NCG613 assignment

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25th April 2018

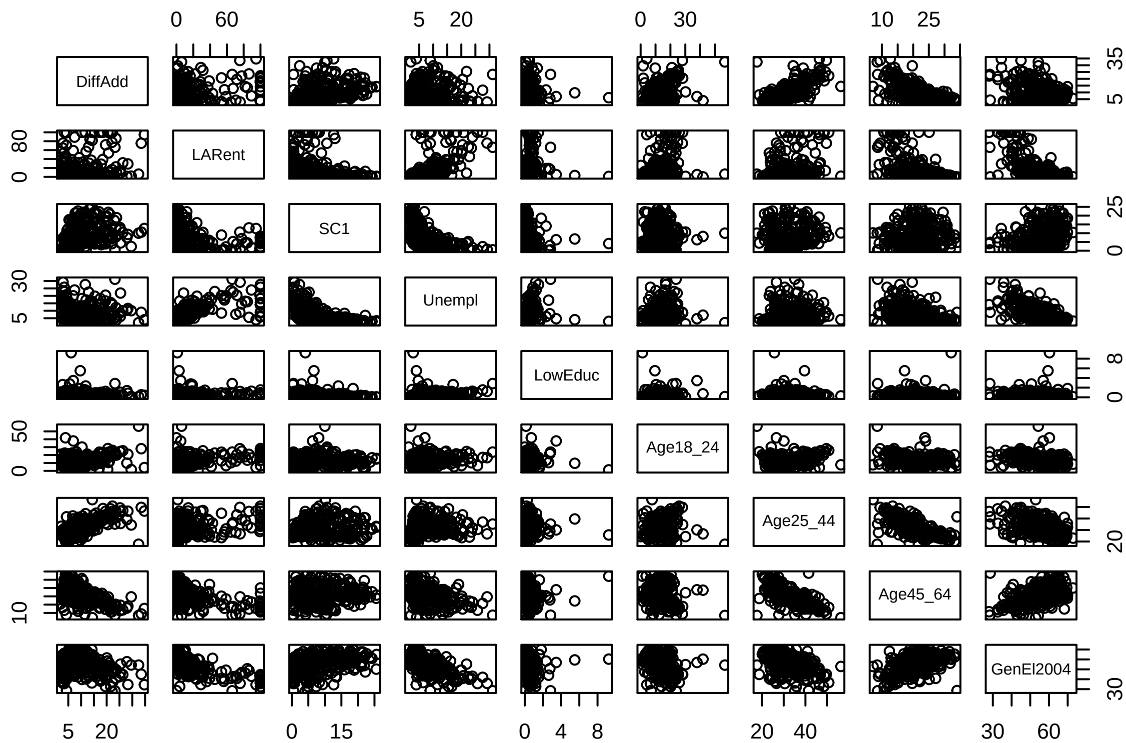
R code for modelling voter turnout in Dublin

```
# set up the code and colour palettes for plotting
map.na = list("SpatialPolygonsRescale", layout.north.arrow(),
  offset = c(329000, 261500), scale = 4000, col = 1)
map.scale.1 = list("SpatialPolygonsRescale", layout.scale.bar(),
  offset = c(326500, 217000), scale = 5000, col = 1,
  fill = c("transparent", "blue"))
map.scale.2 = list("sp.text", c(326500, 217900), "0", cex = 0.9, col = 1)
map.scale.3 = list("sp.text", c(331500, 217900), "5km", cex = 0.9, col = 1)
map.layout <- list(map.na, map.scale.1, map.scale.2, map.scale.3)
mypalette.1 <- brewer.pal(8, "Reds")
mypalette.2 <- brewer.pal(8, "Blues")
mypalette.3 <- brewer.pal(6, "Greens")
mypalette.4 <- brewer.pal(8, "YlGnBu")
mypalette.7 <- brewer.pal(8, "Oranges")
```

```
# Load the Dub.voter data
data(DubVoter)
```

Generate a scatterplot matrix to get an idea of globally correlated variables

```
pairs(Dub.voter[,4:12])
```



These scatterplots show that we have high correlation (some negative, some positive) between the following variables:
- DiffAdd and Age25_44
- Age45_64 and Age25_44
- LARent and Unempl
- LARent and GenEl2004

Their correlation values are shown below.

```r
cor(Dub.voter$DiffAdd, Dub.voter$Age25_44)
```

```
## [1] 0.7030624
```

```r
cor(Dub.voter$Age45_64, Dub.voter$Age25_44)
```

```
## [1] -0.69323
```

```r
cor(Dub.voter$LARent, Dub.voter$Unempl)
```

```
## [1] 0.6687762
```

```r
cor(Dub.voter$LARent, Dub.voter$GenEl2004)
```

```
## [1] -0.6806665
```

```r
cor(Dub.voter$Age45_64, Dub.voter$GenEl2004)
```

```
## [1] 0.4836208
```

```r
# Use Geographically Weighted Summary Statistics
gw.ss.bx <- gwss(Dub.voter, vars = c("GenEl2004", "LARent", "Unempl"),
```

```
                 kernel = "boxcar", adaptive = TRUE, bw = 48, quantile = TRUE)
gw.ss.bs <- gwss(Dub.voter,vars = c("GenEl2004", "LARent", "Unempl"),
                 kernel = "bisquare", adaptive = TRUE, bw = 48)

spplot(gw.ss.bx$SDF, "GenEl2004_LSD", key.space = "right",
       col.regions = mypalette.1, cuts = 7, sp.layout = map.layout,
       main = "Fig 1: GW standard deviations for GenEl2004")
```

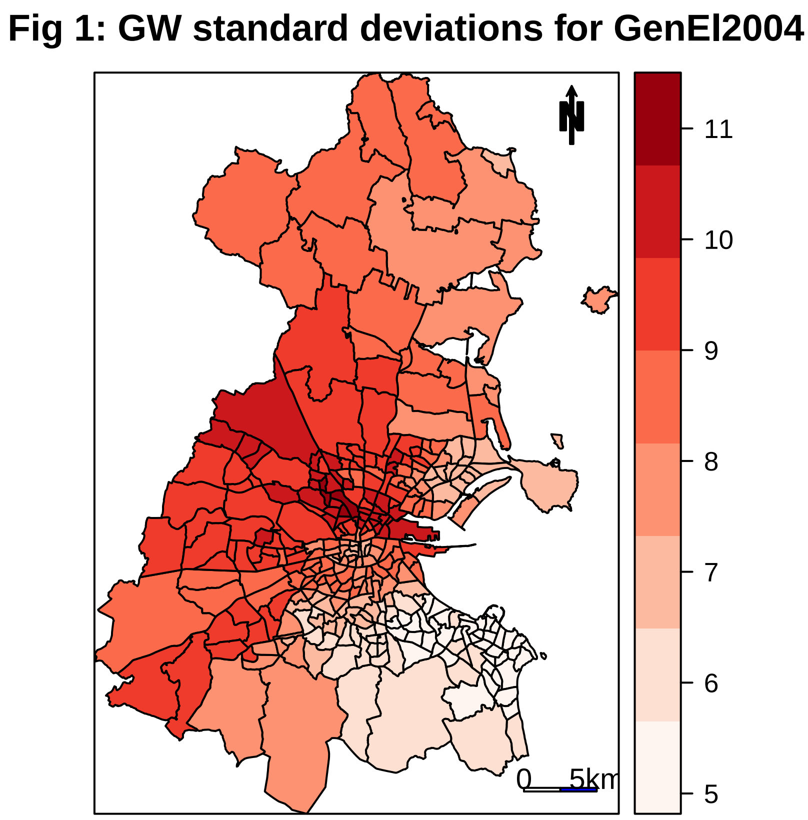


Fig 1 shows variability for the response variable GenEl2004. The areas of highest variability in turnout are North and West Dublin.

Now, plot some correlations.

```
spplot(gw.ss.bs$SDF, "Corr_GenEl2004.LARent", key.space = "right",
       col.regions = mypalette.2, at = c(-1, -0.8, -0.6, -0.4, -0.2, 0),
       main = "Fig 2: GW correlations: GenEl2004 and LARent",
       sp.layout = map.layout)
```

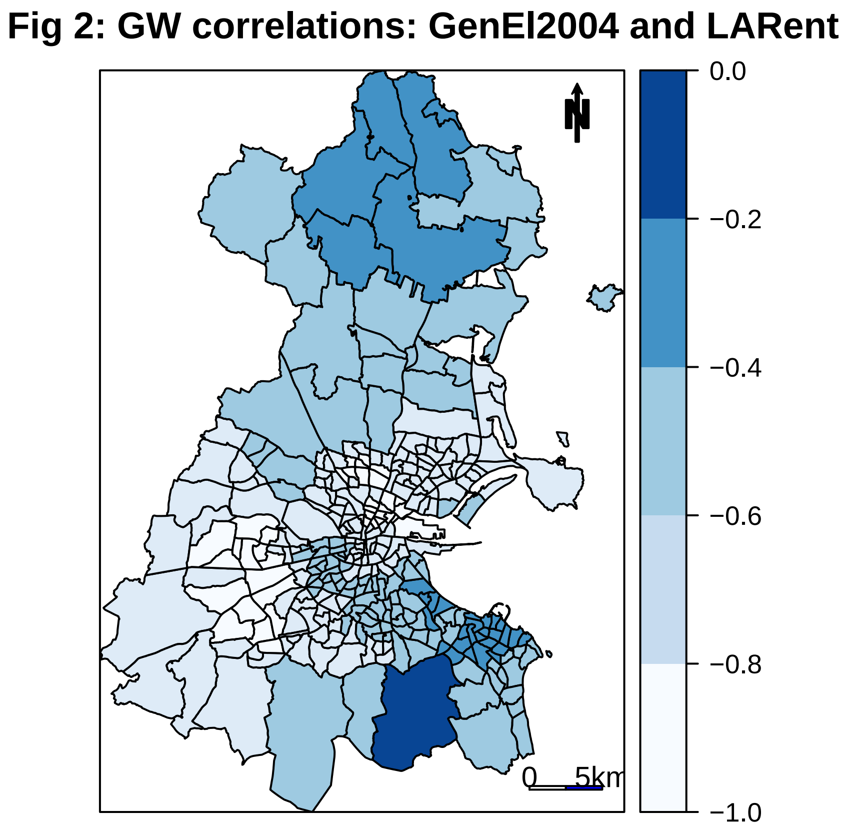


Fig 2 shows the degree of negative correlation between turnout and those living in local authority housing. The lightest blue areas in West Dublin and some areas of Dublin City have the highest correlation.

```
spplot(gw.ss.bs$SDF, "Corr_LARent.Unempl", key.space = "right",
       col.regions = mypalette.3, at = c(-0.2, 0, 0.2, 0.4, 0.6, 0.8, 1),
       main = "Fig 3: GW correlations: LARent and Unempl",
       sp.layout = map.layout)
```

Fig 3: GW correlations: LARent and Unempl

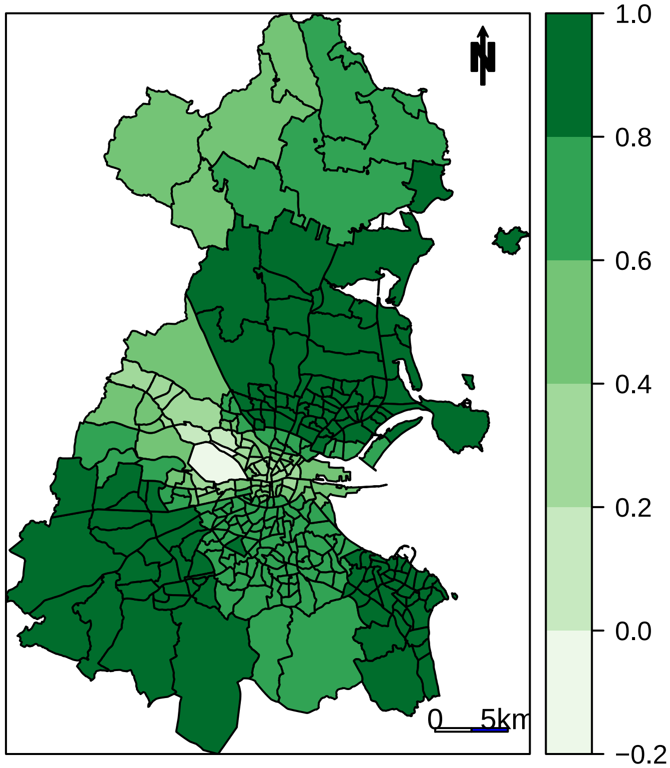


Fig 3 shows that variables LARent and Unempl are positively correlated so this map shows the area of highest correlation in West and North Dublin.

As we have spatial predictors X and Y, we will use GW Principal Component's Analysis (GW PCA). Firstly though, run a basic PCA.

```
# scale the data, run PCA, show loadings
Dub.voter.scaled <- scale(as.matrix(Dub.voter@data[, 4:11]))
pca <- princomp(Dub.voter.scaled, cor = FALSE)
(pca$sdev^2 / sum(pca$sdev^2)) * 100
```

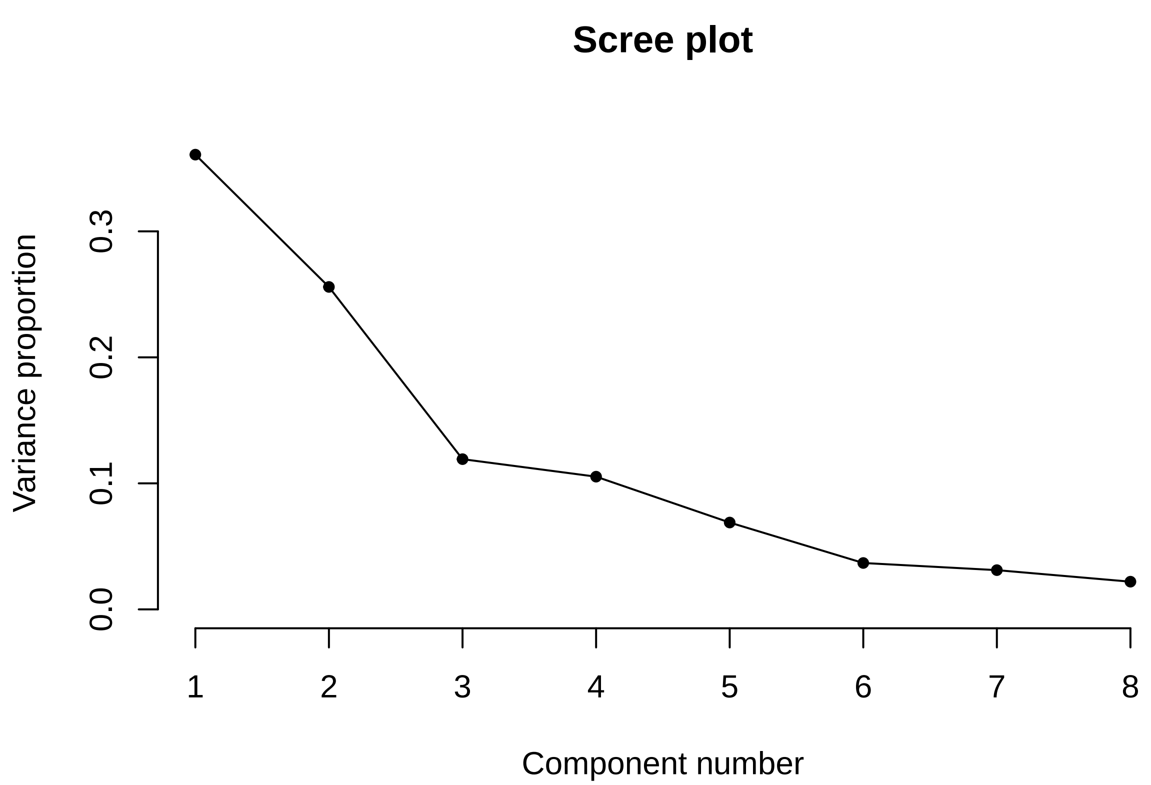
```
##    Comp.1    Comp.2    Comp.3    Comp.4    Comp.5    Comp.6    Comp.7
## 36.084435 25.586984 11.919681 10.530373  6.890565  3.679812  3.111449
##    Comp.8
##  2.196701
```

```
pca$loadings
```

```
##
## Loadings:
##           Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8
## DiffAdd    0.389 -0.444        -0.149  0.123  0.293  0.445  0.575
## LARent     0.441  0.226  0.144  0.172  0.612  0.149 -0.539  0.132
## SC1       -0.130 -0.576        -0.135  0.590 -0.343        -0.401
## Unempl     0.361  0.462         0.189  0.197         0.670 -0.355
## LowEduc    0.131  0.308 -0.362 -0.861
## Age18_24   0.237         0.845 -0.359 -0.224               -0.200
## Age25_44   0.436 -0.302 -0.317        -0.291  0.448 -0.177 -0.546
```

```
## Age45_64 -0.493  0.118  0.179 -0.144  0.289  0.748  0.142 -0.164
##
##                 Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8
## SS loadings      1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
## Proportion Var  0.125  0.125  0.125  0.125  0.125  0.125  0.125  0.125
## Cumulative Var  0.125  0.250  0.375  0.500  0.625  0.750  0.875  1.000
```

```r
# create a scree plot to show the proportion of variance per component
screeplot <- function(p) {
  e <- p$sdev ^ 2
  e <- e / sum(e)
  plot(
    1:length(e),
    e,
    xlab = "Component number",
    pch = 20,
    ylab = "Variance proportion",
    main = "Scree plot",
    axes = F,
    ylim = c(0, max(e)*1.04)
    )
  lines(1:length(e), e)
  axis(1, at = 1:length(e))
  axis(2)
}
screeplot(pca)
```



73.6% of the variance is explained by the first three components. From the tables of loadings, the first component would appear to represent older residents (Age45_64). The second component, appears to represent affluent residents (SC1). The third component is mostly explained by the younger population (Age18_24).

Now, let's use GW PCA as these results may not reliably represent local social structure.

```
# The scaled data is converted to a spatial data frame using the SpatialPointsDataFrame function.
coordinates <- as.matrix(cbind(Dub.voter$X, Dub.voter$Y))
Dub.voter.scaled.spdf <- SpatialPointsDataFrame(coordinates, as.data.frame(Dub.voter.scaled))
# selecting the bandwidth, k is pre-chosen as 3
bandwidth.gwpca <- bw.gwpca(Dub.voter.scaled.spdf,
                            vars = colnames(Dub.voter.scaled.spdf@data), k = 3,
                            robust = FALSE, adaptive = TRUE)
```

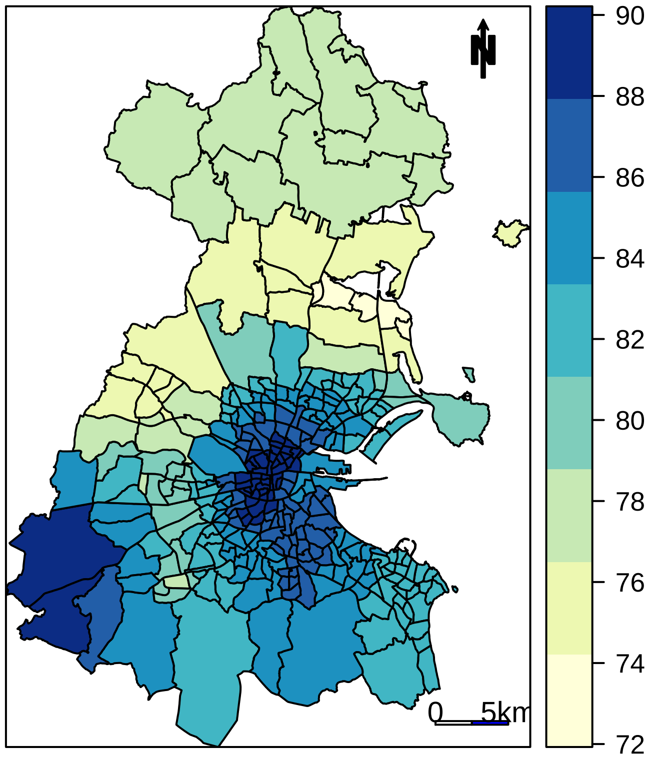
```
## Adaptive bandwidth(number of nearest neighbours): 199 CV score: 700.8372
## Adaptive bandwidth(number of nearest neighbours): 124 CV score: 614.7564
## Adaptive bandwidth(number of nearest neighbours): 76 CV score: 648.8595
## Adaptive bandwidth(number of nearest neighbours): 152 CV score: 630.3535
## Adaptive bandwidth(number of nearest neighbours): 105 CV score: 619.4017
## Adaptive bandwidth(number of nearest neighbours): 134 CV score: 614.0499
## Adaptive bandwidth(number of nearest neighbours): 142 CV score: 620.5101
## Adaptive bandwidth(number of nearest neighbours): 130 CV score: 611.0627
## Adaptive bandwidth(number of nearest neighbours): 127 CV score: 613.0468
## Adaptive bandwidth(number of nearest neighbours): 131 CV score: 610.6125
## Adaptive bandwidth(number of nearest neighbours): 133 CV score: 614.2431
## Adaptive bandwidth(number of nearest neighbours): 131 CV score: 610.6125
```

```
bandwidth.gwpca
```

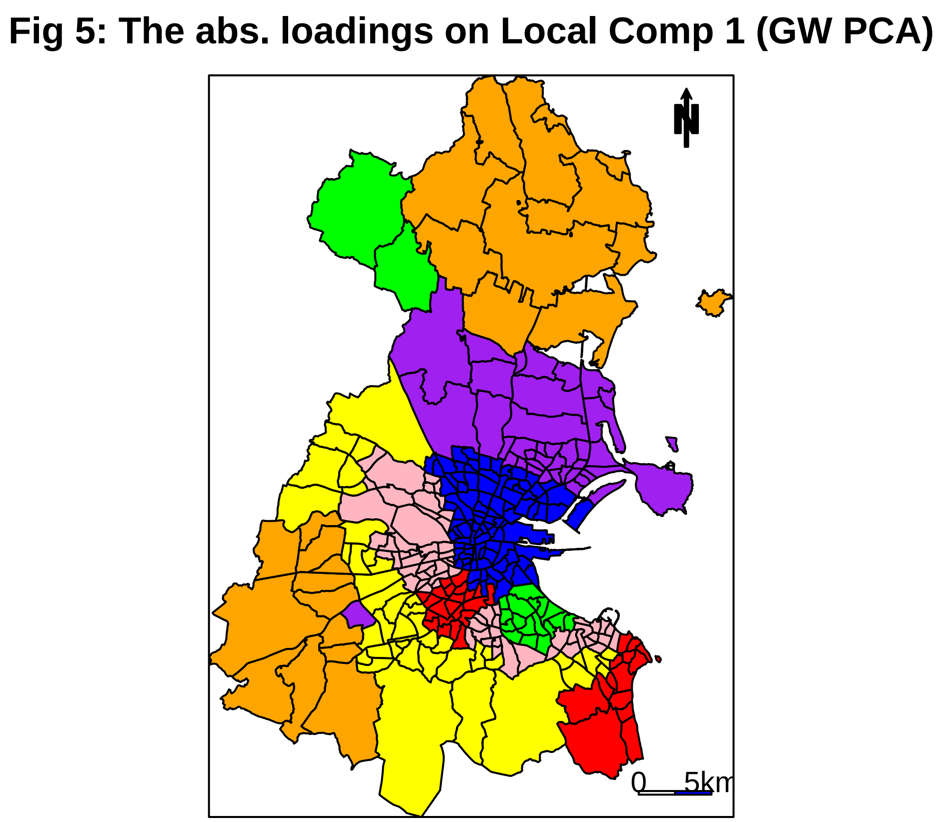
```
## [1] 131
```

```
gw.pca <- gwpca(Dub.voter.scaled.spdf,
                vars = colnames(Dub.voter.scaled.spdf@data),
                bw = bandwidth.gwpca, k = 8, robust = FALSE, adaptive = TRUE)


# Visualise and interpret GW PCA output
prop.var <- function(gwpca.obj, n.components)
  {return((rowSums(gwpca.obj$var[, 1:n.components]) /rowSums(gwpca.obj$var)) * 100)}
var.gw.pca <- prop.var(gw.pca, 3)
Dub.voter$var.gw.pca <- var.gw.pca

spplot(Dub.voter, "var.gw.pca", key.space = "right",
       col.regions = mypalette.4, cuts = 7, sp.layout = map.layout,
       main = "Fig 4: % total variance for local components 1 to 3 (GW PCA)")
```

Fig 4: % total variance for local components 1 to 3 (GW PCA)




```r
loadings.pc1 <- gw.pca$loadings[, , 1]
win.item = max.col(abs(loadings.pc1))
Dub.voter$win.item <- win.item
mypalette.5 <- c("lightpink", "blue", "grey", "purple", "orange", "green", "red", "yellow")
spplot(Dub.voter, "win.item", key.space = "right",
       col.regions = mypalette.5, at = c(1, 2, 3, 4, 5, 6, 7, 8, 9),
       main = "Fig 5: The abs. loadings on Local Comp 1 (GW PCA)",
       colorkey = FALSE, sp.layout = map.layout)
```



The map colours are:
DiffAdd - light pink
LARent - blue
SC1 - grey
Unempl - purple
LowEduc - orange
Age18_24 - green
Age25_44 - red
Age45_64 - yellow

For GW PCA, Low_Educ dominates in the northern and southwestern EDs, whilst LARent dominates in the EDs of central Dublin. Unempl dominates north of the city.

Now run Basic GW Regression, calculate the local Variance Inflation Factor's (VIFs) and local Condition Numbers (CN).

```
# Basic GWR model, all predictors
bandwidth.gwr <- bw.gwr(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                        + LowEduc + Age18_24 + Age25_44 + Age45_64,
                        data = Dub.voter, approach = "AICc",
                        kernel = "bisquare", adaptive = TRUE)
```

```
## Adaptive bandwidth (number of nearest neighbours): 206 AICc value: 1950.248
## Adaptive bandwidth (number of nearest neighbours): 135 AICc value: 1925.648
## Adaptive bandwidth (number of nearest neighbours): 90 AICc value: 1927.43
## Adaptive bandwidth (number of nearest neighbours): 161 AICc value: 1933.323
## Adaptive bandwidth (number of nearest neighbours): 116 AICc value: 1921.995
## Adaptive bandwidth (number of nearest neighbours): 107 AICc value: 1921.608
```

```
## Adaptive bandwidth (number of nearest neighbours): 99 AICc value: 1922.882
## Adaptive bandwidth (number of nearest neighbours): 109 AICc value: 1921.287
## Adaptive bandwidth (number of nearest neighbours): 113 AICc value: 1921.645
## Adaptive bandwidth (number of nearest neighbours): 109 AICc value: 1921.287
```

```r
bgwr <- gwr.basic(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                  + LowEduc + Age18_24 + Age25_44 + Age45_64,
                  data = Dub.voter, bw = bandwidth.gwr,
                  kernel = "bisquare", adaptive = TRUE)
print(bgwr)
```

```
##    ***********************************************************************
##    *                       Package   GWmodel                             *
##    ***********************************************************************
##    Program starts at: 2018-04-25 00:30:18
##    Call:
##    gwr.basic(formula = GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl +
##     LowEduc + Age18_24 + Age25_44 + Age45_64, data = Dub.voter,
##     bw = bandwidth.gwr, kernel = "bisquare", adaptive = TRUE)
##
##    Dependent (y) variable:  GenEl2004
##    Independent variables:  DiffAdd LARent SC1 Unempl LowEduc Age18_24 Age25_44 Age45_64
##    Number of data points: 322
##    ***********************************************************************
##    *                    Results of Global Regression                     *
##    ***********************************************************************
##
##    Call:
##     lm(formula = formula, data = data)
##
##    Residuals:
##      Min       1Q   Median       3Q      Max
## -23.9343  -3.3500   0.4952   3.4707  13.4373
##
##    Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
##    (Intercept) 77.70467    3.93928  19.726  < 2e-16 ***
##    DiffAdd     -0.08583    0.08594  -0.999   0.3187
##    LARent      -0.09402    0.01765  -5.326 1.92e-07 ***
##    SC1          0.08637    0.07085   1.219   0.2238
##    Unempl      -0.72162    0.09387  -7.687 1.96e-13 ***
##    LowEduc     -0.13073    0.43022  -0.304   0.7614
##    Age18_24    -0.13992    0.05480  -2.554   0.0111 *
##    Age25_44    -0.35365    0.07450  -4.747 3.15e-06 ***
##    Age45_64    -0.09202    0.09023  -1.020   0.3086
##
##    ---Significance stars
##    Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##    Residual standard error: 5.304 on 313 degrees of freedom
##    Multiple R-squared: 0.6383
##    Adjusted R-squared: 0.629
##    F-statistic: 69.03 on 8 and 313 DF,  p-value: < 2.2e-16
##    ***Extra Diagnostic information
##    Residual sum of squares: 8805.251
##    Sigma(hat): 5.245609
```

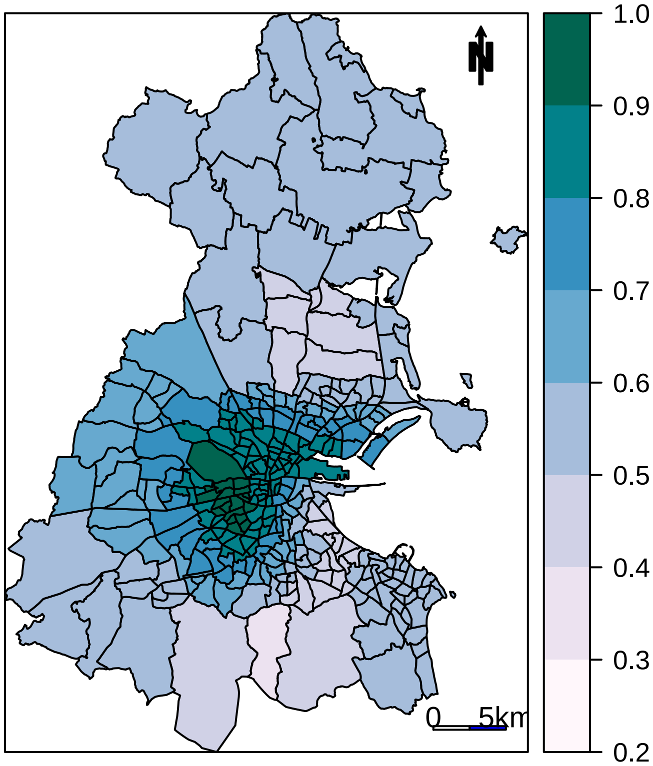
```
##    AIC:  1999.15
##    AICc:  1999.858
##    ***********************************************************************
##    *          Results of Geographically Weighted Regression              *
##    ***********************************************************************
##
##    *********************Model calibration information*********************
##    Kernel function: bisquare
##    Adaptive bandwidth: 109 (number of nearest neighbours)
##    Regression points: the same locations as observations are used.
##    Distance metric: Euclidean distance metric is used.
##
##    ****************Summary of GWR coefficient estimates:******************
##                     Min.     1st Qu.      Median     3rd Qu.     Max.
##    Intercept 53.22830962 73.31782964 81.66277747 95.06908086 116.7660
##    DiffAdd   -0.72807886 -0.33380997 -0.15837712  0.15858002   0.5465
##    LARent    -0.19491170 -0.12060836 -0.08443575 -0.03691619   0.0940
##    SC1       -0.15781787  0.03528402  0.30881760  0.42006638   0.8796
##    Unempl    -2.31794903 -1.14350301 -0.76487866 -0.47532711  -0.0925
##    LowEduc   -7.67491216 -0.73694598  0.53323357  1.80977357   3.4140
##    Age18_24  -0.39700178 -0.25290301 -0.14571296  0.00076421   0.3669
##    Age25_44  -1.09503913 -0.72092749 -0.45360107 -0.30484438   0.2184
##    Age45_64  -0.92361942 -0.40984558 -0.11024847  0.04679070   0.4931
##    ************************Diagnostic information*************************
##    Number of data points: 322
##    Effective number of parameters (2trace(S) - trace(S'S)): 79.90559
##    Effective degrees of freedom (n-2trace(S) + trace(S'S)): 242.0944
##    AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 1921.287
##    AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 1826.147
##    Residual sum of squares: 4516.821
##    R-square value:  0.8144397
##    Adjusted R-square value:  0.7529397
##
##    ***********************************************************************
##    Program stops at: 2018-04-25 00:30:18
```

```
gwr.coll.data <- gwr.collin.diagno(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                                   + LowEduc + Age18_24 + Age25_44 + Age45_64,
                                   data = Dub.voter, bw = bandwidth.gwr,
                                   kernel = "bisquare", adaptive = TRUE)
```

Now, calculate some local correlations, local VIFs and local CNs. This model shows that the significant predictors are LARent, Unempl and Age25_44.

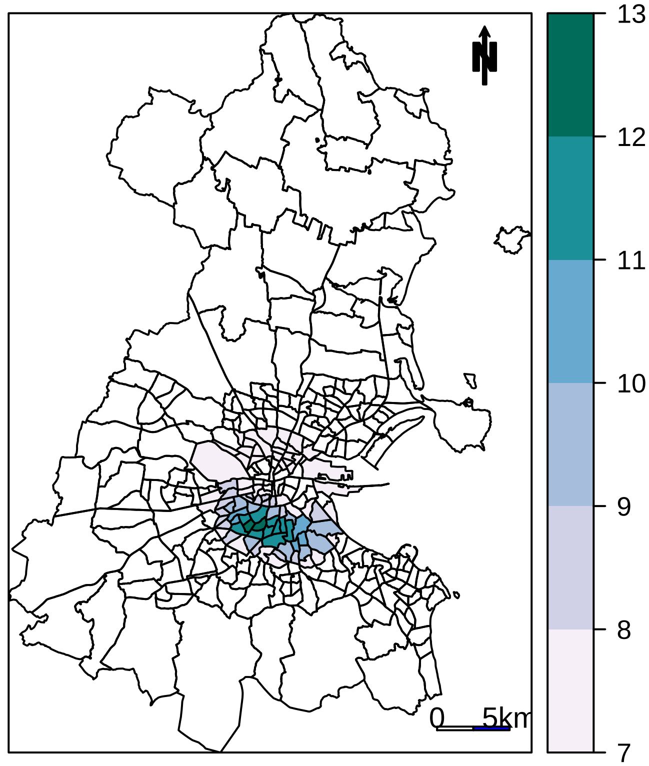
```
# GW correlations between predictor variables
mypalette.1 <-brewer.pal(8,"PuBuGn")
spplot(gwr.coll.data$SDF,"Corr_DiffAdd.Age25_44",key.space = "right",
       col.regions=mypalette.1,at=c(0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
       main=list(label="Fig 6: GW correlations: DiffAdd and Age25_44", cex=1.25),
       sp.layout=map.layout)
```

Fig 6: GW correlations: DiffAdd and Age25_44



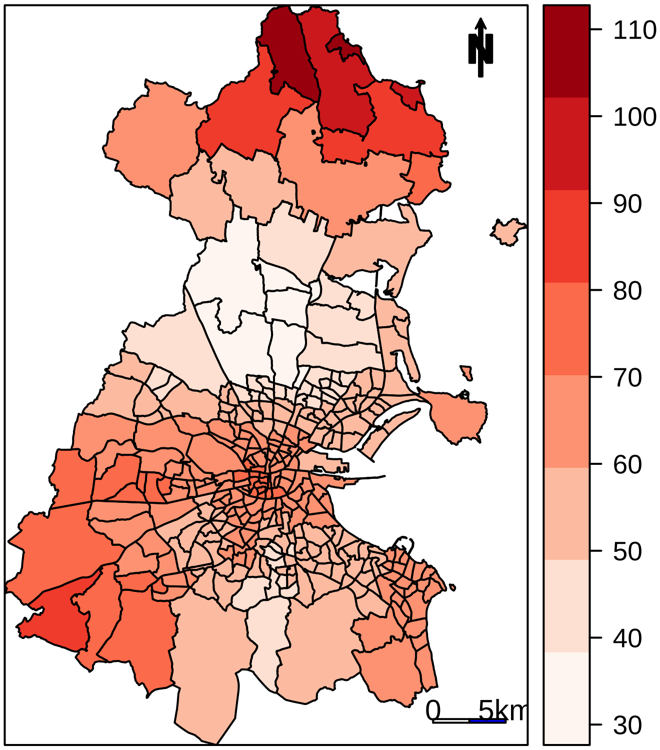

```
# Local VIFs
mypalette.2 <-brewer.pal(6,"PuBuGn")
spplot(gwr.coll.data$SDF,"DiffAdd_VIF",key.space = "right",
       col.regions=mypalette.2,at=c(7,8,9,10,11,12,13),
       main=list(label="Fig 7: Local VIFs for DiffAdd", cex=1.25),
       sp.layout=map.layout)
```

Fig 7: Local VIFs for DiffAdd




```r
# Local Condition Numbers
mypalette.3 <-brewer.pal(8,"Reds")
spplot(gwr.coll.data$SDF,"local_CN",key.space = "right",
       col.regions=mypalette.3,cuts=7,
       main=list(label="Fig 8: Local condition numbers", cex=1.25),
       sp.layout=map.layout)
```

Fig 8: Local condition numbers



We have found evidence of local collinearity, VIFs > 10 and CNs >> 30. Let's use Locally Compensated GW Ridge Regression.

```
bandwidth.lcr <- bw.gwr.lcr(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                            + LowEduc + Age18_24 + Age25_44 + Age45_64,
                            data = Dub.voter, kernel = "bisquare",
                            adaptive = TRUE,
                            lambda.adjust = TRUE, cn.thresh = 30)
```

```
## Adaptive bandwidth(number of nearest neighbours): 206 CV score: 8407.722
## Adaptive bandwidth(number of nearest neighbours): 135 CV score: 8258.53
## Adaptive bandwidth(number of nearest neighbours): 90 CV score: 9116.669
## Adaptive bandwidth(number of nearest neighbours): 161 CV score: 8195.65
## Adaptive bandwidth(number of nearest neighbours): 179 CV score: 8256.931
## Adaptive bandwidth(number of nearest neighbours): 151 CV score: 8199.961
## Adaptive bandwidth(number of nearest neighbours): 168 CV score: 8203.788
## Adaptive bandwidth(number of nearest neighbours): 157 CV score: 8192.326
## Adaptive bandwidth(number of nearest neighbours): 154 CV score: 8200.415
## Adaptive bandwidth(number of nearest neighbours): 158 CV score: 8197.002
## Adaptive bandwidth(number of nearest neighbours): 155 CV score: 8193.485
## Adaptive bandwidth(number of nearest neighbours): 157 CV score: 8192.326
```

```
bandwidth.lcr
```

```
## [1] 157
```

```
lcr <- gwr.lcr(GenEl2004 ~ DiffAdd + LARent + SC1+ Unempl
               + LowEduc + Age18_24 + Age25_44 + Age45_64,
```

```
                data = Dub.voter, bw = bandwidth.lcr, kernel = "bisquare",
                adaptive = TRUE,
                lambda.adjust = TRUE, cn.thresh = 30)
summary(lcr$SDF$Local_CN)
```

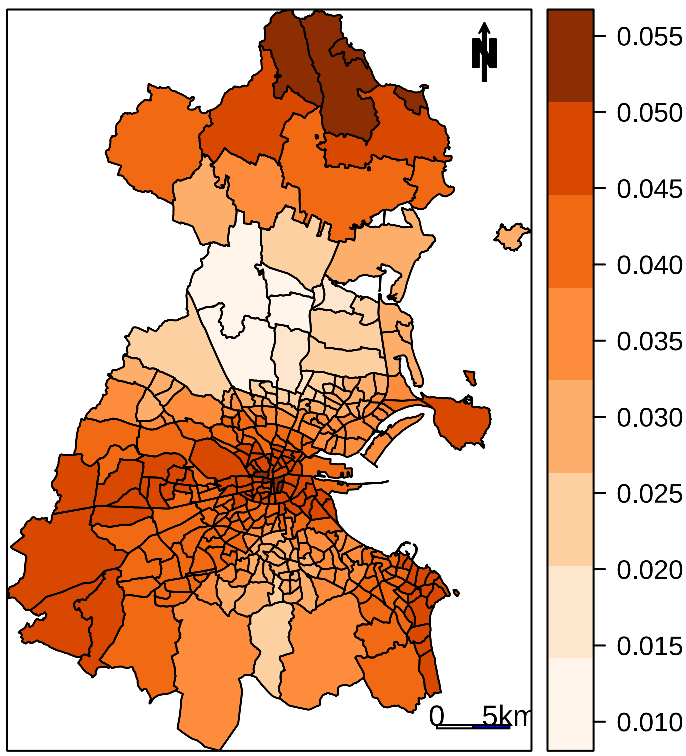
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   34.34   47.08   53.84   52.81   58.66   73.72
```

```
summary(lcr$SDF$Local_Lambda)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.01108 0.03284 0.04038 0.03859 0.04506 0.05374
```

```
spplot(lcr$SDF, "Local_Lambda", key.space = "right",
       col.regions = mypalette.7,cuts = 7, sp.layout = map.layout,
       main = "Fig 9: Local ridge terms for LCR GW regression")
```

Fig 9: Local ridge terms for LCR GW regression

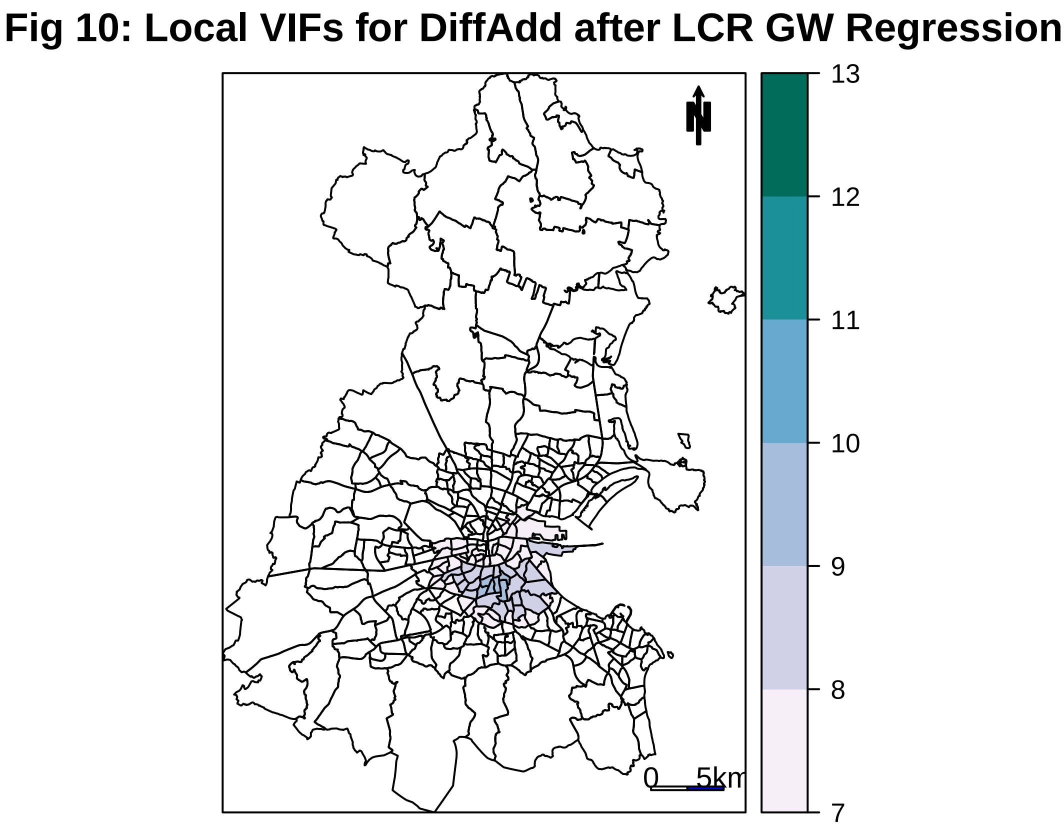



```
gwr.coll.data <- gwr.collin.diagno(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                                   + LowEduc + Age18_24 + Age25_44 + Age45_64,
                                   data = Dub.voter, bw = bandwidth.lcr,
                                   kernel = "bisquare", adaptive = TRUE)
```

Now, recheck VIFs, CNs.

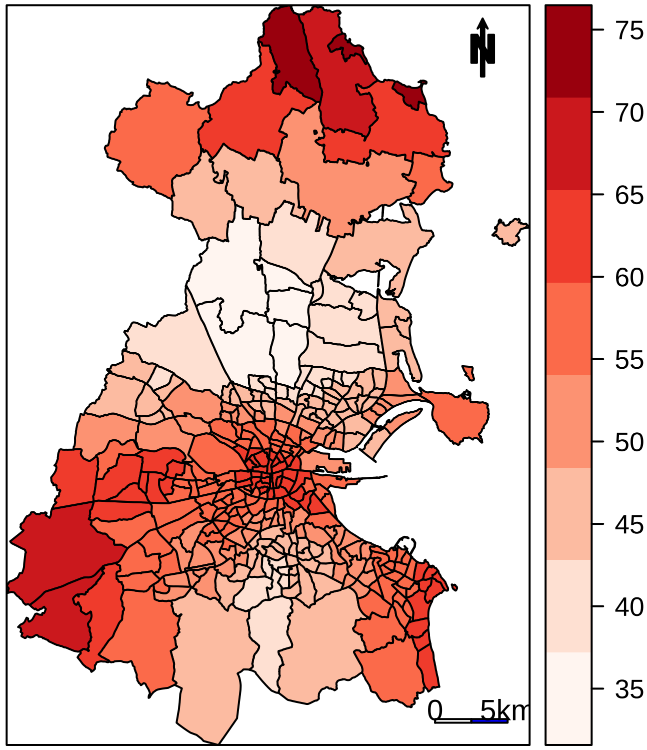
```
# Local VIFs
mypalette.2 <-brewer.pal(6,"PuBuGn")
spplot(gwr.coll.data$SDF,"DiffAdd_VIF",key.space = "right",
       col.regions=mypalette.2,at=c(7,8,9,10,11,12,13),
```

```
        main=list(label="Fig 10: Local VIFs for DiffAdd after LCR GW Regression", cex=1.25),
        sp.layout=map.layout)
```




```
# Local CNs
mypalette.3 <-brewer.pal(8,"Reds")
spplot(gwr.coll.data$SDF,"local_CN",key.space = "right",
        col.regions=mypalette.3,cuts=7,
        main=list(label="Fig 11: Local condition numbers after LCR GW Regression", cex=1.25),
        sp.layout=map.layout)
```

Fig 11: Local condition numbers after LCR GW Regression



One or two of the electoral areas have a VIF for the variable DiffAdd of 11. Most are a 7 or an 8. The CNs have reduced from a max of 110 to a max of 75.

At this point, we could see if removing a predictor will lower the CN values. Removing a single predictor has a negligible effect. Try removing two collinear predictors.

```
# Basic GWR model - removing Age25_44 and Age45_64
bandwidth.gwr <- bw.gwr(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                        + LowEduc + Age18_24,
                        data = Dub.voter, approach = "AICc",
                        kernel = "bisquare", adaptive = TRUE)
```

```
## Adaptive bandwidth (number of nearest neighbours): 206 AICc value: 2006.035
## Adaptive bandwidth (number of nearest neighbours): 135 AICc value: 1985.447
## Adaptive bandwidth (number of nearest neighbours): 90 AICc value: 1965.701
## Adaptive bandwidth (number of nearest neighbours): 63 AICc value: 1974.846
## Adaptive bandwidth (number of nearest neighbours): 107 AICc value: 1970.973
## Adaptive bandwidth (number of nearest neighbours): 79 AICc value: 1966.729
## Adaptive bandwidth (number of nearest neighbours): 96 AICc value: 1966.288
## Adaptive bandwidth (number of nearest neighbours): 85 AICc value: 1966.283
## Adaptive bandwidth (number of nearest neighbours): 91 AICc value: 1965.546
## Adaptive bandwidth (number of nearest neighbours): 94 AICc value: 1965.699
## Adaptive bandwidth (number of nearest neighbours): 91 AICc value: 1965.546
```

```
bgwr <- gwr.basic(GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl
                  + LowEduc + Age18_24,
                  data = Dub.voter, bw = bandwidth.gwr,
                  kernel = "bisquare", adaptive = TRUE)
```

```r
print(bgwr)
```

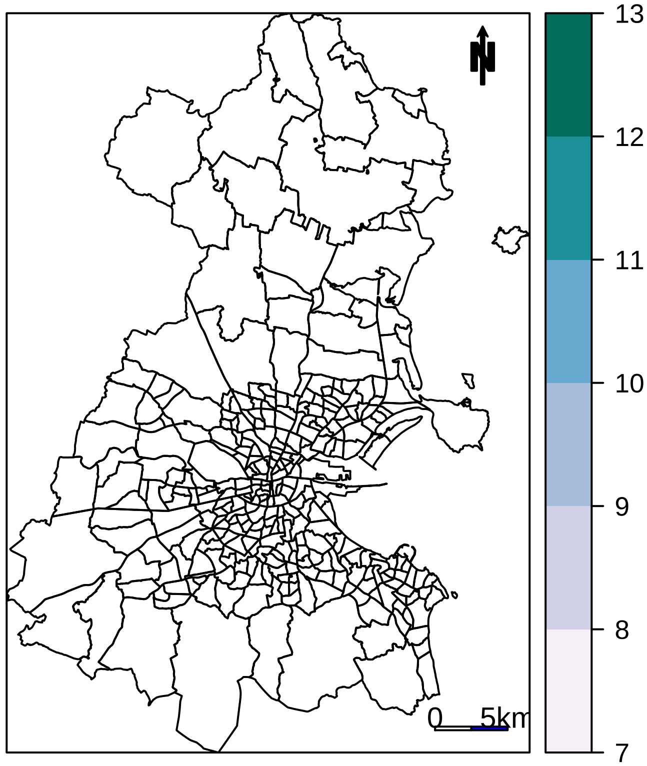
```
##    ***********************************************************************
##    *                       Package   GWmodel                             *
##    ***********************************************************************
##    Program starts at: 2018-04-25 00:30:59
##    Call:
##    gwr.basic(formula = GenEl2004 ~ DiffAdd + LARent + SC1 + Unempl +
##     LowEduc + Age18_24, data = Dub.voter, bw = bandwidth.gwr,
##     kernel = "bisquare", adaptive = TRUE)
##
##    Dependent (y) variable:  GenEl2004
##    Independent variables:  DiffAdd LARent SC1 Unempl LowEduc Age18_24
##    Number of data points: 322
##    ***********************************************************************
##    *                    Results of Global Regression                     *
##    ***********************************************************************
##
##    Call:
##     lm(formula = formula, data = data)
##
##    Residuals:
##      Min       1Q   Median       3Q      Max
## -29.6392  -3.1539   0.4079   3.4050  15.7336
##
##    Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
##    (Intercept) 65.61879    1.24796  52.581  < 2e-16 ***
##    DiffAdd     -0.35668    0.06284  -5.676 3.13e-08 ***
##    LARent      -0.10122    0.01810  -5.593 4.84e-08 ***
##    SC1          0.15895    0.07130   2.229   0.0265 *
##    Unempl      -0.68217    0.09498  -7.182 4.97e-12 ***
##    LowEduc     -0.12212    0.44480  -0.275   0.7838
##    Age18_24    -0.07532    0.05506  -1.368   0.1723
##
##    ---Significance stars
##    Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##    Residual standard error: 5.489 on 315 degrees of freedom
##    Multiple R-squared: 0.6101
##    Adjusted R-squared: 0.6027
##    F-statistic: 82.16 on 6 and 315 DF,  p-value: < 2.2e-16
##    ***Extra Diagnostic information
##    Residual sum of squares: 9490.065
##    Sigma(hat): 5.445774
##    AIC:  2019.267
##    AICc:  2019.727
##    ***********************************************************************
##    *          Results of Geographically Weighted Regression              *
##    ***********************************************************************
##
##    *********************Model calibration information*********************
##    Kernel function: bisquare
##    Adaptive bandwidth: 91 (number of nearest neighbours)
##    Regression points: the same locations as observations are used.
```

```
##    Distance metric: Euclidean distance metric is used.
##
##    ****************Summary of GWR coefficient estimates:*****************
##                    Min.   1st Qu.    Median   3rd Qu.    Max.
##    Intercept 53.119343 62.622018 64.896369 70.923995 79.1684
##    DiffAdd   -1.040597 -0.619542 -0.429067 -0.239161  0.3190
##    LARent    -0.235072 -0.140800 -0.076412  0.024171  0.1521
##    SC1       -0.604922  0.043809  0.315692  0.511332  0.9822
##    Unempl    -2.634154 -1.383324 -0.860685 -0.514533 -0.1284
##    LowEduc   -8.279801 -0.292798  1.462641  2.839764  9.9632
##    Age18_24  -0.427062 -0.168794 -0.052357  0.102811  0.6301
##    ***********************Diagnostic information***********************
##    Number of data points: 322
##    Effective number of parameters (2trace(S) - trace(S'S)): 73.69005
##    Effective degrees of freedom (n-2trace(S) + trace(S'S)): 248.3099
##    AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 1965.546
##    AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 1880.546
##    Residual sum of squares: 5431.085
##    R-square value:  0.7768798
##    Adjusted R-square value:  0.7103975
##
##    *********************************************************************
##    Program stops at: 2018-04-25 00:30:59
```

```
gwr.coll.data <- gwr.collin.diagno(GenEl2004 ~ DiffAdd + LARent + SC1
                                   + Unempl + LowEduc + Age18_24,
                                   data = Dub.voter, bw = bandwidth.gwr,
                                   kernel = "bisquare", adaptive = TRUE)
```

```
# Local VIFs
mypalette.2 <-brewer.pal(6,"PuBuGn")
spplot(gwr.coll.data$SDF,"DiffAdd_VIF",key.space = "right",
       col.regions=mypalette.2,at=c(7,8,9,10,11,12,13),
       main=list(label="Fig 12: Local VIFs for DiffAdd after LCR GW Regression", cex=1.25),
       sp.layout=map.layout)
```

Fig 12: Local VIFs for DiffAdd after LCR GW Regression




```r
# Local Condition Numbers
mypalette.3 <-brewer.pal(8,"Reds")
spplot(gwr.coll.data$SDF,"local_CN",key.space = "right",
       col.regions=mypalette.3,cuts=7,
       main=list(label="Fig 13: Local condition numbers after LCR GW Regression", cex=1.25),
       sp.layout=map.layout)
```

Fig 13: Local condition numbers after LCR GW Regression