

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)

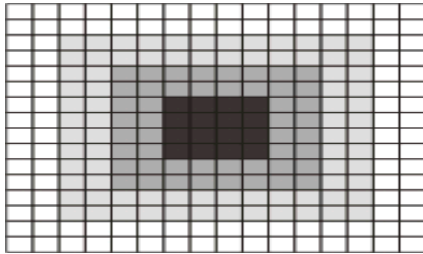
Spatial Autocorrelation

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

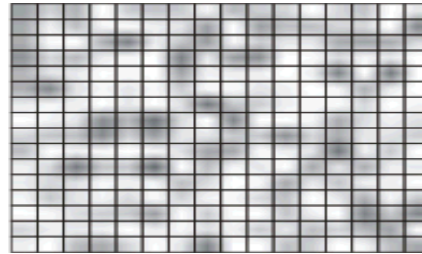
Spatial Autocorrelation of Areal Data

Spatial Autocorrelation

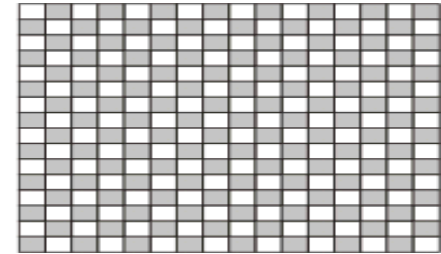
- Tobler's first law of geography
- Spatial auto/cross correlation



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



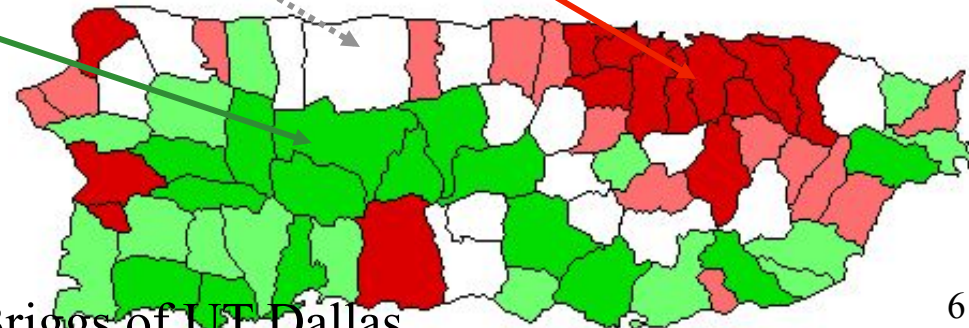
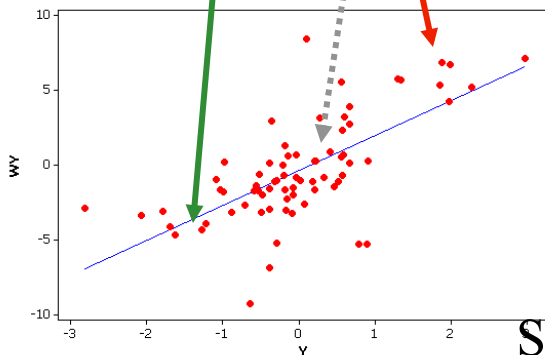
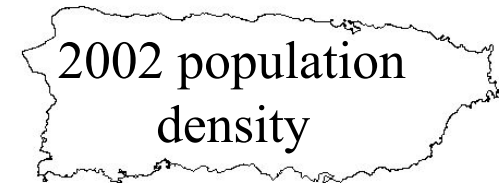
If there is no apparent
relationship between
attribute value and
location then there is
**zero spatial
autocorrelation**



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

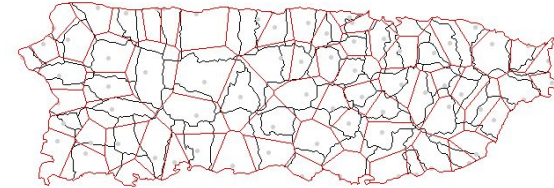


Source: Ron Briggs of UT Dallas

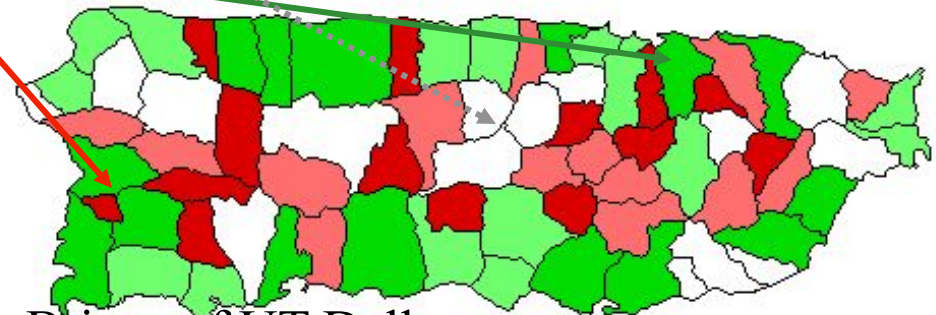
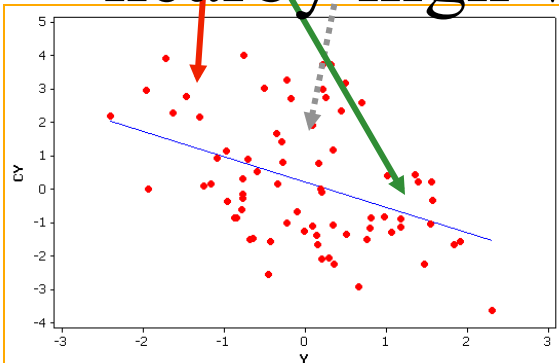
Negative spatial autocorrelation

- 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 measure this?

Seems simple and obvious,
but it is not!



Spatial Weight Matrix

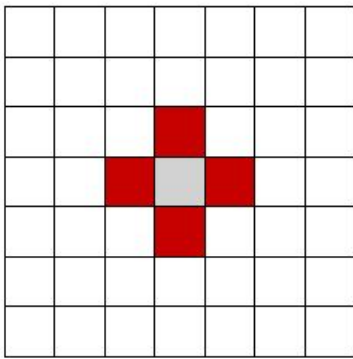
- **Core** concept in statistical analysis of areal data
- Two steps involved:
 - define which relationships between observations are to be given a nonzero weight, i.e., define spatial neighbors
 - assign weights to the neighbors

Spatial Neighbors

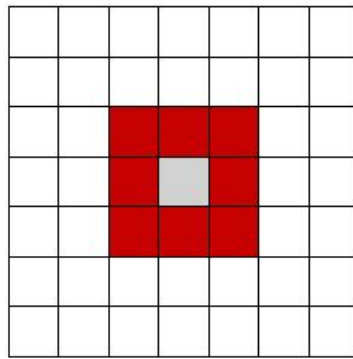
- **Contiguity-based neighbors**
 - Zone i and j are neighbors if zone i is contiguity or adjacent to zone j
 - But what constitutes contiguity?
- **Distance-based neighbors**
 - Zone i and j are neighbors if the distance between them are less than the threshold distance
 - But what distance do we use?

Contiguity-based Spatial Neighbors

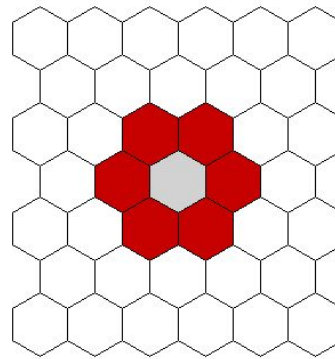
- Sharing a border or boundary
 - Rook: sharing a border
 - Queen: sharing a border or a point



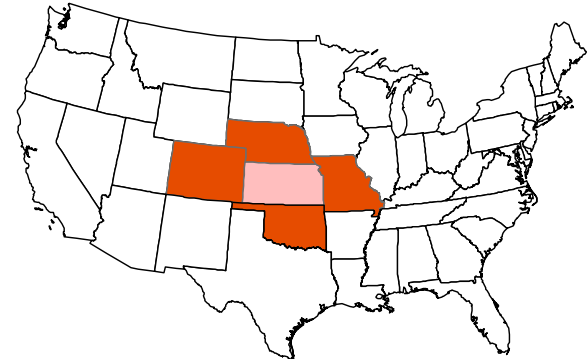
rook



queen



Hexagons



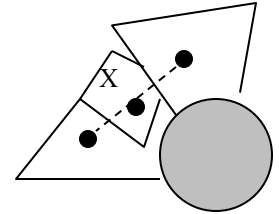
Irregular

Which use?

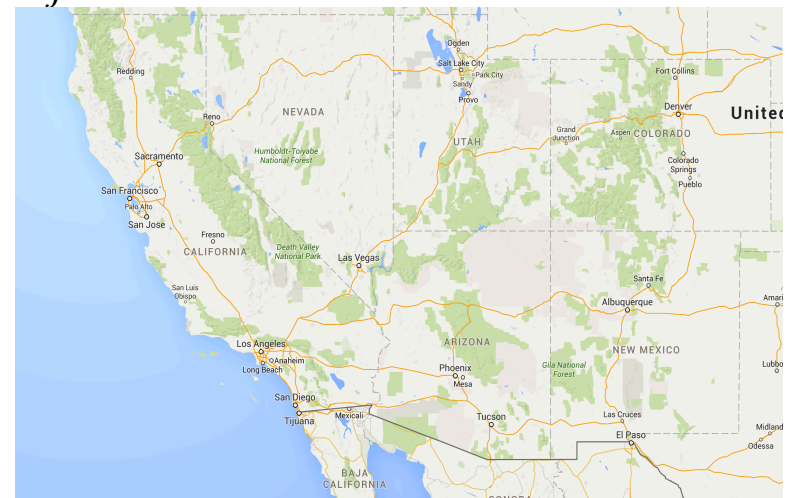
Problem Situations for Irregular Polygons

“Close” but no common border

Length of border



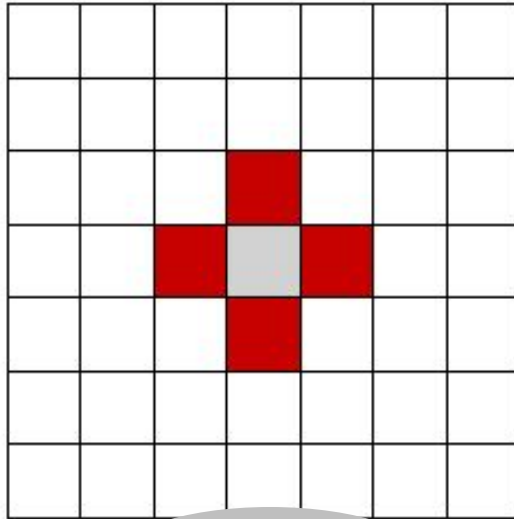
- Is Arizona “as close to” California as to Utah?
- Base “closeness” on proportion of shared border, not just one (1) or zero (0)
- $w_{ij} = \text{border length}_{ij} / \text{border length}_j$



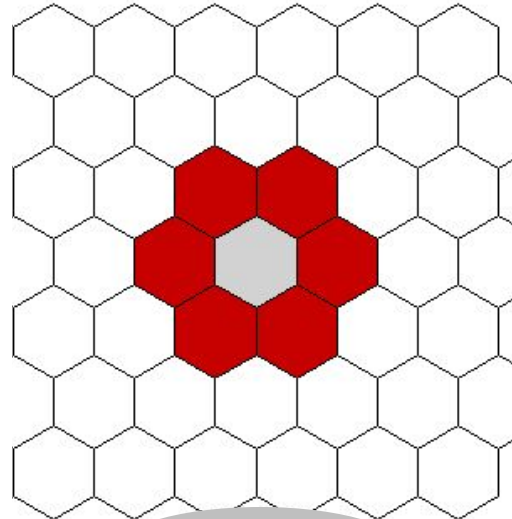
Higher-Order Contiguity

1st
order

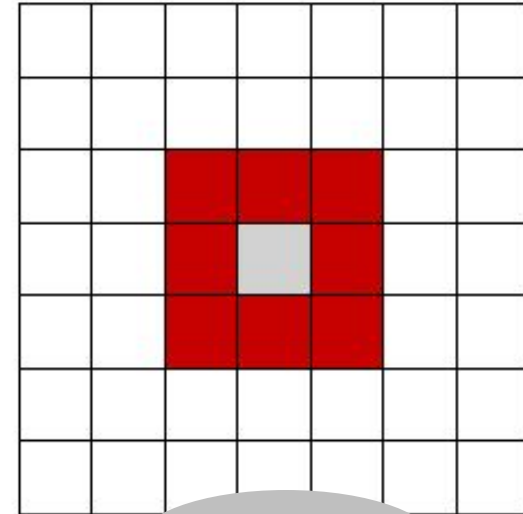
Nearest
neighbor



rook



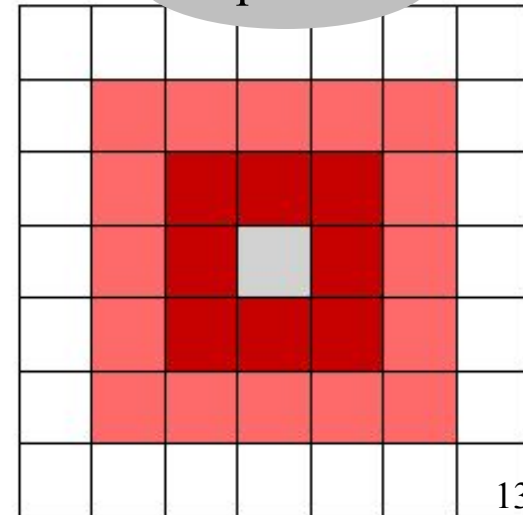
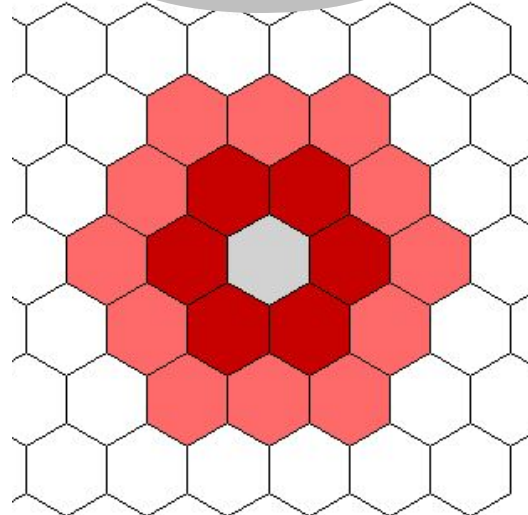
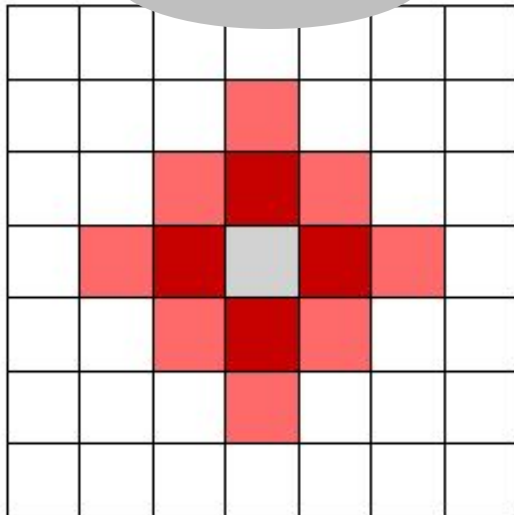
hexagon



queen

2nd
order

Next
nearest
neighbor



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 $a = \sin^2(\Delta\phi/2) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2(\Delta\lambda/2)$

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

$d = R \cdot c$

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

Distance-based Neighbors

- k -nearest neighbors

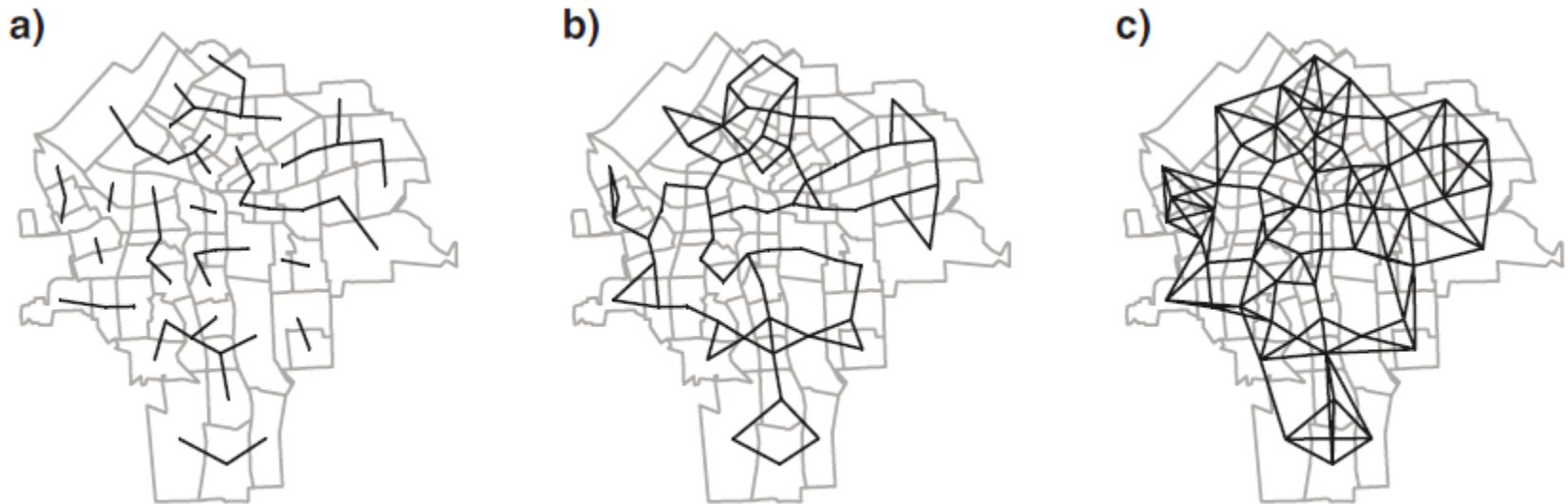


Fig. 9.5. (a) $k = 1$ neighbours; (b) $k = 2$ neighbours; (c) $k = 4$ neighbours

Source: Bivand and Pebesma and Gomez-Rubio

Distance-based Neighbors

- thresh-hold distance (buffer)

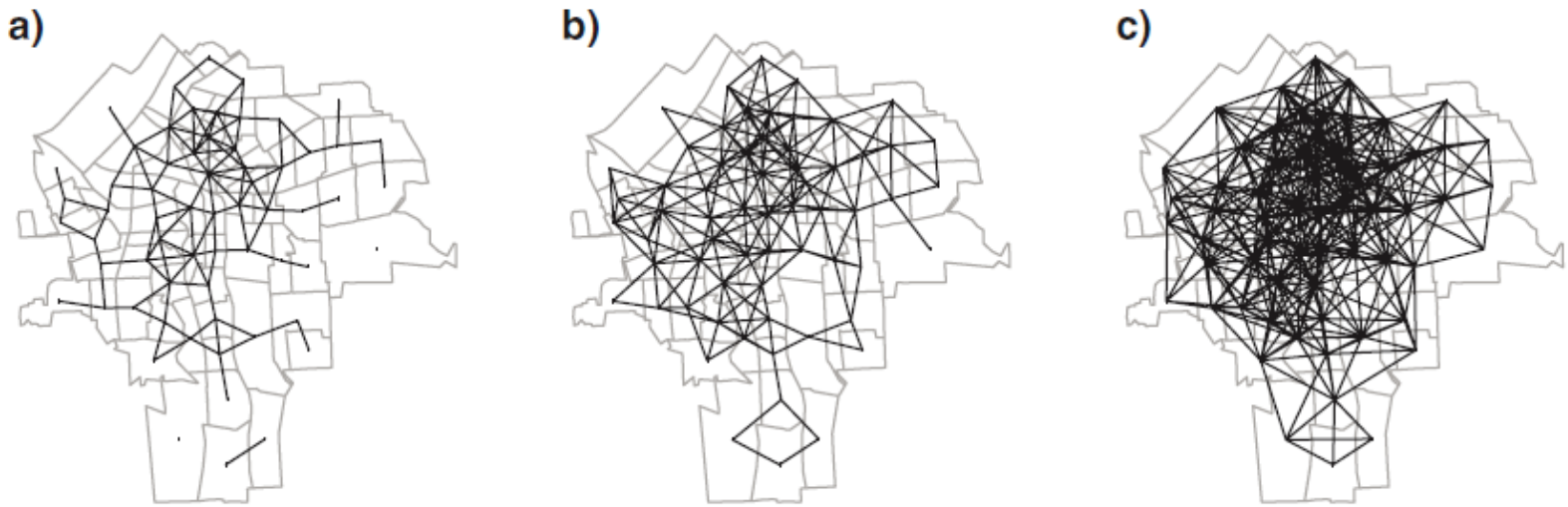
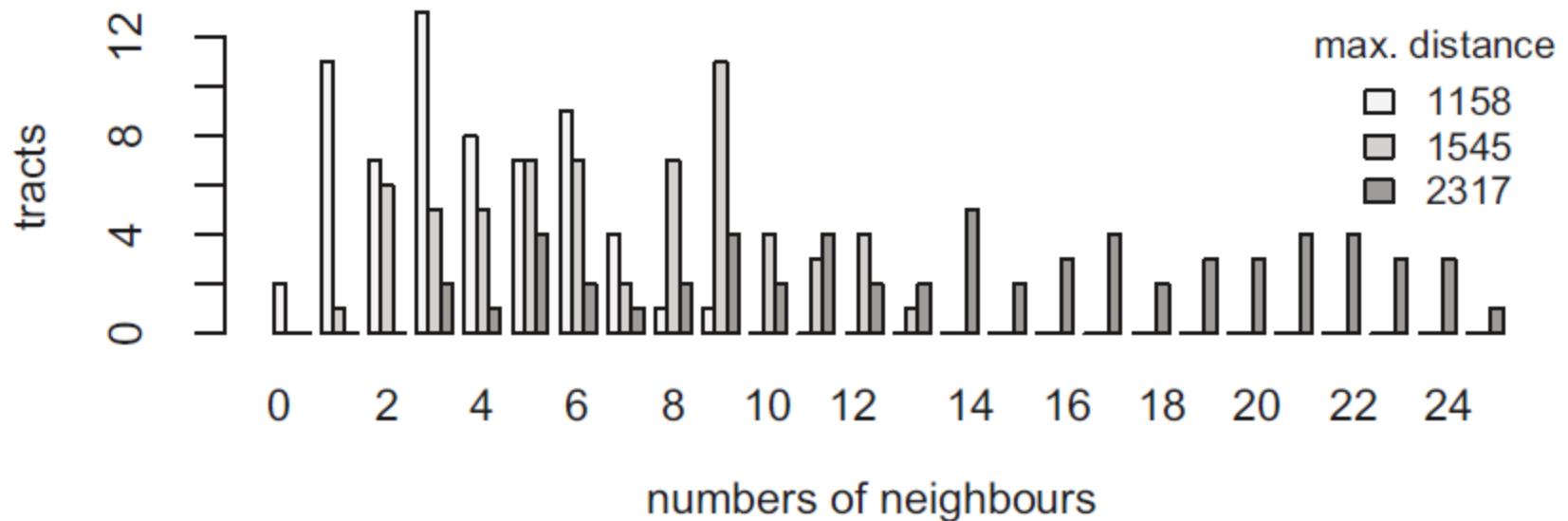


Fig. 9.6. (a) Neighbours within 1,158 m; (b) neighbours within 1,545 m; (c) neighbours within 2,317 m

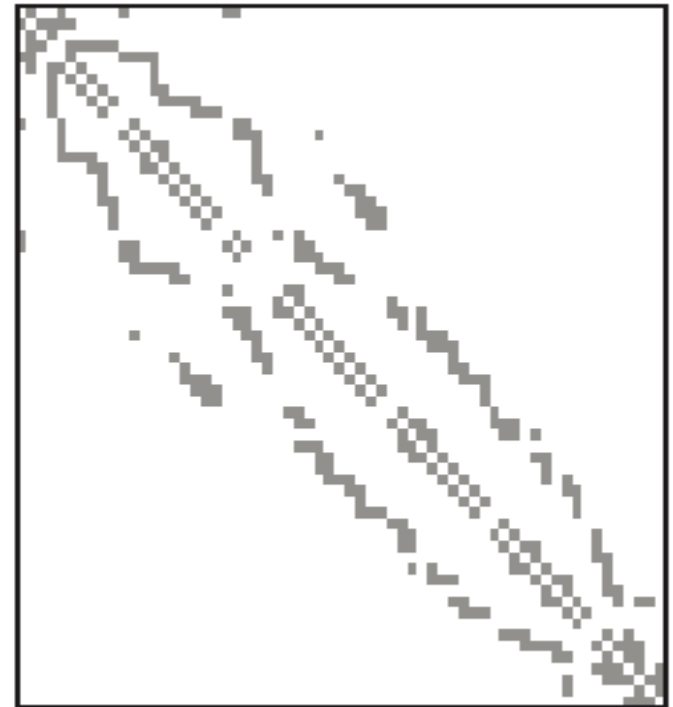
Neighbor/Connectivity Histogram



Source: Bivand and Pebesma and Gomez-Rubio

Spatial Weight Matrix

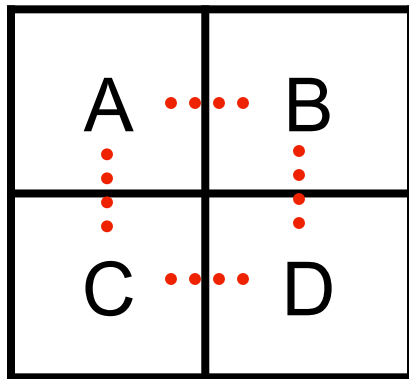
- Spatial weights can be seen as a list of weights indexed by a list of neighbors
- If zone j is not a neighbor of zone i , weights W_{ij} will set to zero
 - The weight matrix can be illustrated as an image
 - Sparse matrix



A Simple Example for Rook case

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

4 areal units

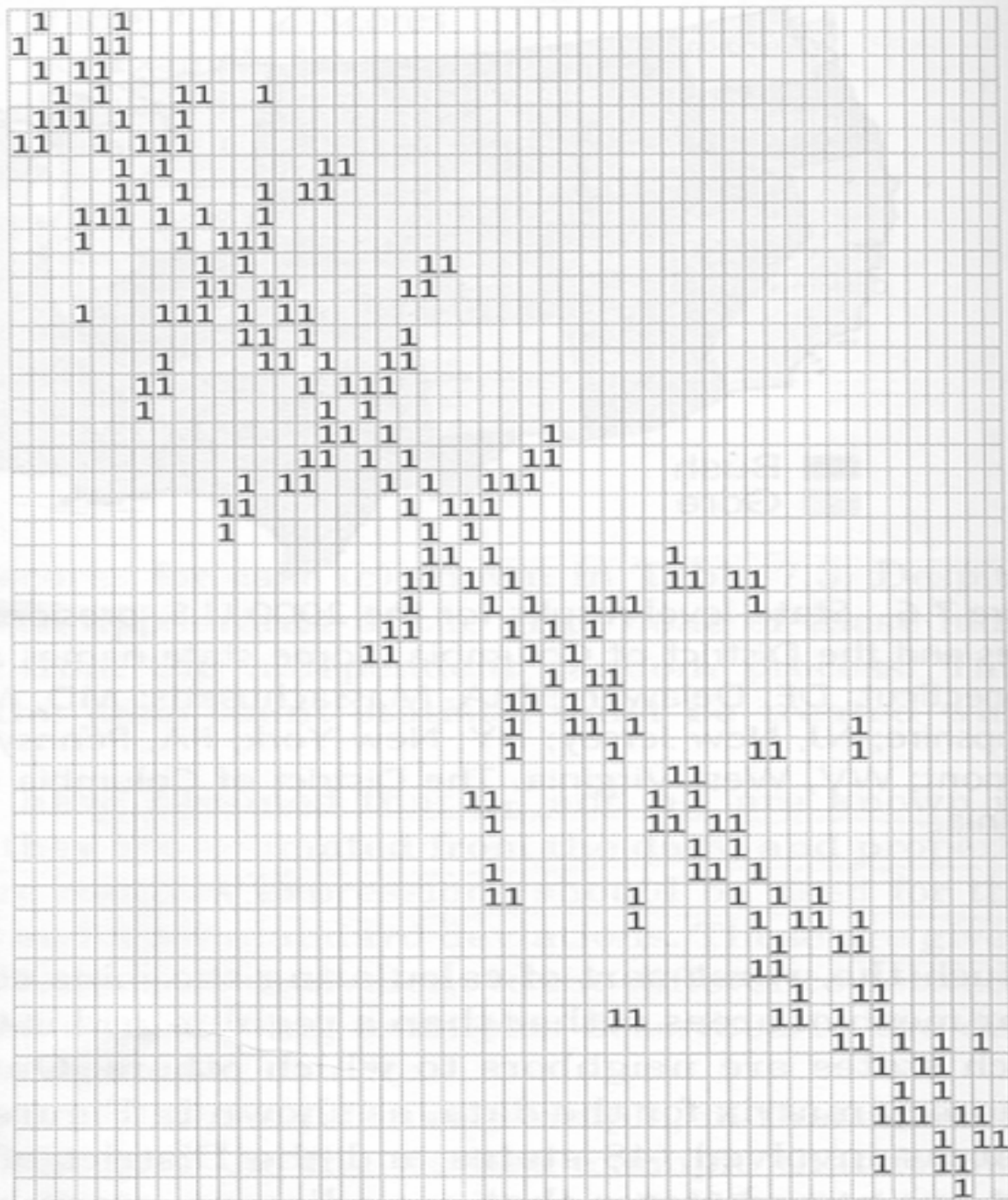


Common border

4x4 matrix

	A	B	C	D
A	0	1	1	0
B	1	0	0	1
C	1	0	0	1
D	0	1	1	0

- 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 Massachusetts
- 47 New Hampshire
- 48 Vermont
- 49 Maine



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

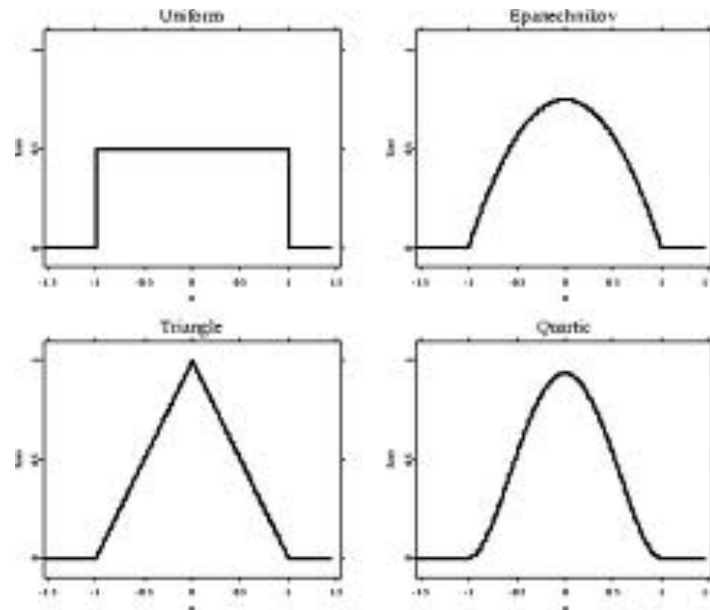
	A	B	C	D	E	F	Row Sum
A	0	1	0	1	0	0	2
B	1	0	1	0	1	0	3
C	0	1	0	0	0	1	2
D	1	0	0	0	1	0	2
E	0	1	0	1	0	1	3
F	0	0	1	0	1	0	2

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 $w_{ij} = e^{-d^2}$)



Measure of Spatial Autocorrelation

Global Measures and Local Measures

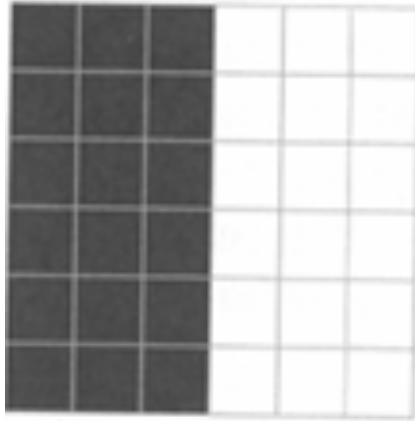
- Global Measures
 - A single value which applies to the entire data set
 - The same pattern or process occurs over the entire geographic area
 - An average for the entire area
- Local Measures
 - A value calculated for each observation unit
 - Different patterns or processes may occur in different parts 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

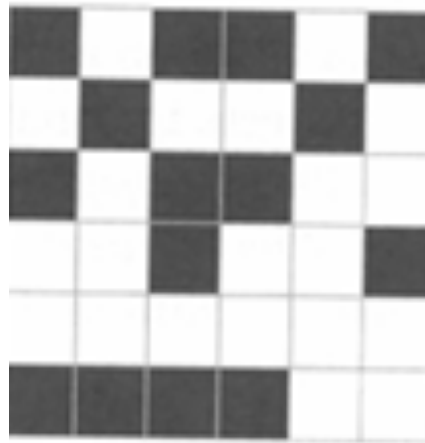
- Global Measures
 - Join Count
 - Moran's I (and Getis-Ord's G)
- Local Measures
 - Local Moran's I (and Getis-Ord's G)

Join (or Joint or Joins) Count Statistic

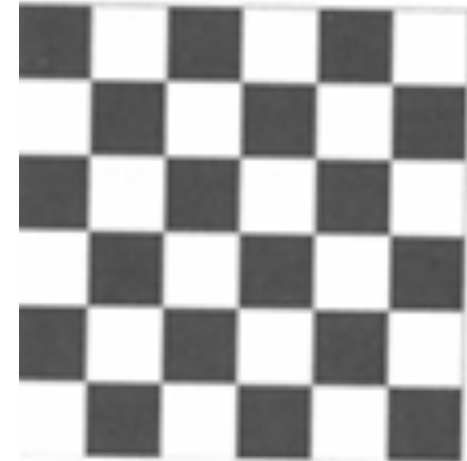
Positive autocorrelation



No autocorrelation



Negative autocorrelation



Rook's case

$$J_{BB} = 27$$

$$J_{WW} = 27$$

$$J_{BW} = 6$$

Queen's case

$$J_{BB} = 47$$

$$J_{WW} = 47$$

$$J_{BW} = 16$$

$$J_{BB} = 6$$

$$J_{WW} = 19$$

$$J_{BW} = 35$$

$$J_{BB} = 14$$

$$J_{WW} = 40$$

$$J_{BW} = 56$$

$$J_{BB} = 0$$

$$J_{WW} = 0$$

$$J_{BW} = 60$$

$$J_{BB} = 25$$

$$J_{WW} = 25$$

$$J_{BW} = 60$$

- 60 for Rook Case
- 110 for Queen Case

Join Count: Test Statistic

Test Statistic given by: $Z = \frac{\text{Observed} - \text{Expected}}{\text{SD of Expected}}$

Expected = random pattern generated by tossing a coin in each cell.

Expected given by: Standard Deviation of Expected (standard error) given by:

$$E(J_{BB}) = kp_B^2$$

$$E(s_{BB}) = \sqrt{kp_B^2 + 2mp_B^3 - (k + 2m)p_B^4}$$

$$E(J_{WW}) = kp_W^2$$

$$E(s_{WW}) = \sqrt{kp_W^2 + 2mp_W^3 - (k + 2m)p_W^4}$$

$$E(J_{BW}) = 2kp_Bp_W$$

$$E(s_{BW}) = \sqrt{2(k + m)p_Bp_W - 4(k + 2m)p_B^2p_W^2}$$

Where: k is the total number of joins (neighbors)

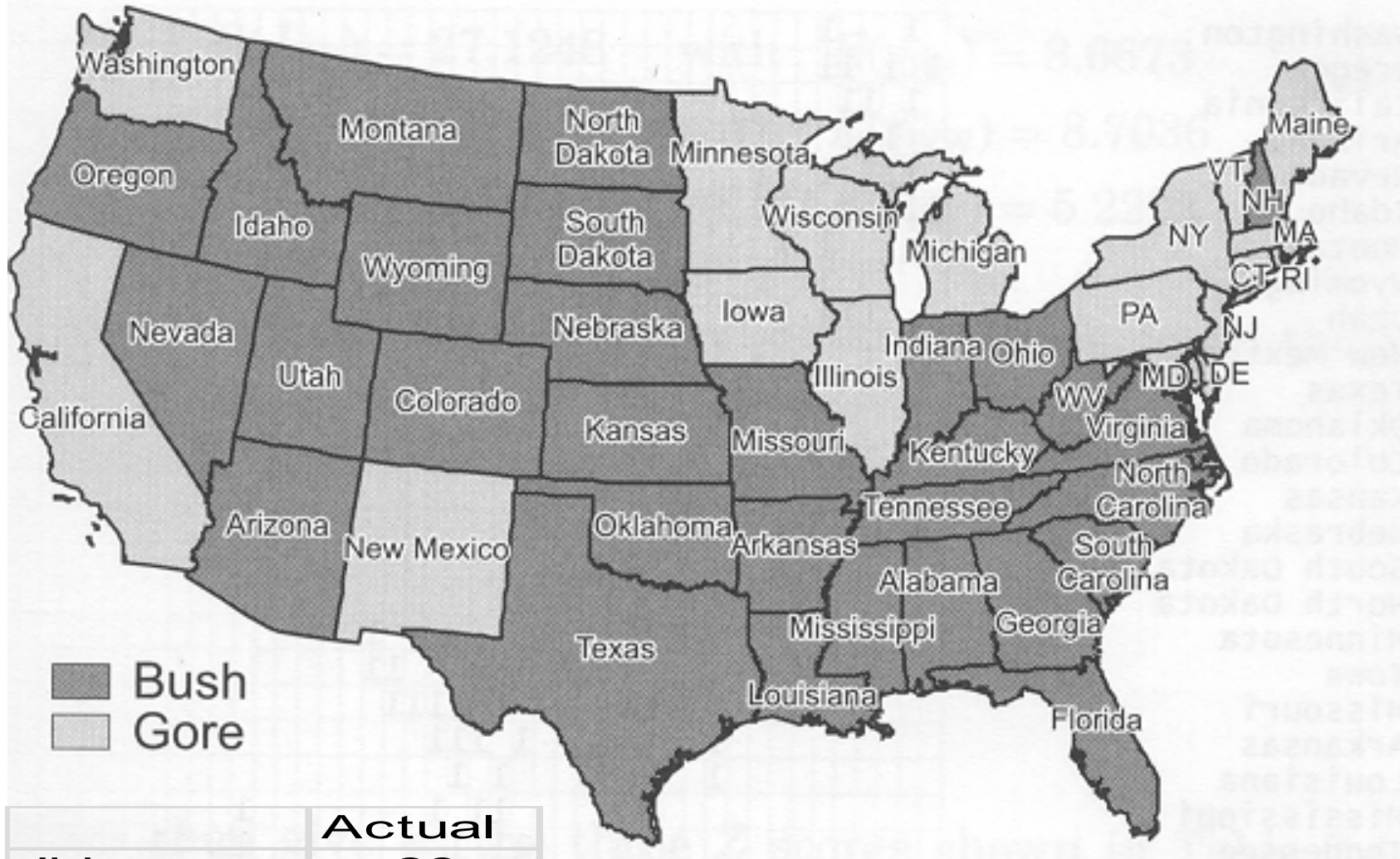
p_B is the expected proportion Black, if random

p_W is the expected proportion White

m is calculated from k according to:

$$m = \frac{1}{2} \sum_{i=1}^n k_i(k_i - 1)$$

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 more Bush/Bush joins (actual = 60) than would be expected (27)
 - Positive autocorrelation
- There are far fewer 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 or 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

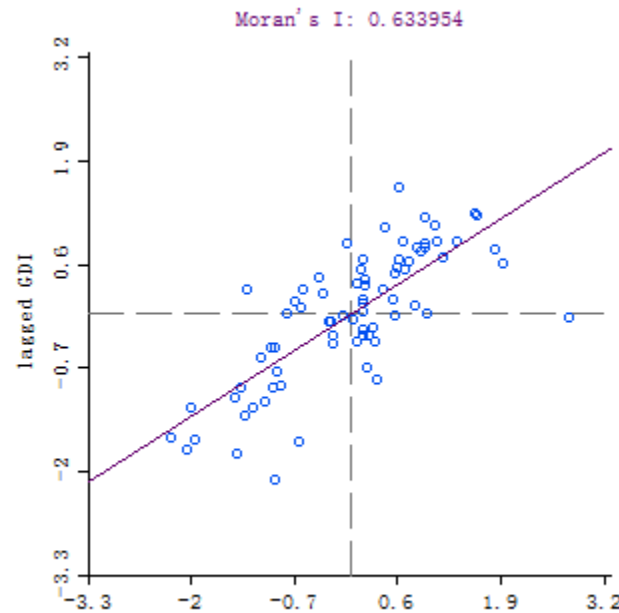
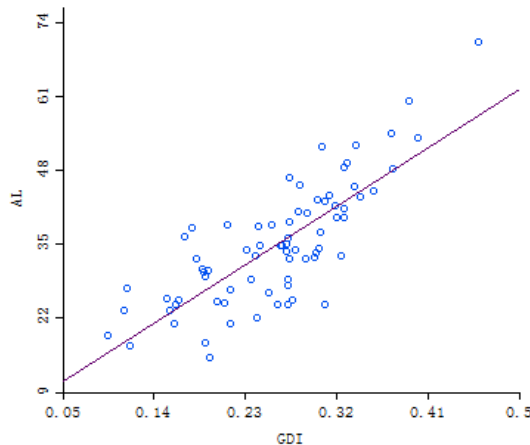
$$I = \frac{N \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^n \sum_{j=1}^n w_{ij} \right) \sum_{i=1}^n (x_i - \bar{x})^2}$$

- 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 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

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

(see next slide)

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

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

Spatial
auto-correlation

=

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

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

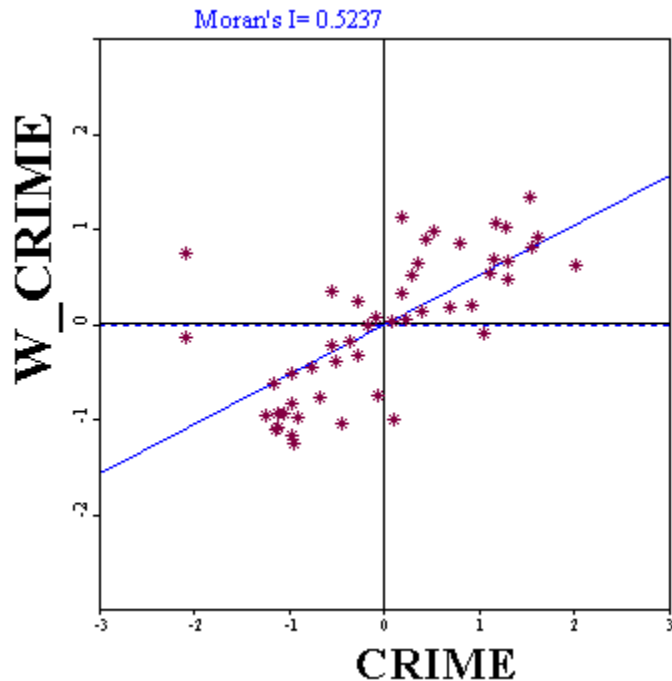
$$\frac{N \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} =$$

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

Moran's I

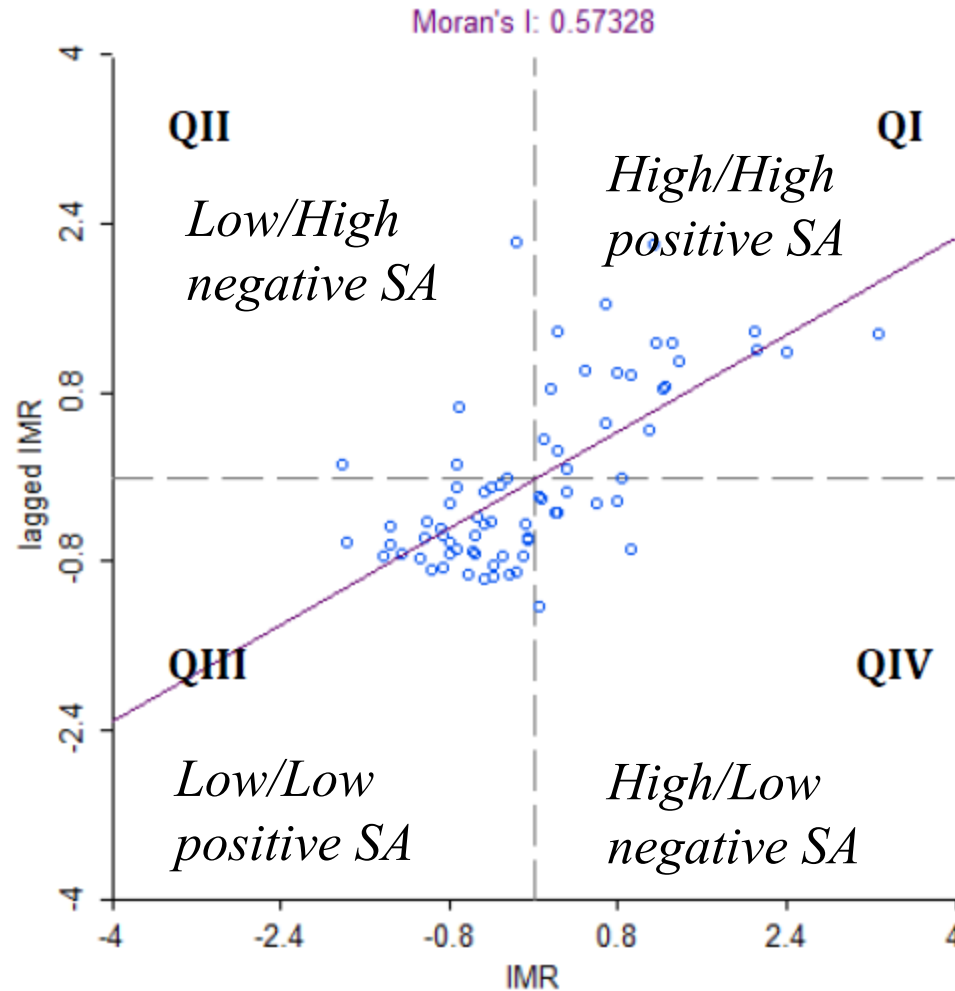
Moran Scatter Plots

We can draw a scatter diagram between these two variables (in standardized form): X and $\text{lag-}X$ (or W_X)

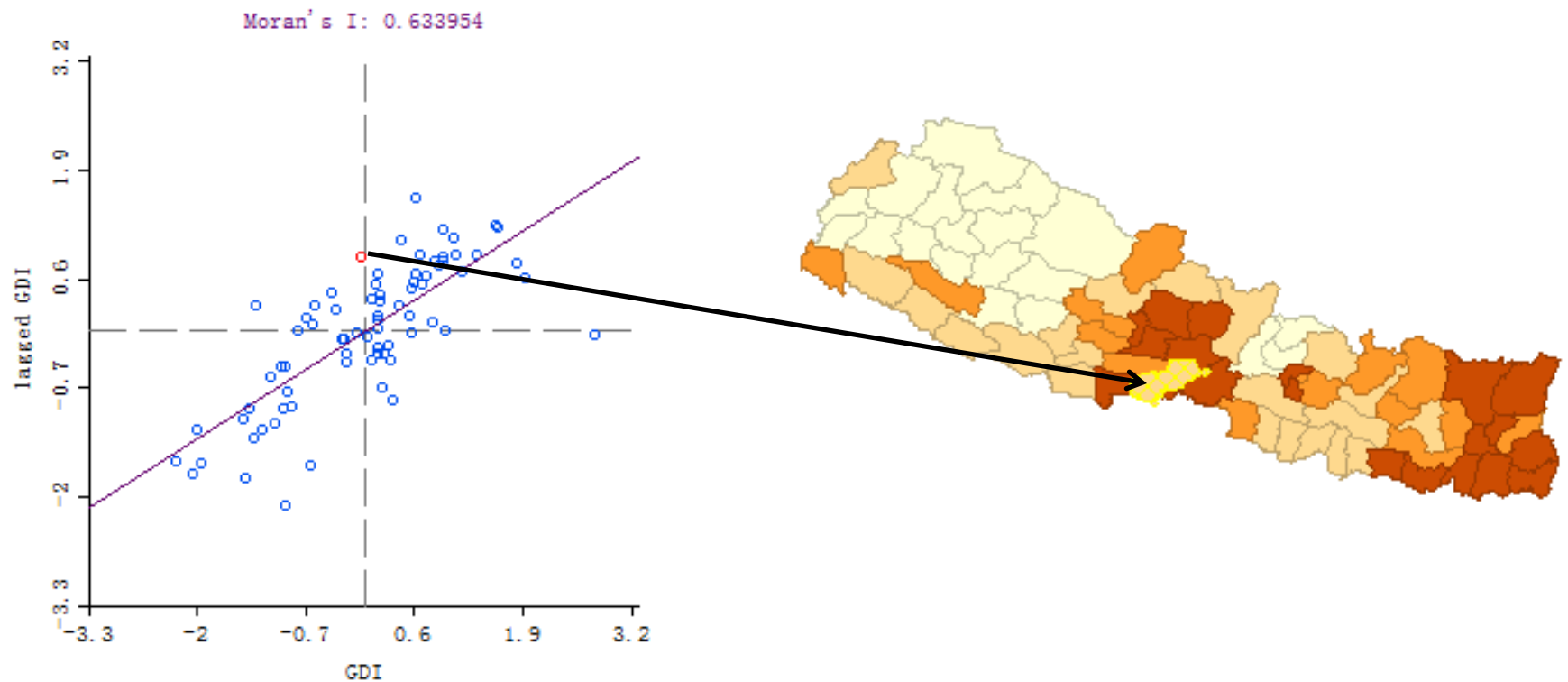


The slope of this *regression line* is
Moran's I

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 known as the *EB adjustment*:
 - see Assuncao-Reis *Empirical Bayes Standardization Statistics in Medicine*, 1999
- *GeoDA* software includes an option for this adjustment

Statistical Significance Tests for Moran's I

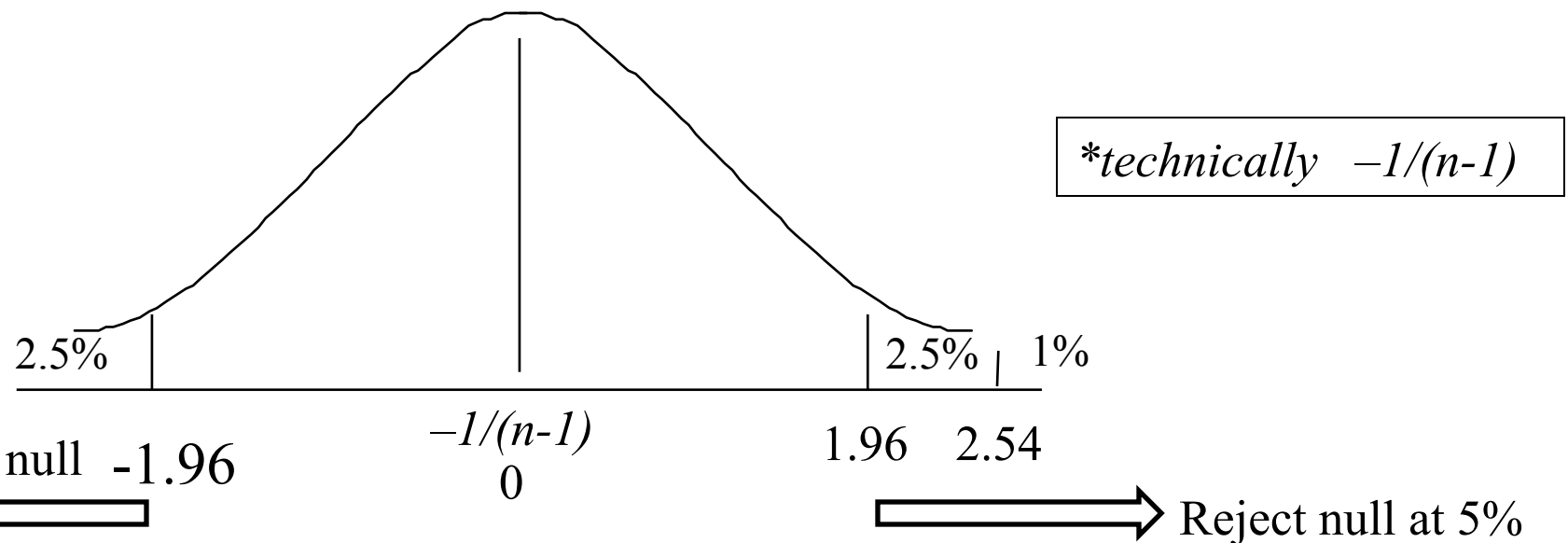
- Based on the normal frequency distribution with

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

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



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 exists

Null Hypothesis: no spatial autocorrelation

*Moran's $I = 0$

Alternative Hypothesis: spatial autocorrelation exists

*Moran's $I > 0$

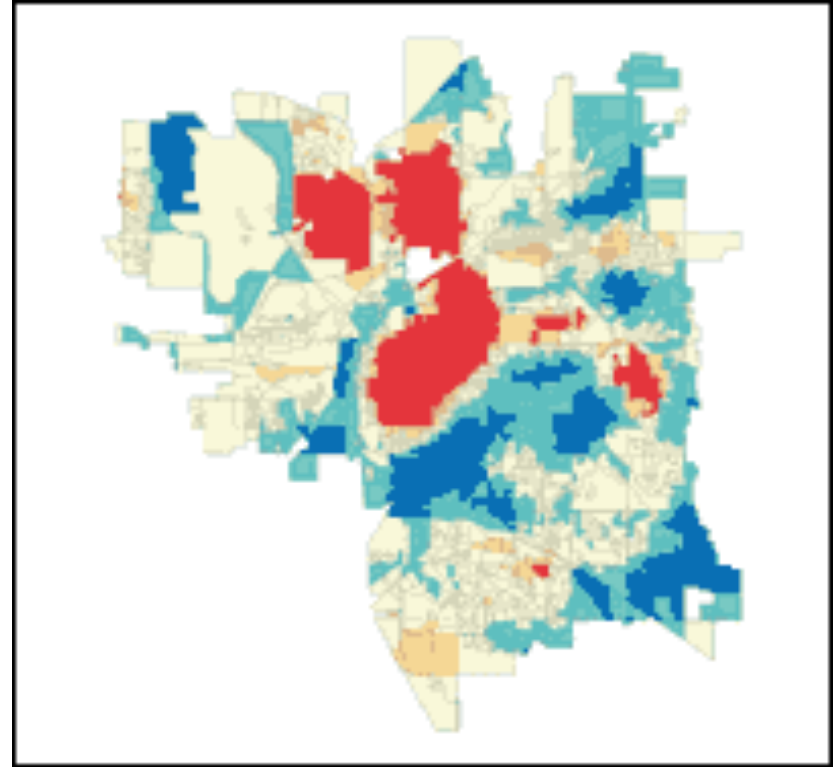
Reject *Null Hypothesis* if Z test statistic > 1.96 (or < -1.96)

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

---95% confident that spatial auto correlation exists

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

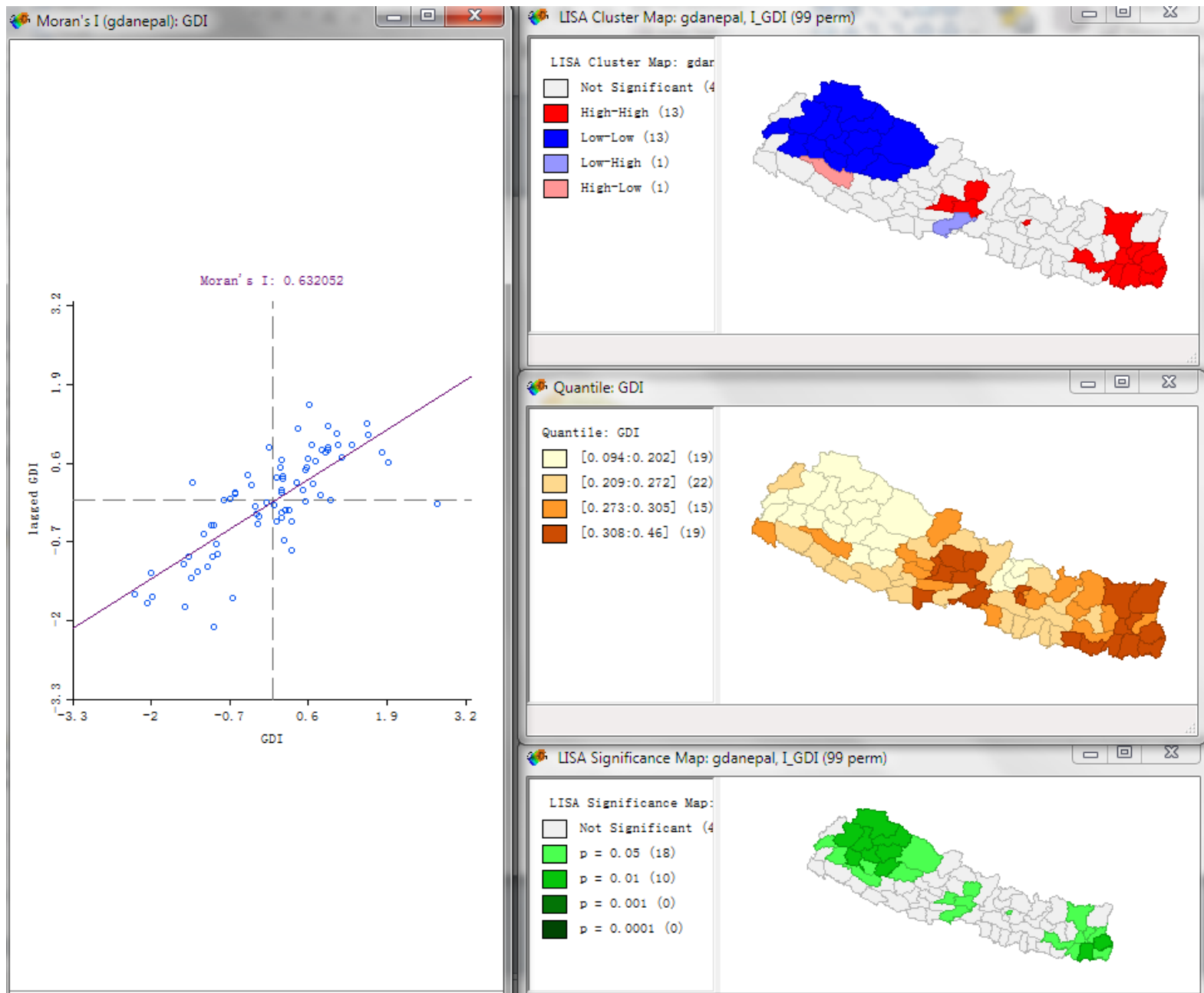
See:

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

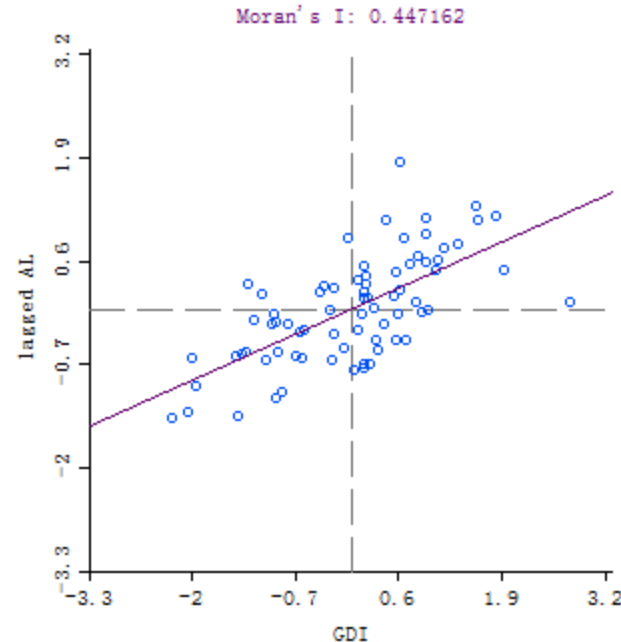
Example:



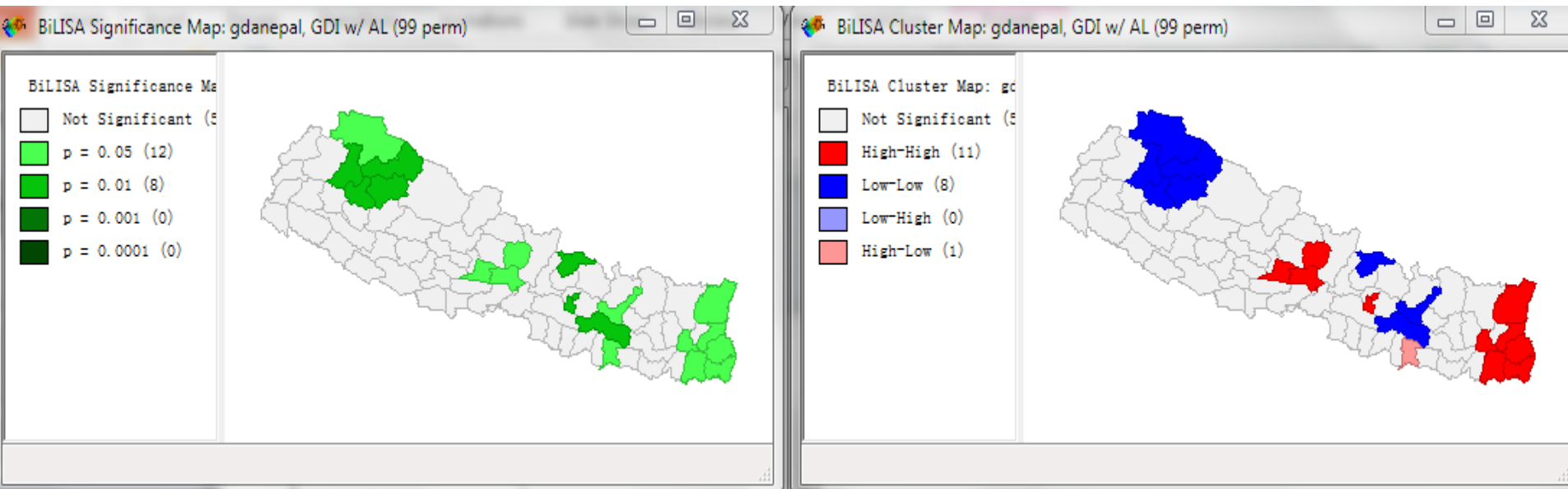
Bivariate LISA

- 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 Scatter Plot for GDI vs AL



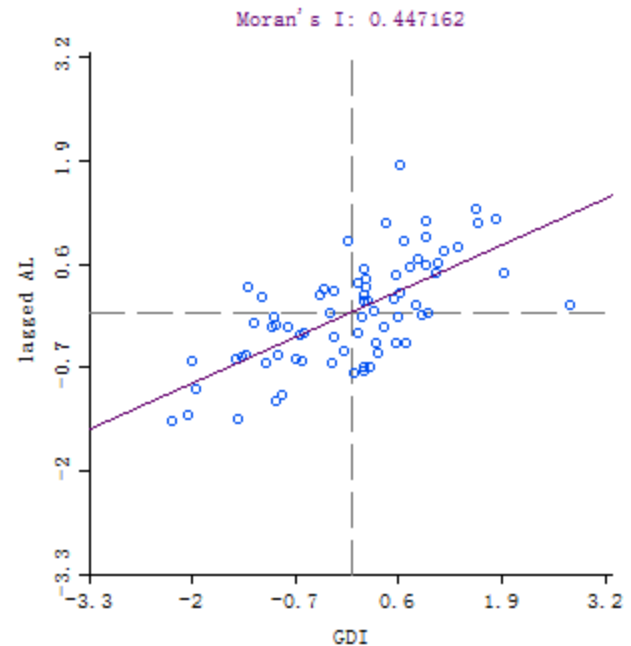
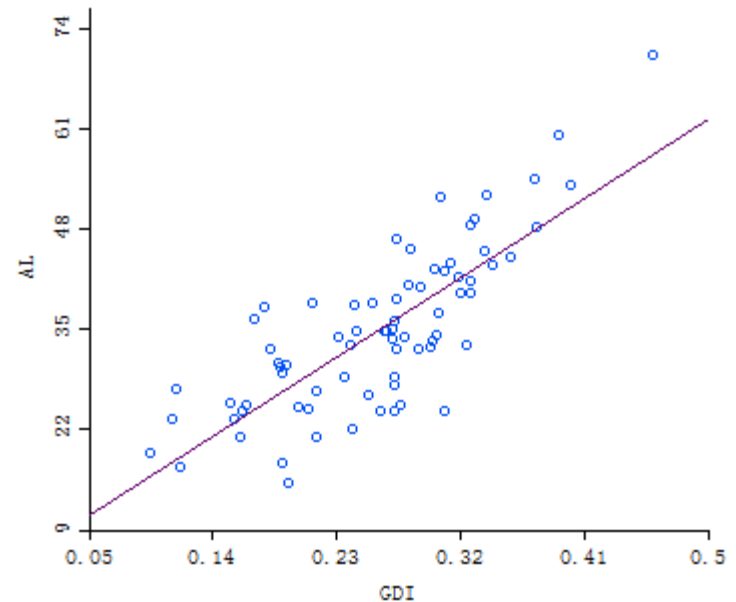
Moran Significance Map for GDI vs. AL



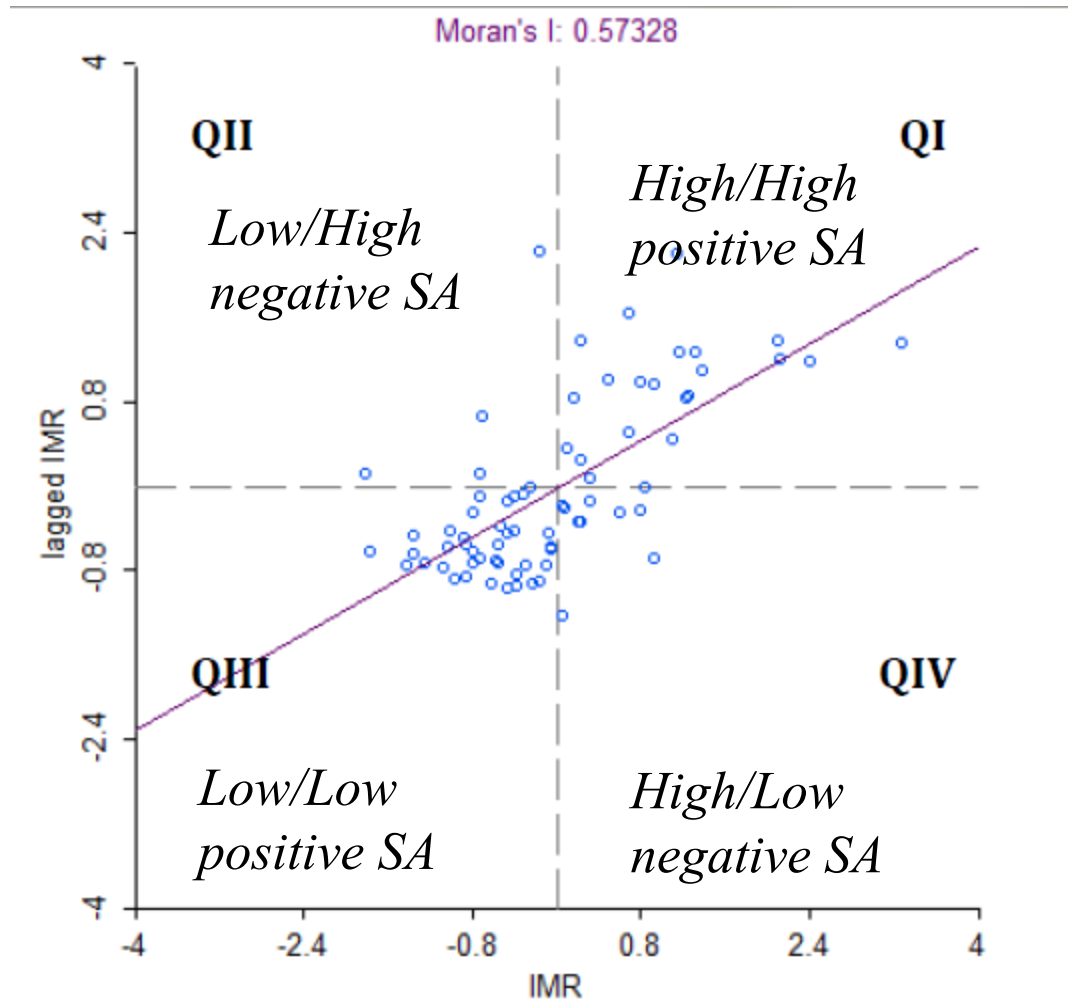
Bivariate LISA

and the Correlation Coefficient

- 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