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)
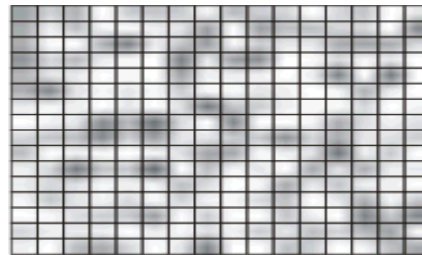 - Geostatistical data (next topic)

Spatial Autocorrelation of Areal Data
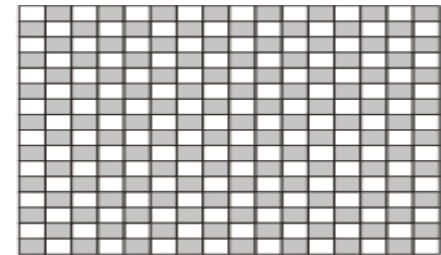
Spatial Autocorrelation

- Tobler's first law of geography
- Spatial auto/cross correlation
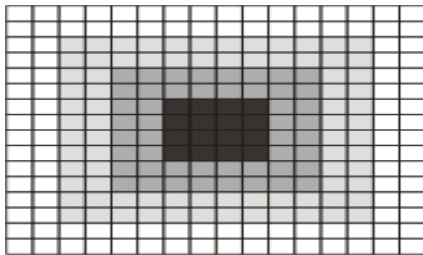
If like values tend to cluster together, then the field exhibits high **positive spatial autocorrelation**

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
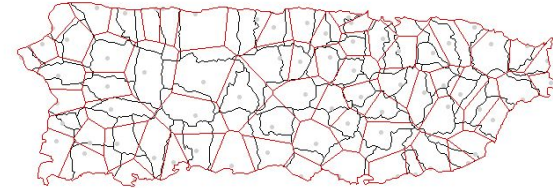
nearby low values

2002 population density
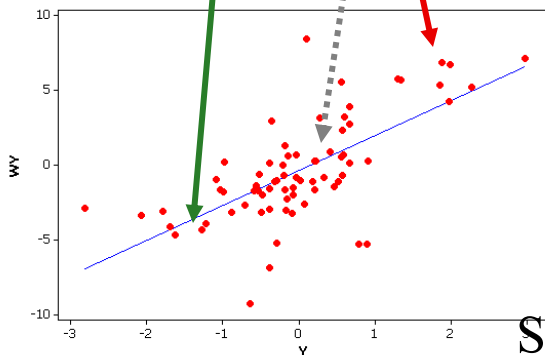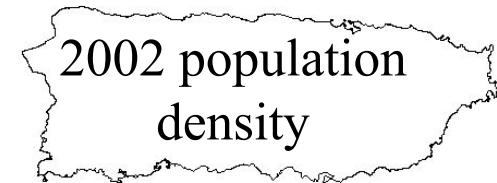
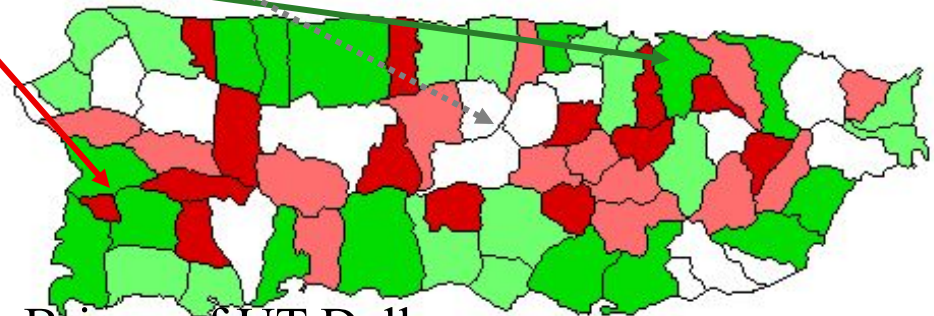Source: Ron Briggs of UT Dallas

Negative spatial autocorrelation

- high values

 surrounded by nearby low values

- intermediate values surrounded

 by nearby intermediate values

- low values surrounded by

 nearby high values

Grocery store density
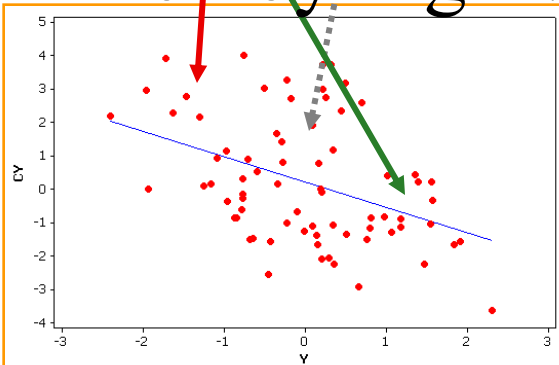
Source: Ron Briggs of UT Dallas

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
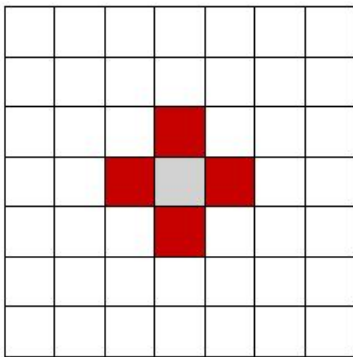
rook
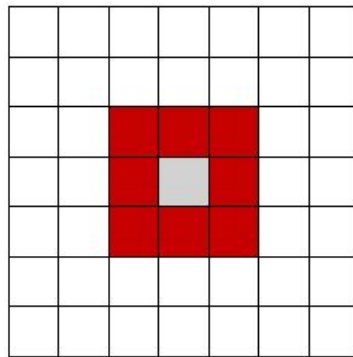
queen
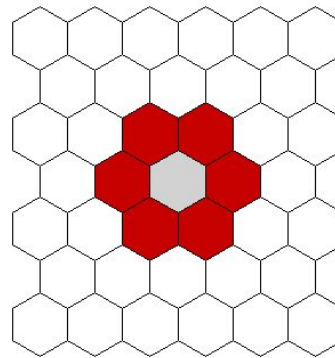
Hexagons
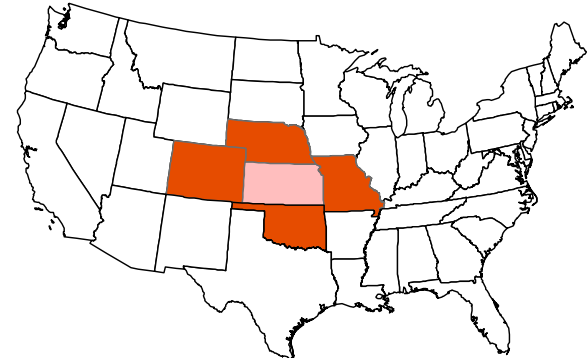
Irregular

Which use?

Higher-Order Contiguity

1ˢᵗ order

Nearest neighbor
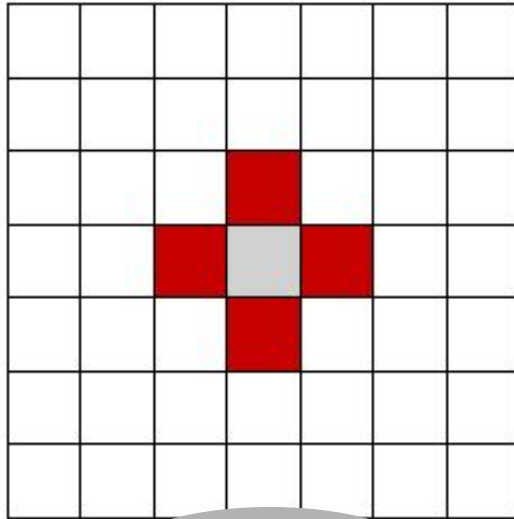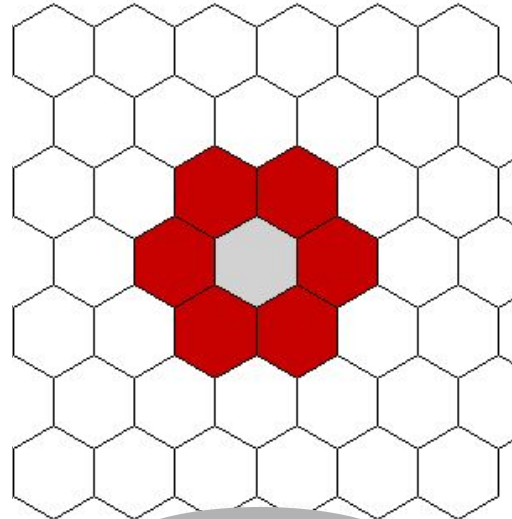
2ⁿᵈ order

Next nearest neighbor

rook

hexagon

queen
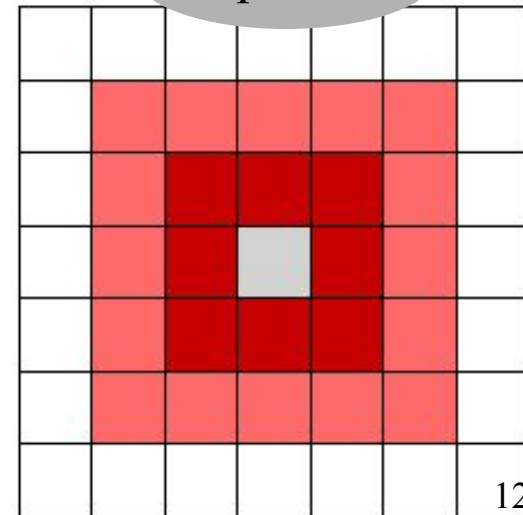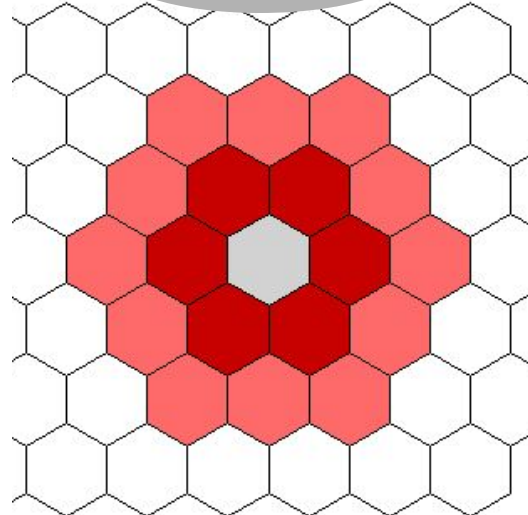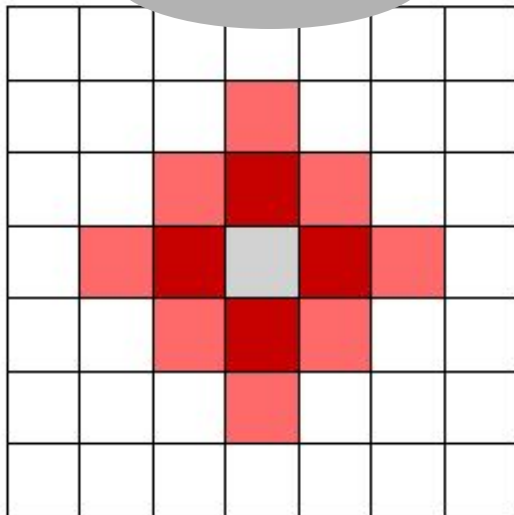
Distance-based Neighbors

- How to measure distance between polygons?

- Distance metrics
  - 2D Cartesian distance (projected data)
  - 3D spherical distance/great-circle distance (lat/long data)
    - Haversine formula

$$\text{Haversine formula:} \quad a = \sin^2(\Delta\varphi/2) + \cos(\varphi_1).\cos(\varphi_2).\sin^2(\Delta\lambda/2)$$

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

$$d = R.c$$

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

Distance-based Neighbors

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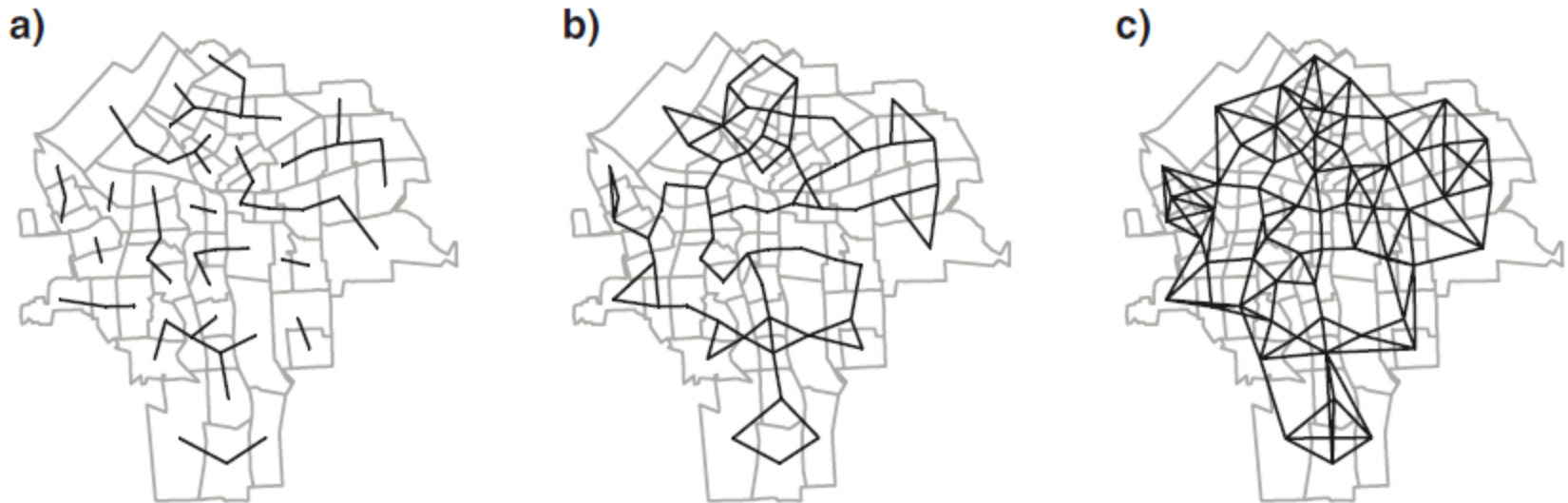
Fig. 9.5. (a) $k = 1$ neighbours; (b) $k = 2$ neighbours; (c) $k = 4$ neighbours

Source: Bivand and Pebesma and Gomez-Rubio

Distance-based Neighbors

- thresh-hold distance (buffer)
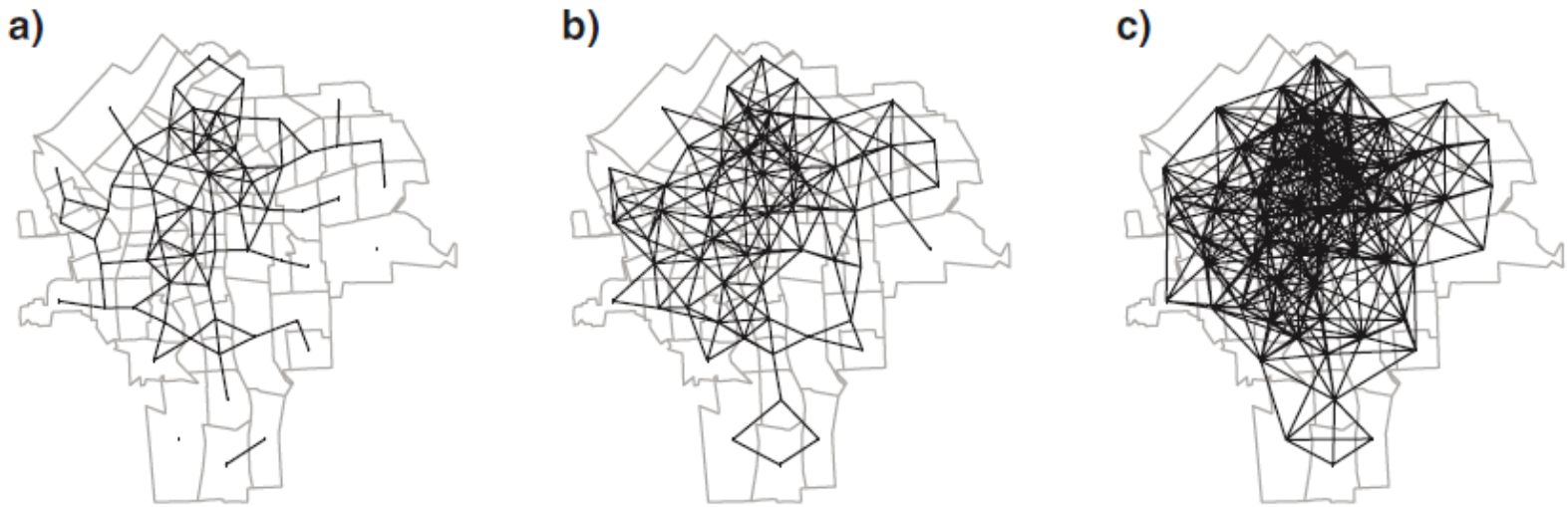
Fig. 9.6. (a) Neighbours within 1,158 m; (b) neighbours within 1,545 m; (c) neighbours within 2,317 m

Source: Bivand and Pebesma and Gomez-Rubio

Neighbor/Connectivity Histogram
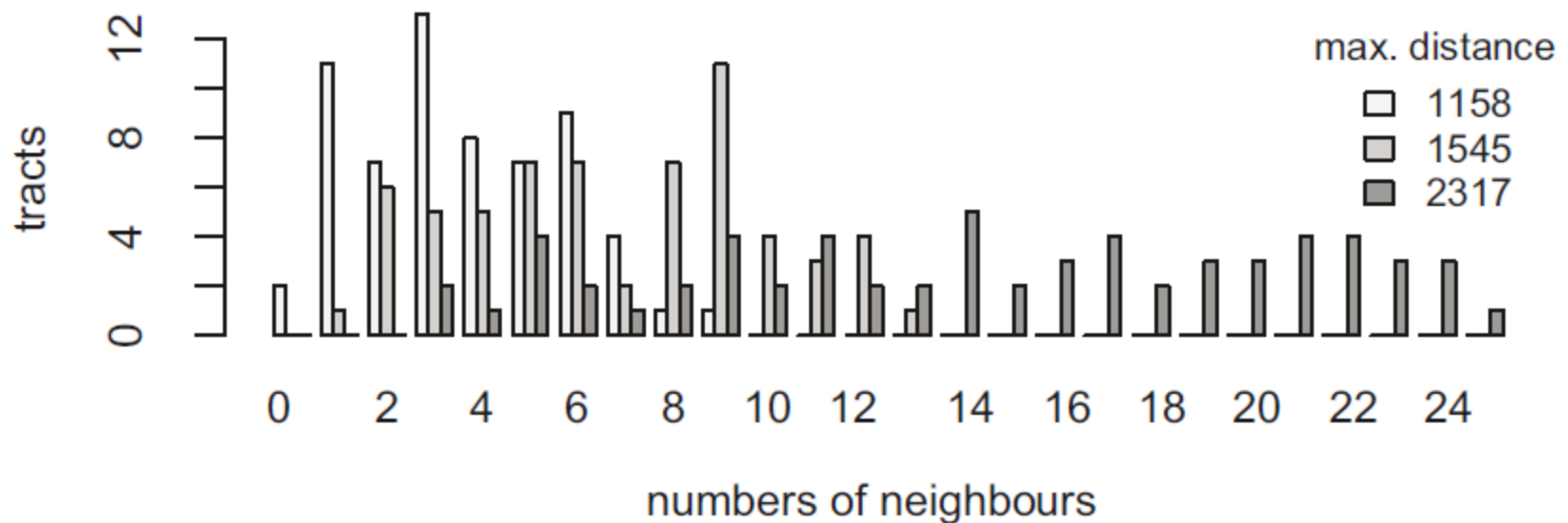
Source: Bivand and Pebesma and Gomez-Rubio

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 W_{ij} will set to zero

  – The weight matrix can be

  illustrated as an image

  – Sparse matrix
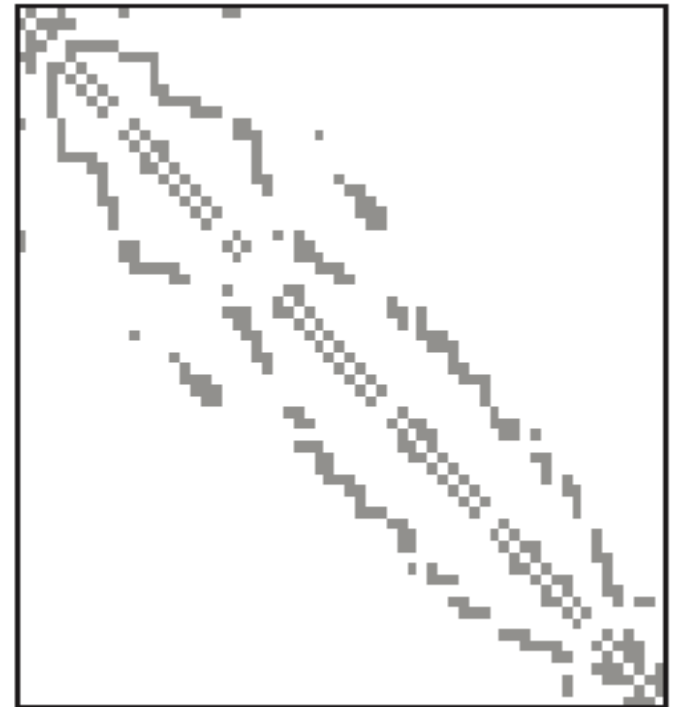
A Simple Example for Rook case

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

4 areal units
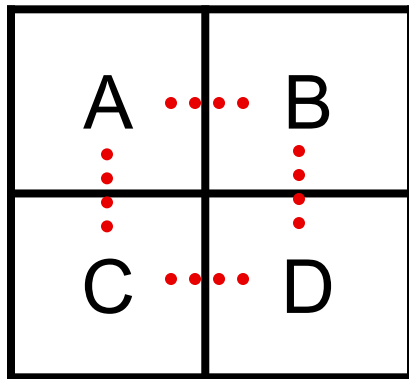
Common border

4x4 matrix

$$
\begin{array}{c c c c c}
 & A & B & C & D \\
A & 0 & 1 & 1 & 0 \\
\mathbf{W} = B & 1 & 0 & 0 & 1 \\
C & 1 & 0 & 0 & 1 \\
D & 0 & 1 & 1 & 0 \\
\end{array}
$$
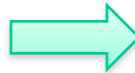
1 Washington
2 Oregon
3 California
4 Arizona
5 Nevada
6 Idaho
7 Montana
8 Wyoming
9 Utah
10 New Mexico
11 Texas
12 Oklahoma
13 Colorado
14 Kansas
15 Nebraska
16 South Dakota
17 North Dakota
18 Minnesota
19 Iowa
20 Missouri
21 Arkansas
22 Louisiana
23 Mississippi
24 Tennessee
25 Kentucky
26 Illinois
27 Wisconsin
28 Michigan
29 Indiana
30 Ohio
31 West Virginia
32 Florida
33 Alabama
34 Georgia
35 South Carolina
36 North Carolina
37 Virginia
38 Maryland
39 Delaware
40 District of Columbia
41 New Jersey
42 Pennsylvania
43 New York
44 Connecticut
45 Rhode Island
46 Massachussets
47 New Hampshire
48 Vermont
49 Maine

Name	Fips	Ncount	N1	N2	N3	N4	N5	N6	N7	N8
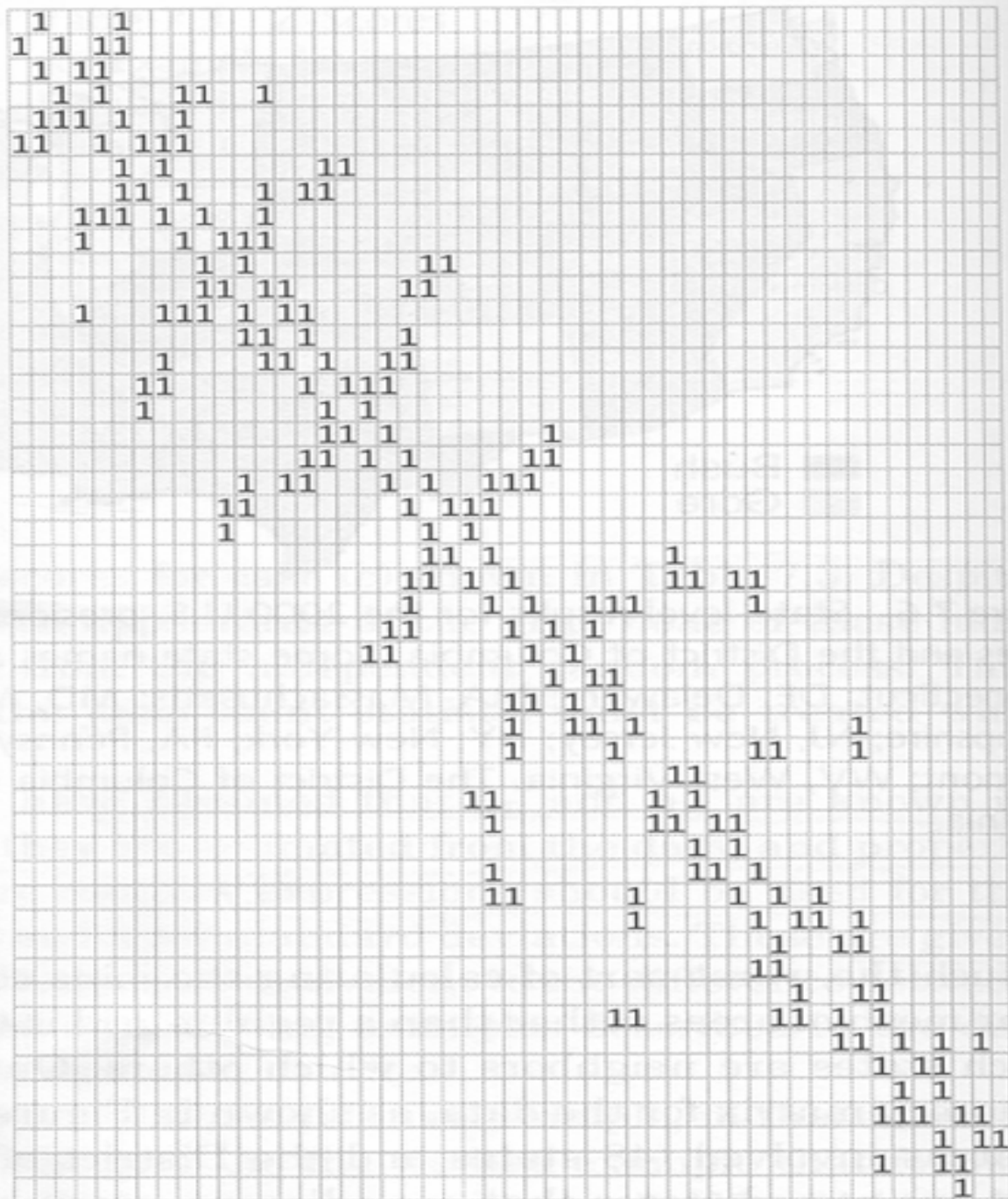
Sparse Contiguity Matrix for US States -- obtained from Anselin's web site (see powerpoint for link)										
Name	Fips	Ncount	N1	N2	N3	N4	N5	N6	N7	N8
Alabama	1	4	28	13	12	47				
Arizona	4	5	35	8	49	6	32			
Arkansas	5	6	22	28	48	47	40	29		
California	6	3	4	32	41					
Colorado	8	7	35	4	20	40	31	49	56	
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		

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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
A	B	C	
D	E	F	

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* $w_{ij} = e^{-d^2}$)
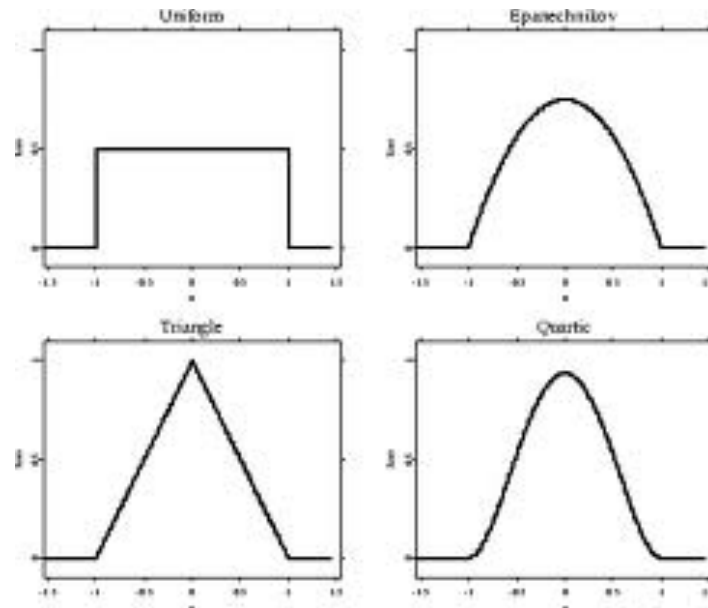
Measure of Spatial Autocorrelation

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
  - 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)
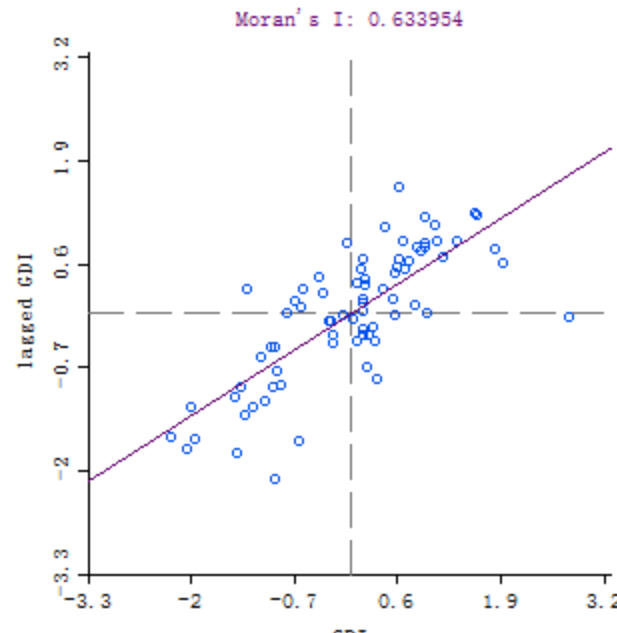
Formula for Moran's I

$$I = \frac{N \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{(\sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} w_{ij}) \sum\limits_{i=1}^{n} (x_i - \overline{x})^2}$$

- Where:

N is the number of observations (points or polygons)
$\overline{X}$ 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

$$\frac{\sum\limits_{i=1}^{n} 1(y_i - \overline{y})(x_i - \overline{x})/n}{\sqrt{\dfrac{\sum\limits_{i=1}^{n}(y_i - \overline{y})^2}{n}} \sqrt{\dfrac{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2}{n}}}$$
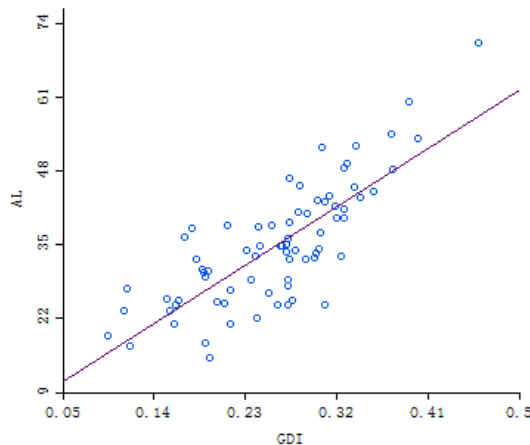
Note the similarity of the numerator (top) to the measures of spatial association discussed earlier if we view Yi as being the Xi for the neighboring polygon

(see next slide)

Spatial auto-correlation

$$\frac{N\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{(\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij})\sum\limits_{i=1}^{n}(x_i - \overline{x})^2} \quad = \quad \frac{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})/\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}}{\sqrt{\dfrac{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2}{n}} \sqrt{\dfrac{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2}{n}}}$$

Source: Ron Briggs of UT Dallas

Correlation Coefficient

$$\frac{\sum\limits_{i=1}^{n} 1 (y_i - \overline{y})(x_i - \overline{x})/n}{\sqrt{\dfrac{\sum\limits_{i=1}^{n} (y_i - \overline{y})^2}{n}} \sqrt{\dfrac{\sum\limits_{i=1}^{n} (x_i - \overline{x})^2}{n}}}$$

Spatial weights

Yi is the Xi for the neighboring polygon

$$\frac{N\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{(\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij})\sum\limits_{i=1}^{n}(x_i - \overline{x})^2} = \frac{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})/\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}}{\sqrt{\dfrac{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2}{n}}\sqrt{\dfrac{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2}{n}}}$$

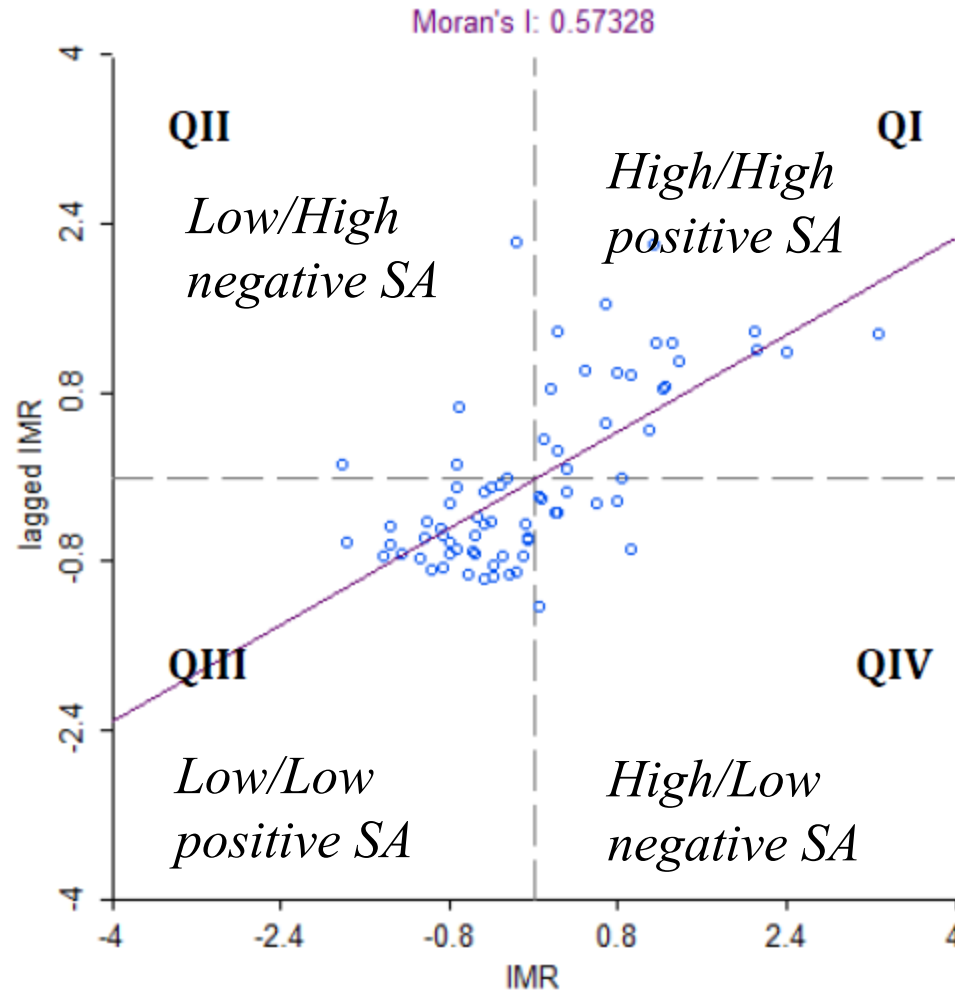Moran's I

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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)
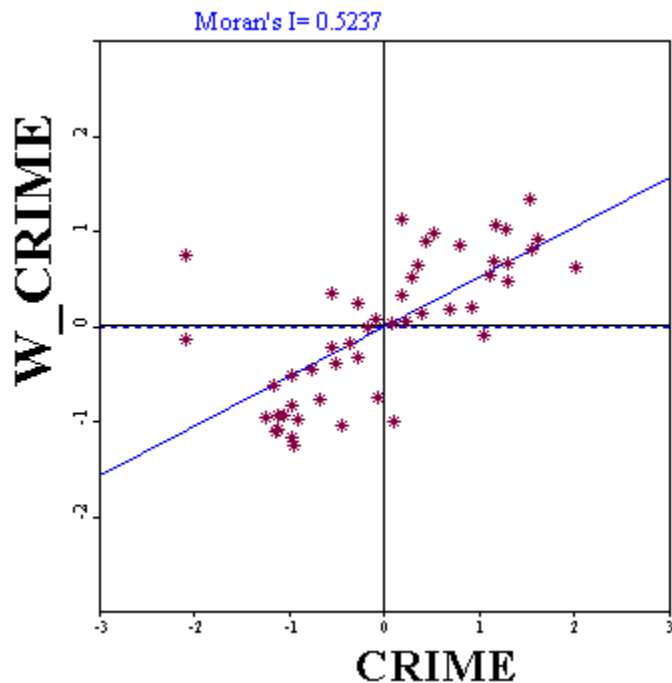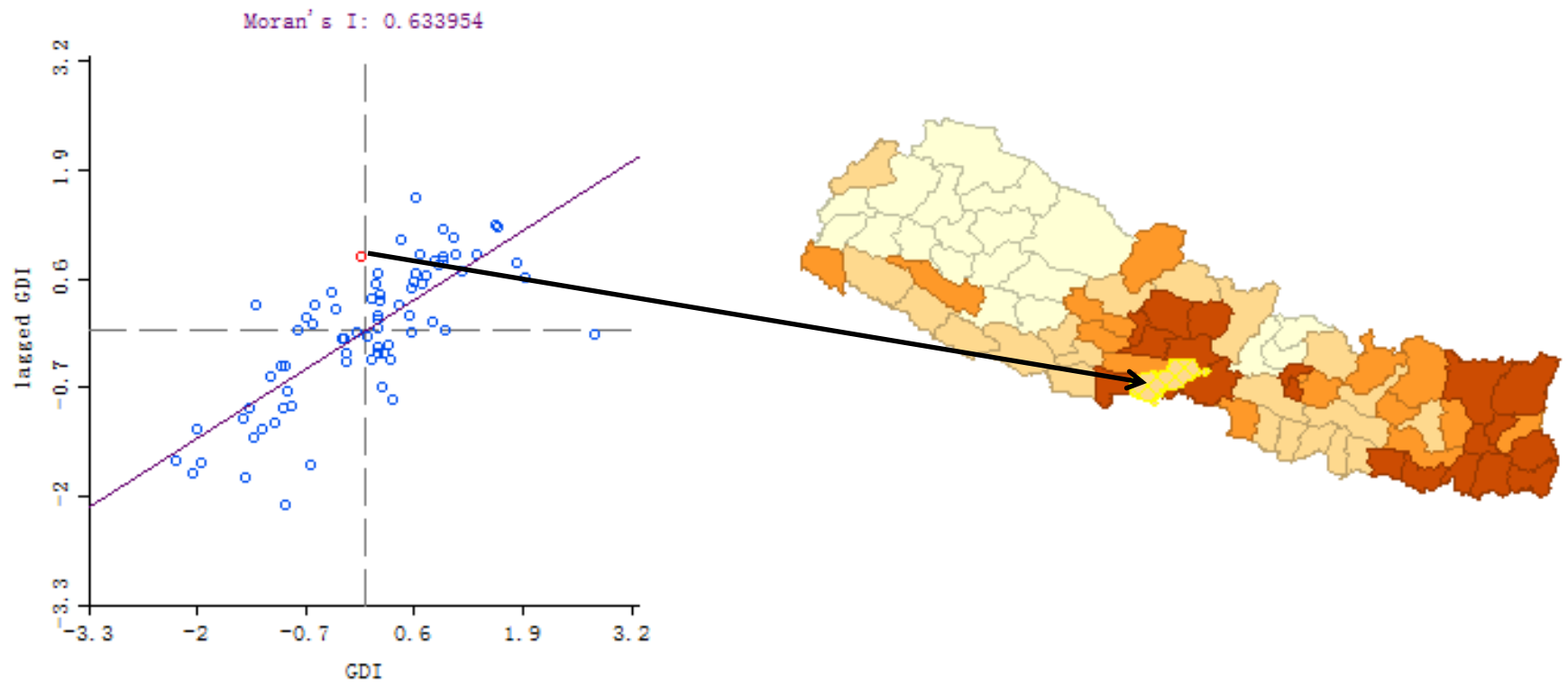

The <u>slope</u> of this *regression line* is Moran's I

Moran Scatter Plots

Moran Scatterplot: Example

Statistical Significance Tests for Moran's I

- Based on the normal frequency distribution with

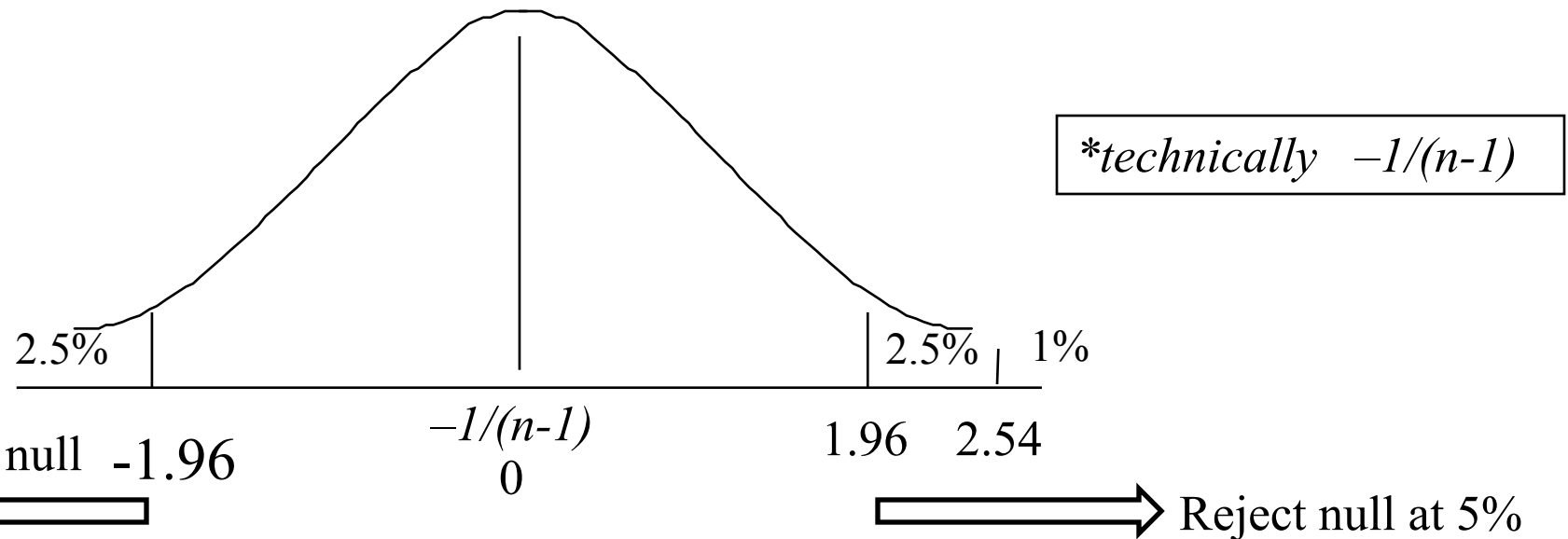$$Z = \frac{I - E(I)}{S_{error(I)}}$$

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)

2.5%   2.5%   1%

−1/(n-1)
0

1.96   2.54

Reject null -1.96

⟵⟵⟵⟵⟵   ⟹⟹⟹⟹⟹ Reject null at 5%

Null Hypothesis: no spatial autocorrelation   ⟹ Reject null at 1%

    *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

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    ---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
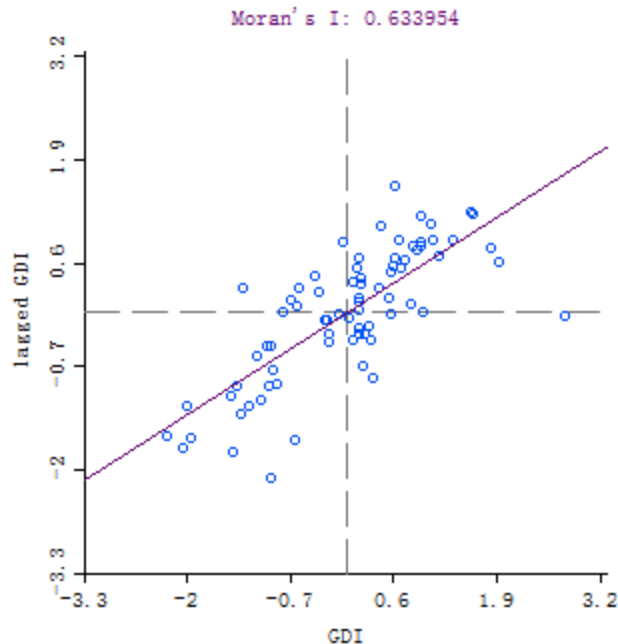Reject *Null Hypothesis* if Z test statistic > 1.96 (or < -1.96)
   ---less than a 5% chance that, in the population, there is no
        spatial autocorrelation
   ---95% confident that spatial auto correlation exits
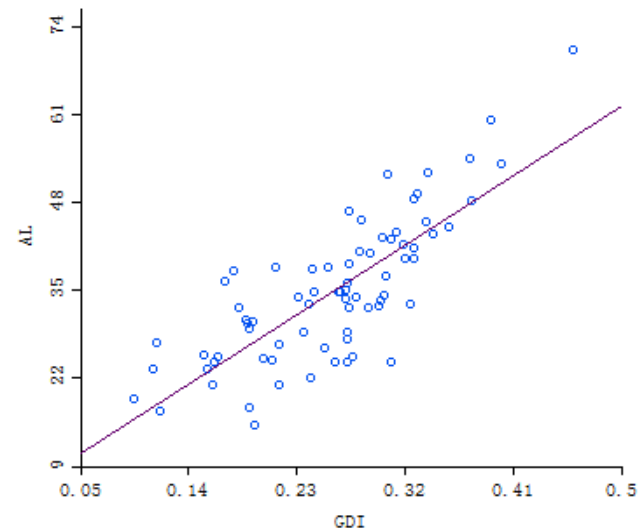
Spatial Autocorrelation vs Correlation

Spatial Autocorrelation:
shows the association or relationship between the <u>same</u> variable in "near-by" areas.
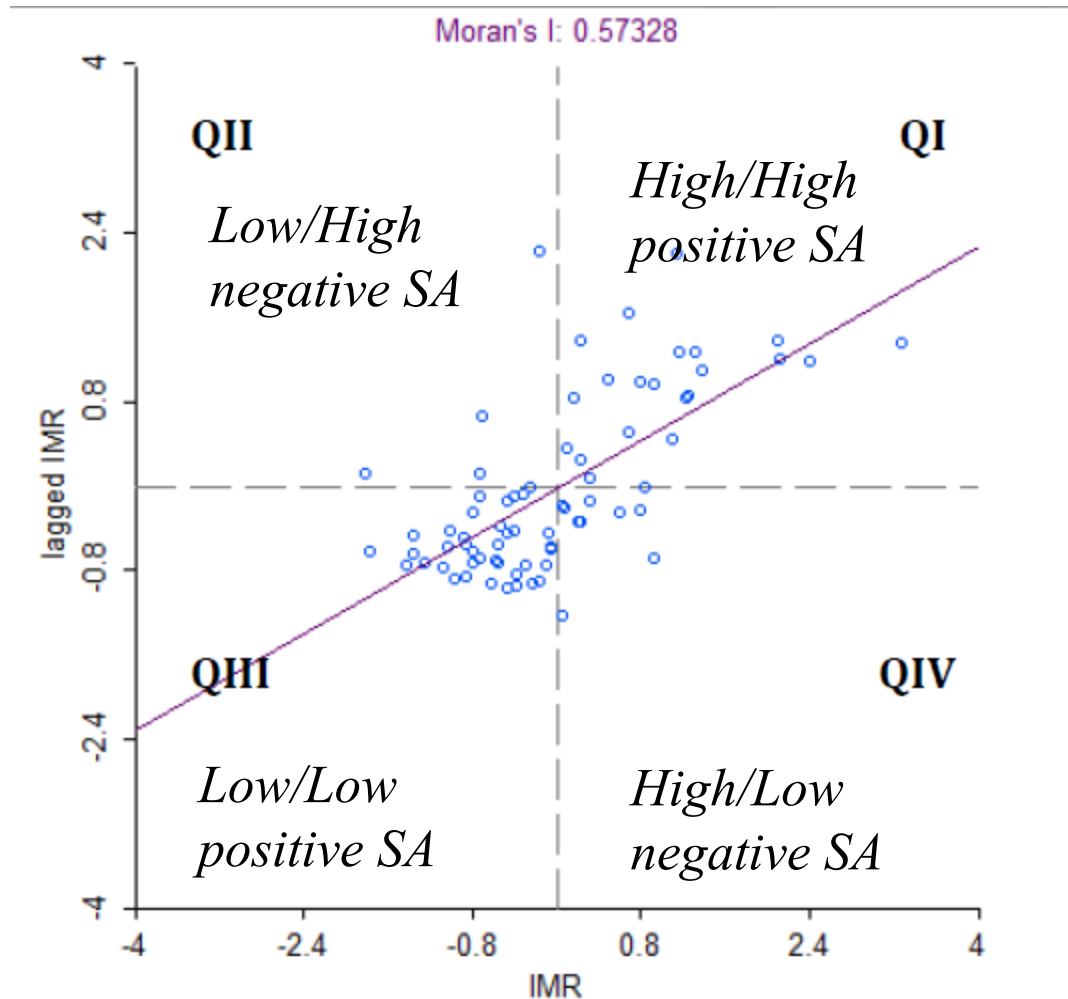
Standard Correlation
shows the association or relationship between two <u>different</u> variables

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
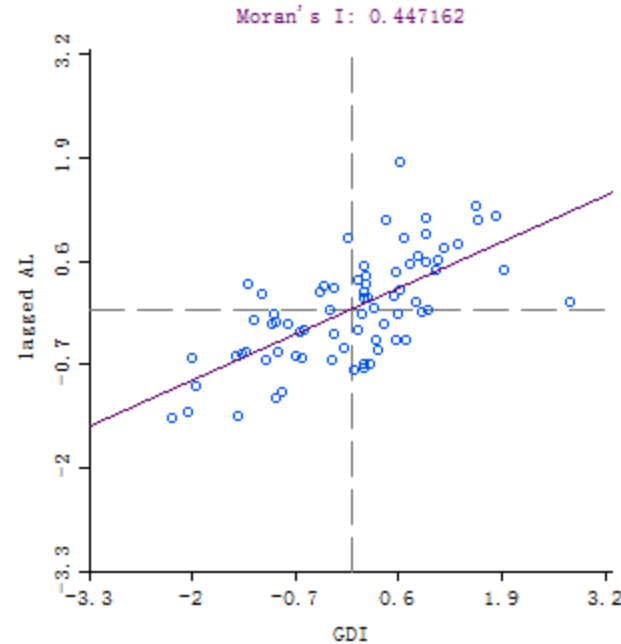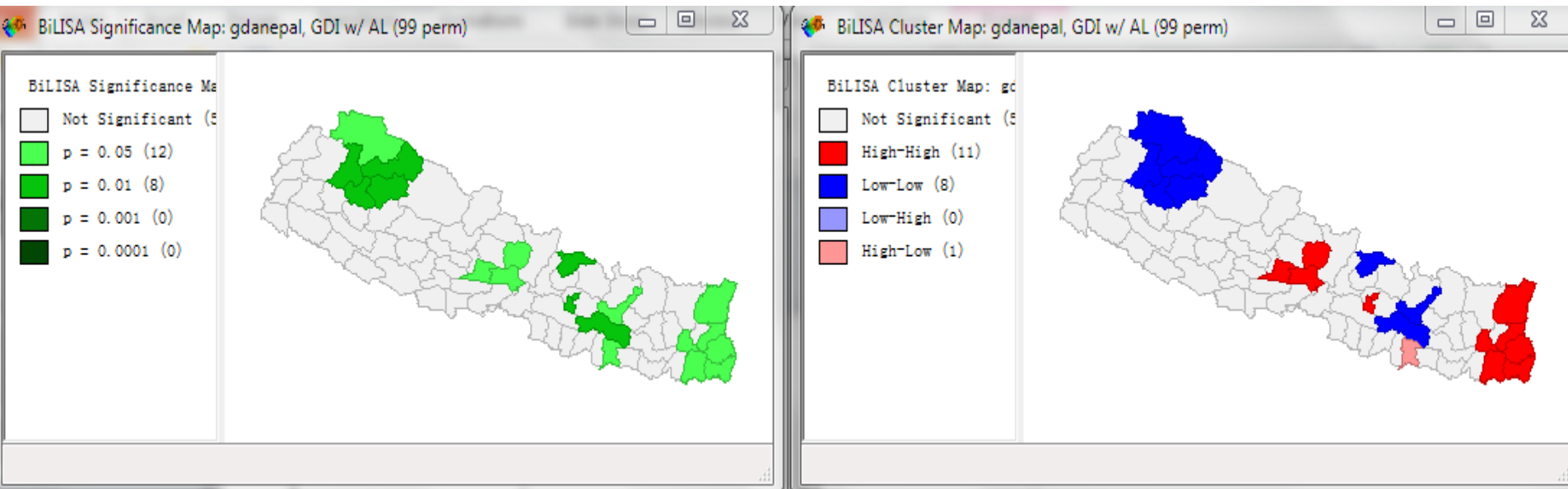
Example:
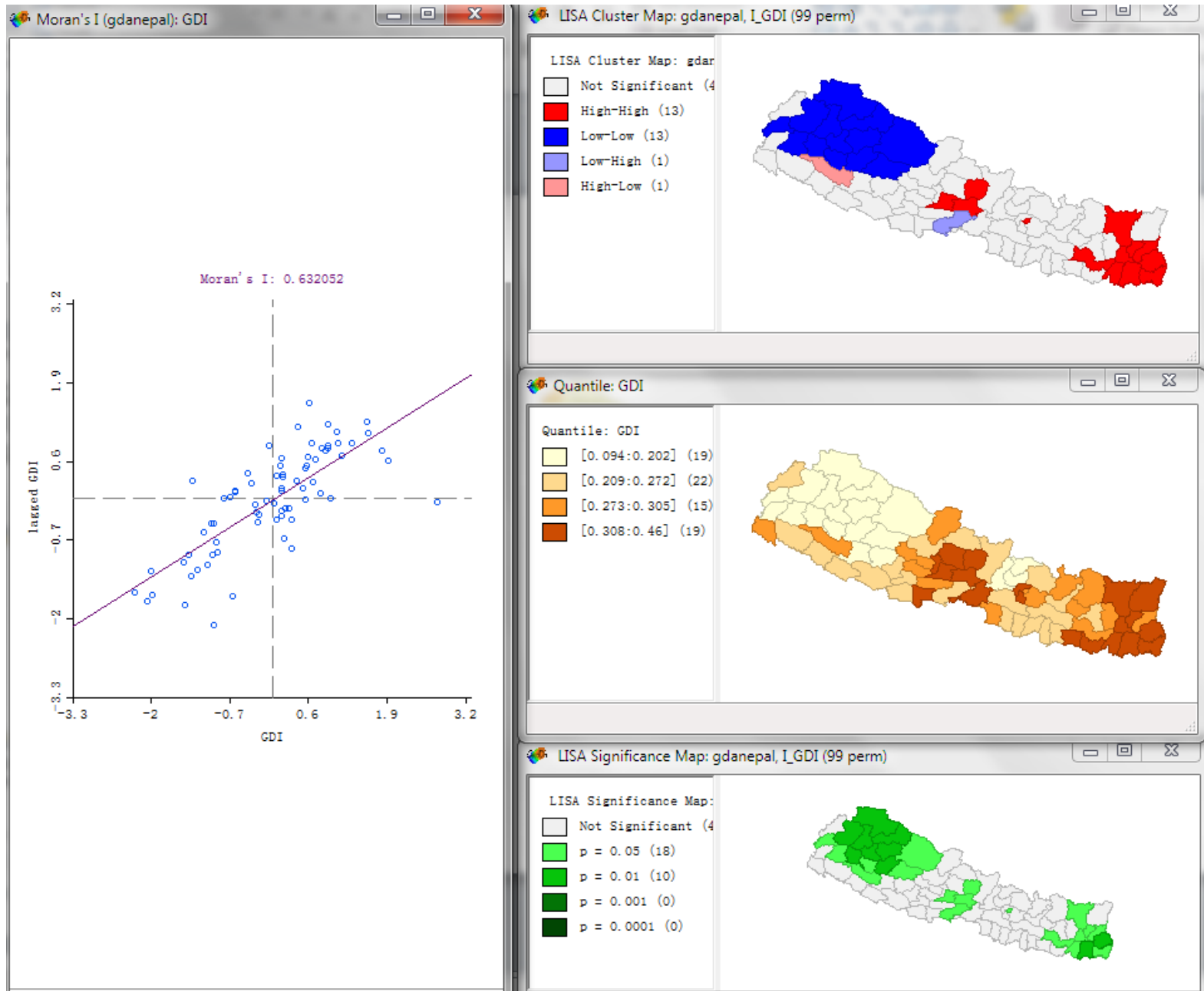
Bivariate LISA

Moran Scatter Plot for GDI vs AL

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

Moran's I: 0.447162

BiLISA Significance Map: gdanepal, GDI w/ AL (99 perm)

BiLISA Significance Ma
- Not Significant (5
- p = 0.05 (12)
- p = 0.01 (8)
- p = 0.001 (0)
- p = 0.0001 (0)

BiLISA Cluster Map: gdanepal, GDI w/ AL (99 perm)

BiLISA Cluster Map: gd
- Not Significant (5
- High-High (11)
- Low-Low (8)
- Low-High (0)
- High-Low (1)

Bivariate LISA
and the Correlation Coefficie

- Correlation Coefficient is the relationship between two <u>different</u> variables in the <u>same</u> area

- Bivariate LISA is a correlation between two <u>different</u> variables in an area and in <u>nearby</u> areas.

Moran's I: 0.447162

45
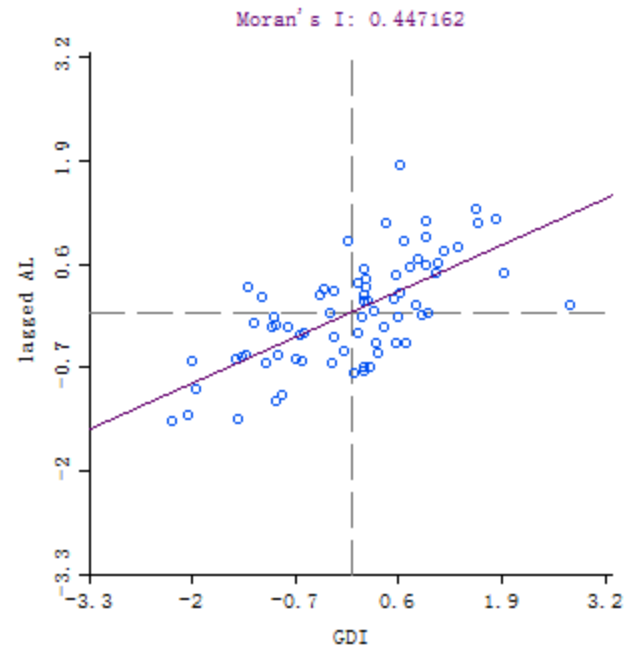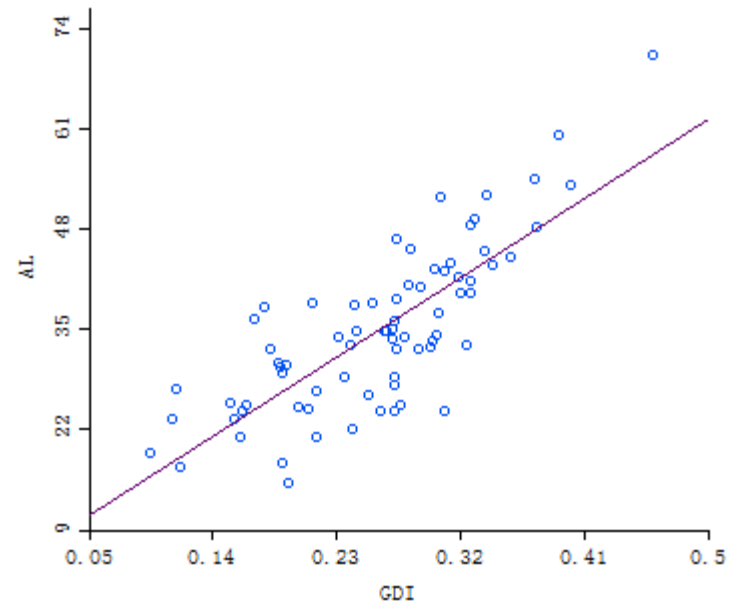
Consequences of Ignoring Spatial Autocorrelation

- 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

- End of this topic