Machine learning applied to urban building energy modelling and climate risk assessment

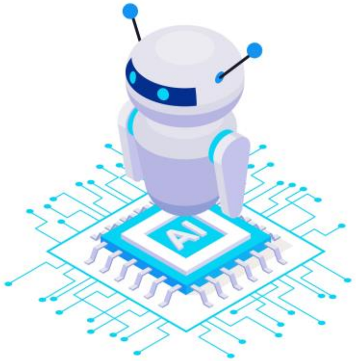
Dr. Miguel Martin

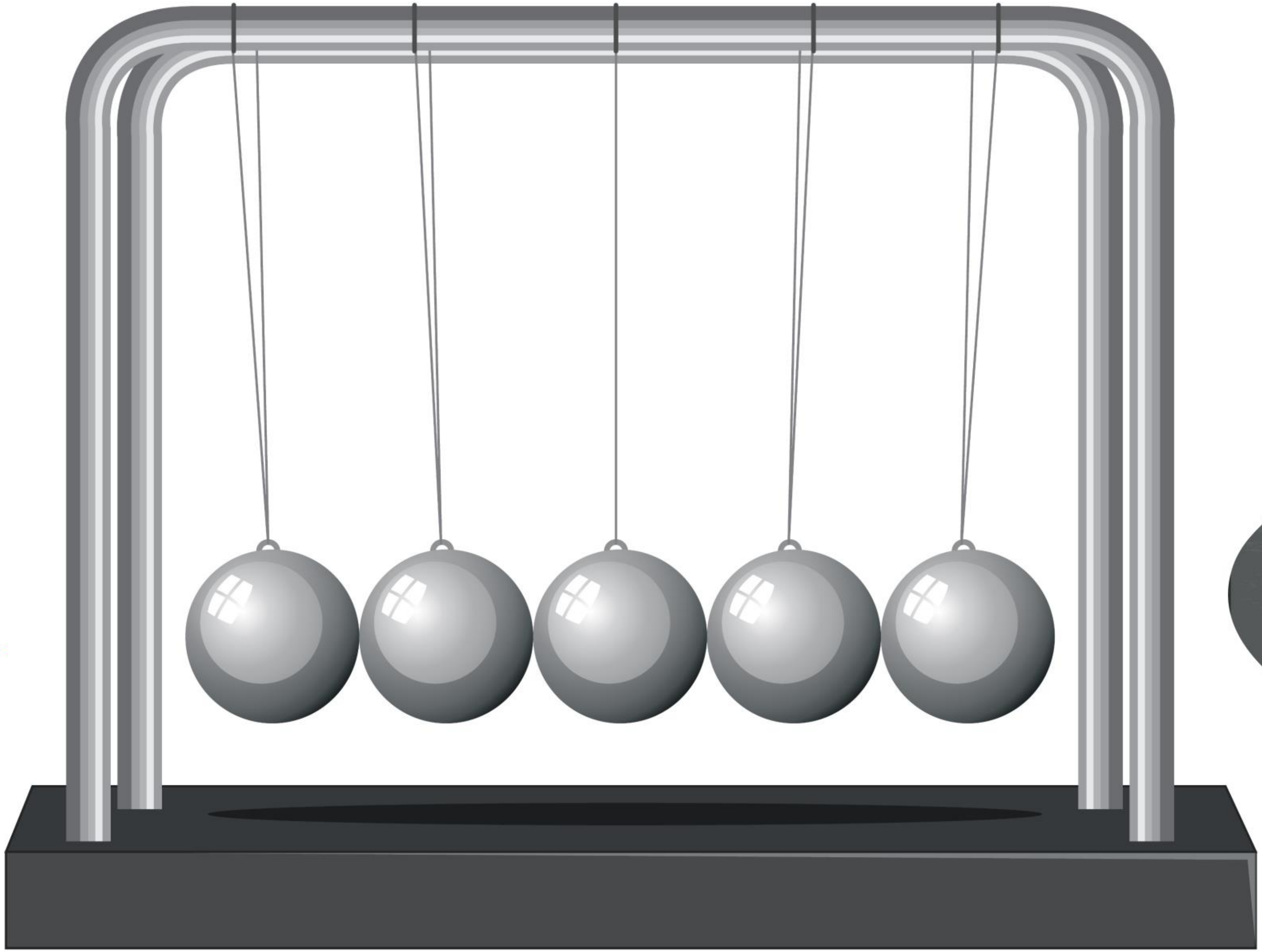
Questions to be discussed

- How can knowledge in computer science and physics help in solving major challenges related to urban sustainability?
- How can machine learning be used to predict outdoor conditions in an urban area in combination with physics?
- How can the reliability of urban building energy models be improved using machine learning?
- How can climate risk be assessed using machine learning?

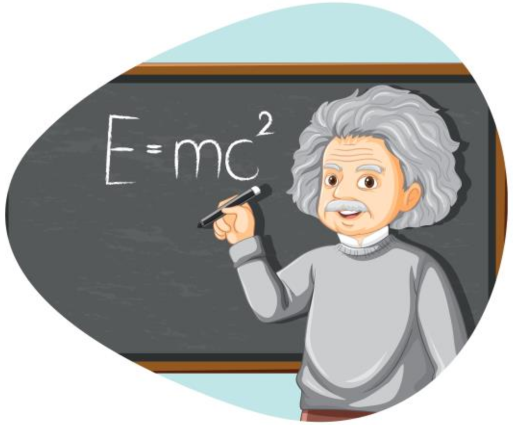
Computer science and physics to study urban sustainability

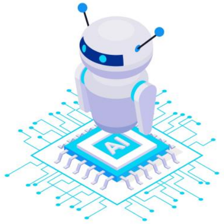
Andy Roid





Albert





Machine learning

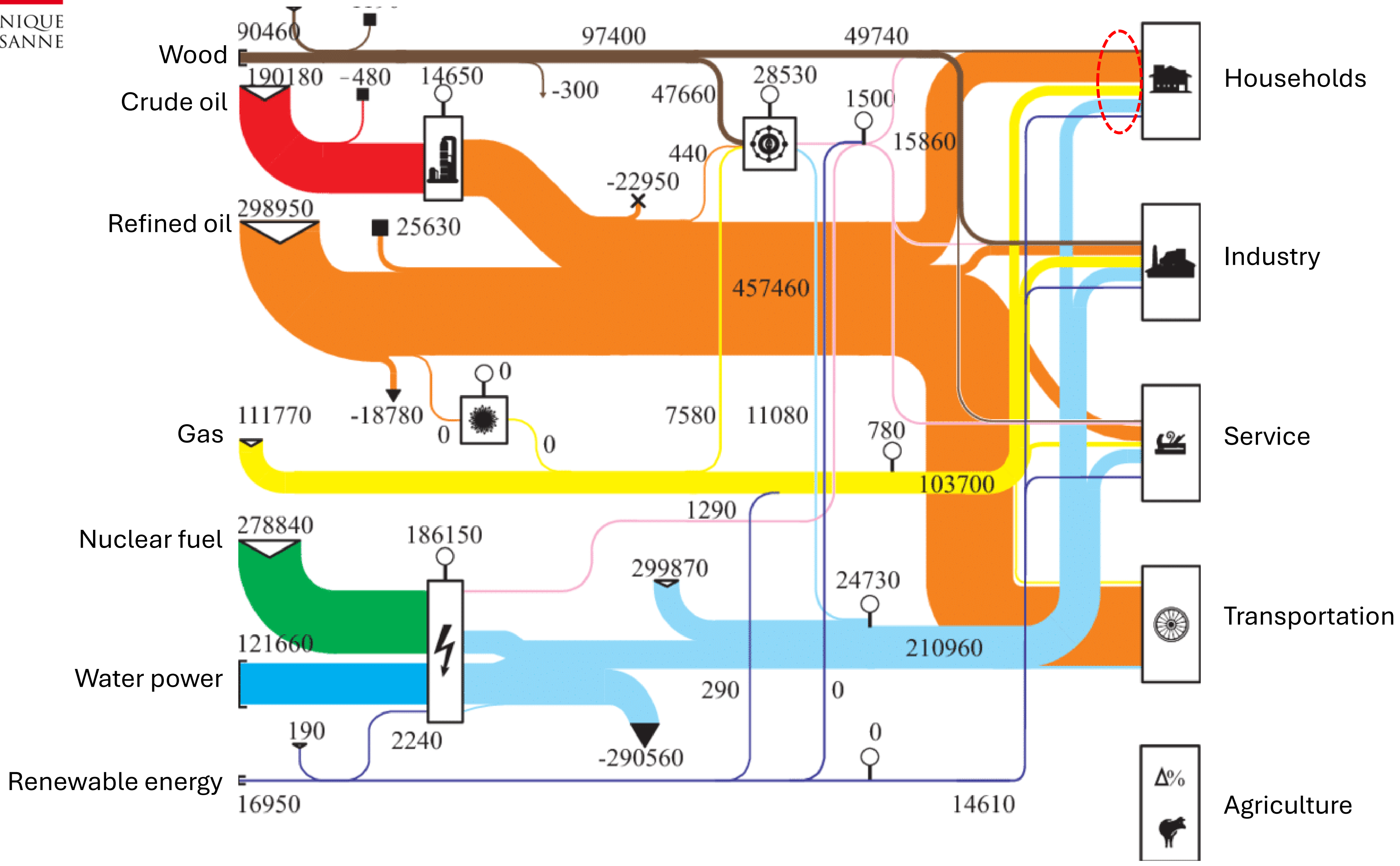
Image processing

Robotics

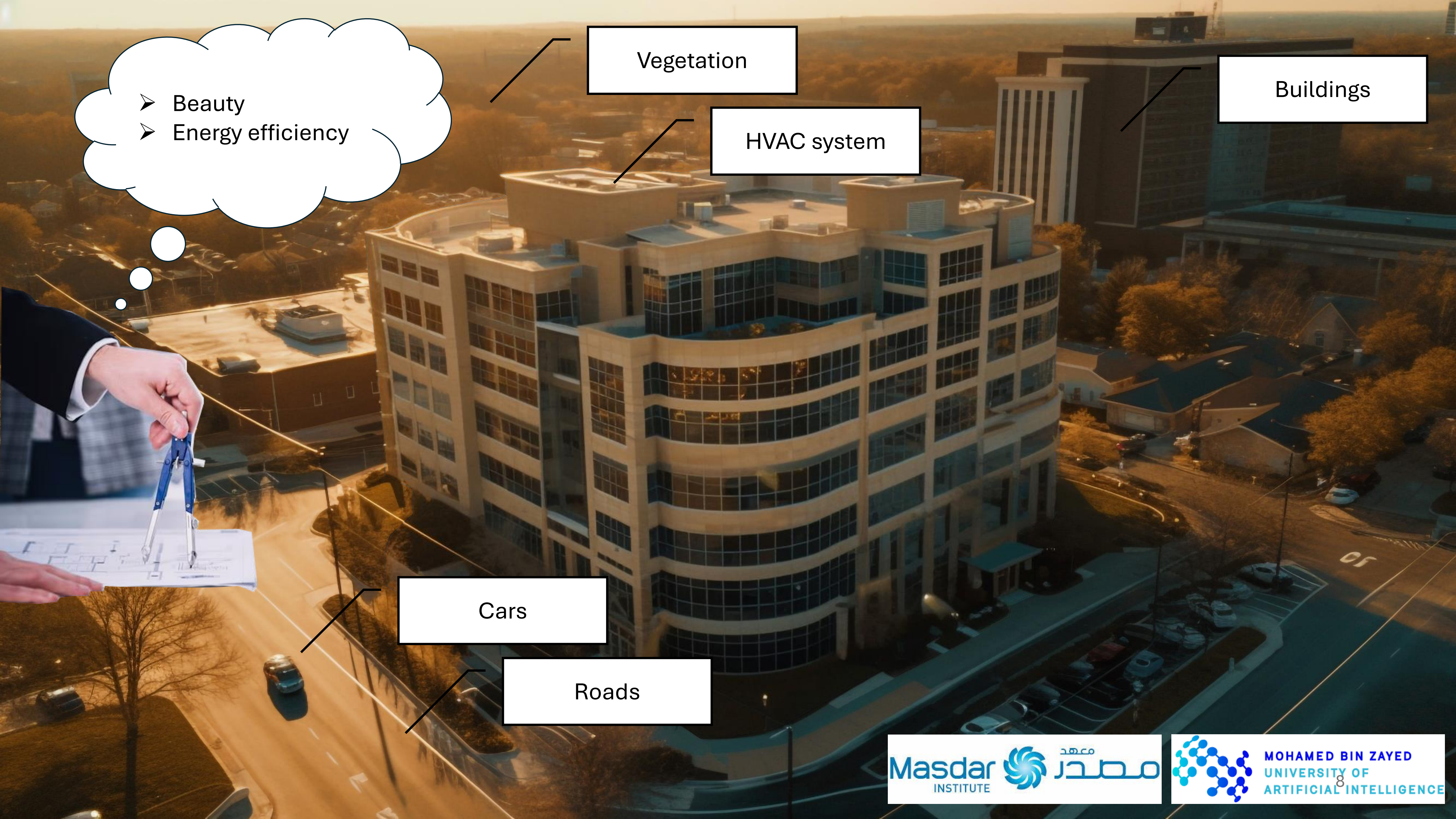
Human brain interface

Apply


HOME
Film by Yann Arthus Bertrand (2009)



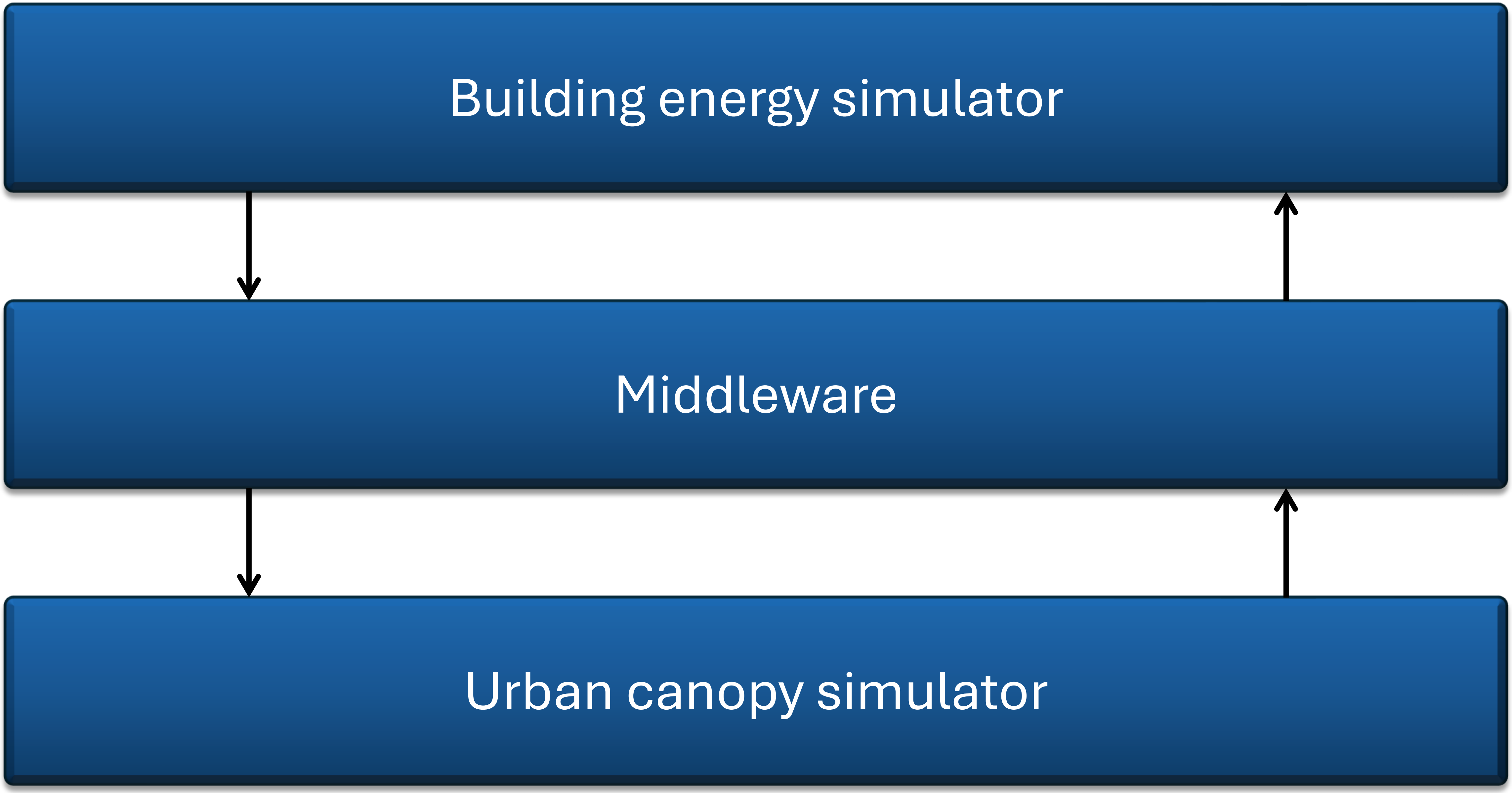
Wood
Crude oil
Refined oil
Gas
Nuclear fuel
Water power
Renewable energy
90460
97400
49740
190180
-480
14650
-300
47660
28530
1500
15860
440
-22950
298950
25630
457460
0
111770
-18780
0
0
7580
11080
780
103700
1290
278840
186150
299870
24730
121660
210960
290
0
190
2240
-290560
0
16950
14610
Households
Industry
Service
Transportation
Agriculture
Δ%



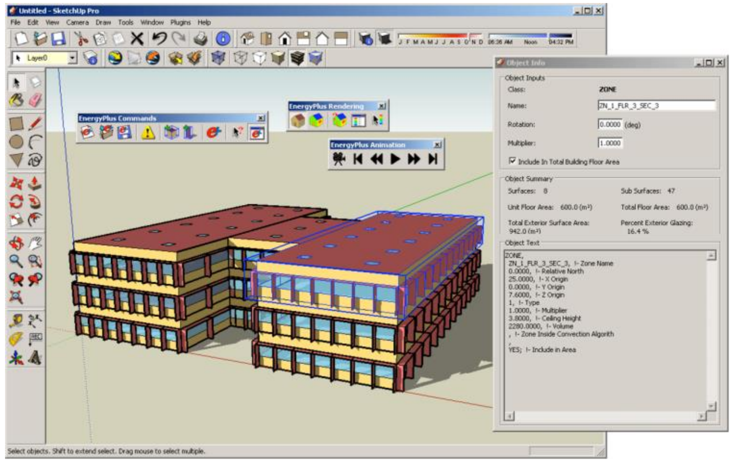
Masdar INSTITUTE معهد مصدر

MOHAMED BIN ZAYED UNIVERSITY OF ARTIFICIAL INTELLIGENCE

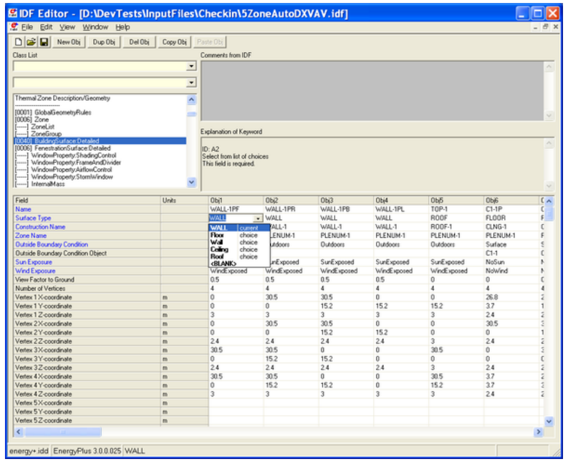

Temp.
Hum.
Heat
Vapour
American Girl Place
BUSES ONLY
TGI FRIDAYS
NO STOPPING ANYTIME


Building energy simulator
Middleware
Urban canopy simulator

2 Define building parameters and weather data

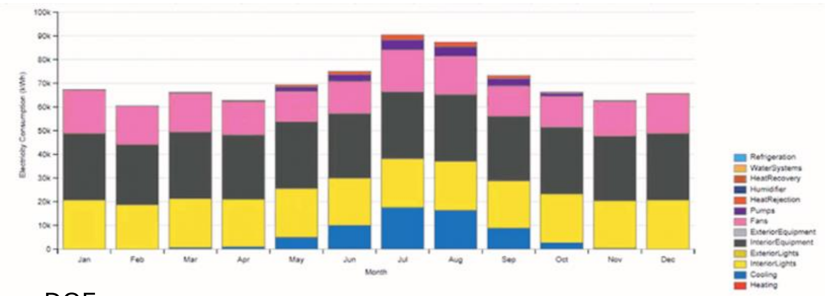


Ellis et al. (2008)



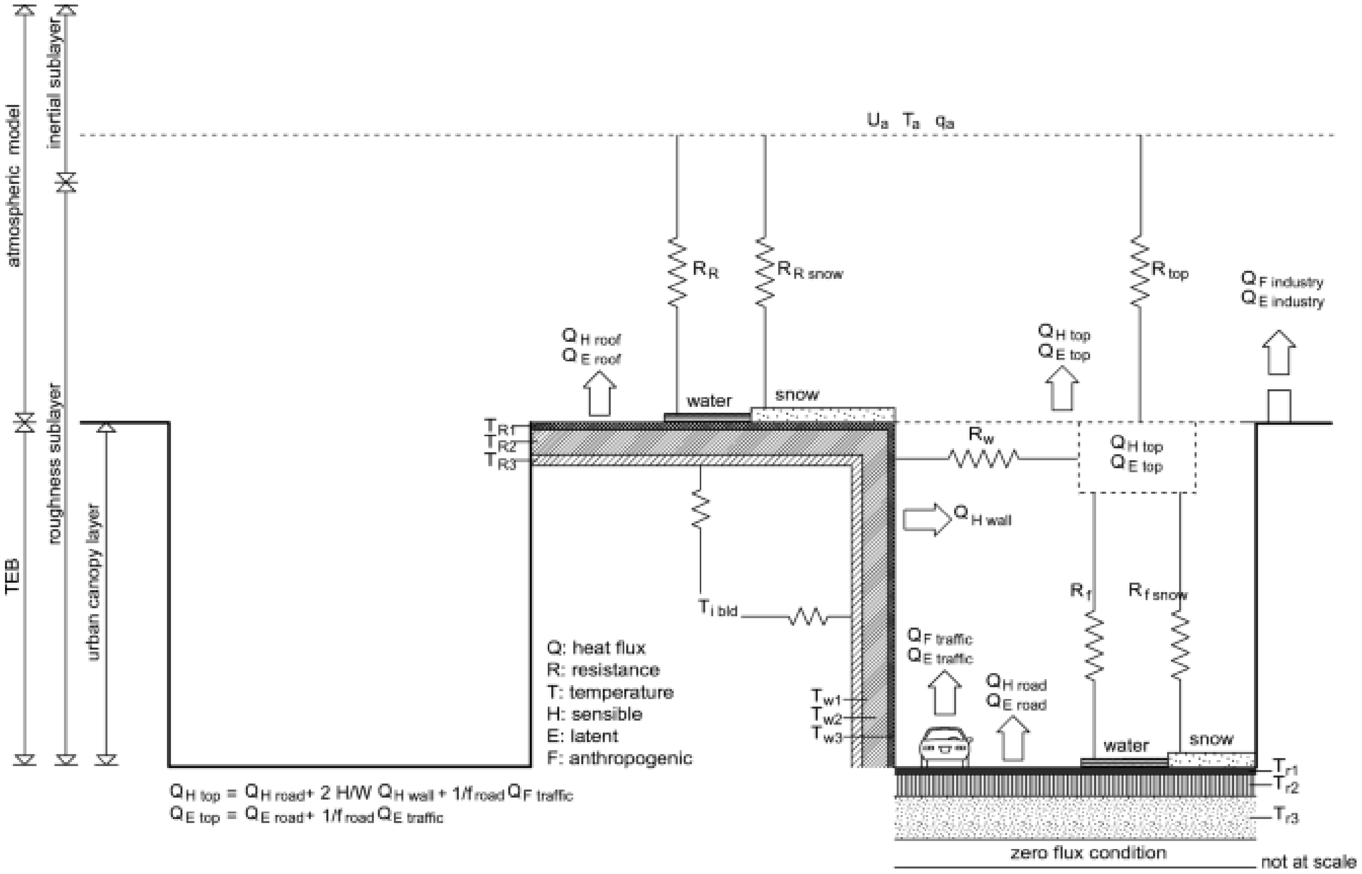
1 Define building geometry using a graphical interface

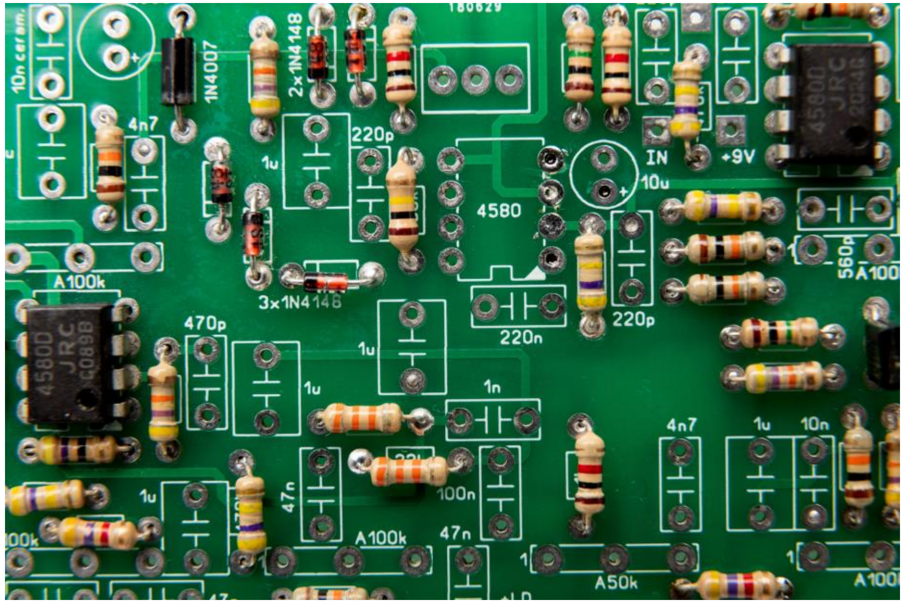
3 Run simulation



DOE

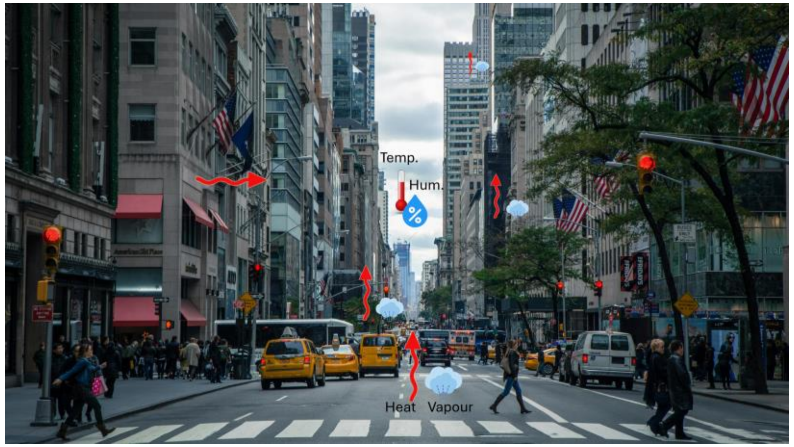
Energy and mass balance (or RC model)



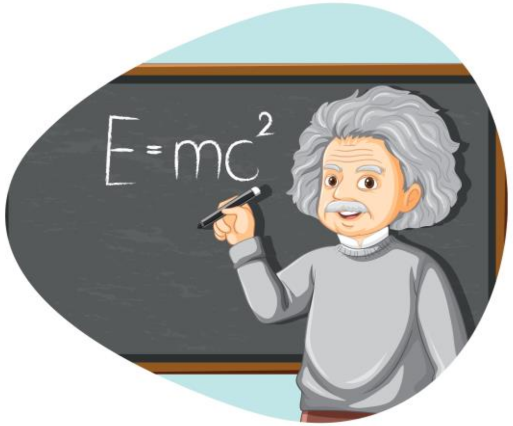


Ali-Toudert and Bottcher (2018)

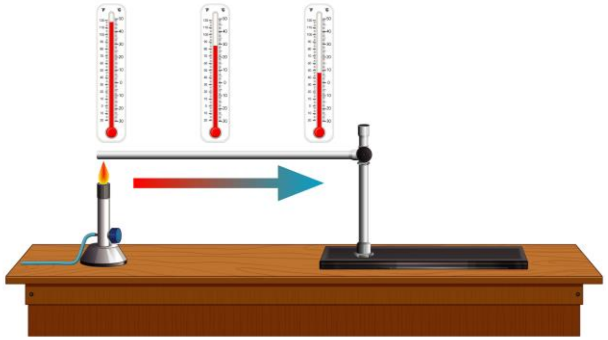
???



Learn more

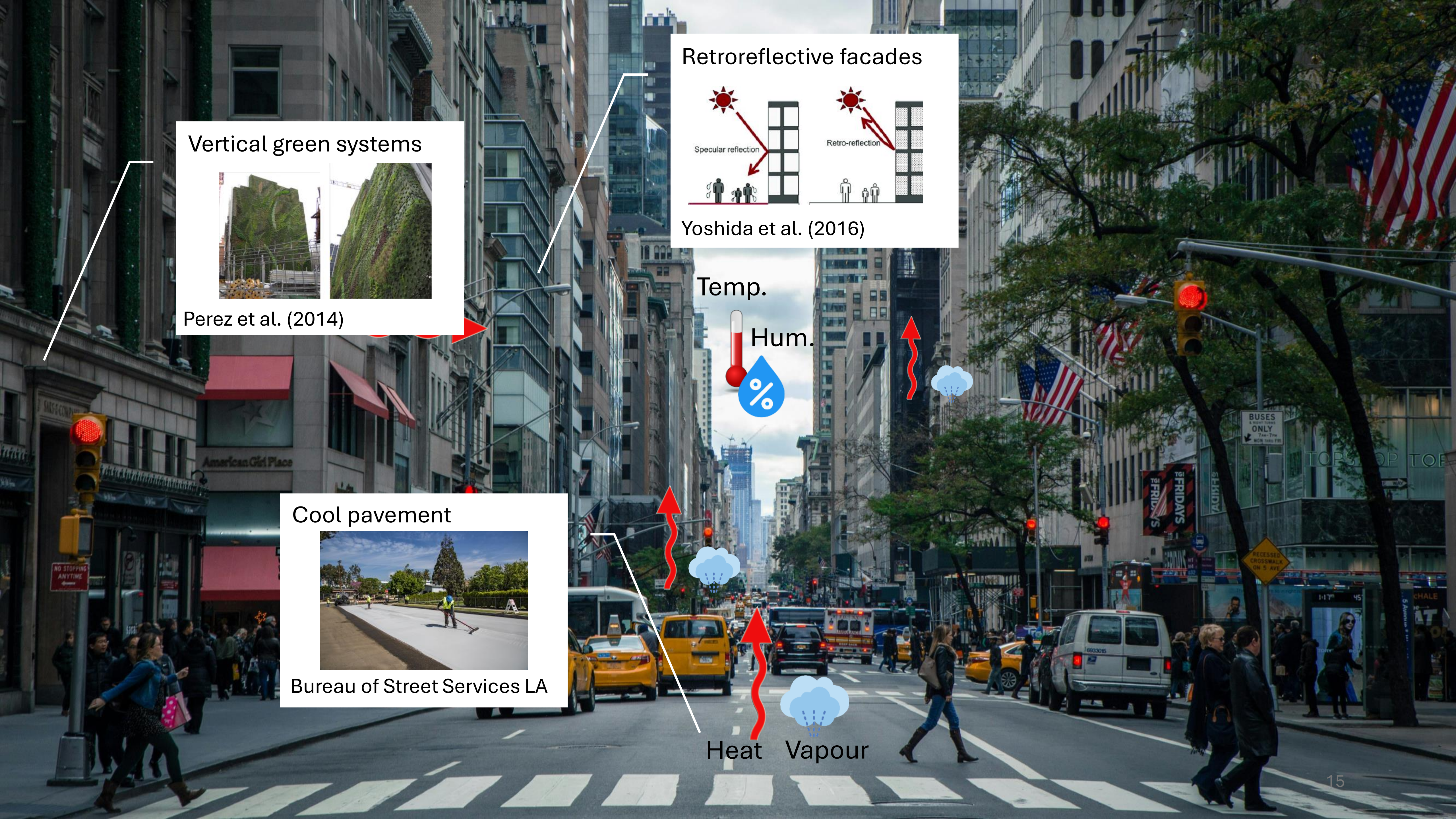


Heat and mass transfer



Fluid dynamics

Meteorological experiments


Vertical green systems
Perez et al. (2014)
Retroreflective facades
Specular reflection
Retro-reflection
Yoshida et al. (2016)
Temp.
Hum.
Cool pavement
Bureau of Street Services LA
Heat
Vapour

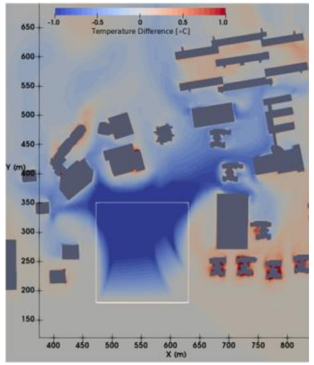
Machine learning to predict outdoor conditions

White box

Grey box

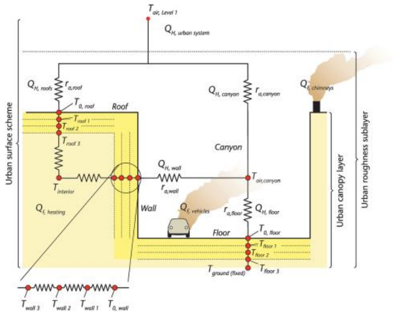
Black box

Computational fluid dynamics



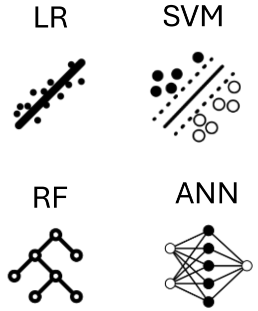
Yap (2021)

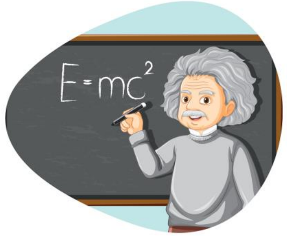
Energy and mass balance (or RC model)

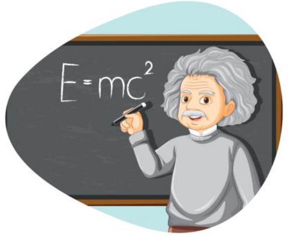


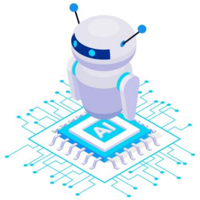
Oke et al. (2017)

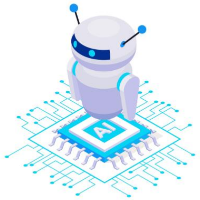
Statistical models

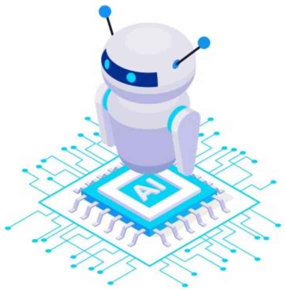






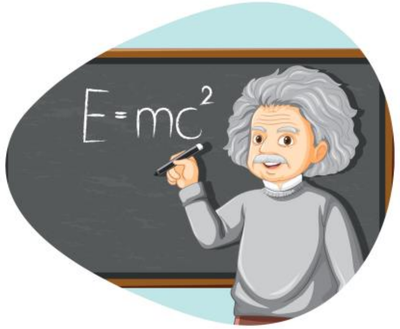


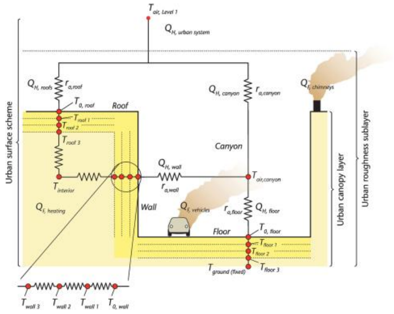




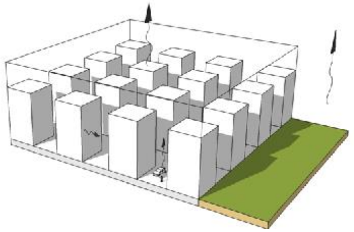
Explore

Energy and mass balance

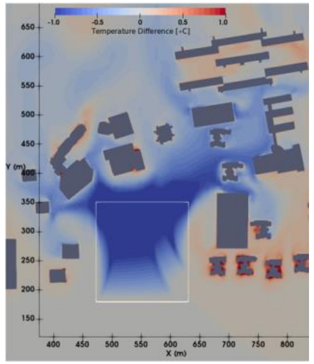




Low fidelity

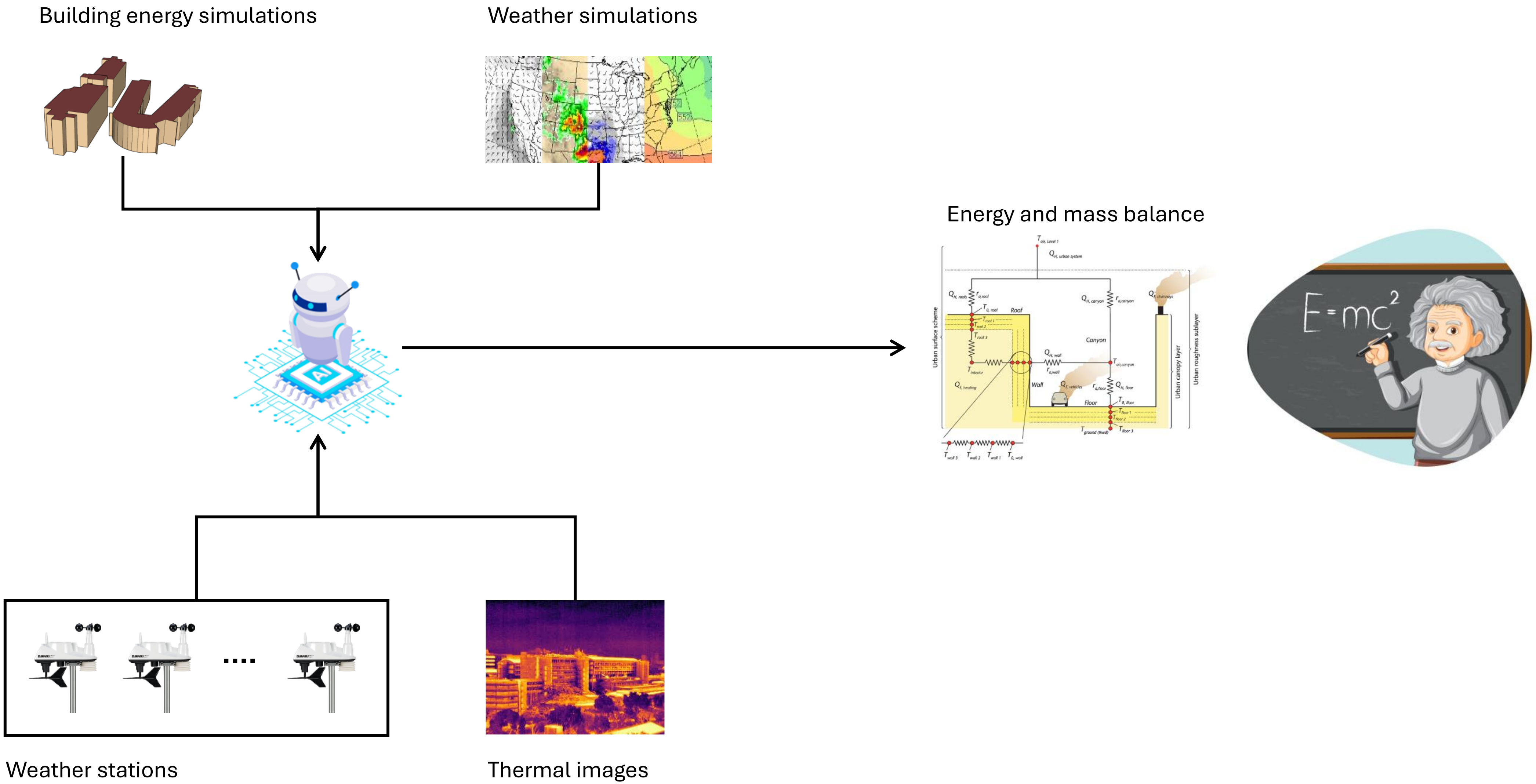


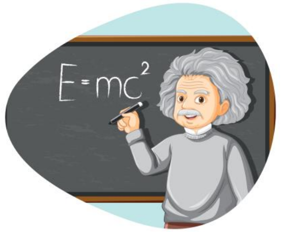
Computational fluid dynamics



High computational cost


Temp.
Hum.
Heat
Vapour

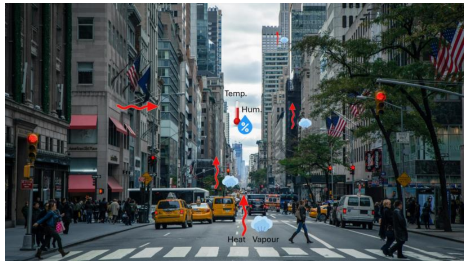

Building energy simulations
Weather simulations
Energy and mass balance
Roof
Canyon
Wall
Floor
E=mc²
Weather stations
Thermal images



Heat and water mass stored by the street canyon

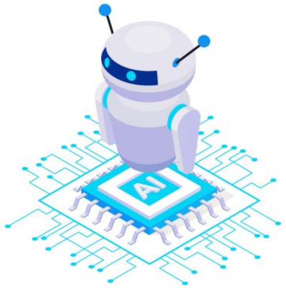
Convective heat and mass transfer between surfaces and the air volume

Sensible and latent heat releases by buildings and traffic



$$
\boxed{C\frac{d\bar{T}_{can}}{dt}} = \boxed{\sum_{m=1}^{M} h_m A_m(\bar{T}_m - \bar{T}_{can})} + \boxed{\sum_{n=1}^{N} H_n}
$$

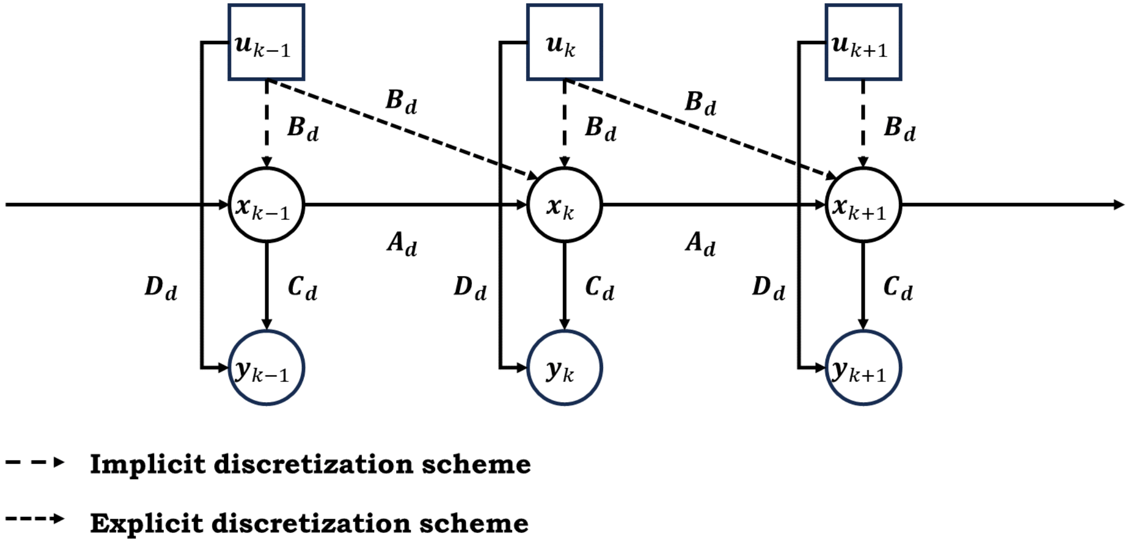
$$
\boxed{C\frac{d\bar{q}_{can}}{dt}} = \boxed{\sum_{p=1}^{P} h_p A_p(\bar{q}_m - \bar{q}_{can})} + \boxed{\frac{c_p}{L}\sum_{q=1}^{Q} LE_q}
$$

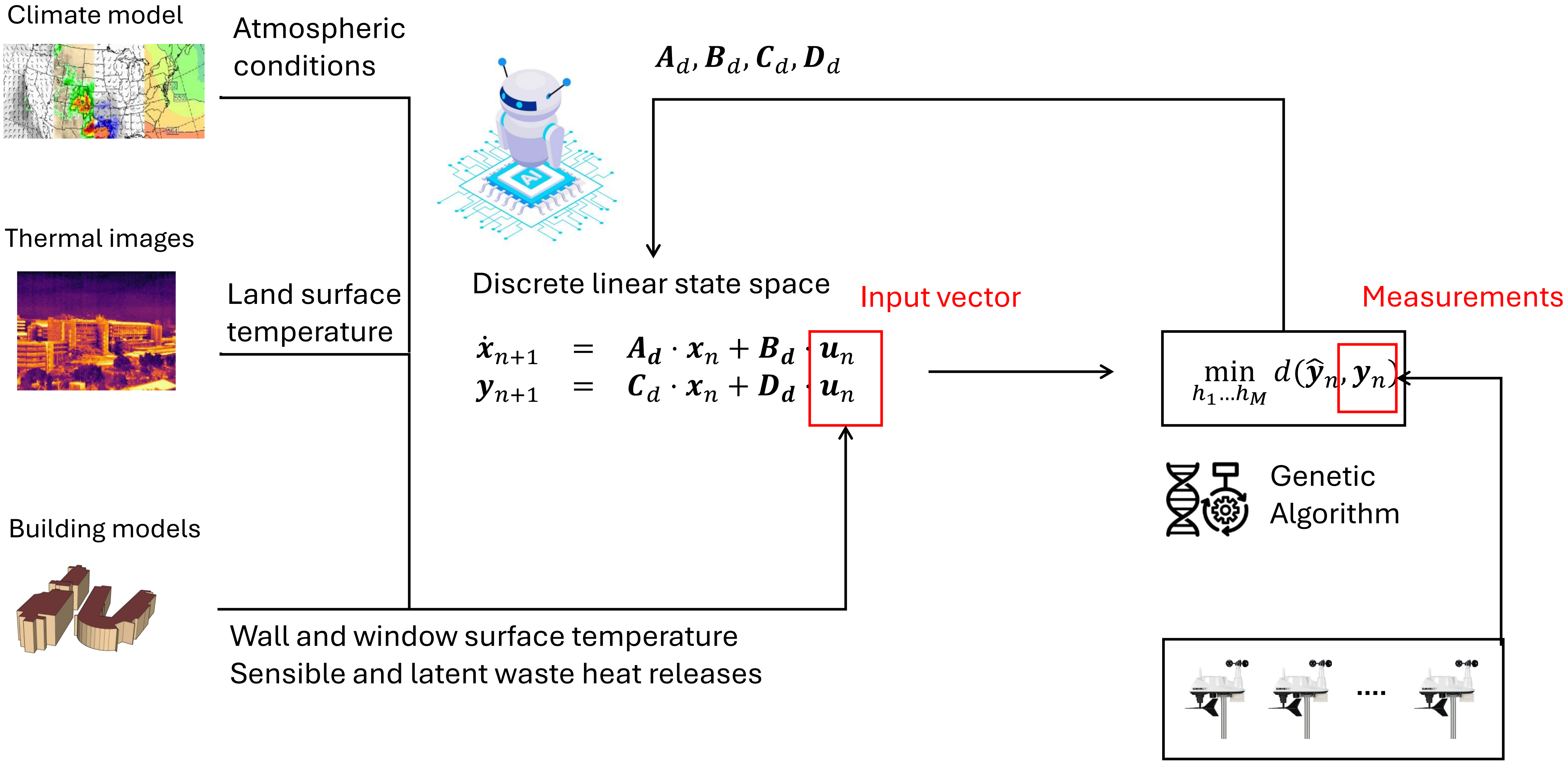


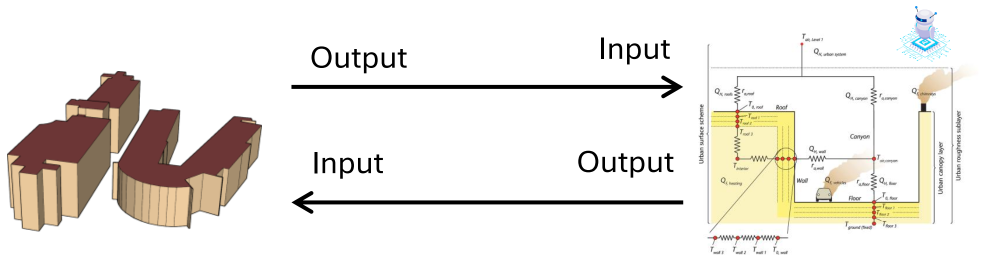
Linear state space

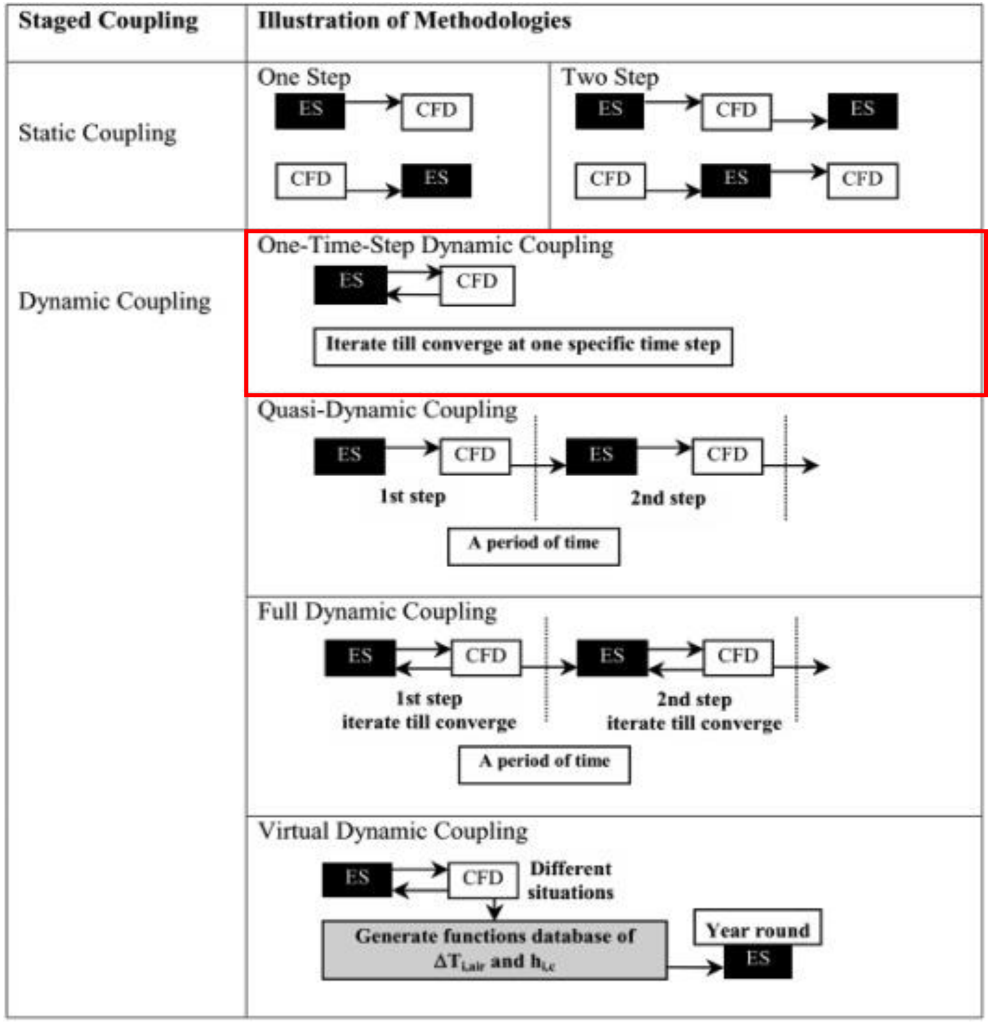
$$
\begin{aligned}
\dot{\boldsymbol{x}} &= \boldsymbol{A}\cdot\boldsymbol{x} + \boldsymbol{B}\cdot\boldsymbol{u} \\
\boldsymbol{y} &= \boldsymbol{C}\cdot\boldsymbol{x} + \boldsymbol{D}\cdot\boldsymbol{u}
\end{aligned}
$$

Discrete linear state space

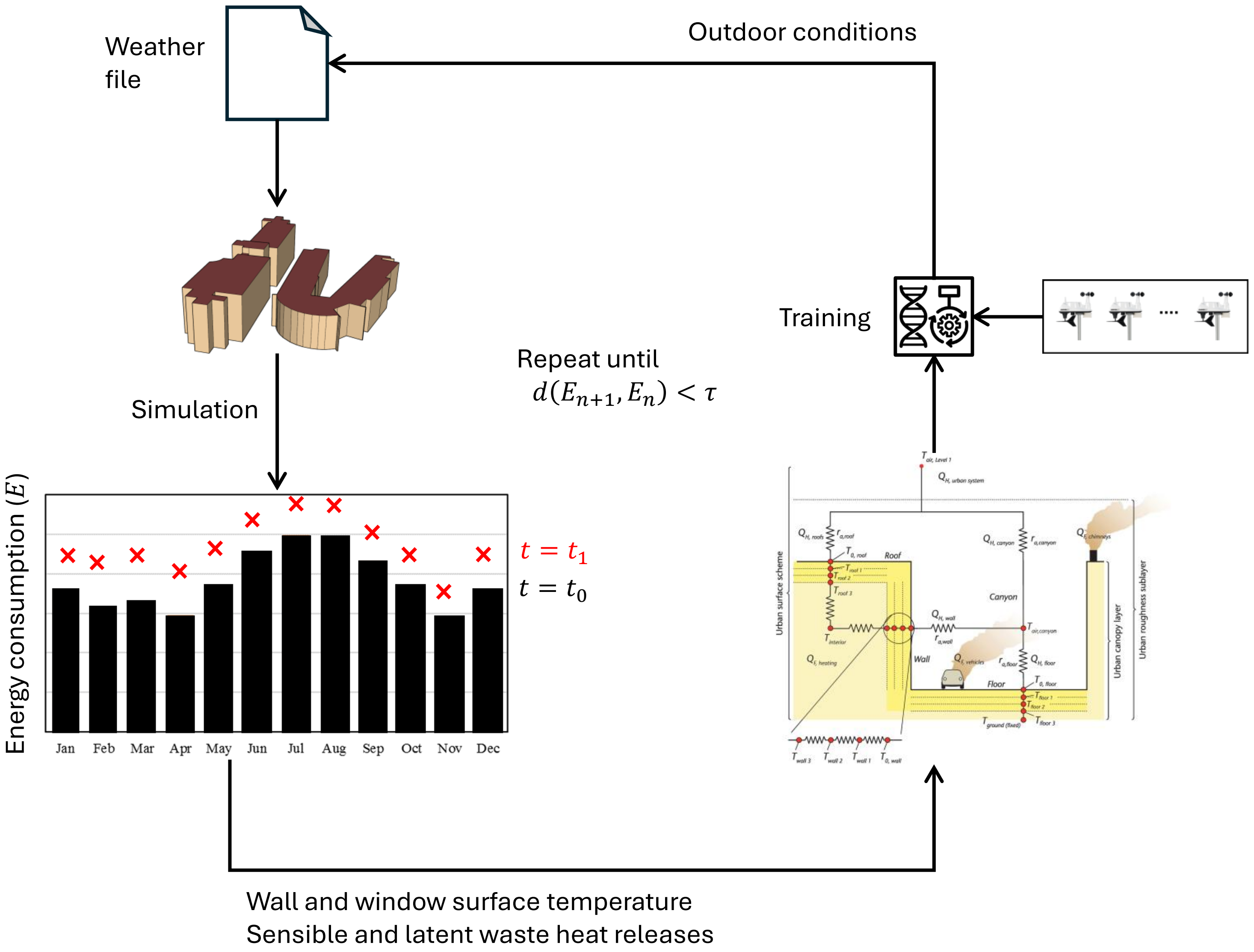


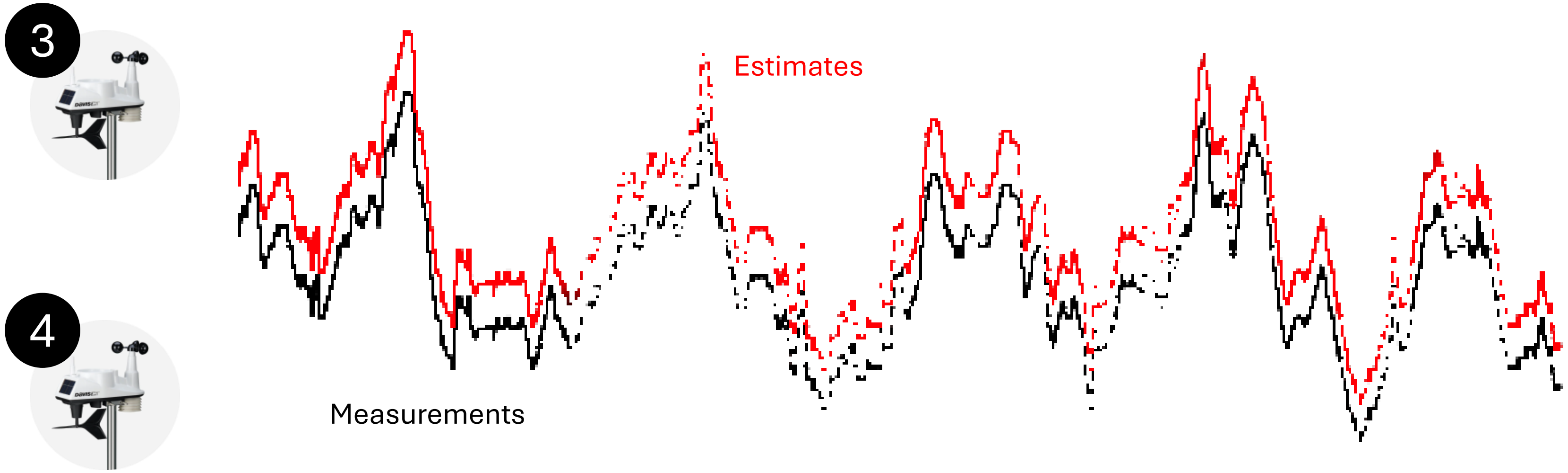

Climate model
Atmospheric conditions
$\boldsymbol{A}_d, \boldsymbol{B}_d, \boldsymbol{C}_d, \boldsymbol{D}_d$
Thermal images
Land surface temperature
Discrete linear state space
Input vector
Measurements
$\dot{\boldsymbol{x}}_{n+1} = \boldsymbol{A_d} \cdot \boldsymbol{x}_n + \boldsymbol{B_d} \cdot \boldsymbol{u}_n$
$\boldsymbol{y}_{n+1} = \boldsymbol{C}_d \cdot \boldsymbol{x}_n + \boldsymbol{D_d} \cdot \boldsymbol{u}_n$
$\min_{h_1 \dots h_M} d(\widehat{\boldsymbol{y}}_n, \boldsymbol{y}_n)$
Genetic Algorithm
Building models
Wall and window surface temperature
Sensible and latent waste heat releases
....



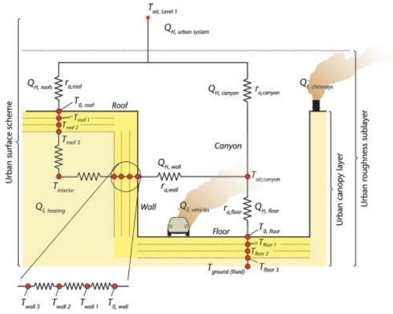


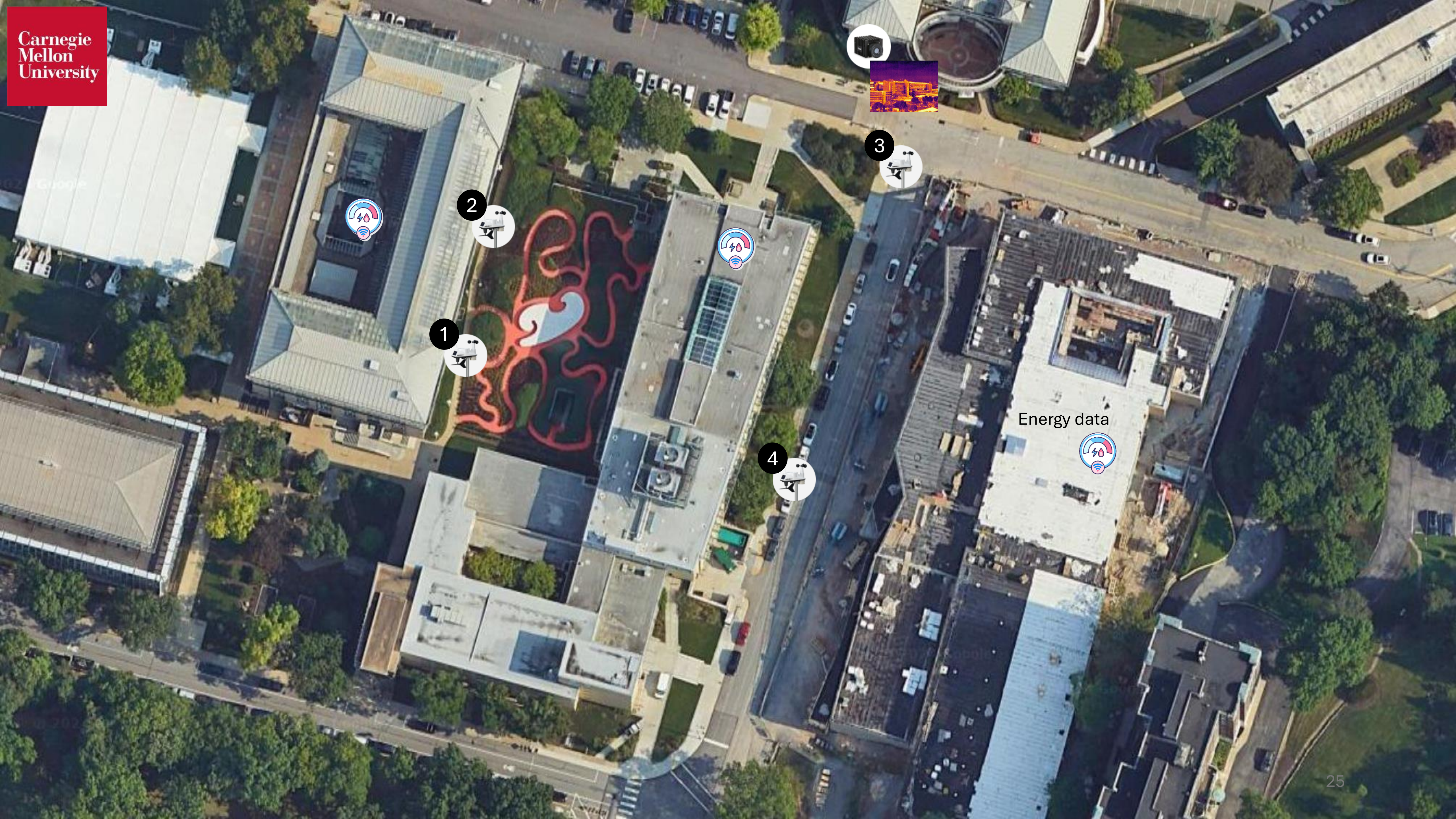
Zhang et al. (2018)



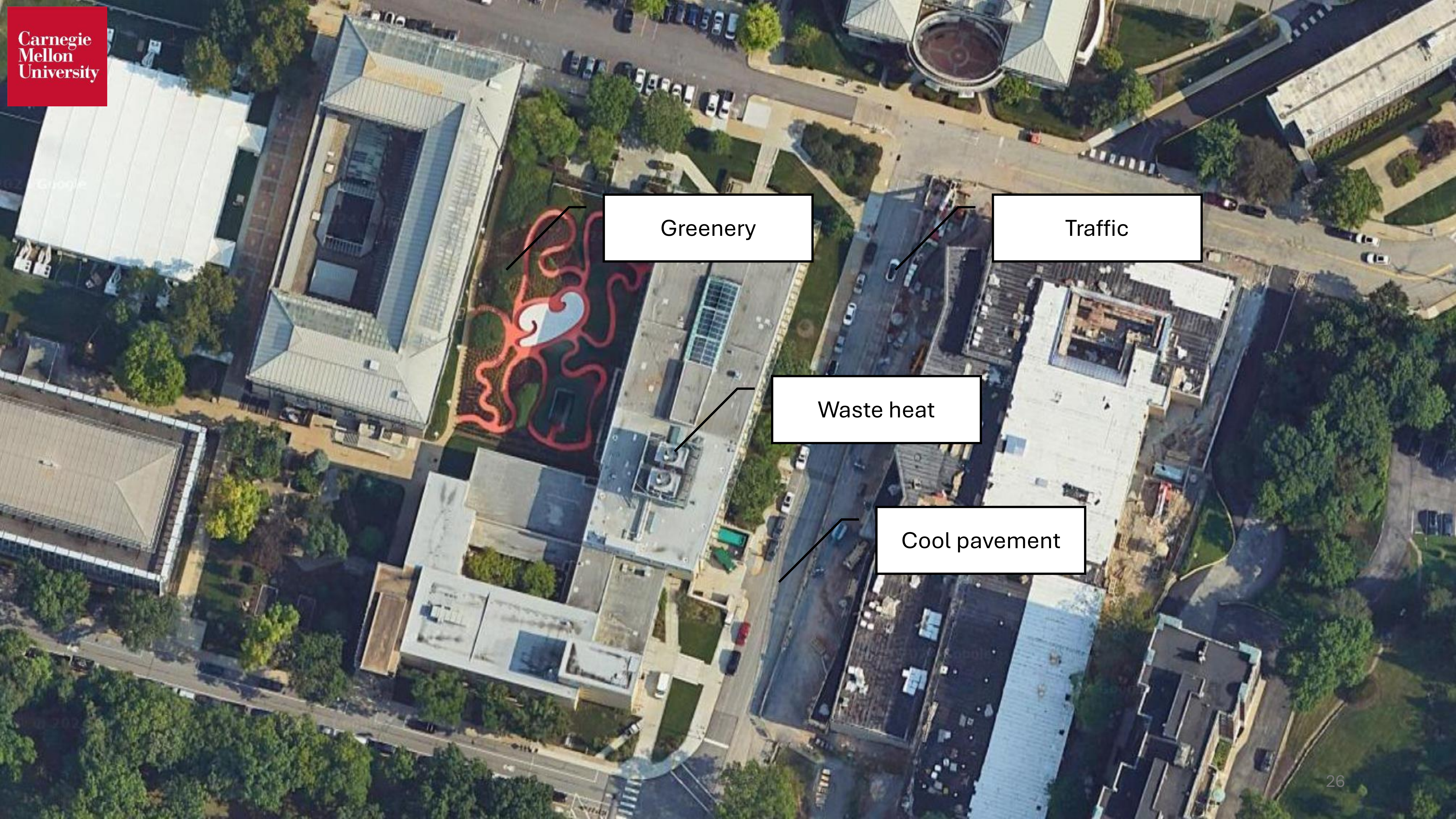


Energy and mass balance

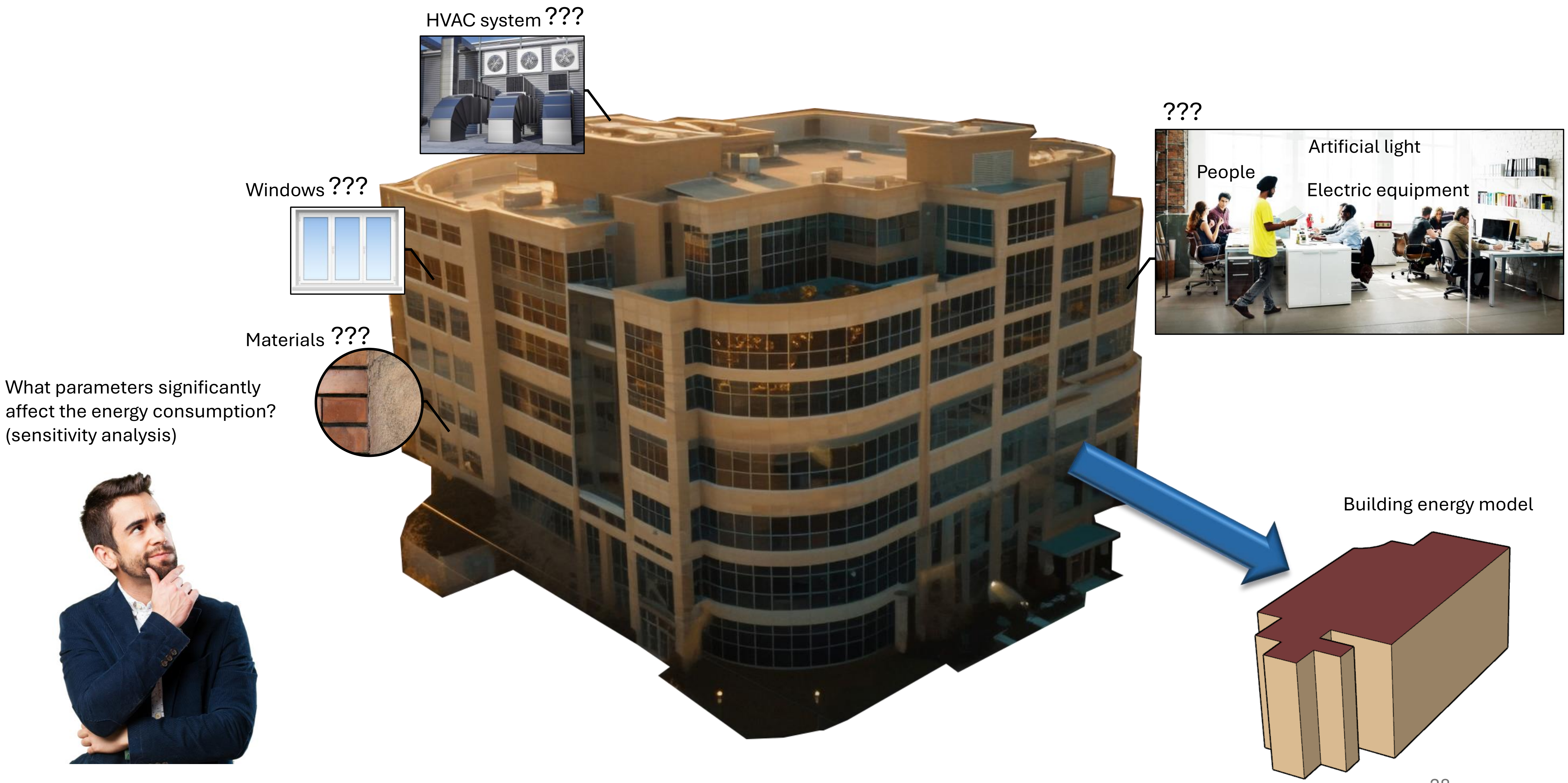


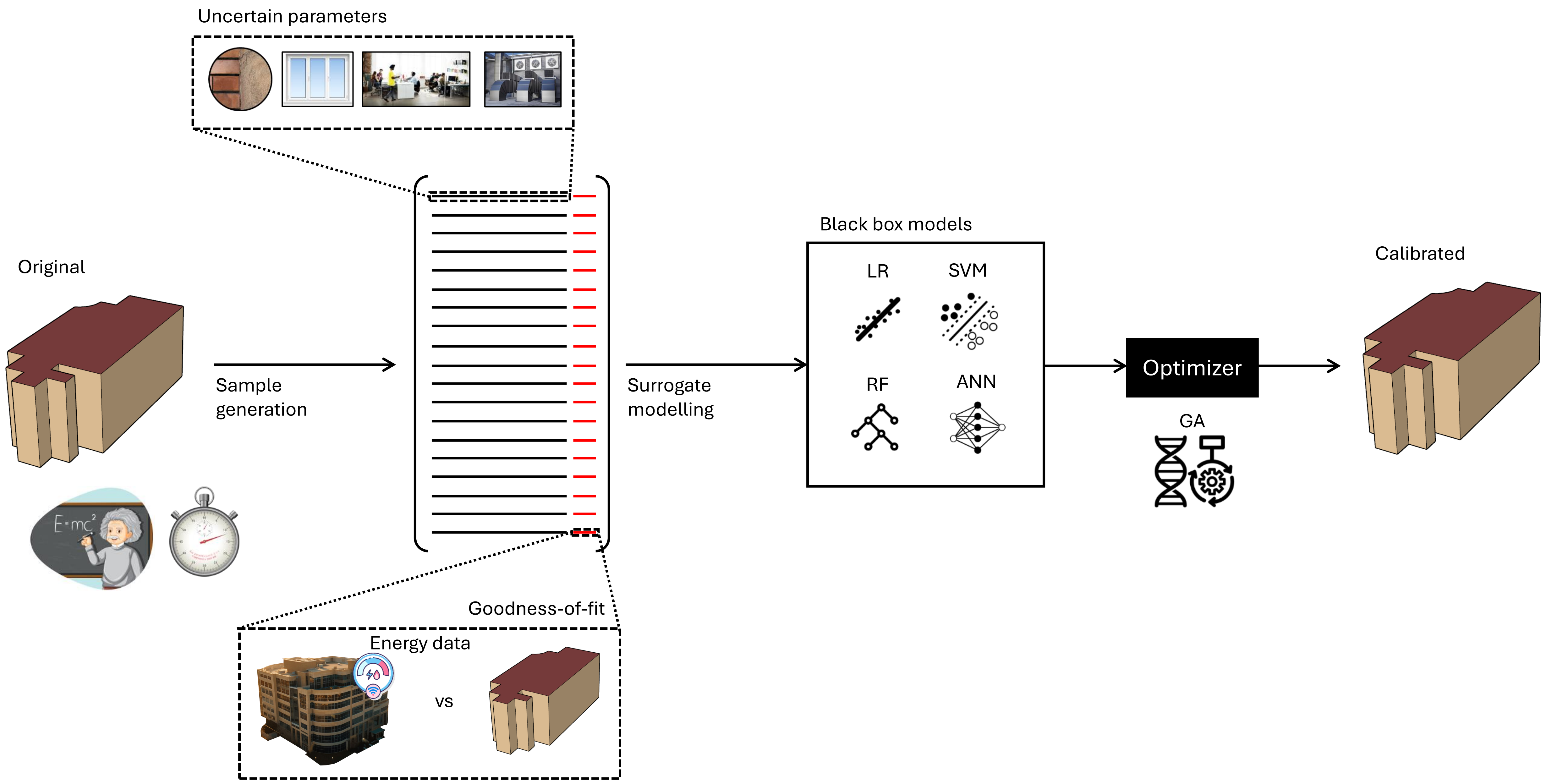


1
2
3
4
Energy data


Greenery
Traffic
Waste heat
Cool pavement

Machine learning to calibrate an urban building energy model


HVAC system ???
Windows ???
Materials ???
???
People
Artificial light
Electric equipment
What parameters significantly
affect the energy consumption?
(sensitivity analysis)
Building energy model


Uncertain parameters
Original
Sample
generation
E=mc²
Surrogate
modelling
Black box models
LR
SVM
RF
ANN
Optimizer
GA
Calibrated
Goodness-of-fit
Energy data
vs

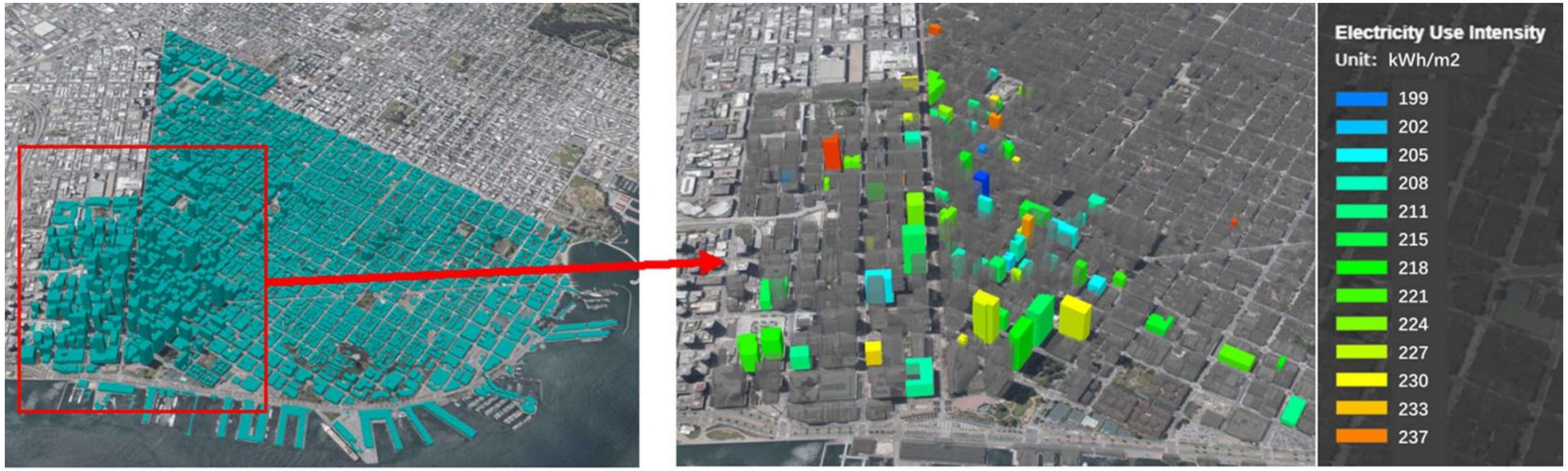
Sensitivity analysis

Sampling generation

Surrogate modelling

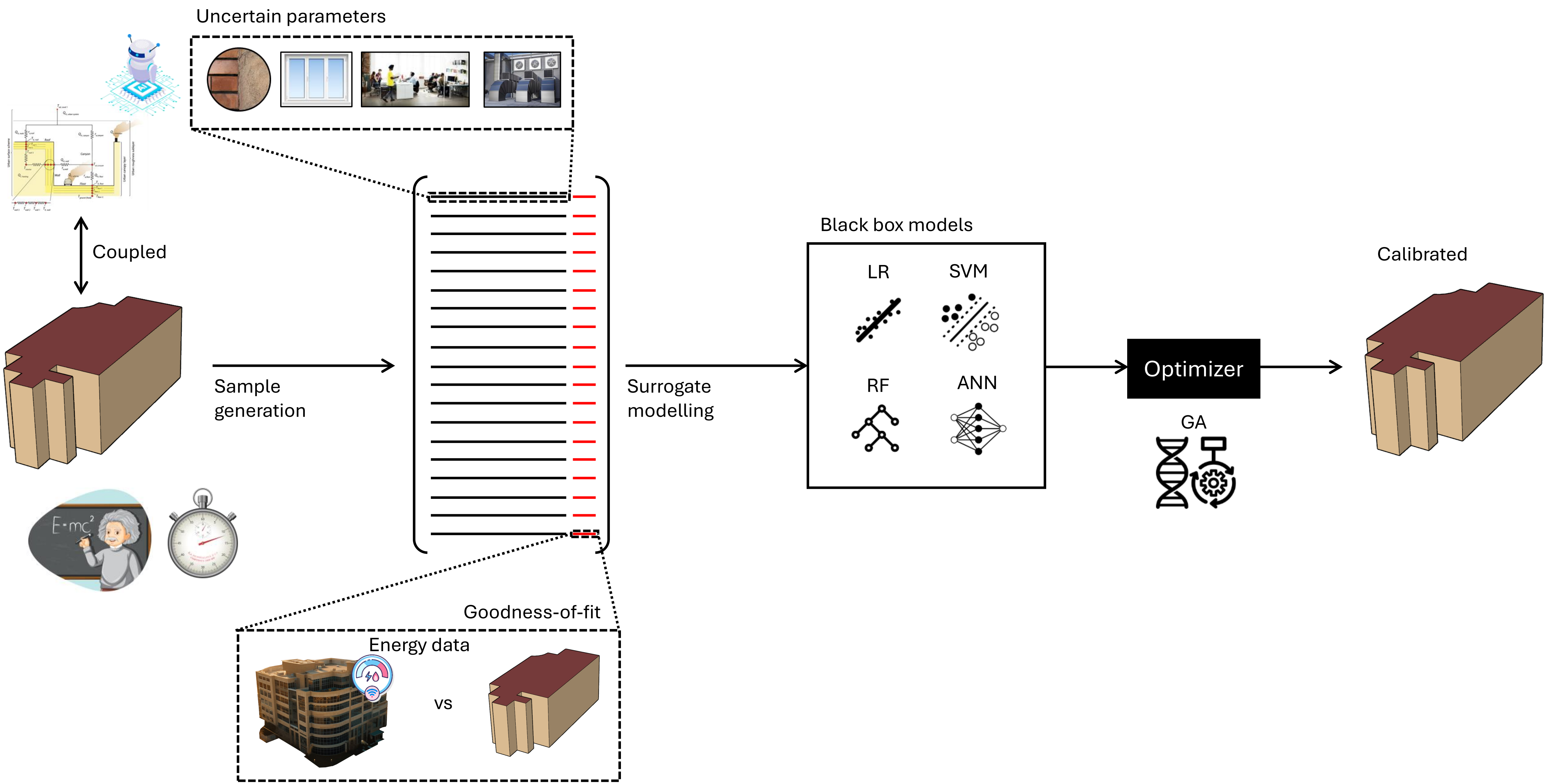
Optimization

Urban building energy model



Chen et al. (2020) (a) (b)

Why are interactions between buildings and their outdoor conditions being ignored in most urban building energy models?


Uncertain parameters
Coupled
Sample
generation
Surrogate
modelling
Black box models
LR
SVM
RF
ANN
Optimizer
GA
Calibrated
Goodness-of-fit
Energy data
vs

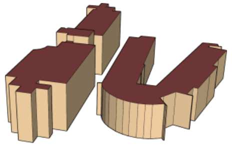
Sensitivity analysis

Sampling generation

Surrogate modelling

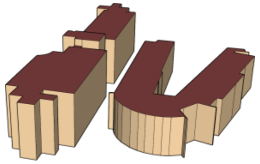
Optimization

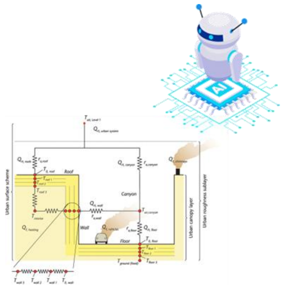
Uncoupled



versus

Coupled

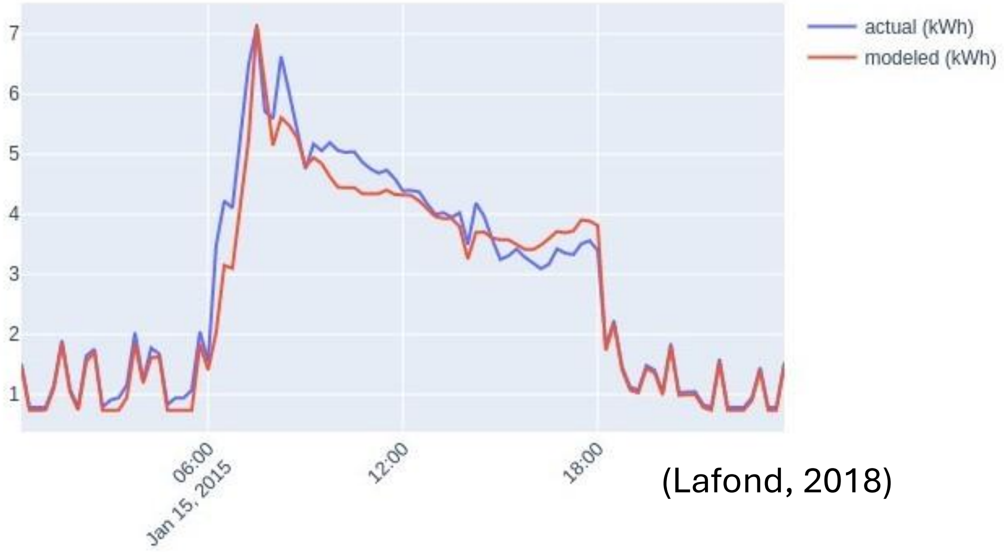




Goodness-of-fit

$$\mathrm{CV(RMSE)} = \frac{1}{\bar{Y}} \sqrt{\frac{\sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2}{N}}$$

Total heating/cooling load



(Lafond, 2018)

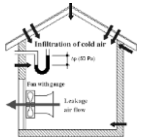
Sensitivity analysis

Sampling generation

Surrogate modelling

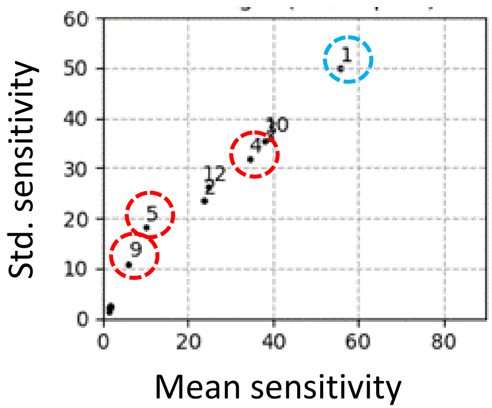
Optimization

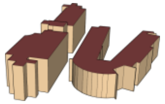
$$S(\theta_i) = \Delta CV(RMSE)/\Delta\theta_i$$

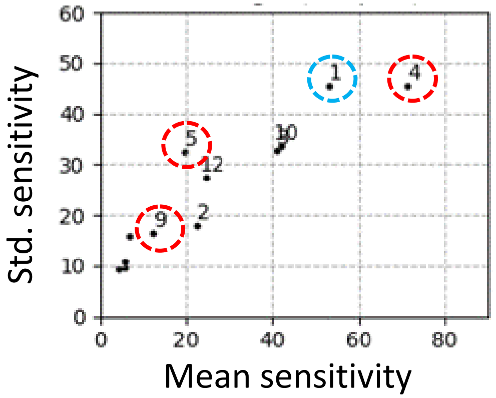


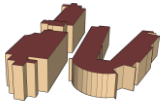
INIVE EEIG (2004)

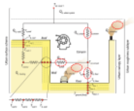
θ	Description	θ_l	θ_u
θ_1	Occupancy (in people)	1.21×10^2	3.03×10^3
θ_2	Light intensity (in W)	1.21×10^4	1.21×10^5
θ_3	Equipment intensity (in W)	1.82×10^4	1.82×10^5
θ_4	Infiltration (in m^3/s)	0.01	10.00
θ_5	Wall thermal resistance (in W/m^2-K)	0.05	3.00
θ_6	Wall density (in kg/m^3)	3.00×10^2	1.80×10^3
θ_7	Wall specific heat capacity (in J/kg-K)	4.00×10^2	1.50×10^3
θ_8	Wall thermal emissivity (0-1)	0.01	0.98
θ_9	Wall solar absorptivity (0-1)	0.05	0.90
θ_{10}	Window-to-wall ratio (0-1)	0.01	0.90
θ_{11}	Window thermal resistance (in W/m^2-K)	0.04	1.50
θ_{12}	Window solar heat gain (0-1)	0.20	0.90









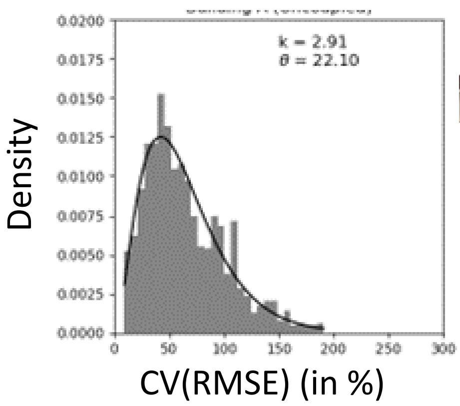


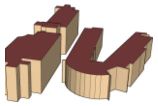
Sensitivity analysis

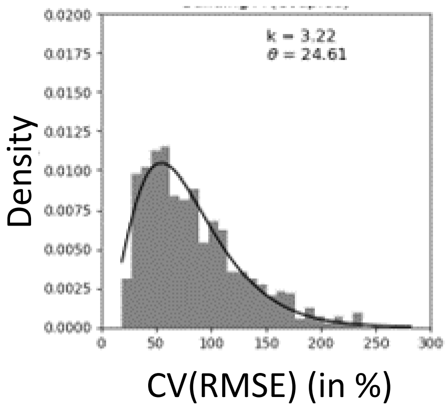
Sampling generation

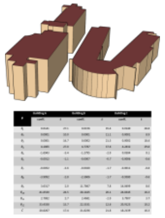
Surrogate modelling

Optimization









	Building A		Building B		Building C	
	20%	30%	20%	30%	20%	30%
Uncoupled	7.2	17.2	3.9	13.5	4.4	13.0
Coupled	3.5	9.6	3.7	9.6	3.0	8.6

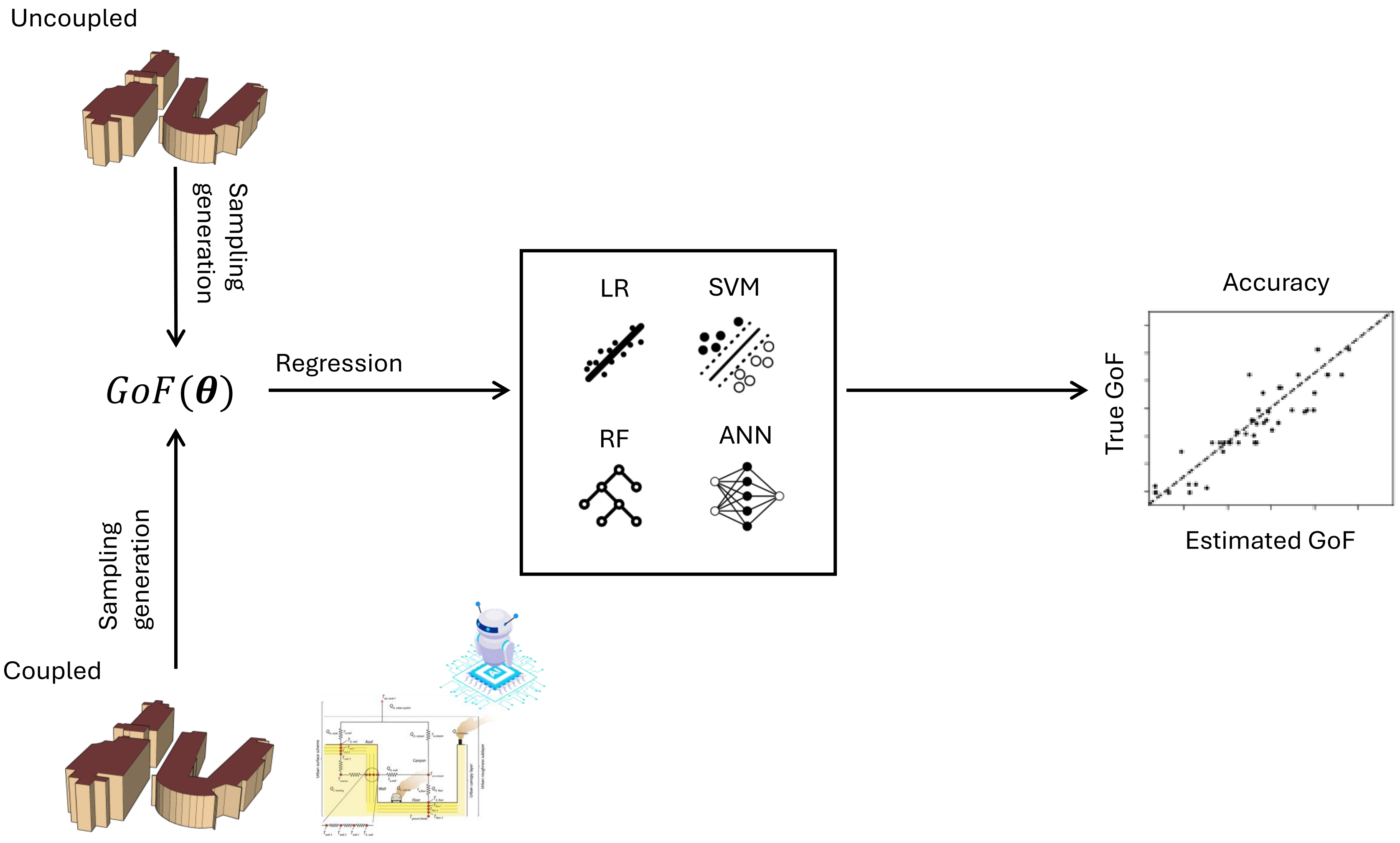
θ	Building A		Building B		Building C	
	coeff.	t	coeff.	t	coeff.	t
θ_1	0.0141	27.1	0.0156	35.4	0.0140	28.8
θ_2	0.0001	10.0	0.0001	11.1	0.0001	8.9
θ_3	0.0001	14.7	0.0002	21.3	0.0002	18.4
θ_4	4.1065	27.0	4.7787	37.6	4.2432	29.8
θ_5	-1.6943	-3.4	-1.2795	-2.9	0.0304	0.1
θ_6	-0.0012	-1.1	-0.0007	-0.7	-0.0006	-0.6
θ_7	-0.0052	-3.6	-0.0020	-1.7	-0.0011	-0.8
θ_8	-3.9092	-2.8	-2.3606	-1.7	-0.9580	-0.6
θ_9	3.6317	2.0	11.7867	7.8	14.0499	8.0
θ_{10}	41.6530	24.5	28.1425	20.1	24.8345	16.3
θ_{11}	2.7882	2.7	2.4681	-2.9	3.7907	3.7
θ_{12}	33.4358	15.7	22.3531	12.6	20.9123	10.2
C	20.8267	17.4	21.8236	21.8	18.2139	16.3

Sensitivity analysis

Sampling generation

Surrogate modelling

Optimization

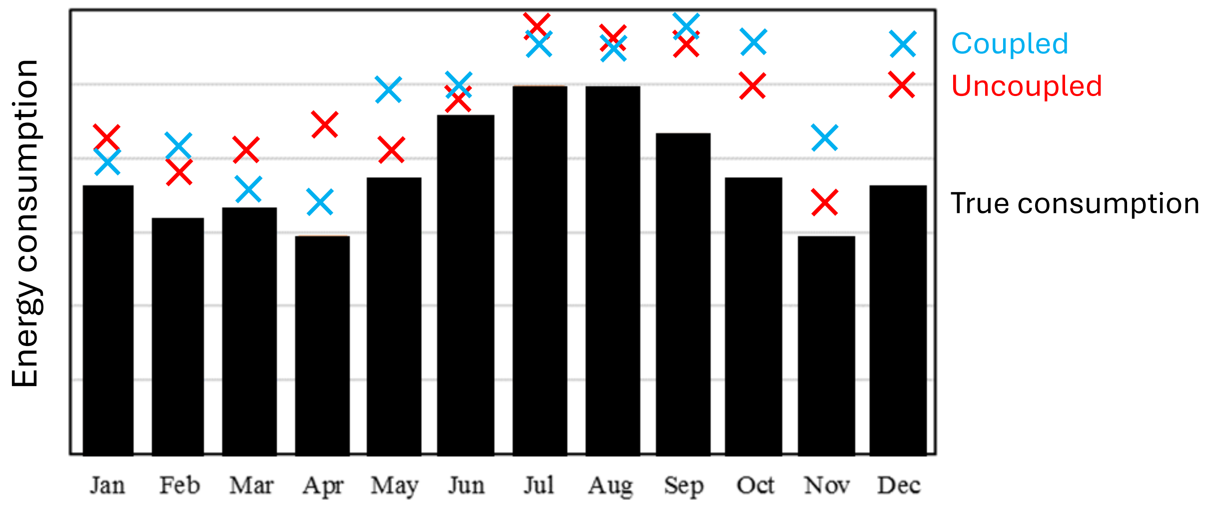


Sensitivity analysis

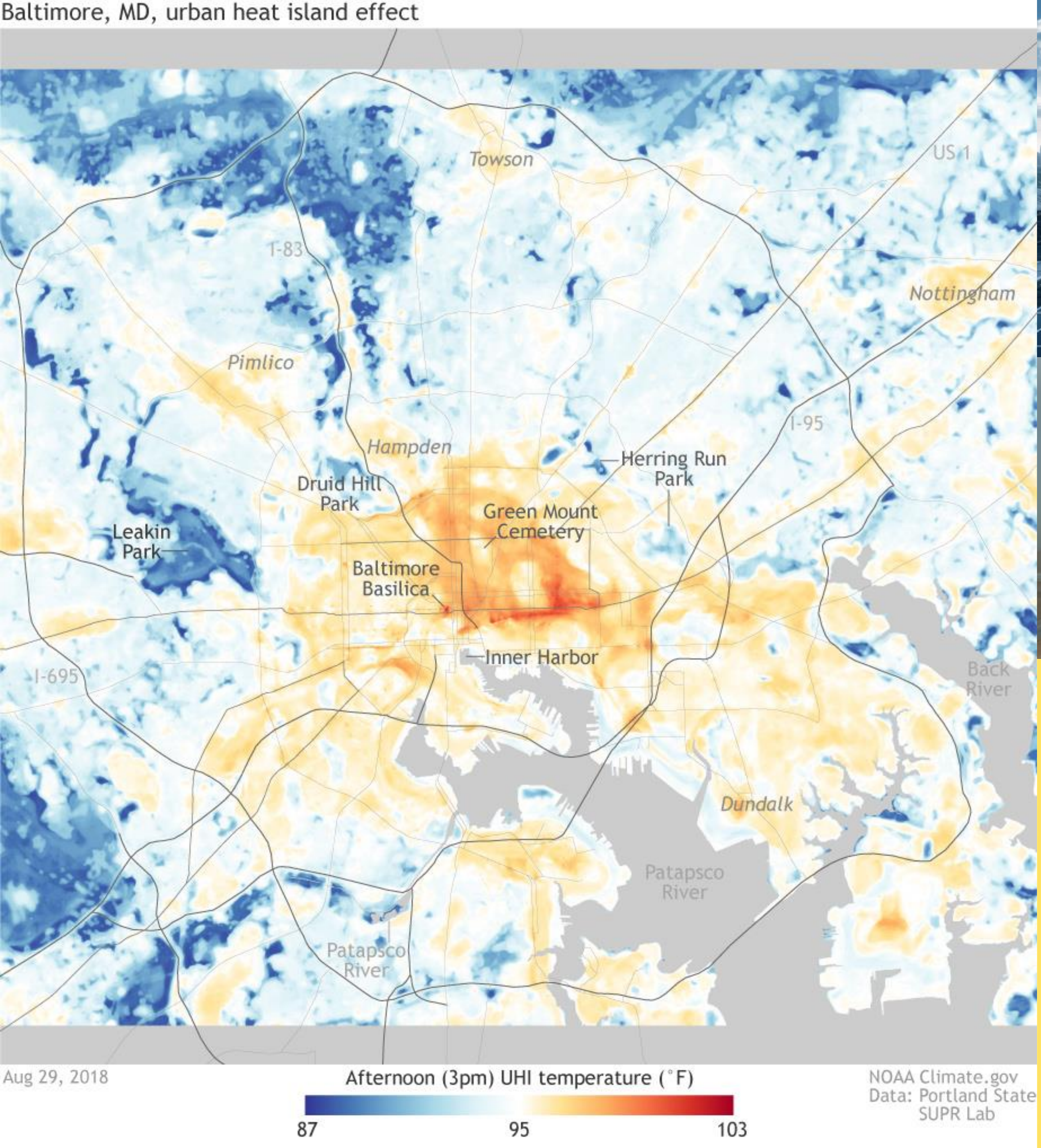
Sampling generation

Surrogate modelling

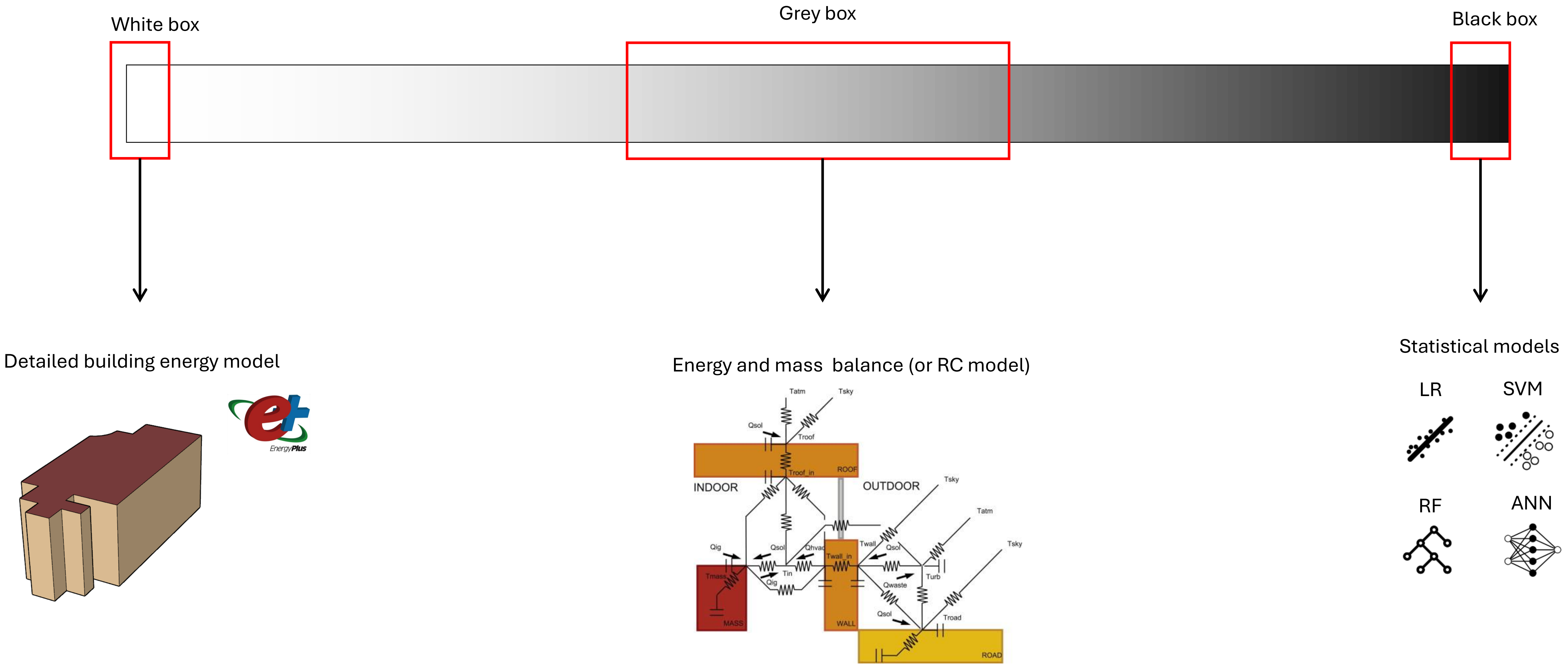
Optimization



Machine learning to assess climate risk

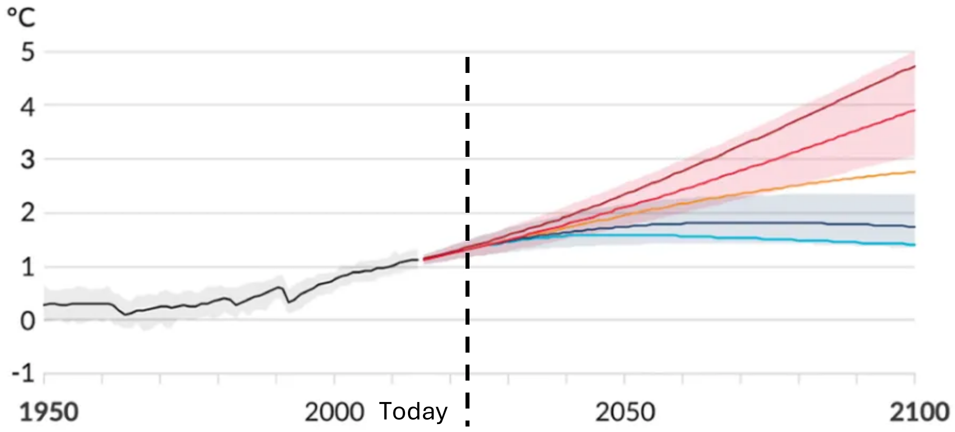

Baltimore, MD, urban heat island effect
Towson
US 1
I-83
Nottingham
Pimlico
I-95
Hampden
Herring Run Park
Druid Hill Park
Green Mount Cemetery
Leakin Park
Baltimore Basilica
Inner Harbor
I-695
Back River
Dundalk
Patapsco River
Patapsco River
Aug 29, 2018
Afternoon (3pm) UHI temperature (˚F)
87
95
103
NOAA Climate.gov
Data: Portland State SUPR Lab


40˚
100˚



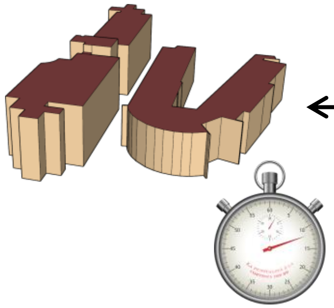
Bueno et al. (2012)

Projected Temperature Increase (°C)

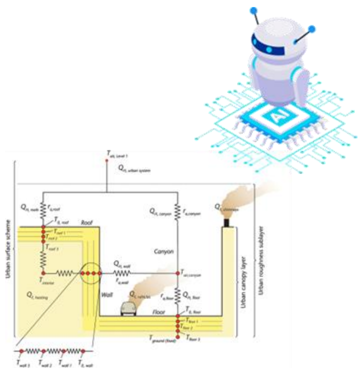


UCAR

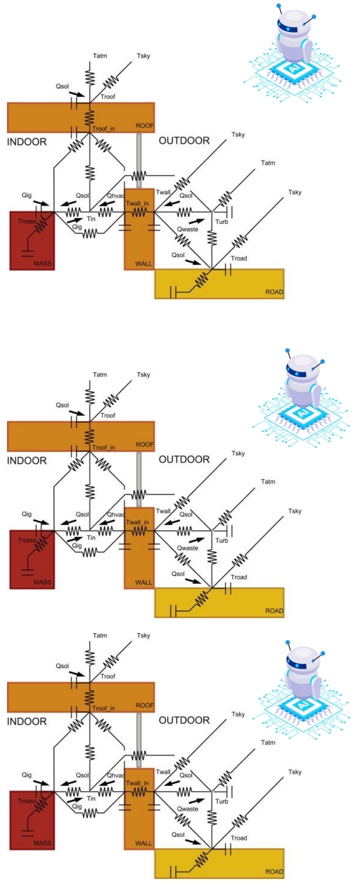
Calibrated model



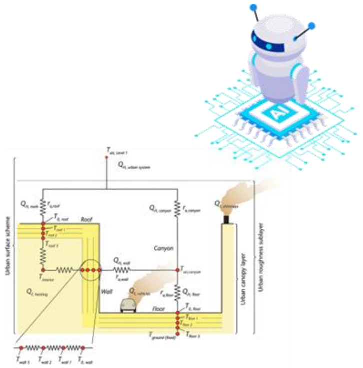
Coupled

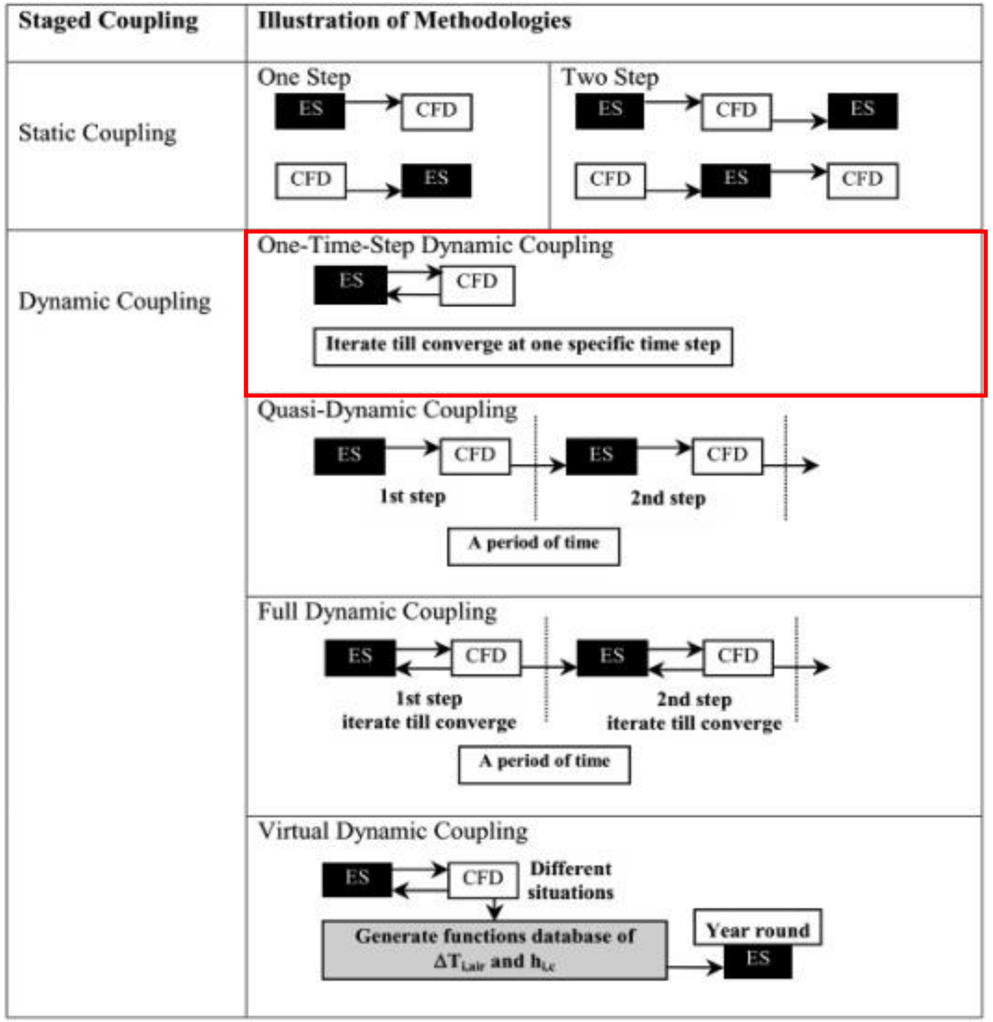


Infer

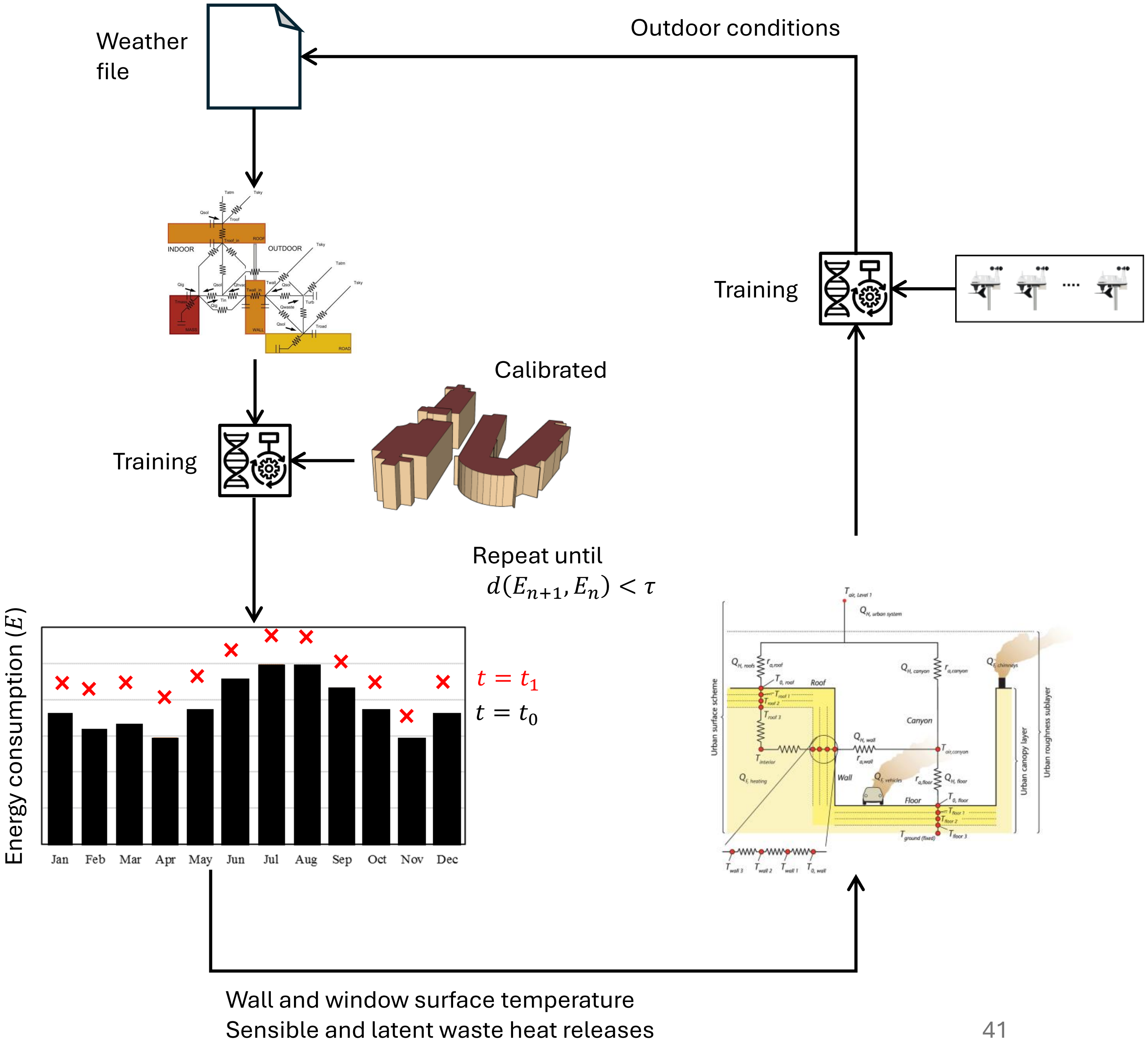


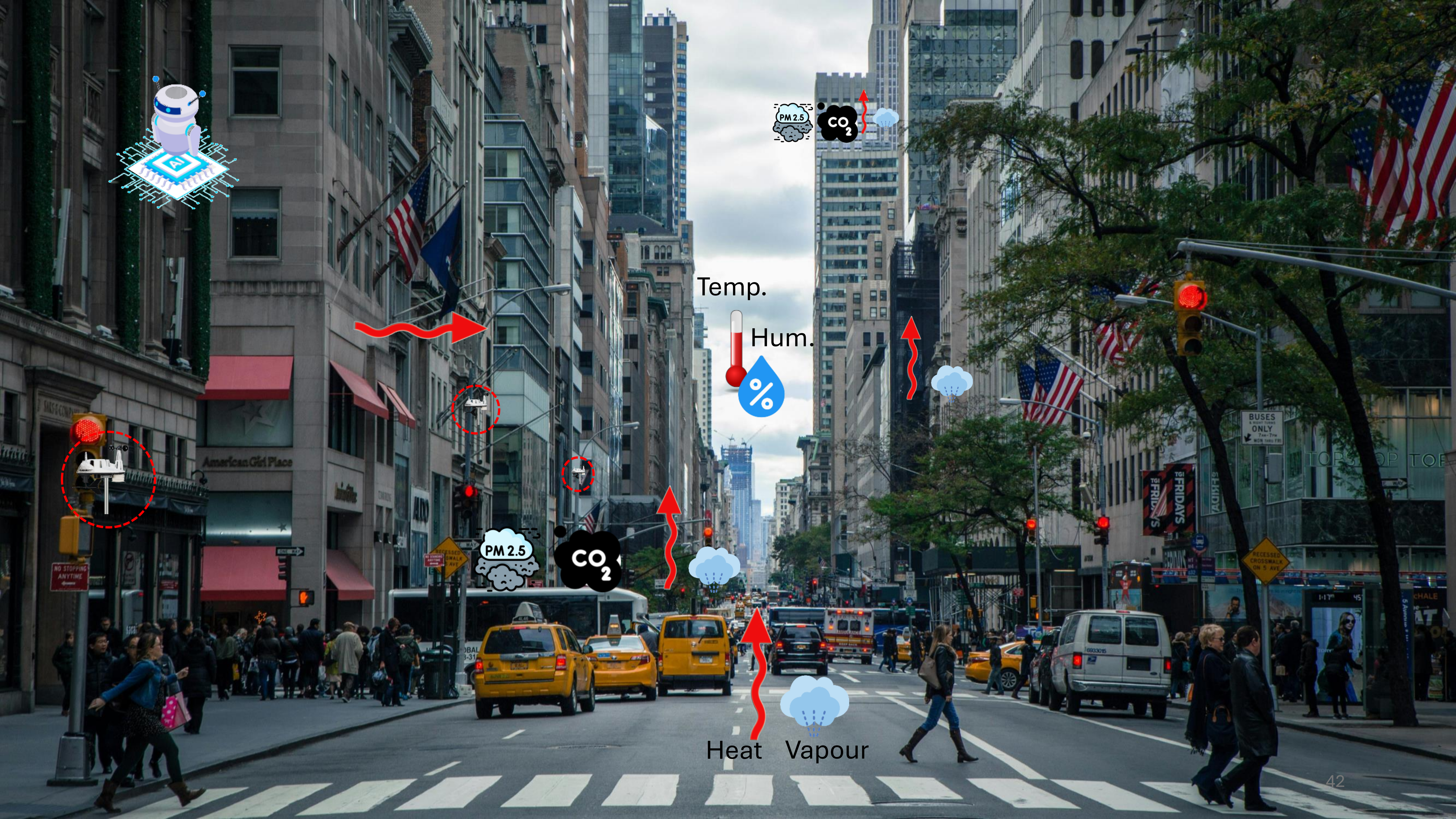
Coupled

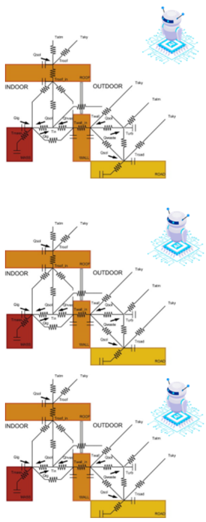




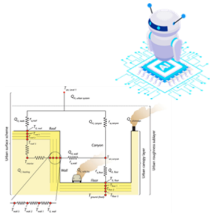
Zhang et al. (2018)



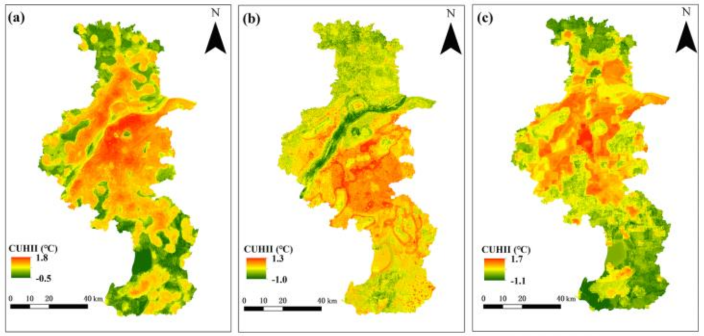

PM 2.5
CO_2
Temp.
Hum.
%
Heat
Vapour
AI
American Girl Place
BUSES ONLY
TGI FRIDAYS



Coupled

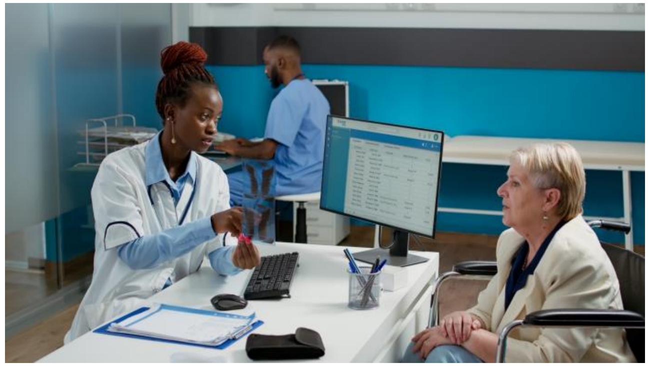


2030 2040 2050



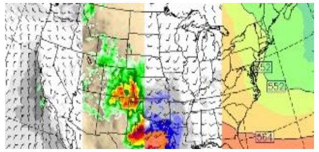
Chen et al. (2022)

Socioeconomic factors



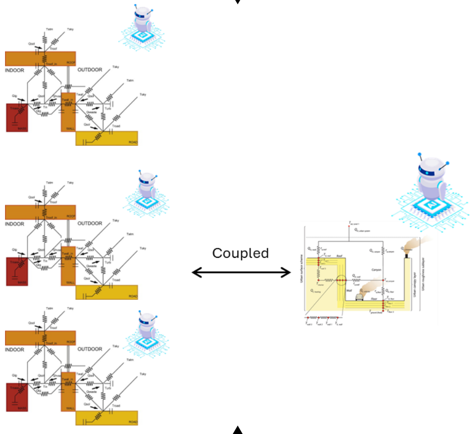
$

Atmospheric conditions



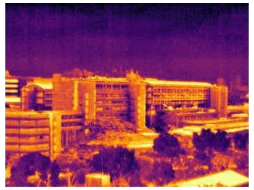
Predict

???



Predict

30 years



Land surface temperature

Predict

???

Miguel Martin

miguelmartin.org

Dr. Miguel Martin

Postdoctoral Research Fellow
M.Martin@tudelft.nl

HOME PUBLICATIONS TEACHING AWARDS CV

I am a postdoctoral researcher sponsored by the Marie-Curie Global fellowship to contribute to the mission Climate Neutral and Smart Cities in collaboration with the Delft University of Technology and Carnegie Mellon University.

Q&A session