Spatial Analysis and Modeling (GIST 4302/5302)

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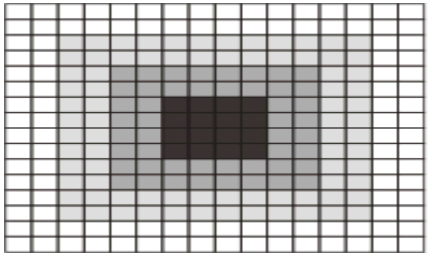
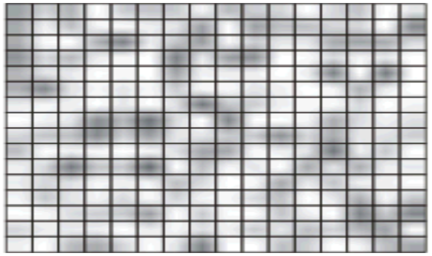
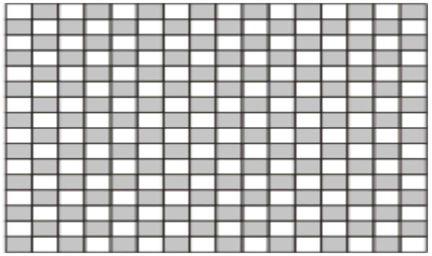
Spatial Autocorrelation

- Tobler's first law of geography
- Spatial auto/cross correlation







If like values tend to cluster together, then the field exhibits high **positive spatial autocorrelation**

If there is no apparent relationship between attribute value and location then there is **zero spatial autocorrelation**

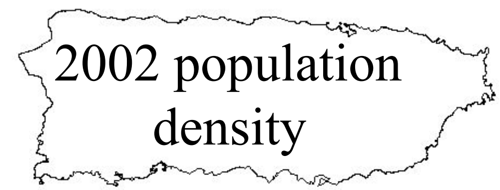
If like values tend to be located away from each other, then there is **negative spatial autocorrelation**

Spatial Autocorrelation

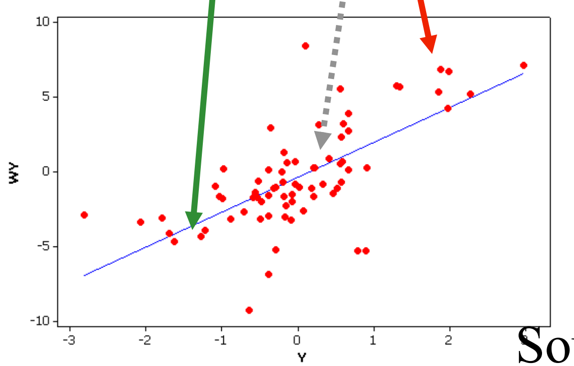
- Spatial autocorrelationship is everywhere
  - Spatial point pattern
    - K, F, G functions
    - Kernel functions
  - Areal/lattice (this topic)
  - Geostatistical data (next topic)

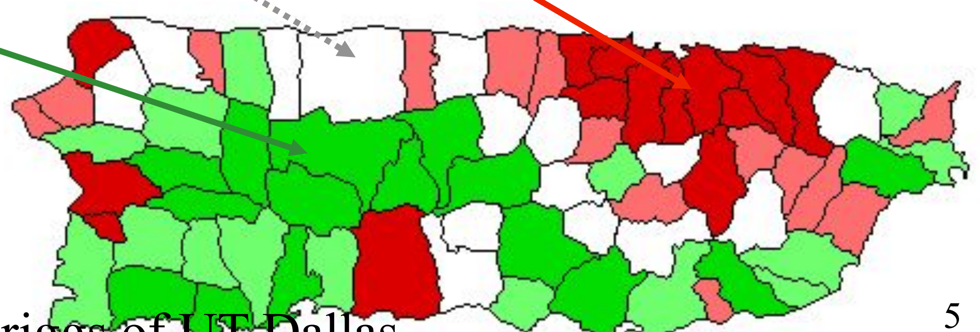
Spatial Autocorrelation of Areal Data

<u>Positive spatial autocorrelation</u>



- high values surrounded by nearby high values
- intermediate values surrounded by nearby intermediate values
- low values surrounded by nearby low values



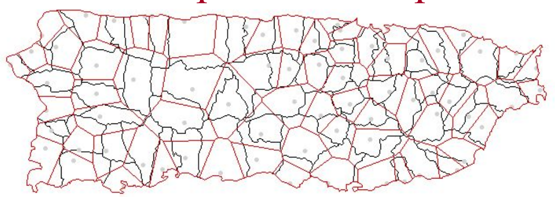


Source: Ron Briggs of UT Dallas

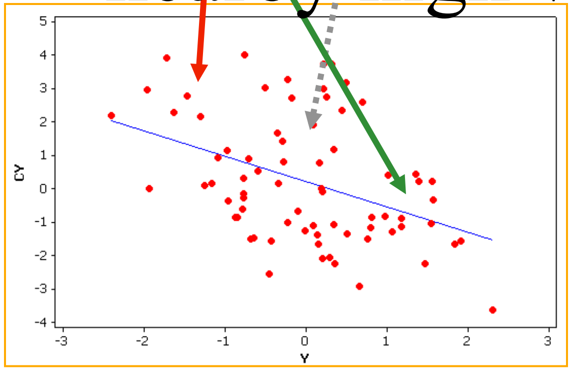
Negative spatial autocorrelation

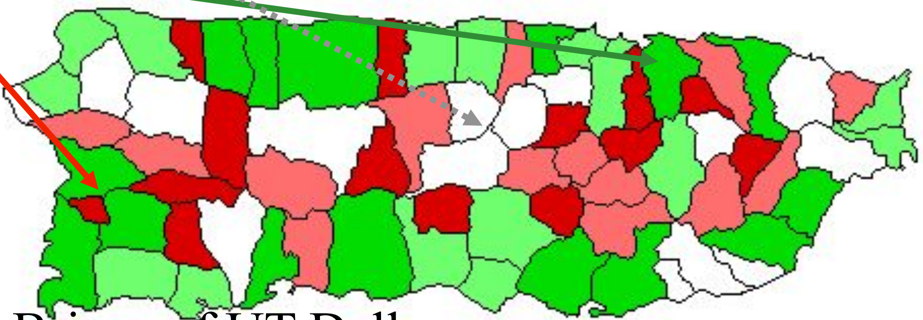
- high values surrounded by nearby low values
- intermediate values surrounded by nearby intermediate values
- low values surrounded by nearby high values

competition for space



Grocery store density





Source: Ron Briggs of UT Dallas

Measuring Spatial Autocorrelation: the problem of measuring "nearness"

To measure spatial autocorrelation, we must know the "nearness" of our observations as we did for point pattern case

- Which points or polygons are " near" or "next to" other points or polygons?
  - *Which states are near Texas?*
  - How to <u>measure</u> this?

Seems simple and obvious,

but it is not!

Spatial Weight Matrix

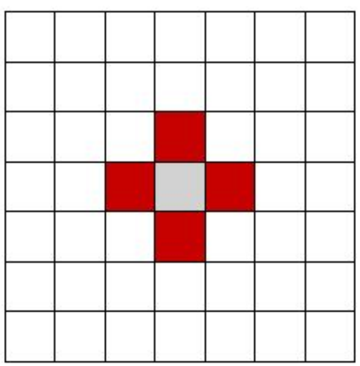
- **Core** concept in statistical analysis of areal data
- Two steps involved:
  - define which relationships between observations are to be given a nonzero weight, i.e., define spatial neighbors
  - assign weights to the neighbors

Spatial Neighbors

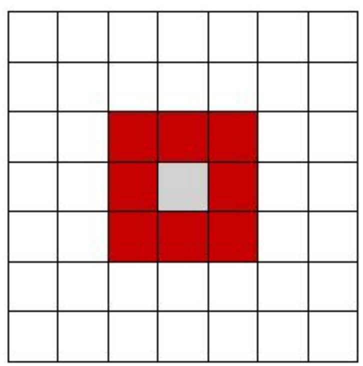
- **Contiguity-based neighbors**
  - Zone *i* and j are neighbors if zone i is contiguity or adjacent to zone *j*
  - But what constitutes contiguity?
- **Distance-based neighbors**
  - Zone i and j are neighbors if the distance between them are less than the threshold distance
  - But what distance do we use?

Contiguity-based Spatial Neighbors

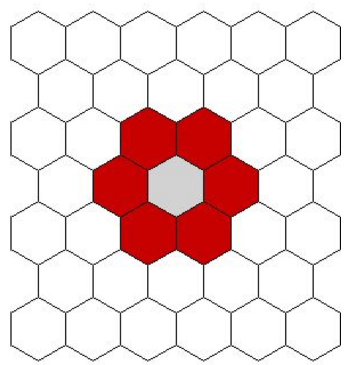
- Sharing a border or boundary
  - Rook: sharing a border
  - Queen: sharing a border or a point



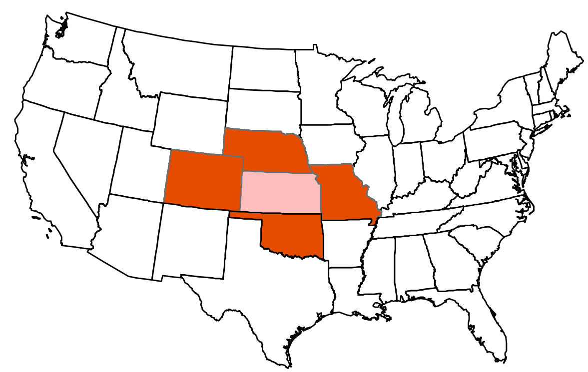
rook



queen



Hexagons

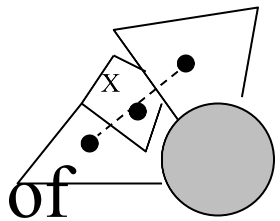


Irregular

Which use?

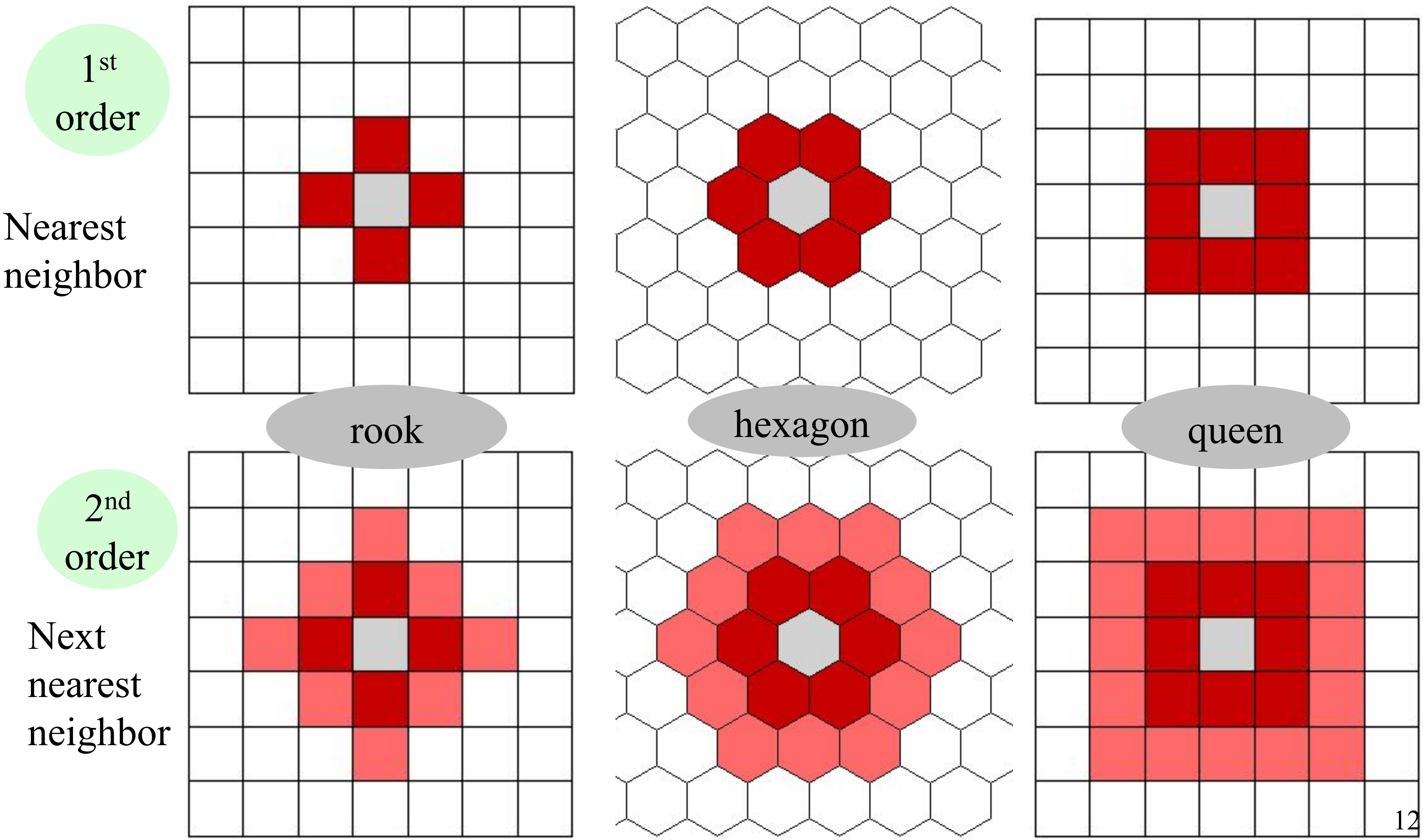
Problem Situations for Irregular Polygons

- “Close” but no common border
  - Include polygons which have a centroid within the “convex hull” for the centroids of polygons that do share a common border



- Length of border
  - Is Shanxi “as close to” Nei Mongol as to Henan?
  - Base “closeness” on proportion of shared border, not just one (1) or zero (0)
  - $w_{ij} = border\ length_{ij} / border\ length_j)$

Higher-Order Contiguity



Distance-based Neighbors

- How to measure distance between polygons?
- Distance metrics
  - 2D Cartesian distance (projected data)
  - 3D spherical distance/great-circle distance (lat/long data)
    - Haversine formula

Haversine formula:

$$a = \sin^2(\Delta\varphi/2) + \cos(\varphi_1).\cos(\varphi_2).\sin^2(\Delta\lambda/2)$$

$$c = 2.\mathrm{atan2}(\sqrt{a}, \sqrt{(1-a)})$$

$$d = R.c$$

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km)

Distance-based Neighbors

- k-nearest neighbors

Fig. 9.5. (**a**) $k = 1$ neighbours; (**b**) $k = 2$ neighbours; (**c**) $k = 4$ neighbours

Source: Bivand and Pebesma and Gomez-Rubio

Distance-based Neighbors

- thresh-hold distance (buffer)

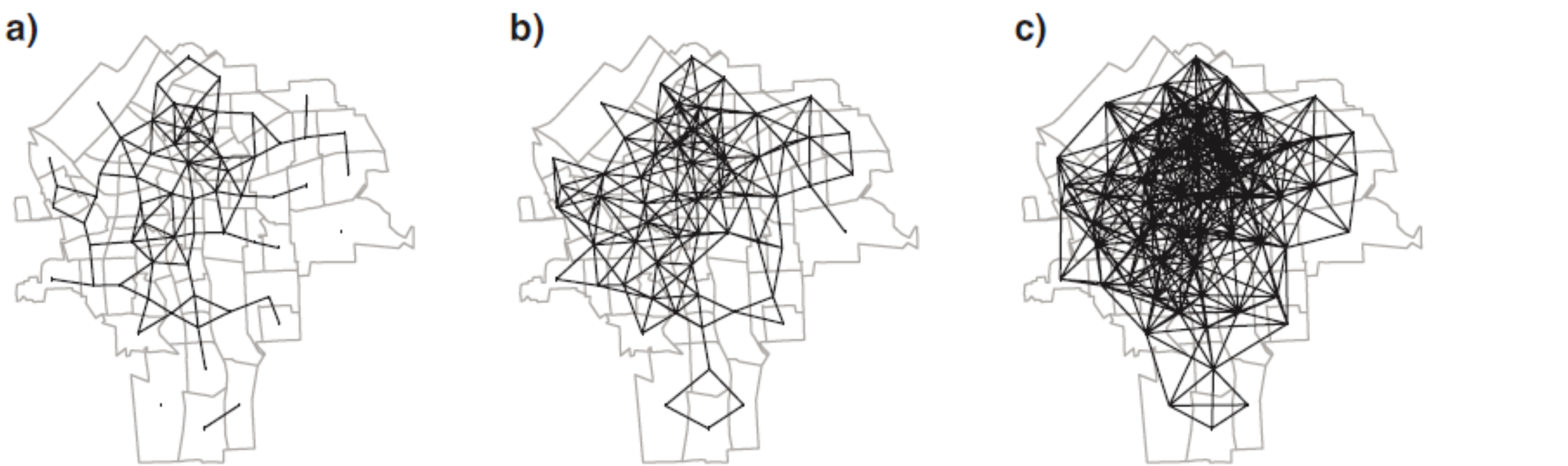
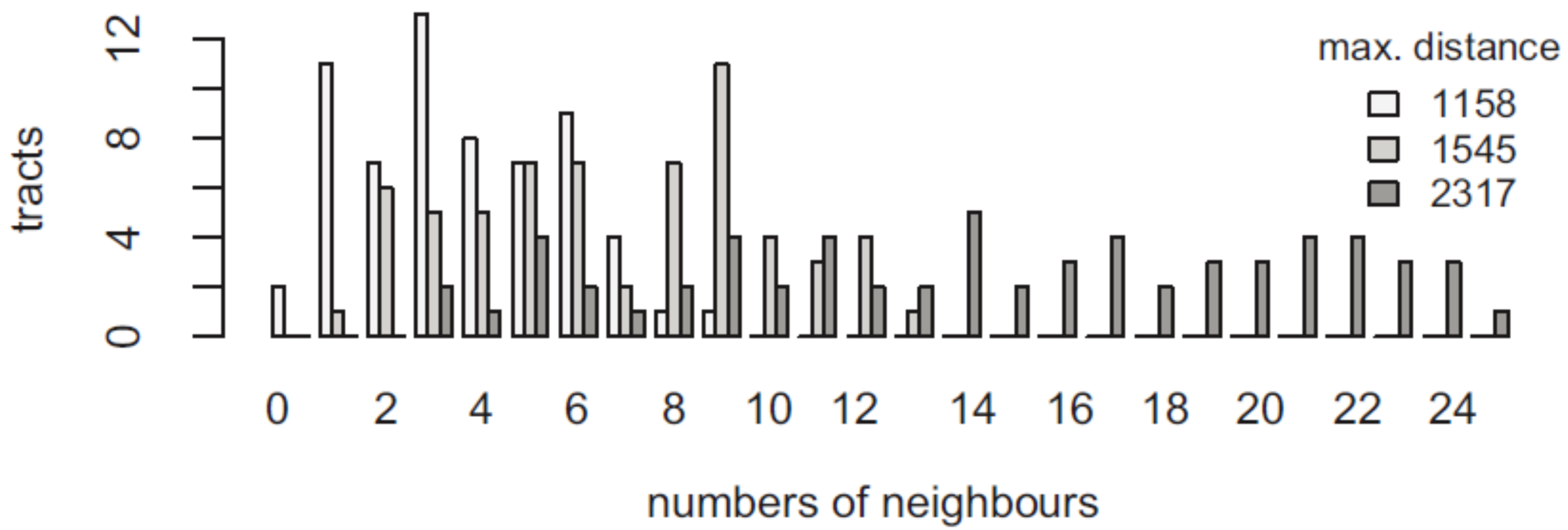


Fig. 9.6. (**a**) Neighbours within 1,158 m; (**b**) neighbours within 1,545 m; (**c**) neigh-
bours within 2,317 m

Source: Bivand and Pebesma and Gomez-Rubio

Neighbor/Connectivity Histogram



Source: Bivand and Pebesma and Gomez-Rubio

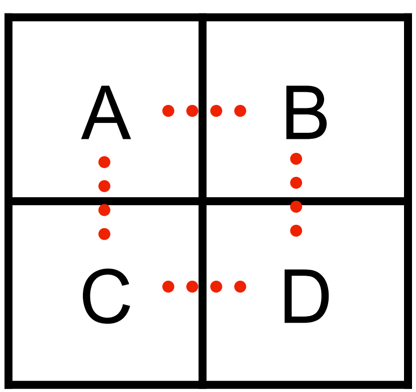
Spatial Weight Matrix

- Spatial weights can be seen as a list of weights indexed by a list of neighbors
- If zone j is not a neighbor of zone i, weights Wij will set to zero
  - The weight matrix can be illustrated as an image
  - Sparse matrix

A Simple Example for Rook case

- Matrix contains a:
  - 1 if share a border
  - 0 if do not share a border

4 areal units



Common border

4x4 matrix

$$
\mathbf{W} = \begin{array}{c|cccc} & A & B & C & D \\ \hline A & 0 & 1 & 1 & 0 \\ B & 1 & 0 & 0 & 1 \\ C & 1 & 0 & 0 & 1 \\ D & 0 & 1 & 1 & 0 \end{array}
$$

1 Washington		1				1																																											
2 Oregon	1		1		1	1																																											
3 California		1		1	1																																											
4 Arizona			1		1				1	1			1																																			
5 Nevada		1	1	1		1			1																																								
6 Idaho	1	1			1		1	1	1																																								
7 Montana						1		1								1	1																																
8 Wyoming						1	1		1				1		1	1																																	
9 Utah				1	1	1		1		1			1																																				
10 New Mexico				1					1		1	1	1																																				
11 Texas										1		1									1	1																											
12 Oklahoma										1	1		1	1						1	1																												
13 Colorado				1				1	1	1		1		1	1																																		
14 Kansas												1	1		1					1																													
15 Nebraska								1					1	1		1			1	1																													
16 South Dakota							1	1							1		1	1	1																														
17 North Dakota							1									1		1																															
18 Minnesota																1	1		1								1																						
19 Iowa															1	1		1		1						1	1																						
20 Missouri												1		1	1				1		1			1	1	1																							
21 Arkansas											1	1								1		1	1	1																									
22 Louisiana											1										1		1																										
23 Mississippi																					1	1		1									1																
24 Tennessee																				1	1		1		1								1	1		1	1												
25 Kentucky																				1				1		1			1	1	1						1												
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27 Wisconsin																		1	1								1		1																				
28 Michigan																											1		1	1																			
29 Indiana																									1	1		1		1																			
30 Ohio																									1			1	1		1											1							
31 West Virginia																									1					1							1	1				1							
32 Florida																																	1	1															
33 Alabama																							1	1								1		1															
34 Georgia																								1								1	1		1	1													
35 South Carolina																																		1		1													
36 North Carolina																								1										1	1		1												
37 Virginia																								1	1						1					1		1		1									
38 Maryland																															1						1		1	1		1							
39 Delaware																																						1			1	1							
40 District of Columbia																																					1	1											
41 New Jersey																																							1			1	1						
42 Pennsylvania																														1	1							1	1		1		1						
43 New York																																									1	1		1		1		1	
44 Connecticut																																											1		1	1			
45 Rhode Island																																												1		1			
46 Massachussets																																											1	1	1		1	1	
47 New Hampshire																																														1		1	1
48 Vermont																																											1			1	1		
49 Maine																																															1		

Sparse Contiguity Matrix for US States -- obtained from Anselin's web site (see powerpoint for link)										
Name	**Fips**	**Ncount**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
Alabama	1	4	28	13	12	47				
Arizona	4	5	35	8	49	6	32			
Arkansas	5	6	22	28	48	47	40	29		
California	6	3	4	32	41					
Colorado	8	7	35	4	20	40	31	49	56	
Connecticut	9	3	44	36	25					
Delaware	10	3	24	42	34					
District of Columbia	11	2	51	24						
Florida	12	2	13	1						
Georgia	13	5	12	45	37	1	47			
Idaho	16	6	32	41	56	49	30	53		
Illinois	17	5	29	21	18	55	19			
Indiana	18	4	26	21	17	39				
Iowa	19	6	29	31	17	55	27	46		
Kansas	20	4	40	29	31	8				
Kentucky	21	7	47	29	18	39	54	51	17	
Louisiana	22	3	28	48	5					
Maine	23	1	33							
Maryland	24	5	51	10	54	42	11			
Massachusetts	25	5	44	9	36	50	33			
Michigan	26	3	18	39	55					
Minnesota	27	4	19	55	46	38				
Mississippi	28	4	22	5	1	47				
Missouri	29	8	5	40	17	21	47	20	19	31
Montana	30	4	16	56	38	46				
Nebraska	31	6	29	20	8	19	56	46		
Nevada	32	5	6	4	49	16	41			
New Hampshire	33	3	25	23	50					
New Jersey	34	3	10	36	42					
New Mexico	35	5	48	40	8	4	49			
New York	36	5	34	9	42	50	25			
North Carolina	37	4	45	13	47	51				
North Dakota	38	3	46	27	30					
Ohio	39	5	26	21	54	42	18			
Oklahoma	40	6	5	35	48	29	20	8		
Oregon	41	4	6	32	16	53				
Pennsylvania	42	6	24	54	10	39	36	34		
Rhode Island	44	2	25	9						
South Carolina	45	2	13	37						
South Dakota	46	6	56	27	19	31	38	30		
Tennessee	47	8	5	28	1	37	13	51	21	29
Texas	48	4	22	5	35	40				
Utah	49	6	4	8	35	56	32	16		
Vermont	50	3	36	25	33					
Virginia	51	6	47	37	24	54	11	21		
Washington	53	2	41	16						
West Virginia	54	5	51	21	24	39	42			
Wisconsin	55	4	26	17	19	27				
Wyoming	56	6	49	16	31	8	46	30		

Style of Spatial Weight Matrix

- Row
  - a weight of unity for each neighbor relationship
- Row standardization
  - Symmetry not guaranteed
  - can be interpreted as allowing the calculation of average values across neighbors
- General spatial weights based on distances

Row vs. Row standardization

A	B	C
D	E	F

Divide each number by the **row sum**

Total number of neighbors
--some have more than others

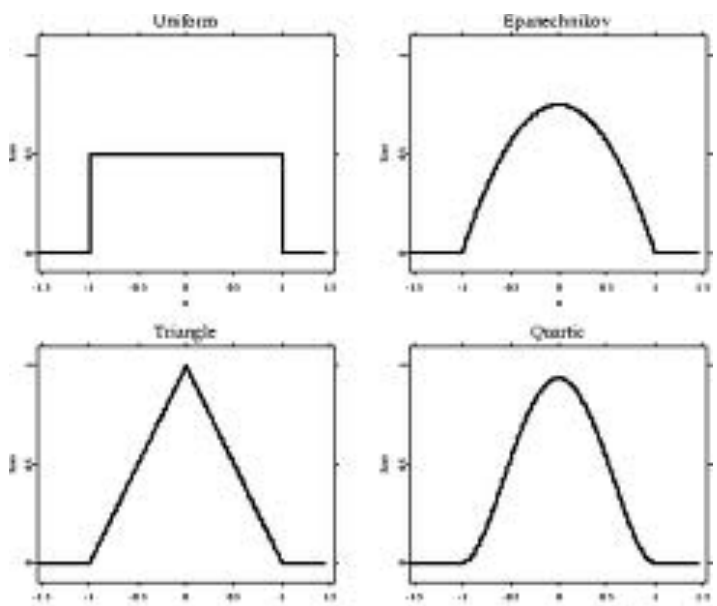
	A	B	C	D	E	F	Row Sum
A	0	1	0	1	0	0	2
B	1	0	1	0	1	0	***3***
C	0	1	0	0	0	1	2
D	1	0	0	0	1	0	2
E	0	1	0	1	0	1	***3***
F	0	0	1	0	1	0	2

Row standardized
--usually use this

	A	B	C	D	E	F	Row Sum
A	0.0	0.5	0.0	0.5	0.0	0.0	1
B	0.3	0.0	0.3	0.0	0.3	0.0	1
C	0.0	0.5	0.0	0.0	0.0	0.5	1
D	0.5	0.0	0.0	0.0	0.5	0.0	1
E	0.0	0.3	0.0	0.3	0.0	0.3	1
F	0.0	0.0	0.5	0.0	0.5	0.0	1

General Spatial Weights Based on Distance

- Decay functions of distance
  - Most common choice is the inverse (reciprocal) of the distance between locations i and j ($w_{ij} = 1/d_{ij}$)
  - Other functions also used
    - inverse of <u>squared</u> distance ($w_{ij} = 1/d_{ij}^2$), or
    - negative exponential ($w_{ij} = e^{-d}$ *or* $w_{ij} = e^{-d^2}$)



Measure of Spatial Autocorrelation

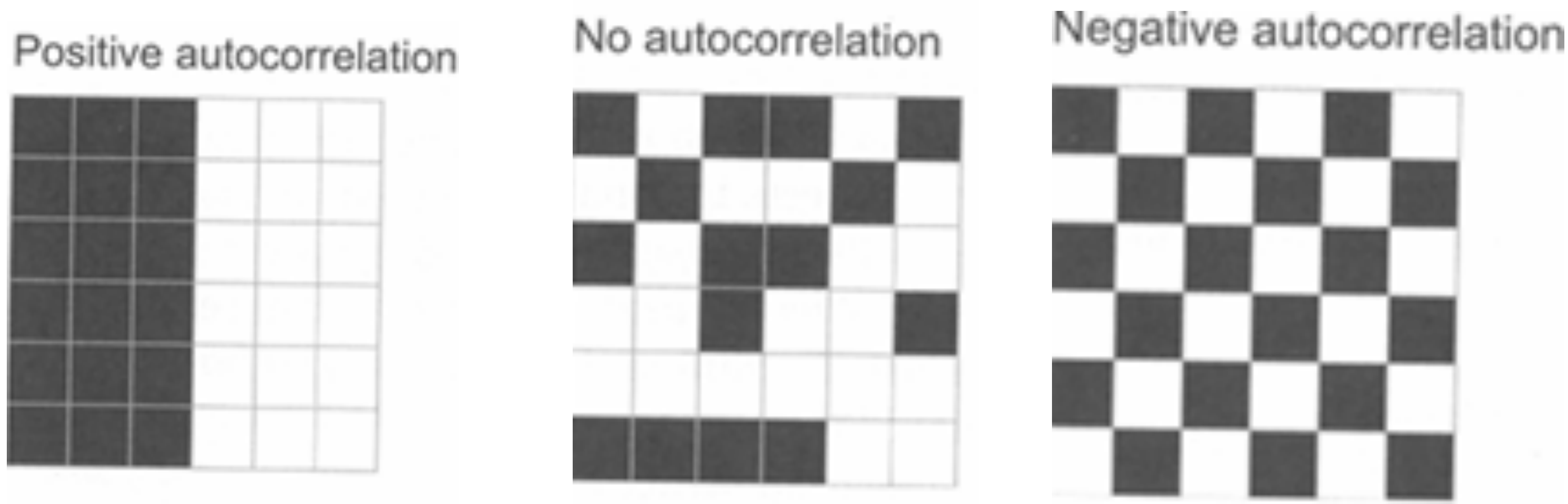
Global Measures and Local Measures

- Global Measures
  - A single value which applies to the entire data set
    - The same pattern or process occurs over the entire geographic area
    - An average for the entire area
- Local Measures
  - A value calculated for <u>each</u> observation unit
    - Different patterns or processes may occur in different parts of the region
    - A unique number for each location
- Global measures usually can be decomposed into a combination of local measures

Global Measures and Local Measures

- Global Measures
  - Join Count
  - Moran's I, Getis-Ord's G
- Local Measures
  - Local Moran's I , Getis-Ord's G

Join (or Joint or Joins) Count Statistic



Rook's case	Queen's case				
$J_{BB} = 27$	$J_{BB} = 47$	$J_{BB} = 6$	$J_{BB} = 14$	$J_{BB} = 0$	$J_{BB} = 25$
$J_{WW} = 27$	$J_{WW} = 47$	$J_{WW} = 19$	$J_{WW} = 40$	$J_{WW} = 0$	$J_{WW} = 25$
$J_{BW} = 6$	$J_{BW} = 16$	$J_{BW} = 35$	$J_{BW} = 56$	$J_{BW} = 60$	$J_{BW} = 60$

- 60 for Rook Case
- 110 for Queen Case

Gore/Bush Presidential Election 2000

	Actual
Jbb	60
Jgg	21
Jbg	28
Total	109

Join Count Statistic for Gore/Bush 2000 by State

candidates	probability
Bush	0.49885
Gore	0.50115

	Actual	Expected	Stan Dev	Z-score
Jbb	60	27.125	8.667	3.7930
Jgg	21	27.375	8.704	-0.7325
Jbg	28	54.500	5.220	-5.0763
Total	109	109.000		

- The expected number of joins is calculated based on the proportion of votes each received in the election (for Bush = 109*.499*.499=27.125)
- There are far <u>more</u> Bush/Bush joins (actual = 60) than would be expected (27)
  - Positive autocorrelation
- There are far <u>fewer</u> Bush/Gore joins (actual = 28) than would be expected (54)
  - Positive autocorrelation
- No strong clustering evidence for Gore (actual = 21 slightly less than 27.375)

Moran's I

- The most common measure of Spatial Autocorrelation
- Use for points <u>or</u> polygons
  - Join Count statistic only for polygons
- Use for a continuous variable (any value)
  - Join Count statistic only for binary variable (1,0)

Patrick Alfred Pierce Moran (1917-1988)

Formula for Moran's I

$$I = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

- Where:

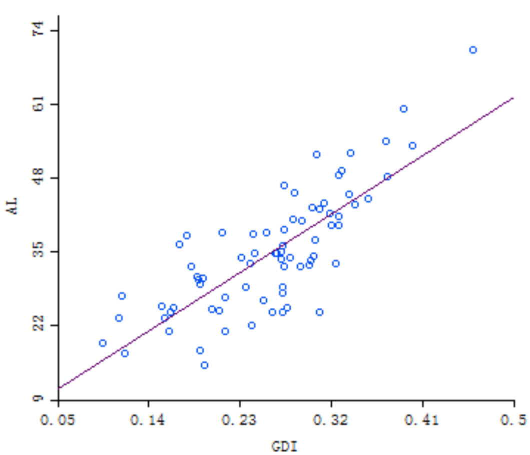
  N is the number of observations (points or polygons)
  $\bar{x}$ is the mean of the variable
  X_i is the variable value at a particular location
  X_j is the variable value at another location
  W_{ij} is a weight indexing location of *i* relative to *j*

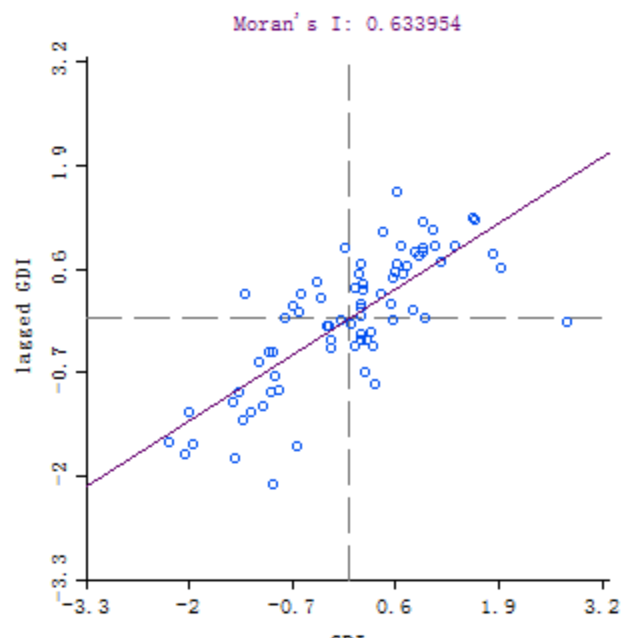
Moran's *I* and Correlation Coefficient

- **Correlation Coefficient [-1, 1]**
  - Relationship between <u>two</u> different variables
- **Moran's I [-1, 1]**

– Spatial autocorrelation and often involves <u>one</u> (spatially indexed) variable only

– Correlation between observations of a spatial variable at location X and "spatial lag" of X formed by averaging all the observation at neighbors of X





Correlation Coefficient

$$\frac{\sum_{i=1}^{n} 1(y_i - \bar{y})(x_i - \bar{x})/n}{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}}$$

Note the similarity of the numerator (top) to the measures of spatial association discussed earlier if we view Yi as being the Xi for the neighboring polygon

(see next slide)

$$\frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})/\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}}$$

Spatial auto-correlation

Source: Ron Briggs of UT Dallas

Correlation Coefficient

$$\frac{\sum_{i=1}^{n} 1(y_i - \bar{y})(x_i - \bar{x})/n}{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}}$$

Spatial weights

Yi is the Xi for the neighboring polygon

$$\frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})/\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}}$$

Moran's I

Source: Ron Briggs of UT Dallas

Statistical Significance Tests for Moran's I

- Based on the normal frequency distribution with

$$Z = \frac{I - E(I)}{S_{error(I)}}$$

Where: I is the calculated value for Moran's I from the sample

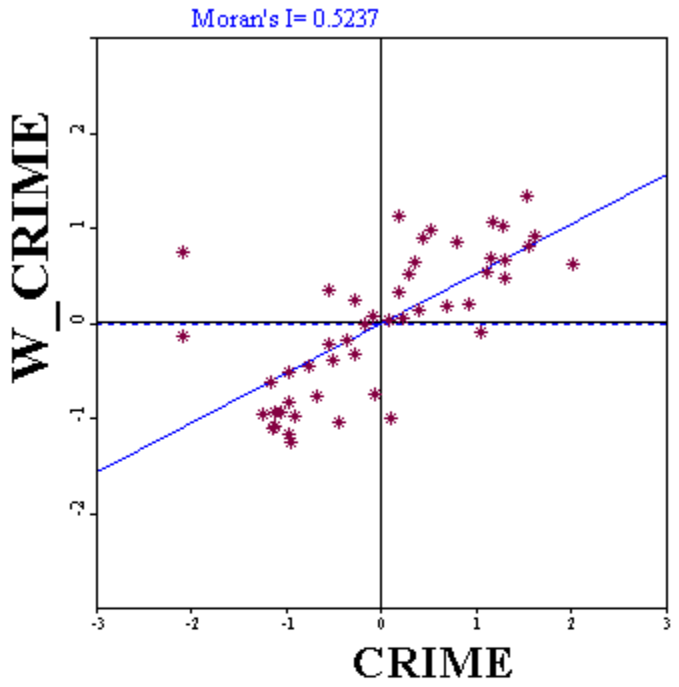
E(I) is the expected value if random

S is the standard error

- Statistical significance test
  - Monte Carlo test, as we did for spatial pattern analysis
  - Permutation test
    - Non-parametric
    - Data-driven, no assumption of the data
    - Implemented in GeoDa

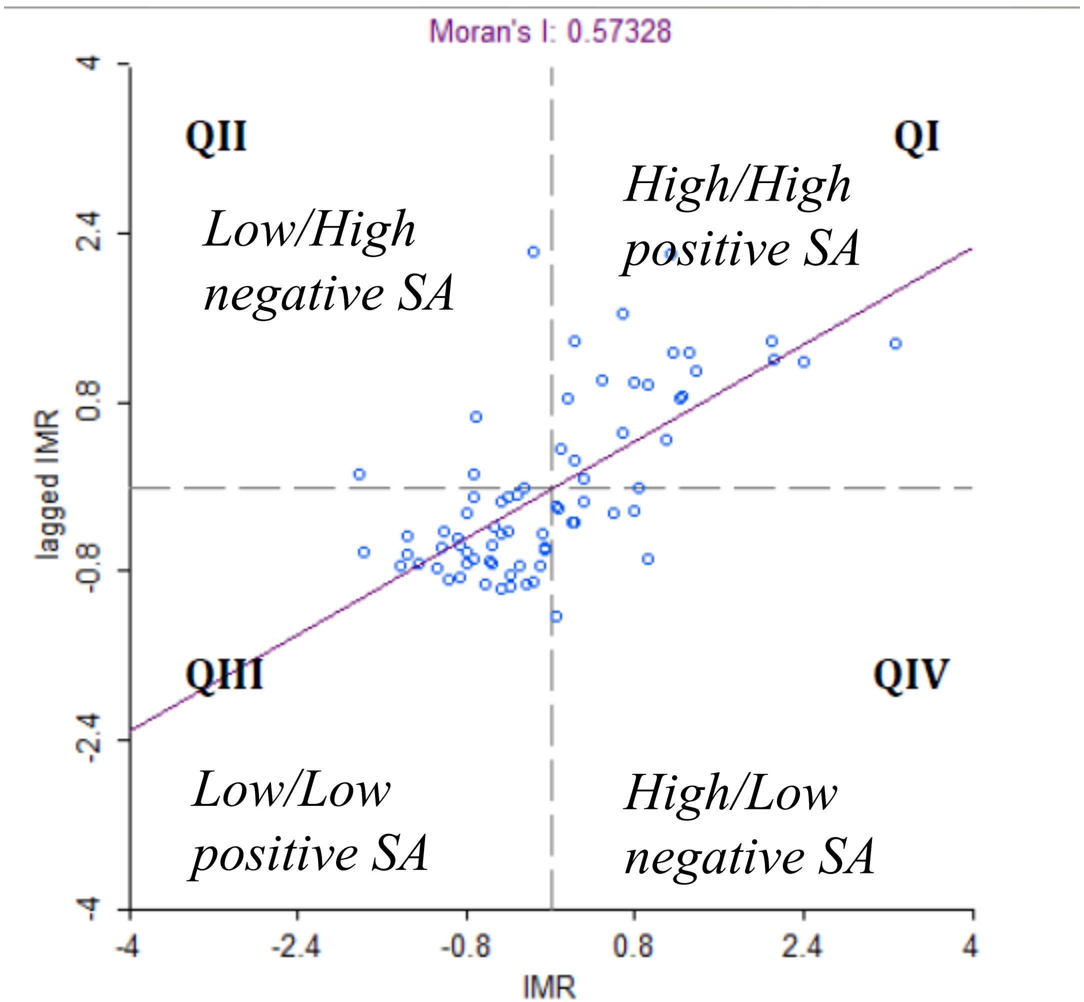
Moran Scatter Plots

We can draw a scatter diagram between these two variables (in standardized form): **X** and **lag-X** (or W_X)

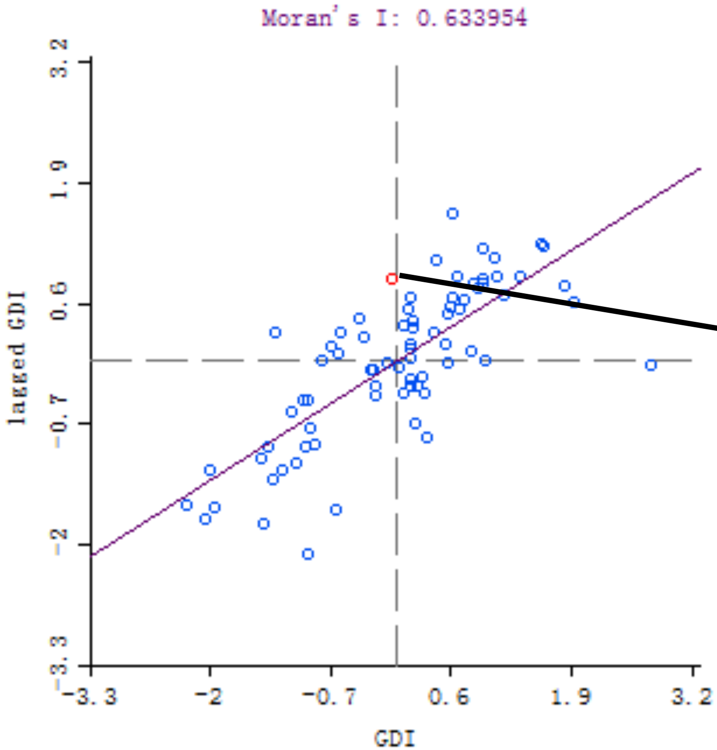


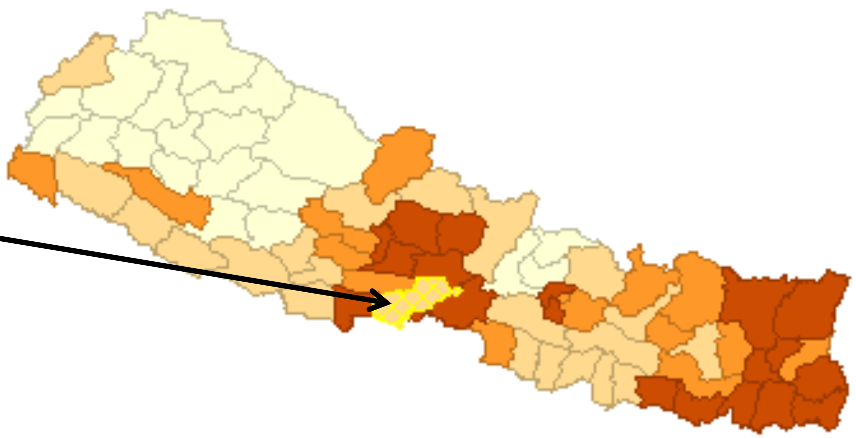
The <u>slope</u> of this *regression line* is Moran’s I

Moran Scatter Plots



Moran Scatterplot: Example

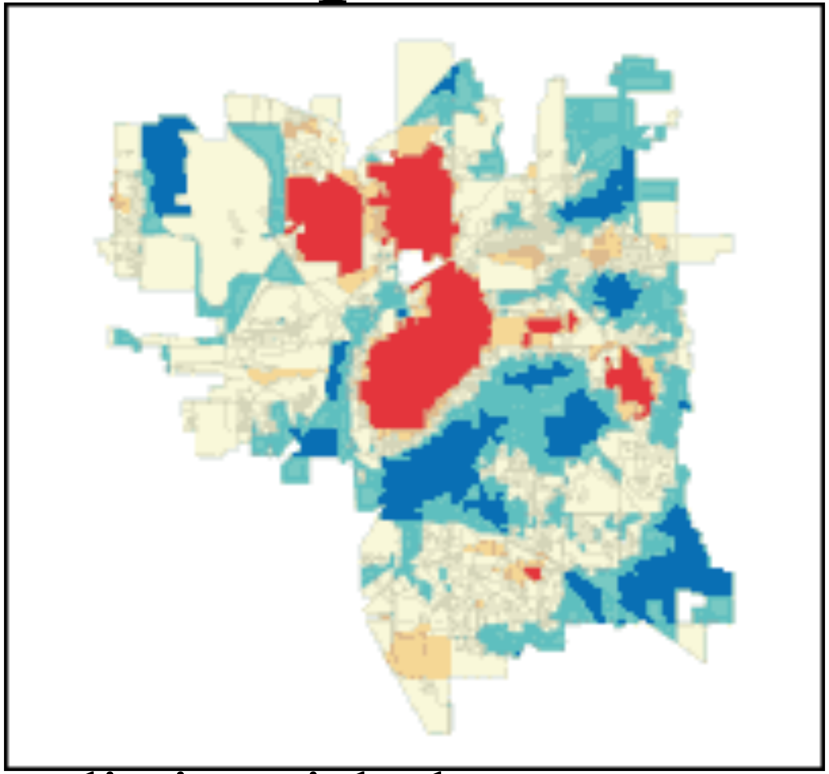




Moran's I for rate-based data

- Moran's I is often calculated for rates, such as crime rates (e.g. number of crimes per 1,000 population) or infant mortality rates (e.g. number of deaths per 1,000 births)
- An adjustment should be made, especially if the denominator in the rate (population or number of births) varies greatly (as it usually does)
- Adjustment is know as the *EB adjust*ment:
  - see Assuncao-Reis *Empirical Bayes Standardization* Statistics in Medicine, 1999
- *GeoDA* software includes an option for this adjustment

Hot Spots and Cold Spots



- What is a *hot spot*?
  - A place where high values cluster together
- What is a *cold spot*?
  - A place where low values cluster together

- Moran's I and Geary's C cannot distinguish them
  - They only indicate clustering
  - Cannot tell if these are hot spots, cold spots, or both

Getis-Ord General/Global G-Statistic

- The G statistic distinguishes between hot spots and cold spots. It identifies *spatial concentrations*.
  - G is relatively large if high values cluster together
  - G is relatively low if low values cluster together
- The General G statistic is interpreted relative to its *expected value*
  - The value for which there is no spatial association
  - G > (larger than) *expected value* ➔ potential "hot spots"
  - G < (smaller than) *expected value* ➔ potential "cold spots"
- Comments:
  - General G will not show negative spatial autocorrelation
  - Should only be calculated for ratio scale data
    - data with a "natural" zero such as crime rates, birth rates
  - Although it was defined using a contiguity (0,1) weights matrix, any type of spatial weights matrix can be used
    - ArcGIS gives multiple options

Local Measures of Spatial Autocorrelation

Local Indicators of Spatial Association (LISA)

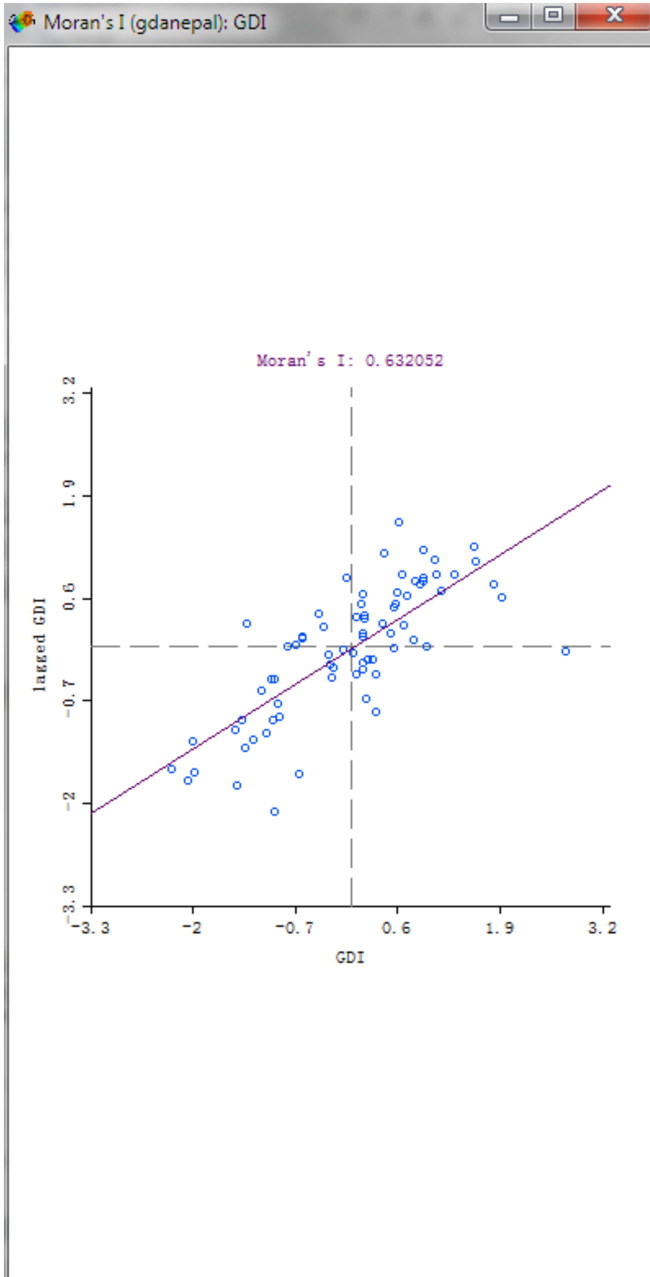
- Local versions of *Moran's I, and the Getis-Ord G statistic*
- Moran's I is most commonly used, and the local version is often called Anselin's LISA, or just LISA

See:
Luc Anselin 1995 *Local Indicators of Spatial Association-LISA* Geographical Analysis 27: 93-115

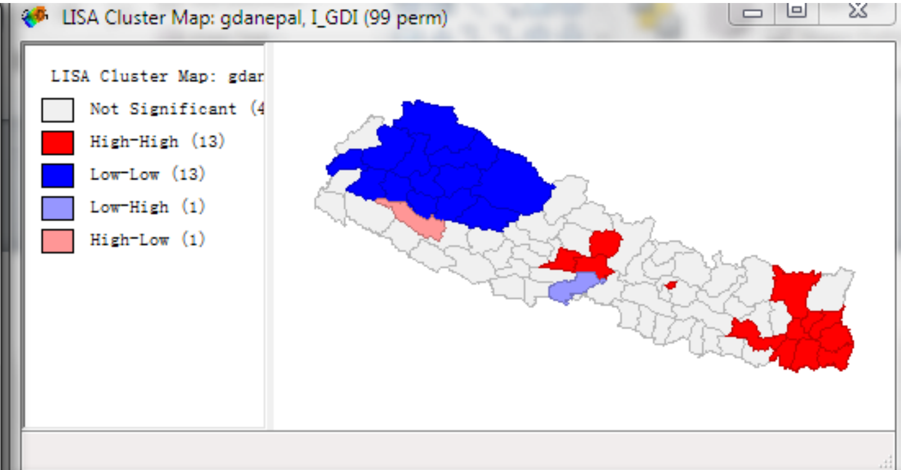
Local Indicators of Spatial Association (LISA)

- The statistic is calculated for **each** areal unit in the data
- For each polygon, the index is calculated based on neighboring polygons with which it shares a border
- A measure is available for each polygon, these can be mapped to indicate how spatial autocorrelation varies over the study region
- Each index has an associated test statistic, we can also map which of the polygons has a statistically significant relationship with its neighbors, and show type of relationship

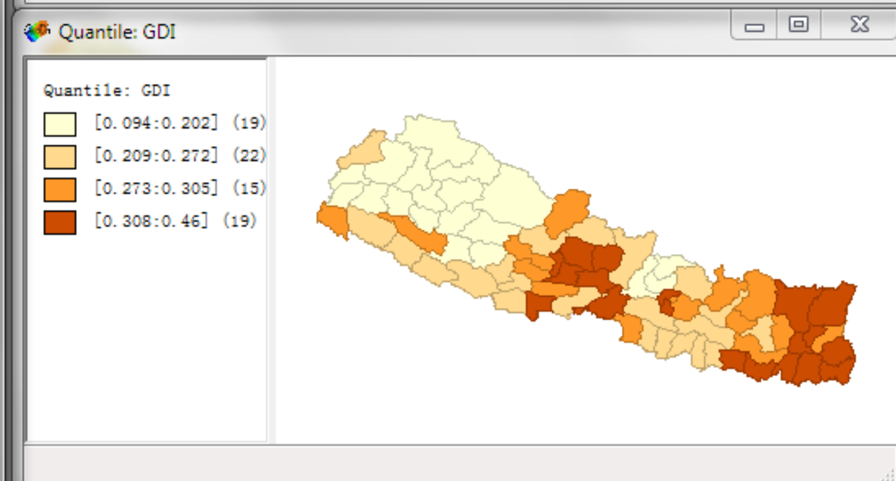
Example:



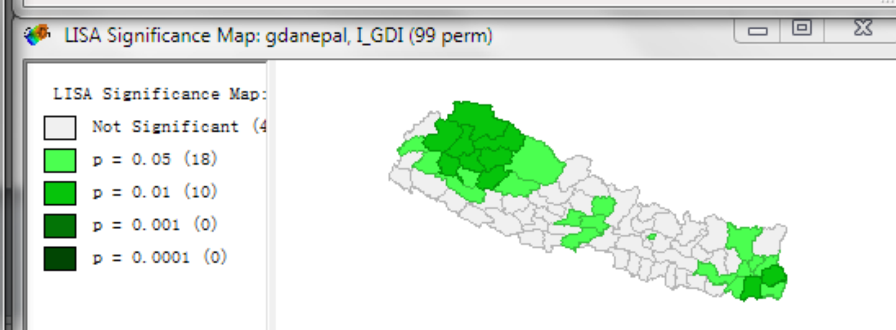
Moran's I (gdanepal): GDI
Moran's I: 0.632052
lagged GDI
GDI
3.2
1.9
0.6
-0.7
-2
-3.3
-3.3
-2
-0.7
0.6
1.9
3.2



LISA Cluster Map: gdanepal, I_GDI (99 perm)
LISA Cluster Map: gdar
Not Significant (4
High-High (13)
Low-Low (13)
Low-High (1)
High-Low (1)



Quantile: GDI
Quantile: GDI
[0.094:0.202] (19)
[0.209:0.272] (22)
[0.273:0.305] (15)
[0.308:0.46] (19)

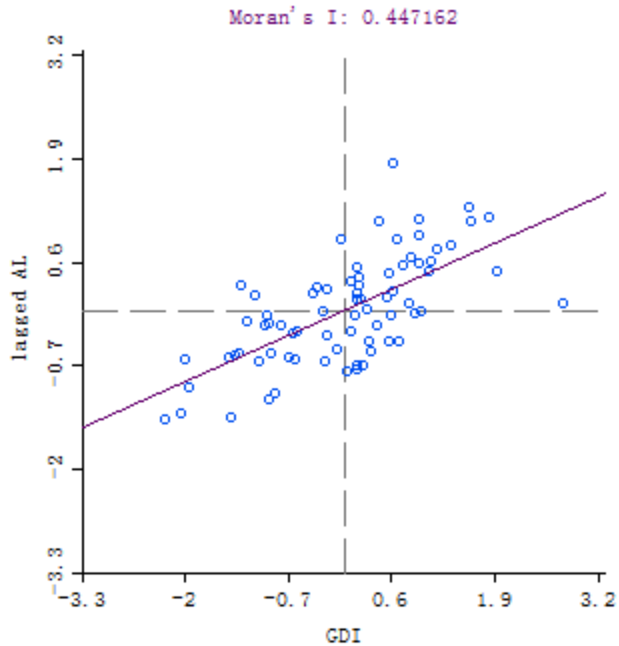


LISA Significance Map: gdanepal, I_GDI (99 perm)
LISA Significance Map:
Not Significant (4
p = 0.05 (18)
p = 0.01 (10)
p = 0.001 (0)
p = 0.0001 (0)

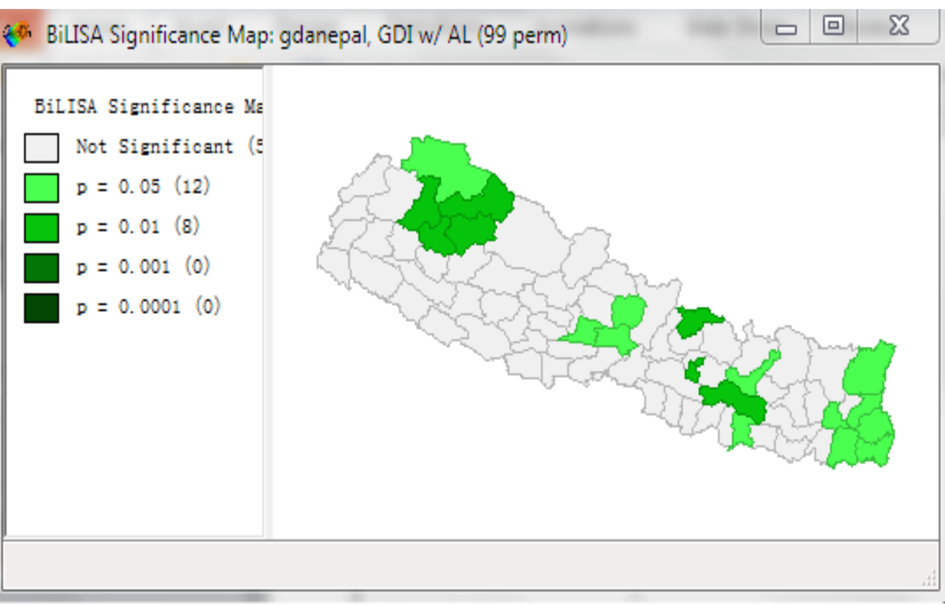
Bivariate LISA

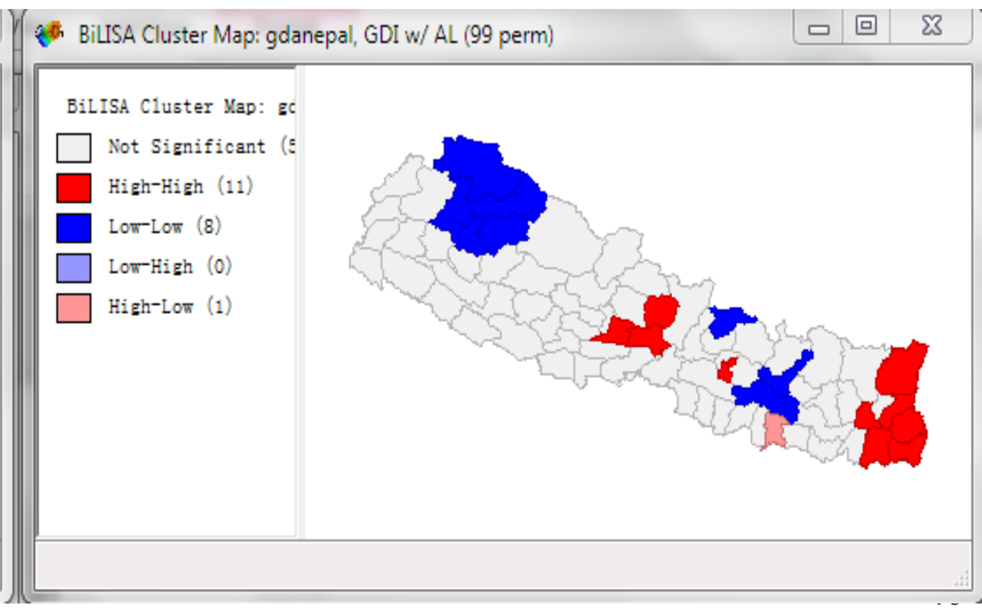
- Moran's I is the correlation between X and Lag-X--the <u>same</u> variable but in <u>nearby</u> areas
  - Univariate Moran's I
- Bivariate Moran's I is a correlation between X and a <u>different</u> variable in <u>nearby</u> areas.

Moran <u>Scatter Plot</u> for GDI vs AL



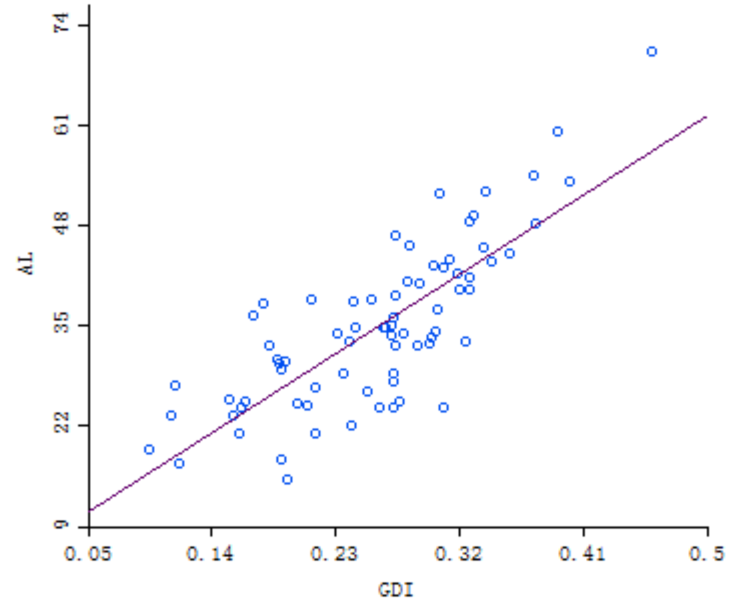
Moran <u>Significance Map</u> for GDI vs. AL

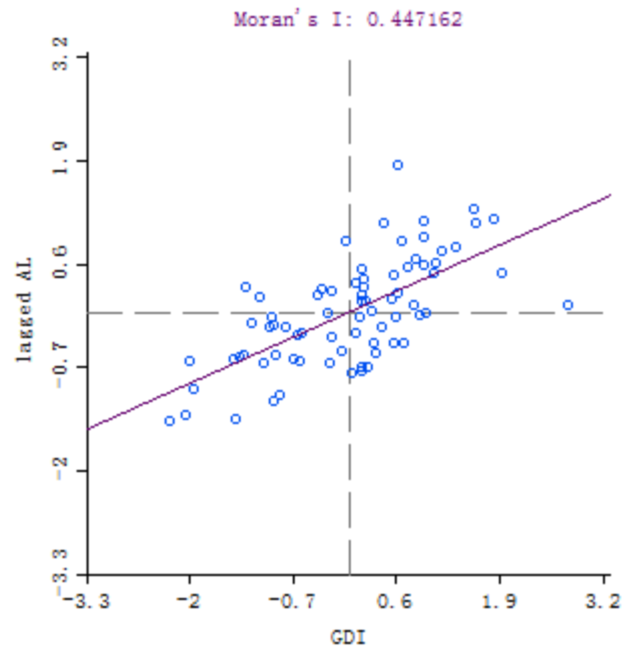




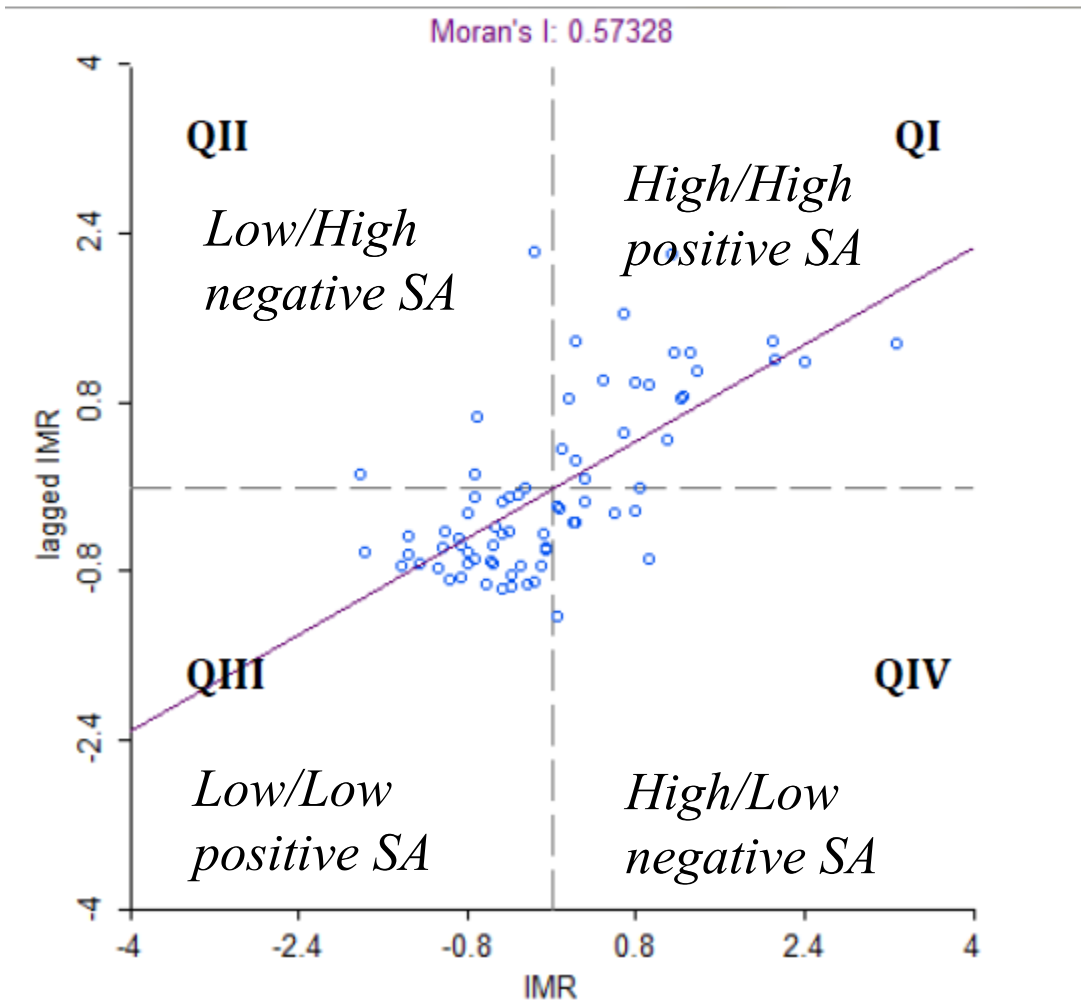
Bivariate LISA and the Correlation Coefficie

- Correlation Coefficient is the relationship between two different variables in the same area
- Bivariate LISA is a correlation between two different variables in an area and in nearby areas.





Bivariate Moran Scatter Plot



Summary

- Spatial autocorrelation of areal data
- Spatial weight matrix
- Measures of spatial autocorrelation
- Global Measure
  - Moran's I/General G and G*
- Local
  - LISA: Moran's I/General G and G*
  - Bivariate LISA
  - Significance test