AIR POLLUTION: KAMPALA

Presented by Mike Smith, University of Sheffield

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WHY DOES IT MATTER?

In 2012, harm equivalent to 2.6 million deaths, due to outdoor air pollution (mostly heart disease or stroke).

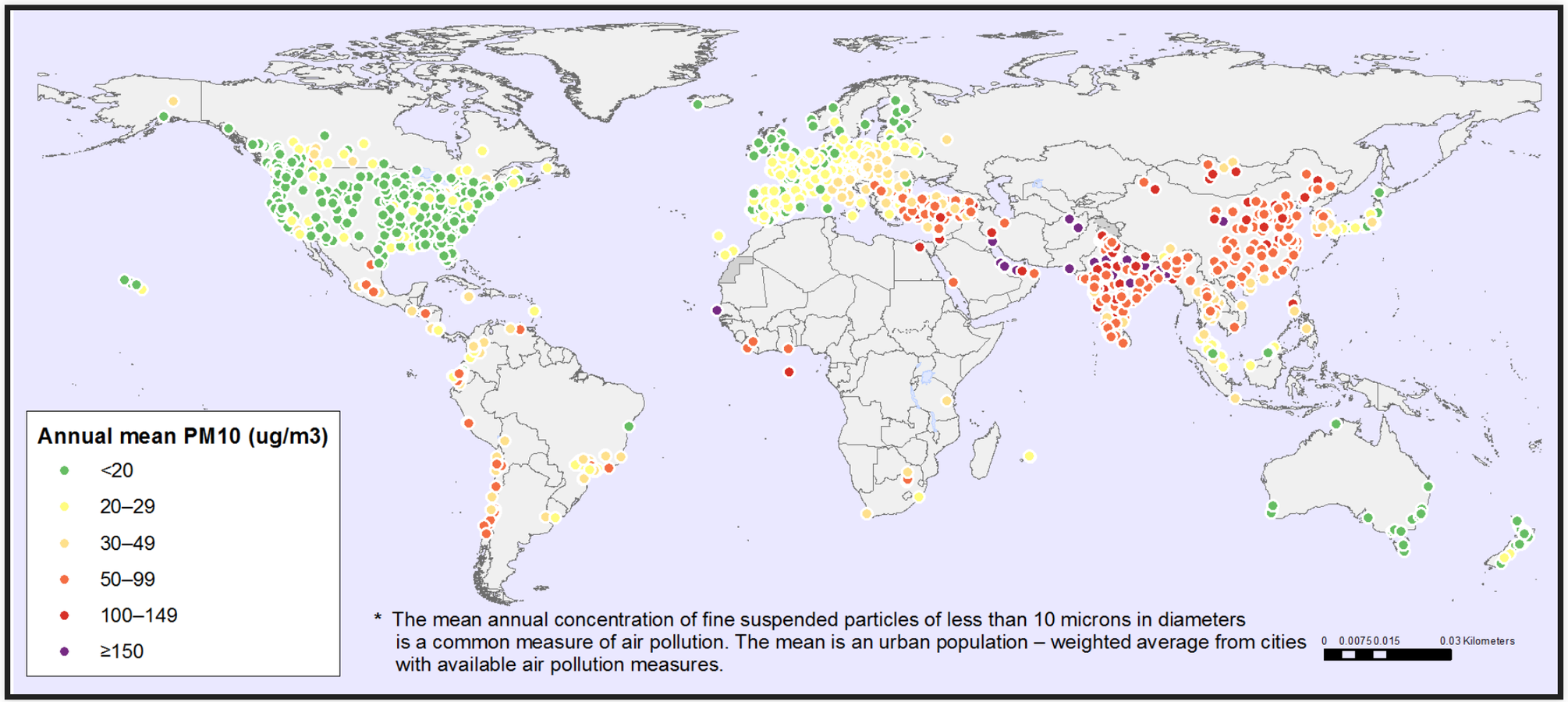
Summary: Air pollution is a big deal (similar scale as malaria?).

Note: We'll focus on PM2.5.

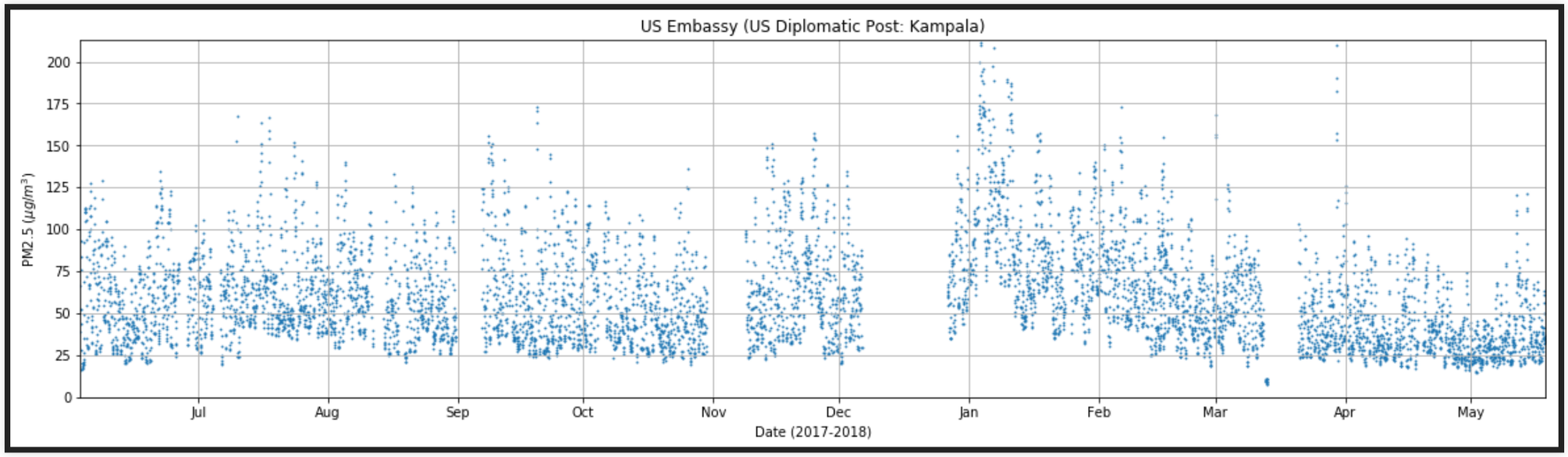
WHO press release 2014: http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/

HOW BAD IS IT?

Only two papers about Kampala's air quality (Stephan Schwander's group), and a new sensor at the US embassy.

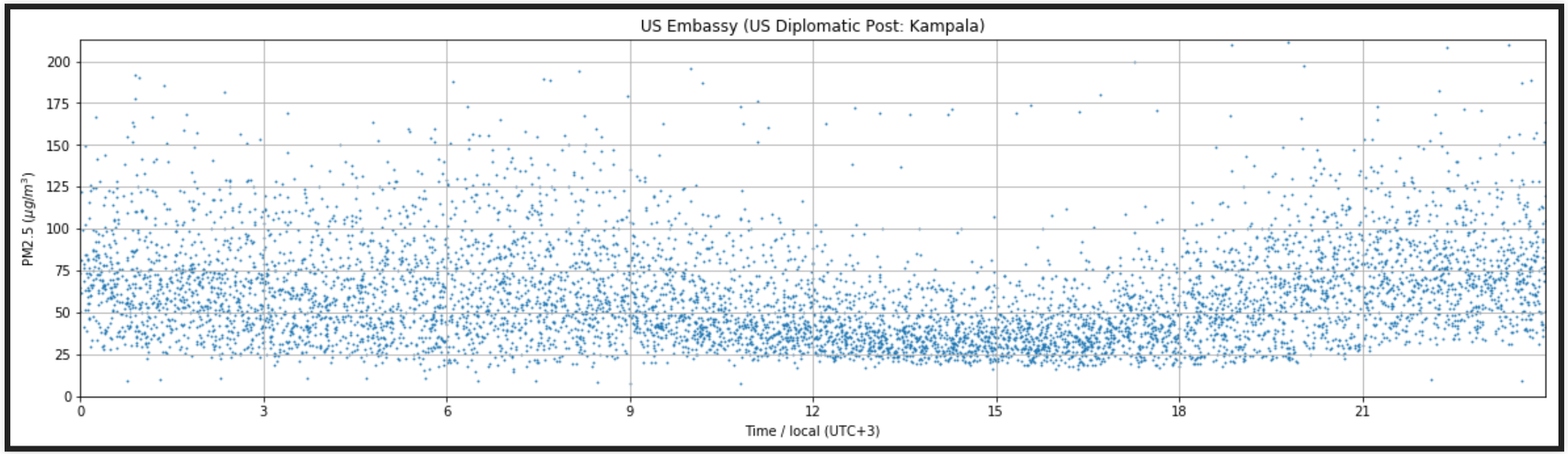


US EMBASSY SENSOR



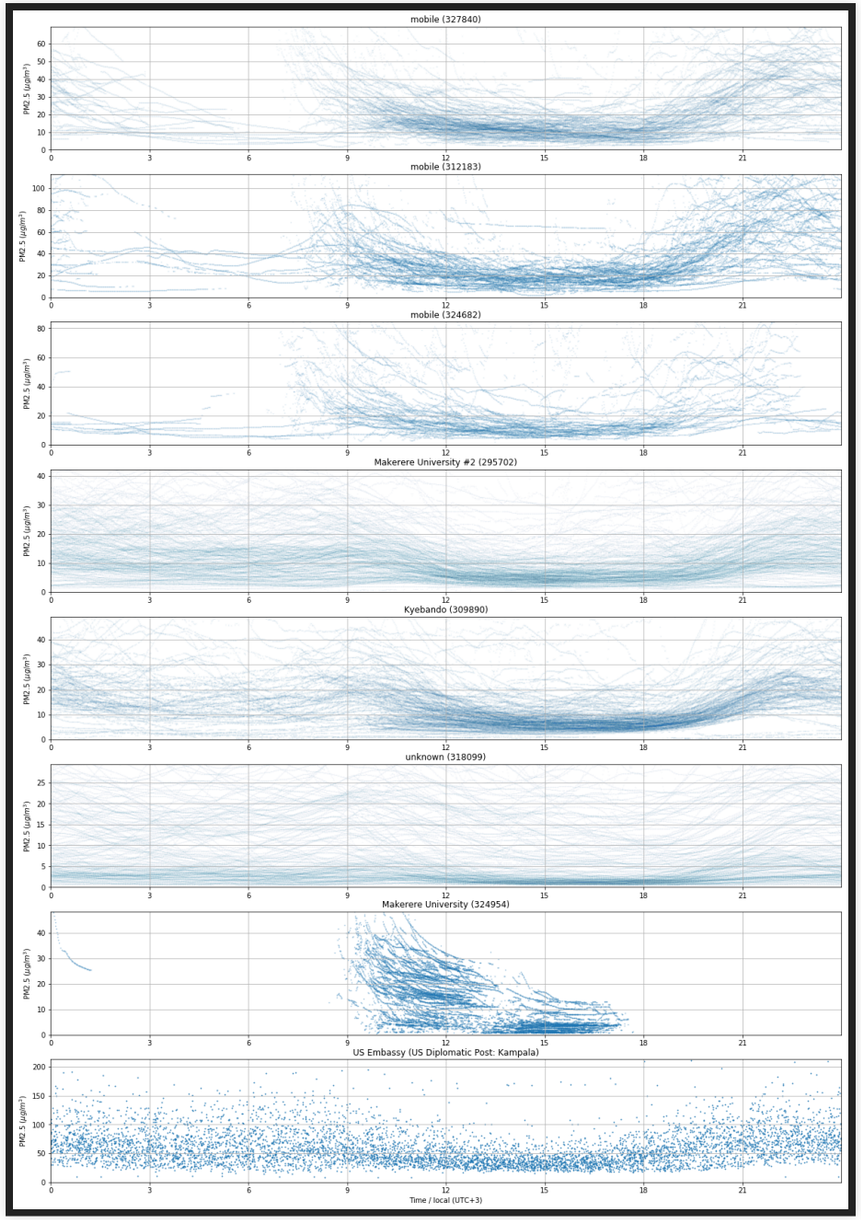
- WHO Guidelines: 10 $\mu g/m^3$ (annual mean)
- EU Guidelines: 18 $\mu g/m^3$
- US Guidelines: 12 $\mu g/m^3$

US EMBASSY SENSOR: BY HOUR

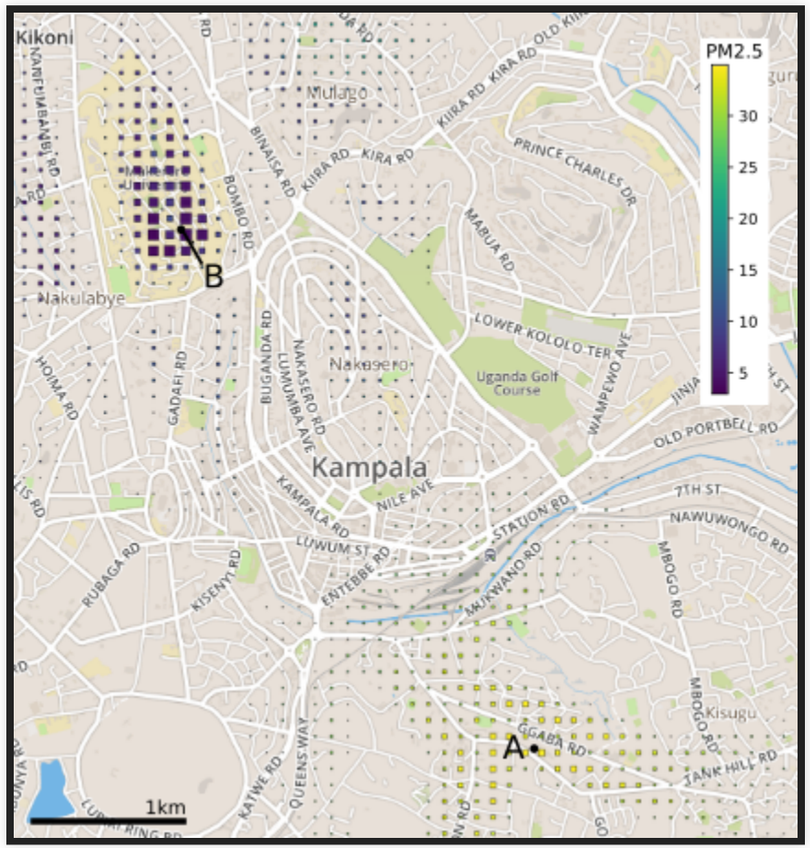


Other sensors in other locations in city agree with general trend.
Night time peak found in other tropical and subtropical cities.

- Any advice or comments?


mobile (327840)
mobile (312183)
mobile (324682)
Makerere University #2 (295702)
Kyebando (309890)
unknown (318099)
Makerere University (324954)
US Embassy (US Diplomatic Post: Kampala)
PM2.5 (µg/m³)
Time / local (UTC+3)

US EMBASSY SENSOR



- Provides good, reliable, calibrated data.
- Only tells us about pollution at the Embassy (A).

METHODS FOR ESTIMATING POLLUTION

- Land Use Regression
  - not probabilistic, typically linear regression, long term avgs
  - Ideally requires 40+ sensors... [expensive]
- Dispersion models (include box and Gaussian plume models). Really depend on having an idea where pollution is from.
- Advection/diffusion models (sources? how to make probabilistic?)
  - our long-term aim (see Wikle 2002)
- Not my expertise, comments?

Hoek, Gerard, et al. "A review of land-use regression models to assess spatial variation of outdoor air pollution." Atmospheric environment 42.33 (2008): 7561-7578.

Wu, Jiansheng, et al. "Applying land use regression model to estimate spatial variation of PM2. 5 in Beijing, China." Environmental Science and Pollution Research 22.9 (2015): 7045-7061.

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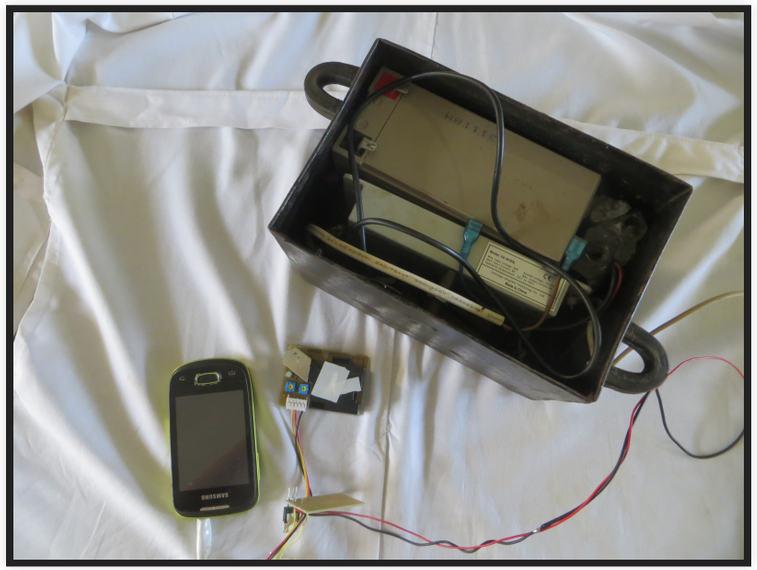
PLAN

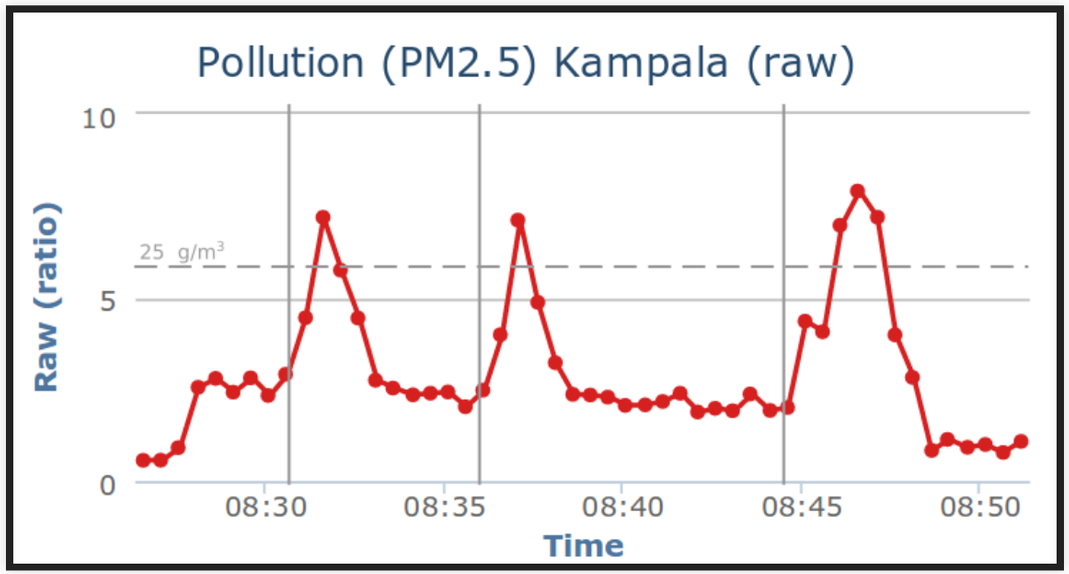
Can we combine lots of low-cost sensors with a few precision devices to acheive similiar accuracies to a full-scale network?

PART 1: HARDWARE DEVELOPMENT

PROJECT DEVELOPMENT

Began with trying the Shinyei sensor hooked up to a phone (2014).





BODA BODA DEPLOYMENT

Engineer Bainomugisha. Ssematimba Joel hardware dev.
Switched to OPC sensor from AlphaSense.

From left to right: Ssekanjako John, the bodaboda driver; me; Engineer Bainomugisha.

STATIC SITE DEPLOYMENT

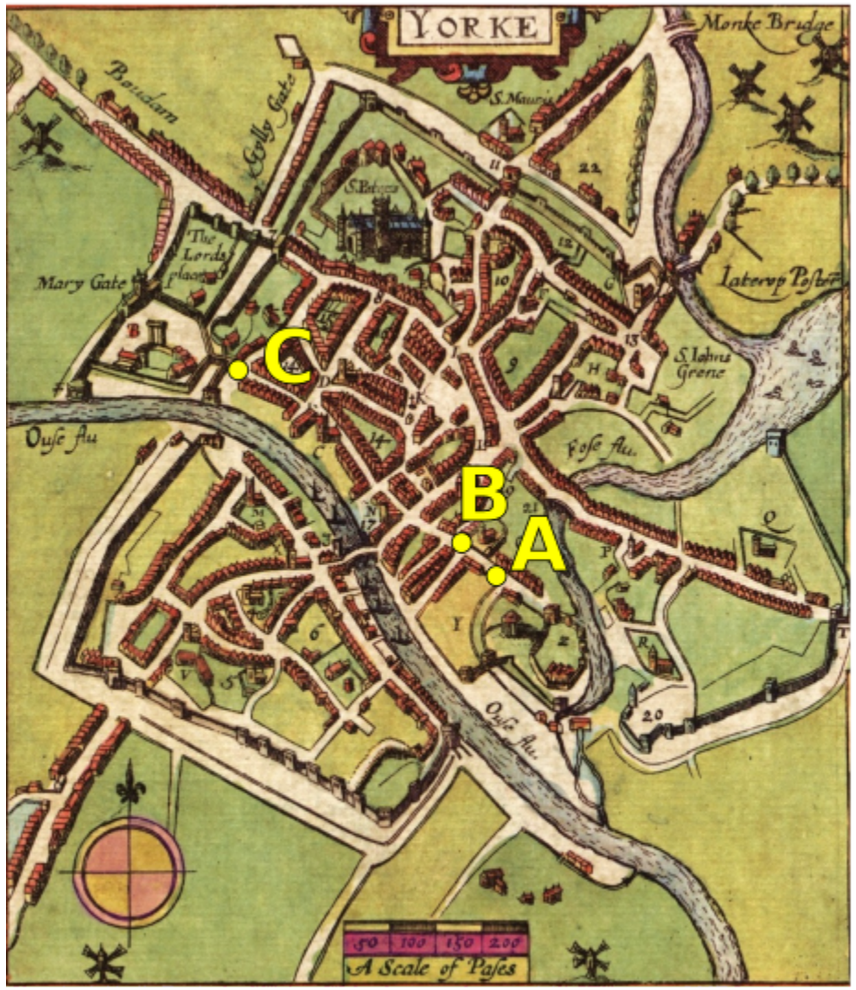
STATIC SITE DEPLOYMENT

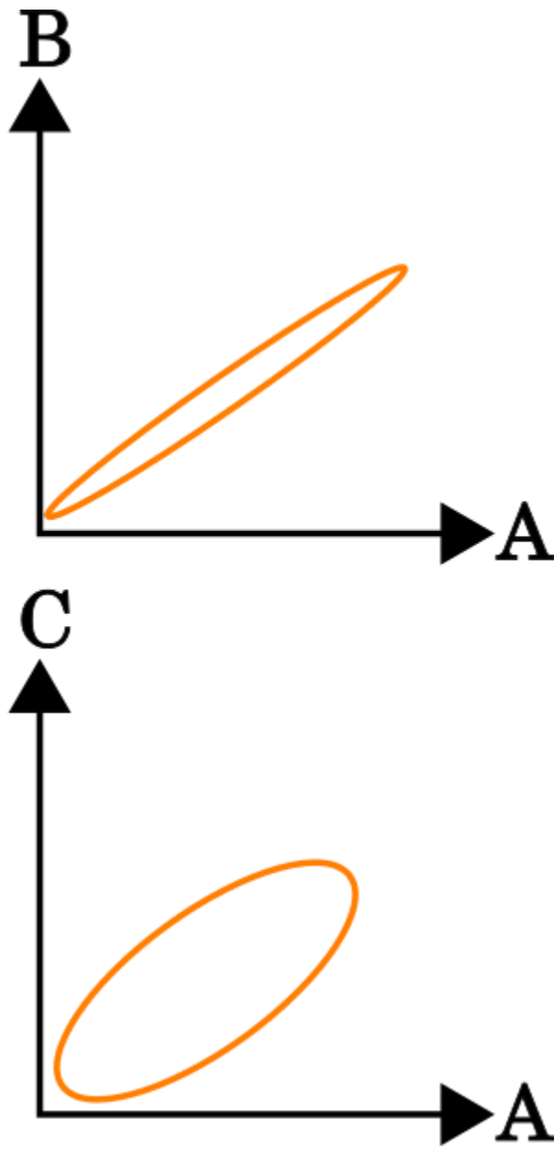
PROJECT DEVELOPMENT

unobtrusive hardware...

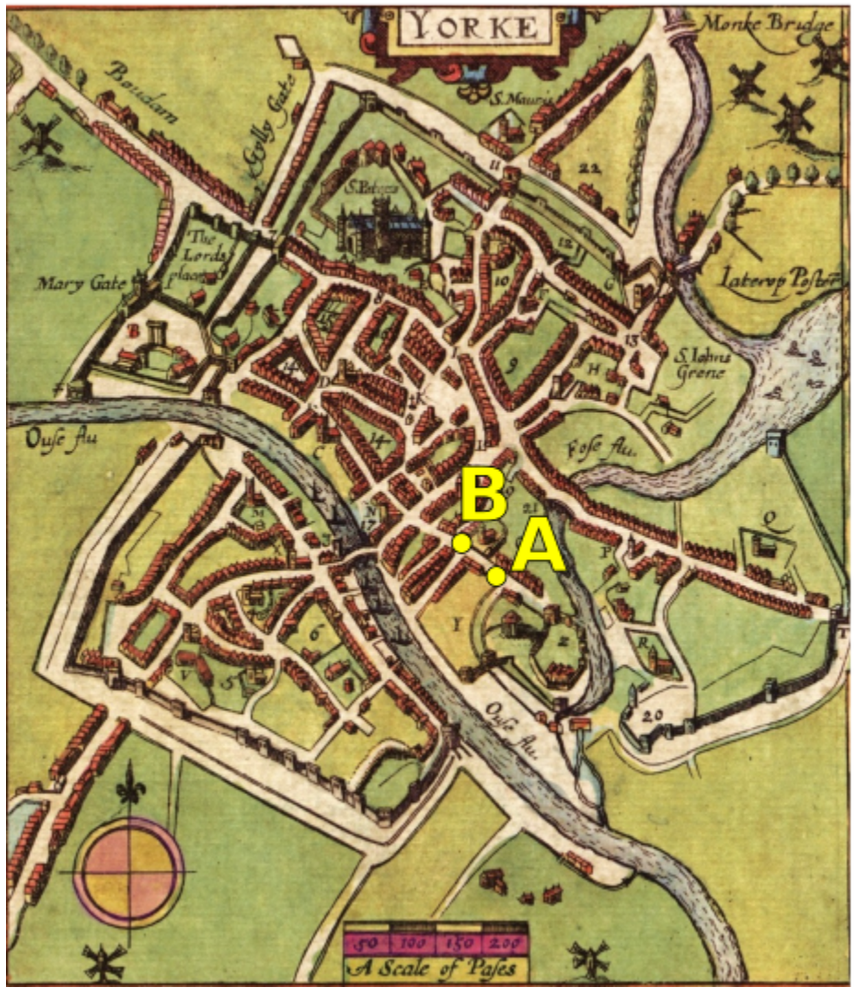
PART 2: COMBINING SENSORS

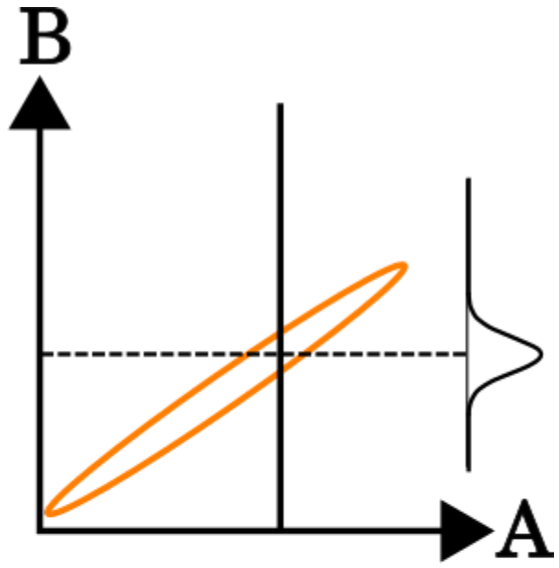
BASIC GAUSSIAN PROCESS REGRESSION



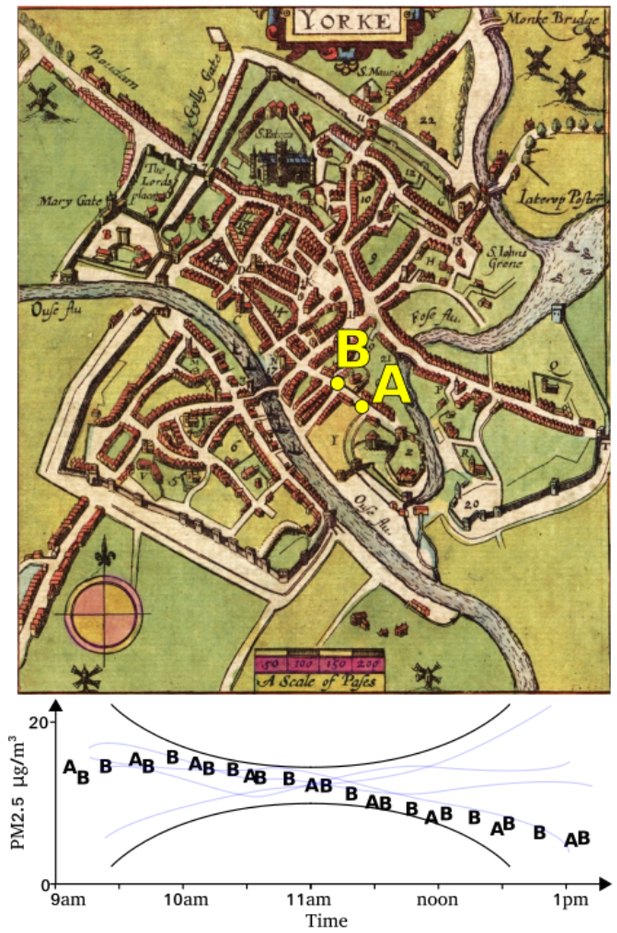


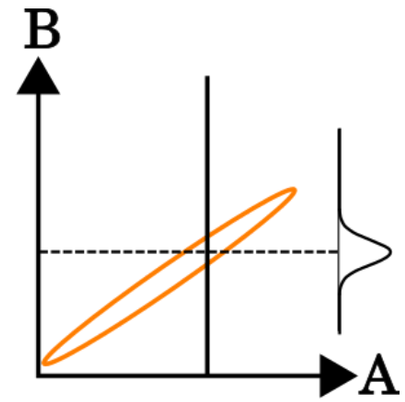
BASIC GAUSSIAN PROCESS REGRESSION

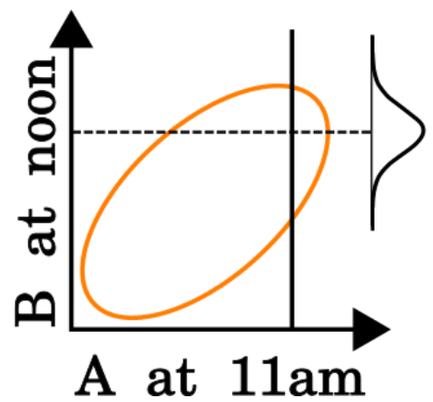




We would also include time as an input.

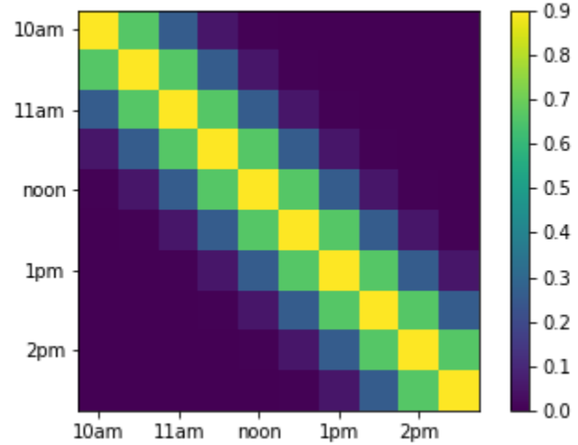






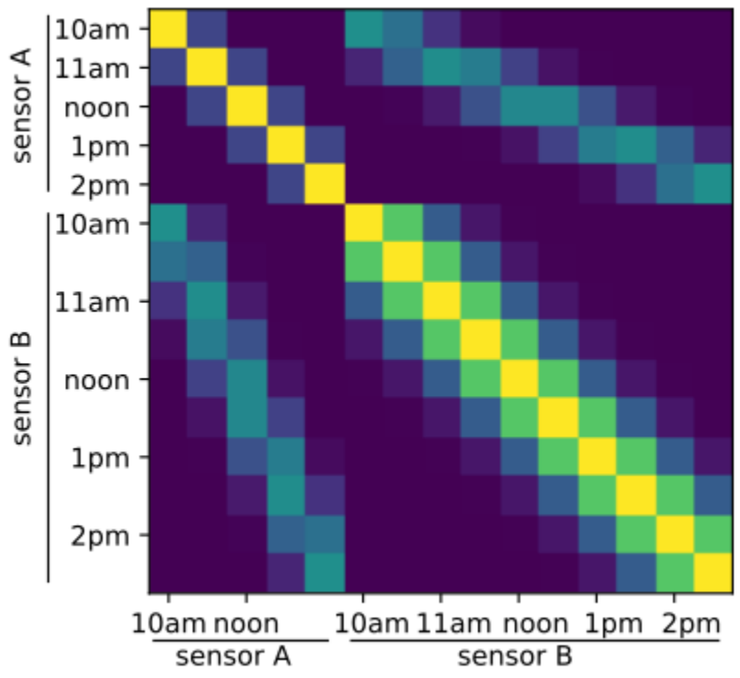
BASIC GAUSSIAN PROCESS REGRESSION

The function that describes this is known as the kernel. It is used to compute the covariance between all the training (and test) points to produce a covariance matrix



BASIC GAUSSIAN PROCESS REGRESSION

We can compute the covariance between two sensors over time,



BASIC GAUSSIAN PROCESS REGRESSION

Using a GP model, with inputs:

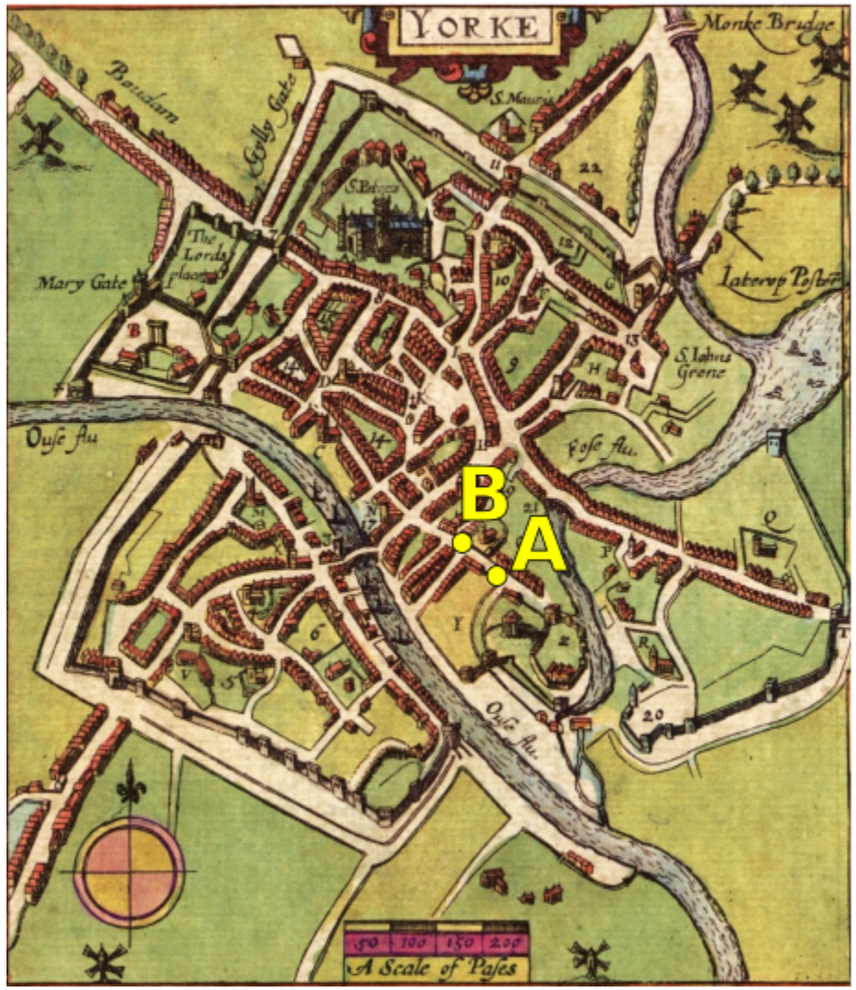
- latitude, longitude and time
- time-of-day
- distance from large roads (data from OSM)
- MSc student scraping traffic data from google maps!

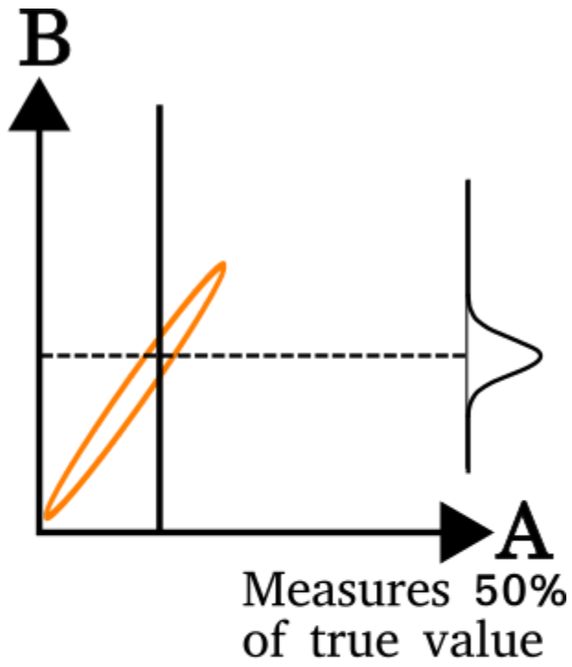
We can treat these variables as simply inputs to the GP.

website

COREGIONALISED GAUSSIAN PROCESS REGRESSION

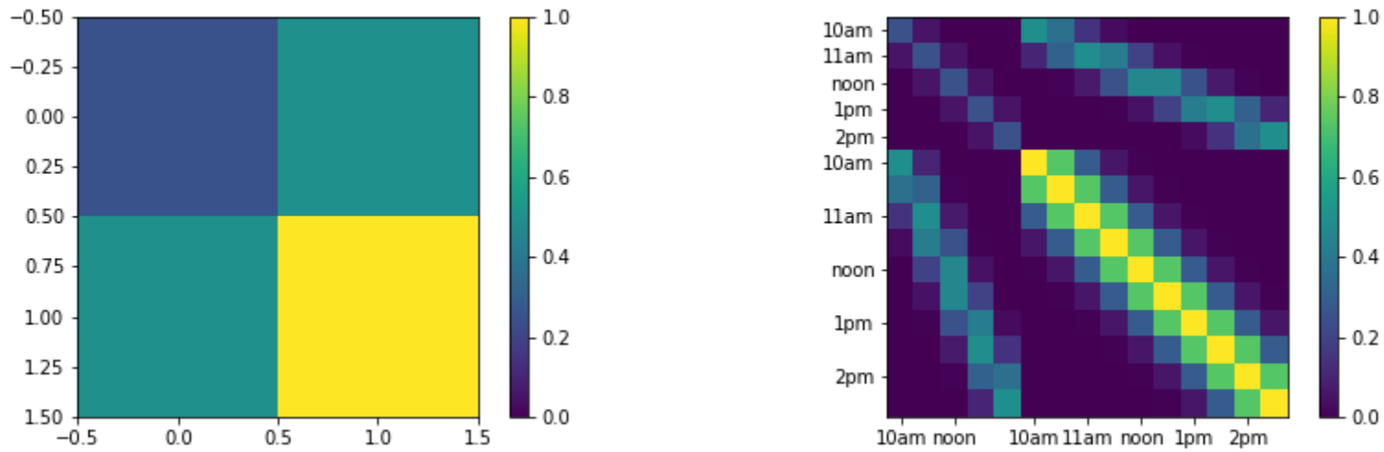
Supposing one sensor reports 50% of the actual value?





COREGIONALISED GAUSSIAN PROCESS REGRESSION

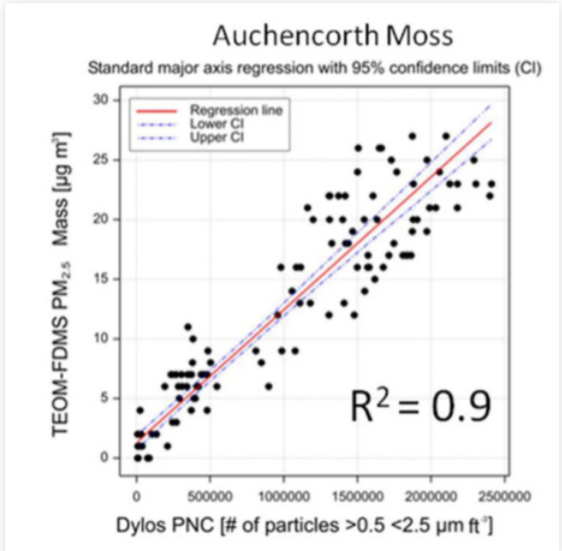
Scale the covariance by elements from a 'coregionalisation' matrix. In this case we assume simply that the sensors are proportional to each other. So we use a rank-one covariance matrix, $\mathbf{w}\mathbf{w}^\top$, and need to estimate a single value for each sensor (in vector $\mathbf{w}$)

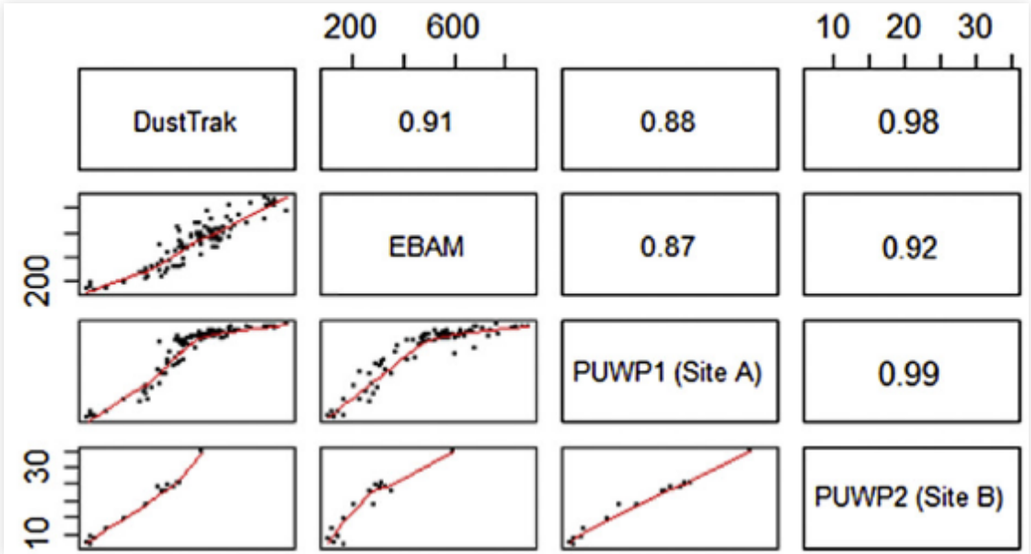


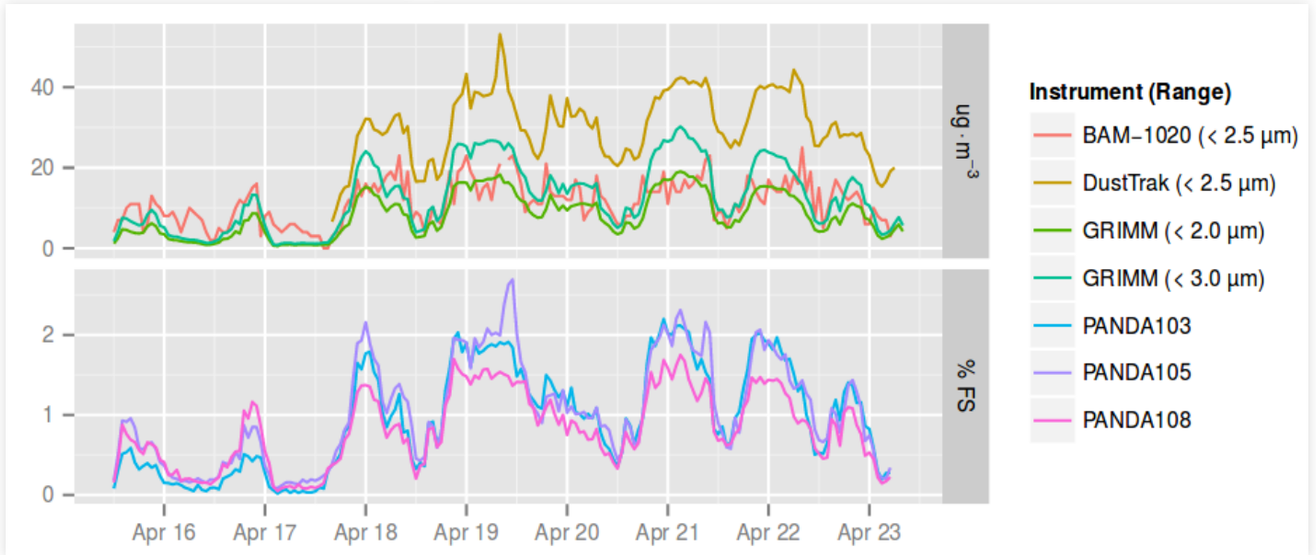
Note: Computationally efficient if measurements are taken at the same times.

COMBINING SENSORS

Sensors aren't necessarily calibrated, but are still correlated







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COMBINING SENSORS

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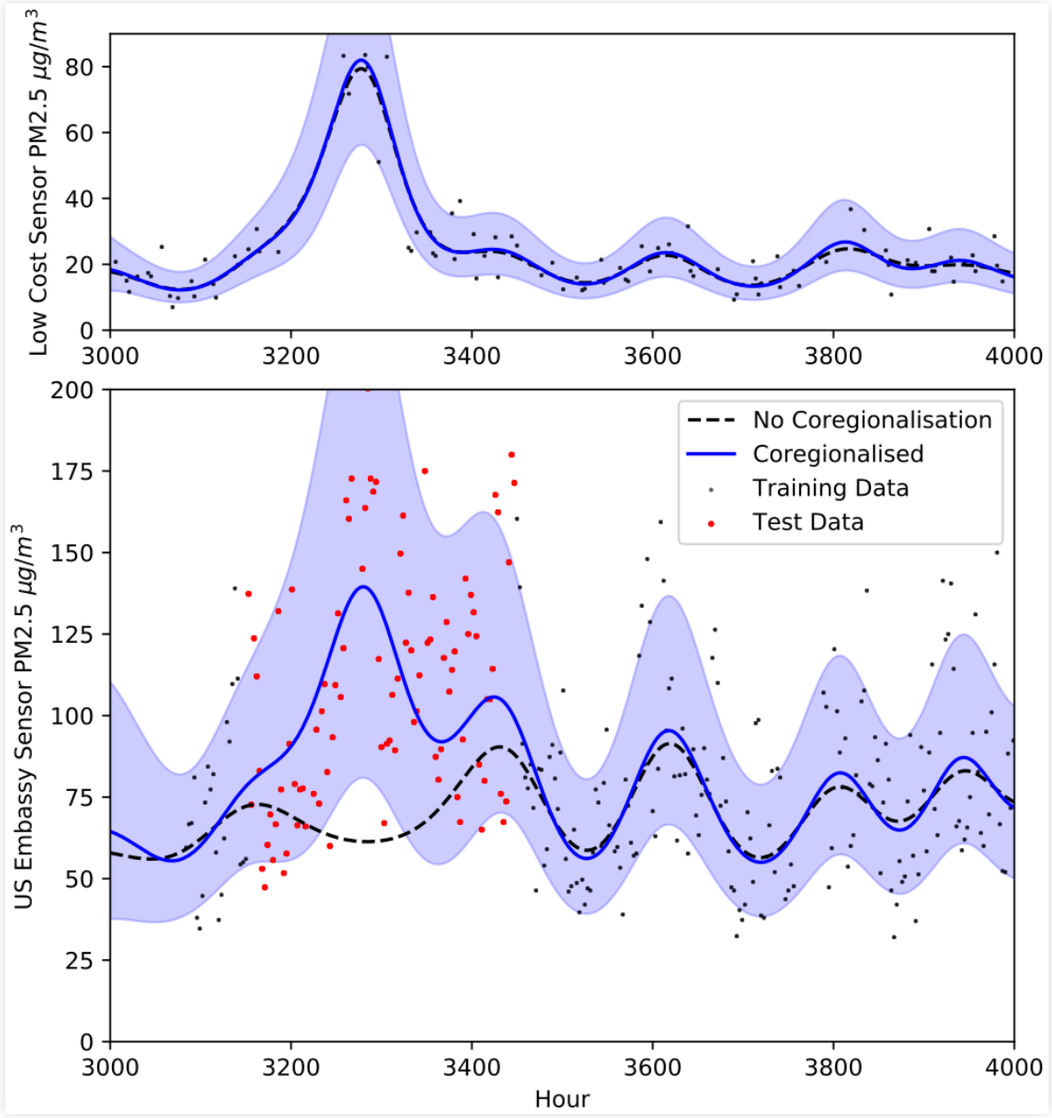
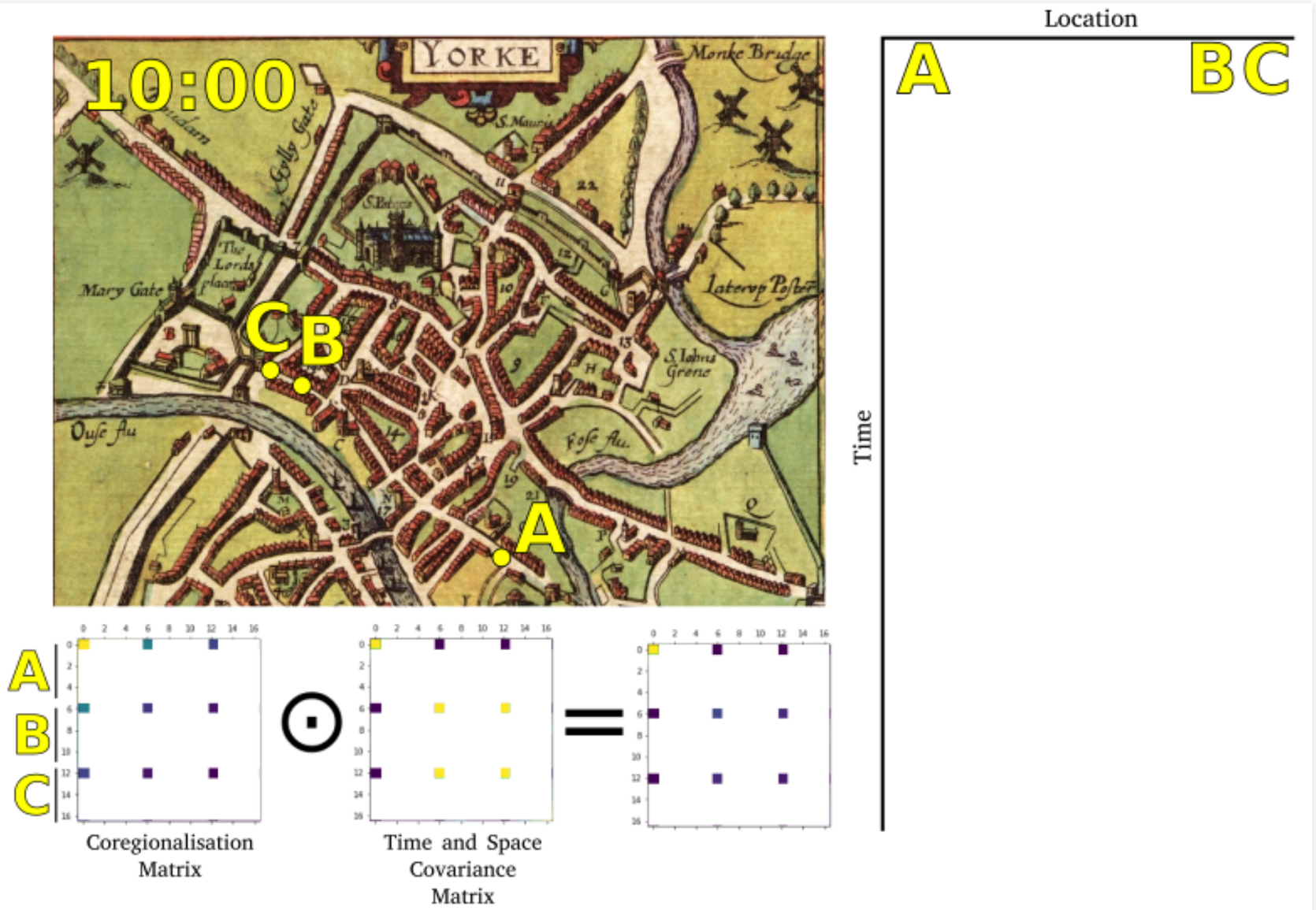


CALIBRATION WITH COREGIONALISATION



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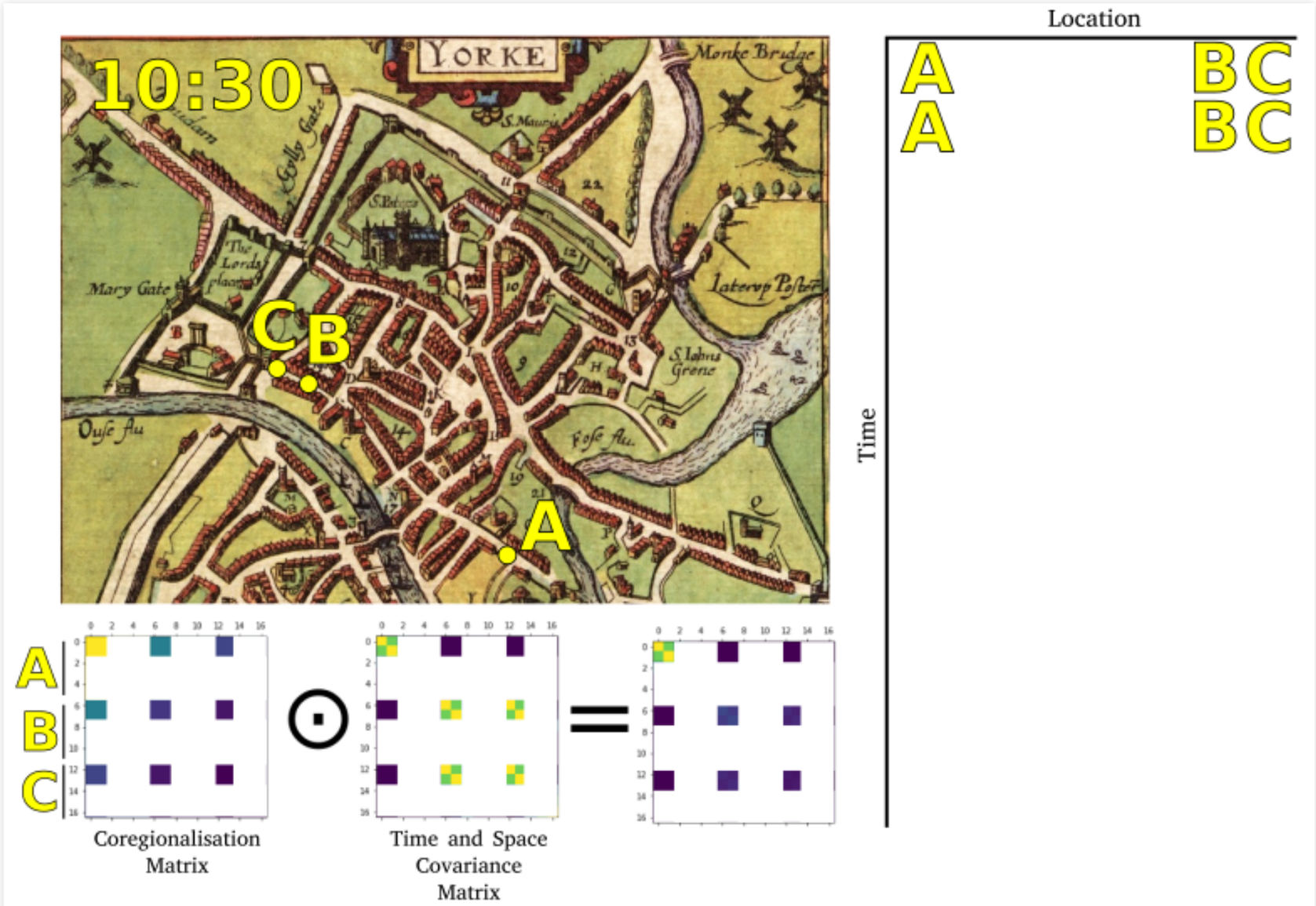

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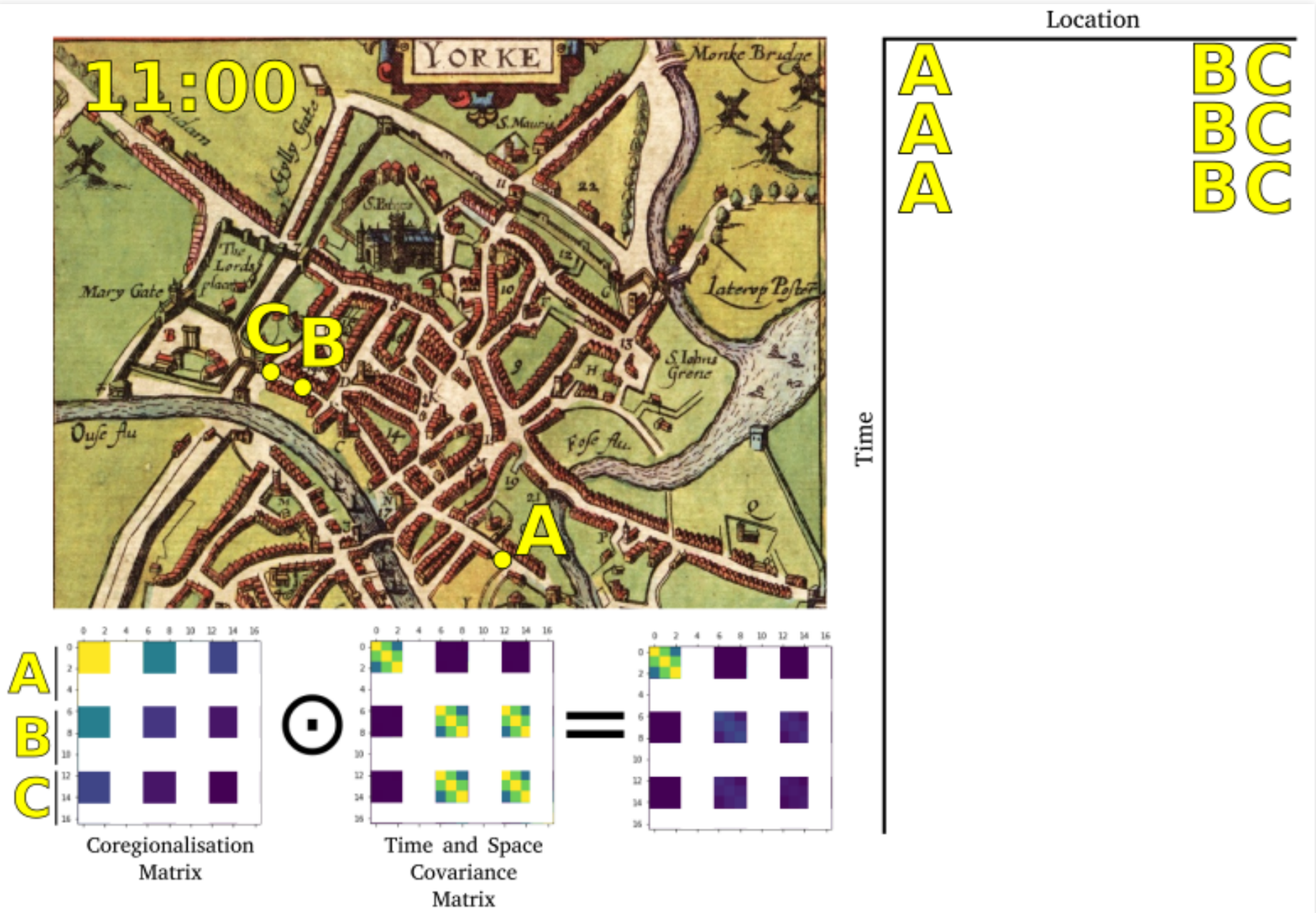

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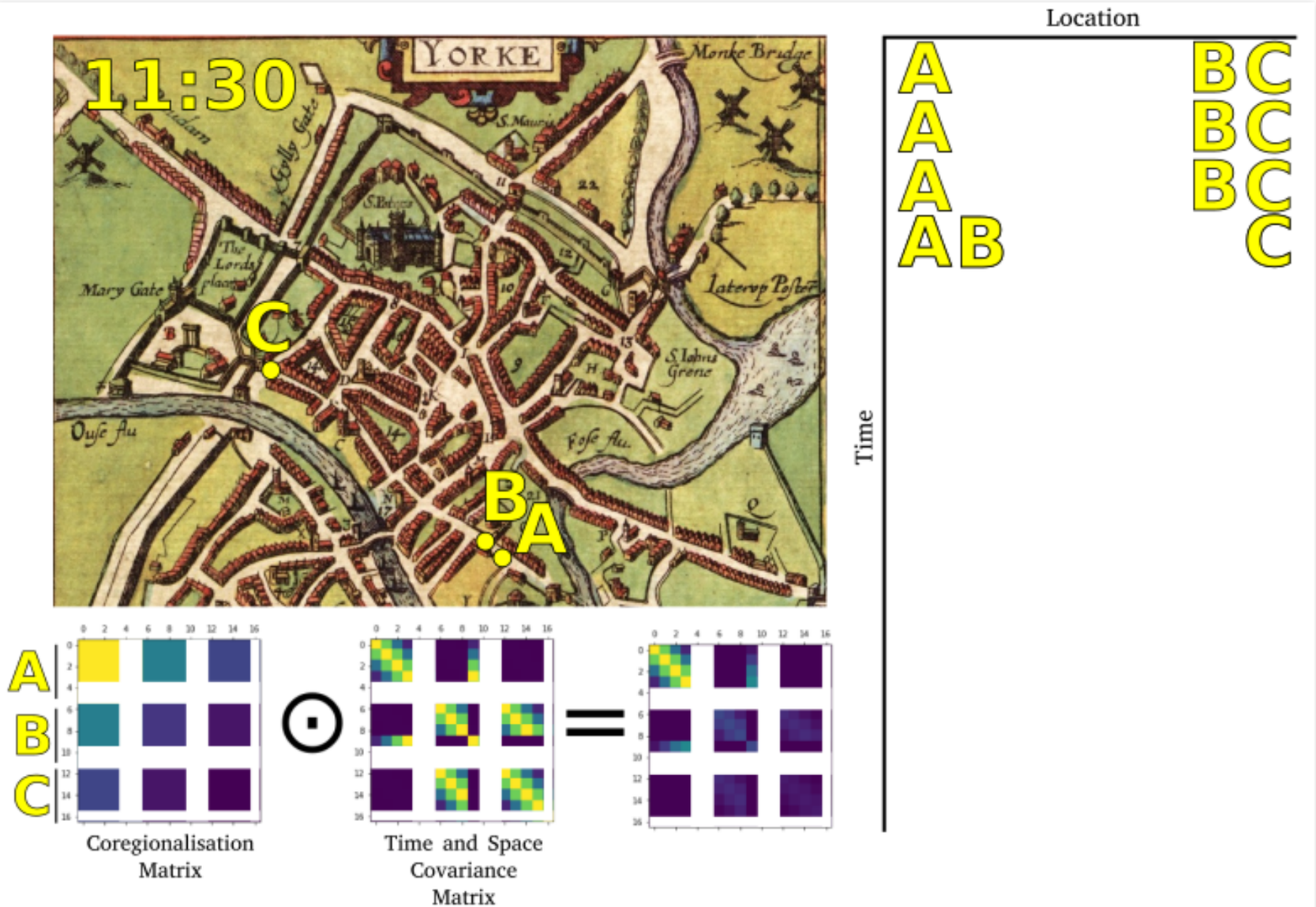

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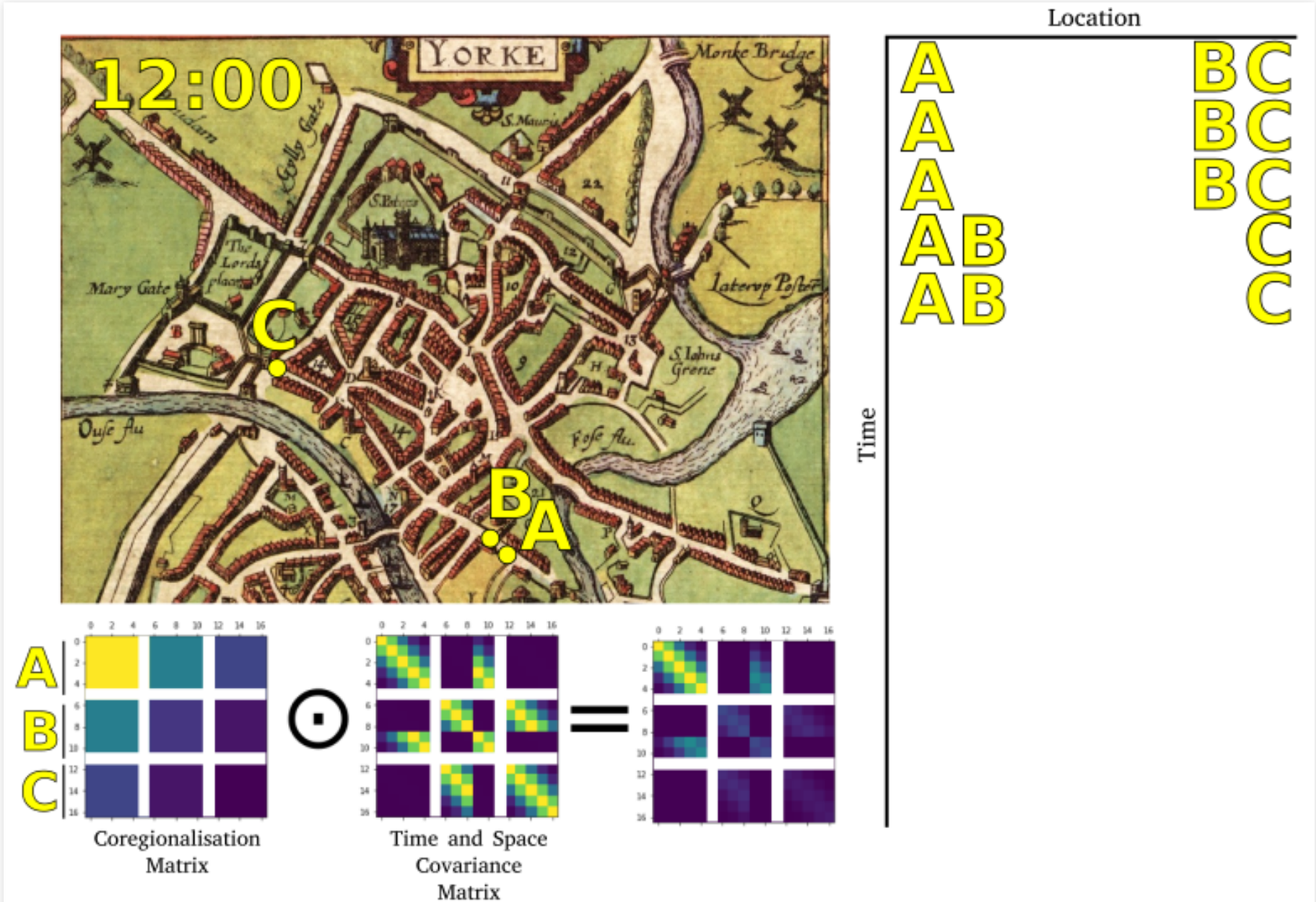

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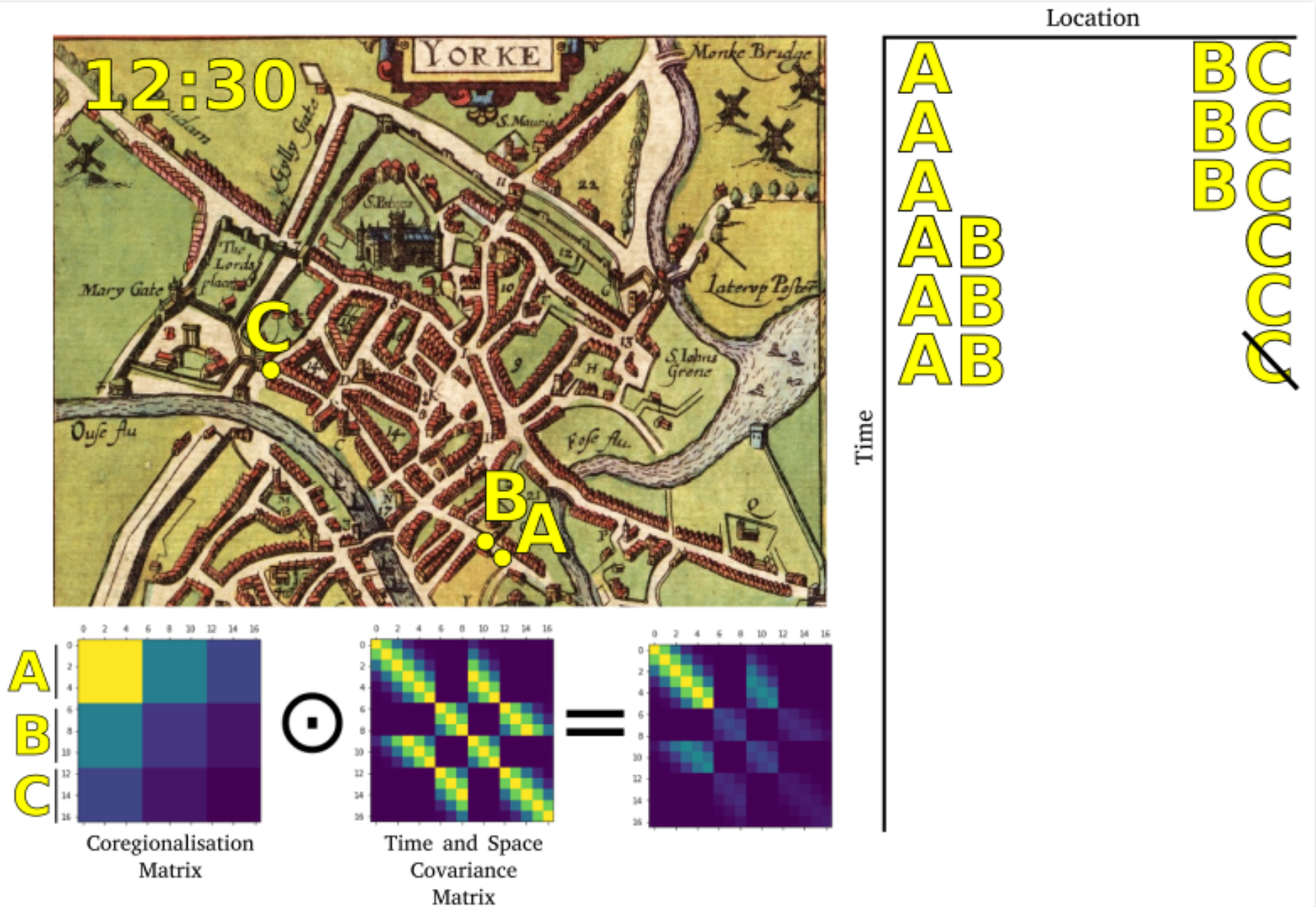
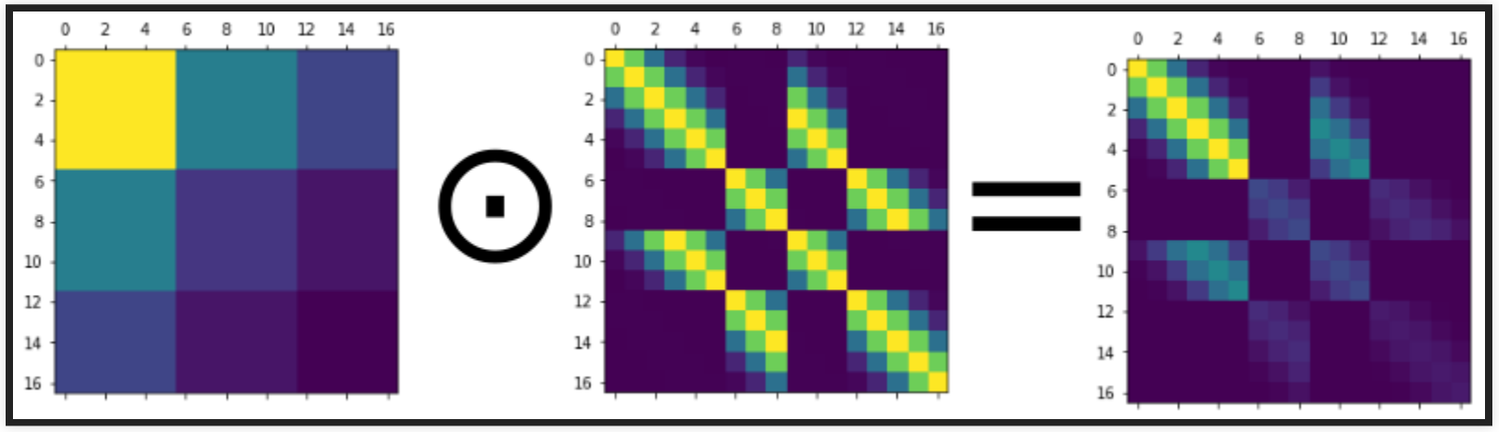


CALIBRATION WITH COREGIONALISATION

- Need to consider sensor proximity
- Assume sensors are proportional (rank-one, $\mathbf{w}\mathbf{w}^\top$)
- Toy example: Three sensors. One sensor swaps location.



Element-wise product (not Kronecker product)

- Hyperparameters $\mathbf{w}$ only relevant where 'proximity' matrix is non-zero. So need to have sensors co-located to estimate these.
- Need to use CCD or similar to incorporate uncertainty in $\mathbf{w}$.

PART 3: BODA BODAS

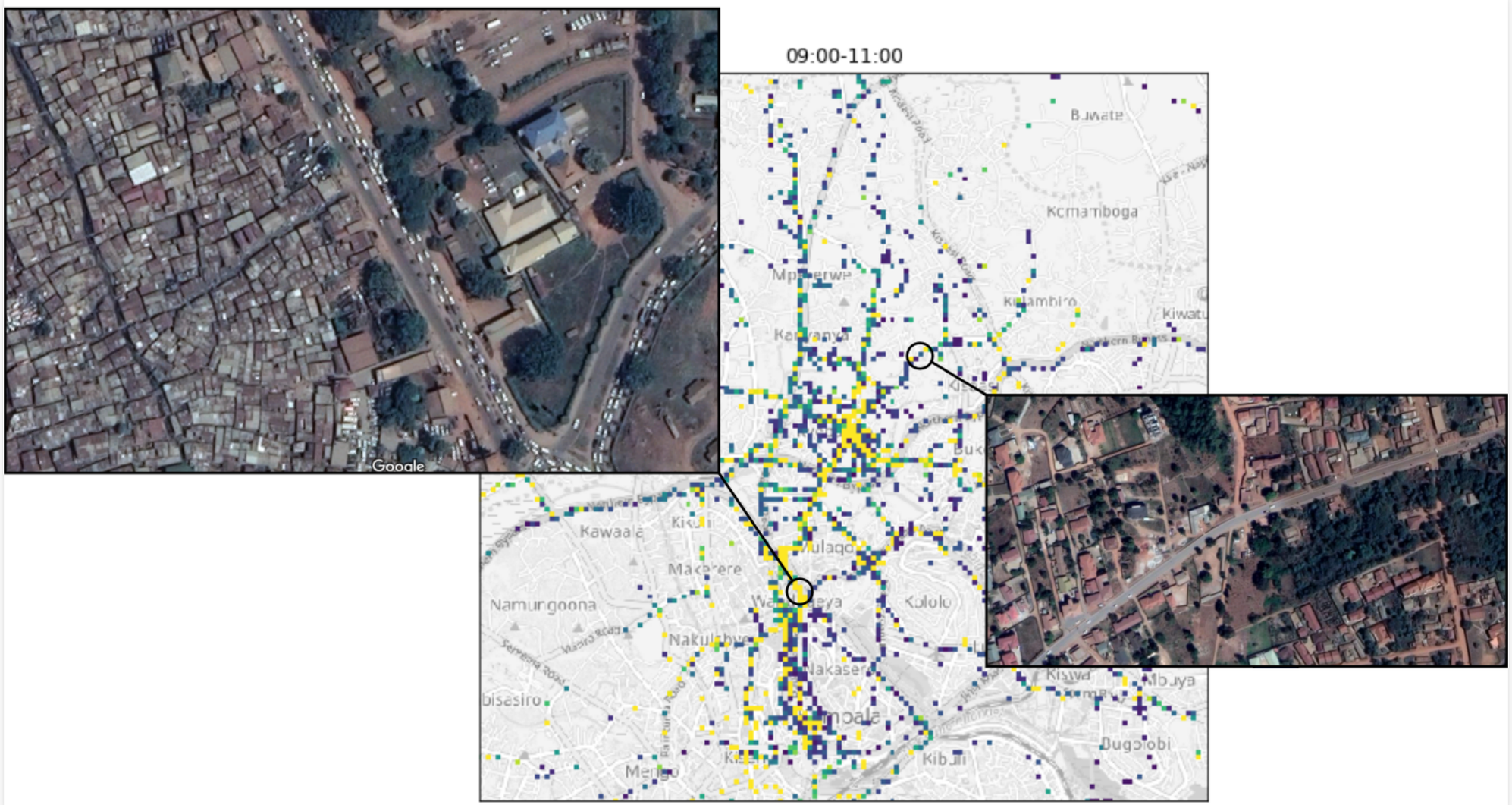
BODA BODAS

video!

BODA BODAS

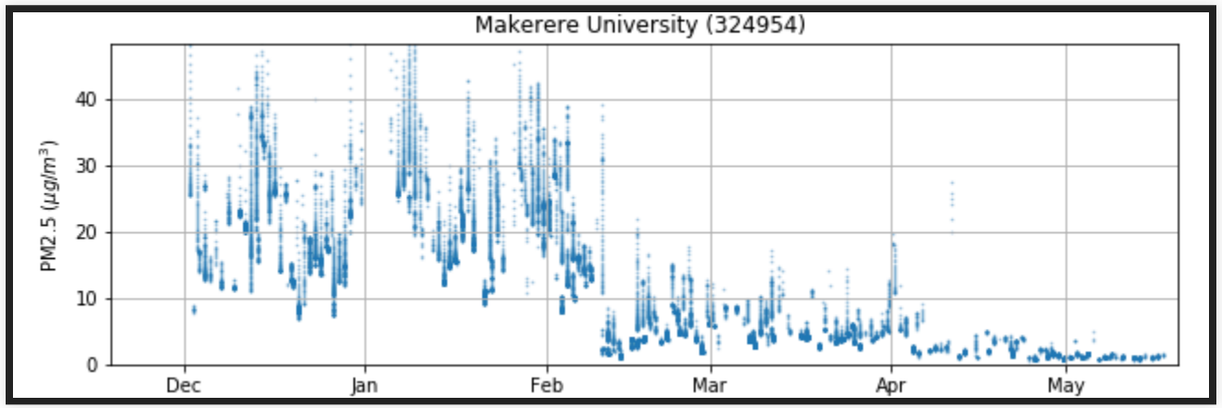
- Boda-bodas provide spatial detail about pollution
- Might help with calibrating fixed sensors?
- Appear to be providing reasonably 'realistic' data

BODA BODA DATA



w MIGHT CHANGE?

- Need very regular calibration (problems with clogging)



- Estimates of $\mathbf{w}$ will need to vary. Model with a GP too?

FUTURE IDEAS

- Use **active learning** to select location for bodaboda to visit
- Look at **sources** of pollution to try to start assigning causality
- Apply **differential privacy** to ensure boda location remains private
- Correlate with **hospital admissions**?

New! The Sheffield Urban Observatory is lending three MCERTS TurnKey OSIRIS OPCs for deployment in Kamapala (and funding 15 low-cost sensors). This will allow us to calibrate the low-cost units.

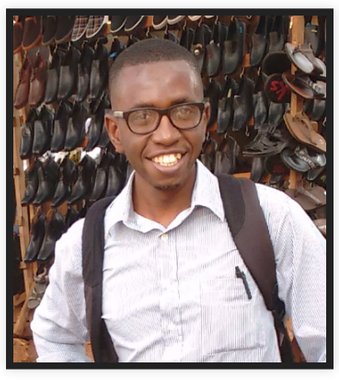
ACTIONS/EFFECTS

- Awareness raising - leads to civic response?
- If we get causation - we'll know what to target.
- Baseline necessary for mitigation to be assessed.
- KCCA planning non-motorised area in Old Kampala!

THANKS

DIL Berkeley award, ARM, the Urban Observatory and the EPSRC.

Engineer Bainomugisha; Ssematimba Joel



Pius Kavuma, AI Lab (3d printer!); Irene Michalaki, ARM;
Mauricio Alvarez and Neil Lawrence

QUESTIONS FOR YOU!

- Protocols for pollution survey?
- Humidity?
- Thoughts on the mobile sensors?
- Distinguishing pollution sources by PM size??
- Other pollutants we should be measuring? (low cost?)
- Fairly simple public health experiments? (currently handing data onwards to the Lung Inst. etc)
- Problems with fairly quick clogging from dust.
- Develop a proposal describing a set of possible interventions? Who have you worked with on this?

REFERENCES

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Latha, K. Madhavi, and K. V. S. Badarinath. "Seasonal variations of PM10 and PM2. 5 particles loading over tropical urban
environment." International journal of environmental health research 15.1 (2005): 63-68.
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