Exploring the Impact of Ambient Population Measures on Crime Hotspots

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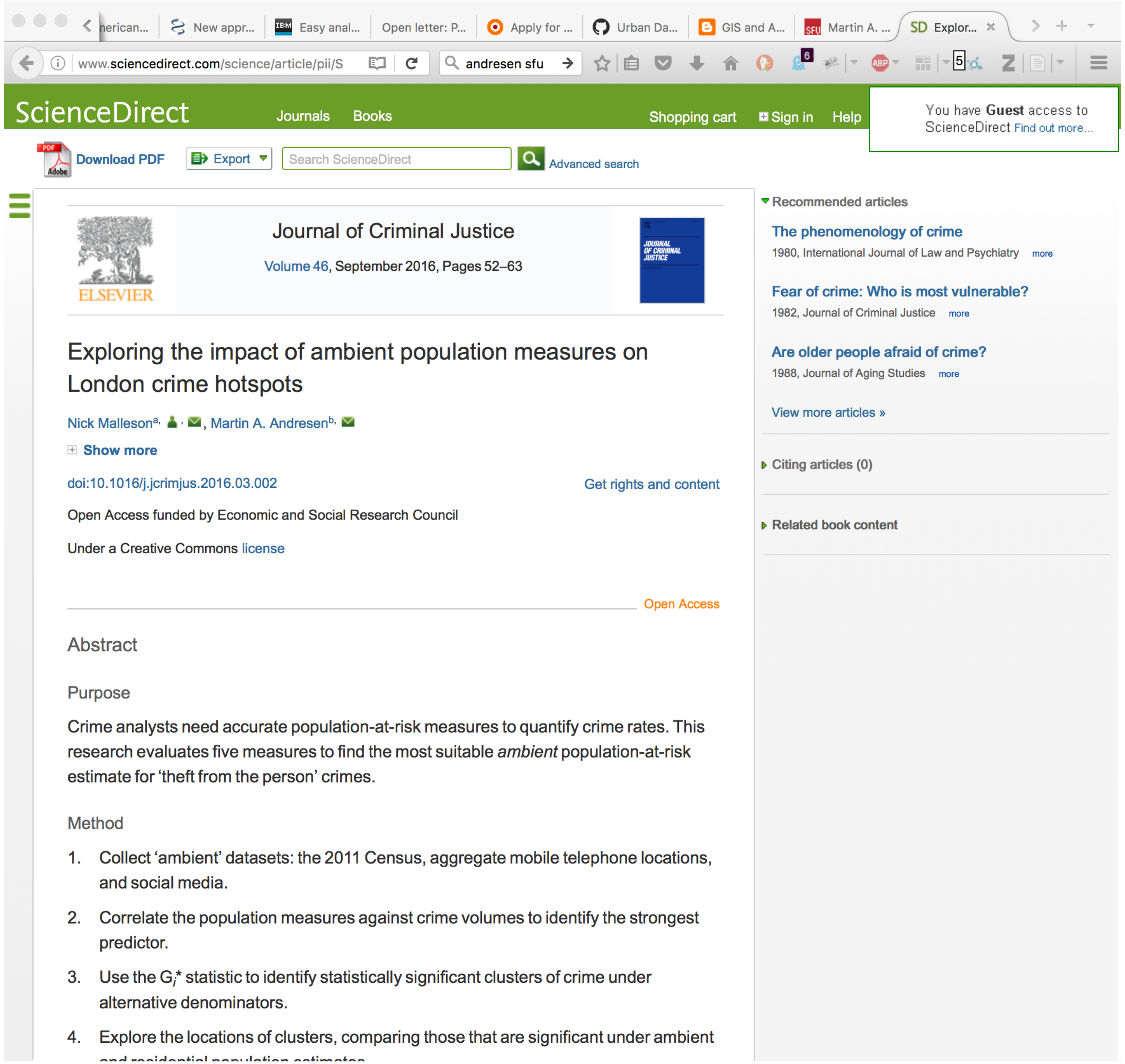
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Abstract

Purpose

Crime analysts need accurate population-at-risk measures to quantify crime rates. This research evaluates five measures to find the most suitable *ambient* population-at-risk estimate for 'theft from the person' crimes.

Method

1. Collect 'ambient' datasets: the 2011 Census, aggregate mobile telephone locations, and social media.
2. Correlate the population measures against crime volumes to identify the strongest predictor.
3. Use the G_i^* statistic to identify statistically significant clusters of crime under alternative denominators.
4. Explore the locations of clusters, comparing those that are significant under ambient

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Overview

What is the most appropriate denominator in crime rate calculations?

- Number of residents or households is common
- Ambient probably better for some crimes (i.e. assaults, robbery, and violent crime) (Boivin, 2013; Zhang et al., 2012; Andresen, 2011)

Method:

- Gather ‘ambient’ and ‘residential’ data and look for correlations with crime
- Identify statistically significant clusters (‘hot spots’) using the ‘best’ ambient data and traditional residential data
- Explore the impacts of using different measures

Results:

- Evidence for the most appropriate dataset for ambient crimes
- Identify new hotspots that only emerge when the *ambient* population is taken into account

Background: The Ambient Population

The residential population is a commonly-used denominator

Questionable for (e.g.) assaults (Boivin, 2013), robbery (Zhang et al., 2012) and violent crime (Andresen, 2011)

Daily flows of people have a significant impact on crime rates (Andresen & Jenion, 2010; Felson & Boivin, 2015; Stults & Hasbrouck, 2015).

Sound theoretical underpinning

Not new! (Boggs, 1965). But difficulties finding data.

Literature

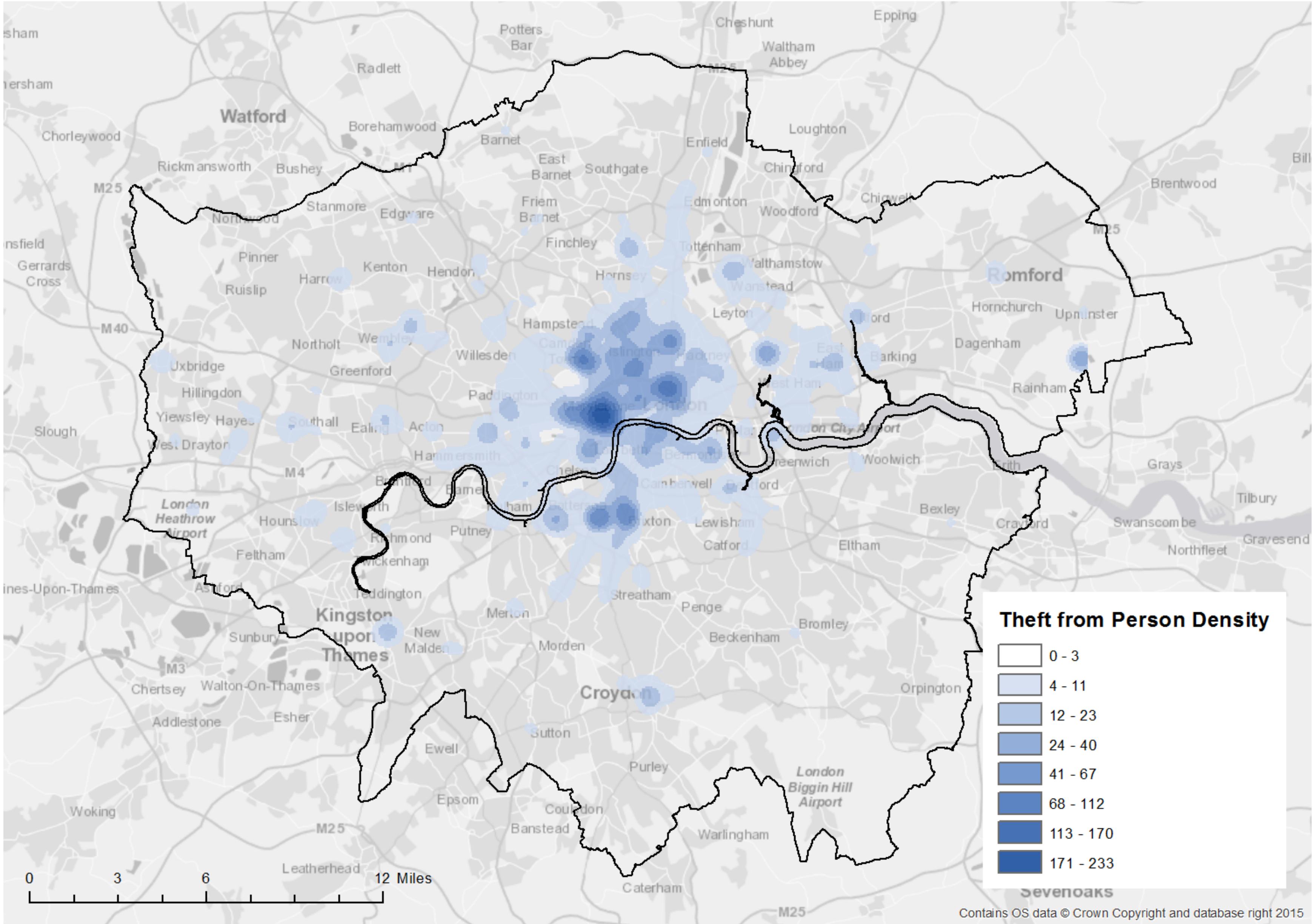
- LandScan (Andresen, Jenion, Kautt, Kurland)
- Commuting patterns (Felson & Boivin, 2015)

“The general patterns of movement towards and away from activity nodes such as work or school locations, major shopping areas, entertainment districts or bedroom suburbs provide a very general image of where crimes will concentrate”

(Kinney et al., 2008)

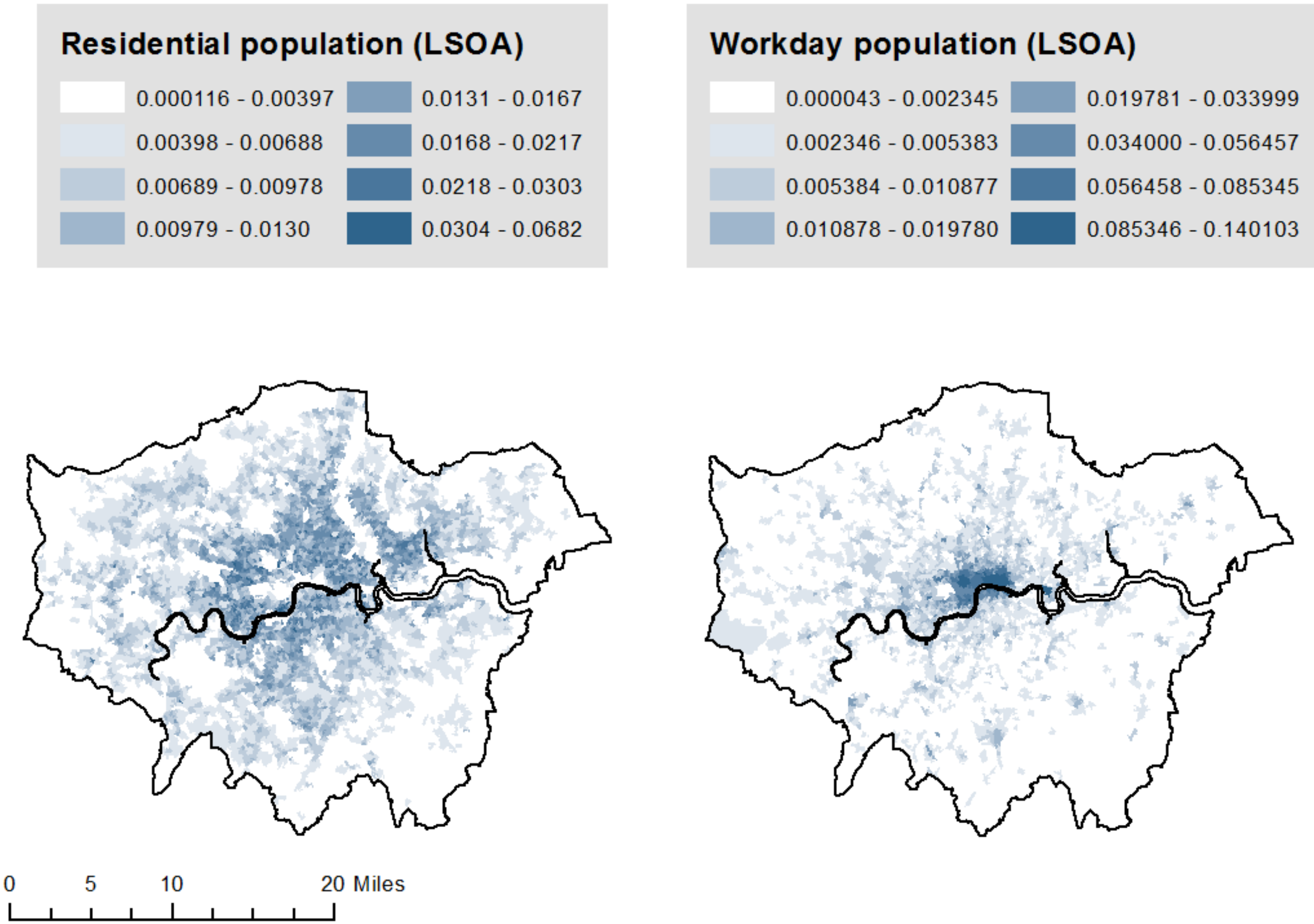
Data

Dependent variable: Theft from Person



Explanatory Variable:

2011 Census (Residential & Workday)



Explanatory Variable: Mobile Phone Counts

Hourly counts aggregated to a regular grid

Provided by a large telecommunications company (~20% UK market share)

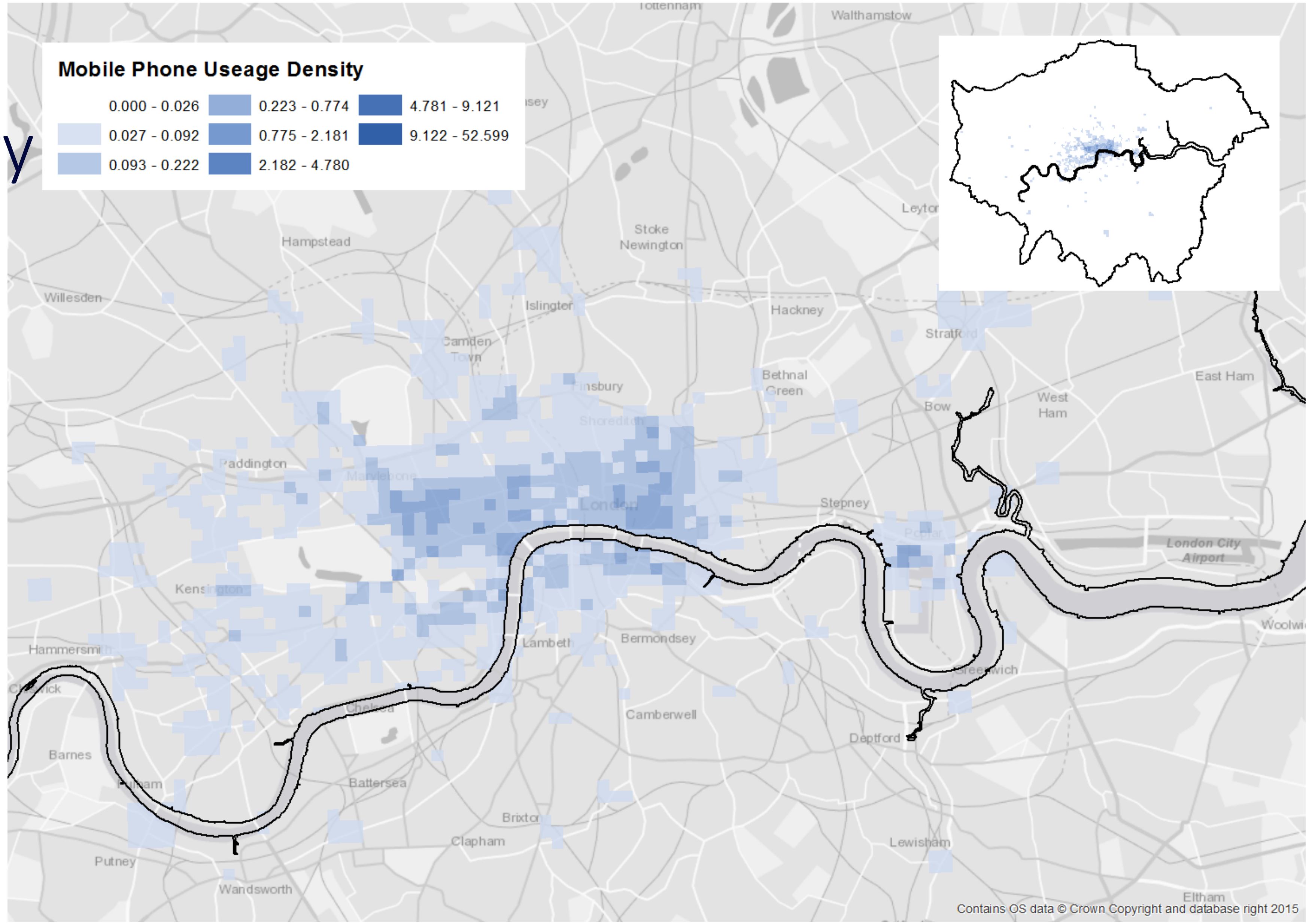
Counts of *events*

Disaggregated by age, gender, and acvitity (home, visitting, work)

Poorly documented

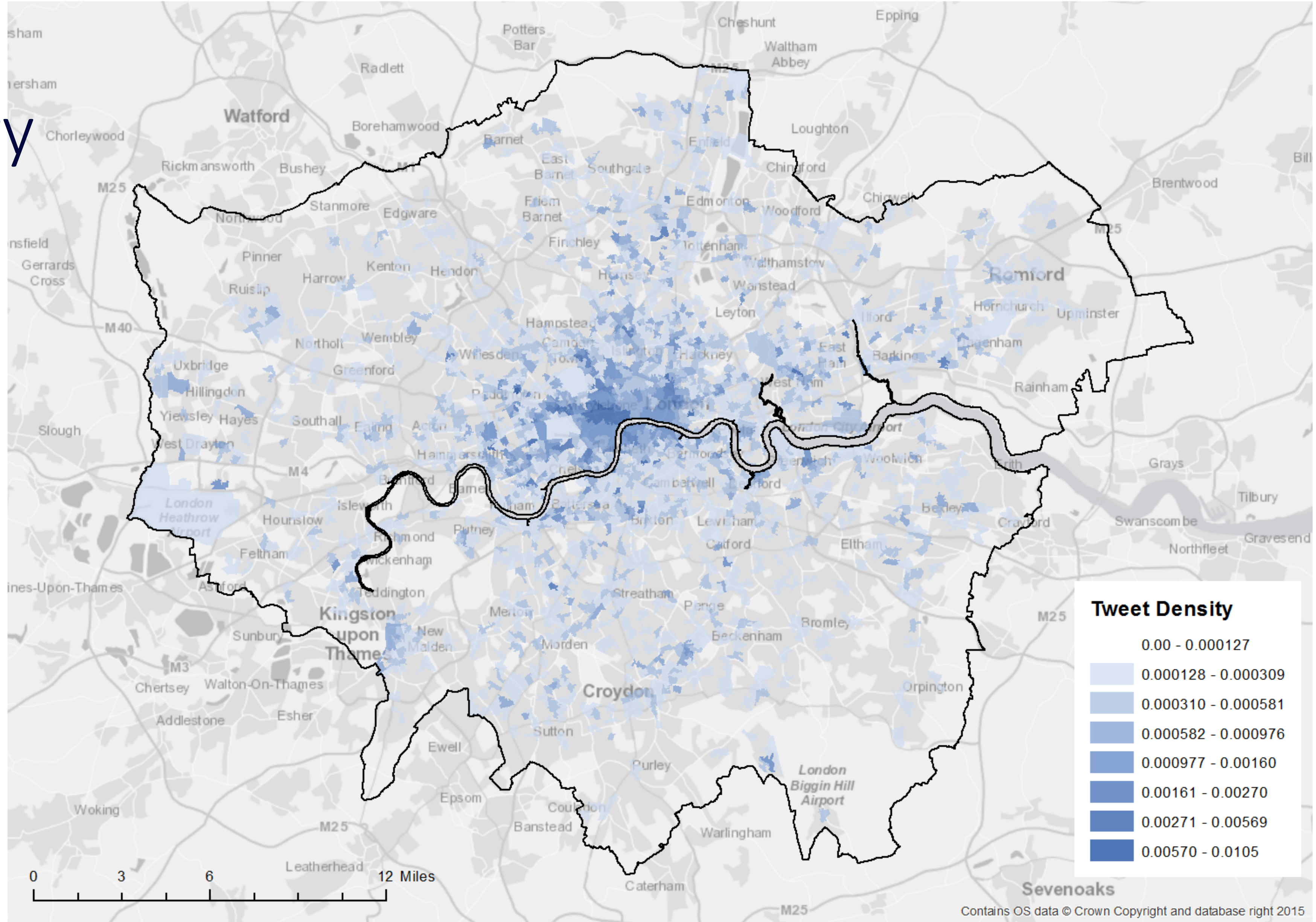
Explanatory Variable

Mobile phone activity (14:00, Tuesday)



Explanatory Variable

Social Media



Explanatory Variable: Pop247

PI: Dave Martin, University of Southampton (Martin et al., 2015, Smith et al., 2014)

Model spatio-temporal population distributions

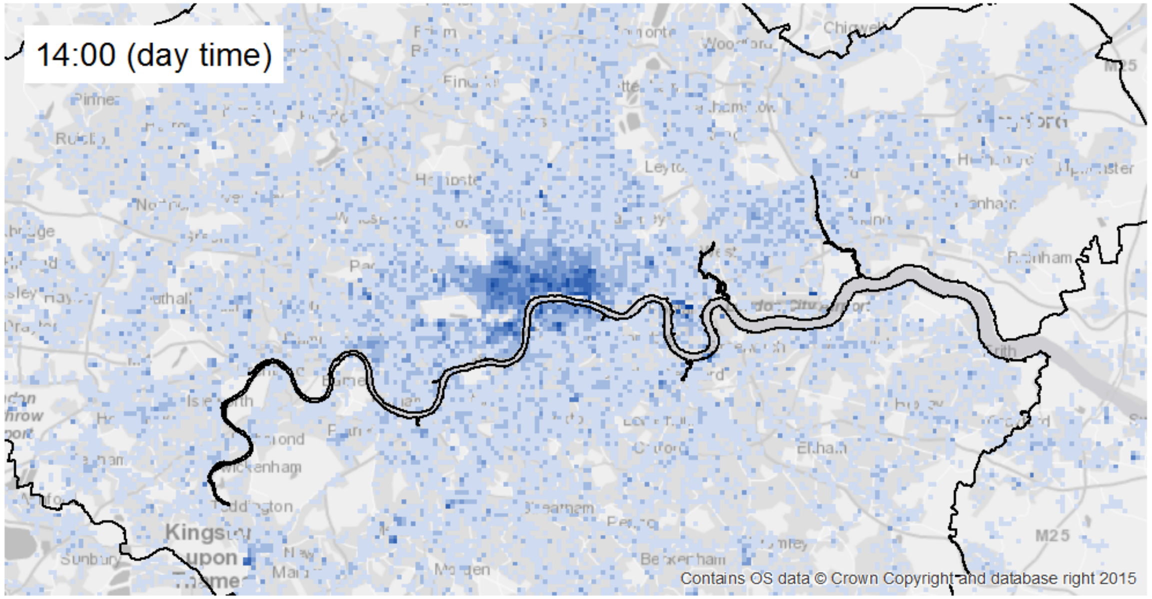
Redistribute populations based on the temporal profiles of attractive destinations (schools, work places, etc.).

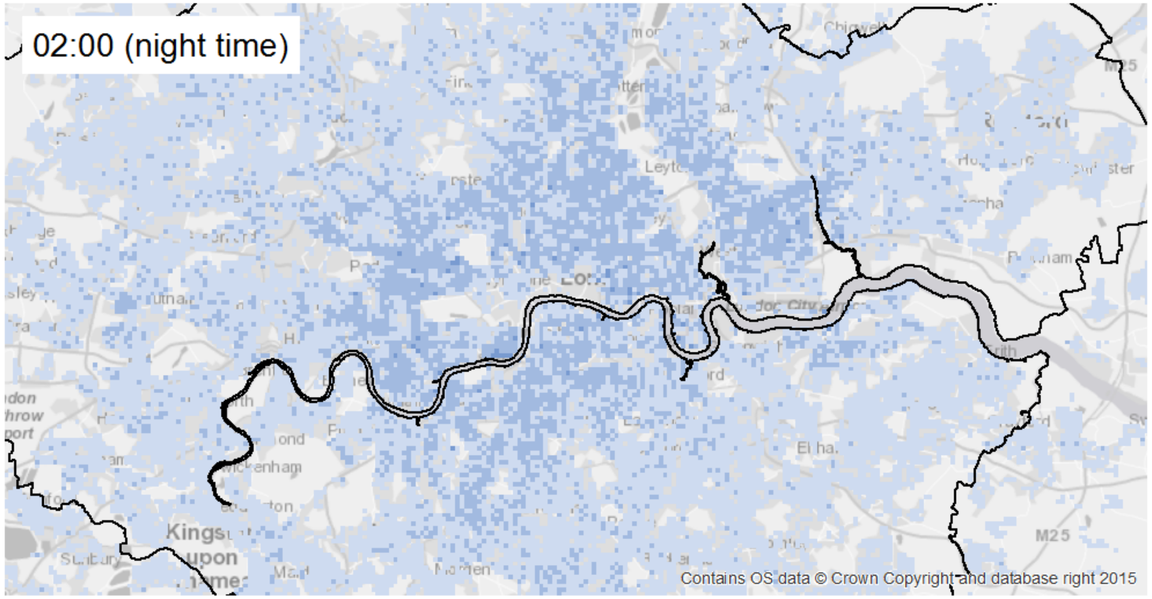
Following example: home, work, education, healthcare and some large visitor attractions

Explanatory Variable

Pop247

(Martin et al., 2015, Smith et al., 2014)





Method

Geographical Analysis

- Consolidate all data (crime, residential, workday, mobile phones, social media, pop247) to shared geographies (LSOA and OA).

Correlations

- Look for relationship between crime and the explanatory variables
- Non-parametric inputs: Spearman's ρ

Cluster analysis

- Identify statistically significant clusters of crime (Getis-Ord GI*) using best and worst population at risk

Exploratory work

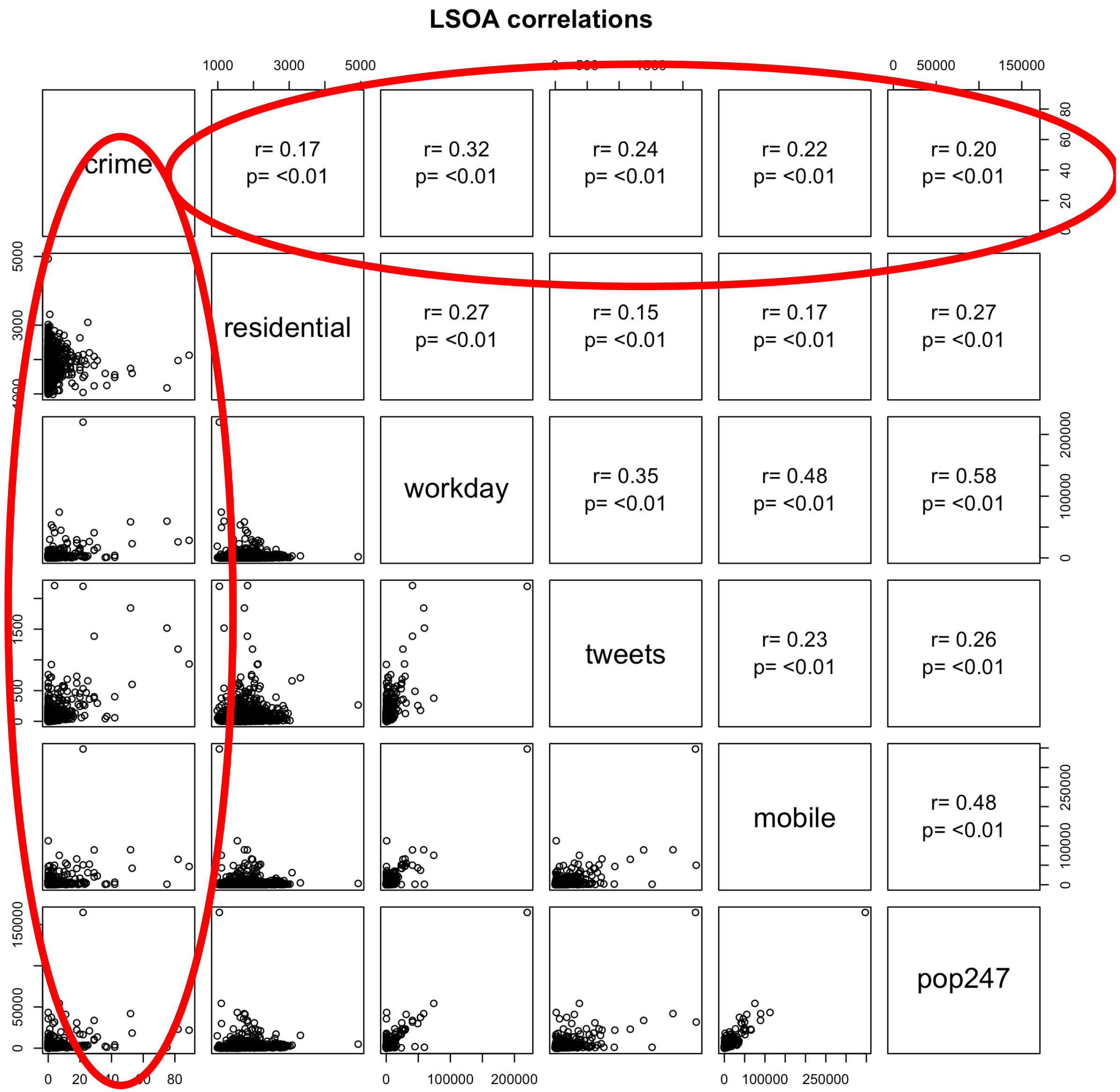
- Analyse the difference in ambient vs. residential hotspots

Correlation Analysis (LSOA)

Census *workday* population shows the strongest correlation with crime

Residential population is the poorest

Data	Correlation
Workday	0.32
Tweets	0.24
Mobile Phones	0.22
Pop247	0.20
Residential	0.17



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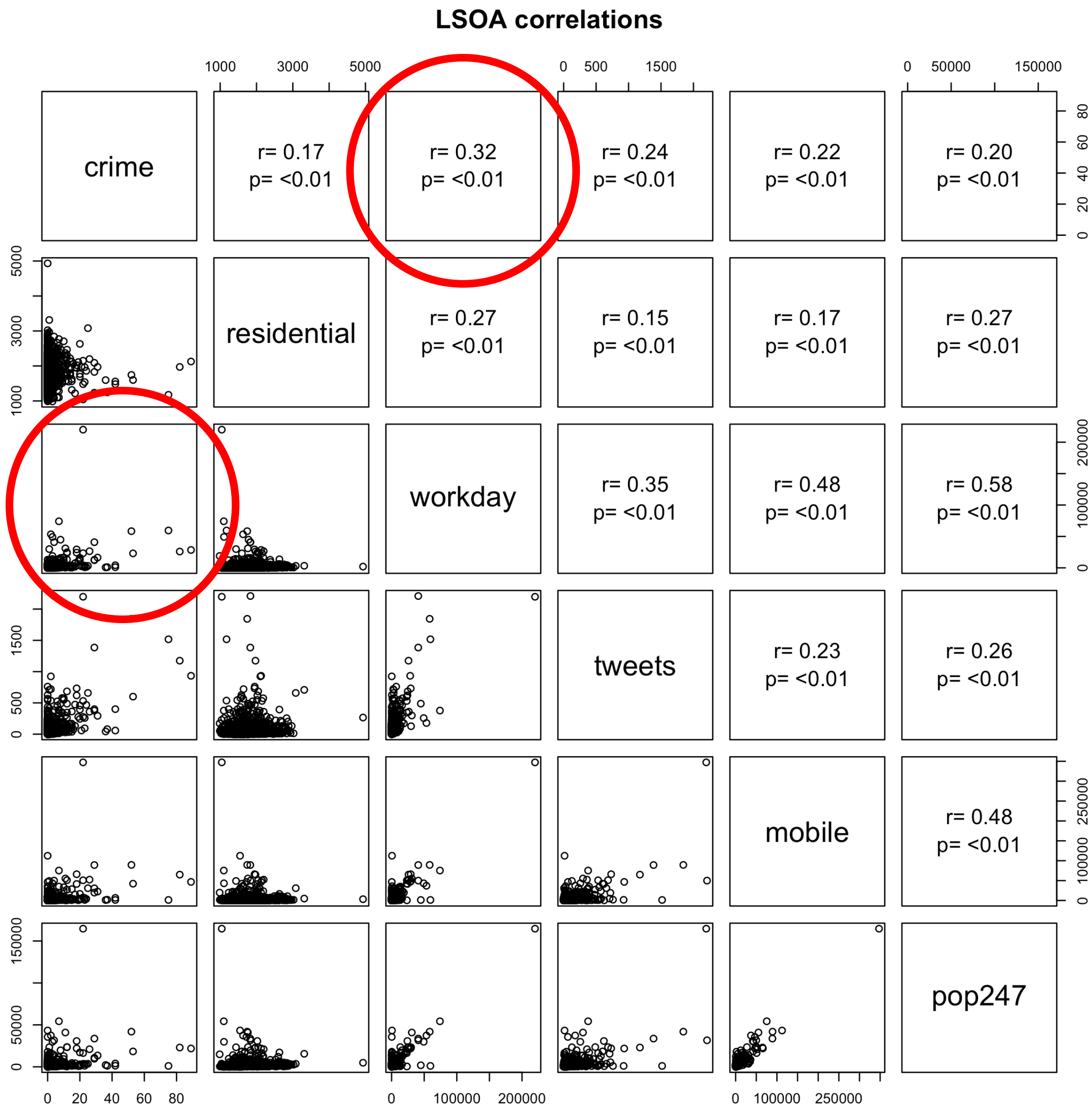


Clustering under different denominators

Two rates:

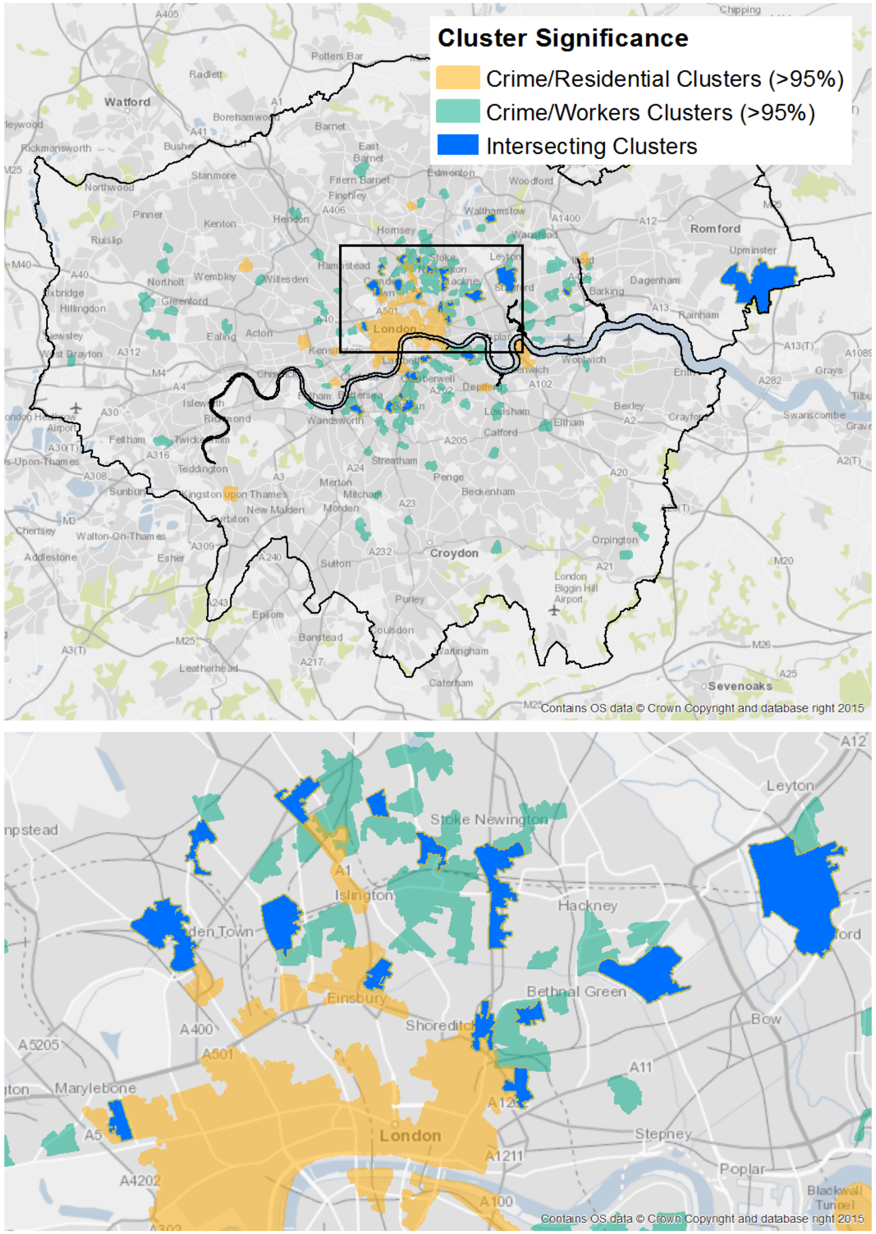
- Crime per *residential* population
- Crime per *workday* population

Getis-Ord GI* - significant crime clusters

City centre hotspot disappears under *ambient* population

Some similarities in North London

New clusters further out



Clustering under different denominators

New West London hotspots

High crime, low ambient population

Warrant further investigation

- Environmental factors
  - Few **generators** (tube stations, music venues, pubs, schools, etc.) but lots of **attractors**?
- Risk Terrain Model
  - Are there more important drivers?
- Socio-economic characteristics

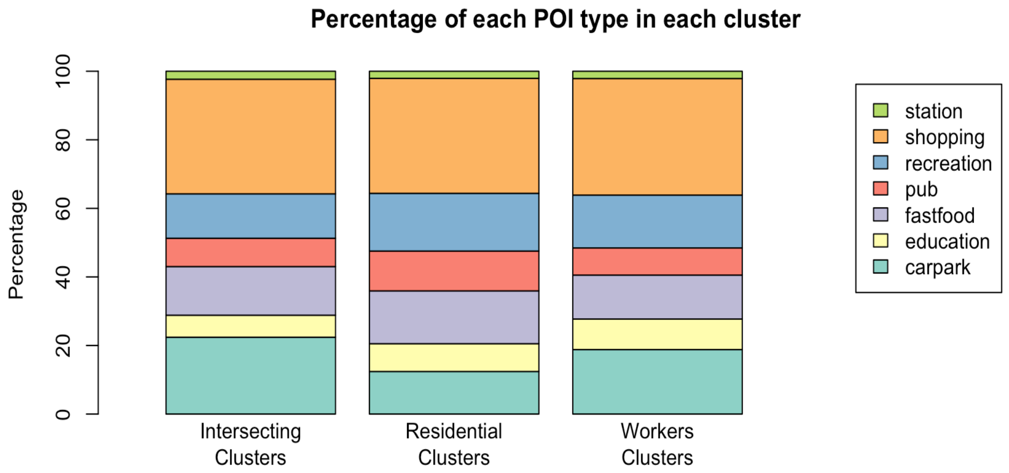
Crime Generators

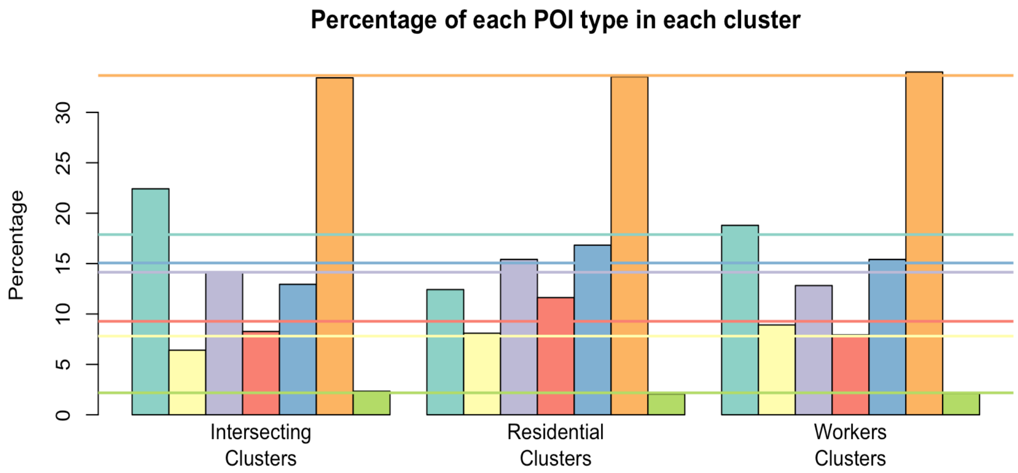
Do the different types of clusters have different amenities in them?

- E.g. ambient clusters could be places with lots of **crime attractors**

Count number of Open Street Map buildings in each cluster

- Only small differences
- Ambient clusters have fewer restaurants, recreation buildings, and pubs. (Many more car parks / garages).
- **Some evidence for fewer generators (?)**





Wider Implications

Population at risk matters!

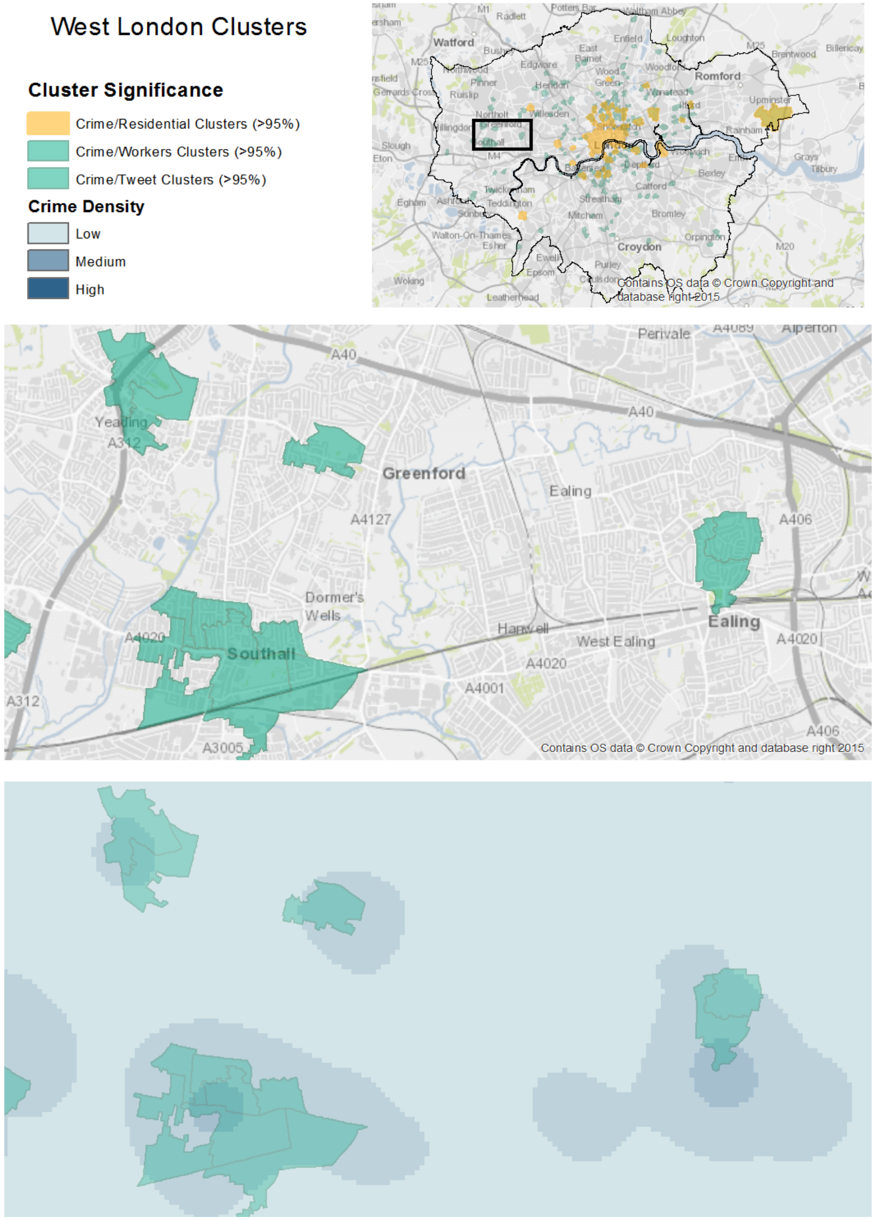
Residential population suggests a city centre hotspot

As expected (Malleson and Andresen, 2015ab)

New hotspots begin to appear in areas that have a ***relatively* low crime volume**

But also **low ambient populations**

This method might help Police (etc.) to decide which areas to focus on



Caveats / Limitations

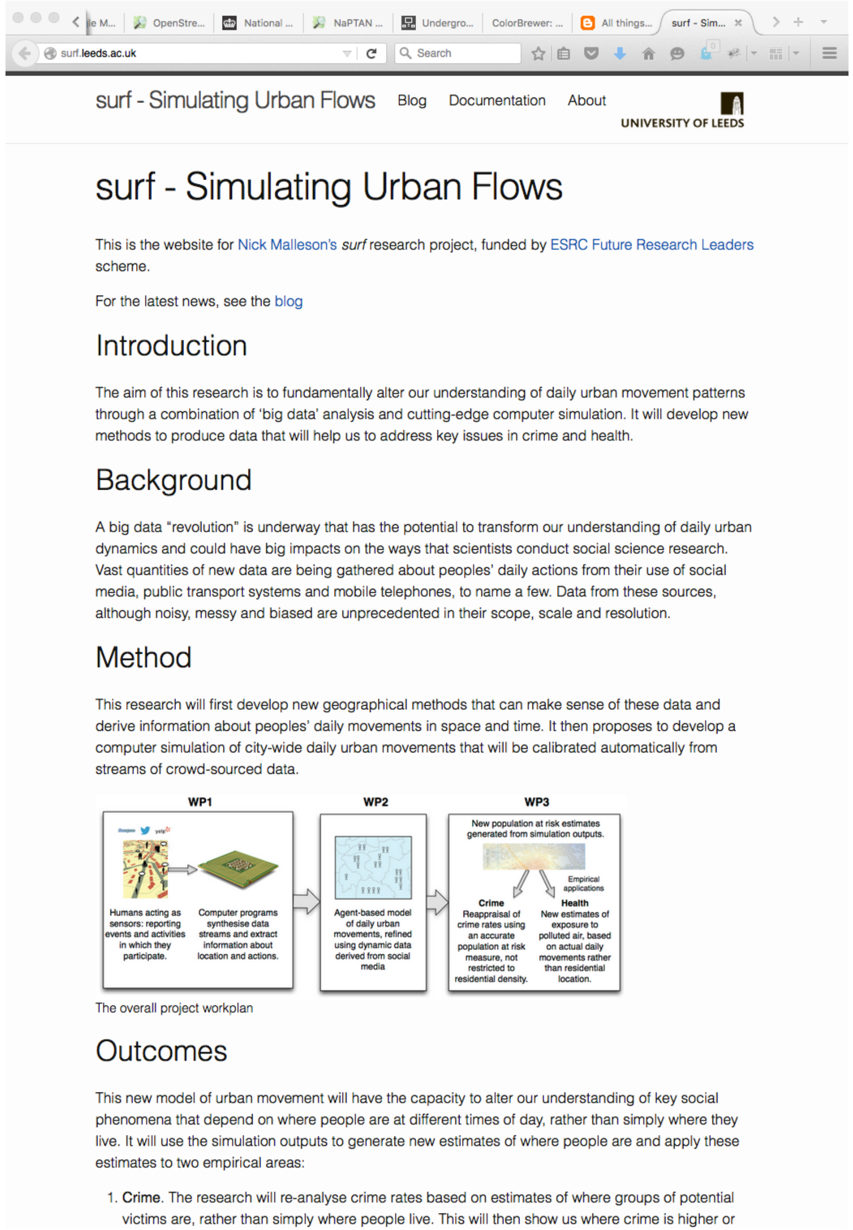
Temporal ambiguities

- Population at risk has high temporal accuracy
- Don’t know the time/day of crimes
- Better to subset evening / daytime crimes and weekday / weekend times

Need more accurate crime data?

Need a better population at risk measure?

- surf - Simulating Urban Flows
- http://surf.leeds.ac.uk/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This is the website for Nick Malleson's *surf* research project, funded by ESRC Future Research Leaders scheme.

For the latest news, see the blog

Introduction

The aim of this research is to fundamentally alter our understanding of daily urban movement patterns through a combination of 'big data' analysis and cutting-edge computer simulation. It will develop new methods to produce data that will help us to address key issues in crime and health.

Background

A big data "revolution" is underway that has the potential to transform our understanding of daily urban dynamics and could have big impacts on the ways that scientists conduct social science research. Vast quantities of new data are being gathered about peoples' daily actions from their use of social media, public transport systems and mobile telephones, to name a few. Data from these sources, although noisy, messy and biased are unprecedented in their scope, scale and resolution.

Method

This research will first develop new geographical methods that can make sense of these data and derive information about peoples' daily movements in space and time. It then proposes to develop a computer simulation of city-wide daily urban movements that will be calibrated automatically from streams of crowd-sourced data.

The overall project workplan

Outcomes

This new model of urban movement will have the capacity to alter our understanding of key social phenomena that depend on where people are at different times of day, rather than simply where they live. It will use the simulation outputs to generate new estimates of where people are and apply these estimates to two empirical areas:

1. **Crime**. The research will re-analyse crime rates based on estimates of where groups of potential victims are, rather than simply where people live. This will then show us where crime is higher or

Conclusion

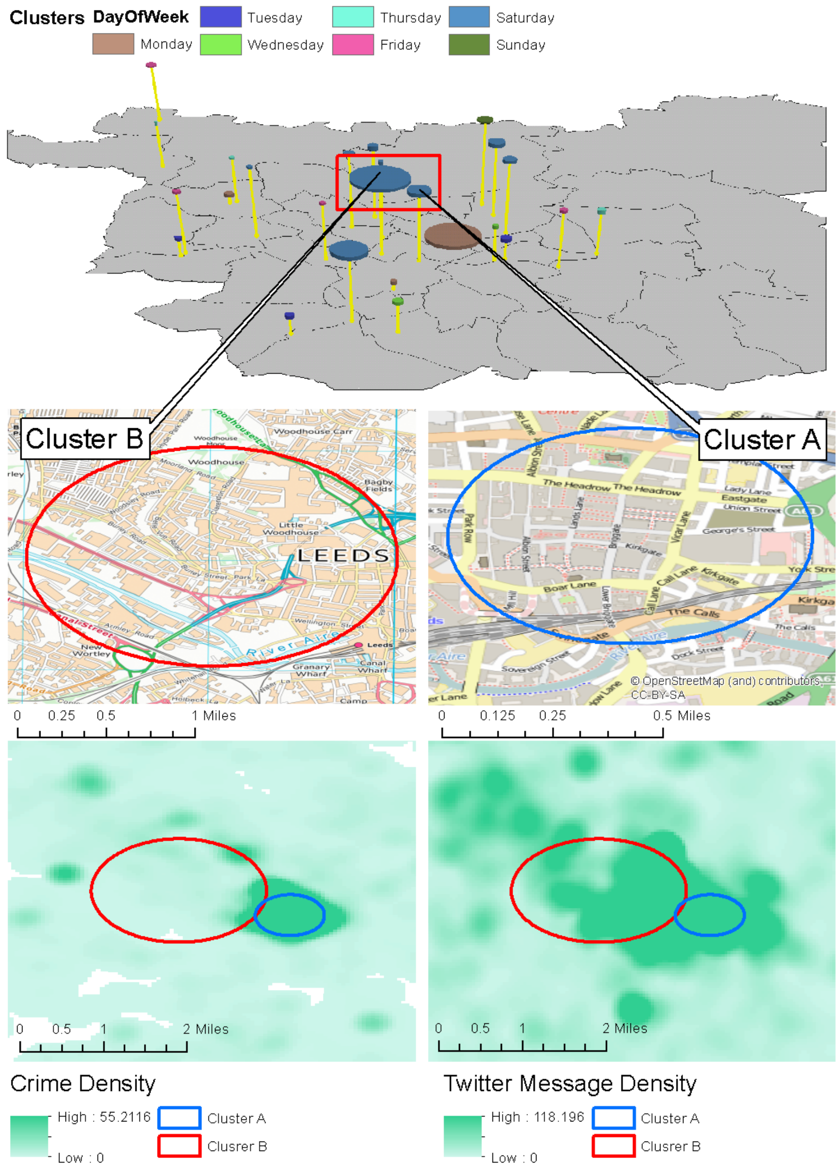
Looked for the best population at risk for analysis of street crime

Most appropriate seems to be Census *workday* population

- This is good news – it is publicly available, robust, detailed

Next steps:

- Temporal analysis
- Validate with the Police (e.g. through the N8 Policing Research Partnership)



N8 POLICING RESEARCH PARTNERSHIP

References

.. see the paper …

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