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Using Thermal Infrared Imagery for Prioritization of Building Retrofits

AI & the Real-World Energy-Turnaround

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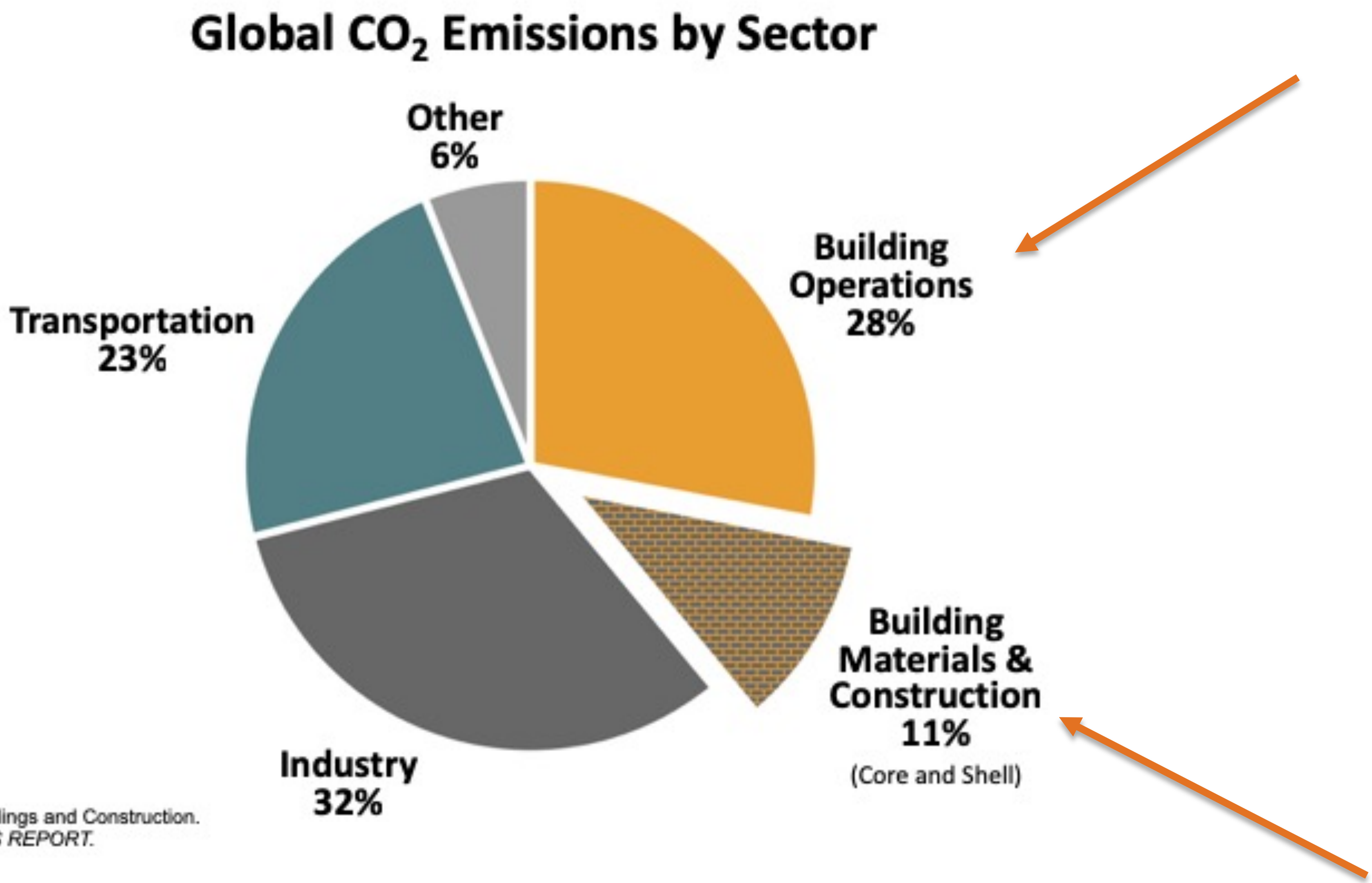
Buildings generate nearly 40% emissions



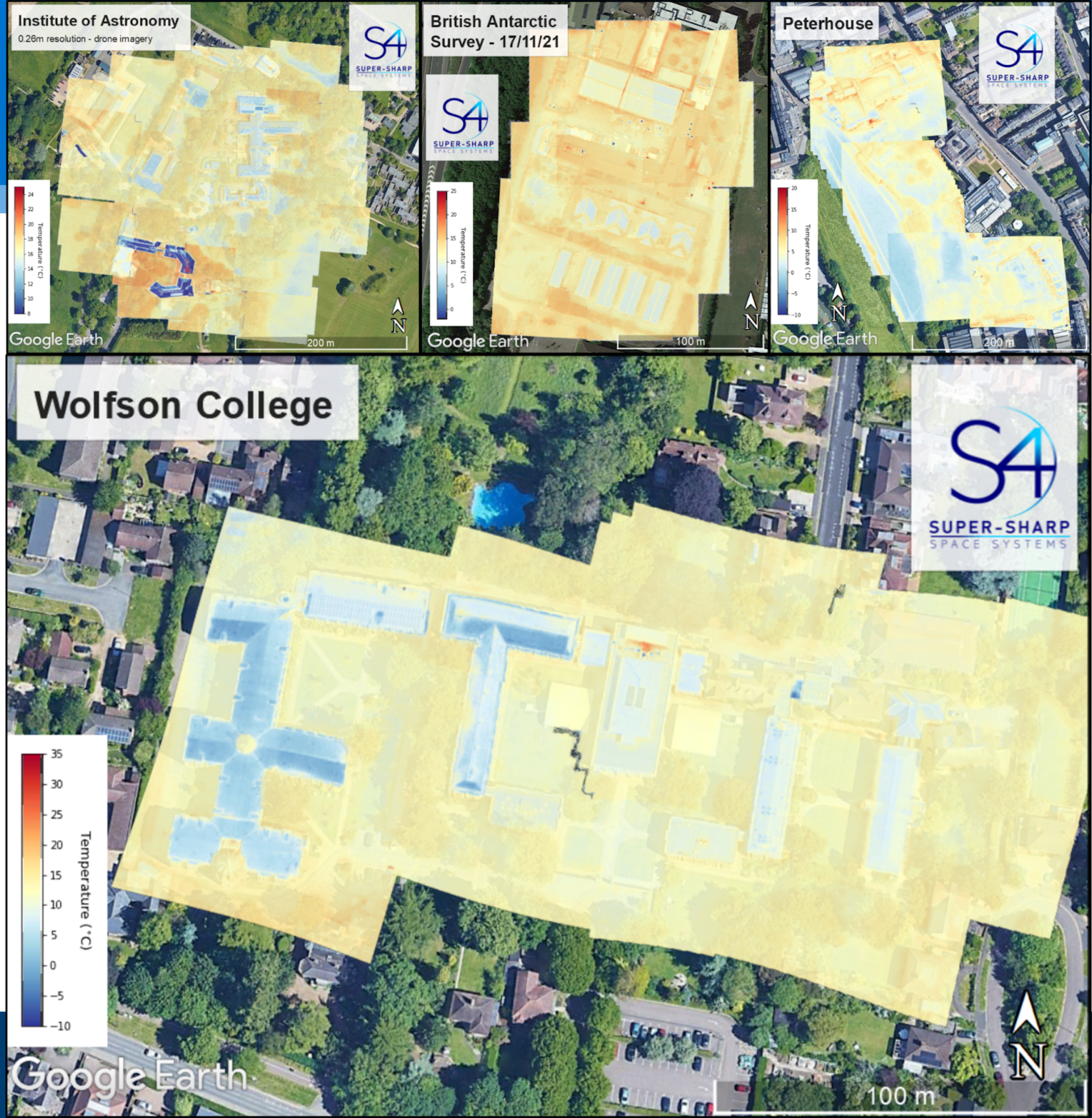
Source:
Global Alliance for Buildings and Construction.
2018 GLOBAL STATUS REPORT.

Improving existing buildings' performance

Infrared thermography for dividing households

Drone imagery

- Drone surveys were carried out and thermal infrared images collected were stitched together.



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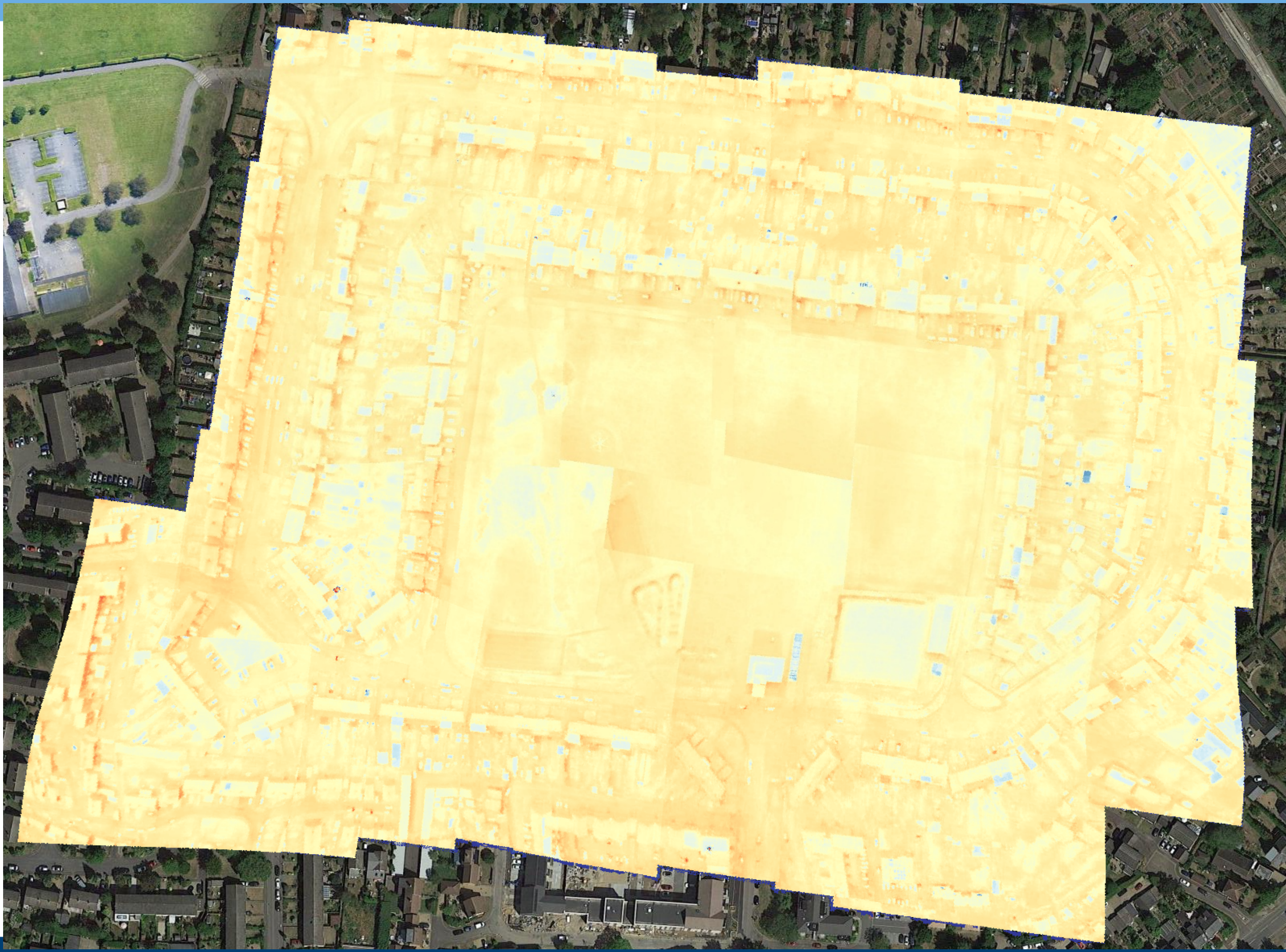
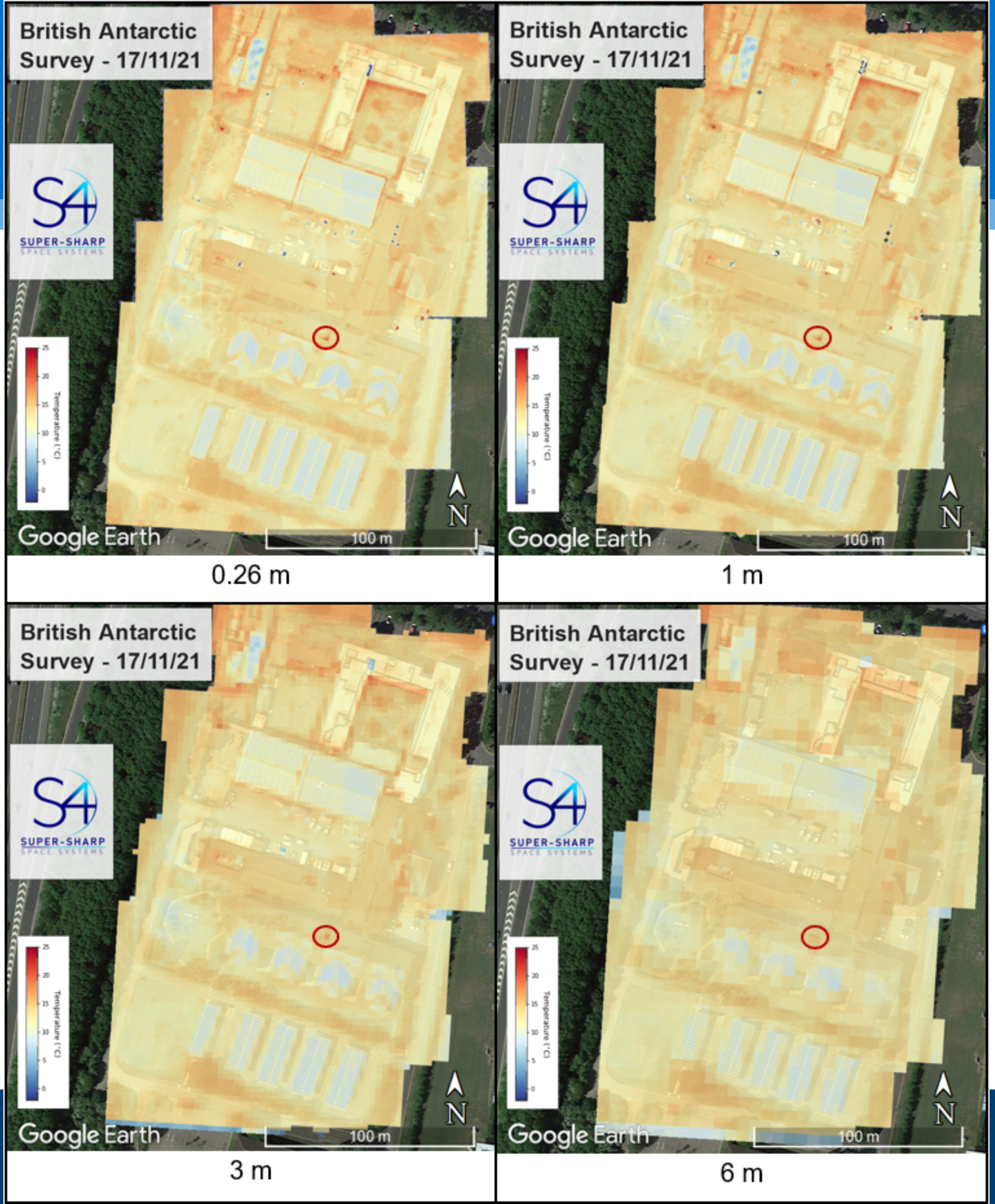
Drone imagery

- Drone survey over Trumpington council estate in Cambridge, UK.



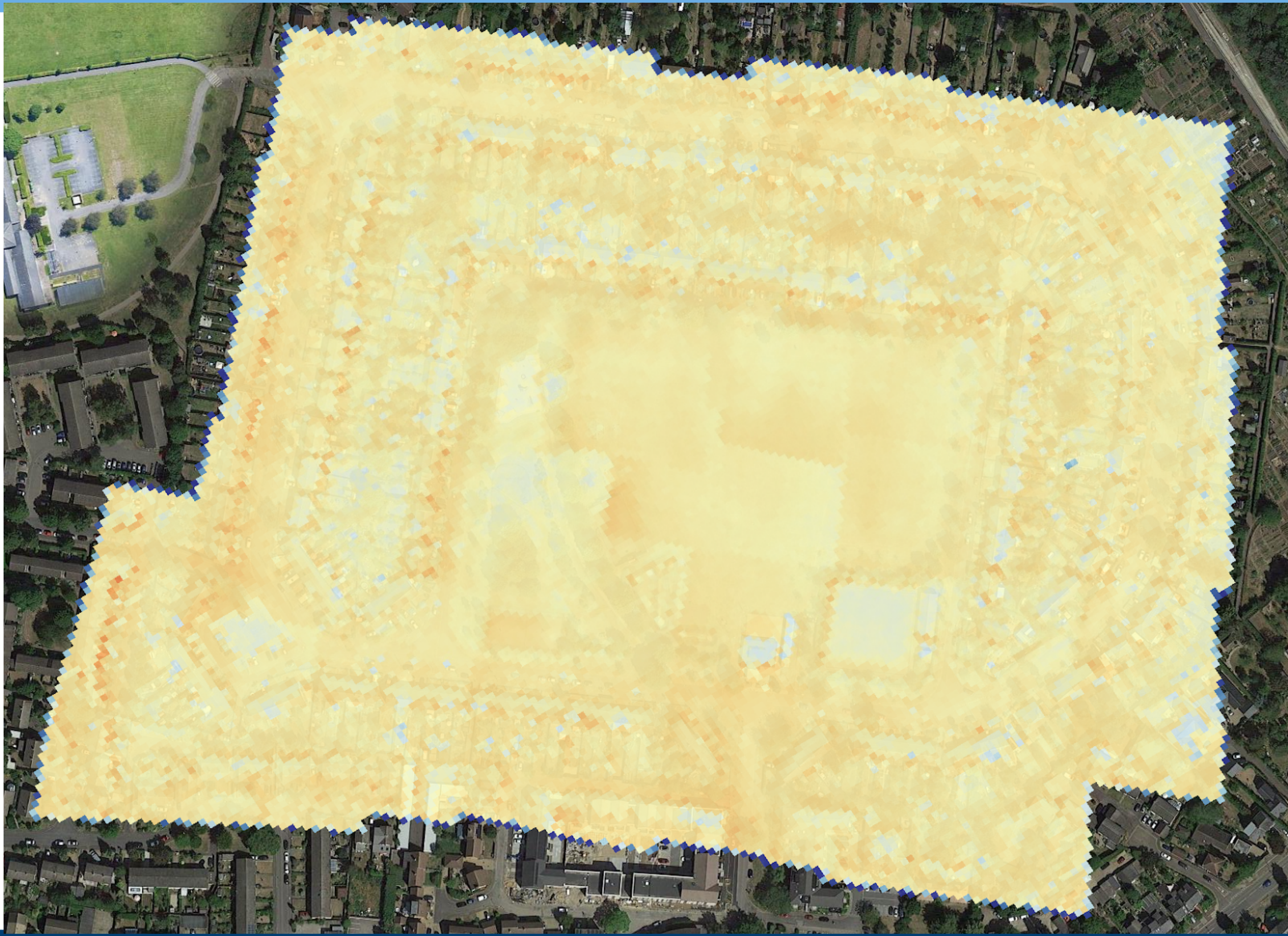
TIR imagery at various resolutions

- Downsampling the data from surveys to resolutions varying from 0.26cm (drone resolution) to possible future satellite resolutions (1m, 3m, 6m). This enables us to evaluate the capacity of different potential resolutions for identifying different types of thermal features.



Trumpington council estate with 3m resolution TIR imagery

- This emulated future satellite image provides building-level thermal information for evaluating building efficiencies and the climate change mitigation potential of retrofitting them.



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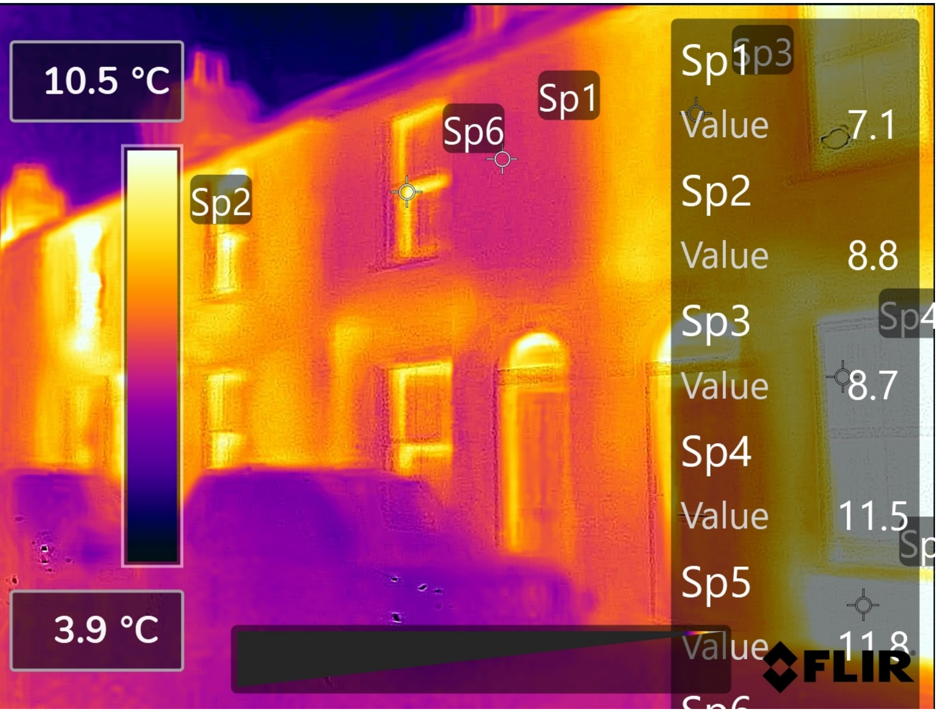
Wall and roof temperature readings



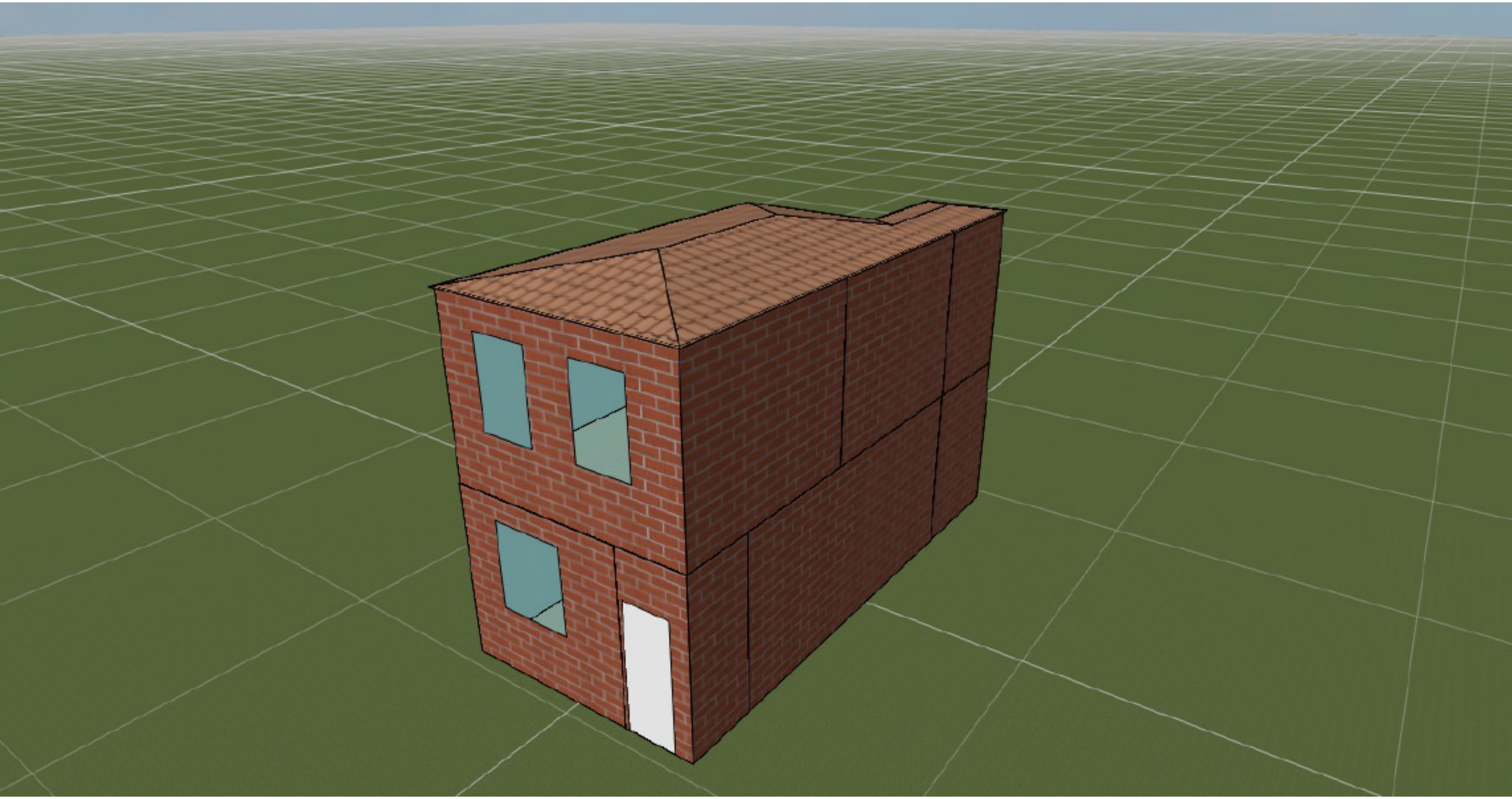
Calculating U values

- $$U = \frac{h(T_s - T_{out})}{T_{in} - T_{out}}$$
- $$h = 5.8 + 3.8054v$$

(Nardi et al., 2016; Dall'O' et al., 2013)

h	T wall	T out	T in	V (m/s)	U value	Category
13.4108	7.1	7	20	2	0.10316	façade --colder one
13.4108	8.8	7	20	2	1.85688	façade
13.4108	7.8	7	20	2	0.82528	roof -colder one
13.4108	8.5	7	20	2	1.5474	roof
13.4108	7.1	7	18	2	0.121916	façade --colder one
13.4108	8.8	7	25	2	1.34108	façade
13.4108	7.8	7	18	2	0.975331	roof -colder one
13.4108	8.5	7	25	2	1.117567	roof
13.4108	7.1	7	19	2	0.111757	façade --colder one
13.4108	8.8	7	22	2	1.609296	façade
13.4108	7.8	7	19	2	0.894053	roof -colder one
13.4108	8.5	7	22	2	1.34108	roof

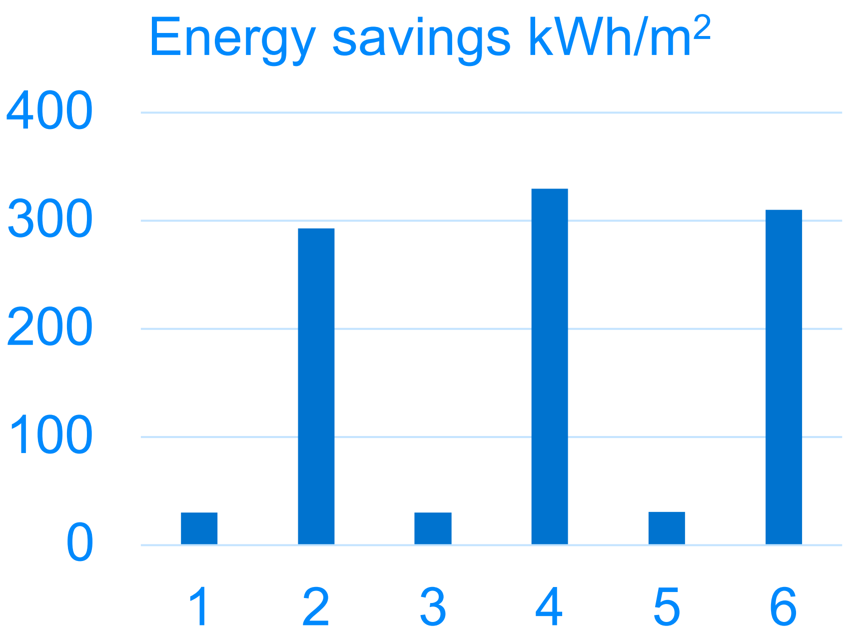
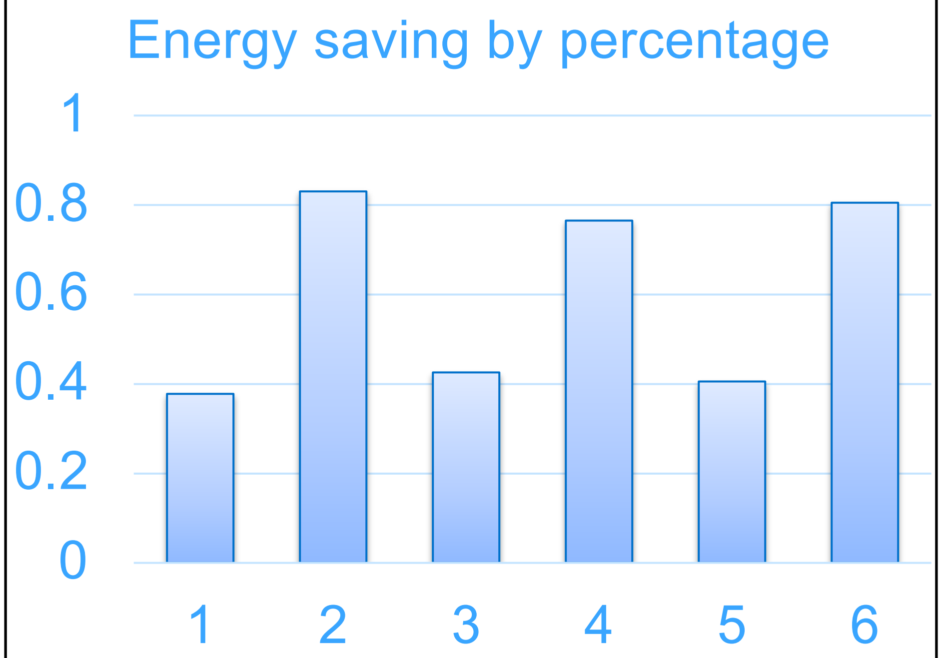
Model of mid-terraced house using IES-VE



Model simulation scenarios

Scenario	Roof U values (W/m²K)	Wall U values (W/m²K)	Heating temperature (°C)	Energy consumption (kWh/m²)
1. colder one , original	0.82528	0.10316	20	80.2
1. colder one, upgrade	0.18	0.10316	20	49.9
2. warmer one, original	1.5474	1.85688	20	352.6
2. warmer one, upgrade	0.18	0.18	20	59.8
3. colder one , original	0.975331	0.121916	18	70.7
3. colder one, upgrade	0.18	0.121916	18	40.6
4. warmer one, original	1.117567	1.34108	25	430.5
4. warmer one, upgrade	0.18	0.18	25	101.1
5. colder one , original	0.894053	0.111757	19	76.2
5. colder one, upgrade	0.18	0.111757	19	45.3
6. warmer one, original	1.34108	1.609296	22	385.4
6. warmer one, upgrade	0.18	0.18	22	75.1

Comparison of energy saving by value and percentage

	
Energy saving potential prediction.	Energy saving potential (by percentage).

Findings using TIR temperature readings

- With different external wall surface temperature levels/readings, one can expect different levels of retrofit thereby prioritize buildings for upgrades.

- Buildings with higher surface temperature will yield higher energy savings.

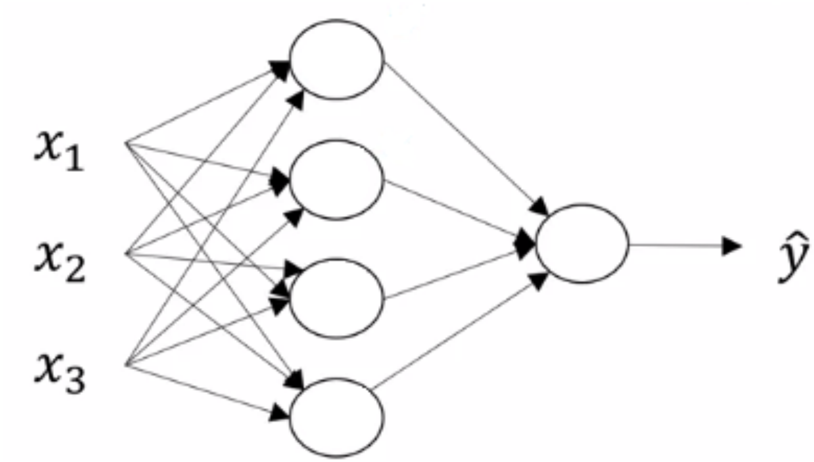
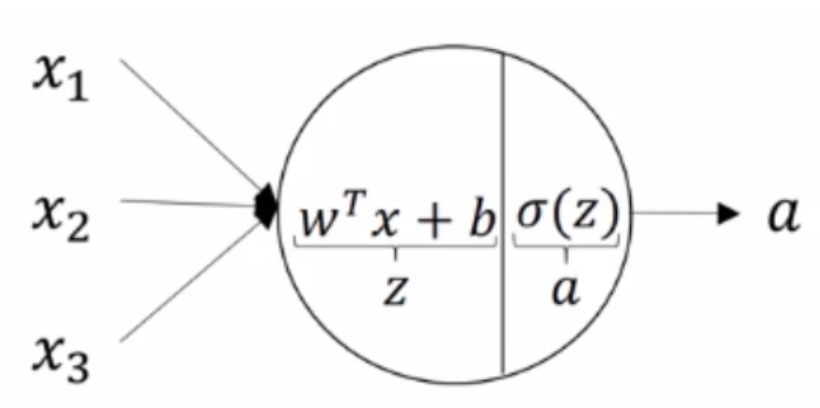
Data collection and partitioning

- $U = \frac{h(T_s - T_{out})}{T_{in} - T_{out}} + Wu,$
- $W_u \sim N(0, 0.1^2)$

Sampling of input variables for typical built environment in winter scenarios

Input variables (unit)	Symbols	Ranges	# of samples	White noises
Outdoor air temperature (℃) (EnergyPlus, 2022)	$T_{outdoorair}$	[-5, 15]	20	$W_0 \sim N(0, 0.5^2)$
Outdoor wall surface temperature (℃)	$T_{outdoorwall}$	[-2, 18]	20	$W_1 \sim N(0, 0.5^2)$
Indoor air temperature (℃)	$T_{indoorair}$	[10, 30]	20	$W_2 \sim N(0, 0.5^2)$
Outdoor wind speed (m/s) (Dall'O, G., et al., 2013)	$v_{outdoorwind}$	[0, 2]	5	$W_3 \sim N(0, 0.2^2)$

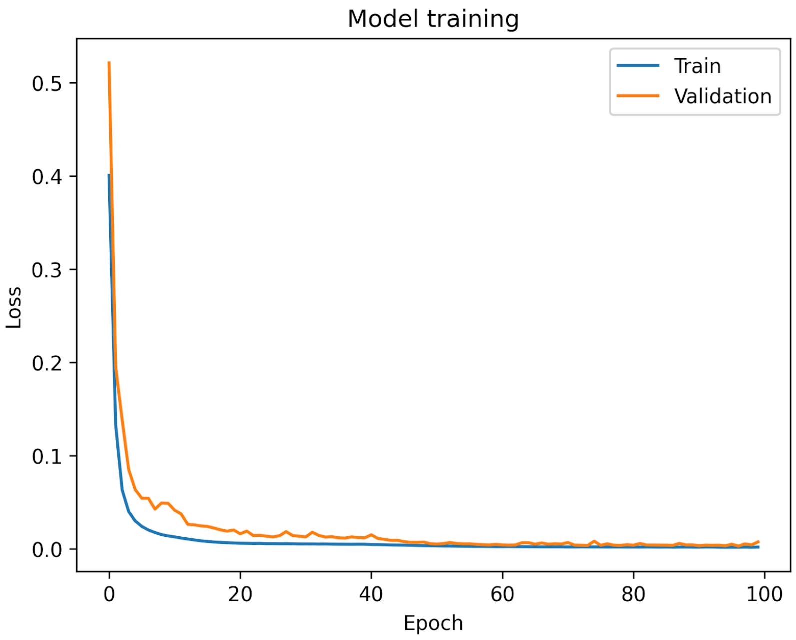
Training and prediction results of NNs

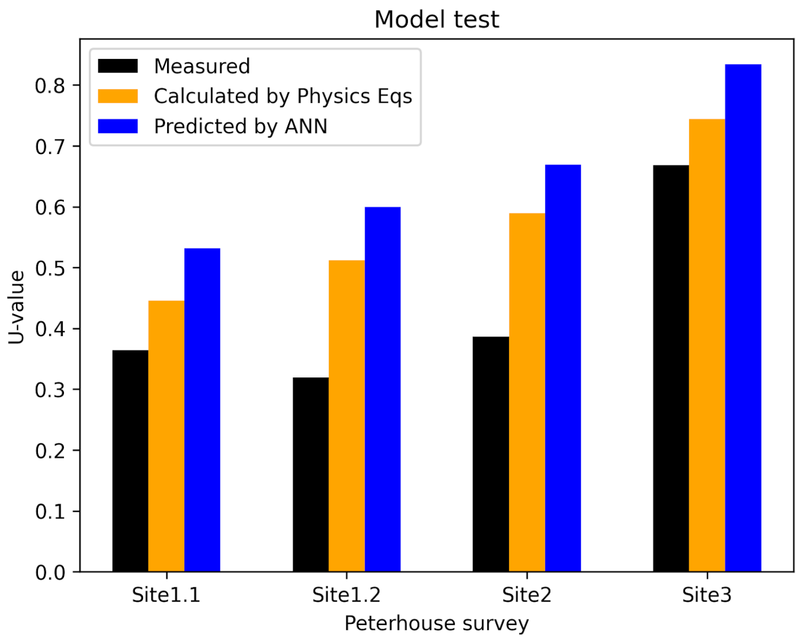
	
An example Feedforward NN.	An example neuron.

Structure of NN-1 and NN-2

- The structure of NN-1 has 1 hidden layer and 10 hidden neurons, resulting in 61 trainable parameters. This model is then trained on 66.6% of the data samples while validated on the rest 33.3%.
- The structure of NN-2 has 2 hidden layers. The 1st and 2nd hidden layers have 10 and 20 hidden neurons, respectively, leading to 291 trainable parameters. The train-validation data split follows the same way as applied to NN-1, i.e., 66.6% for training and 33.3% for validation.

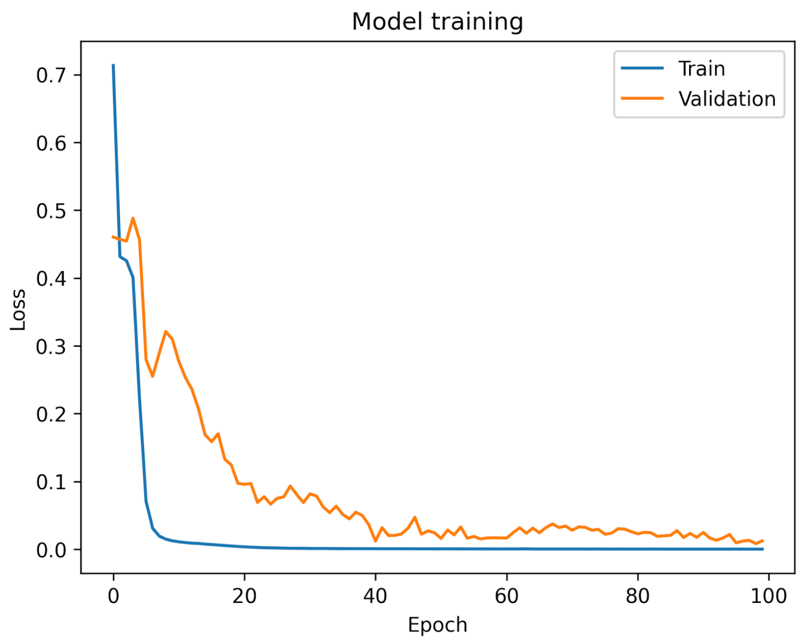
NN-1 model training, validation and testing

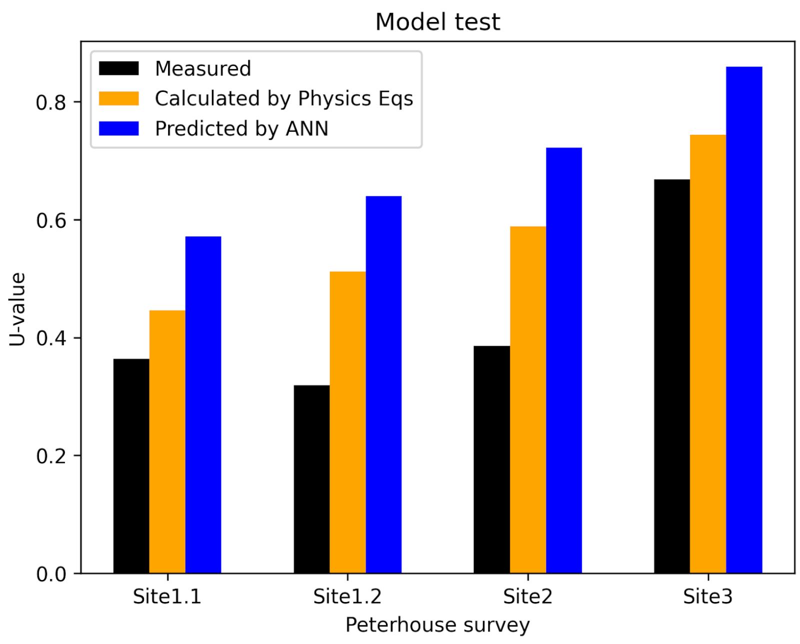




Learning curves of NN-1	Prediction performance of NN-1

NN-2 model training, validation and testing





Learning curves of NN-2	Prediction performance of NN-2

Future work on using AI to analyze satellite TIR imagery

- Identifying individual buildings (both roofs and facades) in satellite TIR imagery;
- Obtain useful temperature readings and heat loss comparisons among buildings in the satellite TIR imagery;
- Scale up the retrofit prioritization process with the building stock in large areas or cities.

Acknowledgement

- The funding from National Space Innovation Programme of UK Space Agency is gratefully acknowledged.

- More info: https://www.cam.ac.uk/research/news/new-research-will-use-space-telescopes-to-monitor-energy-efficiency-of-buildings

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