Ambient populations: Developing robust estimates

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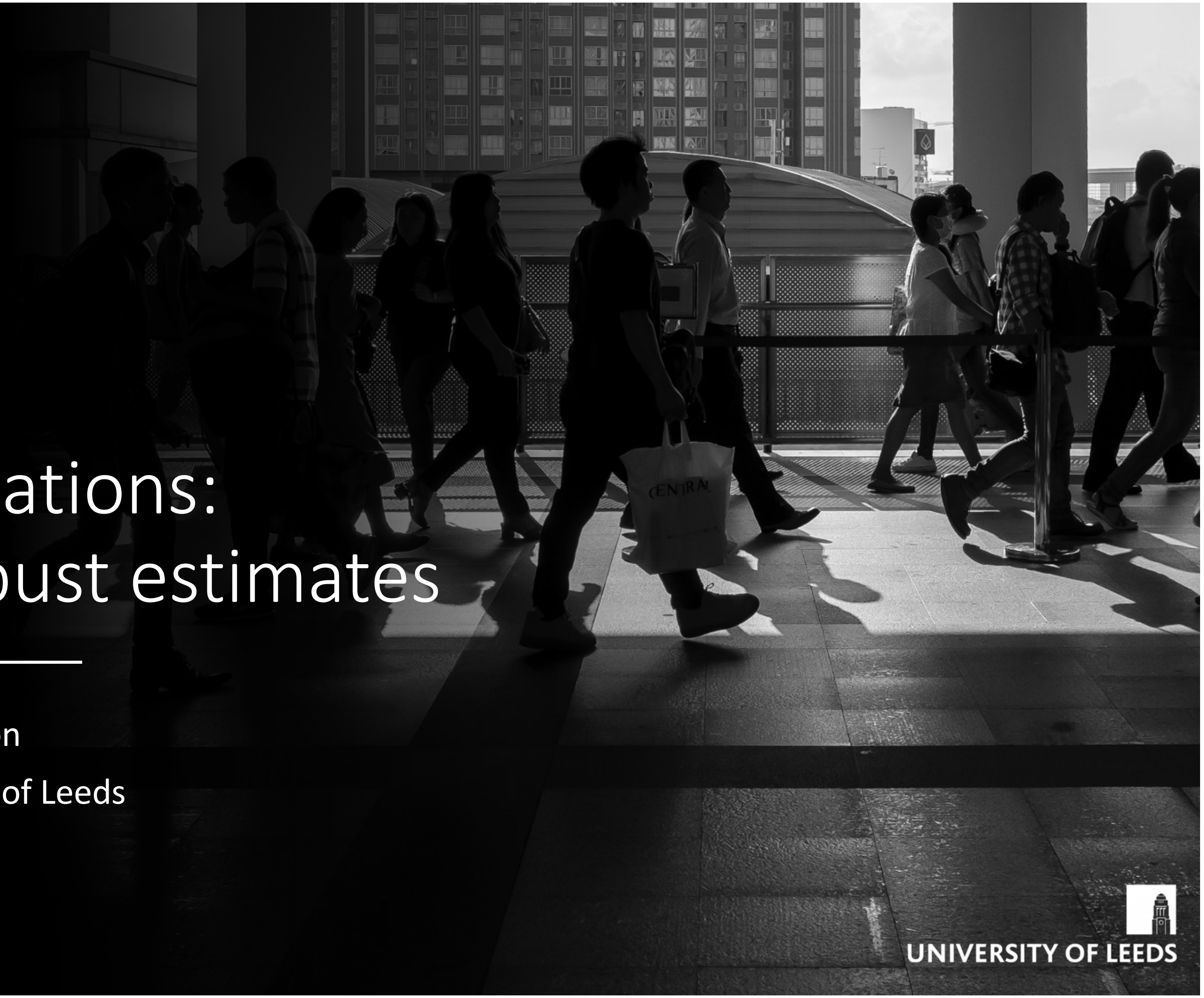

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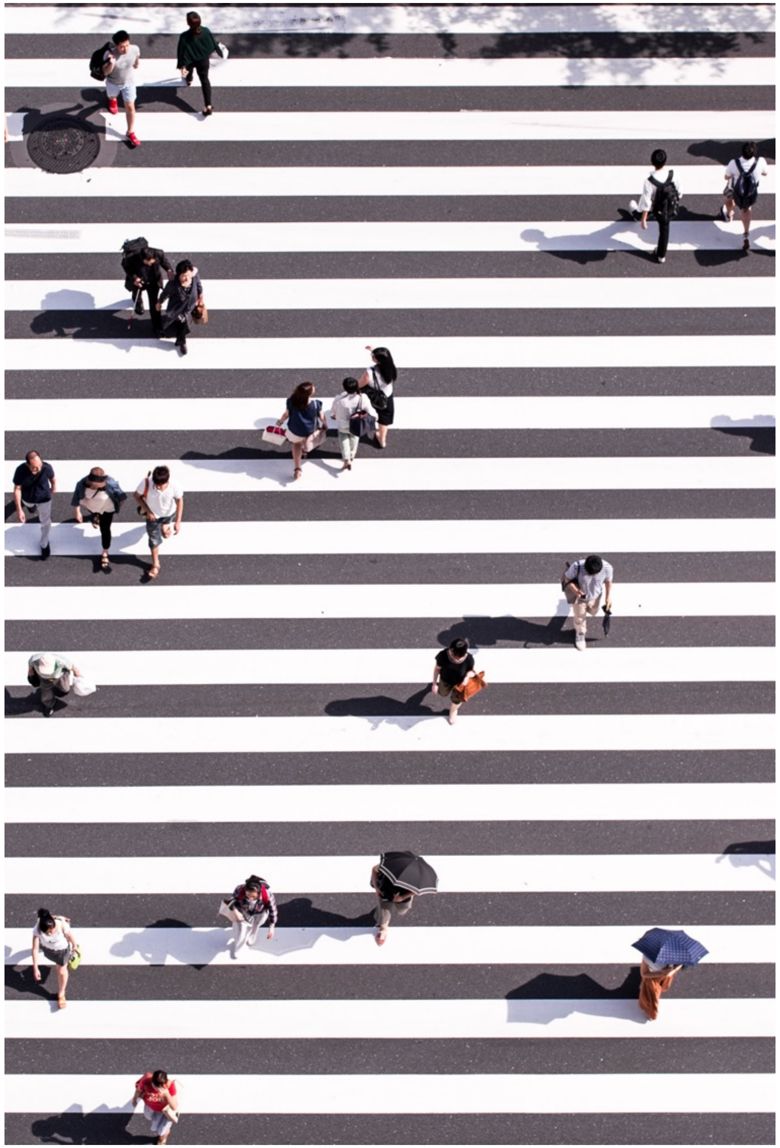
Overview

1. Why estimates of the ambient population need to be developed
2. The ambient population and crime analysis
3. Identifying suitable data sources
4. Towards a comprehensive model of the ambient population
5. Ambient Populations for Smart City Simulations



Why are ambient populations important?

- Crime (examples to follow)
- Planning and infrastructure
- Local economy
- Disease spread
- Transport
- Event management
- Emergencies and public safety
- Etc.

Crime Analysis and the Ambient Population

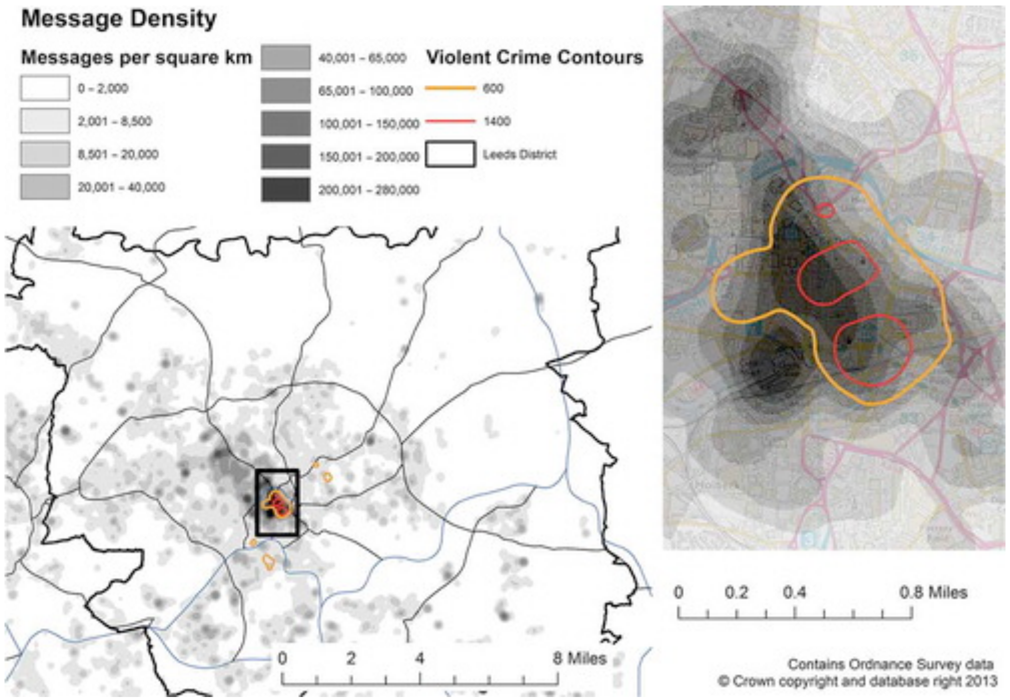
Research Questions

- Are crime hot spots stable under the application of different population-at-risk measures?
- Which areas have the highest crime rates under different denominators?

Data:

- Residential population (census)
- Geo-located tweets
- Publicly-available crime data ('violent crime')

Methods: GI* & GAM



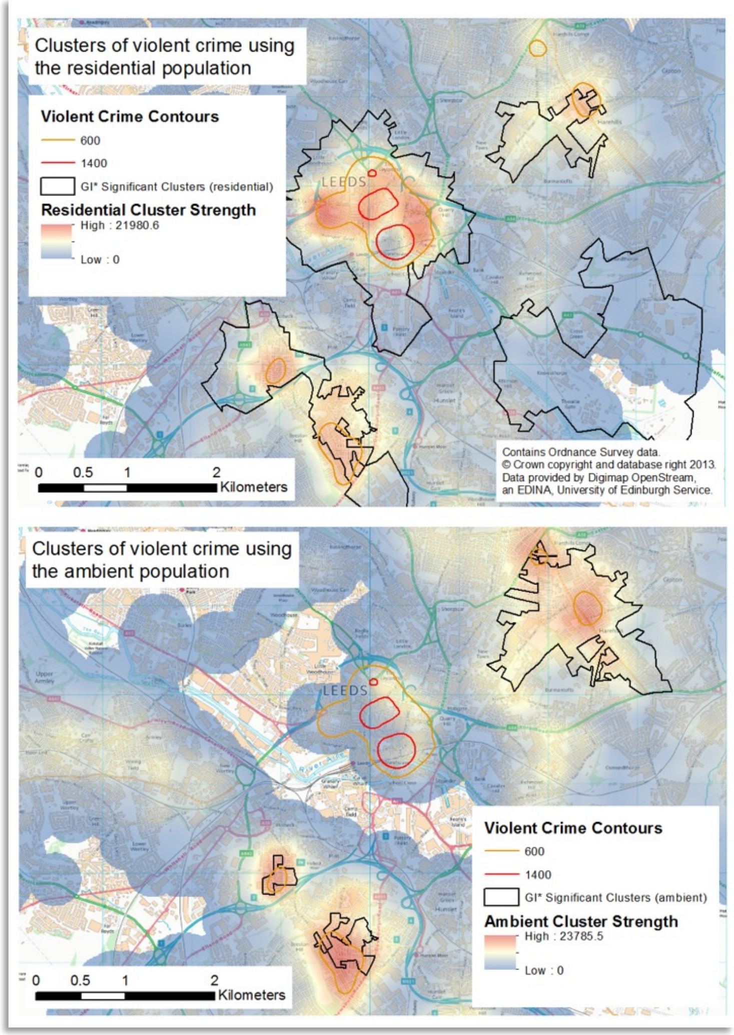
Malleson, N. and M. Andresen (2015) The impact of using social media data in crime rate calculations: shifting hot spots and changing spatial patterns. *Cartography and Geographic Information Science* : 42(2) 112-121

Shifting Hotspots

Results: city-centre hotspot disappears

"… despite the high volume of violent criminal events, there is not a statistically significant elevation in risk … . No such conclusion would have been reached with the residential population."

But what about temporal changes?



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Spatio-Temporal Hotspot Analysis

Aim

Identify significant crime clusters (taking account of the ambient population) and explore their spatio-temporal dynamics.

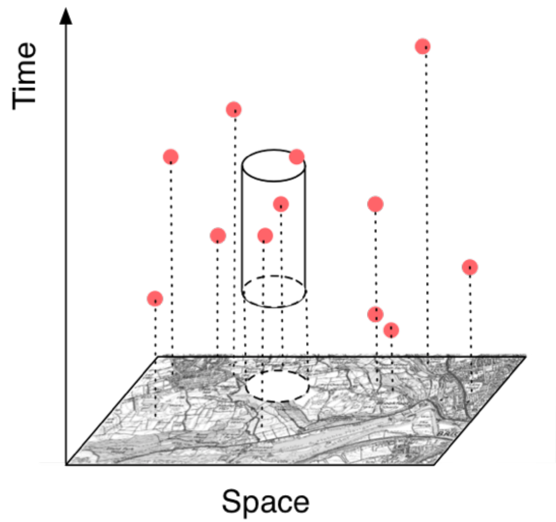
Data:

Residential population (census)

Geo-located tweets

Sensitive crime data (‘street crime’: theft from person and robbery)

Methods: Space-Time Scan Statistics (*SaTScan*)



Spatio-Temporal Hotspot Analysis

Results: the city-centre hotspot reappears!

Cluster (A)

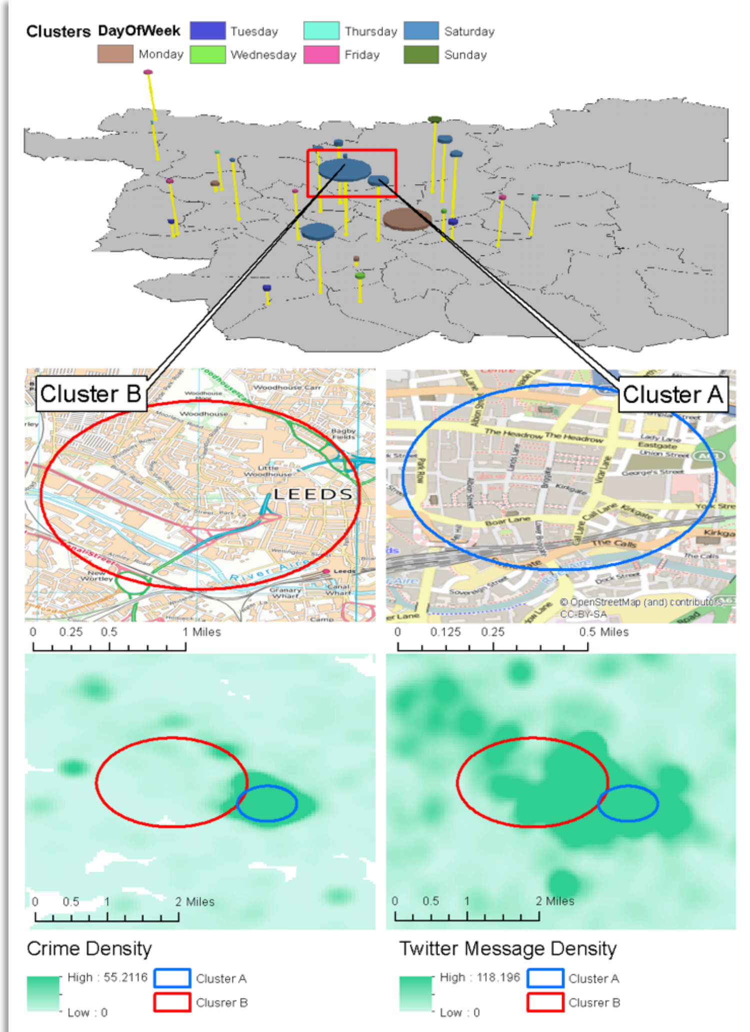
Small city-centre area (shops, bars, etc.)
Saturday, 10:00 – 17:00

Cluster (B)

Larger cluster includes campus and student residences
Saturday, 21:00 – 02:00

Different populations of victims

But are there other, better, data sources?



Malleson, N. and M.A. Andresen (2015) Spatio-temporal crime hotspots and the ambient population. *Crime Science* 4(10). http://dx.doi.org/10.1186/s40163-015-0023-8

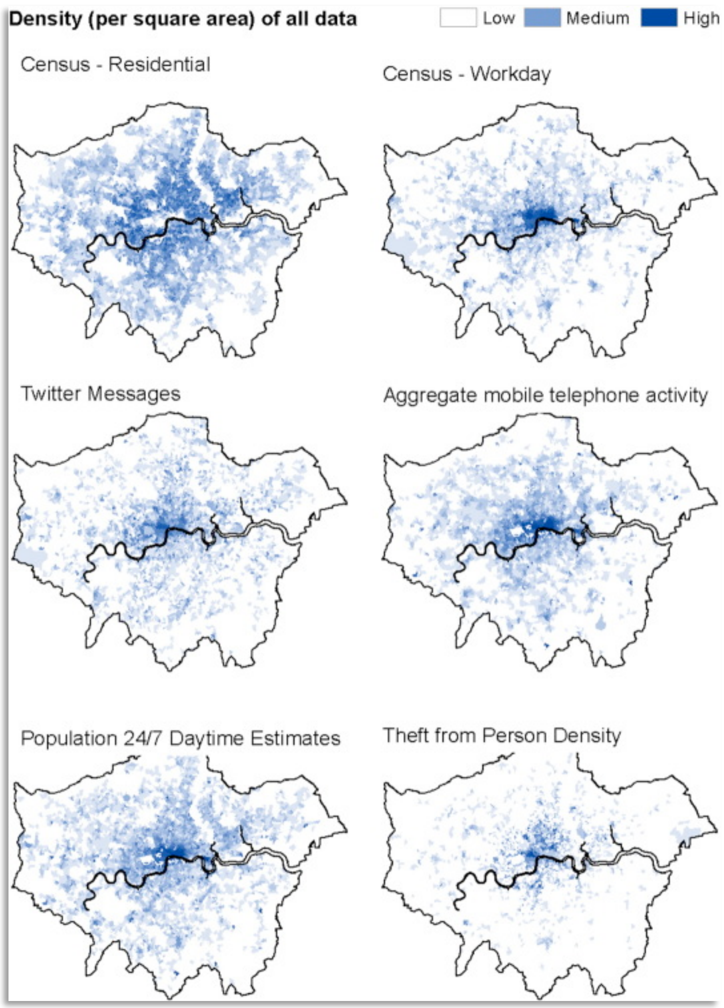
Alternative Data Sets

Aim: evaluate 5 ambient population measures to find the most highly correlated with crime

Data:

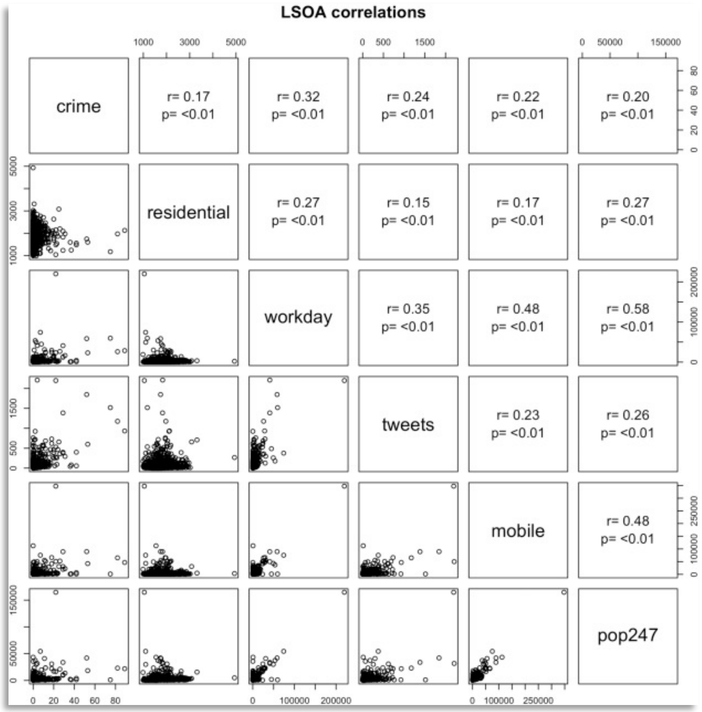
- Ambient population: census (residential and workday), Twitter, mobile telephones, Pop24/7
- Crime: Publicly-available crime data (‘theft from person’)
- Points of interest: Open Street Map

Methods: correlation & GI*



Malleson, N., and Andresen, M.A. (2016) Exploring the impact of ambient population measures on London crime hotspots. *Journal of Criminal Justice* 46 pp 52-63. (Open access) http://dx.doi.org/10.1016/j.jcrimjus.2016.03.002)

Alternative Data Sets



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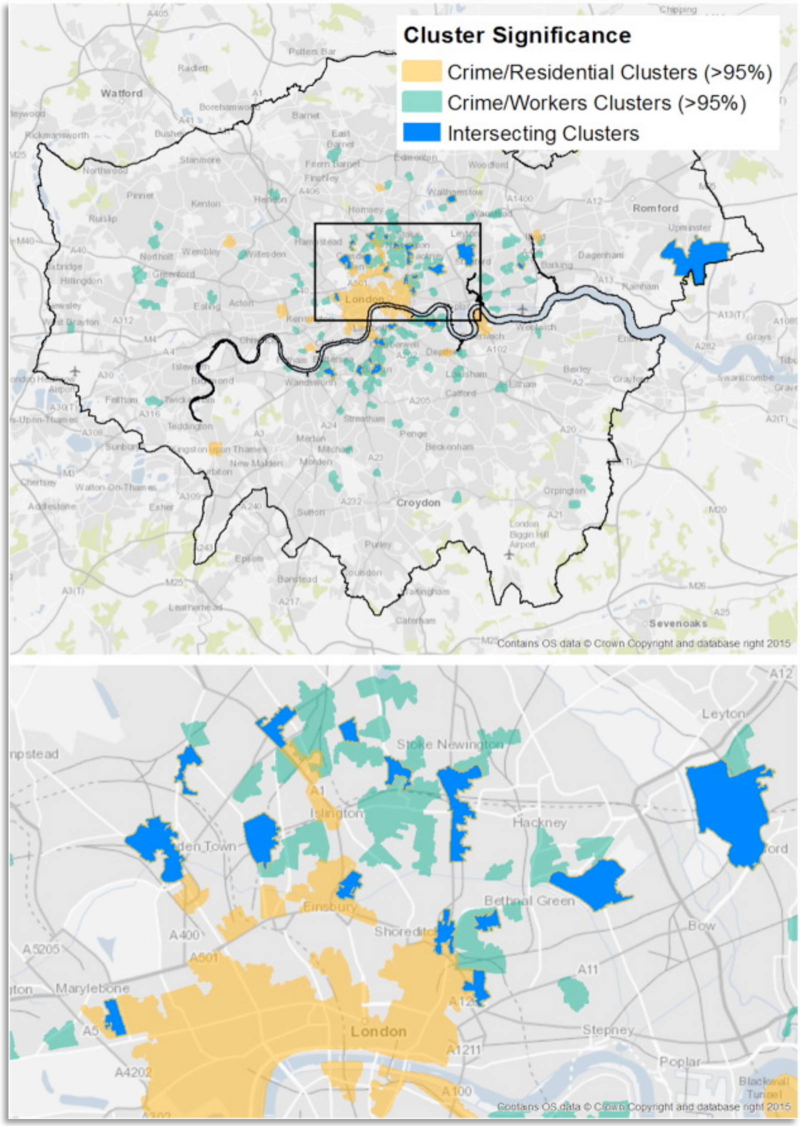


Crime Analysis and the Ambient Population

These studies highlight why estimates of the ambient population are important, but also raise several key questions:

- Which data are the best proxies?
- Are the data representative of the whole ambient population?
- How accurate are the data?

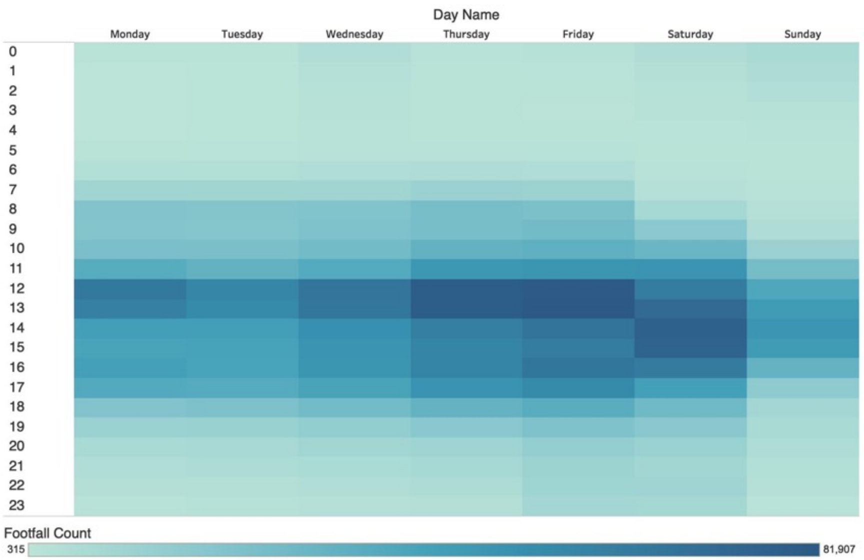
Data for Modelling Ambient Populations

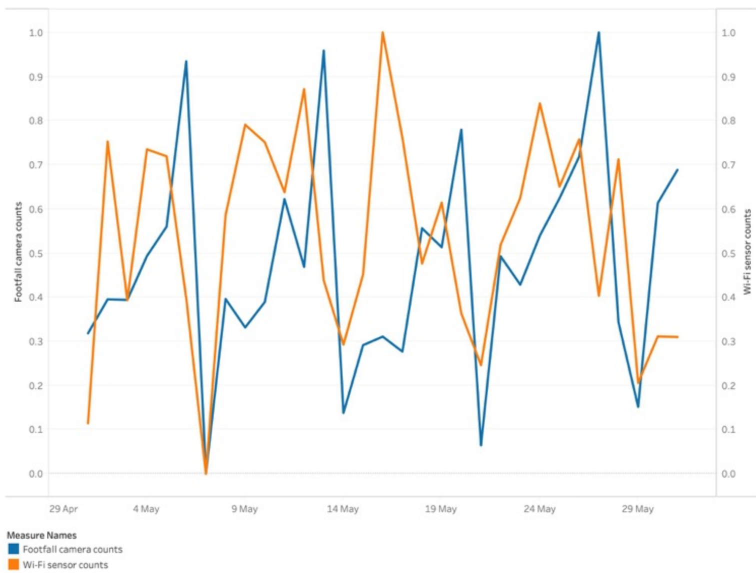
- Census data
- Remote sensing
- Travel surveys
- Mobile phone activity data
- Cell tower locations
- Mobility reports
- Footfall cameras
- Wi-Fi sensors

Estimates of the Ambient Population: Assessing the Utility of Conventional and Novel Data Sources

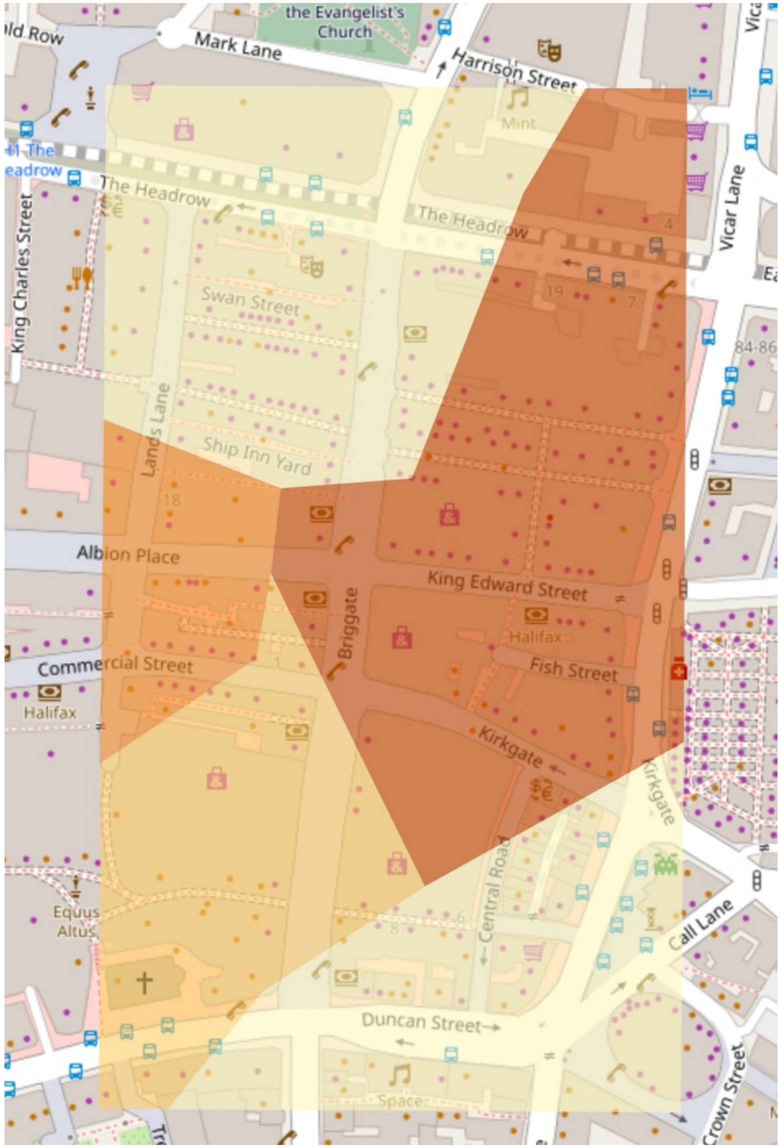
ISPRS International Journal of Geo-Information

Annabel Whipp, Nick Malleson , Jonathan Ward and Alison Heppenstall





https://www.mdpi.com/2220-9964/10/3/131



Towards Holistic Ambient Population Quantification

Aims

- Validate data sources using manual counts
- Build an estimate of the ambient population without replicating groups of individuals
- Predict the ambient population in locations without cameras or counters

Geographically weighted regression

Spatial data are often spatially autocorrelated

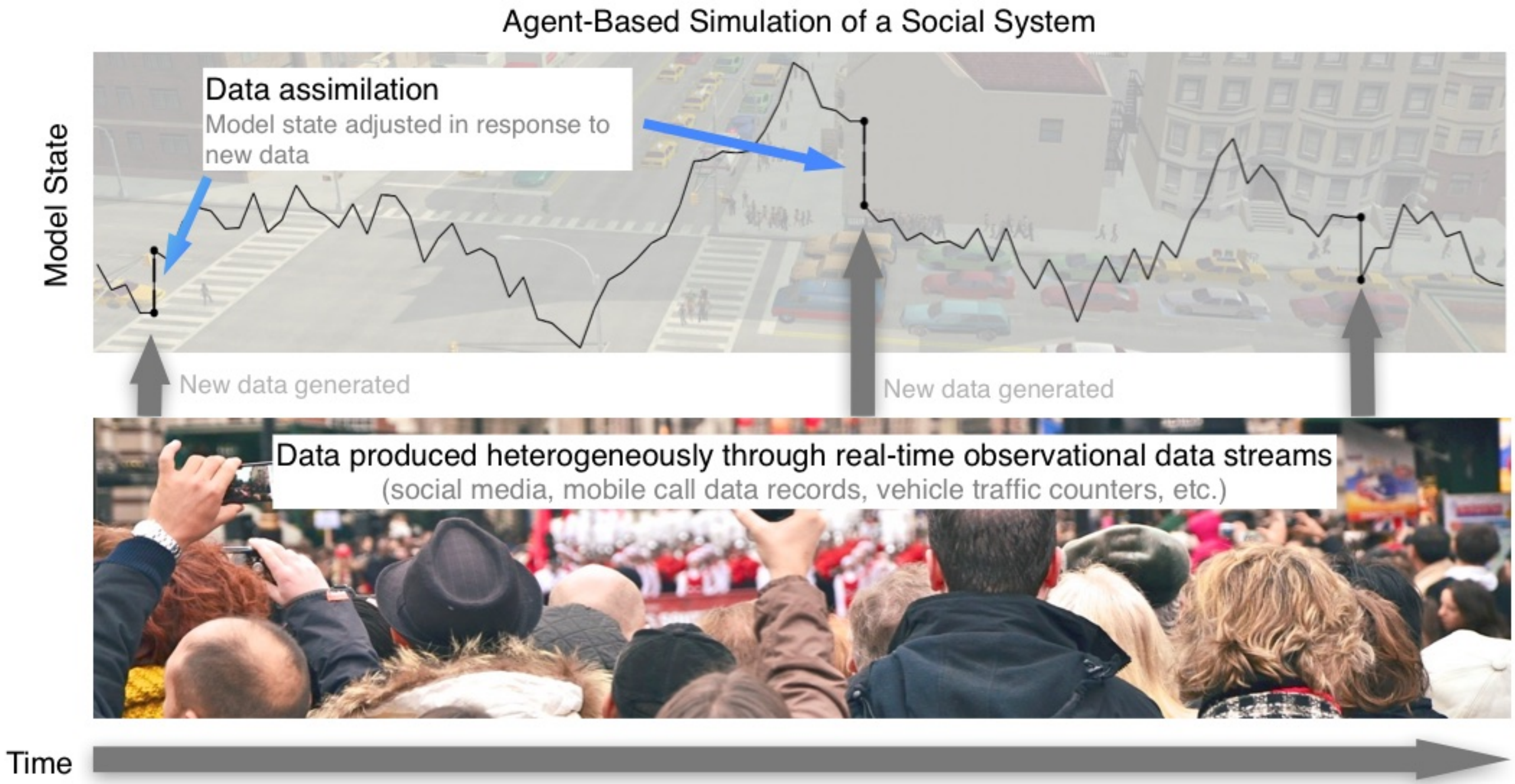
Unlike a global regression model, in a GWR model the relationship between the dependent and independent variables can vary across space

A daytime model and a night-time model will be developed

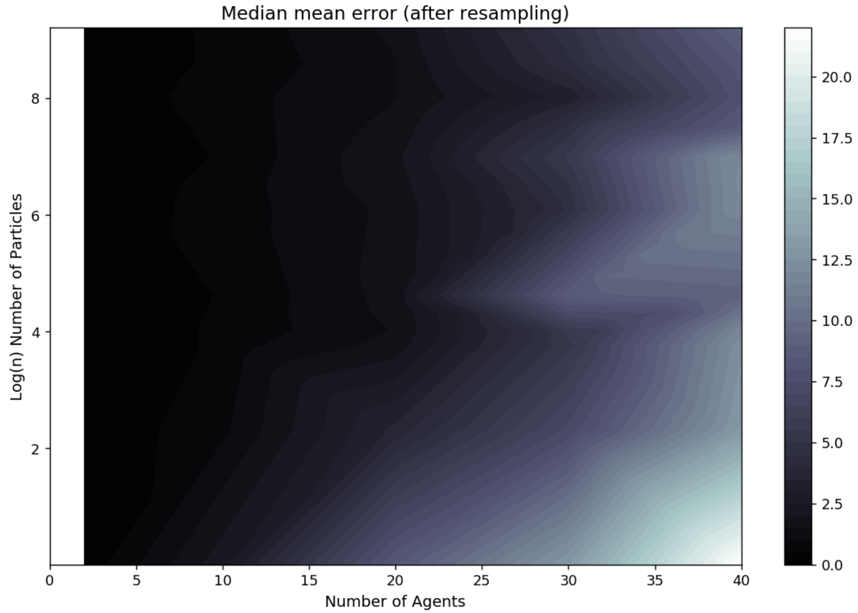
The results will be validated using manual counts

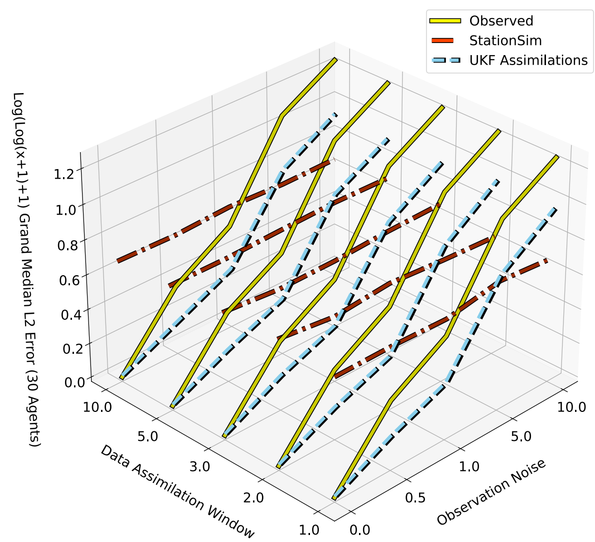
Geographically weighted regression - Data

Workday population	2011 Census
Daytime/night-time population	The counts from 8 footfall cameras in Leeds city centre
Attractors	Shops, bus stops, Wi-Fi hotspots, cafes, bars, train station


Agent-Based Simulation of a Social System
Model State
Data assimilation
Model state adjusted in response to new data
New data generated
New data generated
Data produced heterogeneously through real-time observational data streams
(social media, mobile call data records, vehicle traffic counters, etc.)
Time

Data Assimilation for Agent-Based Models





Data Assimilation for Agent-Based Models

DUST: https://dust.leeds.ac.uk/

So far: DA with Particle Filters and (Ensemble/Unscented) Kalman Filters.

Towards full, real-time crowd models

… and eventually cities

dust Blog Research Publications Presentations UNIVERSITY OF LEEDS

Project Publications and Documentation

The following publications report on the current progress of the DUST project or on related activities

Peer Reviewed Articles

Malleson, N., K. Minors, Le-Minh Kieu , J. A. Ward , A. West and A. Heppenstall (2020) Simulating Crowds in Real Time with Agent-Based Modelling and a Particle Filter. *Journal of Artificial Societies and Social Simulation (JASSS)* 23 (3). http://jasss.soc.surrey.ac.uk/23/3/3.html DOI: 10.18564/jasss.4266 (open access)

Kieu, Le-Minh, N. Malleson, and A. Heppenstall (2019). Dealing with Uncertainty in Agent-Based Models for Short-Term Predictions'. *Royal Society Open Science* 7(1): 191074. DOI: 10.1098/rsos.191074 (open access)

Kieu, Le-Minh, D. Ngoduy, N Malleson, and E. Chung (2019). A Stochastic Schedule-Following Simulation Model of Bus Routes. *Transportmetrica B: Transport Dynamics* 7 (1): 1588–1610. DOI: 10.1080/21680566.2019.1670118.

Crols, T., and N. Malleson (2019) Quantifying the Ambient Population Using Hourly Population Footfall Data and an Agent-Based Model of Daily Mobility. *GeoInformatica* (online first). DOI: 10.1007/s10707-019-00346-1. [Open access].

Preprints

Tang, D. (2020). Finding the Maximum-a-Posteriori Behaviour of Agents in an Agent-Based Model. ArXiv:2005.02096 [Cs].

Tang, D. (2020) Decentralised, Privacy-Preserving Bayesian Inference for Mobile Phone Contact Tracing', 2020. arXiv: 2005.05086 [cs.CY].

Tang, D. (2019). Data Assimilation in Agent-Based Models Using Creation and Annihilation Operators. ArXiv:1910.09442 [Cs].

Malleson, N., Kevin Minors, Le-Minh Kieu, Jonathan A. Ward, Andrew A. West, Alison Heppenstall (2019) Simulating Crowds in Real Time with Agent-Based Modelling and a Particle Filter. arXiv:1909.09397 [cs.MA].

Kieu, Le-Minh, N. Malleson, and A. Heppenstall (2019) Dealing with Uncertainty in Agent-Based Models for Short-Term Predictions'. arXiv:1908.08288 [cs.MA].

Conference proceedings

For a full list of conference presentations, see the presentations page.

R. Clay, Le-Minh Kieu, J. A. Ward, A. Heppenstall, N. Malleson (2020) Towards Real-Time Crowd Simulation Under Uncertainty Using an Agent-Based Model and an Unscented Kalman Filter. In Demazeau Y., Holvoet T., Corchado J., Costantini S. (eds) *Advances in Practical Applications of Agents, Multi-Agent Systems, and Trustworthiness. The PAAMS Collection. PAAMS 2020.* Lecture Notes

Conclusion

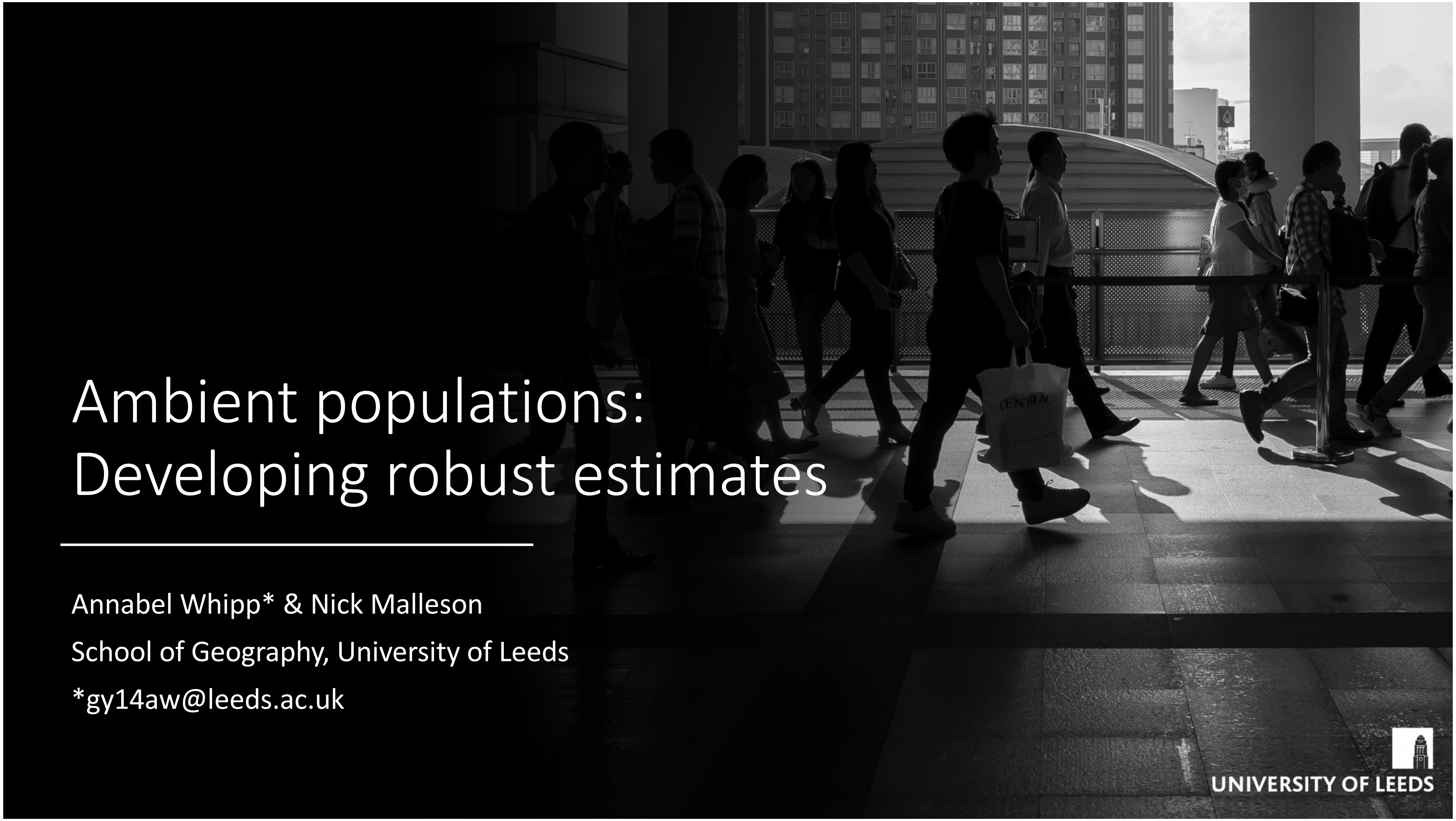
We need better estimates of the ambient population:

More accurate / reliable / detailed **data sources**

Methods / models to create a more **holistic representation**

Towards a comprehensive model of the ambient population

Ambient Populations for Smart City Simulations



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