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## WIRES: A USER FRIENDLY SPATIAL ANALYSIS SOFTWARE

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### ABSTRACT

Spatial analysis is gaining more popularity since Anselin in 1989 defined the newly born field as “The collection of techniques concerning the peculiarities caused by space in the statistical analysis of models on regional sciences” (Billé and Arbia, 2013). Many statistical methods and techniques have been developed for the analysis, however there are still few software available, such as GeoDa, GWR, ArcGIS, and several packages of R. Those software still have some limitation. GeoDa, GWR, and ArcGIS are limited to some spatial methods, while R covers more methods but still uses command line interface, which will be difficult for non-expert users. To overcome this limitation, WIRES, a GUI spatial analytical tool, is developed using C# and R as back-end program. WIRES covers more features, spatial weight matrix generator, exploratory spatial data analysis, spatial regression, explanatory spatial data analysis, spatial logistic regression, ordinary and simple Kriging, and other descriptive tools. WIRES also covers methods which have not been covered by other spatial analytical tools, i.e. spatial cluster, spatial regional inequality (using Gini and Theil method), and spatial shift-share.

### KEYWORDS

Spatial Analysis, Graphical User Interface, C#, R.

### 1. INTRODUCTION

The use of statistics has been applied almost in all field including business, economics, biology, physics, astronomy, meteorology, chemistry, medicine, sociology, psychology and so on. For years, conventional statistical theory based on assumption that among observations are independent. But since Tobler (1970) came with his publication, the researchers finally realize that there are some situations where observations are not independent anymore but correlate in space, for example. This spatial correlation can't be overcome by conventional statistics method because it can lead to inconsistent estimator (Case in Bhat and Sener, 2009). Because of the

conventional statistics' limitation in inferencing spatial data, the spatial analysis exists to overcome the limitation.

Spatial statistics has triggered many new methods which are the extension of conventional statistics to appear. Despite that fact, recent technologies and global positioning system also have led to a rapid expansion of the number and size of available spatially dataset ([Rosenberg and Anderson, 2011](#)). To enable and facilitate spatial analysis on those spatial data, several spatial analysis tools were built.

Today some spatial analytical tools are now available to carry out a wide array of spatial data analytical techniques, they have been created as modules for programming languages, statistical platforms, geographic information systems (GIS) or as standalone software. For example, pySAL is a library of Python intended to aid the development of applications for spatial analysis, R is a statistical languages that can be used to write spatial analysis packages (such as gstat, spgwr, ade4, and so on), ArcGIS is popular for spatial data storage, visualization, and offers a handful of commonly used analysis functions in Spatial Statistics toolbox, PASSage 2 is a software for pattern exploration and spatial description, GeoDa is a free software that focuses in mapping and exploring spatial data, and so on ([Rosenberg and Anderson, 2011](#)).

However, the available spatial software still have some limitations. For example, ArcGIS is powerful software but is not free of charge and only cover some statistical modeling. Open GeoDa and PASSage 2 only focus in mapping and exploring spatial data, and not cover any spatial inference method. R covers more statistical techniques and modeling, but based on command line interface, which forces the user to understand its syntax before using it, of course it will be difficult for non-expert user who used to use graphical user interface (GUI)-based software.

All those limitations have delivered to the need of free, user friendly, and more complete spatial statistical software in describing and inferencing/modeling spatial data. That's why we build WIRES, a GUI-based spatial analytical software. WIRES is intended to help analyzing spatial data not only for expert user but also for non-expert user with its easy to use graphical interface. To describe more about WIRES, in section 2 we will explain about some spatial analysis covered by WIRES, in section 3 we will explain about WIRES, including its architecture and how we implement it into some interfaces, and in section 4 we will give case study to show how to use WIRES to analyze spatial data.

## 2.1 Spatial Statistics

Conventional statistics has been built on assumption that among observations are independent. This can be in contradiction with the fact that there are some situations were among observations are not independent but correlate in space, such as the low income-region tends to clustered with another low income-regions ([Miller, 2004](#)), the auto supplier plants prefer to locate in areas close to other suppliers (Klier and McMillen, 2008), and so on. To analyze the observations that are correlate in space, we can't use standard statistical methods because it can lead to inconsistent estimator (Case in Bhat and Sener, 2009). [Anselin \(1996\)](#) also stated that spatial autocorrelation in spatial data makes the data does not fulfill the assumption in conventional statistics which assumed the observations are independent. The consequence, the inference using conventional

statistics is not efficient anymore. Because of this limitation, the spatial analysis exists to overcome the limitation.

Spatial statistics is the collection of techniques and models in which spatial referencing of each data play an explicit role in the analysis of data ([Goodchild and Haining, 2004](#)). Spatial statistics can be used to describe spatial patterns (exploration) ([Anselin, 2004](#)), test hypothesis about patterns (inference) ([Sherman, 2010](#)), and predicting value in unobserved location ([Fischer and Getis, 2010](#)). There are many spatial statistics methods has been developed, in this paper and software we built we would cover some basic and important methods, including exploratory spatial data analysis, spatial weight, spatial clustering, spatial regression, spatial logistic regression, kriging, inequality region, and shift share.

## **2.2 Exploratory Spatial Data Analysis**

The calculation of spatial autocorrelation is an important step in spatial analysis to detect the spatial structure of the data to be analyzed. Moran's I ([Moran, 1948](#)) and Geary's C ([Geary, 1954](#)) can be used to detect overall/global spatial autocorrelation in the data that consists of one or two variables. Moran's I behaves like Pearson correlation coefficient, in case its value is between -1 and 1. Geary's C is similar to a distance-type structure function and is within the range 0 to 2. The difference of those two statistics is Moran's I is based on cross-products to measure value association, while Geary's C employs squared difference ([Kalkhan, 2011](#)).

Both Moran's I and Geary's C are statistics used to calculate overall/global spatial autocorrelation, but cannot be used to identify spatial autocorrelation in smaller range. For that purpose, Moran Scatterplot is used to check local spatial instability and Local Indicators of Spatial Association (LISA). According to [Anselin \(1995\)](#), LISA's value of each observations indicate how significant is spatial clustering among observation, and the sum of LISA's value of each observations is equal to indicator of global spatial association.

Moran, Geary and LISA are intended to measure spatial autocorrelation of data with one or two variable. For more than two variables, we can use MULTISPATI (Multivariate spatial analysis based on Moran's I) method which the idea is found by [Wartenberg \(2008\)](#) then is developed by [Dray, Saïd, and Debias \(2008\)](#).

## **2.3 Spatial Weight Matrix**

Spatial weight matrix is an important aspect in spatial analysis. This matrix defines spatial interaction among observation ([Anselin in Getis and Aldstadt, 2010](#)). In practices, weight matrix which frequently used is a standardized matrix, therefore if we sum all the element in its row is must be one. There are some spatial weight matrix which is well known, including contiguity matrix, distance based-matrix, and k nearest neighbor matrix ([Getis and Aldstadt, 2010](#)).

## **2.4 Spatial Clustering**

The collaboration of exploratory spatial data analysis and data mining results many new powerful methods that can enhance the analysis of data itself, one of them is spatial clustering. Spatial clustering is a method to cluster object by considering its spatial attribute and identify the closeness of observations in space ([Cao, et al. 2013](#)). [Carvalho,](#)

et al. (2009) showed how important spatial clustering is by stated that “*Specifically concerning geographical data, spatial clustering is a powerful technique that can be adapt to the most varied cases and thus has developed quickly and become increasingly popular*”. In his research, [Carvalho, et al. \(2009\)](#) modify hierarchical clustering algorithm by considering the interaction among observations in space, this resulted new method called Spatial Hierarchical Clustering.

## 2.5 Spatial Regression

Regression is an important statistical method to examine the relationship between a variable of interest (dependent variable) and one or more explanatory variables (predictors). One of the regression assumptions is independence of observations. If this doesn't hold, we obtain inaccurate estimates of the coefficients, and the error term. Spatial dependency is one of reason that can this problem. If spatial dependency occurs, the observations are not independent anymore but correlate in space. To overcome this problem, spatial regression method is developed such as:

- **Spatial lag or spatial autoregressive (SAR) model.** This model includes spatial lag dependent variabel (WY) used as dependent variable.
- **Spatial error model.** This model includes spatial autocorrelation occurs in random error (W $\epsilon$ ) used as independent variable.

## 2.6 Spatial Logistic Regression

Spatial logistic regression is an analysis to model the association between explanatory variables and discrete response variable by considering spatial autocorrelation in characteristics of observations. Spatial autocorrelation which gained a serious attention is spatial autocorrelation in latent response variable(spatial lag) which shows that logit value of an observations is influenced by logit value of neighbor observations, because it can't be handled by classical logistic regression which assumed that among observations are independent and some ways to solve it needs many times iterations and inversion of nxn matrix to get the estimated coefficients, which means it only can be used for small sample (Klier and McMillen, 2008).To overcome this situation, Klier and McMillen (2008) developed spatial logistic regression using linearized GMM. By using linearized GMM, estimated regression coefficients can be calculated in short time and result in more accurate statistics than other method such as non-linearized GMM developed by [Pinkse and Slade \(1998\)](#).

## 2.7 Regional Inequality

Income inequality is a condition where income is not equally distributed to all society in a region/country (Glaeser, 2006). It is also an effect caused by relative poverty (BPS, 2008). Regional inequality analysis is an analysis used to decide whether government succeed to decrease poverty rate in his country. There are some regional inequality methods based on average regional income relative to national income, but they are fail to explain the distribution of national individual income or the dispersion of income in a region (Metwally and Jensen, 1973). To overcome this, Akita (2000) develops regional inequality using decomposed Theil Index, which can explain regional inequality completely. Allinson (1978) also develops regional inequality analysis using Gini Index. Gini Index is a good index, because of its sensitive to transfer, that means the observations with income around average income will have higher effect in inequality calculations than the observations which is not.

## 2.8 Spatial Shift-Share

Shift-share analysis is an analysis used to compare growing rate in many kind of sectors between regency and province or between province and national (Tarigan, 2012). The purpose of this analysis is giving information about economy and man power in 3 sectors, those are: regional economy growth, industry-mix/proportional-shift, and regional-shift/differential shift.

In classical shift-share, the regions are considered to be independent. In fact, this situation could be really wrong because the regions are not isolated and a region could really dependent economically with another region. This idea is then used by Nazara and Hewings (2004) to modified classical shift share developed by Dunn (1960) for spatial shift-share. This modification is needed to consider the positive/negative interaction between one region and another regions.

## 2.9 Kriging

Sometimes we find that not all region in unit we want to observe has value of a variable. Whereas complete information of that variable is needed to perform the analysis. To get the missing value, we can use interpolation techniques. Interpolation is the process of finding unknown values from known values (Sunitha et. al., 2013).

Kriging is one of interpolation method to estimate a missing or unobserved value in a target region based on region around it. To estimate a missing value, Kriging considers spatial and non-spatial factors which can increase the accuracy such as number of sample, coordinate of sample, distance between sample and target point, and spatial continuity of involved variables. Compared to other method such as Invers Distance Weighted (IDW), triangulation, polygon, an others, Kriging estimation can be accounted statistically because it gives BLUE (Best Linear Unbiased Estimator) (Bohling, 2005).

## 3 WIRES

In 2012, the development of a spatial statistical software to analyze spatial data named WIRES was started by five students of Sekolah Tinggi Ilmu Statistik (STIS), Indonesia. At that time WIRES provides tools for creating weight, and analysis including spatial regression, spatial shift-share, classical shift share, exploratory spatial data (univariate Moran's, bivariate moran's, Geary's C and LISA), and inequality region. The purpose of WIRES is to make a user friendly GUI-based software. The technology behind WIRES is a combination of Java, C# language and R-software. WIRES uses R to call package of analysis that have been covered in R output (like spatial regression, spatial weight, and exploratory spatial data) and present it in a new and easy interpreted, and also to calculate analysis that have not been covered in R and other statistical software, like inequality region using Theil index and spatial shift-share.

Recently, several new analysis such as spatial logistic regression, multivariate spatial analysis using Moran's I, spatial hierarchical clustering, inequality region using Gini index, kriging, and geographically weighted regression were added to extend WIRES capabilities by other STIS' students. Several descriptive tools like quantile/percentile map, discrete map, equal map, and box map have been included as well.

### 3.1 Architecture of WIRES

Based on figure 1, architecture of WIRES consists of two main components, user interface component and analysis component.

#### 1) User interface component

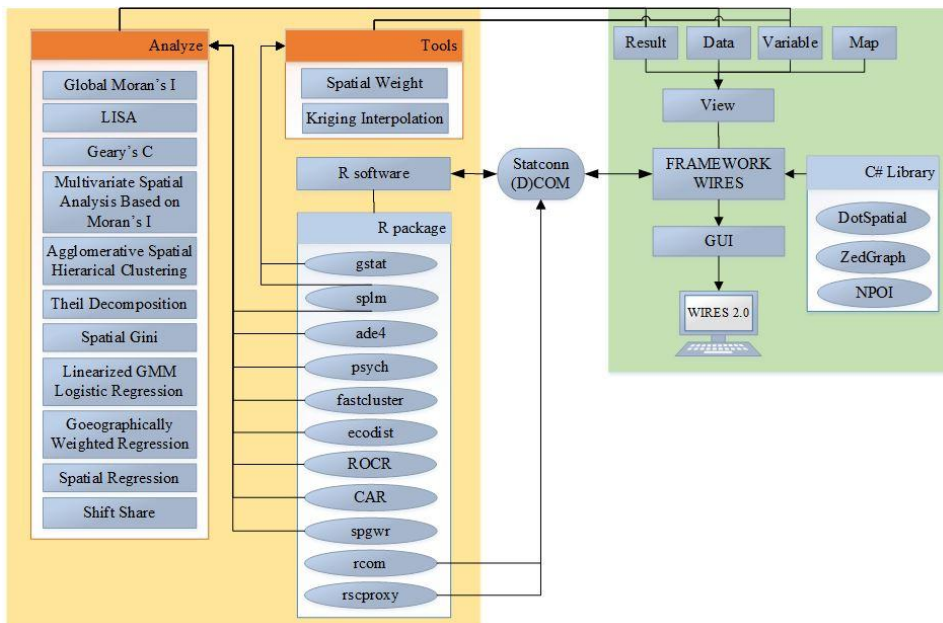
For map visualization, we use DotSpatial 1.7 from MapWindow because it is the new project of MapWindow GIS that has combined all the best component in open source application in .NET GIS like SharpMap, Proj.NET, and MapWindow 6, so it is more complete and easier in executing the available functions.

For graph visualization, we use ZedGraph. ZedGraph is a class library, user control, and web control for .net, written in C#, for drawing 2D Line, Bar, and Pie Charts. It features full, detailed customization capabilities, but most options have defaults for ease of use.

While for importing excel library, we use NPOI library

#### 2) Analysis component

All the analysis use R as back-end program, by using R we can invoke function that has been covered by R and also compute analysis that has not been covered by R with complete array and matrix operations in R. All these simplicity makes us can focus in designing the new and easier interpreted output for each analysis. Table 1 show our primary analysis and R packages that we use for those analysis.



**Fig. 1: Architecture of WIRES**

**Table 1:**  
**WIRES's Primary Analysis and R Packages Used**

Analysis	R packages
Exploratory spatial data analysis (Global Moran's I, LISA, and Geary's C)**	splm
Multivariate spatial analysis based on Moran's I (MULTISPATI)**	ade4, psych
Agglomerative spatial hierarchical clustering*	fastcluster
Inequality region using theil index*	-
Inequality region using Gini index*	-
Linearized GMM logistic regression ***	CAR, ROCR
Spatial regression*	-
Shift share*	-
Kriging**	Gstat

- \* Has not been covered by any other spatial software
- \*\* Has been covered by R, enhanced in output
- \*\*\* Has been covered by R, enhanced in analysis and output

To connect user interface component and analysis component we use Statconn (D)COM developed by Baier dan Neuwirth (2010) and some packages in R including rconn and rscproxy. Statconn (D)COM is a middleware component that integrates R software to application by providing DCOM component for R.

**3.2 Implementation of WIRES**

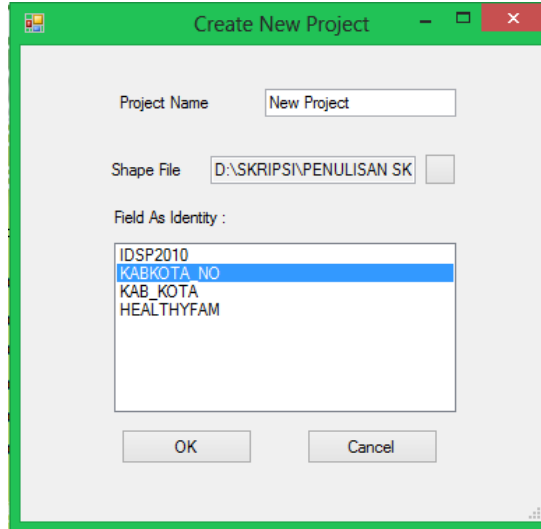
In this part, we will explain some important WIRES' dialogs/screens that explain how we implement our designed architecture into desktop application. The first screen is a screen that appear when user RUN WIRES, it consist of three main functions, create new WIRES project, open WIRES project, or open recent WIRES project like in Figure 2.



**Fig. 2: "Welcome" dialog of Wires**



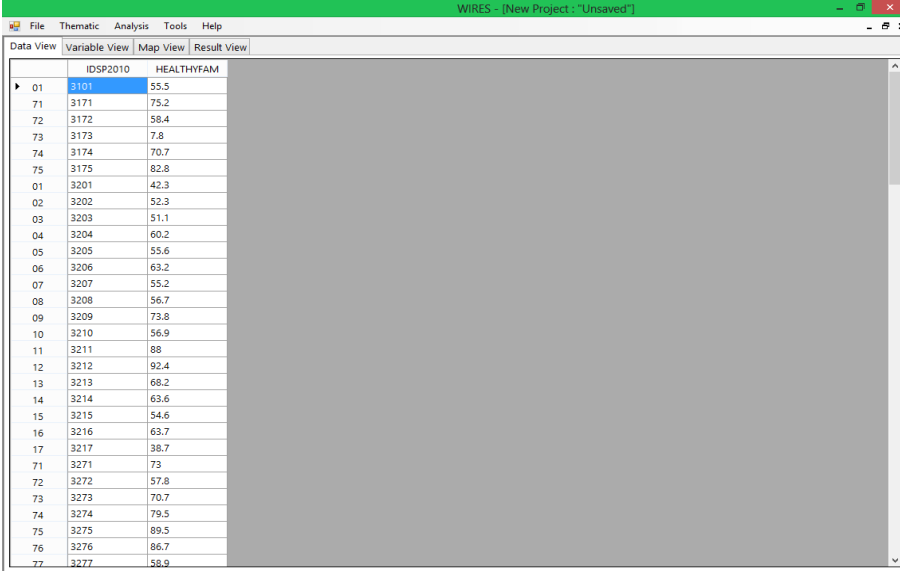
When user choose to create new project, user will be asked to choose the shapefile with extension \*.shp and variable that become identity of data that will be analyzed (Figure 3).



**Fig. 3: Dialog to create new project**

After choosing the shapefile, the structure of the chosen data will be shown in main dialog consists of menu bar and tab view (Figure 4). Tab view consists of 4 views: 1) Data view to see and manipulate the data in database file that correlate with shapefile, 2) Variabe view to delete, create, and rename the variable in database file that correlate with shapefile, 3) Map view to see and explore map/shapefile, 4) Result view to see the result of analysis that have been done.

Menu bar consists of 5 main menus, including: 1) File menu consists of submenus for creating new project, opening project, opening recent project, saving project, saving as project, importing variable from excel file, and exiting application, 2) Thematic menu to do some descriptive analysis using map, like see the distribution of variable in a map based on its percentile values, 3) Analysis menu consists of main analysis which have been explained in section 2, except Kriging and creating spatial weight matrix 4) Tools menu consists of Kriging and creating weight submenus, and 5) Help menu to help user getting further and detail explanation about how to use WIRES.



The screenshot shows the main dialog of WIRES with a data table. The table has two columns: IDSP2010 and HEALTHYFAM. The rows are numbered from 01 to 77. The data is as follows:

	IDSP2010	HEALTHYFAM
01	3101	55.5
71	3171	75.2
72	3172	58.4
73	3173	7.8
74	3174	70.7
75	3175	82.8
01	3201	42.3
02	3202	52.3
03	3203	51.1
04	3204	60.2
05	3205	55.6
06	3206	63.2
07	3207	55.2
08	3208	56.7
09	3209	73.8
10	3210	56.9
11	3211	88
12	3212	92.4
13	3213	68.2
14	3214	63.6
15	3215	54.6
16	3216	63.7
17	3217	38.7
71	3271	73
72	3272	57.8
73	3273	70.7
74	3274	79.5
75	3275	89.5
76	3276	86.7
77	3277	58.9

**Fig. 4: Main dialog of WIRES**

#### 4. CALCULATING MORAN'S I USING WIRES

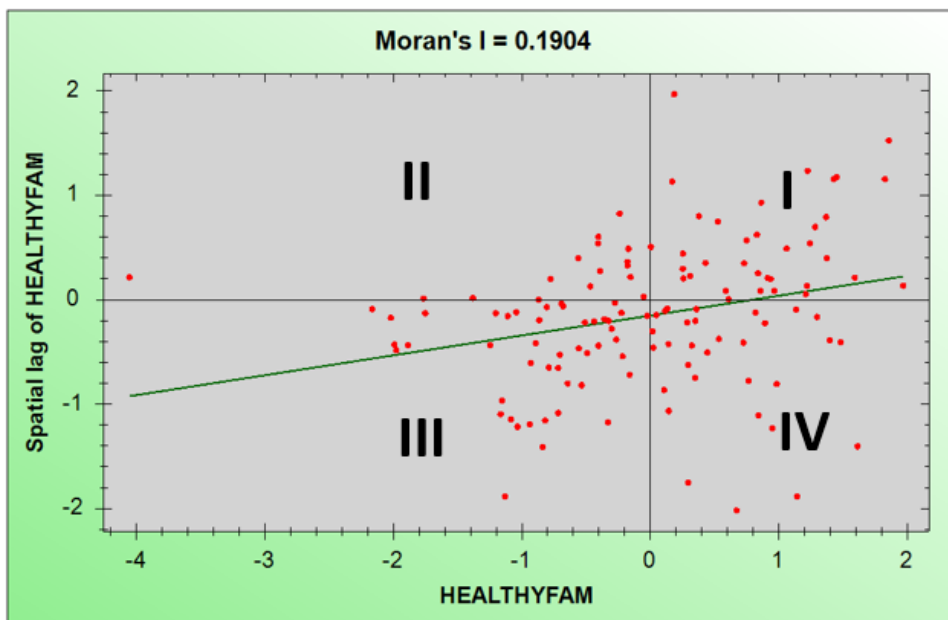
In this section we will show how to calculate Moran's I which reflects spatial autocorrelation of a variable using WIRES. The data we used here are drawn from Indonesia Health Statistics in 2011, you can download the data including shapefile and database file in <https://www.dropbox.com/s/3i4qqjwv20berb8/Jawa%20Bali.zip?dl=0>. The observations are all regencies in Jawa and Bali island. Here we want to explore whether there is spatial autocorrelation of percentage of healthy life style-family in observed regencies.

The first step is creating the weight matrix that contains list of neighborhood between one observations to another. To create weight matrix we choose Tools menu, then choose Create Weight, and choose what kind of spatial matrix we want to create. Here we will choose rook contiguity matrix. After that the application will inform whether the weight matrix is successfully created and if succeed it will give the result tab that consists of 1) map analysis that shows the neighborhood of each observations by connecting the observations with its neighbors with lines, 2) weight matrix that shows the structure of spatial weight matrix, and 3) weight graph that shows graph of observations and their number of neighbours.

After creating the spatial weight matrix, we can calculate Moran's I by select Analysis menu, then choose ESDA, choose Univariate Moran's I, and choose the variable we want to analyze, in this case is percentage of healthy life style-family, then choose the weight we have created. The application will result tab that consist of Moran's I statistics and its scatter plot. Figure 5 and 6 show the result tab for Moran's I.

	Variable(s)	Moran's I	E(I)	Var(I)	p-value	Standard Deviation
▶	HEALTHYFAM	0.1904	-0.0080	0.0045	0.0030	2.9675

**Fig. 5: Statistics of Moran's I for Percentage of Healthy Life Style-Family Variable**



**Fig. 6: Scatter Plot of Moran's I for Percentage of Healthy Life Style-Family Variable**

From Figure 5 we get the Moran's I for percentage of healthy life style-family variable is 0, 1904 and its p-value is 0.0030. It means that with confidence rate (for example) 95%, we believe that there is positive correlation of percentage of healthy life style-family between regencies. To see the distribution of spatial autocorrelation in each regency, we can see Moran's I scatterplot in Figure 6. Figure 6 shows that many observations lies in quadrant I and III, it means that many regencies with high percentage of healthy life style-family have neighbors that also have high percentage of healthy life style-family, and vice versa.

## CONCLUSION

The popularity of spatial analysis and huge number of available spatially dataset have encouraged the need of spatial analysis tools. But the available spatial analysis tools still have some limitations, like not free of charge, only cover descriptive functions, and based on command line interface. That's why we build WIRES.

We build WIRES using C# and powerful R as back-end program, we also use some C# library that enhance the output of WIRES. WIRES covered some tools and analysis to

help expert and non-expert user to do basic and complex spatial analysis. By building WIRES, we have create a free and user friendly application which combine the exploratory functions and inference functions altogether. We also have covered some analysis which have not been covered in any other spatial tools.

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