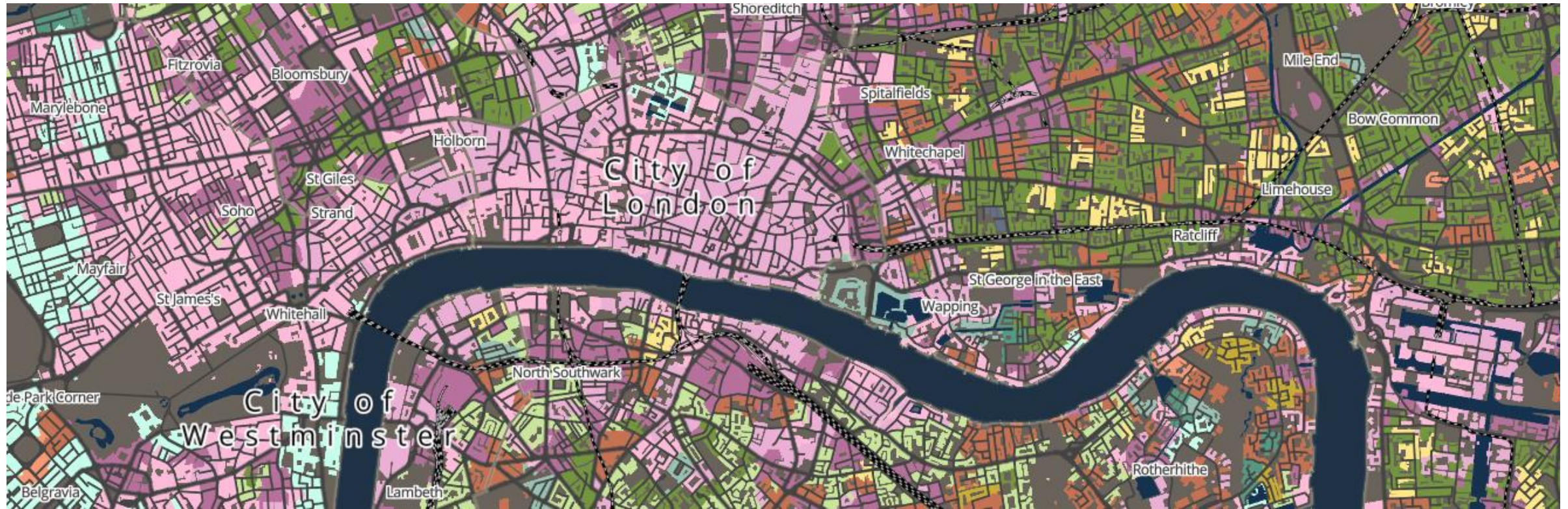


# Geocomputation

## Spatial Models



# Module outline

- W1 Reproducible Spatial Analysis
- W2 Spatial Queries and Geometric Operations
- W3 Point Pattern Analysis
- W4 Spatial Autocorrelation
- W5 Spatial Models
- W6 Raster Data Analysis
- W7 Geodemographic Classification
- W8 Accessibility Analysis
- W9 Beyond the Choropleth
- W10 Complex Visualisations

Core Spatial Analysis

Applied Spatial Analysis

Data Visualisation

# This week

- Managing spatial data
- Linear Models
- Spatial Models
- Assessment: Social Atlas

# Managing spatial data

- R has the capacity to read, load and store a range of file formats.
- Functions in both the base R library plus a huge host of software-specific packages (e.g. STATA, SPSS) for reading, writing and converting data between different file formats associated with those specific software (e.g. from a SPSS file to a `csv` etc.).
- Base R does not handle the reading, loading, and storing of spatial data.

# Managing spatial data

- How do we read in and deal with spatial data?
- GDAL: Geospatial Data Abstraction Library (*reading, writing*)
- GEOS: Geometry Engine Open Source (*spatial operations*)
- PROJ: Cartographic Projection Library (*coordinate transformations*)

**GEOS** Geometry  
Engine  
Open  
Source





# Managing spatial data

- The `sf` (simple features) package facilitates the storage, access and management of geometric objects stored as simple features in R.
- Importantly: `sf` objects are dataframes with a geometry column.

# Managing spatial data

```
## Simple feature collection with 100 features and 6 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -84.32385 ymin: 33.88199 xmax: -75.45698 ymax: 36.58965
## epsg (SRID):    4267
## proj4string:     +proj=longlat +datum=NAD27 +no_defs
## precision:      double (default; no precision model)
## First 3 features:
```

	BIR74	SID74	NWBIR74	BIR79	SID79	NWBIR79	geom
## 1	1091	1	10	1364	0	19	MULTIPOLYGON((( -81.47275543...
## 2	487	0	10	542	3	12	MULTIPOLYGON((( -81.23989105...
## 3	3188	5	208	3616	6	260	MULTIPOLYGON((( -80.45634460...

Simple feature

Simple feature geometry list-column (sfc)

Simple feature geometry (sfg)

# Managing spatial data

sf

- 'Support for simple features, a standardized way to encode spatial vector data'.
- Fully compliant with the dataframe format (*tidyverse*).

sp

- 'Classes and methods for spatial data'.
- First development in using spatial data in R (2005).
- Not fully compliant with the dataframe format.



# Before we start

- Go to [www.menti.com](https://www.menti.com)
- Use code: 7321 6950

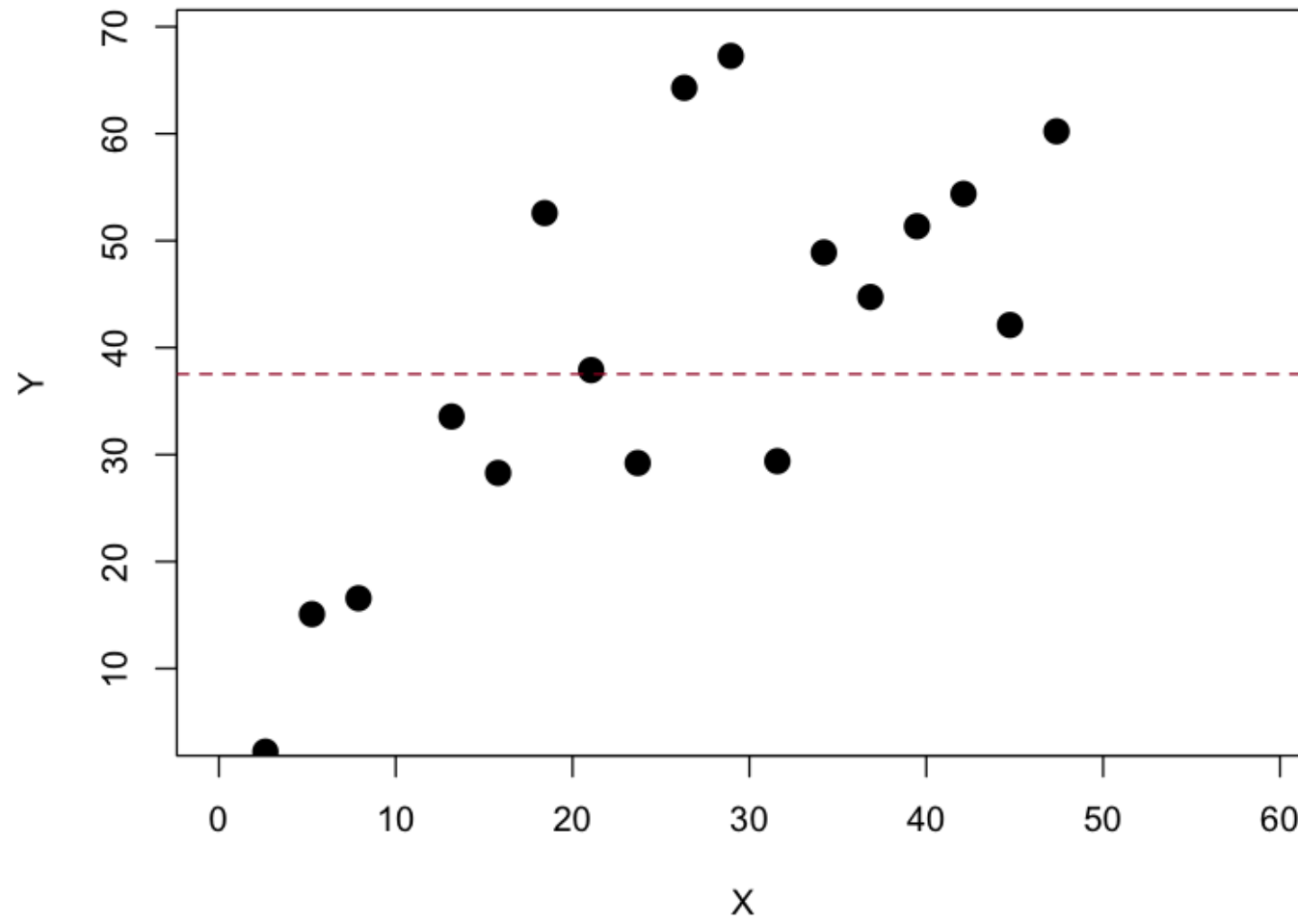
# Linear models

- We often want to know to predict how changes in one variable will affect another variable.
- To do this we can use a regression model to examine the relationship between a dependent variable ( $y$ ) and one or more independent variables ( $x$ ).

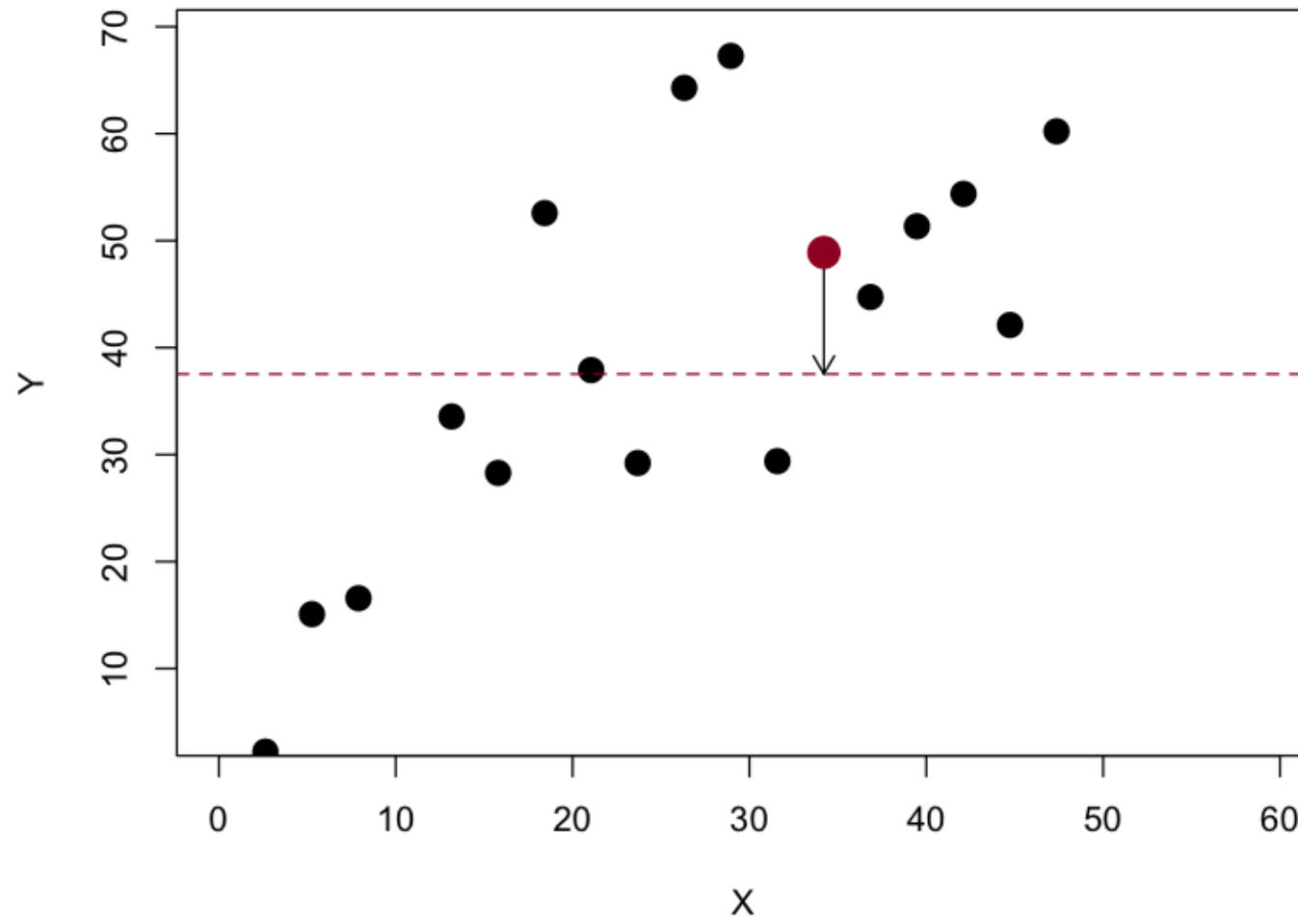
# Linear models

- Linear regression uses a line to summarise the relationship between  $x$  and  $y$ .
- The aim to find the line which best represents the relationships in the data.
- Typically, this line will not pass through every data point meaning we cannot predict  $y$  exactly.

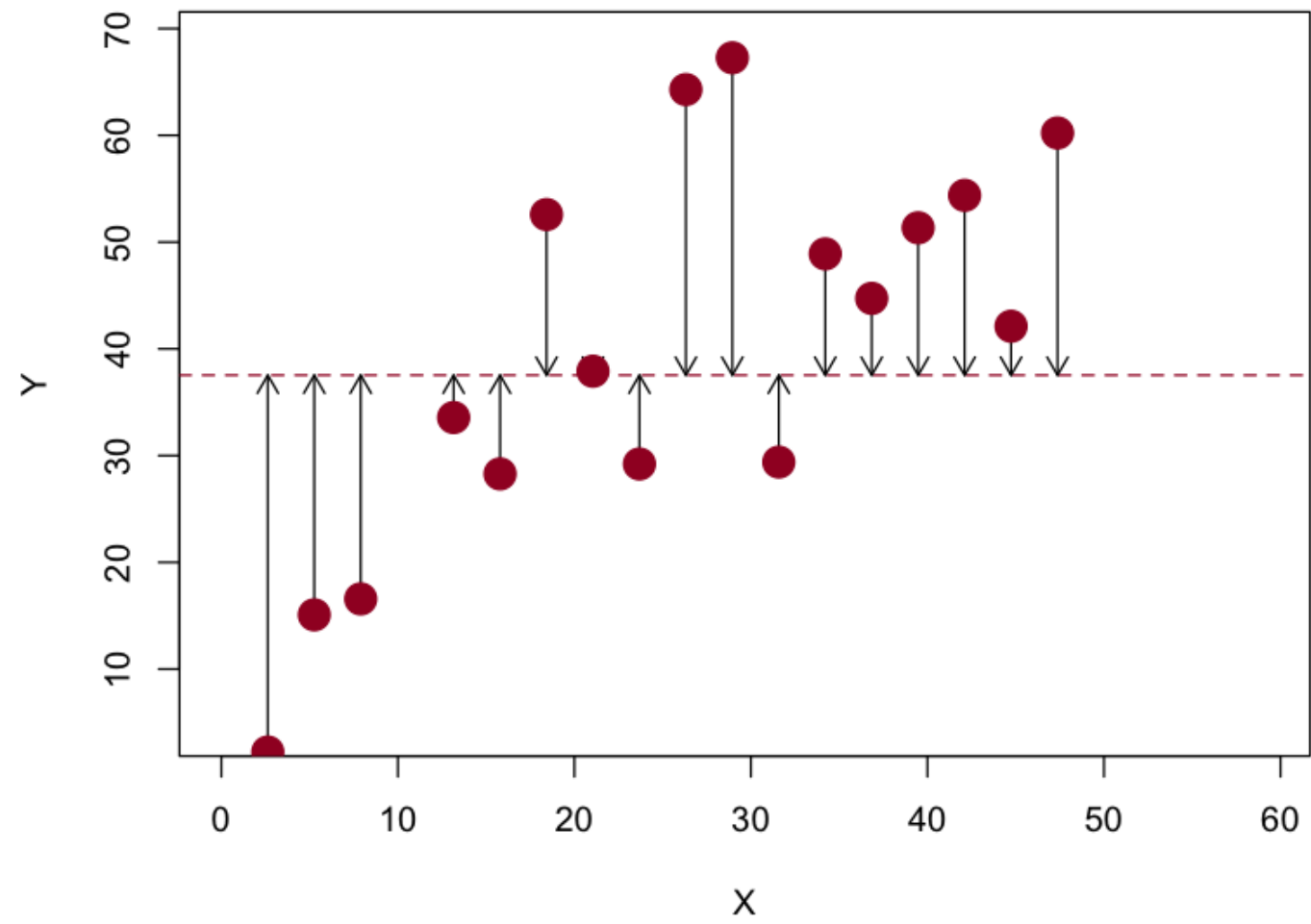
# Linear models



# Linear models

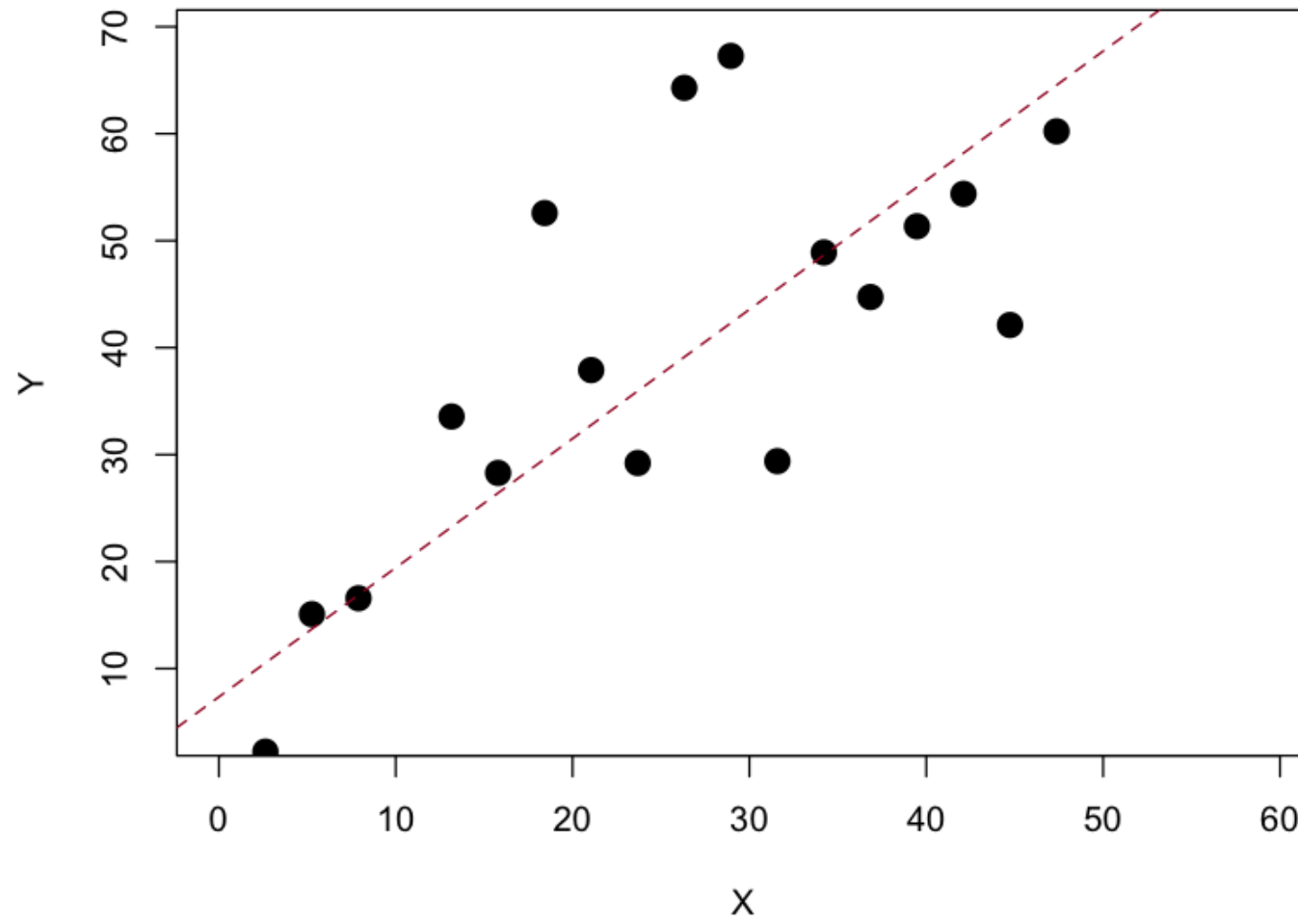


# Linear models

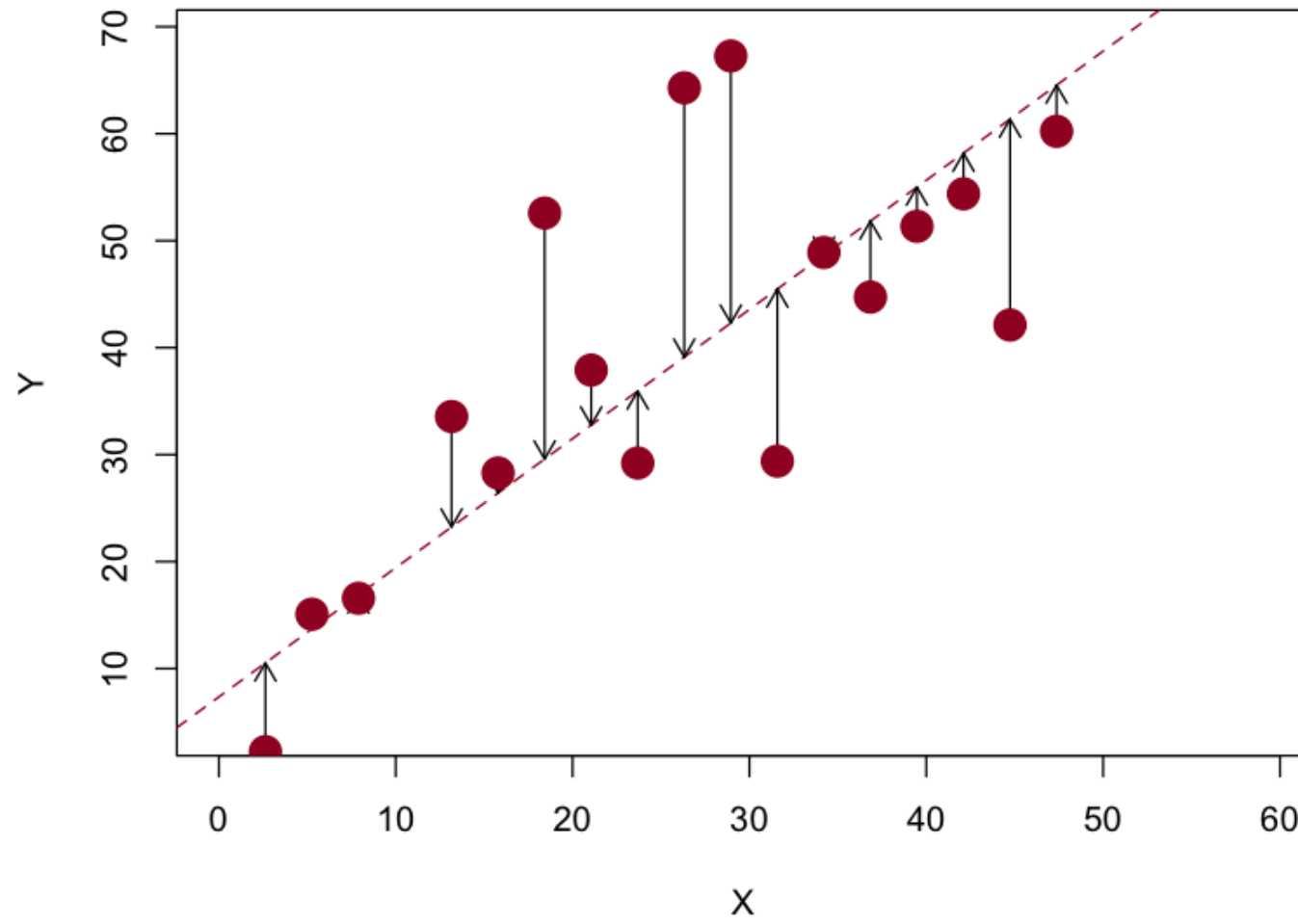




# Linear models



# Linear models



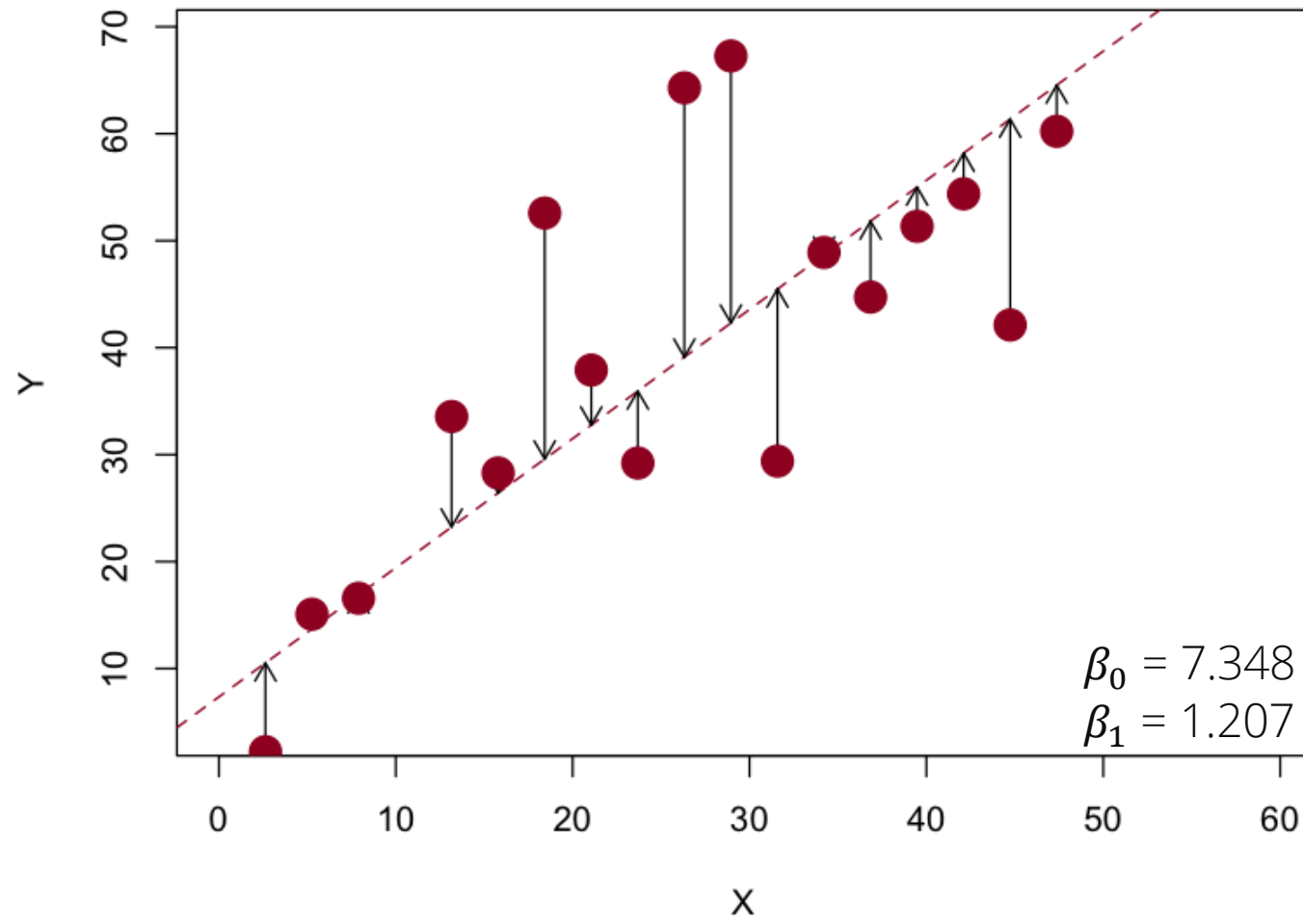
# Linear models

- Ordinary Least Squares (OLS) regression:

$$\hat{y} = \beta_0 + \beta_1 x$$

- The  $\beta$  terms are coefficients that define the regression line.
- The model estimates these parameters to find the line that gives the smallest sum of squared errors: Ordinary Least Squares (OLS) regression.

# Linear models



# Linear models

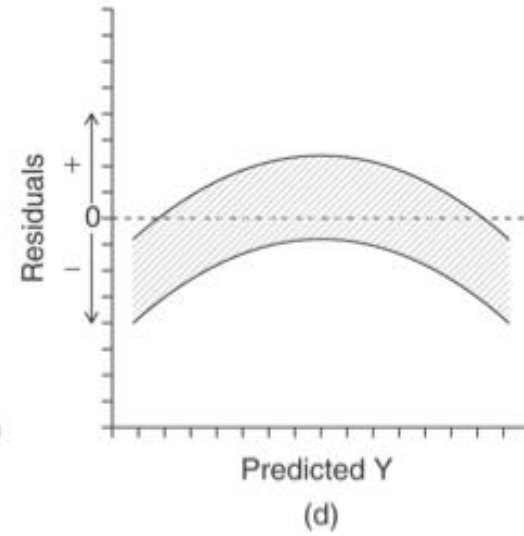
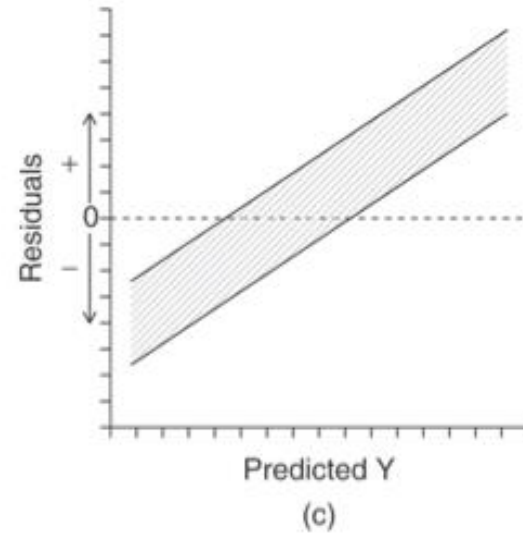
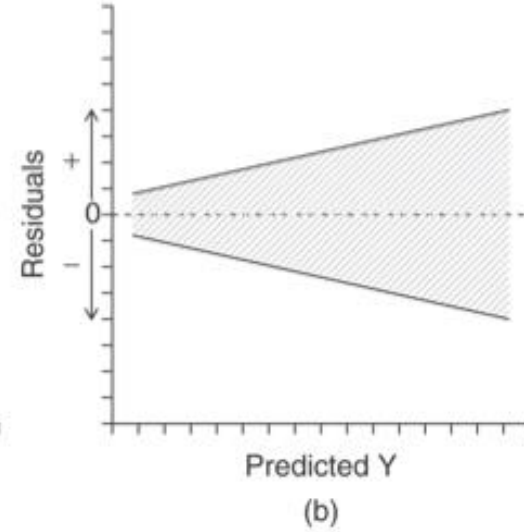
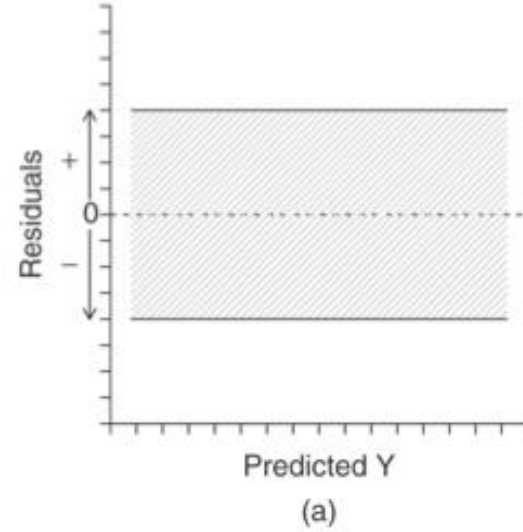
Distribution of dependent variable	Example	Suitable model
Continuous	Income	Linear regression
Binary	Employment status	Logistic regression
Binomial	Proportion of homeowners	Logistic regression
Count	Number of crimes	Poisson regression

# Linear models

- Important assumptions: homoscedasticity.
- Violating this assumption can lead to inefficient estimates and unreliable results.



# Linear models



# Linear models

When building a model based on spatial data:

- Map the residuals of the linear model to visually inspect for spatial patterns.
- Calculate Moran's I statistic on the residuals to assess spatial autocorrelation.
- If spatial autocorrelation is present, fit a **spatial linear model** to account for it.
- Recalculate Moran's I statistic on the residuals of the spatial model to confirm that the autocorrelation has been addressed.

# Spatial models

A **spatial error model** adjusts for spatial autocorrelation by adding a spatially lagged error term to the regression equation:

$$y = X\beta + v, v = \lambda Wv + \epsilon$$

where  $X\beta$  represents the standard regression components,  $\lambda$  is a spatial autoregressive parameter,  $W$  represents the spatially weights matrix, and  $u$  is a vector of spatially autocorrelated errors.

# Spatial models

A **spatial lag model** incorporates a spatially lagged dependent variable, which is the weighted sum of the dependent variable values in neighboring locations, into the regression equation:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where  $\rho$  is the spatial autoregressive coefficient,  $\mathbf{W}\mathbf{y}$  represents the spatially lagged dependent variable, and  $\mathbf{X}\boldsymbol{\beta}$  represents the standard regression components.

# Spatial models

- Both the spatial error and spatial lag models assume that the relationships between variables are the same across the study area, with adjustments made only for spatial dependencies.
- A Lagrange Multiplier Test can be used to make a decision as to which of these two models is most appropriate.
- What about non-stationarity?

# Geographically weighted statistics

- Unlike traditional global models, which estimate a single set of parameters for the entire study area, geographically weighted statistics allow for parameter estimates that vary across different locations.
- Local means, local standard deviations, local variances.
- Typically uses some **kernel function** to weigh observations based on their distance from the location of interest.

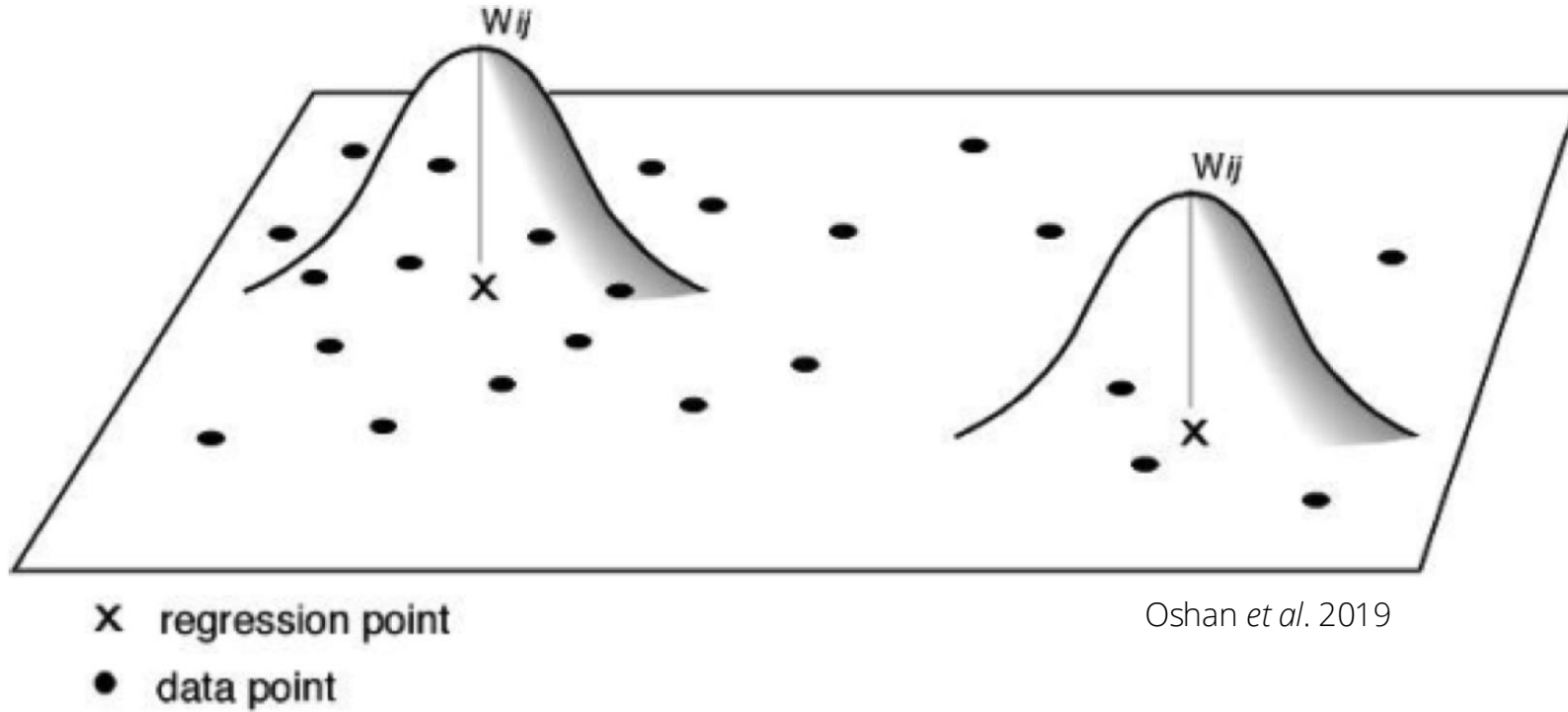


# Geographically weighted statistics

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

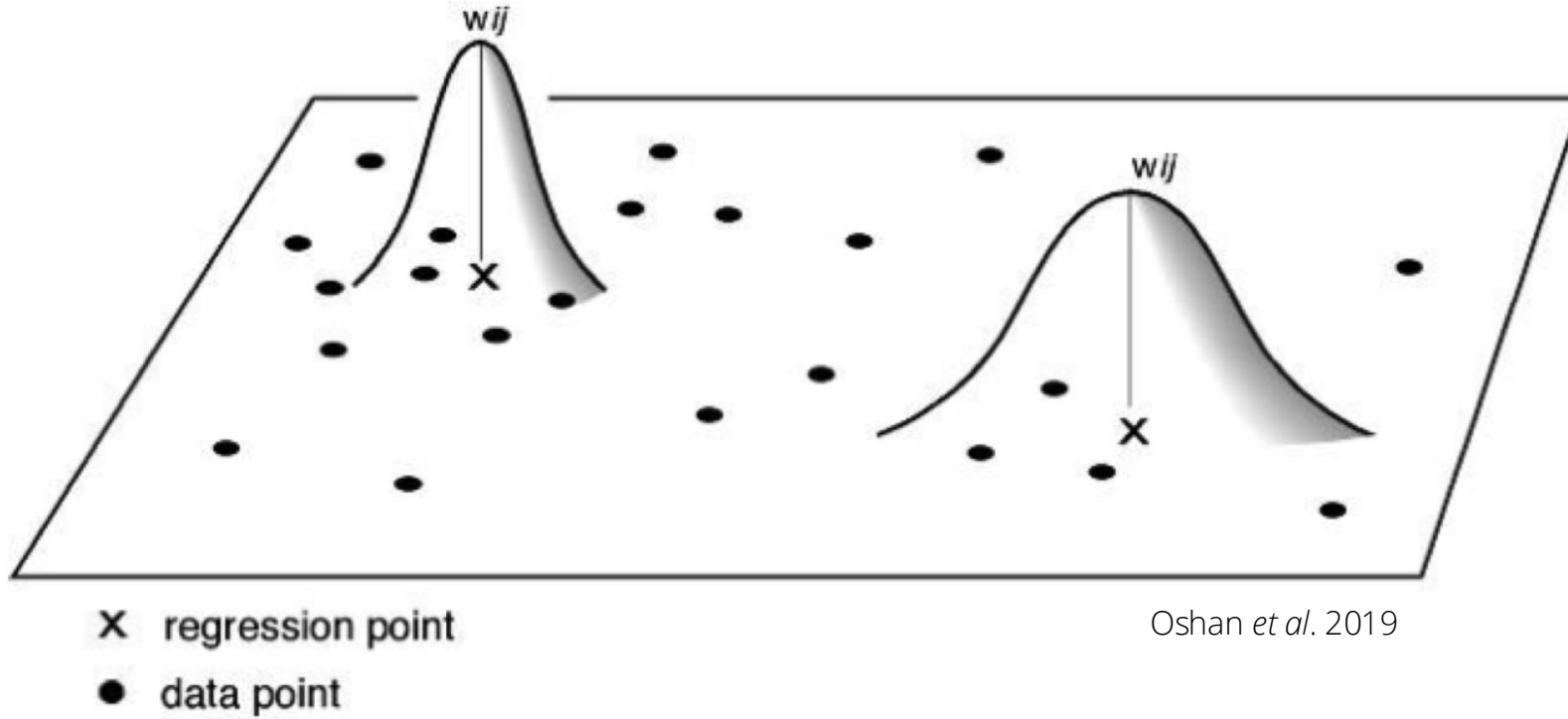
Walter Tobler 1970

# Geographically weighted statistics



Oshan *et al.* 2019

# Geographically weighted statistics



Oshan *et al.* 2019

# Geographically weighted regression

- These ideas can be extended to correlation and regression:
  - Geographically weighted correlation (GWC)
  - Geographically weighted regression (GWR)
- The basic GWR equation is:

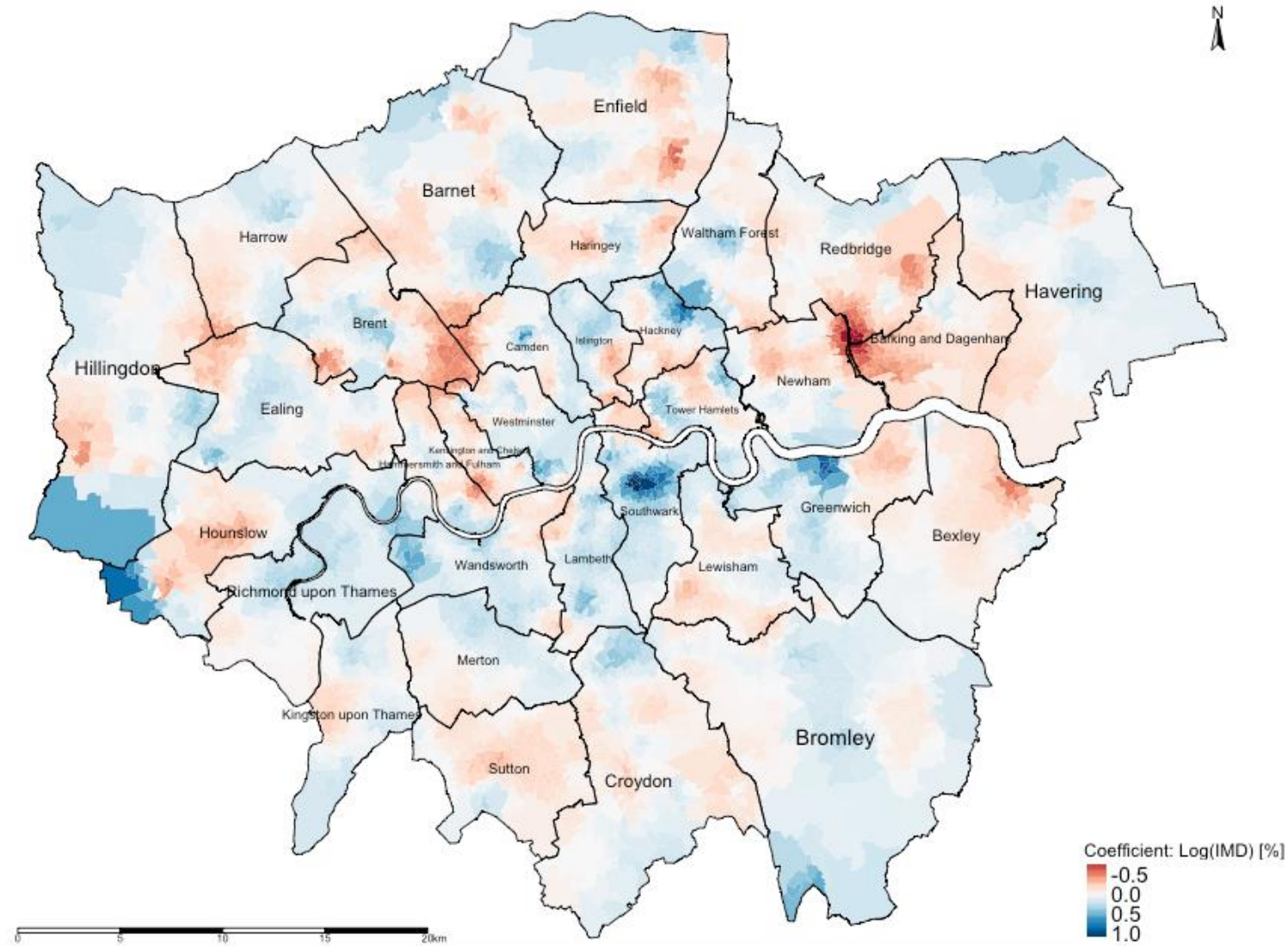
$$y_i = \beta_0(v_i, v_i) + \sum_{k=1}^p \beta_k(v_i, v_i) x_{ik} + \epsilon_i$$

where  $(v_i, v_i)$  are the coordinates of location  $i$  and  $\beta_k(v_i, v_i)$  are the location-specific coefficients.

# Geographically weighted regression

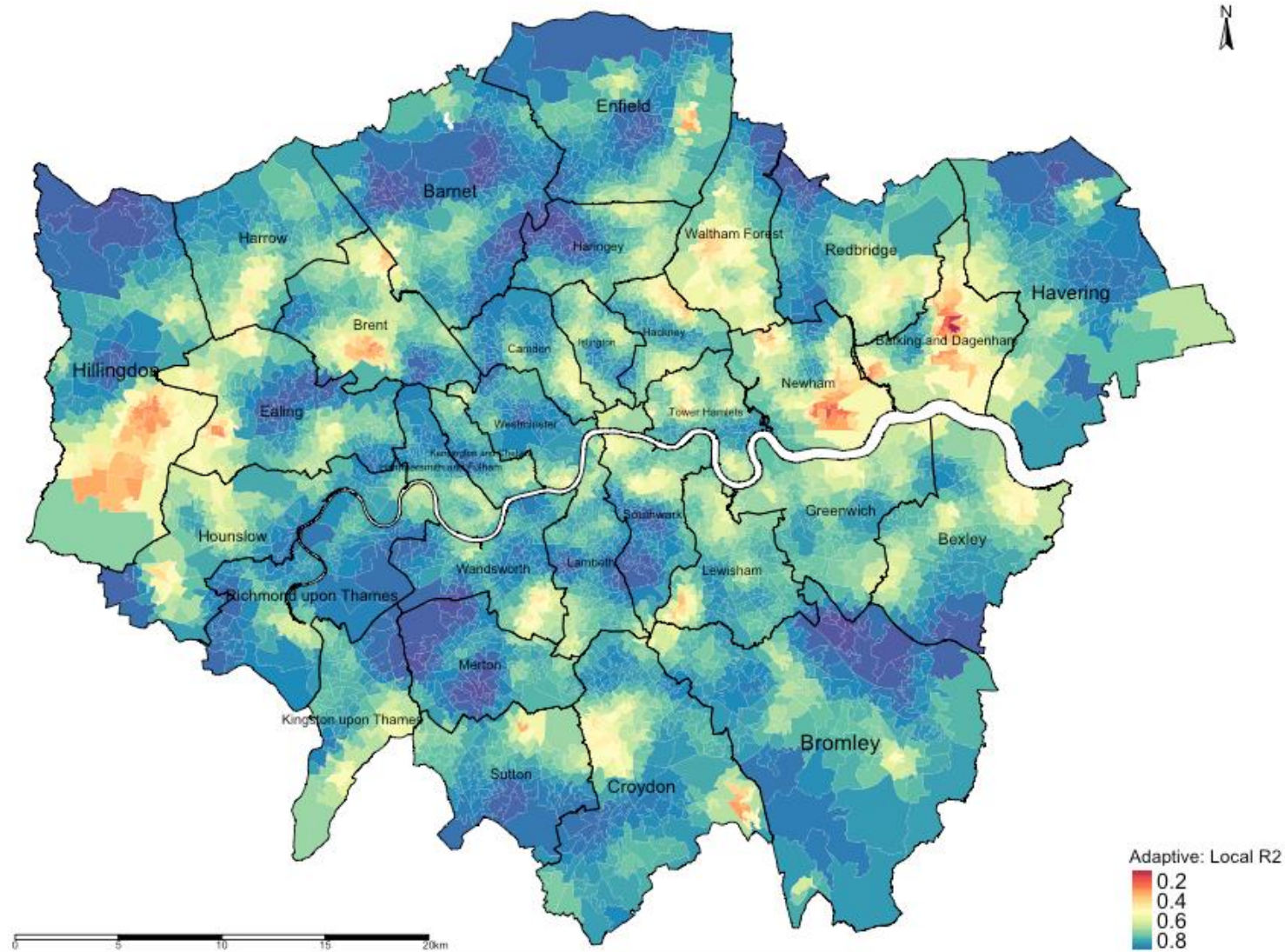
- Each area has its own set of regression coefficients.
- Each location has its own  $R^2$  value.
- Each area has its own standard errors for the coefficient.
- More recently: bandwidths can vary between different variables.

# Geographically weighted regression





# Geographically weighted regression



# Conclusion

- OLS assumes independent and homoscedastic residuals, but spatial autocorrelation violates these assumptions, leading to biased or inefficient estimates.
- Spatial Error and Spatial Lag models are techniques for handling spatial dependence by explicitly modeling spatial relationships in errors or response variables.
- Relationships between variables can vary across space, challenging the global assumption of uniform coefficients in OLS and spatial models.
- GWR captures spatial heterogeneity by estimating local coefficients, addressing both spatial autocorrelation and non-stationarity to reveal location-specific dynamics.

# Questions

Justin van Dijk  
[j.t.vandijk@ucl.ac.uk](mailto:j.t.vandijk@ucl.ac.uk)



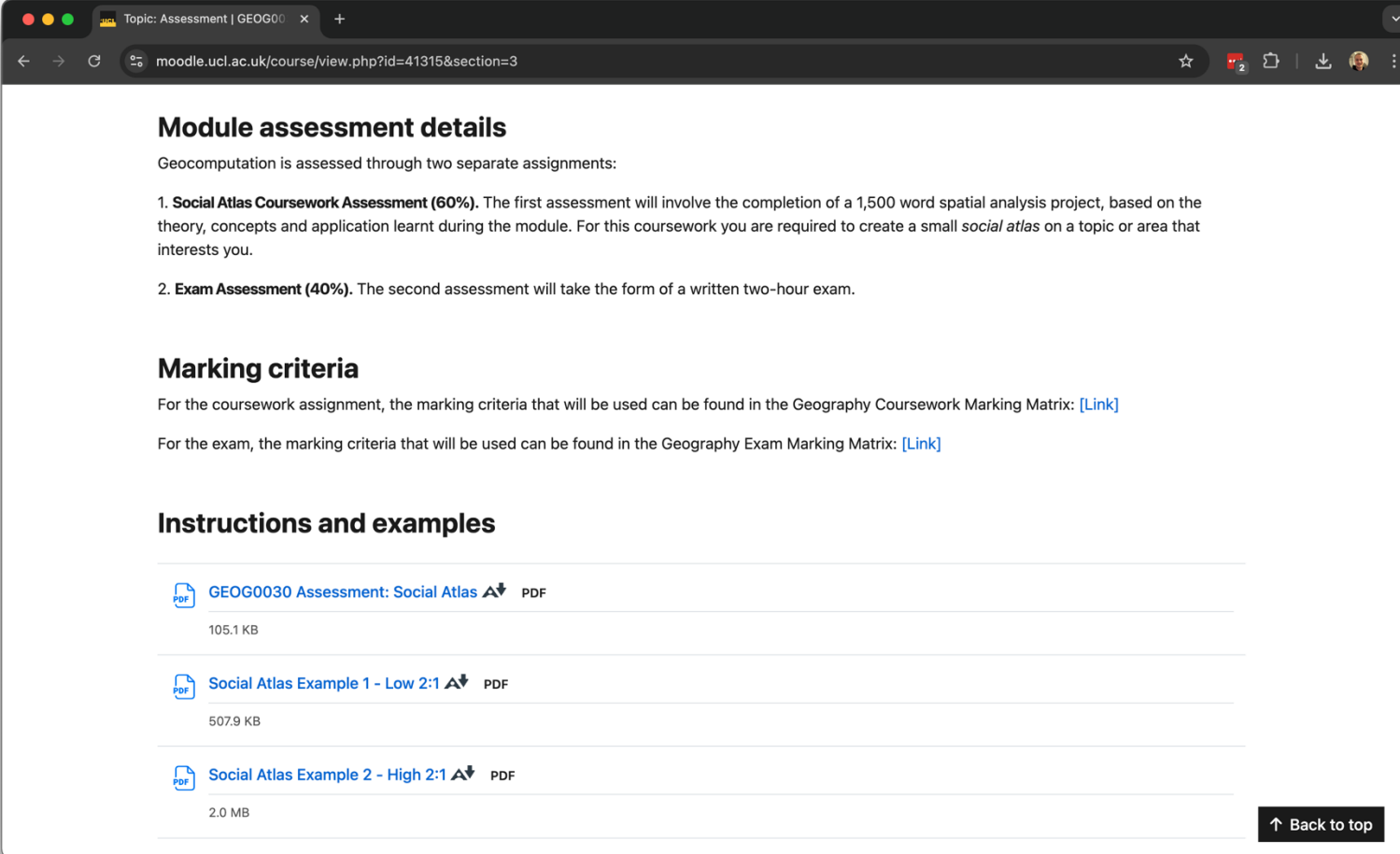
# Assessment

- Social Atlas Coursework Assessment (60%): The first assessment will involve the completion of a spatial analysis project, based on the theory, concepts and application learnt during the module. For this coursework you are required to create a small *social atlas* on a topic or area that interests you. Deadline: April 27, 2026.
- On Moodle: guidance as well as examples from previous years.

# Assessment

- You should create a **minimum** of 4 maps and a maximum of 6.
- You should create a **minimum** of 2 graphs / charts and a maximum of 4.
- You can choose a specific theme or zoom into a particular area.
- You should aim to utilise a range of different techniques taught in the Geocomputation module to explore your topic – but make sure you apply the techniques in appropriate manner and with the right data types.
- Greater London cannot be used as a case study.

# Assessment



Topic: Assessment | GEOG0030

moodle.ucl.ac.uk/course/view.php?id=41315&section=3

## Module assessment details

Geocomputation is assessed through two separate assignments:







- 1. Social Atlas Coursework Assessment (60%).** The first assessment will involve the completion of a 1,500 word spatial analysis project, based on the theory, concepts and application learnt during the module. For this coursework you are required to create a small *social atlas* on a topic or area that interests you.
- 2. Exam Assessment (40%).** The second assessment will take the form of a written two-hour exam.

## Marking criteria

For the coursework assignment, the marking criteria that will be used can be found in the Geography Coursework Marking Matrix: [\[Link\]](#)

For the exam, the marking criteria that will be used can be found in the Geography Exam Marking Matrix: [\[Link\]](#)

## Instructions and examples

	<a href="#">GEOG0030 Assessment: Social Atlas</a>  PDF
	105.1 KB
	<a href="#">Social Atlas Example 1 - Low 2:1</a>  PDF
	507.9 KB
	<a href="#">Social Atlas Example 2 - High 2:1</a>  PDF
	2.0 MB

[↑ Back to top](#)

# Assessment

The screenshot shows a web browser window with the address bar displaying 'jtvandijk.github.io/GEOG0030/11-data.html'. The page features a sidebar on the left with a navigation menu, a main content area with a title and a list of links, and a right-hand sidebar with a table of contents and a 'Report an issue' link.

**GEOG 0030**

Module overview

- Welcome
- Core Spatial Analysis
  - 1 Reproducible Spatial Analysis
  - 2 Spatial Queries and Geometric Operations
  - 3 Point Pattern Analysis
  - 4 Spatial Autocorrelation
  - 5 Spatial Models
- Applied Spatial Analysis
  - 6 Raster Data Analysis
  - 7 Geodemographic Classification
  - 8 Accessibility Analysis
- Data visualisation
  - 9 Beyond the Choropleth
  - 10 Complex Visualisations
- Additional Resources
  - 11 Data Sources

## 11 Data Sources

Below is a list of resources that you may find helpful when sourcing data for your coursework or dissertation. This list is not exhaustive but includes some recommended websites to get you started.

### 11.1 Open Data

The following websites contain Open Data or link to Open Data from several respectable data providers:

- [AfricanUrbanNetwork](#)
- [AirBnB Data](#)
- [Bike Docking Data \(ready for R\)](#)
- [Bing Maps worldwide road detections](#)
- [Camden Air Action](#)
- [Consumer Data Research Centre](#)
- [Department for Environment, Food & Rural Affairs](#)
- [Edina \(e.g. OS mastermap\)](#)
- [EU Tourism Data](#)
- [Eurostat](#)
- [Geofabrik \(OSM data\)](#)
- [Geolytix Supermarket Retail Points](#)
- [Global Urban Areas dataset](#)
- [Global Weather Data](#)
- [Google Dataset Search](#)
- [Google Open Buildings](#)
- [Kaggle Public Datasets](#)
- [King's College Data on Air Pollution](#)

On this page

- 11 Data Sources
  - 11.1 Open Data**
  - 11.2 Safeguarded Data

[Report an issue](#)

# Assessment

TL;DR story of max 1,500 words tied together by 4-6 related maps and 2-4 graphs.



# Questions

Justin van Dijk  
[j.t.vandijk@ucl.ac.uk](mailto:j.t.vandijk@ucl.ac.uk)



Have a good reading week!

