Climate Change AI Summer School 2026

# AI for Cities and Urban Planning

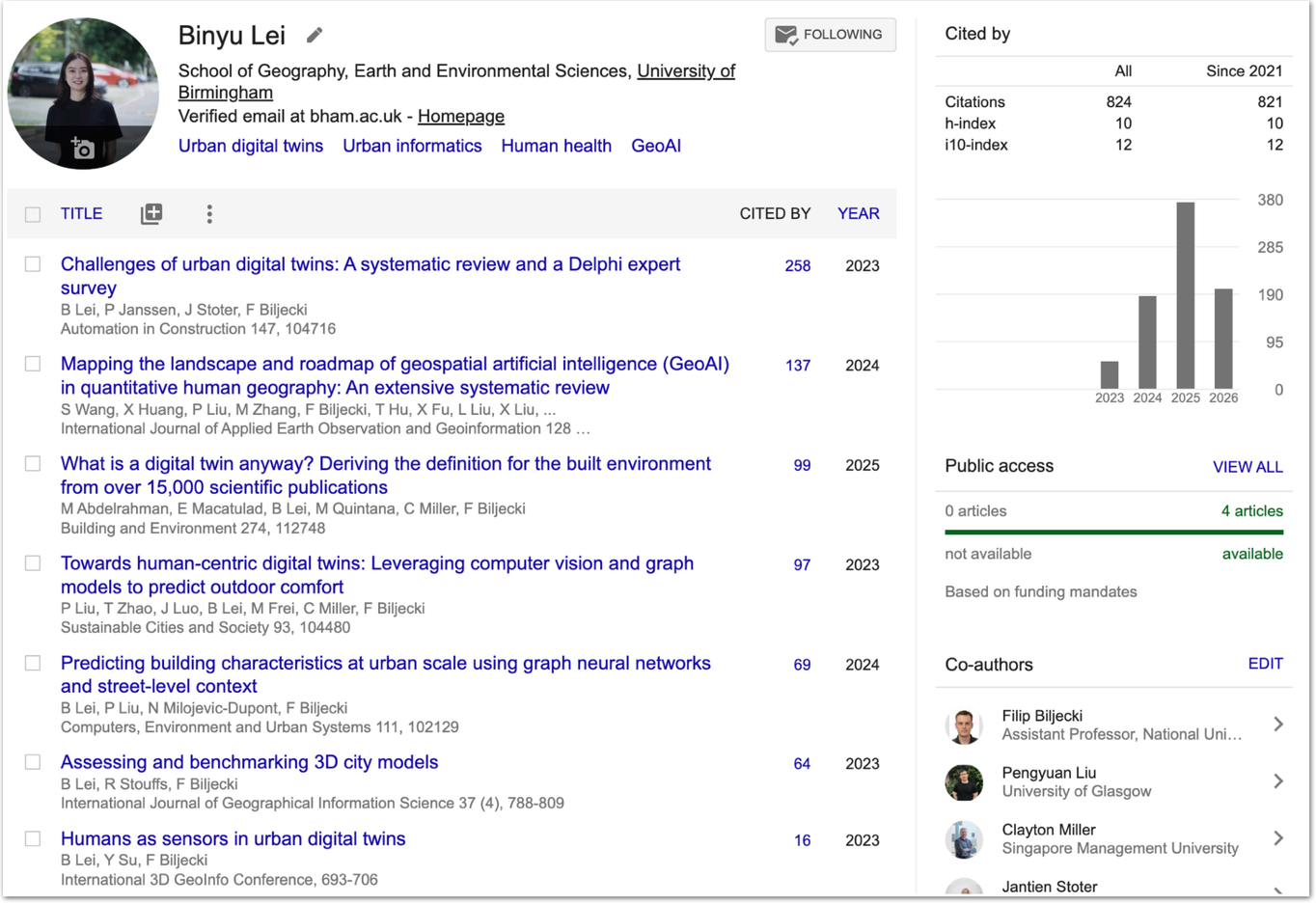
From urban data to decision making

Dr Binyu Lei
Assistant Professor in Urban Planning and Data Analytics
University of Birmingham



# Nice to meet you! 👋

- Assistant Professor in Urban Planning and Data Analytics, University of Birmingham
- Holding Master's degree in Urban Planning from the University of Melbourne, PhD in Urban Analytics from National University of Singapore
- Research — human-centric urban informatics and GeoAI
- Teaching — Master of Urban Analytics and AI
- Service — member of Open Geospatial Consortium, reviewer for international journals, etc.



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FOLLOWING

School of Geography, Earth and Environmental Sciences, University of Birmingham
Verified email at bham.ac.uk - Homepage
Urban digital twins  Urban informatics  Human health  GeoAI

| TITLE | CITED BY | YEAR |
|---|---|---|
| Challenges of urban digital twins: A systematic review and a Delphi expert survey<br>B Lei, P Janssen, J Stoter, F Biljecki<br>Automation in Construction 147, 104716 | 258 | 2023 |
| Mapping the landscape and roadmap of geospatial artificial intelligence (GeoAI) in quantitative human geography: An extensive systematic review<br>S Wang, X Huang, P Liu, M Zhang, F Biljecki, T Hu, X Fu, L Liu, X Liu, ...<br>International Journal of Applied Earth Observation and Geoinformation 128 … | 137 | 2024 |
| What is a digital twin anyway? Deriving the definition for the built environment from over 15,000 scientific publications<br>M Abdelrahman, E Macatulad, B Lei, M Quintana, C Miller, F Biljecki<br>Building and Environment 274, 112748 | 99 | 2025 |
| Towards human-centric digital twins: Leveraging computer vision and graph models to predict outdoor comfort<br>P Liu, T Zhao, J Luo, B Lei, M Frei, C Miller, F Biljecki<br>Sustainable Cities and Society 93, 104480 | 97 | 2023 |
| Predicting building characteristics at urban scale using graph neural networks and street-level context<br>B Lei, P Liu, N Milojevic-Dupont, F Biljecki<br>Computers, Environment and Urban Systems 111, 102129 | 69 | 2024 |
| Assessing and benchmarking 3D city models<br>B Lei, R Stouffs, F Biljecki<br>International Journal of Geographical Information Science 37 (4), 788-809 | 64 | 2023 |
| Humans as sensors in urban digital twins<br>B Lei, Y Su, F Biljecki<br>International 3D GeoInfo Conference, 693-706 | 16 | 2023 |

Cited by

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| Citations | 824 | 821 |
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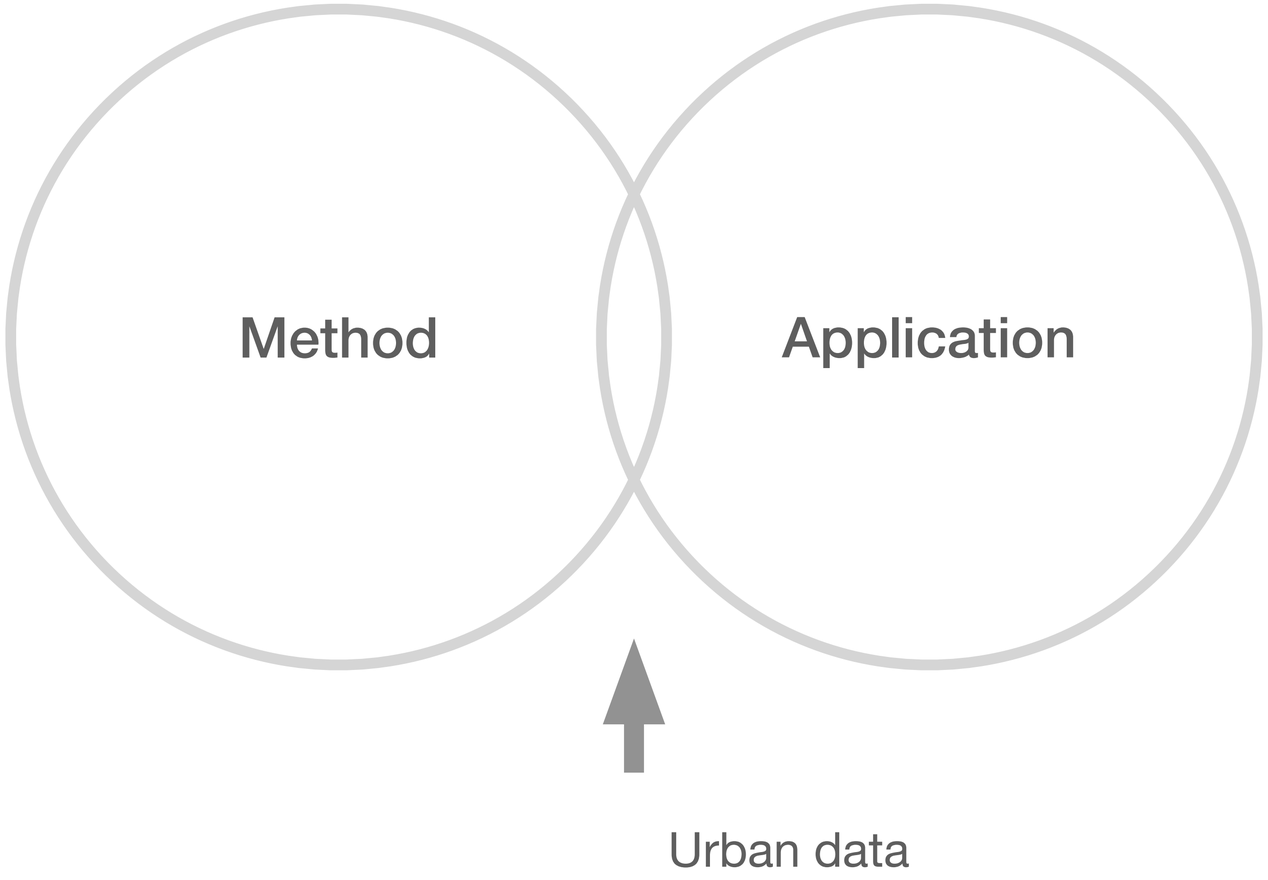
Filip Biljecki
Assistant Professor, National Uni…

Pengyuan Liu
University of Glasgow

Clayton Miller
Singapore Management University

Jantien Stoter

# My research



# Plan for today

- AI in urban studies
- Multisouced urban data
- Methods and models
- Insights for policy making

PART 1

# The role of AI in cities

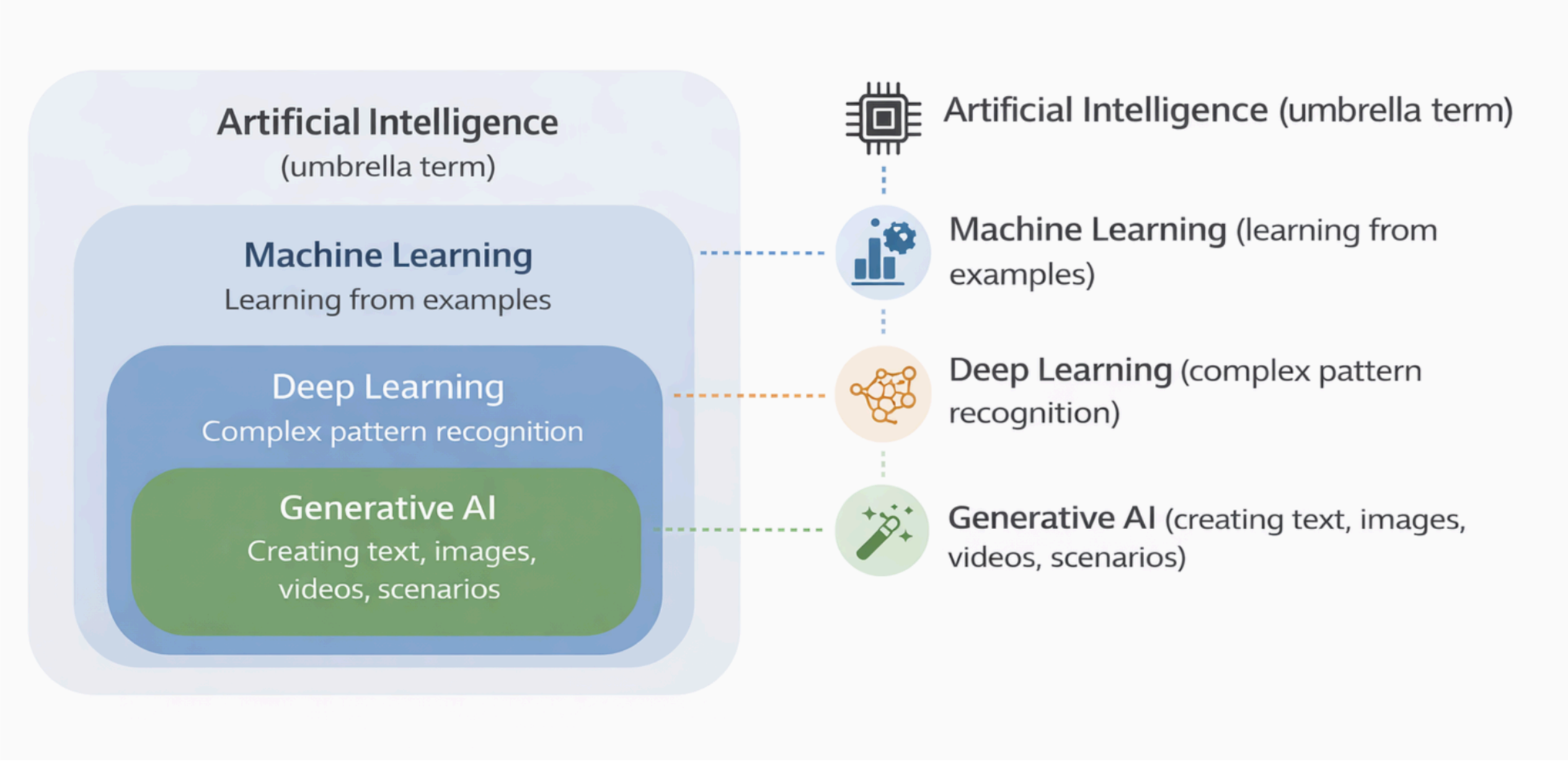


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# AI in urban studies

- What is AI?
- What is the potential of AI in urban studies?
- How can AI facilitate urban planning and design?

# What is AI?


Artificial Intelligence
(umbrella term)
Machine Learning
Learning from examples
Deep Learning
Complex pattern recognition
Generative AI
Creating text, images,
videos, scenarios
Artificial Intelligence (umbrella term)
Machine Learning (learning from examples)
Deep Learning (complex pattern recognition)
Generative AI (creating text, images, videos, scenarios)

# Why do we need AI in urban studies?

# Why does AI matter?

- Cities are complex, dynamic, and human-centred systems
- Planning increasingly relies on data-driven evidence
- AI offers new ways to observe, analyse, and support decisions
- AI provides support not automation

# Why do cities need AI?

- Millions of people, buildings, and daily interactions
- Too much data for manual analysis
- Decisions must be made under uncertainty

# What is AI in urban contexts?

- AI ≠ replacing planners/designers
- AI = pattern recognition from urban information/data
- AI augments human judgement (e.g. imagining it as a cross-validation alternative)
- Planning values always come first

# Roles of AI in urban planning

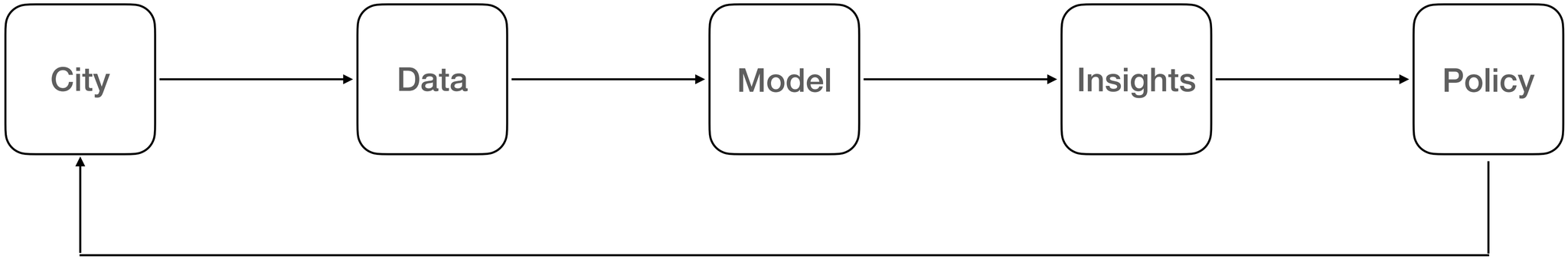
- Prediction
  - Estimate missing or future urban states, such as building attributes, thermal exposure, or mobility conditions
- Simulation
  - Explore consequences of design, policy, environmental, or behavioural scenarios before implementation
- Interpretation
  - Explain why places behave differently and how model drivers connect to planning concepts
- Intervention
  - Support decisions, adaptive actions, prioritization, and feedback loops in practice

# City is a system to accommodate people, goods, and service

- How AI understands the city?
  - People move, feel, and interact
  - Sensors and data capture traces
  - Models learn patterns
  - Insights inform decisions



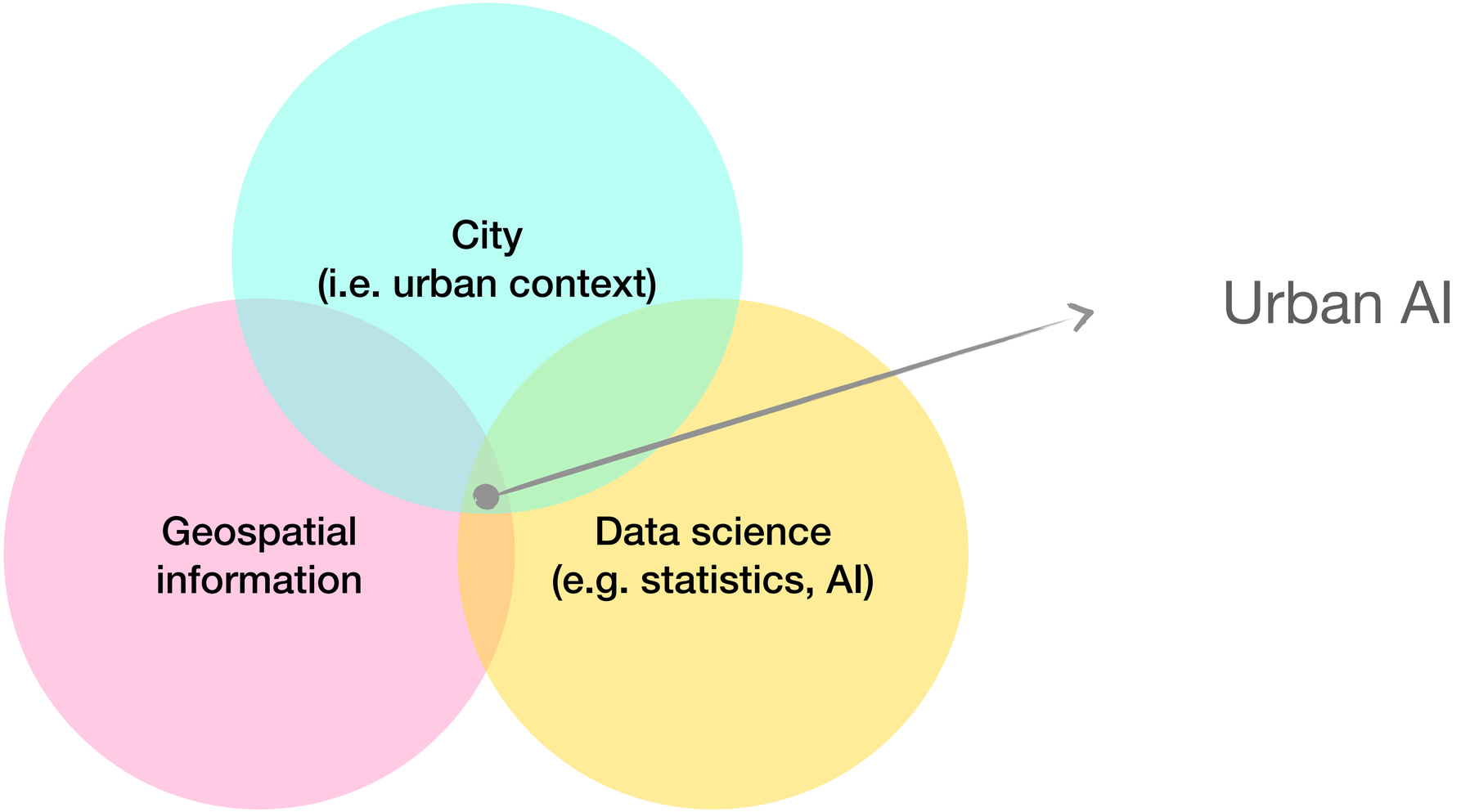
# The city is a system



# What data feeds urban AI?

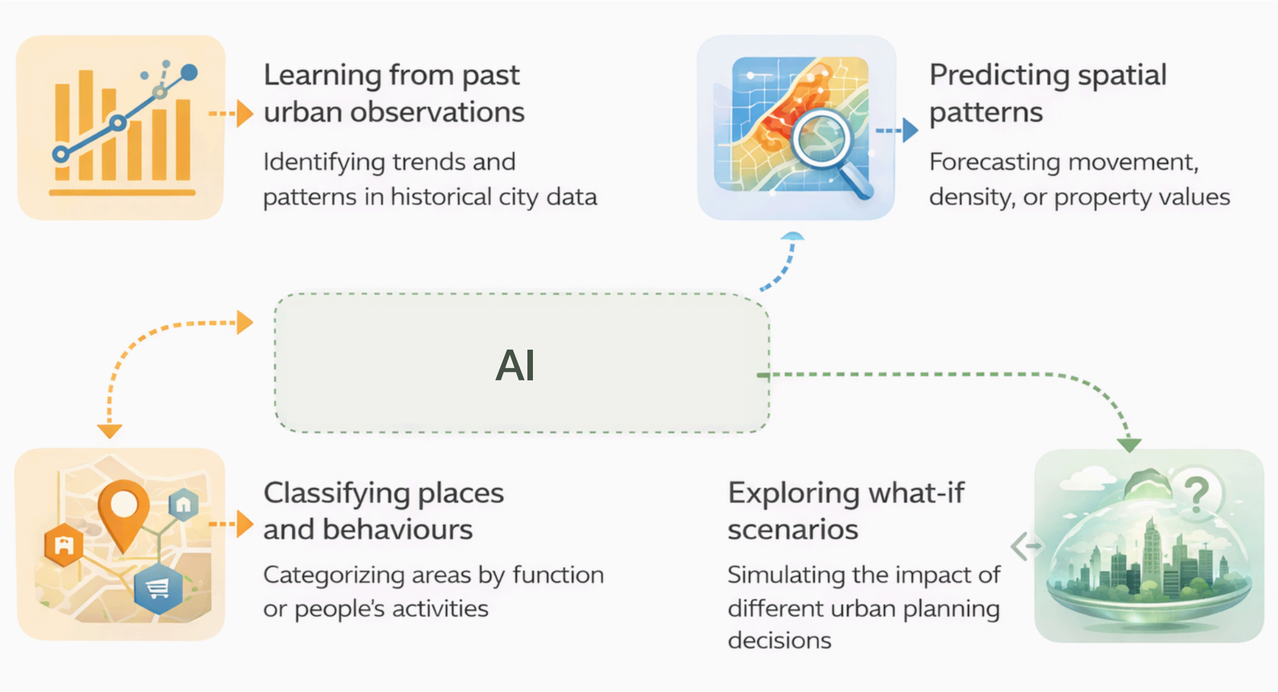
- Mobility traces (e.g. transport cards, cycling)
- Built environment (e.g. buildings, streets, POIs)
- Environmental data (air temperature, humidity, noise)
- Social and economic indicators (e.g. demographics, household income)

# Where is AI used in urban studies?



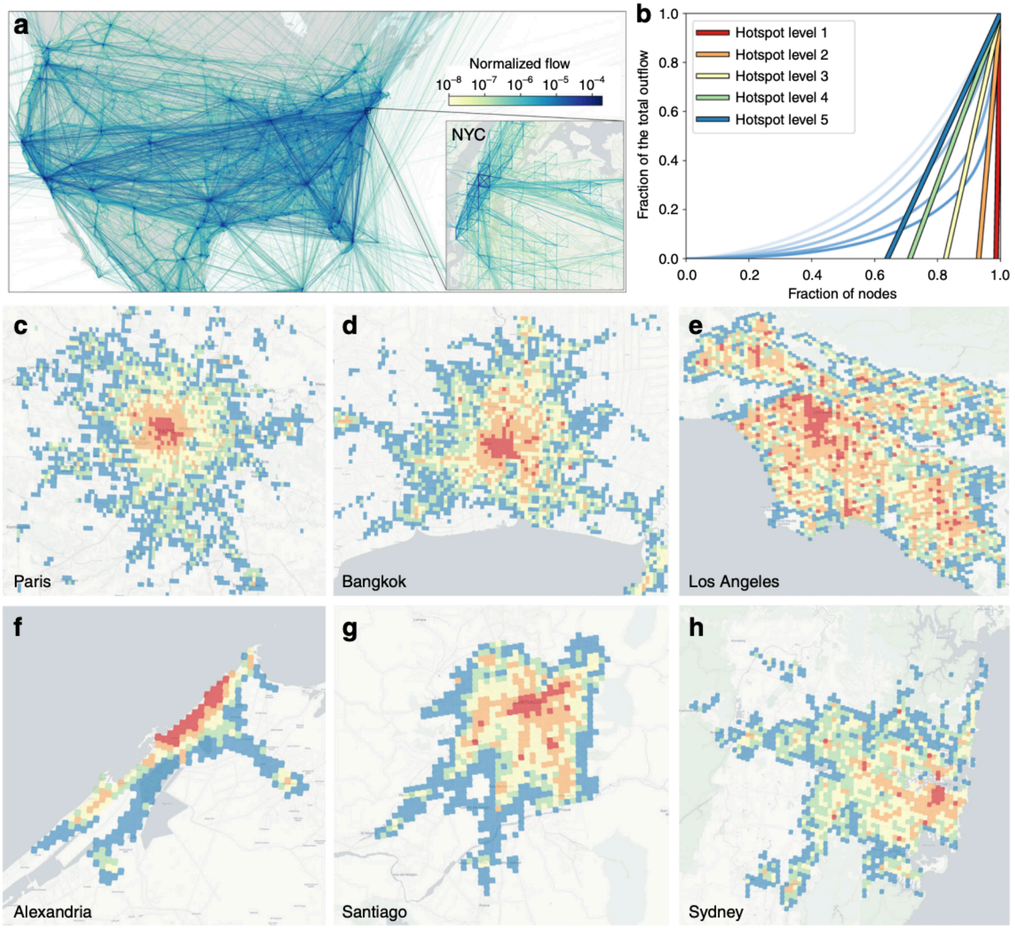
# Translating AI into urban terms

- Learning from past urban observations
- Predicting spatial patterns
- Classifying places and behaviours
- Exploring what-if scenarios



# Example: Mobility

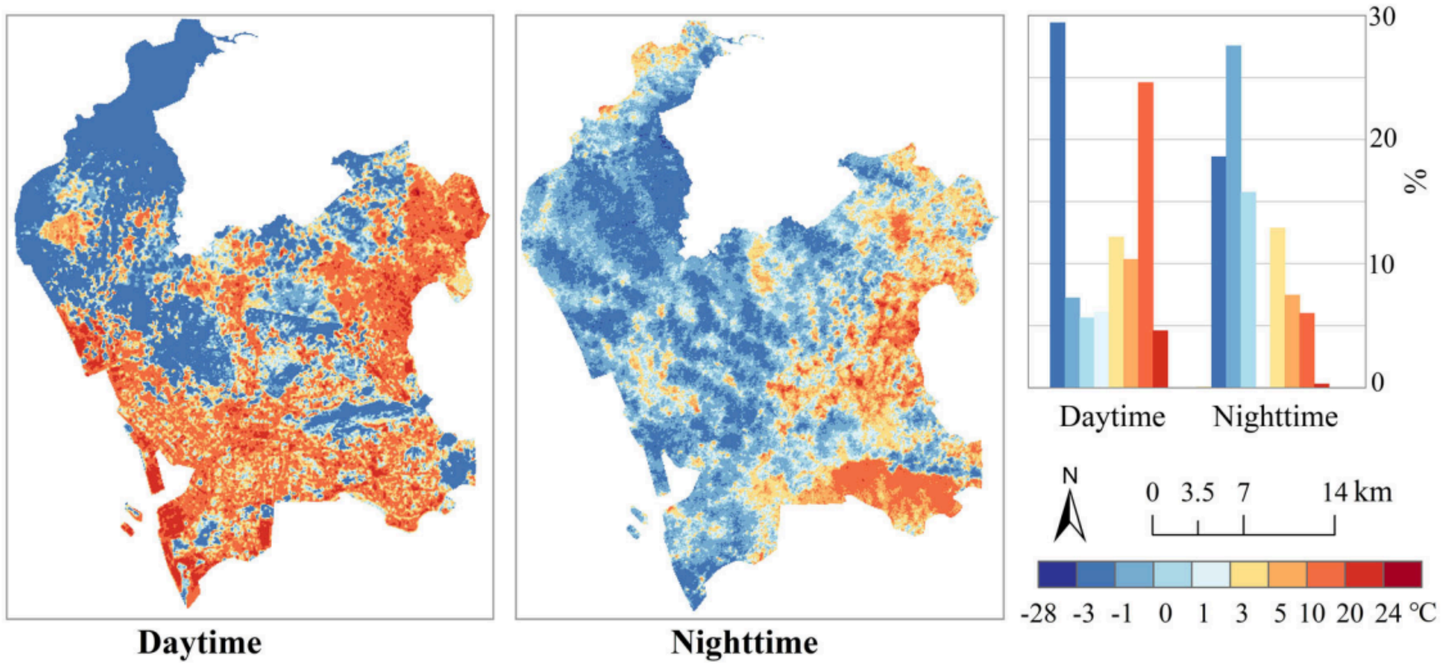
- Predict travel demand
- Analyse accessibility
- Identify mobility inequalities
- Commuting patterns
- Travel behaviour




Human mobility and hierarchical structure of cities.
https://doi.org/10.1038/s41467-019-12809-y

# Example: Urban climate

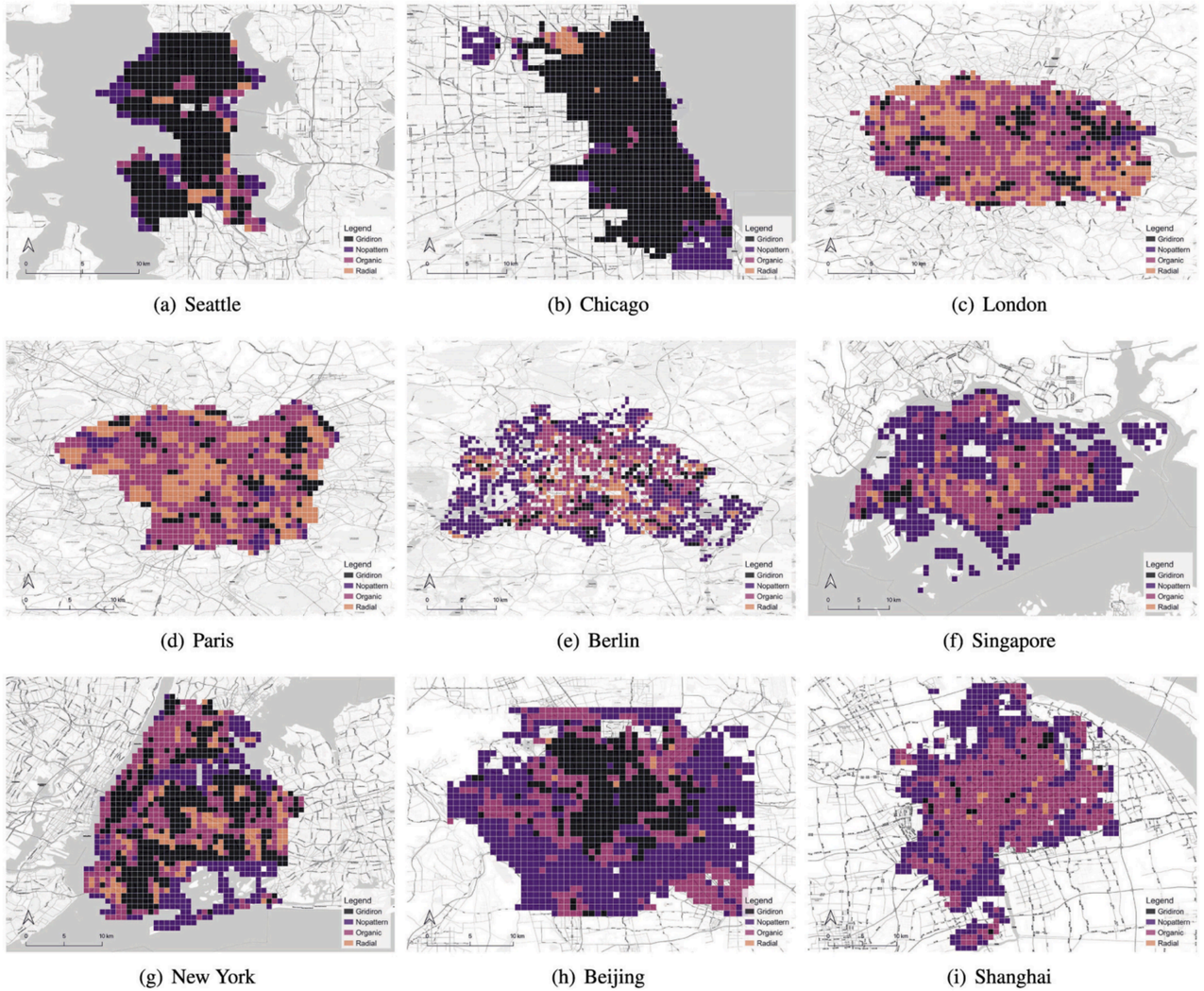
- Urban heat intensity
- Air quality patterns
- Noise distribution
- Outdoor comfort




Daytime and nighttime heat island spatial distribution map and the percentage of daytime and nighttime UHII in each category
https://doi.org/10.1038/s42949-022-00055-z

# Example: Urban form

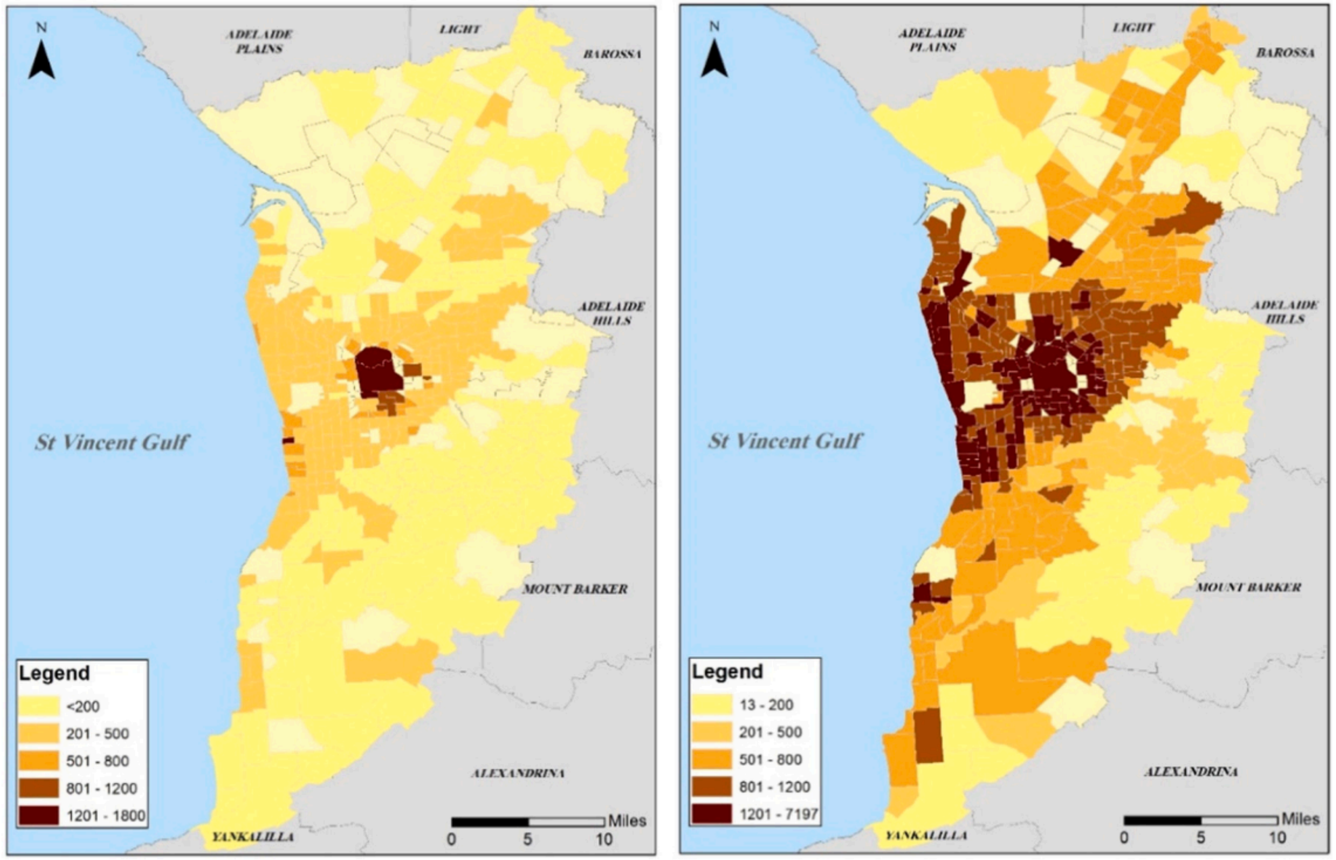
- Density and compactness
- 2D vs 3D urban form
- Building–street relationships
- Morphological clustering




Classification of urban morphology
https://doi.org/10.1016/j.compenvurbsys.2021.101706

# Example: Housing

- Price prediction
- Spatial inequality
- Neighbourhood change/satisfaction
- Gentrification




Spatiotemporal variations of property price in Adelaide, Australia
https://doi.org/10.1016/j.cities.2022.103941

# Strengths of AI in urban studies

- Handling large datasets
- Detecting hidden patterns
- Comparing scenarios (e.g. evaluation)
- Scaling analysis city-wide

# AI is a tool not a solution, and humans make decisions

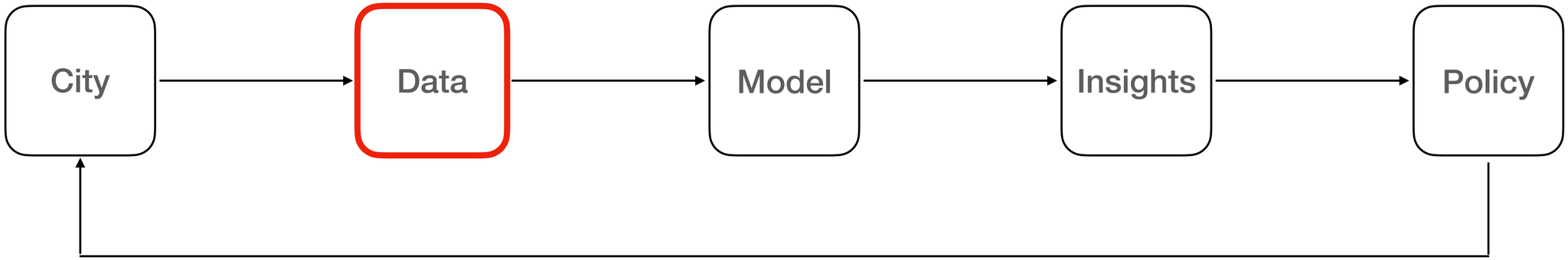
PART 2

# Urban data foundations

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# The city is a system



# Data

- What data do we use?
- How do we analyse it?
- How does this connect to lived experience?
- How will you apply this?

# Urban data

- Understanding the city through data information
- Urban data is the foundation of analysis
- AI and models depend on data
- Urban questions determine what data we collect
- Data choices shape planning outcomes

# Cities as data hubs

- Lived experiences are observed (e.g. how people travel, how people feel)
- Observations are recorded as data
- Data simplifies complex realities



# Types of urban data

- Social (population, behaviour, crime)
- Economic (prices, income)
- Environmental (heat, air, noise)
- Spatial (where things are, i.e. geolocation)
- ***Spatial information connects everything***

# Why spatial information is important?

- Every observation has a location
- Spatial relationships matter
  - e.g. buildings <-> streets, streets <-> streets
- Nearby things influence each other
- Patterns emerge across space

# What spatial data let us ask

- Where does something happen?
- How are places connected?
- How do patterns vary across space?
- Why here and not elsewhere?

# Key concepts in spatial data

- Location (coordinates)
- Distance (proximity, accessibility)
- Scale (local vs city-wide)
- Context (surroundings matter)

# How space is represented in data

- Points (locations, events) — (x, y)
- Lines (streets, paths) — sequence of nodes
- Polygons (areas, buildings) — boundary representation




https://data.cityofnewyork.us/City-Government/Building-Footprints-Map-/jh45-qr5r

# Vector spatial data

- Discrete objects
  - Points (e.g. a metro station)
  - Lines (e.g. roads)
  - Polygons (e.g. a building boundary)
- Usually descriptive data is stored for each — attributes
  - Examples: Name of the Metro station, type of a road and its speed, address of the building
- Common in planning datasets
  - Examples you can list?

# Raster spatial data

- A set of regularly spaced cells with associated field values
- Continuous surfaces
- Pixel-based representation
- Resolution matters
- Often derived from sensors
- Examples: elevation, temperature

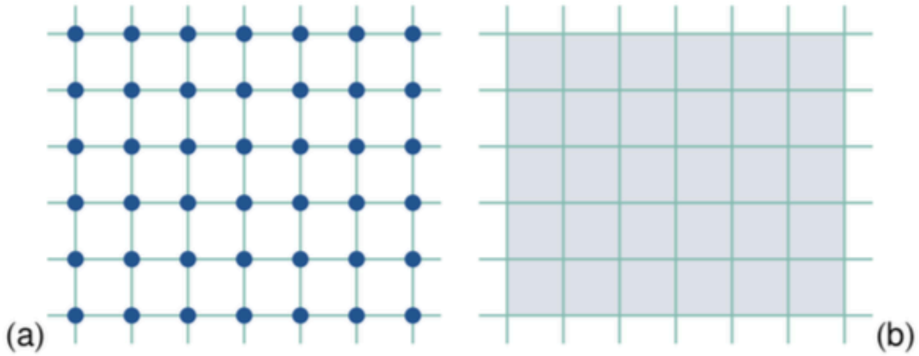
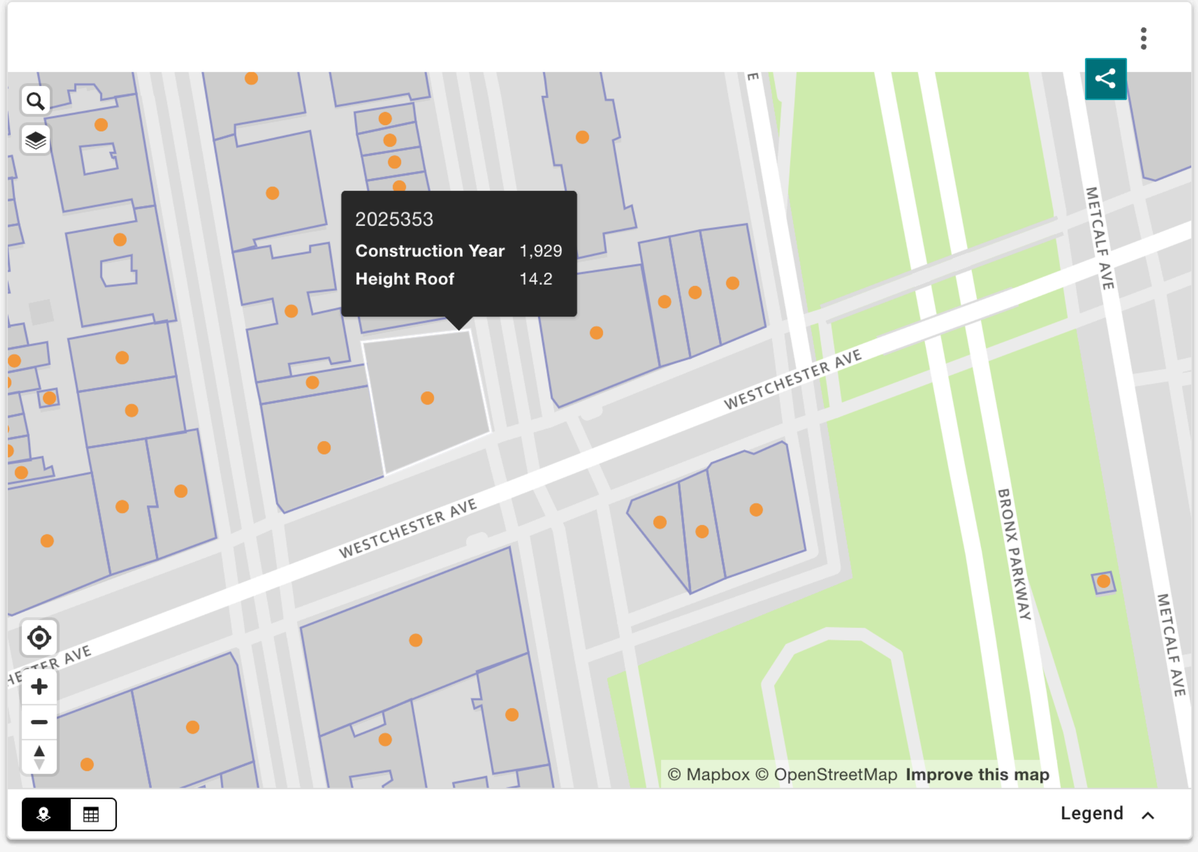



**Figure 2.6:** A grid (a) is a collection of regularly spaced (field) values, while a raster (b) is composed of cells. The associated values with each grid point or raster cell are not illustrated.

# Attributes and geometry

- Geometry: shape and location
- Attributes: descriptive information
- Both are needed for analysis
- Geometry alone is not enough sometimes




*https://data.cityofnewyork.us/City-Government/Building-Footprints-Map-/jh45-qr5r*

# Scale and resolution

- Fine resolution ≠ better insight
- Scale must match the question
- Patterns change with scale
- Planning decisions operate at multiple scales

# Spatial relationships

- Distance and proximity: How far things are from each other
- Adjacency and containment: What touches what, and what lies inside what
- Connectivity and networks: How objects are linked for movement or interaction
- Neighbourhood effects: Nearby things influence each other

# Spatial data quality

- Accuracy (is it correct?)
- Completeness (what is missing?)
- Timeliness (is it up-to-date?)
- Consistency (across sources)

# Data bias

- Some places may be over-measured
- Some groups are under-represented
- Data reflects openness and access

# Urban data sources

- Government / local authorities
- Sensors and IoT
- Remote sensing (e.g. satellite imagery)
- Crowdsourced platforms (e.g. Waze, Google map reviews, OpenStreetMap)
- Surveys and fieldwork

# Access to multisourced data

- Open data enables transparency
- Commercial data may be richer
- Trade-offs between access and control
- Ethical and legal constraints matter

# Linking data to observation

- Data abstracts reality
- Field observation adds context
- Human sensing complements digital sensing
- Both are necessary

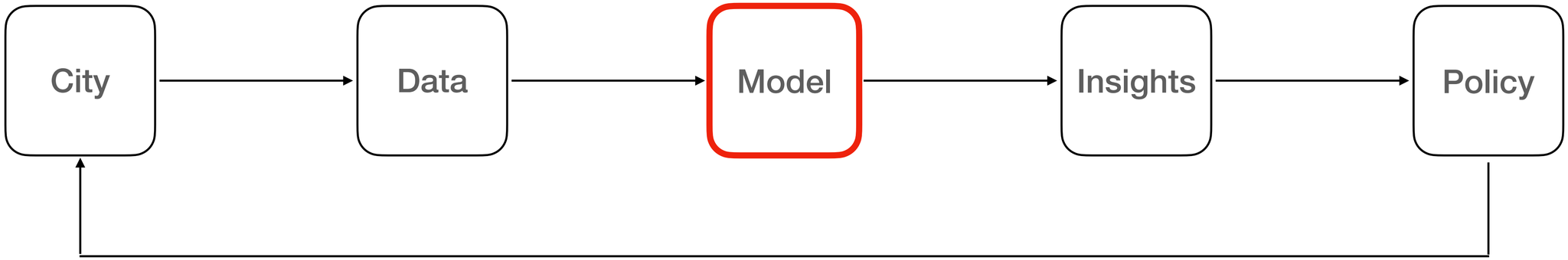
PART 3

# Urban AI models



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# The city is a system



# From data to insight

- Data alone does not answer questions
- Methods structure how we ask why
- Different methods reveal different urban stories

# What are methods in urban analytics?

- Methods ≠ Algorithms
- Ways of asking questions of spatial data
- Not just formulas or code
- Embedded assumptions about cities
- Linked to planning decisions

# Maps are analytical tools

- Mapping is one of the methods
  - Reveal spatial patterns
  - Highlight inequality and clustering
  - Support comparison across places
  - Shape interpretation

# Descriptive spatial analysis

- Describing spatial distribution
- Counts by area
- Densities
- Proportions
- Simple summaries
- E.g. POIs per neighbourhood, population density

# Aggregation and zoning

- Aggregation: Data grouped by zones
- Results depend on boundaries (e.g. neighbourhood, district)
- Planning units shape outcomes

# Accessibility

- Opportunities reachable within constraints
- Time, cost, and effort matter
- Not evenly distributed
- Central to urban equity

# Network thinking

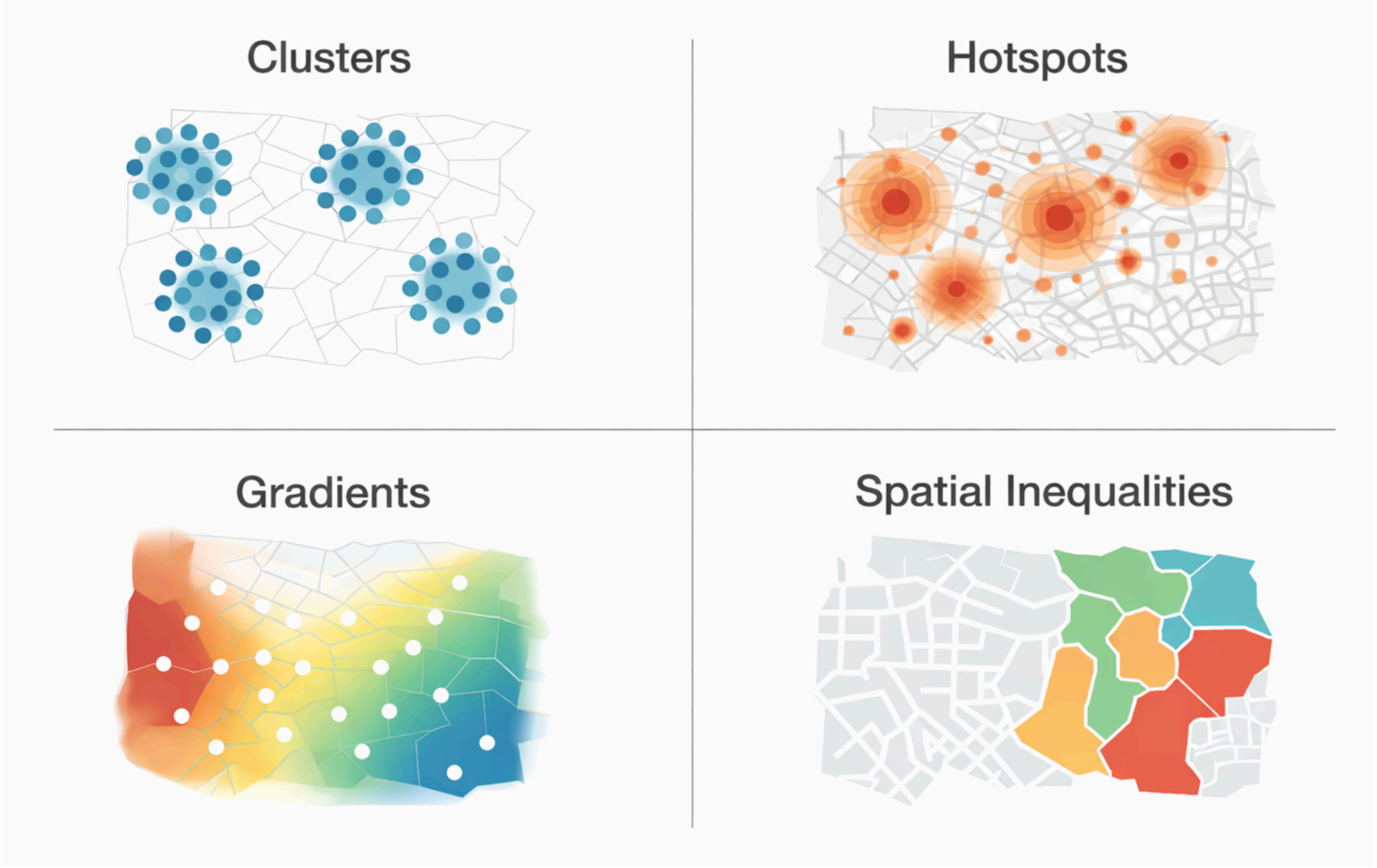
- Streets connect places
- Movement follows networks
- Connectivity shapes behaviour
- Network structure is important

# Temporal thinking

- Adding time to space (e.g. spatiotemporal analysis)
  - Cities change over time
  - Day vs night patterns
  - Short-term vs long-term change
  - Data snapshots vs processes

# Spatial patterns

- Clusters
- Hotspots
- Gradients
- Spatial inequalities



# AI as one method family

- Learns patterns from data
- Scales up analysis
- Supports prediction
- Requires interpretation

# Computer vision: reading the visible city

## Strength

Extract streetscape features, visual qualities, urban greenery, facade cues, and public realm conditions.

## Good use

Use vision as one evidence stream, combined with spatial data, validation, and human interpretation.



```
Provide concise labels for each category using the following JSON format. Select appropriate values from the provided options for each category...

  ```json
  {
    "building_type": "public",
    "building_age": "1900",
    "surface_material": "stone",
    "floors": 3,
    "construction_material": "brick"
  }
  ```
```

https://doi.org/10.1016/j.isprsjprs.2025.10.014

# Graph learning: reading spatial relations

## Nodes

Buildings, parcels, street segments, neighborhoods, sensors, or people depending on the planning question.

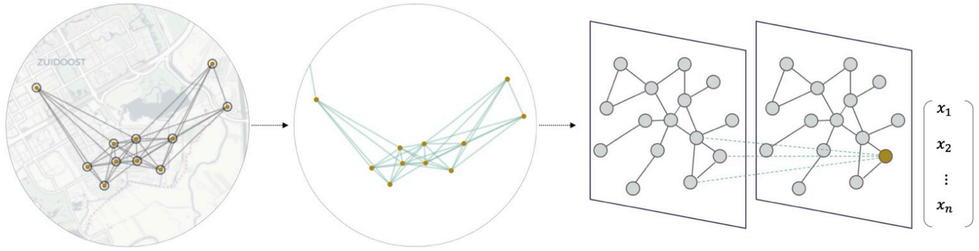
## Edges

Adjacency, connectivity, visibility, similarity, flow, or functional relationship.

## Urban value

Captures topology and spillovers that tables and independent pixels cannot represent.

A graph-based model




https://doi.org/10.1016/j.scs.2024.106121

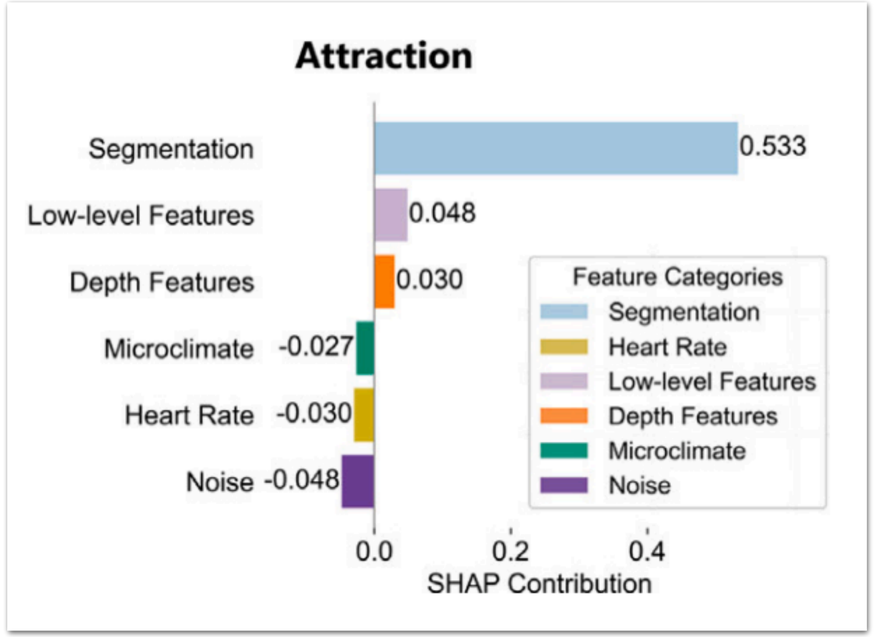
# Explainable AI: from score to reason

## Local explanation

Why did the model classify this street, building, or neighborhood this way?

## Global explanation

Which factors generally drive predictions across the city or across groups?




https://doi.org/10.1016/j.buildenv.2025.113748

# Choose a method for a question

- What is the planning issue?
- What data is available?
- What scale matters?
- Who is affected?

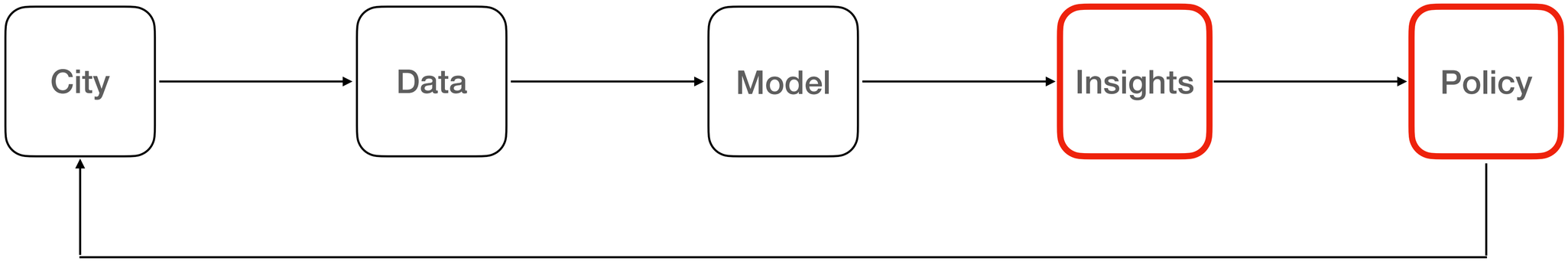
PART 4

# Inform planning and design practices



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# The city is a system



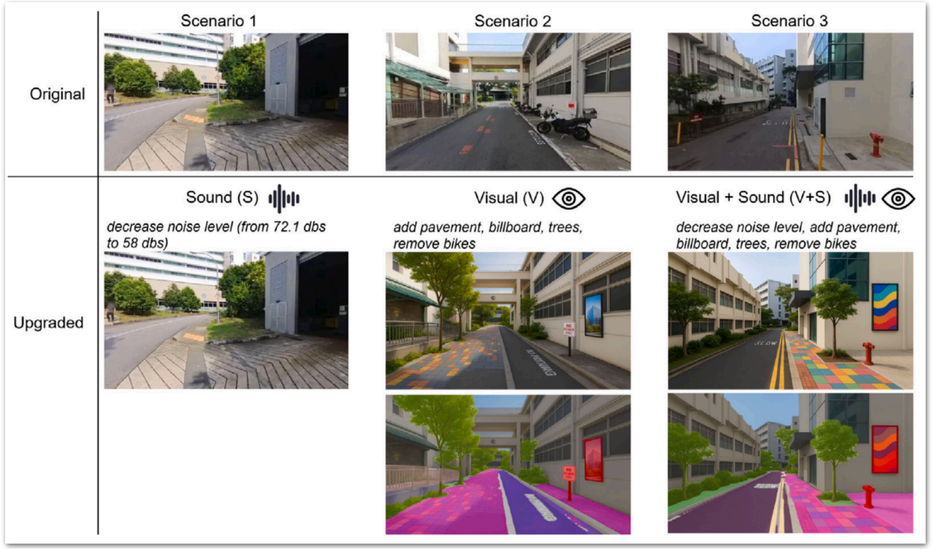
# Simulation turns models into scenarios

## Scenario testing

Compare design alternatives, tree planting, shading, density, or street changes.

## Decision support

Translate model outputs into trade-offs that planners can inspect and debate.




https://doi.org/10.1016/j.buildenv.2025.113748

# Quiz time

# Quiz 1

- What is the **primary value** of AI in urban studies?

A. Replacing urban planners and designers

B. Discovering patterns and generating insights from complex urban data to support decision making

C. Eliminating the need for urban data collection

D. Producing one optimal solution for every city

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# Quiz 2

- You want to estimate how walkable different streets are across a city using AI. Which dataset would likely provide the **most useful information**?

A. Building addresses

B. Street View images

C. Census data

D. Administrative boundary polygons

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# Quiz 3

- An AI model predicts that a neighbourhood has a high risk of traffic accidents. What should planners do?

A. Implement all AI recommendations automatically

B. Ignore the AI because models are never perfect

C. Use AI predictions alongside local knowledge, domain expertise, and stakeholder engagement

D. Replace public consultation with AI

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# AI for cities should help planners ask better questions, see hidden relationships, and act with greater care

Further enquiry
<b.lei@bham.ac.uk>

