SA-TIED Geospatial Analysis Workshop

Overview

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Objectives

We will explore the following topics:

- Fundamentals of using R for data analysis.
- Creating thematic maps using R.
- Quantifying the degree of spatial dependence in a dataset.
- Incorporating space into statistical models.

Schedule

Day 1 – Morning	R for Data Analysis
Day 1 – Afternoon	R for Spatial Analysis
Day 2 – Morning	Spatial Autocorrelation
Day 2 – Afternoon	Spatial Models

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S03 – Spatial Autocorrelation

This session

- Spatial dependence.
- Spatial autocorrelation.
- Formalising space.

Spatial dependence

"Everything is related to everything else, but near things are more related than distant things."

Walter Tobler 1970

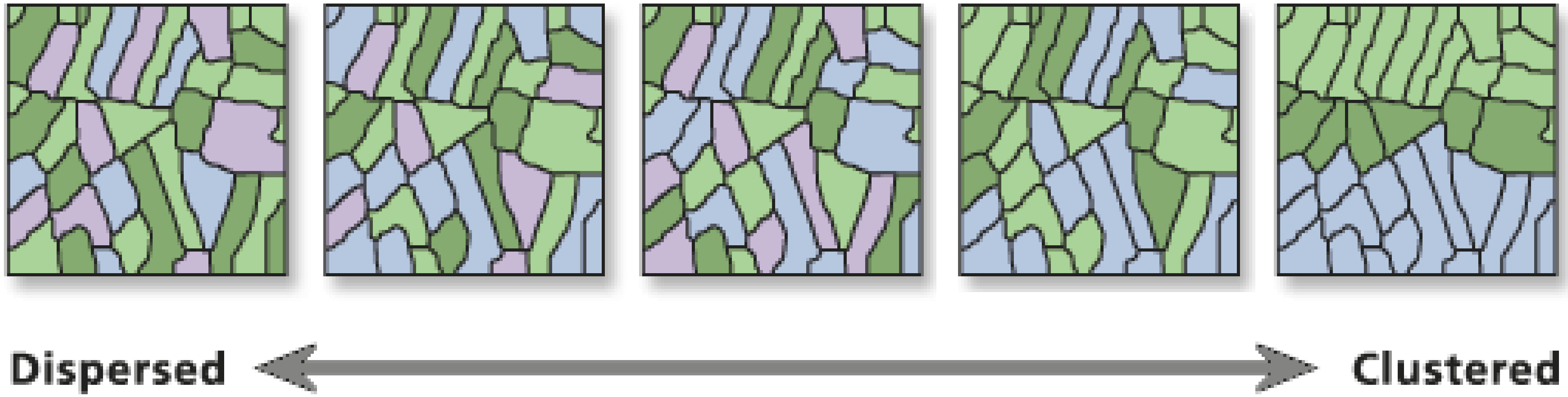
Spatial dependence

- Spatial dependence refers to the concept that the value of a variable at one location is influenced, to some extent, by the value of the same variable at nearby locations.
- This is often understood through the concept of distance decay, where the influence decreases as distance increases.
- Spatial dependence is a key principle in various geographical applications, such as spatial interpolation and spatial interaction modeling.

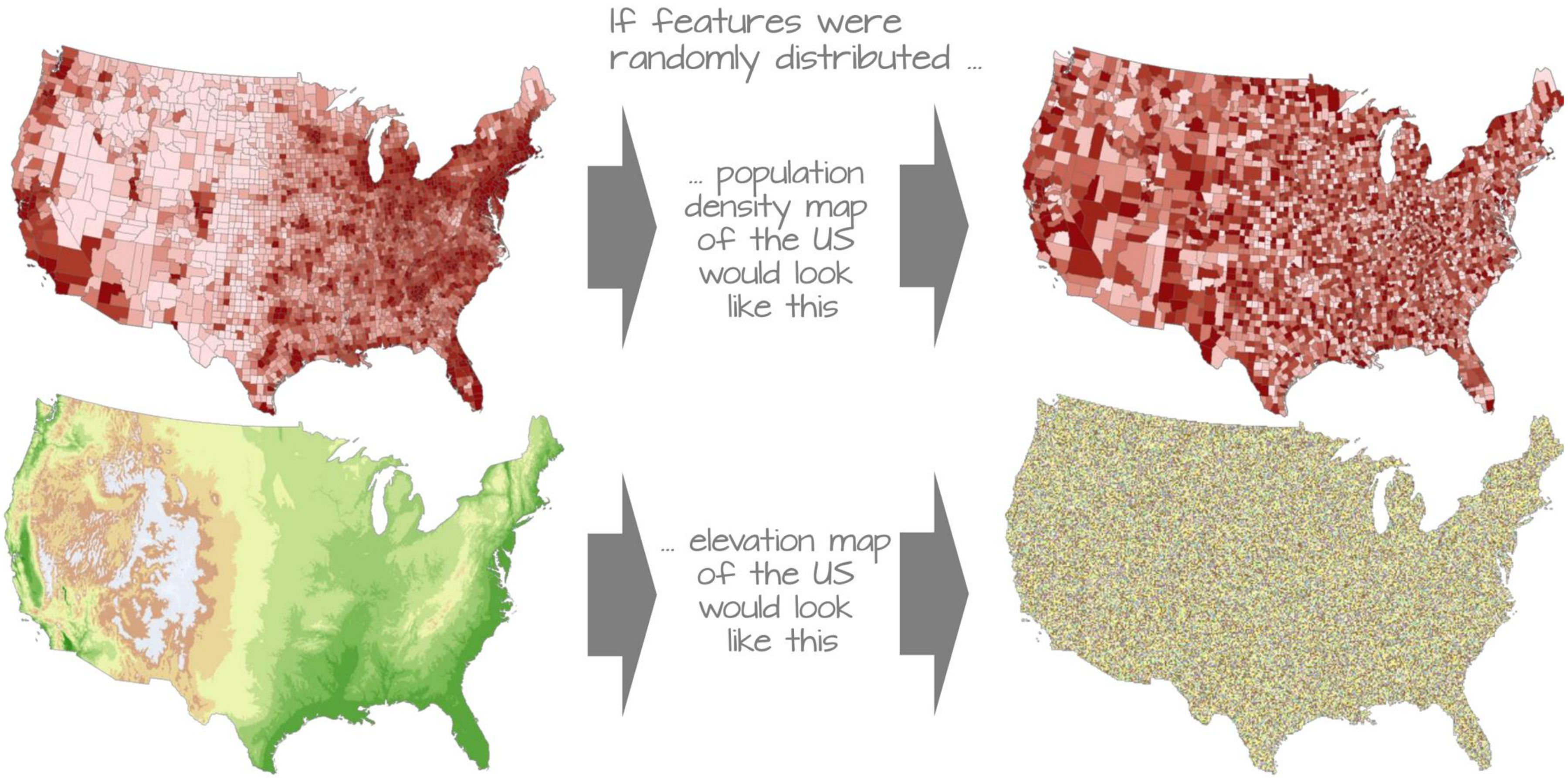
Spatial autocorrelation

- Measurement of spatial autocorrelation is the idea of formalising spatial dependency: measuring the degree to which similar values cluster together in space.
- By measuring spatial autocorrelation, we try to identify hotspots where high values are concentrated versus areas where low values are concentrated.
- Spatial Autocorrelation indicates the absence of Complete Spatial Randomness (CSR).
- CSR suggests that a pattern is entirely the result of random chance, with no underlying spatial structure.

Spatial autocorrelation



Spatial autocorrelation



Gimond, M. 2021. Intro to GIS and Spatial Analysis. [online]
https://mgimond.github.io/Spatial/introGIS.html

Spatial autocorrelation

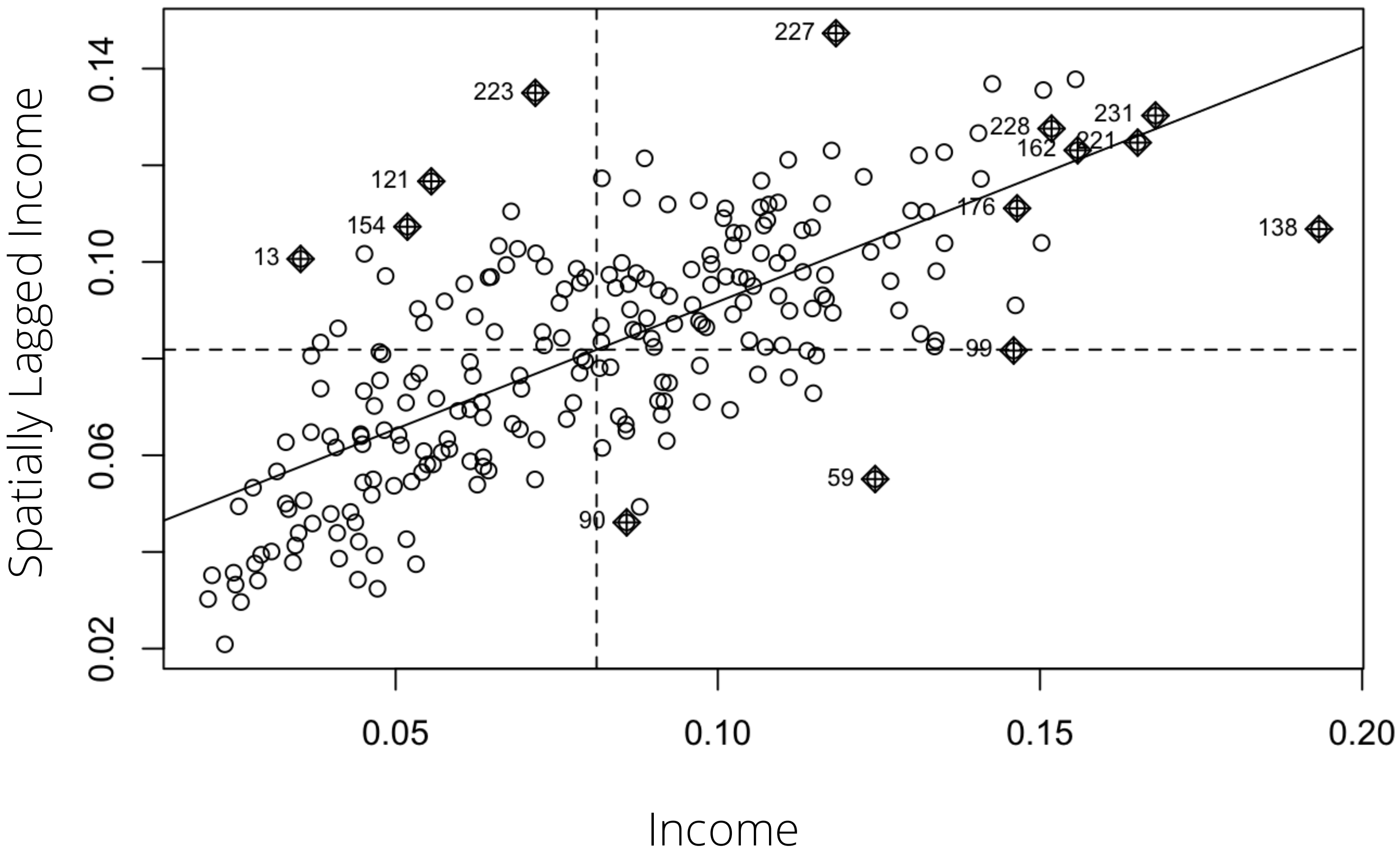
Spatial Autocorrelation can be measured in two ways:

1) Global Spatial Autocorrelation: This assesses the overall spatial dependence across the entire dataset.
2) Local Spatial Autocorrelation: This focuses on the differences between each unit of analysis and its neighbors.

Spatial autocorrelation

- Moran's I: The most commonly used indicator of global spatial autocorrelation.
- Identifies neighbours for each target feature (e.g. polygon) and summarises their values by computing their means to create a spatially lagged variable value.
- Plots the target feature’s value against its spatially lagged mean value and fits a linear model to the points.
- The slope of the fitted line (β estimate) is the Moran’s I statistic.

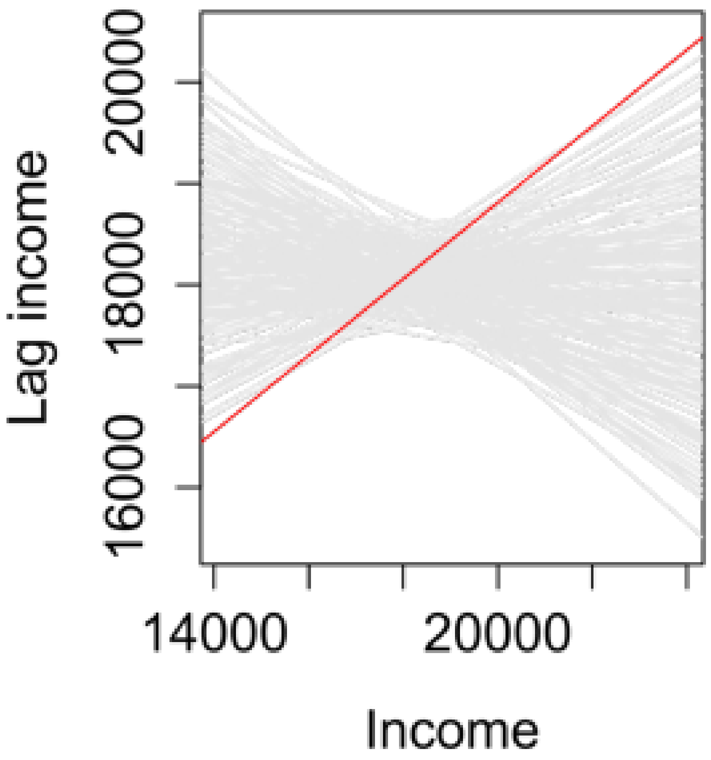
Spatial autocorrelation

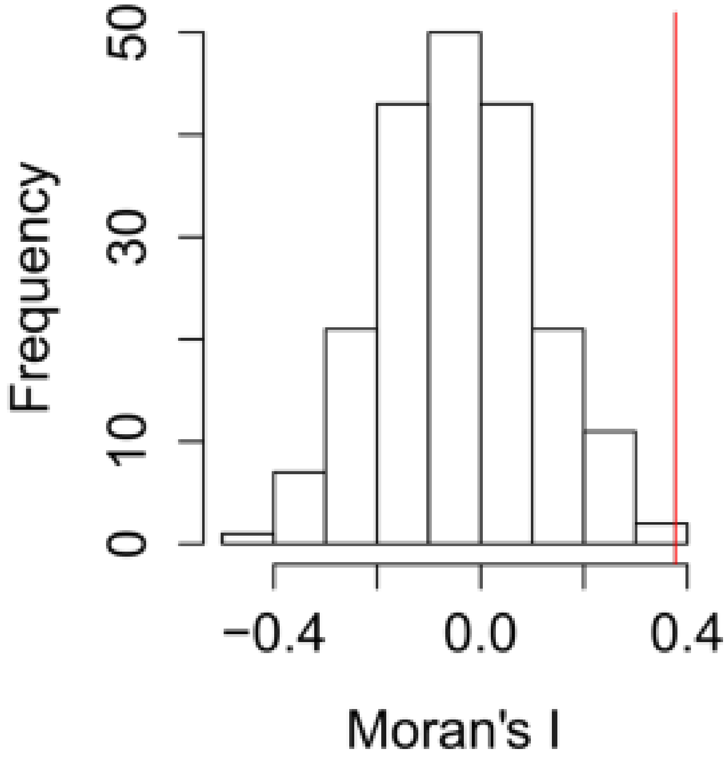


Spatial autocorrelation

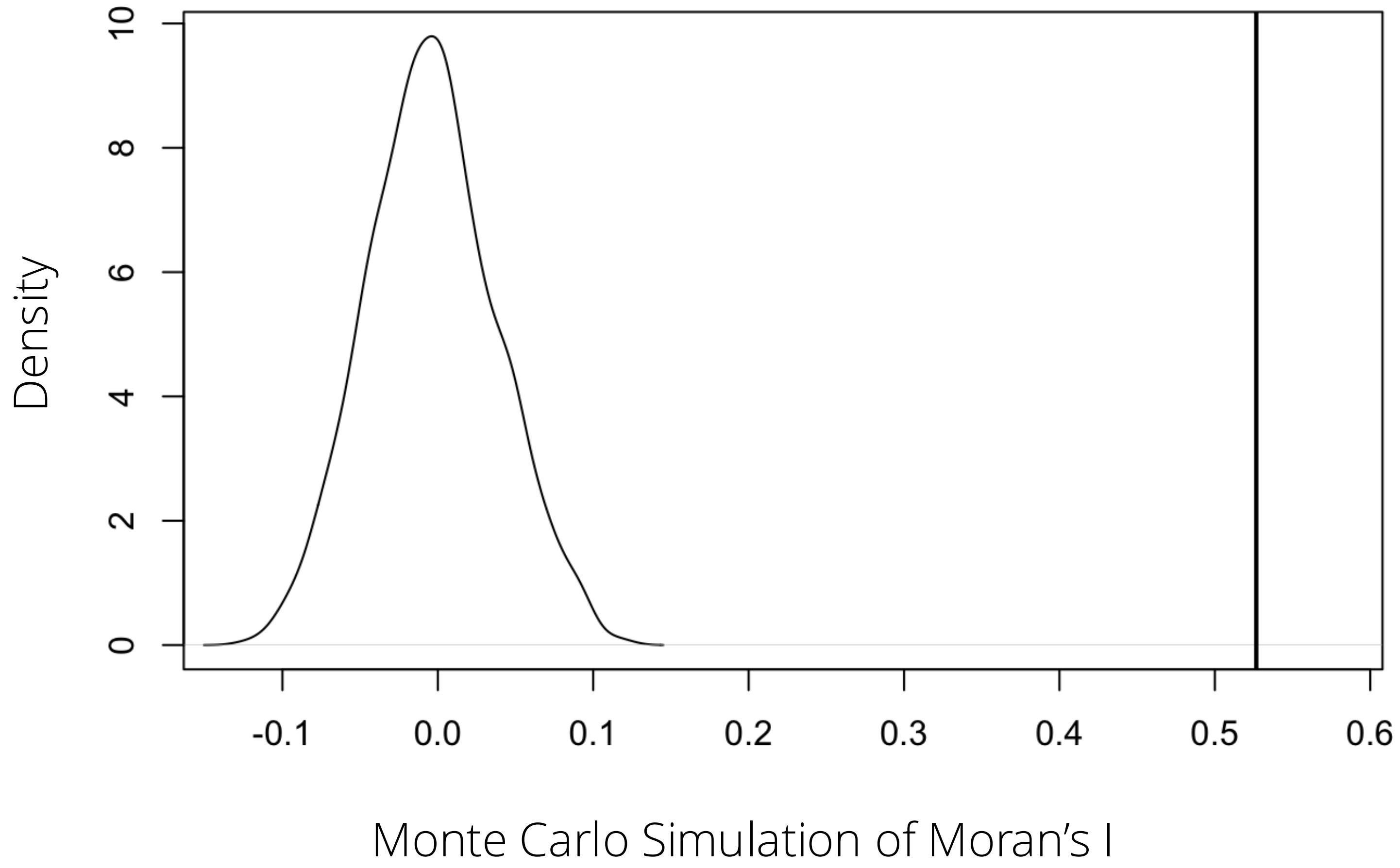
- The Moran's I statistic typically ranges from -1 to +1:
  - +1 Indicates perfect clustering (positive spatial autocorrelation).
  - 0 Suggests a random pattern (no spatial autocorrelation).
  - -1 Indicates perfect dispersion (negative spatial autocorrelation).
- How to assess the significance of the relationship?

Spatial autocorrelation

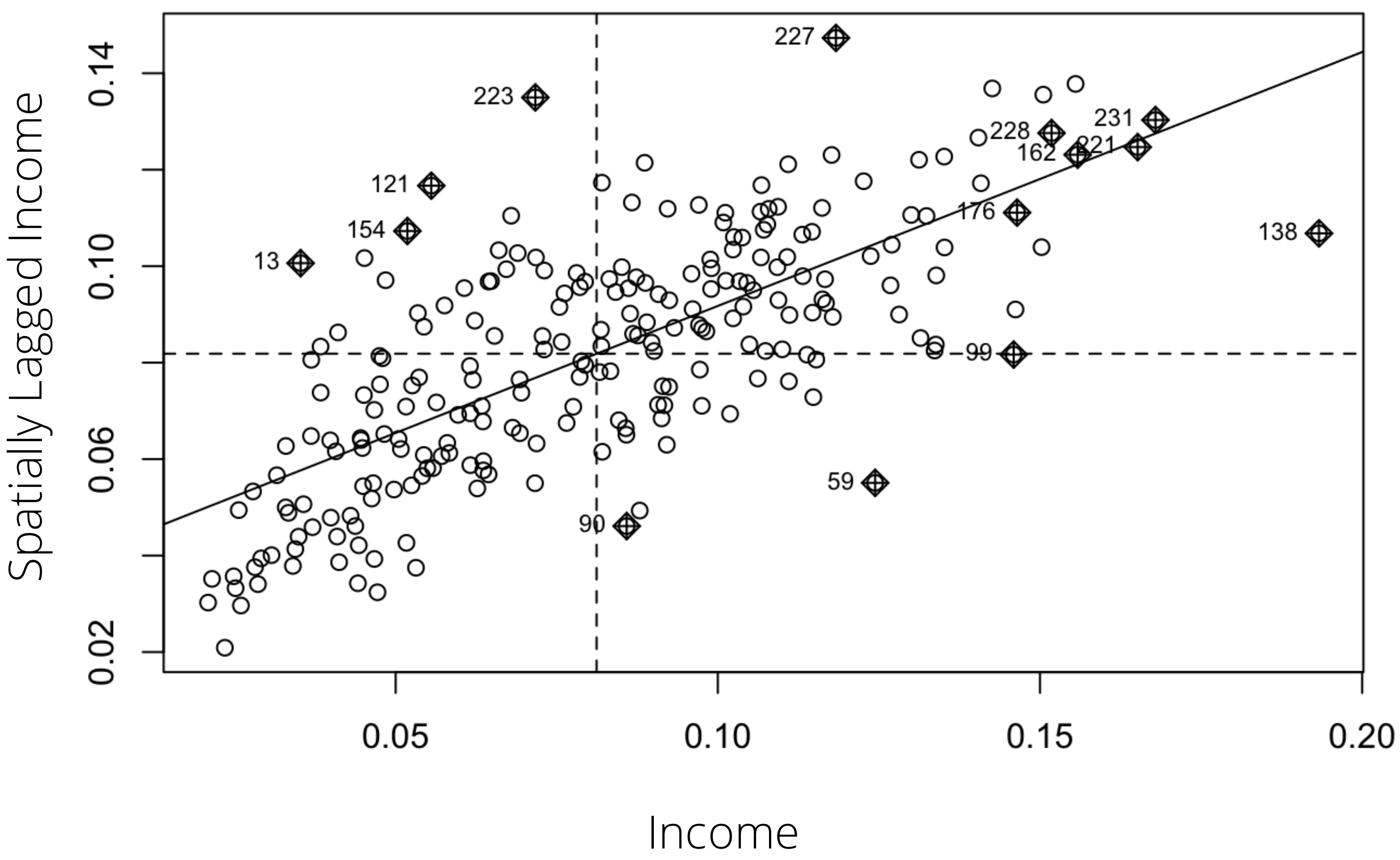




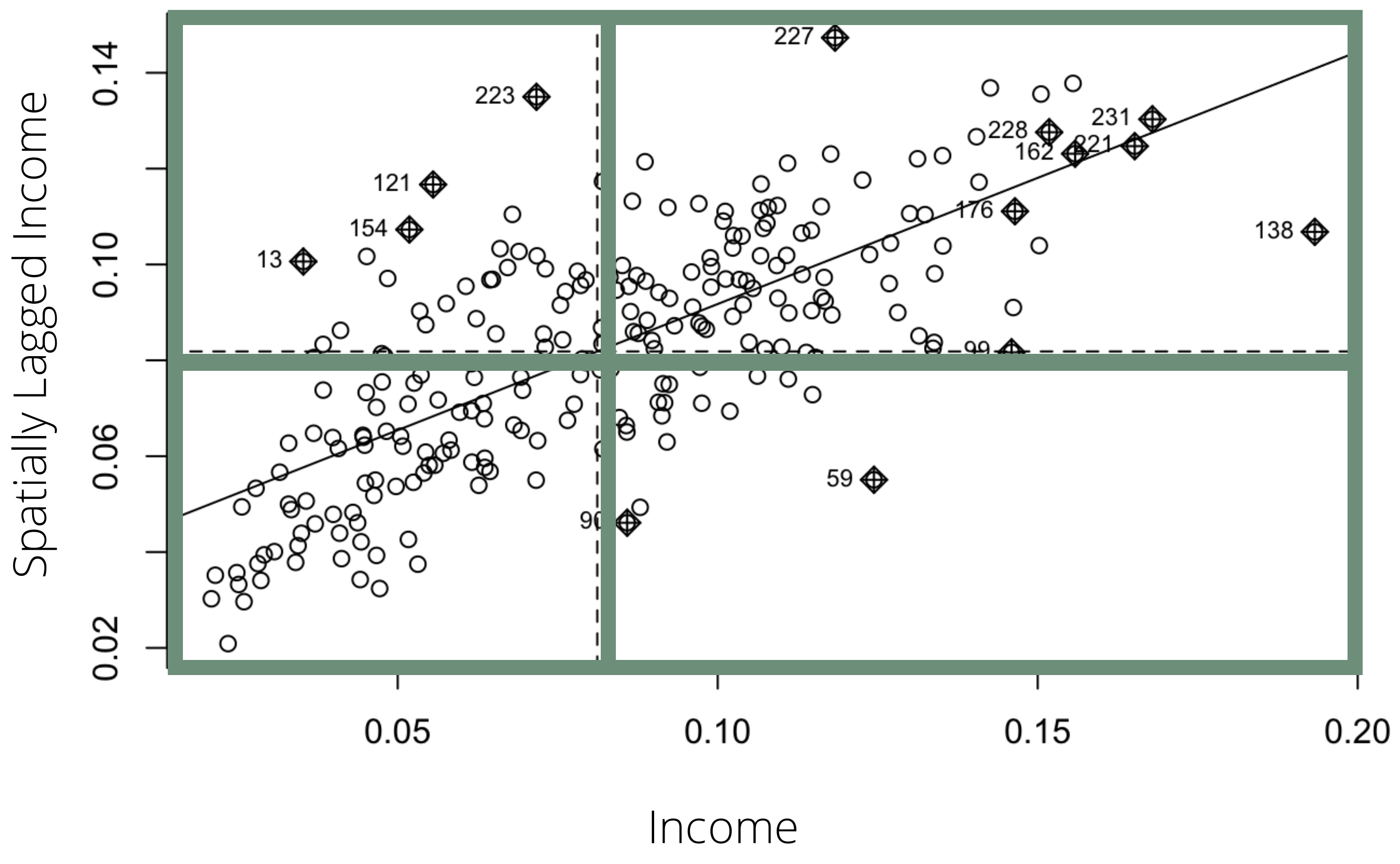
Spatial autocorrelation



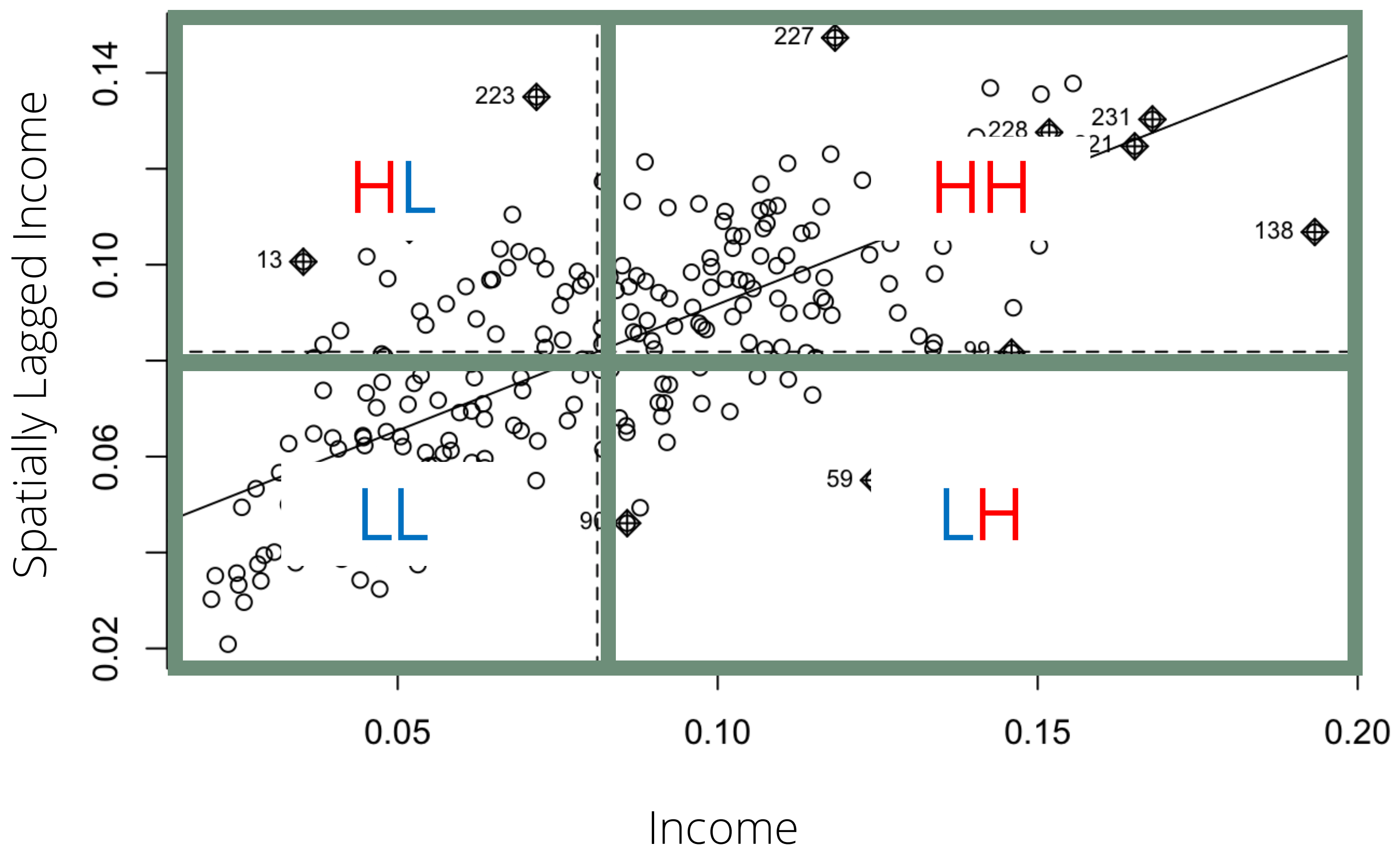
Spatial autocorrelation



Spatial autocorrelation



Spatial autocorrelation



Spatial autocorrelation

- Decomposing the Moran's I statistic: Local Moran's I
- Assesses spatial autocorrelation at the local level by evaluating each feature and its surrounding neighborhood.
- Four cluster types: high-high, low-low, but also outliers: high-low, low-high.
- Commonly known as cluster and outlier analysis.
- Monte Carlo simulation can be used to assess significance of these clusters.

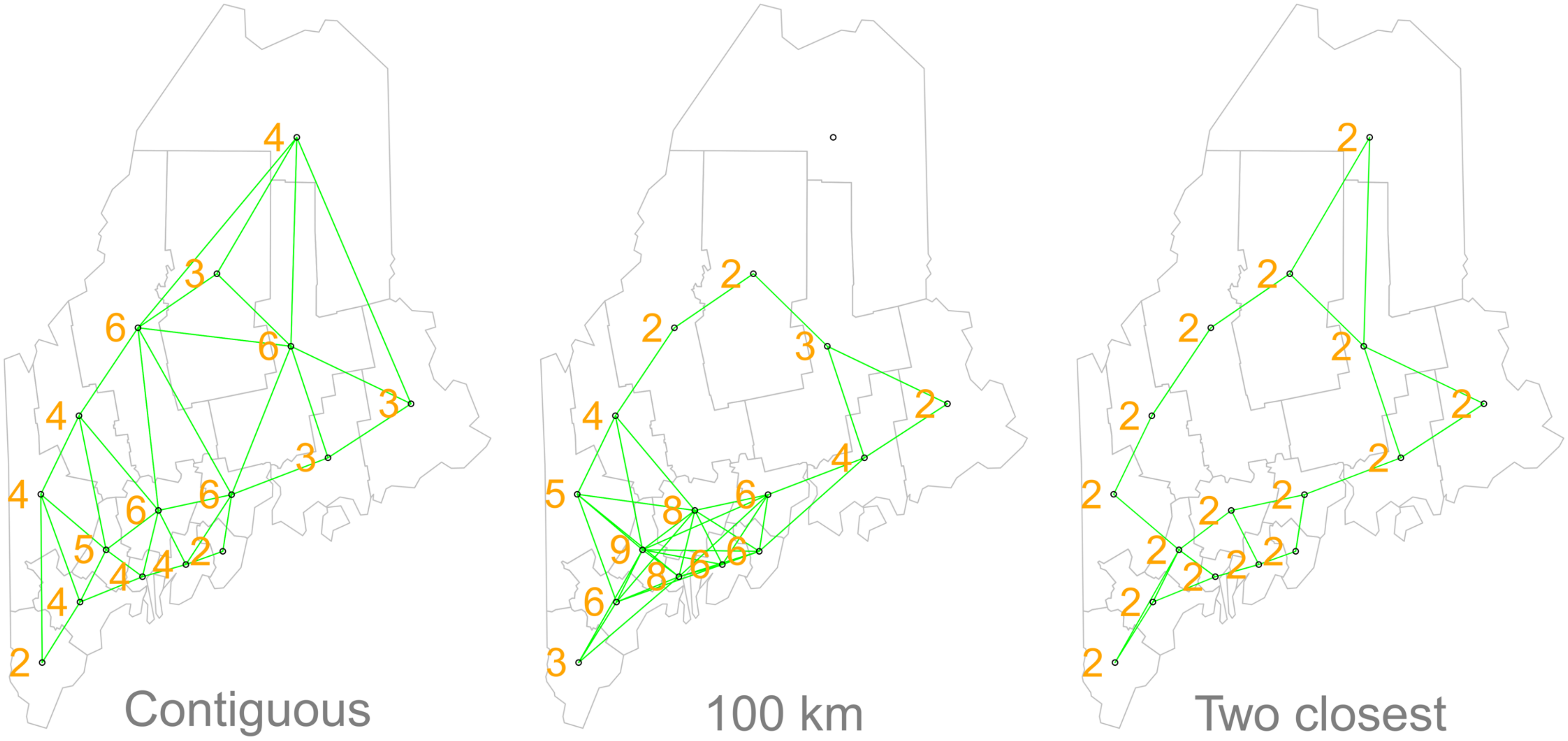
Who is your neighbour?

- To calculate any measure of spatial autocorrelation, it's essential to understand how spatial units relate to each other as neighbours, specifically how we define their spatial relationships.
- There are two primary approaches to defining neighbours:
  - Proximity: Neighbours are determined based on the distance between spatial units.
  - Contiguity: Neighbours are defined by shared boundaries or edges.

Who is your neighbour?

- To calculate any measure of spatial autocorrelation, it's essential to understand how spatial units relate to each other as neighbours, specifically how we define their spatial relationships.
- There are two primary approaches to defining neighbours:
  - Proximity: Neighbours are determined based on the distance between spatial units. A unit is considered a neighbour if it is within a certain distance from another unit.
  - Contiguity: Neighbours are defined by shared boundaries or edges. Spatial units are considered neighbours if they touch each other directly, either along edges (rook contiguity) or at corners (queen contiguity).

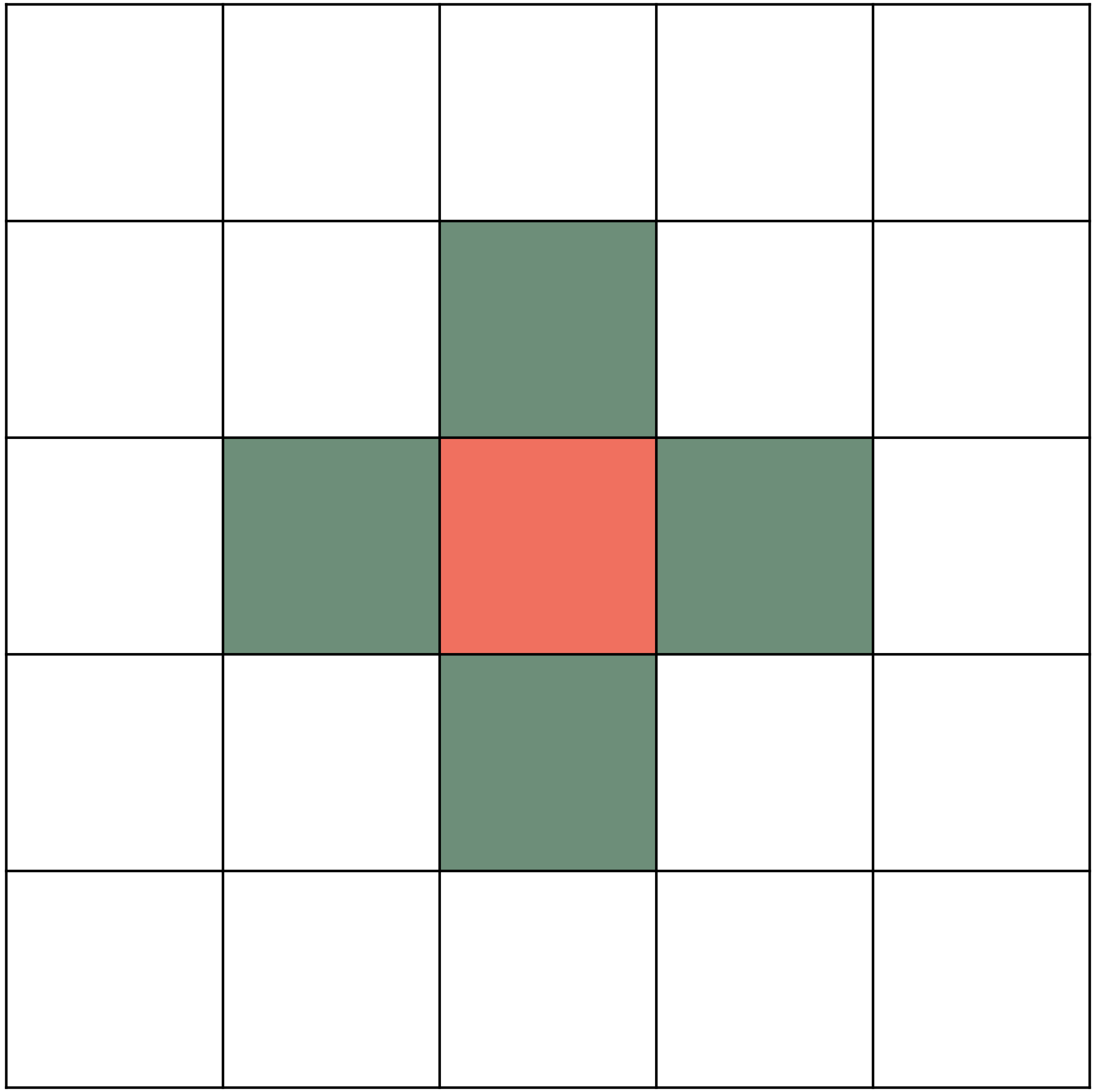
Who is your neighbour?



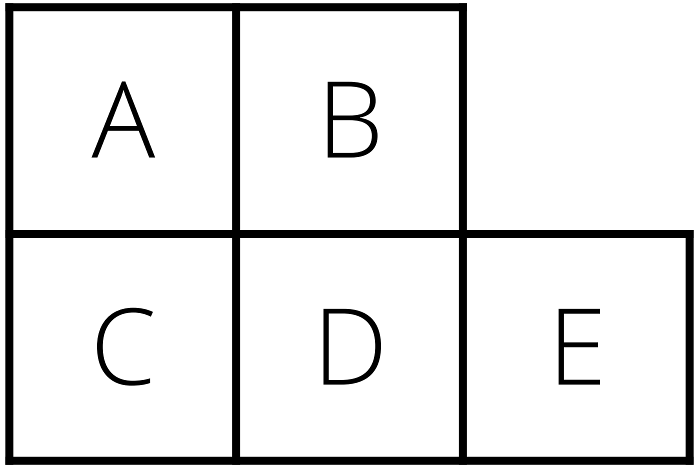
Spatial weights matrix

- How to use the relationships between neighbouring features?
- Spatial weight matrix: an `N x N` positive matrix (`W`) that summarises all spatial relationships between the features in a dataset.
- It provides a formal expression of spatial dependency by quantifying the influence of each feature on every other feature based on their spatial proximity or other relevant criteria.

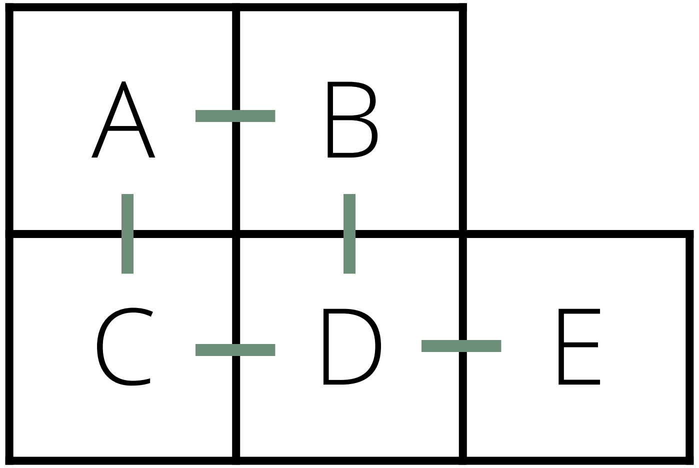
Spatial weights matrix



Spatial weights matrix

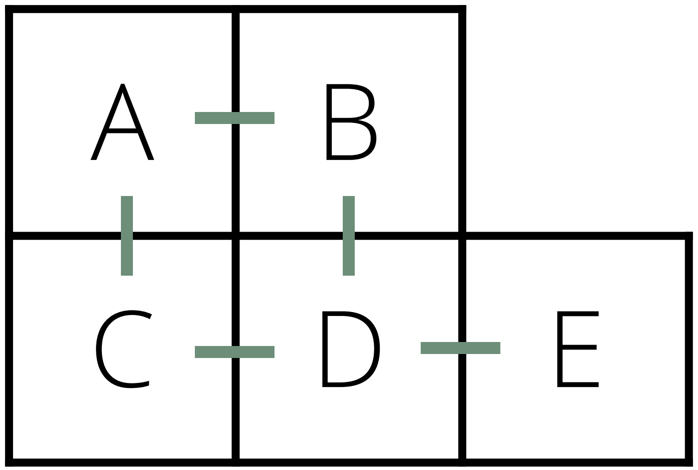


Spatial weights matrix

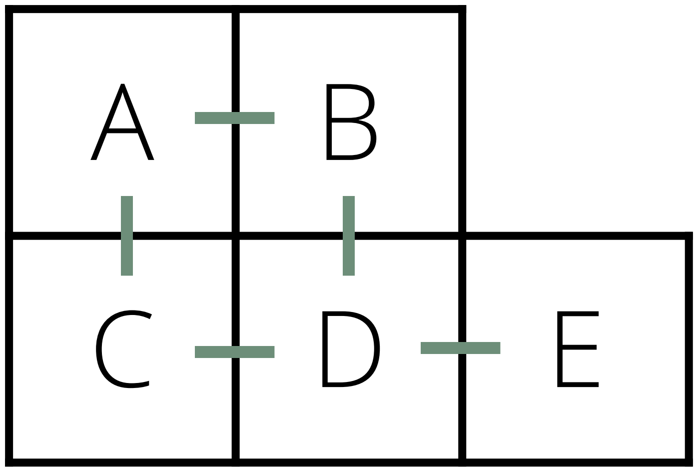


Spatial weights matrix

	a	b	c	d	e
a	0	1	1	0	0
b	1	0	0	1	0
c	1	0	0	1	0
d	0	1	1	0	1
e	0	0	0	1	0



Spatial weights matrix

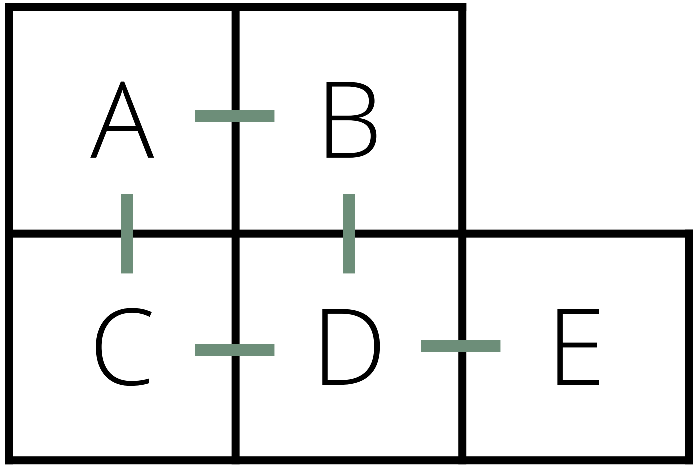


	a	b	c	d	e
a	0	1	1	0	0
b	1	0	0	1	0
c	1	0	0	1	0
d	0	1	1	0	1
e	0	0	0	1	0

=

w
2
2
2
3
1

Spatial weights matrix

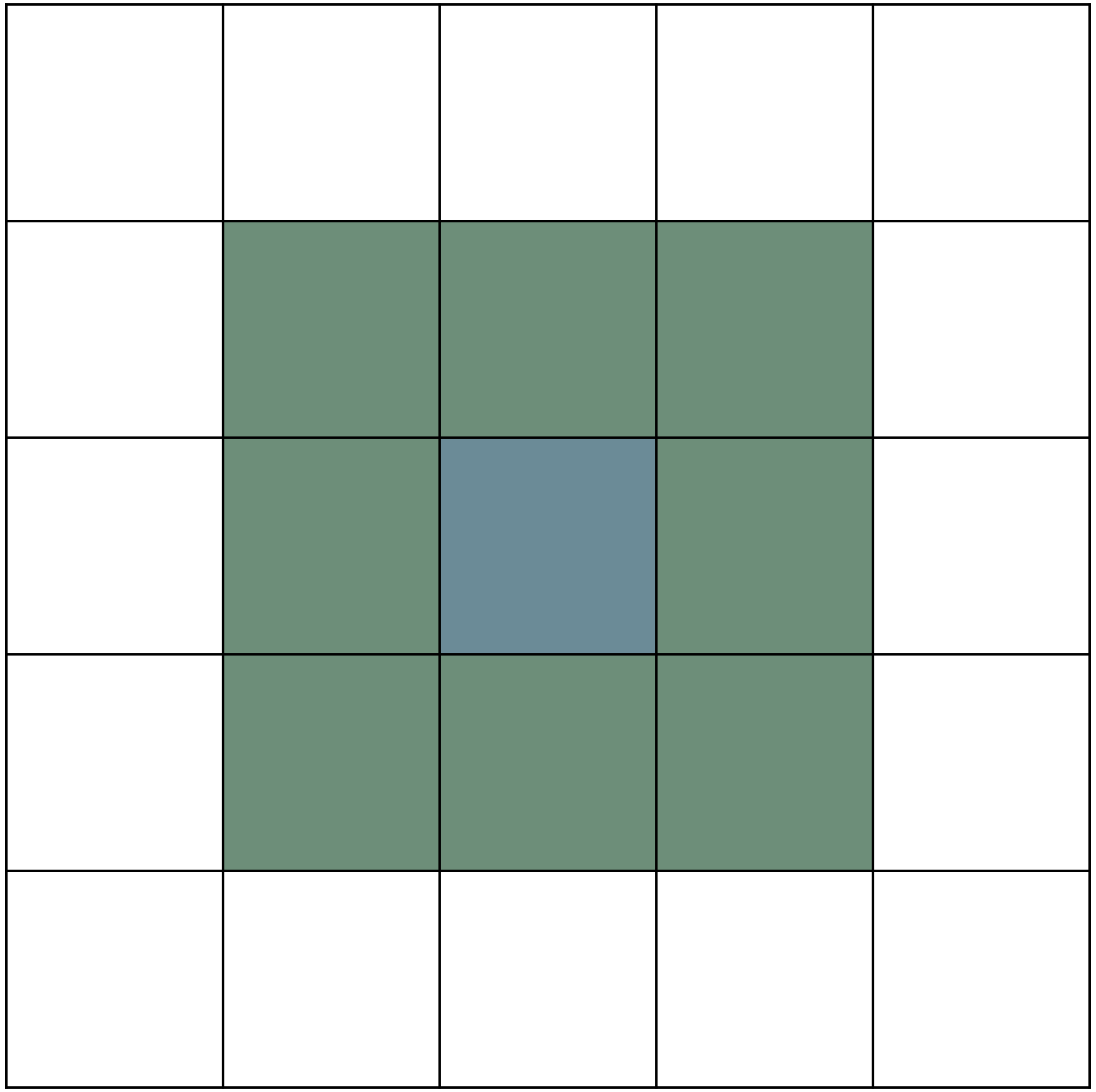


	a	b	c	d	e
a	0	.5	.5	0	0
b	.5	0	0	.5	0
c	.5	0	0	.5	0
d	0	.33	.33	0	.33
e	0	0	0	1	0

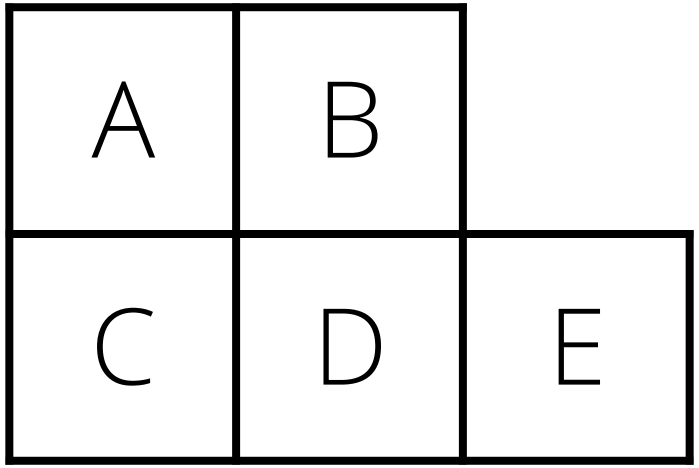
=

w
2
2
2
3
1

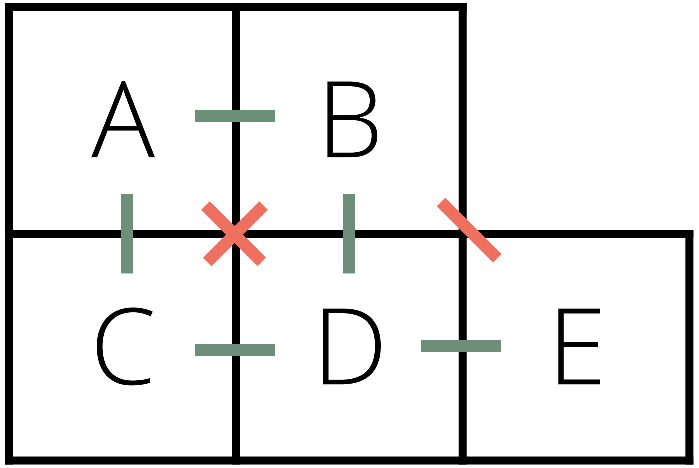
Spatial weights matrix



Spatial weights matrix

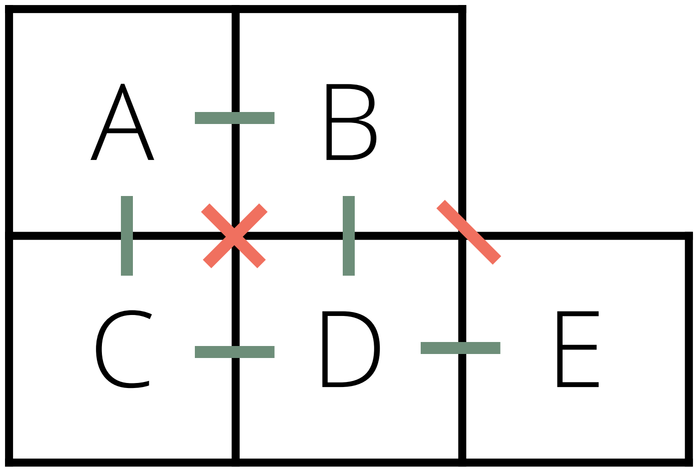


Spatial weights matrix



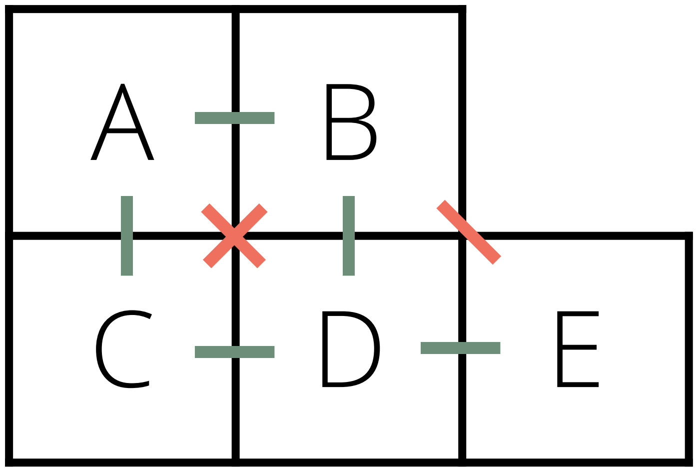
Spatial weights matrix

	a	b	c	d	e
a	0	1	1	1	0
b	1	0	1	1	1
c	1	1	0	1	0
d	1	1	1	0	1
e	0	1	0	1	0



Spatial weights matrix

$$
\begin{array}{c|ccccc|}
 & a & b & c & d & e \\
\hline
a & 0 & 1 & 1 & 1 & 0 \\
b & 1 & 0 & 1 & 1 & 1 \\
c & 1 & 1 & 0 & 1 & 0 \\
d & 1 & 1 & 1 & 0 & 1 \\
e & 0 & 1 & 0 & 1 & 0 \\
\hline
\end{array}
=
\begin{array}{|c|}
w \\
\hline
3 \\
4 \\
3 \\
4 \\
2 \\
\hline
\end{array}
$$

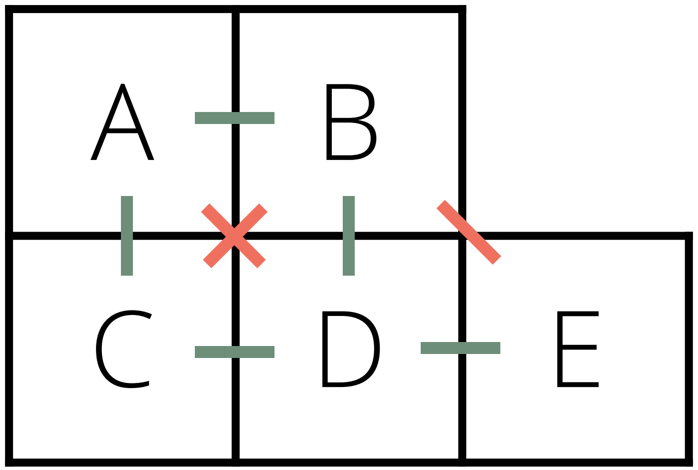


Spatial weights matrix

	a	b	c	d	e
a	0	.33	.33	.33	0
b	.25	0	.25	.25	.25
c	.33	.33	0	.33	0
d	.25	.25	.25	0	.25
e	0	.5	0	.5	0

=

w
3
4
3
4
2



Topology

Conclusion

- Measuring spatial autocorrelation is essential for understanding spatial relationships and patterns in data.
- We discussed two common measures of spatial autocorrelation, though other methods also exist.
- A spatial weights matrix is required to calculate the spatially lagged variable used in these measures.
- The way neighbours are defined (proximity or contiguity) can affect the results of spatial autocorrelation tests.

Questions

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