BUILDINGS AND URBAN HEAT ISLANDS

CS-E407519 Lecture 5

Photo by Austin Scherbarth on *Unsplash*

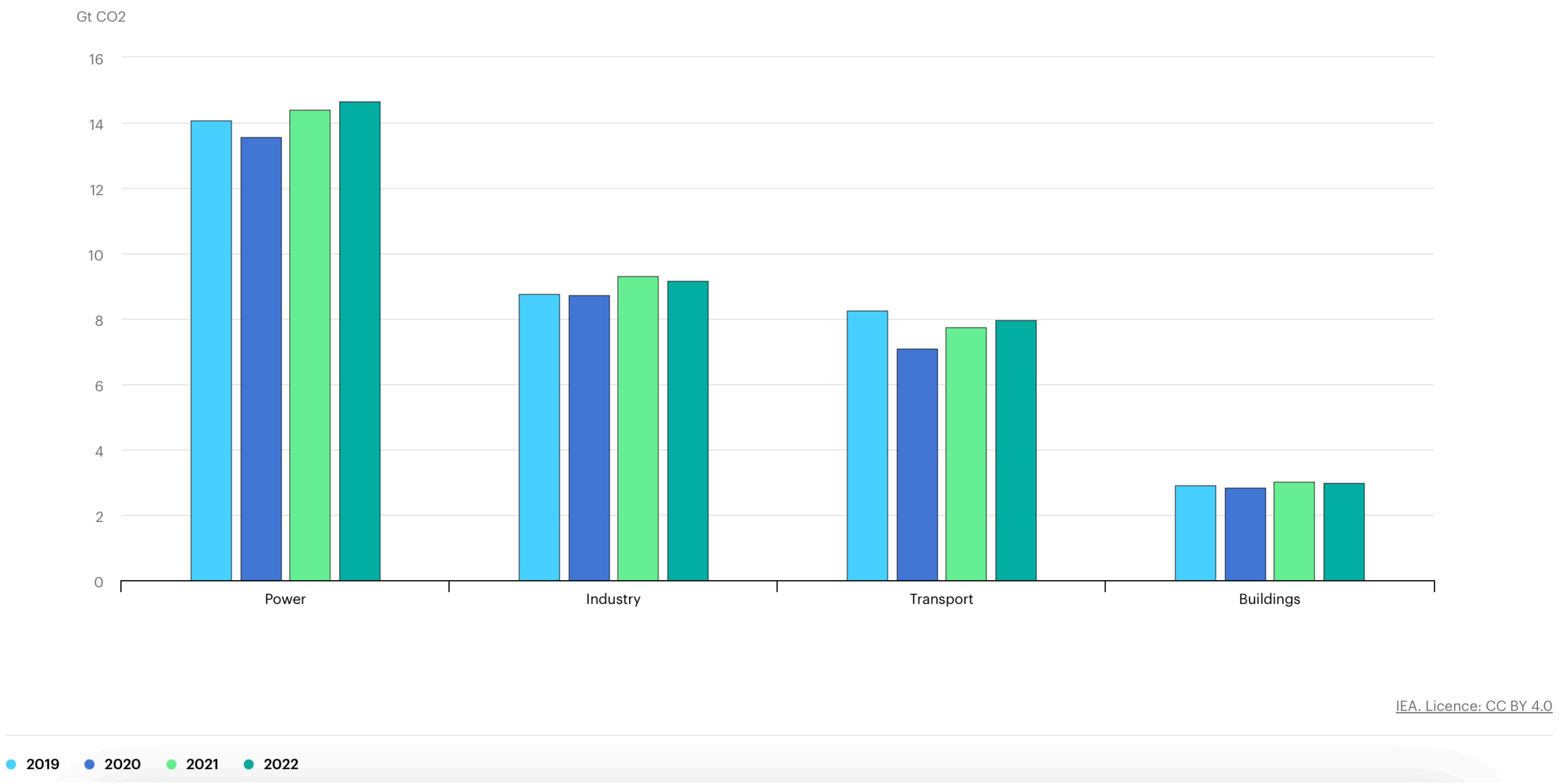
BUILDINGS ≠ URBAN HEAT ISLANDS (UHI)

OUTLINE

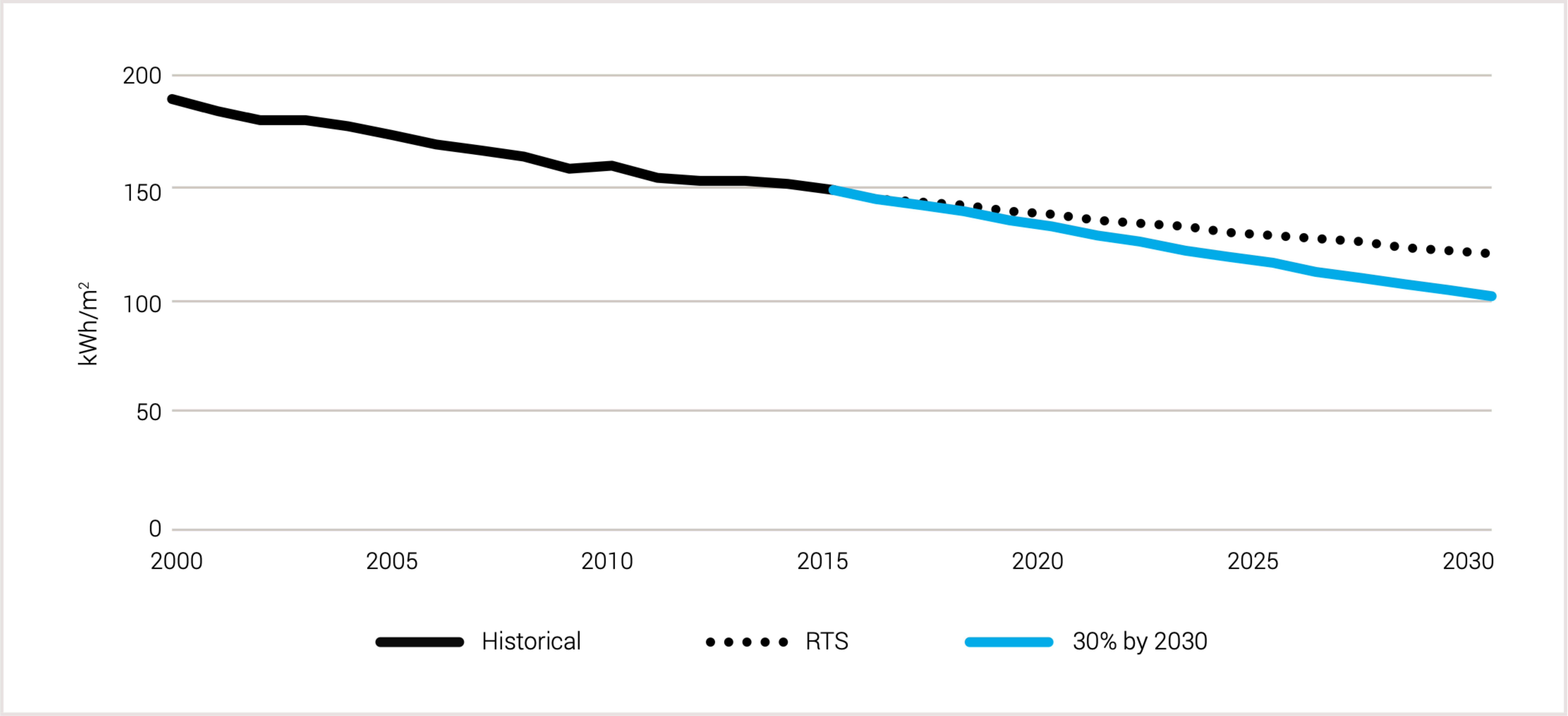
- Buildings
- Urban heat islands
- Time-series modelling
- UHI in Seoul

BUILDINGS

WE USED TO FOCUS ONLY ON OPERATIONAL GHG EMISSIONS (HEAT, COOLING, LIGHTING)



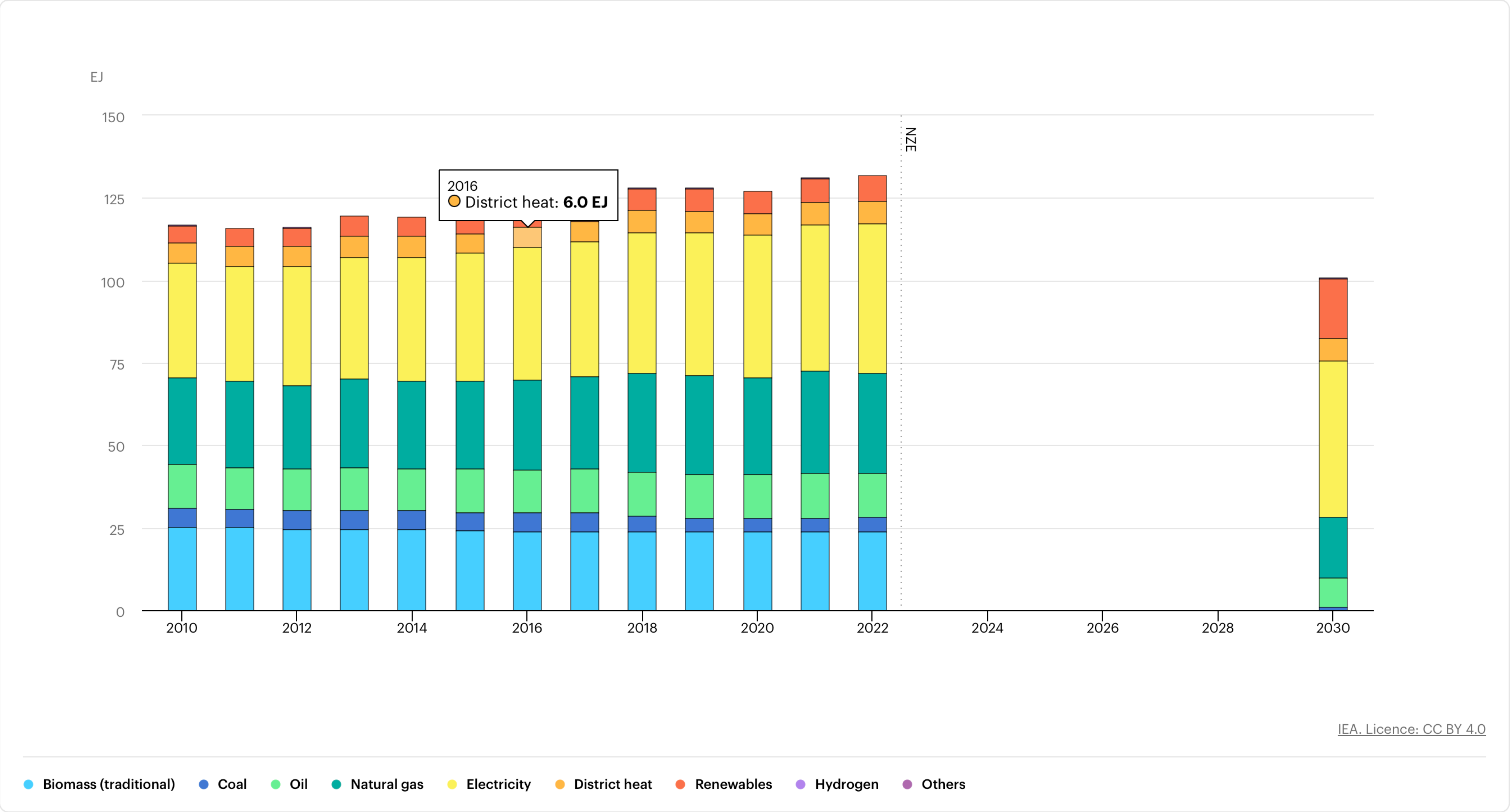
GLOBAL FINAL ENERGY USE PER SQUARE METER



Notes: EJ = exajoules; kWh/m2 = kilowatt-hours per square metre: RTS = Reference Technology Scenario.
Source: IEA (2017), Energy Technology Perspectives 2017, IEA/OECD, Paris www.iea.org/etp/.

Image: Global ABC, Global Status Report 2017

ENERGY CONSUMPTION IN BUILDINGS BY FUEL IN THE NET ZERO SCENARIO, 2010–2030



Renewables include modern biomass, solar and geothermal, while Others refer to non-renewable waste.

DIRECT VS INDIRECT GHG EMISSIONS

- Direct GHG emissions are emitted from sources owned or controlled by the reporting entity
- Indirect GHG emissions are the consequence of activities by the reporting entity but the sources are not owned or controlled by the reporting entity

Images: Unsplash

DISCUSSION: WHAT ARE THE SOURCES ON INDIRECT EMISSIONS IN BUILDINGS?

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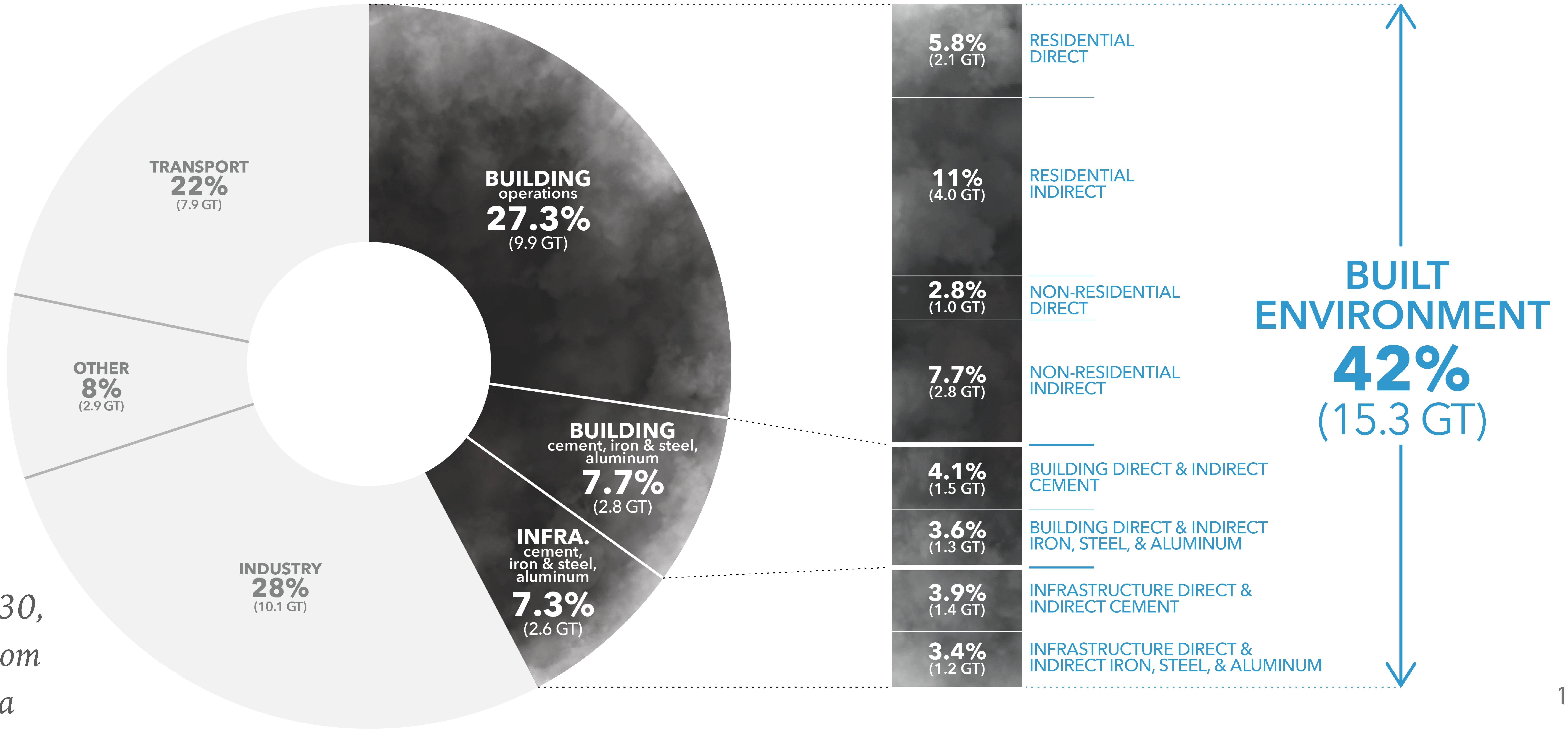
NOW: THINK HOLISTICALLY ABOUT THE BUILT ENVIRONMENT

TOTAL ANNUAL GLOBAL CO_2 EMISSIONS
Direct & Indirect Energy & Process Emissions (36.3 GT)

Building operations: direct emissions are from the use of coal, oil and natural gas in buildings, indirect emissions are from the generation of electricity and heat used in buildings.



Source: Architecture 2030, based on data from IEA and Statista

ROLE OF BUILT ENVIRONMENT

Floor area additions 2017-2060

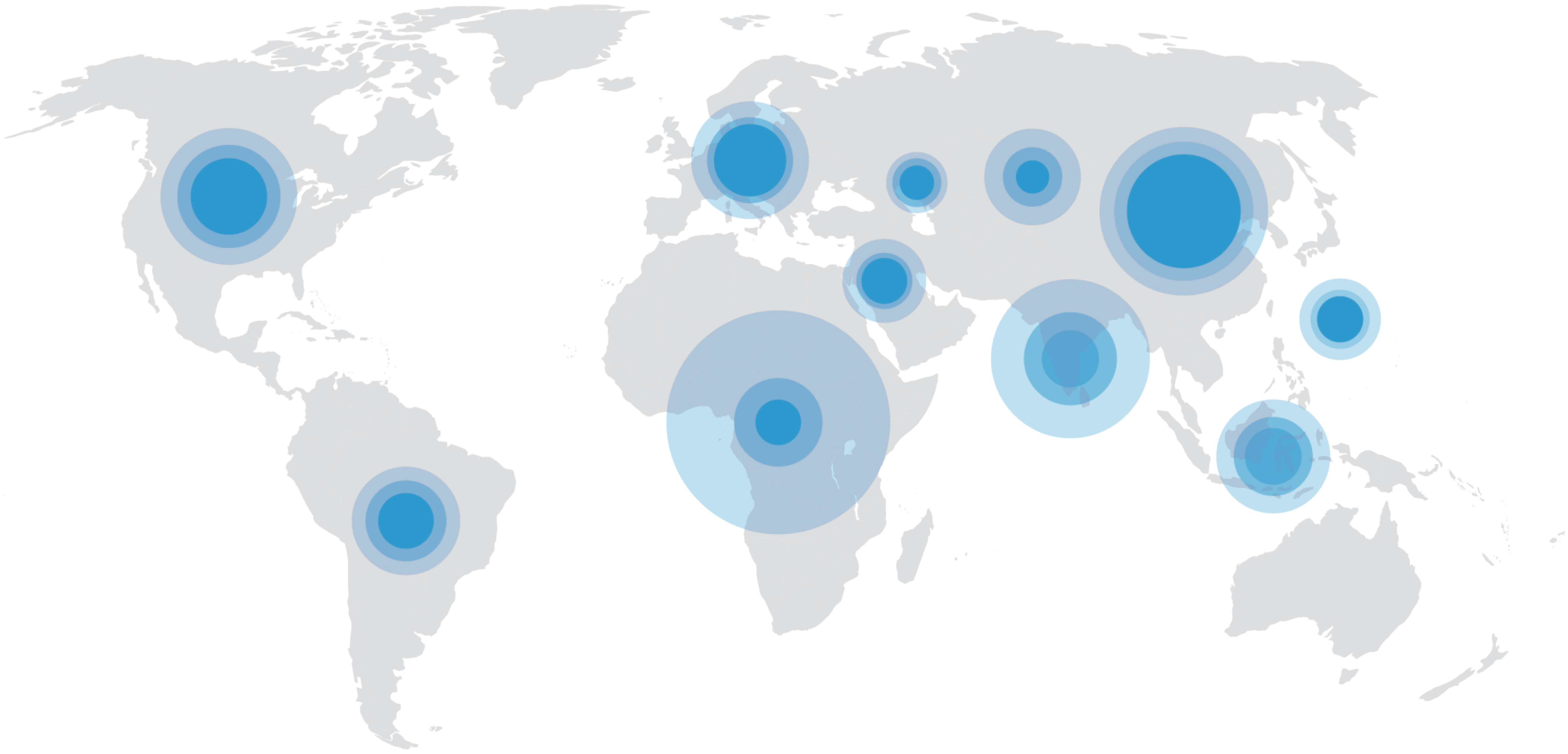
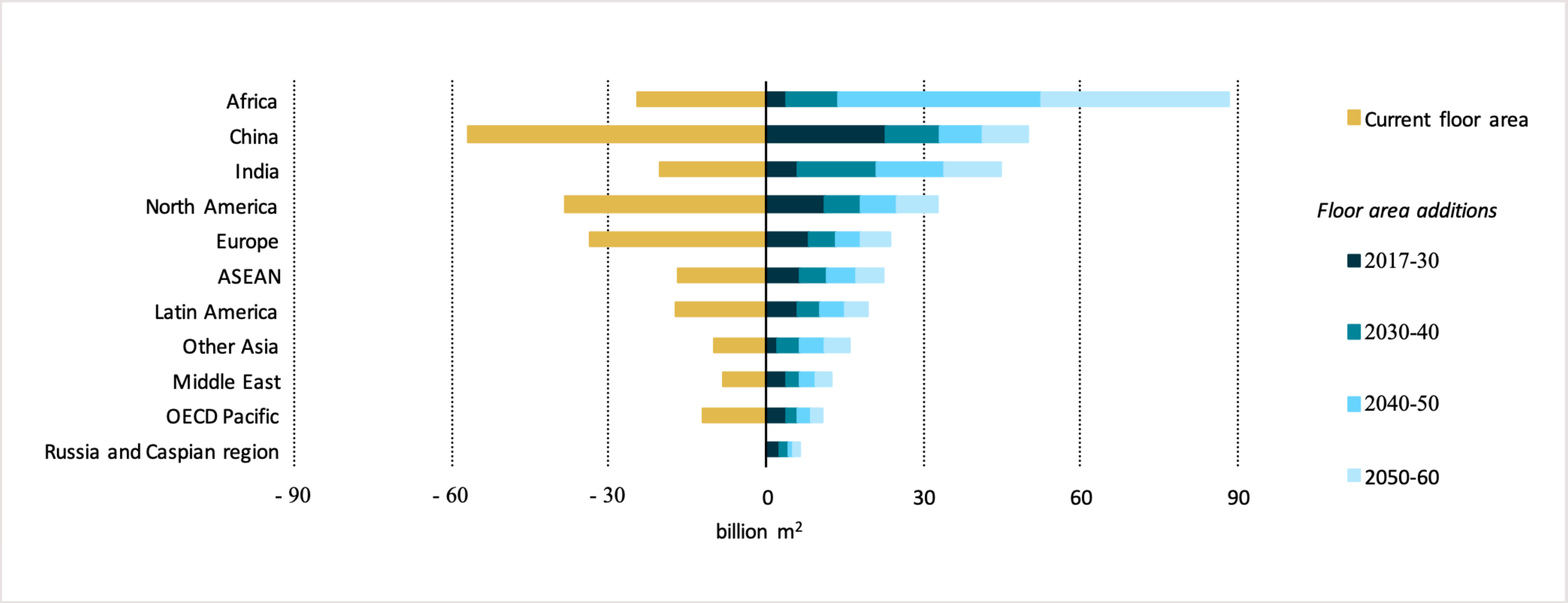


Image: Architecture 2030, based on data from Global ABC, Global Status Report 2017

- In 2021, cities consumed 75% of energy and produce 70% of GHG emissions (Source: UN)
- 82% of final energy consumption in buildings was supplied by fossil fuels in 2015 (Source: Global ABC)
- Global floor area will double by 2060 at current rates of building (Source: IEA)
- 3/4 of infra that will exist in 2050 is yet to be built (Source: UN)
- Will return to this in Lecture VI: Urbanisation

FLOOR AREA ADDITIONS TO 2060 BY KEY REGIONS



Notes: OECD Pacific includes Australia, New Zealand, Japan and Korea; ASEAN = Association of Southeast Asian Nations.
Source: IEA (2017), Energy Technology Perspectives 2017, IEA/OECD, Paris, www.iea.org/etp

Source: Global ABC, Global Status Report 2017

EMISSIONS FROM BUILDINGS

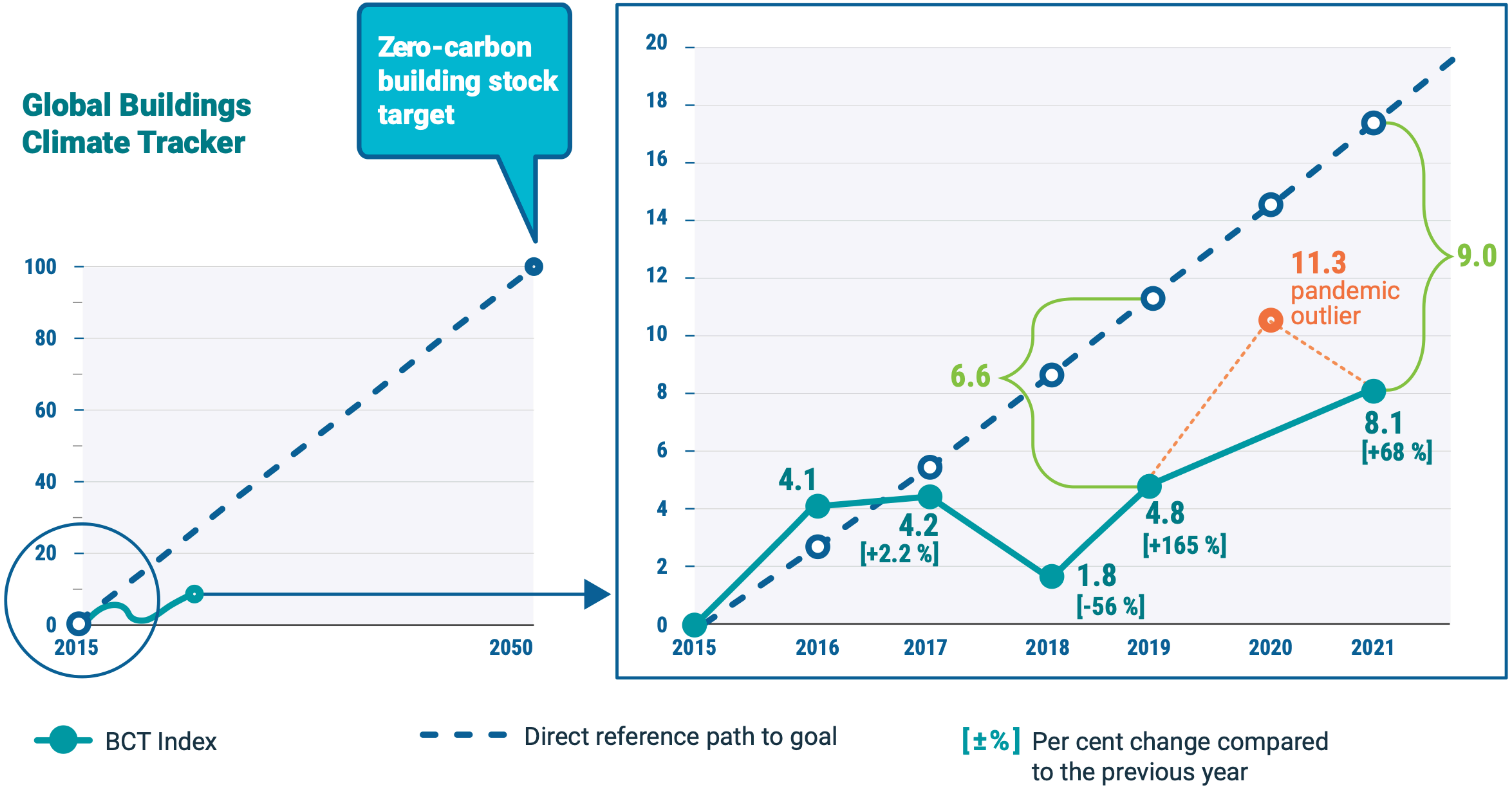
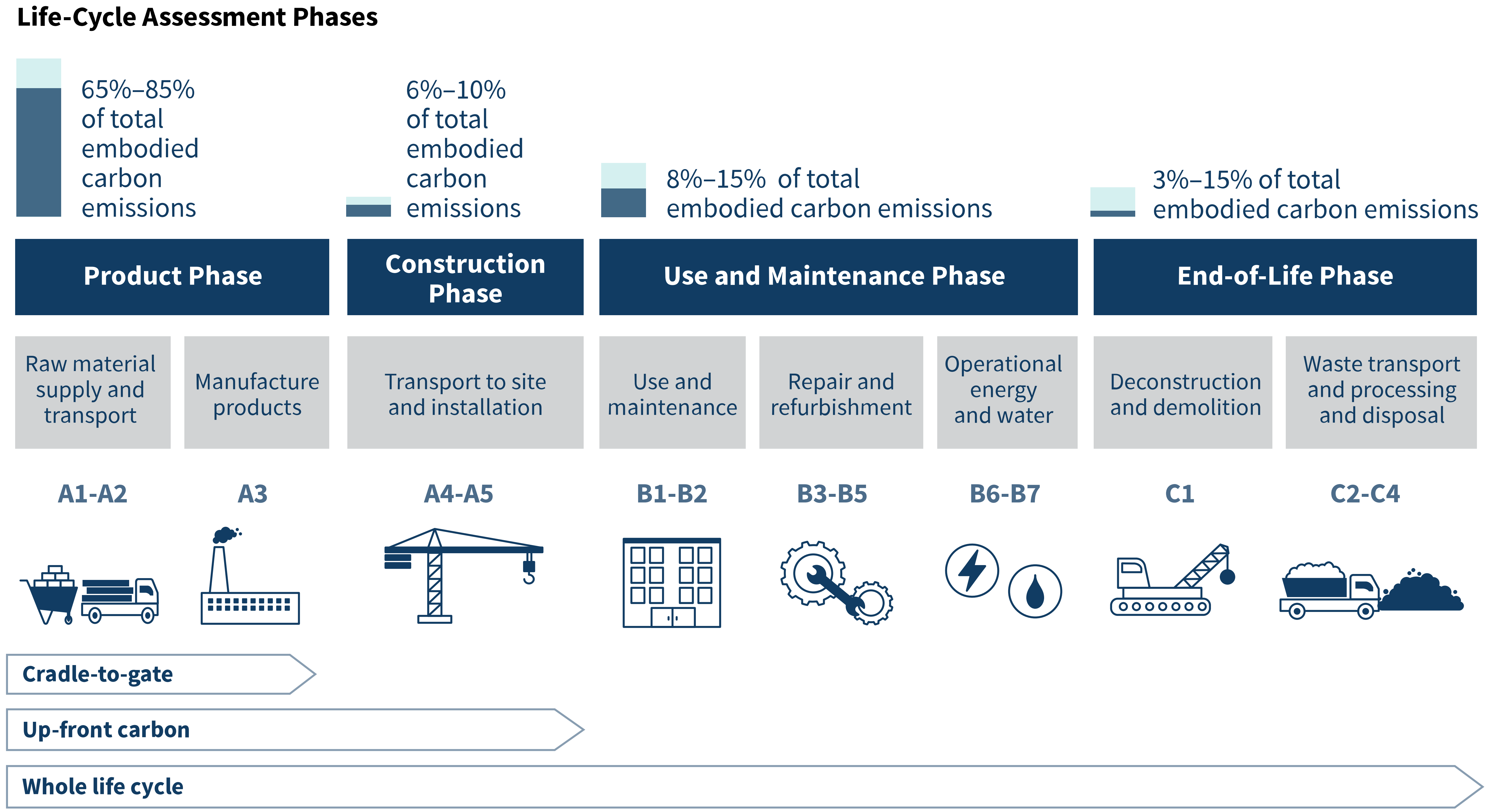


Image: Global ABC, Global Status Report 2022



Source: RMI

STRATEGIES

- Policies:
  - Energy efficiency standard (building energy codes) for new and renovated buildings
  - Urban planning (manage density, improve interconnectedness, traffic management, distributed EV-charging)
- Existing and new buildings:
  - energy efficiency
  - electrification
  - district heating/cooling/waste systems
  - renewable energy
- Embodied carbon
  - Reuse
  - Reduce
  - Store and sequester

Source: UNEP, Architecture 2030

POLL: HOW MANY COUNTRIES HAVE ENERGY BUILDING CODES?

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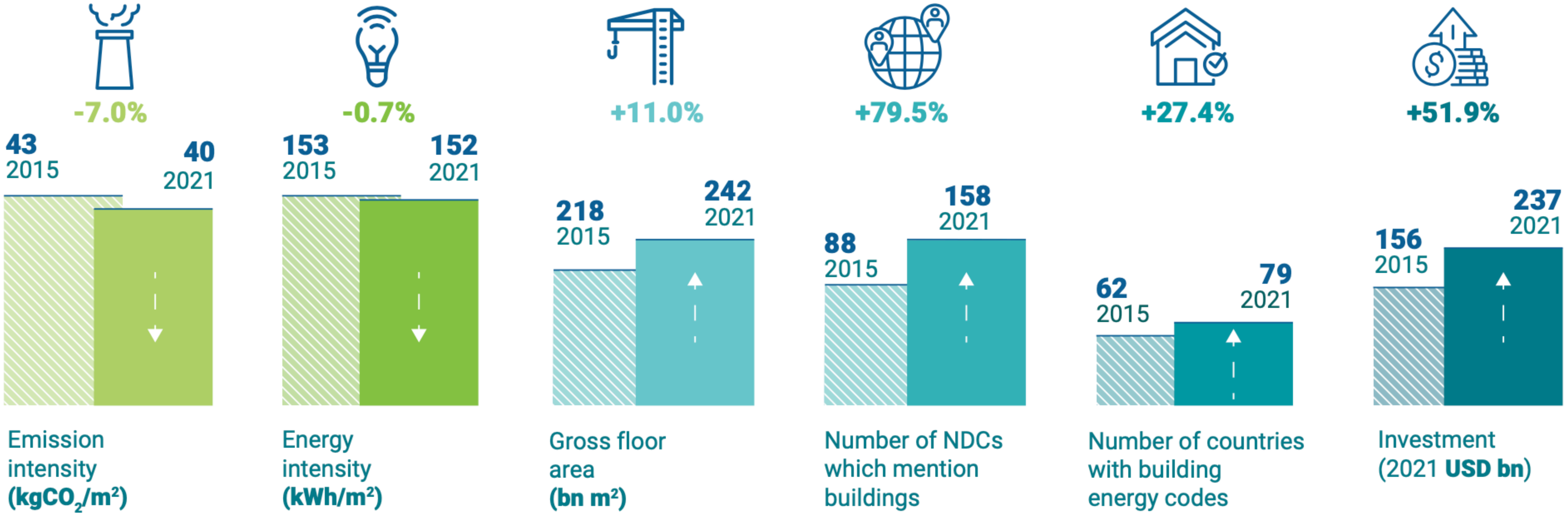
KEY TRENDS IN GLOBAL BUILDINGS AND CONSTRUCTION: 2021 VS 2015

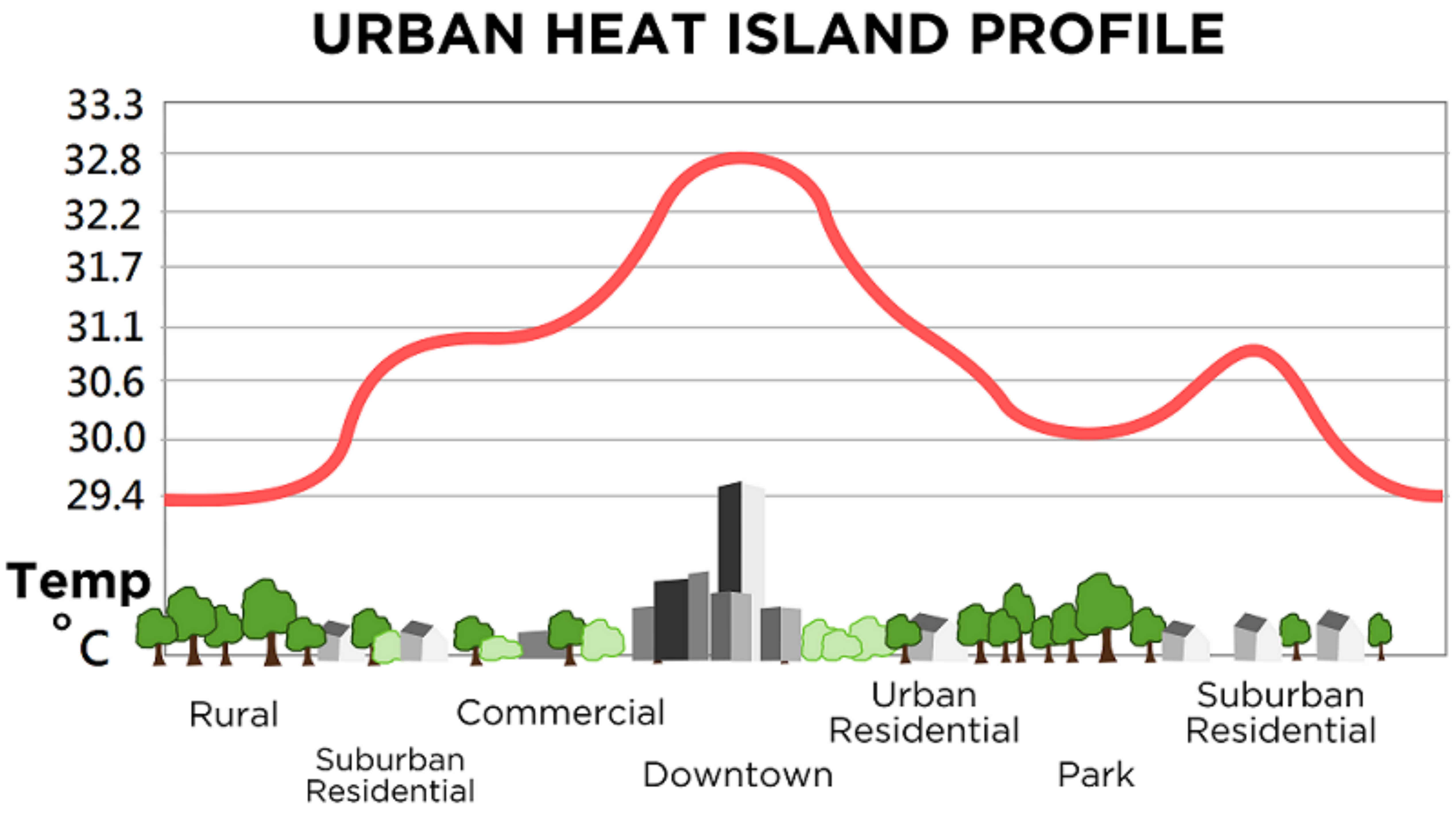


[1] Values included for the baselines have been updated from previous versions of the Buildings-GSR due to both historic input data updates for emissions and floorspace, and also deflation factors for USD. The proportional changes between previous years remains similar.

Image: Global ABC, Global Status Report 2022

URBAN HEAT ISLANDS

URBAN HEAT ISLAND (UHI)



Picture courtesy of Copernicus

Source: EPA

- Urban heat island is an urban area with higher temperature than the surrounding areas
- Causes
  - Reduced natural landscapes
  - Material properties (e.g. concrete)
  - Geometry (dimension and spacing of bldgs & streets)
  - Heat from human activities
  - Weather and geography (clouds, winds)
- Impact
  - Increased energy consumption
  - Higher emissions of pollutants and GHG (due to energy consumption and higher temperatures)
  - Complications for health
  - Impaired water quality

POLL: WHEN IS THE URBAN HEAT ISLAND EFFECT MOST PRONOUNCED?

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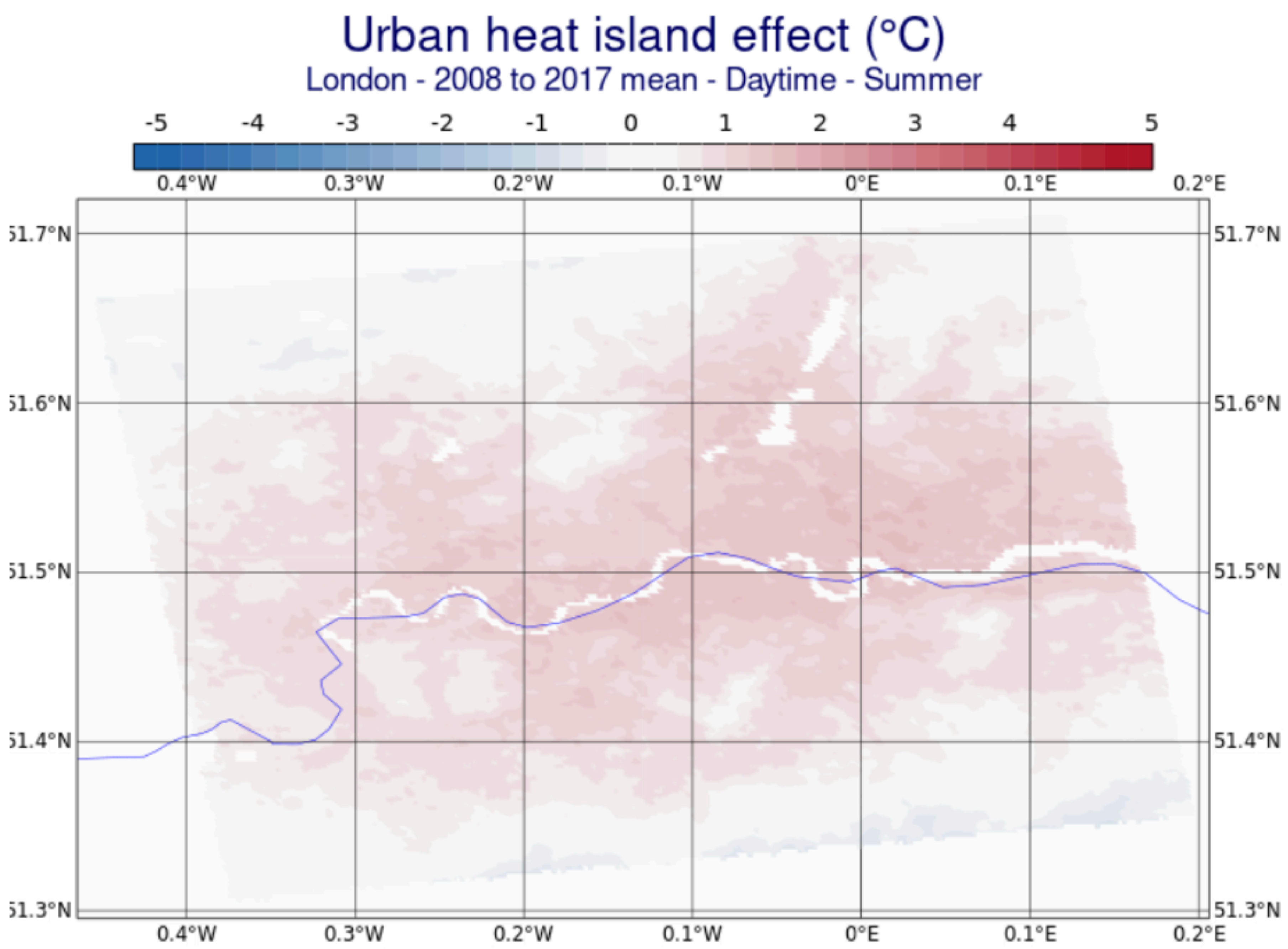
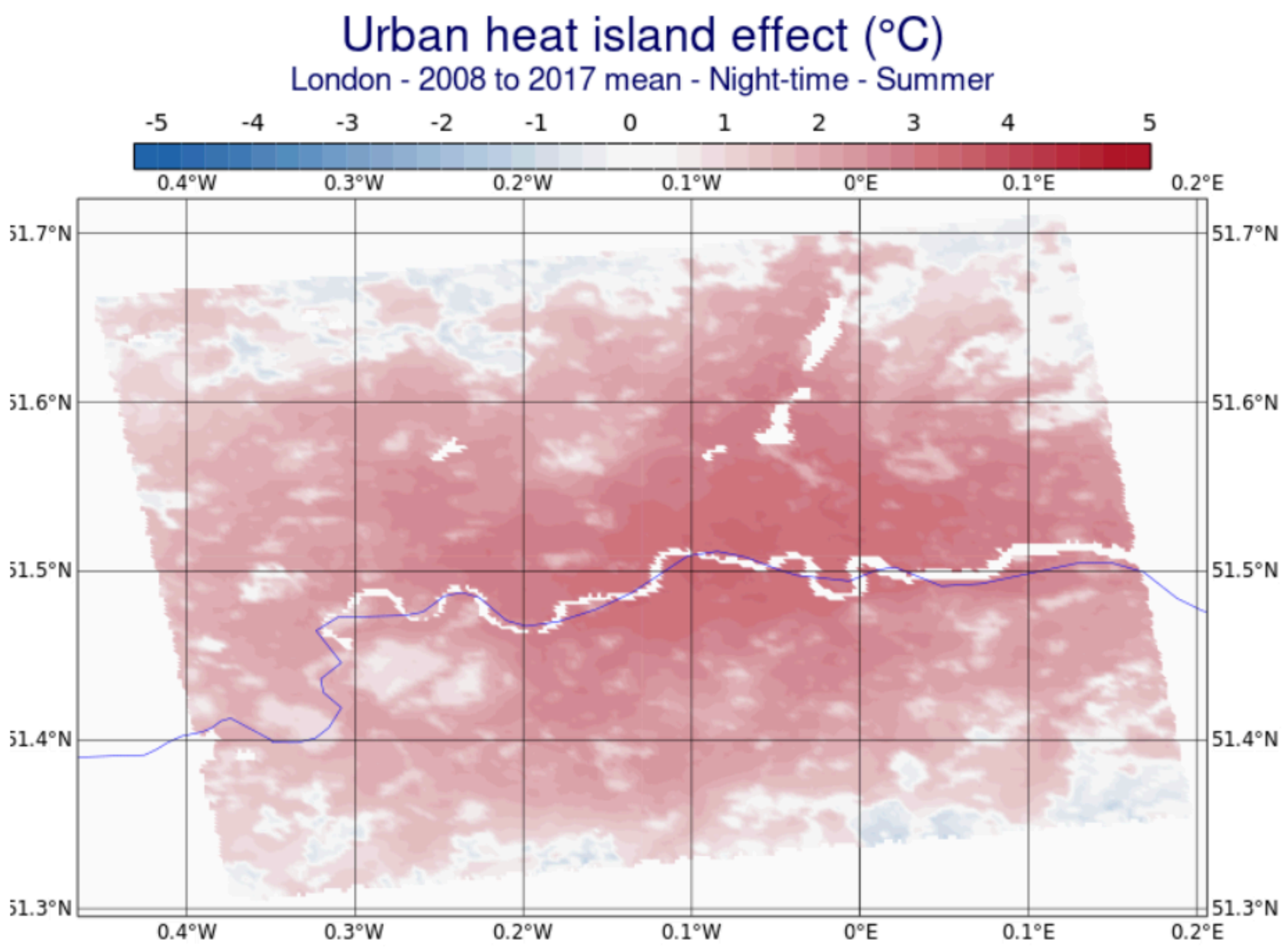
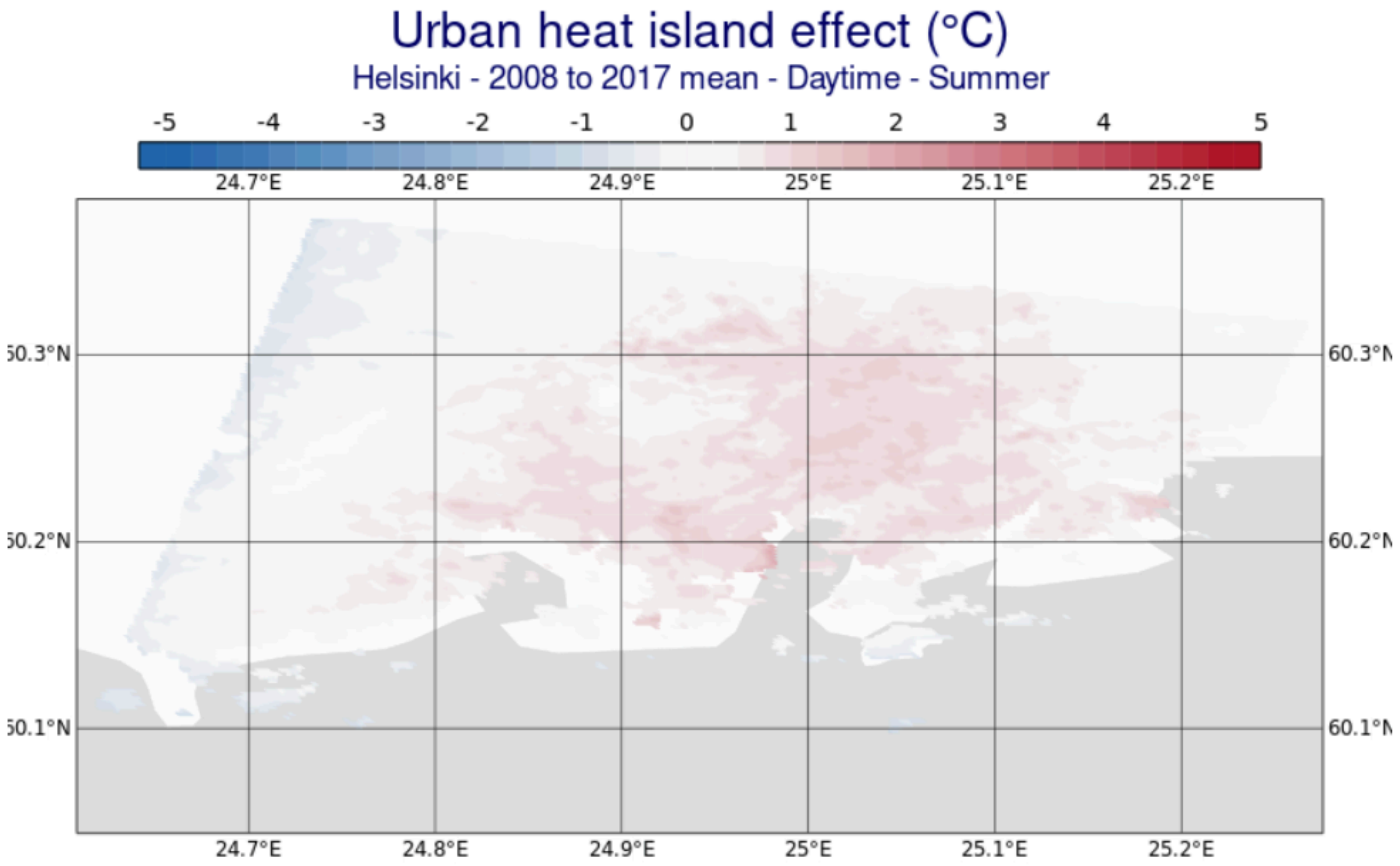
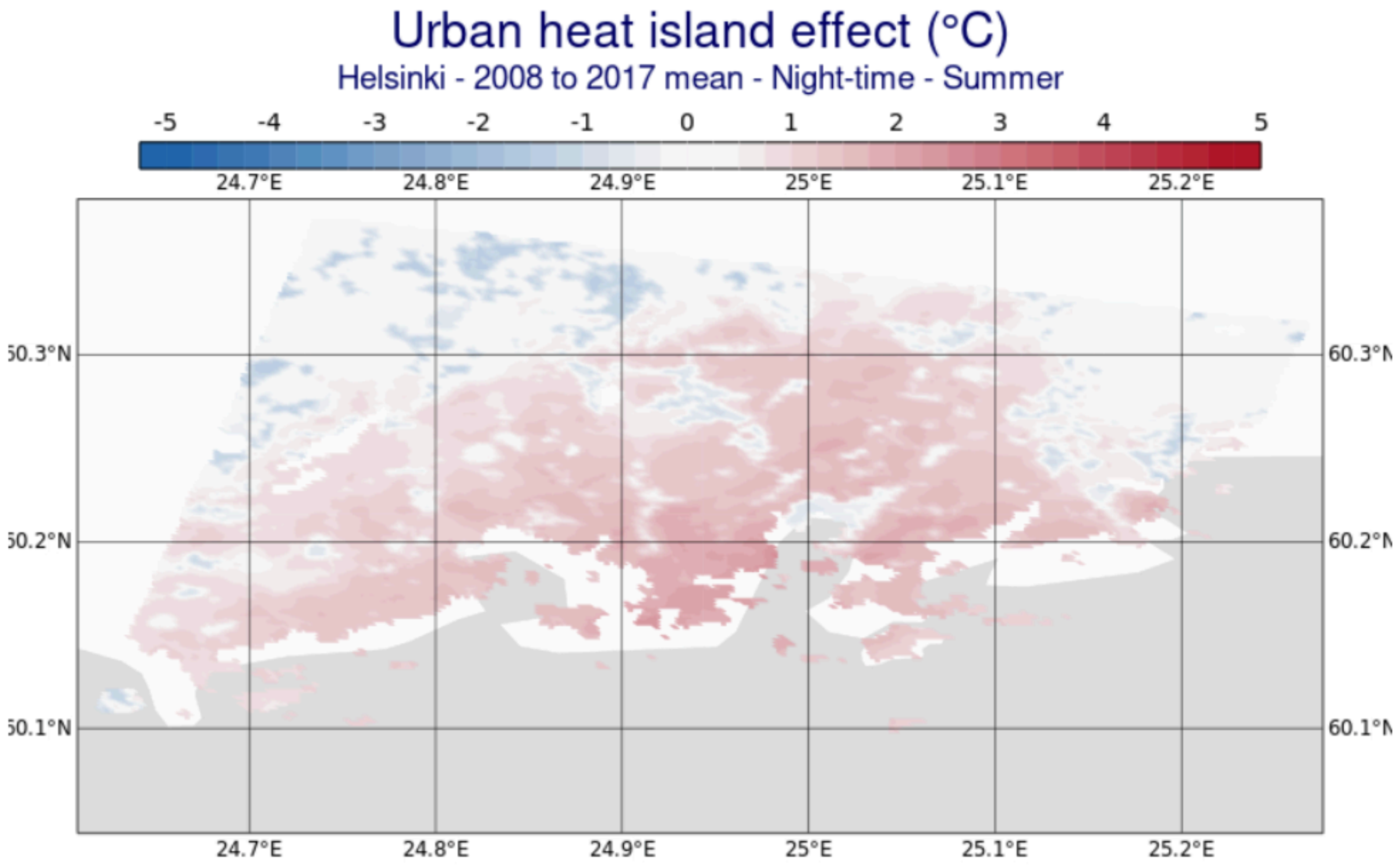
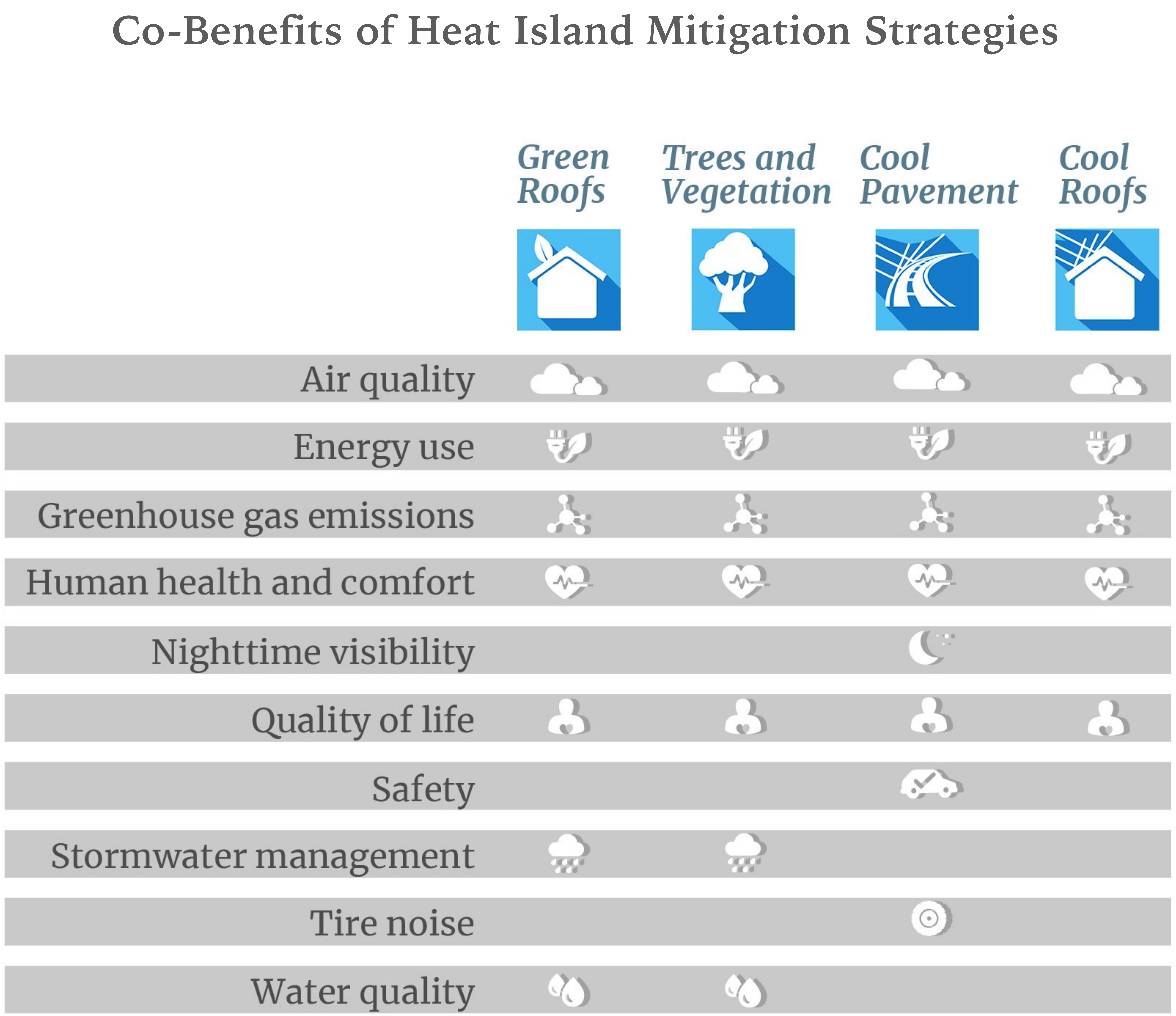








Source: UrbClim

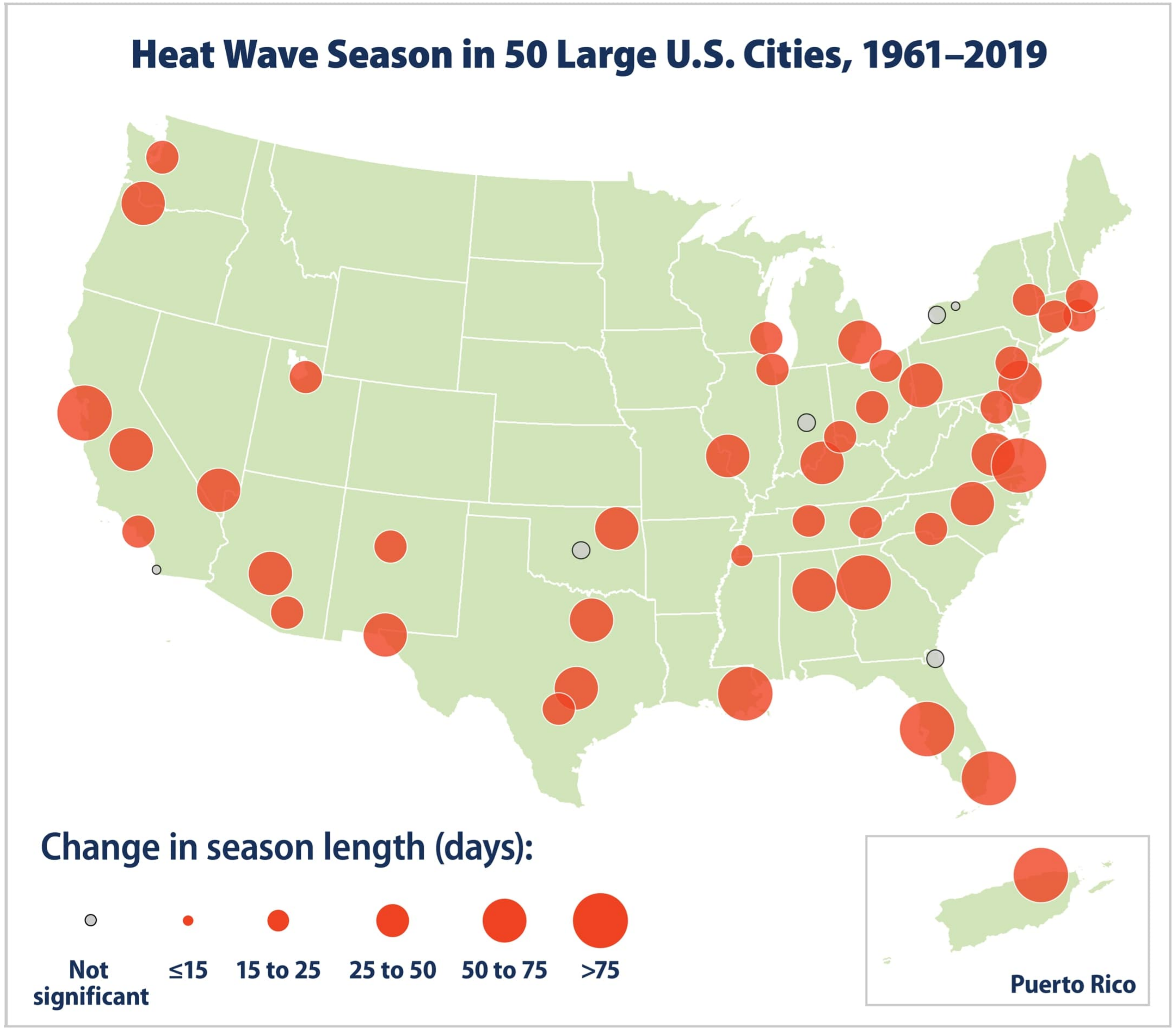


Source: EPA

STRATEGIES AND TECHNOLOGIES

- ➤ Trees and vegetation (5-city study in the US: 1.5-3 USD accrued benefits for 1 USD spent)
- ➤ Green roofs (temperature reduction ~ 2 degrees, lower energy use, stormwater runoff, absorption of pollutants and GHG, recreational space)
- ➤ Cool roofs (temperature reduction ~ 2 degrees, lower energy use, cheaper than green roofs, but ”heating penalty”)
- ➤ Cool pavements (less developed than other strategies)
- ➤ Smart growth

UHI AND CLIMATE CHANGE



Source: EPA

- Two separate compounding processes
- UHI contribute to climate change by requiring more cooling
- Climate change exacerbates the UHI problem
- Shared mitigation strategies (esp. those involved vegetation)
- Opportunity for collaboration between urban planners (local expertise and decision-making) and climate scientists (global expertise and international regulations), see Corburn (2009)

TIME-SERIES MODELLING

POLL: WHAT IS YOUR EXPERIENCE WITH TIME-SERIES MODELLING?

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TRADITIONAL TIME-SERIES MODELLING

- Weakly stationary processes (time-independent mean, variance and covariance)$\sim$ no trends, no seasonality:
  - AR (auto-regressive)

    $$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t , \quad \varphi_i \in \mathbb{R},\ \varepsilon_t \sim N(\mu, \sigma)\ iid\,.$$

  - MA (moving average)

    $$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \quad \mu = \mathbb{E}(X_t),\ \theta_i \in \mathbb{R},\ \varepsilon_t \sim N(\mu, \sigma)\ iid\,.$$

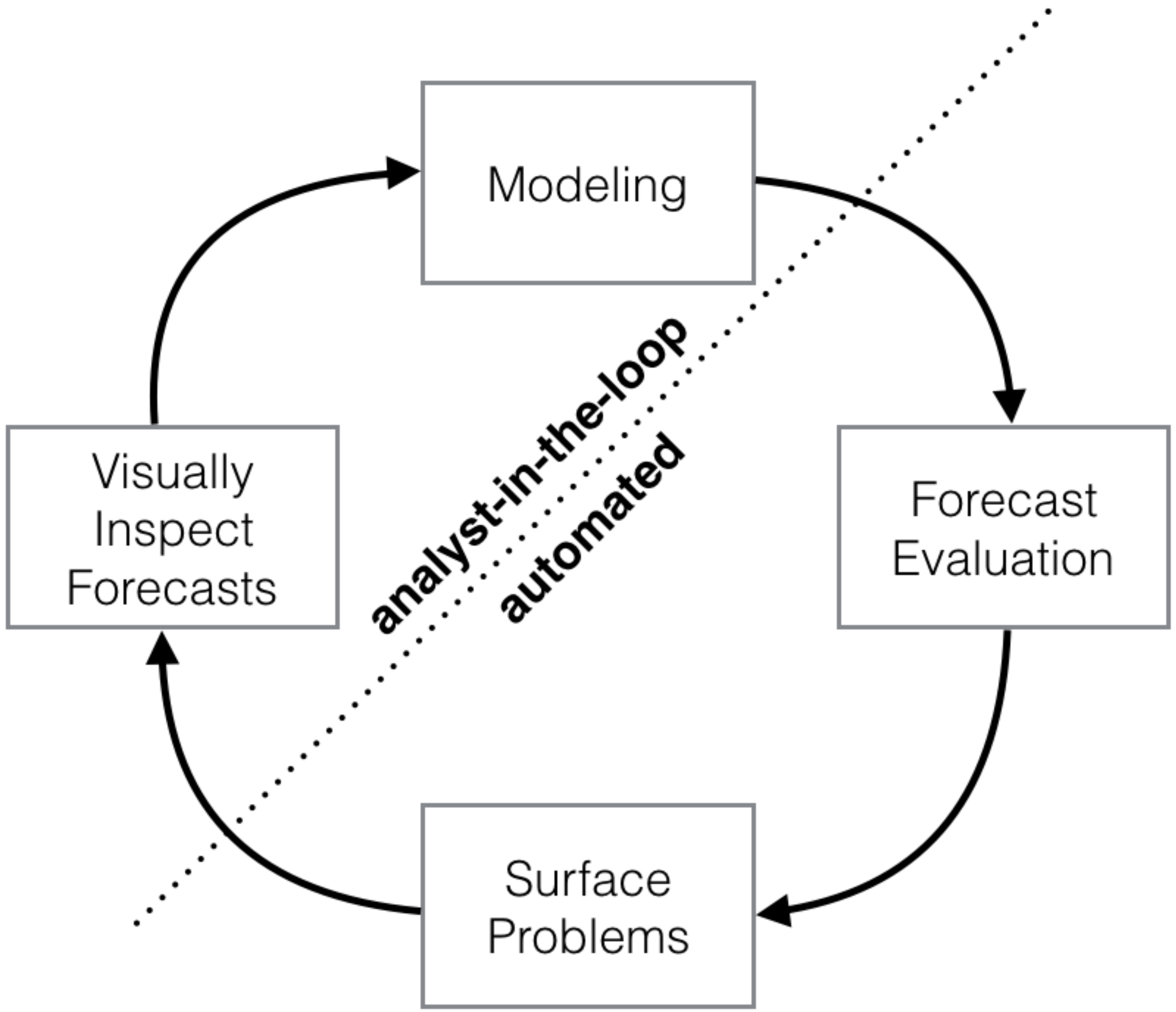
  - ARMA

    $$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}\,.$$

- Trends removable by differencing (instead of X_t model e.g. $X_t - X_{t-1}$) - ARIMA
- Seasonality - SARIMA
- Time-varying volatility or volatility clustering (conditional heteroscedasticity) - ARCH

CHALLENGES

- While AR and MA are interpretable, the modelling process becomes very complicated very quickly
- Difficult to use for panel data (see, e.g., these lectures)
- Non-trivial choice of parameters
- Automated forecasting (e.g., ARIMA) is brittle and inflexible: fail to predict change of trend at cut-off-period (e.g. end of year) or longer-term seasonality
- Few analysts have the data science skills to build high-quality forecasts



FACEBOOK PROPHET

- Origin: Taylor, Sean J., and Benjamin Letham. "Forecasting at scale." *The American Statistician* 72.1 (2018): 37-45.
- Implementation in Python and R
- Practical details on Thu during the exercise session

Source: Taylor and Letham (2018)

FACEBOOK PROPHET

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t,$$

- $g(t)$ - trend function (non-periodic changes), a version of the logistic growth model which is traditionally used for modelling natural growth in ecosystems:
  $g(t) = \dfrac{C}{1 + \exp(-k(t-m))}$, C - carrying capacity, k - growth rate, m - offset parameter. Can incorporate change points
- $s(t)$ - seasonality, modelled using Fourier series

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right)$$

- $h(t)$ - fixed short-term effects of holidays
  $h(t) = Z(t)\kappa, \quad Z(t) = [1(t \in D_1), \ldots, 1(t \in D_L)]$, $\kappa \sim N(0,\nu)$
- $\varepsilon_t \sim N(0,\sigma)$ *iid*

UHI IN SEOUL

Oh, Jin Woo, et al. "Using deep-learning to forecast the magnitude and characteristics of urban heat island in Seoul Korea." Scientific reports 10.1 (2020): 3559.

MOTIVATION

- Need predictive UHI models for mitigation and policy-making
- Currently available simulation models are:
  - computationally heavy;
  - require that the person running them has domain expertise;
  - require data that is not easily available
- Data-driven models:
  - rely only readily available data, e.g., meteorological data;
  - can be deployed on edge devices, e.g. temperature sensors
  - human input unnecessary (?)

PRIOR WORK

- Regression methods - do not reflect non-linear relations easily, require a lot of work to fit a specific dataset
- ANNs, but so far:
  - Shallow
  - Short time period (1 year)
  - Limited sources of observations (few automated weather stations - AWSs)

APPROACH

Oh et al. (2022) DNNs

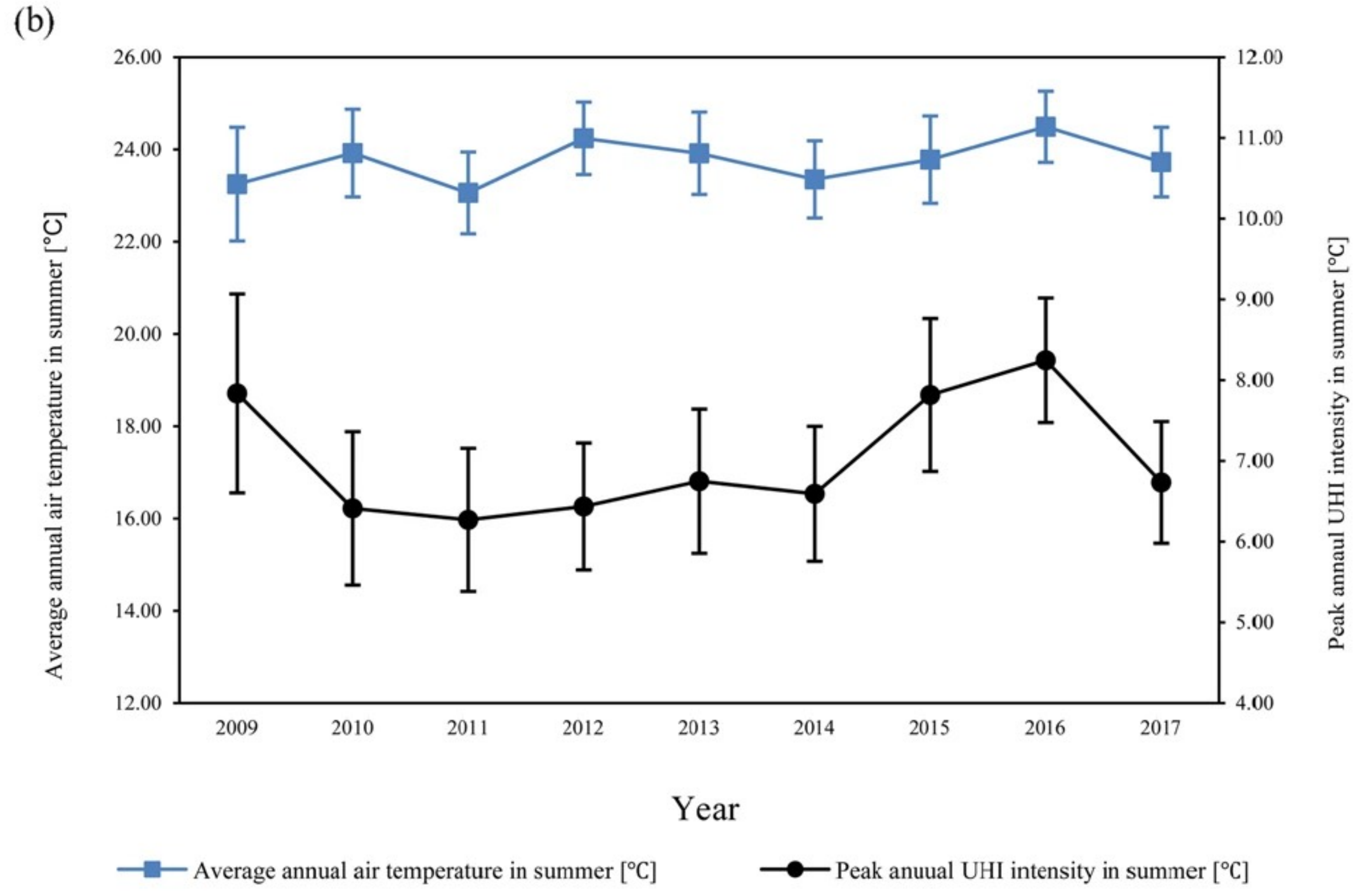
Temporal	Spatial
• Date • Time • Air temperature • Wind speed • Wind direction	• Sky view factor • Total floor areas of entire buildings • Area covered with green vegetation • Building footprints • Area covered with water and crops • Bare land area • Spectral radiance • Surface albedo

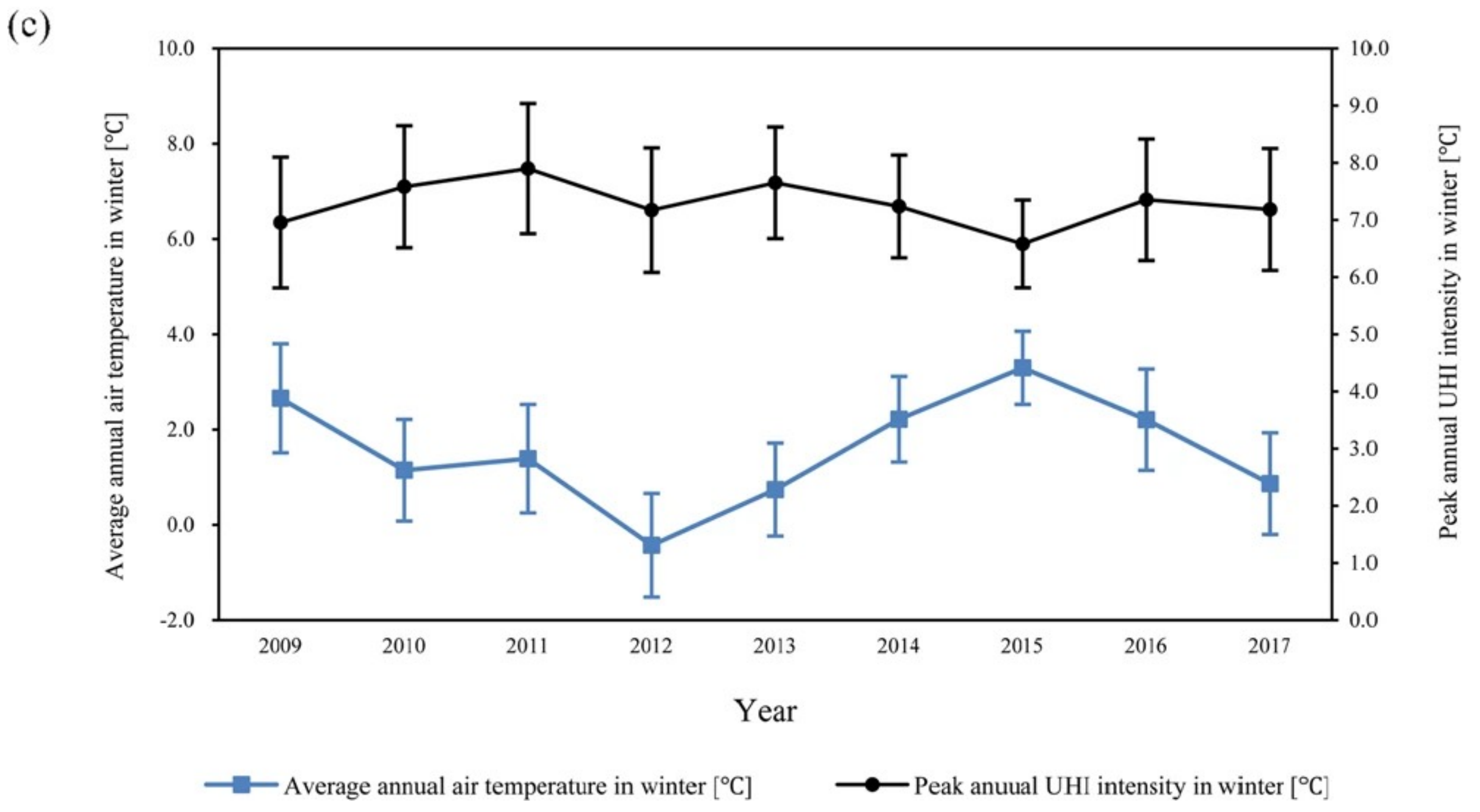
- Data
  - 54 AWSs (1 km radius, 2009–2017)
  - Geographic Information System (GIS) data from ministry of Land, Infrastructure and Transport Korea (2009-2017)
  - Landsat 8 (2014-2017)
- Contribution
  - 2 deep neural networks (temporal and spatial) with penalised loss function (squared error + lasso + ridge)
  - New metric: UHI hours - # hours of UHI in a given area

Locations of the 54 Automatic Weather Stations (AWS) in Seoul city.

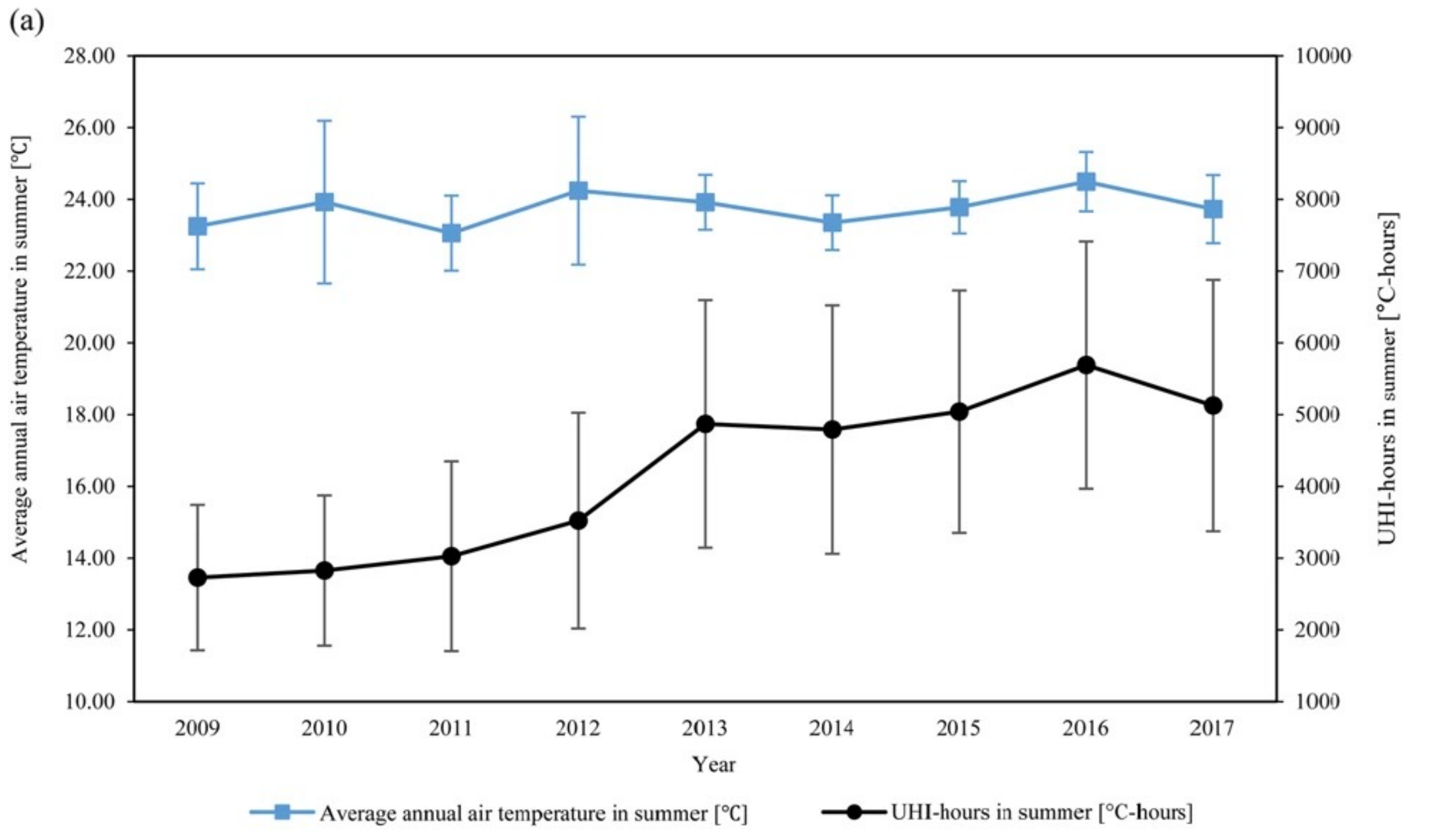
Source: Oh et al. (2022)

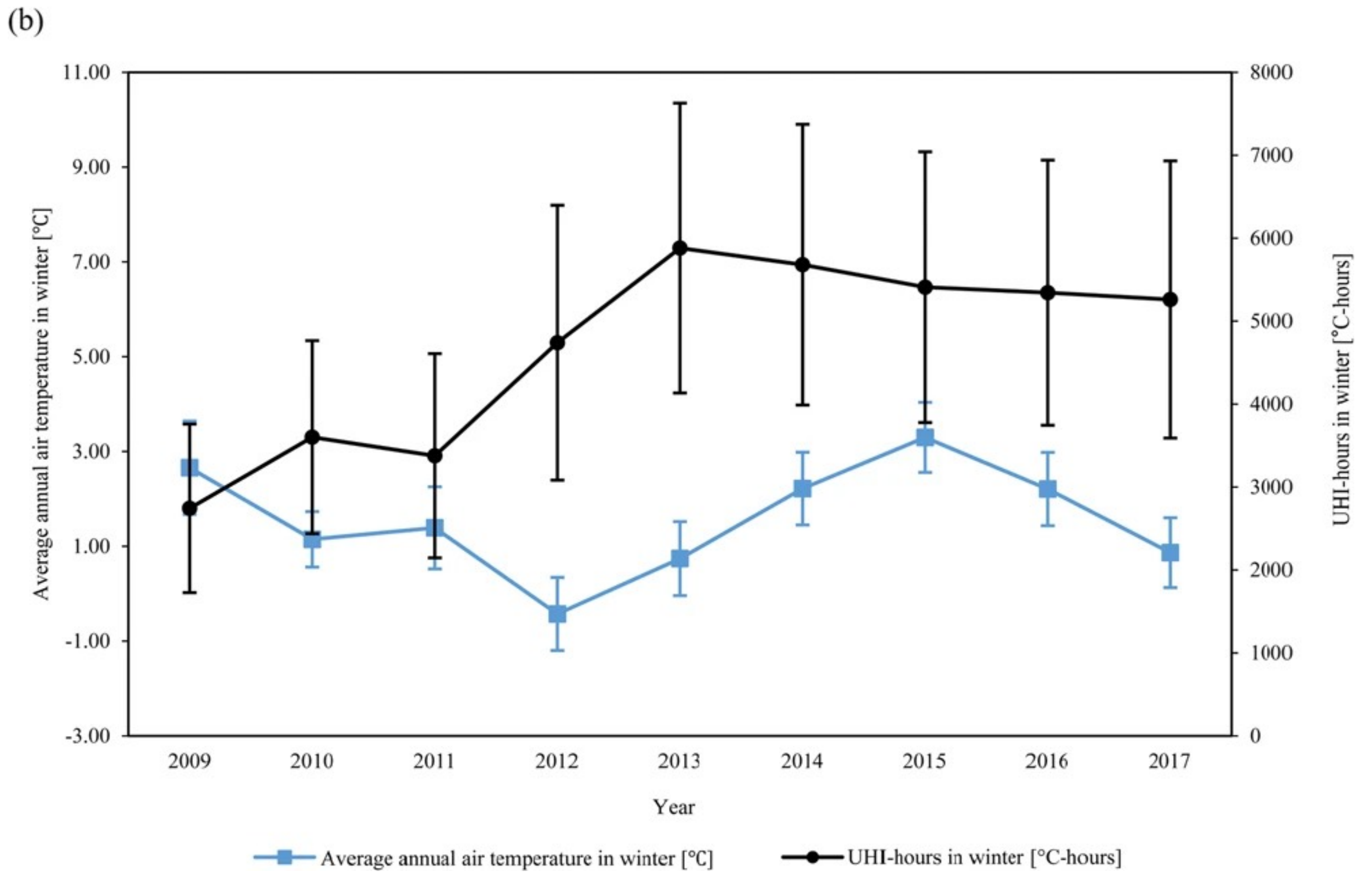
Air temp vs UHI intensity





Air temp vs UHI hours





Source: Oh et al. (2022)

SPATIAL MODEL

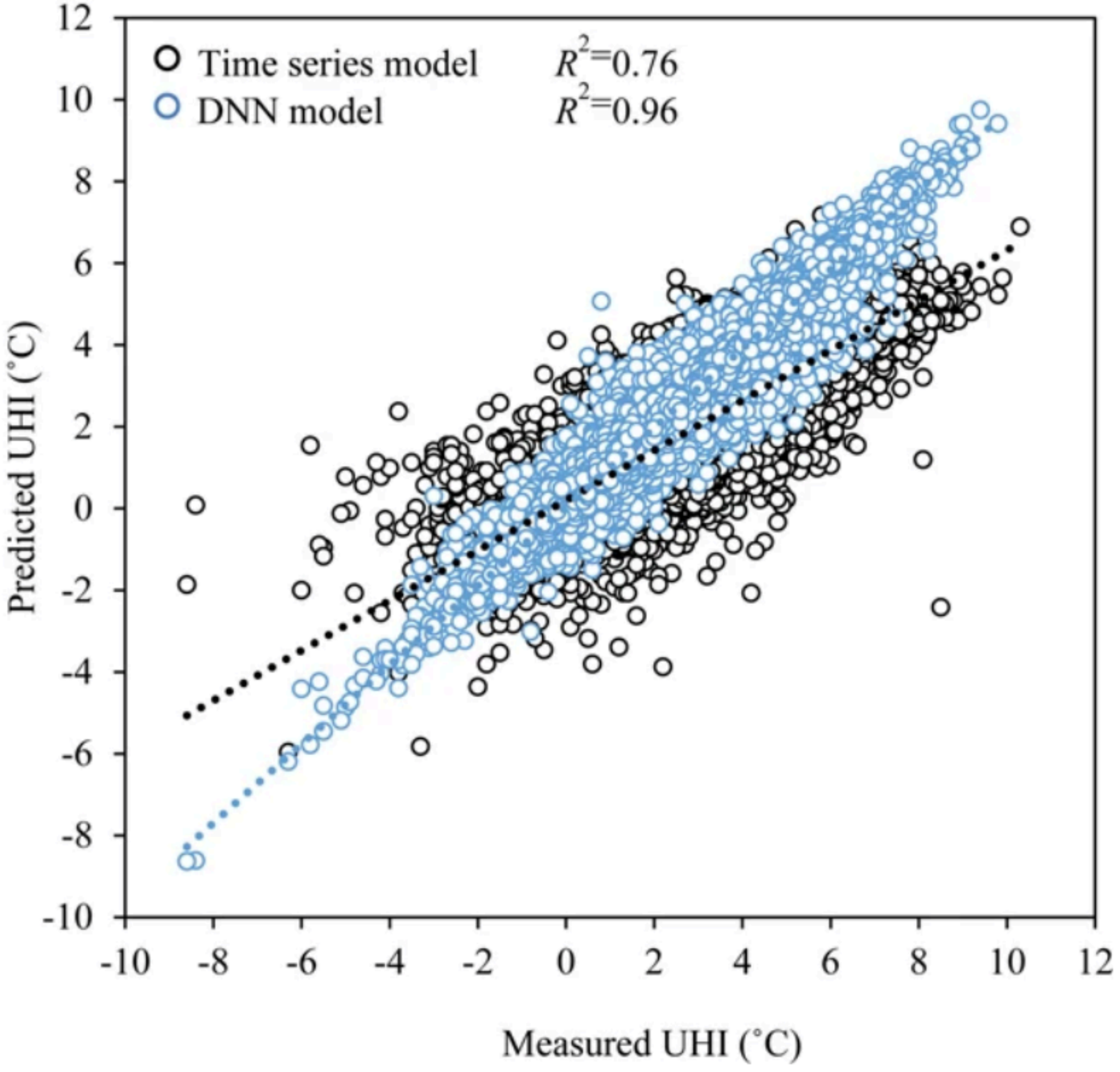
- Predict UHI for the entire Seoul
- Analyse the relative importance of different features in the hidden neurons and show the the most important are
  - In summer - green-area, road-area, cropland-area, and bare-area ratios
  - In winter - green-area and road-area ratios
- Water-area ratio important in the summer but less so in the winter
- Causality (?)

Performance of spatial model

Spatial model	Season	R2	RMSE
UHI intensity	Summer	0.98	0.08
	Winter	0.99	0.09
UHI-hours	Summer	0.99	145.52
	Winter	0.99	170.68

Source: Oh et al. (2022)

ARIMA vs temporal DNN for predicting medians



Source: Oh et al. (2022)

TEMPORAL MODEL

- Max (AWS-17), min (AWS - 35), median (AWS - 45)
- Built a reference ARIMA model and showed that DNN performed better

PRACTICALITIES

ANNOUNCEMENTS

- Lecture VI - Urbanisation
  - Zhu, Xiao Xiang et al. "The urban morphology on our planet -- Global perspectives from space". Remote Sensing of Environment, vol. 269, p. 112794 (2022)
- Exercise session V - R-CNN and Prophet
- Online exercise session on Fri (poll)
- Theses, projects (10 ECTS), conference papers