What do crime and diseases have in common?

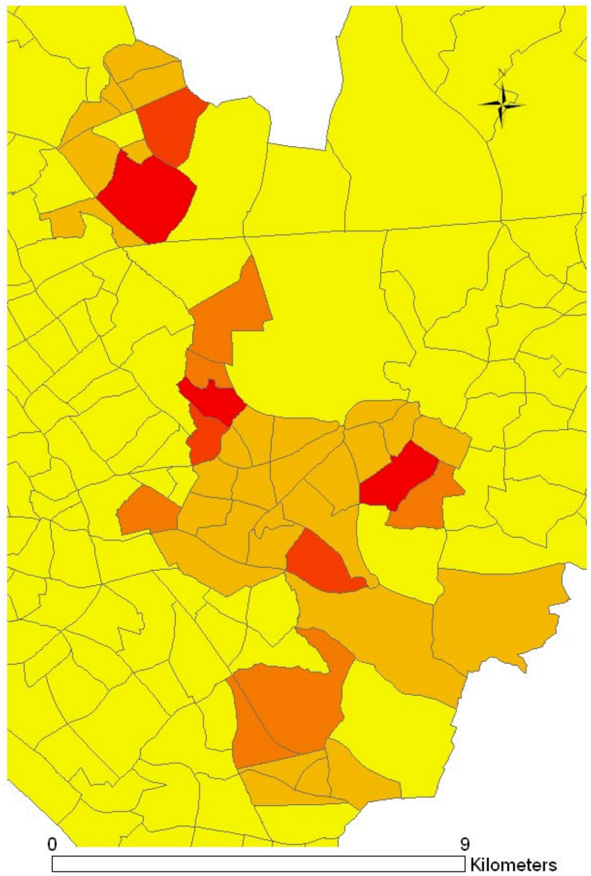
Dr Shane D Johnson

UCL Jill Dando Institute of Crime Science

Overview

- Focus on crime events not CJS or motivations of offenders
- International collaboration - suggestions welcomed
- Crime concentration at the area level
- Space-time patterns of crime risk
  - Theoretical explanations for (near) repeat victimization
  - Triangulation across methods
    - Patterns in victim data
    - Simple simulation experiment
    - Forecasting where and when crime will next occur
    - Patterns in detected offences?
    - Agent-based simulation
    - Ethnography

State of the art?

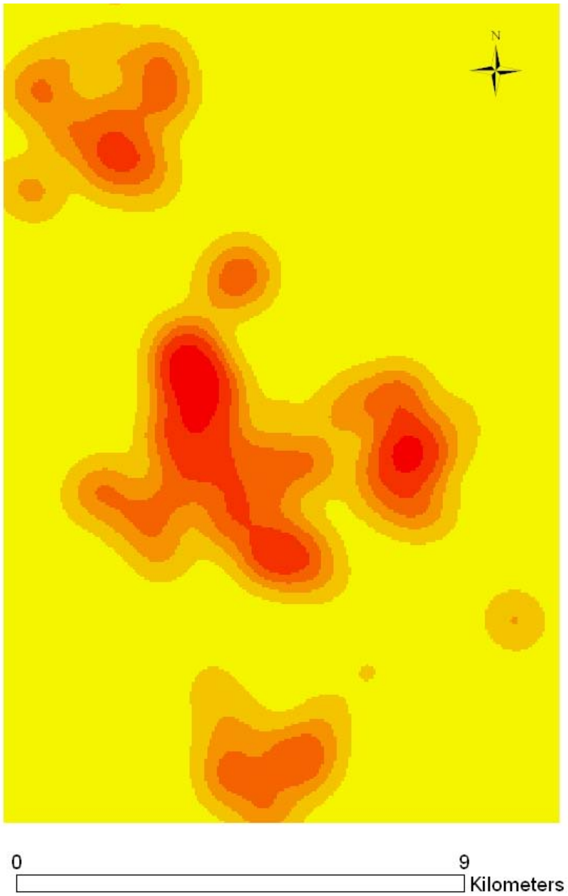


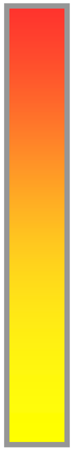
Burglary Concentration

High

Low

State of the art?





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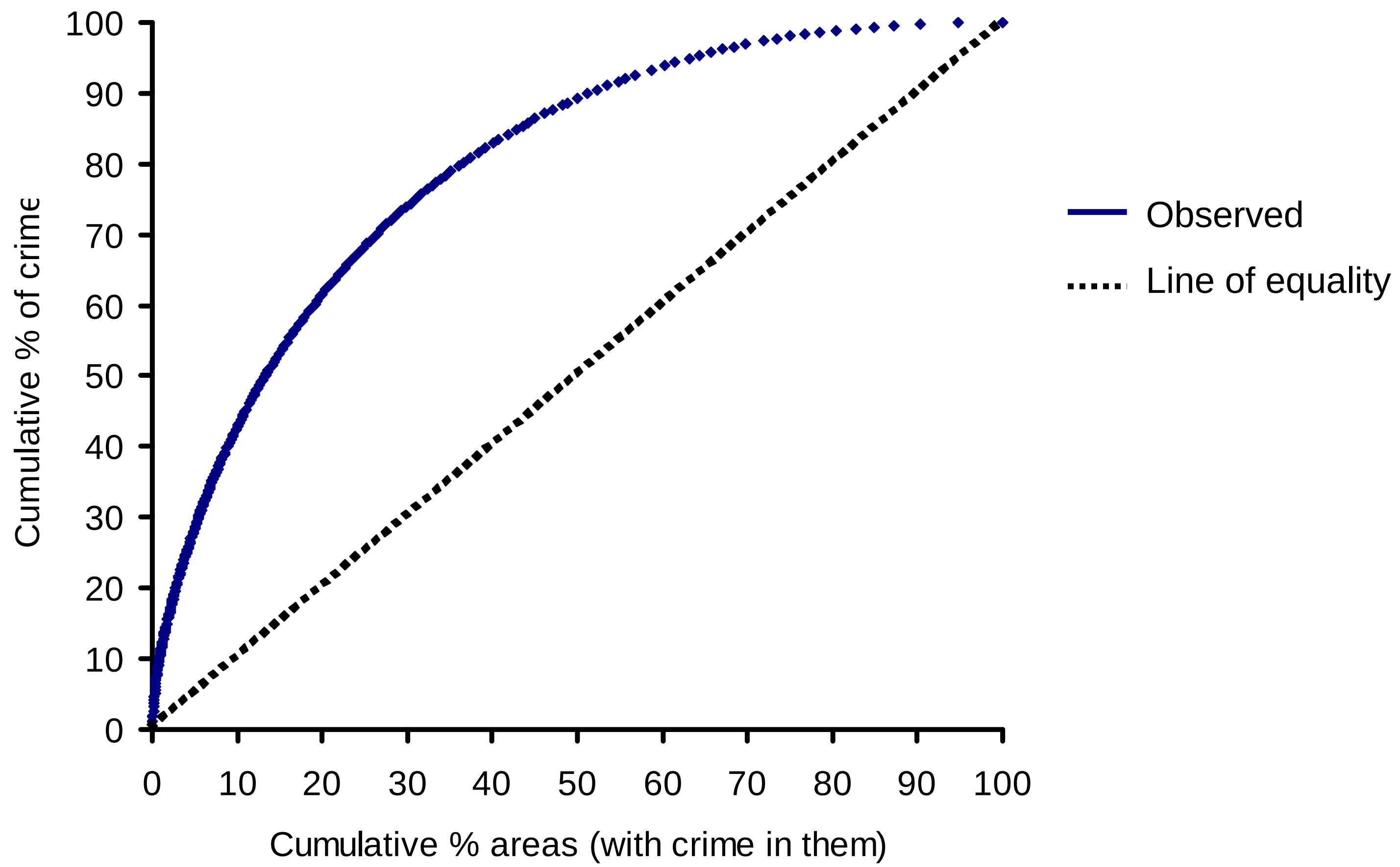
Spatial concentration (acquisitive crime)



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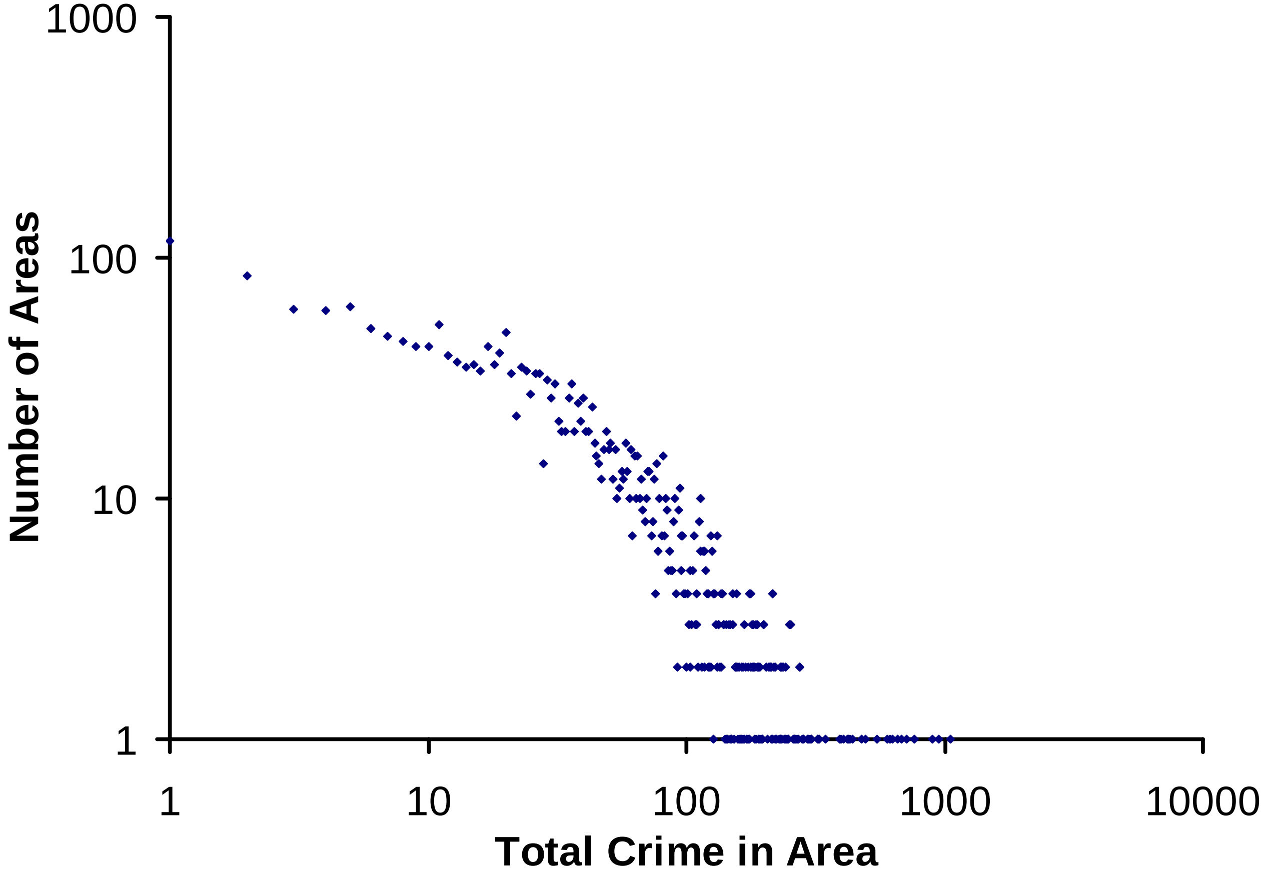
Acquisitive crime concentration (400m cells)



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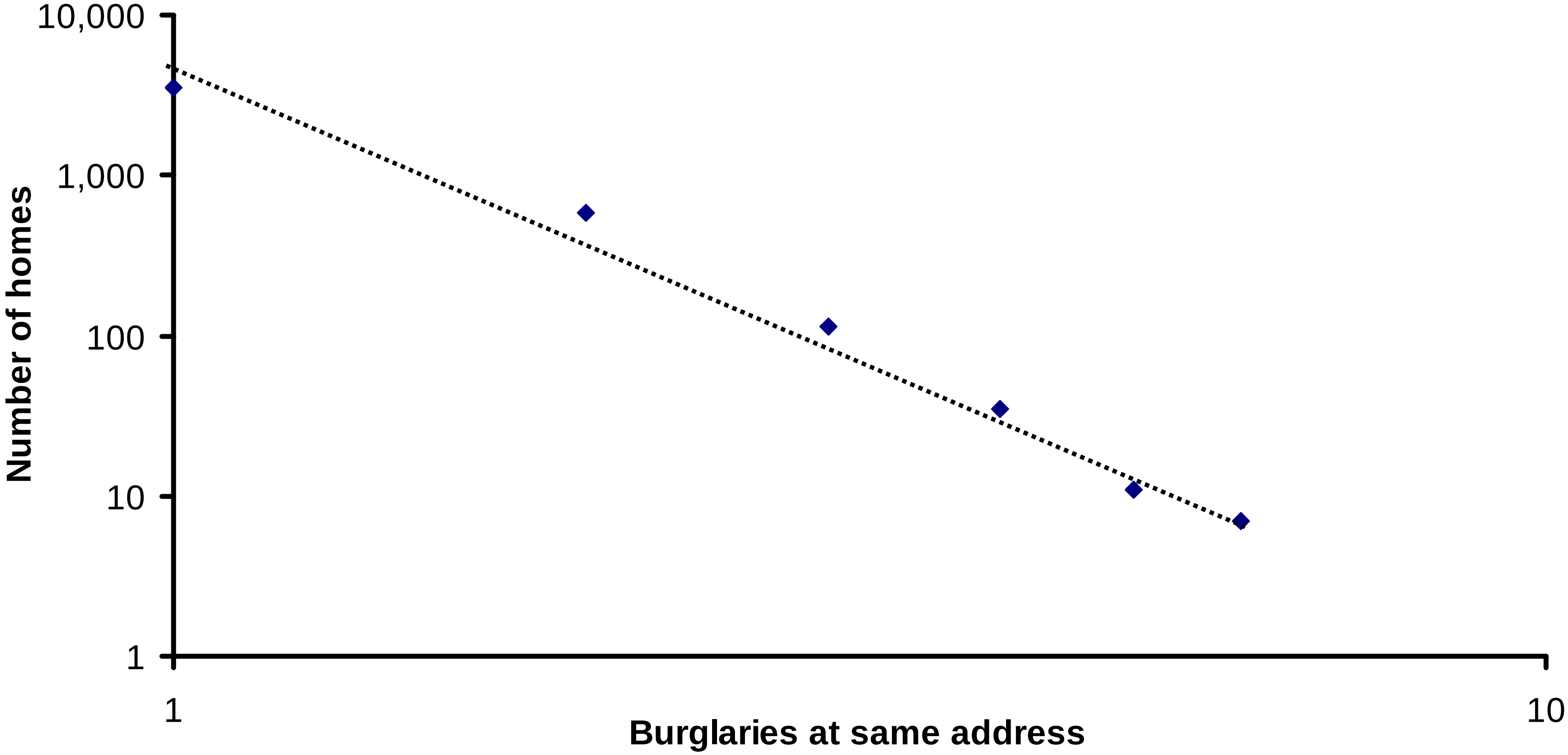
Shane D Johnson, Mathematical models for criminality in urban areas, April 2008

Repeat burglary victimization



Concentration at the household level

N	**Observed**	**Simple Poisson**
0	545,506	542,280
1	41,027	**46,523**
2	3,566	1,996
3	589	57
4	113	2
5	35	<1
6	11	<1
7	7	<1
8+	2	<1
N (RV)	**50,691 (5,341)**	**50,691 (2113)**

Repeat Victimization

- Prior victimisation is an excellent predictor of future risk (Burglary, DV, CIT, hotel theft……)
- Repeat victimization occurs swiftly (e.g. Polivi et al., 1991)
- Repeat victimization is highest in high crime areas

“That crime is concentrated on the same people and places and that this has potential for crime control is the most important criminological insight of the decade”

Skogan (1996)

Theoretical explanations for repeat victimization

Event dependency (e.g. Nagin and Paternoster, 2000)

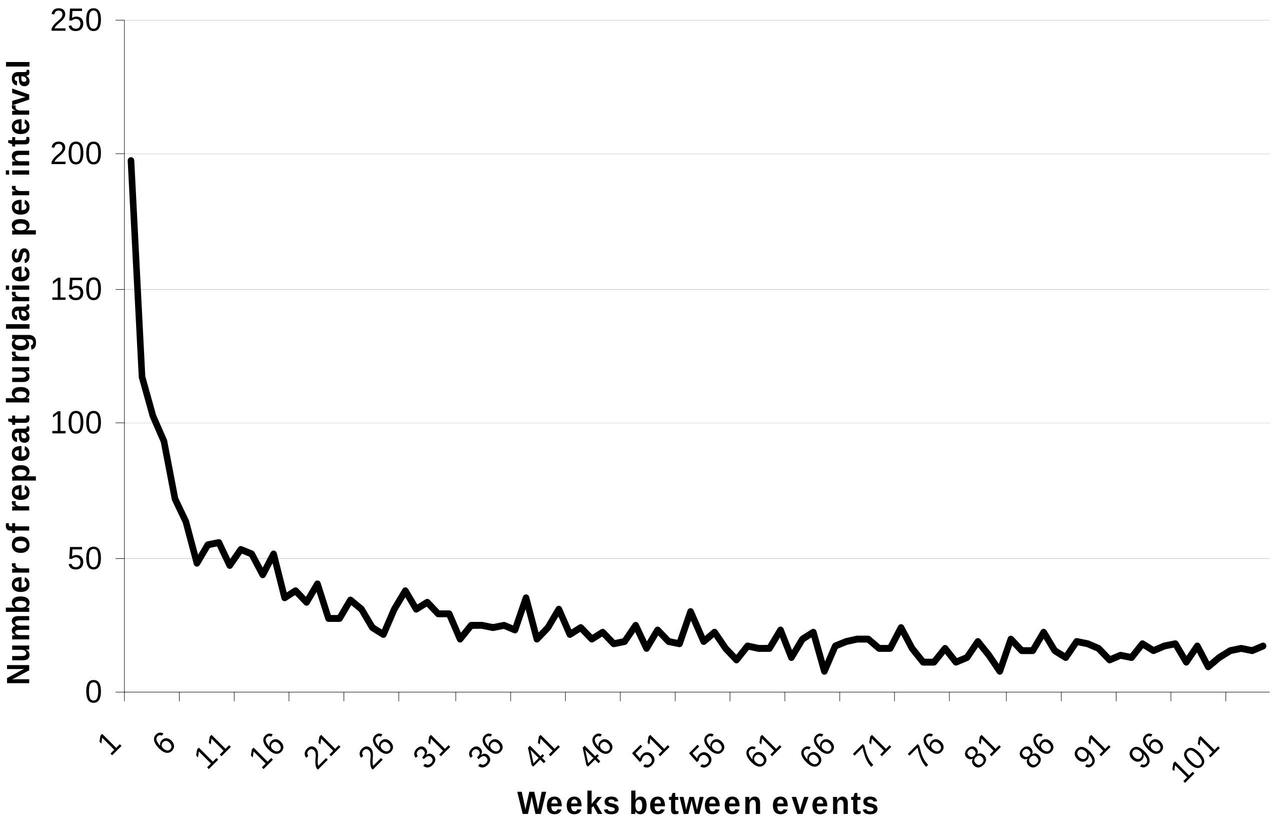
Victimization increases the probability of future victimization- the work of the same offender

"I always go back [to the same places] because, once you've been there, you know just about when you been there before, and when you can go back. And every time I hit a house, it's always the same day [of the week] I done been before cause I know there ain't nobody there"

(offender 51, Wright & Decker (1994), p. 69)

Kleemans (2001) – Of solved repeat burglaries, 63% were cleared to the same offender.

Time-course of repeat victimization: a signature?



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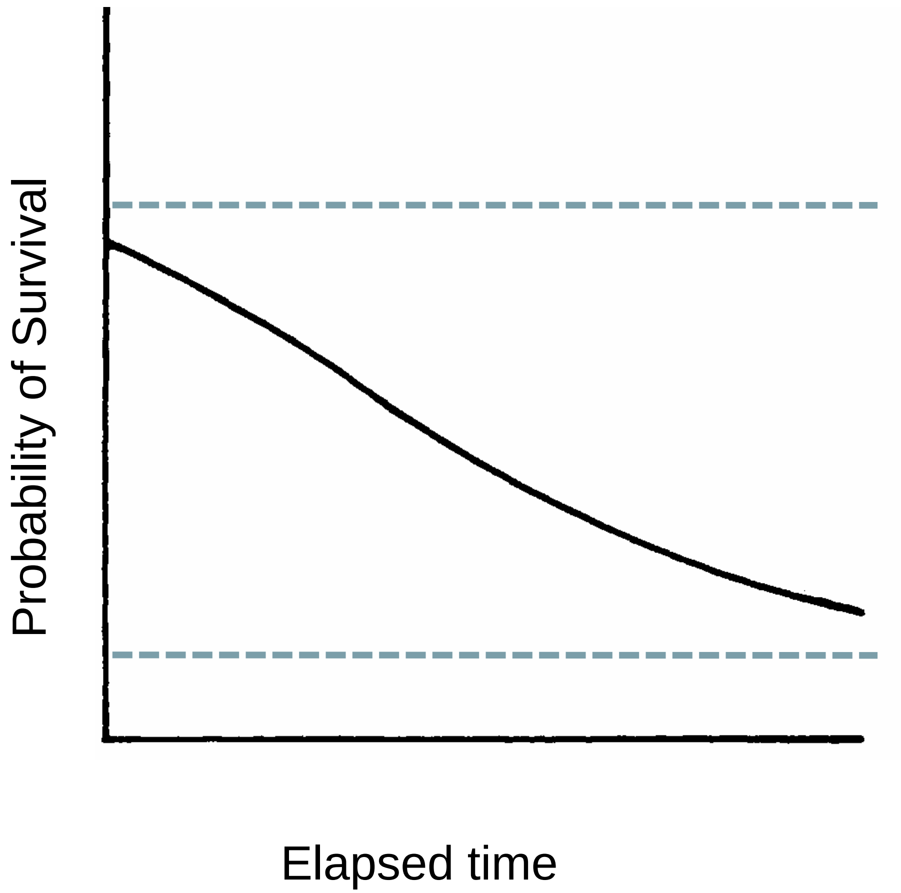
Theoretical explanations for repeat victimization

Risk heterogeneity (e.g. Nagin and Paternoster, 1991; 2000)

- Even if the risk of burglary were homogeneous some repeat victimization would be expected on a chance basis, but risk is heterogeneous
- Different offenders target the same property due to time-stable differences in target attractiveness or accessibility
  - Stability in the variation of risk drives the correlation between past and future risk
- Aggregate patterns may thus be a ruse generated by the heterogeneity or victimization risk
- Systematic differences in risks across areas and type of homes (e.g. Bowers, Johnson and Pease, 2005; Tseloni, 2005)
- Loaded dice

The time course: Heterogeneity's ruse?



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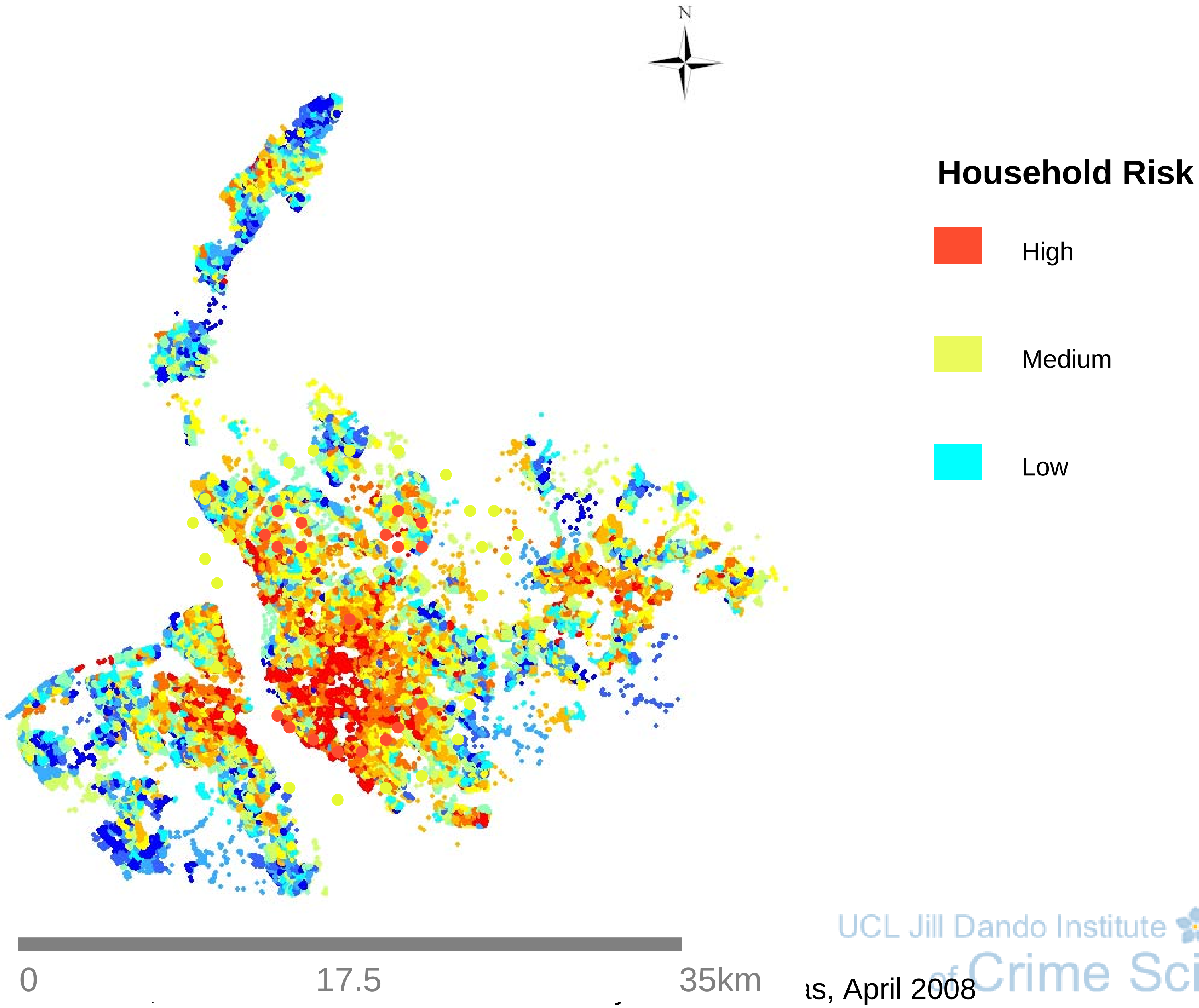
Micro-simulation study

- Bottom-up approach
- Recorded burglary data 1999-2003 (50,691 events)
  - Date, time, location (address and x and y coordinates)
- 2001 Census output area geography
  - In simple terms, the system created Output Areas with around 125 households and populations which tended towards homogeneity (http://www.statistics.gov.uk/census2001/op12.asp)
  - Housing type and various other data
- Ordnance survey address point data (590,856 homes)



Shan ıs, April 2008

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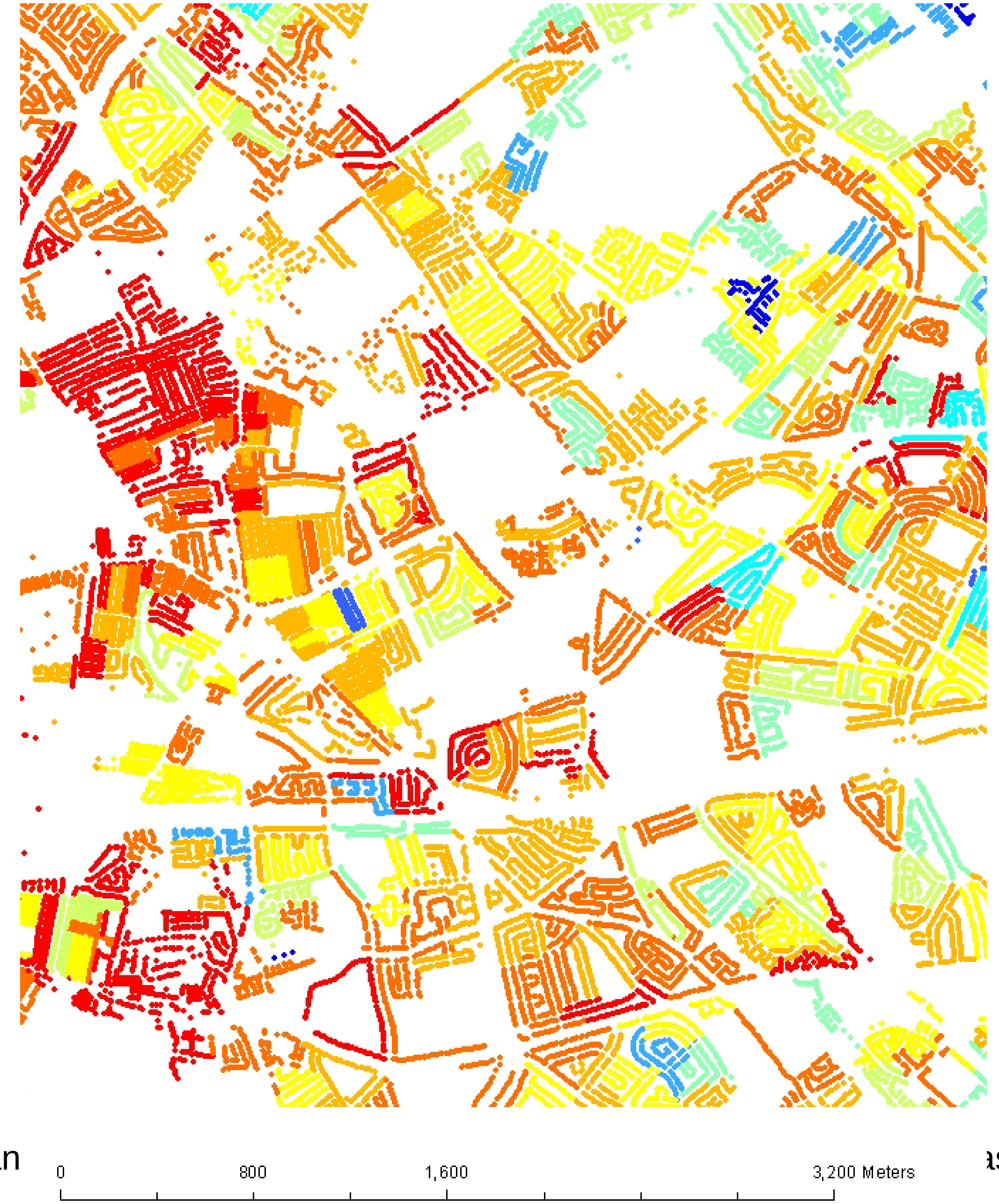

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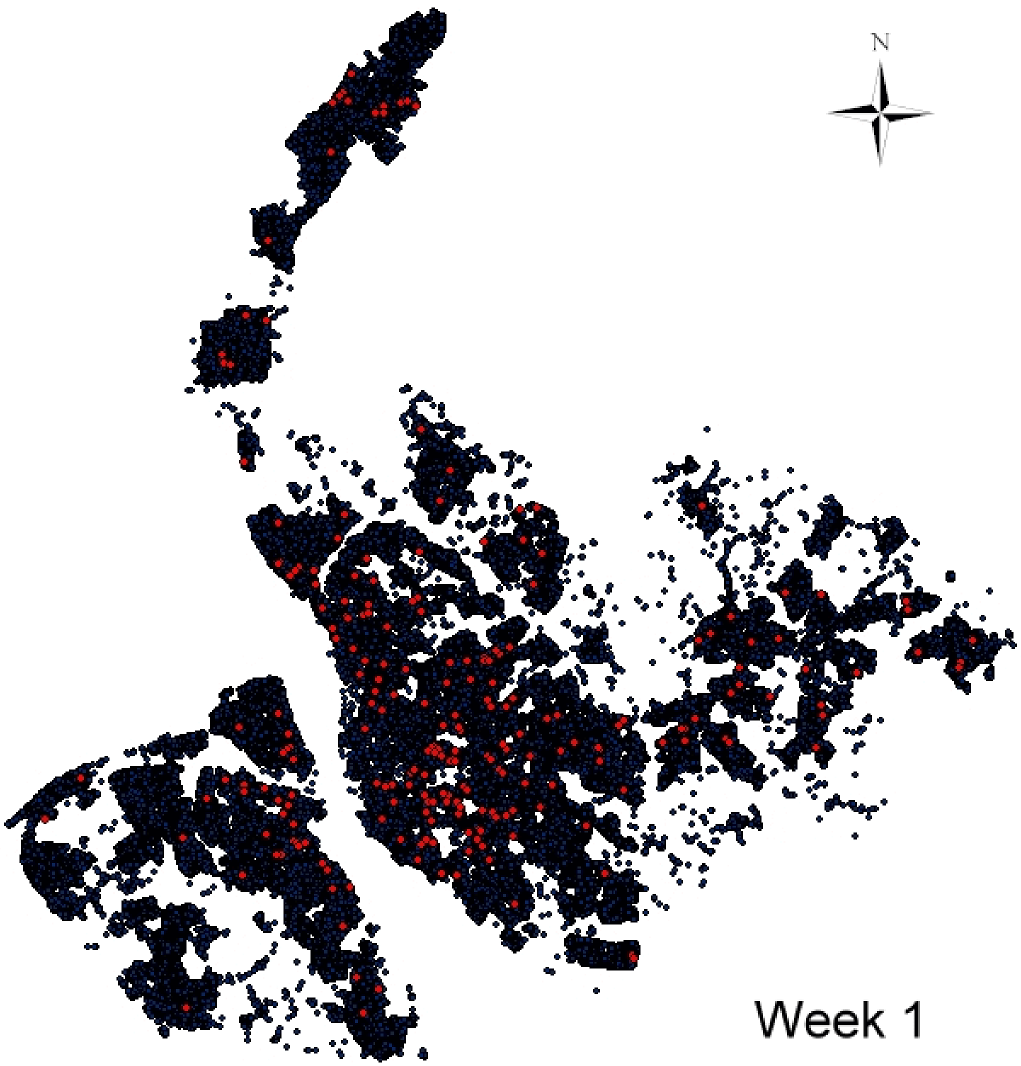
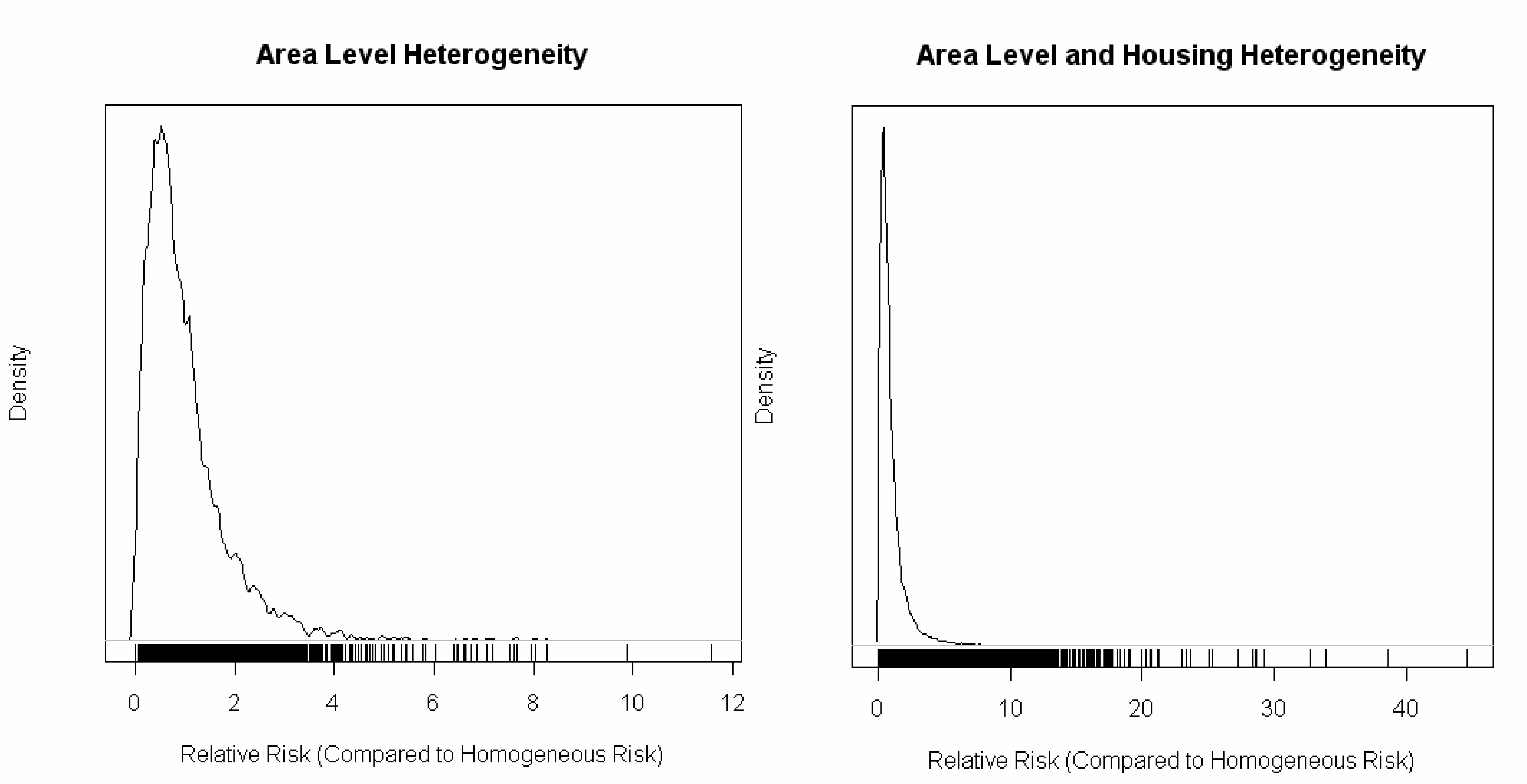
Victim selection (weekly patterns)



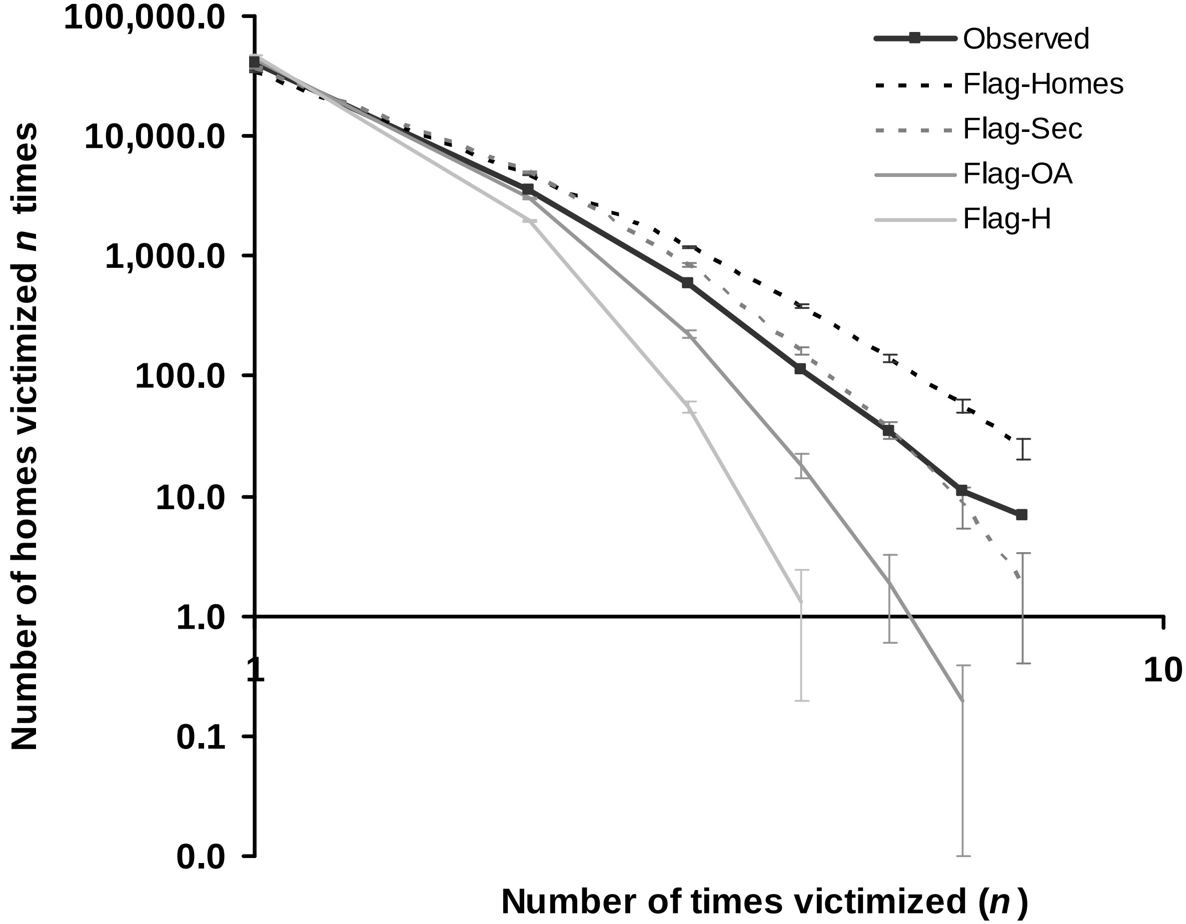
Heterogeneous risk models

- Area level risk
- Area*within area variation models
  - Homes within each area randomly allocated to a particular type with the model calibrated using styalized facts
  - Homes within each area randomly allocated more security
- Seasonal variation

Heterogeneity across models



Heterogeneous risk models



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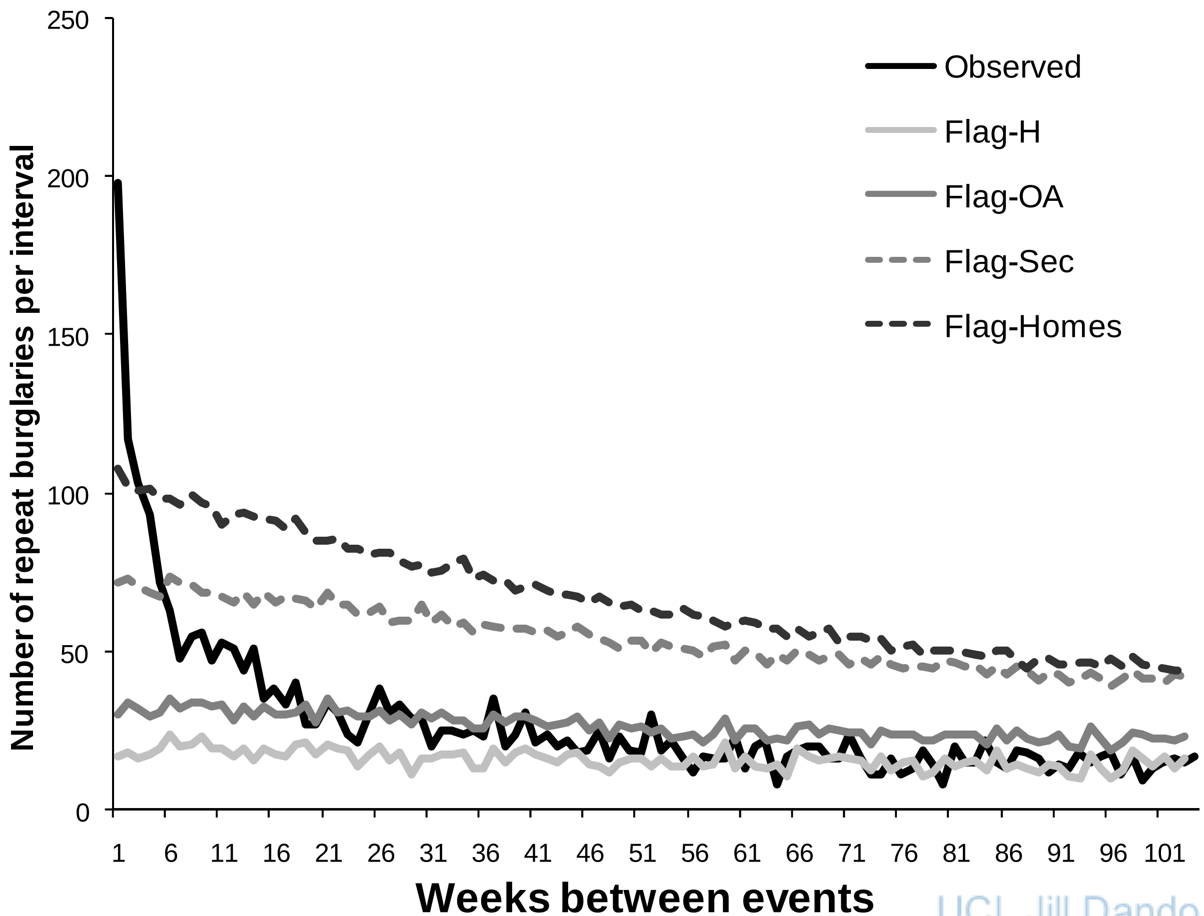
Heterogeneous risk models



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Event dependency

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Near Repeats – extending the concept

- Repeat victimisation can be identified with data routinely available to the police which offers useful predictions for future crime patterns

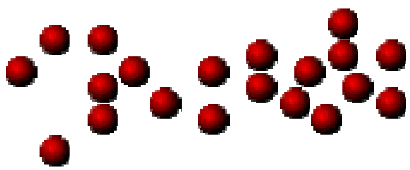
- Self-evidently, prior victimization yields no prediction about properties as yet unvictimized

- *Optimal foraging Theory* - maximising benefit, minimising risk and keeping search time to a minimum-
  - patch selection, departure…..
  - repeat victimisation as an example of this
  - burglaries on the same street in short spaces of time would also be an example of this

- Consider what happens in the wake of a burglary
  - To what extent is risk to non-victimised homes shaped by an initial event?

An analogy with disease Communicability

- Communicability - inferred from closeness in space and time of manifestations of the disease in different people.



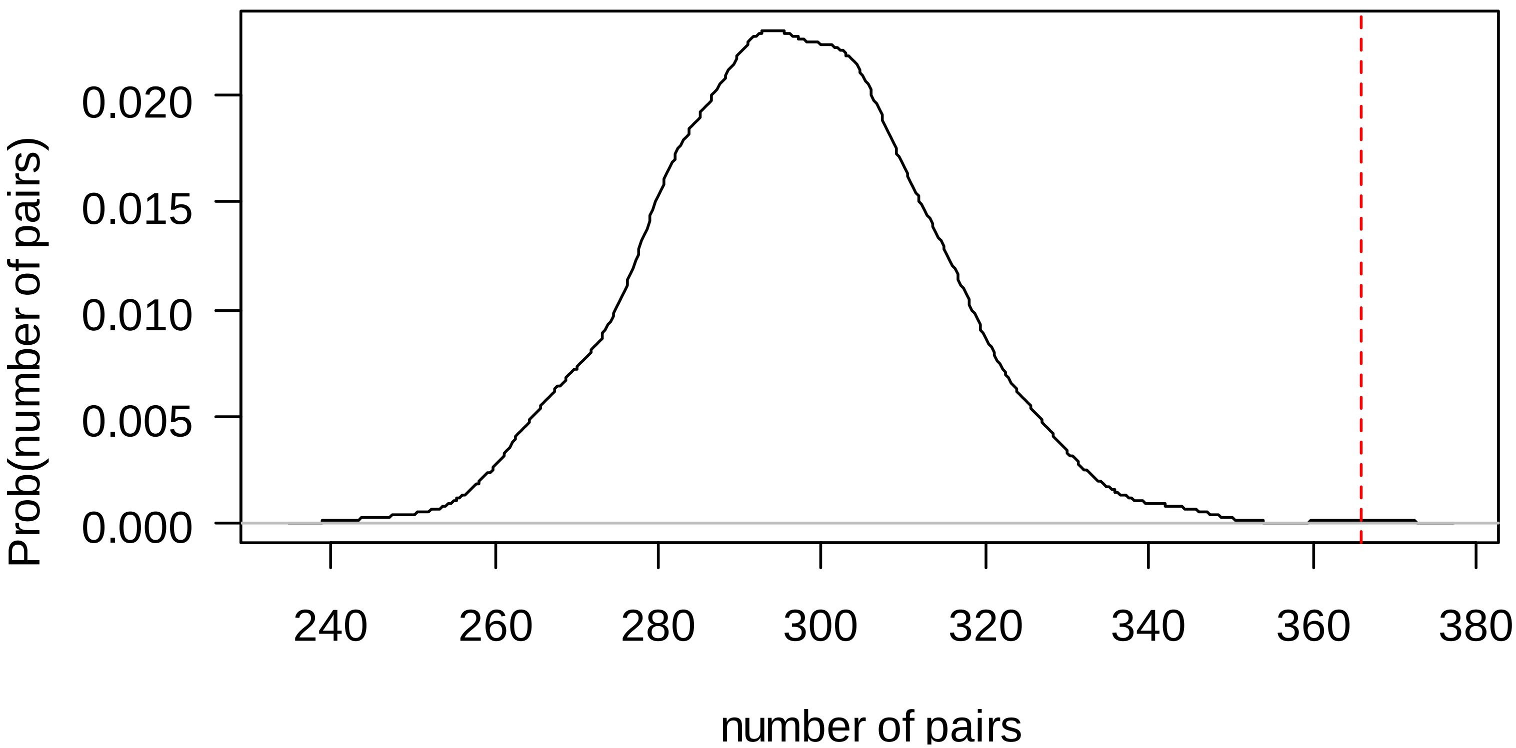
- Does burglary exhibit these features?

Euclidian Analyses

Knox residuals or Monte Carlo variant (Besag & Diggle, 1977)

		Distance between events in pair		
		0-100m	**101-200m**	**201-300m**
Time between events in pair	**7 days**	421	221	189
	14 days	246	209	091
	21 days	102	237	144

Knox ratio and p-valules

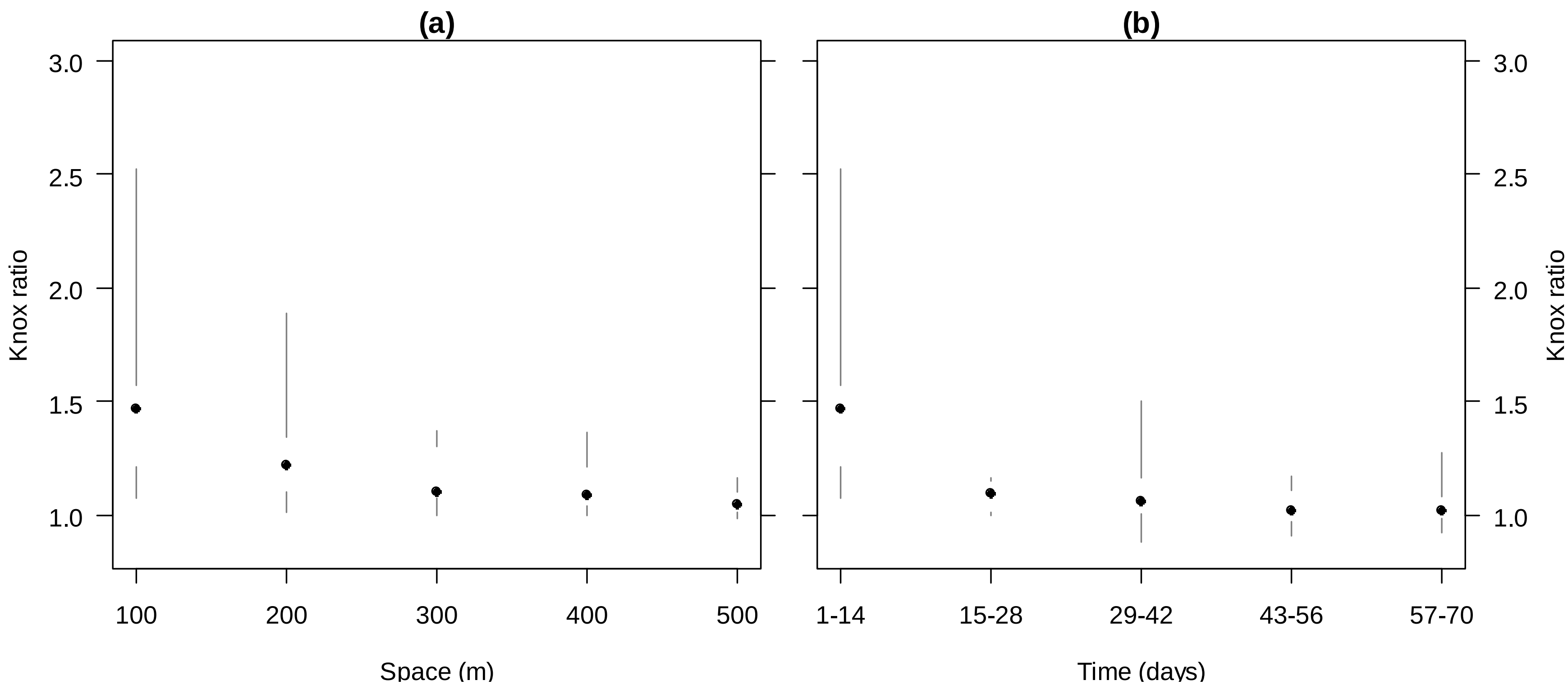


Johnson et al. (2007)

An example

Distance between events	Days between events: 14	28	42	56	70	84	98	112	112+
Same	**4.00**	1.50	**2.00**	1.67	0.83	1.00	0.83	1.17	**0.74**
0-100m	**1.63**	**1.24**	**1.22**	0.87	1.07	0.97	1.02	1.01	**0.95**
101-200m	**1.26**	**1.17**	**1.23**	1.01	1.04	**1.15**	0.95	0.94	**0.96**
201-300m	**1.14**	1.04	**1.11**	0.99	1.01	1.00	1.03	1.02	**0.98**
301-400m	**1.11**	**1.08**	**1.16**	1.01	1.02	0.96	1.00	1.01	**0.98**
401-500m	1.04	1.01	1.02	0.96	1.05	0.97	1.02	0.99	1.00
501-600m	1.07	0.99	**1.08**	1.03	**1.06**	0.97	**1.08**	1.05	**0.98**
601-700m	1.05	1.05	1.03	1.03	1.02	1.02	0.99	0.96	**0.99**
701-800m	**1.09**	1.01	1.03	0.99	1.01	1.02	0.98	1.05	**0.99**
801-900m	1.06	1.00	1.06	1.01	1.08	1.01	0.97	0.95	**0.99**
901-1km	0.96	0.99	1.01	1.00	0.96	1.00	1.01	1.01	1.00
1km+	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00

International comparison (burglary)

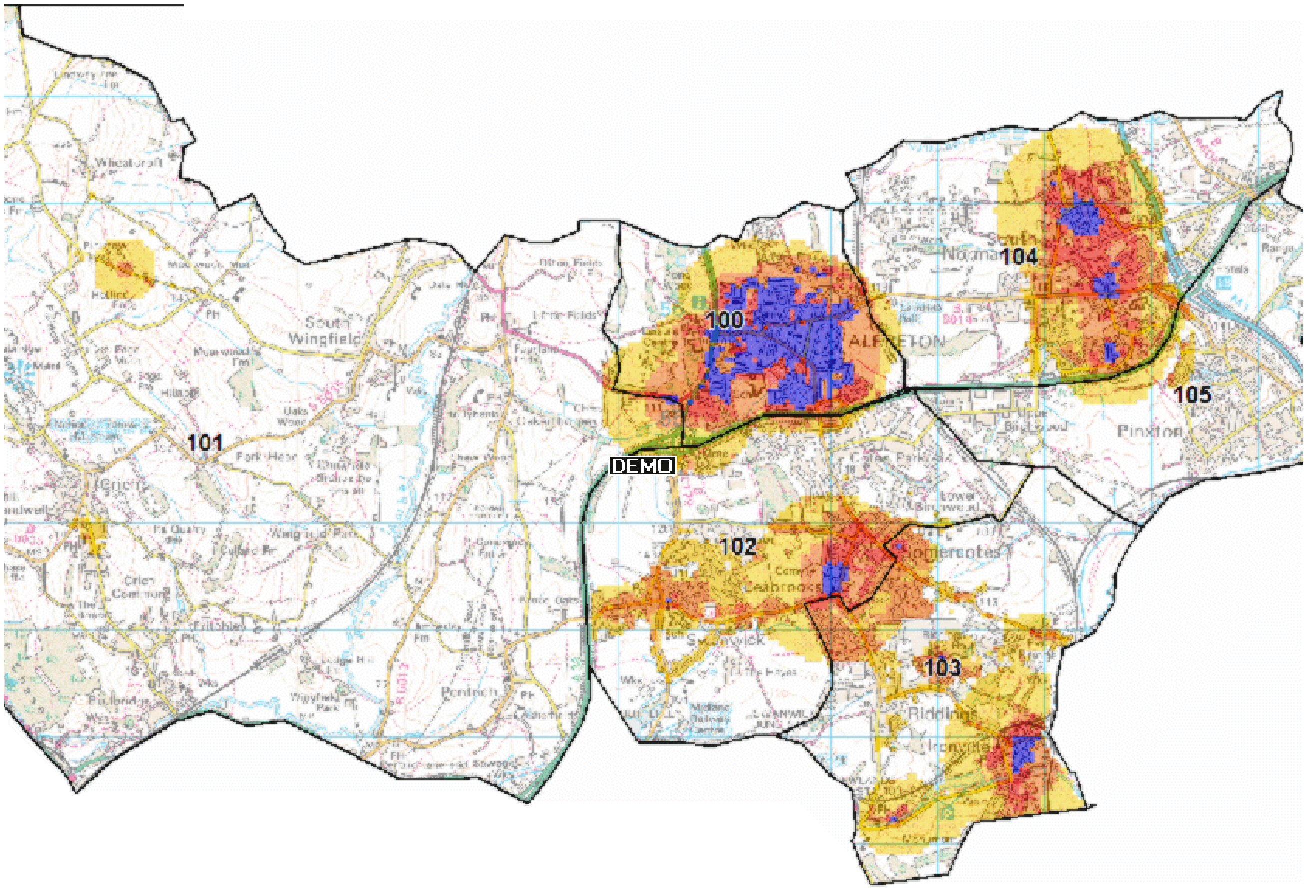


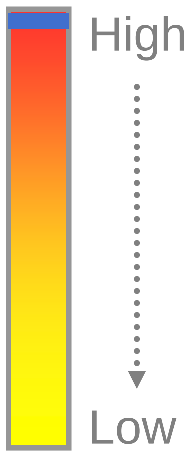
Johnson et al. (2007)

MicroSimulation (area-level variation, mean)

Distance between events	Days between events: 14	28	42	56	70	84	98	112	126
Same	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.01	0.99
0-100m	1.00	0.99	1.00	1.00	1.01	0.99	1.01	1.01	1.00
101-200m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
201-300m	1.01	1.00	1.00	1.00	1.00	0.99	1.00	1.01	1.00
301-400m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
401-500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
501-600m	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
601-700m	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00
701-800m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
801-900m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
901-1km	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.01	0.99

Weekly variation





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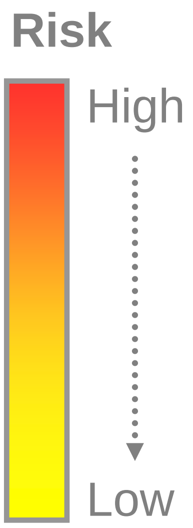
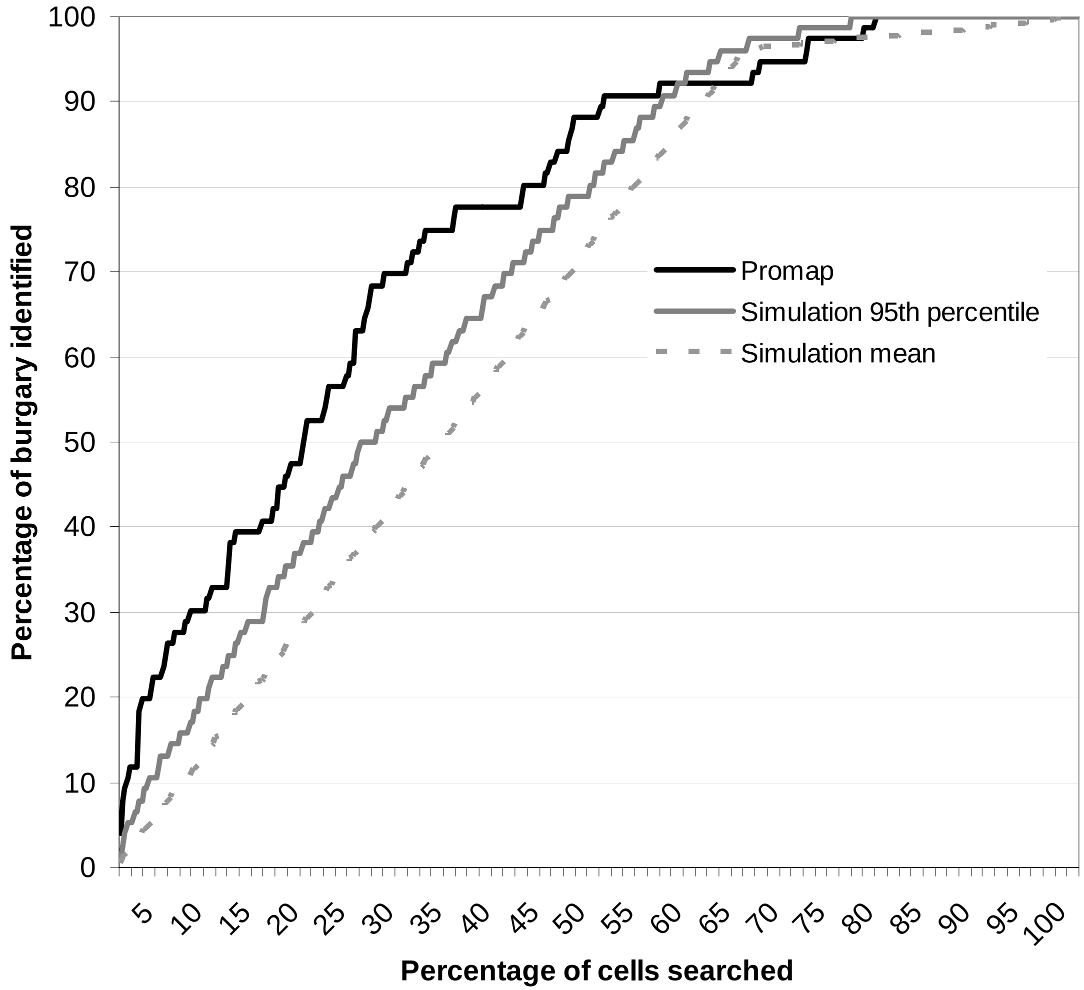
Forecasting as theory testing and application - ProMap

Bowers et al. (2004)

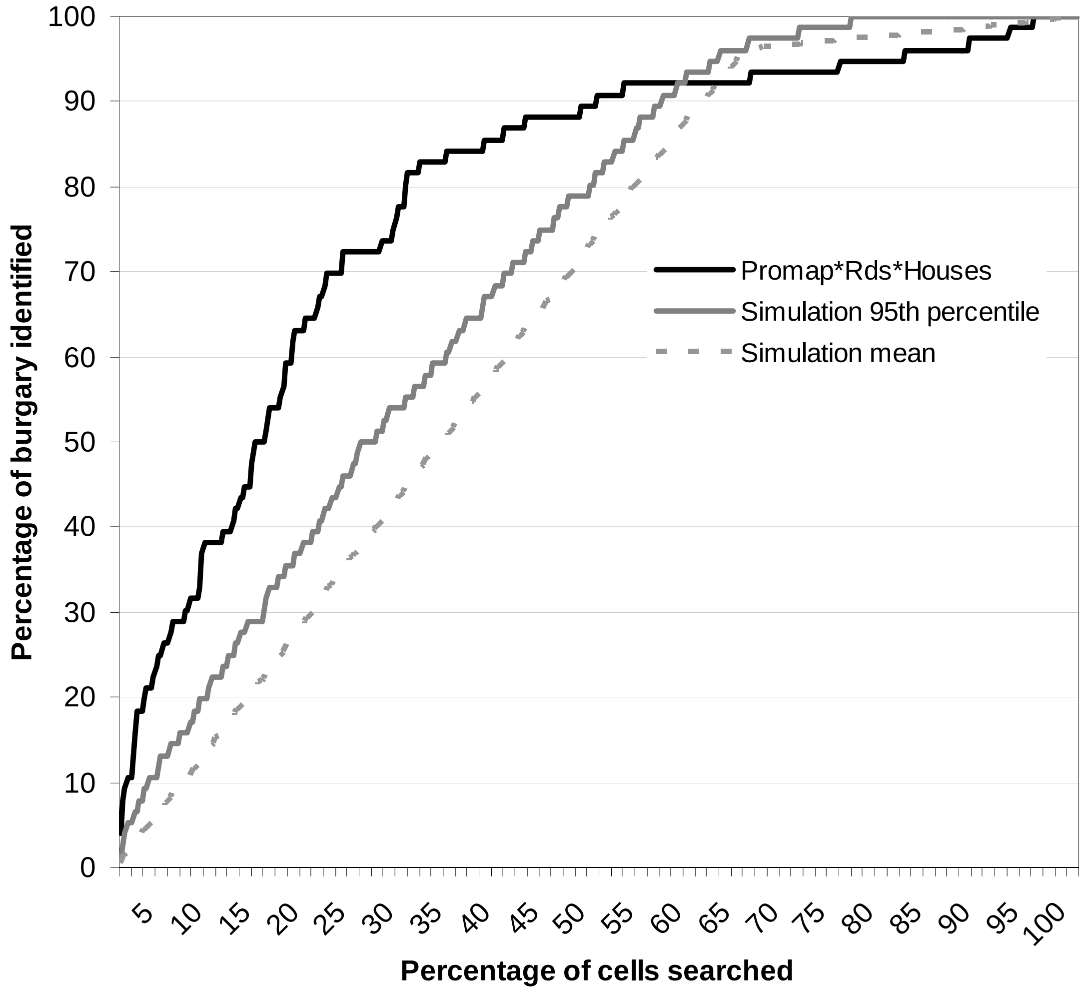


ProMap (burglary)



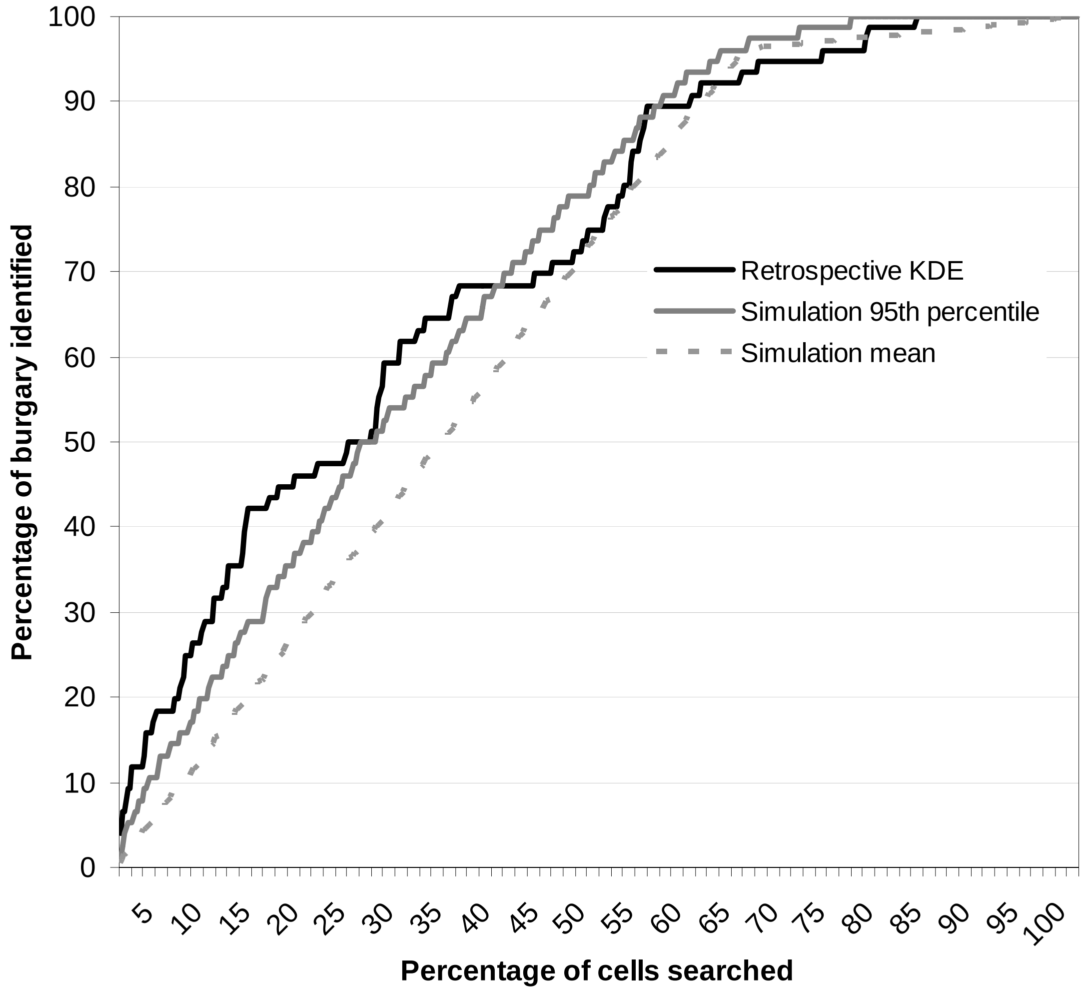
Johnson et al. (2008)

ProMap*Backcloth



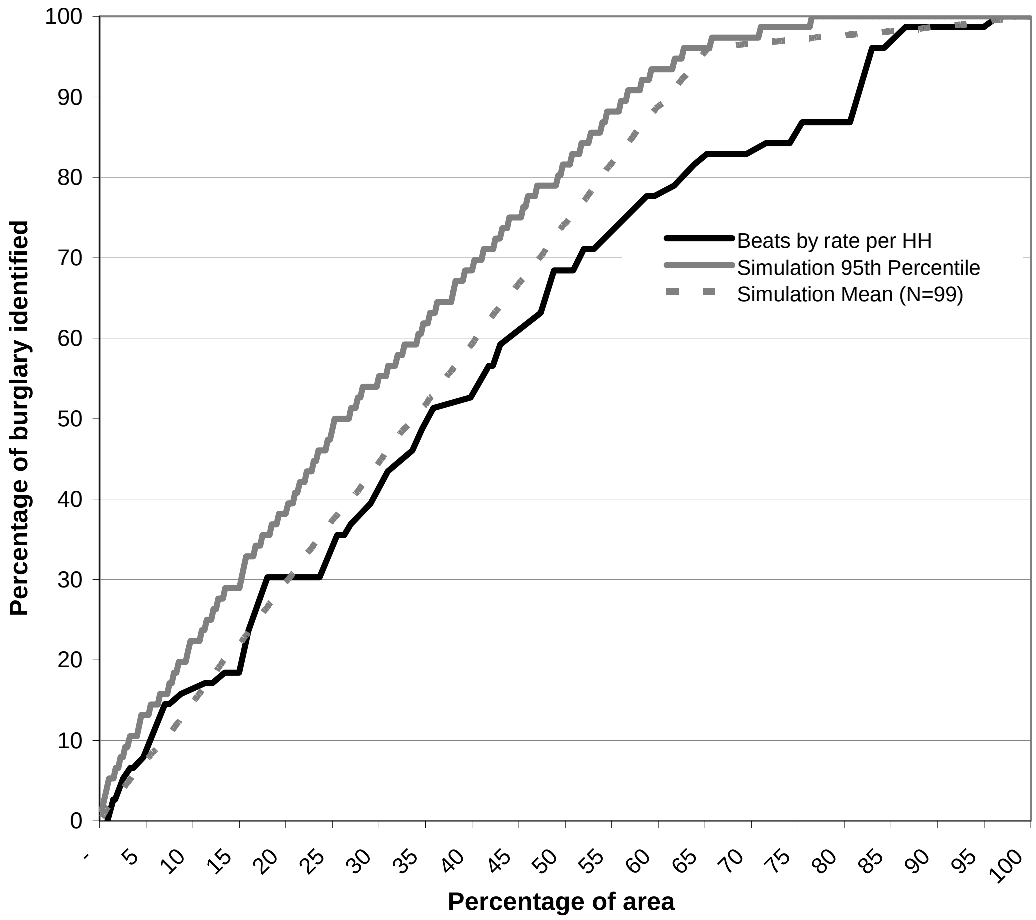
Johnson et al. (2008)

Retrospective KDE



Johnson et al. (2008)

Retrospective Thematic map



Johnson et al. (2008)

Crimes detected by the police?

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Same offender involvement (% cleared to same offender(s))?

Distance between events	Days between events: 14	28	42	56	70	84	98	112	112+
Same	99	92	57	90	67	100	33	67	36
0-100m	79	32	24	31	24	8	7	15	3
101-200m	52	29	20	10	6	10	6	15	3
201-300m	38	23	14	10	6	6	4	5	2
301-400m	46	19	15	9	8	4	3	7	2
401-500m	41	17	13	8	10	1	4	3	2
501-600m	30	16	9	5	1	1	5	7	1
601-700m	34	16	11	8	11	4	4	4	1
701-800m	31	13	14	3	7	4	7	6	1
801-900m	23	14	8	3	6	2	5	3	1
901m-1km	28	14	8	2	5	4	1	2	1
1km+	5	3	2	2	2	1	1	1	<1

Agent based simulation

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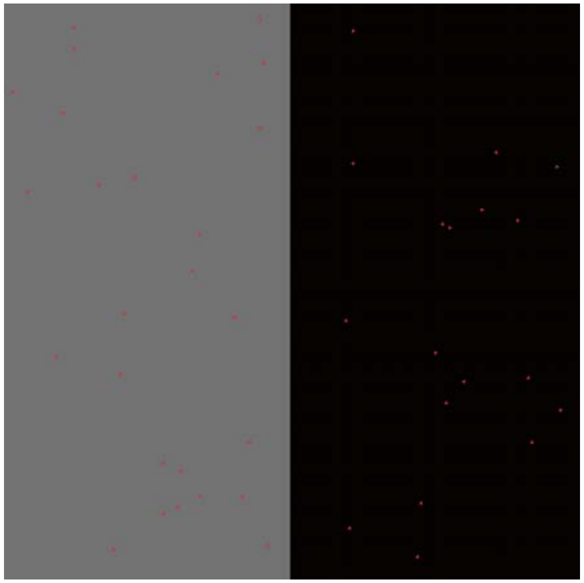
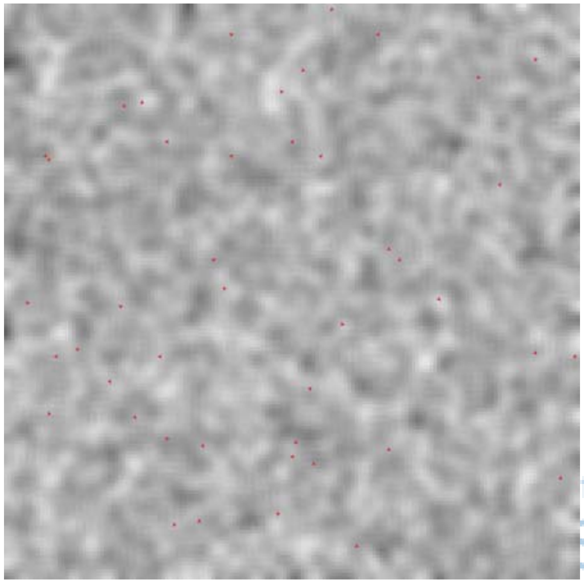
Opportunity surface

- Virtual world is made up of a grid of regular sized cells which represent crime opportunities - homes in this model
- Each home is assigned a crime attractiveness value to represent its risk of victimisation.
  - choice of different distributions to model a range of possibilities





Agent rules

Offenders

- Readiness to offend - Lambda (currently time stable and homogenous)
- Comfort (greatest around home node)

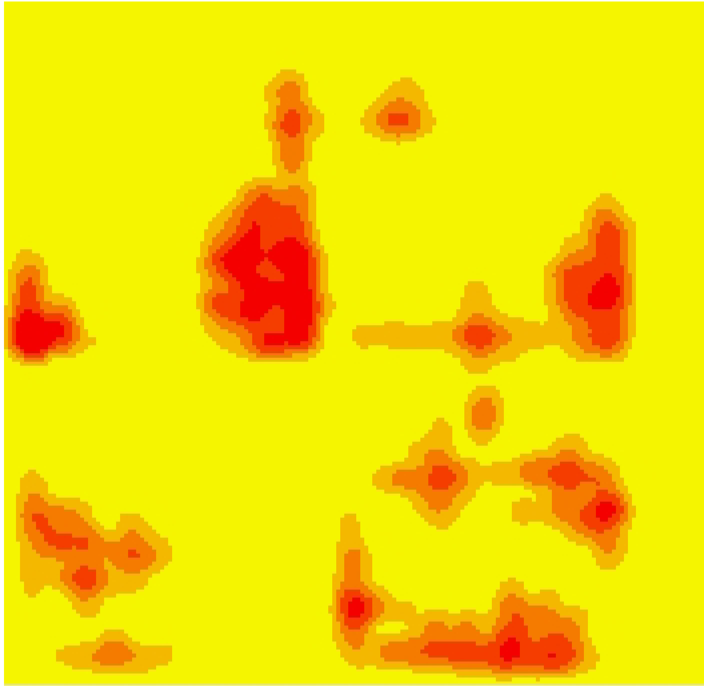
Movement

- Agent vision locally weighted, *n* cells ahead
- Avoid areas with too much heat (time weighted or cumulative)
- Gravity towards the home (variable range 0 +)
- Optimal direction computed (Von-Neuman neighbourhood)

Police

- Hotspot policing or random
- Agent vision locally weighted, *m* cells ahead

Some Results



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Some results

Distance between events	Ticks between events: 28	56	84	112	140	168	196	224	252
0	**4.76**	1.14	0.72	1.04	0.74	0.69	0.48	0.47	0.41
5	**1.75**	**1.49**	**1.22**	**1.13**	1.04	0.96	0.86	0.81	0.79
10	0.91	1.06	1.15	1.15	1.11	1.10	1.08	1.03	1.01
15	0.96	0.95	0.95	0.97	1.05	1.05	1.06	1.03	1.06
20	0.89	0.94	0.92	0.95	0.94	0.92	1.00	1.00	0.96
25	0.96	0.93	0.93	0.96	1.03	1.01	0.98	1.03	1.08
30	0.97	**1.03**	**1.07**	**1.05**	**1.02**	**1.04**	**1.08**	1.03	0.98
35	**1.03**	1.00	1.03	1.00	0.97	1.00	0.99	1.01	1.05
40	0.97	0.98	0.94	1.01	1.02	1.00	0.99	1.03	1.00
45	0.97	0.93	0.97	1.01	0.98	1.08	1.06	1.04	0.95
50	0.99	1.08	1.00	0.96	0.93	0.91	0.97	0.96	1.00
55	1.03	0.97	1.04	1.00	1.06	1.00	1.05	0.95	1.00

Some next steps

- Model non-foraging behaviour
- Add multiple nodes
- Add shifting awareness comfort
- Bounded rationality?
  - Add random error to global parameters
- Levy-type jump when unsuccessful?
- Births and deaths
- Street network and non-homogenous target distribution
- Sweep parameter space

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