Hands-on Exercise 7: Global and Local Measures of Spatial Autocorrelation

In this hands-on exercise, you will learn how to compute Global and Local Measures of Spatial Autocorrelation by using spdep package.

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Contents

Overview

In this hands-on exercise, you will learn how to compute Global and Local Measure of Spatial Autocorrelation (GLSA) by using **spdep** package. By the end to this hands-on exercise, you will be able to:

- import geospatial data using appropriate function(s) of **sf** package,
- import csv file using appropriate function of **readr** package,
- perform relational join using appropriate join function of **dplyr** package,
- compute Global Spatial Autocorrelation (GSA) statistics by using appropriate functions of **spdep** package,
    - plot Moran scatterplot,
    - compute and plot spatial correlogram using appropriate function of **spdep** package.

- compute Local Indicator of Spatial Association (LISA) statistics for detecting clusters and outliers by using appropriate functions **spdep** package;

- compute Getis-Ord's Gi-statistics for detecting hot spot or/and cold spot area by using appropriate functions of **spdep** package; and

- to visualise the analysis output by using **tmap** package.

Getting Started

The analytical question

In spatial policy, one of the main development objective of the local govenment and planners is to ensure equal distribution of development in the province. Our task in this study, hence, is to apply appropriate spatial statistical methods to discover if development are even distributed geographically. If the answer is **No**. Then, our next question will be "is there sign of spatial clustering?". And, if the answer for this question is yes, then our next question will be "where are these clusters?"

In this case study, we are interested to examine the spatial pattern of a selected development indicator (i.e. GDP per capita) of Hunan Provice, People Republic of China.(https://en.wikipedia.org/wiki/Hunan)

The Study Area and Data

Two data sets will be used in this hands-on exercise, they are:

- Hunan province administrative boundary layer at county level. This is a geospatial data set in ESRI shapefile format.

- Hunan_2012.csv: This csv file contains selected Hunan's local development indicators in 2012.

Setting the Analytical Toolls

Before we get started, we need to ensure that **spdep**, **sf**, **tmap** and **tidyverse** packages of R are currently installed in your R.

- sf is use for importing and handling geospatial data in R,

- tidyverse is mainly use for wrangling attribute data in R,

- spdep will be used to compute spatial weights, global and local spatial autocorrelation statistics, and

- tmap will be used to prepare cartographic quality chropleth map.

The code chunk below is used to perform the following tasks:

- creating a package list containing the necessary R packages,
- checking if the R packages in the package list have been installed in R,
  - if they have yet to be installed, RStudio will installed the missing packages,
- launching the packages into R environment.

```
packages = c('sf', 'spdep', 'tmap', 'tidyverse')
for (p in packages){
  if(!require(p, character.only = T)){
    install.packages(p)
  }
  library(p,character.only = T)
}
```

Getting the Data Into R Environment

In this section, you will learn how to bring a geospatial data and its associated attribute table into R environment. The geospatial data is in ESRI shapefile format and the attribute table is in csv fomat.

Import shapefile into r environment

The code chunk below uses *st_read()* of **sf** package to import Hunan shapefile into R. The imported shapefile will be **simple features** Object of **sf**.

```
hunan <- st_read(dsn = "data/geospatial",
                 layer = "Hunan")
```

```
Reading layer `Hunan' from data source
  `D:\tskam\IS415\Hands-on_Ex\Hands-on_Ex07\data\geospatial'
  using driver `ESRI Shapefile'
Simple feature collection with 88 features and 7 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 108.7831 ymin: 24.6342 xmax: 114.2544 ymax: 30.12812
Geodetic CRS:  WGS 84
```

Import csv file into r environment

Next, we will import *Hunan_2012.csv* into R by using *read_csv()* of **readr** package. The output is R data frame class.

```
hunan2012 <- read_csv ("data/aspatial/Hunan_2012.csv")
```

Performing relational join

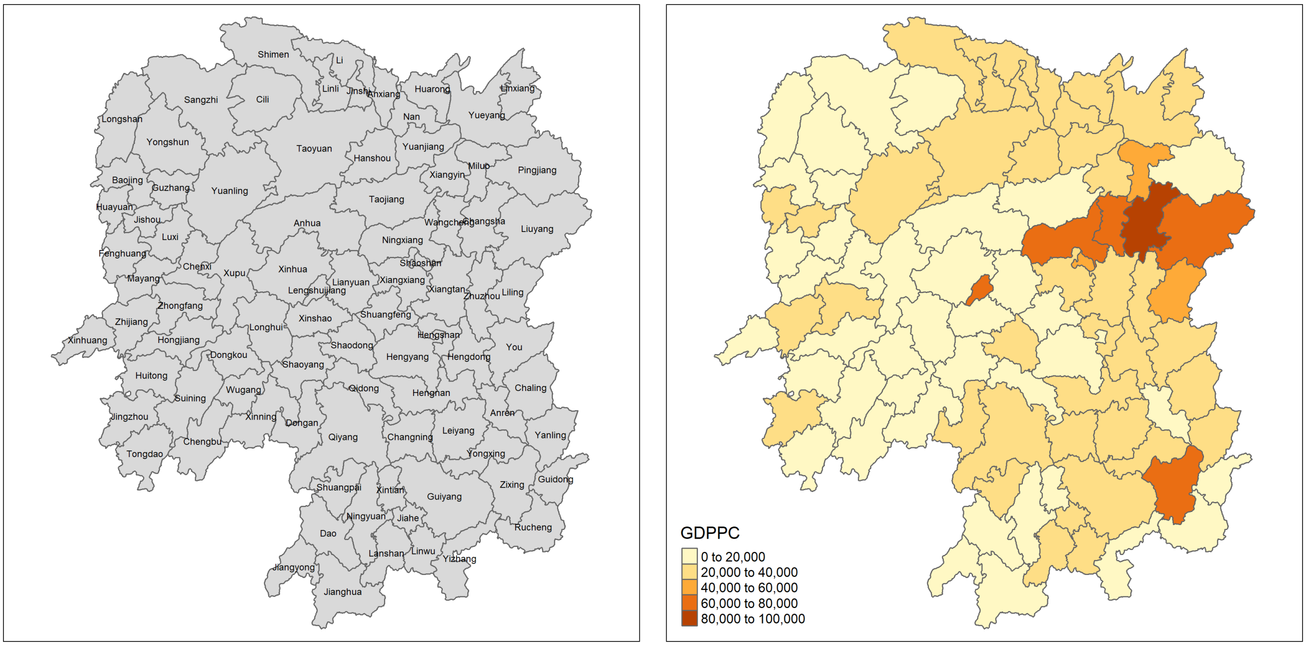
The code chunk below will be used to update the attribute table of *hunan*'s SpatialPolygonsDataFrame with the attribute fields of *hunan2012* dataframe. This is performed by using *left_join()* of **dplyr** package.

```
hunan <- left_join(hunan,hunan2012)
```

Visualising Regional Development Indicator

Now, we are going to prepare a basemap and a choropleth map showing the distribution of GDPPC 2012 by using *qtm()* of **tmap** package.

```
basemap <- tm_shape (hunan) +
  tm_polygons() +
  tm_text ("NAME_3", size=0.5)

gdppc <- qtm (hunan, "GDPPC")
tmap_arrange(basemap, gdppc, asp=1, ncol=2)
```



Global Spatial Autocorrelation

In this section, you will learn how to compute global spatial autocorrelation statistics and to perform spatial complete randomness test for global spatial autocorrelation.

Computing Contiguity Spatial Weights

Before we can compute the global spatial autocorrelation statistics, we need to construct a spatial weights of the study area. The spatial weights is used to define the neighbourhood relationships between the geographical units (i.e. county) in the study area.

In the code chunk below, *poly2nb()* of **spdep** package is used to compute contiguity weight matrices for the study area. This function builds a neighbours list based on regions with contiguous boundaries. If you look at the documentation you will see that you can pass a "queen" argument that takes TRUE or FALSE as options. If you do not specify this argument the default is set to TRUE, that is, if you don't specify queen = FALSE this function will return a list of first order neighbours using the Queen criteria.

More specifically, the code chunk below is used to compute Queen contiguity weight matrix.

```
wm_q <- poly2nb(hunan, queen=TRUE)
summary(wm_q)
```

```
Neighbour list object:
Number of regions: 88
Number of nonzero links: 448
Percentage nonzero weights: 5.785124
Average number of links: 5.090909
Link number distribution:

 1  2  3  4  5  6  7  8  9 11
 2  2 12 16 24 14 11  4  2  1
2 least connected regions:
30 65 with 1 link
1 most connected region:
85 with 11 links
```

The summary report above shows that there are 88 area units in Hunan. The most connected area unit has 11 neighbours. There are two area units with only one heighbours.

Row-standardised weights matrix

Next, we need to assign weights to each neighboring polygon. In our case, each neighboring polygon will be assigned equal weight (style="W"). This is accomplished by assigning the fraction 1/(#ofneighbors) to each neighboring county then summing the weighted income values. While this is the most intuitive way to summaries the neighbors' values it has one drawback in that polygons along the edges of the study area will base their lagged values on fewer polygons thus potentially over- or under-estimating the true nature will base their lagged values on fewer polygons thus potentially over- or under-estimating the true nature of the spatial autocorrelation in the data. For this example, we'll stick with the style="W" option for simplicity's sake but note that other more robust options are available, notably style="B".

```
rswm_q <- nb2listw(wm_q, style="W", zero.policy = TRUE)
rswm_q
```

```
Characteristics of weights list object:
Neighbour list object:
Number of regions: 88
Number of nonzero links: 448
Percentage nonzero weights: 5.785124
Average number of links: 5.090909

Weights style: W
Weights constants summary:
   n   nn S0       S1       S2
W 88 7744 88 37.86334 365.9147
```

The zero.policy=TRUE option allows for lists of non-neighbors. This should be used with caution since the user may not be aware of missing neighbors in their dataset however, a zero.policy of FALSE would return an error.

Global Spatial Autocorrelation: Moran's I

In this section, you will learn how to perform Moran's I statistics testing by using *moran.test()* of **spdep**.

Maron's I test

The code chunk below performs Moran's I statistical testing using *moran.test()* of **spdep**.

```
moran.test(hunan$GDPPC, listw=rswm_q, zero.policy = TRUE, na.action=na.omit)
```

```

    Moran I test under randomisation

data:  hunan$GDPPC
weights: rswm_q

Moran I statistic standard deviate = 4.7351, p-value =
1.095e-06
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
      0.300749970      -0.011494253       0.004348351
```

> *Question: What statistical conclusion can you draw from the output above?*

Computing Monte Carlo Moran's I

The code chunk below performs permutation test for Moran's I statistic by using *moran.mc()* of **spdep**. A total of 1000 simulation will be performed.

```
set.seed(1234)
bperm= moran.mc(hunan$GDPPC, listw=rswm_q, nsim=999, zero.policy = TRUE, na.action=na.omit)
bperm
```

```
	Monte-Carlo simulation of Moran I

data:  hunan$GDPPC
weights: rswm_q
number of simulations + 1: 1000

statistic = 0.30075, observed rank = 1000, p-value = 0.001
alternative hypothesis: greater
```

> *Question: What statistical conclustion can you draw fro mthe output above?*

Visualising Monte Carlo Moran's I

It is always a good practice for us the examine the simulated Moran's I test statistics in greater detail. This can be achieved by plotting the distribution of the statistical values as a histogram by using the code chunk below.

```
mean(bperm$res[1:999])
```

```
[1] -0.01504572
```

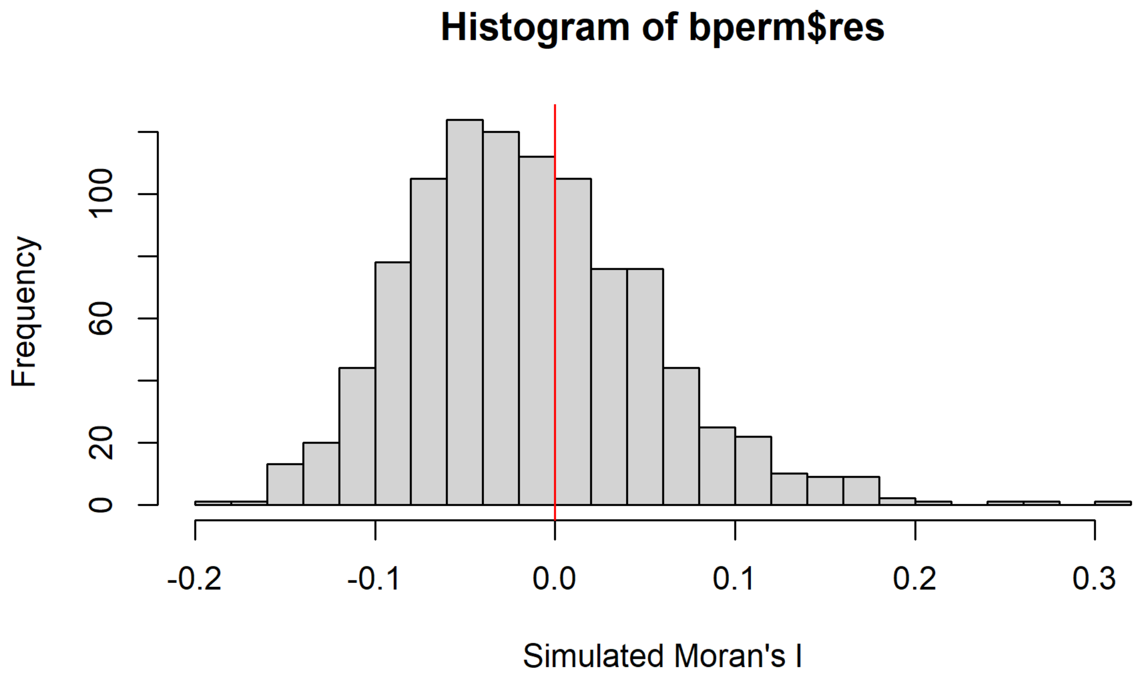
```
var(bperm$res[1:999])
```

```
[1] 0.004371574
```

```
summary(bperm$res[1:999])
```

```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
-0.18339 -0.06168 -0.02125 -0.01505  0.02611  0.27593 
```

```
hist(bperm$res, freq=TRUE, breaks=20, xlab="Simulated Moran's I")
abline(v=0, col="red")
```



> *Question: What statistical observation can you draw fro mthe output above?*

> *Challenge: Instead of using Base Graph to plot the values, plot the values by using ggplot2 package.*

Global Spatial Autocorrelation: Geary's

In this section, you will learn how to perform Geary's c statistics testing by using appropriate functions of **spdep** package.

Geary's C test

The code chunk below performs Geary's C test for spatial autocorrelation by using *geary.test()* of **spdep**.

```
geary.test(hunan$GDPPC, listw=rswm_q)
```

```
	Geary C test under randomisation

data:  hunan$GDPPC  
weights: rswm_q
```

```
weights: rswm_q

Geary C statistic standard deviate = 3.6108, p-value =
0.0001526
alternative hypothesis: Expectation greater than statistic
sample estimates:
Geary C statistic       Expectation          Variance
        0.6907223         1.0000000         0.0073364
```

> *Question: What statistical conclusion can you draw from the output above?*

Computing Monte Carlo Geary's C

The code chunk below performs permutation test for Geary's C statistic by using *geary.mc()* of **spdep**.

```
set.seed(1234)
bperm=geary.mc(hunan$GDPPC, listw=rswm_q, nsim=999)
bperm
```

```
    Monte-Carlo simulation of Geary C

data:  hunan$GDPPC
weights: rswm_q
number of simulations + 1: 1000

statistic = 0.69072, observed rank = 1, p-value = 0.001
alternative hypothesis: greater
```

> *Question: What statistical conclusion can you draw from the output above?*

Visualising the Monte Carlo Geary's C

Next, we will plot a histogram to reveal the distribution of the simulated values by using the code chunk below.

```
mean(bperm$res[1:999])
```

```
[1] 1.004402
```

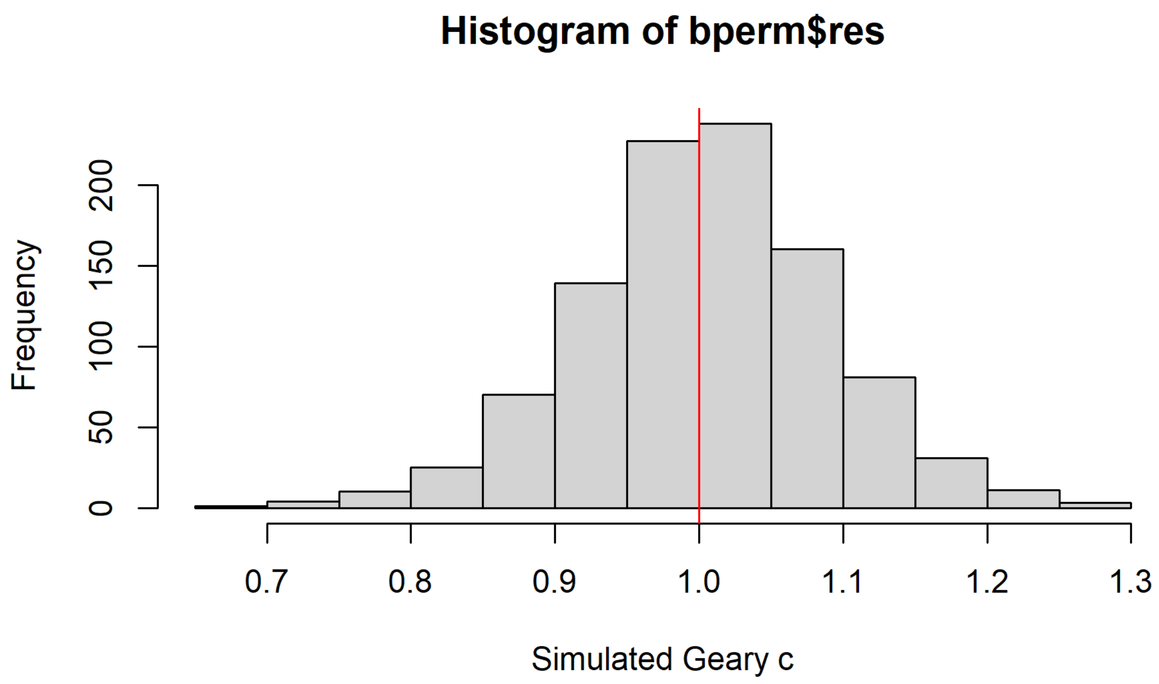
```
var(bperm$res[1:999])
```

```
[1] 0.007436493
```

```
summary(bperm$res[1:999])
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.7142  0.9502  1.0052  1.0044  1.0595  1.2722 
```

```
hist(bperm$res, freq=TRUE, breaks=20, xlab="Simulated Geary c")
abline(v=1, col="red")
```



> *Question: What statistical observation can you draw from the output?*

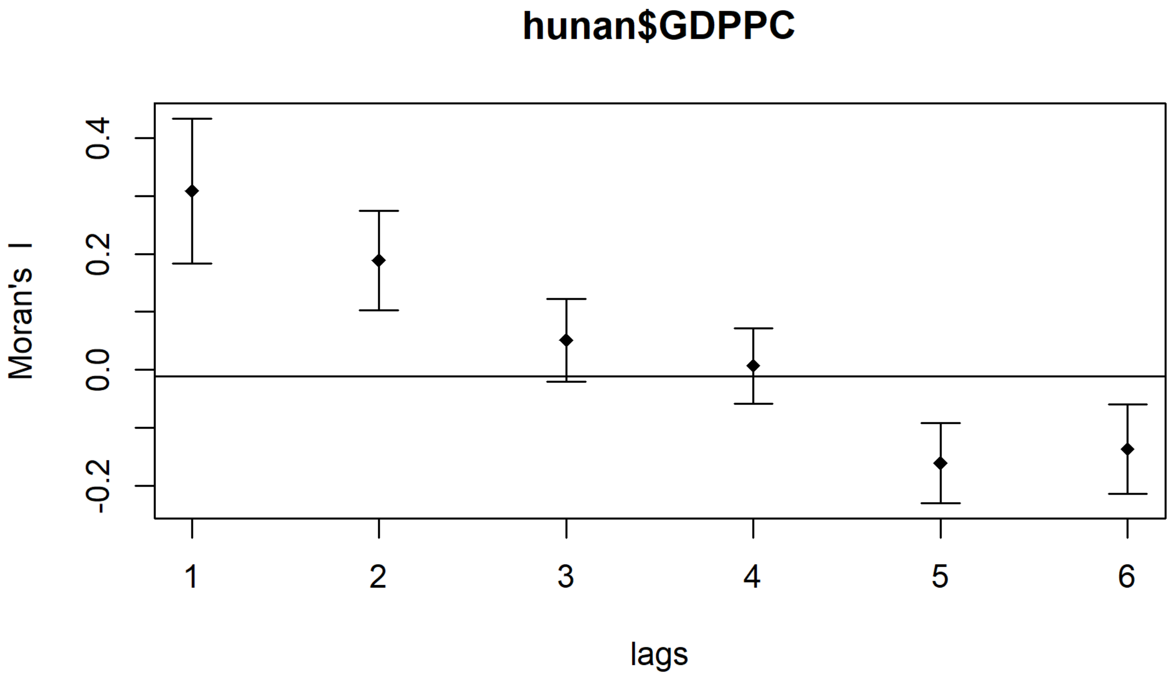
Spatial Correlogram

Spatial correlograms are great to examine patterns of spatial autocorrelation in your data or model residuals. They show how correlated are pairs of spatial observations when you increase the distance (lag) between them - they are plots of some index of autocorrelation (Moran's I or Geary's c) against distance.Although correlograms are not as fundamental as variograms (a keystone concept of geostatistics), they are very useful as an exploratory and descriptive tool. For this purpose they actually provide richer information than variograms.

Compute Moran's I correlogram

In the code chunk below, *sp.correlogram()* of **spdep** package is used to compute a 6-lag spatial correlogram of GDPPC. The global spatial autocorrelation used in Moran's I. The **plot()** of base Graph is then used to plot the output.

```
MI_corr <- sp.correlogram(wm_q, hunan$GDPPC, order=6, method="I", style="B")
plot(MI_corr)
```

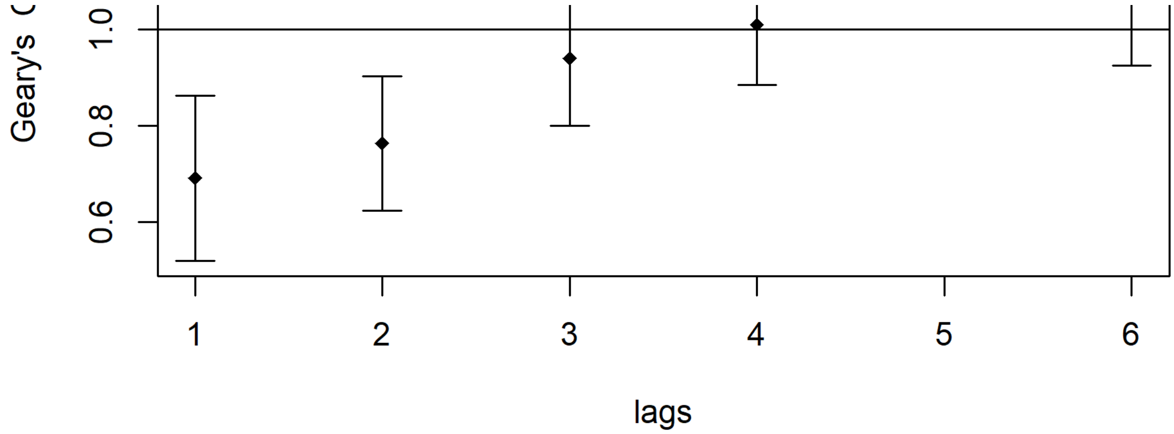


> *Question: What statistical observation can you draw from the plot above?*

Compute Geary's C correlogram and plot

In the code chunk below, *sp.correlogram()* of **spdep** package is used to compute a 6-lag spatial correlogram of GDPPC. The global spatial autocorrelation used in Geary's C. The **plot()** of base Graph is then used to plot the output.

```
GC_corr <- sp.correlogram(wm_q, hunan$GDPPC, order=6, method="C", style="W")
plot(GC_corr)
```



Cluster and Outlier Analysis

Local Indicators of Spatial Association or LISA are statistics that evaluate the existence of clusters in the spatial arrangement of a given variable. For instance if we are studying cancer rates among census tracts in a given city local clusters in the rates mean that there are areas that have higher or lower rates than is to be expected by chance alone; that is, the values occurring are above or below those of a random distribution in space.

In this section, you will learn how to apply appropriate Local Indicators for Spatial Association (LISA), especially local Moran'I to detect cluster and/or outlier from GDP per capita 2012 of Hunan Province, PRC.

Computing local Moran's I

To compute local Moran's I, the *localmoran()* function of **spdep** will be used. It computes *Ii* values, given a set of *zi* values and a listw object providing neighbour weighting information for the polygon associated with the zi values.

The code chunks below are used to compute local Moran's I of *GDPPC2012* at the county level.

```
fips <- order(hunan$County)
localMI <- localmoran(hunan$GDPPC, rswm_q)
head(localMI)
```

```
            Ii          E.Ii       Var.Ii        Z.Ii Pr(z != E(Ii))
1 -0.001468468 -2.815006e-05 4.723841e-04 -0.06626904      0.9471636
2  0.025878173 -6.061953e-04 1.016664e-02  0.26266425      0.7928094
3 -0.011987646 -5.366648e-03 1.133362e-01 -0.01966705      0.9843090
4  0.001022468 -2.404783e-07 5.105969e-06  0.45259801      0.6508382
5  0.014814881 -6.829362e-05 1.449949e-03  0.39085814      0.6959021
6 -0.038793829 -3.860263e-04 6.475559e-03 -0.47728835      0.6331568
```

localmoran() function returns a matrix of values whose columns are:

- Ii: the local Moran's I statistics

- E.Ii: the expectation of local moran statistic under the randomisation hypothesis
- Var.Ii: the variance of local moran statistic under the randomisation hypothesis
- Z.Ii:the standard deviate of local moran statistic
- Pr(): the p-value of local moran statistic

The code chunk below list the content of the local Moran matrix derived by using *printCoefmat()*.

```
printCoefmat(data.frame(localMI[fips,], row.names=hunan$County[fips]), check.names=FALSE)
```

```
                     Ii        E.Ii      Var.Ii        Z.Ii
Anhua       -2.2493e-02 -5.0048e-03  5.8235e-02 -7.2467e-02
Anren       -3.9932e-01 -7.0111e-03  7.0348e-02 -1.4791e+00
Anxiang     -1.4685e-03 -2.8150e-05  4.7238e-04 -6.6269e-02
Baojing      3.4737e-01 -5.0089e-03  8.3636e-02  1.2185e+00
Chaling      2.0559e-02 -9.6812e-04  2.7711e-02  1.2932e-01
Changning   -2.9868e-05 -9.0010e-09  1.5105e-07 -7.6828e-02
Changsha     4.9022e+00 -2.1348e-01  2.3194e+00  3.3590e+00
Chengbu      7.3725e-01 -1.0534e-02  2.2132e-01  1.5895e+00
Chenxi       1.4544e-01 -2.8156e-03  4.7116e-02  6.8299e-01
Cili         7.3176e-02 -1.6747e-03  4.7902e-02  3.4200e-01
Dao          2.1420e-01 -2.0824e-03  4.4123e-02  1.0297e+00
Dongan       1.5210e-01 -6.3485e-04  1.3471e-02  1.3159e+00
Dongkou      5.2918e-01 -6.4461e-03  1.0748e-01  1.6338e+00
Fenghuang    1.8013e-01 -6.2832e-03  1.3257e-01  5.1198e-01
Guidong     -5.9160e-01 -1.3086e-02  3.7003e-01 -9.5104e-01
Guiyang      1.8240e-01 -3.6908e-03  3.2610e-02  1.0305e+00
Guzhang      2.8466e-01 -8.5054e-03  1.4152e-01  7.7931e-01
Hanshou      2.5878e-02 -6.0620e-04  1.0167e-02  2.6266e-01
Hengdong     9.9964e-03 -4.9063e-04  6.7742e-03  1.2742e-01
Hengnan      2.8064e-02 -3.2160e-04  3.7597e-03  4.6294e-01
Hengshan    -5.8201e-03 -3.0437e-05  5.1076e-04 -2.5618e-01
Hengyang     6.2997e-02 -1.3046e-03  2.1865e-02  4.3486e-01
Hongjiang    1.8790e-01 -2.3019e-03  3.1725e-02  1.0678e+00
Huarong     -1.5389e-02 -1.8667e-03  8.1030e-02 -4.7503e-02
Huayuan      8.3772e-02 -8.5569e-04  2.4495e-02  5.4072e-01
Huitong      2.5997e-01 -5.2447e-03  1.1077e-01  7.9685e-01
Jiahe       -1.2431e-01 -3.0550e-03  5.1111e-02 -5.3633e-01
Jianghua     2.8651e-01 -3.8280e-03  8.0968e-02  1.0204e+00
Jiangyong    2.4337e-01 -2.7082e-03  1.1746e-01  7.1800e-01
Jingzhou     1.8270e-01 -8.5106e-04  2.4363e-02  1.1759e+00
Jinshi      -1.1988e-02 -5.3666e-03  1.1334e-01 -1.9667e-02
Jishou      -2.8680e-01 -2.6305e-03  4.4028e-02 -1.3543e+00
Lanshan      6.3334e-02 -9.6365e-04  2.0441e-02  4.4972e-01
Leiyang      1.1581e-02 -1.4948e-04  2.5082e-03  2.3422e-01
Lengshuijiang -1.7903e+00 -8.2129e-02  2.1598e+00 -1.1623e+00
Li           1.0225e-03 -2.4048e-07  5.1060e-06  4.5260e-01
```

Li	1.0225e-03	-2.4648e-07	5.1666e-06	4.5266e-01
Lianyuan	-1.4672e-01	-1.8983e-03	1.9145e-02	-1.0467e+00
Liling	1.3774e+00	-1.5097e-02	4.2601e-01	2.1335e+00
Linli	1.4815e-02	-6.8294e-05	1.4499e-03	3.9086e-01
Linwu	-2.4621e-03	-9.0703e-06	1.9258e-04	-1.7676e-01
Linxiang	6.5904e-02	-2.9028e-03	2.5470e-01	1.3634e-01
Liuyang	3.3688e+00	-7.7502e-02	1.5180e+00	2.7972e+00
Longhui	8.0801e-01	-1.1377e-02	1.5538e-01	2.0787e+00
Longshan	7.5663e-01	-1.1100e-02	3.1449e-01	1.3690e+00
Luxi	1.8177e-01	-2.4855e-03	3.4249e-02	9.9561e-01
Mayang	2.1852e-01	-5.8773e-03	9.8049e-02	7.1663e-01
Miluo	1.8704e+00	-1.6927e-02	2.7925e-01	3.5715e+00
Nan	-9.5789e-03	-4.9497e-04	6.8341e-03	-1.0988e-01
Ningxiang	1.5607e+00	-7.3878e-02	8.0012e-01	1.8274e+00
Ningyuan	2.0910e-01	-7.0884e-03	8.2306e-02	7.5356e-01
Pingjiang	-9.8964e-01	-2.6457e-03	5.6027e-02	-4.1698e+00
Qidong	1.1806e-01	-2.1207e-03	2.4747e-02	7.6396e-01
Qiyang	6.1966e-02	-7.3374e-04	8.5743e-03	6.7712e-01
Rucheng	-3.6992e-01	-8.8999e-03	2.5272e-01	-7.1814e-01
Sangzhi	2.5053e-01	-4.9470e-03	6.8000e-02	9.7972e-01
Shaodong	-3.2659e-02	-3.6592e-05	5.0546e-04	-1.4510e+00
Shaoshan	2.1223e+00	-5.0227e-02	1.3668e+00	1.8583e+00
Shaoyang	5.9499e-01	-1.1253e-02	1.3012e-01	1.6807e+00
Shimen	-3.8794e-02	-3.8603e-04	6.4756e-03	-4.7729e-01
Shuangfeng	9.2835e-03	-2.2867e-03	3.1516e-02	6.5174e-02
Shuangpai	8.0591e-02	-3.1366e-04	8.9838e-03	8.5358e-01
Suining	3.7585e-01	-3.5933e-03	4.1870e-02	1.8544e+00
Taojiang	-2.5394e-01	-1.2395e-03	1.4477e-02	-2.1002e+00
Taoyuan	1.4729e-02	-1.2039e-04	8.5103e-04	5.0903e-01
Tongdao	4.6482e-01	-6.9870e-03	1.9879e-01	1.0582e+00
Wangcheng	4.4220e+00	-1.1067e-01	1.3596e+00	3.8873e+00
Wugang	7.1003e-01	-7.8144e-03	1.0710e-01	2.1935e+00
Xiangtan	2.4530e-01	-3.6457e-04	3.2319e-03	4.3213e+00
Xiangxiang	2.6271e-01	-1.2703e-03	2.1290e-02	1.8092e+00
Xiangyin	5.4525e-01	-4.7442e-03	7.9236e-02	1.9539e+00
Xinhua	1.1810e-01	-6.2649e-03	8.6001e-02	4.2409e-01
Xinhuang	1.5725e-01	-4.1820e-03	3.6648e-01	2.6667e-01
Xinning	6.8928e-01	-9.6674e-03	2.0328e-01	1.5502e+00
Xinshao	5.7578e-02	-8.5932e-03	1.1769e-01	1.9289e-01
Xintian	-7.4050e-03	-5.1493e-03	1.0877e-01	-6.8395e-03
Xupu	3.2406e-01	-5.7468e-03	5.7735e-02	1.3726e+00
Yanling	-6.9021e-02	-5.9211e-04	9.9306e-03	-6.8667e-01
Yizhang	-2.6844e-01	-2.2463e-03	4.7588e-02	-1.2202e+00
Yongshun	6.3064e-01	-1.1350e-02	1.8830e-01	1.4795e+00
Yongxing	4.3411e-01	-9.0735e-03	1.5088e-01	1.1409e+00
You	7.8750e-02	-7.2728e-03	1.2116e-01	2.4714e-01
Yuanjiang	2.0004e-04	-1.7760e-04	2.9798e-03	6.9181e-03
Yuanling	8.7298e-03	-2.2981e-06	2.3221e-05	1.8121e+00
Yueyang	4.1189e-02	-1.9768e-04	2.3113e-03	8.6085e-01
Zhijiang	1.0476e-01	-7.8123e-04	1.3100e-02	9.2214e-01
Zhongfang	-2.2685e-01	-2.1455e-03	3.5927e-02	-1.1855e+00
Zhuzhou	3.2864e-01	-5.2432e-04	7.2391e-03	3.8688e+00

```
Zhuzhou        5.2864e-01 -5.2432e-04  7.2591e-03  5.8088e+00
Zixing        -7.6849e-01 -8.8210e-02  9.4057e-01 -7.0144e-01
              Pr.z....E.Ii..
Anhua                 0.9422
Anren                 0.1391
Anxiang               0.9472
Baojing               0.2230
Chaling               0.8971
Changning             0.9388
Changsha              0.0008
Chengbu               0.1119
Chenxi                0.4946
Cili                  0.7324
Dao                   0.3032
Dongan                0.1882
Dongkou               0.1023
Fenghuang             0.6087
Guidong               0.3416
Guiyang               0.3028
Guzhang               0.4358
Hanshou               0.7928
Hengdong              0.8986
Hengnan               0.6434
Hengshan              0.7978
Hengyang              0.6637
Hongjiang             0.2856
Huarong               0.9621
Huayuan               0.5887
Huitong               0.4255
Jiahe                 0.5917
Jianghua              0.3076
Jiangyong             0.4728
Jingzhou              0.2396
Jinshi                0.9843
Jishou                0.1756
Lanshan               0.6529
Leiyang               0.8148
Lengshuijiang         0.2451
Li                    0.6508
Lianyuan              0.2952
Liling                0.0329
Linli                 0.6959
Linwu                 0.8597
Linxiang              0.8916

Liuyang               0.0052
Longhui               0.0376
Longshan              0.1710
Luxi                  0.3194
Mayang                0.4736
Miluo                 0.0004
Nan                   0.9125
Ningxiang             0.0676
```

```
Ningxiang              0.0070
Ningyuan               0.4511
Pingjiang              0.0000
Qidong                 0.4449
Qiyang                 0.4983
Rucheng                0.4727
Sangzhi                0.3272
Shaodong               0.1468
Shaoshan               0.0631
Shaoyang               0.0928
Shimen                 0.6332
Shuangfeng             0.9480
Shuangpai              0.3933
Suining                0.0637
Taojiang               0.0357
Taoyuan                0.6107
Tongdao                0.2900
Wangcheng              0.0001
Wugang                 0.0283
Xiangtan               0.0000
Xiangxiang             0.0704
Xiangyin               0.0507
Xinhua                 0.6715
Xinhuang               0.7897
Xinning                0.1211
Xinshao                0.8470
Xintian                0.9945
Xupu                   0.1699
Yanling                0.4923
Yizhang                0.2224
Yongshun               0.1390
Yongxing               0.2539
You                    0.8048
Yuanjiang              0.9945
Yuanling               0.0700
Yueyang                0.3893
Zhijiang               0.3565
Zhongfang              0.2358
Zhuzhou                0.0001
Zixing                 0.4830
```

Mapping the local Moran's I

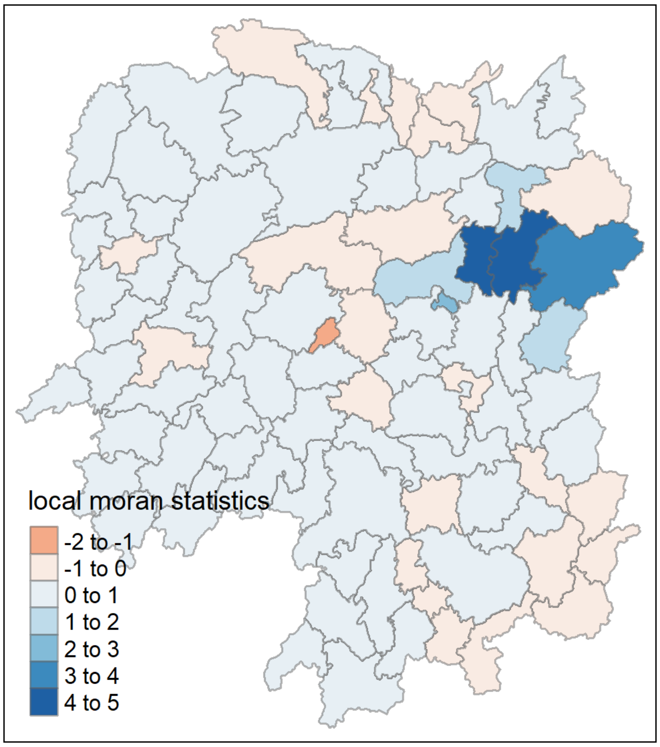
Before mapping the local Moran's I map, it is wise to append the local Moran's I dataframe (i.e. localMI) onto hunan SpatialPolygonDataFrame. The code chunks below can be used to perform the task. The out SpatialPolygonDataFrame is called *hunan.localMI*.

```
hunan.localMI <- cbind(hunan,localMI) %>%
  rename(Pr.Ii = Pr.z....E.Ii..)
```

Mapping local Moran's I values

Using choropleth mapping functions of **tmap** package, we can plot the local Moran's I values by using the code chinks below.

```
tm_shape(hunan.localMI) +
  tm_fill(col = "Ii",
          style = "pretty",
          palette = "RdBu",
          title = "local moran statistics") +
  tm_borders(alpha = 0.5)
```



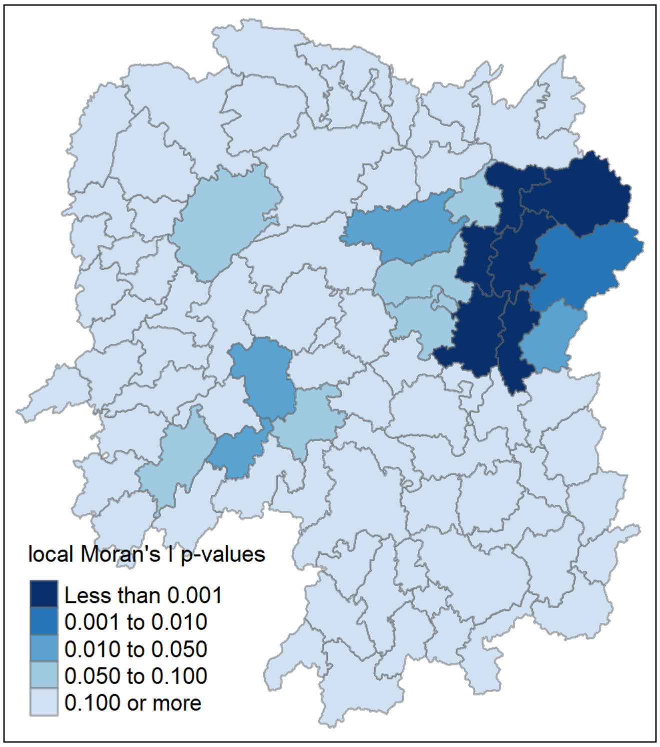
Mapping local Moran's I p-values

The choropleth shows there is evidence for both positive and negative Ii values. However, it is useful to consider the p-values for each of these values, as consider above.

The code chunks below produce a choropleth map of Moran's I p-values by using functions of **tmap** package.

```
tm_shape(hunan.localMI) +
  tm_fill(col = "Pr.Ii",
          breaks=c(-Inf, 0.001, 0.01, 0.05,
0.1, Inf),
          palette="-Blues",
          title = "local Moran's I p-values") +
```

```
  title =         "local Moran's I p-values")        +
  tm_borders(        alpha =         0.5       )
```

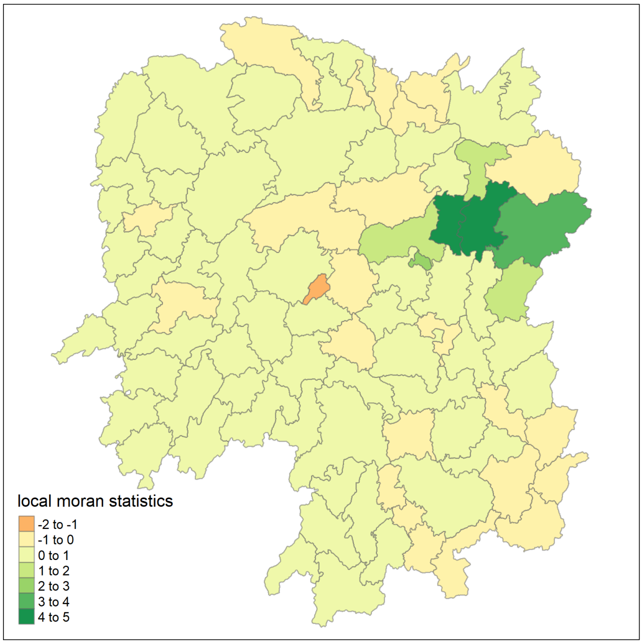


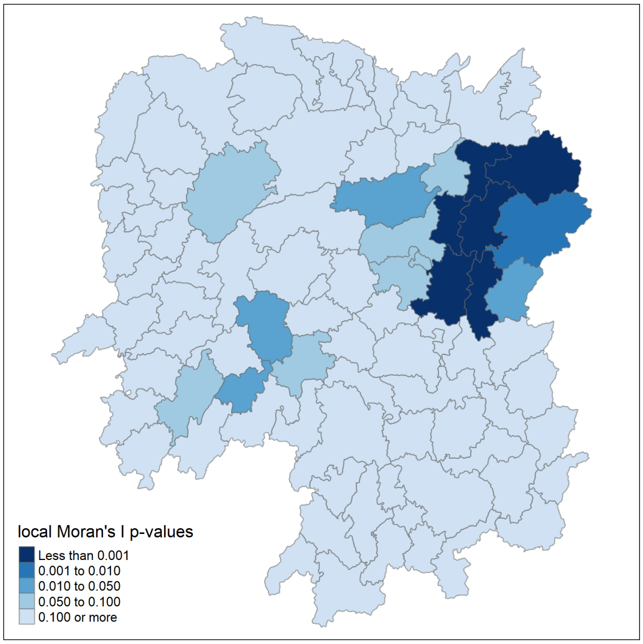
Mapping both local Moran's I values and p-values

For effective interpretation, it is better to plot both the local Moran's I values map and its corresponding p-values map next to each other.

The code chunk below will be used to create such visualisation.

```
localMI.map <-        tm_shape (         hunan.localMI)         +
  tm_fill   (         col =          "Ii"      ,
          style =          "pretty" ,
          title =          "local moran statistics")        +
  tm_borders(        alpha =         0.5       )

pvalue.map <-        tm_shape (         hunan.localMI)         +
  tm_fill   (         col =          "Pr.Ii"   ,
          breaks=        c         (       -         Inf       , 0.001     , 0.01      , 0.05      ,
0.1        , Inf        )         ,
          palette=         "-Blues"        ,
          title =          "local Moran's I p-values")        +
  tm_borders(        alpha =         0.5       )

tmap_arrange(        localMI.map, pvalue.map, asp=        1        , ncol=        2
)
```





Creating a LISA Cluster Map

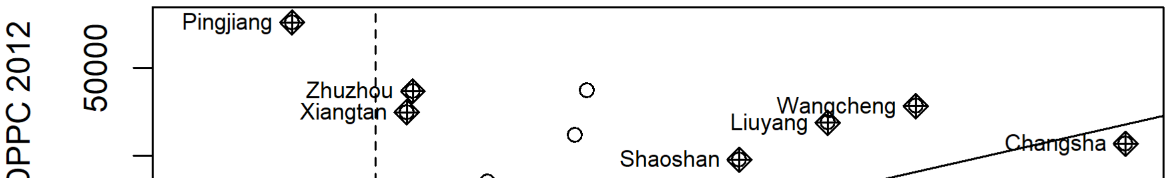
The LISA Cluster Map shows the significant locations color coded by type of spatial autocorrelation. The first step before we can generate the LISA cluster map is to plot the Moran scatterplot.

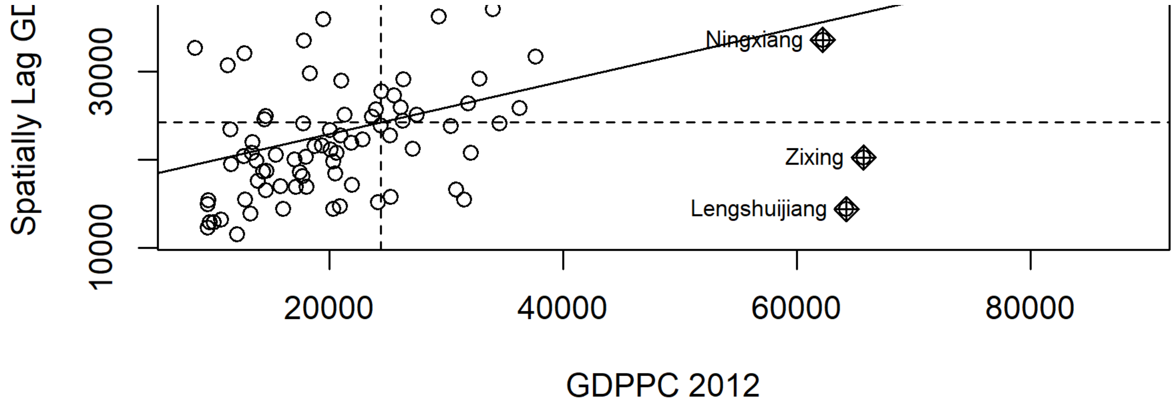
Plotting Moran scatterplot

The Moran scatterplot is an illustration of the relationship between the values of the chosen attribute at each location and the average value of the same attribute at neighboring locations.

The code chunk below plots the Moran scatterplot of GDPPC 2012 by using *moran.plot()* of **spdep**.

```
nci <- moran.plot(hunan$GDPPC, rswm_q,
                  labels=as.character(hunan$County),
                  xlab="GDPPC 2012",
                  ylab="Spatially Lag GDPPC 2012")
```





Notice that the plot is split in 4 quadrants. The top right corner belongs to areas that have high GDPPC and are surrounded by other areas that have the average level of GDPPC. This are the high-high locations in the lesson slide.

Plotting Moran scatterplot with standardised variable

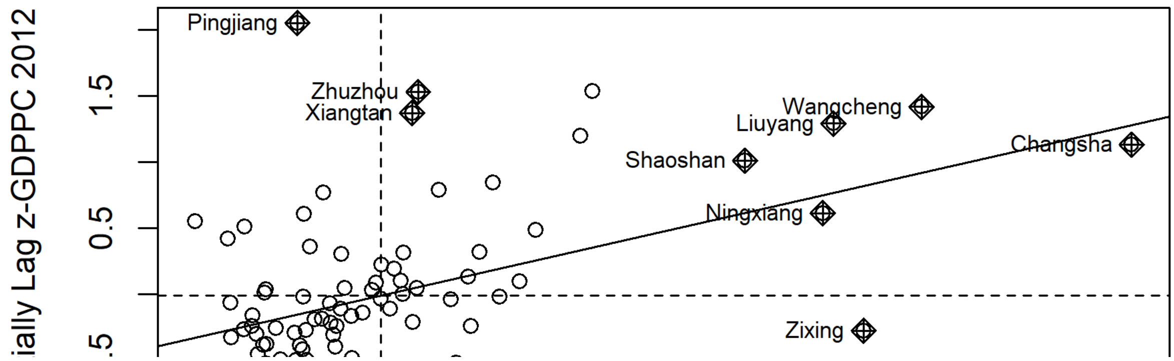
First we will use *scale()* to centers and scales the variable. here centering is done by subtracting the mean (omitting NAs) the corresponding columns, and scaling is done by dividing the (centered) variable by their standard deviations.

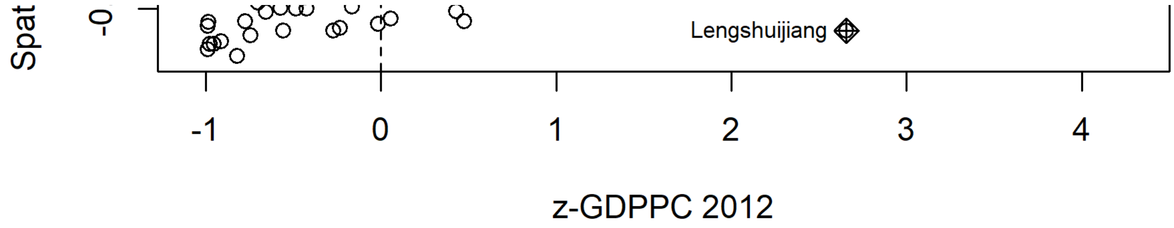
```
hunan$Z.GDPPC <- scale(hunan$GDPPC) %>% as.vector
```

The *as.vector()* added to the end is to make sure that the data type we get out of this is a vector, that map neatly into out dataframe.

Now, we are ready to plot the Moran scatterplot again by using the code chunk below.

```
nci2 <- moran.plot(hunan$Z.GDPPC, rswm_q,
                   labels=as.character(hunan$County),
                   xlab="z-GDPPC 2012",
                   ylab="Spatially Lag z-GDPPC 2012")
```





Preparing LISA map classes

The code chunks below show the steps to prepare a LISA cluster map.

```
quadrant <- vector(mode="numeric",length=nrow(localMI))
```

Next, we centers the variable of interest around its mean.

```
DV <- hunan$GDPPC - mean(hunan$GDPPC)
```

This is follow by centering the local Moran's around the mean.

```
C_mI <- localMI[,1] - mean(localMI[,1])
```

Next, we will set a statistical significance level for the local Moran.

```
signif <- 0.05
```

These four command lines define the high-high, low-low, low-high and high-low categories.

```
quadrant[DV >0 & C_mI>0] <- 4
quadrant[DV <0 & C_mI<0] <- 1
quadrant[DV <0 & C_mI>0] <- 2
quadrant[DV >0 & C_mI<0] <- 3
```

Lastly, places non-significant Moran in the category 0.

```
quadrant[localMI[,5]>signif] <- 0
```

In fact, we can combined all the steps into one single code chunk as shown below:

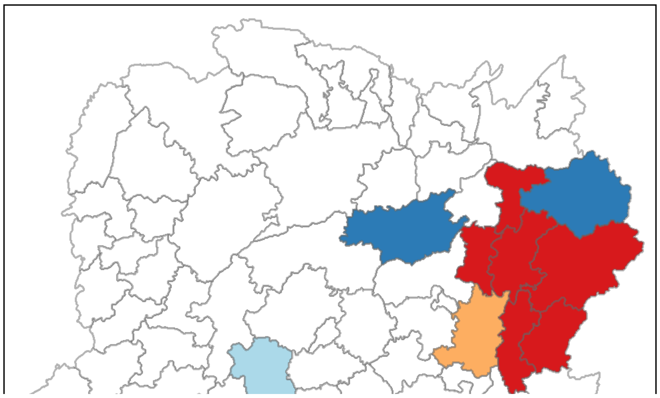
```
quadrant <- vector(mode="numeric",length=nrow(
```

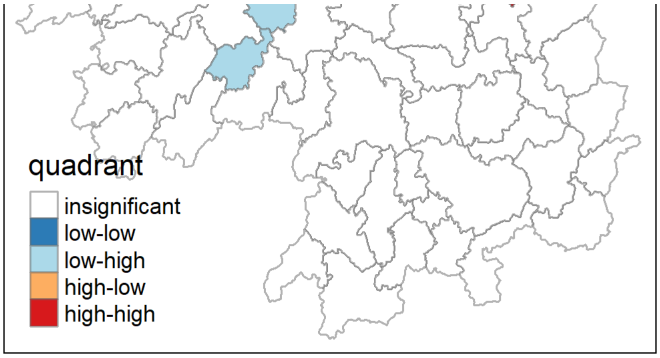
```
quadrant <- vector(mode="numeric",length=nrow(
localMI))
DV <- hunan$GDPPC - mean(hunan$
GDPPC)
C_mI <- localMI[,1] - mean(localMI
[,1])
signif <- 0.05
quadrant[DV >0 & C_mI>0]
<- 4
quadrant[DV <0 & C_mI<0]
<- 1
quadrant[DV <0 & C_mI>0]
<- 2
quadrant[DV >0 & C_mI<0]
<- 3
quadrant[localMI[,5]>signif] <-
0
```

Plotting LISA map

Now, we can build the LISA map by using the code chunks below.

```
hunan.localMI$quadrant <- quadrant
colors <- c("#ffffff", "#2c7bb6", "#abd9e9", "#fdae61", "#d7191c"
)
clusters <- c("insignificant", "low-low", "low-high",
"high-low", "high-high")

tm_shape(hunan.localMI) +
  tm_fill(col = "quadrant",
        style = "cat",
        palette = colors[c(sort(unique
(quadrant)))+1],
        labels = clusters[c(sort(unique
(quadrant)))+1],
        popup.vars = c("")) +
  tm_view(set.zoom.limits = c(11,17)
) +
  tm_borders(alpha=0.5)
```

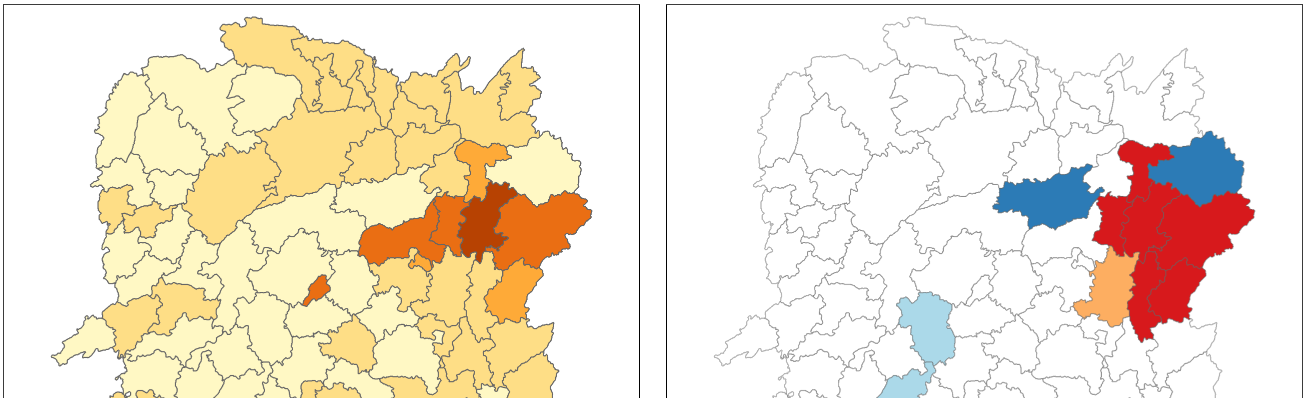


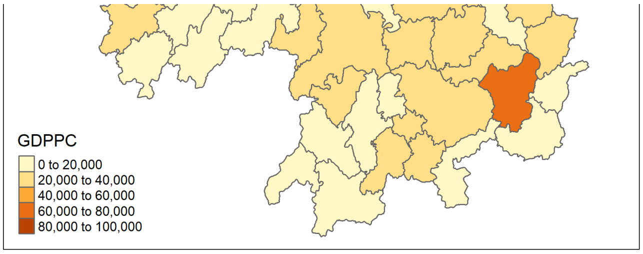


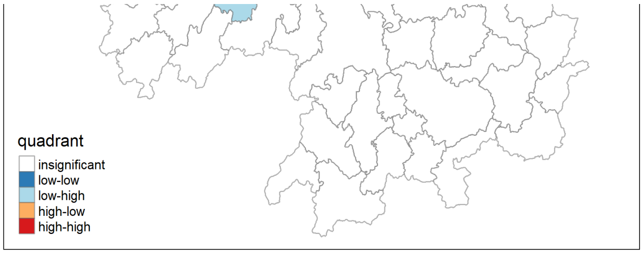
For effective interpretation, it is better to plot both the local Moran's I values map and its corresponding p-values map next to each other.

The code chunk below will be used to create such visualisation.

```
gdppc <- qtm(hunan, "GDPPC")

hunan.localMI$quadrant <- quadrant
colors <- c("#ffffff", "#2c7bb6", "#abd9e9", "#fdae61", "#d7191c")
clusters <- c("insignificant", "low-low", "low-high", "high-low", "high-high")

LISAmap <- tm_shape(hunan.localMI) +
  tm_fill(col = "quadrant",
          style = "cat",
          palette = colors[c(sort(unique(quadrant)))+1],
          labels = clusters[c(sort(unique(quadrant)))+1],
          popup.vars = c("")) +
  tm_view(set.zoom.limits = c(11,17)) +
  tm_borders(alpha=0.5)

tmap_arrange(gdppc, LISAmap, asp=1, ncol=2)
```







> *Question: What statistical observations can you draw from the LISA map above?*

Hot Spot and Cold Spot Area Analysis

Beside detecting cluster and outliers, localised spatial statistics can be also used to detect hot spot and/or cold spot areas.

The term 'hot spot' has been used generically across disciplines to describe a region or value that is higher relative to its surroundings (Lepers et al 2005, Aben et al 2012, Isobe et al 2015).

Getis and Ord's G-Statistics

An alternative spatial statistics to detect spatial anomalies is the Getis and Ord's G-statistics (Getis and Ord, 1972; Ord and Getis, 1995). It looks at neighbours within a defined proximity to identify where either high or low values clutser spatially. Here, statistically significant hot-spots are recognised as areas of high values where other areas within a neighbourhood range also share high values too.

The analysis consists of three steps:

- Deriving spatial weight matrix
- Computing Gi statistics
- Mapping Gi statistics

Deriving distance-based weight matrix

First, we need to define a new set of neighbours. Whist the spatial autocorrelation considered units which shared borders, for Getis-Ord we are defining neighbours based on distance.

There are two type of distance-based proximity matrix, they are:

- fixed diatnce weight matrix; and
- adaptive distance weight matrix.

Deriving the centroid

We will need points to associate with each polygon before we can make our connectivity graph. It will be a little more complicated than just running *st_centroid()* on the sf object: **us.bound**. We need the coordinates in a separate data frame for this to work. To do this we will use a mapping function. The mapping function applies a given function to each element of a vector and returns a vector of the same length. Our input vector will be the geometry column of us.bound. Our function will be *st_centroid()*. We will be using map_dbl variation of map from the purrr package. For more documentation, check out map documentation

To get our longitude values we map the *st_centroid()* function over the geometry column of us.bound and access the longitude value through double bracket notation [[]] and 1. This allows us to get only the longitude, which is the first value in each centroid.

```
longitude <- map_dbl(hunan$geometry, ~st_centroid(.x)[[1]])
```

We do the same for latitude with one key difference. We access the second value per each centroid with [[2]].

```
latitude <- map_dbl(hunan$geometry, ~st_centroid(.x)[[2]])
```

Now that we have latitude and longitude, we use cbind to put longitude and latitude into the same object.

```
coords <- cbind(longitude, latitude)
```

Determine the cut-off distance

Firstly, we need to determine the upper limit for distance band by using the steps below:

- Return a matrix with the indices of points belonging to the set of the k nearest neighbours of each other by using *knearneigh()* of **spdep**.
- Convert the knn object returned by *knearneigh()* into a neighbours list of class nb with a list of integer vectors containing neighbour region number ids by using *knn2nb()*.
- Return the length of neighbour relationship edges by using *nbdists()* of **spdep**. The function returns in the units of the coordinates if the coordinates are projected, in km otherwise.
- Remove the list structure of the returned object by using **unlist()**.

```
#coords <- coordinates(hunan)
k1 <- knn2nb(knearneigh(coords))
k1dists <- unlist(nbdists(k1, coords, longlat =
```

```
TRUE ) )
summary ( k1dists )
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  24.79   32.57   38.01   39.07   44.52   61.79 
```

The summary report shows that the largest first nearest neighbour distance is 61.79 km, so using this as the upper threshold gives certainty that all units will have at least one neighbour.

Computing fixed distance weight matrix

Now, we will compute the distance weight matrix by using *dnearneigh()* as shown in the code chunk below.

```
wm_d62 <- dnearneigh( coords , 0 , 62 , longlat =
TRUE )
wm_d62
```

```
Neighbour list object:
Number of regions: 88 
Number of nonzero links: 324 
Percentage nonzero weights: 4.183884 
Average number of links: 3.681818 
```

Next, *nb2listw()* is used to convert the nb object into spatial weights object. The input of *nb2listw()* must be an object of class **nb**. The syntax of the function has two major arguments, namely style and zero.poly.

- *style* can take values “W”, “B”, “C”, “U”, “minmax” and “S”. B is the basic binary coding, W is row standardised (sums over all links to n), C is globally standardised (sums over all links to n), U is equal to C divided by the number of neighbours (sums over all links to unity), while S is the variance-stabilizing coding scheme proposed by Tiefelsdorf et al. 1999, p. 167-168 (sums over all links to n).
- If *zero policy* is set to TRUE, weights vectors of zero length are inserted for regions without neighbour in the neighbours list. These will in turn generate lag values of zero, equivalent to the sum of products of the zero row t(rep(0, length=length(neighbours))) %*% x, for arbitraty numerical vector x of length length(neighbours). The spatially lagged value of x for the zero-neighbour region will then be zero, which may (or may not) be a sensible choice.

```
wm62_lw <- nb2listw ( wm_d62 , style = 'B' )
summary ( wm62_lw )
```

```
Characteristics of weights list object:
Neighbour list object:
Number of regions: 88 
Number of nonzero links: 324 
Percentage nonzero weights: 4.183884 
Average number of links: 3.681818 
Link number distribution:
```

```
 1  2  3  4  5  6 
 6 15 14 26 20  7 
6 least connected regions:
6 15 30 32 56 65 with 1 link
7 most connected regions:
21 28 35 45 50 52 82 with 6 links

Weights style: B 
Weights constants summary:
   n   nn  S0  S1   S2
B 88 7744 324 648 5440
```

Computing adaptive distance weight matrix

One of the characteristics of fixed distance weight matrix is that more densely settled areas (usually the urban areas) tend to have more neighbours and the less densely settled areas (usually the rural counties) tend to have lesser neighbours. Having many neighbours smoothes the neighbour relationship across more neighbours.

It is possible to control the numbers of neighbours directly using k-nearest neighbours, either accepting asymmetric neighbours or imposing symmetry as shown in the code chunk below.

```
knn <- knn2nb(knearneigh(coords, k=8))
knn
```

```
Neighbour list object:
Number of regions: 88 
Number of nonzero links: 704 
Percentage nonzero weights: 9.090909 
Average number of links: 8 
Non-symmetric neighbours list
```

Next, *nb2listw()* is used to convert the nb object into spatial weights object.

```
knn_lw <- nb2listw(knn, style = 'B')
summary(knn_lw)
```

```
Characteristics of weights list object:
Neighbour list object:
Number of regions: 88 
Number of nonzero links: 704 
Percentage nonzero weights: 9.090909 
Average number of links: 8 
Non-symmetric neighbours list
Link number distribution:

 8 
88 
```

```
oo
88 least connected regions:
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37
88 most connected regions:
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37

Weights style: B
Weights constants summary:
   n   nn  S0   S1    S2
B 88 7744 704 1300 23014
```

Computing Gi statistics

Gi statistics using fixed distance

```
fips      <-        order    (        hunan    $        County    )
gi.fixed  <-        localG   (        hunan    $        GDPPC     , wm62_lw   )
gi.fixed
```

```
 [1]  0.436075843 -0.265505650 -0.073033665  0.413017033  0.273070579
 [6] -0.377510776  2.863898821  2.794350420  5.216125401  0.228236603
[11]  0.951035346 -0.536334231  0.176761556  1.195564020 -0.033020610
[16]  1.378081093 -0.585756761 -0.419680565  0.258805141  0.012056111
[21] -0.145716531 -0.027158687 -0.318615290 -0.748946051 -0.961700582
[26] -0.796851342 -1.033949773 -0.460979158 -0.885240161 -0.266671512
[31] -0.886168613 -0.855476971 -0.922143185 -1.162328599  0.735582222
[36] -0.003358489 -0.967459309 -1.259299080 -1.452256513 -1.540671121
[41] -1.395011407 -1.681505286 -1.314110709 -0.767944457 -0.192889342
[46]  2.720804542  1.809191360 -1.218469473 -0.511984469 -0.834546363
[51] -0.908179070 -1.541081516 -1.192199867 -1.075080164 -1.631075961
[56] -0.743472246  0.418842387  0.832943753 -0.710289083 -0.449718820
[61] -0.493238743 -1.083386776  0.042979051  0.008596093  0.136337469
[66]  2.203411744  2.690329952  4.453703219 -0.340842743 -0.129318589
[71]  0.737806634 -1.246912658  0.666667559  1.088613505 -0.985792573
[76]  1.233609606 -0.487196415  1.626174042 -1.060416797  0.425361422
[81] -0.837897118 -0.314565243  0.371456331  4.424392623 -0.109566928
[86]  1.364597995 -1.029658605 -0.718000620
attr(,"gstari")
[1] FALSE
attr(,"call")
localG(x = hunan$GDPPC, listw = wm62_lw)
attr(,"class")
[1] "localG"
```

The output of localG() is a vector of G or Gstar values, with attributes “gstari” set to TRUE or FALSE, “call” set to the function call, and class “localG”.

The Gi statistics is represented as a Z-score. Greater values represent a greater intensity of clustering and the direction (positive or negative) indicates high or low clusters.

Next, we will join the Gi values to their corresponding hunan sf data frame by using the code chunk below.

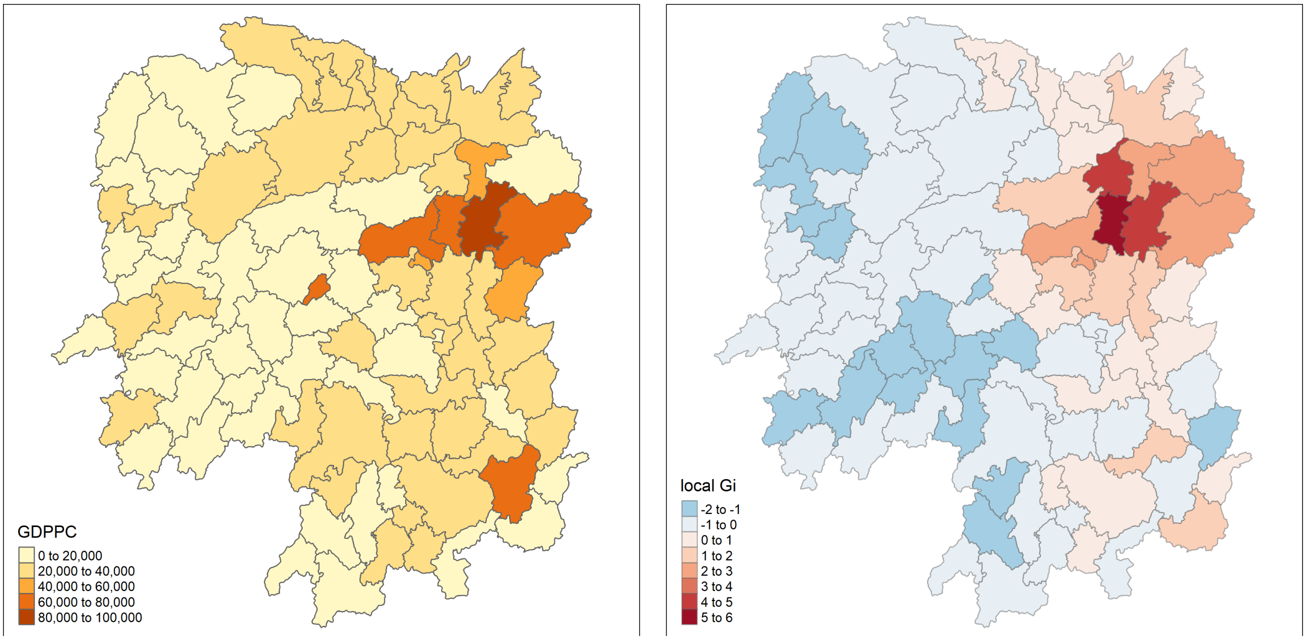
```
hunan.gi <- cbind(hunan, as.matrix(gi.fixed)) %>%
  rename(gstat_fixed = as.matrix.gi.fixed.)
```

In fact, the code chunk above performs three tasks. First, it convert the output vector (i.e. *gi.fixed*) into r matrix object by using *as.matrix()*. Next, *cbind()* is used to join hun@data and *gi.fixed* matrix to produce a new SpatialPolygonDataFrame called *hunan.gi*. Lastly, the field name of the gi values is renamed to *gstat_fixed* by using *names()*.

Mapping Gi values with fixed distance weights

The code chunk below shows the functions used to map the Gi values derived using fixed distance weight matrix.

```
gdppc <- qtm(hunan, "GDPPC")

Gimap <-tm_shape(hunan.gi) +
  tm_fill(col = "gstat_fixed",
          style = "pretty",
          palette="-RdBu",
          title = "local Gi") +
  tm_borders(alpha = 0.5)

tmap_arrange(gdppc, Gimap, asp=1, ncol=2)
```



> *Question: What statistical observation can you draw from the Gi map above?*

Gi statistics using adaptive distance

The code chunk below are used to compute the Gi values for GDPPC2012 by using an adaptive distance weight matrix (i.e *knb_lw*).

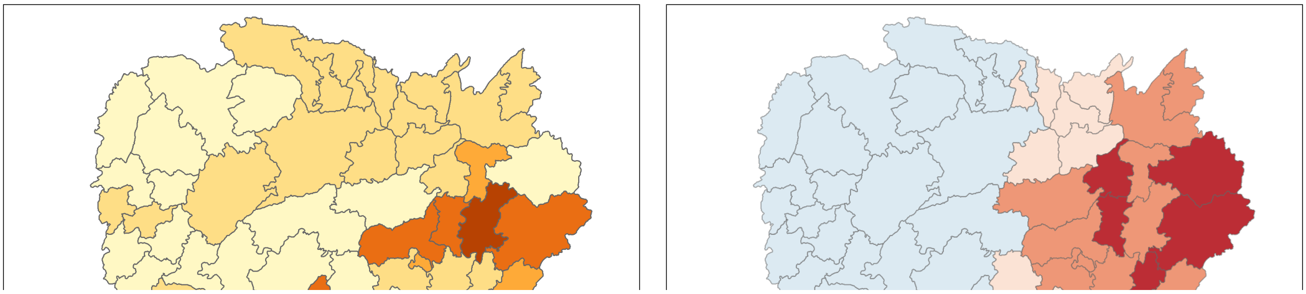
```
fips <- order(hunan$County)
gi.adaptive <- localG(hunan$GDPPC, knn_lw)
hunan.gi <- cbind(hunan, as.matrix(gi.adaptive)) %>%
  rename(gstat_adaptive = as.matrix.gi.adaptive.)
```

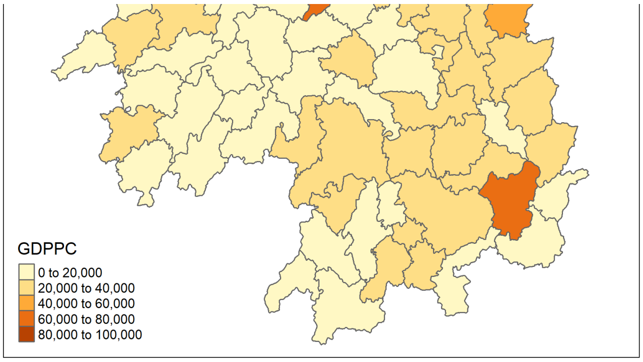
Mapping Gi values with adaptive distance weights

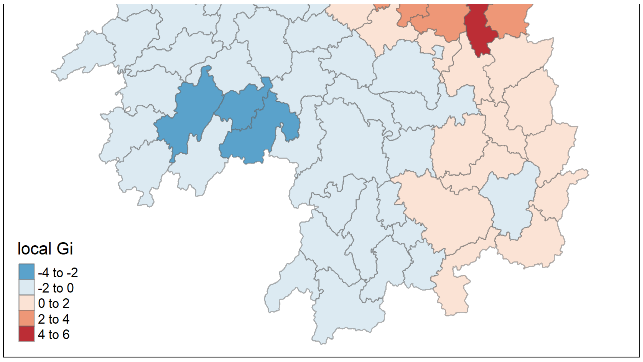
It is time for us to visualise the locations of hot spot and cold spot areas. The choropleth mapping functions of **tmap** package will be used to map the Gi values.

The code chunk below shows the functions used to map the Gi values derived using fixed distance weight matrix.

```
gdppc <- qtm(hunan, "GDPPC")

Gimap <- tm_shape(hunan.gi) +
  tm_fill(col = "gstat_adaptive",
          style = "pretty",
          palette="-RdBu",
          title = "local Gi") +
  tm_borders(alpha = 0.5)

tmap_arrange(gdppc, Gimap, asp=1, ncol=2)
```







> *Question: What statistical observation can you draw from the Gi map above?*