R in spatial analysis for conservation: space is special

Lex Comber

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LEEDS Institute for Data Analytics

UNIVERSITY OF LEEDS

Acknowledgments

Rainfall data: https://catalogue.ceh.ac.uk/documents/f2856ee8-da6e-4b67-bedb-590520c77b3c
Tanguy, M.; Dixon, H.; Prosdocimi, I.; Morris, D. G.; Keller, V. D. J. (2015). Gridded estimates of daily and monthly areal rainfall for the United Kingdom (1890-2014) [CEH-GEAR]. NERC Environmental Information Data Centre. http://doi.org/10.5285/f2856ee8-da6e-4b67-bedb-590520c77b3c

PET data: http://csi.cgiar.org/Aridity/
Trabucco, A., and Zomer, R.J. 2009. Global Aridity Index (Global-Aridity) and Global Potential Evapo-Transpiration (Global-PET) Geospatial Database. CGIAR Consortium for Spatial Information. Published online, available from the CGIAR-CSI GeoPortal at: http://www.csi.cgiar.org

Wildness Quality Index:
Kuiters, A. T., van Eupen, M., Carver, S., Fisher, M., Kun, Z., & Vancura, V. (2011). *Wilderness register and indicator for Europe*. Final Report - http://ec.europa.eu/environment/nature/natura2000/wilderness/pdf/Wilderness_register_indicator.pdf

Pre-amble

- The aim of this talk is to introduce an explicitly ***spatial*** way of thinking
- **All data** are spatial now
- This requires and allows careful consideration of the spatial properties of data
- Distance / location are **not just another variable**

Pre-amble

- As a Geographer I am interested in **how** and **where** processes, relationships, trends, etc **vary** spatially
- I do not expect relationships to be the same everywhere
  - the world is not normally or randomly distributed
- I Expect to find **clusters**, hot / cold spots, etc
- Tobler's 1st Law of Geography

Tobler's First Law of Geography

"Everything is related to everything else, but near things are more related to each other"

http://en.wikipedia.org/wiki/University_of_California,_Santa_Barbara

Waldo Tobler in front of the Newberry Library. Chicago, November 2007 (http://en.wikipedia.org/wiki/Waldo_R._Tobler)

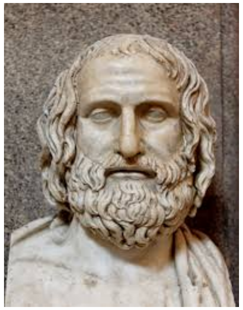
Tobler W., (1970) A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46(2): 234-240

Pre-amble

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

- Key concept in spatial statistics / quant geog
- Not the first – similar ideas found in:
  - Crop science (Fischer & Gosset 1935)
  - Meteorology (Kolmogorov 1941; Gandin 1965)
  - Mining (Krige 1951; Matheron 1963)
  - Forestry (Matérn 1960)
  - Theory (Yaglom 1955)

- Euripides: *Slight not what's near, though aiming for what is far*:



Pre-Amble

- There are many spatial statistics paradigms:
  - Geostatistical models
  - Spatial regression models
  - Spatial point process models
  - Spatial ecology models
  - Spatial movement (trajectories) models
  - Spatial interaction models
  - Geographically weighted models
  - & more...

Pre-Amble

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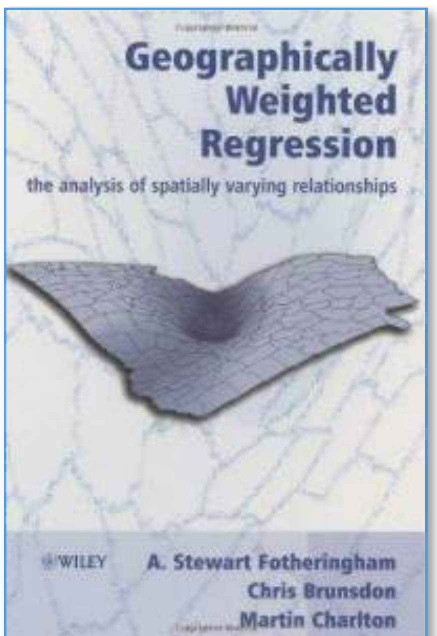
  - **Geographically weighted models**
  - & more...

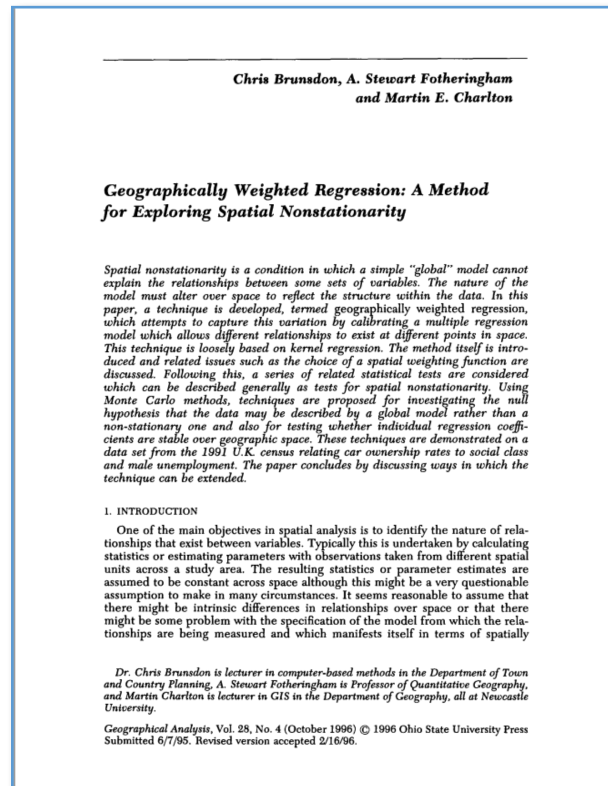
Pre-Amble

- There are many spatial statistics paradigms:
  - Geostatistical models
  - Spatial regression models
  - Spatial point process models
  - Spatial ecology models
  - Spatial movement (trajectories) models
  - Spatial interaction models
  - **Geographically weighted models**
  - & more...
- Choose one according to: (i) spatial process, (ii) spatial data type, (iii) inferential framework & (iv) research objectives
- BUT there are numerous overlaps…

GW Models

- Brunsdon C, Fotheringham AS, Charlton ME (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis* 28(4):281-298
- Many papers & a book in 2002…





Chris Brunsdon, A. Stewart Fotheringham
and Martin E. Charlton

Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity

Spatial nonstationarity is a condition in which a simple "global" model cannot explain the relationships between some sets of variables. The nature of the model must alter over space to reflect the structure within the data. In this paper, a technique is developed, termed geographically weighted regression, *which attempts to capture this variation by calibrating a multiple regression model which allows different relationships to exist at different points in space. This technique is loosely based on kernel regression. The method itself is introduced and related issues such as the choice of a spatial weighting function are discussed. Following this, a series of related statistical tests are considered which can be described generally as tests for spatial nonstationarity. Using Monte Carlo methods, techniques are proposed for investigating the null hypothesis that the data may be described by a global model rather than a non-stationary one and also for testing whether individual regression coefficients are stable over geographic space. These techniques are demonstrated on a data set from the 1991 U.K. census relating car ownership rates to social class and male unemployment. The paper concludes by discussing ways in which the technique can be extended.*

1. INTRODUCTION

One of the main objectives in spatial analysis is to identify the nature of relationships that exist between variables. Typically this is undertaken by calculating statistics or estimating parameters with observations taken from different spatial units across a study area. The resulting statistics or parameter estimates are assumed to be constant across space although this might be a very questionable assumption to make in many circumstances. It seems reasonable to assume that there might be intrinsic differences in relationships over space or that there might be some problem with the specification of the model from which the relationships are being measured and which manifests itself in terms of spatially

Dr. Chris Brunsdon is lecturer in computer-based methods in the Department of Town and Country Planning, A. Stewart Fotheringham is Professor of Quantitative Geography, and Martin Charlton is lecturer in GIS in the Department of Geography, all at Newcastle University.

Geographical Analysis, Vol. 28, No. 4 (October 1996) © 1996 Ohio State University Press
Submitted 6/7/95. Revised version accepted 2/16/96.

Outline

- The Problem and Data:
  - describe a hypothetical and simplified problem
  - data from *GBIF* linked to other data
- GW Model and GWR
- Results
  - Some maps
- GW Considerations

Problem & Data

- Data of presence of *Acer campestre*, field maple, downloaded from *GBIF*
  - `dismo` package

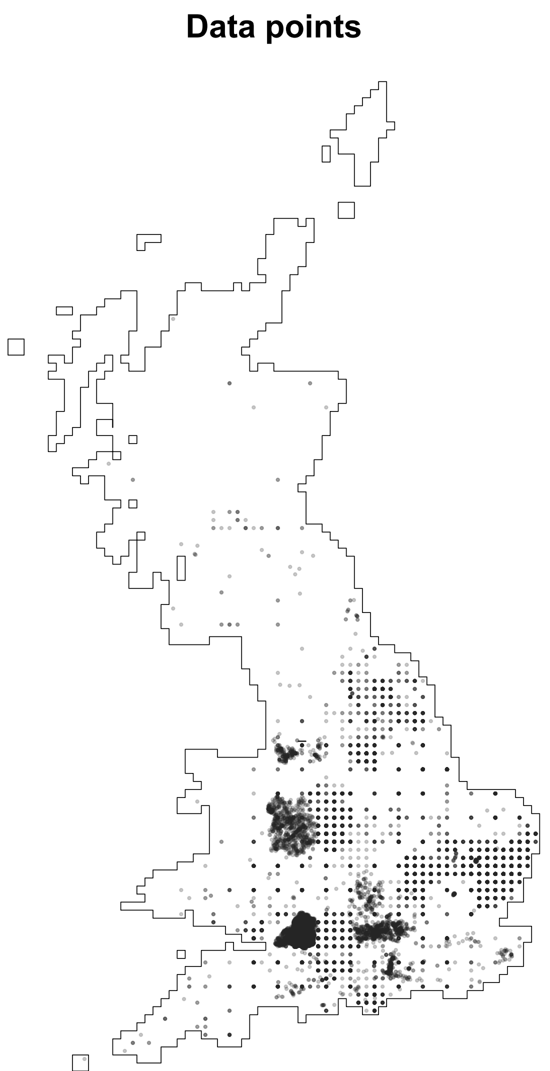
- Data for UK, 1980 to 2010 subsetted

- Aims: to roughly test the model suggested by Coudun et al (2006)[1]
  - Presence significantly related to
    - Autumn rainfall (October, November and December)
    - Actual Thornthwaite evapotranspiration

Coudun, C., Gégout, J.-C., Piedallu, C. and Rameau, J.-C. (2006), Soil nutritional factors improve models of plant species distribution: an illustration with Acer campestre (L.) in France. *Journal of Biogeography,* 33: 1750–1763

Problem & Data

- Data points in UK, 22781 records
  - Uneven distribution in time & space
  - Considered absence points
  - Background vs Pseudo-absences (e.g. Phillips et al. 2009)



Problem & Data

- Data points in UK, 22781 records
  - Uneven distribution in time & space
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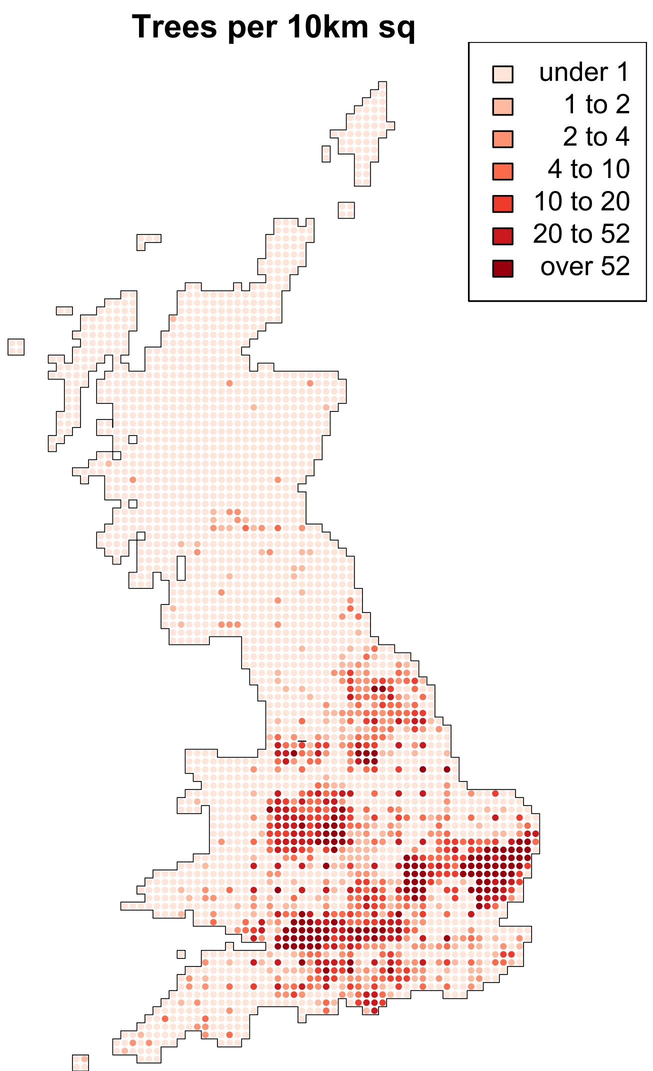
- BUT took a much simpler approach
  - All years together
  - Counts over OS 10k grid



Problem & Data

- Data points in UK, 22781 records
  - Uneven distribution in time & space
  - Considered absence points
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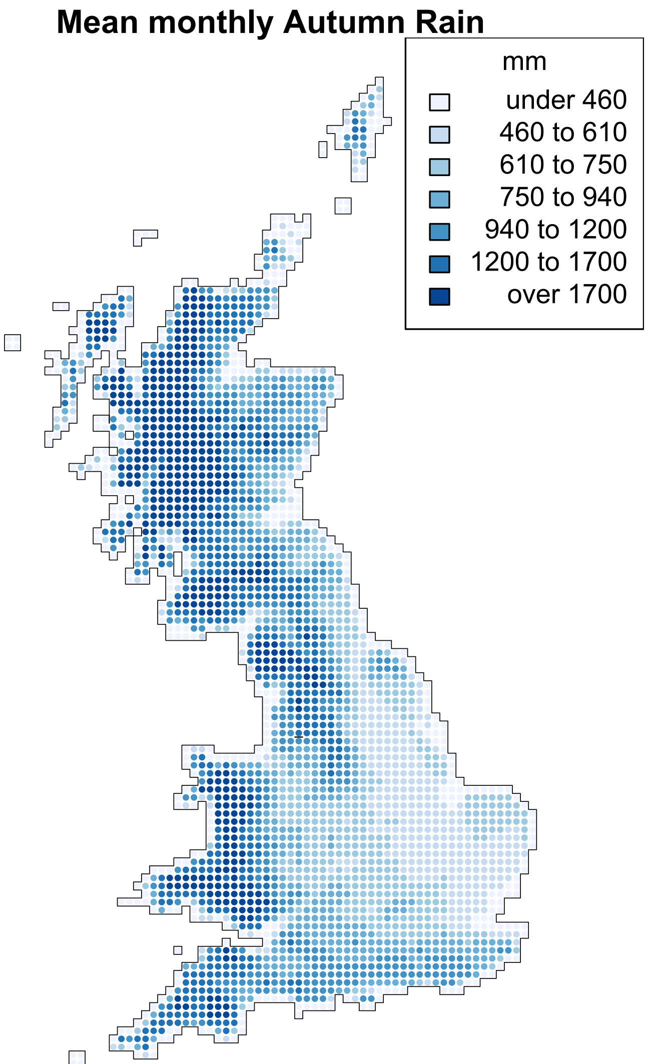
- Linked the counts to other data:
  - Mean Autumn rainfall



Problem & Data

- Data points in UK, 22781 records
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  - Considered absence points
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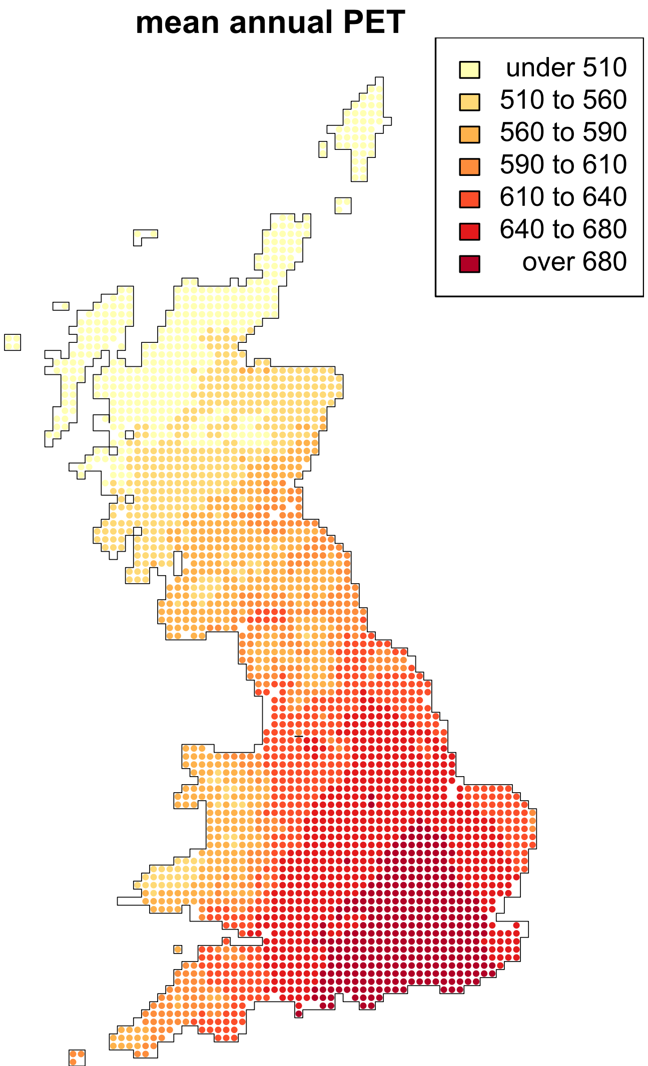
- Linked the counts to other data:

  - Mean Annual PET

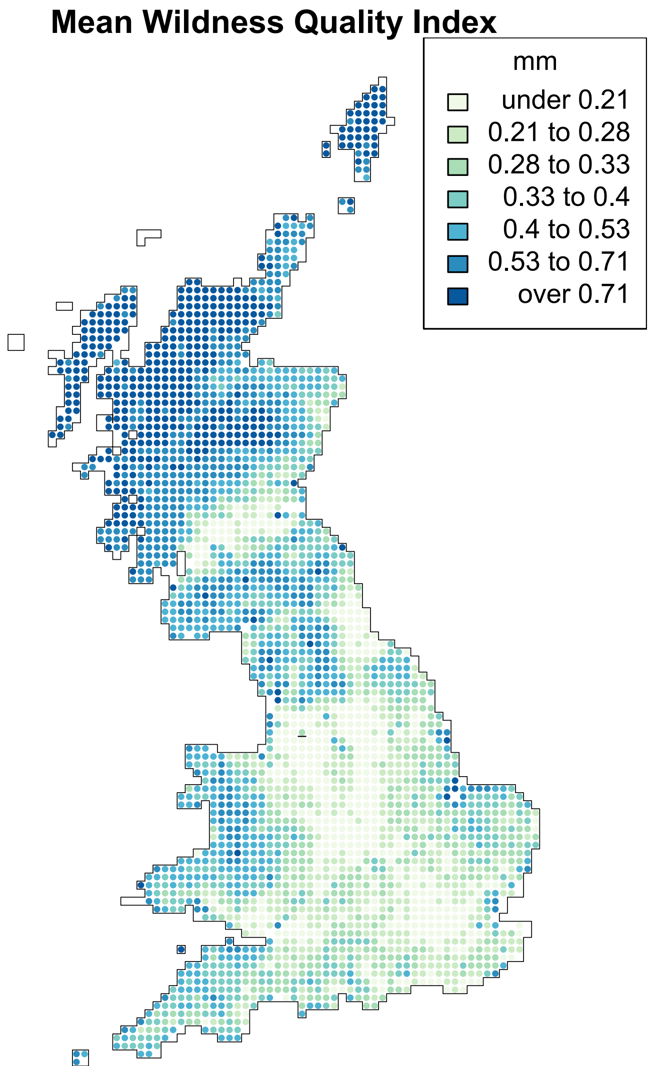


Problem & Data

- Data points in UK, 22781 records
  - Uneven distribution in time & space
  - Considered absence points
  - Background vs Pseudo-absences (e.g. Phillips et al. 2009)

- Linked the counts to other data:

  - Wildness Index



Problem & Data

- Data with 4 variables
- Some correlation
  - Come back to that later

```
>
> data.agg@data[sample(1:nrow(data.agg), 6),]
     tree      pet      rain       wqi
2442    1 721.4783  185.6486 0.3272968
1911   34 630.9040  755.9915 0.3188434
1356   14 651.9789 1082.2011 0.1222428
1900   20 621.7727  815.5709 0.4161045
512     0 549.7136  958.5777 0.3367307
887     0 555.8598 2440.5218 0.5235970
>
```

```
>
> round(cor(data.agg@data,
+   use = "pairwise.complete.obs"), 3)
       tree    pet   rain    wqi
tree  1.000  0.193 -0.066 -0.183
pet   0.193  1.000 -0.335 -0.823
rain -0.066 -0.335  1.000  0.379
wqi  -0.183 -0.823  0.379  1.000
>
```

Problem & Data

- OLS model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \beta_n x_n$$

Where y is tree count, x_1, x_2 and x_3 are the predictor variables

- Autumn rainfall
- PET
- Wildness (WQI)

Problem & Data

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Where y is tree count, x_1, x_2 and x_3 are the predictor variables

- Autumn rainfall
- PET
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```
> m <- lm(tree~pet+rain+wqi, data = data.frame(data.agg))
> summary(m)

Call:
lm(formula = tree ~ pet + rain + wqi, data = data.frame(data.agg))

Residuals:
   Min      1Q  Median      3Q     Max 
-23.77 -11.36   -6.51    1.54  707.60 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -2.812e+01  1.322e+01  -2.128   0.0335 *  
pet          7.173e-02  1.822e-02   3.936  8.5e-05 ***
rain        -2.819e-04  1.208e-03  -0.233   0.8155    
wqi         -1.427e+01  6.443e+00  -2.215   0.0269 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Problem & Data

- OLS model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \beta_n x_n$$

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---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

- Not quite same as Coudun et al
- Interested in **spatial variation**

Outline

- The Problem and Data:
  - describe a hypothetical and simplified problem
  - data from *GBIF* linked to other data
- GW Models (inc. GWR)
- Results
  - Some maps
- GW Considerations

GW Models

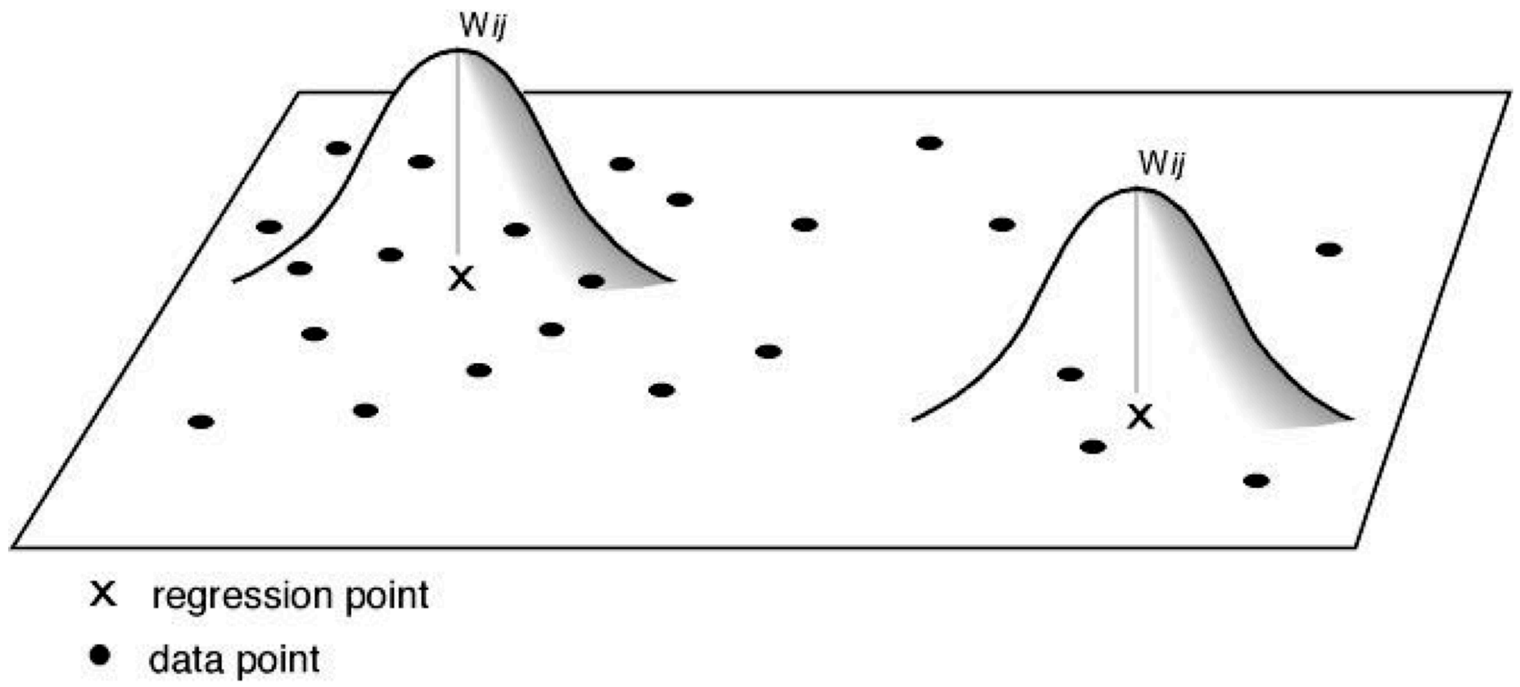
- Use a **moving window** or **kernel**
  - the '*geographically*' bit

- Data under the kernel are weighted by their **distance to the kernel centre**
  - the '*weighted*' bit

- A local model constructed **at that kernel location**
  - Regression, PCA, correspondence analysis, etc

GW Models

- Use a **moving window** or **kernel**
  - the '*geographically*' bit



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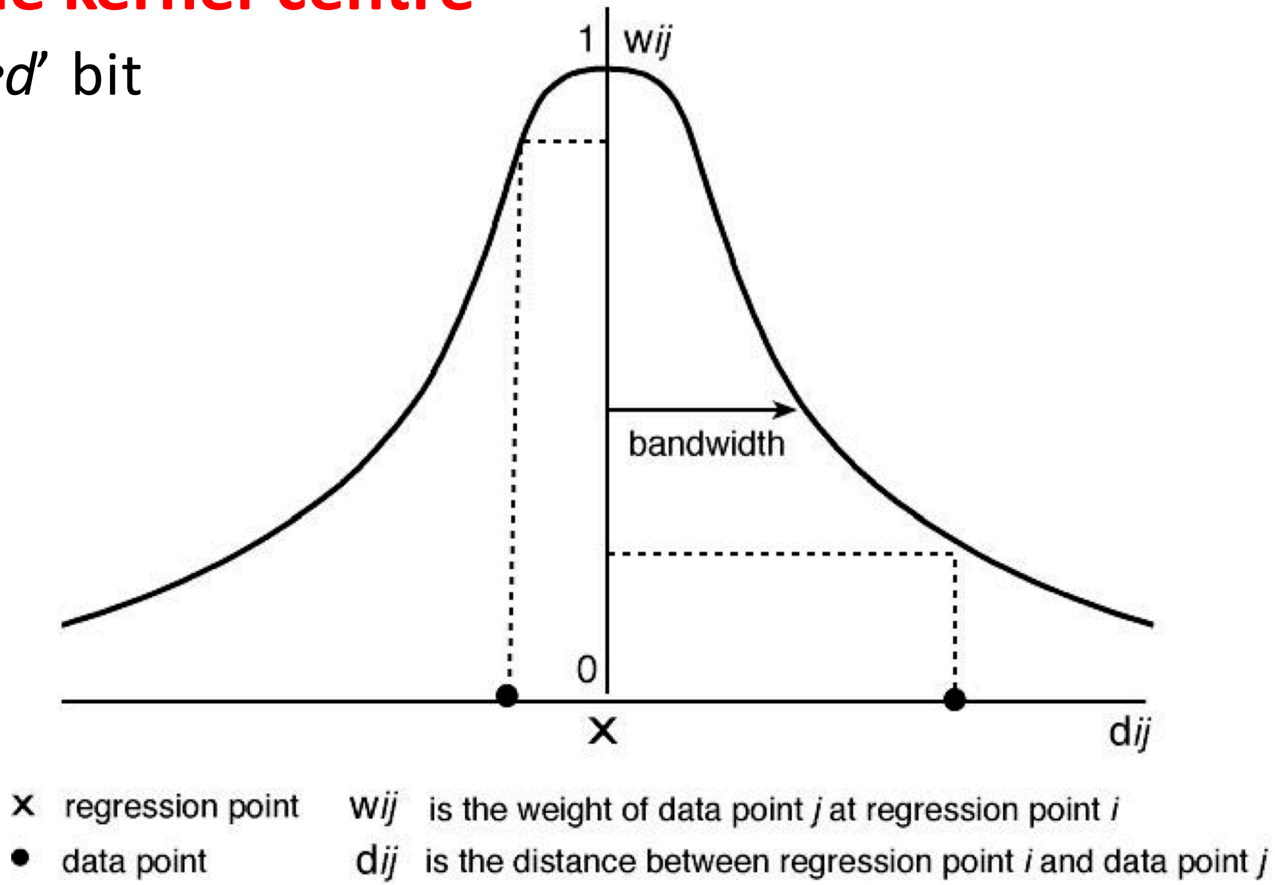

GW Models

- A local model constructed at that **kernel location**, using that **weighted data**
  - Regression, PCA, correspondence analysis, etc

$$y = \beta_{0(u_i,v_i)}0 + \beta_1 x_{1(u_i,v_i)} + \beta_2 x_{2(u_i,v_i)} \dots \beta_n x_{n(u_i,v_i)}$$

- GW Models
  - **coefficients** assumed to **vary spatially** over the space defined by the **coordinates (*u*, *v*)**

GW Models

- A local model constructed at that **kernel location**, using that **weighted data**
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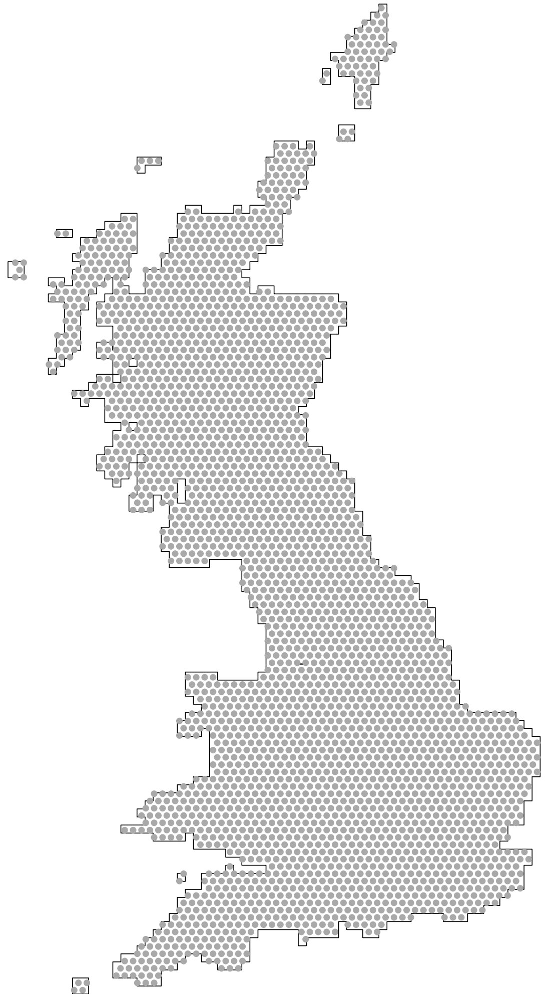
- GW Models
  - **coefficients** assumed to **vary spatially** over the space defined by the **coordinates (*u*, *v*)**

GW Models

- Kernel bandwidth optimally selected
  - 21 data points
- Hexagonal grid of 3028 locations
- Local regression model constructed at each location

Regression locations



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Results

- Examine how ***local*** GW coefficient estimates vary

	Min.	1st Qu.	Median	3rd Qu.	Max.
Intercept	-2.057e+04	-2.770e+01	0.000e+00	1.338e+01	37490.000
d.a.pet	-5.134e+01	-2.055e-02	0.000e+00	4.343e-02	30.430
d.a.rain	-3.086e+00	-1.149e-04	0.000e+00	2.339e-03	3.372
d.a.wqi	-4.842e+03	-3.563e+00	0.000e+00	1.995e+00	1391.000

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- Compared to ***global*** estimate

Coefficients:

	Estimate
(Intercept)	-2.812e+01
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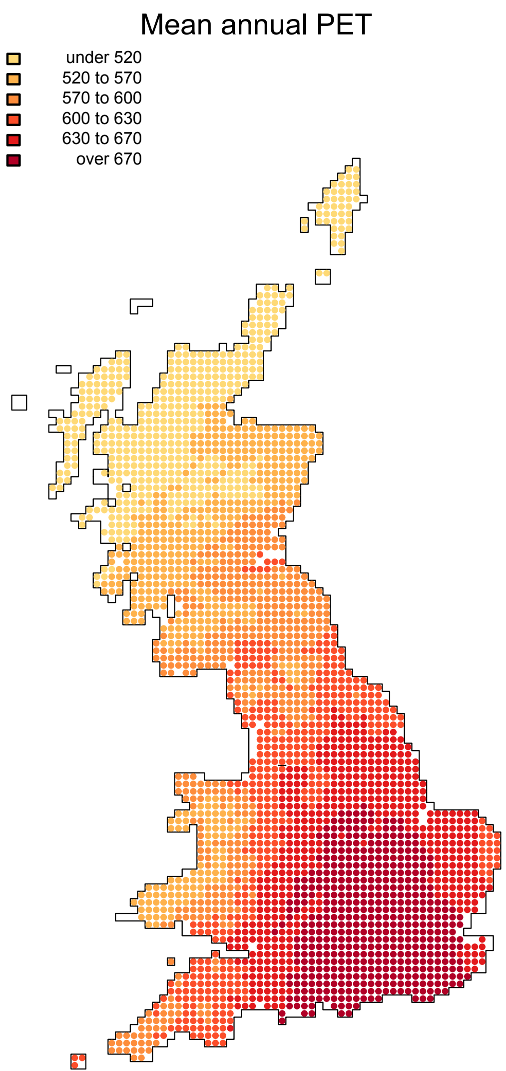
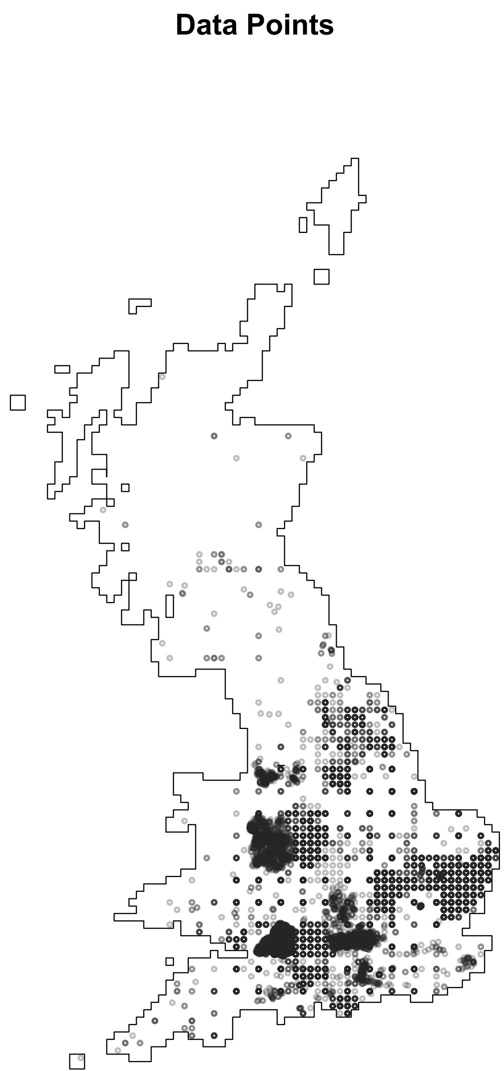
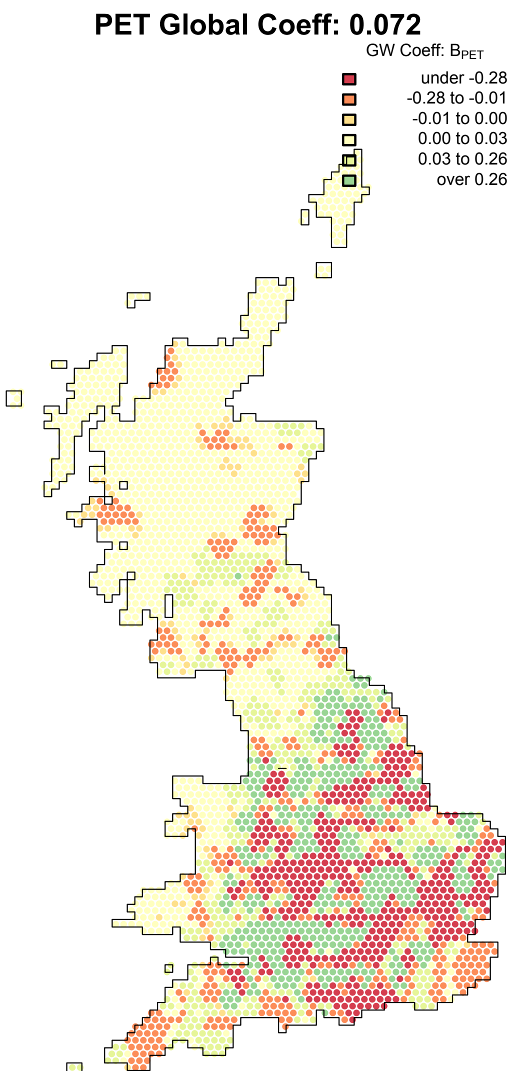
rain	-2.819e-04
wqi	-1.427e+01

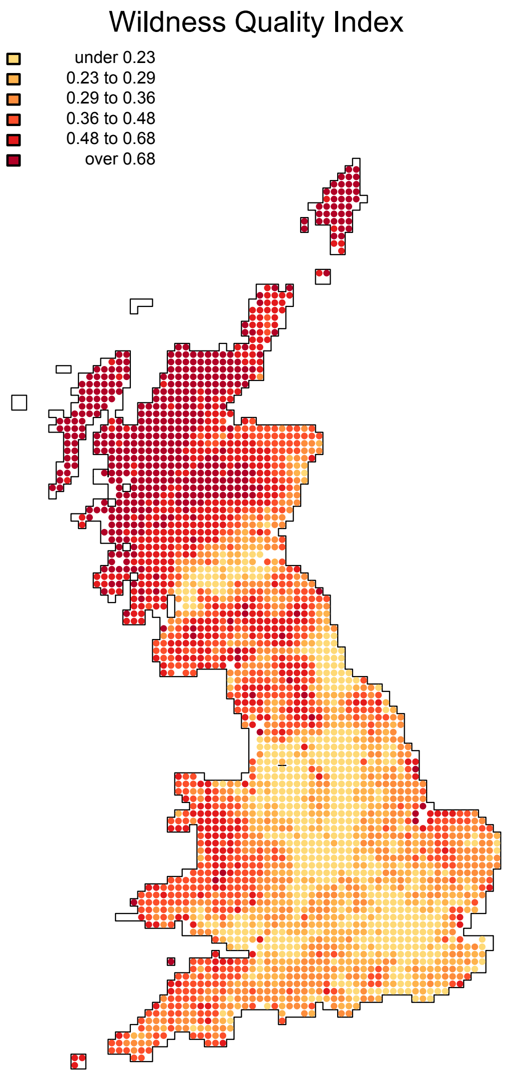
Results

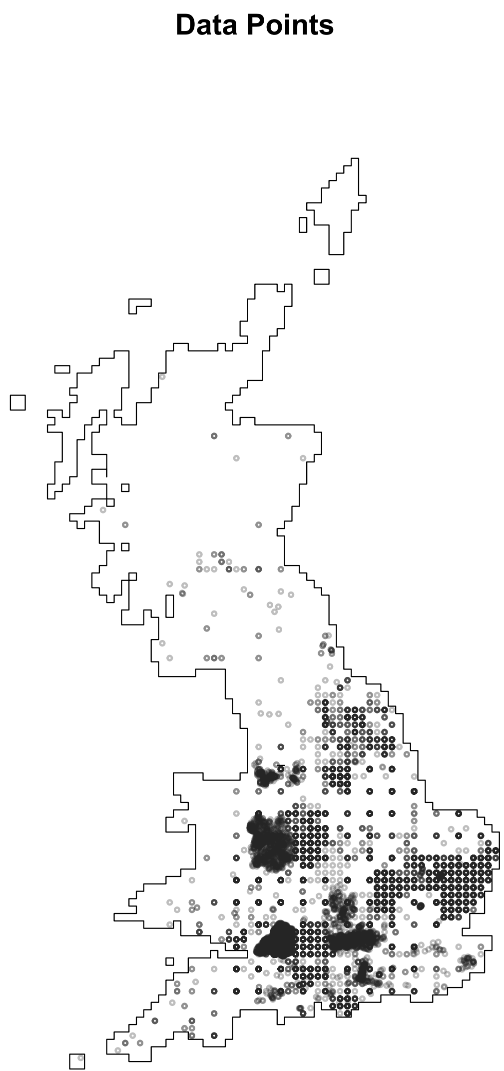

Mean annual PET
under 520
520 to 570
570 to 600
600 to 630
630 to 670
over 670

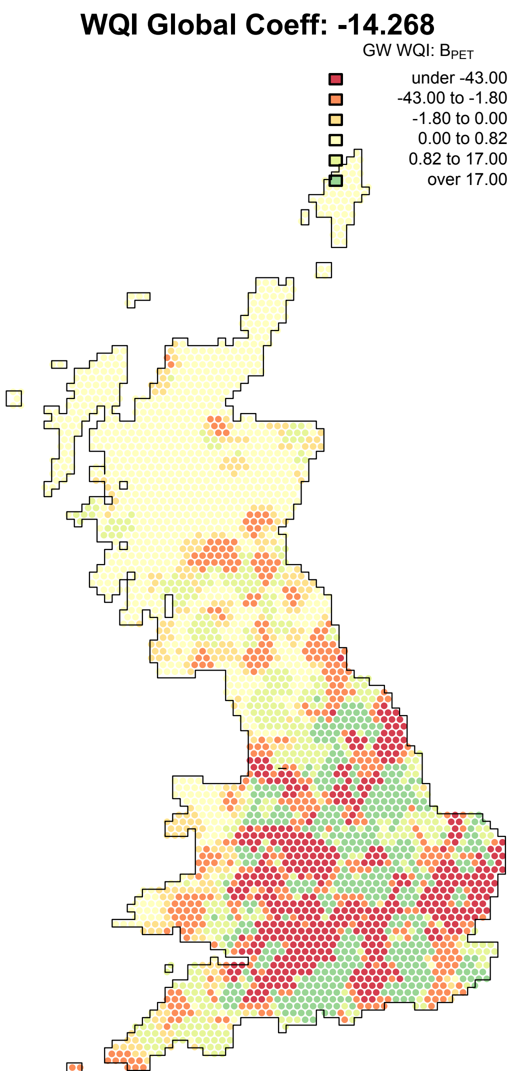

Data Points


PET Global Coeff: 0.072
GW Coeff: B_{PET}
under -0.28
-0.28 to -0.01
-0.01 to 0.00
0.00 to 0.03
0.03 to 0.26
over 0.26

Results


Wildness Quality Index
under 0.23
0.23 to 0.29
0.29 to 0.36
0.36 to 0.48
0.48 to 0.68
over 0.68


Data Points


WQI Global Coeff: -14.268
GW WQI: B_{PET}
under -43.00
-43.00 to -1.80
-1.80 to 0.00
0.00 to 0.82
0.82 to 17.00
over 17.00

Results

- Distinct **local patterns** in the degree to which the independent variables predict the target variable

- Relationships vary spatially

- Suggests areas for further investigation
  - GBIF sample representativeness
  - Guide absence data creation
  - Granularity of the auxiliary data

BUT

- ‘*What about collinearity*?’ I hear you ask

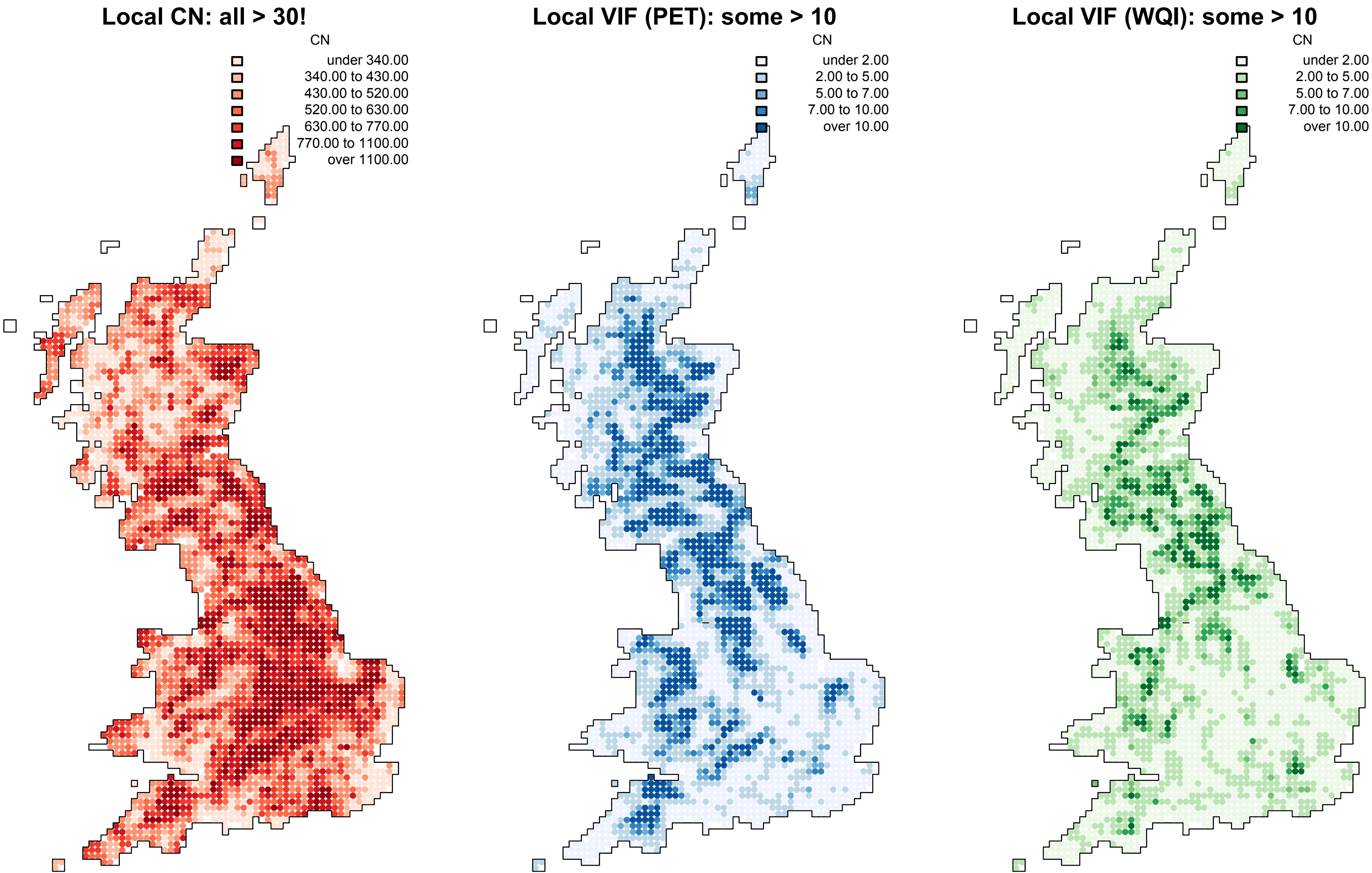
Collinearity in GW Models

- When variables exhibit linear or near linear relationships
- A problem in any regression model –
  - affects model reliability and precision
  - results in unstable parameter estimates
  - and inflated standard errors and inferential biases
- Reduces model inferential power, eroneous extrapolation & problems in separating variable effects
- GWR uses a moving window
  - Collinearity may be more be pronounced
  - Even when not observed globally counterpart
  - Some data subsets under the kernel exhibit strong collinearity

Collinearity in GW Models

- The `GWModel` package has tools to test for and correct local collinearity
- Collinearity found, **quite a lot!**
- Locally compensated ridge regression applied

Collinearity in GW Models



Locally-compensated ridge GWR

- Generates a slightly different set of coefficient estimates

LCR GWR

	Min.	1st Qu.	Median	3rd Qu.	Max.
Intercept	-2.057e+04	-2.770e+01	0.000e+00	1.338e+01	37490.000
d.a.pet	-5.134e+01	-2.055e-02	0.000e+00	4.343e-02	30.430
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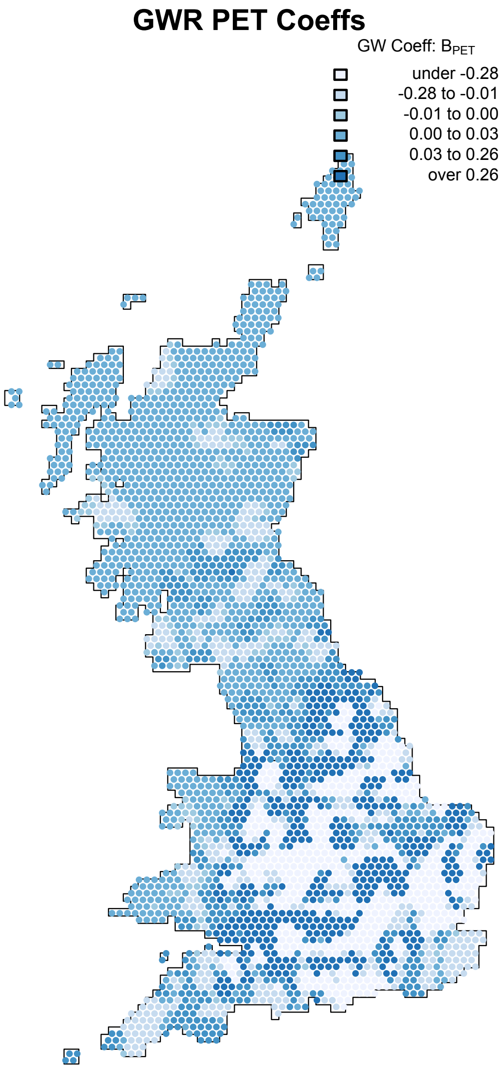
Original

	Min.	1st Qu.	Median	3rd Qu.	Max.
Intercept	-3.052e+01	-8.229e-02	0.000e+00	7.856e-02	96.7800
d.a.pet	-9.477e-01	0.000e+00	1.977e-06	4.964e-03	0.9358
d.a.rain	-4.087e-01	-2.456e-04	0.000e+00	7.995e-04	1.1200
d.a.wqi	-3.929e+03	-3.263e+00	0.000e+00	5.932e-01	650.7000
Local_CN	8.188e+01	3.846e+02	5.148e+02	7.302e+02	3878.0000

Result (LCR)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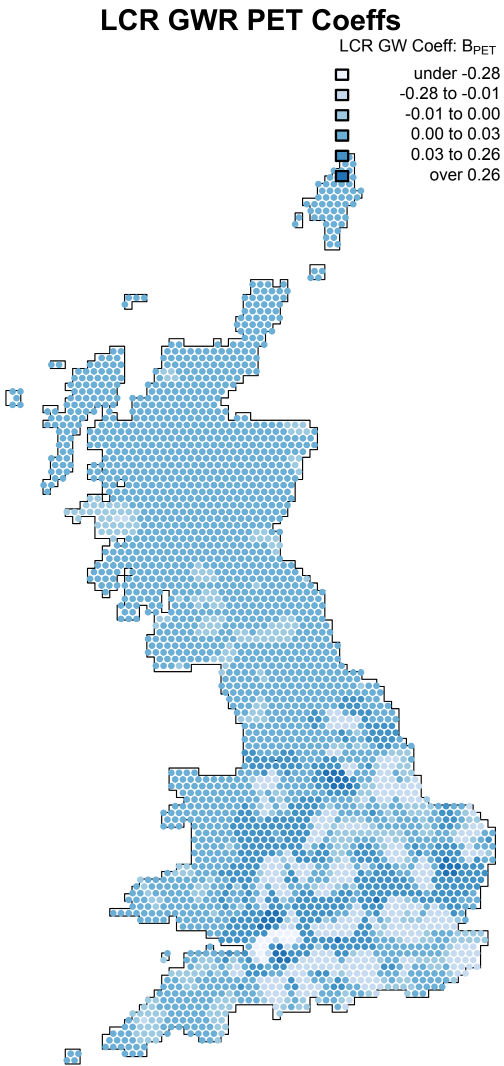
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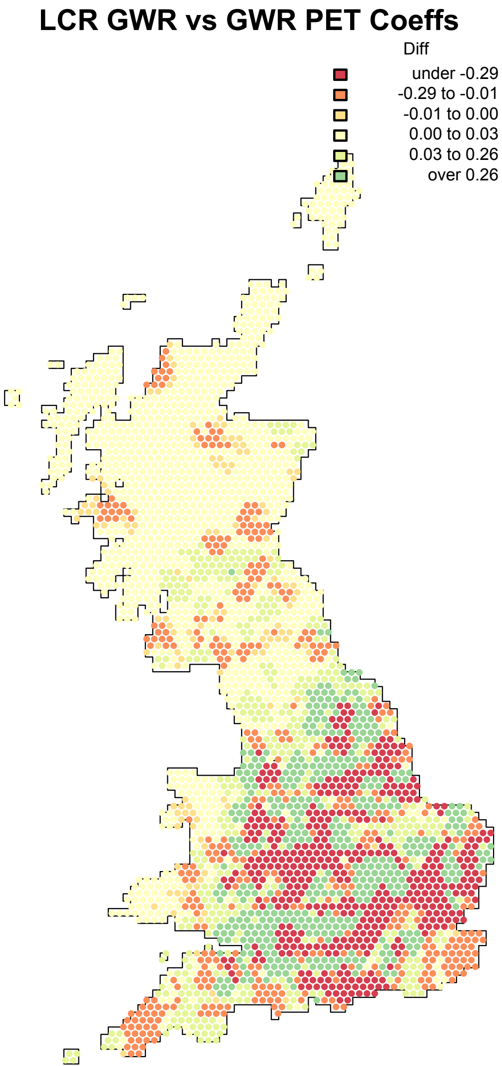
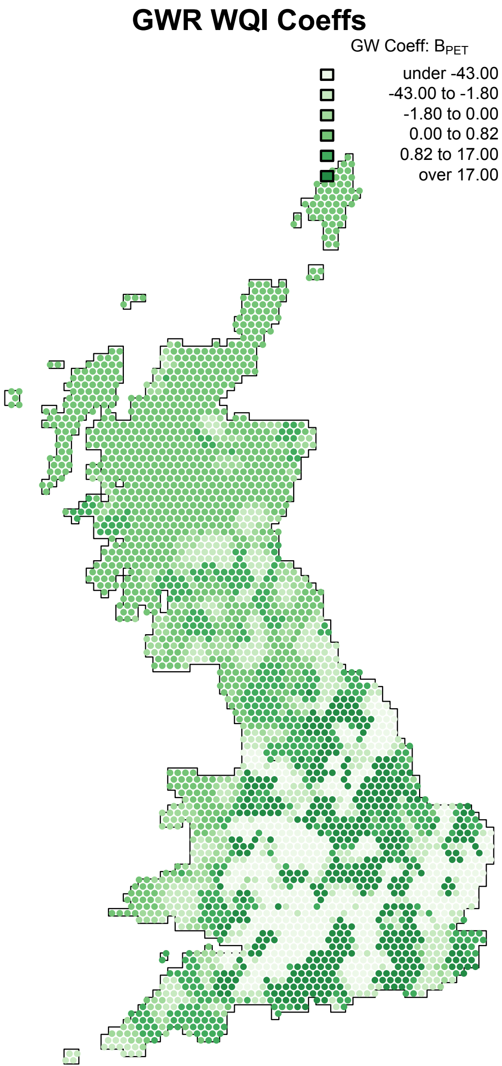
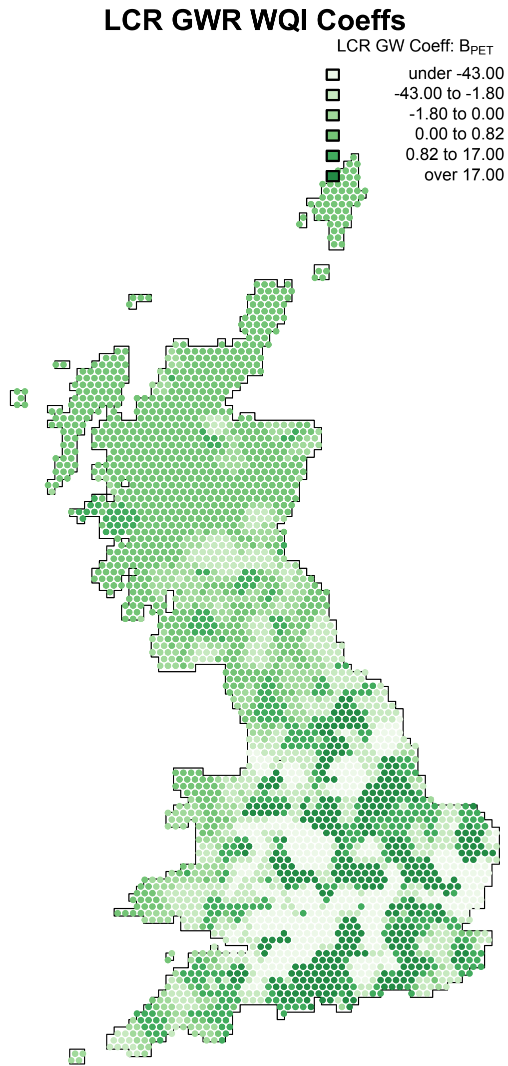
0.03 to 0.26
over 0.26


LCR GWR vs GWR PET Coeffs
Diff
under -0.29
-0.29 to -0.01
-0.01 to 0.00
0.00 to 0.03
0.03 to 0.26
over 0.26

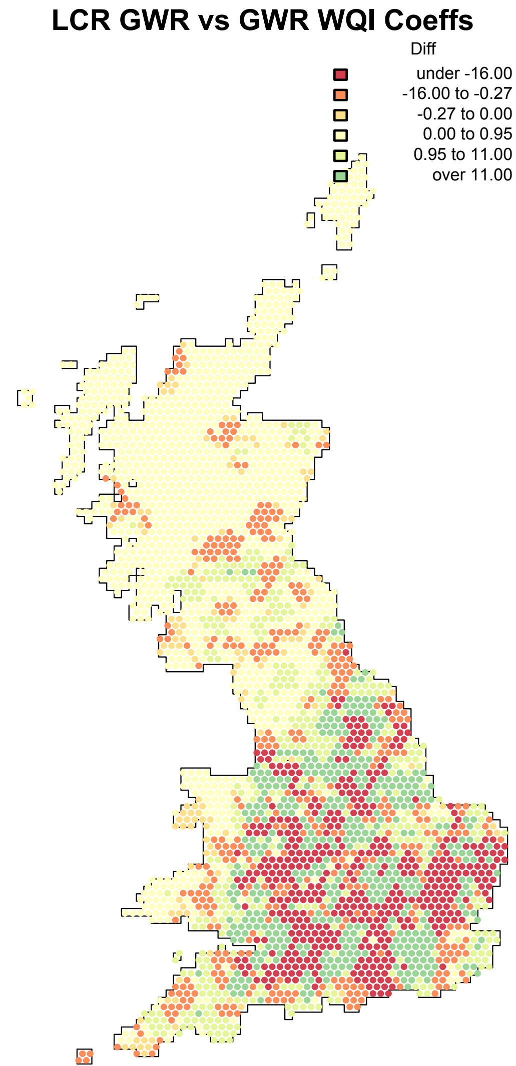
Result (LCR)



GWR WQI Coeffs
GW Coeff: B_{PET}
under -43.00
-43.00 to -1.80
-1.80 to 0.00
0.00 to 0.82
0.82 to 17.00
over 17.00



LCR GWR WQI Coeffs
LCR GW Coeff: B_{PET}
under -43.00
-43.00 to -1.80
-1.80 to 0.00
0.00 to 0.82
0.82 to 17.00
over 17.00



LCR GWR vs GWR WQI Coeffs
Diff
under -16.00
-16.00 to -0.27
-0.27 to 0.00
0.00 to 0.95
0.95 to 11.00
over 11.00

Result

- Summary

- GW framework support local analyses that quantify spatial heterogeneity in processes
    - More informative than global approaches
    - Investigative tool as well as model

- BUT local approaches can be subject to collinearity
    - Even when none exists globally

Outline

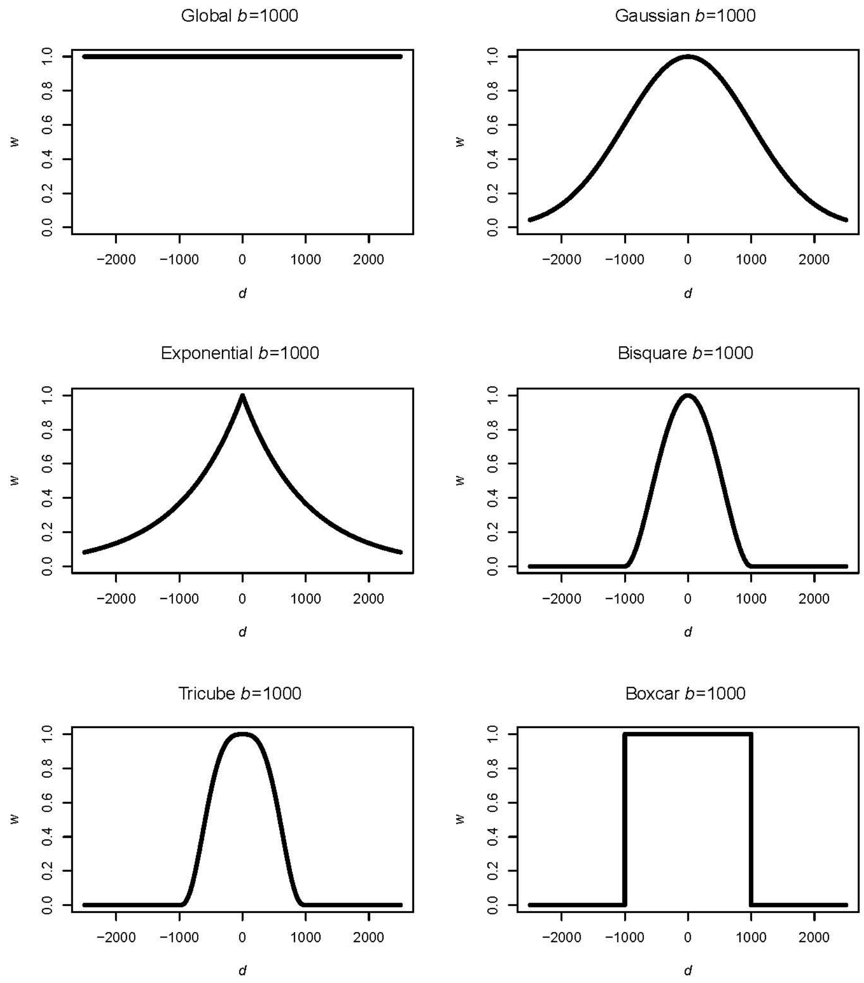
- The Problem and Data:
  - describe a hypothetical and simplified problem
  - data from *GBIF* linked to other data
- GW Model and GWR
- Results
  - Some maps
- GW Considerations

GW Considerations

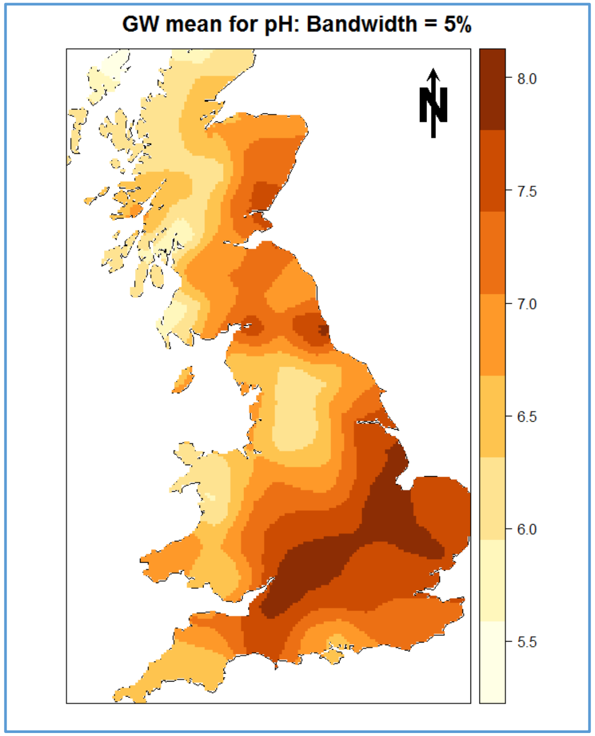
- Weighting
- Kernel type (weighting function)
- Bandwidth type
- Crucial to the whole GW approach…

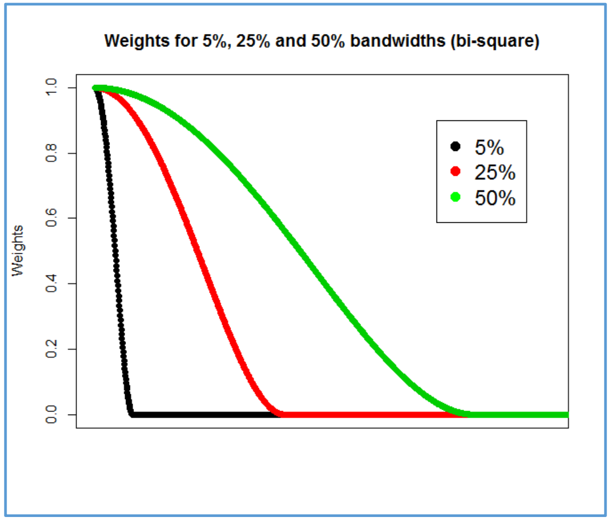
GW weighting: bandwidth

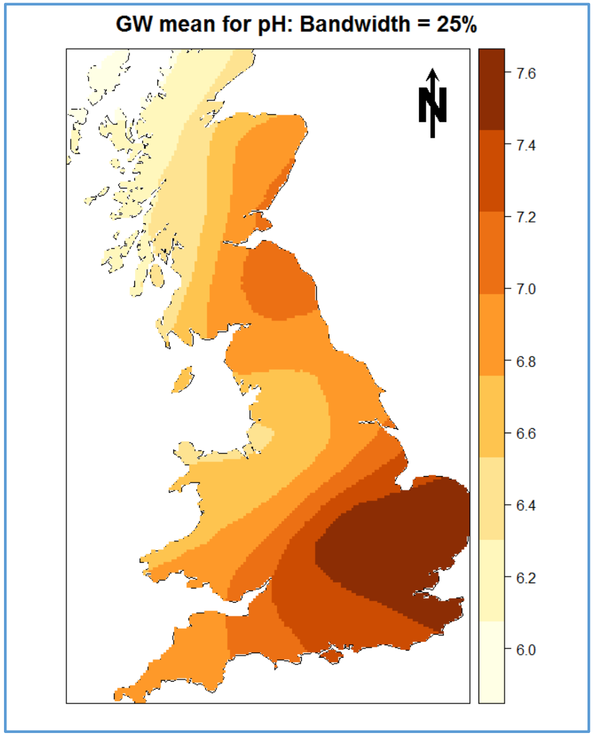
- All have same bandwidth of b=1000 distance units
- Weights (w) decrease as distance extends from 0
- **Global model**: all weights = 1
- **Continuous kernels**: Gaussian & Exponential
  - No zero weights – weights just get very close to zero at large distances
- **Discontinuous kernels**: Bi-square, Tri-cube & Boxcar
  - Zero weights when d > b

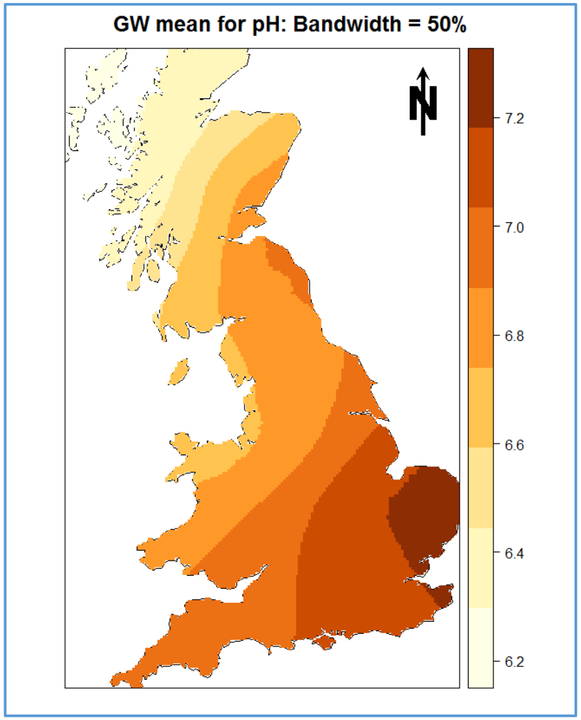


Effect of varying the bandwidth...









Two options:

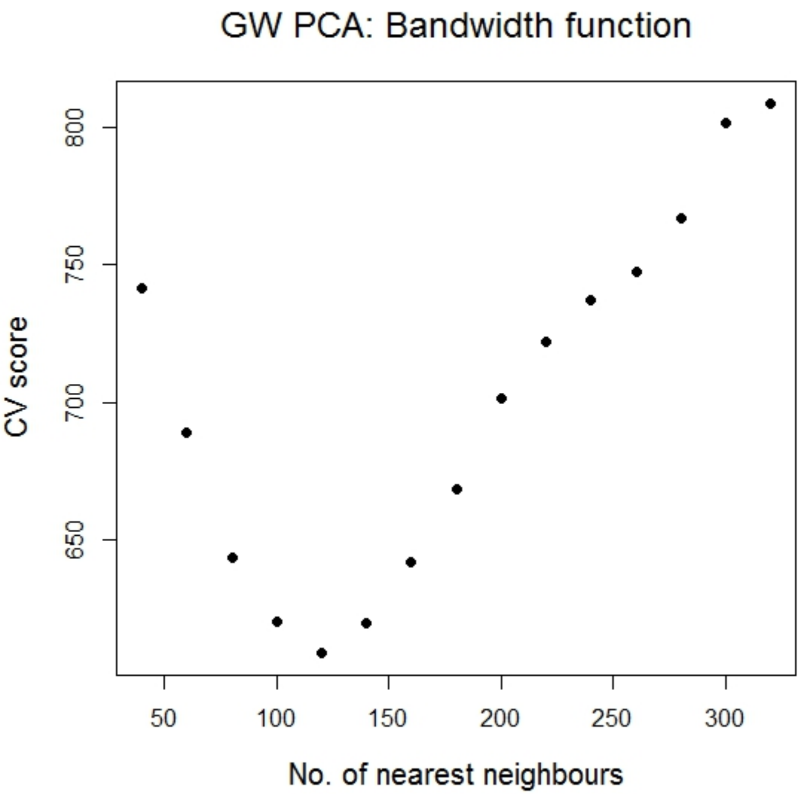
Fixed by distance
→ adaptive local sample size

Fixed by no. of nearest neighbours
→ adaptive local distances

Bi-square kernel in all 3 cases

CARE MUST ALWAYS BE TAKEN IN BANDWIDTH SELECTION

Optimal (objective) bandwidth selection



Provided the GW model can 'predict' or provide a 'goodness of fit' statistic then an OPTIMAL bandwidth can be found via cross-validation

Optimal bandwidths can be found for:

- GW averages (mean, median, etc.,)
- GW regressions (& related)
- GW PCAs)

Surrogate 'optimal' bandwidths can also be found for:

- GW variances
- GW correlations
- GW variograms

For all other GW models, the bandwidth must be user-specified.

GW Considerations

- So…Essentially all about constructing a **spatial version** of a some **non-spatial model**
  - Map & investigate the outputs…

- If happy with the concept – can do this for virtually **any** statistical technique

- Originates from quantitative geography in 1980/90's & the need to move away ***whole map statistics***
  - Stan Openshaw (Newcastle & Leeds groups)
  - Julian Besag's (Durham).

- See also Luc Anselin and **LISA** statistics (Arizona & GeoDa).

GW Considerations

- Spatial Data **Exploration** & (Dynamic) Visualisation
  - GW Sum Stats, GW Boxplots, GW Correlations, GW PCA, GW Parallel Coordinates
- Spatial **Regression**
  - GW Regression, GW Mixed Regression, Generalised GWR, & many, many variants of…
- Spatial **Prediction**
  - GW Averages, Any GWR, GWR-Kriging, GWR-Indicator Kriging, Kriging with GW Variograms
- Spatial **Classification**
  - GW Discriminant Analysis, GW PCA outputs as input variables to some standard classifier
- Spatial **Anomaly Detection**
  - Via robust versions of many the above GW models
- Spatial **Sample Re-design**
  - GW model outputs with some optimisation algorithm (greedy, sim. annealing etc.)

GW Considerations

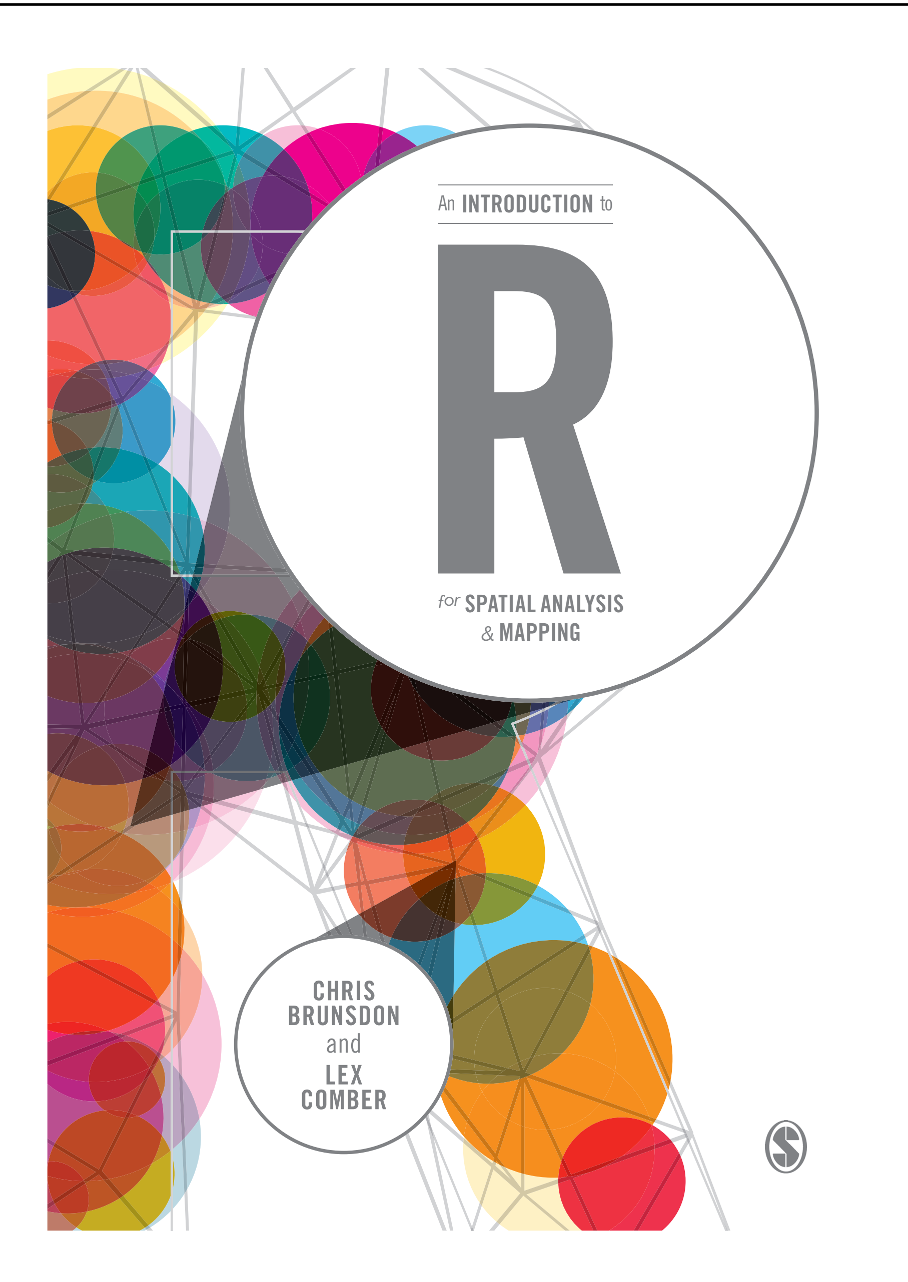
- Local Collinearity: **Tools exist** within `GWModel` package
- Some relationships **ARE** globally fixed: **Mixed GWR** models
- Relationship varies at different scale: **Flexible Bandwidth GWR**
- Geostatistics: **Area to point** GWR

Finally …

- Tried to demonstrate the GW **framework** and approach

- You can put **any statistic** under the kernel
  - Eg recently working with `gwxtab` package on Github

- Ecology driven by **natural** laws BUT these are increasingly being threatened by **anthropogenic** disturbance
  - Expect many of these processes to be **non-stationary** …



… a quick advert

- All of this work was done in R (& all my other work!)
- Recent Book for all your mapping and **spatial analysis** needs
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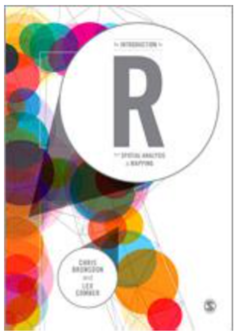

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"In an age of big data, data journalism and with a wealth of quantitative information around us, it is not enough for students to be taught only 100 year old statistical methods using 'out of the box' software. They need to have 21st-century analytical skills too. This is an excellent and student-friendly text from two of the world leaders in the teaching and development of spatial analysis. It shows clearly why the open source software R is not just an alternative to commercial GIS, it may actually be the better choice for mapping, analysis and for replicable research. Providing practical tips as well as fully working code, this is a practical 'how to' guide ideal for undergraduates as well as those using R for the first time. It will be required reading on my own courses."
- Richard Harris, Professor of Quantitative Social Science, University of Bristol

R is a powerful open source computing tool that supports geographical analysis and mapping for the many geography and 'non-geography' students and researchers interested in spatial analysis and mapping.

This book provides an introduction to the use of R for spatial statistical analysis, geocomputation and the analysis of geographical information

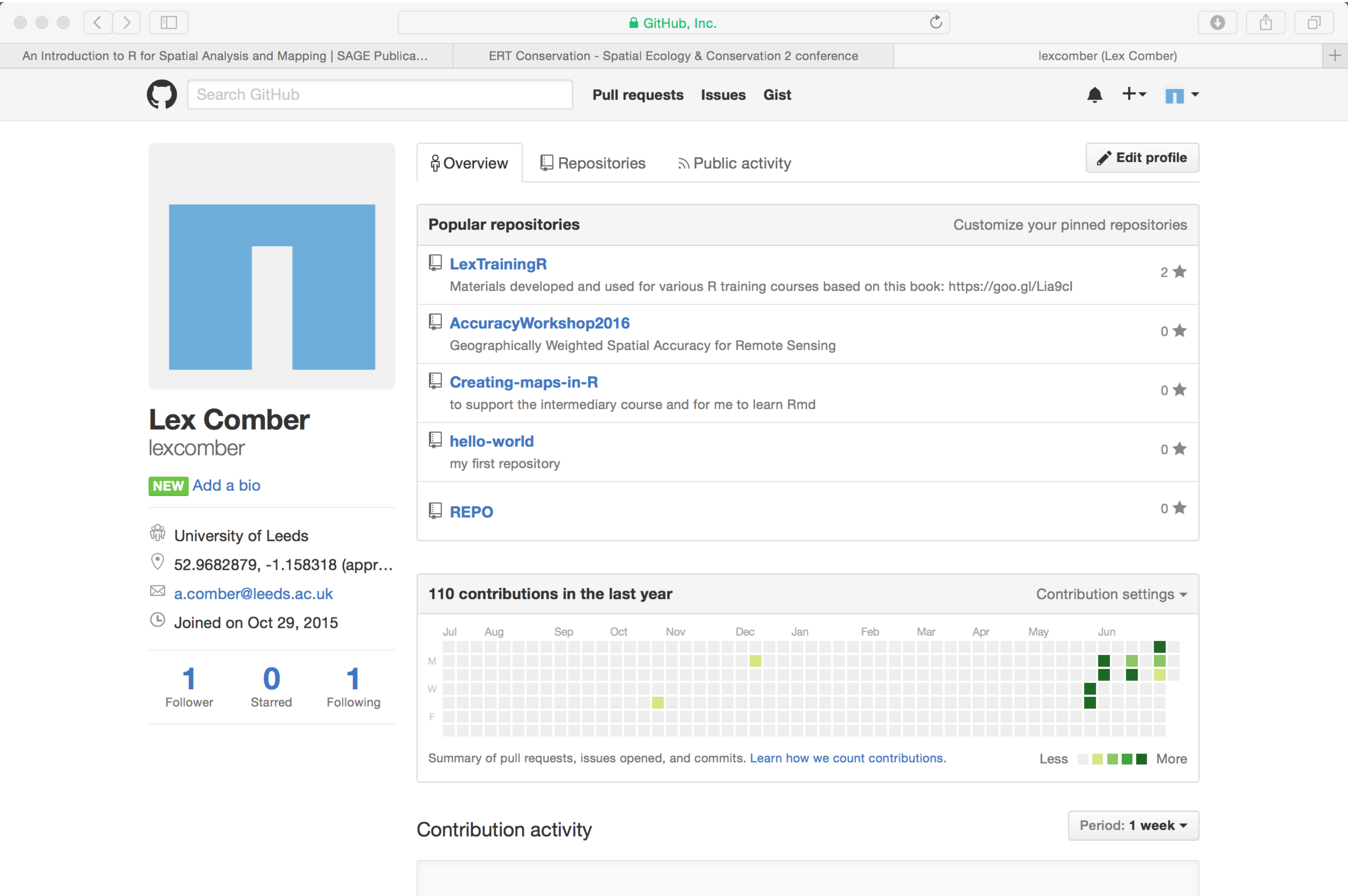
RELATED PRODUCTS

Geocomputation

Statistical Methods for Geography

Finally …

- Good to look at other domains for methods
  - Using GW approaches in a lot of remote sensing now
- Need for ‘geography goggles’ to analyse landscape ***spatially***:
  - How and where things vary
  - Expect spatial non-stationarity (relationships to vary), clusters, hotspots, coldspots, etc
- All data are spatial (GPS enabled devices)
- BUT distance / location cannot be treated in the same way as other variables
- Space is Special!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More
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Thank you!

&

Questions

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