

GEOG0114: PRINCIPLES OF SPATIAL ANALYSIS

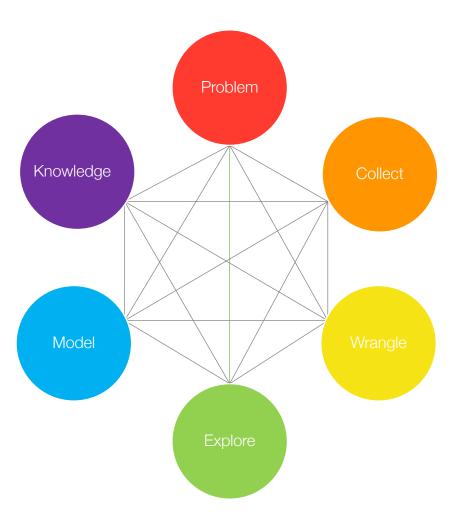
WEEK 10: SPATIAL MODELS (PART 2)

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Contents

- 1. Introduction to Geographically Weighted Regression Modelling
- 2. Extending the standard linear regression to GWR
 - Using GWRs to estimate the local (not global) relationships between a dependent and independent variable
 - Determination of whether local relationships are statistically significant or not
 - Model performance through Local R-squared
- 3. Methodology for statistical analysis and interpretation
- 4. Overarching summary of the GEOG0114



Spatial Models

Week 9

Spatial Lag and Error Models

Week 10

Geographically Weighted Regression (GWR) Models

In Week 9, we learnt special types of spatial model which accounts for spatial configuration of areal data

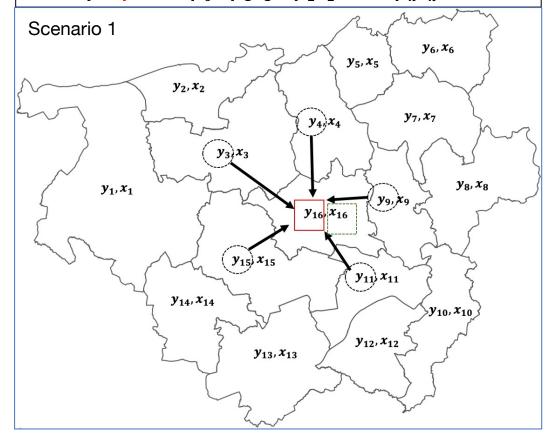
Recap

Multivariable Linear Regression

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$

1. Spatial Lag Model (lagged on the dependent variable)

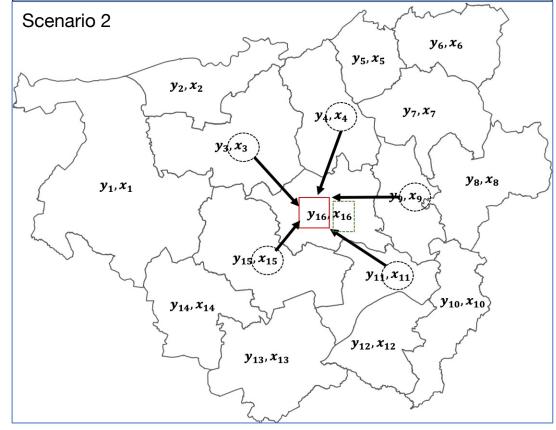
$$y = \rho WY + \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$



- W is a spatial weights matrix (contiguity based)
- Y in the right hand of the equation represents the observed outcome from other areas neighbouring that influences what we're trying to predict
- ρ "Rho" is the degree of how our predicted outcome are influenced by its neighbouring Y measures.

2. Spatial Lag Model (lagged on the independent variable)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \theta W X + \varepsilon$$



- W is a spatial weights matrix (contiguity based)
- X in the right hand of the equation represents the observed values from the independent variable in other areas neighbouring that influences what we're trying to predict
- θ "theta" is the degree of how our predicted outcome are influenced by its 4 neighbouring X measures.

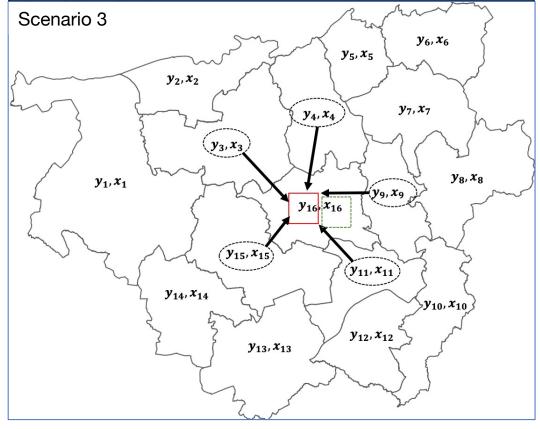
Recap

Multivariable Linear Regression

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$

3. Spatial Lag Model (lagged on both the dependent and independent variable)

$$y = \rho WY + \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \theta WX + \varepsilon$$

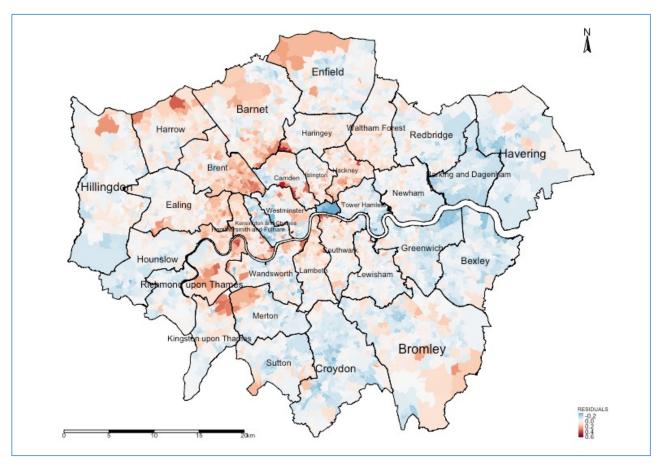


• Refer to slide number 3 to see the meanings of each parameters

4. Spatial Error Model $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \lambda W \mathbf{u} + \varepsilon$ Scenario 4 y_6, x_6, ε_6 y_5, x_5, ε_5 y_2, x_2, ε_2 y_7, x_7, ε_7 y_8, x_8, ε_8 y_1, x_1, ε_1 $y_{16}, x_{16}(\varepsilon_{16})$ $y_{15}, x_{15}, \varepsilon_{15}$ $y_{11}, x_{11}, \varepsilon_{11}$ $y_{10}, x_{10}, \varepsilon_{10}$ $y_{14}, x_{14}, \varepsilon_{14}$ $y_{12}, x_{12}, \varepsilon_{12}$ $y_{13},x_{13},\varepsilon_{13}$

- · u are the correlated spatial error terms
- λ "lambda" estimated coefficient for the product W and u.

Recap



Examining the residuals for determining spatial patterning and evidence of spatial autocorrelation. Moran's I test was 0.475 (p < 0.001) meaning that the residuals are clustered.

Broadly, there's an over-estimation in the house-price and spatial aspects needs to be accounted for.

Modelled results from Linear and Spatial Lag (Y) regression model

Variable(s)	Linear Model	Lag (Y) Model (Total effects)
log(Income)	2.036*	2.217*
log(Deprivation)	0.136*	0.079*
log(PTAL)	0.031*	0.019*
AIC	-8510.8	-9863.3
R ²	0.7889 (78.89%)	N/A

- While we have accounted for spatial configuration using the spatial model, as well as accounted for spatial autocorrelation, we were able to determine the Global relationships between dependent and independent variables.
- What about if we want to investigate further patterns but a much local-level?
- LM, and any of the spatial Lag and error models cannot solve this problem

Spatial Models

Week 9

Spatial Lag and Error Models

Week 10

Geographically Weighted Regression (GWR) Models What is a Geographically Weighted Regression

Definition of Geographically Weighted Regression (GWR) model:

GWR is a statistical model which can indicate where non-stationarity may take place across space; it can be used to identify how **locally** weighted regression coefficients may vary across the study area (unlike its counterpart i.e., the **Spatial Lagged and/or Error Models** which provides **global coefficients**)

We use GWRs to:

- Determine area-specific relationship or association between a specified outcome (i.e., dependent variable) with one or more predictors (i.e., independent variable(s))
- 2) Find out whether those area-specific relationship or associations are statistically significant across geographic space.

GWRs fall under the family of linear regression models. Recall last week the various model types and families?

Here is a board overview:

Distribution of dependent variable	Suitable Model
Continuous measures: e.g., average income in postcode (£); concentrations of ambient particular matter (PM2.5); Normalised Vegetative Difference Index (NDVI) etc.,	Linear regression
Binary measures (1 = "present" or 0 = "absent") : e.g., Person's voting for a candidate, Lung cancer risk, house infested with rodents etc.,	Logistic Regression
Binomial measure (or proportion): e.g., prevalence of houses in a postcode infested with rodents, percentage of people in a village infected with intestinal parasitic worms, prevalence of household on a street segment victimised by crime etc.,	Logistic Regression
Counts or discrete measures: e.g., number of reported burglaries on a street segment, number of riots in a county etc.,	Poisson Regression
Time-to-event binary measures : e.g., Lung cancer risk due to chronic exposure to environmental levels of indoor radon. Risk of landslide and time dependence of surface erosion etc.,	Survival Analysis with Cox regression

Multivariable Linear Regression Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \varepsilon$$

Variables

- y is the dependent variable
- $x_1, x_2, x_3, ..., x_k$ are the independent variables

Parameters

- β_0 is the intercept
- $\beta_1, \beta_2, \beta_3, ..., \beta_k$ are the slopes (or coefficients) for the corresponding variables $x_1, x_2, x_3, ..., x_k$
- ε is the error term

Geographical Weighted Regression Model

$$y_i = \beta_{i,0}(u_i, v_i) + \beta_{i,1}(u_i, v_i)x_{i,1} + \beta_{i,2}(u_i, v_i)x_{i,2} + \cdots + \beta_{i,k}(u_i, v_i)x_{i,k} + \varepsilon_i$$

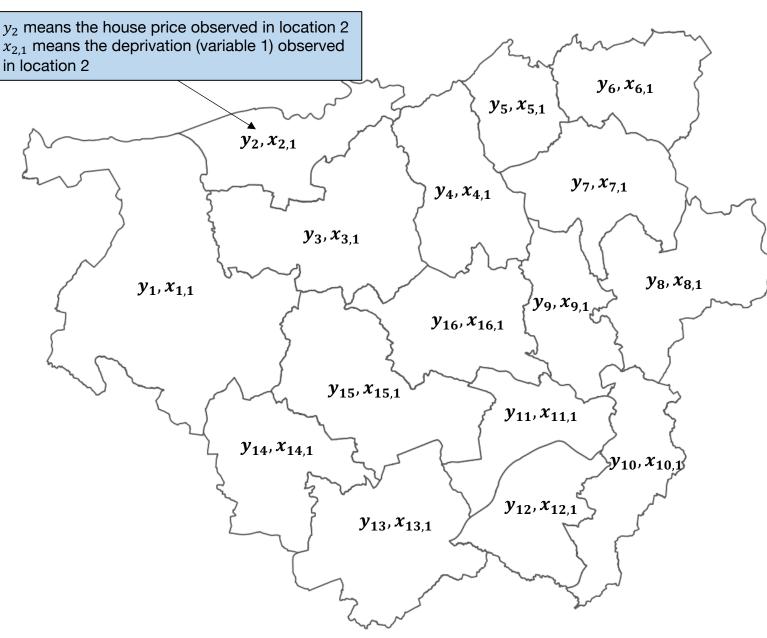
Variables

- y_i is the dependent variable indexed at observation (or location) i
- x_{i1} , x_{i2} and so to x_{ik} are the k-number of independent variables indexed at at

Parameters

- $\beta_{i0}(u_i, v_i)$ is the intercept as a function of a geographic location (i.e., coordinates on a grid)
- $\beta_{i1}(u_i, v_i)$, $\beta_{i2}(u_i, v_i)$, $\beta_{i3}(u_i, v_i)$,..., $\beta_{ik}(u_i, v_i)$ are the slopes (or coefficients) for the corresponding variables $x_{i1}, x_{i2}, x_{i3}, ..., x_{ik}$ which are function of a geographic location (u_i, v_i)
- ε is the error term

Suppose we have a hypothetical study area with 16 areas



Notes:

Let Y be some dependent variable that is continuous and normally distributed, where there are 16 observation for Y at some illocation (i.e. $y_1, y_2 \dots y_{16}$)

• For example: Averaged house price (£)

Let X be some k^{th} independent variable $x_{i,k}$, (in this case k=1) where there are 16 locations for X (i.e. $x_{1,1}, x_{2,1} \dots x_{16,1}$)

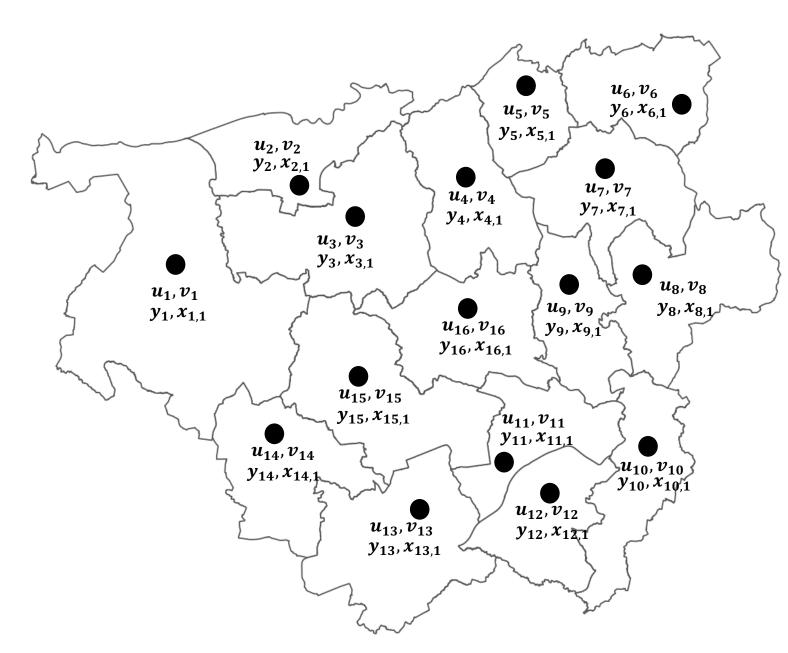
 For example: Socioeconomic deprivation score

Research question: To investigate the geospatial impacts of socioeconomic deprivation on house price in each area in this hypothetical study area.

Insufficient to use the typical linear regression model for this context

$$y = \beta_0 + \beta_1 x_1 + \varepsilon$$

Suppose we have a hypothetical study area with 16 areas



Notes:

We want to model the relationship of y_i , $x_{i,1}$ at location (u_i, v_i)

Because y_i , $x_{i,1}$ is calibrated on (u_i, v_i) as a function, we are able to use some model (i.e., GWR) to compute coefficients at each location of i.

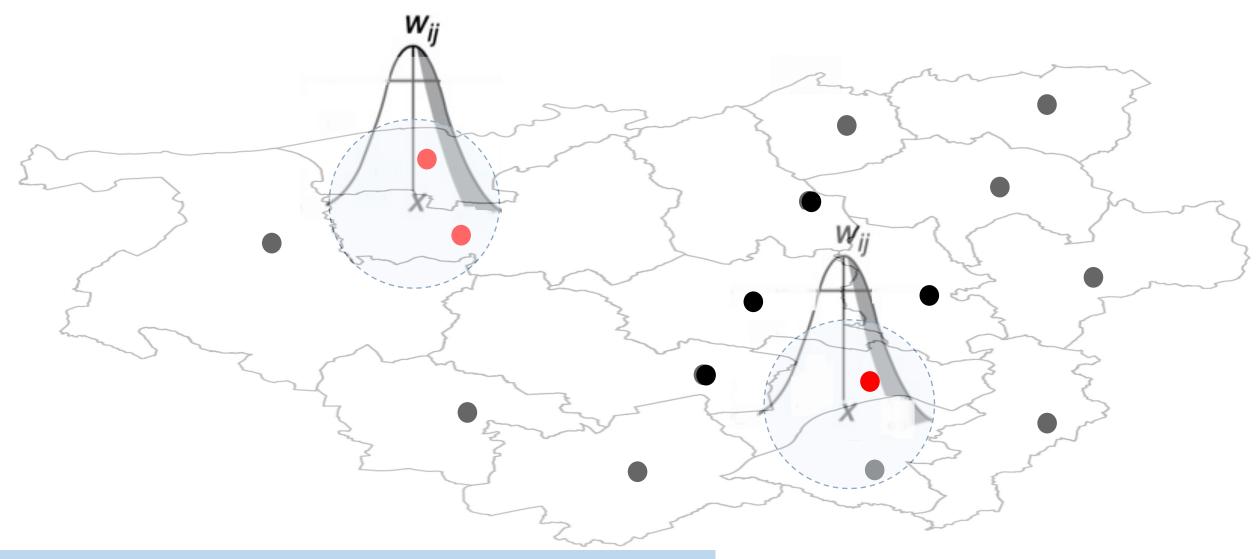
In this example for IMD, these coefficients are represented as $\beta_{i,1}(u_i, v_i)$

The GWRs implicitly use distance-based weights through **spatial kernels** or **bandwidths**. Hence, it relies on points.

Centroids are extracted from areas and used for such analysis.

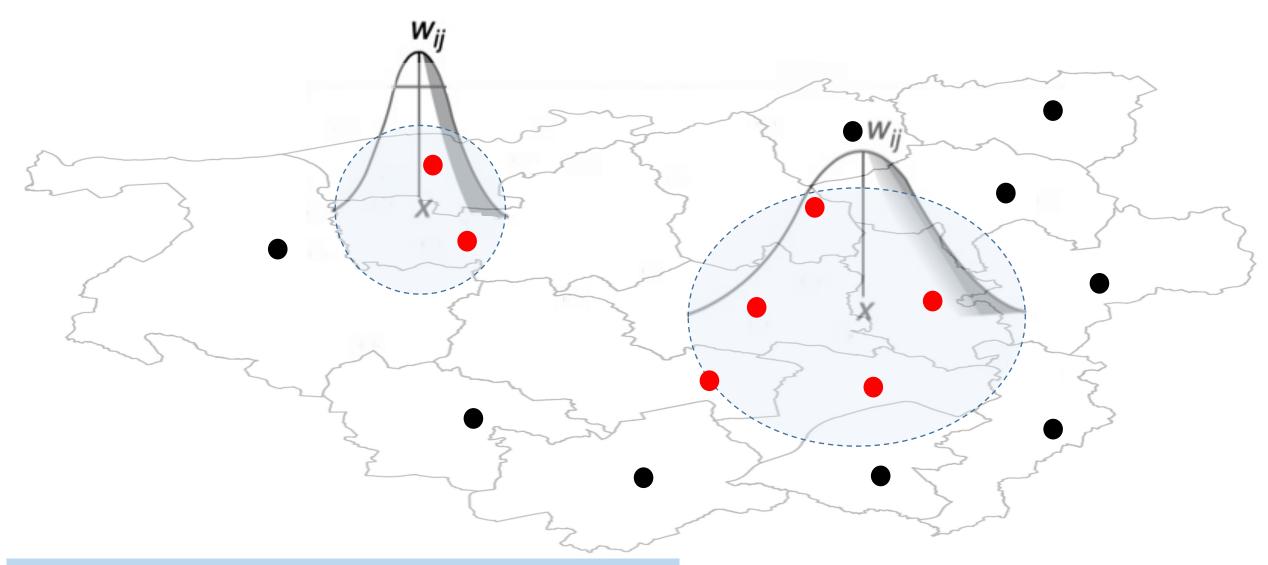
$$\mathbf{y}_{i} = \boldsymbol{\beta}_{i,0}(u_{i}, v_{i}) + \boldsymbol{\beta}_{i,1}(u_{i}, v_{i})\boldsymbol{x}_{i,1} + \boldsymbol{\varepsilon}_{i}$$

GWR with fixed spatial kernel (or bandwidth)



Note: GWRs are distance-based models. It uses bandwidth to consider nearest neighbours when accounting spatial configuration.

GWR with adaptive spatial kernel (or bandwidth)



Use the Adaptive spatial kernel for building your spatial weights! It is much better than using the fixed bandwidth

Workflow for GWR modelling

Modelling process using GWR

When you want to conduct evidence-based analysis with spatial data – especially if the outcome is from a continuous distribution – you might want to follow these steps:

- STEP 1: Carry some descriptive analysis to understand the underlying spatial distribution
- STEP 2: Perform a Linear regression in order to assess the residuals for the model output to determine whether not the assumptions of independence have been violated.
- You can check for multicollinearity among independent variable using the Variance Inflation Factor (VIF < 10)

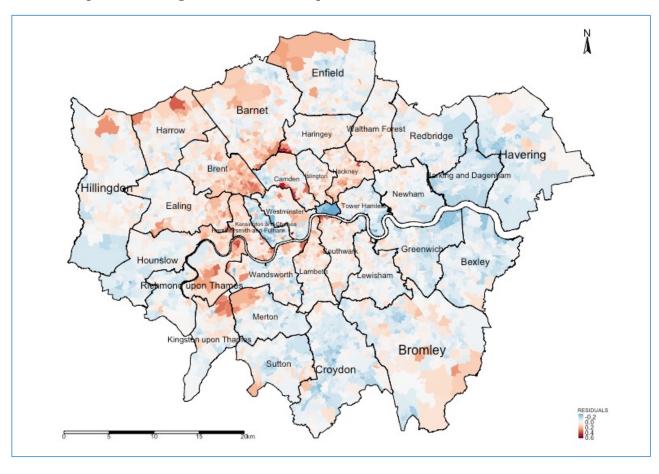
If there's a violation:

- STEP 3: Examine whether there is evidence of spatial dependence in the residuals using Moran's I test.
- If Moran's I test is not significant STOP! NO EVIDENCE OF SPATIAL DEPENDENCE HENCE NO NEED OF SPATIAL APPROACH

If Moran's I test is significant and positive – then map the residuals accordingly to examine the spatial patterning of the residual.

- STEP 4: Extract the centroids of the areas and use them for computing the kernel bandwidths. [I] Highly recommend to use the adaptive bandwidths, which is flexible than the fixed for estimating the optimal bandwidth.
- STEP 5: The estimated bandwidth is fitted into the GWR model to estimate the following quantities: 1.) Local R-squared, 2.) area-specific coefficients and 3.) standard errors for significance test for each areas.
- STEP 6: Extract the coefficients and desired results and map them accordingly to examine the spatial variation in the relationship between dependent and independent variables.
- STEP 7: Interpretation

Example using the house price data for London



Examining the residuals for determining spatial patterning and evidence of spatial autocorrelation. Moran's I test was 0.475 (p < 0.001) meaning that the residuals are clustered.

Broadly, there's an over-estimation in the house-price and spatial aspects needs to be accounted for.

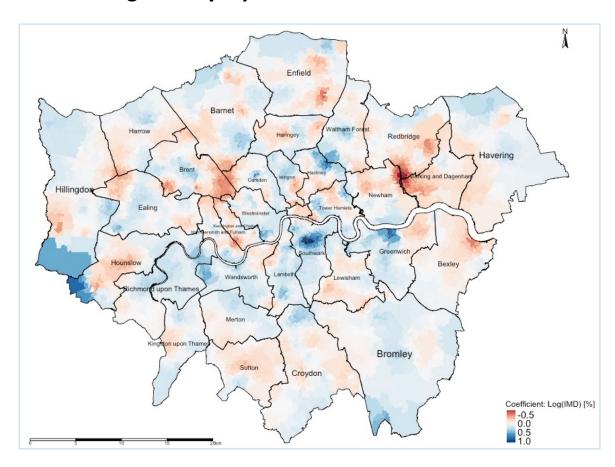
Reporting the Global estimates

Modelled results in table are from Linear, Spatial Lag (Y) and GWR regression model

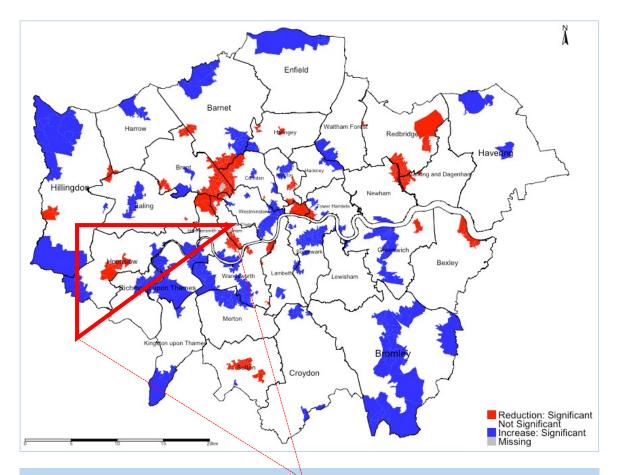
Variable(s)	Linear	Lag (Y)	GWR
log(Income)	2.036*	1.267*	2.036
log(Deprivation)	0.136*	0.045*	0.137
log(PTAL)	0.031*	0.011*	0.030
AIC	-8510.8	-9863.3	-11242
R ²	0.7889 (78.89%)	N/A	0.9318 (93.18%)

 The GWR model is better than the linear and Spatial Lag regression. We take the model with the highest R-squared value, as well as the lowest AIC value.

Reporting the local estimates (using socioeconomic deprivation (adjusted for other risk factors) as an motivating example)



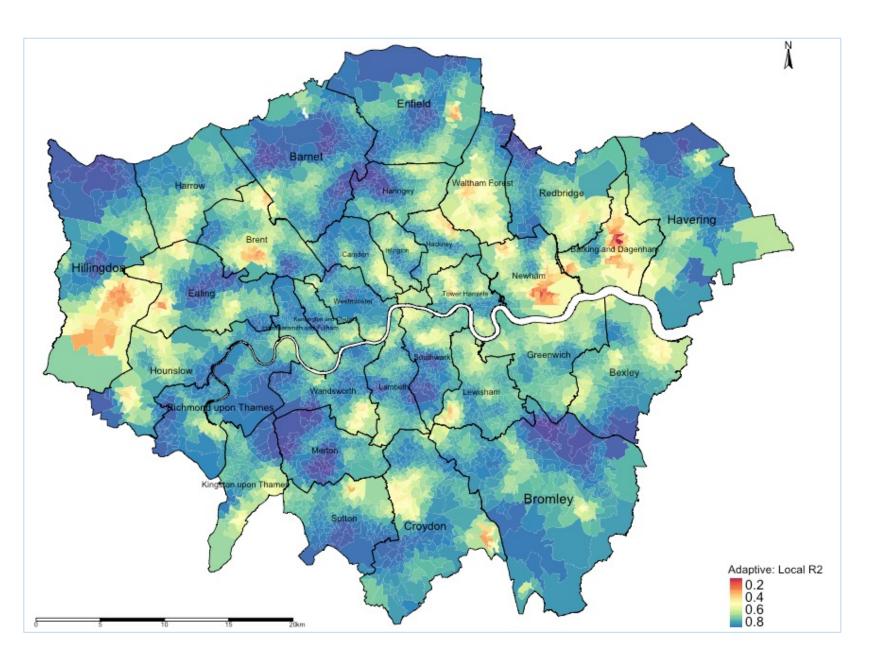
Interpretation: There is spatial variability in the relationship between our variable socioeconomic deprivation (transformed) and averaged house price (transformed) in London. The GWR outputs reveals that local coefficients range from a minimum value of -0.946 to a maximum value of 1.085, indicating that one percentage point increase in the levels of deprivation in LSOAs of London is associated with a reduction of 0.946% in house prices in some LSOAs and (weirdly) an increase of 1.085% in others. Broadly, the relationship are opposing.



Interpretation: For instance, in the Borough of Hounslow, we can see a significant reduction in house prices in relation to increased levels of socioeconomic deprivation (adjusted for income and accessibility). Such reduction are clustered in the midsection of Borough of Hounslow which were coloured red. Note that in far north eastern section of the Borough of Hounslow with pockets of LSOA's coloured blue shows a significant increase in house price in relationship to IMD which is difficult to explain and thus can be interpreted as a chance finding. All sections that are coloured white are not significant.

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Reporting the local R-squared to assess the model's performance for each areas



Interpretation: The areas that are going towards the shade of dark reds (i.e., value of 0) are local regression models that have broadly performed poorly in its prediction for house price and its association with the three variables (income, deprivation and PTAL). Likewise, the areas that are going towards the shade of dark blues (i.e., value of 1) are local regression models that have broadly performed very well in its prediction for house price and its association with the three variables (income, deprivation and PTAL).

Note: These results are essential as the local R2 values of each area show the model's ability to predict the explained variance in house prices caused by deprivation, income and accessibility for specific areas. Any questions?

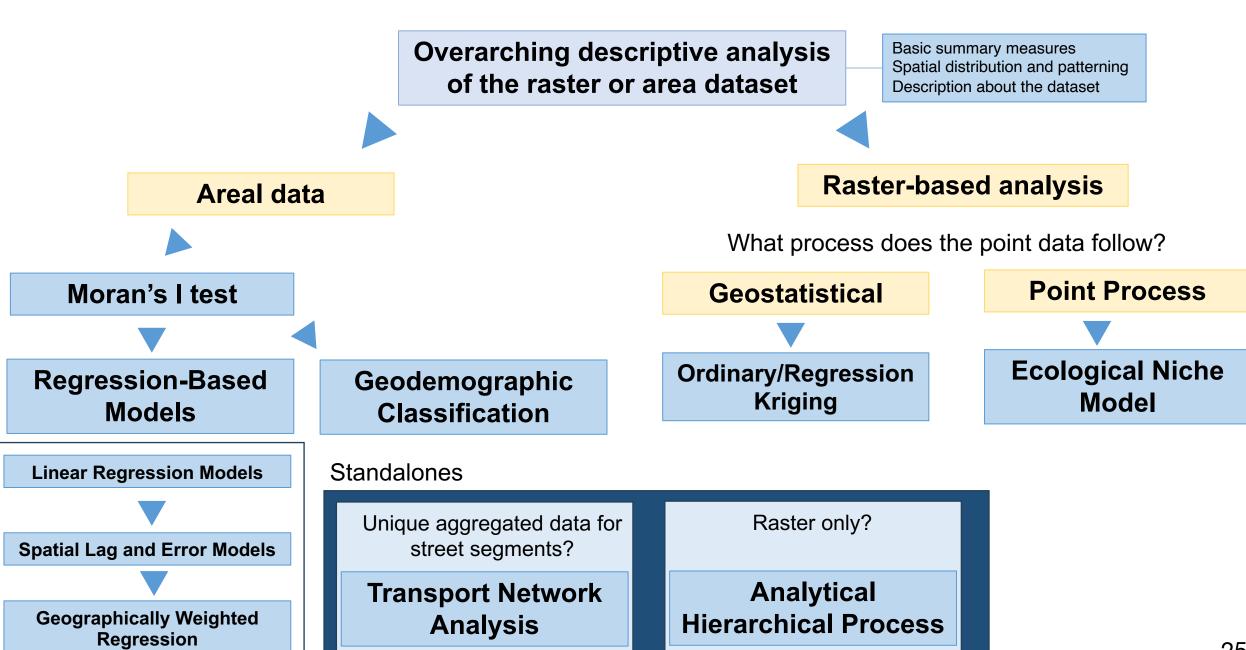


Summary of GEOG0114 & Assessment

What have we covered in the last 10 weeks...

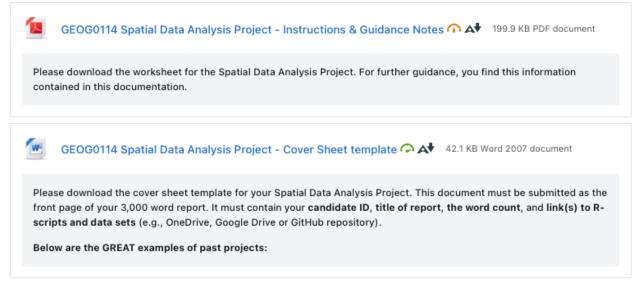
Week	Weekly Topics
1	Spatial Analysis for Data Science
2	Graphical Representation of Spatial Data
3	Spatial Autocorrelation
4	Suitability Mapping: Part I (Qualitative approach)
5	Suitability Mapping: Part II (Quantitative approach)
Reading Week (Assessment)	
6	Geostatistics using Kriging
7	Geodemographics
8	Transport Network Analysis
9	Spatial Models: Part I (Spatial Lag & Error Models)
10	Spatial Models: Part II (Geographically Weighted Regression)

Tips/Strategy for the Assignment



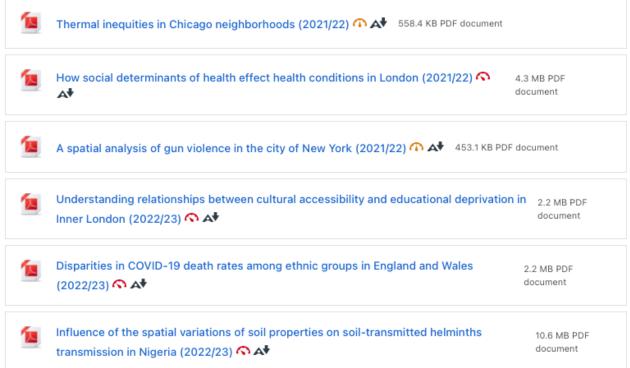
Go to Moodle's Assessment

Assignment Documentation: Guidance notes and Cover Sheet



PLEASE GO THROUGH THE DOCUMENTATION!

See Best examples of past projects from 2021/22 and 2022/23



Example Data source(s)

UK Census 2021: https://www.nomisweb.co.uk/sources/census 2021 bulk

UK Deprivation 2019: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019

UK population 2010-2020 estimates: https://shorturl.at/BCKX1

Police: https://data.police.uk/
CDRC: https://data.cdrc.ac.uk

Mosquito/species data:

- https://experience.arcgis.com/experience/7228a5a27442468494caec2934c2b73d/page/Page/
- https://www.gbif.org

Wildfire FIRMS: https://firms.modaps.eosdis.nasa.gov

Disease data: https://espen.afro.who.int/

https://espen.afro.who.int/tools-resources/cartography-database

https://espen.afro.who.int/tools-resources/download-data

Domestic fires I SOA:

https://assets.publishing.service.gov.uk/media/64be67369c2df000129402cf/low-level-geography-dataset-270723.ods https://www.gov.uk/government/statistics/fire-statistics-incident-level-datasets/low-level-geography-dataset-guidance

Inspiration for writing methodology

Musah et al. (2020): https://doi.org/10.1016/j.apgeog.2019.102126

Todd et al. (2022): https://doi.org/10.1177/23998083211001836

Li et al. (2022): https://doi.org/10.1016/j.apgeog.2022.102718

Any questions about the assignment?



GEOG0114: Course Evaluation & Student Feedback (Week 7-10)

https://forms.gle/55AydSPLrV8cBcwn7

Dear Students,

As part of the Continuous Module Dialogue, we are conducting this survey to gauge the levels of student satisfaction with the learning experience in module **GEOG0114: Principles of Spatial Analysis**. We would like to receive your feedback, which would be greatly appreciated. This will help us make improvements to the course. The survey should only take up to 5 or 10 minutes, and your responses are completely anonymous.

Thank you,

Anwar and Justin.

See you in term 2

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