The Alan Turing Institute

Data Sciences for the Built Environments

Dr. Ruchi Choudhary

Reader of Architectural Engineering, University of Cambridge, UK

EPSRC
Engineering and Physical Sciences Research Council

UK Research and Innovation

Subsurface Environments

Dr. Monika Kreitmair, PDRA, U. of Cambridge, UK
+ new PDRA to be appointed 2020-2022

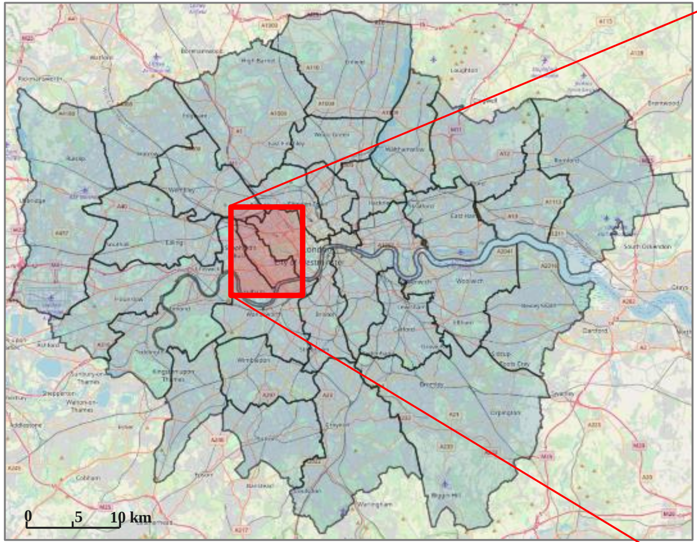
Dr. Asal Bidarmaghz, UNSW Sydney, Australia
Dr. Kathrin Menberg, Karlsruhe Institute of Technology, Germany
Professor Kenichi Soga, UC Berkeley, USA
British Geological Survey, UK

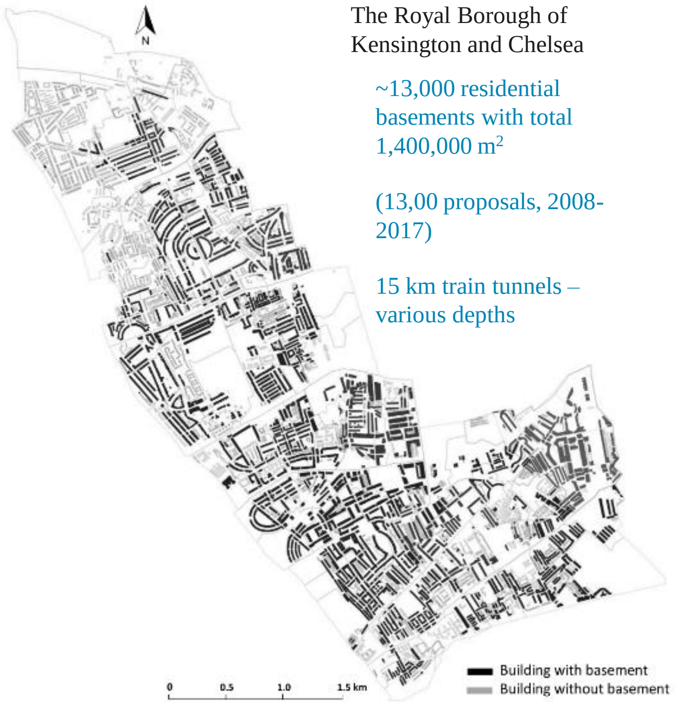
Funded by EPSRC (ASG + NSF/EPSRC Collaborative Grants)

Why Subsurface Environments?

- Subsurface Congestion: Land constraints resulting in wider use of underground & construction of ever-deeper underground structures.
- First master-plans of the underground: Helsinki (2010) & Singapore (2019).
- Underground structures have a significant influence on the surrounding ground (hydro-thermal): heat flux ~2-20 W/m^2 & groundwater temperature increase more than 5 ^{o}C.
- Need for tracking **underground climate** important for (a) resilience of ground resources (such as water, energy, etc.), (b) energy efficiency of underground structures & geothermal systems.

Ground Temperature Modelling





The Royal Borough of Kensington and Chelsea

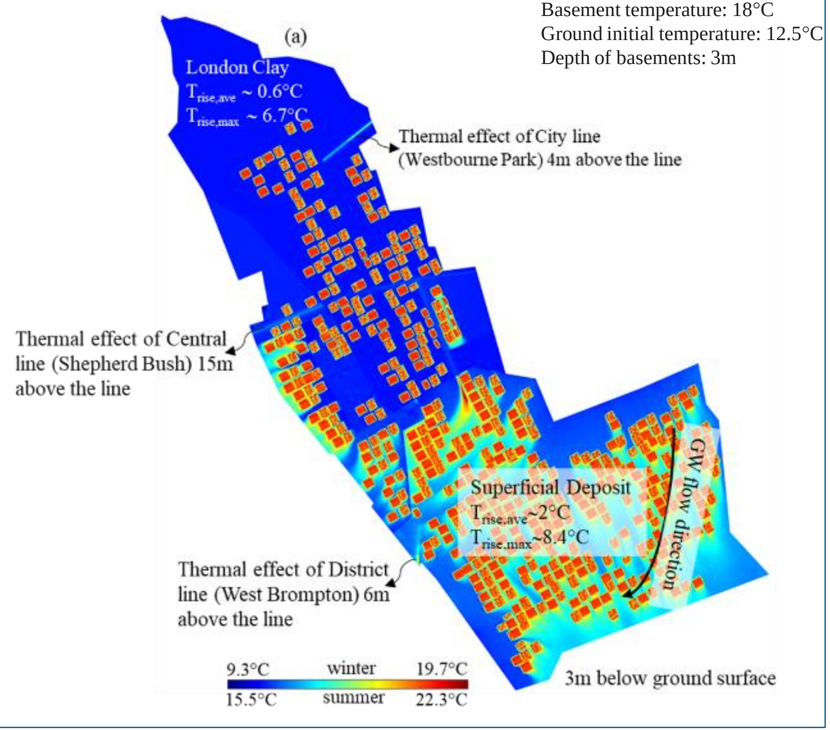
~13,000 residential basements with total 1,400,000 m^2

(13,00 proposals, 2008-2017)

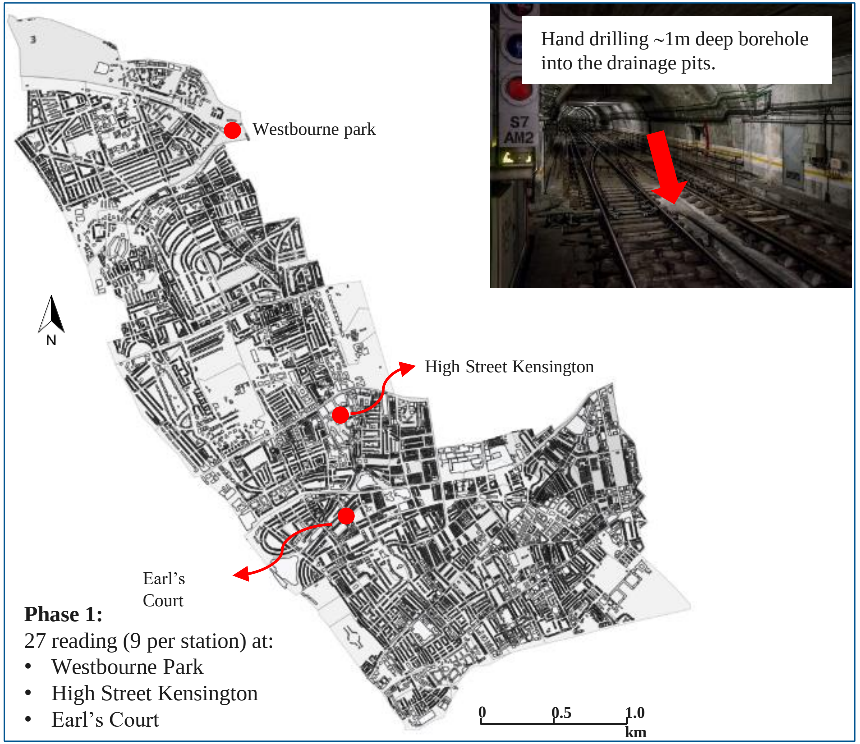
15 km train tunnels – various depths

Ground temperature disturbance – Kensington and Chelsea

Numerical evaluation - FE modelling



Measurements in collaboration with **TfL**



Phase 1:

27 reading (9 per station) at:

- Westbourne Park
- High Street Kensington
- Earl's Court

Multi-fidelity Bayesian parameter estimation framework

single-fidelity approach

m: data

n: model outputs, *k* LHS samples

GP covariance formulation:

$$\Sigma_Z = \Sigma_\eta + \begin{pmatrix} \Sigma_\delta + \Sigma_\varepsilon & 0 \\ 0 & 0 \end{pmatrix}$$

Σ_η ⇩ model emulator [*m* + *n*]

$\begin{pmatrix} \Sigma_\delta + \Sigma_\varepsilon & 0 \\ 0 & 0 \end{pmatrix}$ ⇩ model bias & observational error [*m*]

multi-fidelity approach

m: data

n_h: high fidelity model outputs, *i* LHS samples

n_l: low fidelity model outputs, *j* LHS samples

with *k* > *j* > *i*

GP covariance formulation:

$$\Sigma_Z = \Sigma_{\eta l} + \begin{pmatrix} \Sigma_\mu & 0 \\ 0 & 0 \end{pmatrix} + \begin{pmatrix} \Sigma_\delta + \Sigma_\varepsilon & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$\Sigma_{\eta l}$ ⇩ low fidelity model emulator [$m + n_h + n_l$]

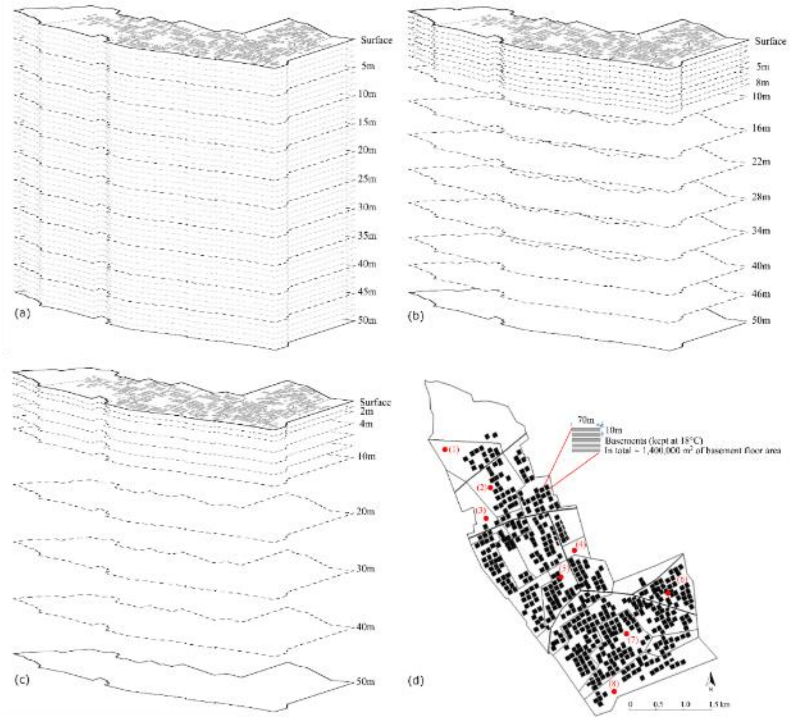
$\begin{pmatrix} \Sigma_\mu & 0 \\ 0 & 0 \end{pmatrix}$ ⇩ model mismatch (low - high fidelity) [$m + n_h$]

$\begin{pmatrix} \Sigma_\delta + \Sigma_\varepsilon & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ ⇩ model bias (data - high fidelity) & observational error [*m*]

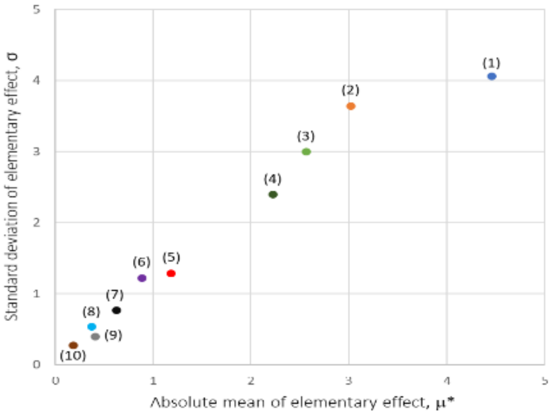
Parameter estimation for fully-coupled numerical model

Semi-3D model for groundwater and heat transfer in the urban underground of Kensington and Chelsea

Variable number of 2D planes incorporated in the approach to reflect different levels of model fidelity



Parameter screening with Morris method:

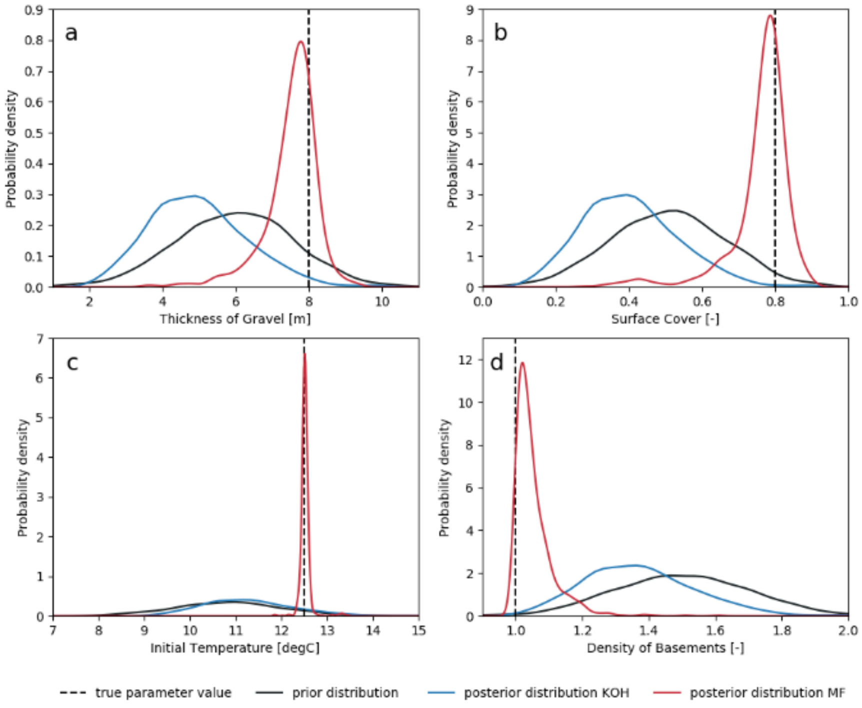


(1) Initial ground temperature [°C]
(2) Thickness of gravel deposits [m]
(3) Surface cover type [-]
(4) Density of basements [-]

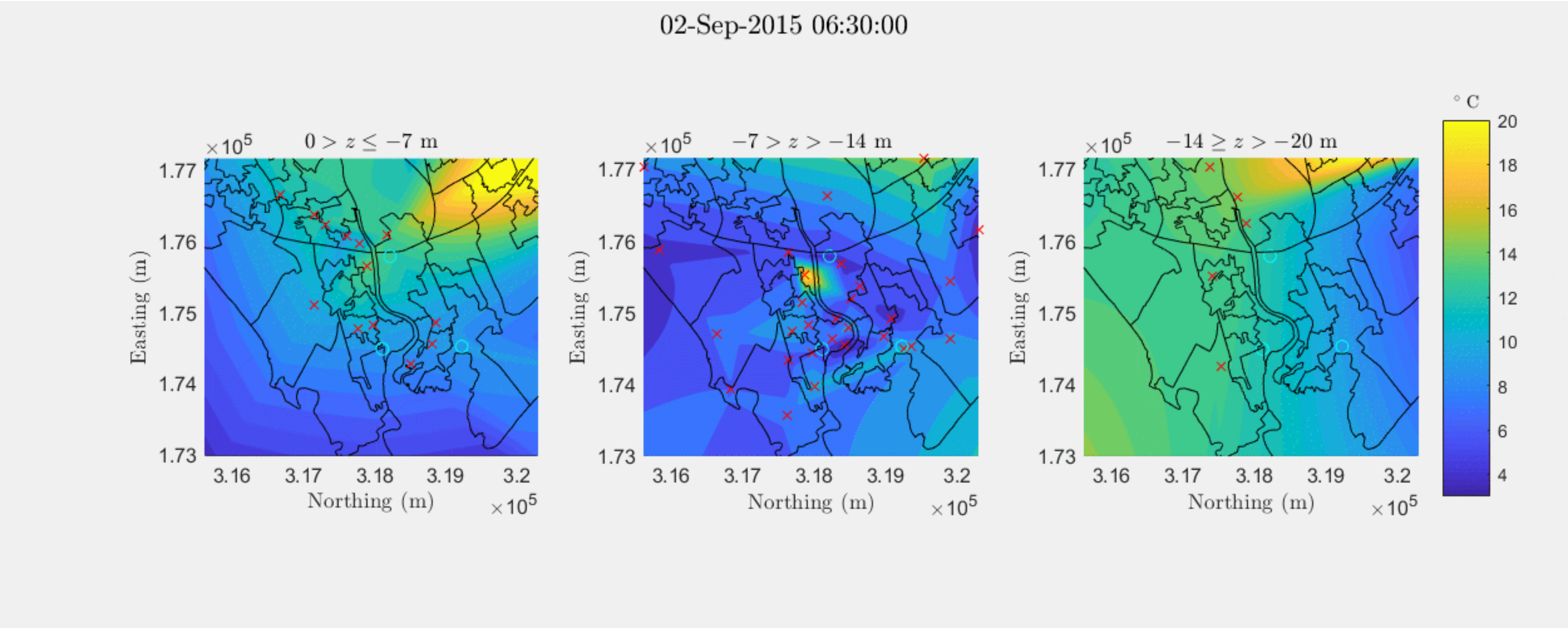
Comparison of results with standard KOH framework

→ Parameter identifiability significantly increased with multi-fidelity approach

→ “true” parameter values correctly identified with good precision

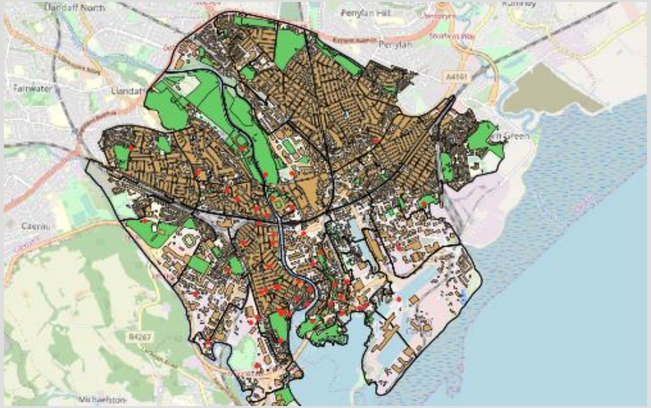


Current work with real data

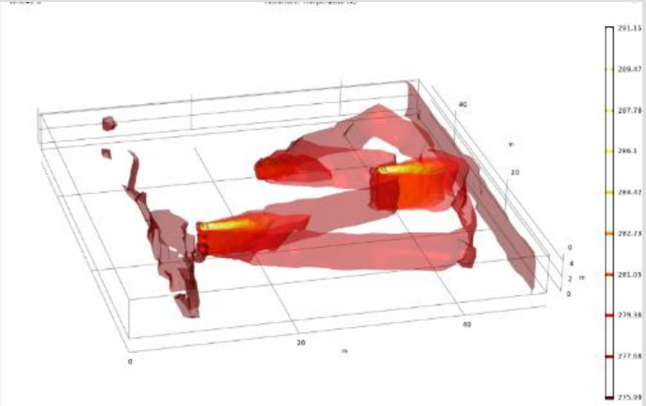


~ 60 temperature time-series throughout city of Cardiff from boreholes at different depths

Next Steps…



Calibrate model of Cardiff underground heat flow using mixed-fidelity approach.



Couple low fidelity large-scale model with emulators of detailed small-scale 3D models of archetypes.

Urban Agriculture

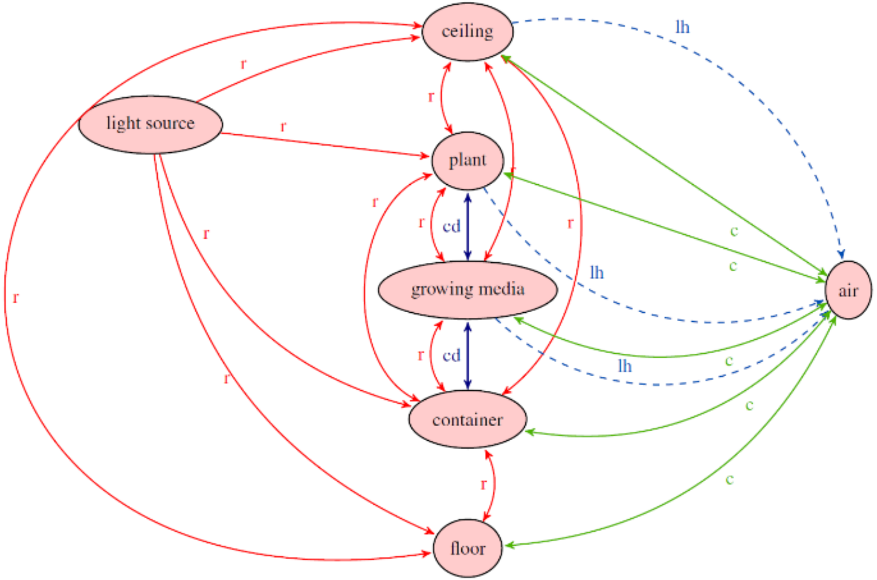
Rebecca Ward, ASG Turing RA
Melanie Jans-Singh, PhD Student, U. of Cambridge

Growing Underground, UK
Research Software Engineers, Alan Turing Institute

Why Urban Agriculture?

SeaWater Greenhouse's roof, London

Research Challenges



- Coupled ODE models of heat & mass exchange and plant growth. Largely empirical and limited to specific crops

- No models that couple greenhouse environment with standard buildings

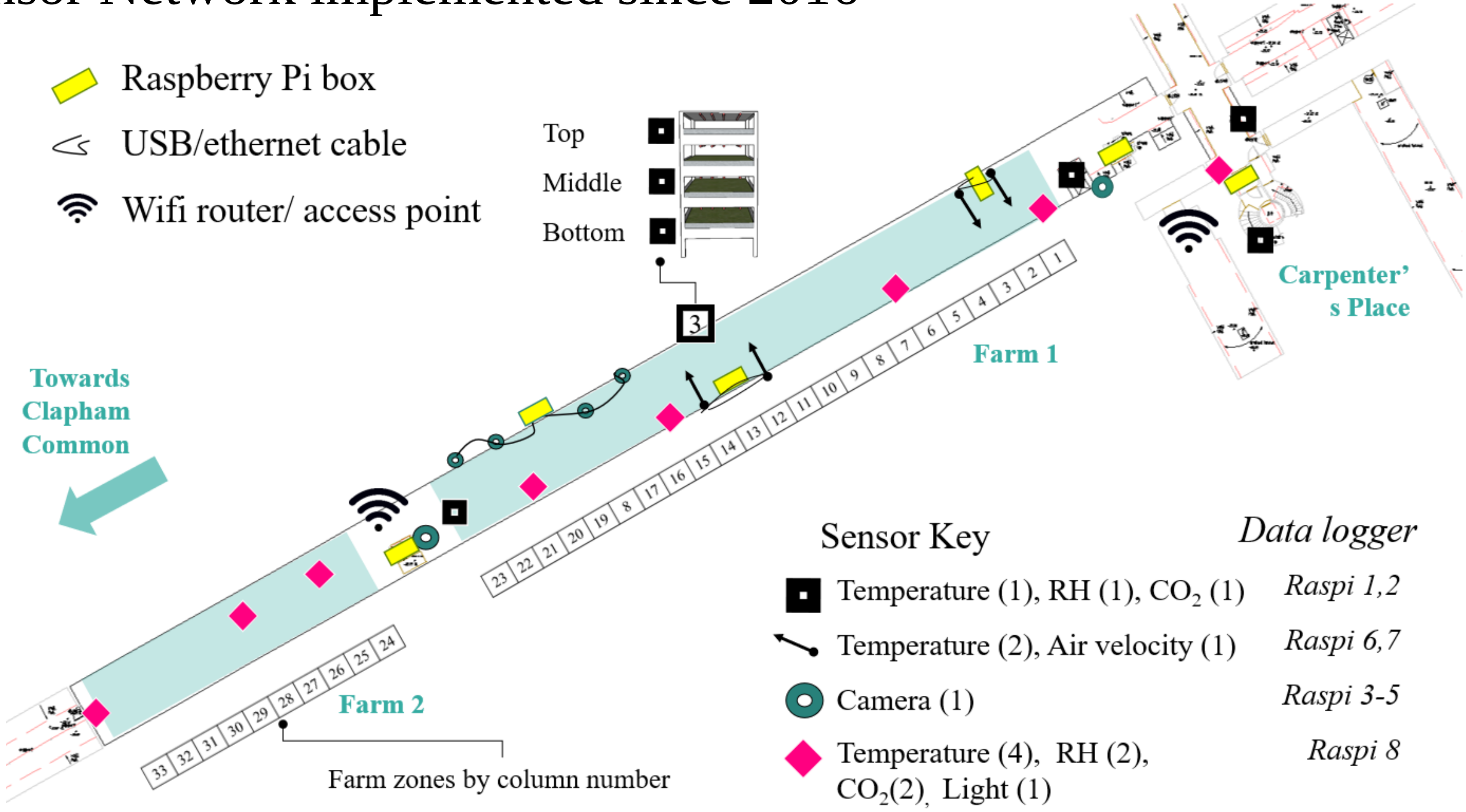
Growing Underground: our poster child…

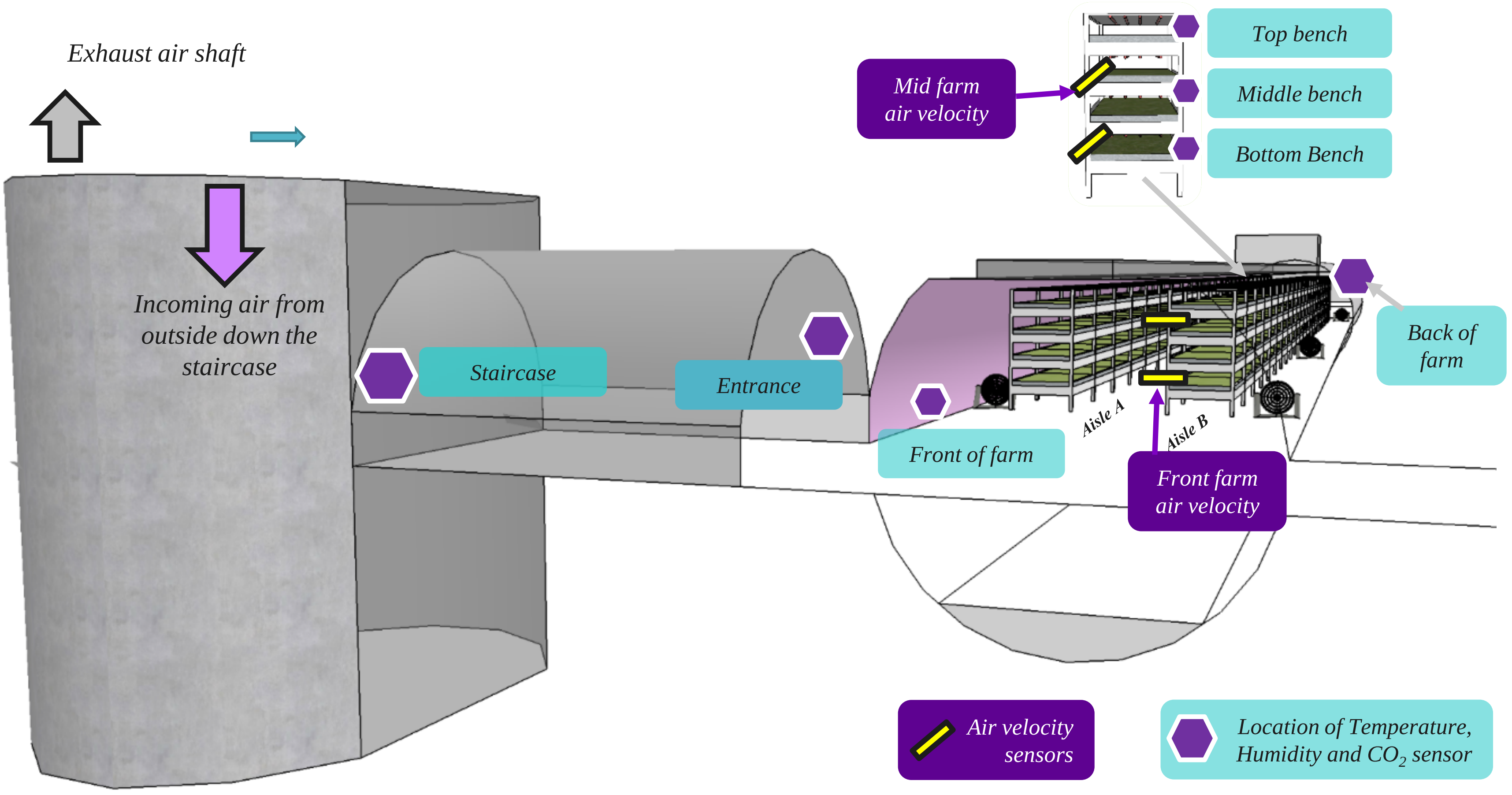
Derelict Tunnels

Initial Farm Trials

Commercial Farm (2015-)

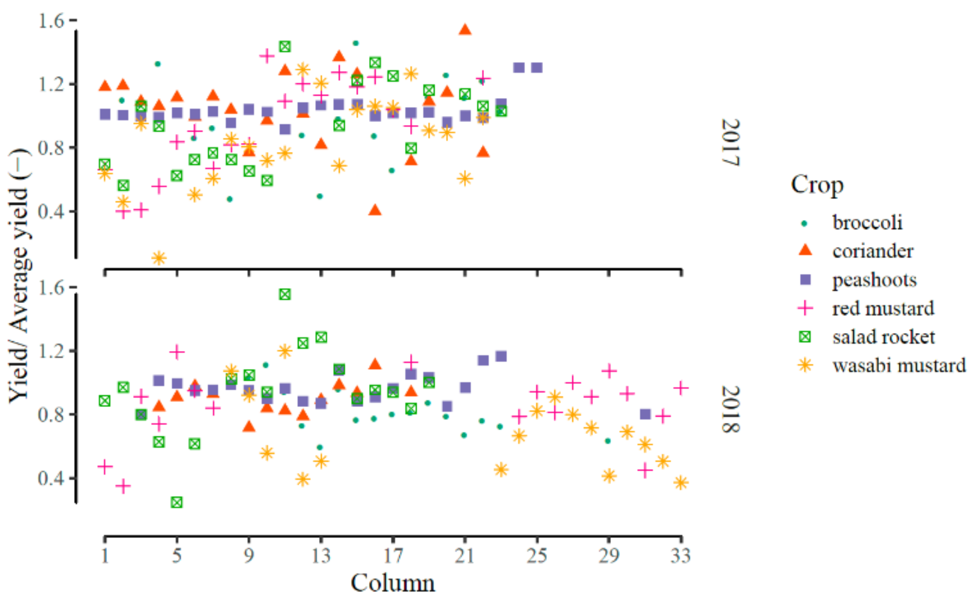
Sensor Network implemented since 2016

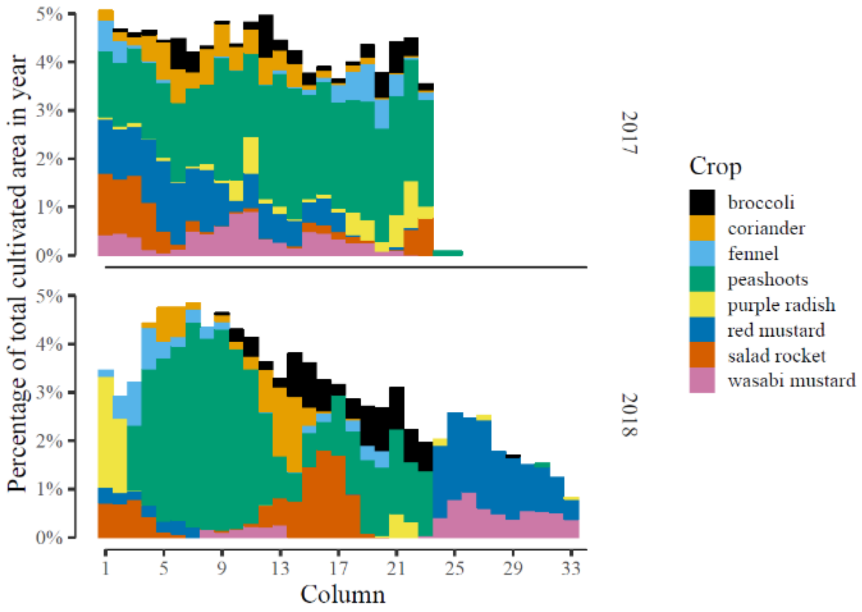




3D sensor network to capture spatial variations

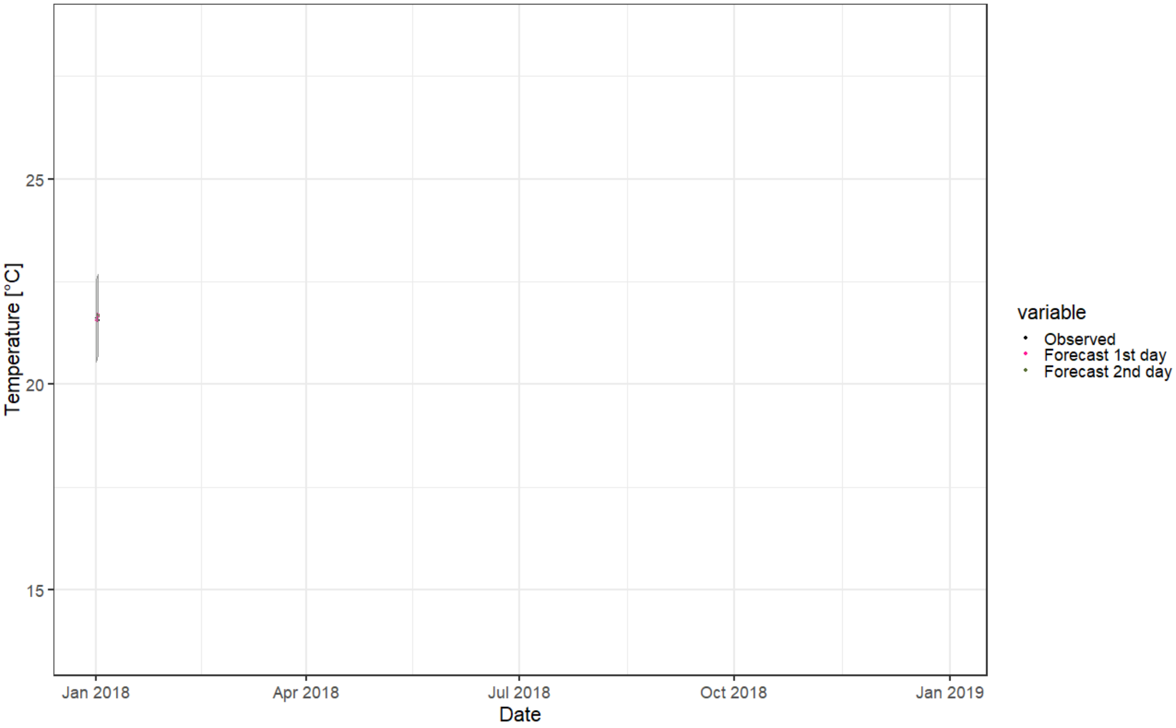
Crops have different yields at different locations





A. Data Models

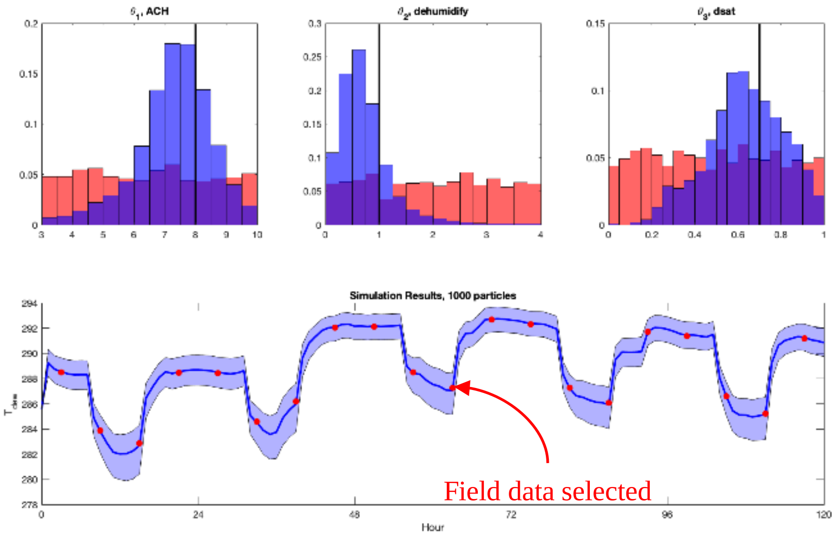
Forecasting environment in the tunnels



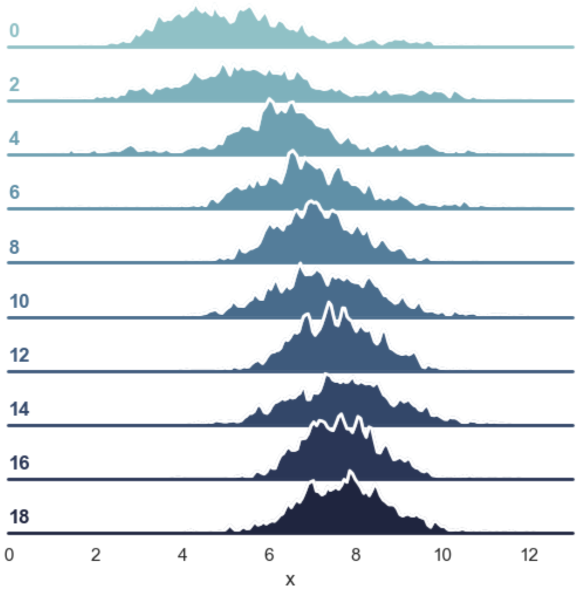
Objectives

- Forecast environment
- Forecast even with missing data
- Estimate spatial variations
- Optimize location of crops
- Use statistical model to test operational improvements

B. Sequential Updating of physics-based model using sensor data

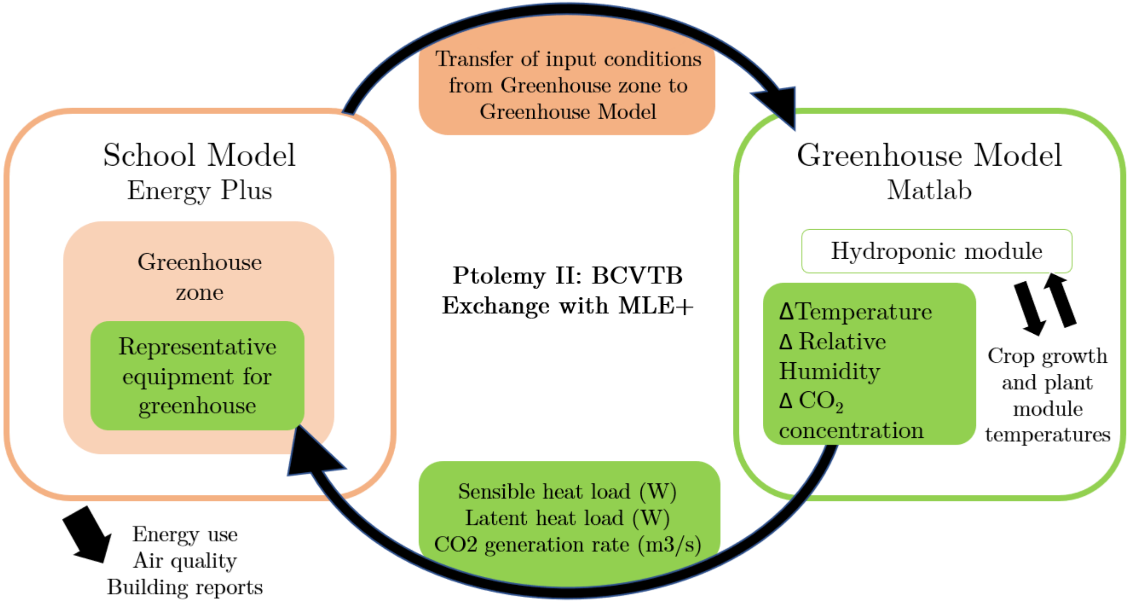


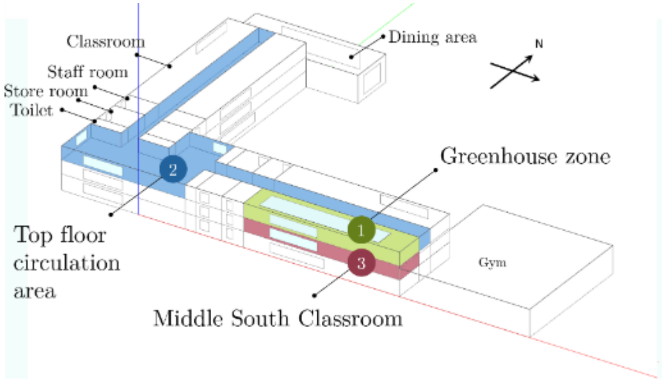
1000 particles, Run time = 5 minutes 20 seconds



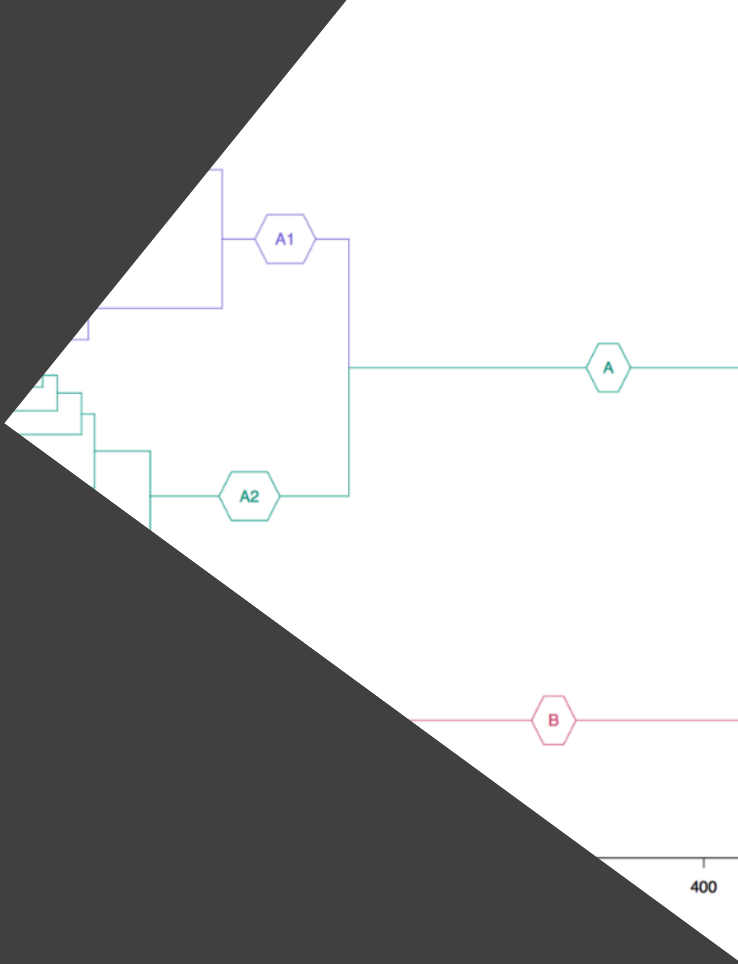
Sequential evolution of ventilation rates in the tunnel

C. Coupling of greenhouse model with building energy model





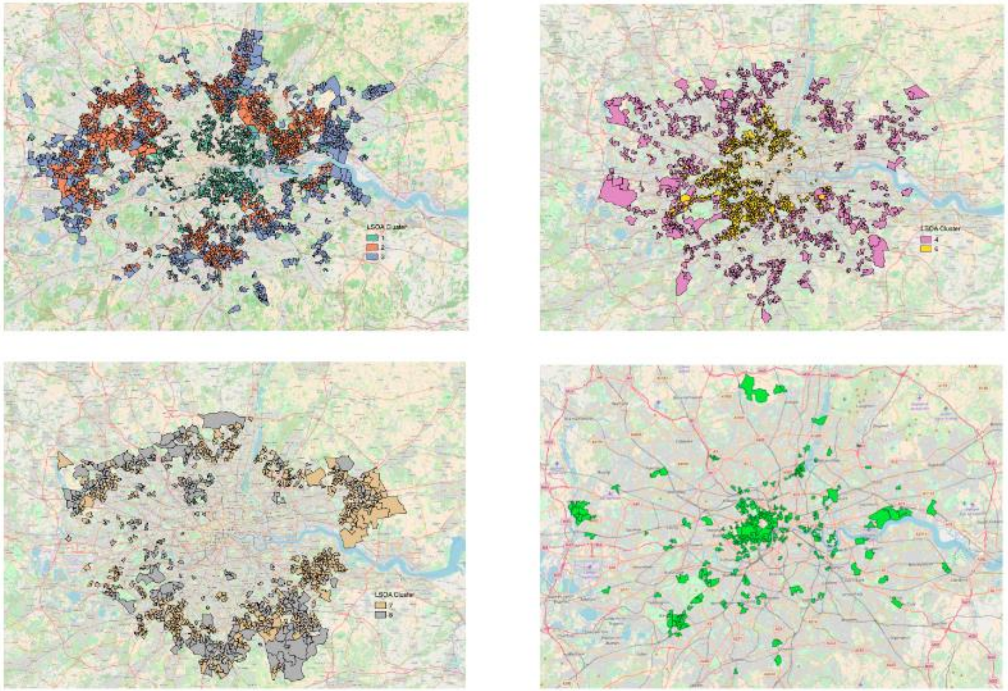
Energy Planning



Andre Neto-Bradley, PhD Student, U. of Cambridge
Indian Institute of Human Settlements, India

Mingda Yuan, PhD Student, U. of Cambridge
Perkins + Will (Innovate UK Secondment)

Locally Tailored Design of Energy Policies

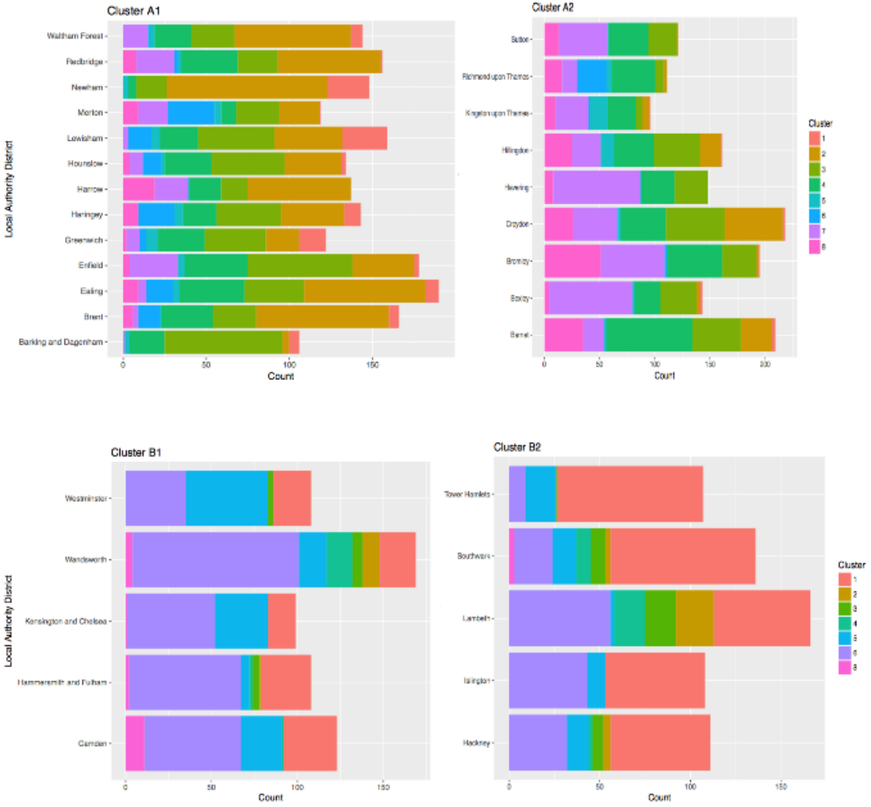


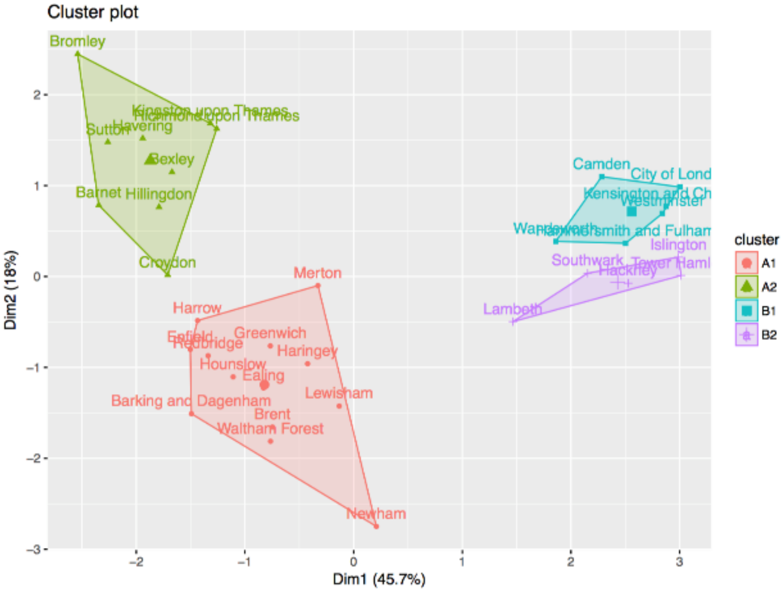
8 clusters of residential gas consumption across ~4345 LSOA's of London based on 19 variables per LSOA using Gaussian Mixture Model

Heating consumption is explained both by socio-economic factors and physical features.

We want to understand variations of consumption through these.

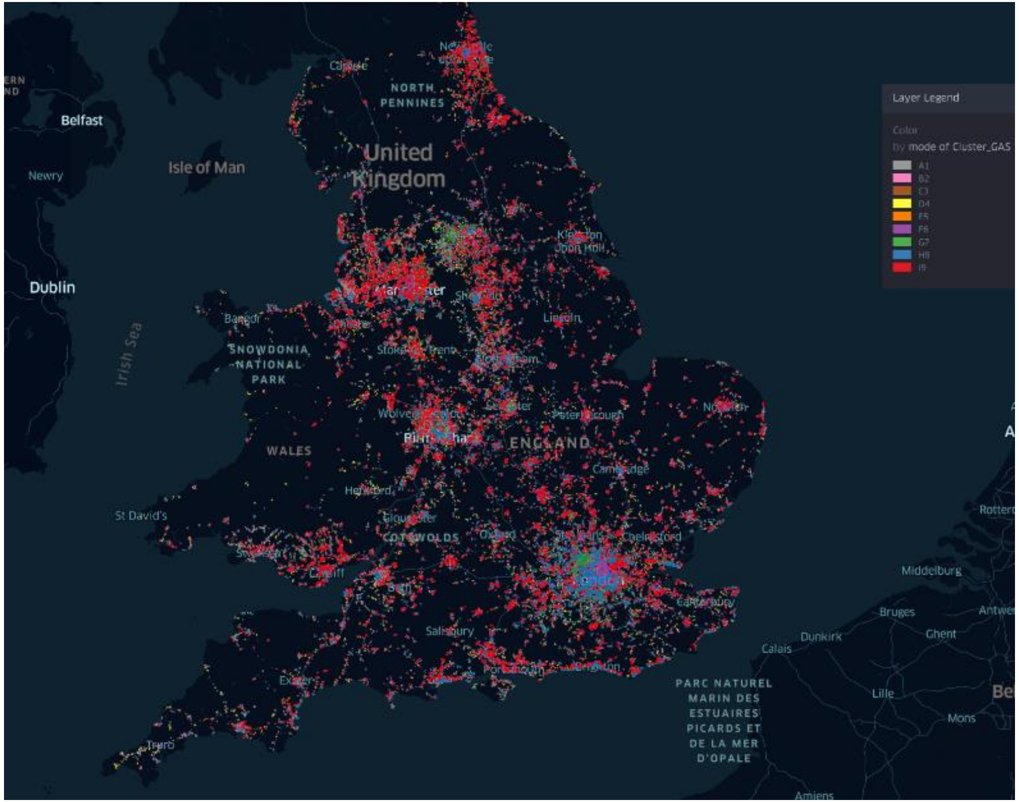
- Household composition
- Income & employment
- Home ownership
- Health
- Physical properties of dwelling





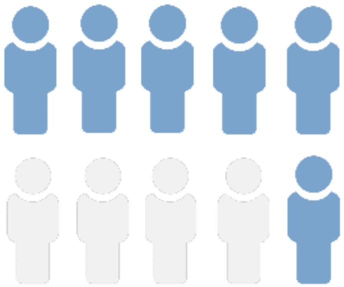
4 clusters of 32 local authorities with 8 clusters of 4345 LSOA’s (19 variables per LSOA)

Extension to national/sub-national analysis



- For India: new data collected across 5 states
- For the UK: public databases

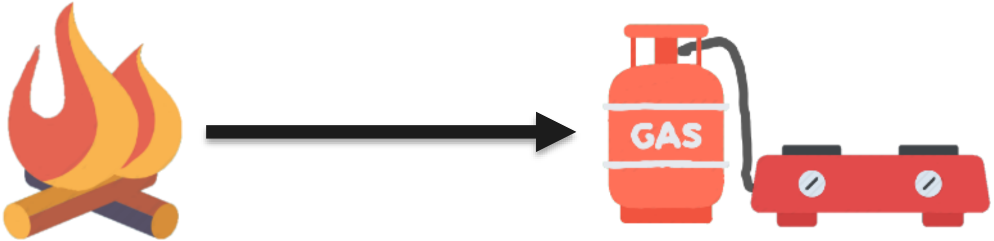
60% of **Indians** rely on **biomass** fuel…



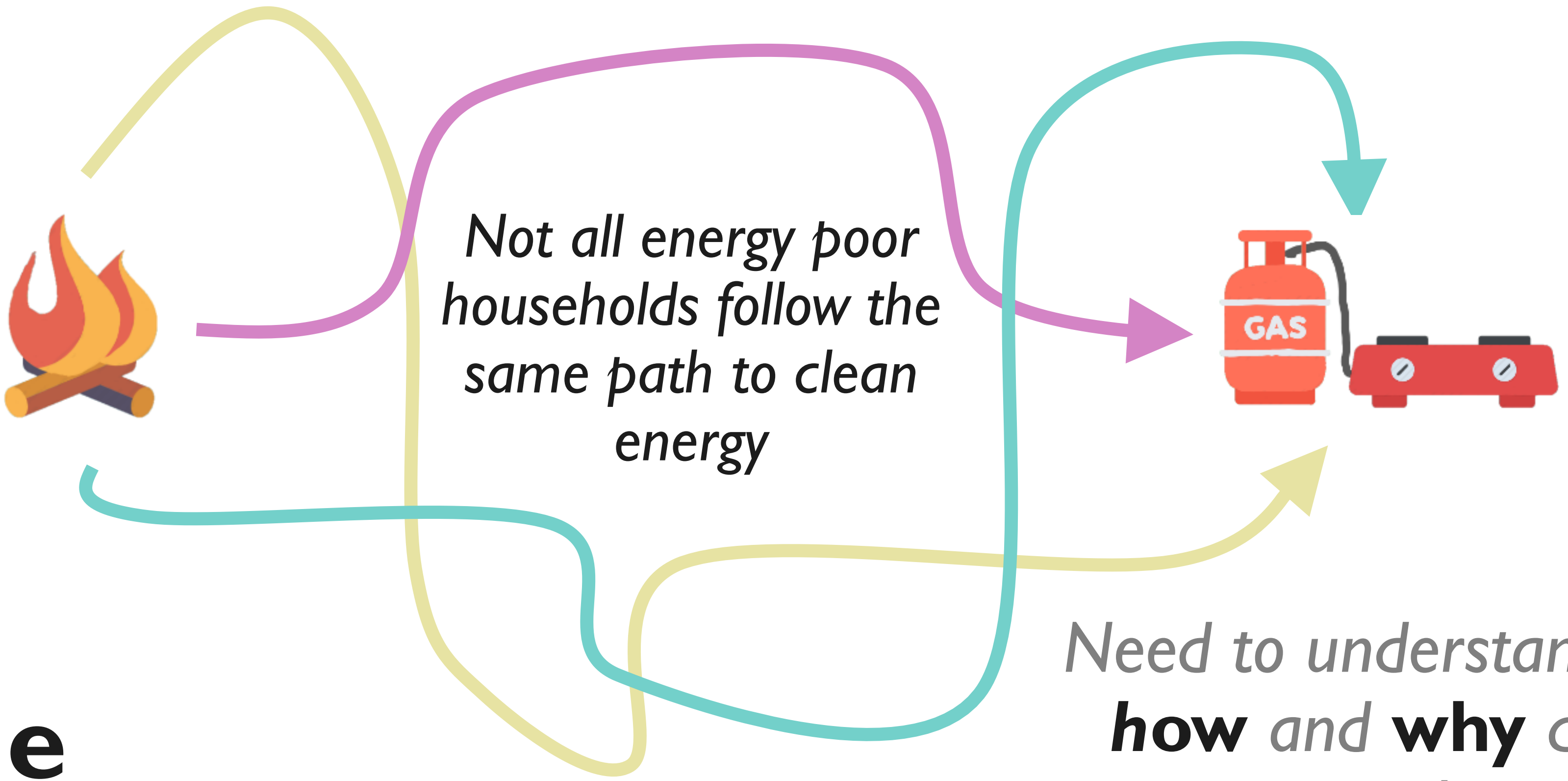
… with **1.2 million deaths a year** from **air pollution.**

The Problem

A **residential clean energy transition** is needed

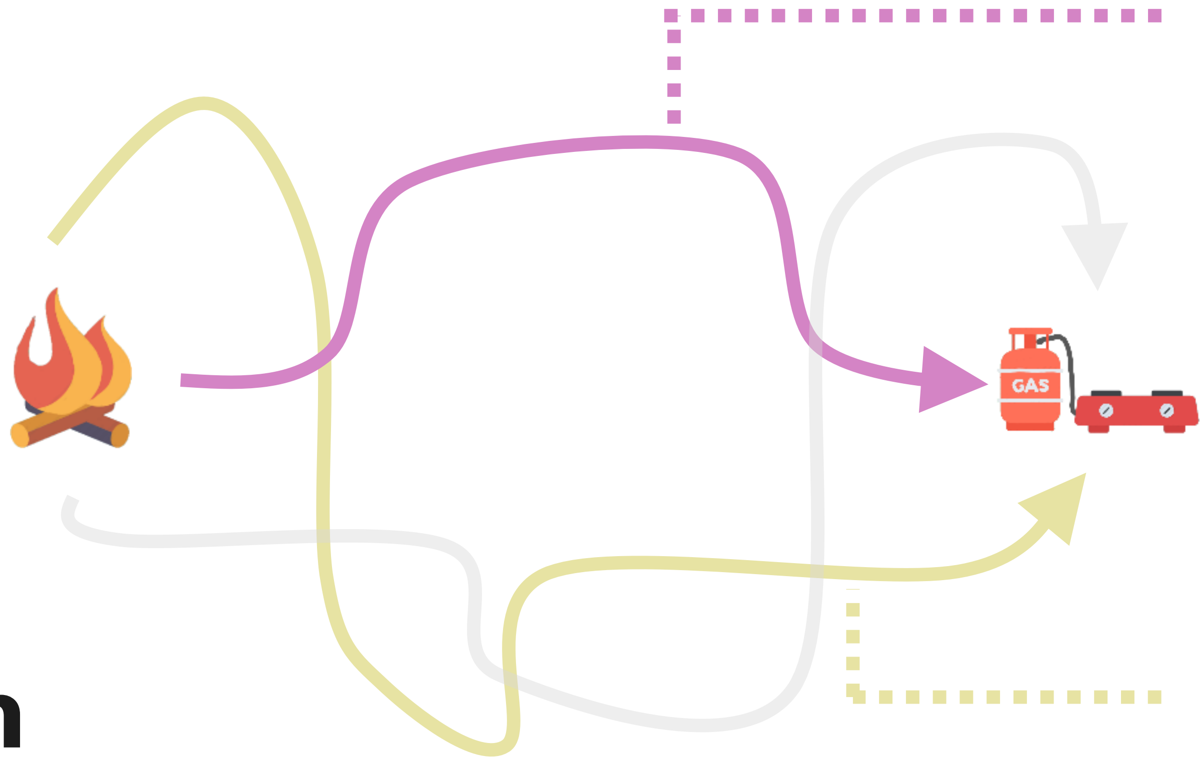


The Challenge



Need to understand ***how*** *and* ***why*** *do people* ***use energy****?*

In Practice

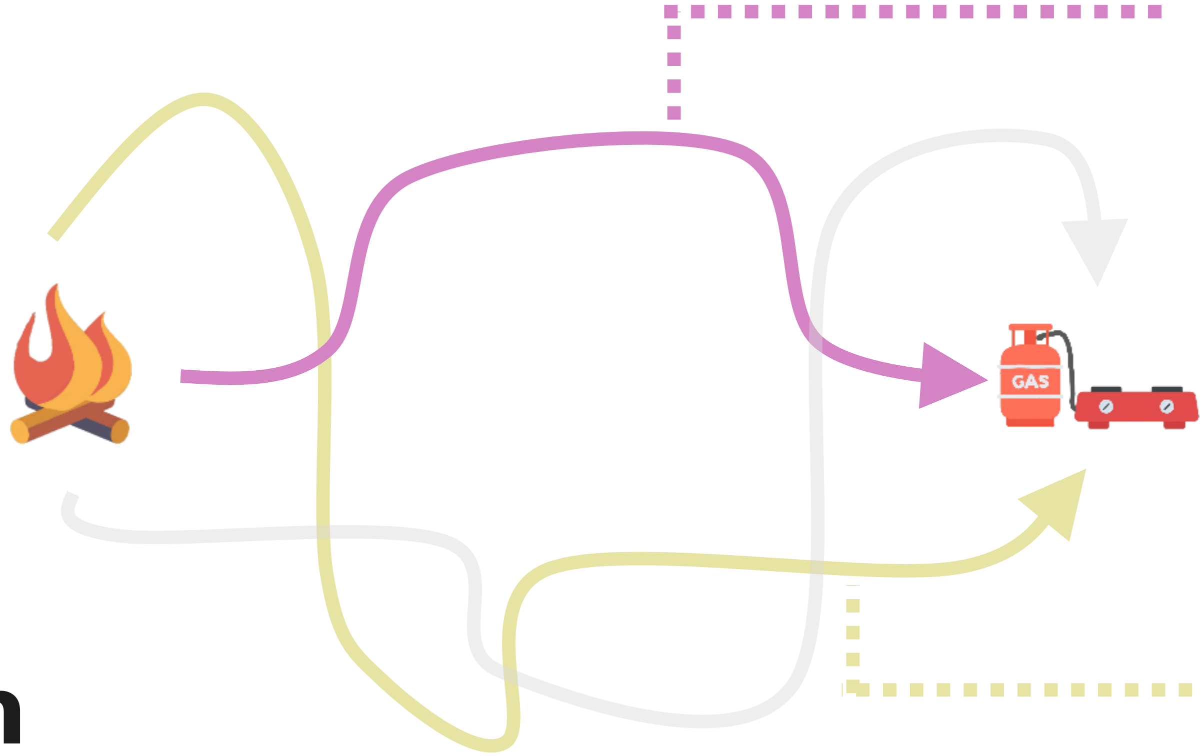


Pathway A
[i.e. Educated 2nd generation]
+ *Job security*
+ *Higher level of education*
+ *Established community*
+ *Legal tenancy*

Barriers to transition:
- Different saving priorities
- No LPG shop nearby

Pathway B
[i.e. Migrant daily wage labourers]
+ *Lack of job security*
+ *Poor house quality*
+ *No community support*
+ *No legal tenancy*

Barriers to transition:
- Informal living arrangements
- Poor access to infrastructure and community



Outlook for Pathway A

Current subsidy and supply policies are effective at encouraging uptake of cleaner fuels.

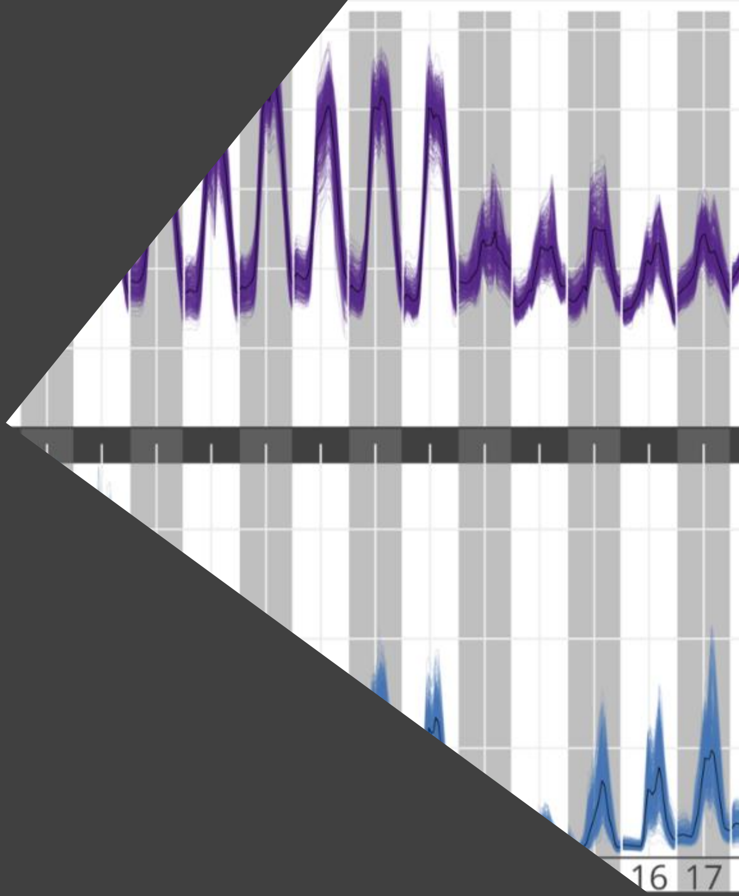
Outlook for Pathway B

Current subsidy and supply policies are NOT effective for such households, alternatives might be:

- Policy to address utility access for informal settlements?
- More flexible payment systems?
- Support for better housing?

In Practice

Stochastic Energy Models



Rebecca Ward, PhD Student, U. of Cambridge

Dr. Bryn Pickering, ETH Zurich
National University of Singapore
Institute of Infocomm Research, Singapore

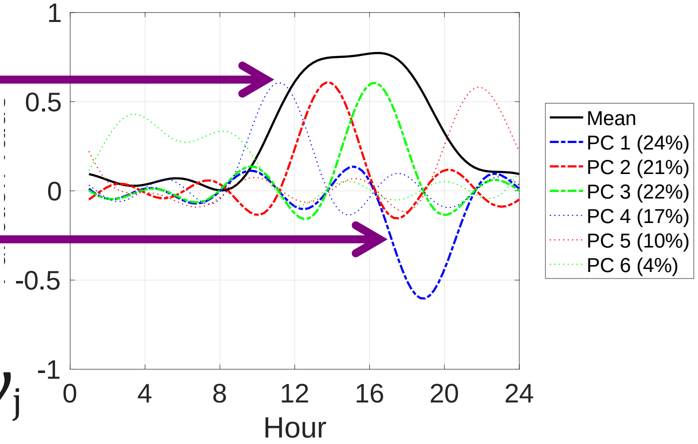
Funded by Laing O'Rourke & EPSRC

We want to associate each distinct space within a building with a **functional signature** as its identifier

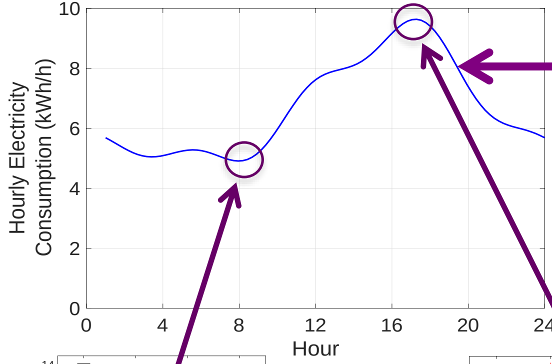
	Ground	First	Second
East	Admin	Student	Student
South-East	Mixed	Mixed	Mixed
South-West	Canteen	Classroom	Classroom
West	Classroom (Lecture theatre)		
North-West	Library	Meeting space	Classroom
North-East	Admin	IT Lab	IT Lab

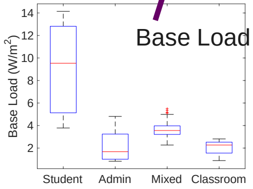
Functional signatures

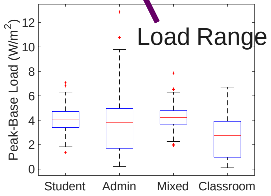
Express profile as a weighted sum of a mean function, $\boldsymbol{\mu}$ and $\boldsymbol{N}$ functional principal components, $\boldsymbol{v}$, with weighting coefficients or 'scores', $\boldsymbol{\alpha_{i,j}}$ for each space, $\boldsymbol{i}$, for each principal component $\boldsymbol{j=1..N}$

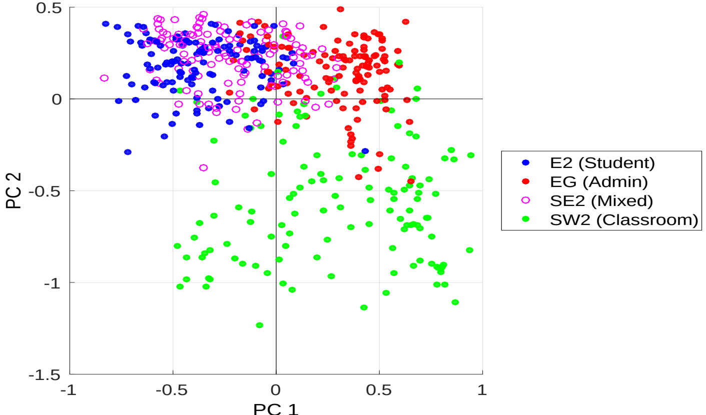


$$\mathbf{Diversity} = \boldsymbol{\mu} + \Sigma\alpha_{i,j}\boldsymbol{v}_j$$



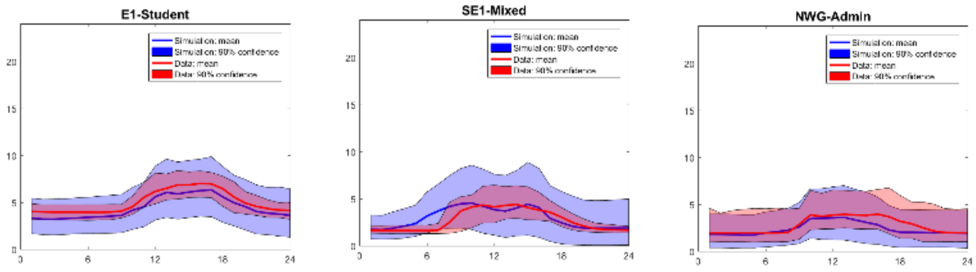




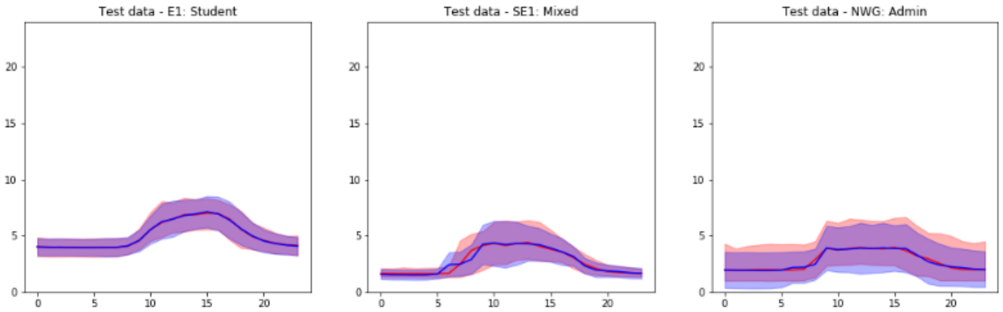


Test results for plug loads in Buildings

FDA Model



Autoencoder



Red: Actual Data
Blue: Profile from Sampled Data

Next Steps:

- Links across building and urban scales through new projects with urban analytics and the Data Sciences

In summary

Subsurface Environments

Urban Agriculture

Energy Planning

Stochastic Energy Models