## School of Geography FACULTY OF ENVIRONMENT



## GeoCrimeData

Understanding Crime Context with Novel Geo-Spatial Data

**Nick Malleson\*** 

Mark Birkin\*

Alex Hirschfield\* \*University of Leeds

Andrew Newton<sup>+</sup> <sup>+</sup>University of Huddersfield





### Outline

The GeoCrimeData Project

Police / Crime Analyst Requirements

Geospatial Data Sources and Methods

**New Data** 

**Preliminary Results** 

- Violent crime and twitter
- Burglary, house type and street accessibility

Conclusions



#### **Motivation**

### Wide range of new, publicly available, data sources

- Road network data
- Land-use data
- Social network data

### But these are rarely used by crime analysis

- What would analysts like to know?
- What are the barriers to using the data?

Focus (at this stage) on residential burglary

## Geo Crime Data

#### GeoCrimeData

Exploring Geospatial Data for Crime Analysis



Small (~£90k, 9 month) JISC-funded collaboration between the School of Geography in Leeds and the Applied Criminology Centre in Huddersfield

Aim: analyse existing spatial data, identify crime-relevant features and rerelease for crime analysts.

#### For example:

- House visibility or type influences burglary risk
- Road traffic volume influences street robbery

#### Methodology:

- Identify crime analysts' needs
- Explore available spatial data
- Develop and use algorithms
- Re-release new data

## User Needs Analysis



**Exploring Geospatial Data** for Crime Analysis



### User survey

- Online survey to explore user needs and experiences with geospatial data
- 40% response rate (N = 33)
- Roughly 60/40 UK USA split

 Police (42%), academics (30%), Community Safety Partnerships (15%), Consultants (4%), Others (9%)

## Follow-up workshop

- 50% split between academics and practitioners
- Detailed discussion of user requirements



# Workshop Findings



Exploring Geospatial Data for Crime Analysis



#### Important environmental factors re. roads

- Road type (through road or cul-de-sac)
- Cul-de-sac type: linear, sinuous, true, leaky.
- Cul-de-sac with linked pathway?
- Volume of traffic outside road
- Volume of traffic at nearest junction
- Speed of traffic on road outside
- Access restrictions on road

#### Important factors re. buildings

- Visible from footpath?
- Footpath at rear?
- House Type
- Corner plot?
- Visible from: Road Junction, School, Park, Community Centre, Commercial Establishment
- Overlooked by other properties?

## GeoCrimeData

#### **Data Sources**

Exploring Geospatial Data for Crime Analysis



As with the US, in the UK/EU there is a drive towards making (spatial) data publicly available

- OS Open Data the national mapping agency (Ordnance Survey) have released a large number of products
- data.gov.uk government organisations releasing physical/social data that was previously held privately
- INSPIRE EU directive making it mandatory for government organisations to formally describe their spatial data

Data are potentially extremely useful for exploring the social or environmental context surrounding crime.

But: often large barriers to their use by crime analysts:

- Insufficient meta-data
- Unusual GIS data format
- Resources (time and software) required for spatial analysis

# Data Sources: Examples



Exploring Geospatial Data for Crime Analysis



#### Land Use

- LandMap Building heights and class
- OS MasterMap Topographic Area
- Generalised Land Use Database

#### Road Network

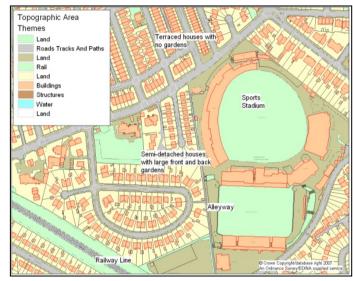
- OpenStreetMap (limited buildings)
- OS Strategi
- OS MasterMap Integrated Transport Network

#### Public transport

- National Public Transport Data Repository (NPTDR)
- National Public Transport Access Nodes (NaPTAN)

#### Physical disorder

Derelict buildings





## Geospatial Methods: Buildings



### House Type

Detached, semi detached, terraced, corner terrace, (flat)

## House Isolation / Visibility

Number of surrounding houses

#### **Road Distance**

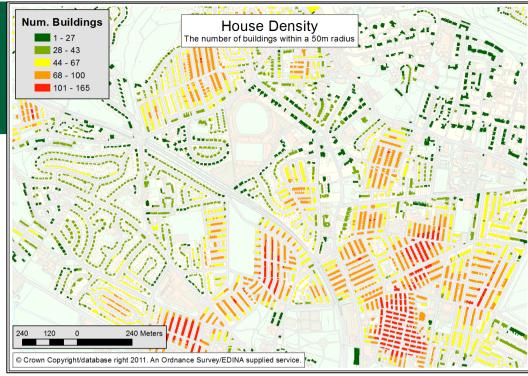
Distance to nearest road or footpath

## Vulnerability

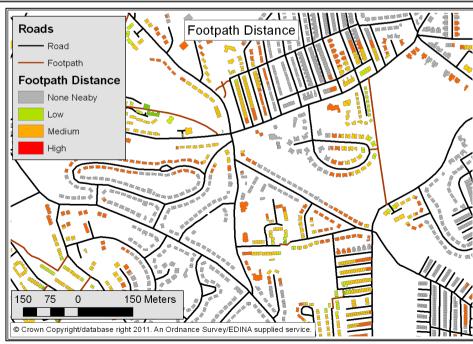
Aim to create an overall measure of vulnerability

## **New Building Data**

Data: MasterMap Topographic Area (commercial license)







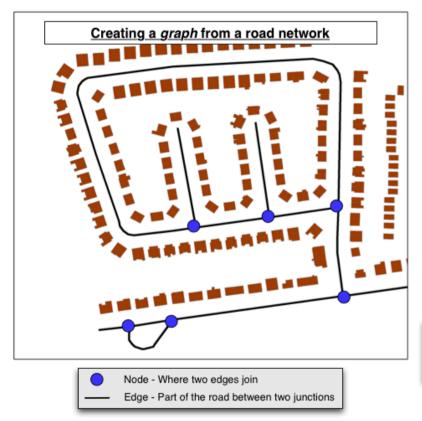
## Geospatial Methods: Roads



Exploring Geospatial Data for Crime Analysis

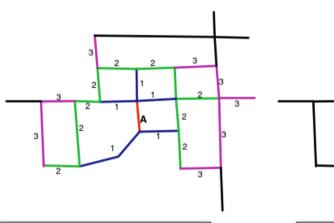


### Space Syntax Integration



#### Mean Path Depth Example

The diagrams illustrates how to calculate the *mean path depth* of the road highlighted red using a radius of 3. Edges coloured blue, green and purple can be reached from the starting edge within one, two and three steps respectively. All other edges are ignored.





mpd = (1\*5 + 2\*9 + 3\*8) / 22 = 2.14

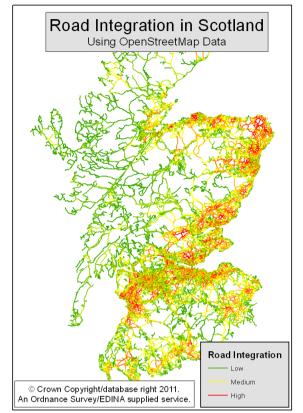


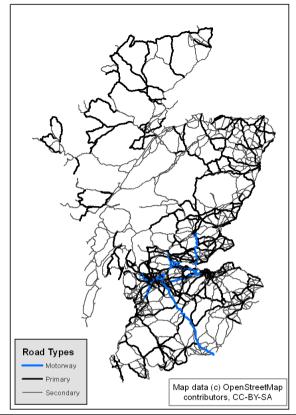
mpd = (1\*2 + 2\*3 + 3\*5) / 10= 2.3

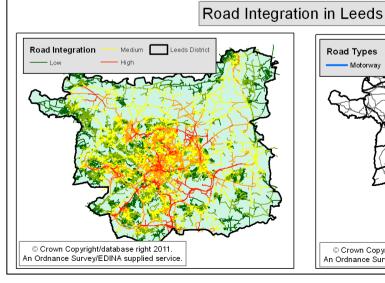
### **New Road Data**

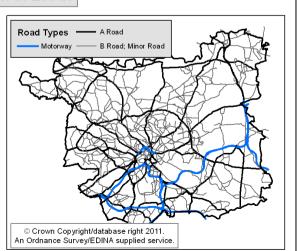
OperStreetMap (free) and MasterMap ITN (commercial)

Calculate integration and mean-path-depth for GB (using OSM) and Leeds (using ITN)









# Preliminary results: violent crime



Exploring Geospatial Data for Crime Analysis

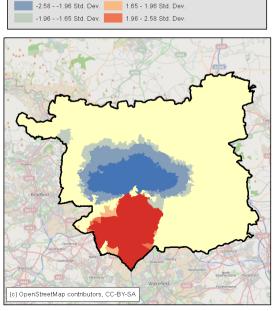


Explore violent crime using various (novel) populations at risk

- Street accessibility (traffic volume)
- Number of tweets (fluid population)

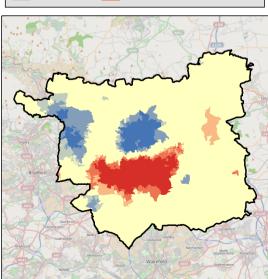
-1.65 - 1.65 Std. Dev. > 2.58 Std. Dev

Rates of Violent Crime
Using Different Populations at Risk



GI\* - Crime Rate Per Tweets

< -2.58 Std. Dev.



-1.65 - 1.65 Std. Dev.

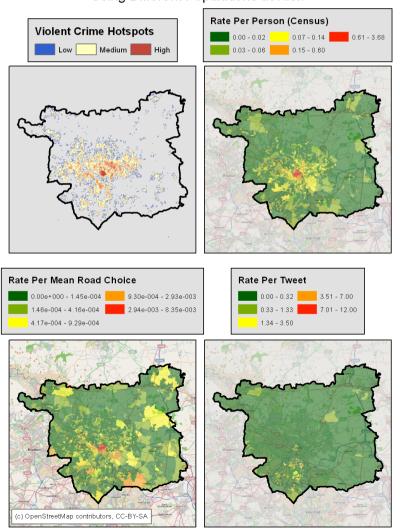
GI\* - Crime Rate Per Mean Road Choice

< -2.58 Std. Dev.

-2 58 - -1 96 Std. Dev.

-1.96 - -1.65 Std. Dev.

## Rates of Violent Crime Using Different Populations at Risk



# Preliminary results: burglary (I)



Exploring Geospatial Data for Crime Analysis



Explore relationship between house type and residential burglary

- Are certain house types more at risk?
- And do community demographics have an effect?

Burglary rates by Housing Type by OAC Super Group

OAC	Burglary rate					
Super Group						
	Per 1,000	Per 1,000	Per 1,000	Per 1,000	Per 1,000	
	Detached	Semis	Terraced No.	Corner	Properties*	
Blue-Collar	32.2	25.1	14.4	hasian?	22.5	
Communities				hesion?	Low	
2. City Living	93.4	64.5	78.5	83.6	76.4	0 ما ما م
<ol><li>Countryside</li></ol>	21.6	13.2	3.2	14.4	16.4 guardi	anship?
4. Prospering	25.3	23.9	9.6	24.4	24.0	
Suburbs	Aff	uence within				
<ol><li>Constrained by</li></ol>	7 1111	advantage?	27.1	29.6	33.6	
Circumstances	<b>U</b> IS	advantage:				
6. Typical Traits	27.6	25.9	16.6	24.6	23.2	
7. Multicultural	79.7	45.1	33.7	60.5	41.7	
Leeds	33.6	28.7	27.5	33.2	29.7	

<sup>\*</sup> This figure excludes flats

# Preliminary results: burglary (II)



Exploring Geospatial Data for Crime Analysis



Explore relationship between house type, residential burglary and street accessibility

Does street accessibility influence house type burglary risk?

Burglary rates by Housing Type and Accessibility of Streets (mean accessibility per OA)

Street	Burglary rate				
Accessibility					
Decile					
	Per 1,000	Per 1,000	Per 1,000	Per 1,000	Per 1,000
	Detached	Semis	Terraced	Corner	Properties*
Decile 1*	21.4	17.6	13.5	20.7	18.2
Decile 2	24.4	20.2	15.0	16.0	19.7
Decile 3	25.6	20.0	25.1	23.5	22.5
Decile 4	27.8	31.2	25.9	28.4	29.1
Decile 5	31.3	28.4	35.2	36.5	31.5
Decile 6	40.2	32.4	33.8	46.5	35.3
Decile 7	38.7	30.6	33.9	41.4	33.6
Decile 8	37.5	34.6	35.2	38.8	35.5
Decile 9	53.7	32.8	22.4	41.9	33.2
Decile 10**	65.6	38.0	26.2	44.2	40.3
Leeds	33.6	28.7	27.5	33.2	29.7

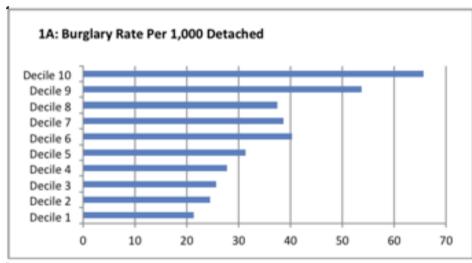
Notes: \*10% of OAs with least accessible streets \*\*10% of OAs with most accessible streets

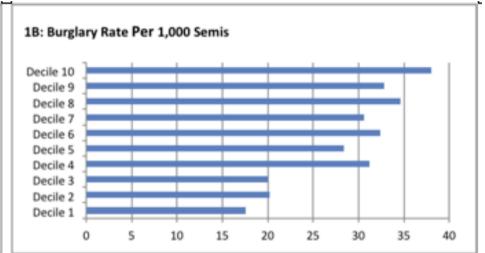
# Preliminary results: burglary (II)

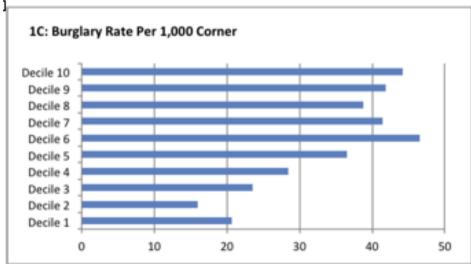
## **GeoCrimeData**

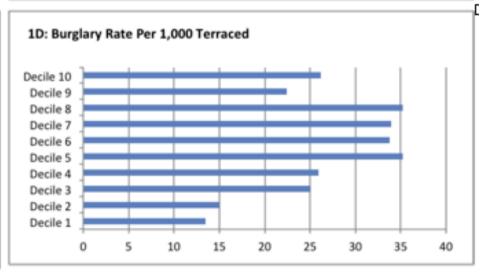
Exploring Geospatial Data for Crime Analysis











# Future Work: Improvements



#### More accurate road integration calculations

• Jiang, B., and C. Liu (2009). Street-Based Topological Representations and Analyses for Predicting Traffic Flow in GIS. *International Journal of Geographic Information Science* 23 (9).

#### Further building geospatial analysis to estimate further useful attributes

- Footpath at rear (and leading to shops)
- Visible from: Road Junction, School, Park, Community Centre, Commercial Establishment

#### More detailed analysis of road networks, e.g. permeability, sinuosity

• Johnson, S., and K. Bowers (2009). Permeability and Burglary Risk: Are Cul-De-Sacs Safer? *Journal of Quantitative Criminology* 26 (1): 89–111.

#### Confidence in data: release publicly

'Beta' data already available



## Conclusions

Potential offered by novel geospatial data for crime analysis

New insights that were not possible previously

Further analysis and validation required

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## Thankyou

More information:

n.malleson06@leeds.ac.uk

geocrimedata.blogspot.com

Nick Malleson\*

Mark Birkin\*

Alex Hirschfield\* \*University of Leeds

Andrew Newton<sup>+</sup> <sup>+</sup>University of Huddersfield

