

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)

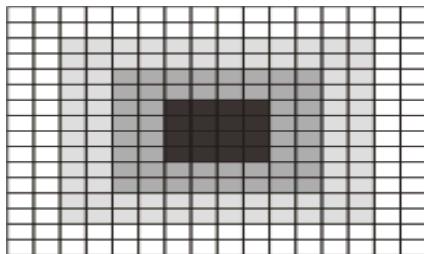
Spatial Autocorrelation

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

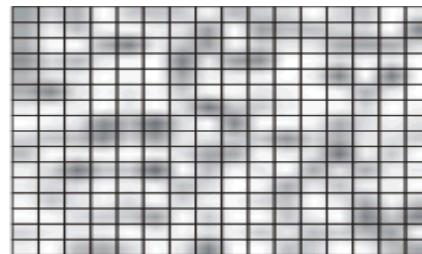
Spatial Autocorrelation of Areal Data

Spatial Autocorrelation

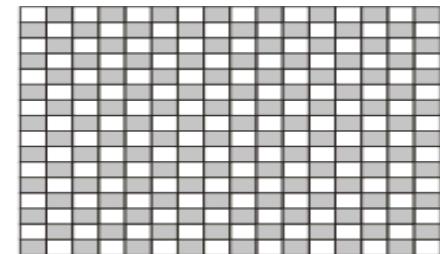
- Tobler's first law of geography
- Spatial auto/cross correlation



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



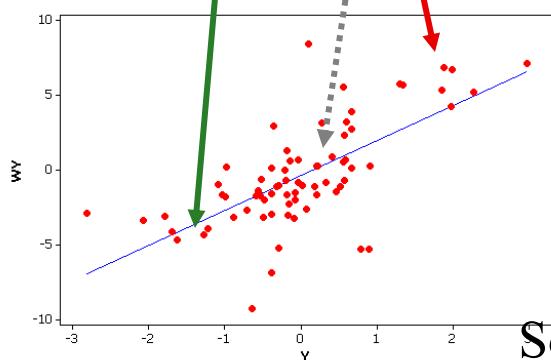
If there is no apparent relationship between attribute value and location then there is **zero spatial autocorrelation**



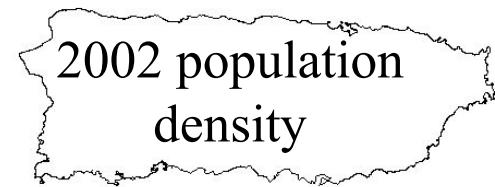
If like values tend to be located away from each other, then there is **negative spatial autocorrelation**

Positive spatial autocorrelation

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

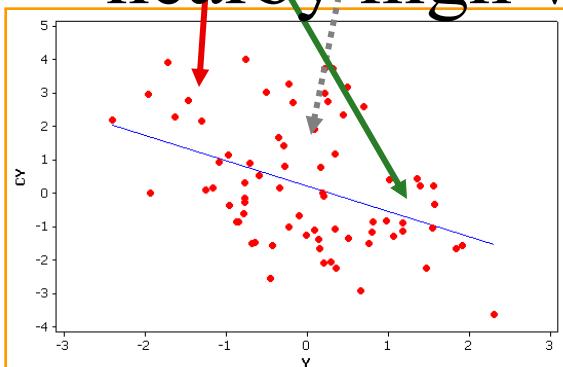


Source: Ron Briggs of UT Dallas

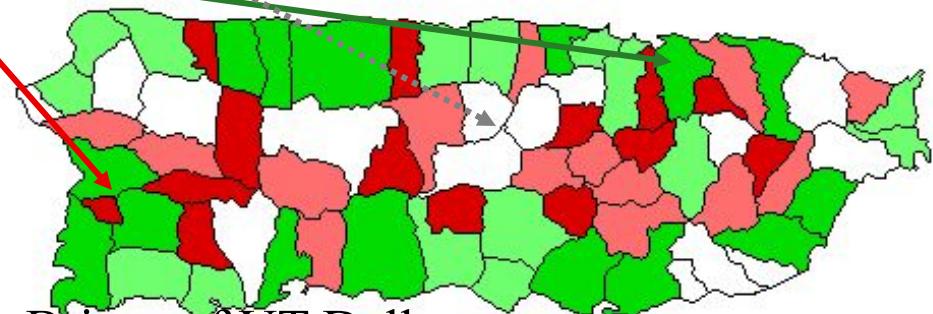


Negative spatial autocorrelation

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



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

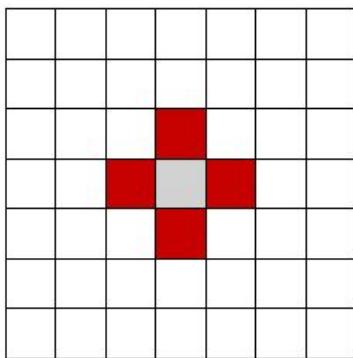
- **Core** concept in statistical analysis of areal data
- Two steps involved:
 - define which relationships between observations are to be given a nonzero weight, i.e., define spatial neighbors
 - assign weights to the neighbors

Spatial Neighbors

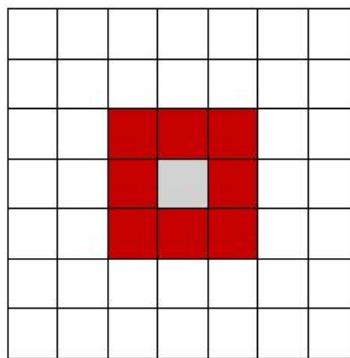
- **Contiguity-based neighbors**
 - Zone i and j are neighbors if zone i is contiguous or adjacent to zone j
 - But what constitutes contiguity?
- **Distance-based neighbors**
 - Zone i and j are neighbors if the distance between them are less than the threshold distance
 - But what distance do we use?

Contiguity-based Spatial Neighbors

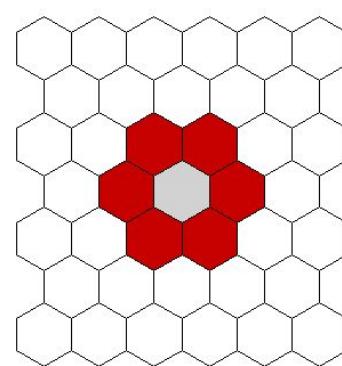
- Sharing a border or boundary
 - Rook: sharing a border
 - Queen: sharing a border or a point



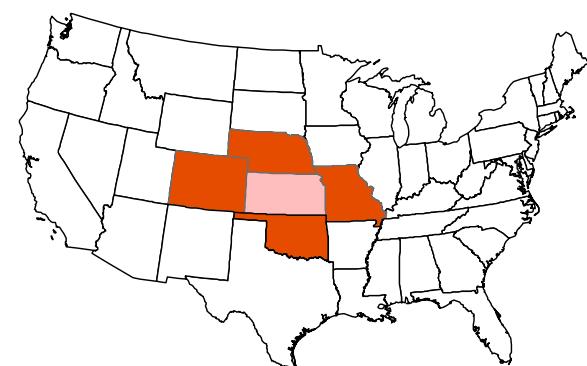
rook



queen



Hexagons



Irregular

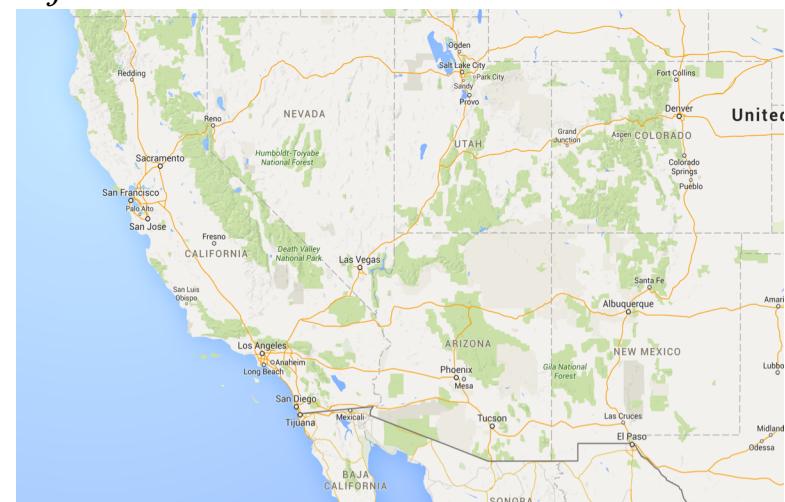
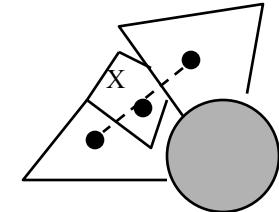
Which use?

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)
- $w_{ij} = \text{border length}_{ij} / \text{border length}_j$



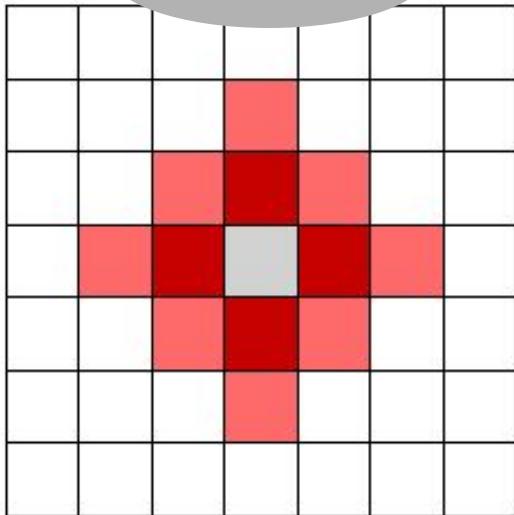
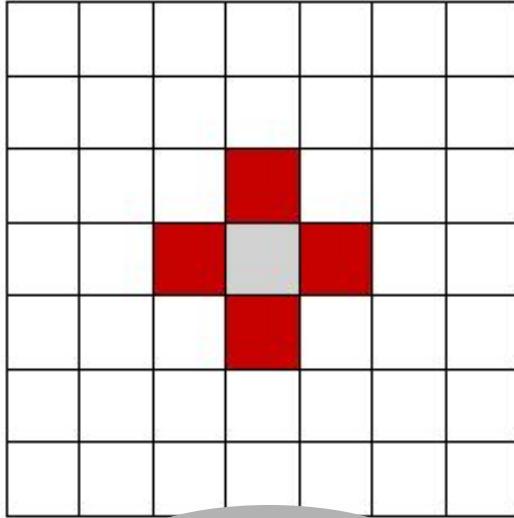
Higher-Order Contiguity

1st
order

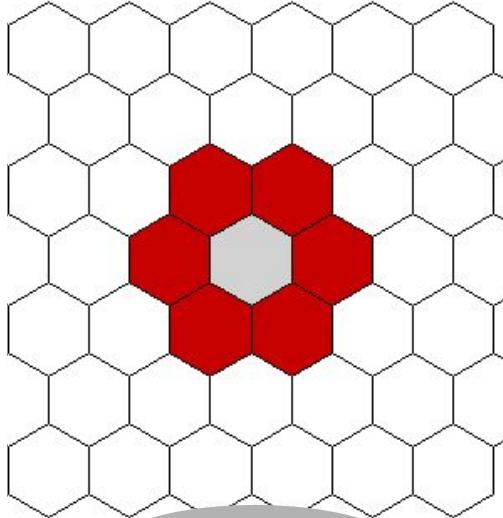
Nearest
neighbor

2nd
order

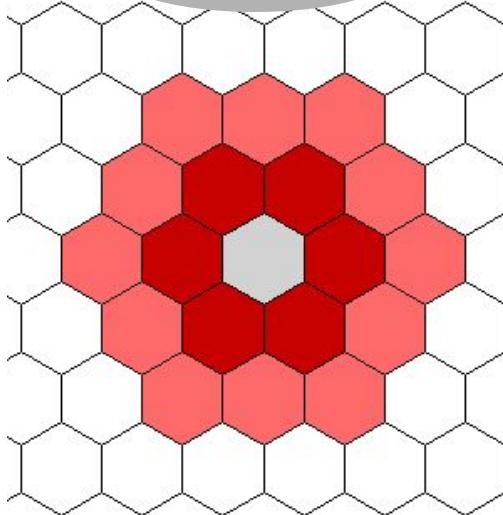
Next
nearest
neighbor



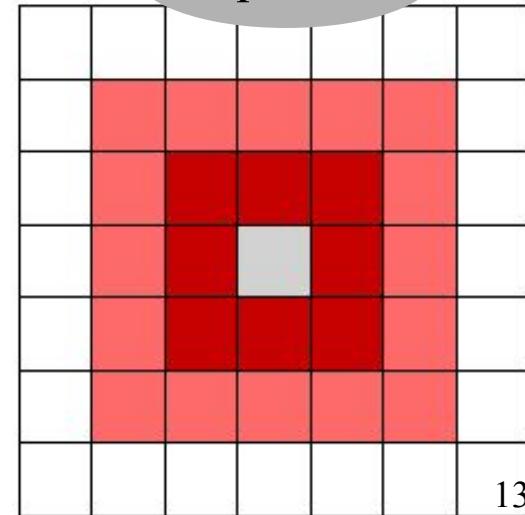
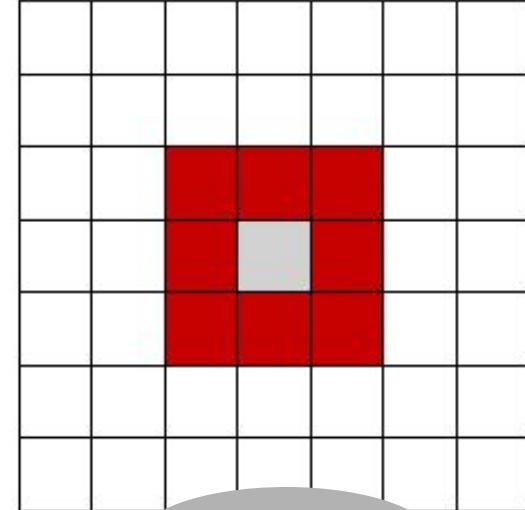
rook



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

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

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

$$d = R.c$$

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

Distance-based Neighbors

- k-nearest neighbors

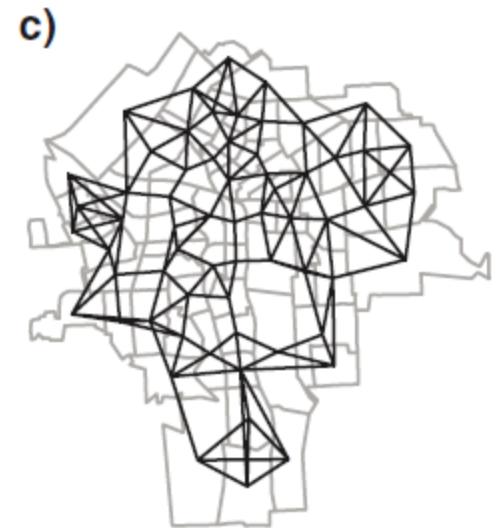
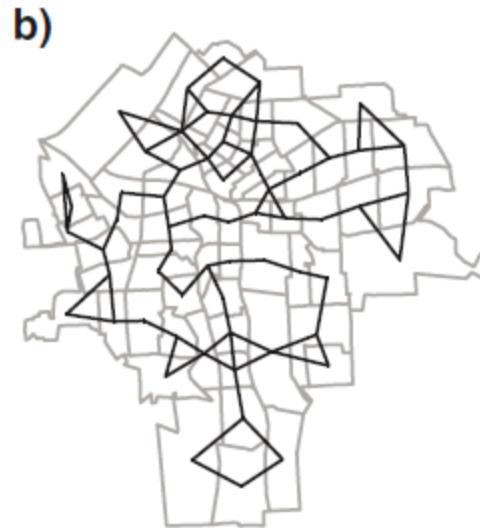


Fig. 9.5. (a) $k = 1$ neighbours; (b) $k = 2$ neighbours; (c) $k = 4$ neighbours

Source: Bivand and Pebesma and Gomez-Rubio

Distance-based Neighbors

- thresh-hold distance (buffer)

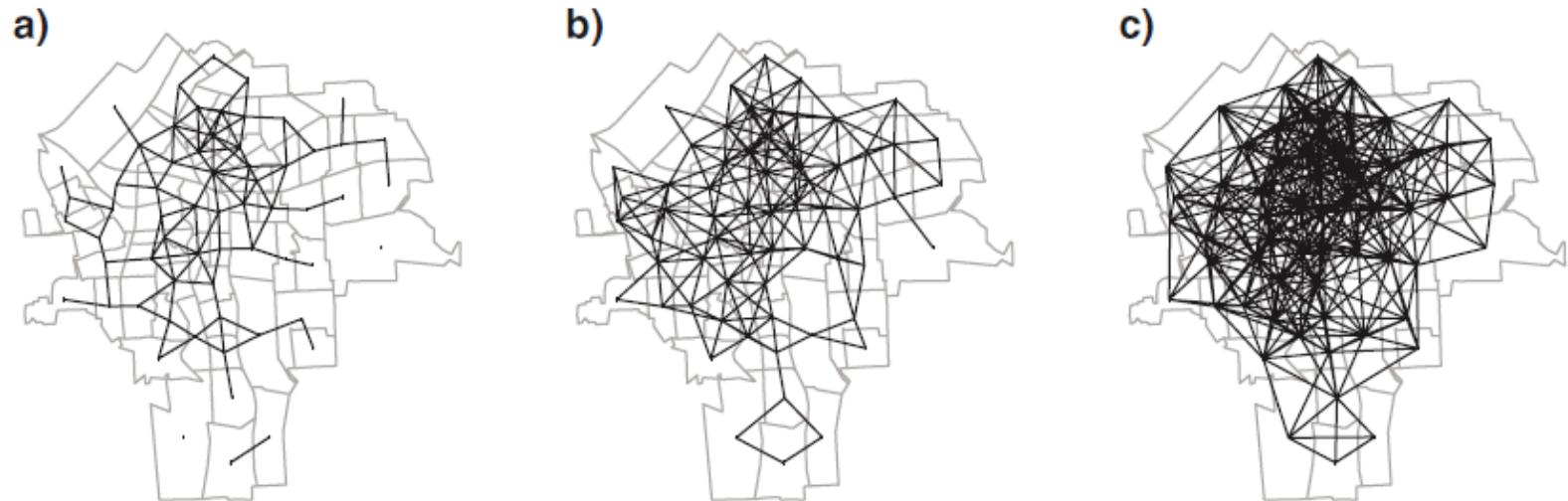
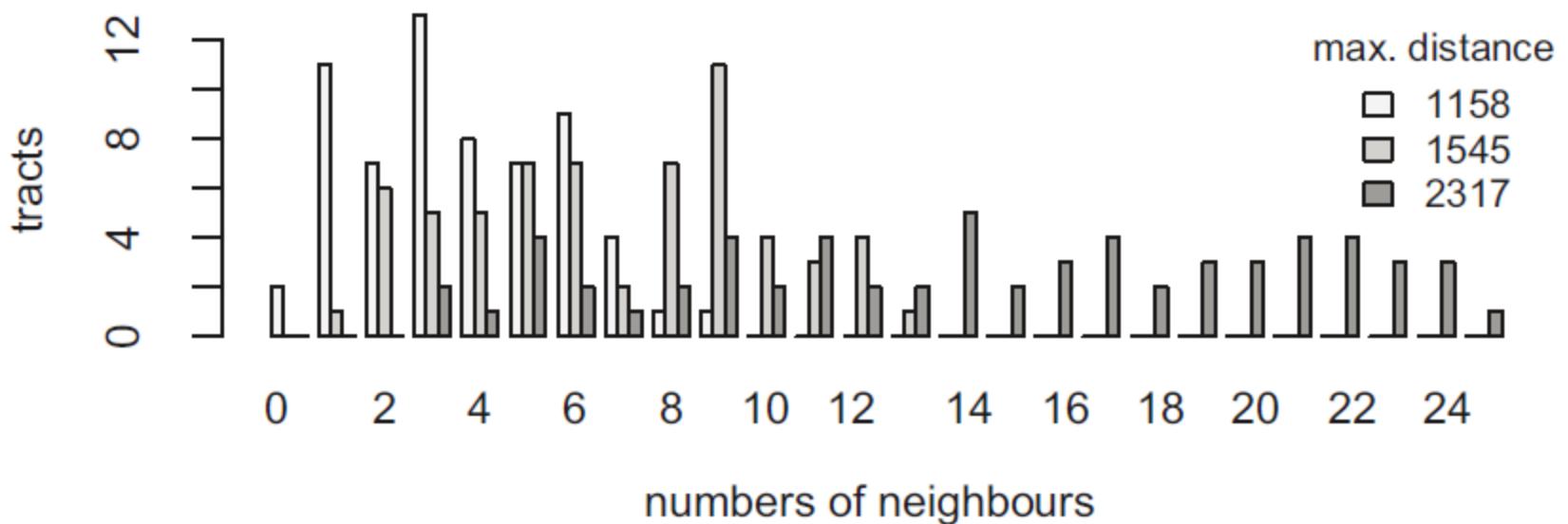


Fig. 9.6. (a) Neighbours within 1,158 m; (b) neighbours within 1,545 m; (c) neighbours within 2,317 m

Source: Bivand and Pebesma and Gomez-Rubio

Neighbor/Connectivity Histogram



Source: Bivand and Pebesma and Gomez-Rubio

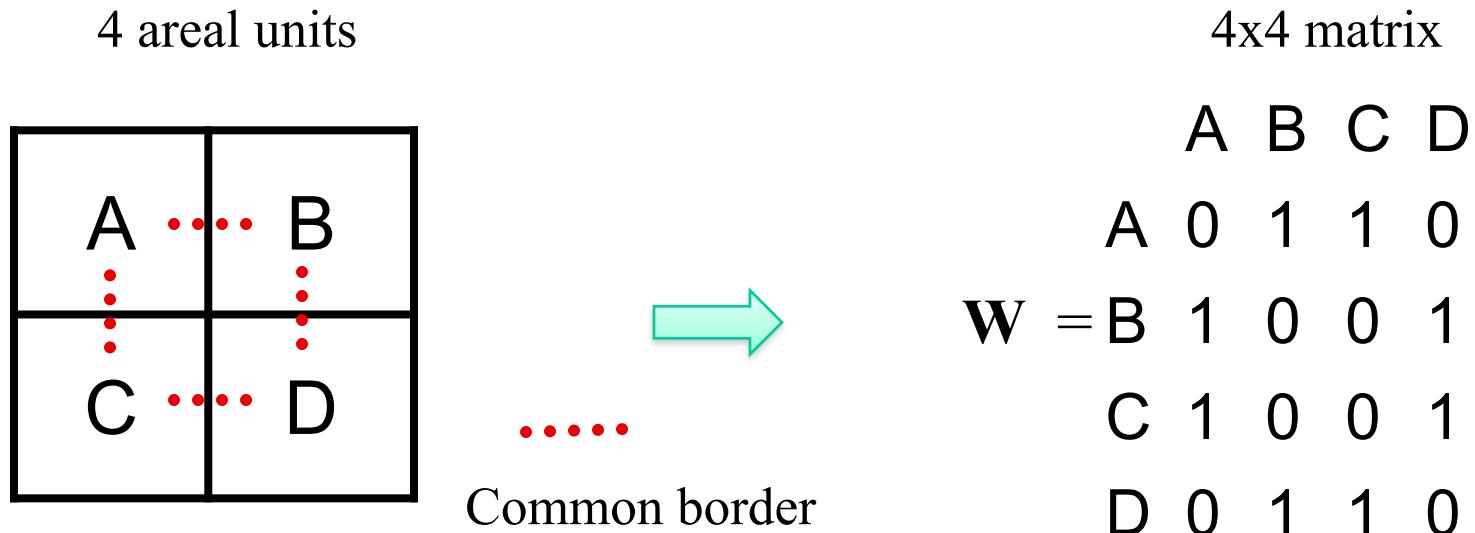
Spatial Weight Matrix

- 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

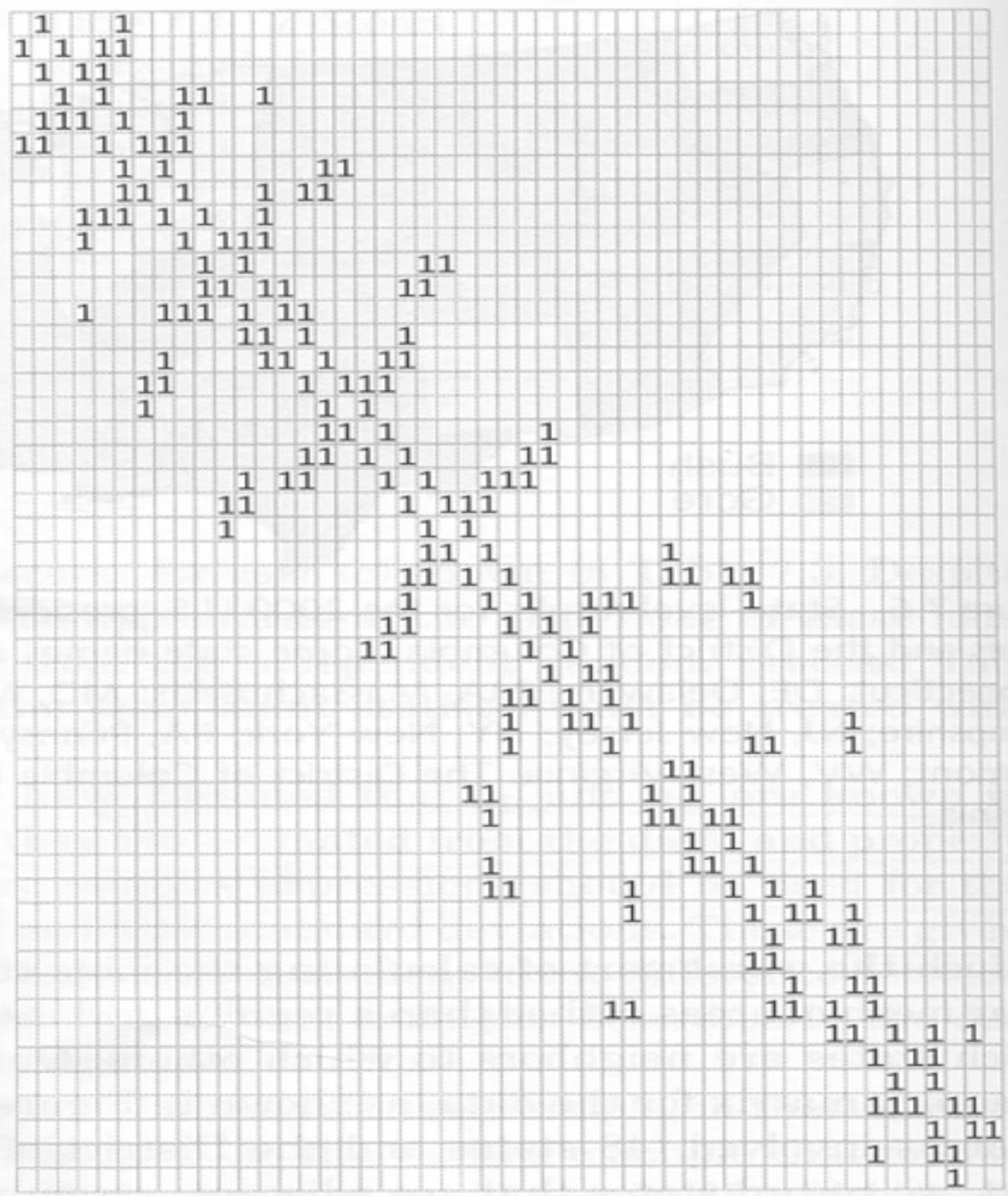


A Simple Example for Rook case

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



- 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

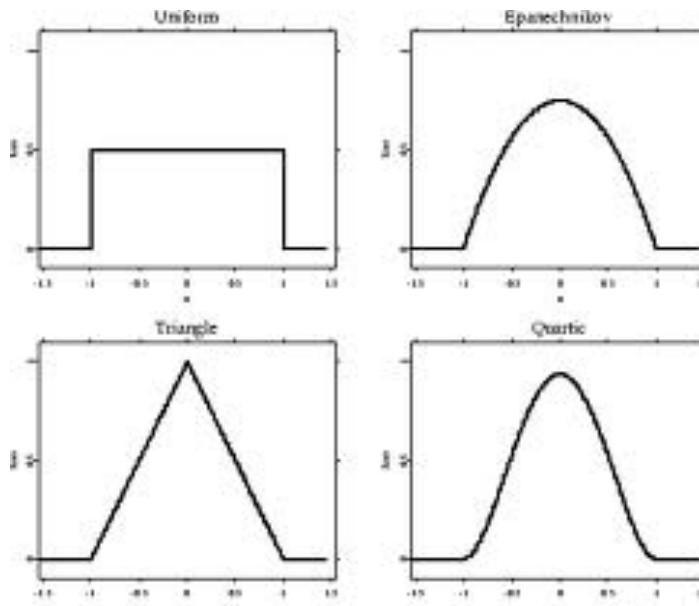
Row standardized
--usually use this



	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

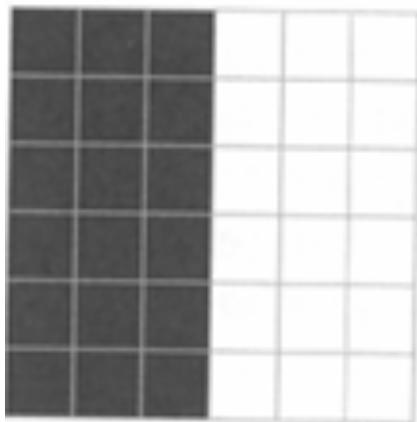
- Global Measures
 - A single value which applies to the entire data set
 - The same pattern or process occurs over the entire geographic area
 - An average for the entire area
- Local Measures
 - A value calculated for each observation unit
 - Different patterns or processes may occur in different parts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

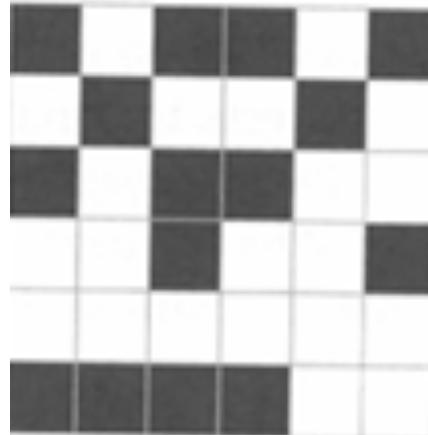
- Global Measures
 - Join Count
 - Moran's I
- Local Measures
 - Local Moran's I

Join (or Joint or Joins) Count Statistic

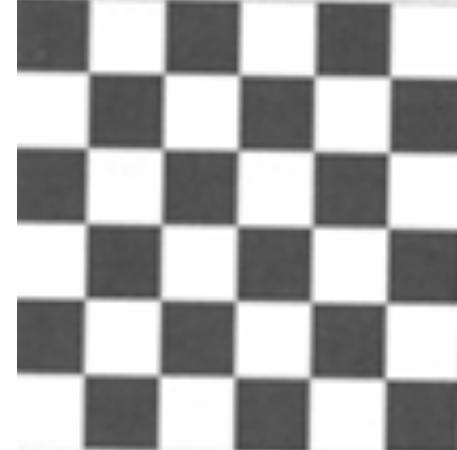
Positive autocorrelation



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:

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

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

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

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

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

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

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 = $109 \times .499 \times .499 = 27.125$)
- 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

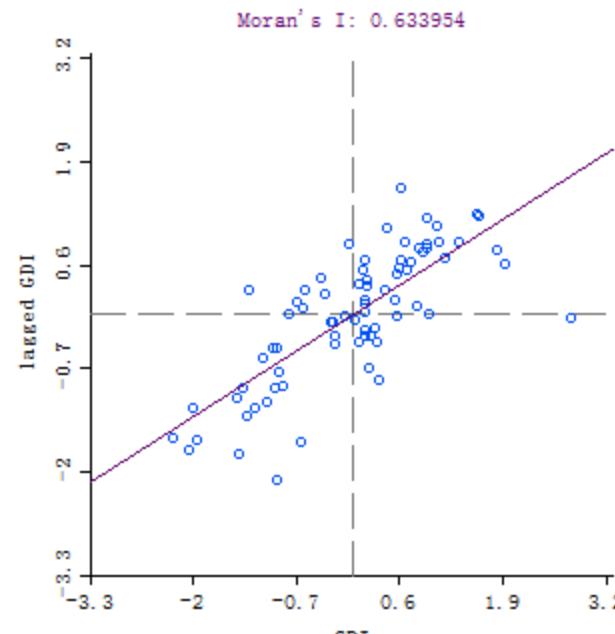
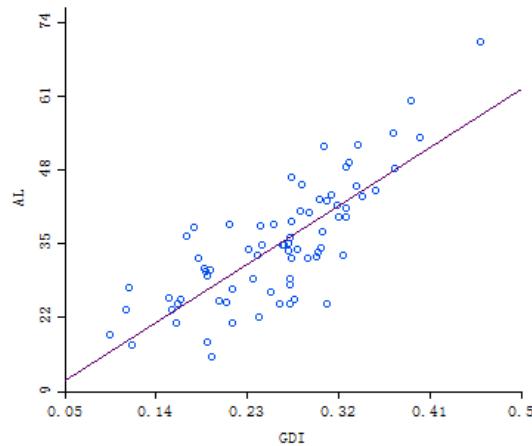
$$I = \frac{N \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2}$$

- 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

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

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

(see next slide)

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

Spatial auto-correlation

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

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

y_i is the x_i for the neighboring polygon

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

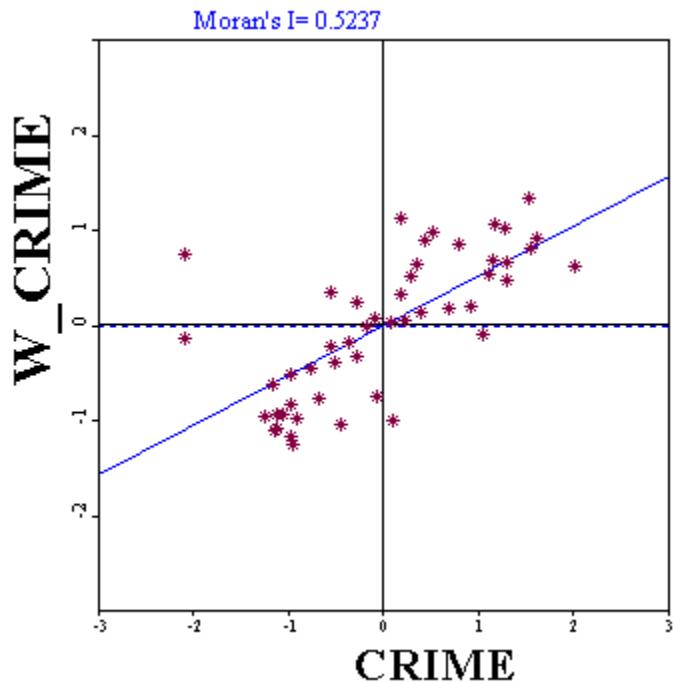
Moran's I

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

Source: Ron Briggs of UT Dallas

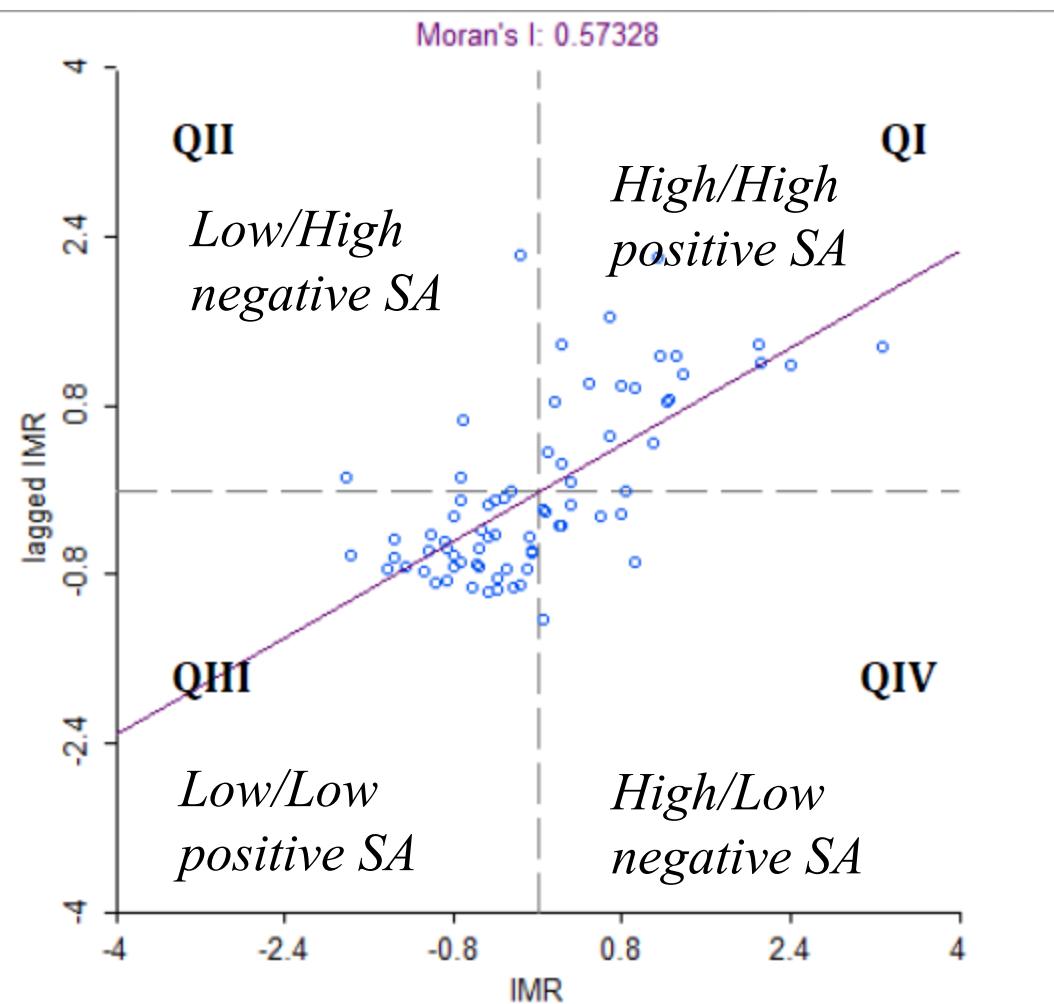
Moran Scatter Plots

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

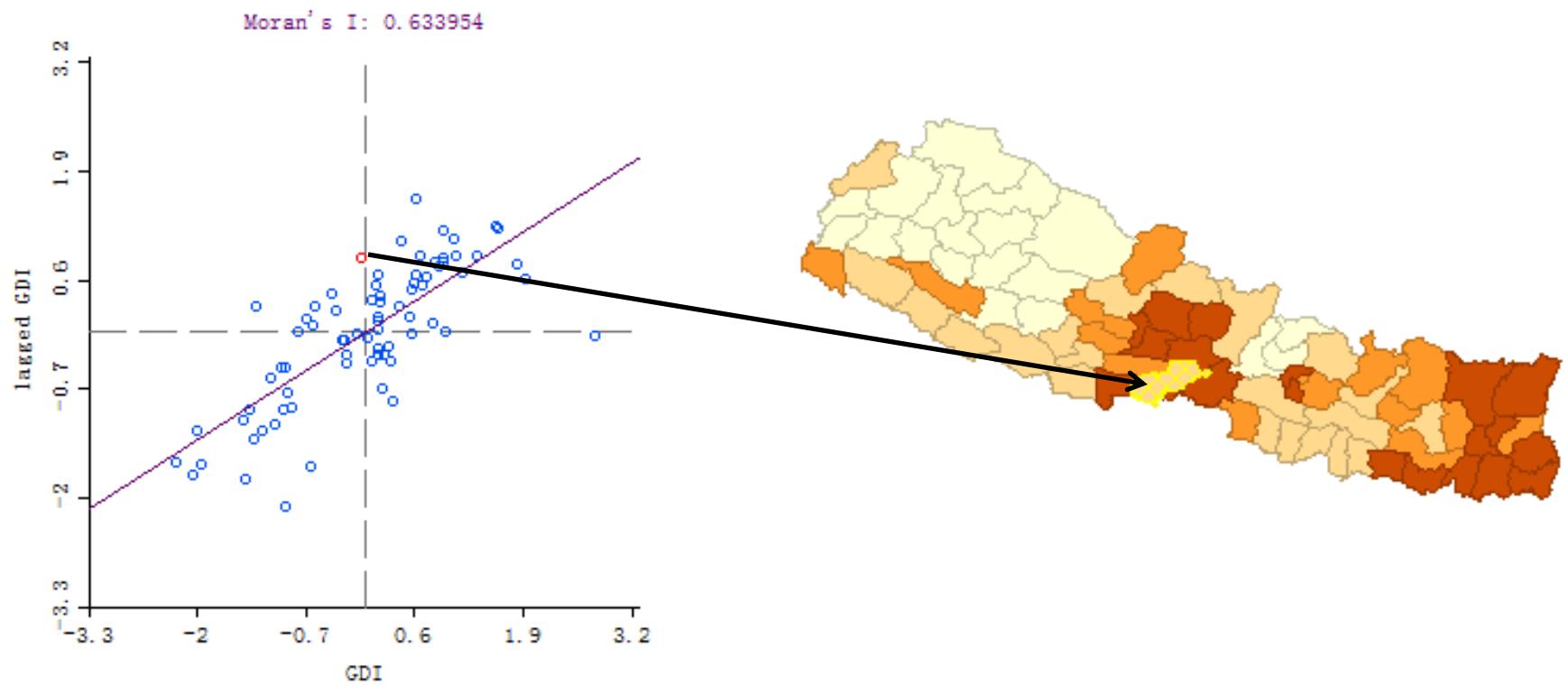


The slope of this *regression line* is
Moran's I

Moran Scatter Plots



Moran Scatterplot: Example



Statistical Significance Tests for Moran's I

- Based on the normal frequency distribution with

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

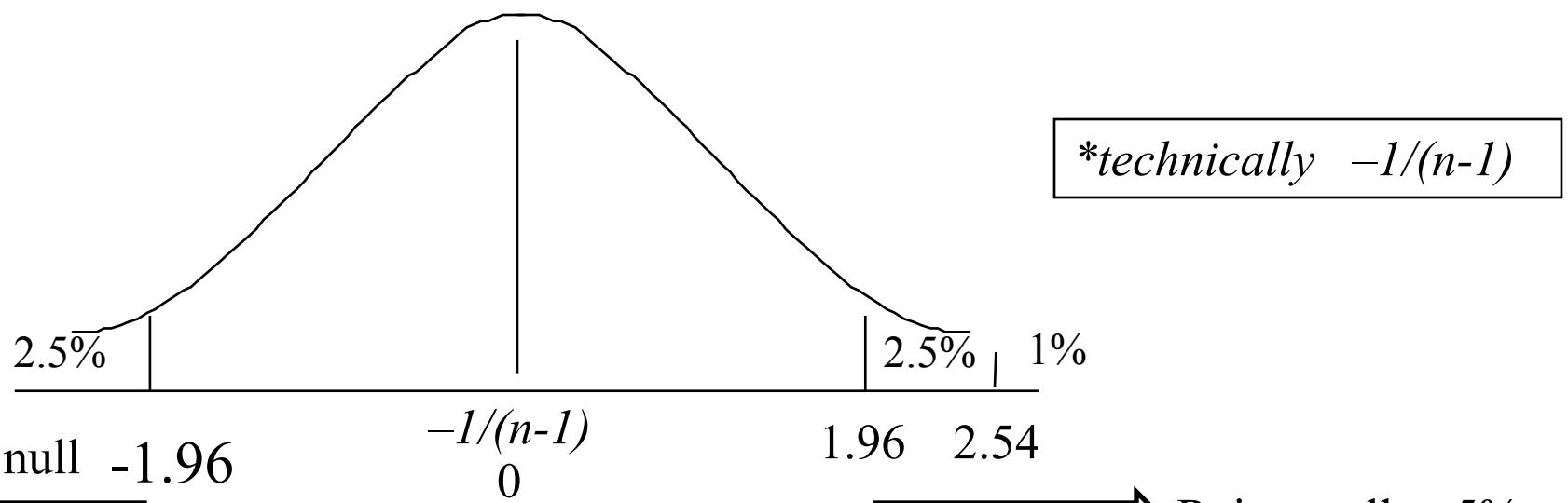
$$Z = \frac{I - E(I)}{S_{error(I)}}$$

$E(I)$ 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

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

Summary

- Spatial autocorrelation of areal data
- Spatial weight matrix
- Measures of spatial autocorrelation
- Global Measure
 - Moran's I
- Local
 - LISA: Moran's I
- Significance test

Diagnostic of Spatial Dependence

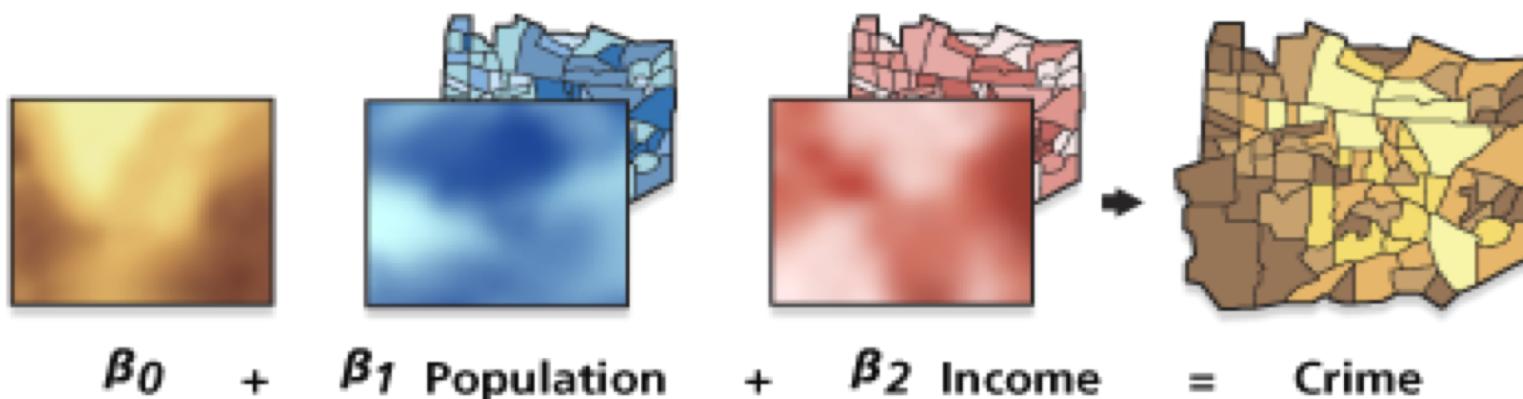
- Moran's I is commonly used to diagnose if spatial dependence exists
 - **For regression**
 - calculate the residuals
 - map the residuals: do you see any spatial patterns?
 - Calculate Moran's I for the residuals: is it statistically significant?

Consequences of Ignoring Spatial Autocorrelation

- Autocorrelation/dependence -> information redundancy
- Correlation coefficients and coefficients of determination appear bigger 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 smaller than they really are
 - *exaggerated precision*
 - You think your predictions are better than they really are since standard errors measure *predictive accuracy*

Consequences of Ignoring Spatial Autocorrelation

- Conventional statistical methods may not be reliable
 - E.g., for regression case, the assumption of *independence* is often required
 - Spatial regression is needed



Spatial Regression Methods

- Spatial Econometrics Approaches (available in GeoDa)
 - Lag model
 - Error model
- Other methods:
 - Spatial autoregressive model
 - Bayesian hierarchical models

- End of this topic