Spatial Neighbors

Lecture #15 | GEOG 510
GIS & Spatial Analysis in Public Health

Varun Goel

Outline

- Neighborhoods and neighbors
- Distance and topology based
- Neighborhood weight matrix
- How to choose?

Tobler's First Law

- 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!

Spatial Autocorrelation

- Spatial Autocorrelation
  - The degree of similarity between objects that are located near each other
    - Attribute similarity
  - Can be measured, quantitatively
    - Over an entire region (global)
    - In a smaller area within the region (local)
    - Use in health geography
      - Prediction, distance decay, cluster analysis

Neighborhood

- What is a neighborhood?
  - Neighborhood has many definitions
    - Zone of influence
    - Idea of nearness or connectedness
      - Things or objects that are near one another
      - Things or objects that affect one another
- Why important?
  - To describe or characterize spatial relationships among objects requires us to define a neighborhood

Neighbors

- Neighbors are features located within a neighborhood
  - To describe or characterize spatial relationships among objects requires us to define the neighbor relationships
    - Neighbors for each observation!

Neighbors

- Required for…
  - Spatial point pattern tests
  - Spatial autocorrelation tests/measures
  - Spatial regression

Neighbors

- Basic approaches to characterize neighbors
  - Binary (Y,N)
    - Either you are a neighbor, or not
  - Continuous
    - Amount of “neighborliness”
      - Generally, based on distance
      - On a conceptual level, some neighbors may be strong, while others are weaker

Neighbors

- Basic approaches to characterize neighbors
  - Absolute distance
    - Objects are considered neighbors based upon the actual distance separating them
  - Relative distance
    - Nearest feature
      - The nearest feature is considered a neighbor
      - Or, nearest *k* features
    - Topology-based
      - Connecting features are considered neighbors

Neighbors

- Absolute distance approach
  - Objects are considered neighbors based upon a predetermined threshold distance
  - For points
    - Distance between points
  - For polygons
    - Distance between polygon centroids

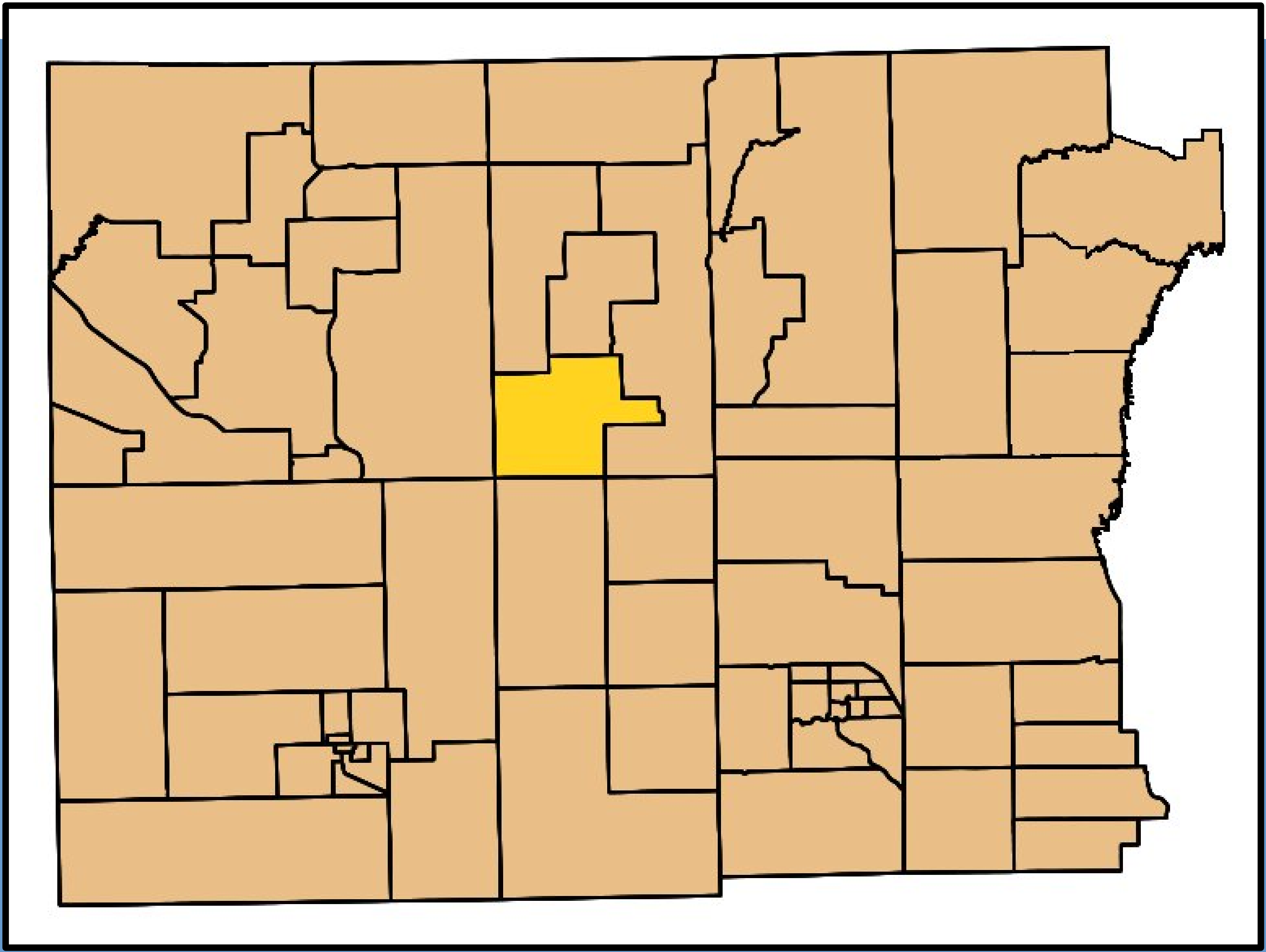
Neighbors

- Relative distance approach
  - Nearest feature
  - For points
    - Distance between points
  - For polygons
    - Distance between polygon centroids

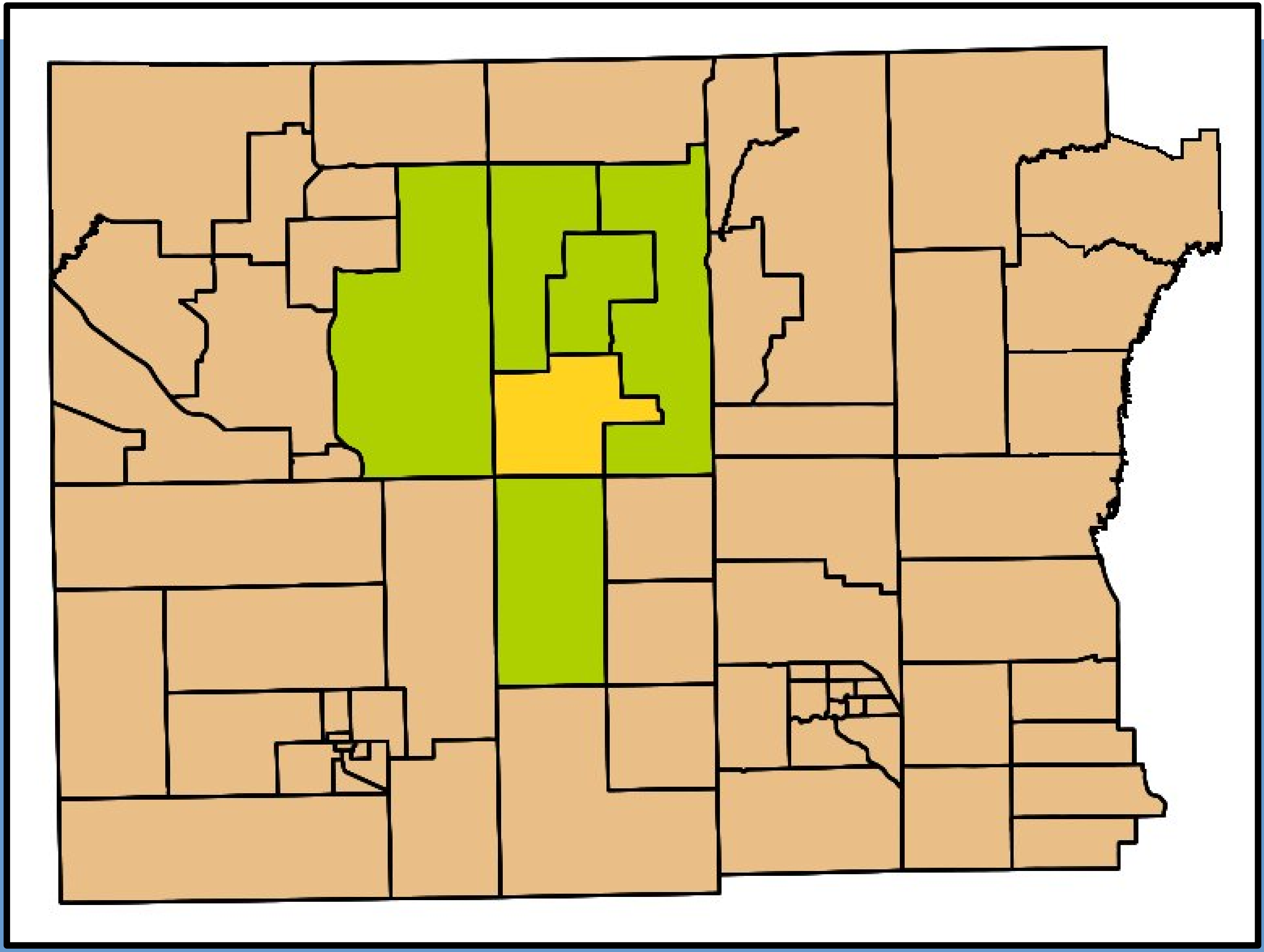
Neighbors

- Relative distance approach
  - Topology-based
  - For points
    - Not available
  - For polygons
    - Based on shared borders (points)

RELATIVE DISTANCE, TOPOLOGY

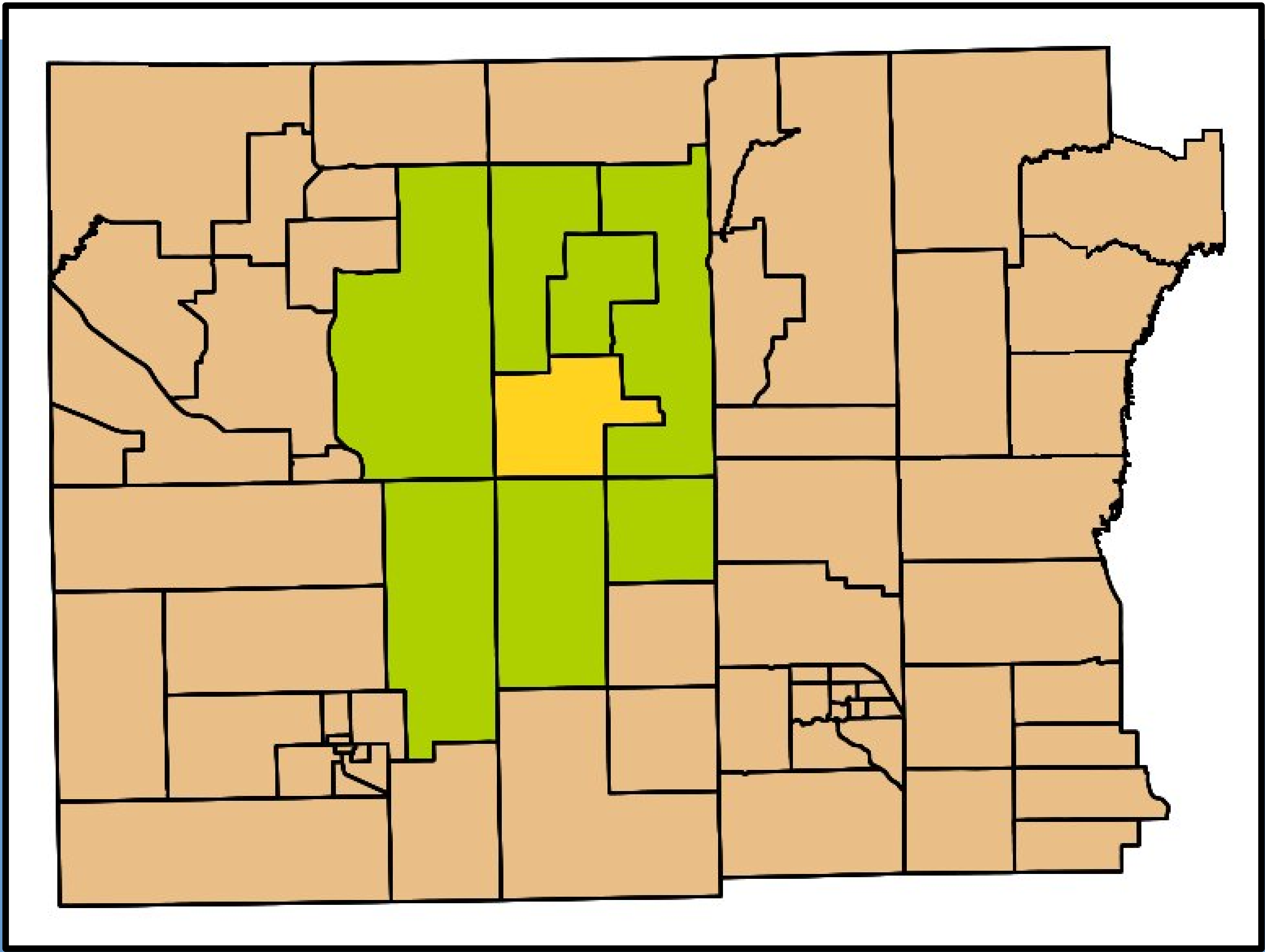


RELATIVE DISTANCE, TOPOLOGY



Rook's case, 1st order neighbors

RELATIVE DISTANCE, TOPOLOGY



Queen's case, 1st order neighbors

Neighbors

- Stored in a neighborhood weight matrix
  - ...or, a similar format
- Matrix is *n* x *n*
  - The number of observations = *n*
  - Entries in this matrix describe <u>the relationships</u> between observations

Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	1	0	1	0	0	0	0	0
B	1	0	1	0	1	0	0	0	0
C	0	1	0	0	0	1	0	0	0
D	1	0	0	0	1	0	1	0	0
E	0	1	0	1	0	1	0	1	0
F	0	0	1	0	1	0	0	0	1
G	0	0	0	1	0	0	0	1	0
H	0	0	0	0	1	0	1	0	1
I	0	0	0	0	0	1	0	1	0

A	B	C
D	E	F
G	H	I

Rook
Contiguity

Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	1	0	1	0	0	0	0	0
B	1	0	1	0	1	0	0	0	0
C	0	1	0	0	0	1	0	0	0
D	1	0	0	0	1	0	1	0	0
E	0	1	0	1	0	1	0	1	0
F	0	0	1	0	1	0	0	0	1
G	0	0	0	1	0	0	0	1	0
H	0	0	0	0	1	0	1	0	1
I	0	0	0	0	0	1	0	1	0

A	B	C
D	E	F
G	H	I

Rook Contiguity

Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	1	0	1	0	0	0	0	0
B	1	0	1	0	1	0	0	0	0
C	0	1	0	0	0	1	0	0	0
D	1	0	0	0	1	0	1	0	0
E	0	1	0	1	0	1	0	1	0
F	0	0	1	0	1	0	0	0	1
G	0	0	0	1	0	0	0	1	0
H	0	0	0	0	1	0	1	0	1
I	0	0	0	0	0	1	0	1	0

A	B	C
D	E	F
G	H	I

Rook Contiguity

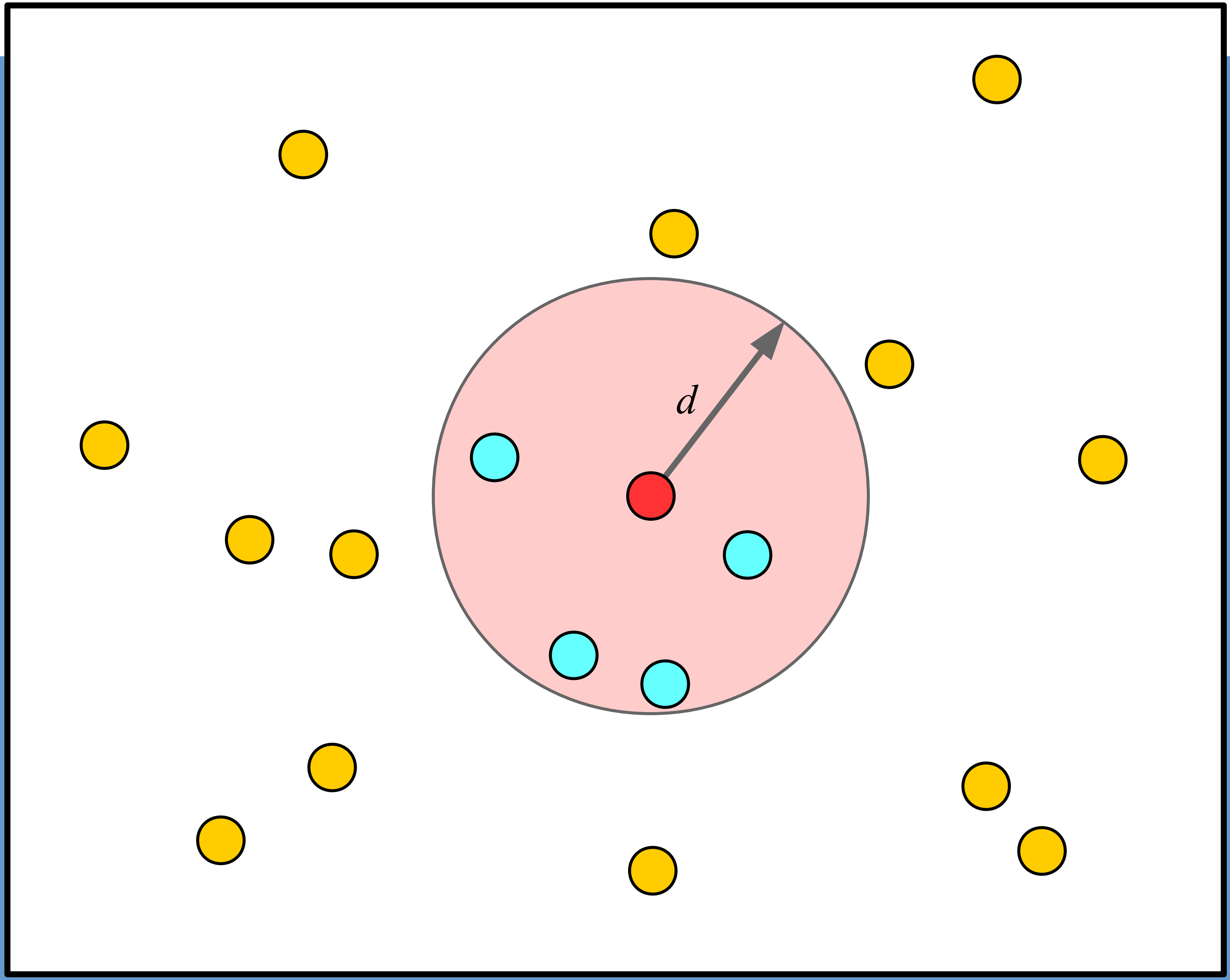
Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	1	0	1	1	0	0	0	0
B	1	0	1	1	1	1	0	0	0
C	0	1	0	0	1	1	0	0	0
D	1	1	0	0	1	0	1	1	0
E	1	1	1	1	0	1	1	1	1
F	0	1	1	0	1	0	0	1	1
G	0	0	0	1	1	0	0	1	0
H	0	0	0	1	1	1	1	0	1
I	0	0	0	0	1	1	0	1	0

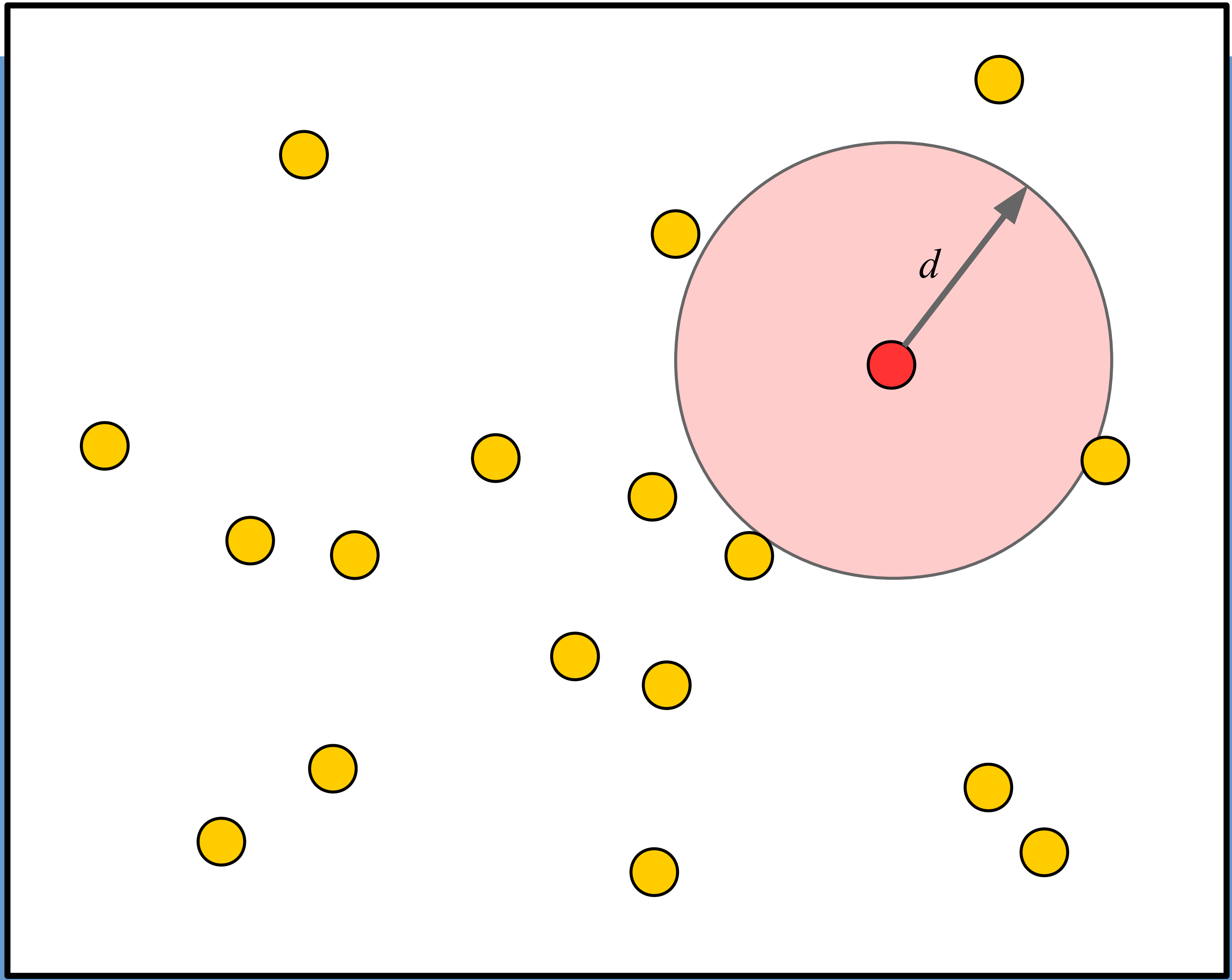
A	B	C
D	E	F
G	H	I

Queen Contiguity

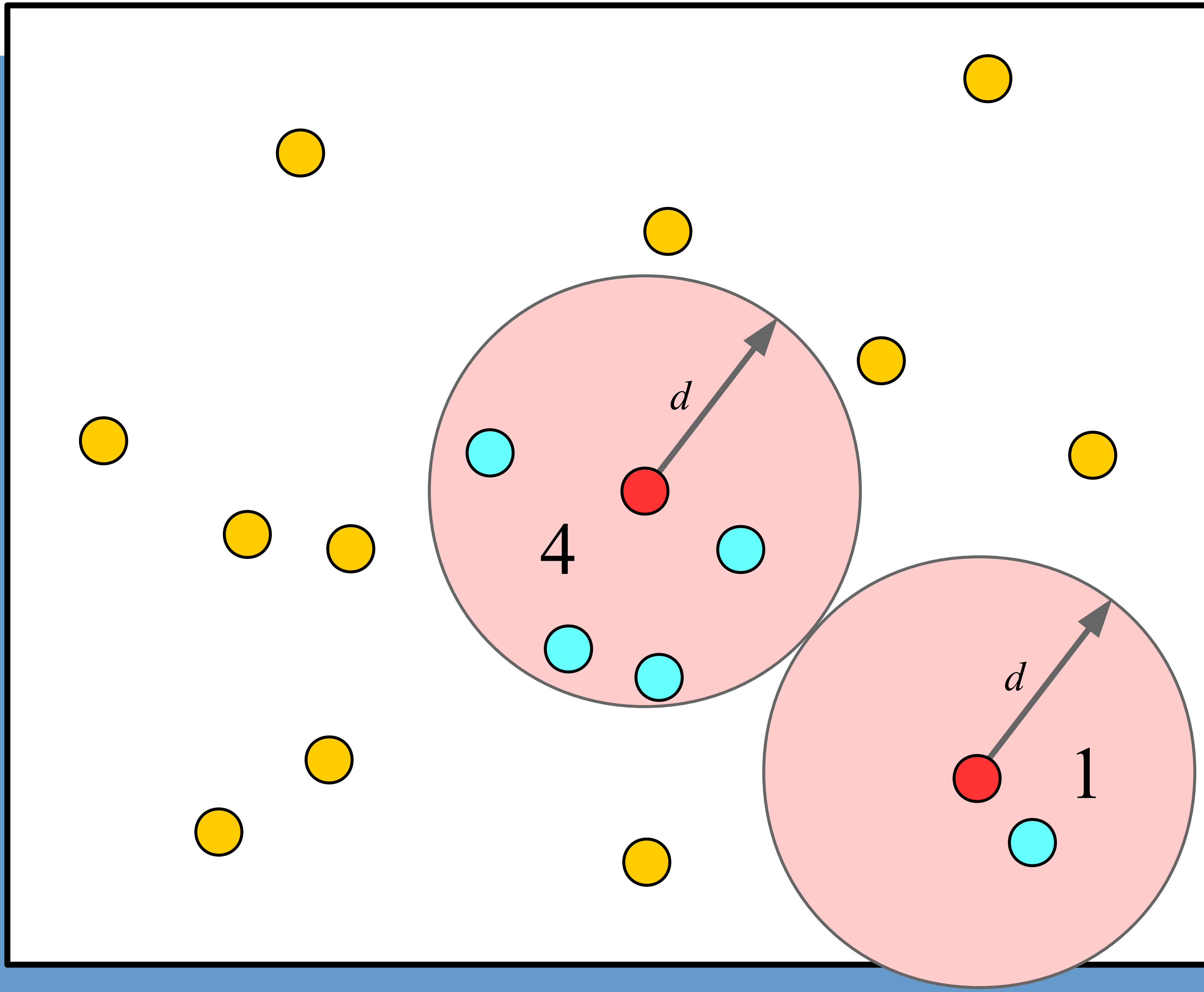
ABSOLUTE DISTANCE, BINARY



ABSOLUTE DISTANCE, BINARY



ABSOLUTE DISTANCE, BINARY



Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	1	0	1	0	0	0	0	0
B	1	0	1	0	1	0	0	0	0
C	0	1	0	0	0	1	0	0	0
D	1	0	0	0	1	0	1	0	0
E	0	1	0	1	0	1	0	1	0
F	0	0	1	0	1	0	0	0	1
G	0	0	0	1	0	0	0	1	0
H	0	0	0	0	1	0	1	0	1
I	0	0	0	0	0	1	0	1	0

A	B	C
D	E	F
G	H	I

Rook Contiguity

No Row Standardization

Neighborhood Weight Matrix

	A	B	C	D	E	F	G	H	I
A	0	0.50	0	0.50	0	0	0	0	0
B	0.33	0	0.33	0	0.33	0	0	0	0
C	0	0.50	0	0	0	0.50	0	0	0
D	0.33	0	0	0	0.33	0	0.33	0	0
E	0	0.25	0	0.25	0	0.25	0	0.25	0
F	0	0	0.33	0	0.33	0	0	0	0.33
G	0	0	0	0.50	0	0	0	0.50	0
H	0	0	0	0	0.33	0	0.33	0	0.33
I	0	0	0	0	0	0.50	0	0.50	0

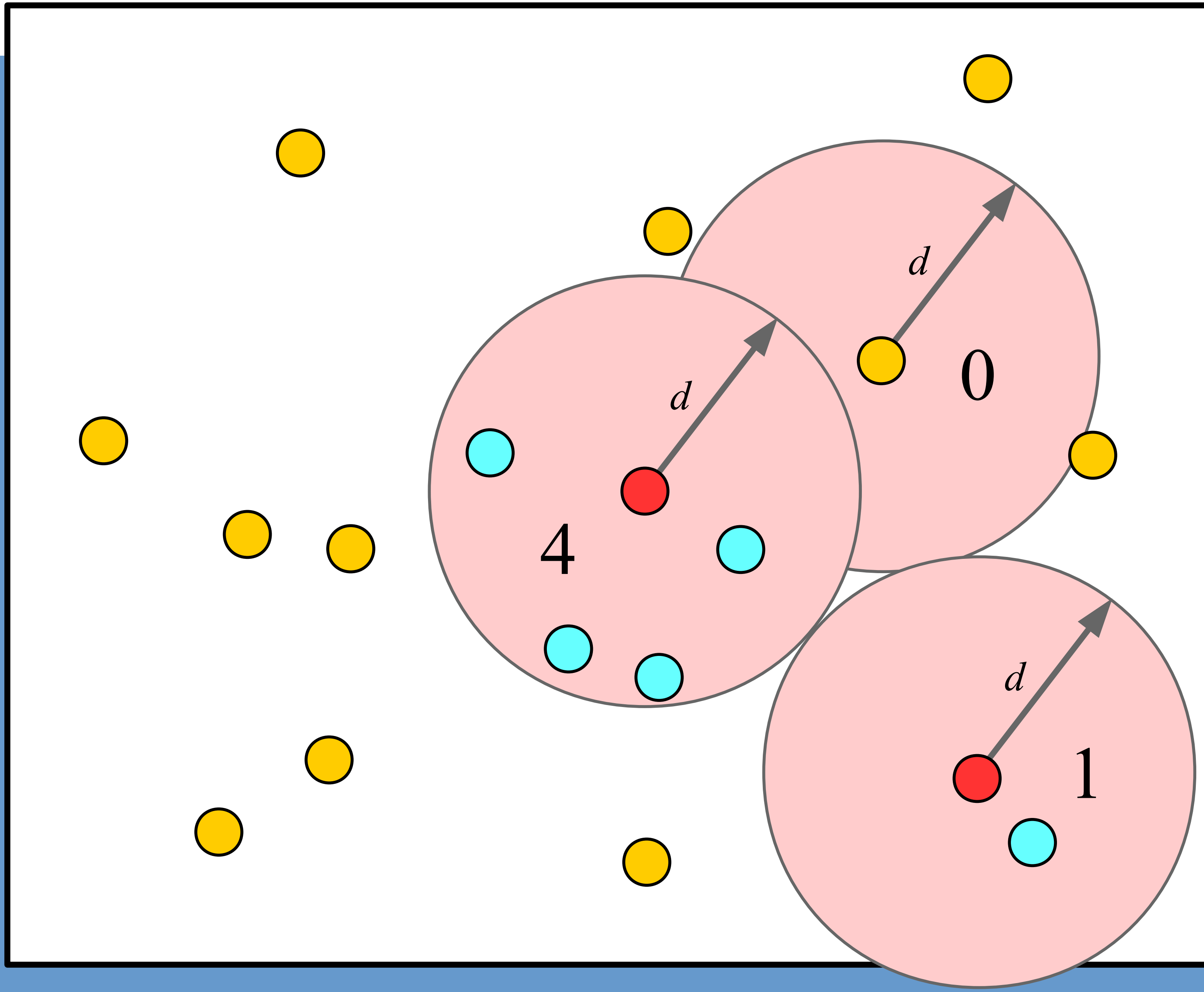
A	B	C
D	E	F
G	H	I

Rook Contiguity

Row Standardized

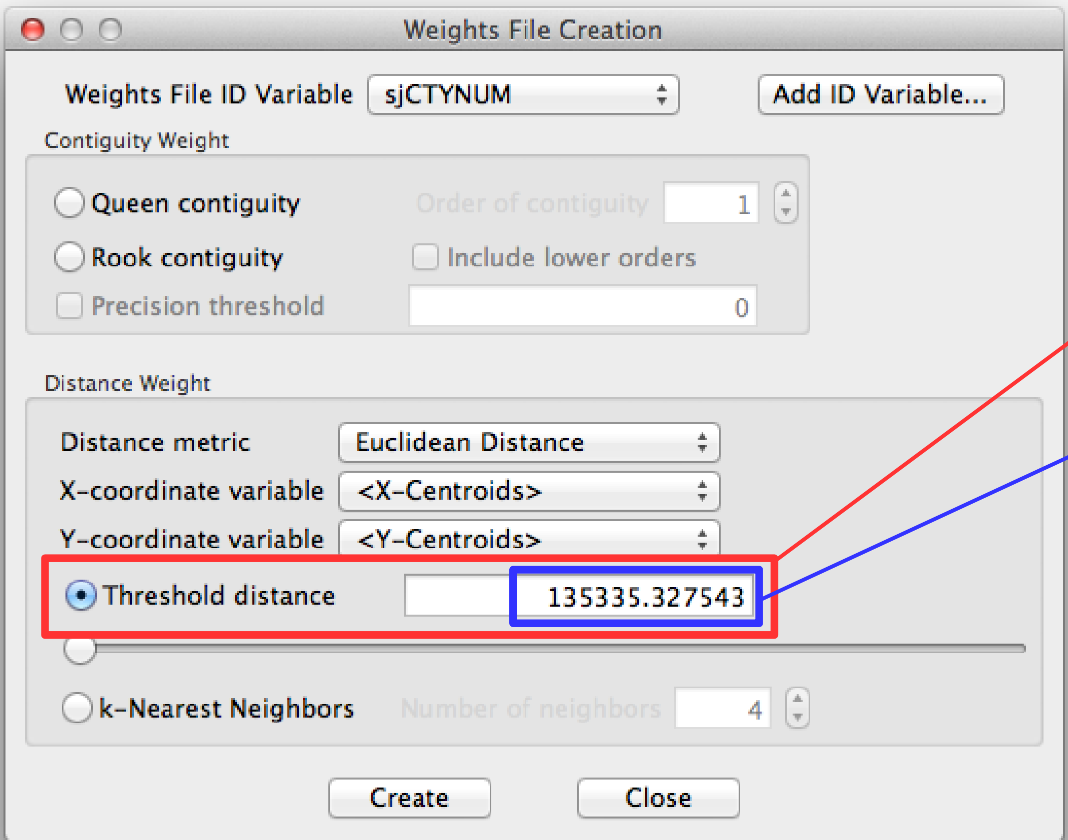
Divide by Row Sum

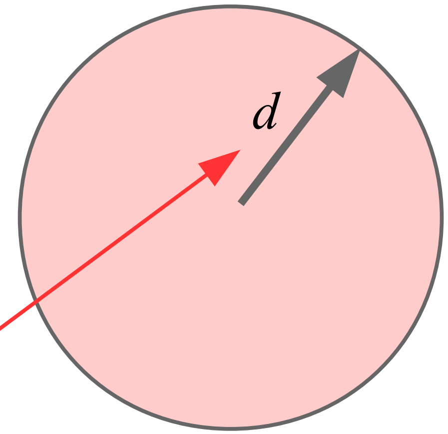
ABSOLUTE DISTANCE, BINARY



ABSOLUTE DISTANCE, BINARY

GeoDa



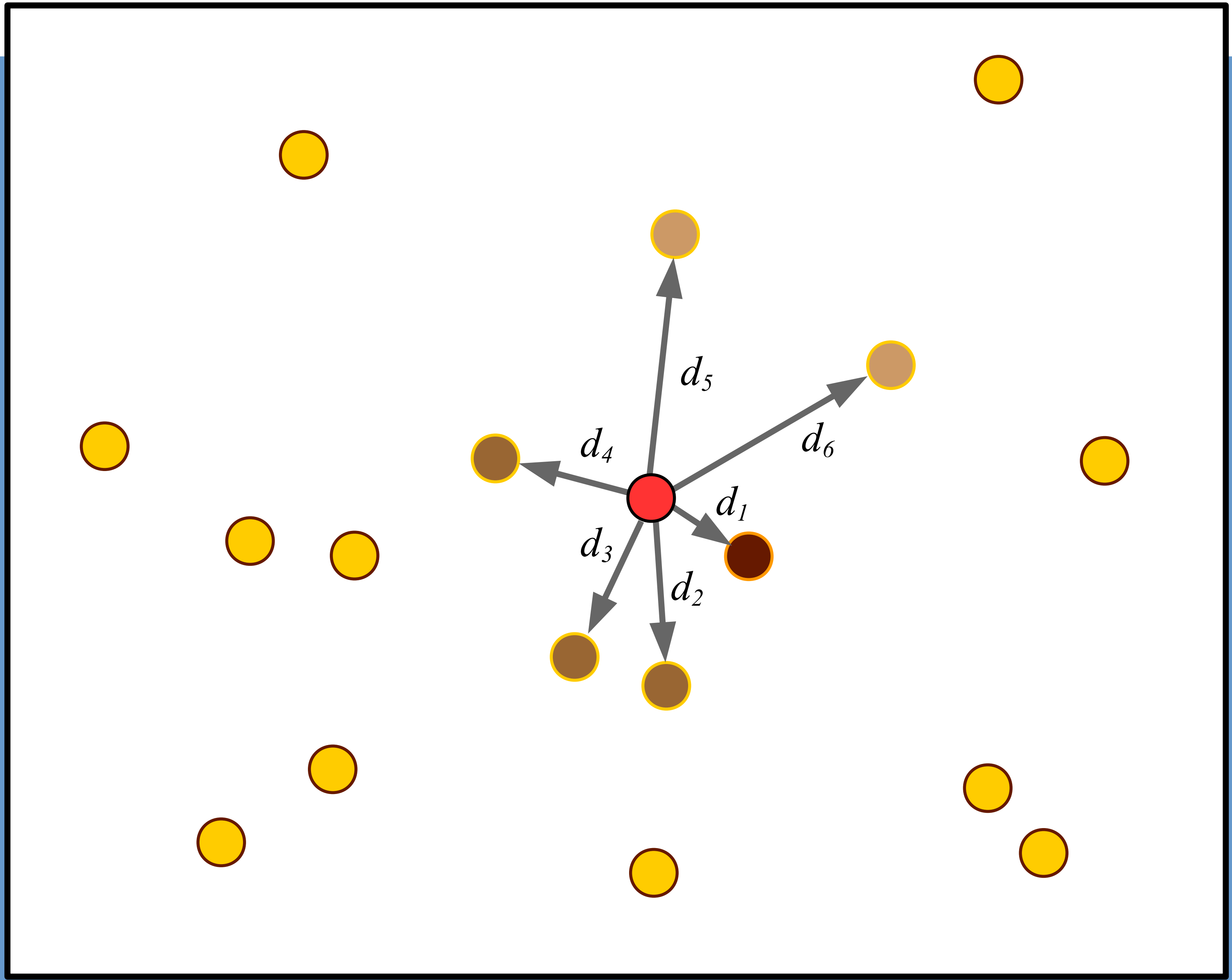


Default (auto) Distance:

Minimum distance for each feature to have at least one neighbor

All neighborhood weight matrices are Row Standardized

ABSOLUTE DISTANCE, CONTINUOUS



Distance Parameter

- Weight of relationship determined by an “inverse” relationship with distance
  - Short distance = High weight
  - Long distance = Low weight

$$w_{i,j} = \frac{1}{d_{i,j}^{x}}$$

$w_{i,j}$ = Weight value in neighborhood weight matrix for observation i to observation j
$d_{i,j}$ = Distance from observation i to observation j
x = Distance effect parameter

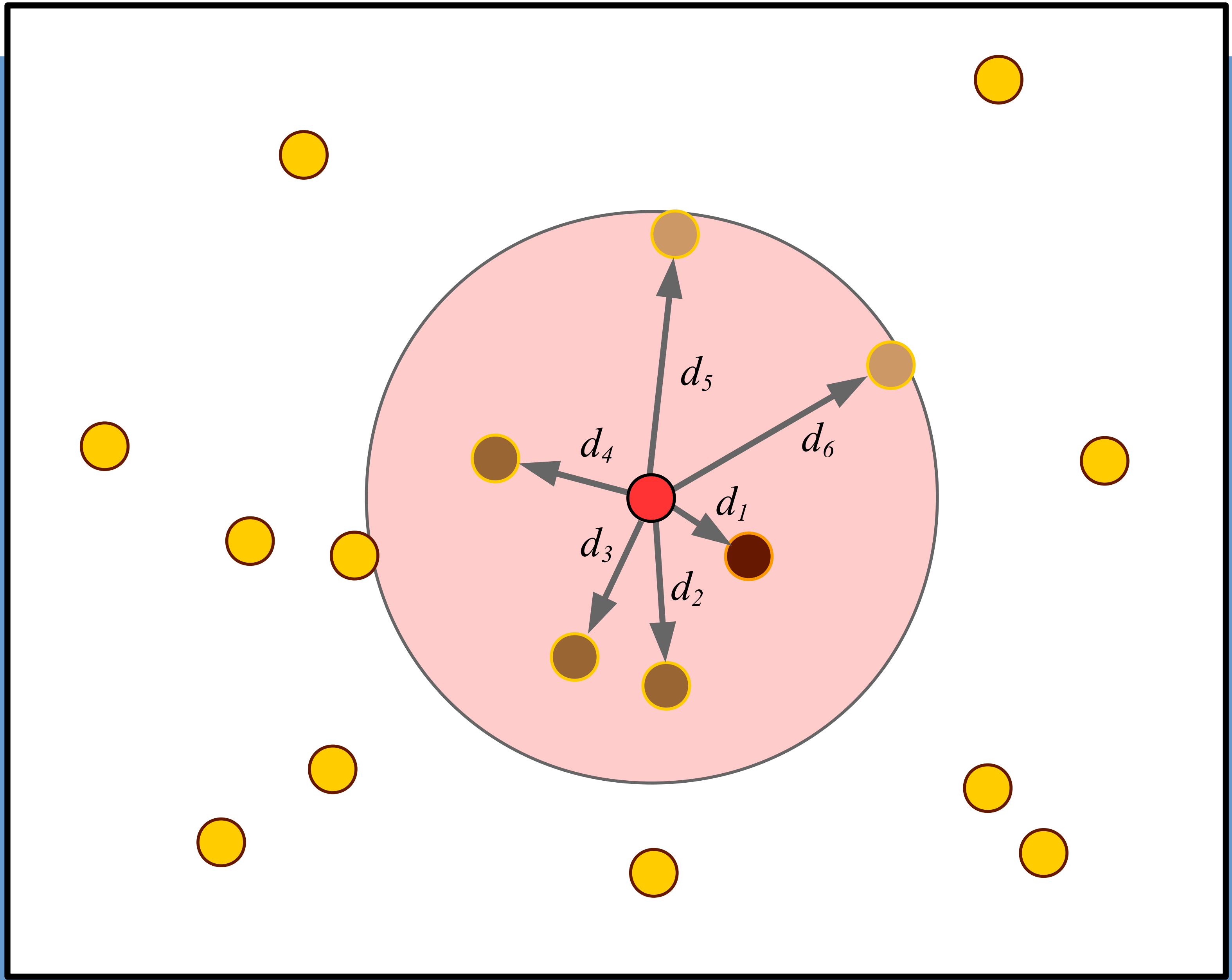
Distance Parameter

$$w_{i,j} = \frac{1}{d_{i,j}} \quad \bigg| \quad w_{i,j} = \frac{1}{d^2_{i,j}}$$

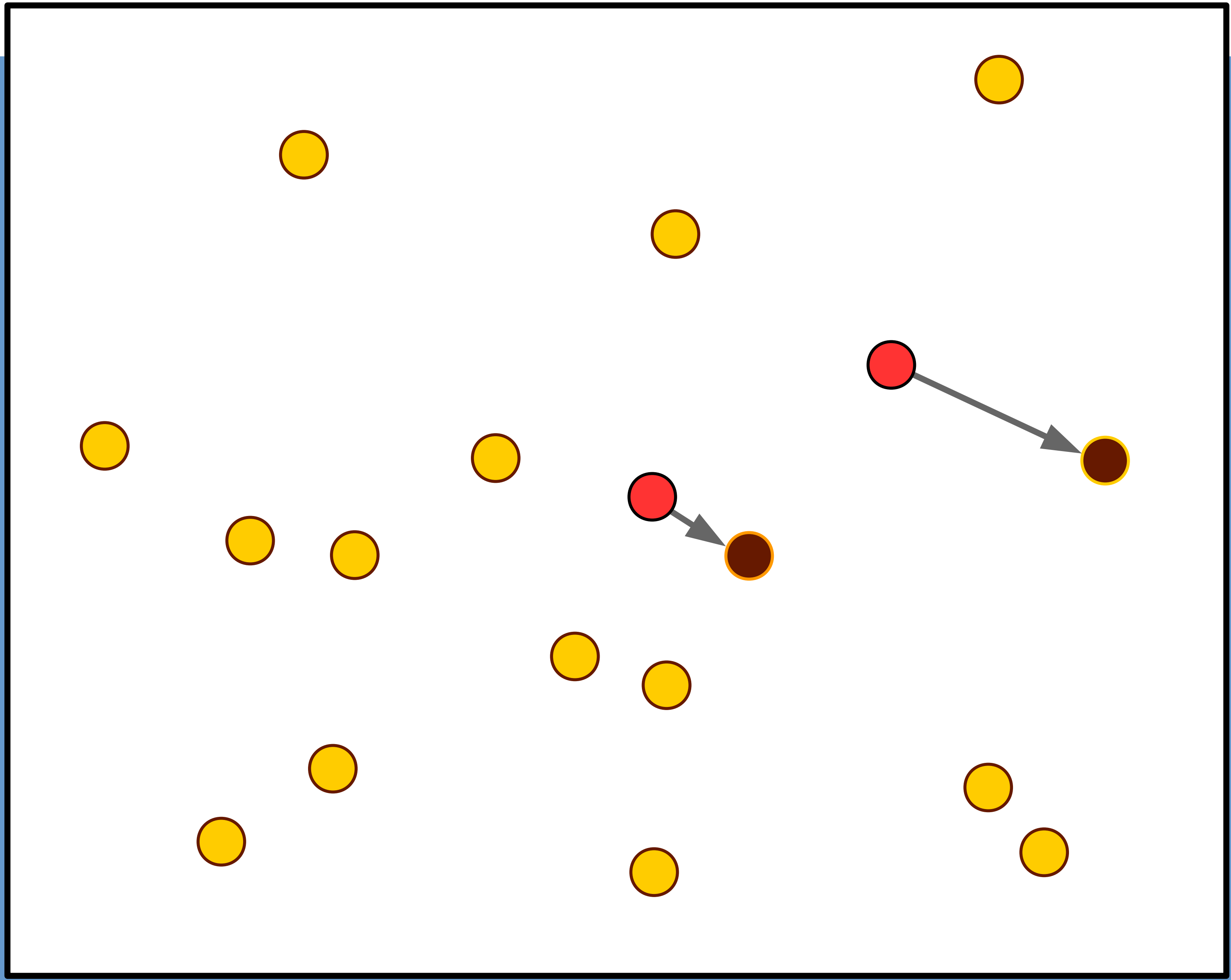
Distance (*d*)	*w(1)*	*w(2)*
10	0.1000	0.0100
12	0.0833	0.0069
20	0.0500	0.0025
42	0.0238	0.0006
46	0.0217	0.0005
58	0.0172	0.0003

Important to note the relative differences among weights!

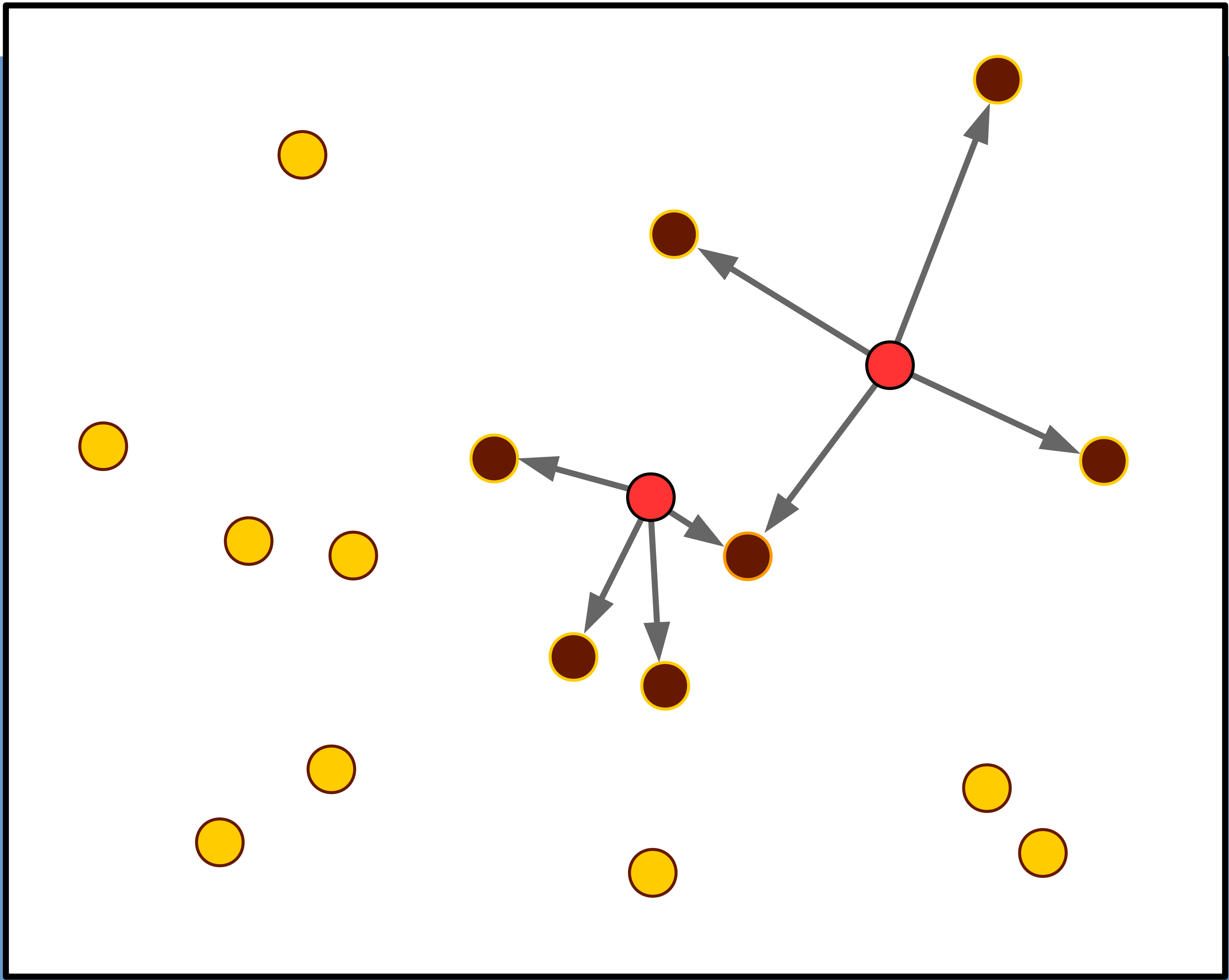
ABSOLUTE DISTANCE, CONTINUOUS



RELATIVE DISTANCE, *K(1)* NEAREST

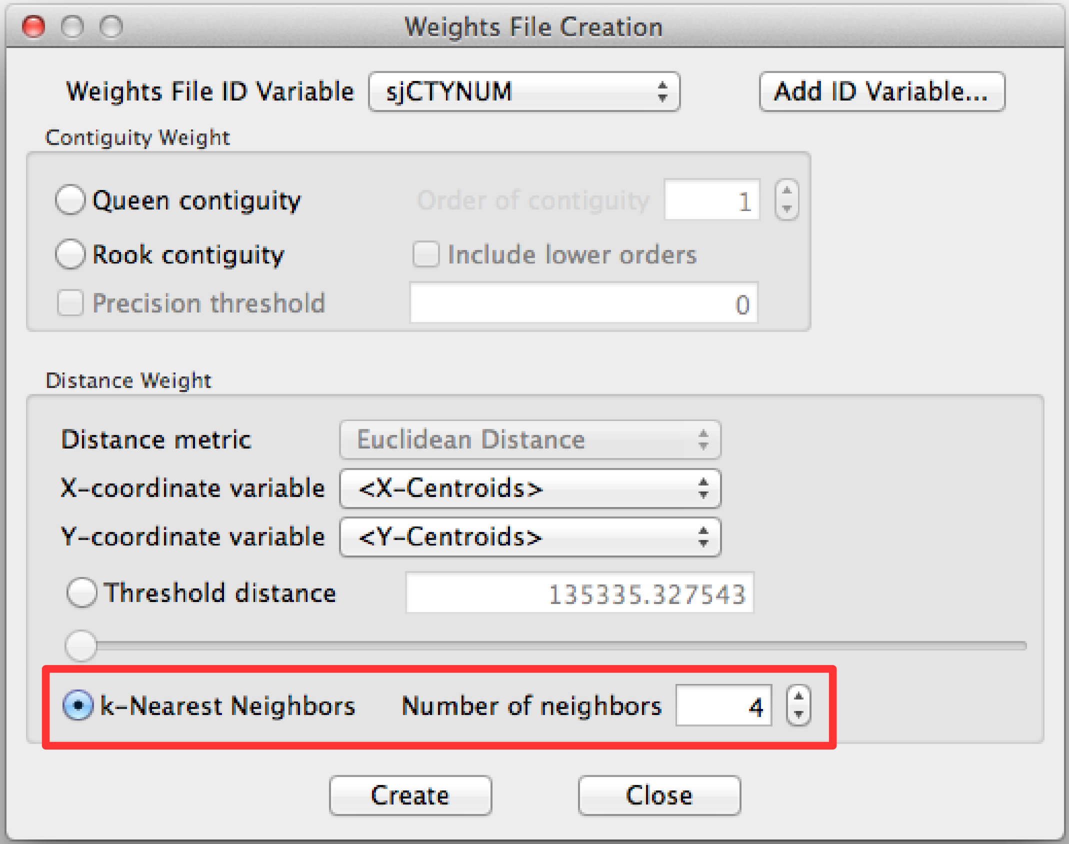


RELATIVE DISTANCE, *K(4)* NEAREST

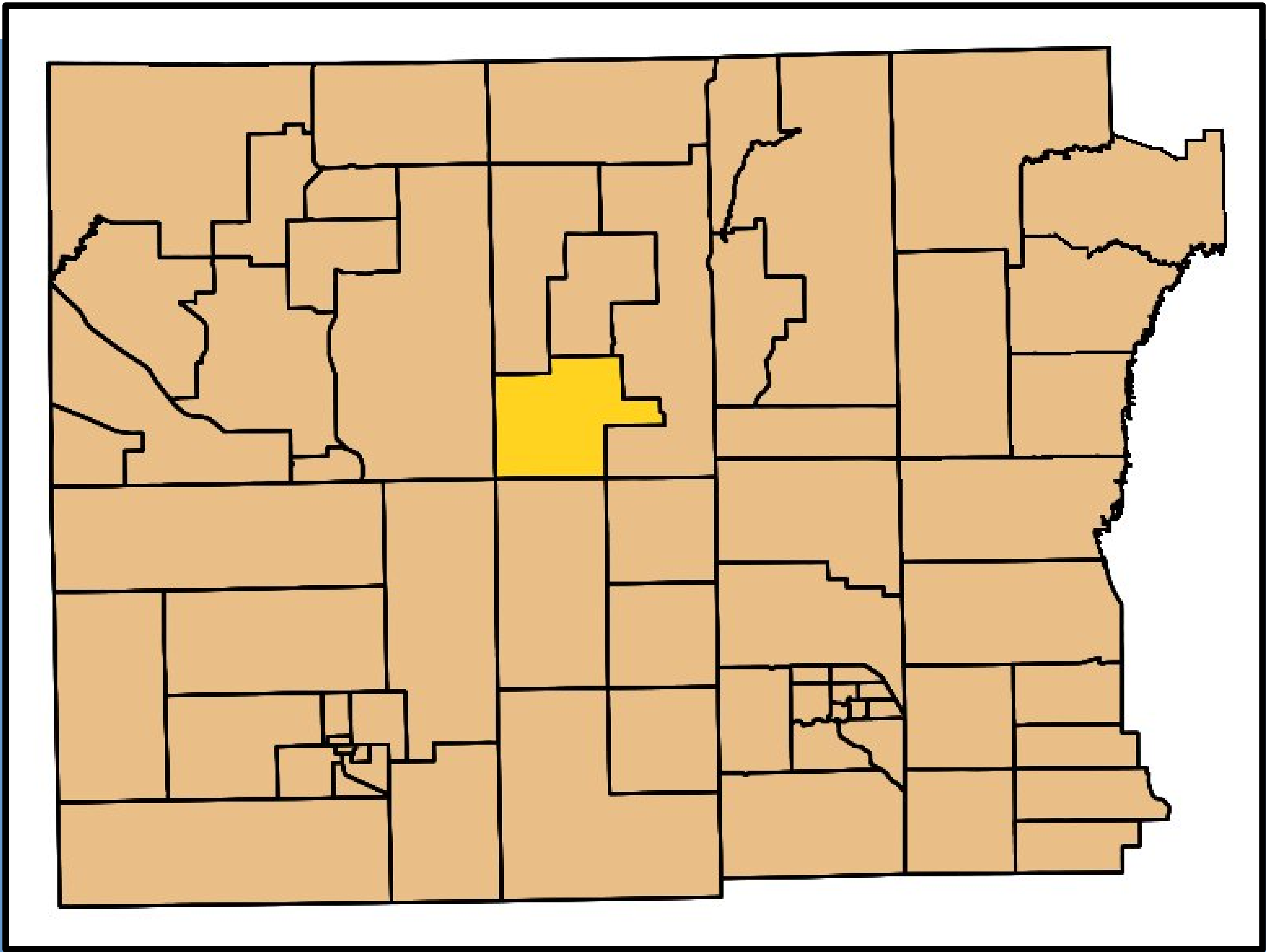


RELATIVE DISTANCE, *K(4)* NEAREST

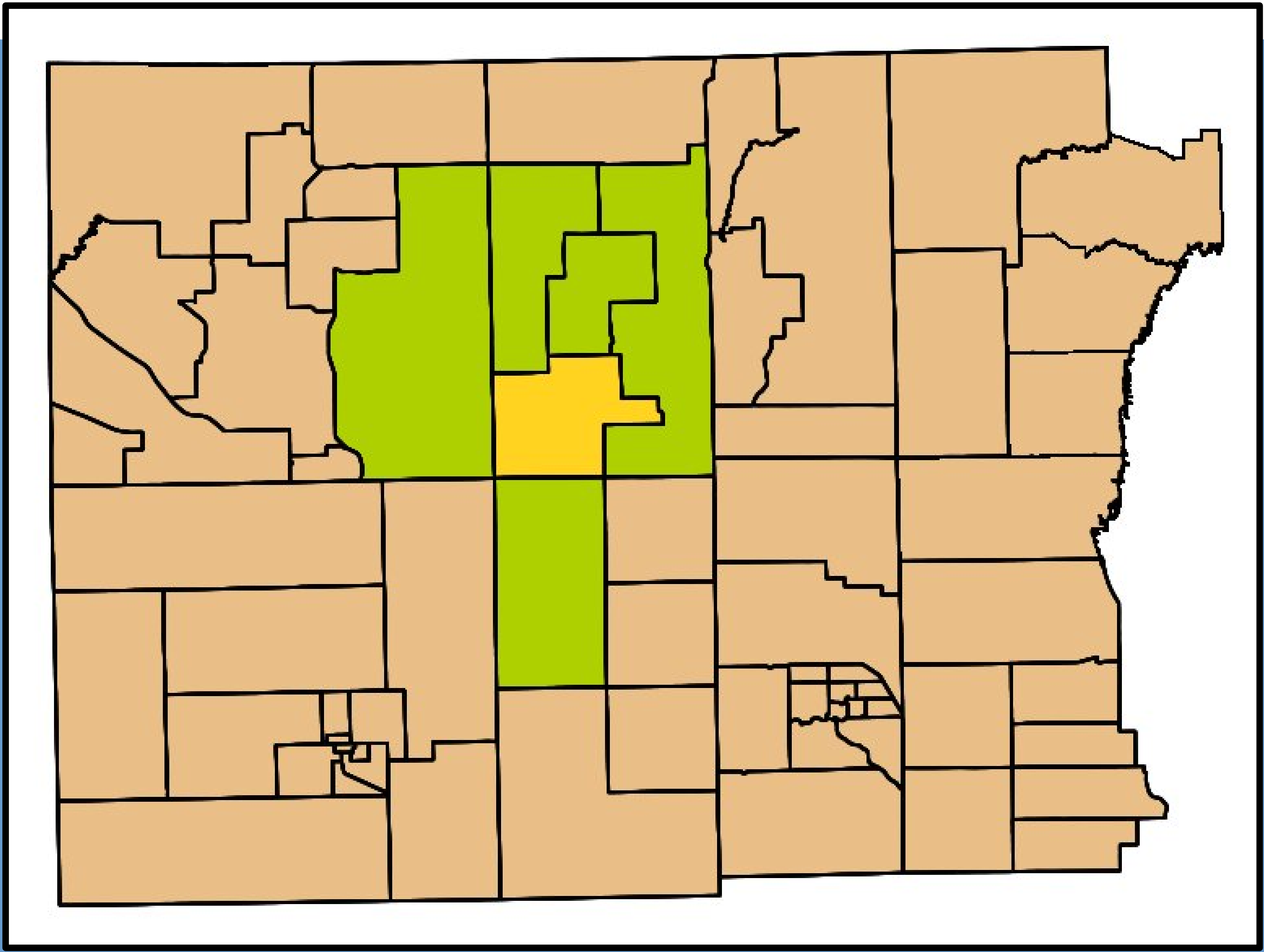
GeoDa



RELATIVE DISTANCE, TOPOLOGY



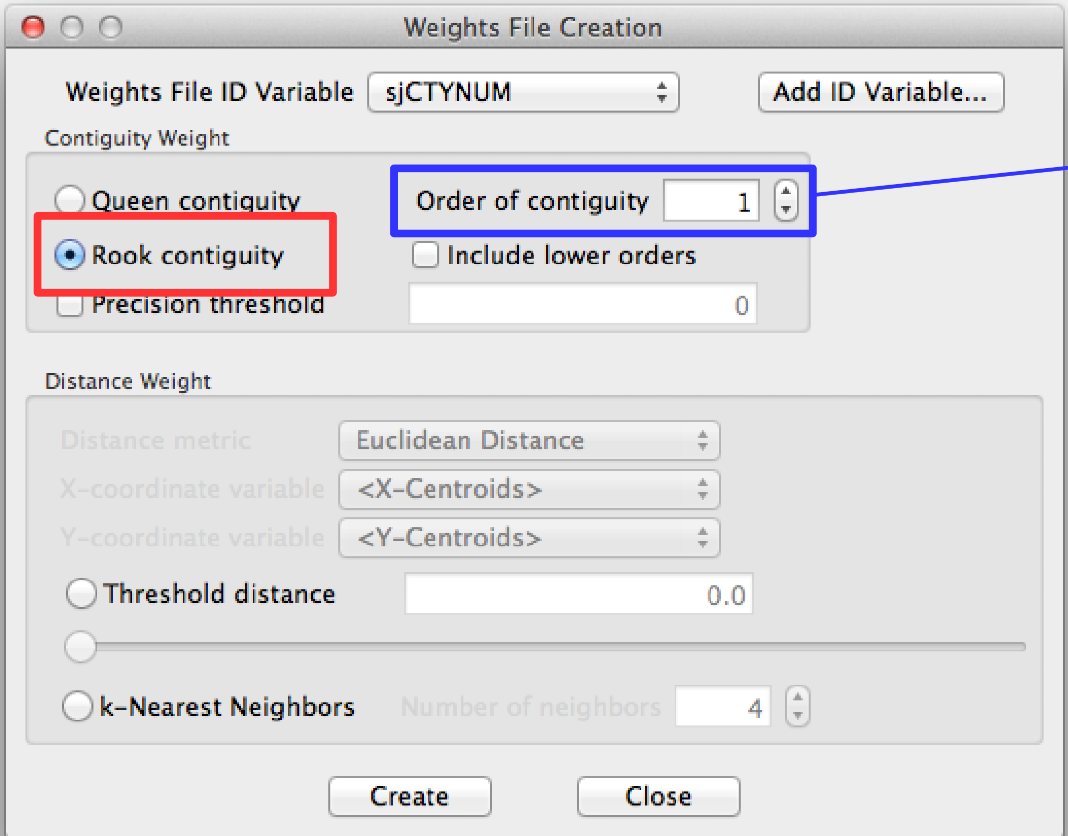
RELATIVE DISTANCE, TOPOLOGY



Rook's case, 1^{st} order neighbors

RELATIVE DISTANCE, TOPOLOGY

GeoDa

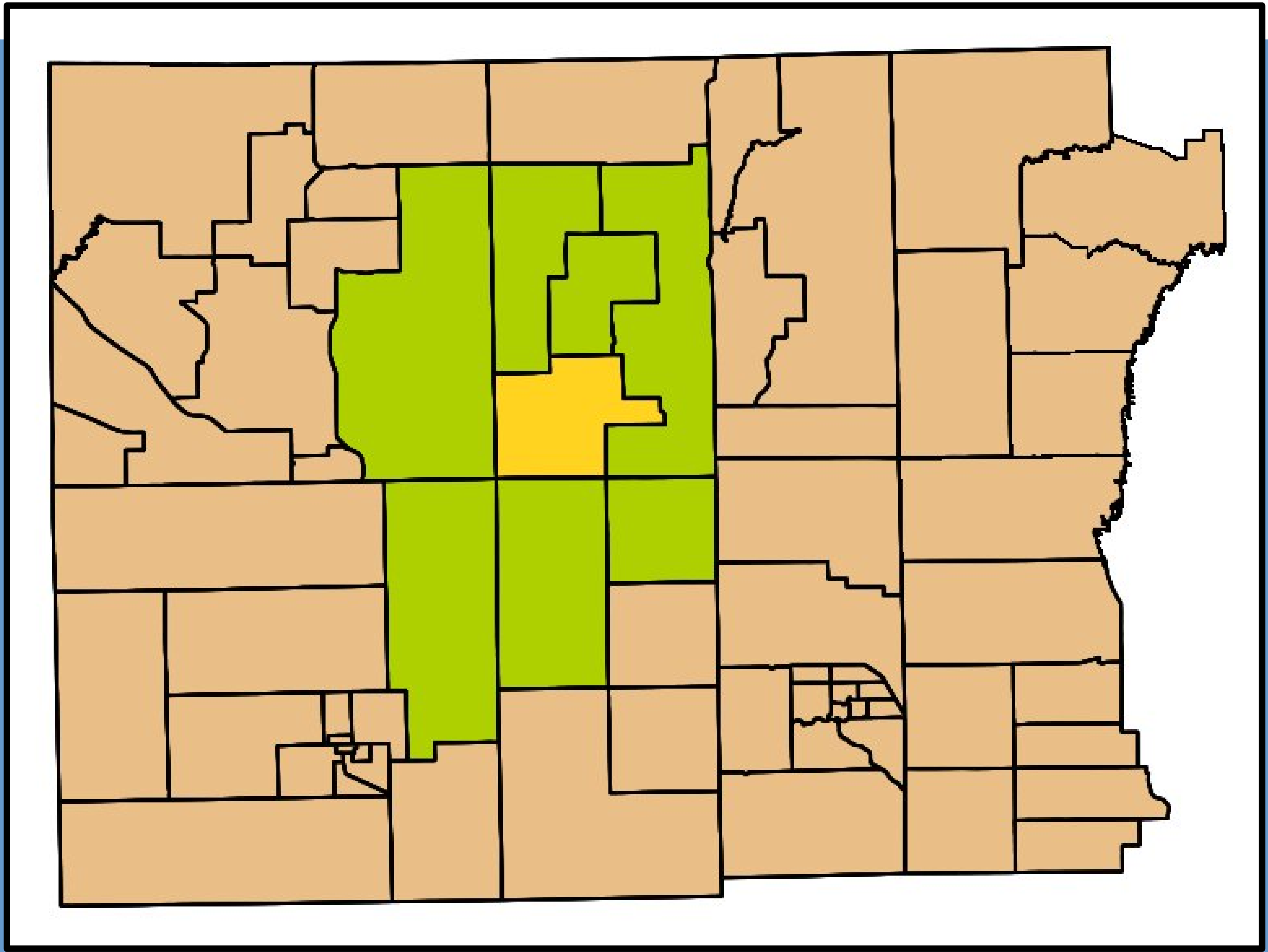


Order Number:

All neighborhood weight matrices are Row Standardized

Rook's case, 1st order neighbors

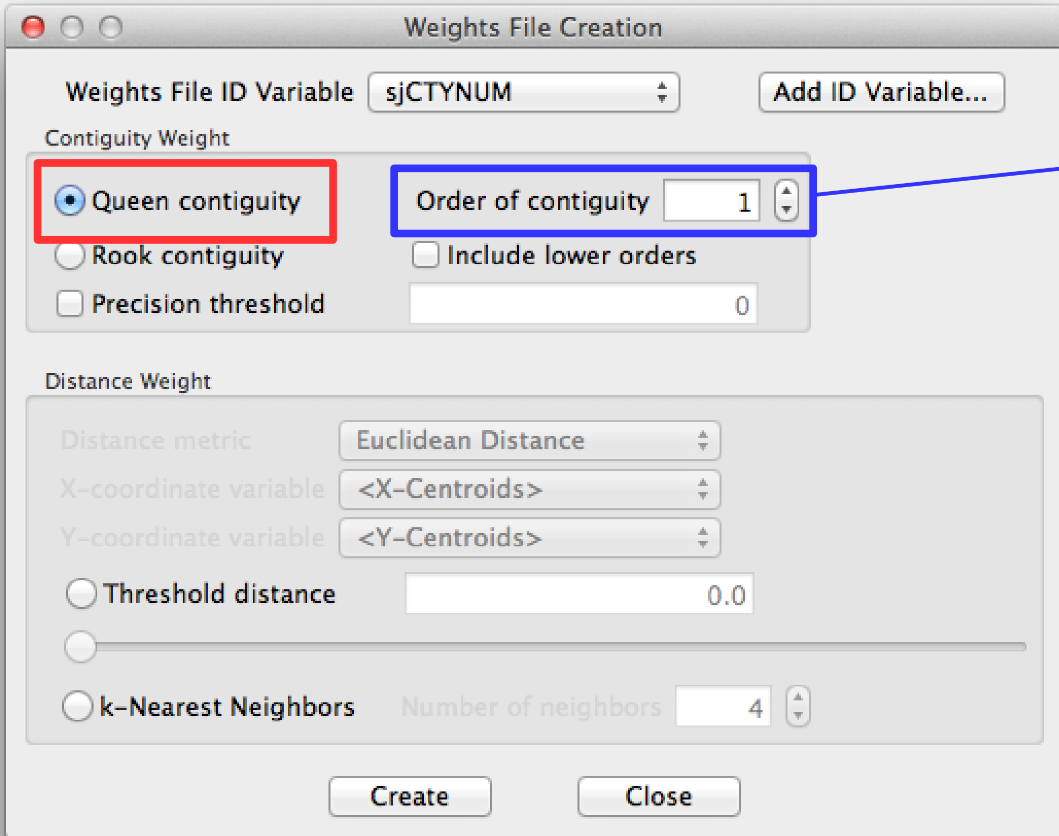
RELATIVE DISTANCE, TOPOLOGY



Queen's case, 1st order neighbors

RELATIVE DISTANCE, TOPOLOGY

GeoDa

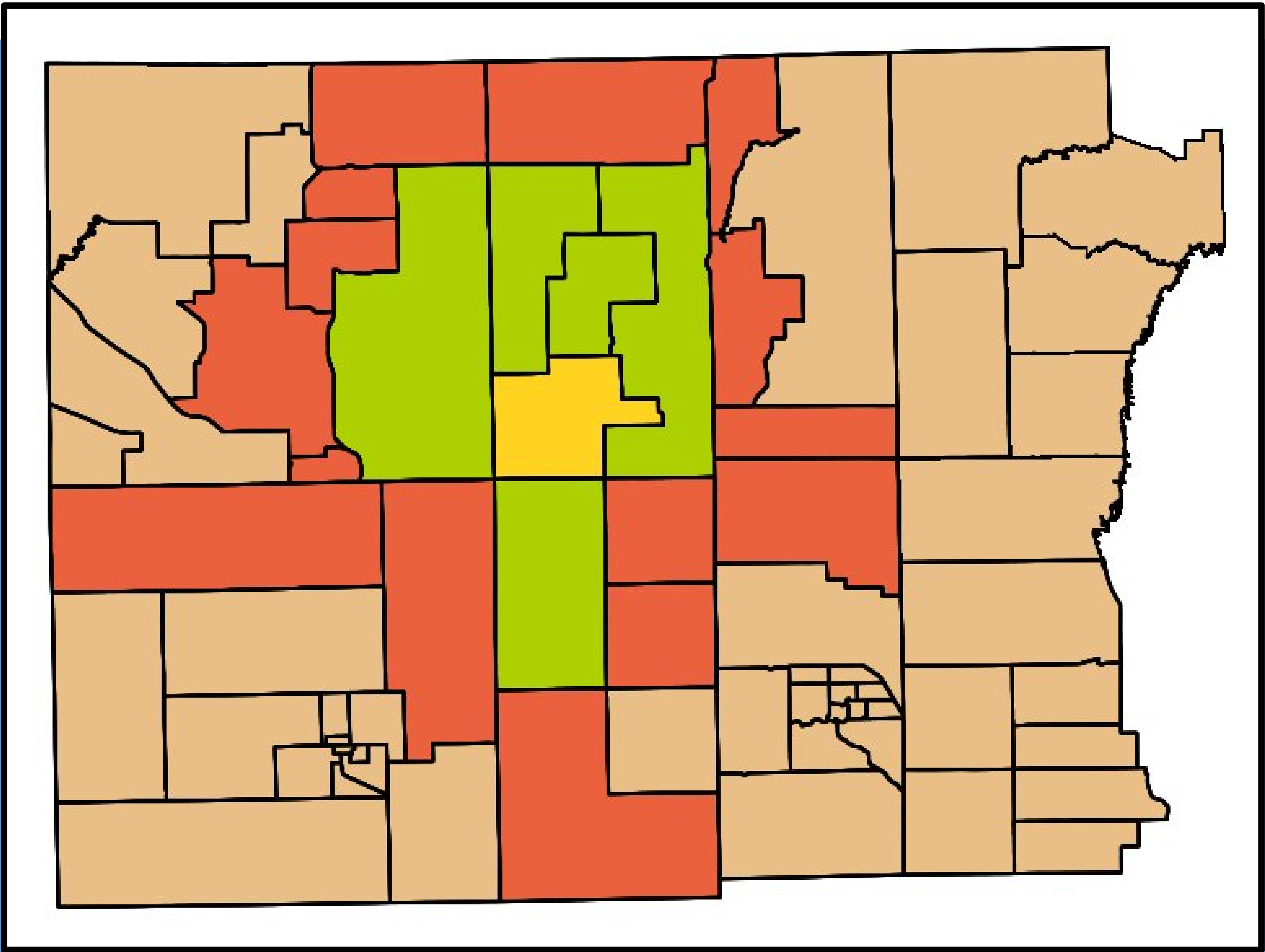


Order Number:

All neighborhood weight matrices are Row Standardized

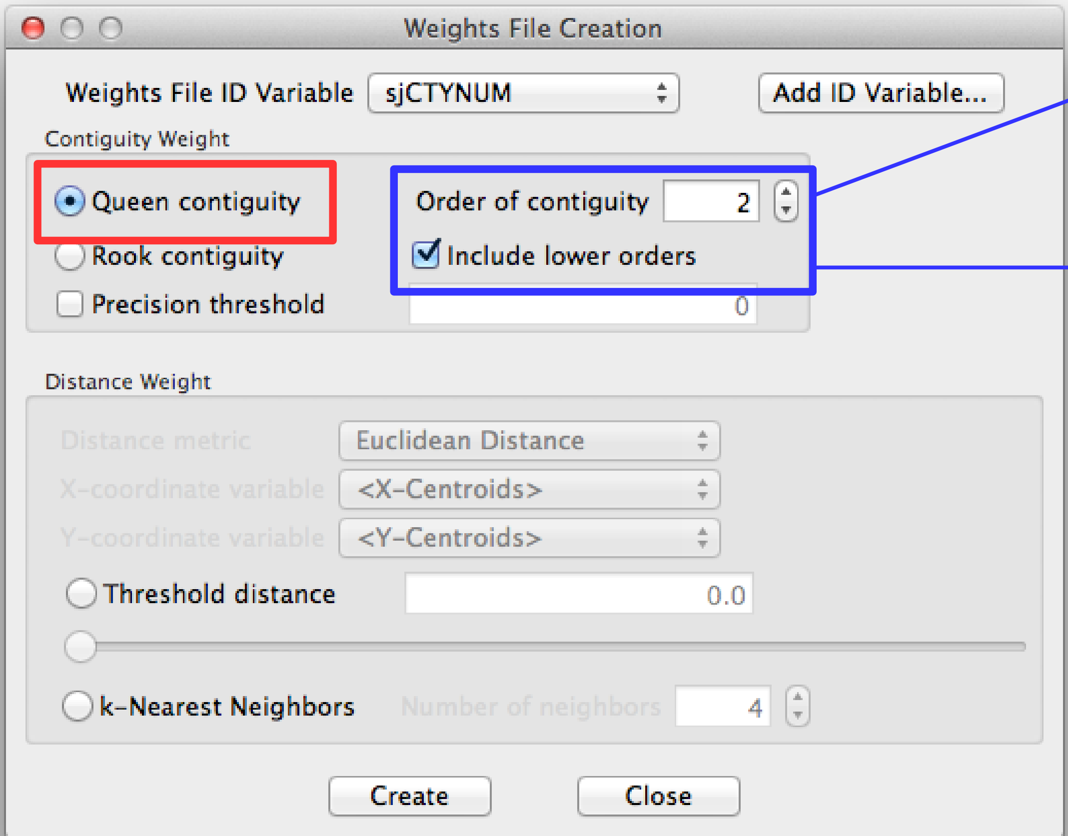
Queen's case, 1st order neighbors

RELATIVE DISTANCE, TOPOLOGY



Rook's case, 2^{nd} order neighbors

RELATIVE DISTANCE, TOPOLOGY



Order Number:
Up to K orders

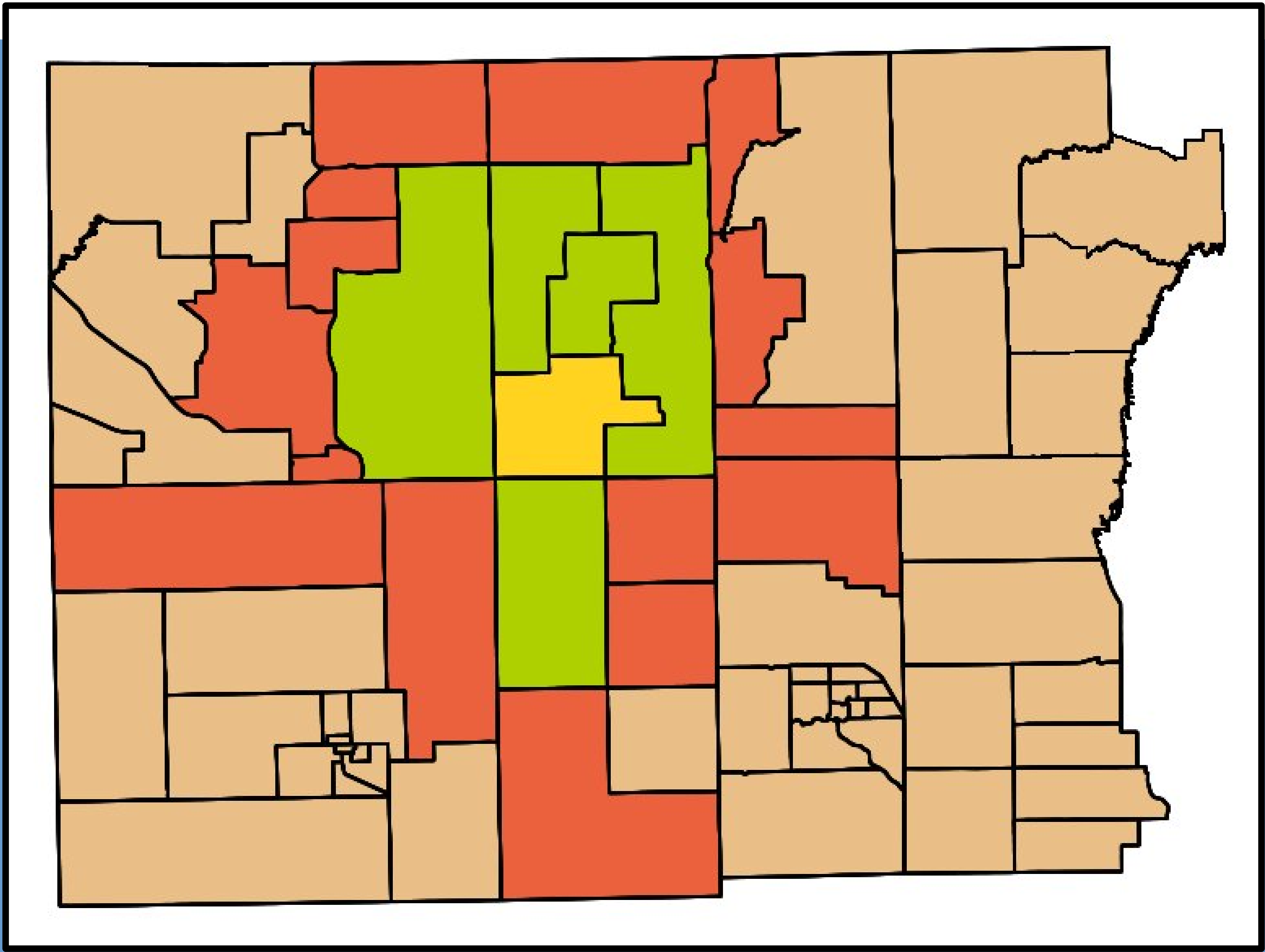
Includes 1st order neighbors as well

All neighbors are treated as equals!

All neighborhood weight matrices are Row Standardized

Rook's case, 2nd order neighbors

RELATIVE DISTANCE, TOPOLOGY



Queen's case, 2nd order neighbors

Neighborhoods

- How do I decide how to define my neighborhood?... and how to weigh my neighbors?
  - Unfortunately, no simple answer to this question
    - Theory-driven approach
      - Cite previous literature
    - Empirical approach
      - Rules of thumb: there are many, “each worse than the previous one”
      - ESDA: explore, optimize

Empirical Approaches

- Exploratory Spatial Data Analysis
  - Explore your data!
    - Choose a spatial autocorrelation metric
      - Test the metric over multiple neighborhood definitions
      - Test the metric over multiple neighborhood parameters
  - Chances are that your results will be semi-consistent
    - If not, eureka!... or oh no!

Empirical Approaches

- Exploratory Spatial Data Analysis
  - Example: test data for global spatial autocorrelation using multiple neighborhood definitions
    - Calculate Moran's *I* with multiple neighbor definitions
      - Inverse Distance, Rook Contiguity, Queen Contiguity
      - KNN, Inverse Distance, Inverse Distance sq
      - 1NN, 2NN, 5NN, 10NN, 20NN

Robustness Tests

- Run your analysis using multiple neighborhood definitions or neighbor relationships
  - Similar to testing over multiple scales
  - If your results are similar, they are robust with regard to neighbor(hood) definition!

Empirical Approaches

- Optimization
  - Find the neighborhood definition that produces the most "extreme" results
    - Beware!
    - Circular logic

Neighborhood Weight Matrix

- Entries in the neighborhood weight matrix describe <u>the relationships</u> between observations
  - These do not have to be based on geographic relationships!
    - e.g., network connectivity
    - e.g., sociodemographic similarity
  - Some software allows you to import your own matrix

Keywords

- Neighborhood, neighbors
- Binary, continuous
- Absolute, relative distance
- Neighborhood weight matrix
- Row standardization
- ESDA, robustness