Spatial Analysis and Modeling (GIST 4302/5302)

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Outline of This Week

- Last week, we learned:
  - spatial point pattern analysis (PPA)
  - focus on location distribution of ‘events’
  - Measure the cluster (spatial autocorrelation)in point pattern
- This week, we will learn:
  - How to measure and detect clusters/spatial autocorrelation in areal data (regional data)

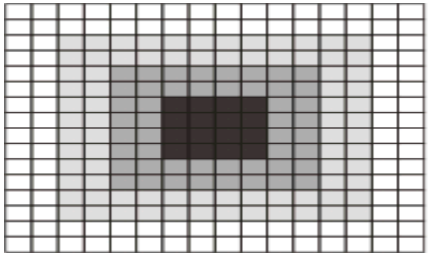
Spatial Autocorrelation

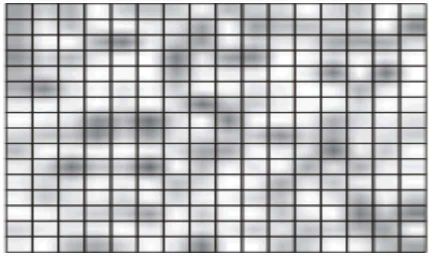
- Spatial autocorrelationship is everywhere
  - Spatial point pattern
    - K, G functions
    - Kernel functions
  - Areal/lattice (this topic)
  - Geostatistical data (next topic)

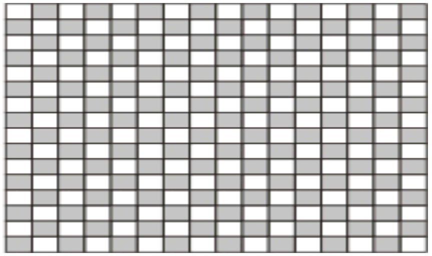
Spatial Autocorrelation of Areal Data

Spatial Autocorrelation

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





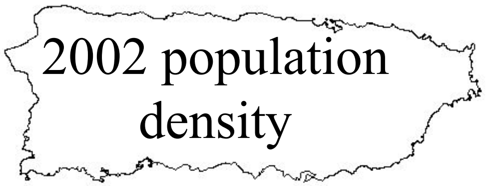


If like values tend to cluster together, then the field exhibits high **positive spatial autocorrelation**

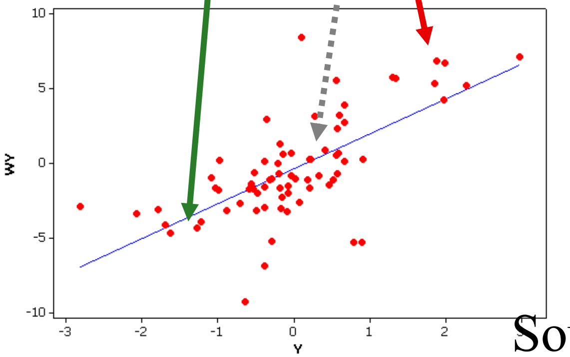
If there is no apparent relationship between attribute value and location then there is **zero spatial autocorrelation**

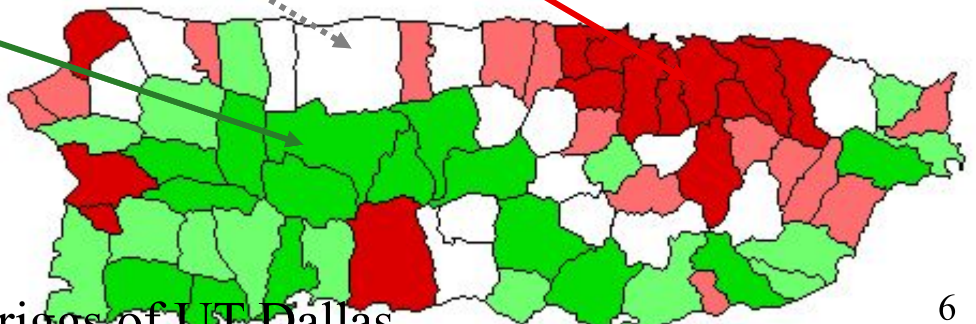
If like values tend to be located away from each other, then there is **negative spatial autocorrelation**

Positive spatial autocorrelation



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



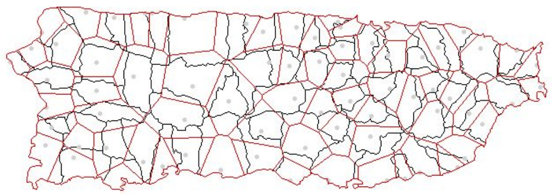


Source: Ron Briggs of UT Dallas

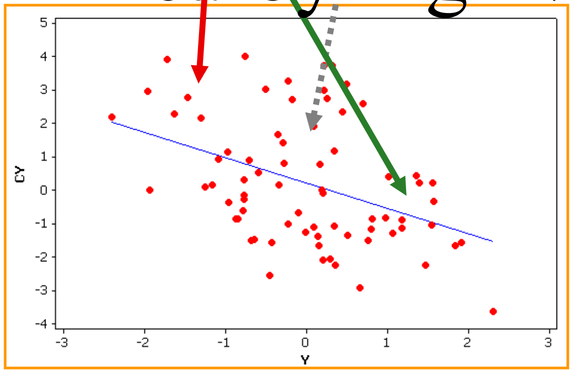
Negative spatial autocorrelation

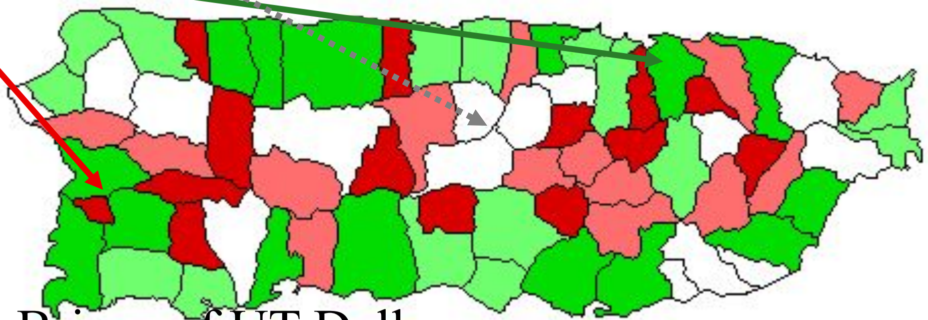
- high values surrounded by nearby low values
- intermediate values surrounded by nearby intermediate values
- low values surrounded by nearby high values

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

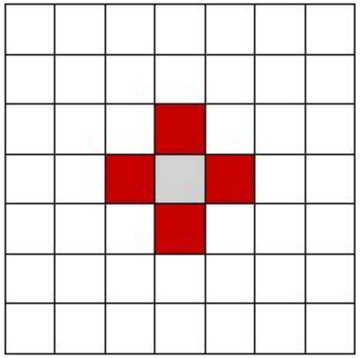
- **Core** concept in statistical analysis of areal data
- Two steps involved:
  - define which relationships between observations are to be given a nonzero weight, i.e., define spatial neighbors
  - assign weights to the neighbors

Spatial Neighbors

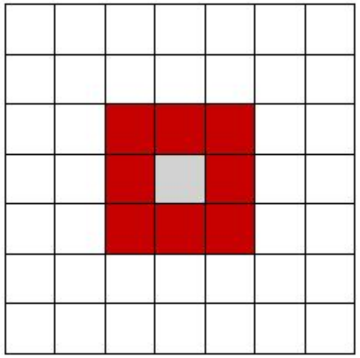
- **Contiguity-based neighbors**
  - Zone *i* and j are neighbors if zone i is contiguity or adjacent to zone *j*
  - But what constitutes contiguity?
- **Distance-based neighbors**
  - Zone i and j are neighbors if the distance between them are less than the threshold distance
  - But what distance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

Contiguity-based Spatial Neighbors

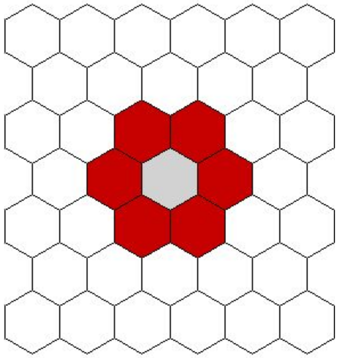
- Sharing a border or boundary
  - Rook: sharing a border
  - Queen: sharing a border <u>or</u> a point



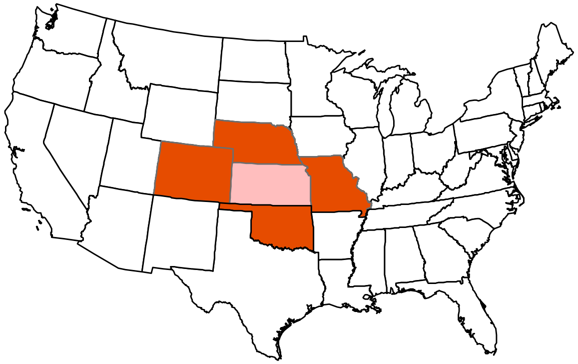
rook



queen



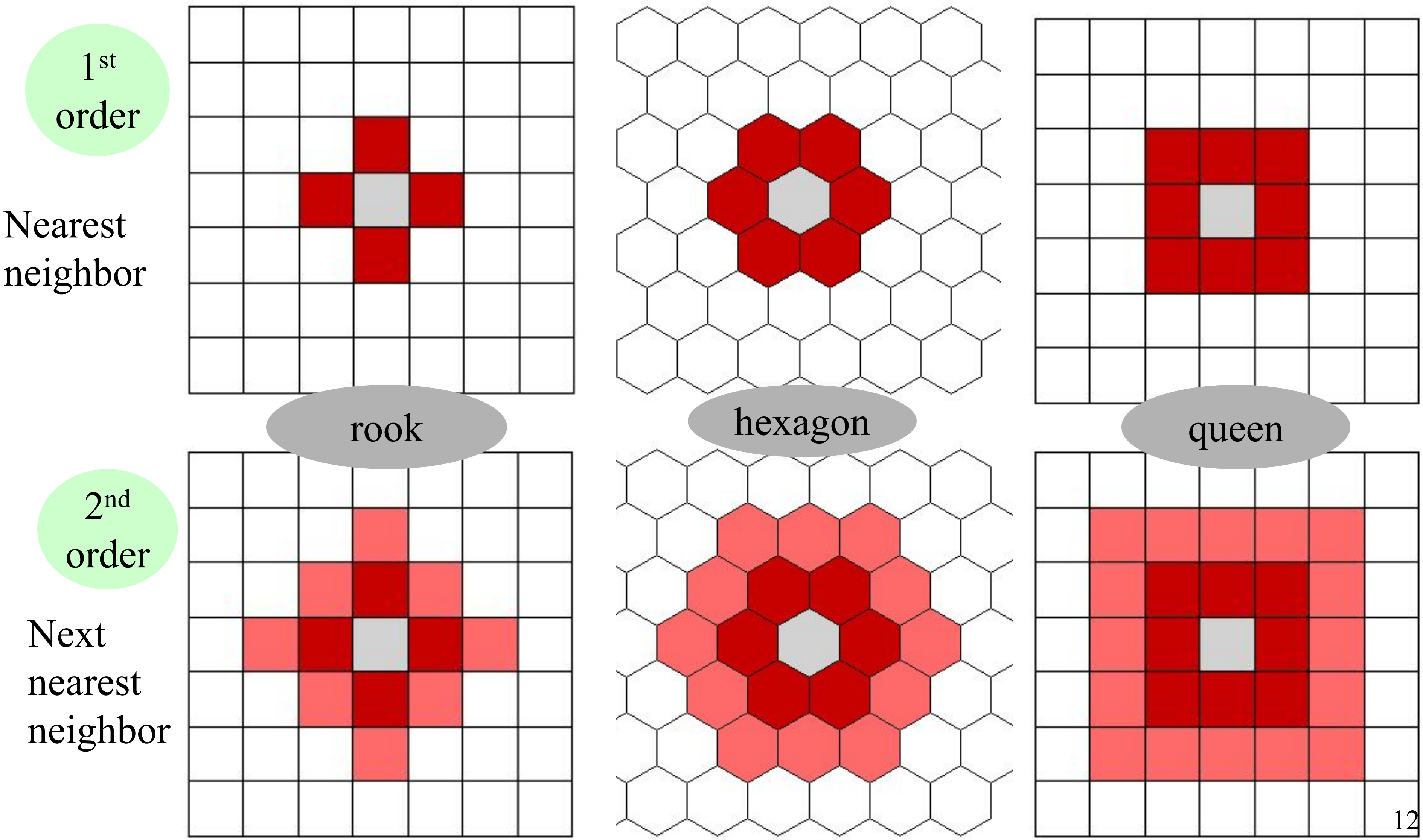
Hexagons



Irregular

Which use?

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)

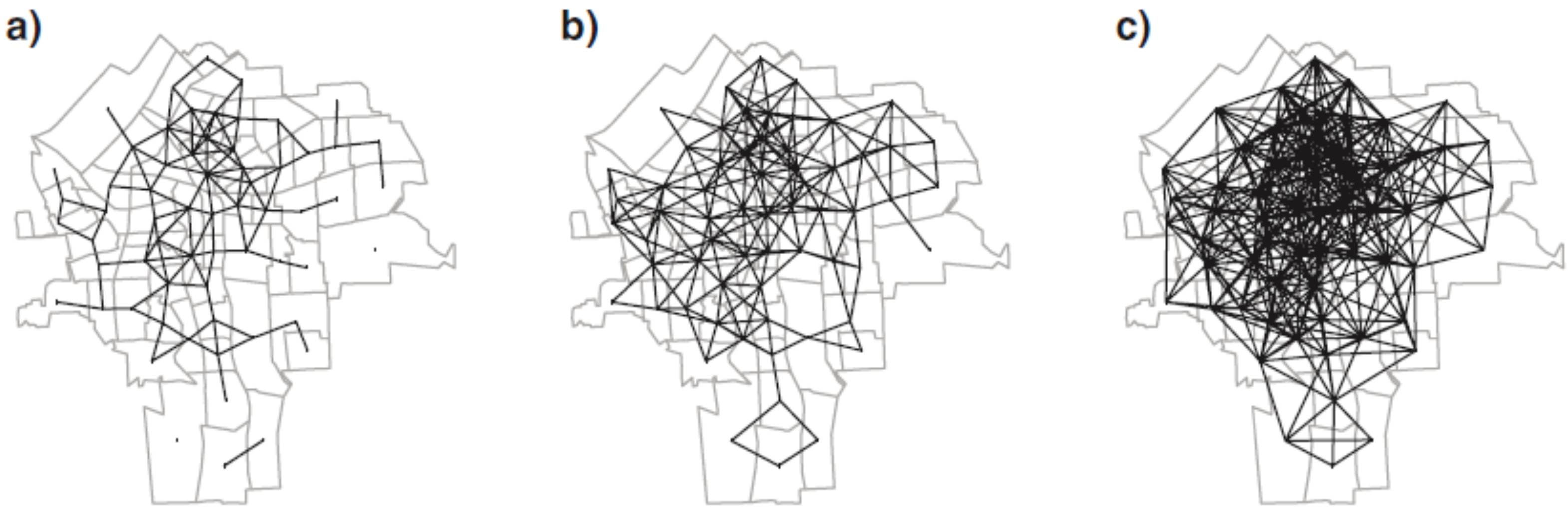
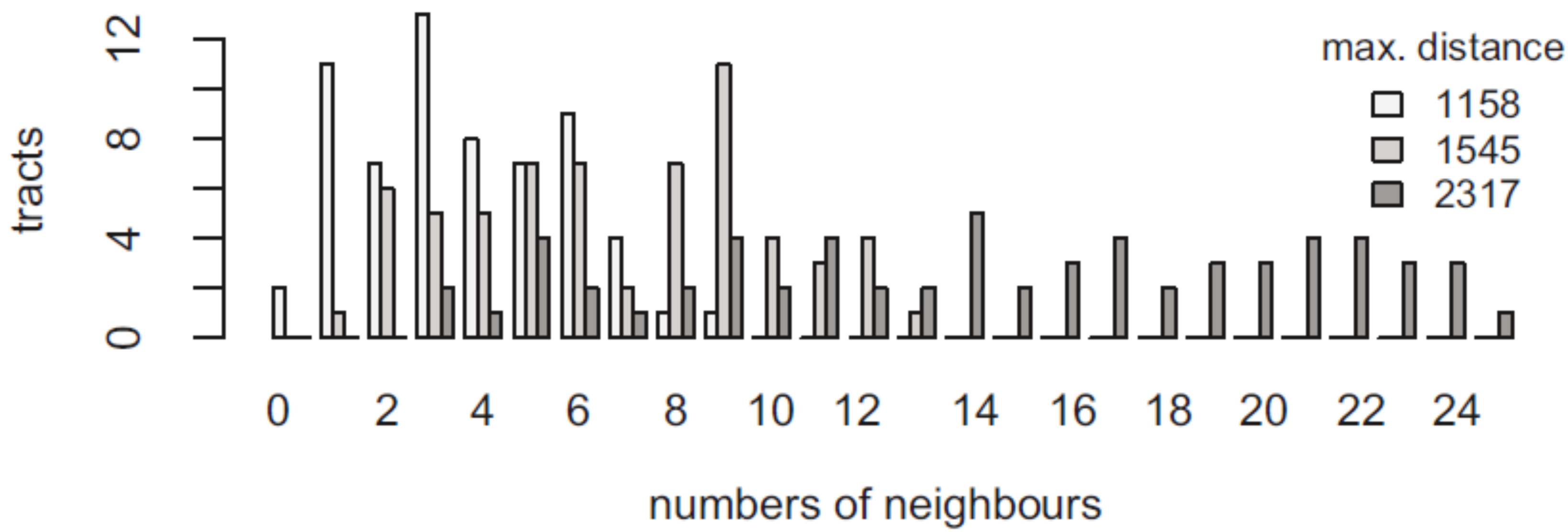


Fig. 9.6. (**a**) Neighbours within 1,158 m; (**b**) neighbours within 1,545 m; (**c**) neigh-
bours within 2,317 m

Source: Bivand and Pebesma and Gomez-Rubio

Neighbor/Connectivity Histogram



Source: Bivand and Pebesma and Gomez-Rubio

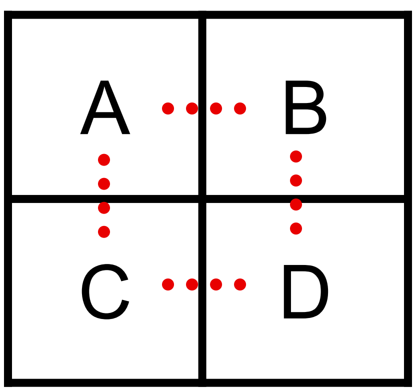
Spatial Weight Matrix

- 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												
26 Illinois																			1	1					1		1		1																				
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

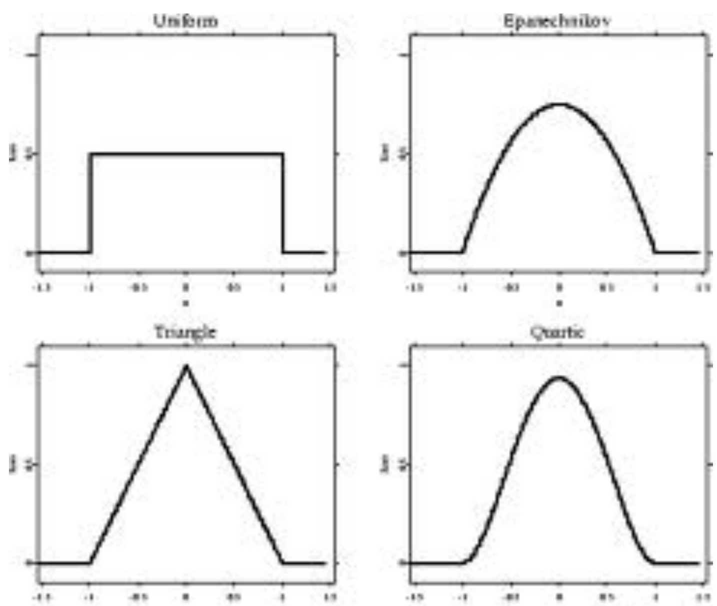
	A	**B**	**C**	**D**	**E**	**F**	**Row Sum**
A	0	1	0	1	0	0	2
B	1	0	1	0	1	0	***3***
C	0	1	0	0	0	1	2
D	1	0	0	0	1	0	2
E	0	1	0	1	0	1	***3***
F	0	0	1	0	1	0	2

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

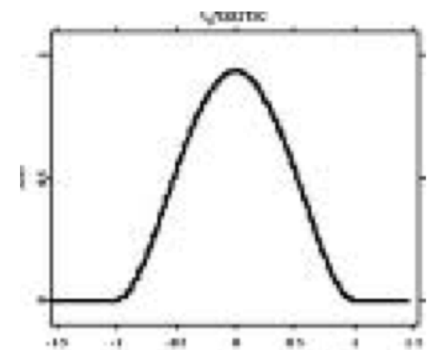
General Spatial Weights Based on Distance

- 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 squared distance ($w_{ij} = 1/d_{ij}^2$), or
    - negative exponential ($w_{ij} = e^{-d}$ *or* $w_{ij} = e^{-d^2}$)



Distance-based Spatial Weight Matrix

A	B	C
D	E	F



	A	B	C	D	E	F
A	0	2	0	2	1	0
B	2	0.0	2	1	2	1
C	0	2	0	0	1	2
D	2	1	0	0	2	0
E	1	2	1	2	0	2
F	0	1	2	0	2	0

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
  - Moran's I
- Local Measures
  - Local Moran's I

Moran's I

- The most common measure of Spatial Autocorrelation
- Use for points <u>or</u> polygons

Patrick Alfred Pierce Moran (1917-1988)

Formula for Moran's I

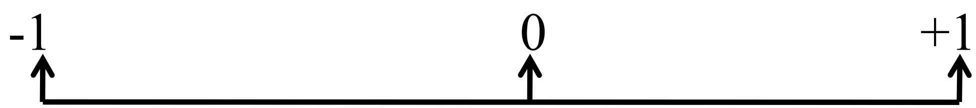
$$I = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

- 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

- Varies on a scale between –1 through 0* to + 1

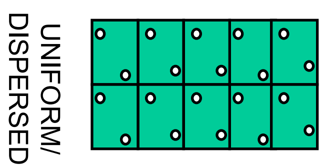


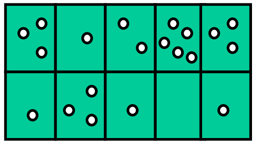
**technically it is: –1/(n-1)*

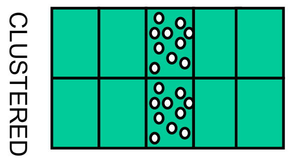
high negative spatial autocorrelation	no spatial autocorrelation*	high positive spatial autocorrelation

Can also use it as an index for dispersion/random/cluster patterns.

Dispersed Pattern	Random Pattern	Clustered Pattern





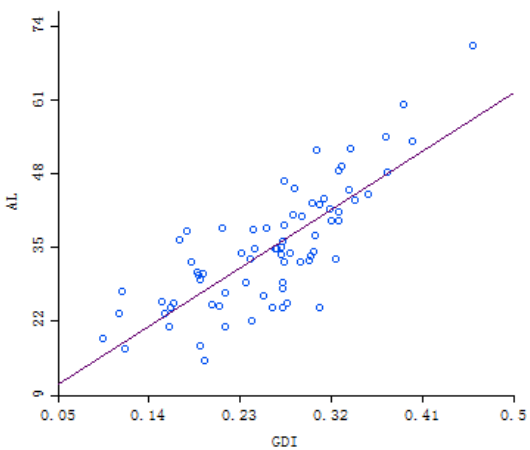


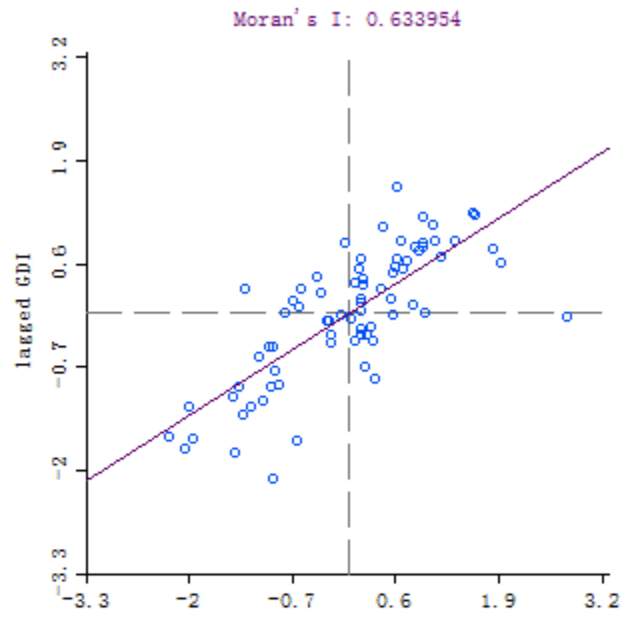
Moran's *I* and Correlation Coefficient

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

– Spatial autocorrelation and often involves one (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)

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

Spatial auto-correlation

Source: Ron Briggs of UT Dallas

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

Correlation Coefficient

Spatial weights

Yi is the Xi for the neighboring polygon

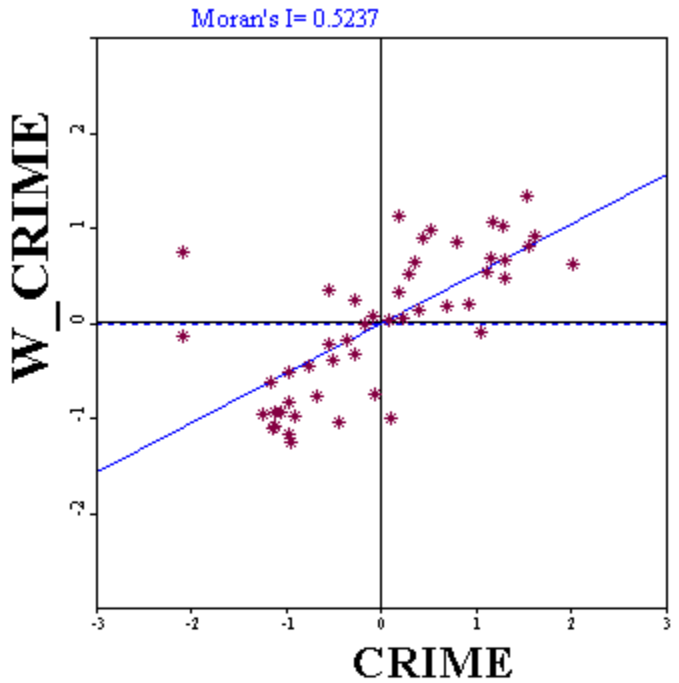
$$\frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})/\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}}\sqrt{\frac{\sum_{i=1}^{n}(x_i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

Moran's I

Source: Ron Briggs of UT Dallas

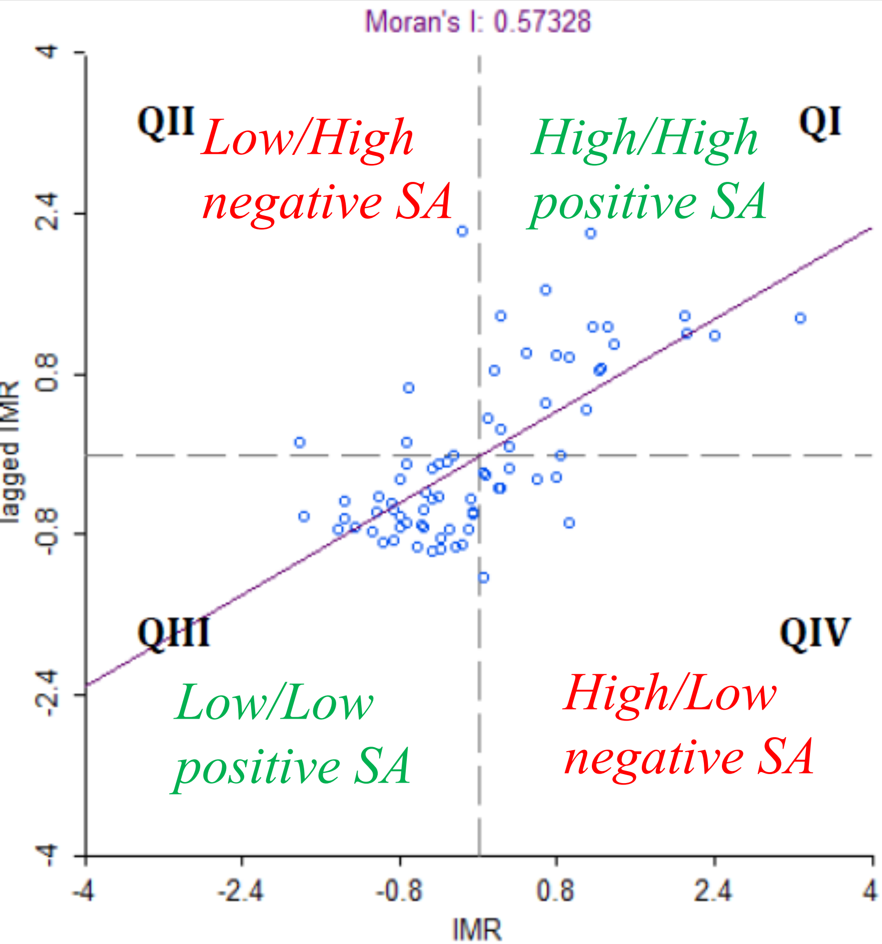
Moran Scatter Plots

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



The slope of this *regression line* is Moran's I

Moran Scatter Plots



Locations of positive spatial association ("I'm similar to my neighbors").

Q_1 (values [+], nearby values [+]): **H-H**

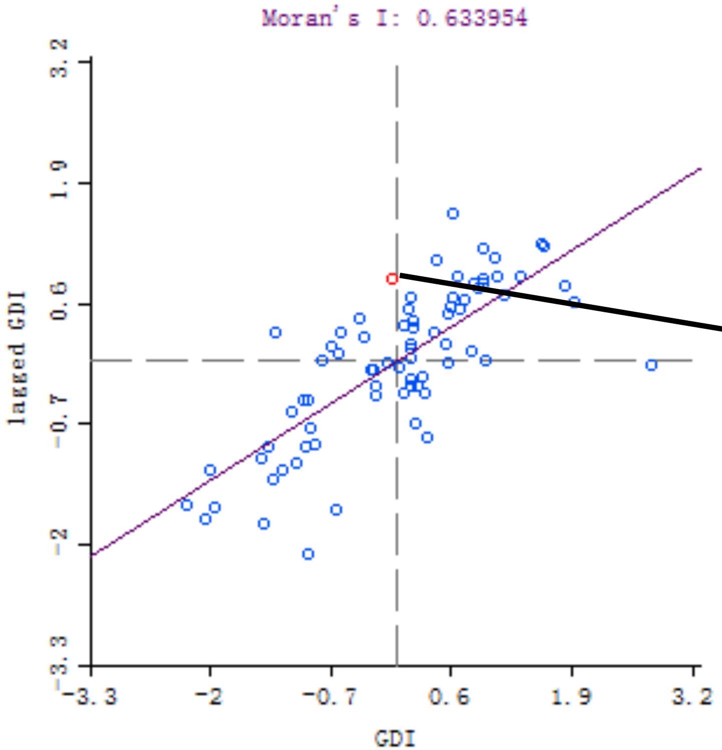
Q_3 (values [-], nearby values [-]): **L-L**

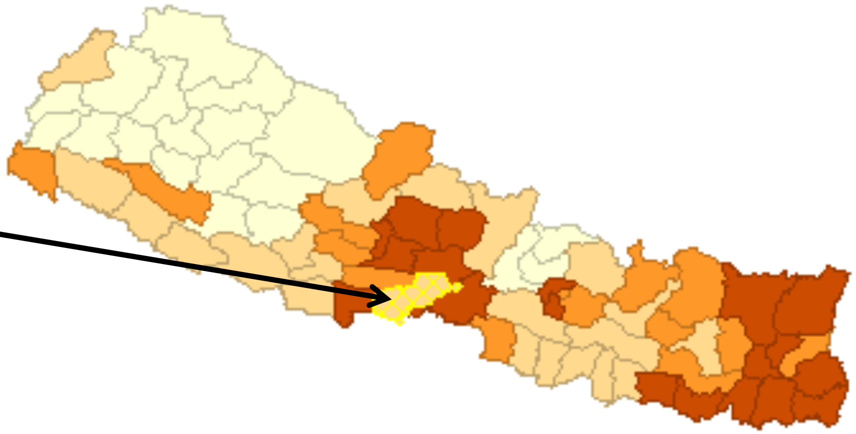
Locations of negative spatial association ("I'm different from my neighbors").

Q_2 (values [-], nearby values [+]): **L-H**

Q_4 (values [+], nearby values [-]): **H-L**

Moran Scatterplot: Example





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

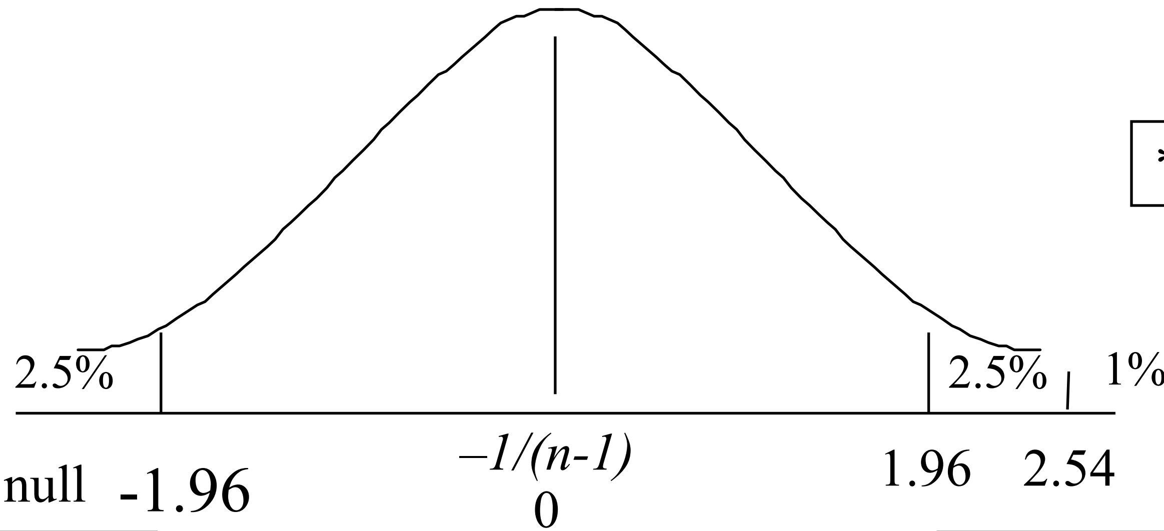
E(I) is the expected value if random

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

Test Statistic for Normal Frequency Distribution

**technically –1/(n-1)*



Reject null

Reject null at 5%

Reject null at 1%

Null Hypothesis: no spatial autocorrelation

*Moran's I = 0

Alternative Hypothesis: spatial autocorrelation exists

*Moran's I > 0

Reject *Null Hypothesis* if Z test statistic > 1.96 (or < -1.96)

---less than a 5% chance that, in the population, there is no spatial autocorrelation

---95% confident that spatial auto correlation exits

Null Hypothesis: no spatial autocorrelation

*Moran's I = 0

Alternative Hypothesis: spatial autocorrelation exists

*Moran's I > 0

Reject *Null Hypothesis* if Z test statistic > 1.96 (or < -1.96)

---less than a 5% chance that, in the population, there is no spatial autocorrelation

---95% confident that spatial auto correlation exits

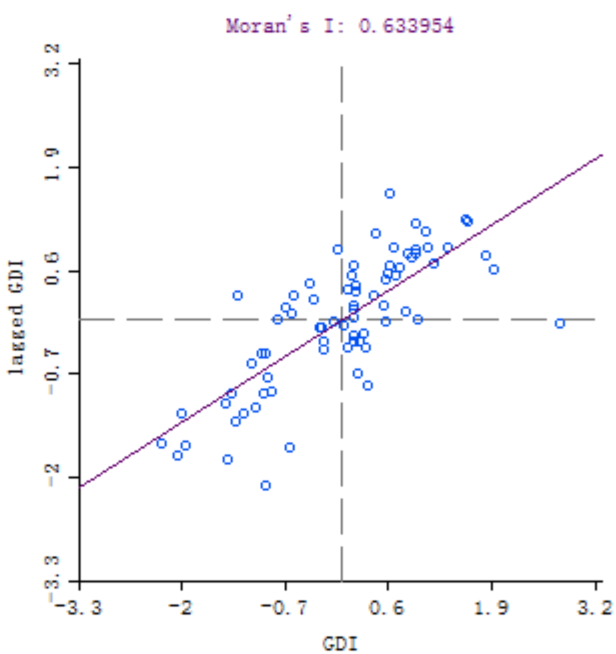
Spatial Autocorrelation vs Correlation

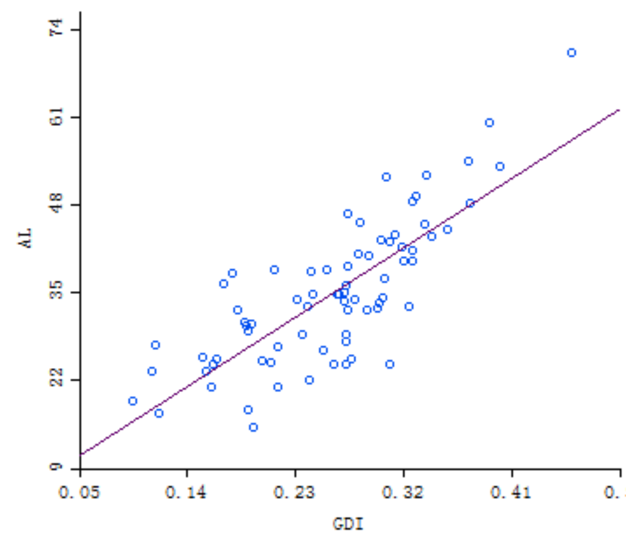
Spatial Autocorrelation:

shows the association or relationship between the <u>same</u> variable in "near-by" areas.

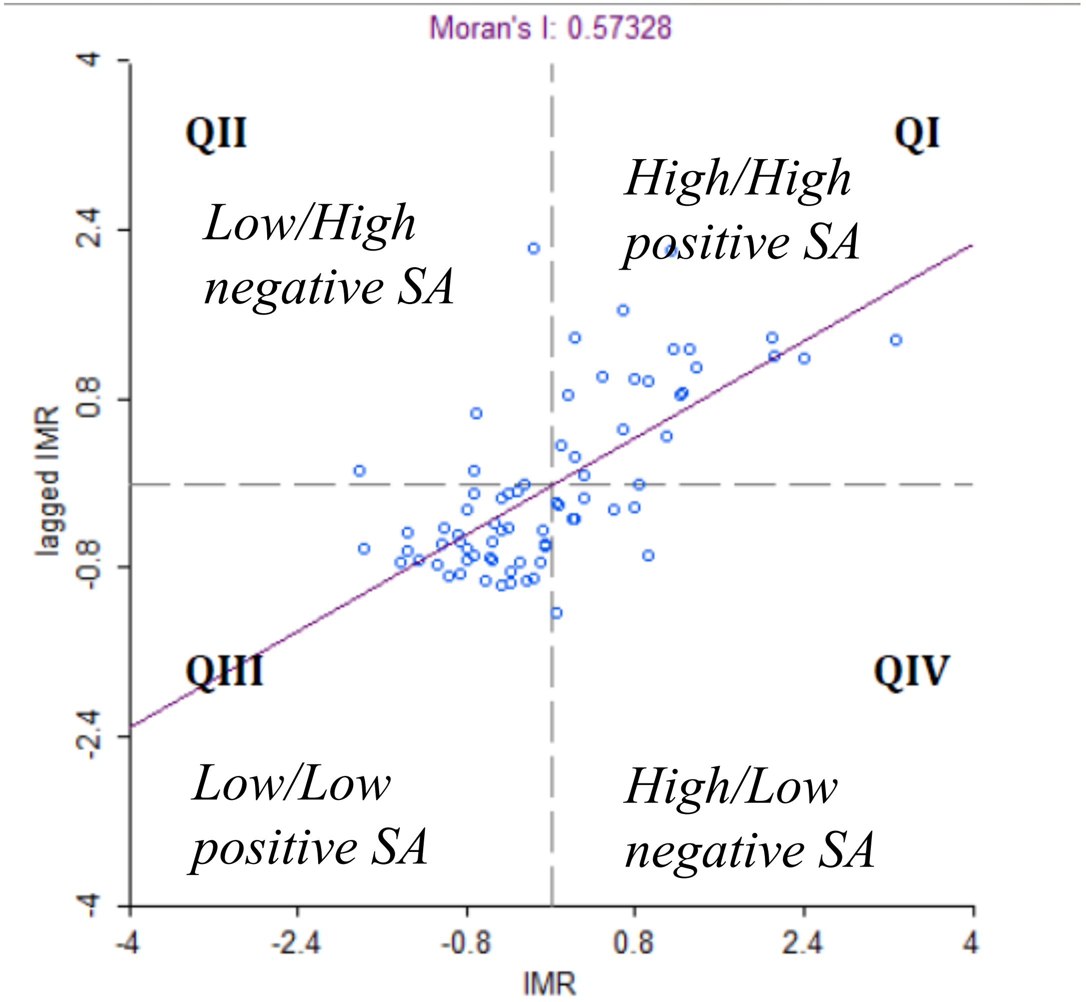
Standard Correlation

shows the association or relationship between two <u>different</u> variables





Bivariate Moran Scatter Plot



Local Measures of Spatial Autocorrelation

Local Indicators of Spatial Association (LISA)

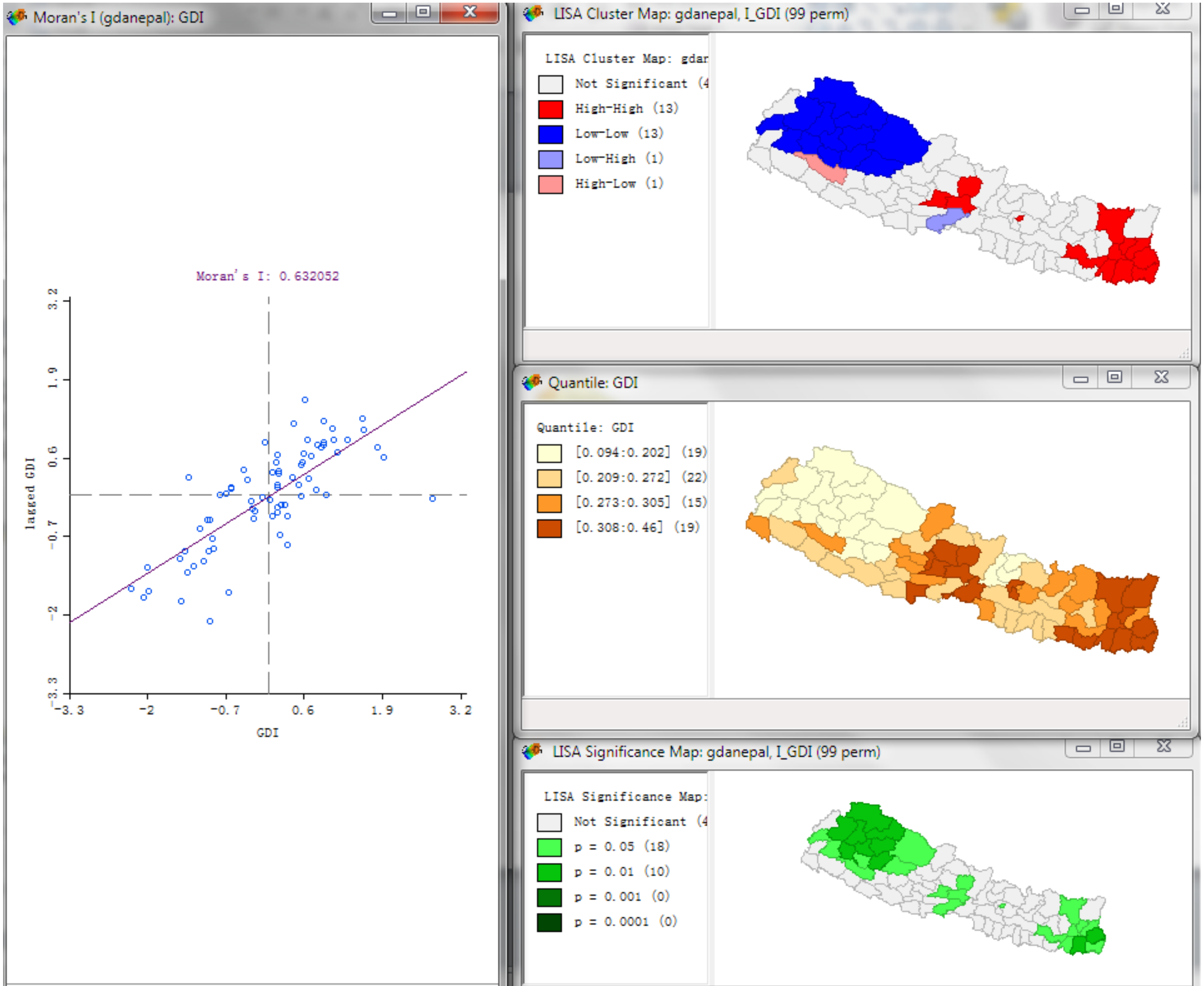
- <u>Local</u> versions of *Moran's I*
- Moran's I is most commonly used, and the local version is often called Anselin's LISA, or just LISA

See:
Luc Anselin 1995 *Local Indicators of Spatial Association-LISA* <u>Geographical Analysis</u> 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)

Calculating Anselin's LISA

- The local Moran statistic for areal unit i is:

$$I_i = z_i \sum_j w_{ij} z_j$$

where z_i is the original variable x_i in "standardized form" $z_i = \frac{x_i - \bar{x}}{SD_x}$

or it can be in "deviation form" $x_i - \bar{x}$

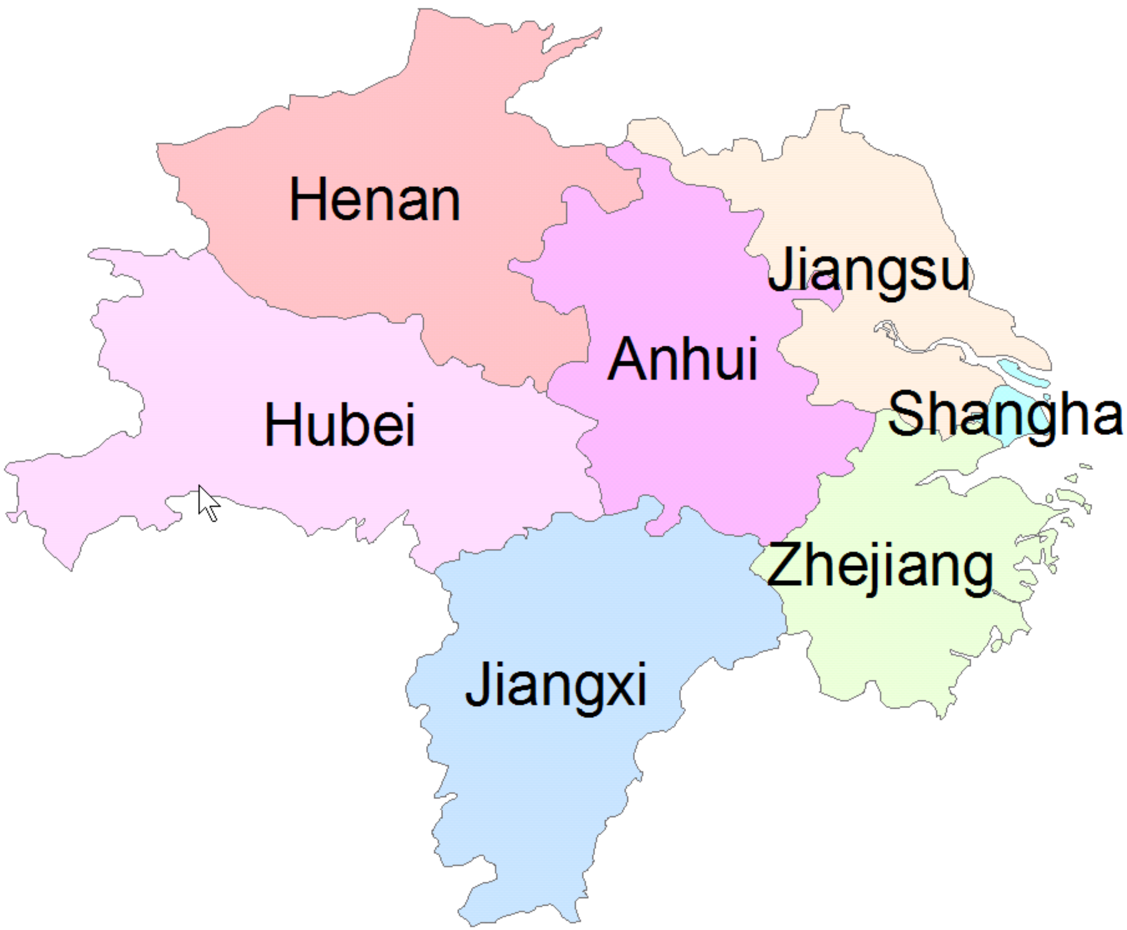
and w_{ij} is the spatial weight

The summation $\sum_j$ is across each <u>row</u> i of the spatial weights matrix.

An example follows

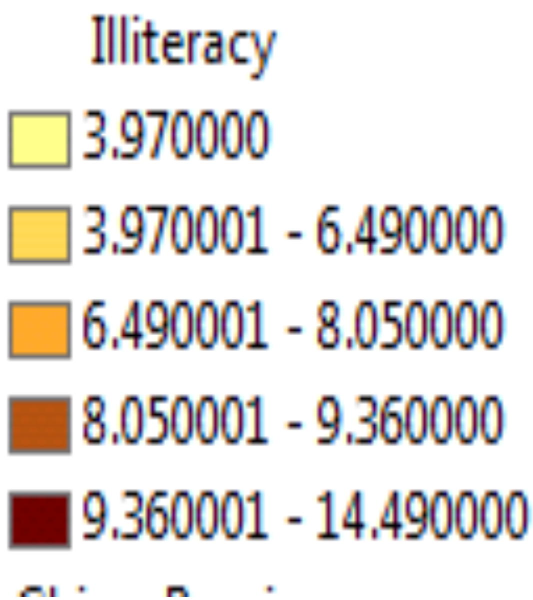
Example using seven China provinces

--caution: "edge effects" will strongly influences the results because we have a very small number of observations



Source: Ron Briggs of UT Dallas

Contiguity Matrix	Code	1 Anhui	2 Zhejiang	3 Jiangxi	4 Jiangsu	5 Henan	6 Hubei	7 Shanghai	Sum	Neighbors	**Illiteracy**
Anhui	1	0	1	1	1	1	1	0	5	6 5 4 3 2	**14.49**
Zhejiang	2	1	0	1	1	0	0	1	4	7 4 3 1	**9.36**
Jiangxi	3	1	1	0	0	0	1	0	3	6 2 1	**6.49**
Jiangsu	4	1	1	0	0	0	0	1	3	7 2 1	**8.05**
Henan	5	1	0	0	0	0	1	0	2	6 1	**7.36**
Hubei	6	1	0	1	0	1	0	0	3	1 3 5	**7.69**
Shanghai	7	0	1	0	1	0	0	0	2	2 4	**3.97**



Source: Ron Briggs of UT Dallas

Contiguity Matrix and Row Standardized Spatial Weights Matrix

Contiguity Matrix		1	2	3	4	5	6	7	
	Code	Anhui	Zhejiang	Jiangxi	Jiangsu	Henan	Hubei	Shanghai	Sum
Anhui	1	0	1	1	1	1	1	0	5
Zhejiang	2	1	0	1	1	0	0	1	4
Jiangxi	3	1	1	0	0	0	1	0	3
Jiangsu	4	1	1	0	0	0	0	1	3
Henan	5	1	0	0	0	0	1	0	2
Hubei	6	1	0	1	0	1	0	0	3
Shanghai	7	0	1	0	1	0	0	0	2

1/3

Row Standardized Spatial Weights Matrix									
	Code	Anhui	Zhejiang	Jiangxi	Jiangsu	Henan	Hubei	Shanghai	Sum
Anhui	1	0.00	0.20	0.20	0.20	0.20	0.20	0.00	1
Zhejiang	2	0.25	0.00	0.25	0.25	0.00	0.00	0.25	1
Jiangxi	3	0.33	0.33	0.00	0.00	0.00	0.33	0.00	1
Jiangsu	4	0.33	0.33	0.00	0.00	0.00	0.00	0.33	1
Henan	5	0.50	0.00	0.00	0.00	0.00	0.50	0.00	1
Hubei	6	0.33	0.00	0.33	0.00	0.33	0.00	0.00	1
Shanghai	7	0.00	0.50	0.00	0.50	0.00	0.00	0.00	1

Source: Ron Briggs of UT Dallas

Calculating standardized (z) scores

$$z_i = \frac{x_i - \bar{x}}{SD_x}$$

Deviations from Mean and z scores.

	X	**X-Xmean**	**X-Mean2**	**z**
Anhui	14.49	6.29	39.55	2.101
Zhejiang	9.36	1.16	1.34	0.387
Jiangxi	6.49	(1.71)	2.93	(0.572)
Jiangsu	8.05	(0.15)	0.02	(0.051)
Henan	7.36	(0.84)	0.71	(0.281)
Hubei	7.69	(0.51)	0.26	(0.171)
Shanghai	3.97	(4.23)	17.90	(1.414)

Mean and Standard Deviation

Sum	57.41		0.00		62.71
Mean	57.41	/	7	=	8.20
Variance	62.71	/	7	=	8.96
SD	√ 8.96			=	2.99

Source: Ron Briggs of UT Dallas

Calculating LISA

Row Standardized Spatial Weights Matrix

	Code	Anhui	Zhejiang	Jiangxi	Jiangsu	Henan	Hubei	Shanghai
Anhui	1	0.00	0.20	0.20	0.20	0.20	0.20	0.00
Zhejiang	2	0.25	0.00	0.25	0.25	0.00	0.00	0.25
Jiangxi	3	0.33	0.33	0.00	0.00	0.00	0.33	0.00
Jiangsu	4	0.33	0.33	0.00	0.00	0.00	0.00	0.33
Henan	5	0.50	0.00	0.00	0.00	0.00	0.50	0.00
Hubei	6	0.33	0.00	0.33	0.00	0.33	0.00	0.00
Shanghai	7	0.00	0.50	0.00	0.50	0.00	0.00	0.00

W_{ij}

$$I_i = z_i \sum_j w_{ij} z_j$$

Z-Scores for row Province and its potential neighbors

	Zi	Anhui	Zhejiang	Jiangxi	Jiangsu	Henan	Hubei	Shanghai
Anhui	2.101	***2.101***	0.387	(0.572)	(0.051)	(0.281)	(0.171)	(1.414)
Zhejiang	0.387	2.101	***0.387***	(0.572)	(0.051)	(0.281)	(0.171)	(1.414)
Jiangxi	(0.572)	2.101	0.387	***(0.572)***	(0.051)	(0.281)	(0.171)	(1.414)
Jiangsu	(0.051)	2.101	0.387	(0.572)	***(0.051)***	(0.281)	(0.171)	(1.414)
Henan	(0.281)	2.101	0.387	(0.572)	(0.051)	*(0.281)*	(0.171)	(1.414)
Hubei	(0.171)	2.101	0.387	(0.572)	(0.051)	(0.281)	***(0.171)***	(1.414)
Shanghai	(1.414)	2.101	0.387	(0.572)	(0.051)	(0.281)	(0.171)	***(1.414)***

z_j

$W_{ij}Z_j$

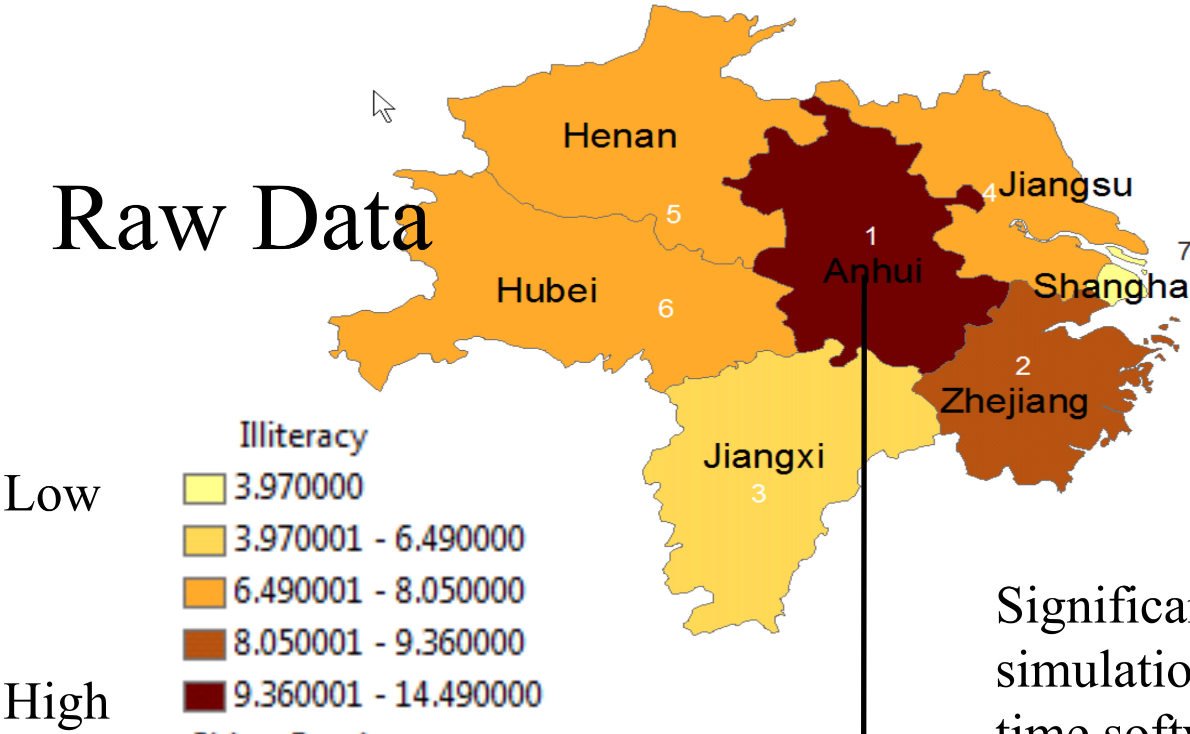
Spatial Weight Matrix multiplied by Z-Score Matrix (cell by cell multiplication)

	Zi	**Anhui**	**Zhejiang**	**Jiangxi**	**Jiangsu**	**Henan**	**Hubei**	**Shanghai**	**SumWijZj**	**LISA**	**Lisa from GeoDA**
									0.000		
Anhui	**2.101**	-	0.077	(0.114)	(0.010)	(0.056)	(0.034)	-	**(0.137)**	**-0.289**	-0.248
Zhejiang	**0.387**	0.525	-	(0.143)	(0.013)	-	-	(0.353)	**0.016**	**0.006**	0.005
Jiangxi	**(0.572)**	0.700	0.129	-	-	-	(0.057)	-	**0.772**	**-0.442**	-0.379
Jiangsu	**(0.051)**	0.700	0.129	-	-	-	-	(0.471)	**0.358**	**-0.018**	-0.016
Henan	**(0.281)**	1.050	-	-	-	-	(0.085)	-	**0.965**	**-0.271**	-0.233
Hubei	**(0.171)**	0.700	-	(0.191)	-	(0.094)	-	-	**0.416**	**-0.071**	-0.061
Shanghai	**(1.414)**	-	0.194	-	(0.025)	-	-	-	**0.168**	**-0.238**	-0.204

Source: Ron Briggs of UT Dallas

Results

Raw Data

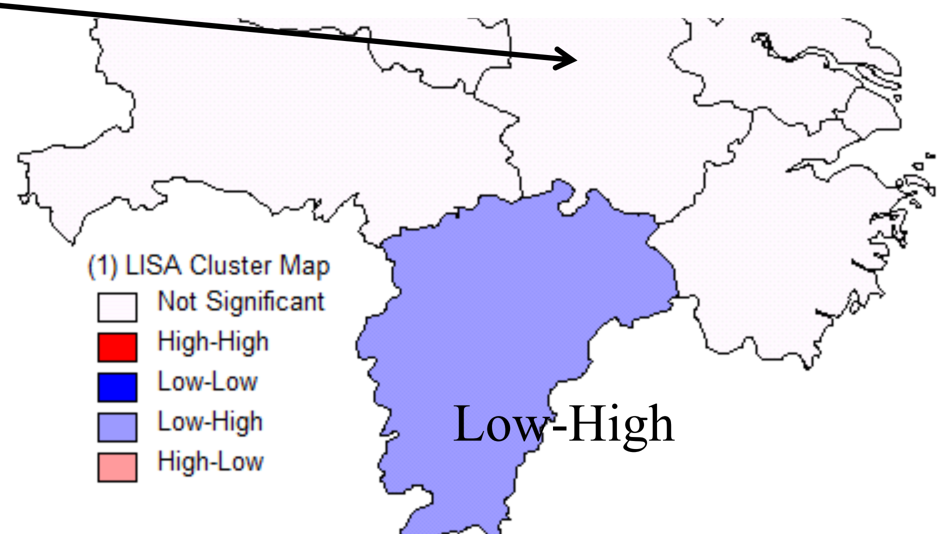


Moran's I = -.01889

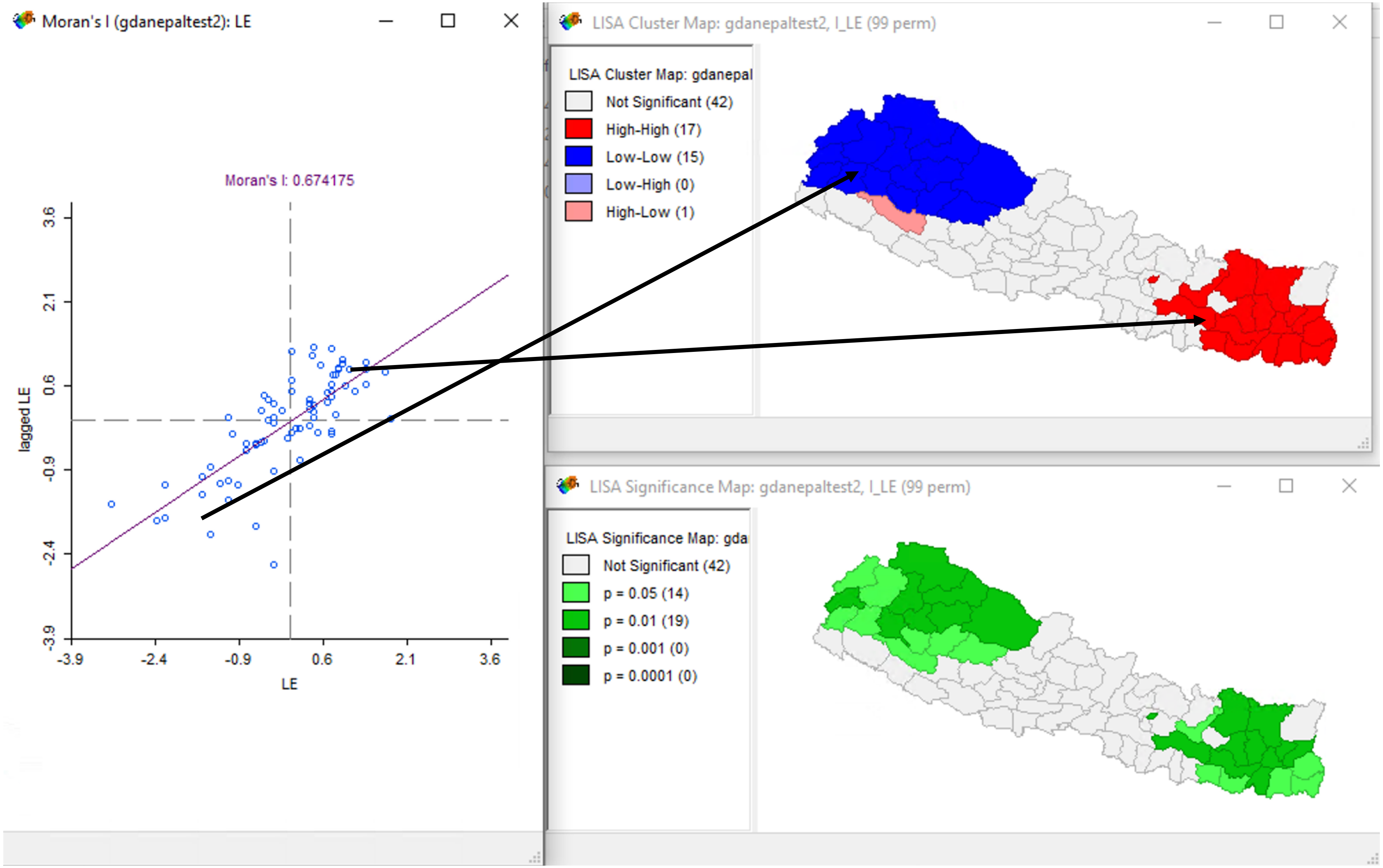
I expected Anhui to be *High-Low!*
(high illiteracy surrounded by low)

Significance levels are calculated by simulations. They may differ each time software is run.

Province	Literacy %	LISA	Significance
Anhui	14.49	-0.25	0.12
Zhejiang	9.36	0.01	0.46
Jiangxi	6.49	-0.38	0.04
Jiangsu	8.05	-0.02	0.32
Henan	7.36	-0.23	0.14
Hubei	7.69	-0.06	0.28
Shanghai	3.97	-0.20	0.37

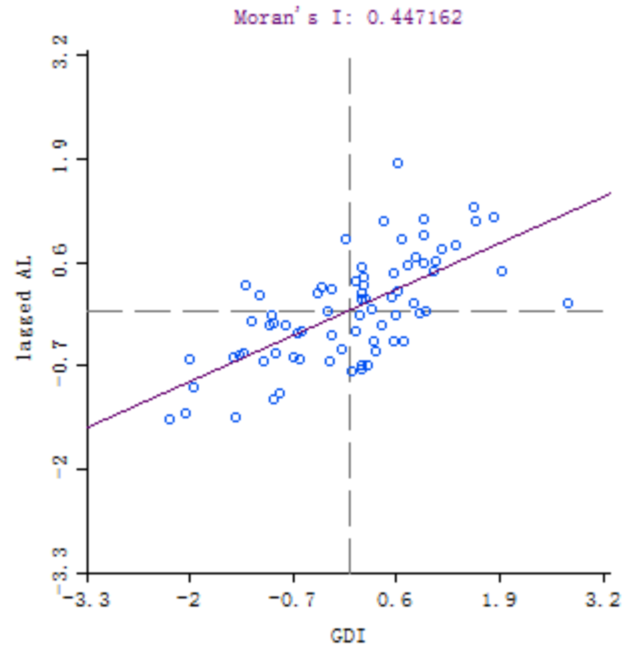


Example: Nepal Data



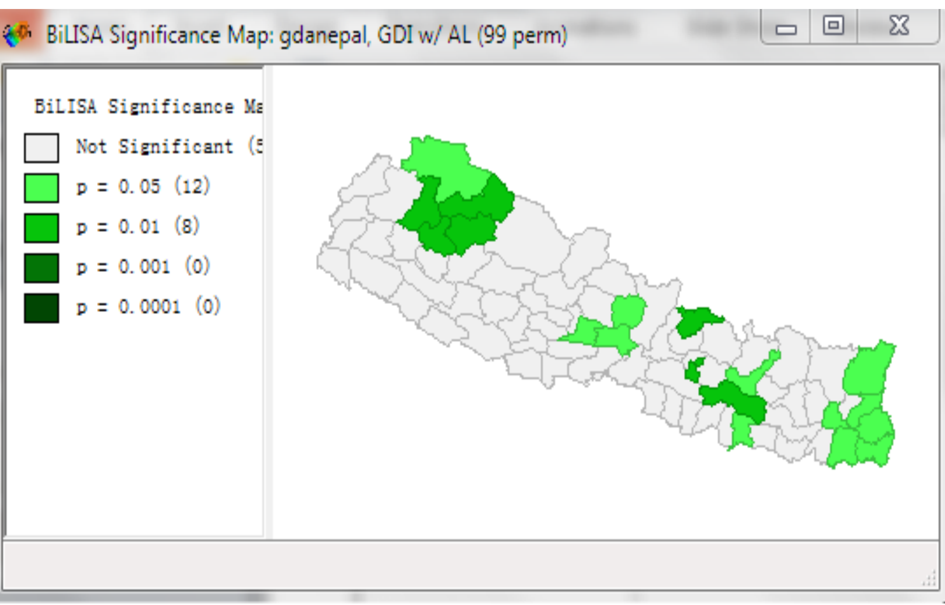
Bivariate LISA

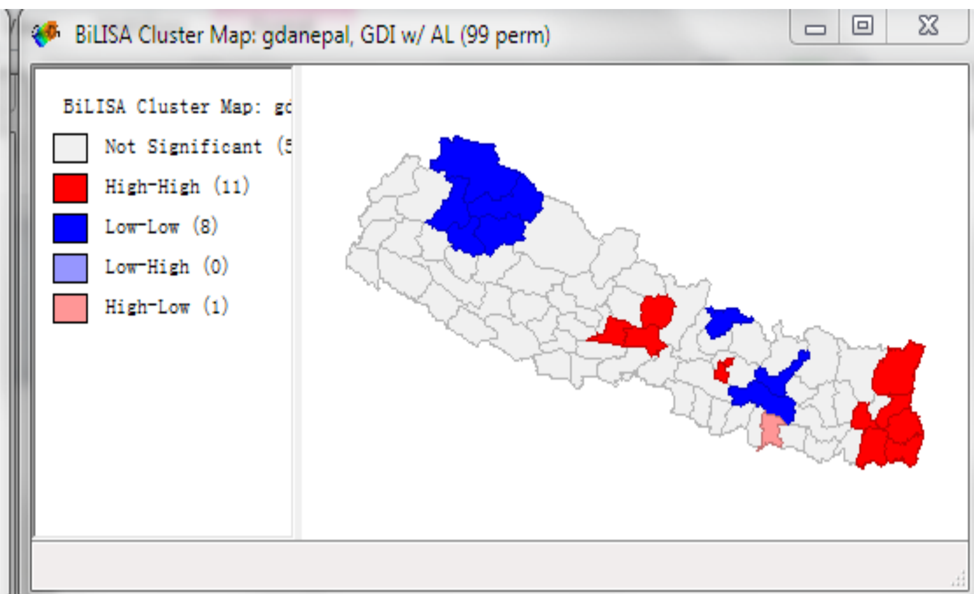
Moran Scatter Plot for GDI vs AL



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

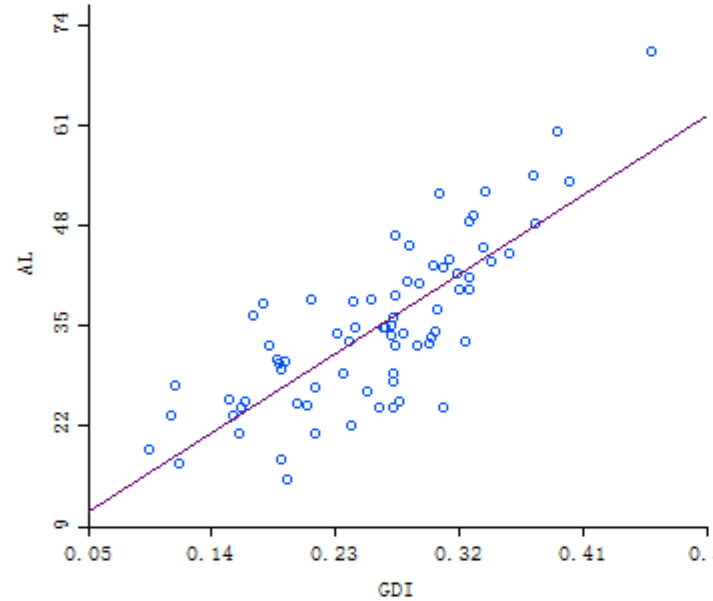
Moran Significance Map for GDI vs. AL

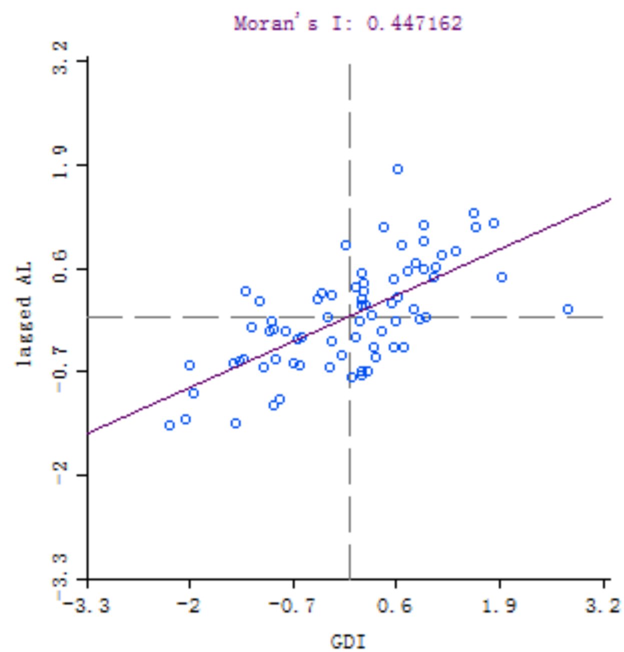




Bivariate LISA
and the Correlation Coefficie

- 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.





Consequences of Ignoring Spatial Autocorrelation

- correlation coefficients and coefficients of determination appear <u>bigger</u> than they really are
  - You think the relationship is stronger than it really is
  - the variables in nearby areas affect each other
- Standard errors appear <u>smaller</u> than they really are
  - *exaggerated precision*
  - You think your predictions are better than they really are since standard errors measure *predictive accuracy*
  - More likely to conclude relationship is *statistically significant*.

Diagnostic of Spatial Dependence

- **For correlation**
  - calculate Moran's I for each variable and test its statistical significance
  - If Moran's I is significant, you may have a problem!
- **For regression**
  - calculate the residuals

    map the residuals: do you see any spatial patterns?
  - Calculate Moran's I for the residuals: is it statistically significant?

Summary

- Spatial autocorrelation of areal data
- Spatial weight matrix
- Measures of spatial autocorrelation
- Global Measure
  - Moran's I
- Consequences of ignoring spatial autocorrelation
- Significance test

- Please read O’S & Unwin Ch. 7 and Ch. 8.1 and 8.2
- End of this topic