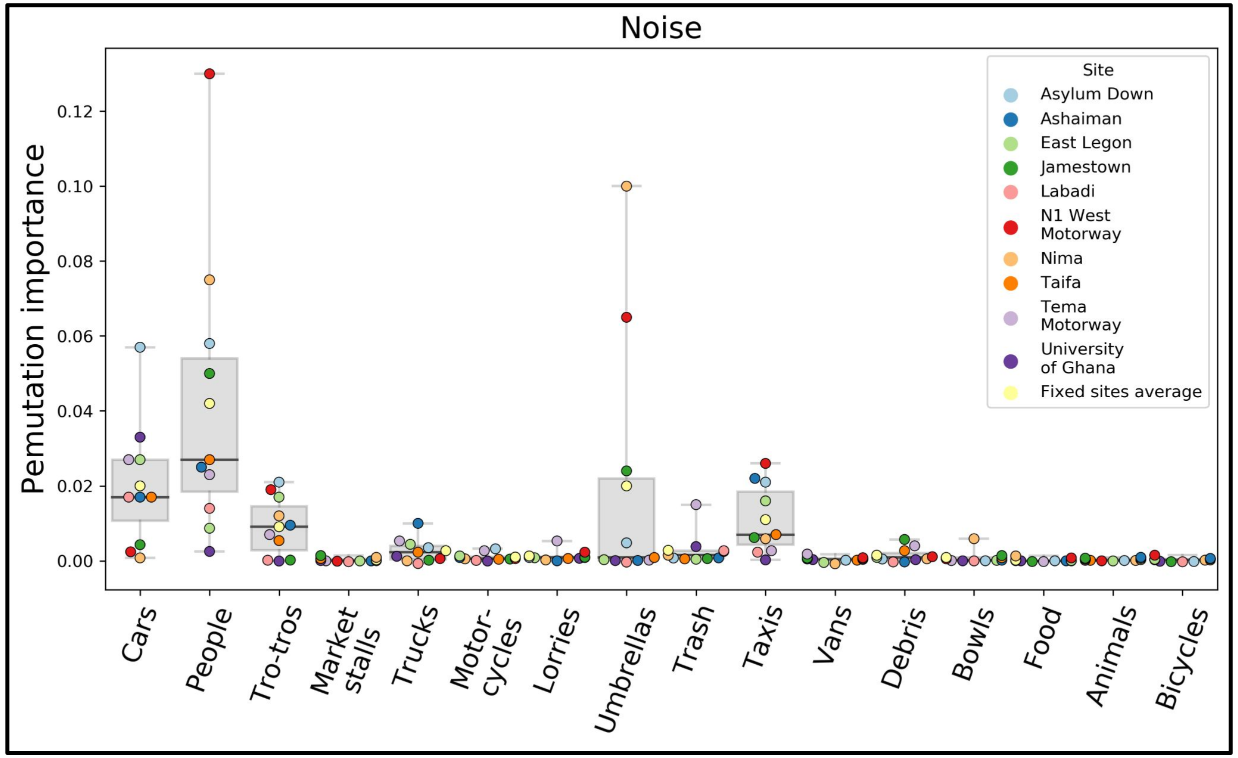
Classes for air and noise

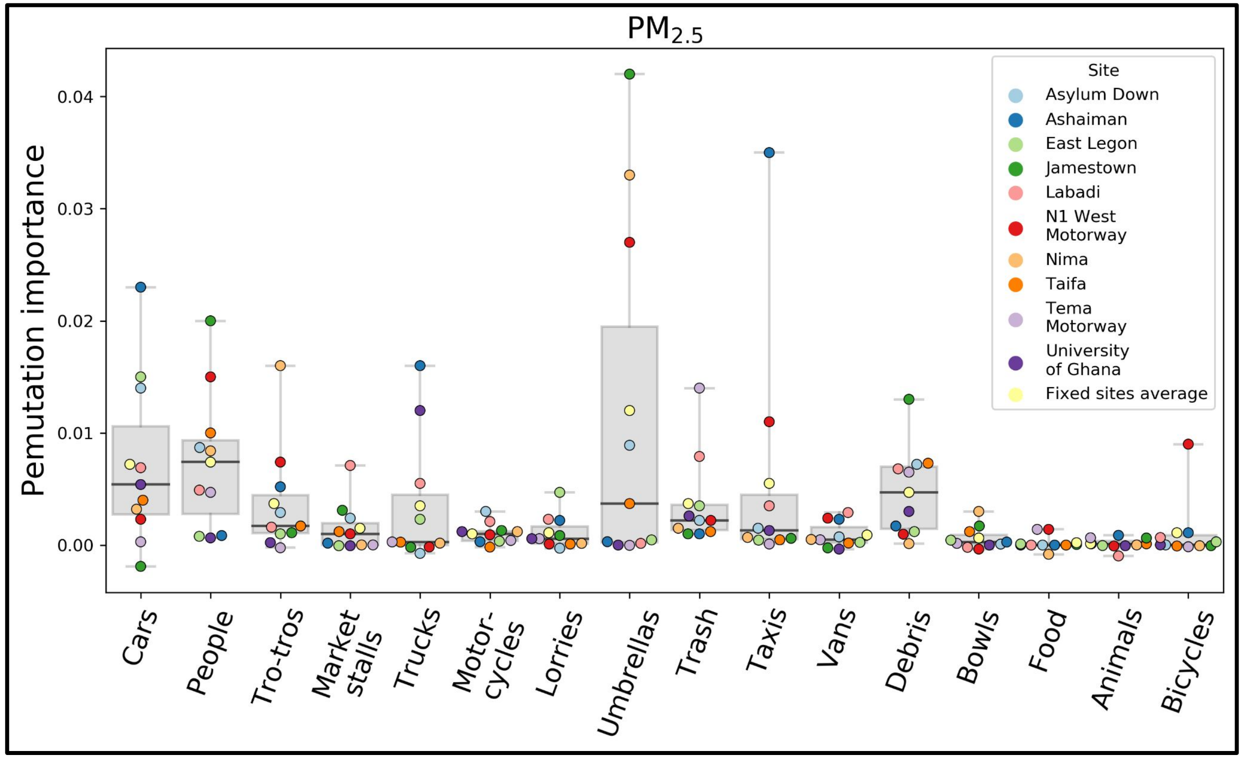
The classes for noise were: <=39, 40 to <45, 45 to <50, 50 to <55, 55 to <60, 60 to <65, 65 to <70, 70 to <75, 75 to <80, >=80 dBA. **Intervals of 5 dBA**

The classes for $PM_{2.5}$ were: 0 to <5, 5 to <10, 10 to <15, 15 to <20, 20 to <25, 25 to <30, 30 to <40, 40 to <50, 50 to <100, 100 to <150, >=150 µg/m3.

Permutation importances

Permutation importance: randomly shuffle each input feature, and measure relative decrease in model performance

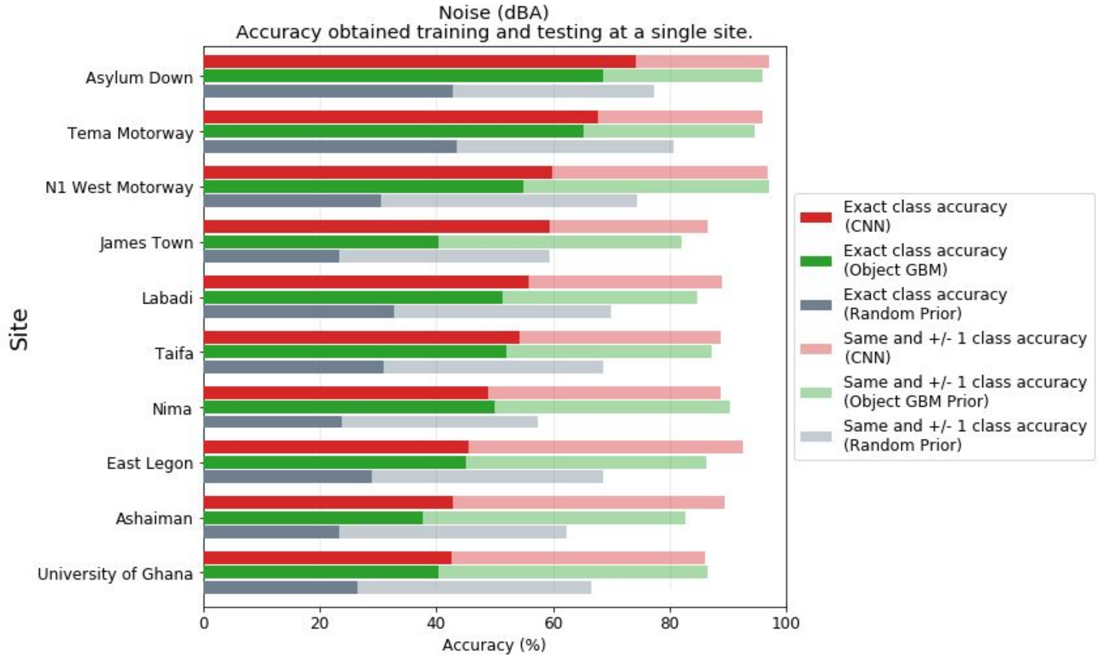




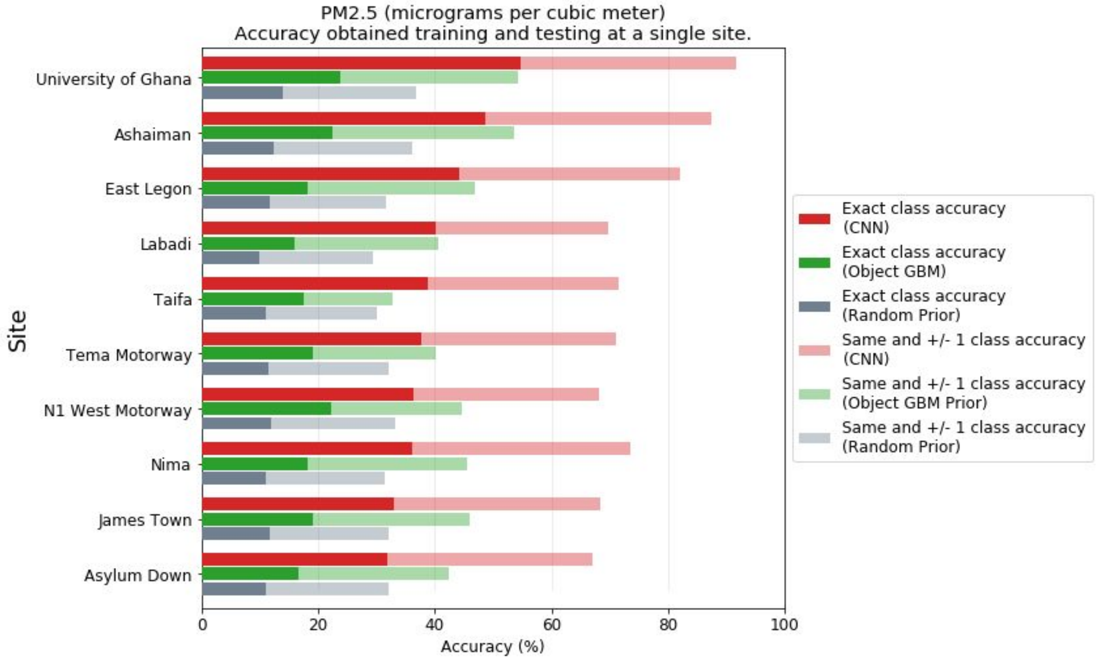
Single (fixed) site, model performance

- Noise prediction models tend to outperform air prediction models.
- Both methods do similarly for noise, and the CNN out-performed the Object-GBM for air.

Noise



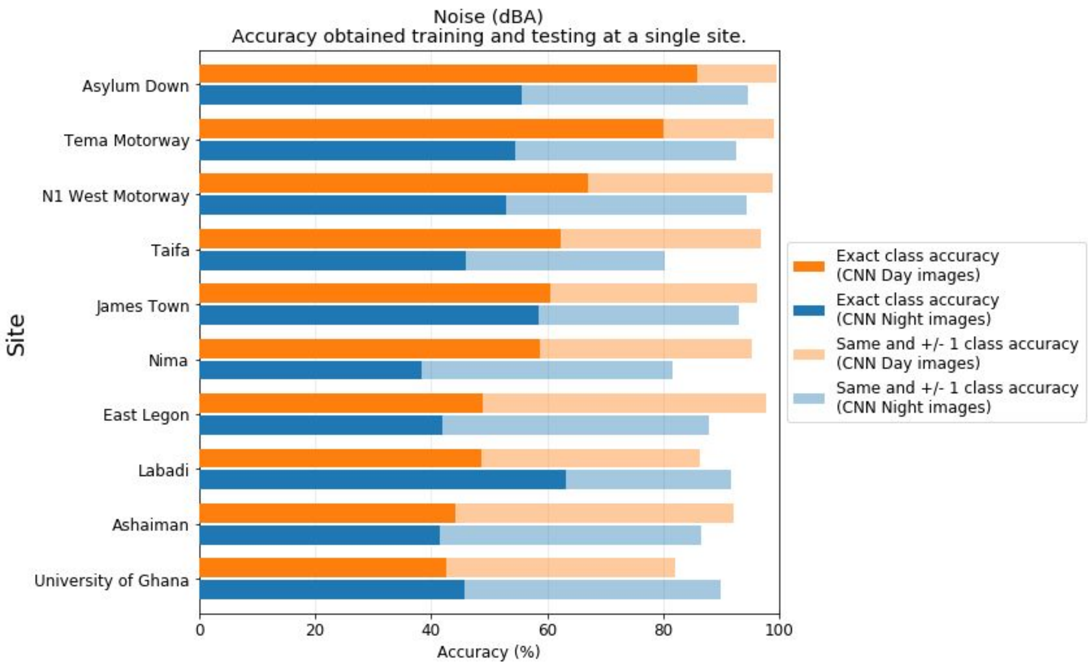
Air



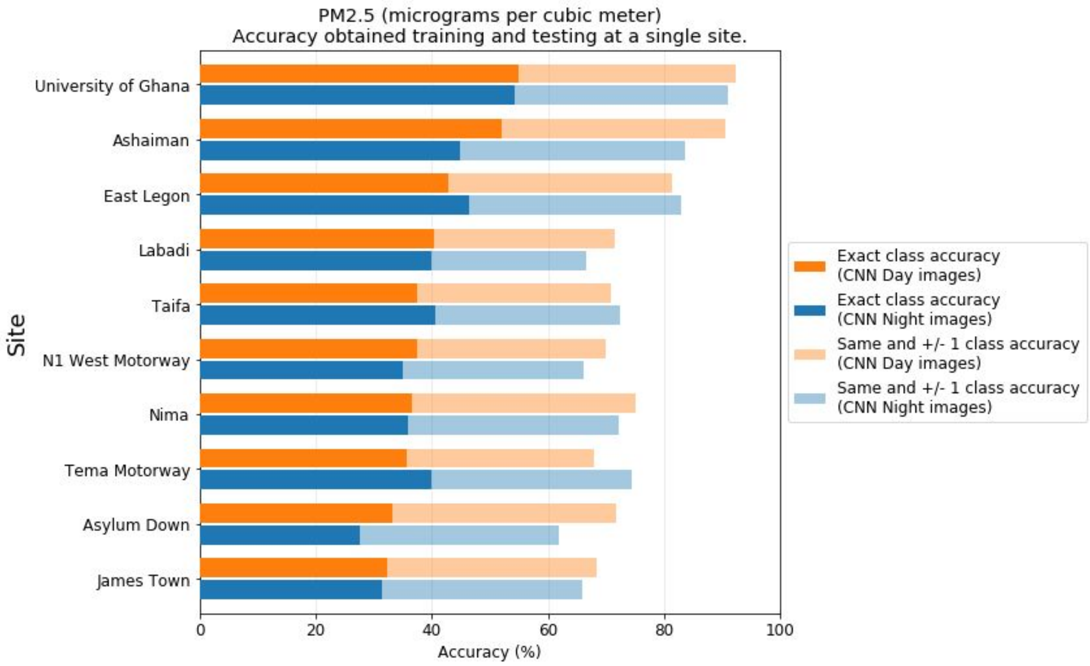
Single (fixed) site, model performance - Day vs Night

- Noise prediction CNN models tend to perform better in the day time (colour images).
- Little difference for air pollution CNN models

Noise



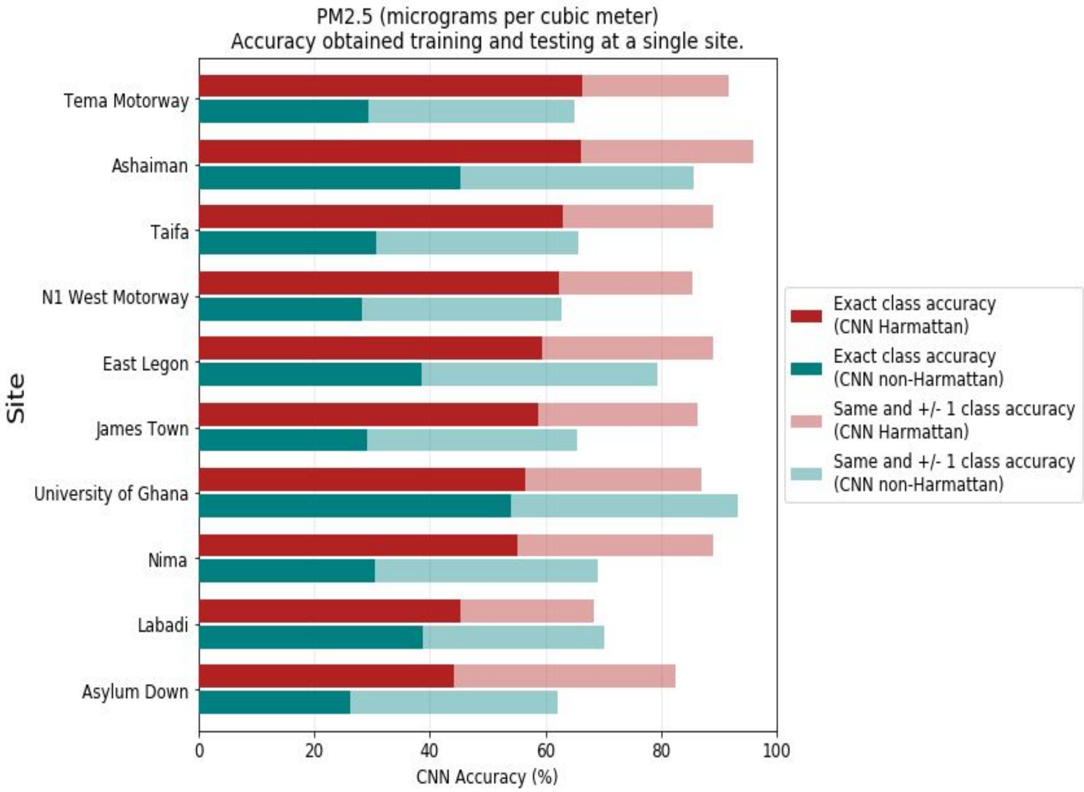
Air



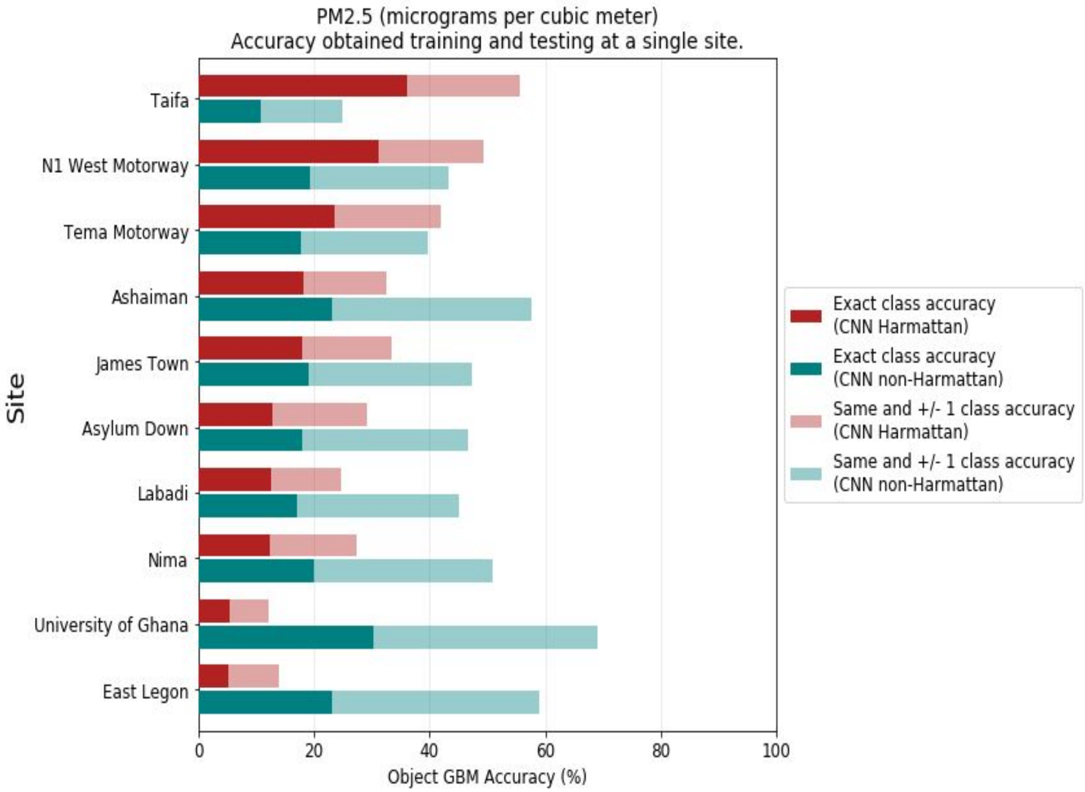
Single (fixed) site, model performance - Harmattan vs non-Harmattan

- For the CNN, the models perform better during the Harmattan than outside the Harmattan - no such trend for object-based models.

Air: CNN

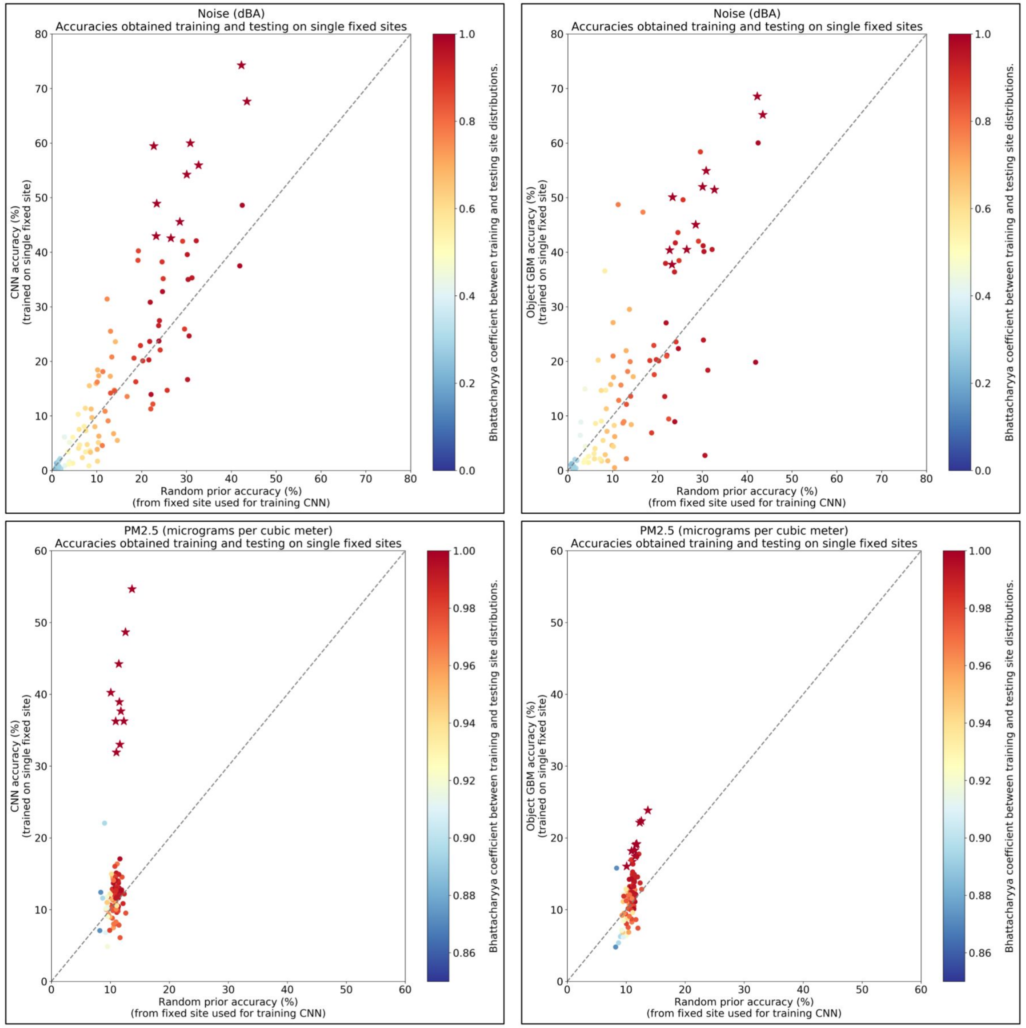


Air: Object-GBM



Single (fixed) site - test on different site, model performance

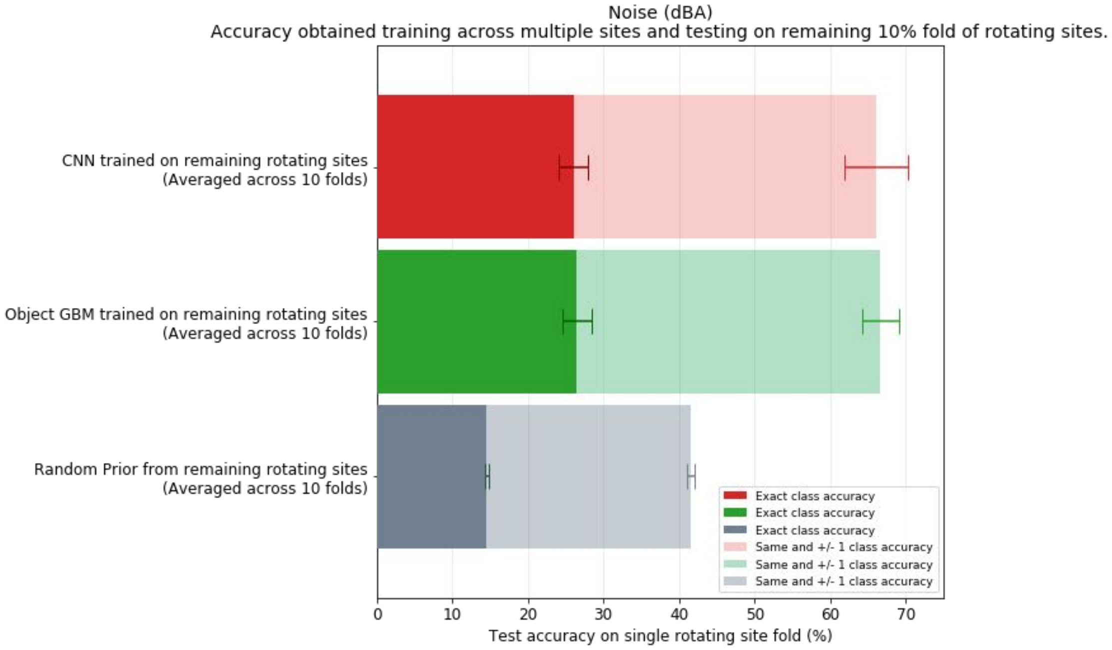
- Basically, no generalisation, noise models do better than air in at least reaching random prior performance



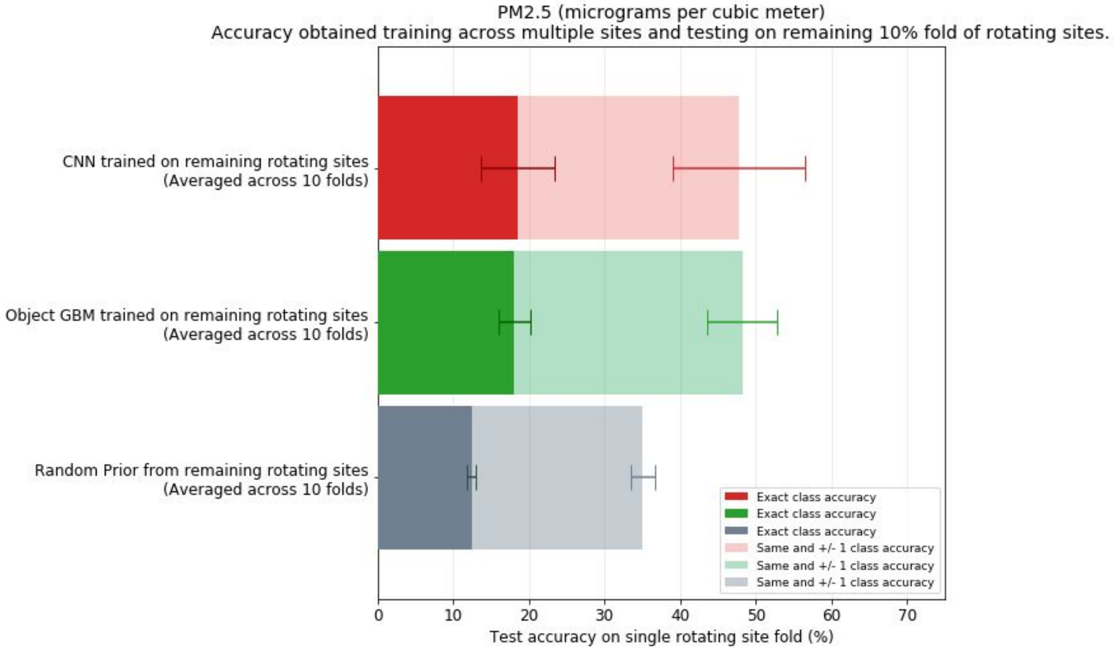
Multiple (rotating) sites, model performance

- Noise prediction models still tend to outperform air prediction models.
- No relative advantage between models, though all still outperform the random prior.

Noise



Air



Multiple (rotating) sites, model performance - Day vs Night

- Noise prediction CNN models tend to perform better in the day time, despite similar random priors.

Noise

Air