Lattice Data

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1. Lattice Data
   - Representation
   - Examples

2. Spatial Autocorrelation and Dependence
   - Data Types and Spatial Autocorrelation
   - Spatial Dependence
Outline

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Lattice Data

Spatial Domain: $D$

- Discrete and fixed
- Locations nonrandom
- Locations countable

Examples of lattice data

- Attributes collected by ZIP code
- Census tract
- Remotely sensed data reported by pixels
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Site

- Each location is now an area or site
- One observation on $Z$ for each site
- Need a spatial index: $Z(s_i)$

$Z(s_i)$

- $s_i$ is a representative location within the site
- e.g., centroid, largest city
- Allows for measuring distances between sites
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Sites are areal units

- Attribute is typically aggregated or averaged
- Aggregated: event counts (number of crimes per tract)
- Averaged: per capita income by state

Coverage

- Lattice data is usually exhaustive in coverage
- e.g., U.S. states, census tracts in San Diego
- Prediction or interpolation not meaningful
- Explaining attribute variation across sites is the focus
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Lattice Data: State Per Capita Incomes

[Map of the United States showing states colored by per capita incomes in 1929, with percentiles indicated.]
Lattice Data: Spatial Autocorrelation

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## Data Types and Autocorrelation

### Point Data
- focus on geometric pattern
- random vs. nonrandom
- clustered vs. uniform

### Geostatistics
- 2-D modeling of spatial covariance (pairs of observations in function of distance)
- kriging, spatial prediction
Data Types and Autocorrelation

Lattice Data
- areal units: states, counties, census tracts, watersheds
- points: centroids of areal units
- focus on the spatial nonrandomness of attribute values
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2 Spatial Autocorrelation and Dependence
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There is no question with respect to emergent geospatial science. The important harbingers were Geary’s article on spatial autocorrelation, Dacey’s paper about two- and K-color maps, and that of Bachi on geographic series. – Berry, Griffith, Tiefelsdorf (2008)
Spatial Dependence

Working Concept

- what happens at one place depends on events in nearby places
- all things are related but nearby things are more related than distant things (Tobler)
- central focus in lattice data analysis

Goodchild 1991

- a world without positive spatial dependence would be an impossible world
- impossible to describe
- impossible to live in
- hell is a place with no spatial dependence
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Spatial Dependence

Categorizing
- Type: Substantive versus nuisance
- Direction: Positive versus negative

Issues
- Time versus space
- Inference
Process Based

- Part of the process under study
- Leaving it out
  - Incomplete understanding
  - Biased inferences
Substantive Spatial Dependence

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Substantive Spatial Dependence

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Nuisance Spatial Dependence

Not Process Based

- Artifact of data collection
- Process boundaries not matching data boundaries
- Scattering across pixels
- GIS induced

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Boundary Mismatch

- Even if $A$ and $B$ are independent
- $A'$ and $B'$ will be dependent
Nuisance vs. Substantive Dependence

Issues

- Not always easy to differentiate from substantive
- Different implications for each type
- Specification strategies (Econometrics)
- Both can be operating jointly
Space versus Time

Temporal Dependence

- Past influences the future
- Recursive
- One dimension

![Diagram showing temporal dependence with t, t+1, t+2, t+3]
Space versus Time

Spatial Dependence

- Multi-directional
- Simultaneous