GW Kappa

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Introduction

The final Geographically weighted extension is to calculate spatially distributed measures of the Kappa statistic estimate $\hat{\kappa}$, also known as k-hat. A full description of $\hat{\kappa}$ can be found in the classic Congalton (1991) paper at http://uwf.edu/zhu/evr6930/2.pdf.

What $\hat{\kappa}$ seeks to do is to measure the relationship between chance agreements between *Observed* and *Predicted* classes and the expected disagreement. It uses all the elements in the correspondence matrix and not just the diagonal ones and provides a measure of the proportion of agreement after chance agreement has been removed.

Data

Then the packages can be called and the data can be loaded into R after you have set the working directory using the `setwd()` function. The example from my computer is below:

You can download the data from github:

```
library(GISTools)
library(spgwr)
library(repmis)
source_data("github.com/lexcomber/LexTrainingR/blob/master/SpatialAccuracy.RData?raw=True")
```

```
## [1] "data"   "roilib"
```

And this can be set up for the analysis as before - this time making sure the data have a projection:

```
# the projection
lib.proj <- CRS("+proj=utm +zone=33 +ellps=WGS84 +datum=WGS84 +units=m +no_defs ")
proj4string(roilib) <- lib.proj
# create the point data file
lib <- SpatialPointsDataFrame(cbind(data$East, data$North),
  data.frame(field = data$Boolean_FS, sat = data$Boolean_RS),
  proj4string = lib.proj)
# convert the data to numeric form
class.lut <- data.frame(code = unique(lib$field), num = c(1:5))
# Urban 1; Bare 2; Woodland 3;  V = 4; Grazing land = 5
# and reformat the attributes in 'lib'
index = match(lib$field, class.lut$code)
lib$field = class.lut$num[index]
index = match(lib$sat, class.lut$code)
lib$sat = class.lut$num[index]
```

Create the matrix

The code below creates the change / correspondence / accuracy matrix as before:

```
tab <- table(data$Boolean_RS, data$Boolean_FS)
class.names.long <- c("Bare", "Grazing", "Urban", "Vegetation", "Woodland")
rownames(tab) <- class.names.long
colnames(tab) <- class.names.long
tab <- cbind(tab, rowSums(tab))
tab <- rbind(tab, colSums(tab))
rownames(tab)[6] <- "Total"
colnames(tab)[6] <- "Total"
tab
```

```
##            Bare Grazing Urban Vegetation Woodland Total
## Bare         18       8     7          2        4    39
## Grazing       3      23     3          8        6    43
## Urban         0       0    27          1        2    30
## Vegetation    0       4     7         31        5    47
## Woodland      0       4     2         18       27    51
## Total        21      39    46         60       44   210
```

Calulating a Kappa Estimate

The formal notation of the derivation of the Kappa statistic estimate $\hat{\kappa}$ is below:

$$verylargeequation$$

.

Essentially what this does is:

1. Multiply the sum of the diagonals by the table sum.
2. Then subtract from this the sum of the row and column marginal totals products. In this case these would be $[(21x39) + (39 * 43) + (46 * 30) + (60 * 47) + (44 * 51)]$
3. Next, divide this by the sum of the table squared - minus the sum of the row and column marginal totals products as above

The top part of the equation gives a measure of chance agreement and the bottom part a measure of the expected disagreements.

So in this case this could be calculated from the table as follows:

```
tab.tmp <- tab[1:5, 1:5]
part.1 <- sum(diag(tab.tmp)) * sum(tab.tmp)
part.2 <- sum(colSums(tab.tmp) * rowSums(tab.tmp))
part.3 <- sum(tab.tmp)^2
k <- (part.1 - part.2) / (part.3 - part.2)
cat("Kappa estimate (k-hat): ", round(k,3))
```

```
## Kappa estimate (k-hat):  0.498
```

GW crosstabs

For this we will use the `gwxtab` package which can be downloaded from `github` in the following way (**NB**: you may have to install the `devtools` package to do this):

```
install.packages("devtools", dep = T)
library(devtools)
install_github('chrisbrunsdon/gwxtab')
```

And the the package can be loaded:

```
library(gwxtab)
```

You should explore the documentation around `gwxtabs` - Harry and I have have both worked extensively with Chris Brunsdon - he does some great work and creates great code.

Step 1: create a dummy crosstab

Once the data and libraries area loaded the first step is to create a dummy `crosstabs` object using the `new_spxt` function:

```
dummy_xtab <- new_spxt(lib,'field','sat')
```

Have a look at this `Spatial Crosstabulation` object.

```
dummy_xtab
```

```
## Spatial Crosstabulation object
## Number of locations: 210
## Dimension: 5 x 5
## Proj4 String: +proj=utm +zone=33 +ellps=WGS84 +datum=WGS84 +units=m +no_defs +towgs84=0,0,0
```

```
head(coordinates(dummy_xtab))
```

```
##      coords.x1 coords.x2
## [1,]    301847   3631819
## [2,]    302491   3632155
## [3,]    303834   3631818
## [4,]    304480   3631008
## [5,]    306691   3632967
## [6,]    308175   3630784
```

The SpatialCrossTabs object has a location associated with each cross-tabulation, and a projection. The `coordinates` function gives the locations of each cross tab at each location and the square brackets `[]` reference individual cross-tabulations

```
dummy_xtab[7]
```

```
##      sat
## field 1 2 3 4 5
##     1 0 1 0 0 0
##     2 0 0 0 0 0
##     3 0 0 0 0 0
##     4 0 0 0 0 0
##     5 0 0 0 0 0
```

Step 2: create a GW crosstab

The next step is to create a set of dummy crosstabs at any geographical point location u_1, u_2. Functions that take a location as an argument and return the cross tabulation are called probe functions. The function `gwxtab_probe` is a tool for making probe functions. It takes a dummy cross-tabulation 'SpatialCrossTabs' object and a bandwidth to create a new function that maps a geographical location (u_1, u_2) on to a geographically weighted cross-tabulation. At this stage in the code development it defaults to bisquare kernel.

The kernel can be fixed - e.g. 20km

```
gwxt <- gwxtab_probe(dummy_xtab,fixed(20))
# test it
round(gwxt(330749, 3627772 ), 3)
```

```
##      sat
## field     1     2     3     4     5
##     1 8.174 2.186 0.447 1.438 1.479
##     2 0.000 3.742 0.000 0.000 0.204
##     3 0.791 0.728 7.242 1.516 0.761
##     4 0.383 0.239 1.802 7.253 1.358
##     5 0.000 2.042 1.023 0.389 4.126
```

Or it can be adaptive to take the nearest n data points. First define a bandwidth - say 15% of the data points:

```
bw = 0.15
nrow(lib)
```

```
## [1] 210
```

```
bw = round(nrow(lib)*0.15, 0)
bw
```

```
## [1] 32
```

Then define the `gwxtab_probe` function:

```
gwxt_ad <- gwxtab_probe(dummy_xtab,adapt(bw))
round(gwxt_ad(330749, 3627772 ), 3)
```

```
##      sat
## field     1     2     3     4     5
##     1 1.472 0.406 0.000 0.000 0.886
##     2 0.000 0.287 0.000 0.000 0.000
##     3 0.289 0.145 2.530 0.000 0.178
##     4 0.000 0.000 0.000 2.133 0.000
##     5 0.000 0.186 0.122 0.000 0.584
```

Step 3: define a function to apply to the crosstab

The initial code below defines a function to calculate local measures of overall accuracy form each cross-tab:

```
# overall accuracy function
ov <- function(x) data.frame(ov=sum(diag(x))/sum(x))
```

This can be tested:

```
ov(gwxt_ad(330749, 3627772))
```

```
##          ov
## 1 0.7600426
```

And then incorporated into a `probe` function:

```
gw_ov <- gwxtab_probe(dummy_xtab,adapt(bw),melt=ov)
# test it!
gw_ov(330749, 3627772)
```

```
##          ov
## 1 0.7600426
```

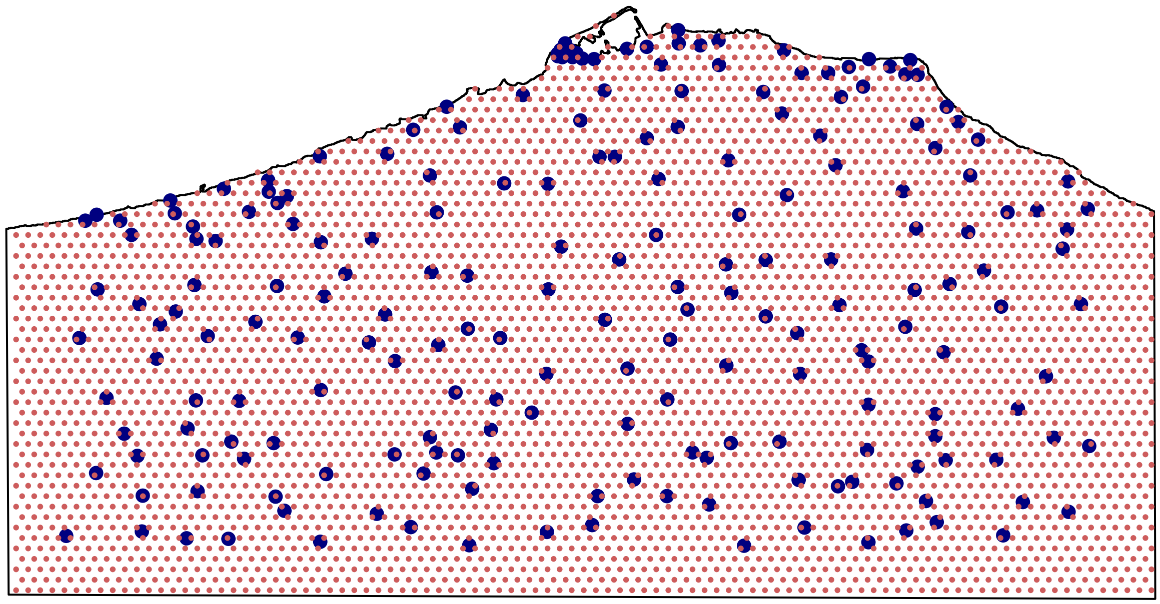
Step 4: Spatial Extension and Visualisation of local crosstab measures

The results can be visualized using the code used for the `spgwr` approaches described in earlier practicals. In this example hexbins are used.

```
# create the hexbin objects
hg <- spsample(roilib,5000,'hexagonal',offset=c(0.5,0.5))
```

This creates around 5000 points on a hexagonal grid covering the study areas (the polygon `roilib`). These can be plotted:

```
par(mar=c(0,0,0,0)+0.1)
plot(roilib)
plot(lib,pch=16,col='navy', add = T)
plot(hg,pch=16,col='indianred',cex=0.4,add=TRUE)
```

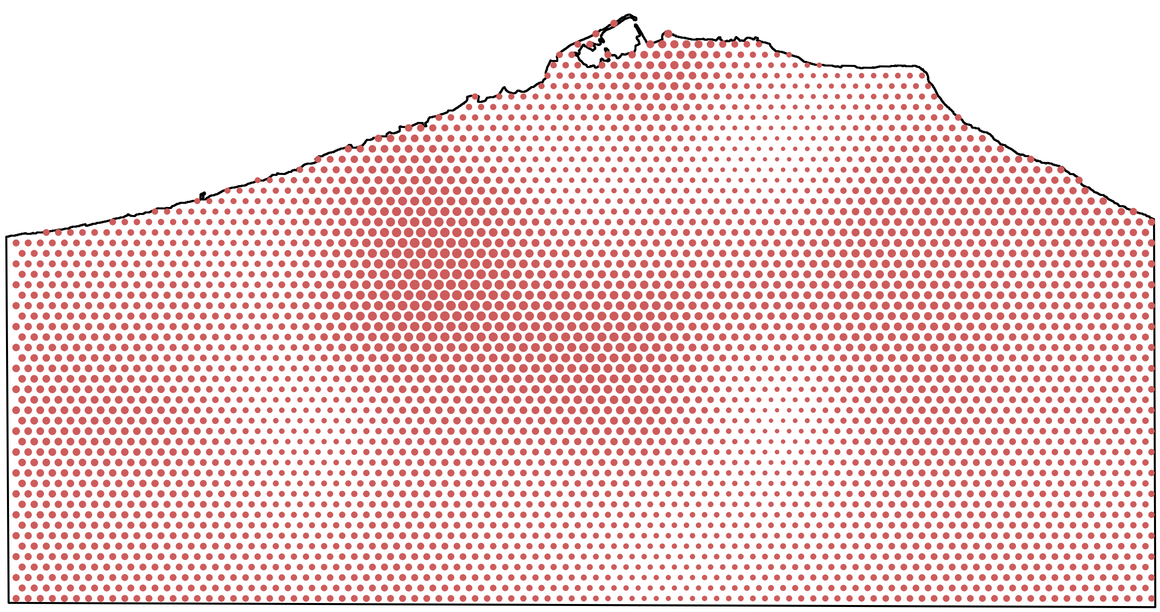


The SpatialPointsDataFrame object can finally be created - this may take a couple of seconds :

```
hg_ov <- gwxtab_sample(hg,dummy_xtab,adapt(bw),melt=ov)
```

And the spatially varying Overall Accuracy can be visualized allow the size of each hexbin to vary in proportion to the value of the cross tab statistic - in this case overall accuracy:

```
par(mar=c(0,0,0,0)+0.1)
plot(roilib)
plot(hg_ov,pch=16,col='indianred',cex=0.8*hg_ov$ov,add=TRUE)
```



Sumamry

The steps above provide a framework for calculating any GW statistic from a correspondence matrix of cross tabulation. You should explore the parameters that are passed to the various functions here. For example, what is the effect of changing the `bw` variable to 15? How do the maps differ?
GW Kappa

The above code can be modified, replacing the function for overall accuracy `ov`, with a function for calculating local Kappa estimates. In this case we will use an adaptive bandwidth of 15 data points.

Step 1: create a dummy crosstab

This is the same as above but repeated for clarity.

```
dummy_xtab <- new_spxt(lib,'field','sat')
```

Step 2: create a GW crosstab

```
gwxt_ad <- gwxtab_probe(dummy_xtab,adapt(15))
round(gwxt_ad(330749, 3627772 ), 3)
```

```
##      sat
## field     1     2     3     4     5
##     1 0.896 0.138 0.000 0.000 0.807
##     2 0.000 0.000 0.000 0.000 0.000
##     3 0.040 0.000 1.500 0.000 0.000
##     4 0.000 0.000 0.000 1.320 0.000
##     5 0.000 0.000 0.000 0.000 0.338
```

Step 3: define a function to apply to the crosstab

In this case this is the Kappa estimate:

```
# Define Kappa estimate
kp <- function(x) {
    part.1 <- sum(diag(x)) * sum(x)
    part.2 <- sum(colSums(x) * rowSums(x))
    part.3 <- sum(x)^2
    k <- (part.1 - part.2) / (part.3 - part.2)
    return(data.frame(kappa = k))
}
```

Step 4: Spatial Extension and Visualisation of local crosstab measures

Create the hexbin objects:

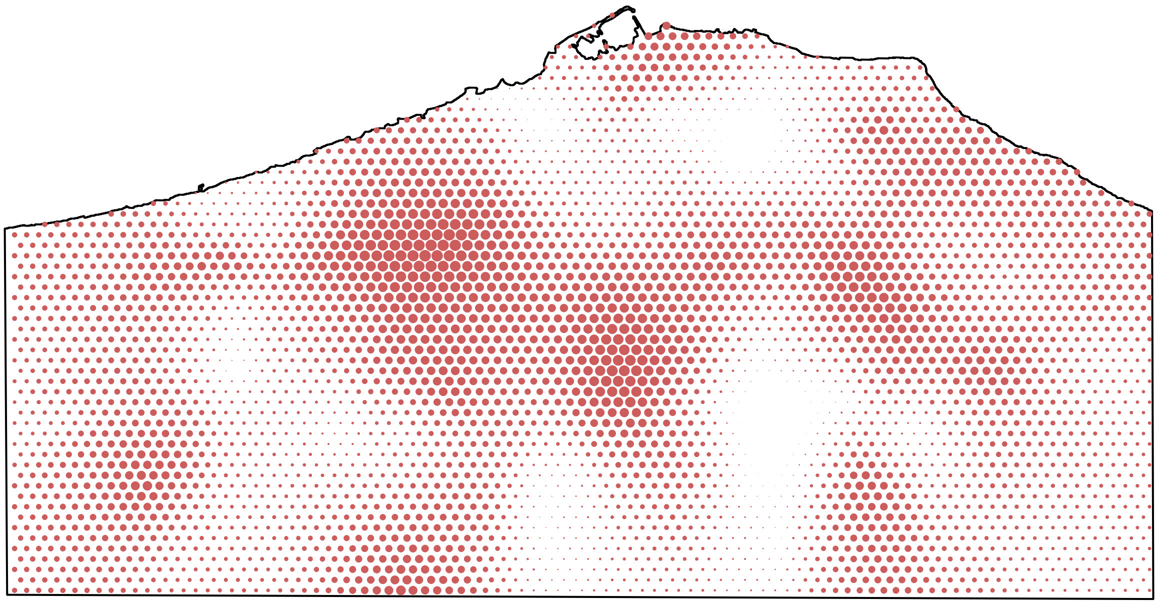
```
hg <- spsample(roilib,5000,'hexagonal',offset=c(0.5,0.5))
```

Create the `SpatialPointsDataFrame` object:

```
hg_kp <- gwxtab_sample(hg,dummy_xtab,adapt(15),melt=kp)
```

Plot the hexagonal grid of points:

```
par(mar=c(0,0,0,0)+0.1)
plot(roilib)
#plot(lib,pch=16,col='navy',add=TRUE)
plot(hg_kp,pch=16,col='indianred',cex=0.8*hg_kp$kappa,add=TRUE)
```



Familiar visulisation

The code below visualizes the data in the same way as you have done in previous exercises. A slightly different grid has to be created to support he `level.plot` function and then the local kappa re-calculated over that grid:

```
# create a polygon for the study area
ext <- t(bbox(roilib))
ext <- rbind(ext, cbind(ext[1,1], ext[2,2]))
ext <- ext[c(1,3,2),]
ext <- rbind(ext, cbind(ext[3,1], ext[1,2]))
ext <- rbind(ext, ext[1,])
ext
```

```
##            x       y
## min 297345.8 3610249
##     297345.8 3644007
## max 362785.2 3644007
##     362785.2 3610249
##     297345.8 3610249
```

This can be used to make a polygon from which to create a regular sample grid:

```r
poly <- Polygon(ext)
poly <- Polygons(list(poly), ID = "1")
poly <- SpatialPolygons(list(poly), integer(1))
# now use this to create a sample grid
grid <- spsample(poly,6000,'regular',offset=c(0.5,0.5))
proj4string(grid) <- lib.proj
```

Now the SpatialPointsDataFrame object can be created over this grid:

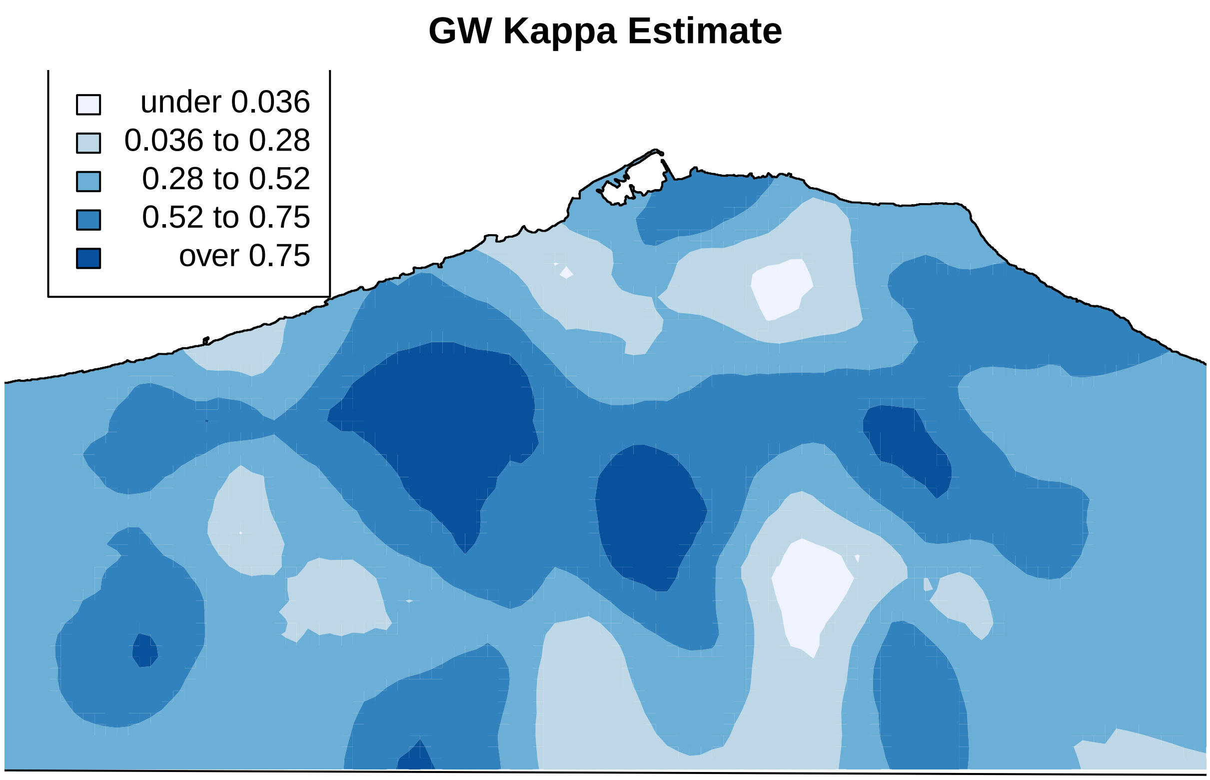
```r
hg_kp <- gwxtab_sample(grid,dummy_xtab,adapt(15),melt=kp)
```

And plotted in the same way as in previous exercises:

```r
shades = auto.shading(hg_kp$kappa, n=5,cols=brewer.pal(5,"Blues"),
  cutter=rangeCuts, digits = 2)
kp.spdf = SpatialPixelsDataFrame(hg_kp, data.frame(hg_kp$kappa))
par(mar=c(0,1,2,0)+0.1)
level.plot(kp.spdf,shades)
lib.masker = poly.outer(kp.spdf, roilib, extend = 100)
```

```
## Warning in RGEOSBinTopoFunc(spgeom1, spgeom2, byid, id, drop_lower_td,
## unaryUnion_if_byid_false, : spgeom1 and spgeom2 have different proj4
## strings
```

```r
add.masking(lib.masker)
plot(roilib, add = T)
choro.legend(300000, 3648500, shades)
title("GW Kappa Estimate")
```



#

End