# Spatial Autocorrelation: Theory and Concepts

GEOG 215 - April 6, 2020

## **Today's Agenda**

- SPATIAL AUTOCORRELATION
  - Moran's I
    - Global Moran's I
    - Local Moran's I
    - Spatial Correlograms
    - Extensions to traditional Moran's I

### Recall

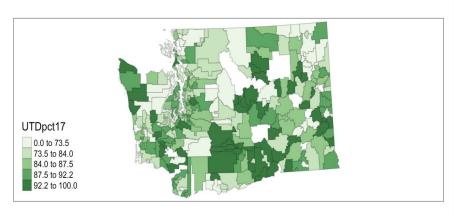
- Tobler's first law of Geography
  - Everything is related to everything else, but near things are more related than distant things
    - Values at locations near each other tend to be similar, with similarity decreasing with distance
  - Implies that phenomena are not distributed randomly (throughout space)
    - Imagine how the world would appear if everything were randomly distributed

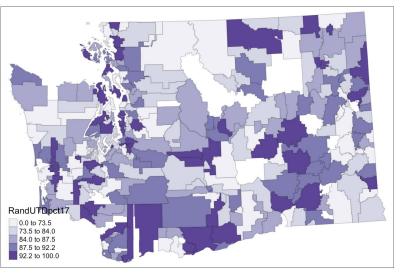
- Oft-used statistic for describing/testing the spatial autocorrelation within a region
  - Global (Considers the whole region)
    - Measures the magnitude of spatial autocorrelation
    - Returns a single result (I)
    - In addition, it provides a p-value
    - Probability value to test help statistical significance

- Global value
  - Moran's I ranges from -1 to 1 (continuous)
    - Perfectly dispersed/ordered: -1
    - Random: 0
    - Perfectly Clustered: 1 (close to 1 actually)
      - Some exceptions
  - Compares *I* of observed data to expected *I* (expected is under Complete Spatial Randomness)

## **Complete Spatial Randomness (CSR)**

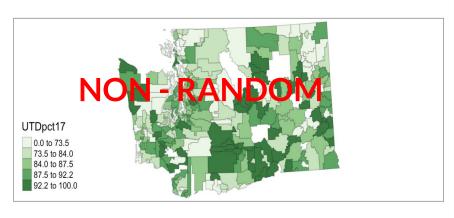
- Imagine that you could pick up the values for the attribute you are analyzing and throw them down onto your features, letting each value fall where it may
  - Random chance spatial process
    - Many many possible realizations (no single pattern)
  - Usual reference point (null hypothesis) for Moran's I

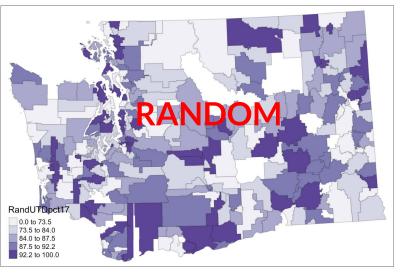




## **Complete Spatial Randomness (CSR)**

- Imagine that you could pick up the values for the attribute you are analyzing and throw them down onto your features, letting each value fall where it may
  - Random chance spatial process
    - Many many possible realizations (no single pattern)
  - Usual reference point (null hypothesis) for Moran's I





Formula

$$I = \frac{n}{S} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \overline{X}) (x_j - \overline{X})}{\sum_{i=1}^{n} (x_i - \overline{X})^2}$$

n = number of areas

 $w_{ij}$  = the weight between area i and j

 $x_i$  = the value for area i

 $x_j$  = the value for area j

 $\overline{X}$  = mean of all values

S = sum of all weights

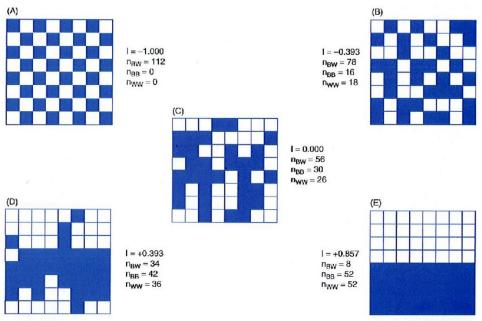
$$S = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$$

Formula

For every i, compare deviation from mean of self value and neighbors' values

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

n = number of areas  $w_{ij} =$  the weight between area i and j  $x_i =$  the value for area i  $x_j =$  the value for area j  $\overline{X} =$  mean of all values S = sum of all weights  $S = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ 



**Figure 4.1** Field arrangements of blue and white cells exhibiting: (A) extreme negative spatial autocorrelation; (B) a dispersed arrangement; (C) spatial independence; (D) spatial clustering; and (B) extreme positive spatial autocorrelation. The values of the *I* statistic are calculated using the equation in Section 4.6 (*Source*: Goodchild 1986 CATMOG, GcoBooks, Norwich)

- Interpreting output
  - Magnitude
    - The closer to 1, the more clustered the values are
    - The closer to -1, the more dispersed the values are
    - Close to 0 means high likelihood of complete spatial randomness
  - Significance
    - Statistical
      - Interpret p-value (e.g., <0.05)</li>
    - Substantive
      - Look at the actual values
      - Some phenomena have weaker clustering than others
      - Assess whether local statistics might be better

https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm

- Interpreting output
  - Importance/Substantive significance
    - Beware of significant, but unimportant deviation from random pattern
      - For example, I = 0.04, p < 0.001</li>
    - p value is affected by sample size
      - Personal interpretation system:
        - 0 to 0.1, barely clustered (pretty much random)
        - 0.1 to 0.3, slightly clustered
        - 0.3 to 0.5, modertately clustered
        - > 0.5, highly clustered

#### Potential Applications

- Help identify an appropriate neighborhood distance for a variety of spatial analysis methods by finding the distance where spatial autocorrelation is strongest.
- Measure broad trends in ethnic or racial segregation over time—is segregation increasing or decreasing?
- Summarize the diffusion of an idea, disease, or trend over space and time—is the idea, disease, or trend remaining isolated and concentrated, or spreading and becoming more diffuse?
- Many more applications -
  - Is there an external variable that might be explaining clustering or dispersion patterns?
- Examples of previous student projects

- Robustness test
  - Multiple neighborhood definitions
    - K-nearest Neighbors
    - Neighbors based on distance/ distance threshold
    - Contiguity based neighbors (queen / rook)
    - Neighbors based on connectivity / thiessen polygons

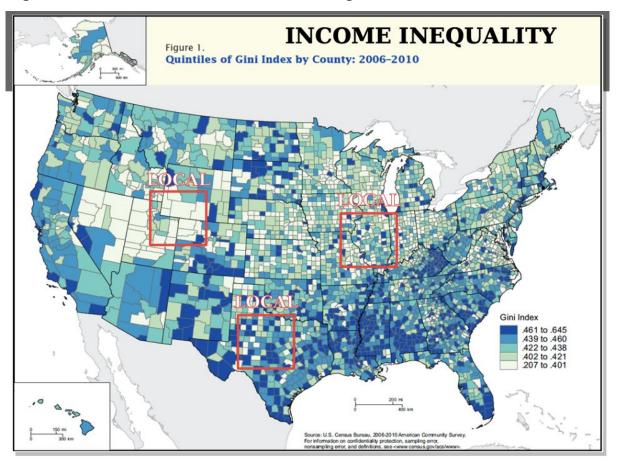
$ Table \ A2. \ Moran's \ \textit{I} \ values \ for \ NME \ rate \ (\%) \ for \ block \ group \ observations, \ under \ ten \ neighborhood \ definitions. $										
YEAR	ID(5)	ID(10)	ID(15)	ID(20)	KNN(5)	KNN(10)	KNN(15)	KNN(20)	CON(Q)	CON(R)
2000	0.073	0.076	0.078	0.079	0.106	0.093	0.083	0.079	0.119	0.104

- Other important considerations
  - Works with continuous data
    - There are extensions for binary data
  - Measures autocorrelation not correlation
    - You can use bivariate Moran' I (with caution)
  - Sensitive to outliers and skewed data
    - Check your variable histograms to see if your data is normal or not
      - If not, consider transforming to normal, run robustness checks
  - Comparisons are only relevant when the study area is fixed
    - And, when your variables are similar (counts, rates, etc)
  - Consider neighborhood definitions
    - Remove areas with no neighbors/ artificial neighbors due to edge effects
    - Neighborhood definition should represent real world process

## **Stationary vs Non-stationary**

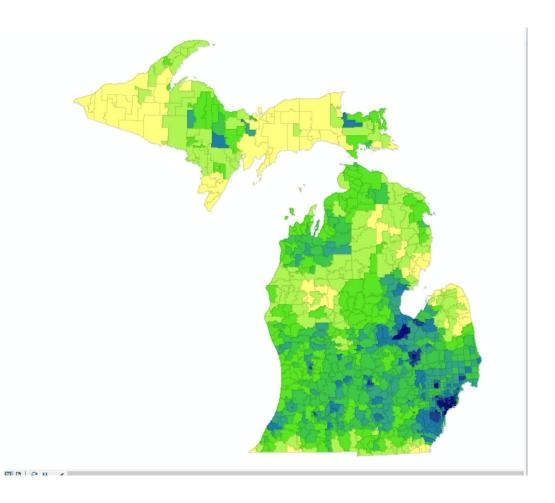
- Spatial autocorrelation
  - Global
    - Assumes that autocorrelation is stationary across space
      - Invariant from place to place
        - Similar to thinking about usefulness of an "average"
  - Local
    - Assumes that autocorrelation is non-stationary cross space
      - Varies from place to place

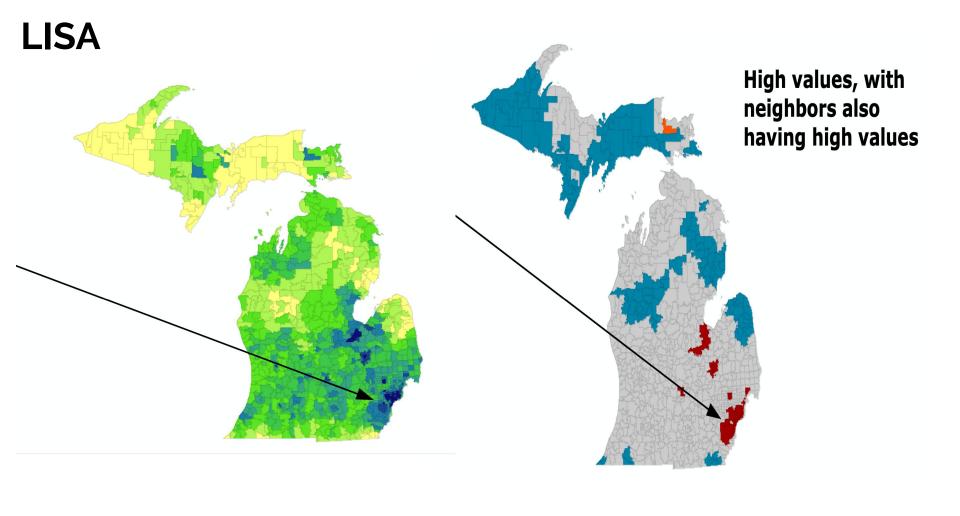
## **Stationary vs Non-stationary**

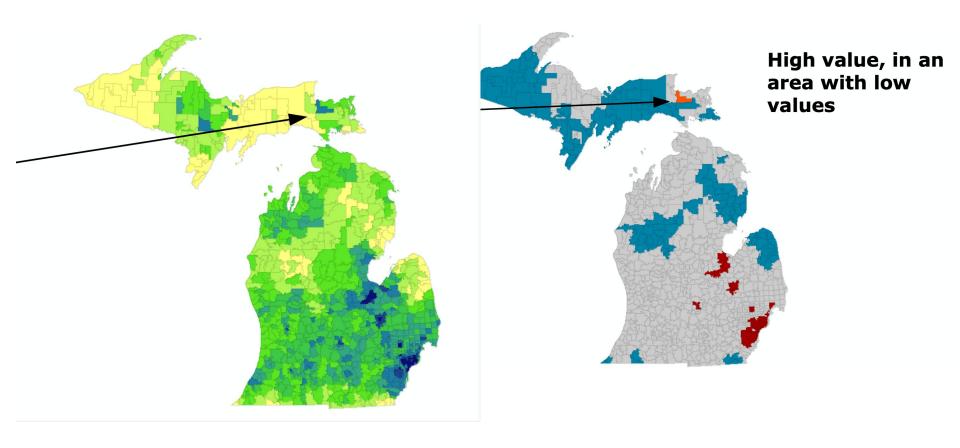


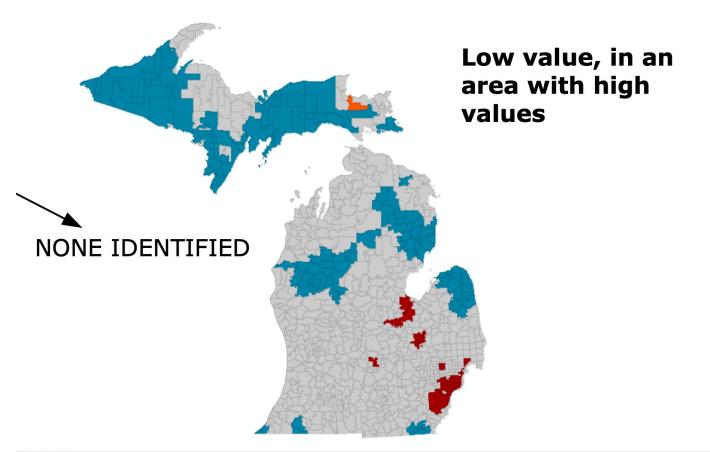
- Local Indicator of Spatial Association
  - Local version of Moran's I
    - Iterates through each observation and provides a measure of autocorrelation
      - And, association p-value
    - Unlike global measures, results can be mapped
      - Reveals the nature of spatial autocorrelation throughout the study area

- Local Indicator of Spatial Association
  - Observations can be "hot" or "cold" spots, high or low outliers, or not significant
    - High-High (observation high, neighbors high)
    - Low-Low (observation low, neighbors low)
    - High outlier (observation high, neighbors low)
    - Low outlier (observation low, neighbors high)
  - Extremely useful for understanding "where" spatial autocorrelation is strong/weak

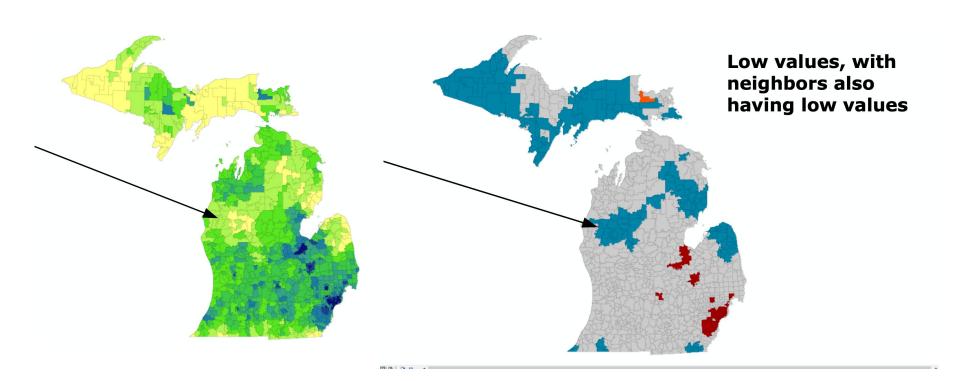


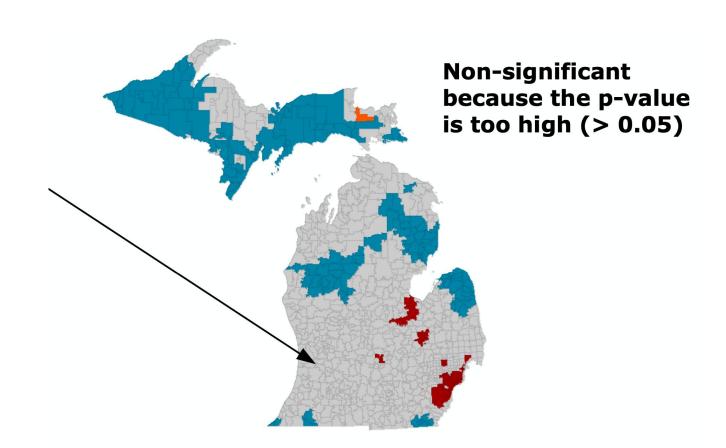






10 0 11 <





## **Spatial Correlograms**

- Non-parametric approach to measure Global Spatial Autocorrelation
  - Does not rely on the specification of a spatial weight matrix (parametric approach)
  - Calculates spatial autocorrelation at various distance bands
    - Tells up how spatial autocorrelation varies with distance
      - Generally, spatial autocorrelation decreases with increasing distance (distance decay)

## **Spatial Correlograms**

- Non-parametric approach to measure Global Spatial Autocorrelation
  - Does not rely on the specification of a spatial weight matrix (parametric approach)
  - Calculates spatial autocorrelation at various distance bands
    - Tells up how spatial autocorrelation varies with distance
      - Generally, spatial autocorrelation decreases with increasing distance (distance decay)

## **Spatial Correlograms**

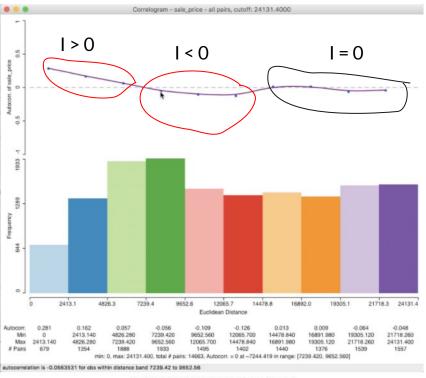


Figure 31: Correlogram with half max distance

#### **Extensions**

- Bivariate Moran's I
  - Measures the degree to which the value for a given variable at a location is correlated with its neighbors for a different variable
    - Does not take into account correlation between variables at the same location
  - Can also extend to time lags
    - Looking at correlation of the value of a variable at one location with values of neighbors for the same variable at a previous time period
    - Differential Moran's I
      - Takes into account time lags but also controls for temporal autocorrelation

#### **Extensions**

- Moran's I for rates data
  - Corrects for varying population densities when the variable of interest is a rate or proportion
  - Similar to smoothing
    - Transforms the crude rate to a new variable using empirical bayes techniques (same technique used to smooth data) and then calculate Morans' I
- Moran's I for binary data (0 and 1)
  - You can use join count statistics to calculate spatial autocorrelation for dichotomous data
- Similar extensions to Location Moran's I