Modelling individual-building energy use and indoor health exposures for urban areas using machine learning

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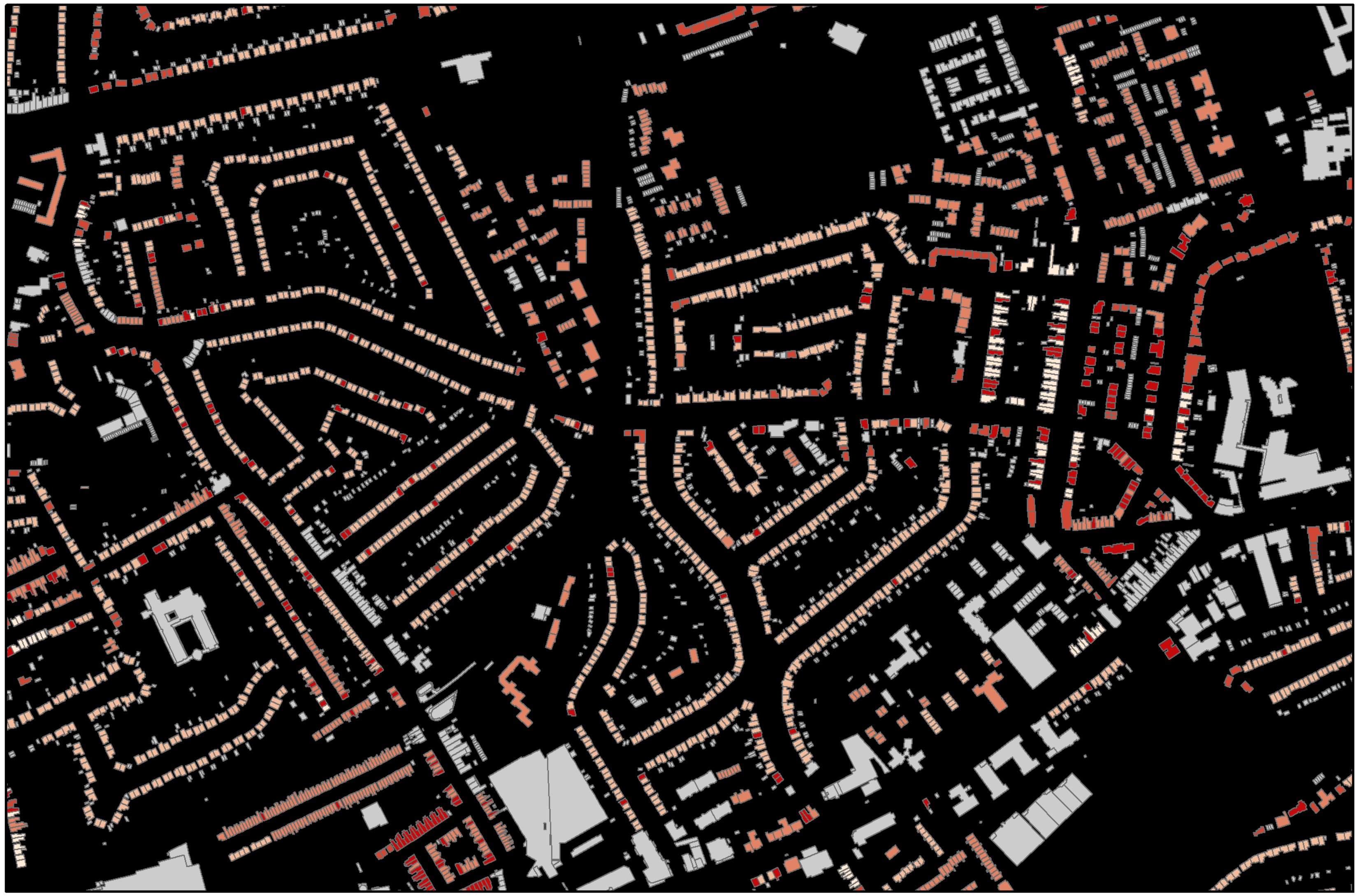
Outline

1. Background
2. Tools we use
3. Example results
4. Conclusions



1. About Us

- The Bartlett
  - UCL's school of the Built Environment
    - #1 Institution in the world for Architecture/Built Environment (QS)
  - Institute for Environmental Design and Engineering
    - "pursues a deeper understanding of the interactions between the built environment and health, human wellbeing, productivity, energy use and climate change"

1. Research we do

- Interested in the intersection between health and energy in the buildings
- Involvement in a number of projects estimating exposure to environmental hazards in indoor environments, e.g. for
    - UK Government
    - Public Health England
    - UK Committee on Climate Change
    - World Health Organisation
- Longstanding collaboration with environmental epidemiologists at LSHTM to combine buildings and health data.

1. Background – Why Housing?

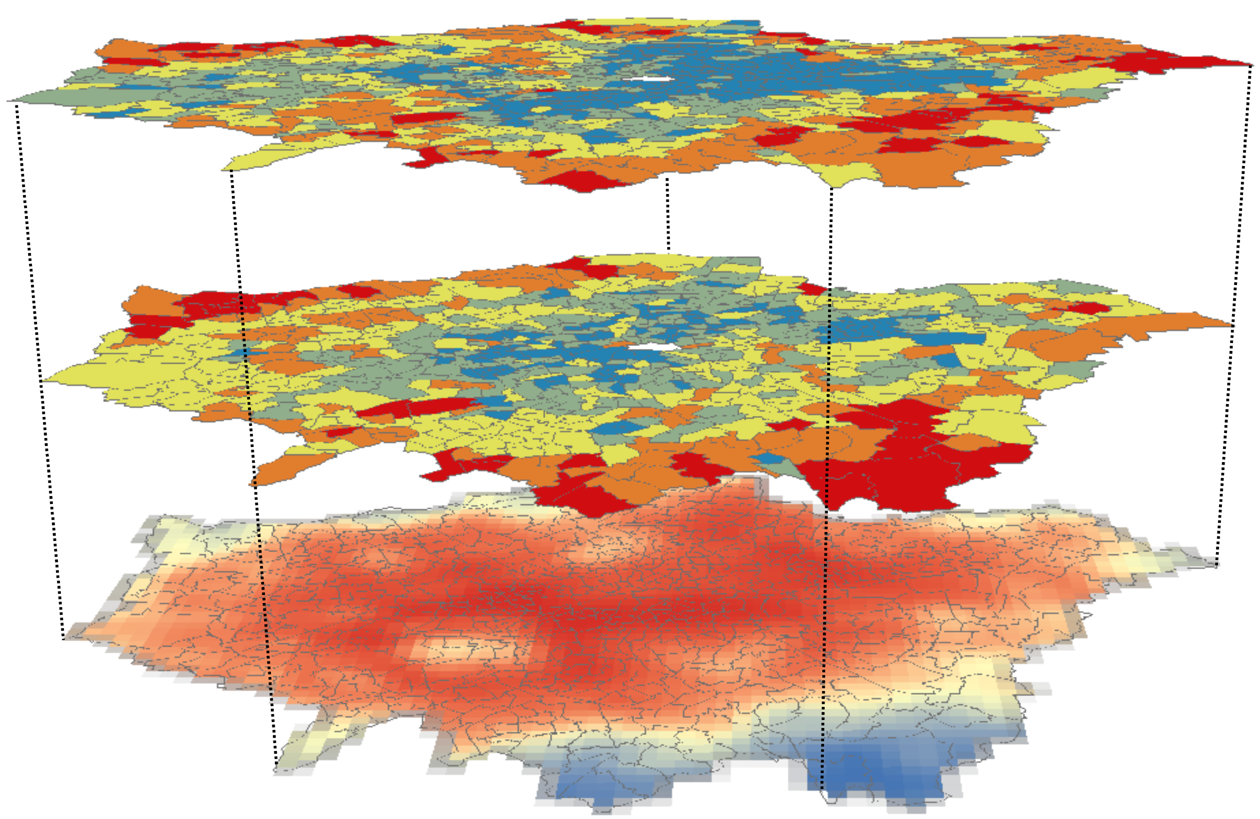
- There is a critical need to reduce energy consumption and CO_2 emissions
  - Buildings are responsible for 25% of all greenhouse gas emissions in the UK
  - Very poor energy performance
- In developed countries, around 90% of time spent indoors
- Around 60% or our time is spent in our own homes
- Housing can modify population exposures to e.g:
  - Cold
  - Heat exposure during hot weather
  - Air pollution from both outdoor and indoor sources
  - Communicable disease, damp, etc….

1. Background – Hazards, exposures, and vulnerabilities

- Climate change means higher average temperatures and an increasing number of heatwave events will occur in the future
  - Heatwaves such as the 2003 heatwave that is thought to have caused 70,000 excess deaths across Europe will become the norm
- The population is also aging
  - The elderly are significantly more vulnerable during hot weather and air pollution episodes.
- Cities are developing
  - Urban areas are growing
- Houses are changing
  - We need to build energy efficient housing

1. Background – Research Questions

- What is the role of housing on population health?
- How might changes to housing from different policies impact energy consumption and population health?
- Where are the areas at risk due to the environment, vulnerable populations, and poor housing?



2. Tools we use – Building Physics

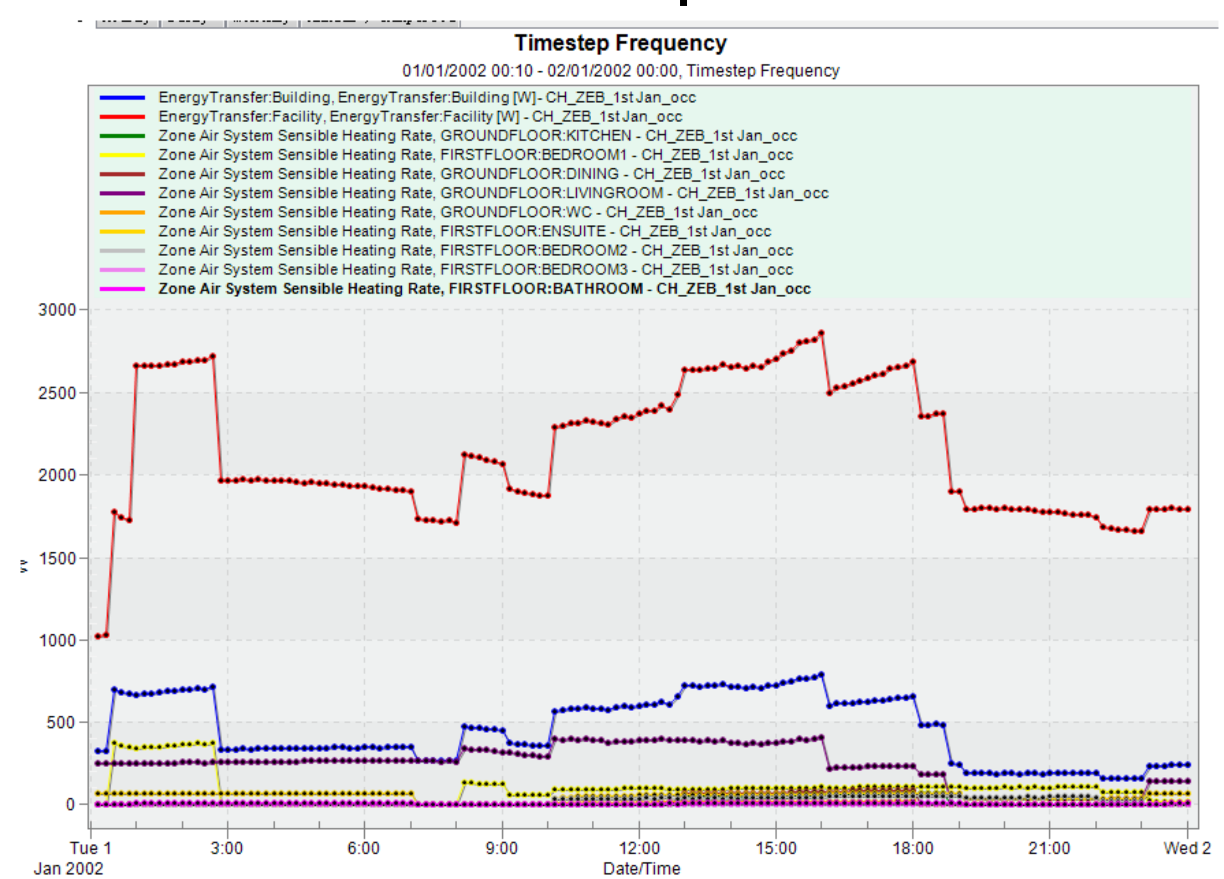
- We use **EnergyPlus**, a dynamic building simulation tool, to model typical archetypes within the English housing stock
- EnergyPlus is a building simulation software which can estimate dynamic indoor conditions given outdoor weather conditions and occupant behaviours

Building inputs

.epw file input

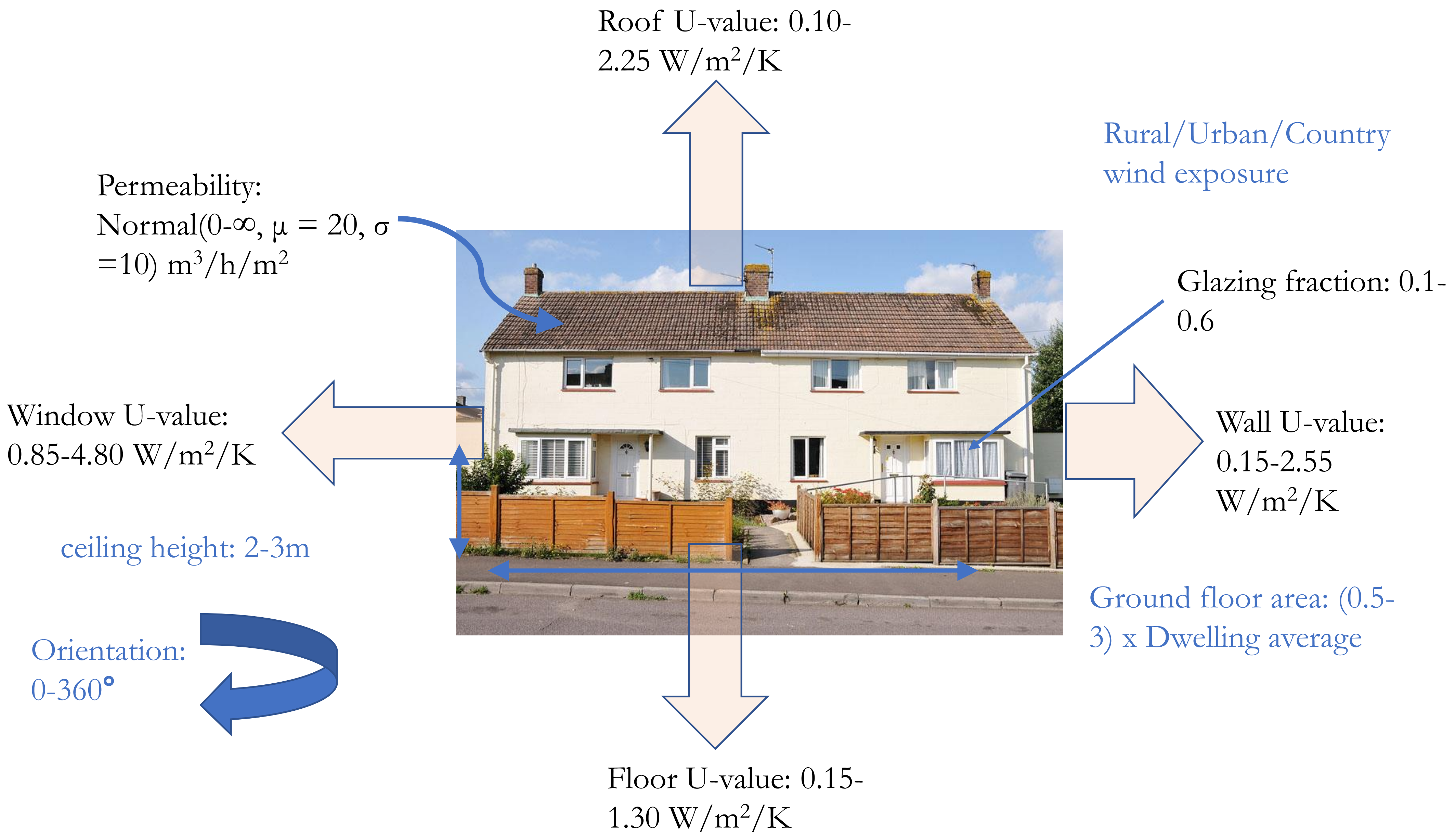
EnergyPlus

Output:



2. Tools we use – Building Physics

- A Python tool (EPG2) can mass generate unlimited numbers of EnergyPlus files using specific or random input data



2. Tools we use – Building Physics

- Model results for energy, temperature, and ventilation (as proxy for indoor air quality) compare quite well with measured values
  - Scope for additional (Bayesian) calibration with measured values

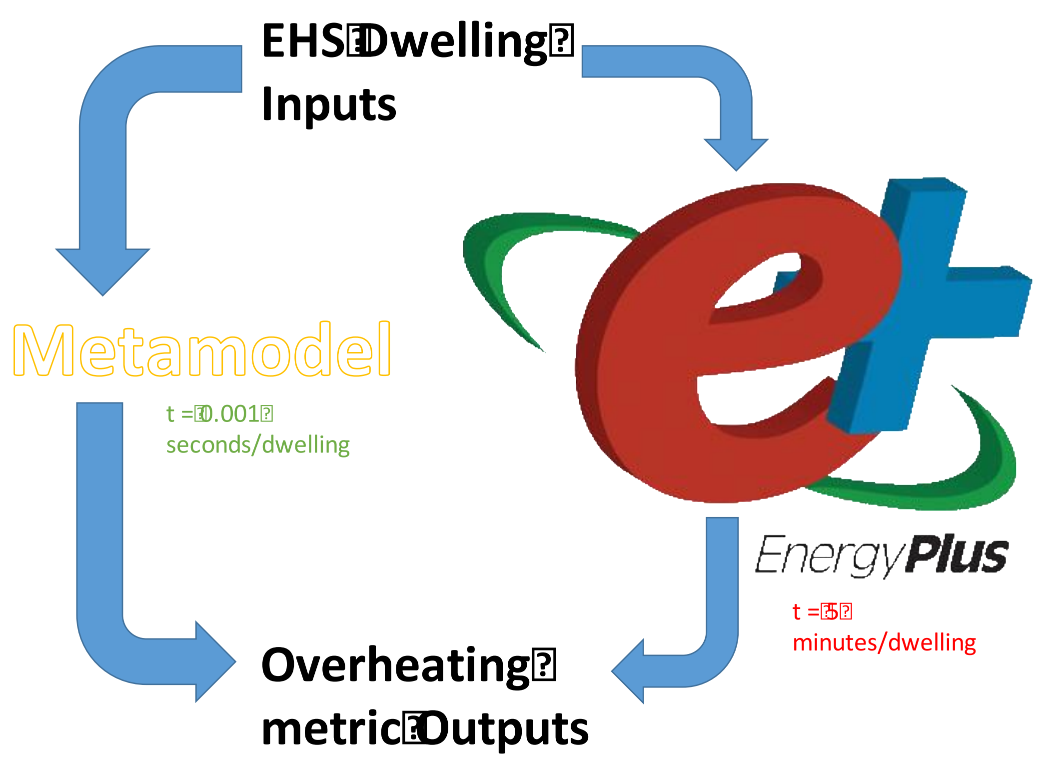
- Problem:
  - EnergyPlus is slow – it can take 5-10 minutes to simulate a single dwelling for a year on a laptop
  - We want to do things at population or stock-level
  - We want to be able to rapidly compare housing and environment policies

- Solution
  - High Throughput Computing
  - Machine learning

2. Tools we use – Building Physics

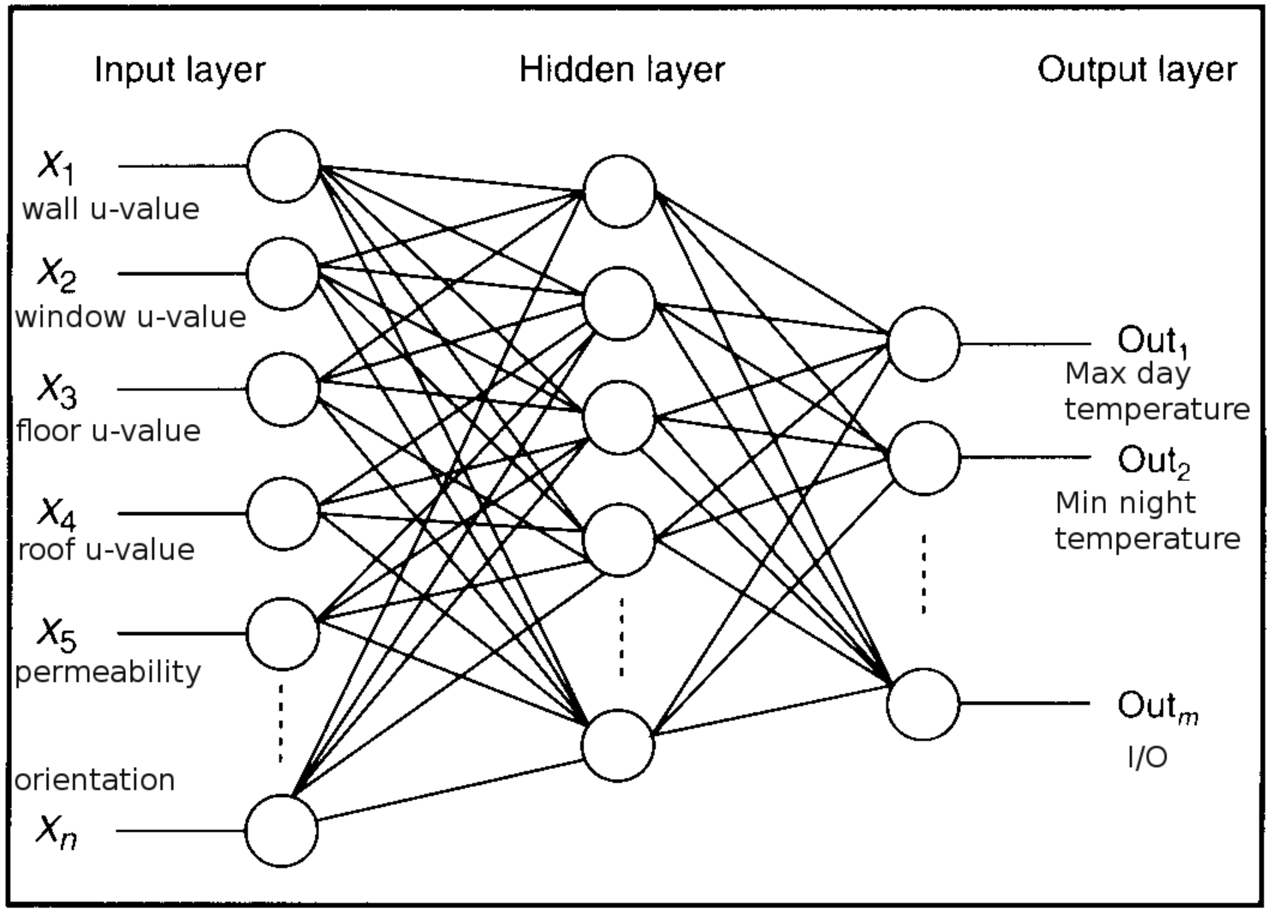
- A ***metamodelling framework*** is used to replicate the EnergyPlus models...

  1. Generate a relatively large number of dwellings with input parameters randomly selected from building surveys (e.g. The English Housing Survey, representative sample of ~16,000 dwellings) (PyDoE)
  2. Run simulations on them on UCL HTC Legion
  3. Collate the simulation metrics into something meaningful
  4. Use machine learning to develop a model that relates the inputs from step 1 to the outputs from step 3 (PyBrain, now Keras)



2. Tools we use – Machine learning

- Neural Networks performed best of all machine learning methods
  - Much faster!
    - Can do around 10,000 dwellings a minute
  - We have developed NN models for:
    - Space heating energy demand
    - Indoor overheating risk
    - Indoor cold risk
    - Indoor air pollution (with flags for houses with indoor sources of pollution)
    - Moisture/Damp

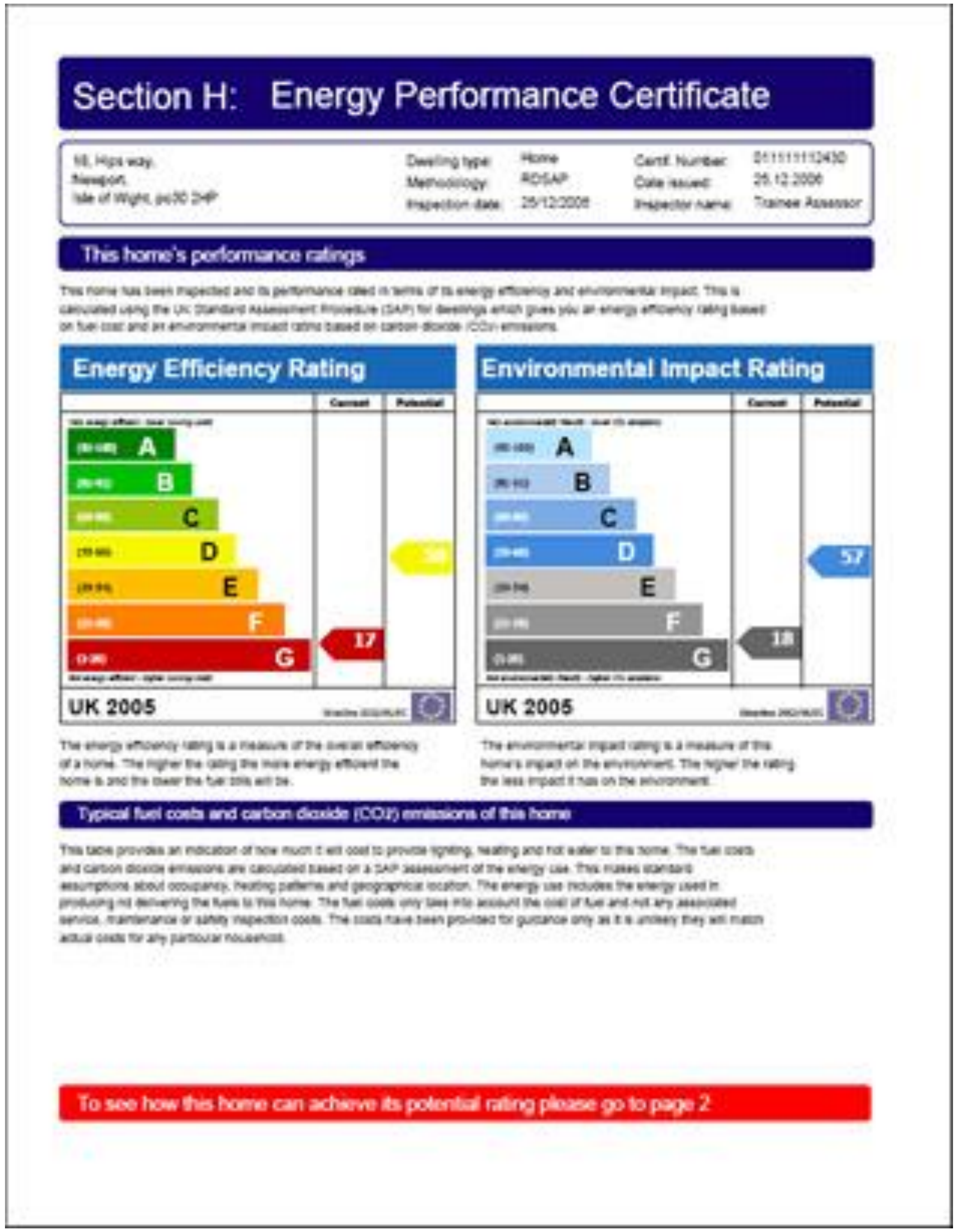


Example of a typical neural network architecture

Symonds et al, (2016). Development of an England-wide indoor overheating and air pollution model using artificial neural networks. JBPS, 1-14

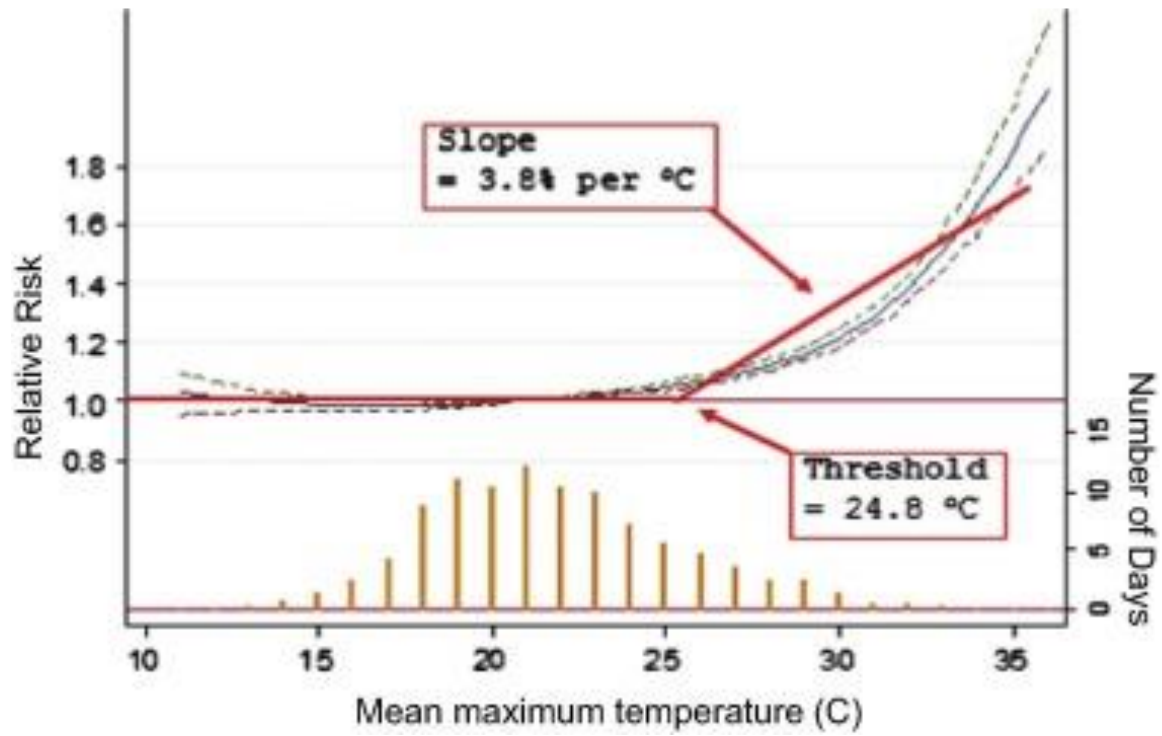
2. Tools we use – Building Stock Models

- Model can be applied to parameterised housing stock models:
  - English Housing Survey (~16,000 dwellings)
    - Representative
    - Includes occupant info where vulnerabilities can be inferred
  - Energy Performance Certificate (EPC) database
    - Database of around 11 million homes in England and Wales with address-level information
    - Can be located (useful for local UHI or ambient air pollution)



2. Tools we use – Health Calculations

- Health models can be used to relate exposures to health outcomes.
  - Usually derived using outdoor relationships which we assume are valid for indoors
  - Metamodel estimates exposure
- E.g. Heat Exposure
  - The age(s) of the dwelling occupant
  - Background mortality rate for age groups
  - Outdoor weather conditions
  - Housing modification of temperature exposure

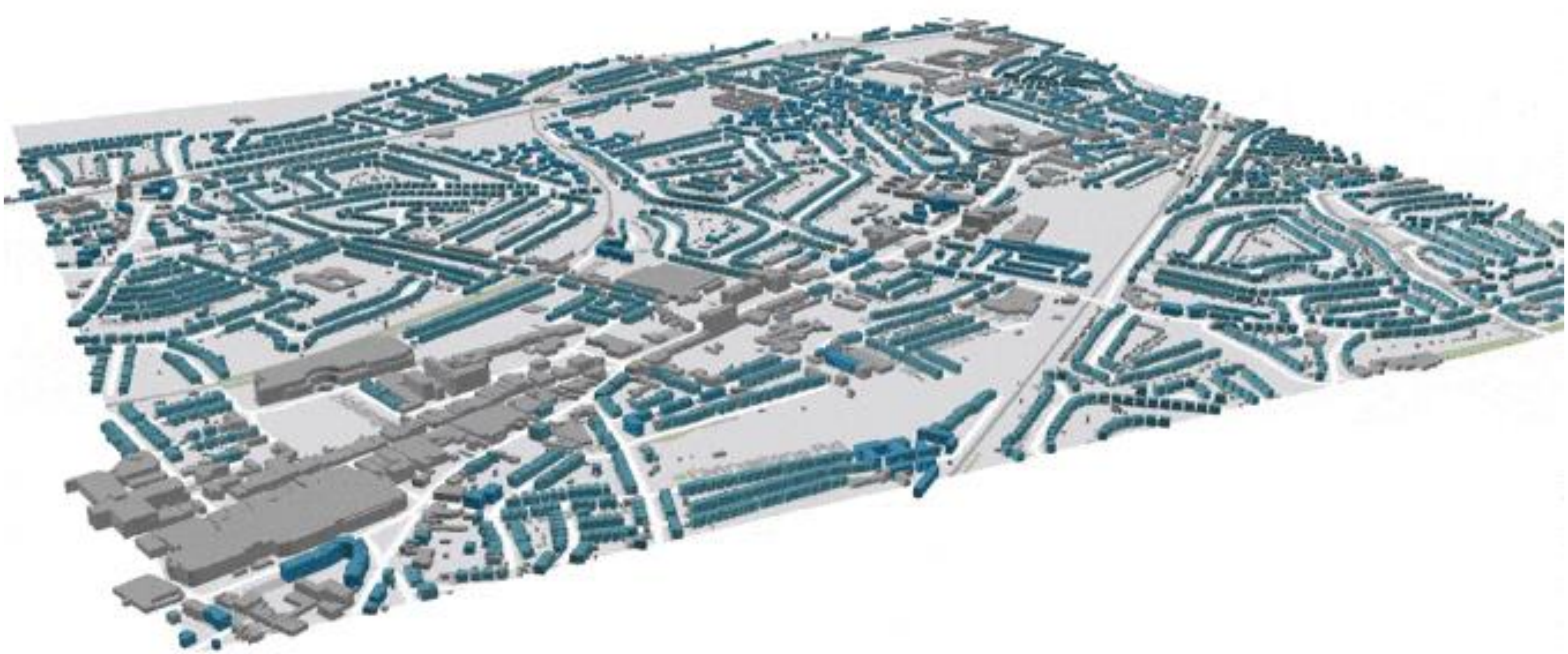


Armstrong et al (2011)

$$\sum_i [occupants_i \times deathrate_i \times (RR_{heat,i} - 1)]$$

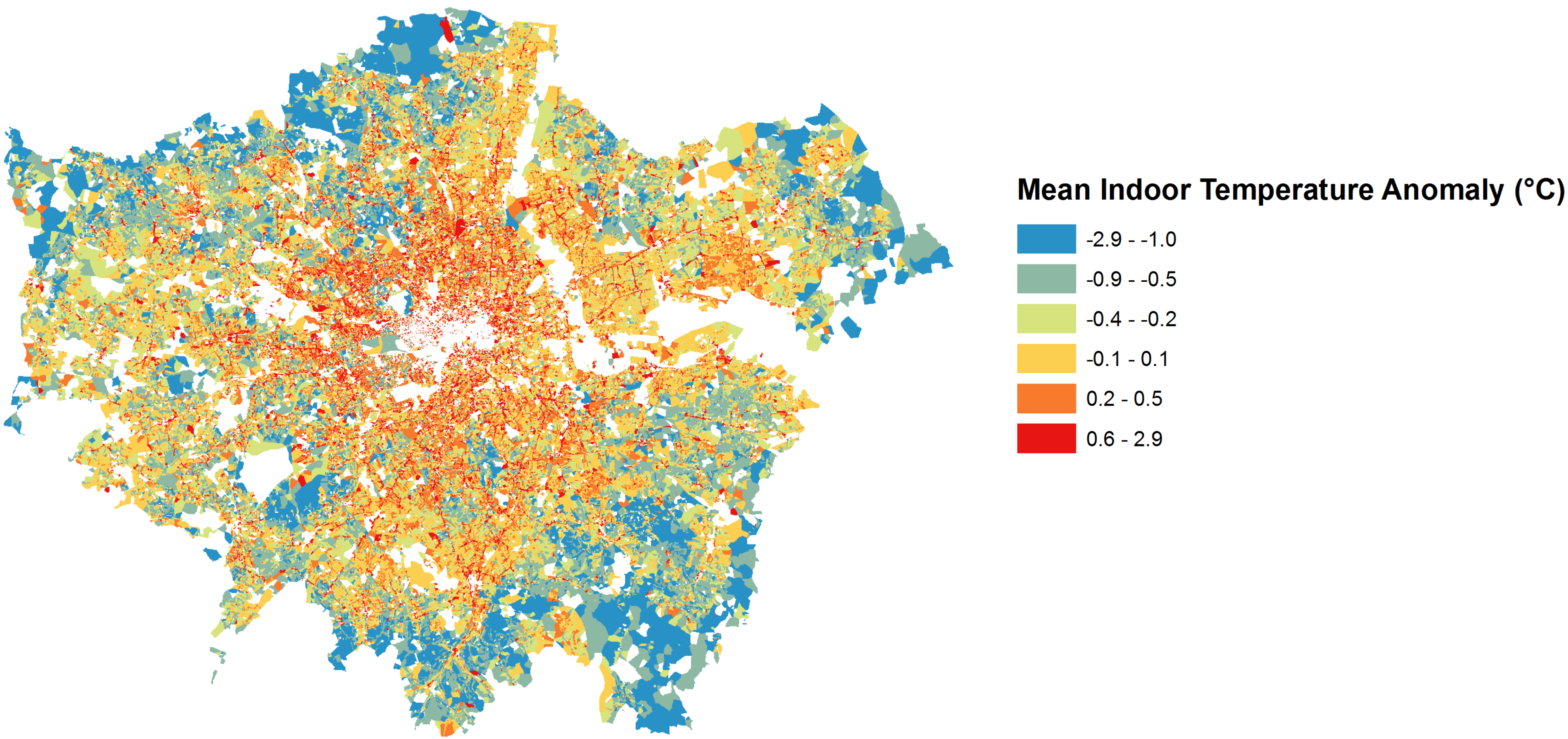
3. Example Results - Overheating

- Model may be used to predict risks due to housing and UHI over time at the individual-building level.



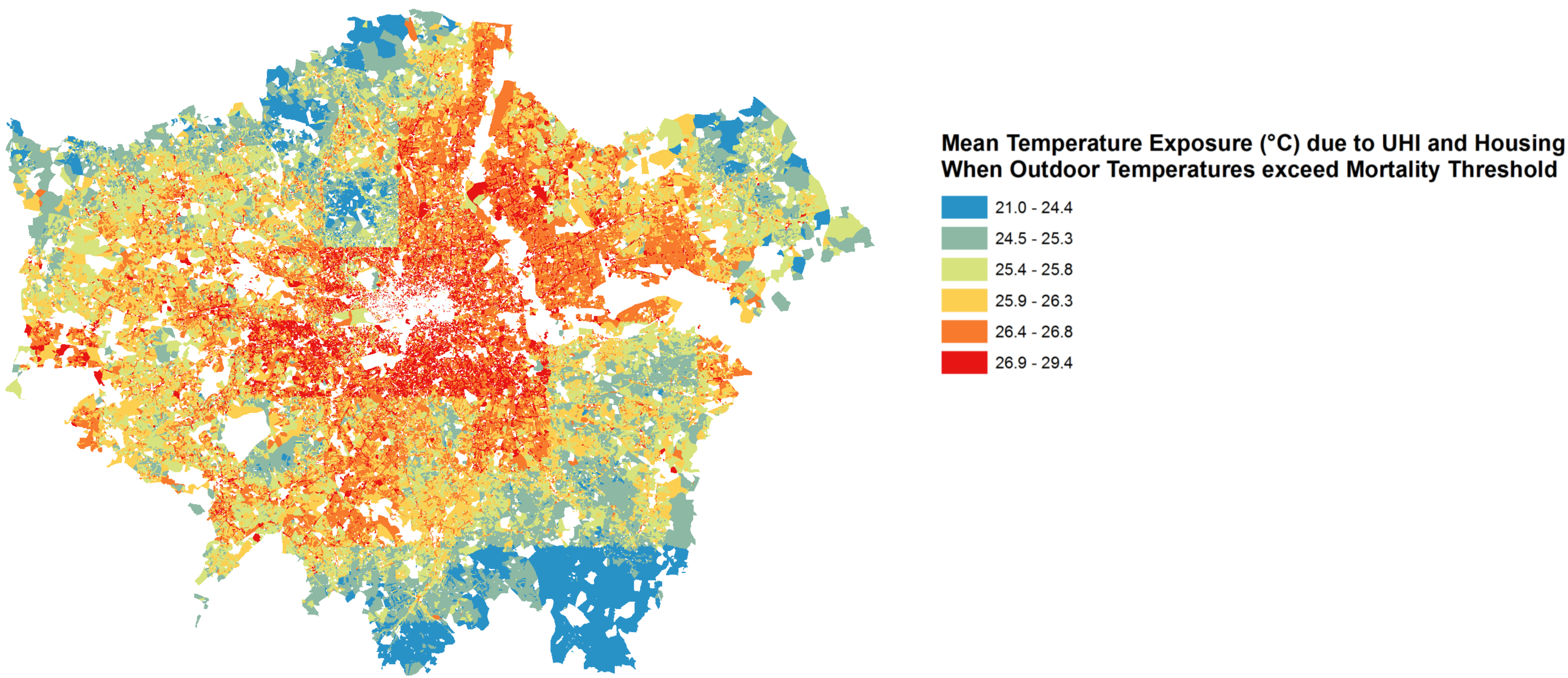
3. Example Results - Overheating

- Metamodel may also be applied to the 11 million dwellings in the EPC dataset
- Below – London average anomaly (or difference from London mean) by postcode



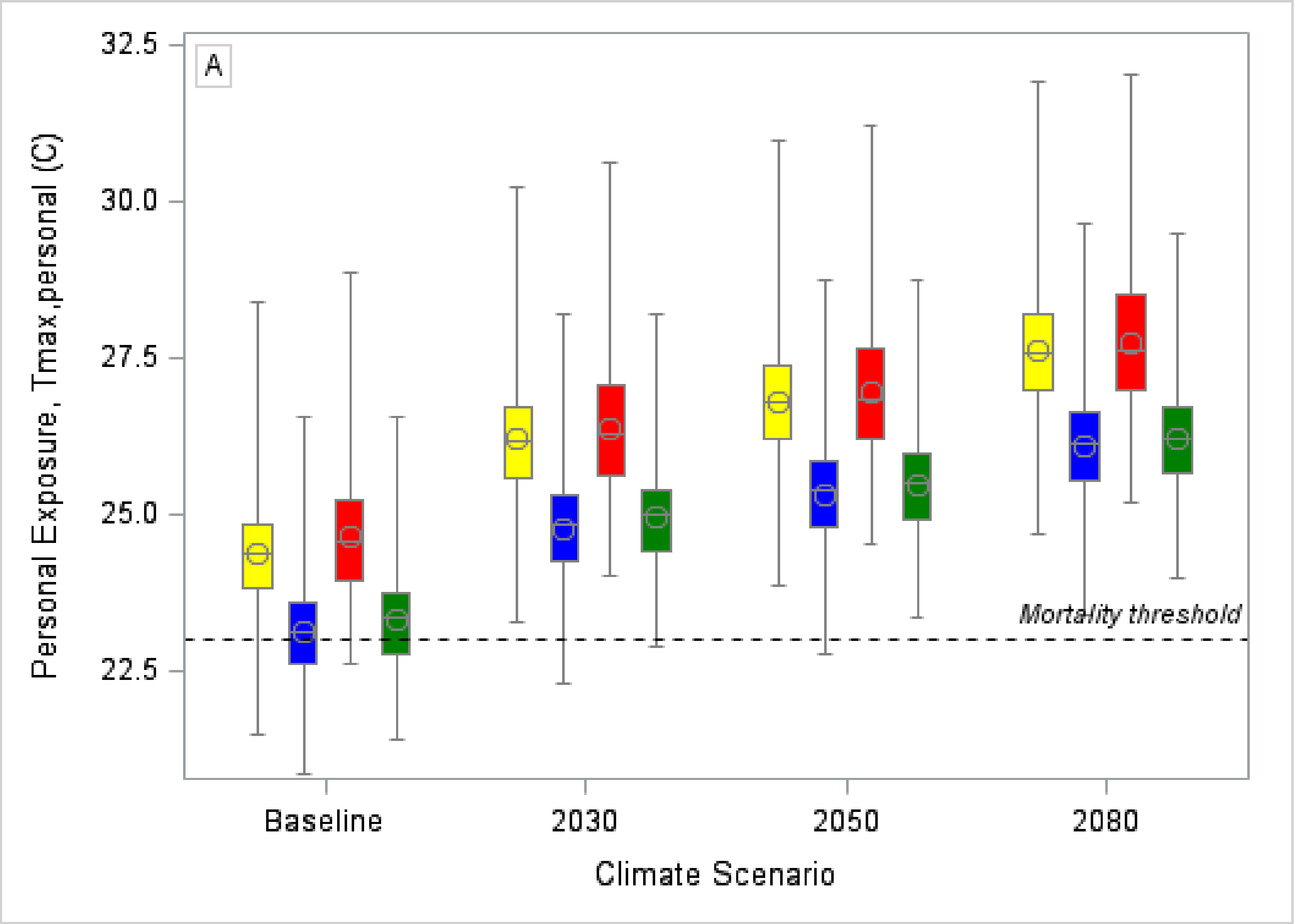
3. Example Results - Overheating

- Indoor temperatures can be adjusted relative to local outdoor temperatures
- Here, it's adjusted using a coarse resolution national air temperature map, but could use any UHI



3. Example Results – Overheating in West Midlands

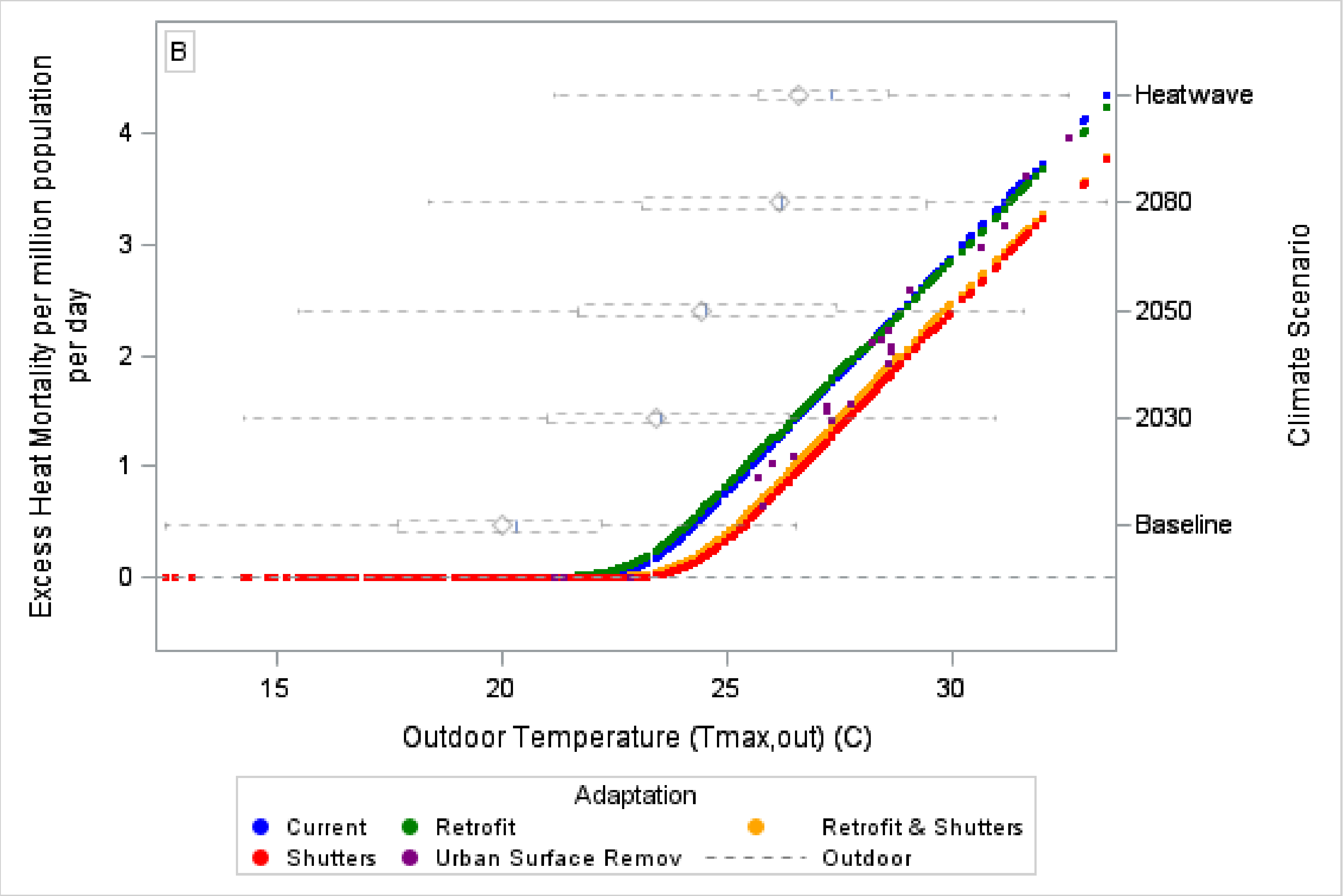
- Houses currently have a range of indoor temperature exposures (yellow)
- Shutters significantly reduce temperature exposure (blue)
- Retrofits have a very small increase (red)
- Combined shutters/retrofit significant reduce (and save energy)(green)



Taylor et al (2018) Comparison of built environment adaptations to heat exposure and mortality during hot weather, West Midlands region, UK, Environment International, doi:10.1016/j.envint.2017.11.005

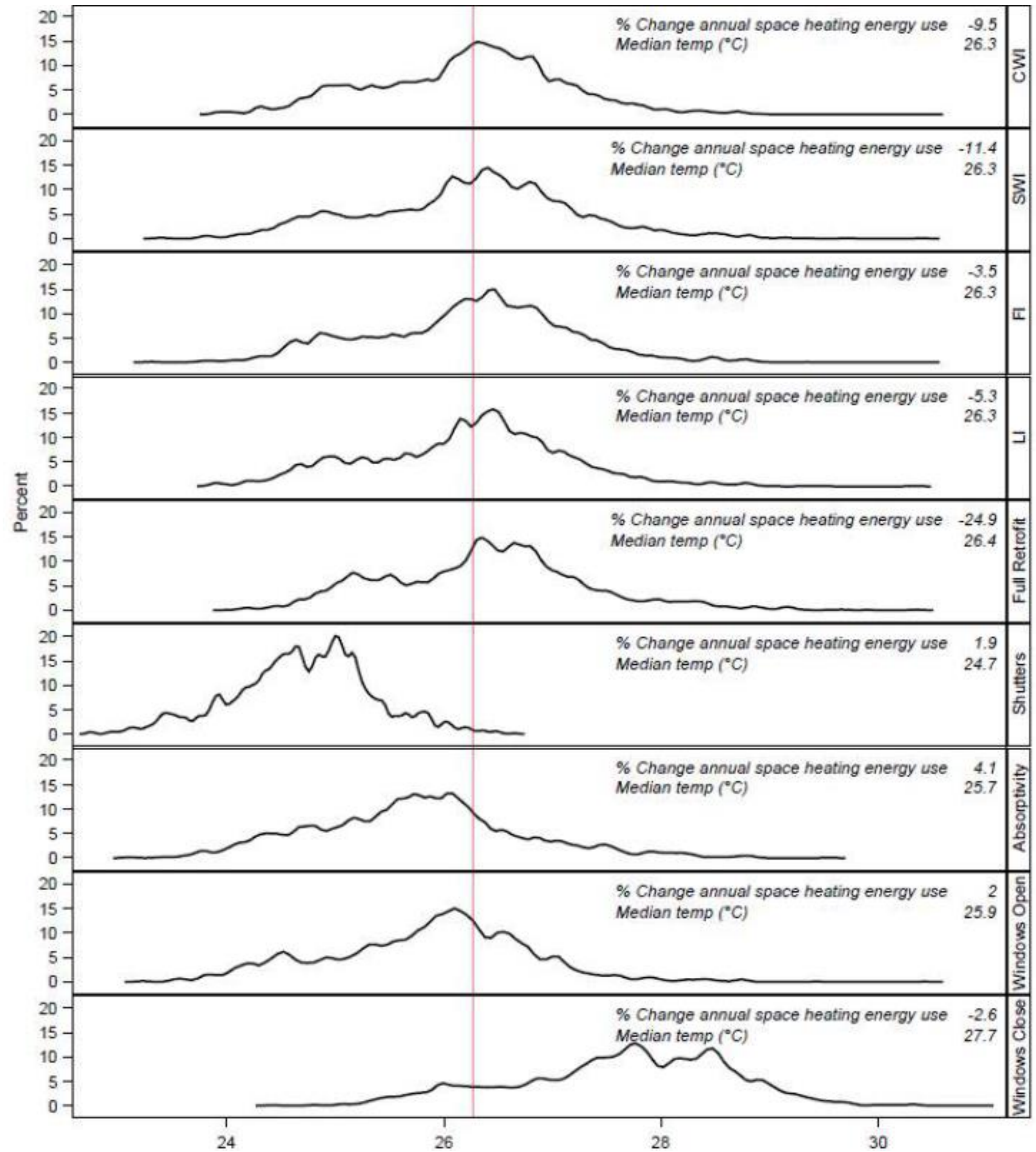
3. Example Results - Overheating in West Midlands

- Shutters may decrease mortality by
  - 60% in current conditions
  - 30% in heatwave conditions
- Retrofits may increase mortality by when not combined with additional cooling
  - 14% in current conditions
  - 1% in heatwave conditions
- Effectiveness of shutters at preventing mortality decreases as temperatures increase



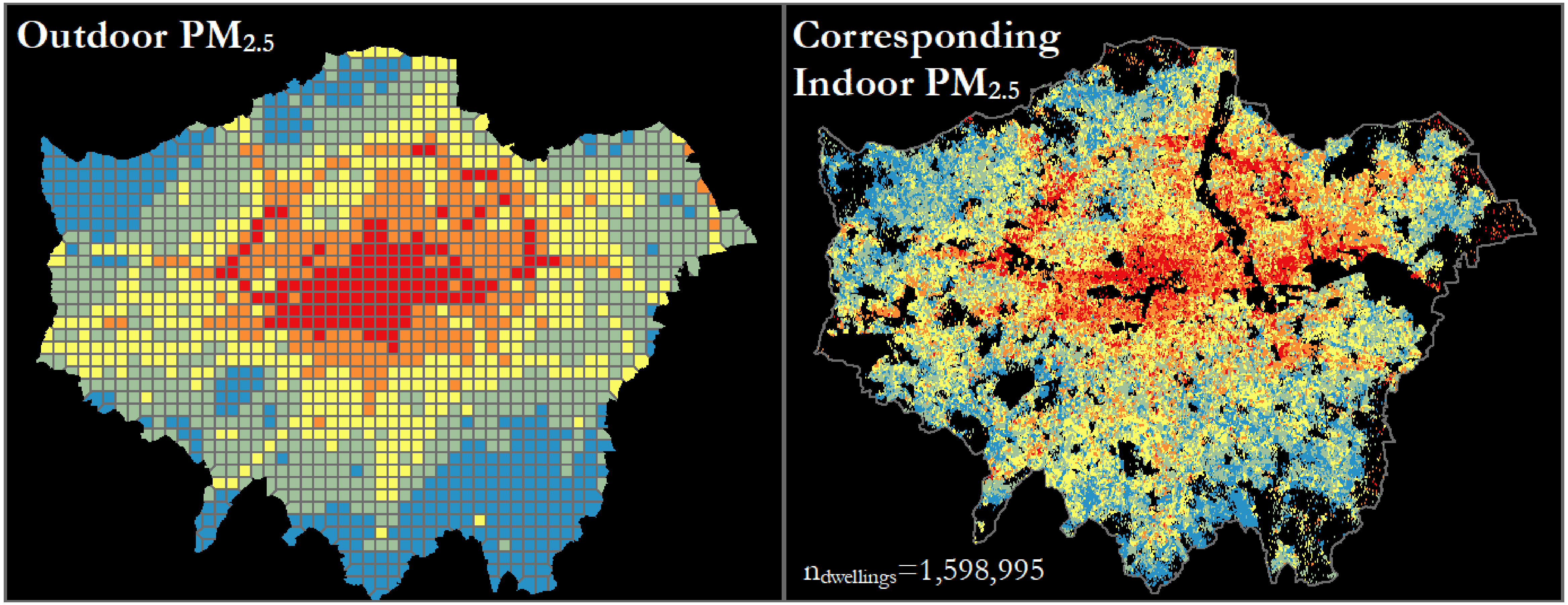
3. Example Results - Overheating in West Midlands

- Adaptations can have implications for energy use
  - Painting the roof white reduces temperature exposures
  - But, increases winter space heating energy consumption by 4%
  - Energy efficiency upgrades reduce energy use, but can increase overheating



3. Example Results – Air Pollution

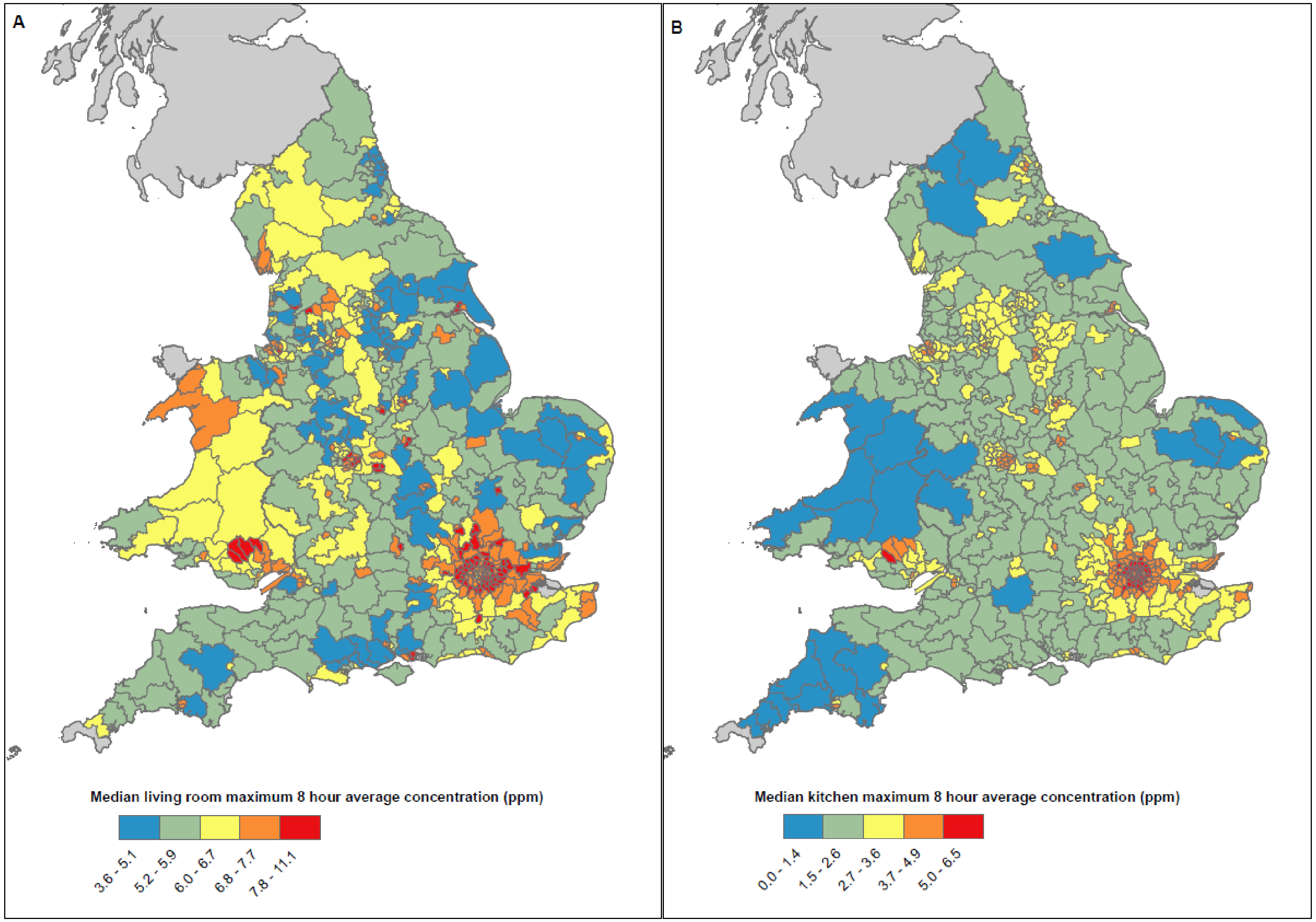
- Model may be used to predict housing modification of outdoor air pollution exposure (~1.6 million London dwellings)



Taylor et al (2019) Application of an indoor air pollution metamodel to a spatially-distributed housing stock. Science of the Total Environment. In Press.

3. Results – Air Pollution

- Model may be used to predict exposure from both indoor and outdoor sources (~11.5 million dwellings)
- Full energy efficient retrofit of the stock may reduce space heating demands by around 25% but increase e.g. CO exposures by 17.6%



3. Conclusions

- Housing is an important area to reduce energy consumption
- Primary environment where people spend their time.
- We can use building physics tools, stock models, and health models to explore housing energy/health trade-offs at population level
- We can model changes to exposures from, e.g.
  - Energy efficient retrofit
  - Housing adaptations to climate change
  - Outdoor environmental changes

Questions?

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