Spatial regression models: from theory to practice

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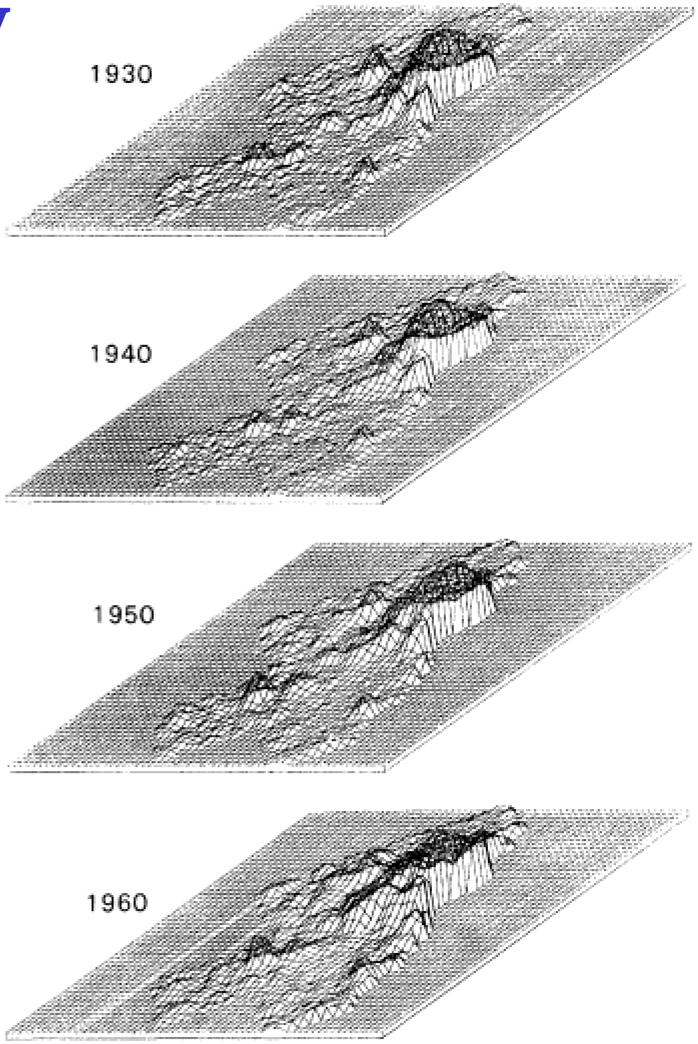
Waldo R. Tobler's (1930 -) 1st law of geography

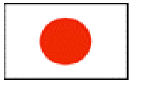
" Everything is related to everything else, but near things are more related than distant things."



Actual population growth, Detroit Region (non-linear vertical scale).

W. R. Tobler, A computer movie simulating urban growth in the Detroit region
Economic Geography ***46, 234-240 (1970)***

Plan

1. Background
2. Spatial data
3. Spatial Autocorrelation / Neighbour
4. Spatial regressions
5. Centenarian rates and climate conditions 

AIM

- Describe spatial regression techniques
- Illustrate their use in the study of the association of geographic, climatic and longevity data from Japan.

Deaths from cholera in 1854 compared with calculated mortality

Snow, "Cholera and the water supply in the south districts of London," Table 6

http://johnsnow.matrix.msu.edu/book_images10.php

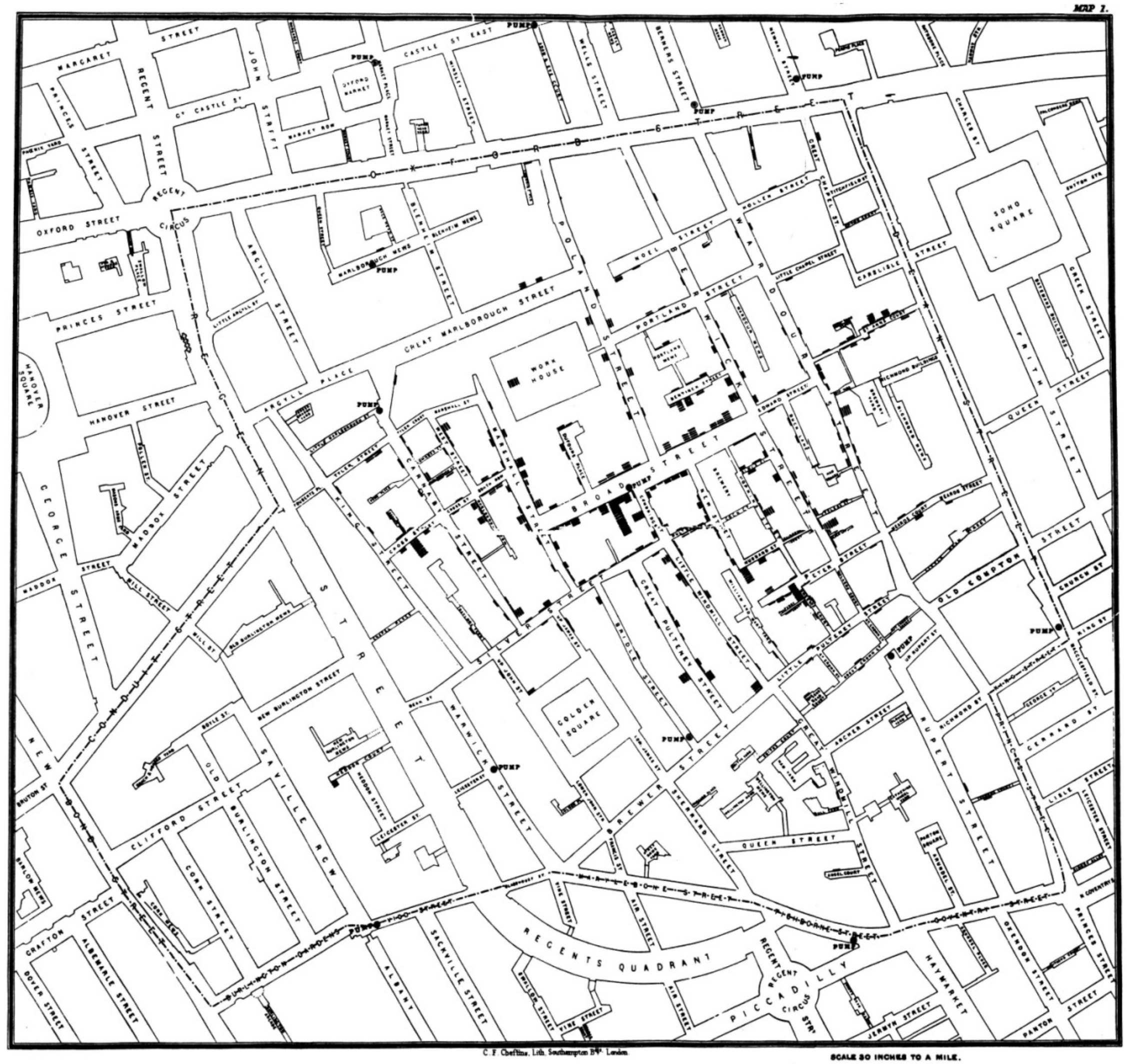
31 Sub-Districts

Actual number of deaths

Predicted deaths by mathematical model

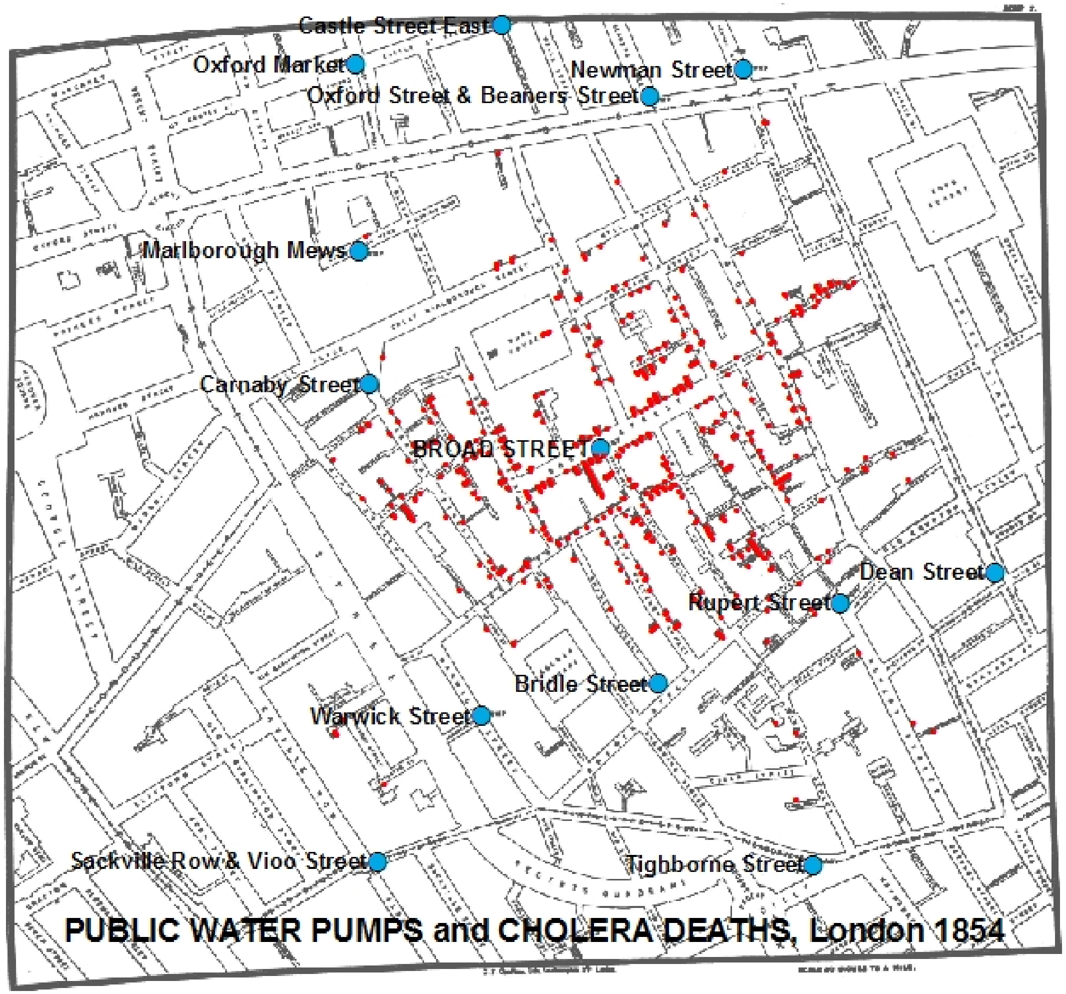
Registration Districts.	Registration Sub-Districts.	Population in 1851.	Estimated population supplied with water as under. Southwark and Vauxhall Co.	Lambeth Co.	Both Companies together.	Deaths from cholera in 1854. Total deaths.	Deaths per 10,000 living.	Calculated mortality in the population, supplied with water as under. Southwark and Vauxhall Co. at 160 per 10,000.	Lambeth Co. at 27 per 10,000.	The two Companies.	Calculated deaths per 10,000 supplied by the two Companies.
St. Saviour, Southw.	1. Christchurch	16,022	2,015	13,234	16,149	113	71	46	36	82	57
	2. St. Saviour	19,709	16,337	898	17,235	378	192	261	2	263	153
St. Olave	1. St. Olave	8,015	8,745	0	8,745	161	201	140	0	140	160
	2. St. John, Horselydown	11,360	9,360	0	9,360	152	134	150	0	150	160
Bermondsey	1. St. James	18,899	23,173	693	23,866	362	192	370	2	372	156
	2. St. Mary Magdalen	13,934	17,258	0	17,258	247	177	276	0	276	160
	3. Leather Market	15,295	14,003	1,092	15,095	237	155	224	3	227	150
St. George, Southw.	1. Kent Road	18,126	12,630	3,997	16,627	177	98	202	11	213	134
	2. Borough Road	15,862	8,937	6,672	15,609	271	171	143	18	161	104
	3. London Road	17,836	2,872	11,497	14,369	95	53	46	31	79	55
Newington	1. Trinity	20,922	10,132	8,370	18,502	211	101	162	22	184	99
	2. St. Peter, Walworth	29,861	14,274	10,724	24,998	391	131	228	29	257	103
	3. St. Mary	14,033	2,983	5,484	8,467	92	66	48	15	63	74
Lambeth	1. Waterloo, part 1	14,088	3,548	11,939	15,487	59	42	57	31	86	55
	2. Waterloo, part 2	18,348	7,171	12,533	19,704	118	64	115	34	149	76
	3. Lambeth church, pt. 1	18,409	3,113	15,878	18,991	49	27	50	43	93	49
	4. Lambeth church, pt. 2	26,784	7,868	16,023	23,891	195	73	126	43	167	71
	5. Kennington, part 1	24,261	15,775	2,708	18,483	305	126	253	7	260	146
	6. Kennington, part 2	18,848	7,874	5,620	13,494	143	75	126	15	141	105
	7. Brixton	14,610	1,922	9,356	11,278	48	33	31	25	56	49
	8. Norwood	3,977	0	1,066	1,066	10	25	0	3	3	28
Wandsworth	1. Clapham	16,290	6,747	134	6,881	167	103	108	0	108	158
	2. Battersea	10,560	6,276	276	6,552	171	162	100	1	101	152
	3. Wandsworth	9,611	907	94	1,001	59	61	15	0	15	149
	4. Putney	5,280	74	0	74	9	17	1	0	1	160
	5. Streatham	9,023	0	3,244	3,244	15	17	0	9	9	27
Camberwell	1. Dulwich	1,632	0	25	25	0	0	0	0	0	0
	2. Camberwell	17,742	9,139	639	9,778	242	136	146	2	148	151
	3. Peckham	19,444	5,438	392	5,830	175	90	87	1	88	151
	4. St. George	15,849	4,295	5,437	9,732	132	83	69	15	84	86
Rotherhithe	Rotherhithe	17,805	12,218	0	12,218	283	159	196	0	196	160
Houses supplied in streets where no death occurred		..	28,929	23,338	52,267	..	..	..	..	..	..
Houses not identified		..	2,712	165	2,877	..	..	..	..	..	..
Totals		482,435	267,625	171,528	439,153	5,067	105	4,282	462	4,744	108
Population as estimated by the Registrar-General		..	266,516	173,748	440,264	..	..	4,267	473	4,740	108

John Snow's Original map (1854)



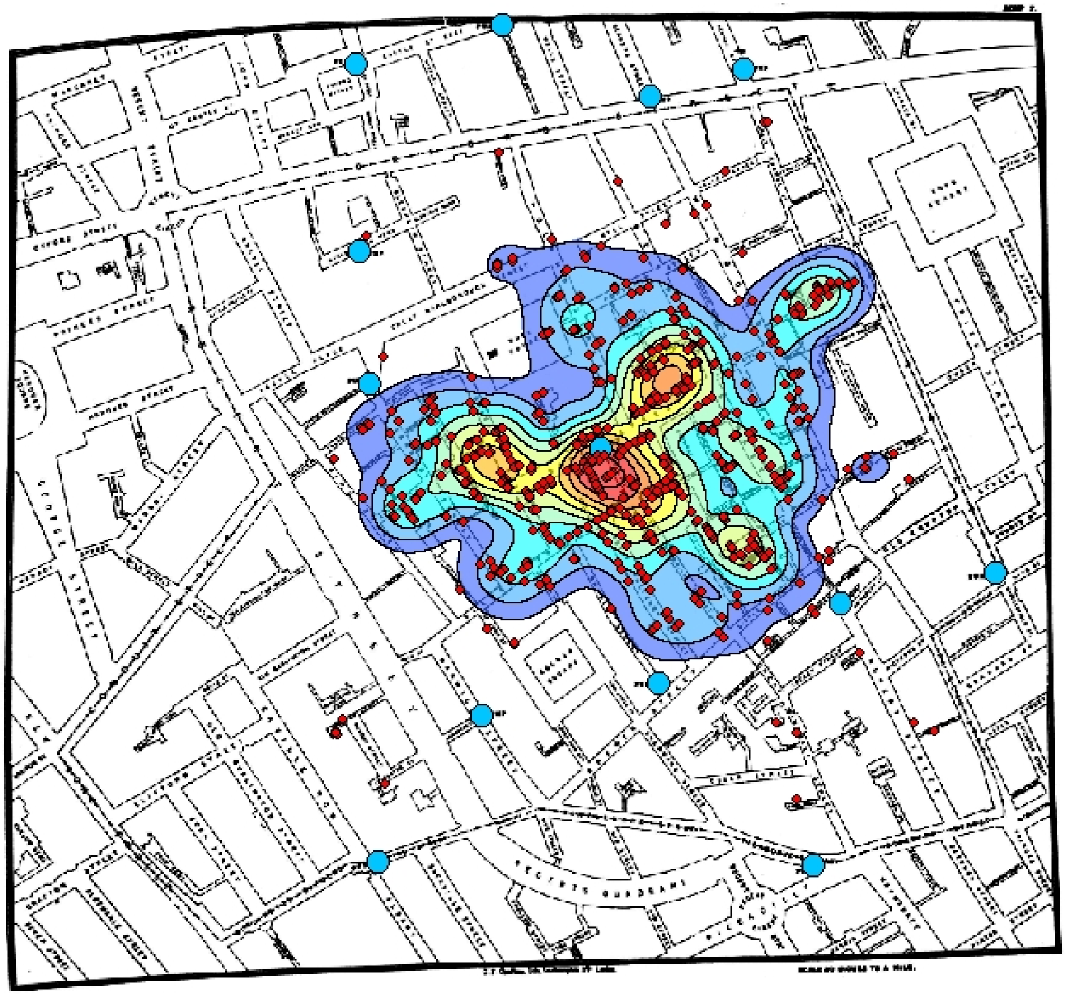
Snow, John. On the Mode of Communication of Cholera, 2nd Ed, John Churchill, New Burlington Street, London, England, 1855.

John Snow's Map of cholera deaths London 1854



http://www.udel.edu/johnmack/frec682/cholera/cholera2.html

Kernel Density to calculate the spatial densities of deaths around each of the wells

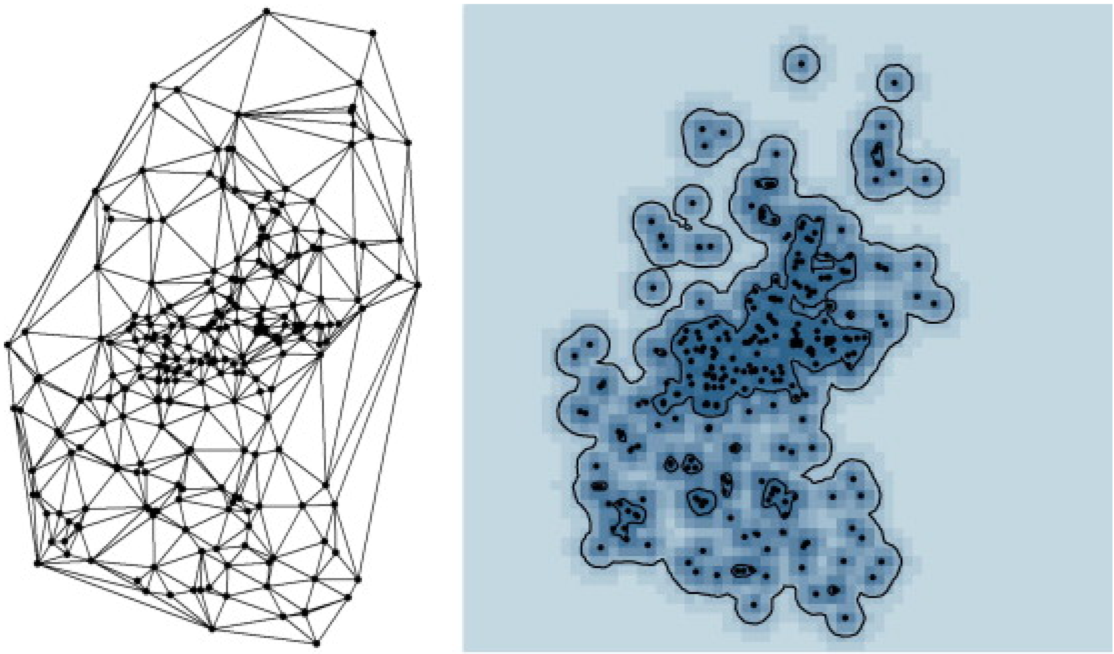


http://www.udel.edu/johnmack/frec682/cholera/cholera2.html

Animal movements

Global positioning system (GPS) and satellite tracking

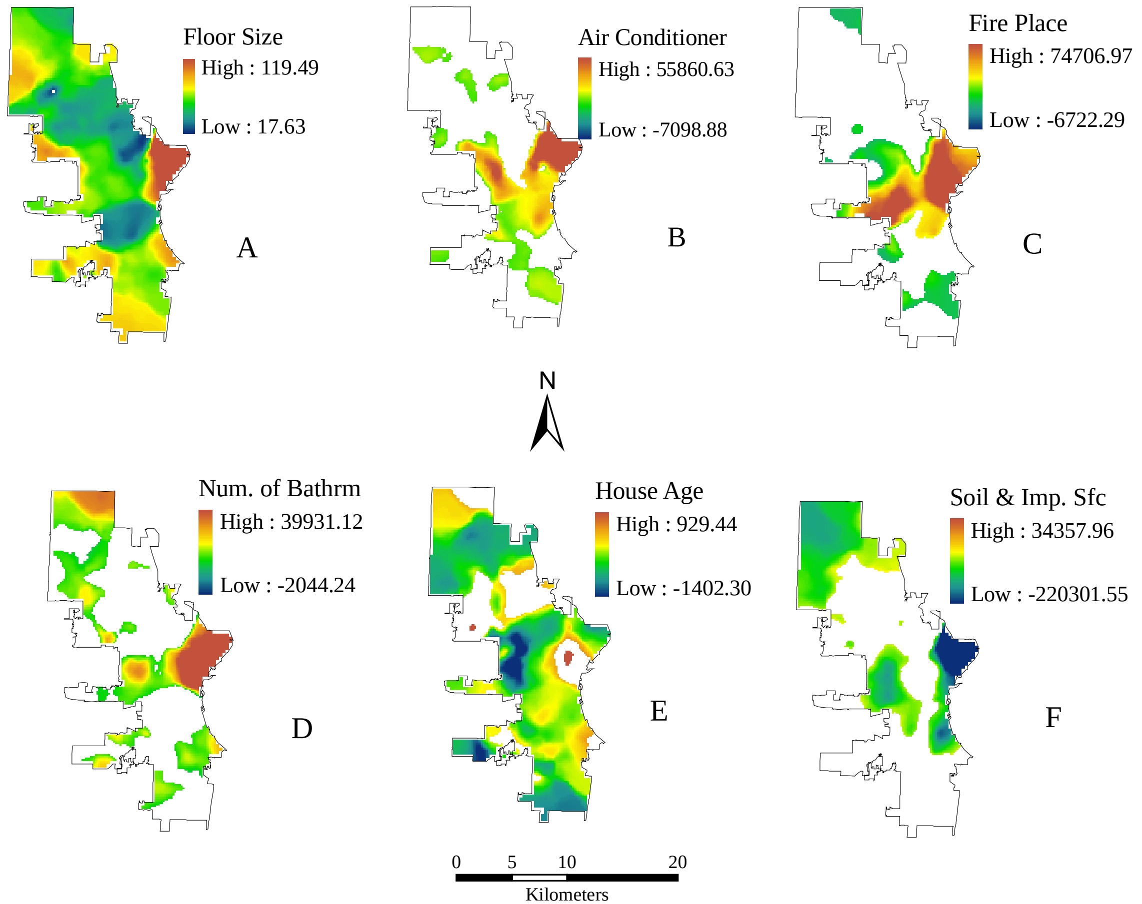
Delaunay triangulation model of movement trajectories (a) and corresponding density surface, home range, and core area delineation (b) for a Florida panther.



(a) (b)

J. A. Downs *et al.*, *Computers, Environment and Urban Systems* ***36, 302-310 (2012).***

Housing price in Milwaukee



From Geographically weighted regression
By Danlin Yu Yehua Dennis Wei Dept. of Geog., UWM

Background

Botanic	plant distributions
Ethology	animal movements
Epidemiology	disease mapping
Economics	spatial econometrics
Computer science	computational geometry
Mathematics	fractals
Statistics	spatial statistics
Geographic information system (GIS)	

Adapted from: http://en.wikipedia.org/wiki/Spatial_analysis

Spatial data

- **Points**

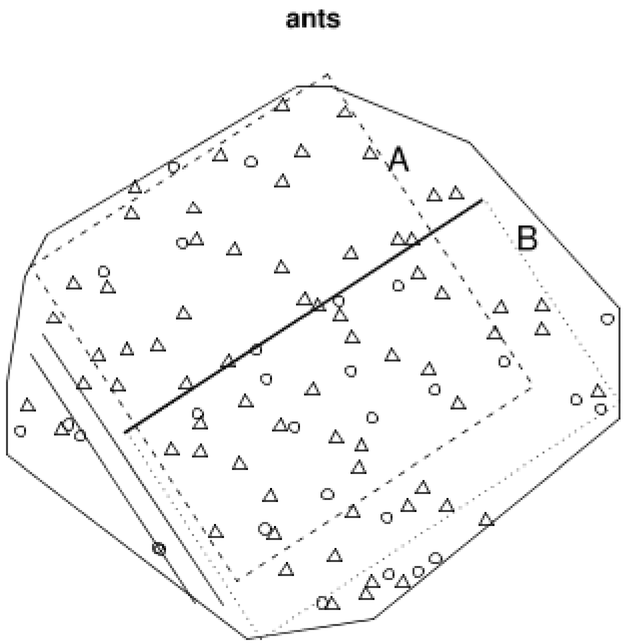
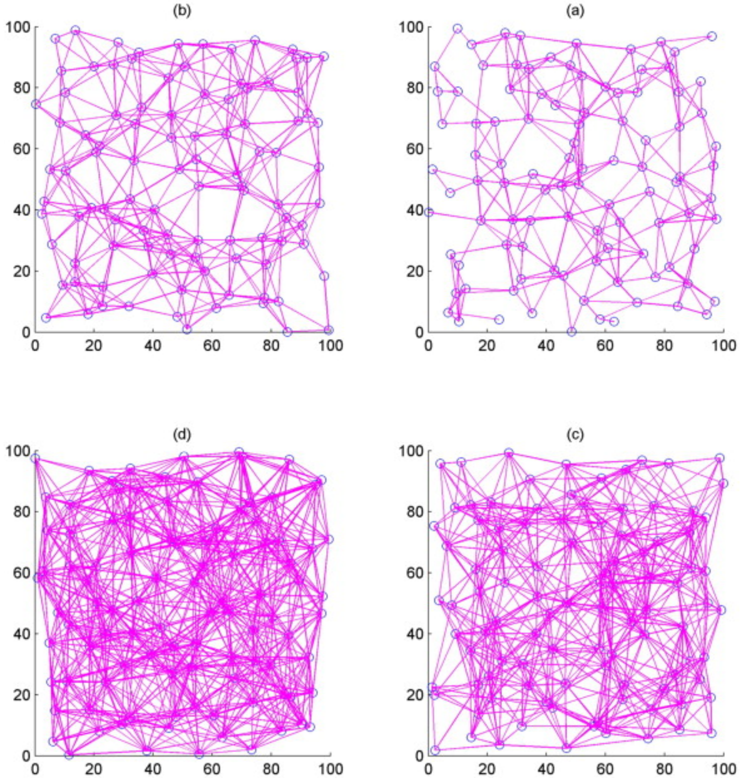


Figure 4: Harkness-Isham ant nests data. Map of the locations of nests of two species of ants, *Messor wasmanni* (△) and *Cataglyphis bicolor* (○) in an irregular region 425 feet in diameter. Data kindly supplied by Professors R.D. Harkness and V. Isham.

From Baddeley A et Turner R. **Spatstat: An R Package for Analyzing Spatial Point Patterns;** J. of Statistical Software 12(6) 2005
http://www.mendeley.com/catalog/journal-statistical-software-24/#page-1

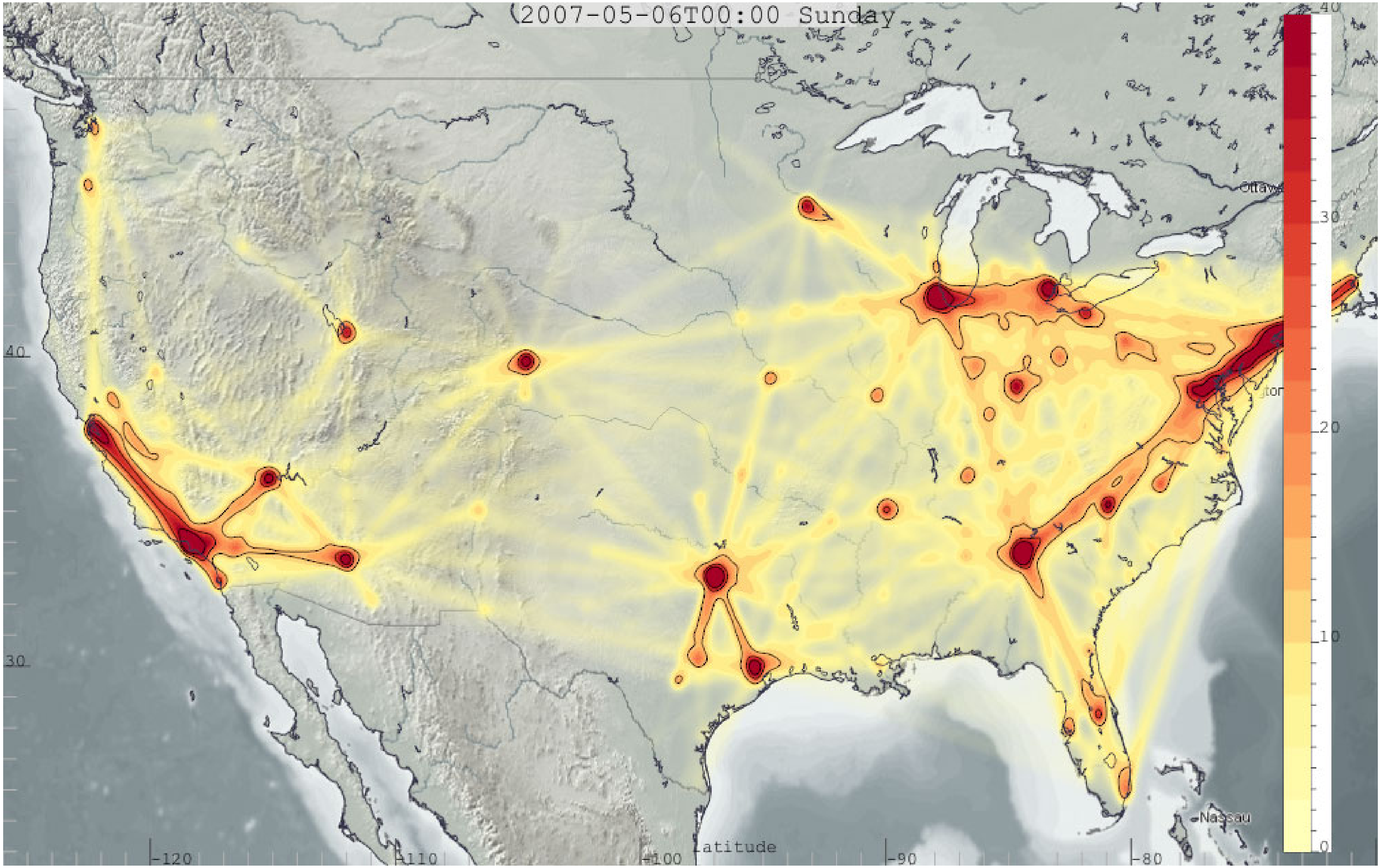
Spatial data

- Points
- **Lattice**



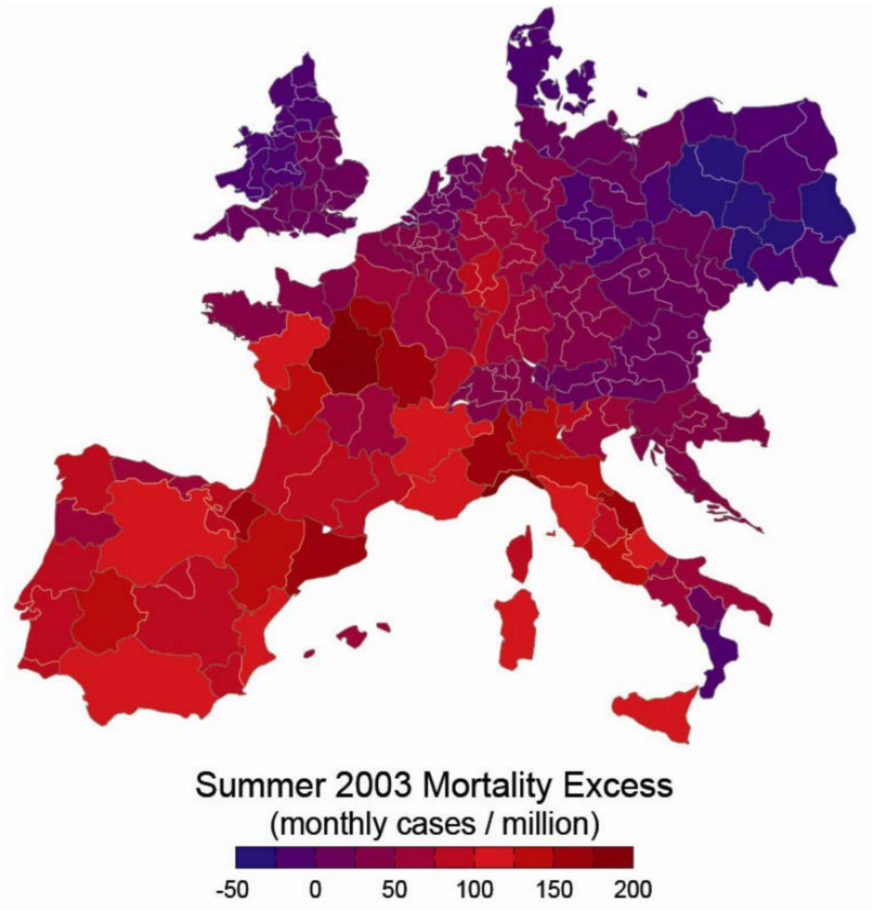
M. Jalili *et al.*, Weighted coupling for geographical networks: Application to reducing consensus time in sensor networks *Physics Letters A* ***374, 3920-3925 (2010).***

Air trafic interactive visualization of streaming data with kernel density estimation



Spatial data

- Points
- Lattice
- **Area**



J. Ballester, JM Robine, FR Herrmann, X Rodó. Long-term projections and acclimatization scenarios of temperature-related mortality in Europe. *Nat Commun 2:358 (2011)*

Spatial data

- Key components of spatial data:
  - Spatial information (coordinates)
  - Attributes

J. Ballester *et al.*, *Nat Commun* ***2:358 (2011)***

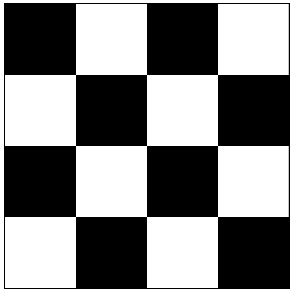
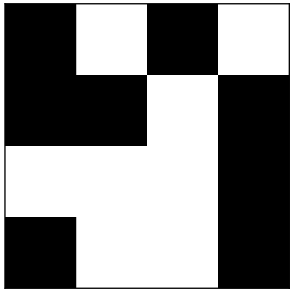
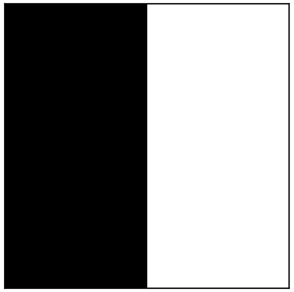
Spatial Autocorrelation

Test for the presence of spatial autocorrelation

- **Global**
  - Moran's *I*
  - Geary's C

- **Local** (LISA – Local Indicators of Spatial Autocorrelation)
  - Local Moran's *I* and Getis G_i*

Moran's *I*

-1 **0** **+1**

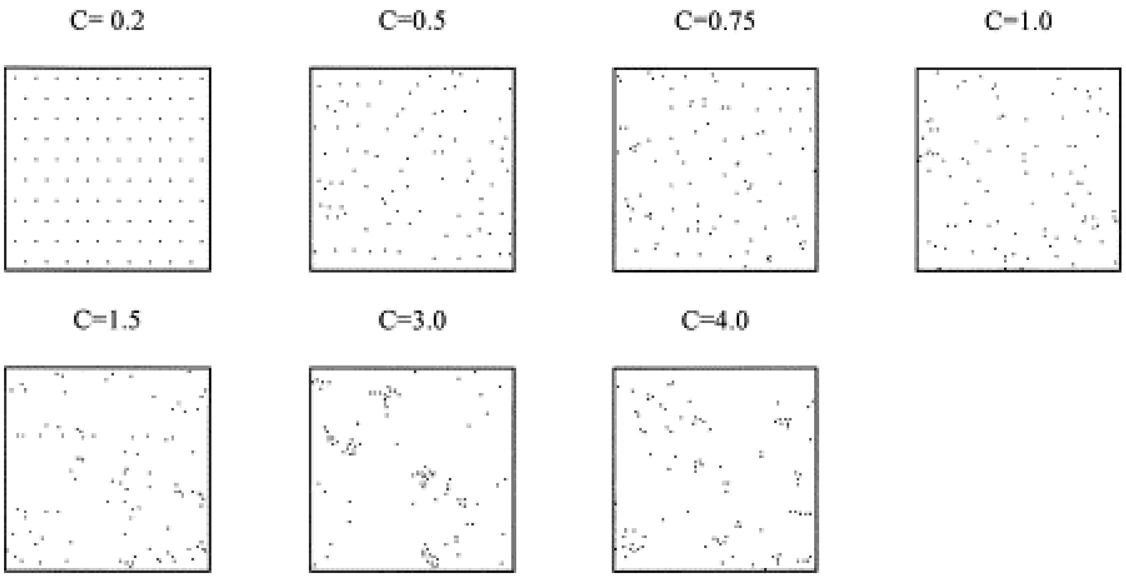
Perfect dispersion **Random spatial pattern** **Perfect correlation**

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}$$

http://en.wikipedia.org/wiki/Moran%27s_I

C measure of non-randomness

- **Points**



$$C = \frac{\sum r_{lp}^2}{\sum r_{pp}^2}$$

r_{lp} distance from random location to its nearest points

r_{pp} distance from sample points to nearest point

Pielou, E. C. (1969)

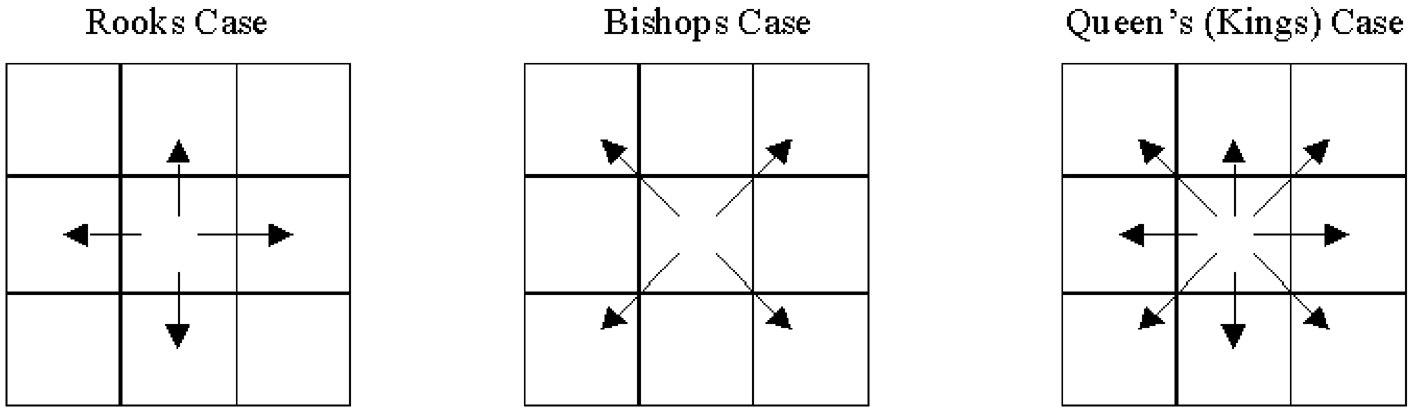
N. Coops *et al.*, *Remote Sensing of Environment* ***71, 248-260 (2000).***

Spatial Weights Matrices

Neighborhoods can be defined in multiple ways

– **Contiguity** (common boundary)

  • But what is a "shared" boundary?



www.clas.ufl.edu/**user**s/forrest/teaching_geo.html
Forest R. Stevens, University of Florida 2012

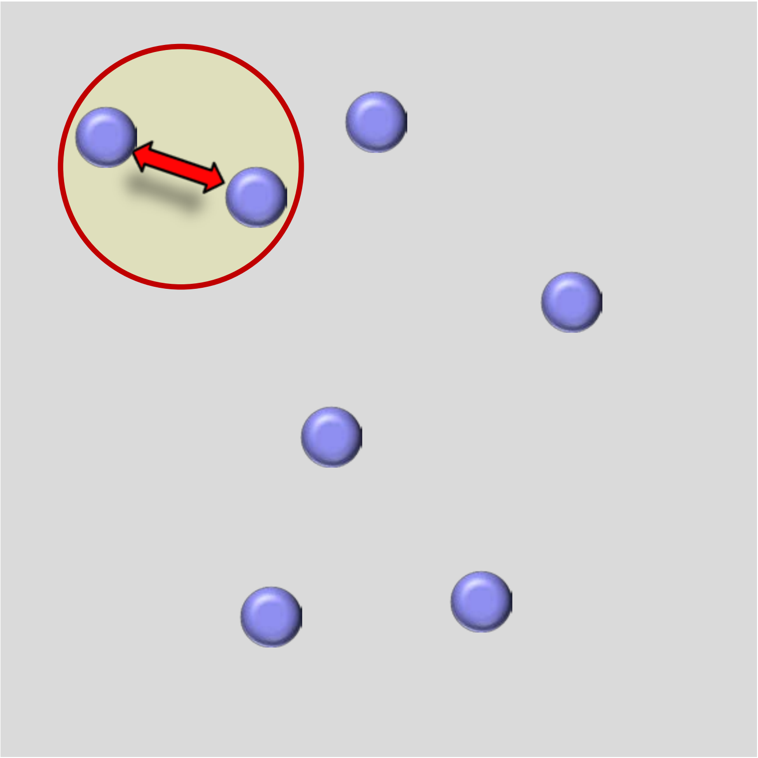
Spatial Weights Matrices

Neighborhoods can be defined in multiple ways

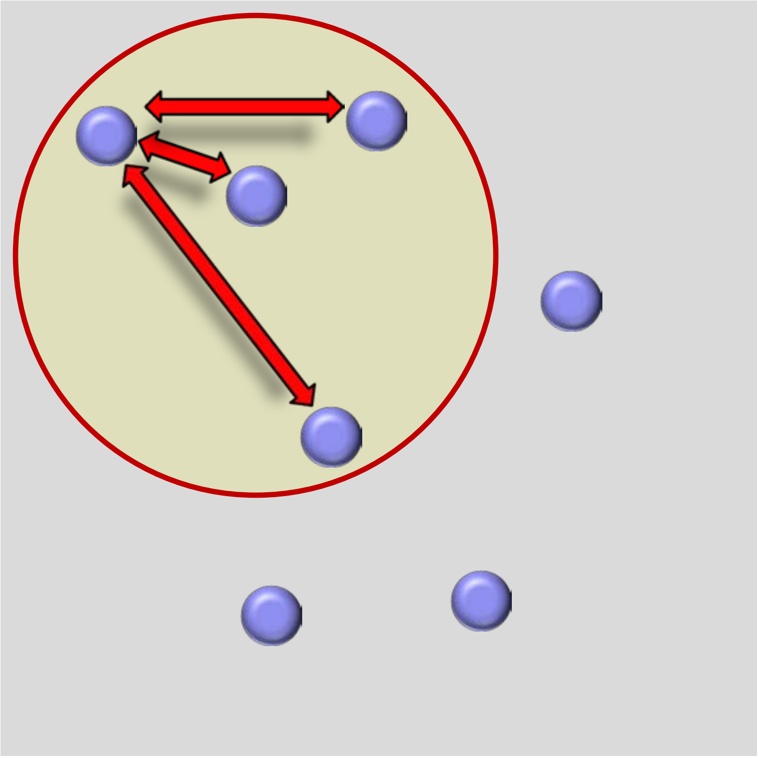
- **Contiguity** (common boundary)
  - But what is a “shared” boundary?
- **Distance** (distance band, K-nearest neighbors)
  - How many “neighbors” to include, what distance do we use?
- **General weights** (social distance, exponential decay)

Neighbours and bandwidth
W spatial weight matrix

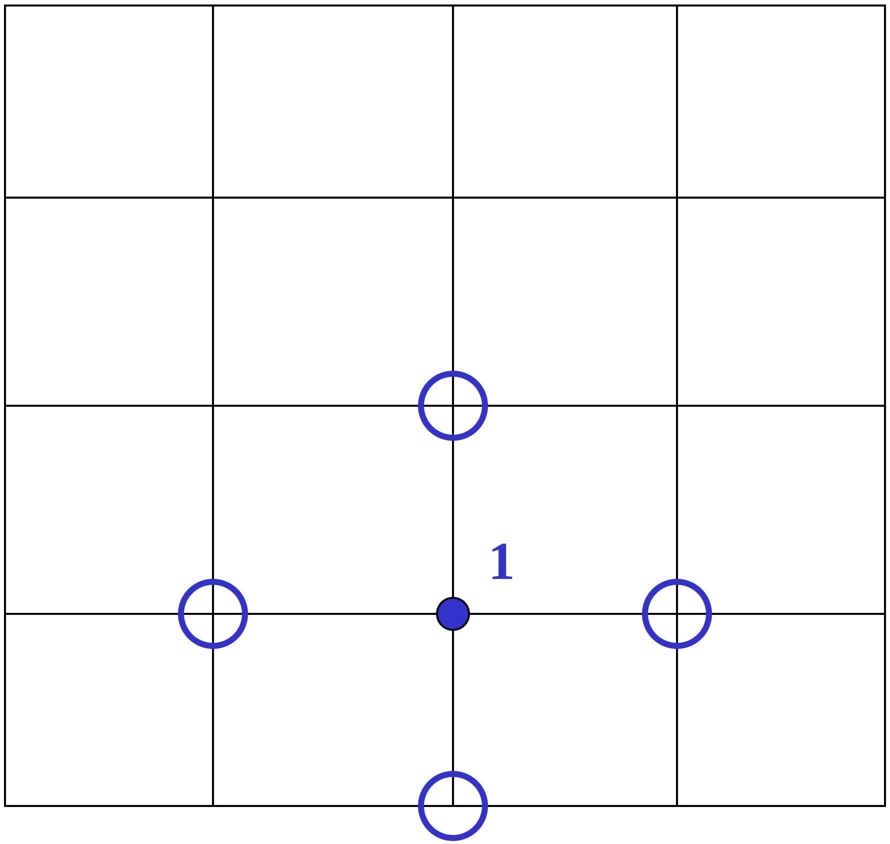
1 Neighbor
Distance Band 1 unit



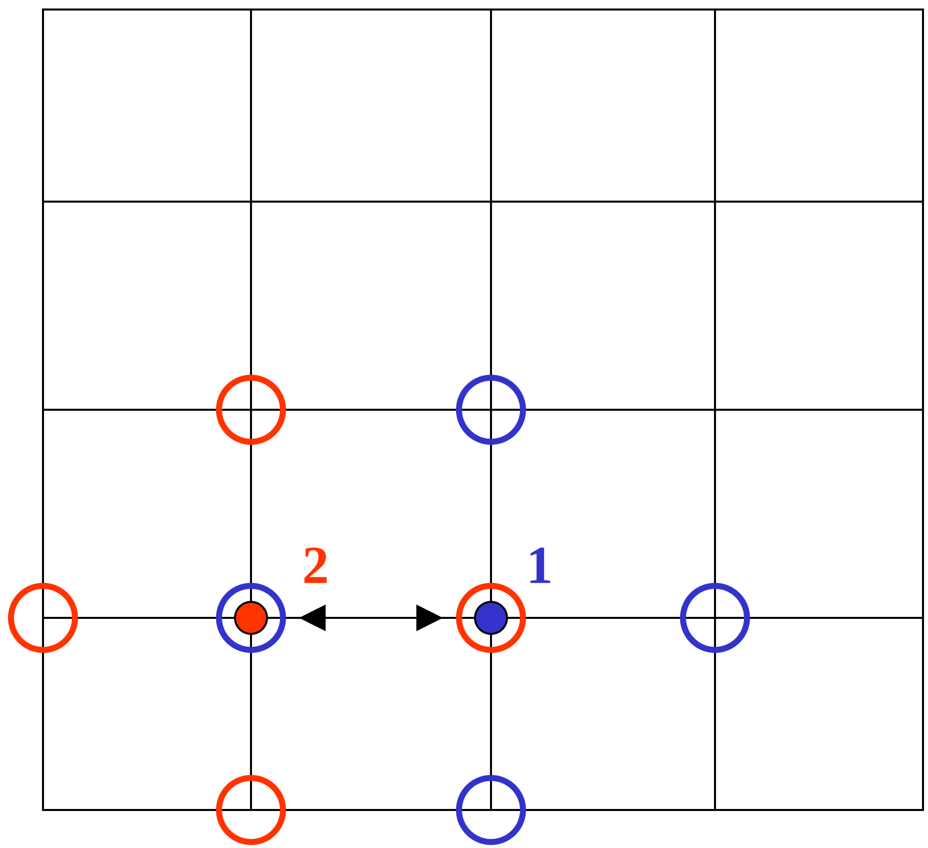
3 Neighbors
Distance Band 2 units



Intuition: you are your neighbours neighbour

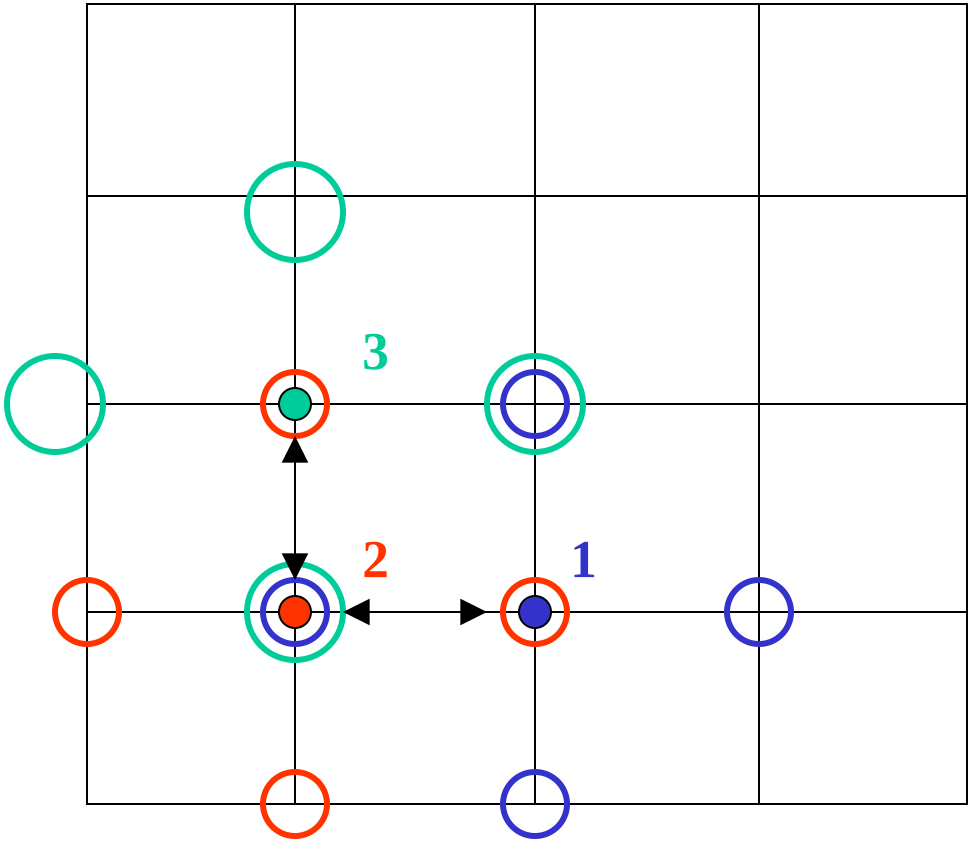


Intuition: you are your neighbours neighbour

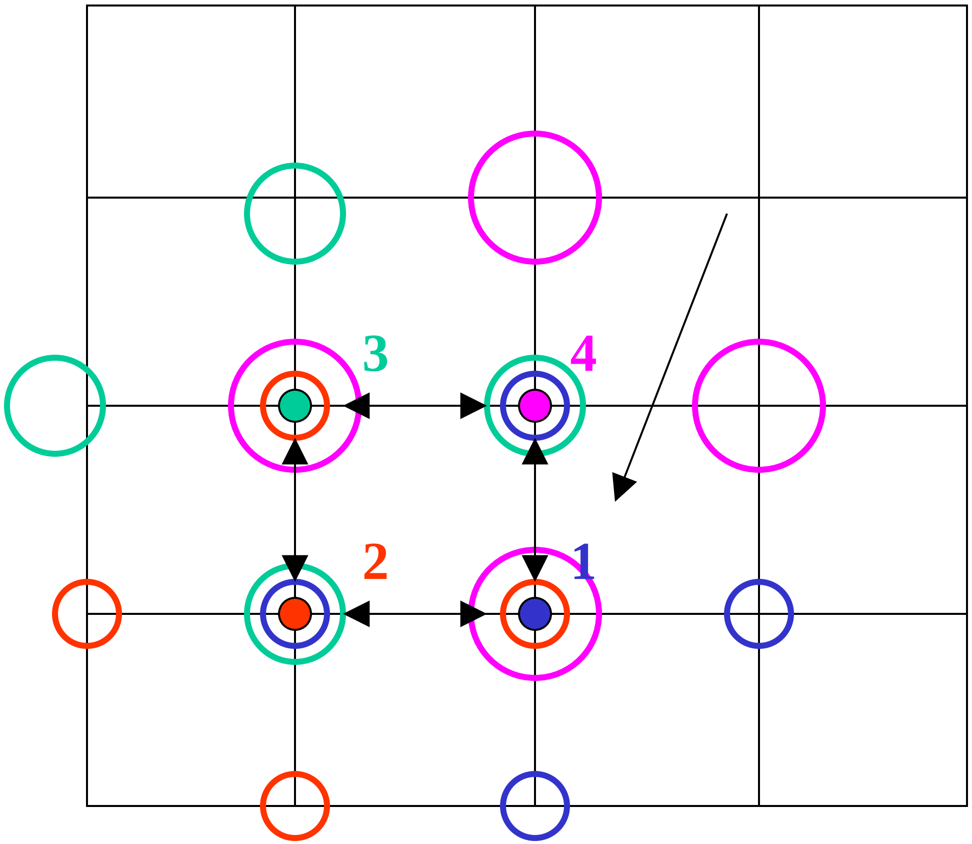


Steve Gibbons 2008, GY460 Techniques of Spatial Analysis
Lecture 3: Spatial regression and 'neighbourhood' effects models
http://www.docstoc.com/docs/109574884/GY460_Lecture_3_Spatial_Regressions_Oct_08

…and your neighbour's neighbour's neighbour's neighbour…

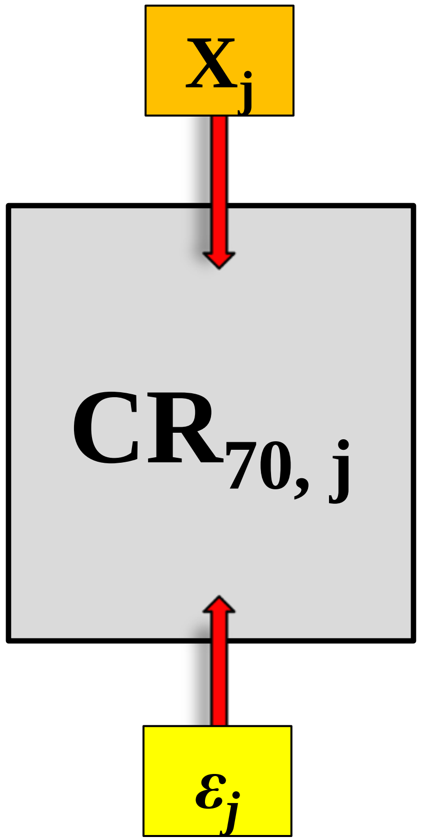


…and your neighbour's neighbour's neighbour's neighbour…



Shocks at 1 affect 2 and 4 directly
And 3 indirectly via 2 and 4
Shocks at 1 get reflected back to 1 from 2 and 4
And from 2 to 3 to 4 to 1 etc…

Linear regression models



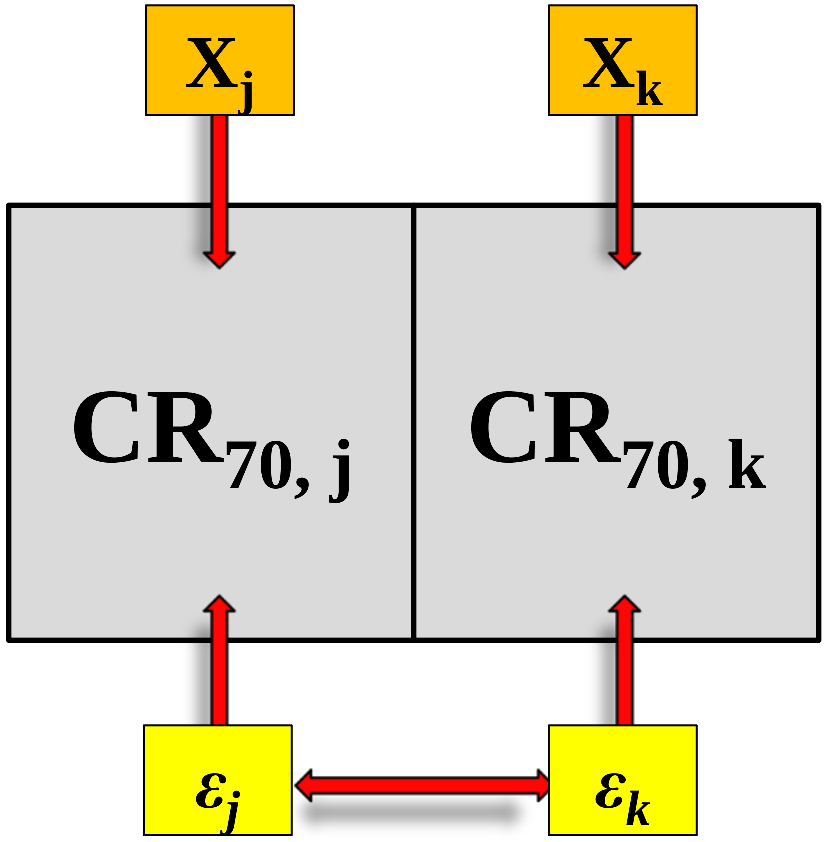
$$CR_{70} = \beta_0 + \beta_1 X + \varepsilon$$

Linear Regression

- When applied to spatial data, it assumes a stationary spatial process
  - The same stimulus provokes the same response in all parts of the study region
  - Highly untenable for spatial process

From Geographically weighted regression
By Danlin Yu Yehua Dennis Wei Dept. of Geog., UWM

Spatial error regression models



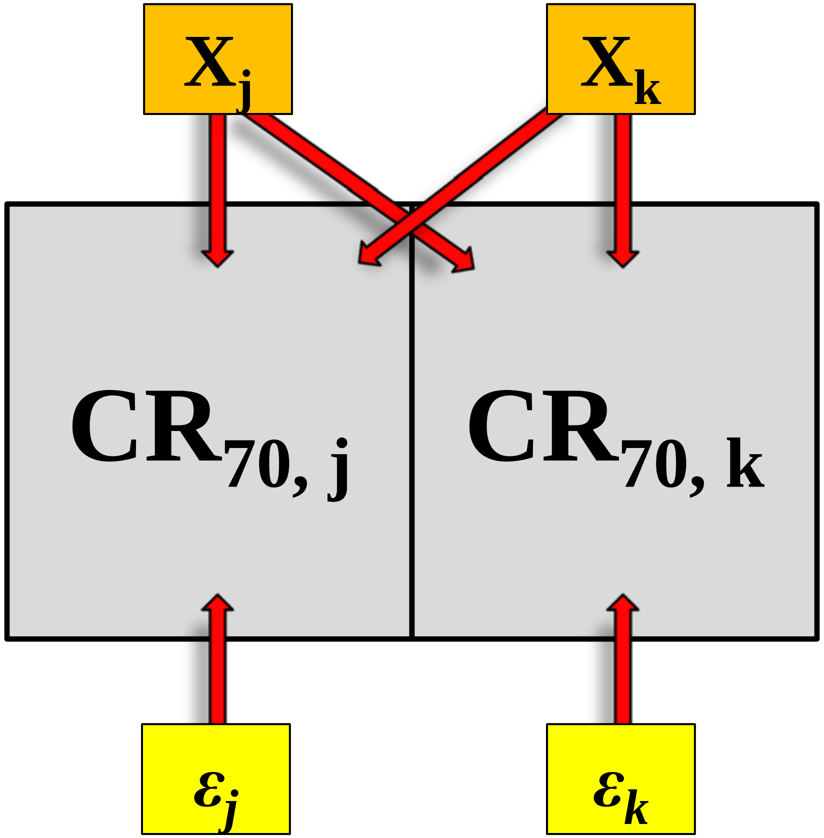
$$CR_{70} = \beta_0 + \beta_1 X + u$$

$$u = \lambda W \rho + \varepsilon$$

W spatial weight matrix,
λ degree of spatial autocorrelation
λ > 0 : neighbors are similar
λ < 0 : neighbors are dissimilar

Addapted from *Lab 9..pdf* Spatial Regression. *SOC 261, Spring 2005.* Spatial *Thinking in Social Science*
www.s4.brown.edu/s4/courses/SO261.../lab9.pdf

Spatial lag regression models



$$CR_{70} = \lambda W \rho + \beta_1 X + \varepsilon$$

W spatial weight matrix,

λ degree of spatial autocorrelation

λ > 0 : neighbors are similar

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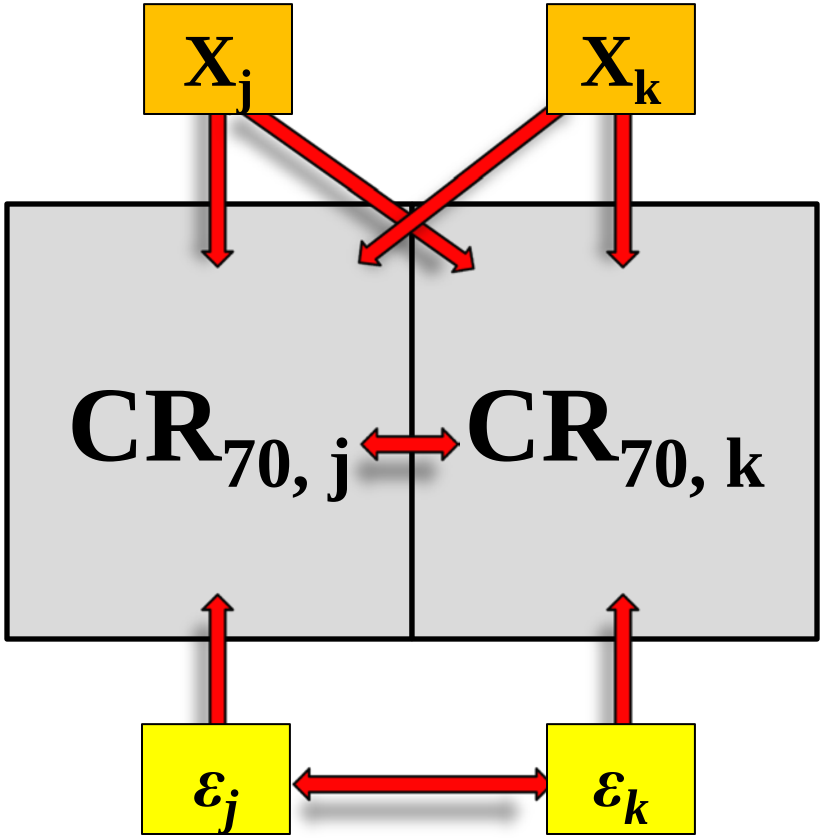
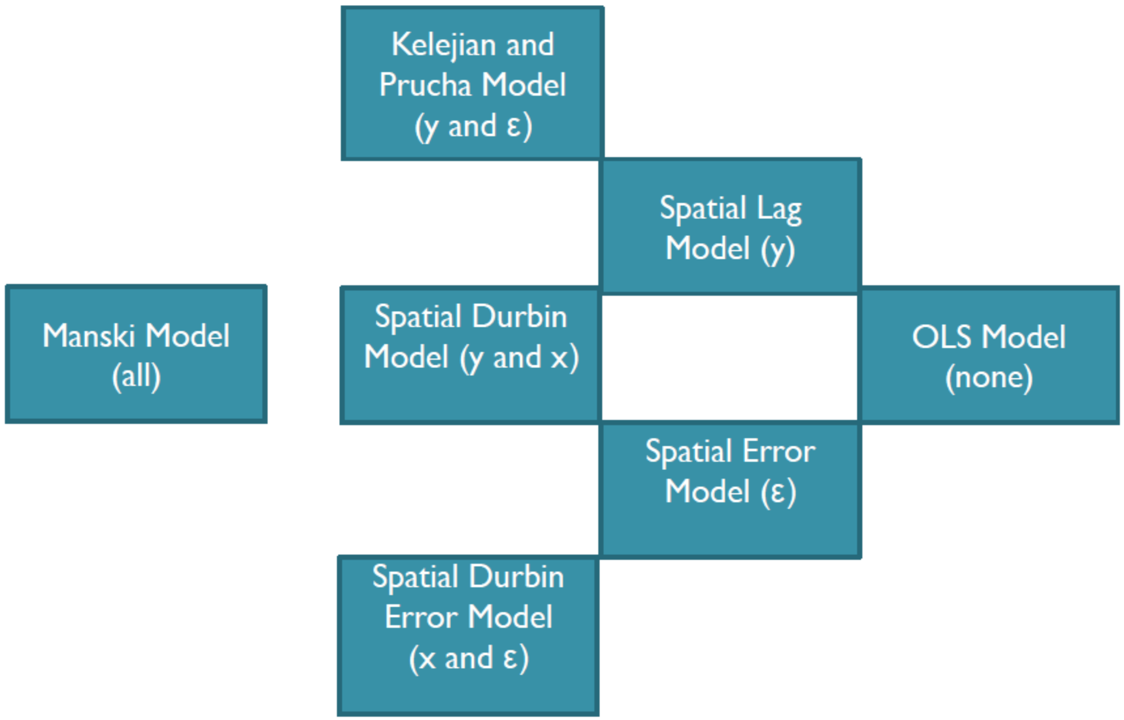
Addapted from *Lab 9..pdf* Spatial Regression. *SOC 261, Spring 2005.* Spatial *Thinking in Social Science*
www.s4.brown.edu/s4/courses/SO261.../lab9.pdf

Manski regression models



Addapted from Lab 9..pdf Spatial Regression. *SOC 261, Spring 2005.* Spatial *Thinking in Social Science*
www.s4.brown.edu/s4/courses/SO261.../lab9.pdf

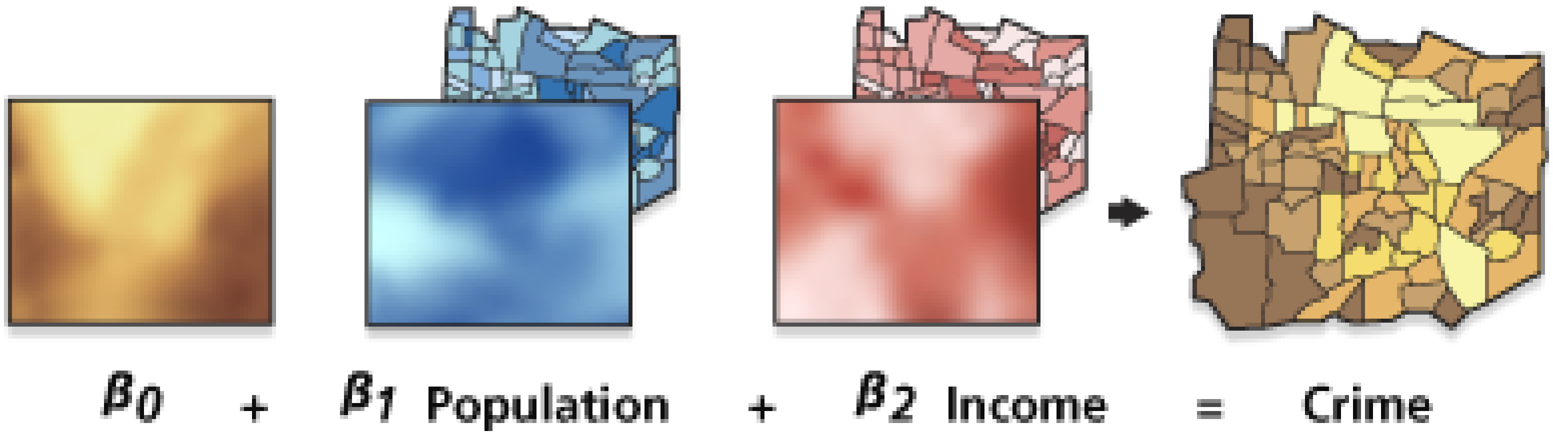
Combinations of lagged error, lagged dependent, and lagged



From: Fowler Christopher S. CSDE Statistics Workshop 3.5.2011
University of Washington Center for Studies in Demography and Ecology

http://csde.washington.edu/services/gis/workshops/Resources/SPREG_Presentation.pdf

Geographically Weighted Regression (GWR)



http://webhelp.esri.com/arcgisdesktop/

Linear regression models

$$y_i = \beta_0 + \sum_{k=1,m} \beta_k X_{ik} + \varepsilon_i$$

Geographically Weighted Regression (GWR)

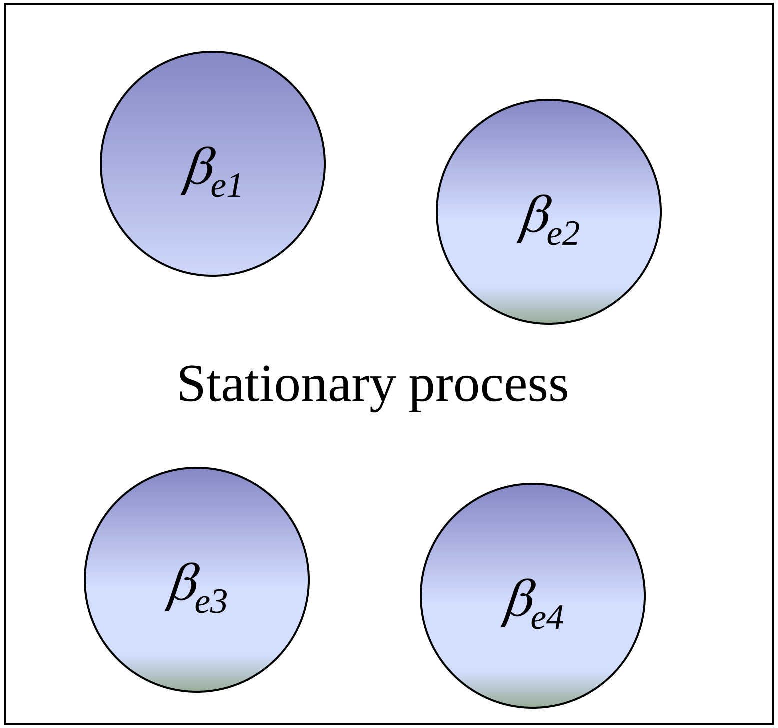
$$y_i = \beta_{i0} + \sum_{k=1,m} \beta_{ik} X_{ik} + \varepsilon_i$$

Brunsdon C et al. *Geographical Analysis*, ***28 (4); 1996***

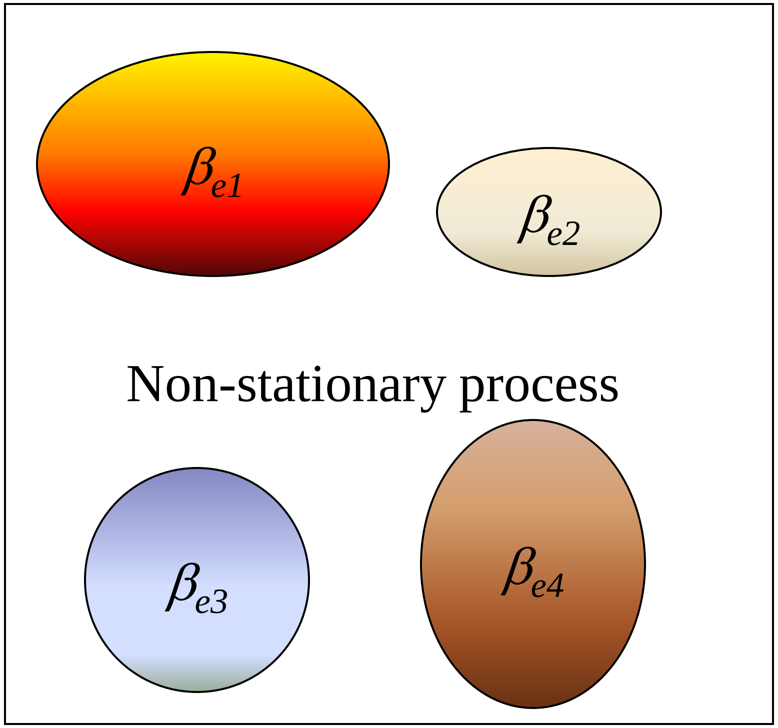
Stationary v.s. non-stationary

$y_i = \beta_0 + \beta_1 x_{1i}$

$y_i = \beta_{i0} + \beta_{i1} x_{1i}$

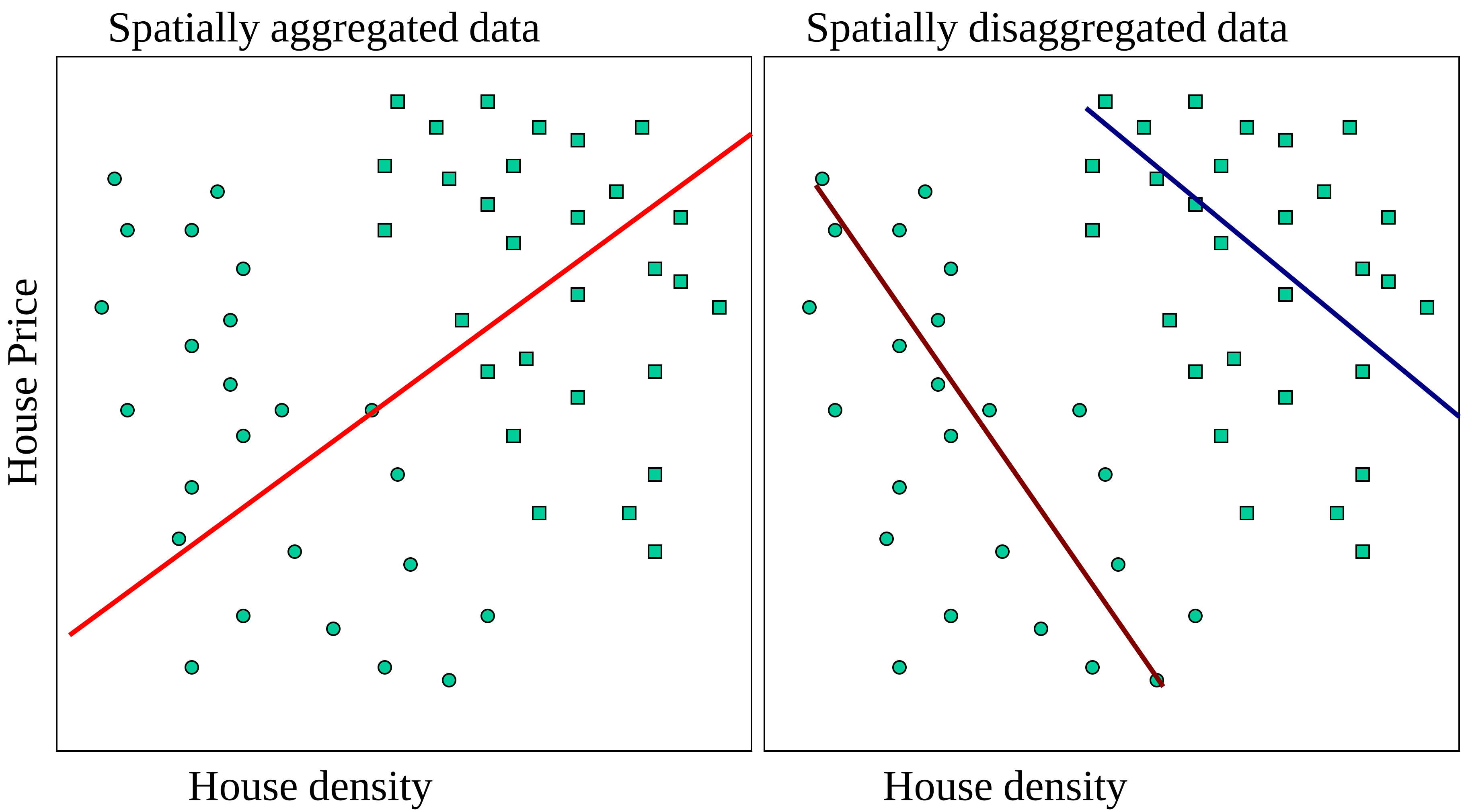


Assumed



More realistic

Simpson's paradox



Global v.s. local statistics

- Global statistics
  - Similarity across space
  - Single-valued statistics
  - Not mappable
  - GIS “unfriendly”
  - Search for regularities
  - Aspatial
- Local statistics
  - Difference across space
  - Multi-valued statistics
  - Mappable
  - GIS “friendly”
  - Search for exceptions
  - Spatial

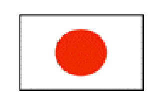
From Geographically weighted regression
By Danlin Yu Yehua Dennis Wei Dept. of Geog., UWM

Spatial Regression

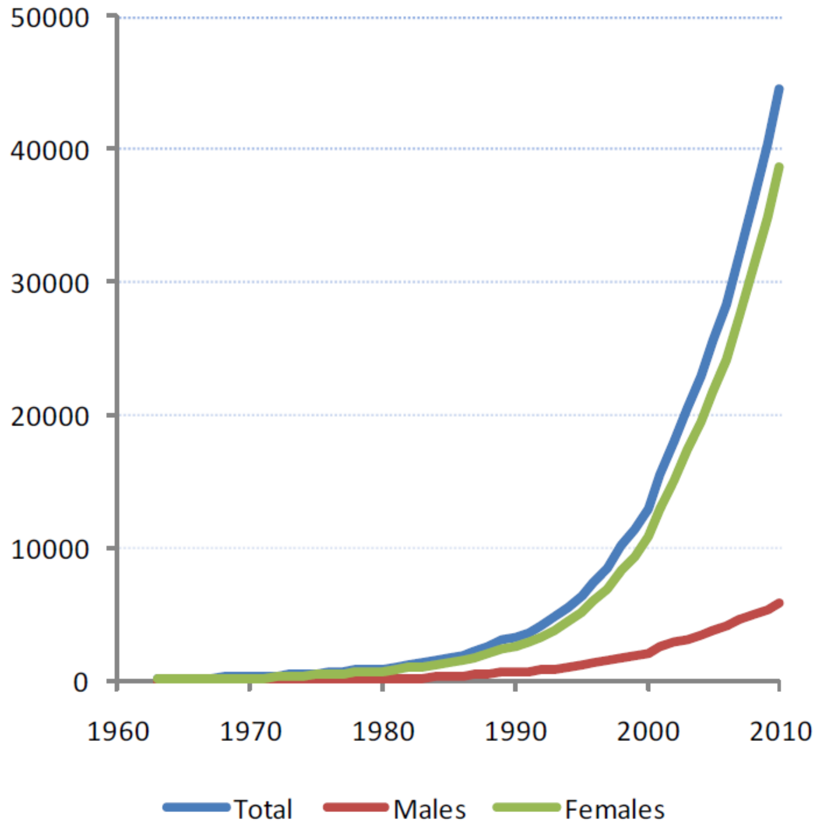
Steps in determining the extent of spatial autocorrelation in your data and running a spatial regression:

1. Choose a neighborhood criterion
   - Which areas are linked?
2. Assign weights to the areas that are linked
   - Create a spatial weights matrix
3. Run statistical test to examine spatial autocorrelation
4. Run an OLS regression
5. Run a spatial regression(s)
   - By applying weights matrices

Plan

1. Background
2. Spatial data
3. Spatial Autocorrelation / Neighbour
4. Spatial regressions
5. Centenarian rates and climate conditions 

Number of centenarians in Japan



N = **44’449** in 2010

N ~ **30’000** in 2005

Y. Saito *et al.*, *Demographic Research* ***26, 239-252 (2012).***

Experimental Gerontology 47 (2012) 660–671

Contents lists available at SciVerse ScienceDirect

Experimental Gerontology

journal homepage: www.elsevier.com/locate/expgero

Exploring the impact of climate on human longevity

Jean-Marie Robine [a,*], François R. Herrmann [b], Yasumichi Arai [c], D. Craig Willcox [d,e,f], Yasuyuki Gondo [g], Nobuyoshi Hirose [c], Makoto Suzuki [d,e,h], Yasuhiko Saito [i]

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[e] Okinawa Research Center for Longevity Science, Urasoe, Japan
[f] Department of Research, Kuakini Medical Center, HI, USA
[g] Osaka University, Graduate School of Human Sciences, Clinical Thanatology and Geriatric Behavioral Science, Osaka, Japan
[h] Faculty of Medicine, University of the Ryukyus, Nishihara, Japan
[i] Nihon University Advanced Research Institute for the Sciences and Humanities, Tokyo, Japan

Question

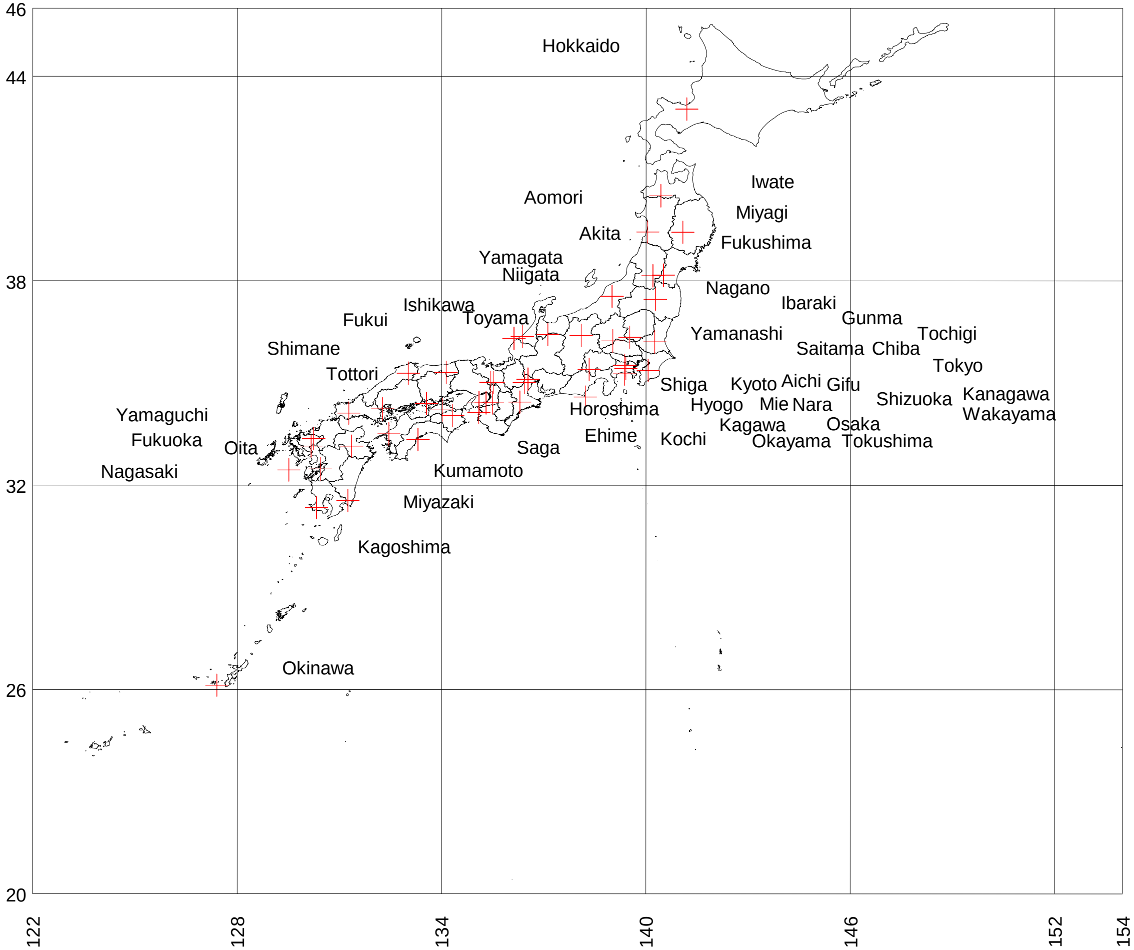
What is the impact of physical geographic factors and climate conditions on human longevity?

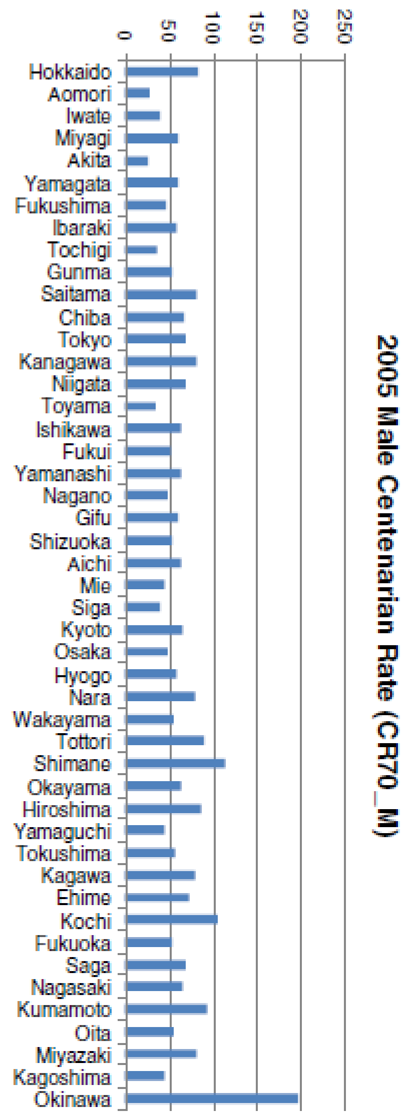
Robine JM, Herrmann FR, Arai Y, Willcox DC, Gondo Y, Hirose N, Suzuki M, Saito Y. *Exp Gerontol 2012;**47(9):660-71.***

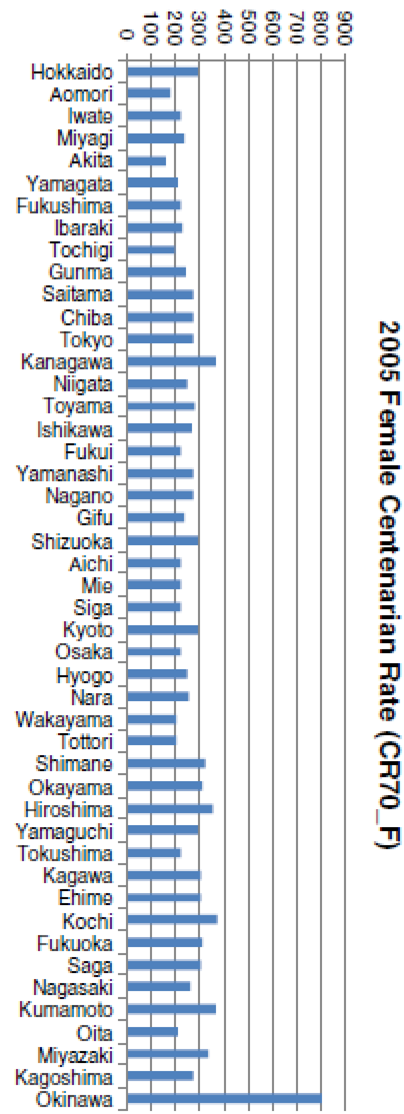
Methods

$$\text{Centenarian prevalence} = \frac{\text{Number centenarians}}{\text{Total population}}$$

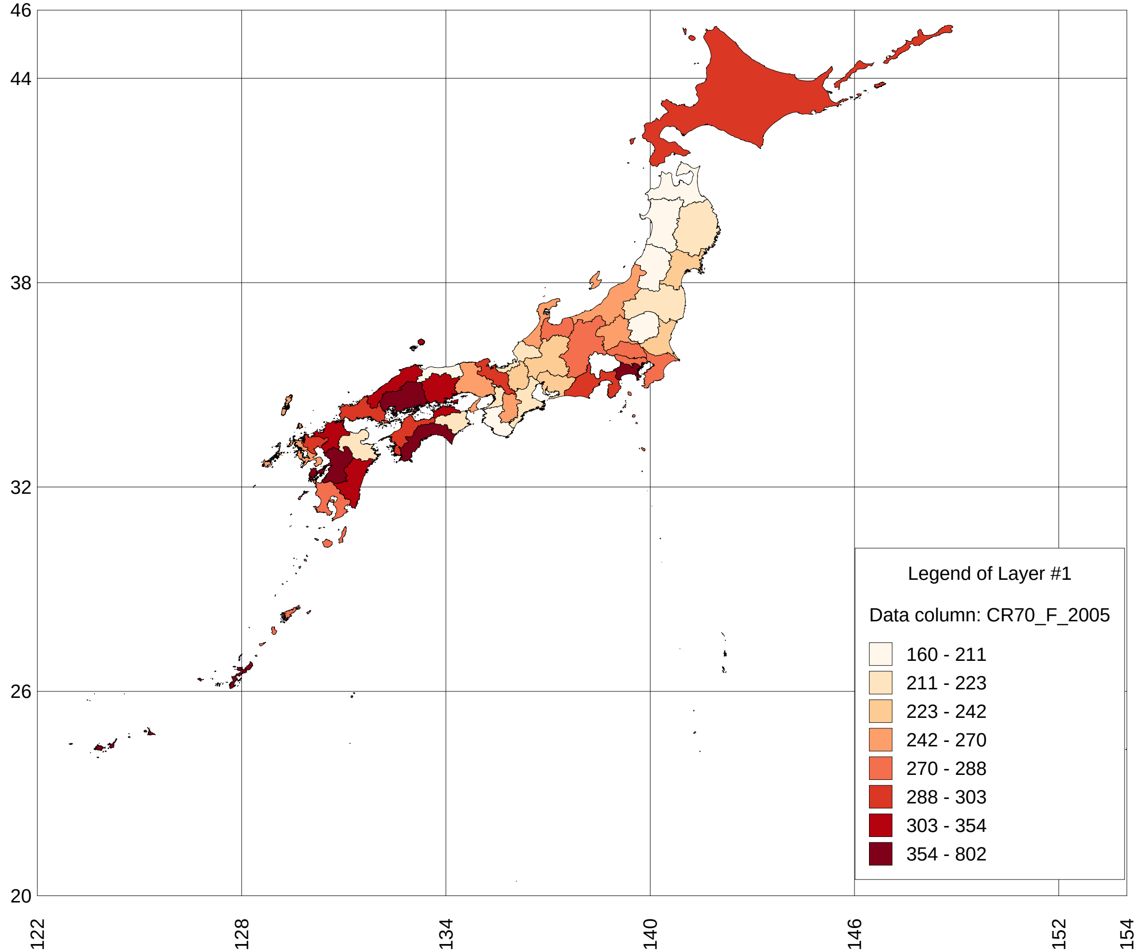
Japan 47 prefectures



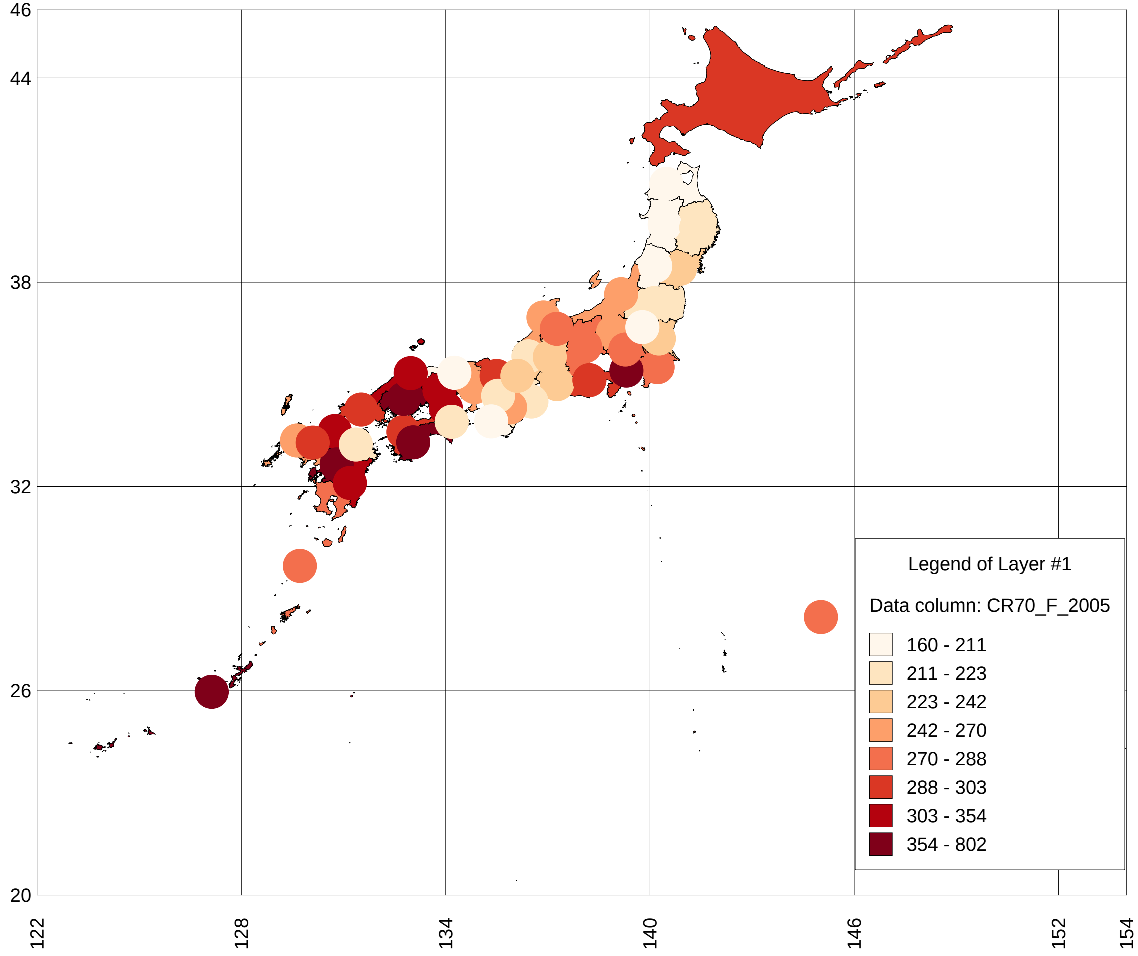

2005 Male Centenarian Rate (CR70_M)
0
50
100
150
200
250


2005 Female Centenarian Rate (CR70_F)
0
100
200
300
400
500
600
700
800
900

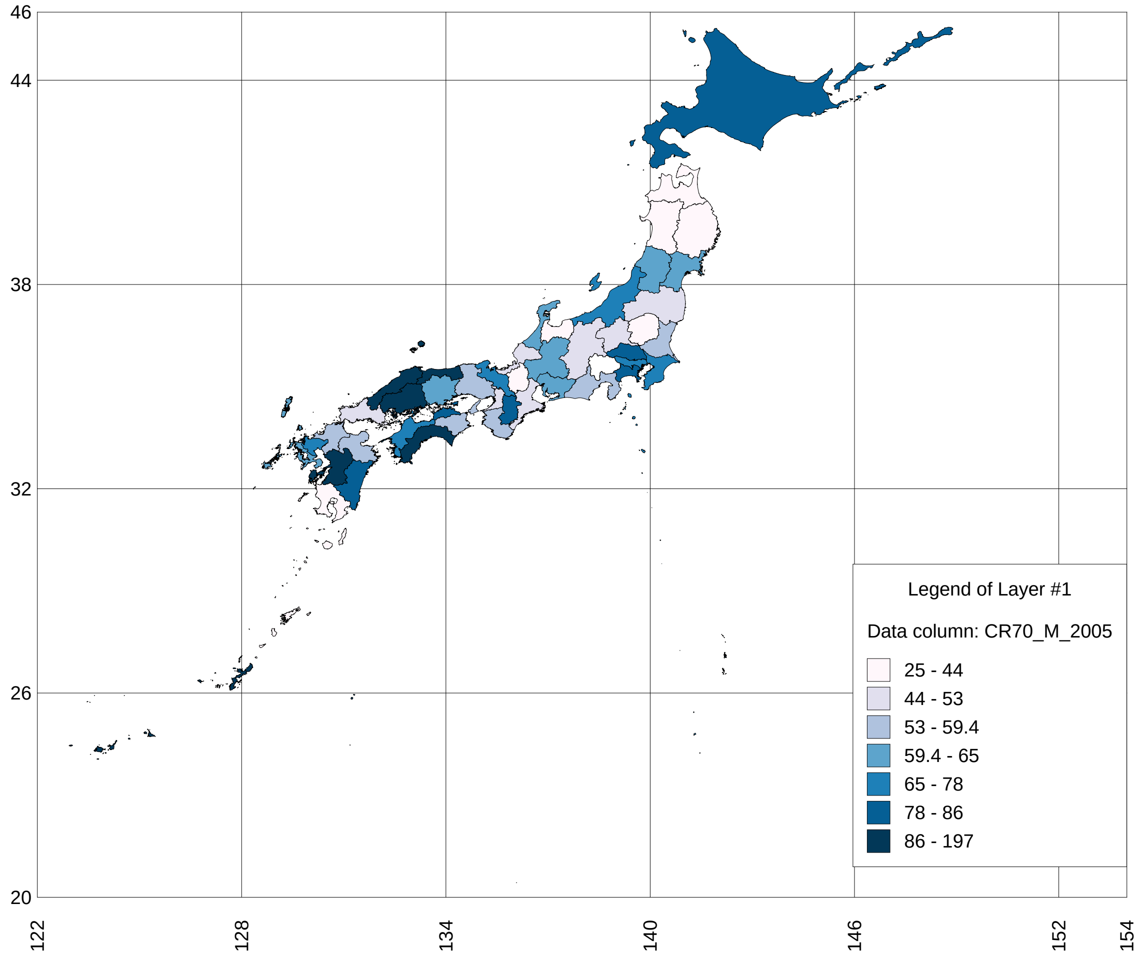
Female centenarian rate (CR_{70})



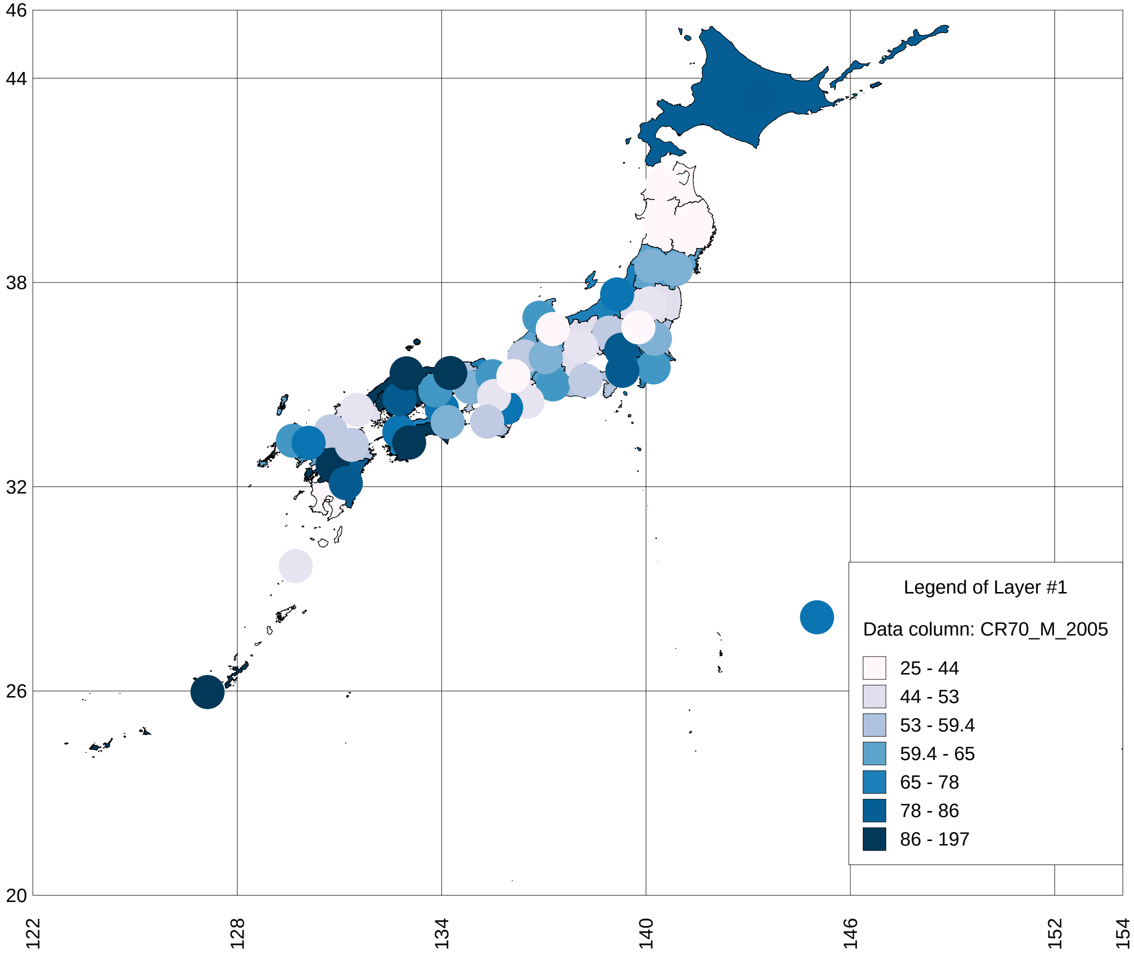
Female centenarian rate (CR_{70})



Male centenarian rate (CR_{70})



Male centenarian rate (CR_{70})



31 Independent variables

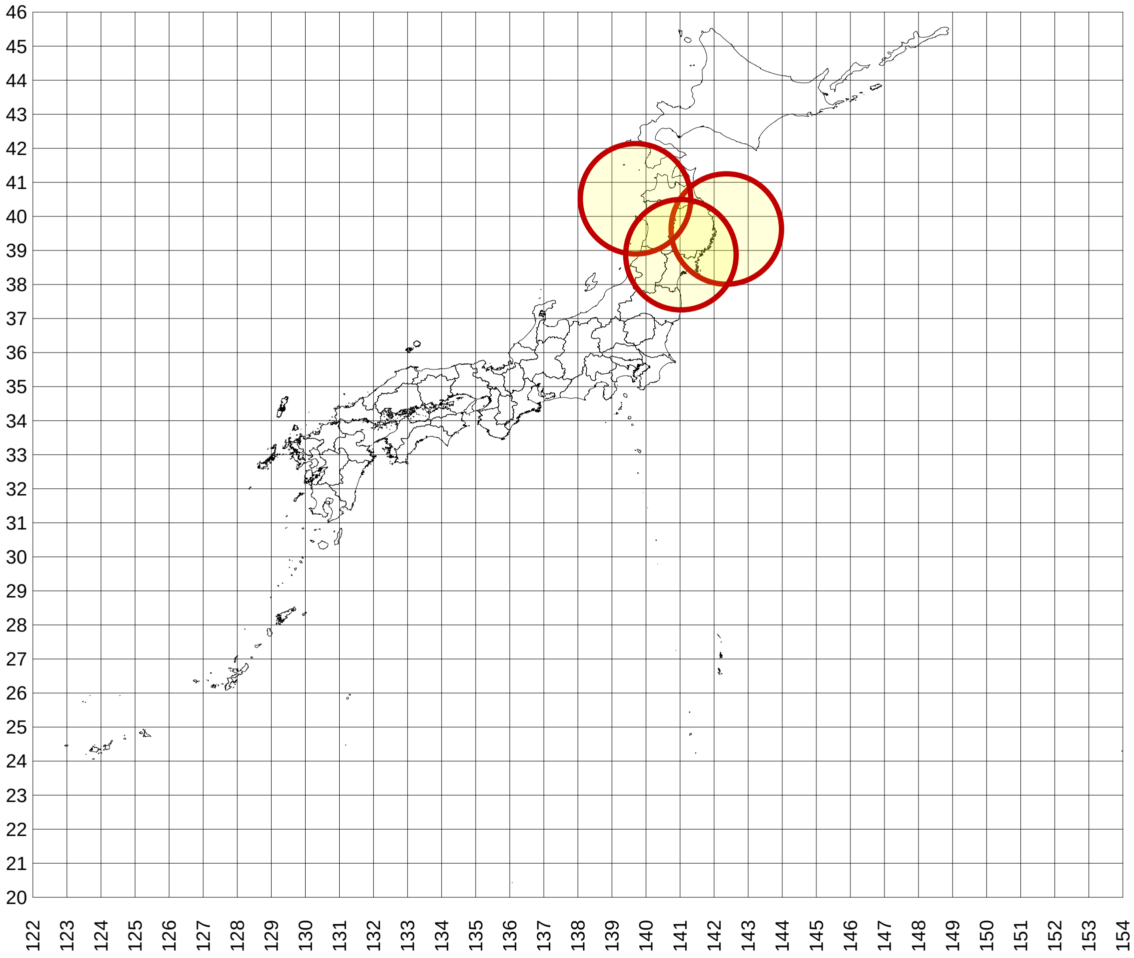
In 2005

- 3 Locations parameters (latitude, longitude, altitude)
- 4 physical and geographical factors (surface area occupied by mountains, hill land, upland and lowland)
- 8 land use and agriculture (forests, pastures, grasslands, rice, wheat, etc,…)
- 14 climate conditions (temperature, humidity, snowy days, etc..)
- Income per capita

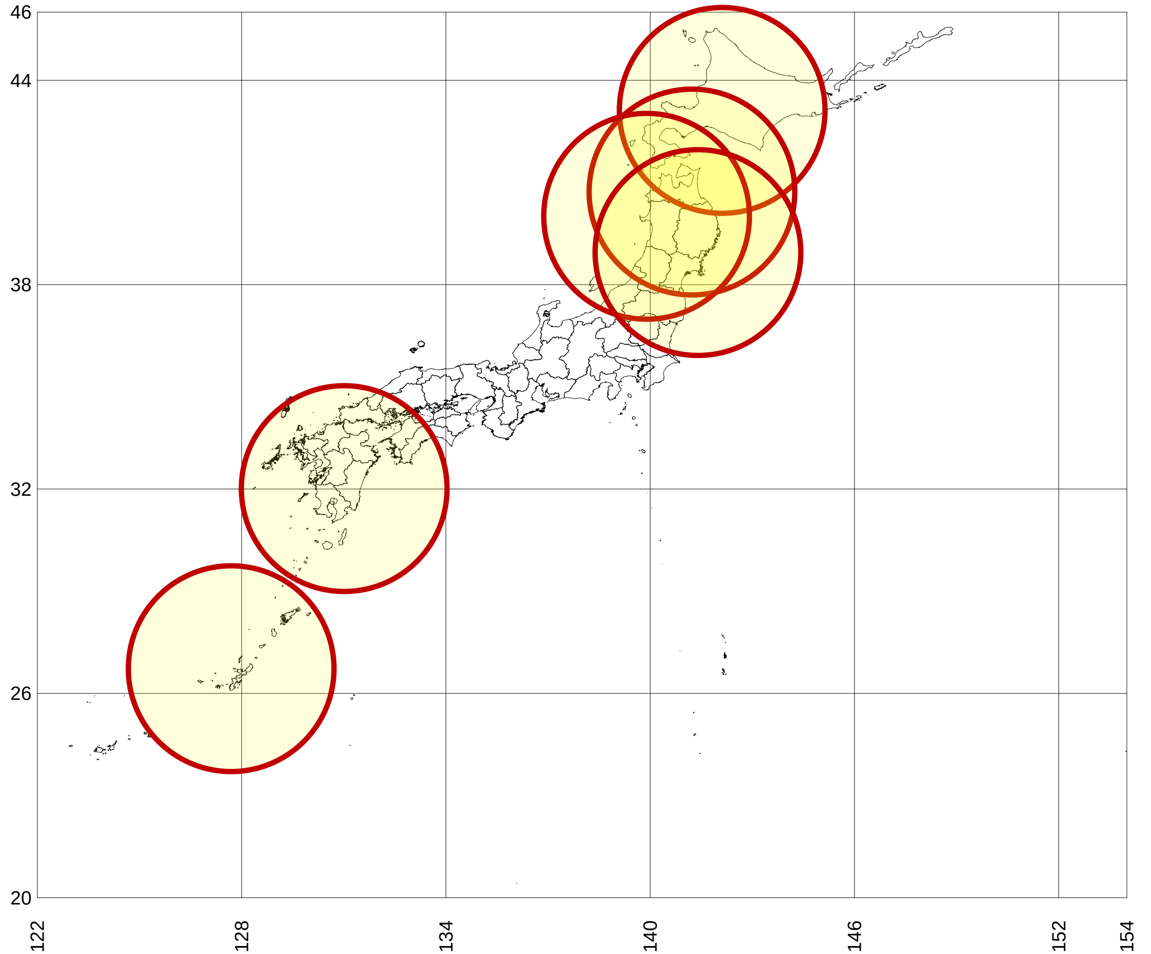
In 1900

- Infant mortality rate (IMR)

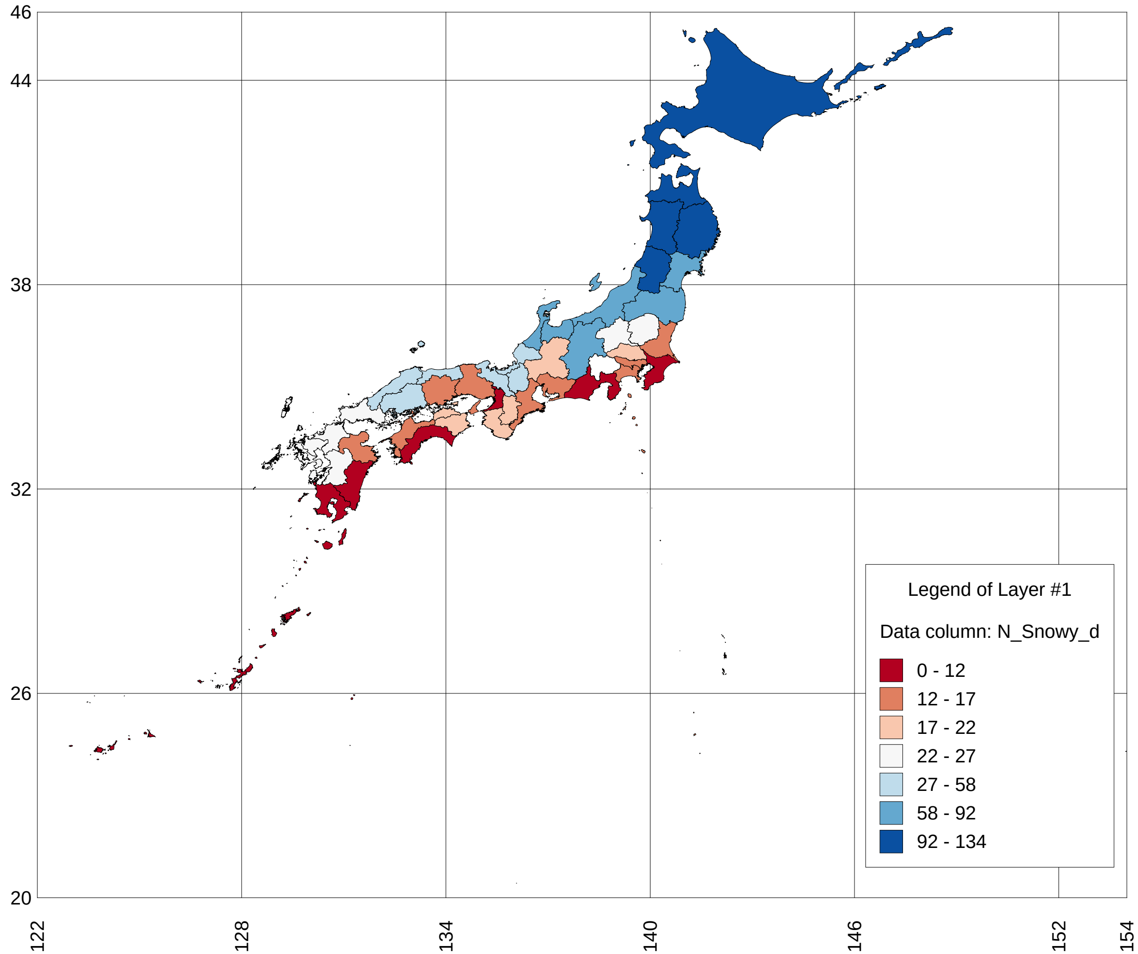
Distance bands (0-3)



Distance bands (0-6)



Number of snowy days



of Snowy day

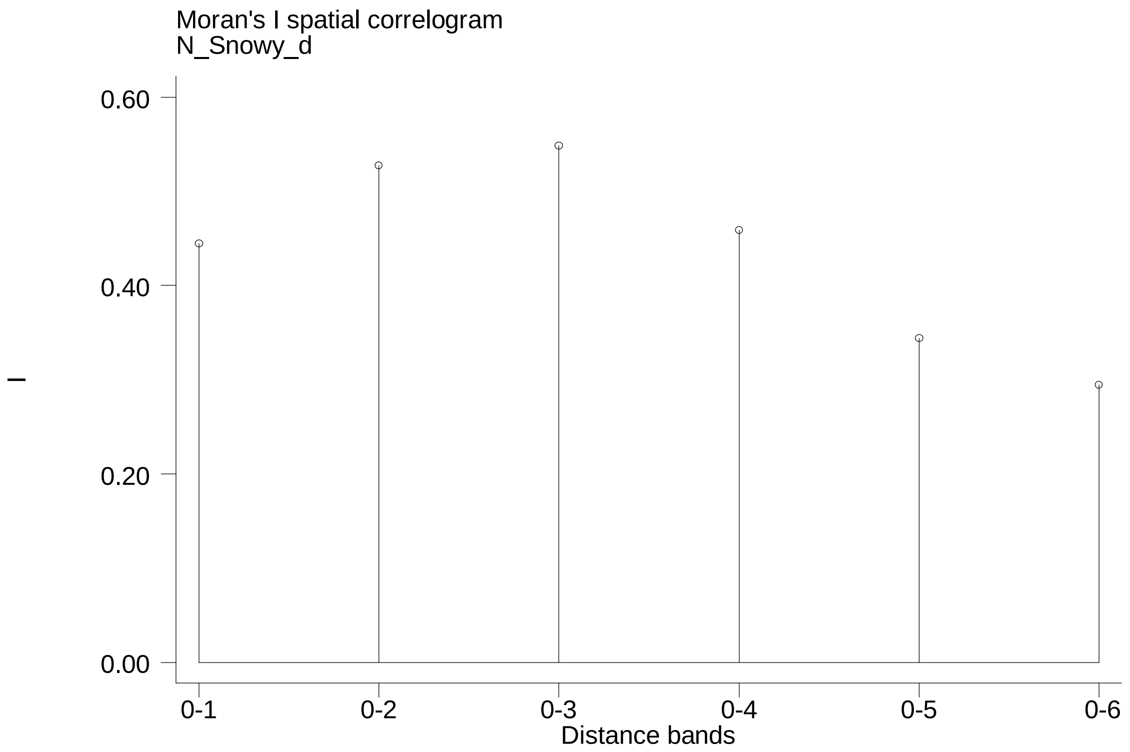
Moran's I spatial correlogram

N_Snowy_d

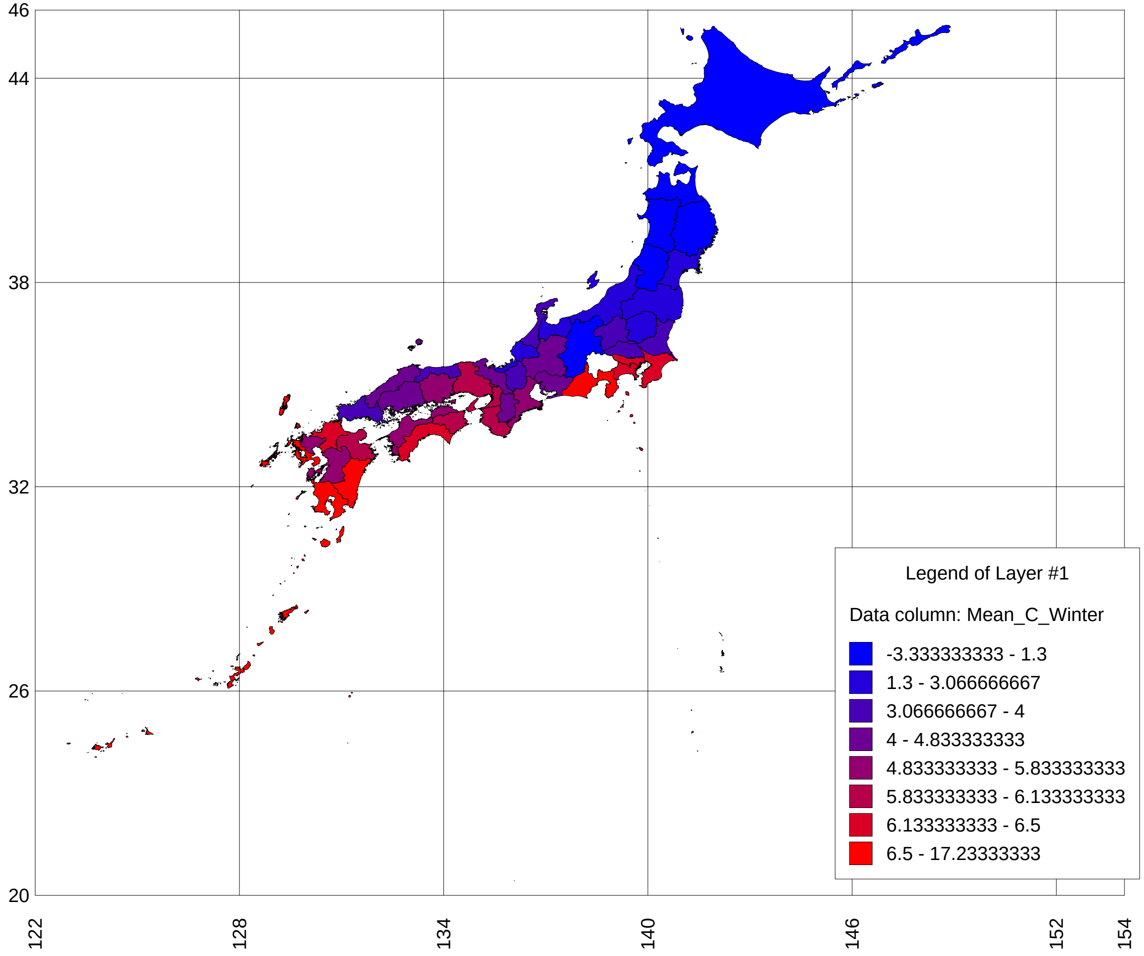
Distance bands	I	E(I)	sd(I)	z	p-value*
(0-1]	0.444	-0.022	0.144	3.248	0.001
(0-2]	0.528	-0.022	0.067	8.148	0.000
(0-3]	**0.548**	-0.022	0.052	10.883	0.000
(0-4]	0.459	-0.022	0.039	12.450	0.000
(0-5]	0.344	-0.022	0.030	12.313	0.000
(0-6]	0.295	-0.022	0.032	10.007	0.000

*1-tail test

Moran's I spatial correlogram



Mean winter temperature



Stepwise spatial lag regression models explaining variability in female centenarian rates (CR_{70})

Step	Variable entered	Sign of β	Partial R^2	Model R^2	p
(i) All prefectures [47]					
1	Mean winter temperature	+	0.492	0.492	<.0001
2	Snowy weather days	+	0.119	0.611	0.0001
3	Average pressure	-	0.053	0.664	0.006
4	Infant mortality rates 1900	-	0.037	0.702	0.024
5	Maximum wind speed	-	0.027	0.729	0.027
6	Proportion hill land	+	0.044	0.773	0.002
7	Maximum precipitation per day	+	0.021	0.794	0.030

Distance bands : 0-6 degree when n=47

Stepwise spatial lag regression models explaining variability in male centenarian rates (CR_{70})

Step	Variable entered	Sign of β	Partial R^2	Model R^2	p
(i) All prefectures [47]					
1	Mean winter temperature	+	0.491	0.491	<.0001
2	Per capita income (1000 yen)	-	0.052	0.543	0.015
3	% Rice	-	0.045	0.588	0.031
4	Maximum wind speed	-	0.017	0.605	0.114
5	Snowy weather days	+	0.012	0.616	0.083

Distance bands : 0-6 degree when n=47

Table 9
Stepwise spatial lag regression models explaining variability in centenarian rates (CR70) by physical geographical factors, climate conditions, land use and socio-economical conditions (Per capita income 2005, infant mortality rates 1900) (Final model).

Female Centenarian Rate (CR70)

Step	Variable entered	Sign of β	Partial R^2	Model R^2	p	rho	p(LM)
(i) All prefectures [47]							
1	Winter_T	+	0.492	0.492	<0.0001	−0.535	0.348
2	Snowy_D	+	0.119	0.611	0.0001	−0.241	0.630
3	Pressure	−	0.053	0.664	0.006	−0.173	0.694
4	IMR_1900	−	0.037	0.702	0.024	−0.521	0.316
5	Max_W_Sp	−	0.027	0.729	0.027	−0.465	0.347
6	% Hill land	+	0.044	0.773	0.002	−0.320	0.478
7	Max_Rain	+	0.021	0.794	0.030	−0.417	0.350
(ii) Without Okinawa and Hokkaido [45]							
1	Highest_T	+	0.334	0.334	0.021	0.587	<.001
2	% Hill Land	+	0.060	0.394	0.044	0.622	<.001
3	IMR_1900	−	0.027	0.421	0.041	0.441	0.039
4	% Rice	−	0.035	0.456	0.074	0.393	0.070
5	% Grassland	−	0.026	0.482	0.125	0.383	0.074

Male Centenarian Rate (CR70)

Step	Variable entered	Sign of β	Partial R_square	Model R_square	p	rho	p(LM)
(i) All prefectures [47]							
1	Winter_T	+	0.491	0.491	<0.0001	−1.036	0.033
2	nIncome_PC	−	0.052	0.543	0.015	−0.961	0.047
3	% Rice	−	0.045	0.588	0.031	−1.038	0.030
4	Max_W_Sp	−	0.017	0.605	0.114	−0.963	0.043
5	Snowy_D	+	0.012	0.616	0.083	−0.631	0.222
(ii) Without Okinawa and Hokkaido [45]							
1	T_snow	−	0.218	0.218	0.025	0.354	0.225
2	Income_PC	−	0.071	0.289	0.035	0.373	0.212
3	% Pastures	−	0.046	0.336	0.062	0.304	0.330
4	% Rice	−	0.044	0.379	0.061	0.201	0.544

CR70 Absolute Gender Gap (AGG)

Step	Variable entered	Sign of β	Partial R_Square	Model R_Square	p	rho	p(LM)
(i) All prefectures [47]							
1	Winter_T	+	0.441	0.441	<.0001	−0.085	0.879
2	Snowy_D	+	0.138	0.579	0.000	0.040	0.935
3	Altitude	+	0.072	0.651	0.002	0.015	0.972
4	IMR_1900	−	0.037	0.688	0.022	−0.343	0.524
5	% Hill land	+	0.034	0.722	0.015	−0.279	0.587
6	Max_W_Sp	−	0.046	0.768	0.002	−0.199	0.670
7	Max_Rain	+	0.023	0.791	0.027	−0.331	0.486
8	Clear_D	+	0.012	0.803	0.104	−0.433	0.367
(ii) Without Okinawa and Hokkaido [45]							
1	Highest_T	+	0.277	0.277	0.045	0.545	0.001
2	% Hill Land	+	0.071	0.348	0.033	0.582	<.0001
3	IMR_1900	−	0.067	0.415	0.007	−0.313	0.177

CR70 Relative Gender Gap (RGG)

Step	Variable entered	Sign of β	Partial R_Square	Model R_Square	p	rho	p(LM)
(i) All prefectures [47]							
1	T_snow	+	0.109	0.109	0.021	−0.298	0.446
2	IMR_1900	−	0.066	0.175	0.067	−0.470	0.256
3	% Rice	+	0.060	0.235	0.052	−0.441	0.275
4	Income_PC	+	0.052	0.286	0.052	−0.272	0.493
(ii) Without Okinawa and Hokkaido [45]							
1	T_snow	+	0.154	0.154	0.009	0.125	0.754
2	IMR_1900	−	0.065	0.219	0.052	0.078	0.843
3	Income_PC	+	0.085	0.304	0.022	0.210	0.582
4	% Pastures	+	0.047	0.351	0.063	0.116	0.775
5	% Pulses	+	0.056	0.407	0.038	−0.011	0.980

Distance bands : 0-6 degree when n=47, 0-3 degree when n=45

Rho

- Rho reflects the spatial dependence inherent in the data, measuring the average influence on observations by their neighboring observations.

LM

Lagrange multiplier test was used to test whether the spatial lag regression model differs statistically from a linear model.

Summary

About ¾ of the variance in CR70 for females and ½ for males are explained by the physical environment and land use, even when variations in the level of socio-economic status between prefectures are controlled.

Climate conditions like warm winter are associated with longevity.

Perspective

- Spatial demography

DEMOGRAPHIC RESEARCH
A peer-reviewed, open-access journal of population sciences

DEMOGRAPHIC RESEARCH

VOLUME 28, ARTICLE 10, PAGES 271-312
PUBLISHED 13 FEBRUARY 2013
http://www.demographic-research.org/Volumes/Vol28/10/
DOI: 10.4054/DemRes.2013.28.10

Research Article

Progress in Spatial Demography

Stephen A. Matthews

Daniel M. Parker

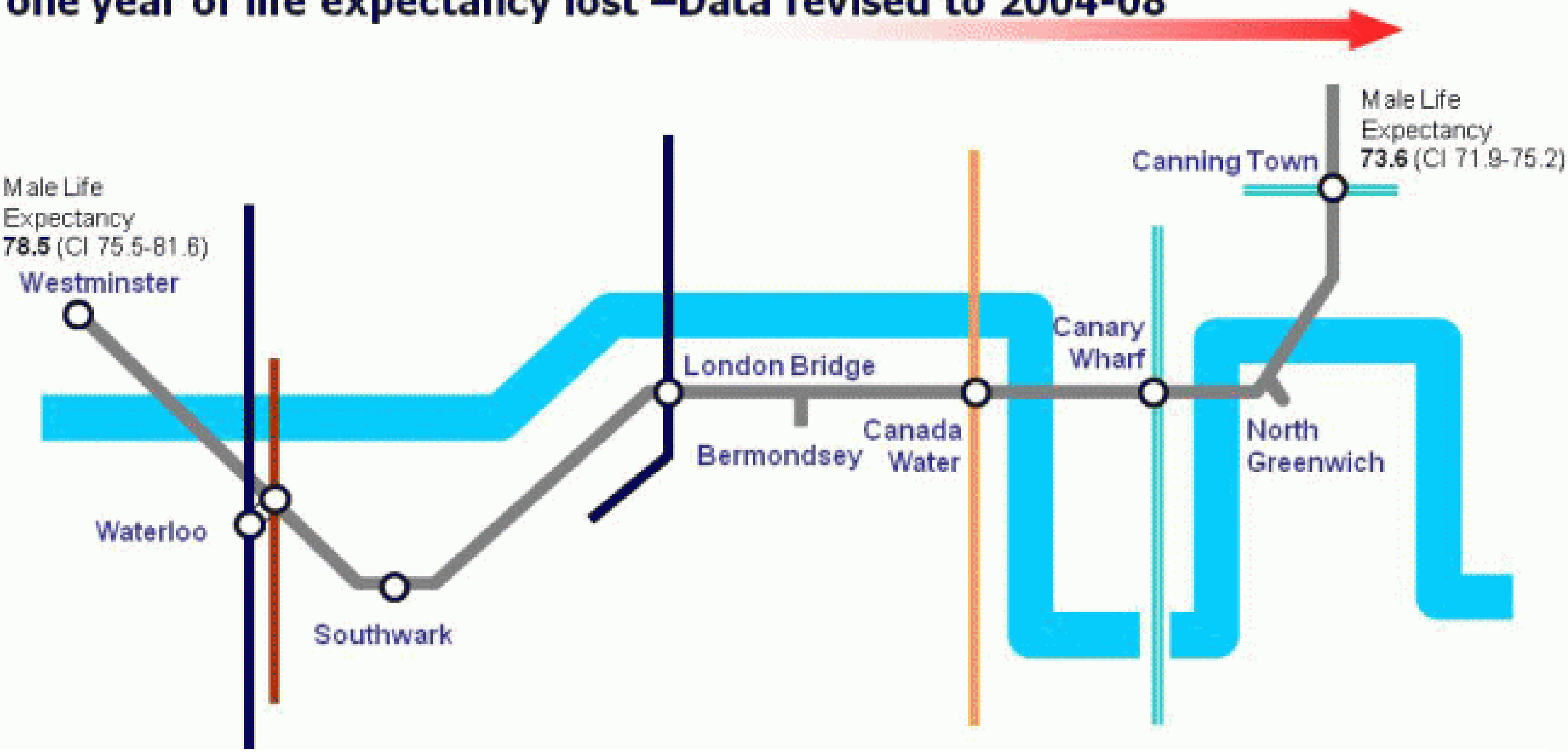
This publication is part of the Special Collection on “Spatial Demography”, organized by Guest Editor Stephen A. Matthews.

Perspective

- Spatial demography
- Time can also be added to spatial model
- HLE should also be measured at local levels and analyzed using spatial regression techniques

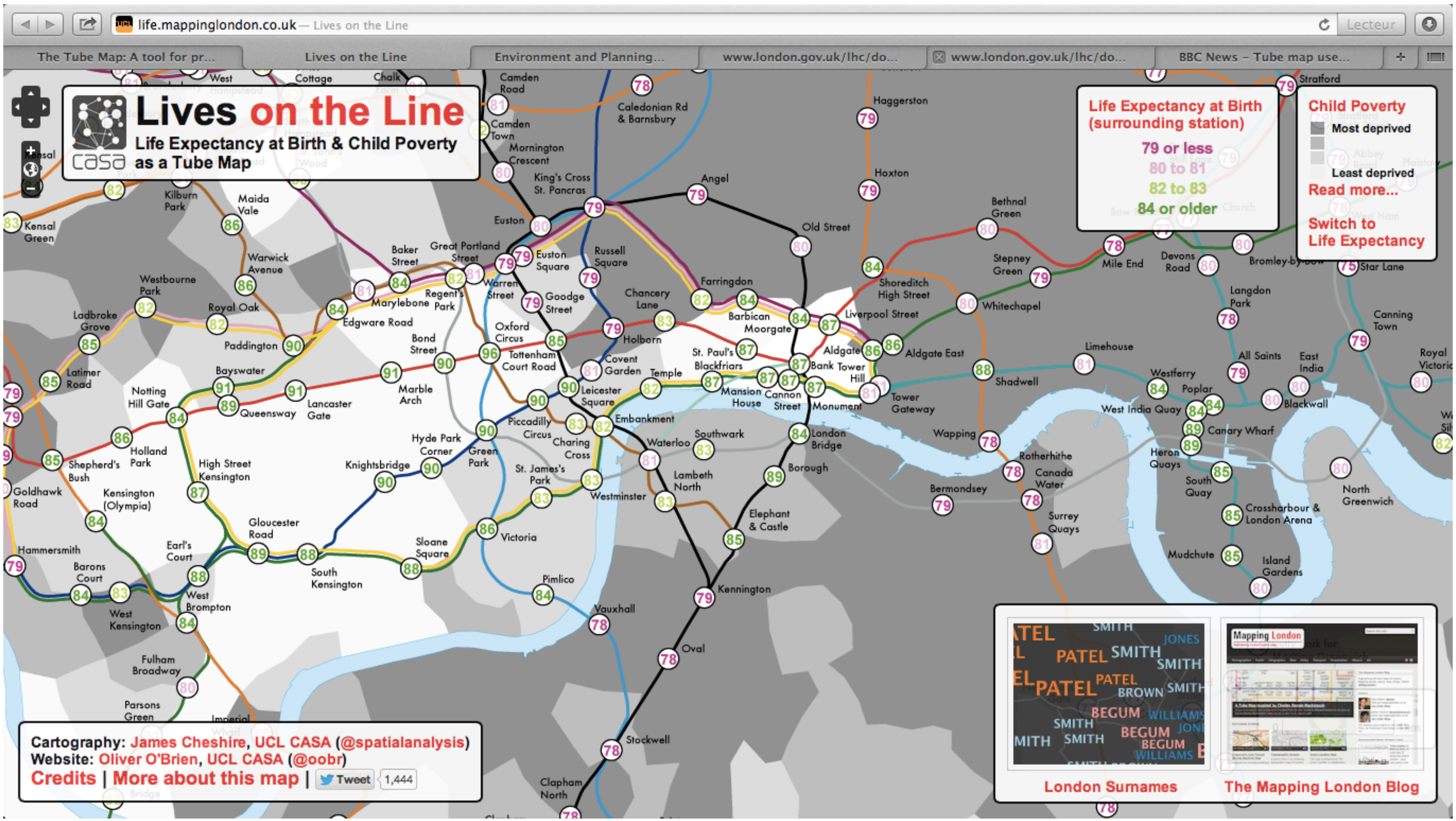
Differences in Male Life Expectancy within a small area in London

Travelling east from Westminster, every two tube stops represent over one year of life expectancy lost –Data revised to 2004-08



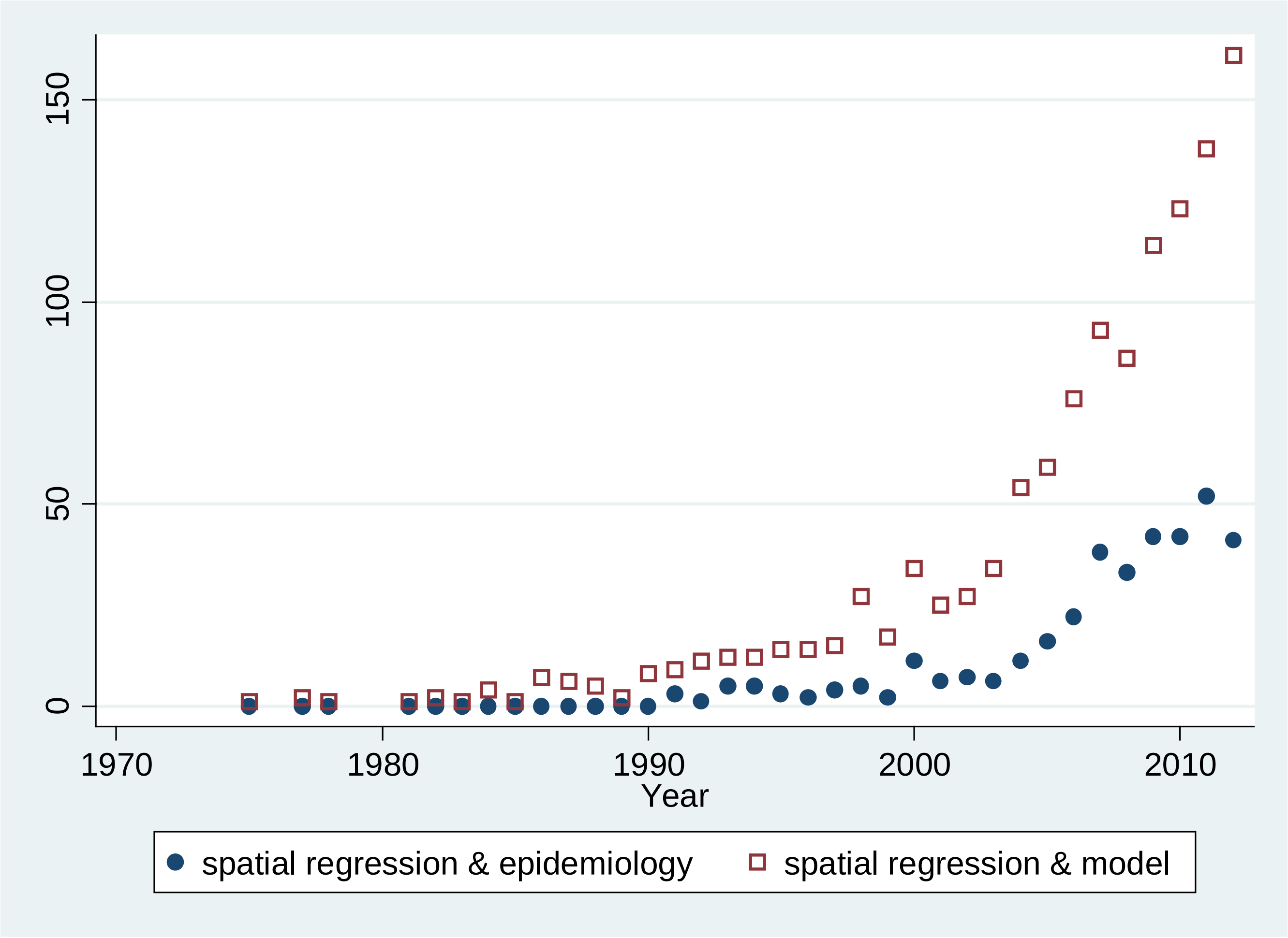
Atkinson S, 2006 Health Inequalities in London: Where Are We Now?,
http://www.london.gov.uk/lhc/docs/publications/healthinlondon/2006/Section02.pdf

Cheshire, J. 2012. Lives on the Line: Mapping Life Expectancy Along the London Tube Network. *Environment and Planning A*. 44 (7). Doi: 10.1068/a45341.



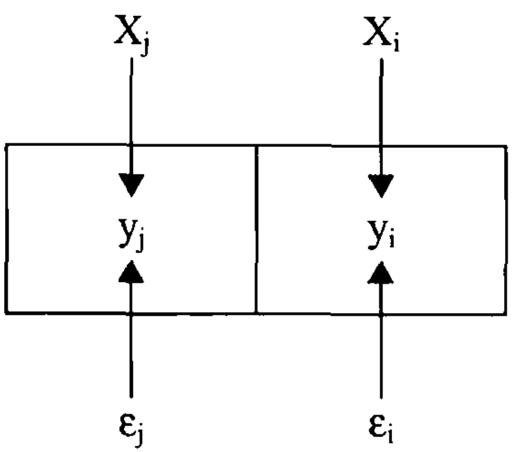
http://life.mappinglondon.co.uk

Bibliometry (Medline 11.2.2013)



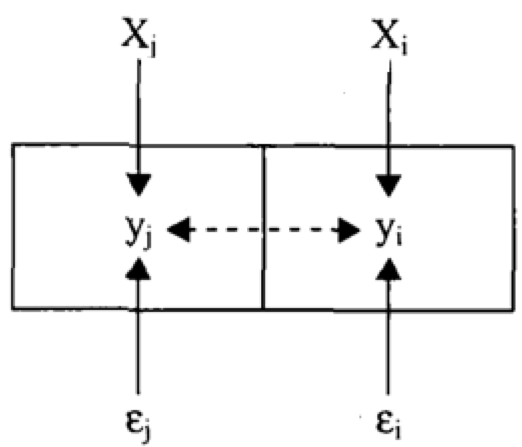
Spatial Lag and Spatial Error Models: Conceptual Comparison

Ordinary Least Squares



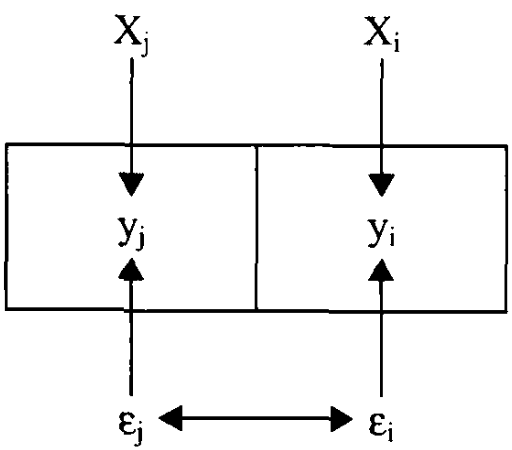
No influence from neighbors

Spatial lag



Dependent variable influenced by neighbors

Spatial error



Residuals influenced by neighbors

Baller, R., L. Anselin, S. Messner, G. Deane and D. Hawkins. 2001. *Structural covariates of US County homicide rates: incorporating spatial effects*,. Criminology , 39, 561-590