10 –Spatial Autoregressive Models

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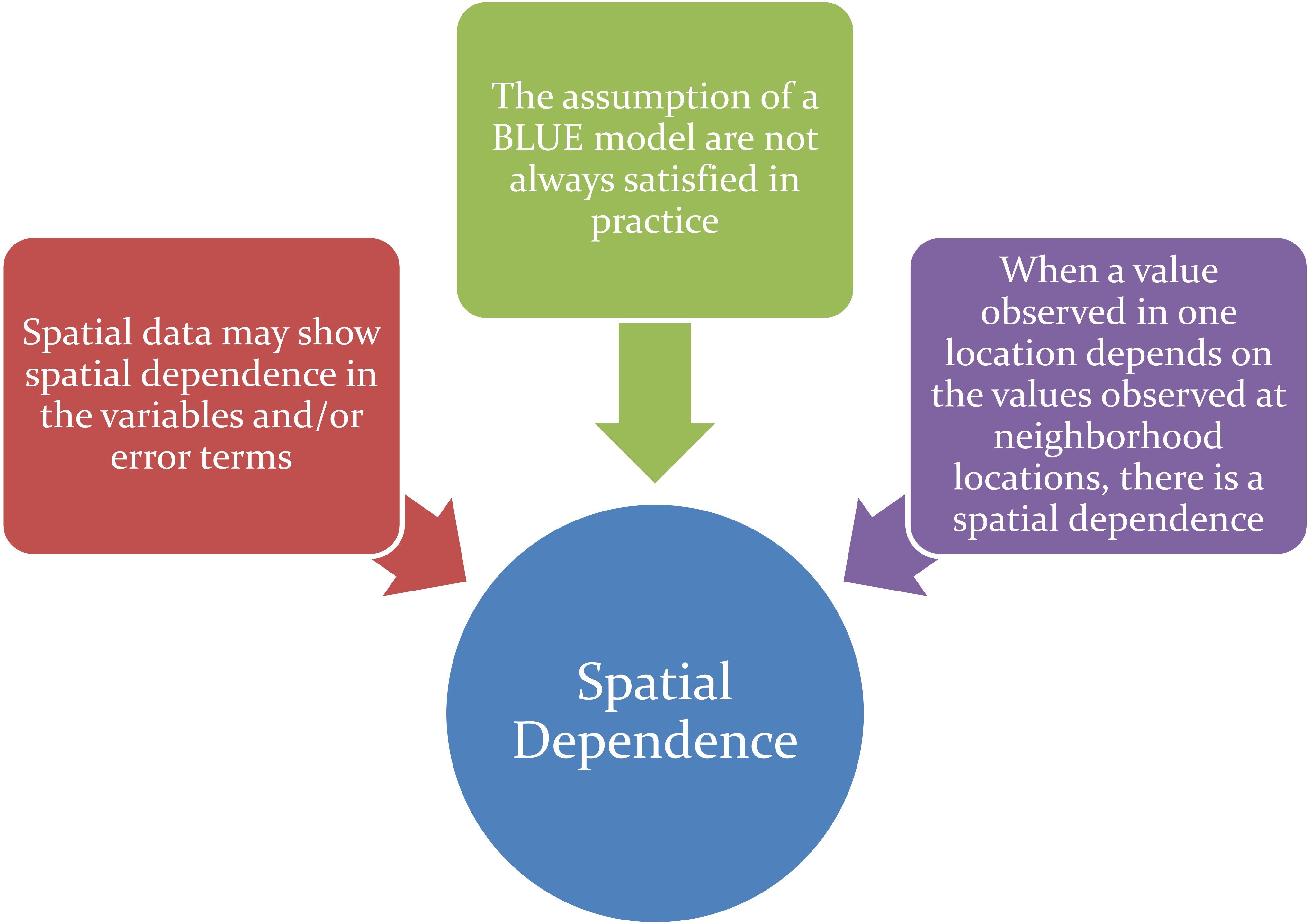
Outline

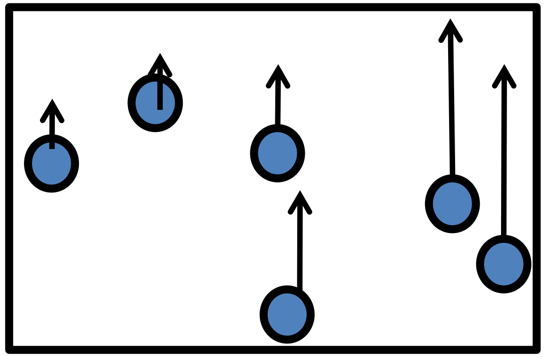
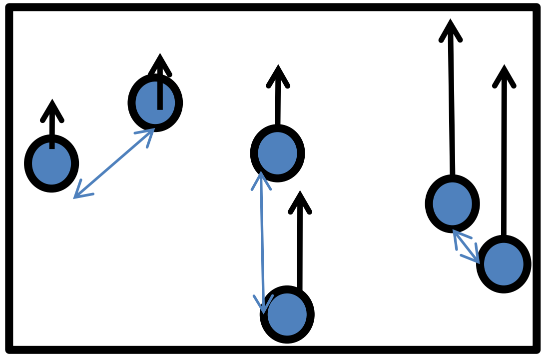
- Spatial Dependence
- OLS
- Spatial Weights
- Spatial Lag Models
- Spatial Error Models
- Goodness of Fit Statistics
- GeoDa Decision Tree
- Spatial Weights
- Lab Example

Spatial Dependence


The assumption of a BLUE model are not always satisfied in practice
Spatial data may show spatial dependence in the variables and/or error terms
When a value observed in one location depends on the values observed at neighborhood locations, there is a spatial dependence
Spatial Dependence

If Spatial Autocorrelation exists:

- *correlation coefficients* and *coefficients of determination* appear <u>bigger</u> than they really are:
  1. The statistics are biased upward
  2. You think the relationship is stronger than it really is
  3. The variables in nearby areas affect each other

If Spatial Autocorrelation exists:

- *Standard errors* appear smaller than they really are:
  - You have exaggerated precision in your model
  - You think your predictions are better than they really are since standard errors measure predictive accuracy
  - More likely to conclude relationship is statistically significant.
  - You will more a Type I error.

$$t = \frac{b}{\mathrm{SE(b)}}$$

Spatial Dependence

- The assumption of uncorrelated error terms is violated
  - Estimates are inefficient
- The assumption of independent observations is violated
  - Estimates are biased
- Analogous to the time-series lagged dependent variable model
- Possible diffusion process – events in place predict an increased likelihood of similar events in neighboring places.

OLS

Regression modelling

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i$$

ε_i

error captures all the determinants that you:

can't think of;

can't model;

can't measure correctly; and

don't have data to measure.

Regression Report

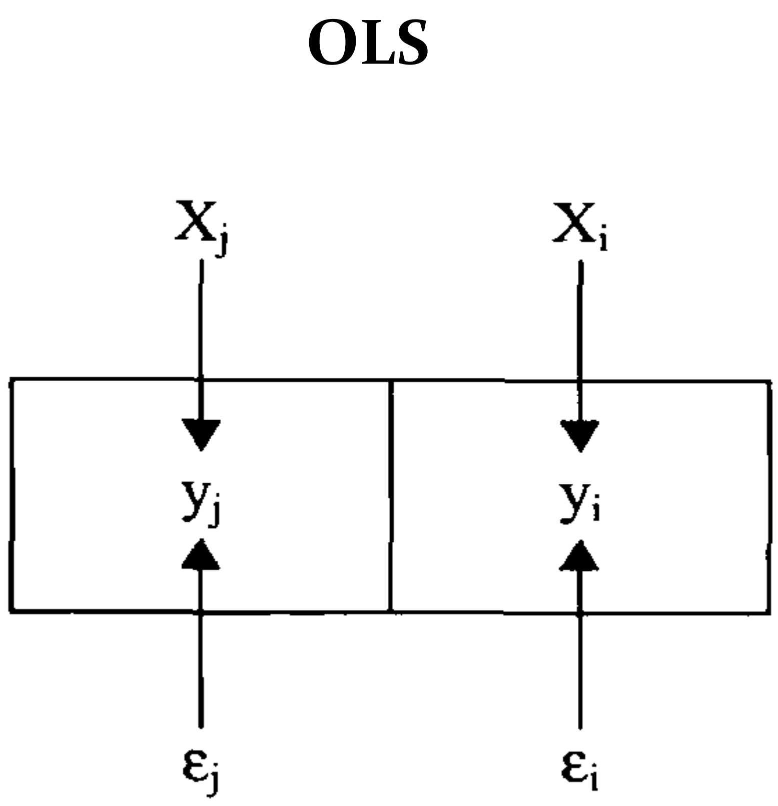
```
Regression
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set             :  spat_reg_geoda
Dependent Variable   :   CRIME_RAT  Number of Observations:  106
Mean dependent var   :     2.97606  Number of Variables   :    2
S.D. dependent var   :     3.22049  Degrees of Freedom    :  104



R-squared            :    0.260503  F-statistic           :       36.636
Adjusted R-squared   :    0.253392  Prob(F-statistic)     :2.28155e-008
Sum squared residual:      812.994  Log likelihood        :     -258.384
Sigma-square         :     7.81725  Akaike info criterion :      520.767
S.E. of regression   :     2.79593  Schwarz criterion     :      526.094
Sigma-square ML      :     7.66975
S.E of regression ML:      2.76943



-----------------------------------------------------------------------
     Variable     Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT    -0.1545553       0.5841786     -0.2645686     0.7918673
    POV_RATE       11.5417        1.906845       6.052772     0.0000000
-----------------------------------------------------------------------


REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.055746
TEST ON NORMALITY OF ERRORS
TEST                     DF          VALUE            PROB
Jarque-Bera               2           39.77458         0.0000000
```

$$y_i = -.1545553 + 11.5417 x_1 + \varepsilon_i$$

OLS ad the Spatial Context

- Fail to Reject the Null Hypothesis is assumed.

- This implies that there is no considerable positive association between the dependent variable and it neighbors or the error terms



No influence from neighbors

Spatial Lag Models

Spatial Dependence - Spatial Lag

- Incorporates spatial dependence by adding a "spatially lagged" DV (y) on the right-hand side of the regression equation

- Treats spatial correlation as a process or effect of interest

- The values of y in one area are directly influenced by the values of y found in neighboring areas

- Positive spatial lag provides evidence that the y's adjacent areas co-vary

- If we ignore the influence of spatially lagged terms:
  - Coefficients will be biased
  - If there is a positive effect of neighboring y's, usually coefficients are biased upward
  - Standard errors are wrong (p-values wrong)

Spatial Lag Model

$$(1) Y_{crime} = B_0 + B_1 X_1 + error$$

$$(2a) Y_{crime} = B_0 + W * crime + B_1 X_1 + error$$

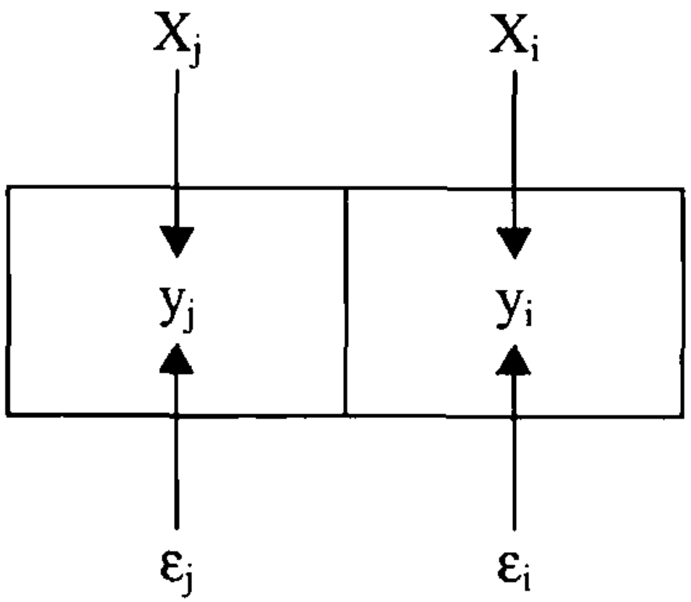
where W is a spatial weight matrix

$$(2b) Y_{crime} = B_0 + \rho w_i y_i + B_1 X_1 + error$$

$\rho w =$ the "spatial lag" of Y_{crime}

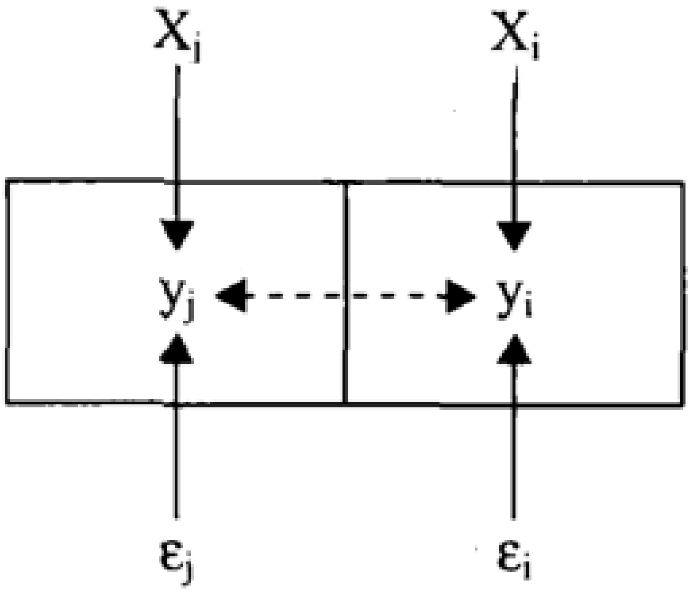
Spatial Lag and Spatial Error Models: *conceptual comparison*

OLS



No influence from neighbors

SPATIAL LAG



Dependent variable influenced by neighbors

Spatial Error Models

Spatial Error

- Spatial lag is viewed as a substantial issue, spatial error is viewed as a nuisance.

- It is an estimation problem, that needs to be fixed.

- The spatial error assumes that the errors are from the model are spatially correlated.

- Unmeasured factors, for some unknown reason, are correlated across the distance among the observations.

Spatial Error Model

$$(1) Y_{crime} = B_0 + B_1 X_1 + error$$

$$(2a) Y_{crime} = B_0 + B_1 X_E + error$$

error=W*error+μ

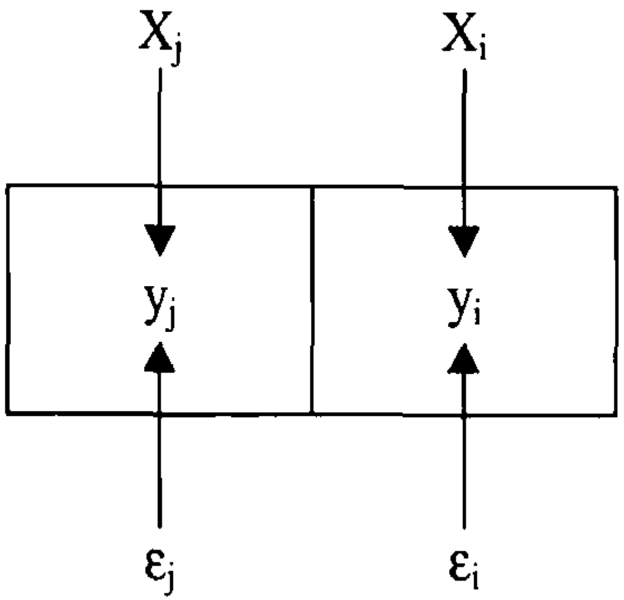
$$(2b) Y_{crime} = B_0 + B_1 X_E + \lambda \mathrm{W} \varepsilon + \xi$$

values of the residuals in neighboring locations (Wε)

are included as an extra term in the equation.

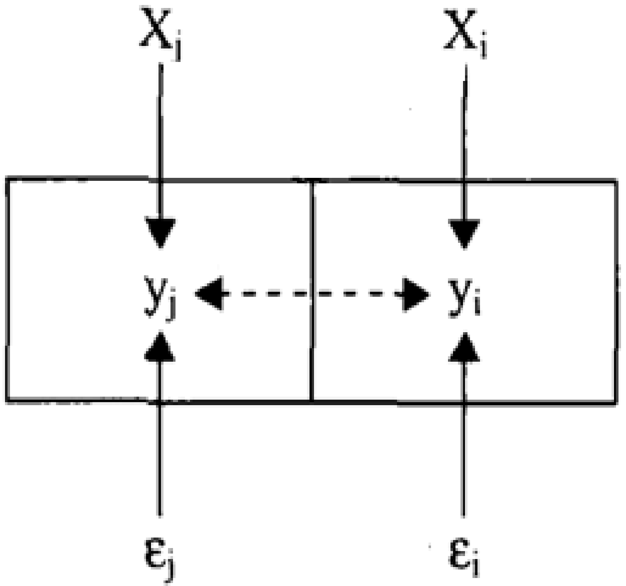
Spatial Lag and Spatial Error Models:
conceptual comparison

OLS



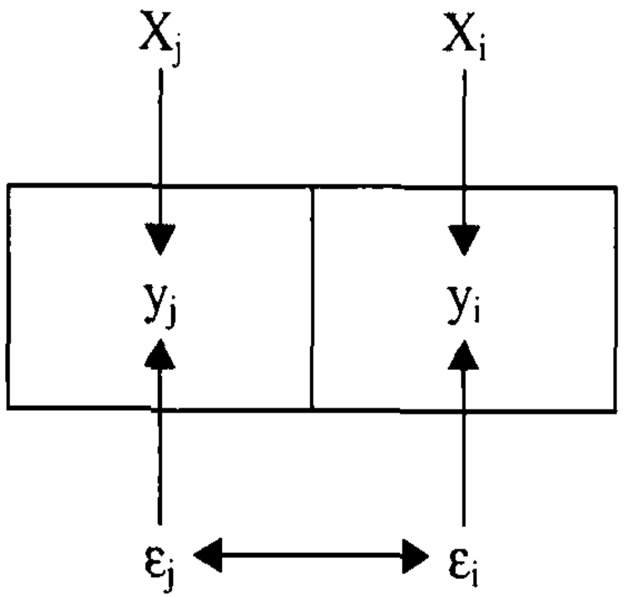
No influence from neighbors

SPATIAL LAG



Dependent variable influenced by neighbors

SPATIAL ERROR



Residuals influenced by neighbors

Goodness of Fit Statistics

Comparing our models

- R^2 should be used with caution to compare different spatial regression models

- Instead, Log Likelihood (LL) and/or *Akaike Information Criteria* (AIC) is recommended

  - the higher the LL value the better the model

  - the smaller the AIC value the better the model

GeoDa Decision Tree

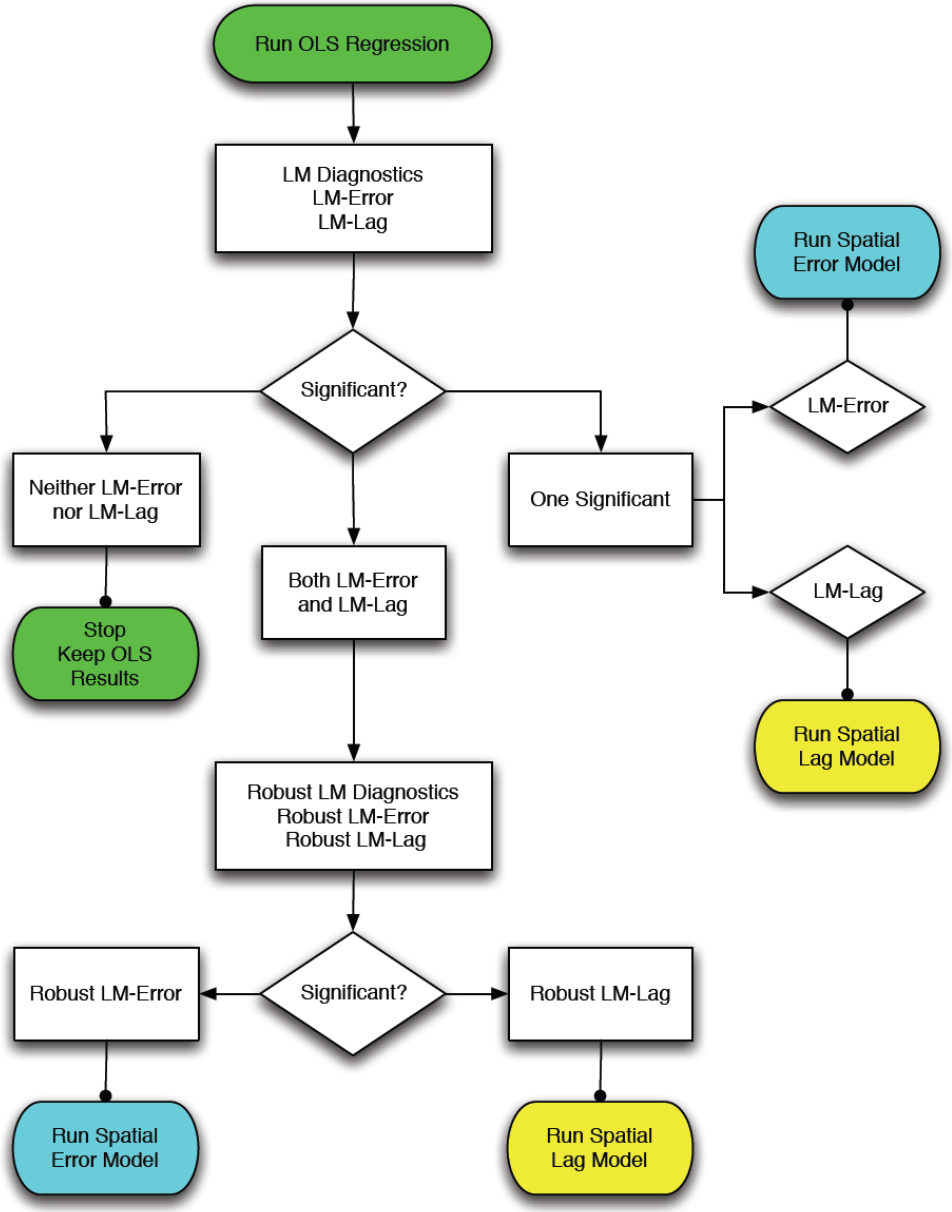


Figure 23.24: Spatial regression decision process.

Spatial Weights

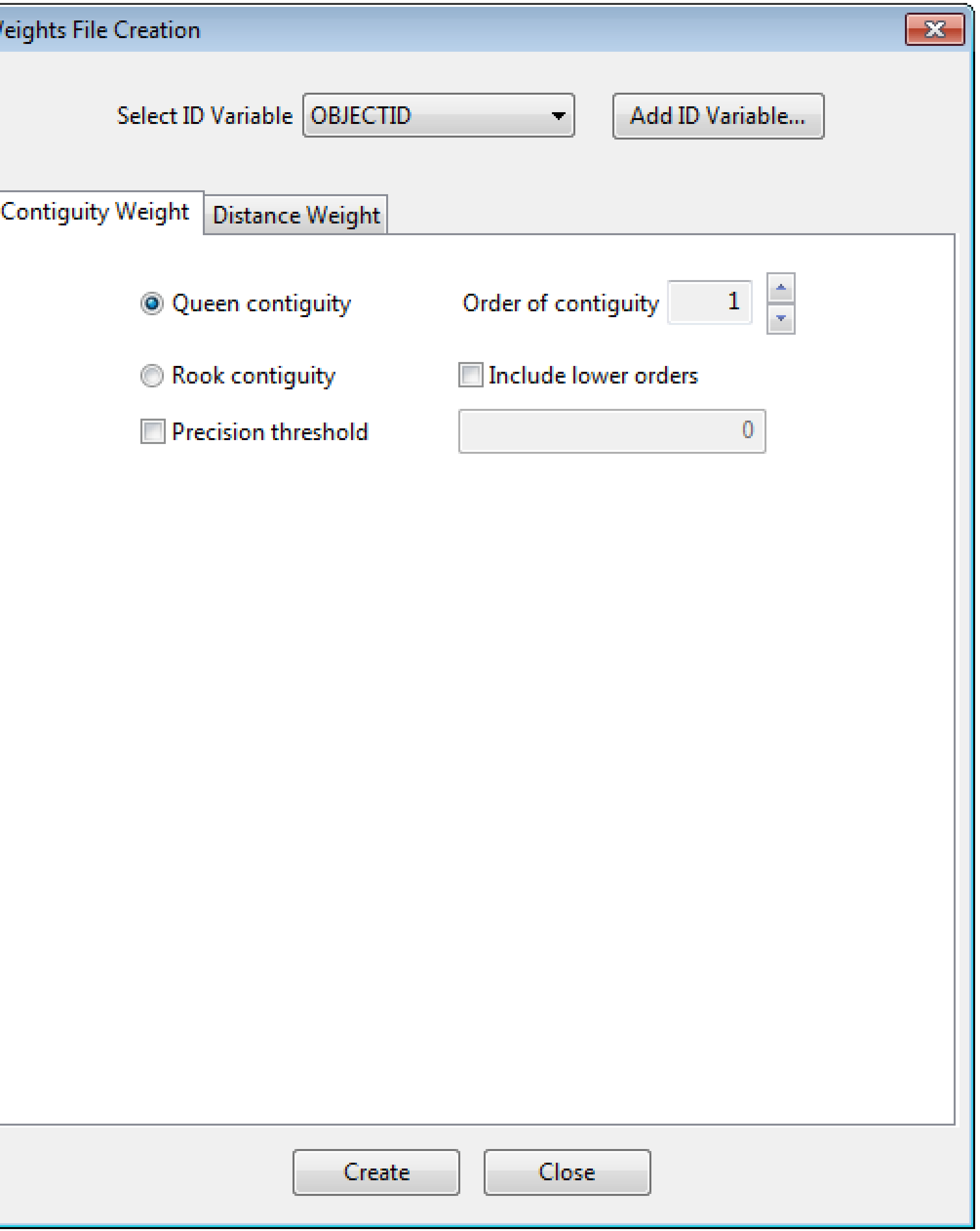
Why Spatial Weights? Part 1

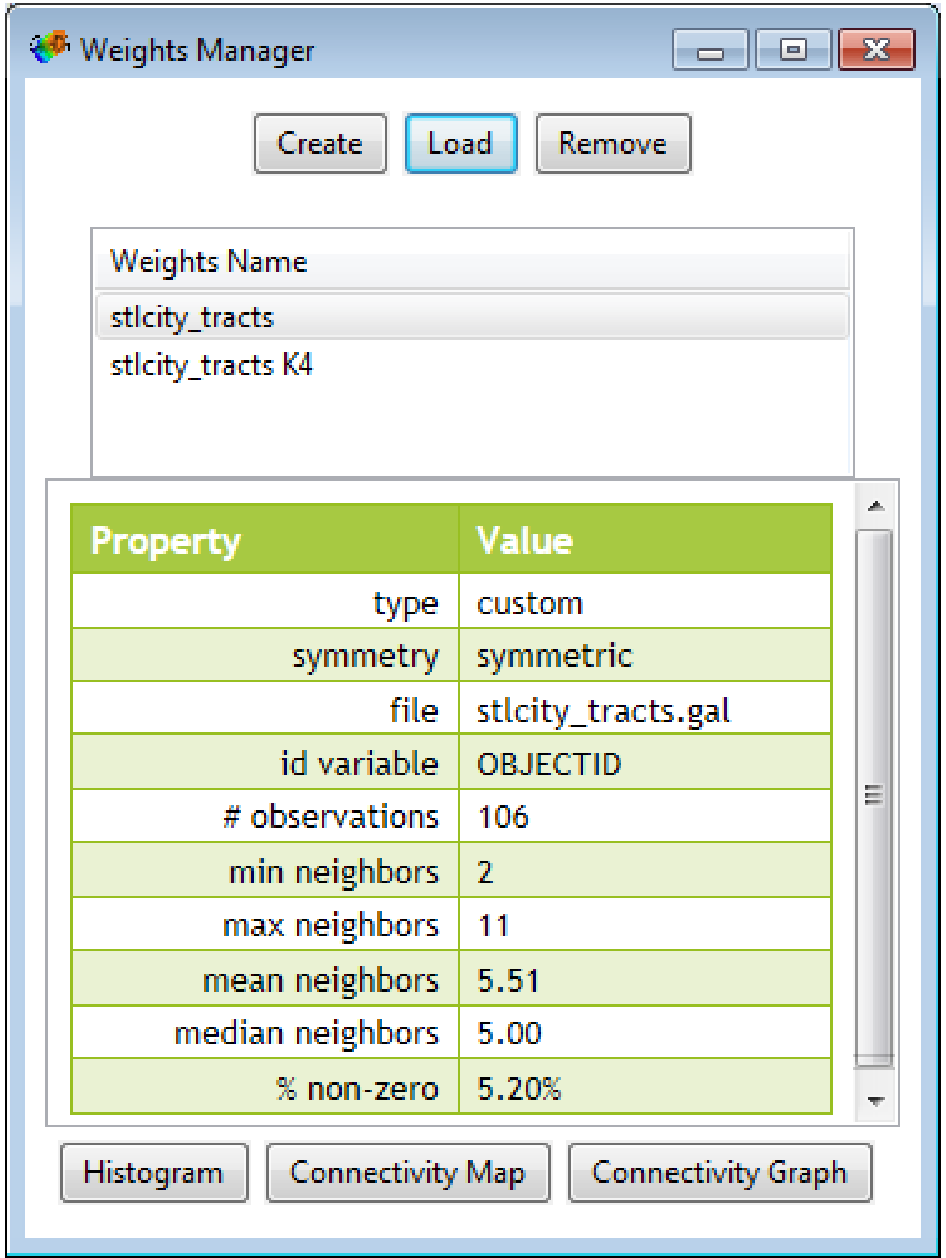
- The problem with spatial data is identification
  - (i.e., spatial co-variance)
  - How do neighbors interact with each other?
  - N2=100*100= 10000 interactions – This is not possible.

- Spatial weights imposes structure on the data (i.e., connectivity)
  - What if the interactions were structure?
    - Assume the structure…
    - Quantify spatial similarity

Why Spatial Weights? Part 2

- Pre-specified the interaction
  - In practice, we don't work with non-interactions, we work with interactions
    - 1=interaction – only focus on neighbor
    - 0=non interaction
- Everything you do is based on the assumption of the spatial weight matrix
  - There is no best weight matrix or optimal weight matrix
  - We will use reasonable assumptions and use goodness of fit to justify choice


Weights File Creation
Select ID Variable
OBJECTID
Add ID Variable...
Contiguity Weight
Distance Weight
Queen contiguity
Order of contiguity
1
Rook contiguity
Include lower orders
Precision threshold
0
Create
Close


Weights Manager
Create
Load
Remove
Weights Name
stlcity_tracts
stlcity_tracts K4
Property
Value
type
custom
symmetry
symmetric
file
stlcity_tracts.gal
id variable
OBJECTID
observations
106
min neighbors
2
max neighbors
11
mean neighbors
5.51
median neighbors
5.00
% non-zero
5.20%
Histogram
Connectivity Map
Connectivity Graph

spatial_regression.gal - Notepad

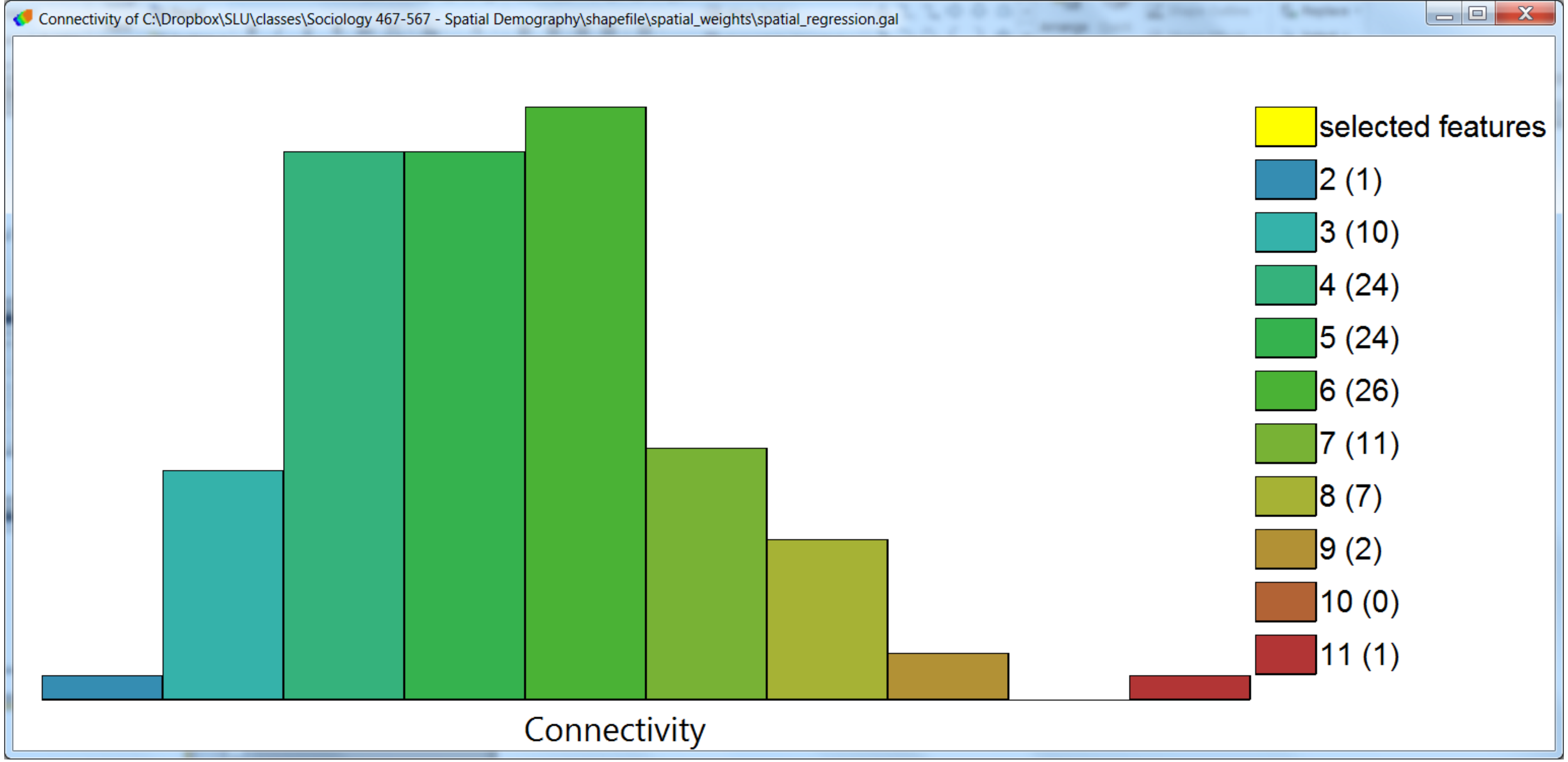
File Edit Format View Help

```
0 106 spatial_regression OBJECTID
1 4
106 105 96 42
2 5
105 104 87 81 42
3 4
87 5 4 37
4 7
106 87 41 37 58 60 3
5 4
3 37 6 7
6 3
37 7 5
7 6
8 9 38 37 6 5
8 3
9 7 10
9 5
38 10 15 8 7
10 6
11 12 14 15 9 8
11 3
12 88 10
12 5
13 14 88 11 10
13 4
14 16 88 12
14 5
15 16 13 12 10
15 7
39 38 33 16 14 10 9
```

Polygon ID

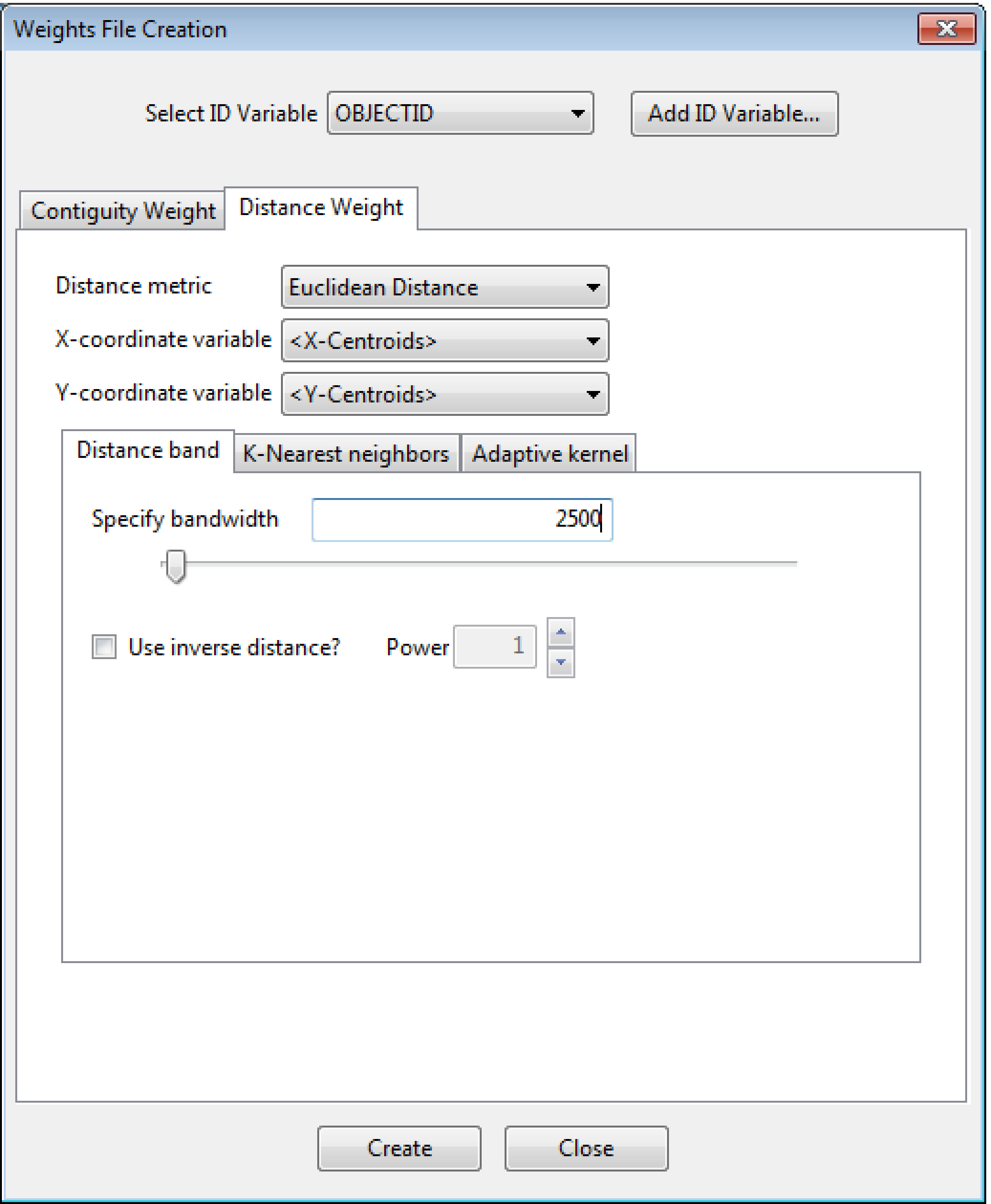
Number of Neighbors

Neighbors



The histogram is particularly useful to identify:

- islands,
- bimodal neighbor distributions,
- data quality problems (e.g., digitizing errors), and
- for linking with the map.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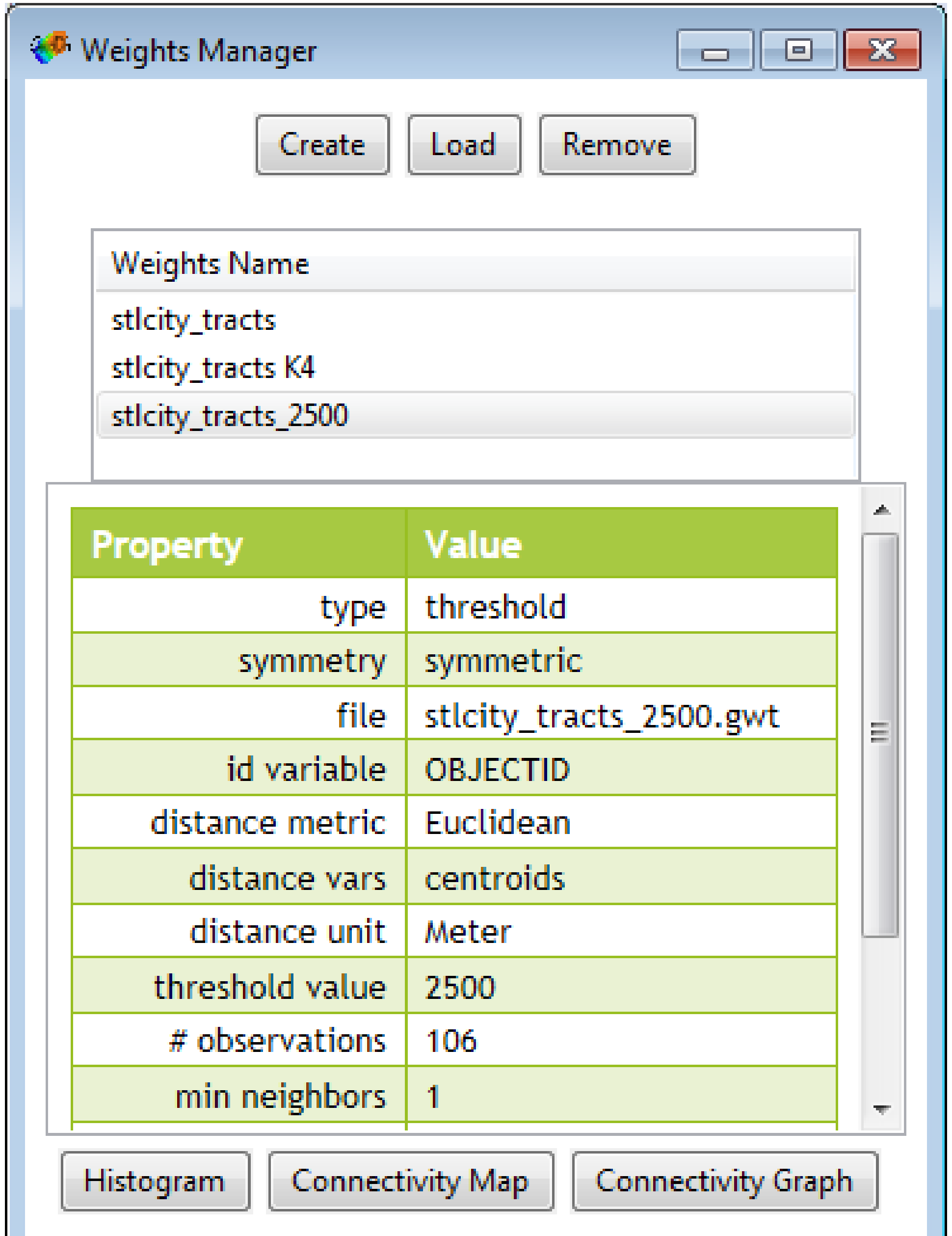
OBJECTID
Add ID Variable...
Contiguity Weight
Distance Weight
Distance metric
Euclidean Distance
X-coordinate variable
<X-Centroids>
Y-coordinate variable
<Y-Centroids>
Distance band
K-Nearest neighbors
Adaptive kernel
Specify bandwidth
2500
Use inverse distance?
Power
1
Create
Close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Load
Remove
Weights Name
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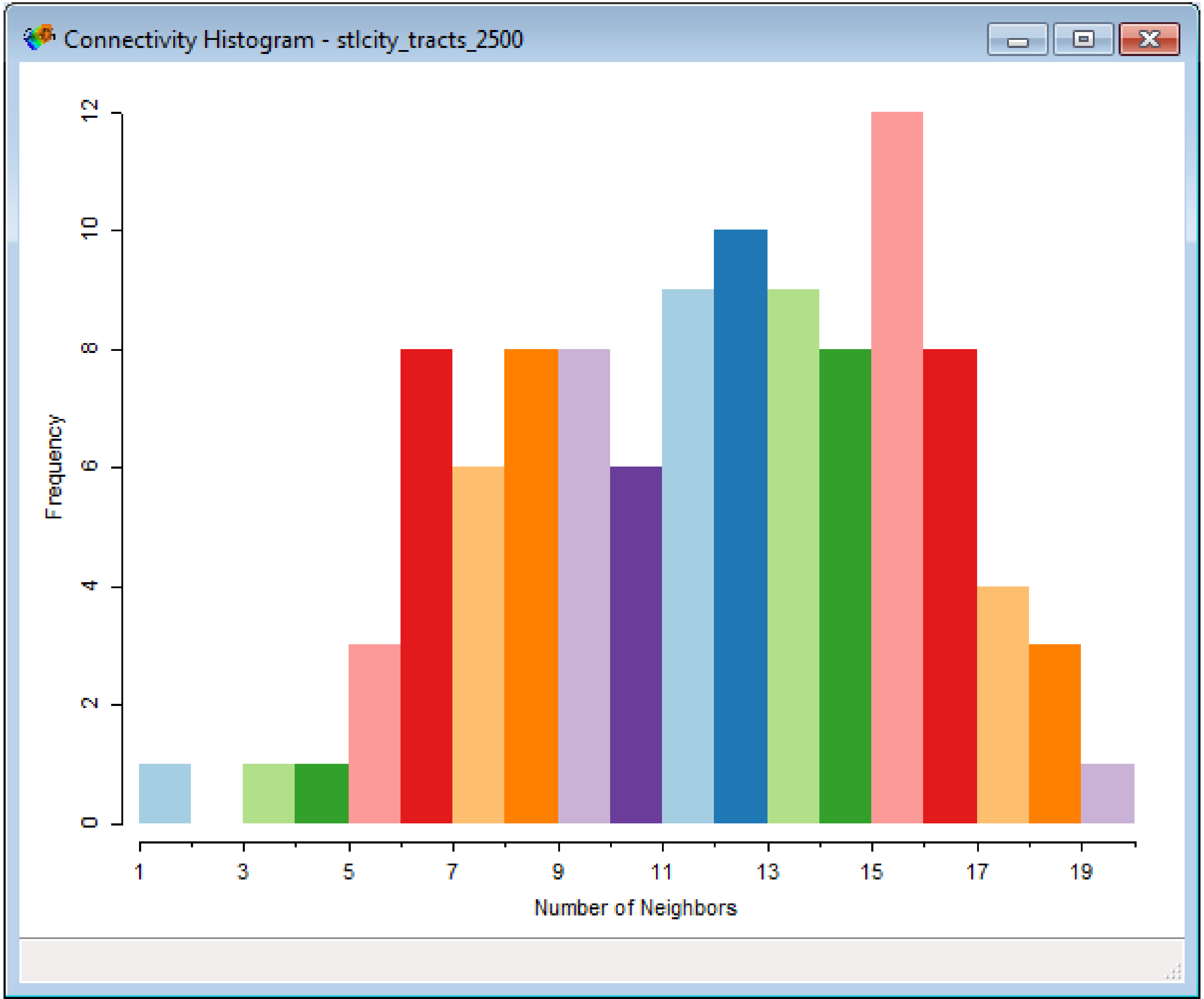
stlcity_tracts K4
stlcity_tracts_2500
Property
Value
type
threshold
symmetry
symmetric
file
stlcity_tracts_2500.gwt
id variable
OBJECTID
distance metric
Euclidean
distance vars
centroids
distance unit
Meter
threshold value
2500
observations
106
min neighbors
1
Histogram
Connectivity Map
Connectivity Graph

stlcity_tracts_2500.gwt - Notepad

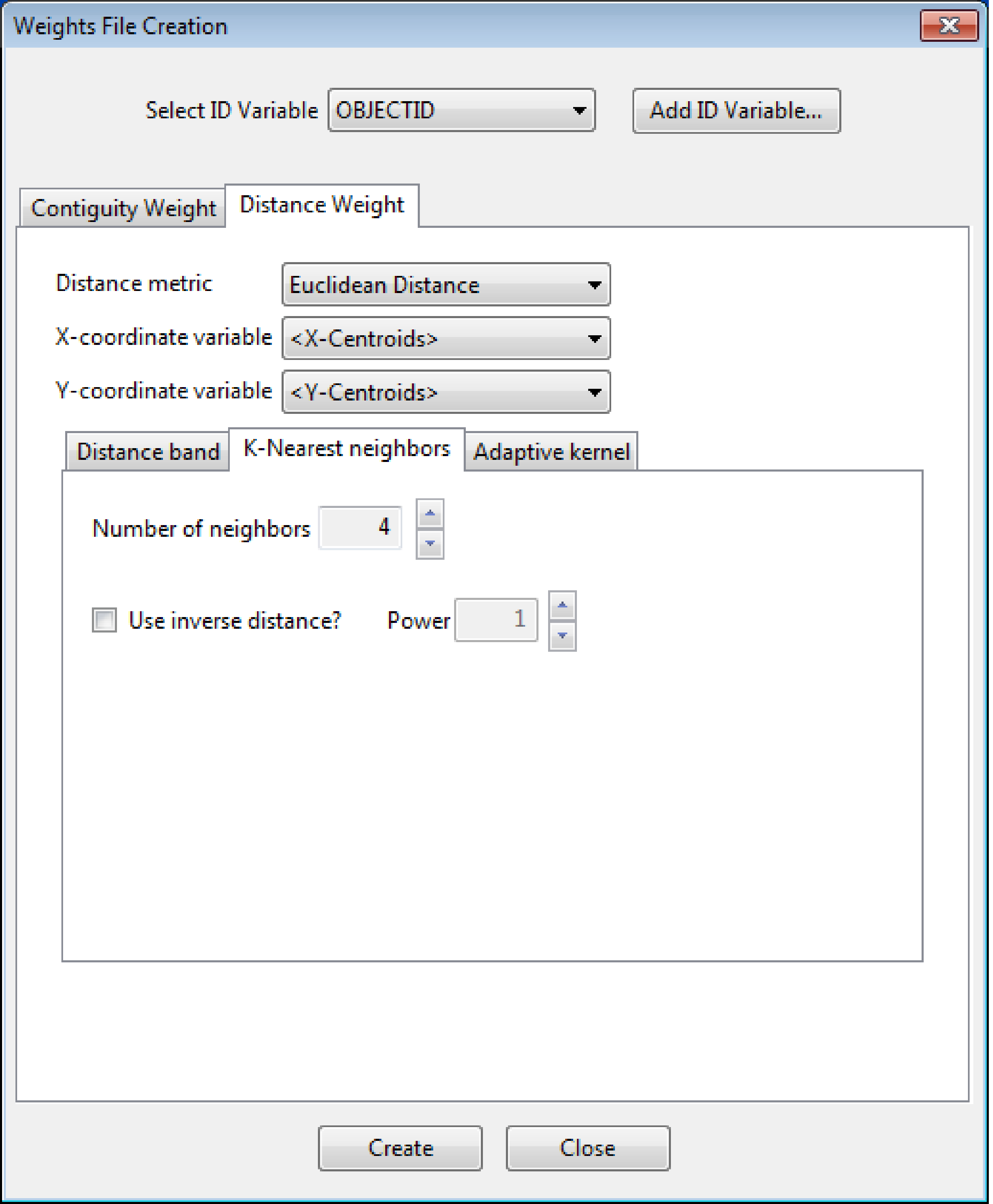
File Edit Format View Help

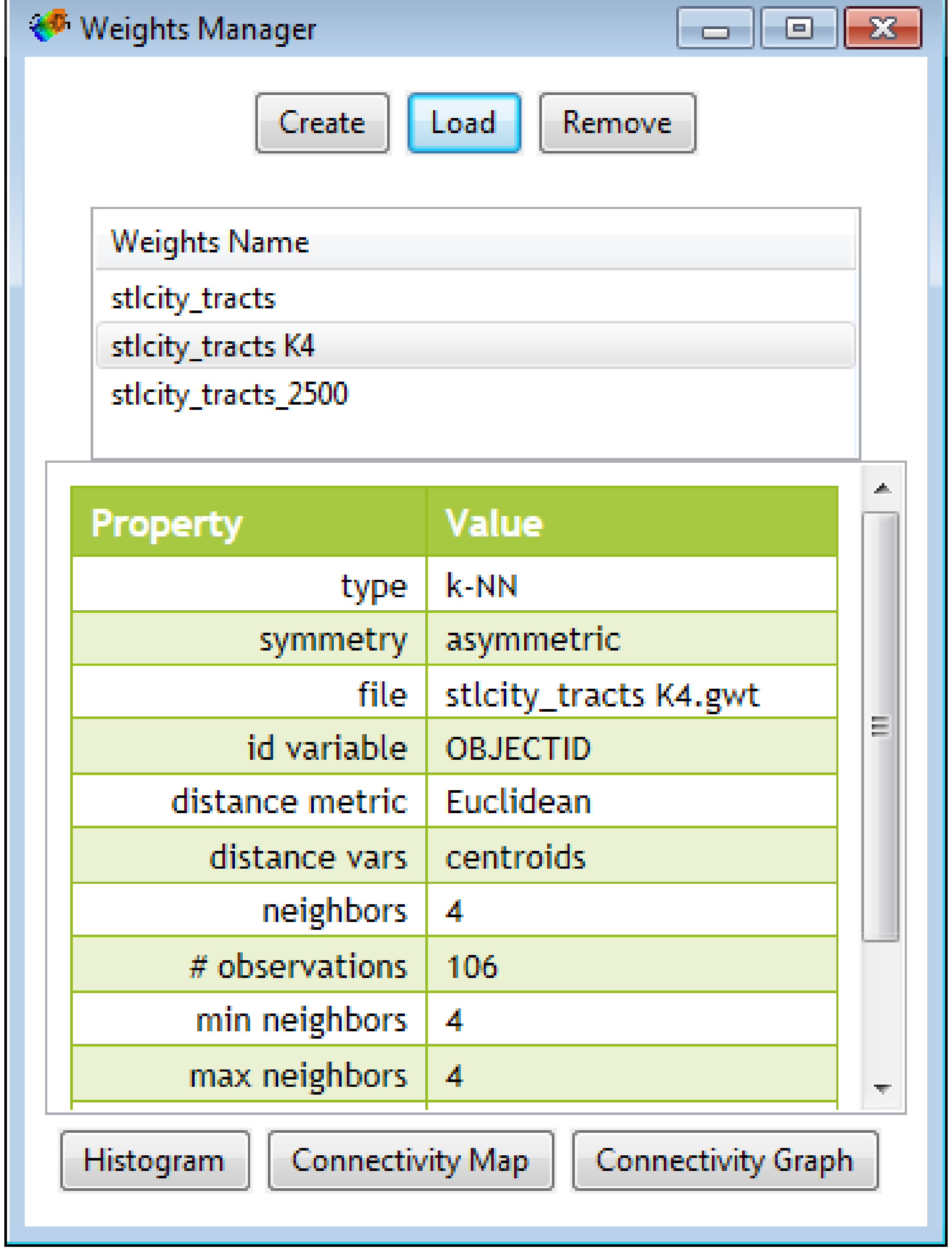
```
0 106 stlcity_tracts OBJECTID
1 92         1177.41994
1 46         2179.00684
1 45         2263.80172
1 44         2431.65114
1 64         1908.76364
1 48         2185.98615
1 43         1072.64548
1 66         2303.49923
1 41         971.210583
1 39         840.547398
1 40         1502.06285
1 52         2382.19591
1 85         1601.85718
1 31         1901.30634
1 32         2222.71147
2 96         2357.62575
2 94         1643.99834
2 105         2195.12636
2 10         1272.09773
2 3         1159.66219
3 102         2289.79647
3 96         1203.06277
3 94         2347.64747
3 105         1729.23739
3 10         1444.70625
3 2         1159.66219
4 8         894.390491
4 104         2231.15848
4 95         953.196096
4 9         1891.71994
4 7         1211.09944
4 88         1833.64691
4 6         1255.04656
4 26         1838.08672
4 5         2315.57495
4 106         1519.19684
4 94         1910.38127
5 4         2315.57495
5 9         1530.92091
5 7         1215.18162
5 88         2415.24293
5 6         1205.08339
5 26         1517.50601
5 99         1741.88825
5 98         1437.16727
5 82         2207.59257
5 67         2090.6468
5 54         2172.44456
5 55         1996.27822
5 75         803.901515
```

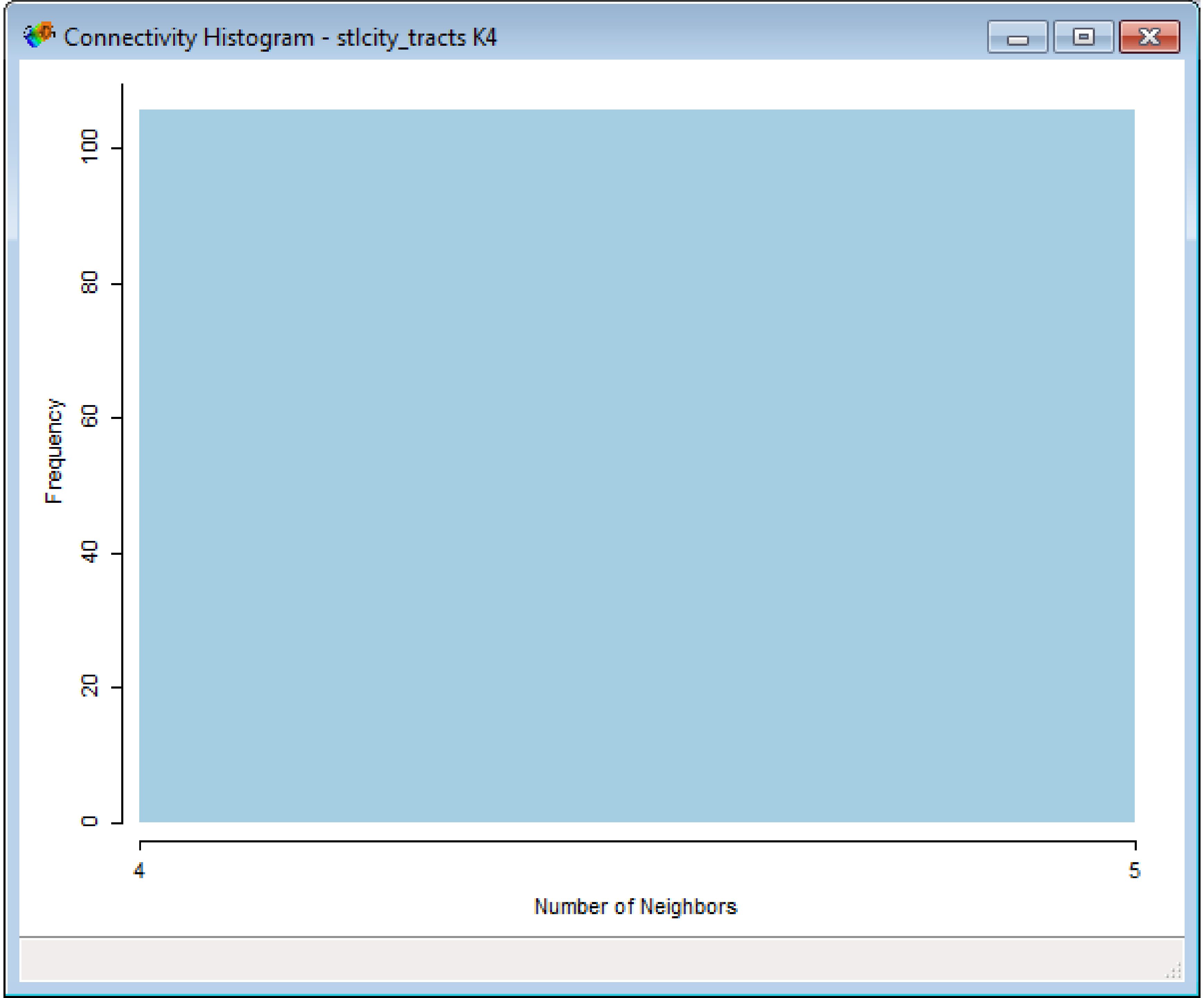
Polygon ID 1 – has 15 neighbors



Connectivity Histogram - stlcity_tracts_2500
Frequency
0
2
4
6
8
10
12
1
3
5
7
9
11
13
15
17
19
Number of Neighbors


Weights File Creation
Select ID Variable
OBJECTID
Add ID Variable...
Contiguity Weight
Distance Weight
Distance metric
Euclidean Distance
X-coordinate variable
<X-Centroids>
Y-coordinate variable
<Y-Centroids>
Distance band
K-Nearest neighbors
Adaptive kernel
Number of neighbors
4
Use inverse distance?
Power
1
Create
Close


Weights Manager
Create
Load
Remove
Weights Name
stlcity_tracts
stlcity_tracts K4
stlcity_tracts_2500
Property
Value
type
k-NN
symmetry
asymmetric
file
stlcity_tracts K4.gwt
id variable
OBJECTID
distance metric
Euclidean
distance vars
centroids
neighbors
4
observations
106
min neighbors
4
max neighbors
4
Histogram
Connectivity Map
Connectivity Graph

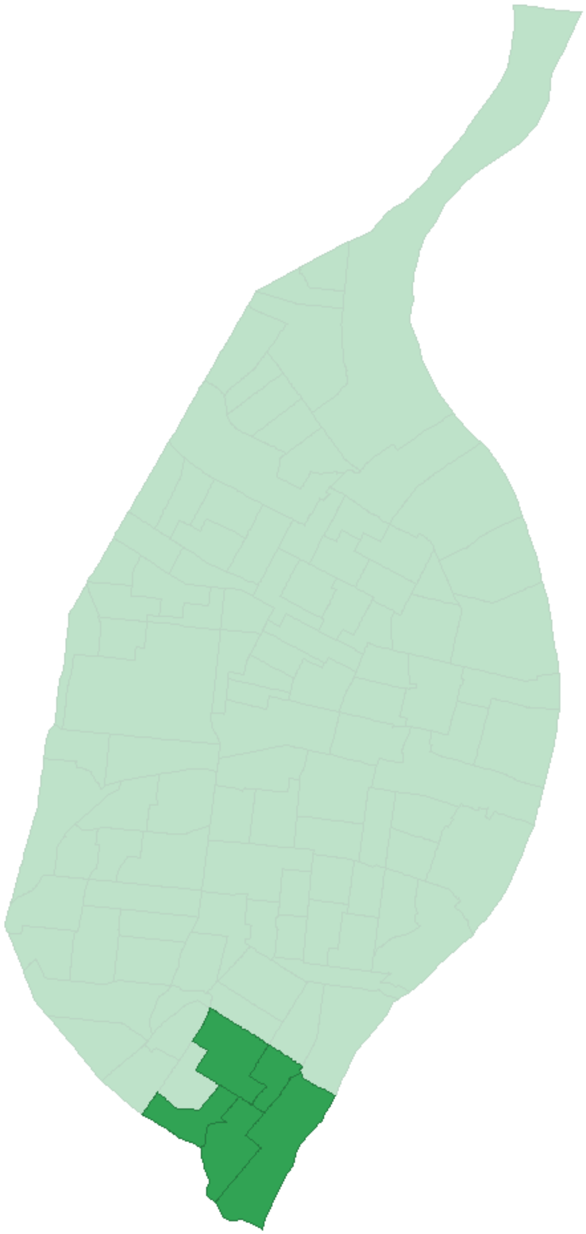


Connectivity Histogram - stlcity_tracts K4
Frequency
0
20
40
60
80
100
4
5
Number of Neighbors

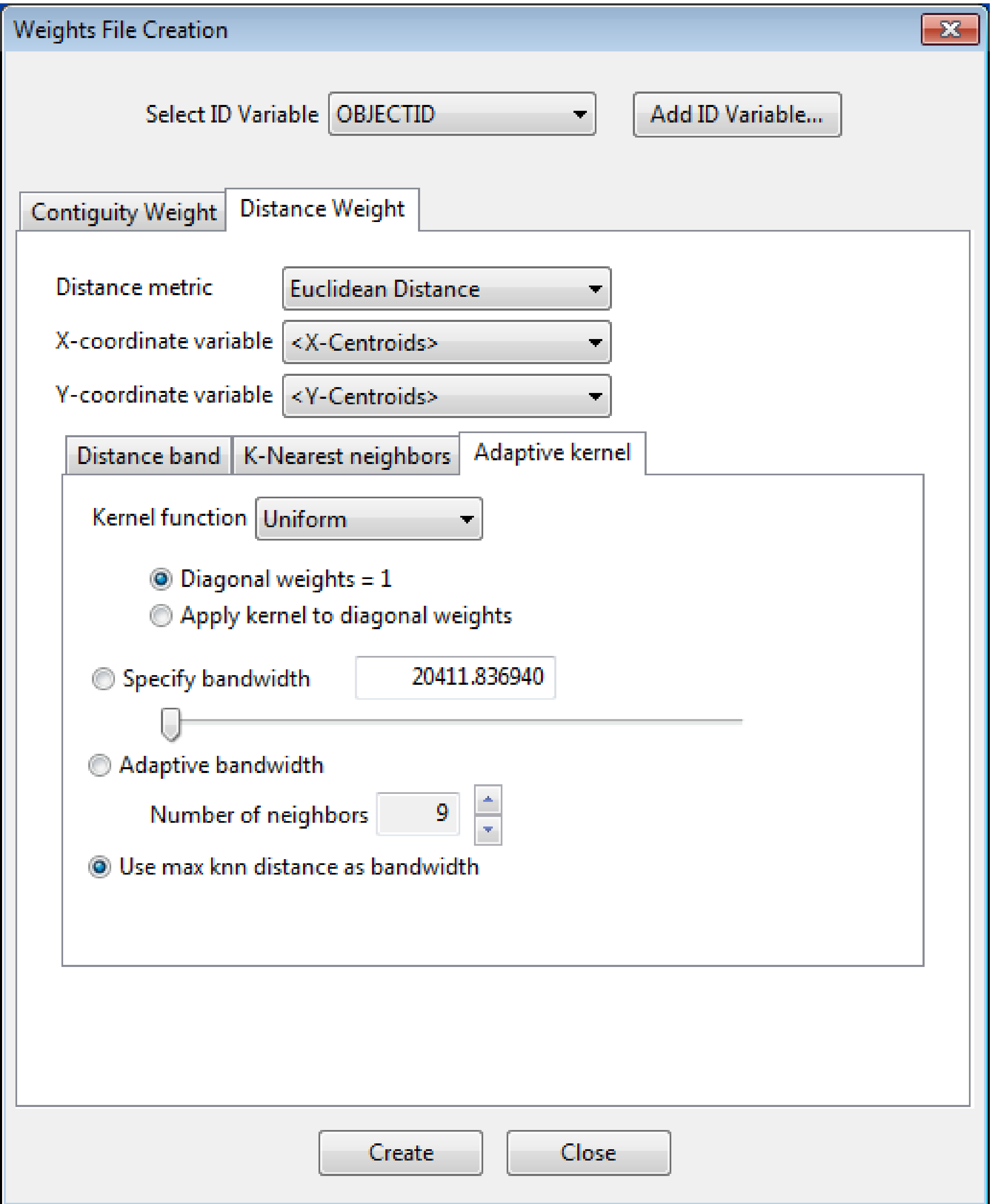
Connectivity Map (Weights: stlcity_tracts K4)

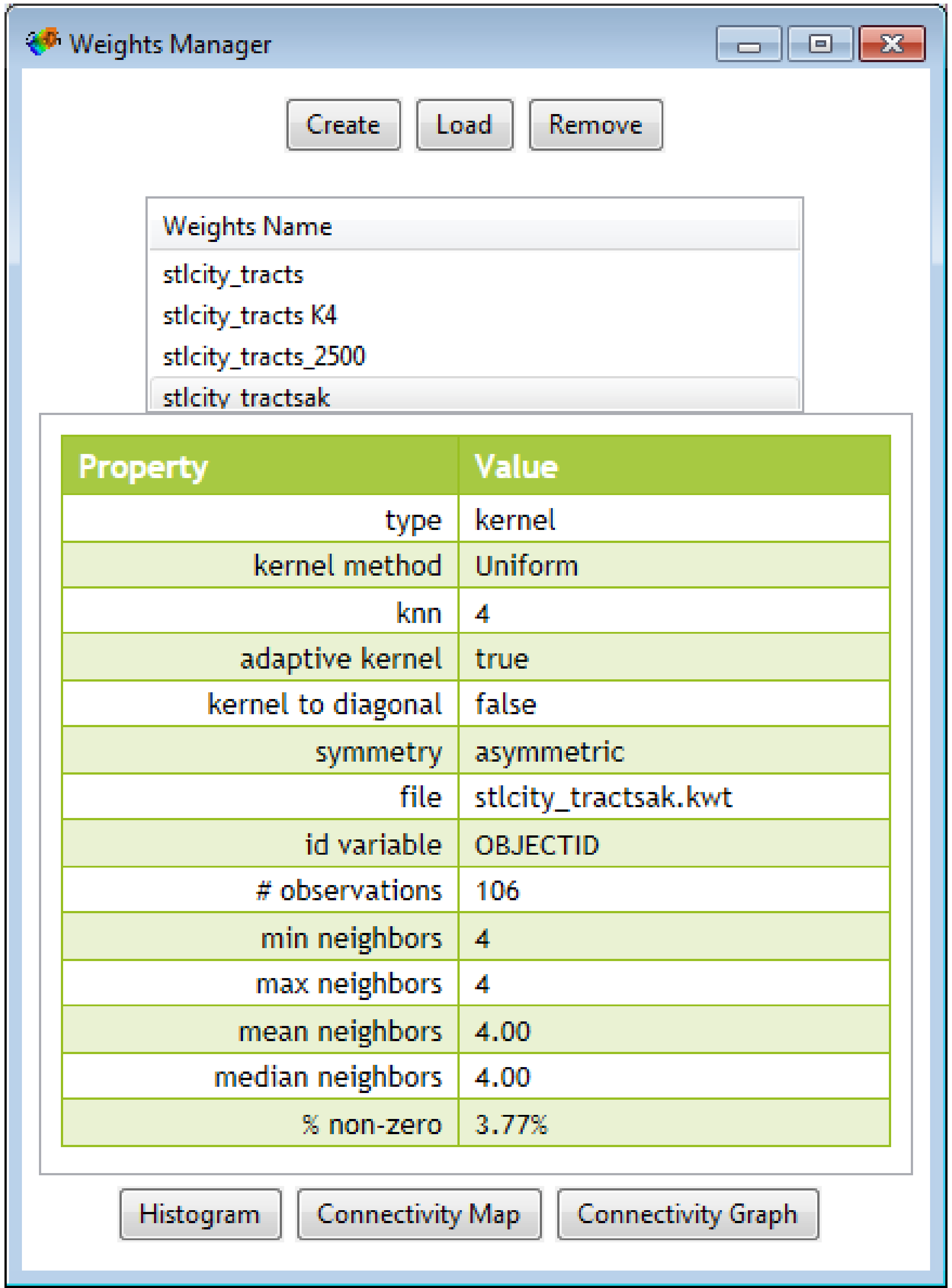
Map - stlcity_tracts

(106)



#obs=106 #selected=1 obs 17 has 4 neighbors: 22, 20, 24, 23


Weights File Creation
Select ID Variable
OBJECTID
Add ID Variable...
Contiguity Weight
Distance Weight
Distance metric
Euclidean Distance
X-coordinate variable
<X-Centroids>
Y-coordinate variable
<Y-Centroids>
Distance band
K-Nearest neighbors
Adaptive kernel
Kernel function
Uniform
Diagonal weights = 1
Apply kernel to diagonal weights
Specify bandwidth
20411.836940
Adaptive bandwidth
Number of neighbors
9
Use max knn distance as bandwidth
Create
Close


Weights Manager
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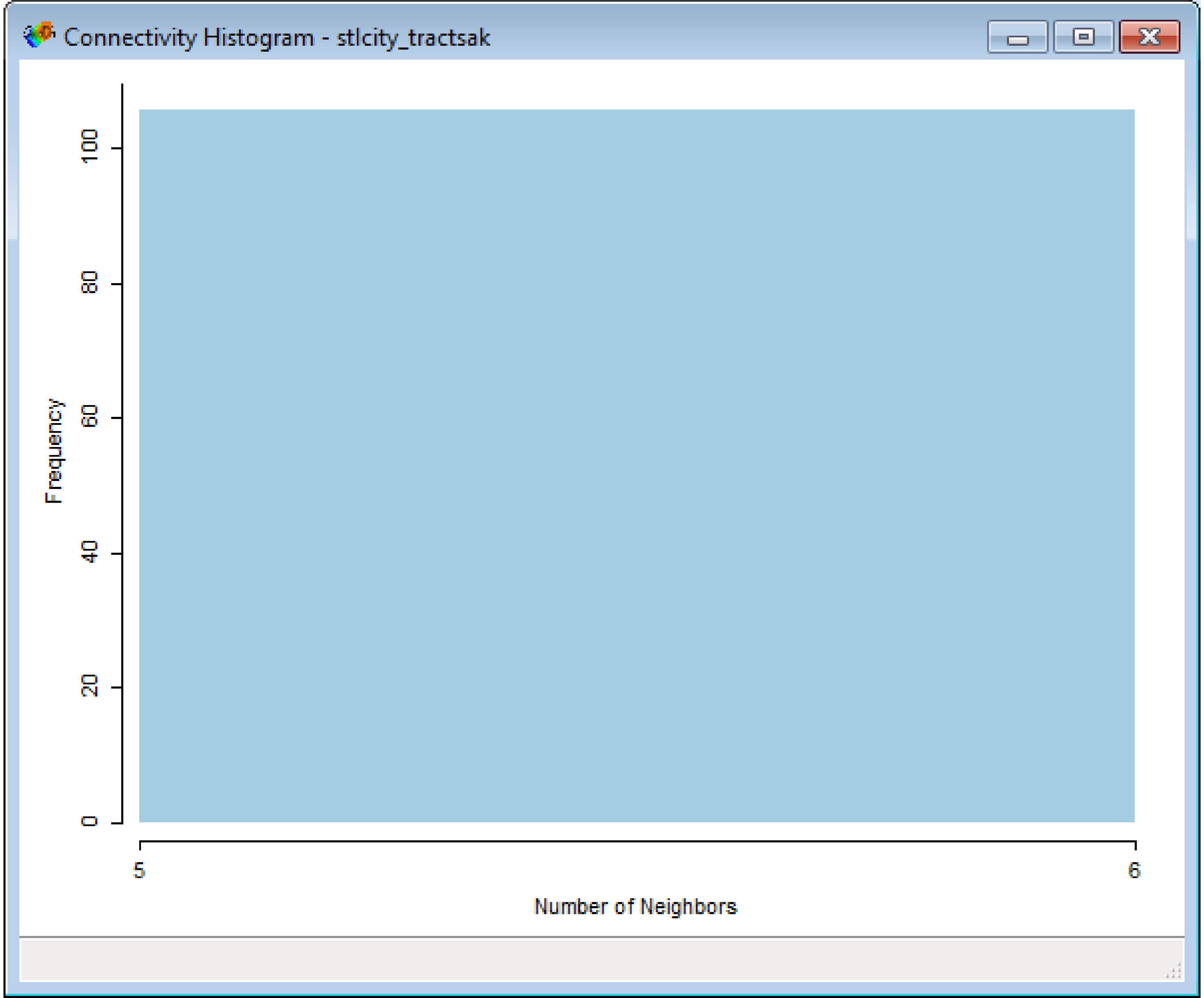
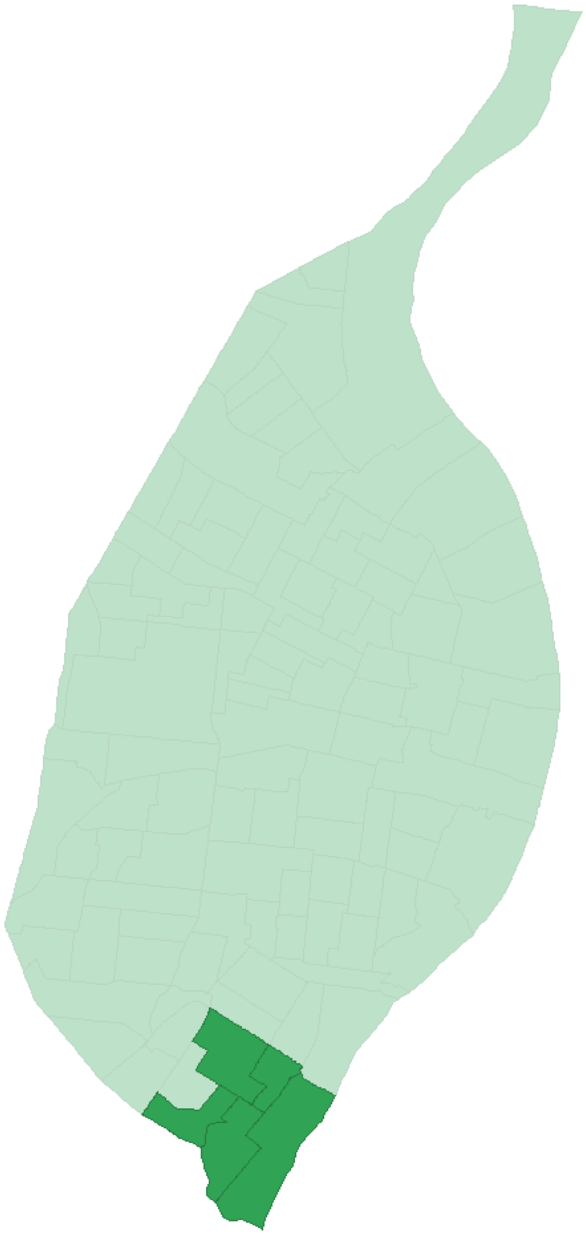
stlcity_tracts_2500
stlcity_tractsak
Property
Value
type
kernel
kernel method
Uniform
knn
4
adaptive kernel
true
kernel to diagonal
false
symmetry
asymmetric
file
stlcity_tractsak.kwt
id variable
OBJECTID
observations
106
min neighbors
4
max neighbors
4
mean neighbors
4.00
median neighbors
4.00
% non-zero
3.77%
Histogram
Connectivity Map
Connectivity Graph


Connectivity Histogram - stlcity_tractsak
Frequency
0
20
40
60
80
100
5
6
Number of Neighbors

Connectivity Map (Weights: stlcity_tractsak)

Map - stlcity_tracts

(106)

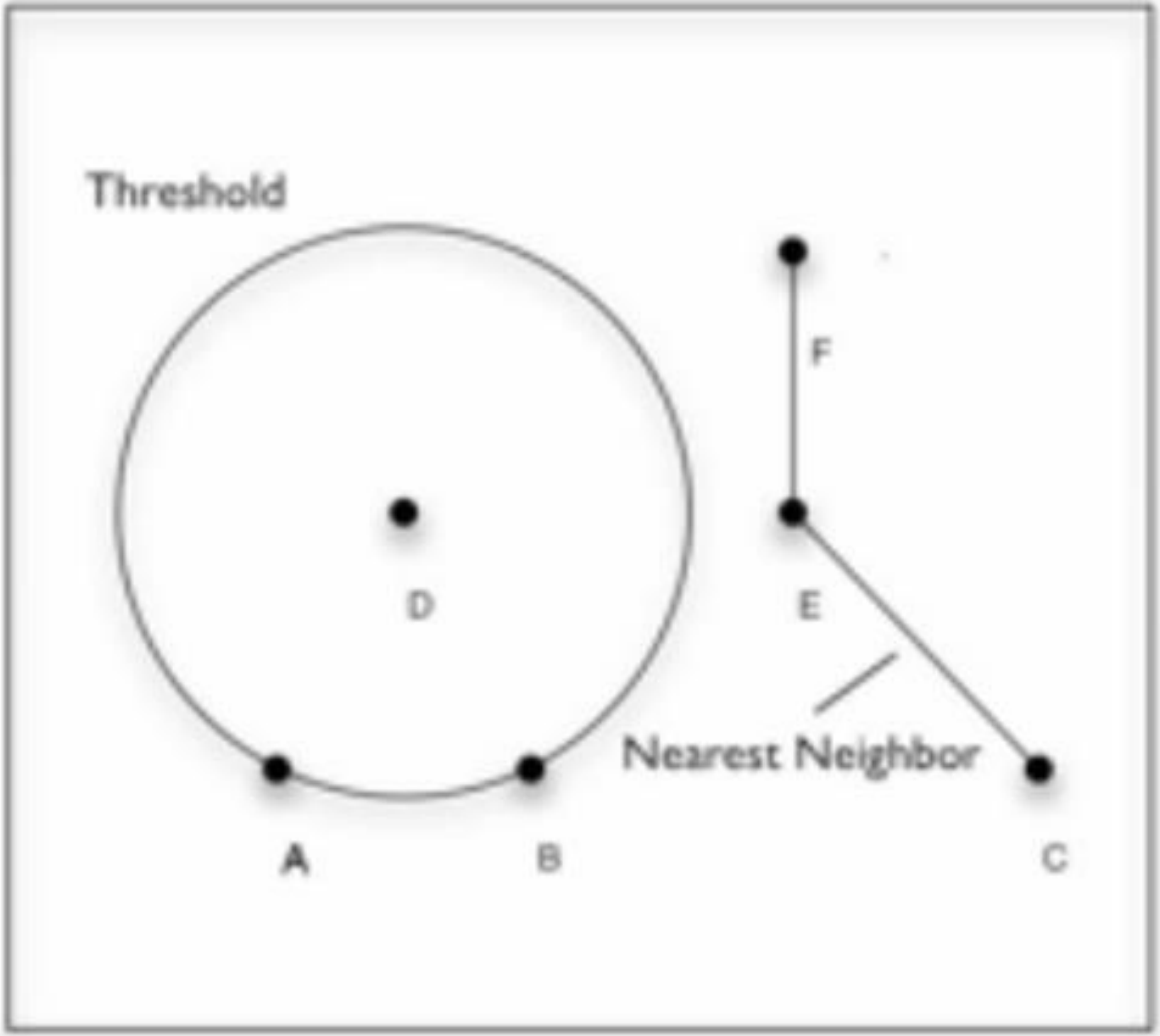


#obs=106 #selected=1 obs 17 has 5 neighbors: 22, 20, 17, 24, 23

Important Note

- KNN is asymmetric (e.g., point A is B's nearest neighbor but point B does not have to be point A's nearest neighbor).

- Because of this asymmetry, it is difficult to correctly estimate spatial lag or error models with KNN weights in GeoDa. You have to compute this function in GeoSpace.



Let’s Focus on D
A and B are in radius

Let’s Focus on E
F is NN of E

E is the NN of C
Therefore C is not the NN of E

This is a problem - Asymmetrical

Distance Band Weight (e.g., 14.1 Distance Band)

	A	B	C	D	E	F
A	0	10	30	11.2	22.4	28.3
B	10	0	20	11.2	14.1	22.4
C	30	20	0	26.9	14.1	22.4
D	11.2	11.2	26.9	0	15.0	18.0
E	22.4	14.1	14.1	15.0	0	10.0
F	28.3	22.4	22.4	18.0	10.0	0

Symmetric

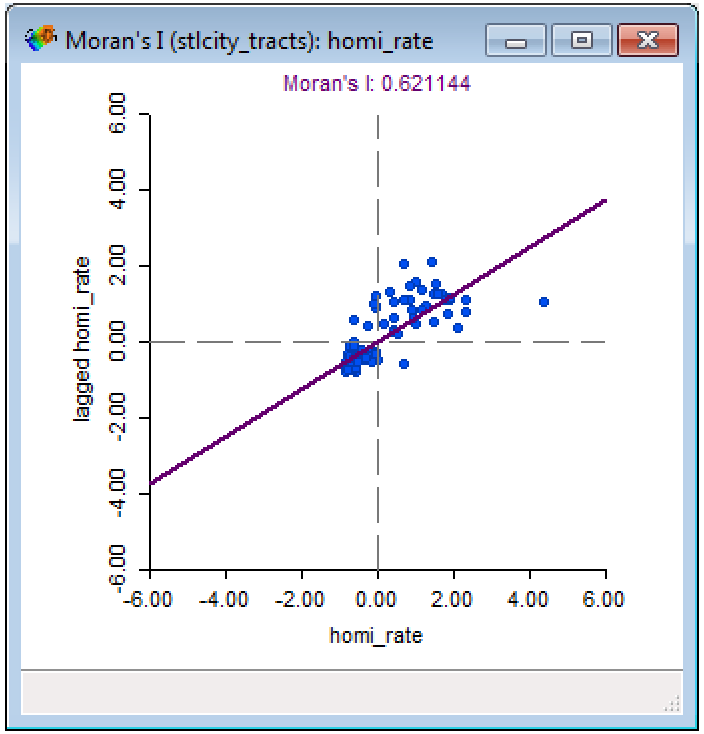
	A	B	C	D	E	F
A	0	1	0	1	0	0
B	1	0	0	1	1	0
C	0	0	0	0	1	0
D	1	1	0	0	0	0
E	0	1	1	0	0	1
F	0	0	0	0	1	0

K – Nearest Neighborhood (e.g., k=3)

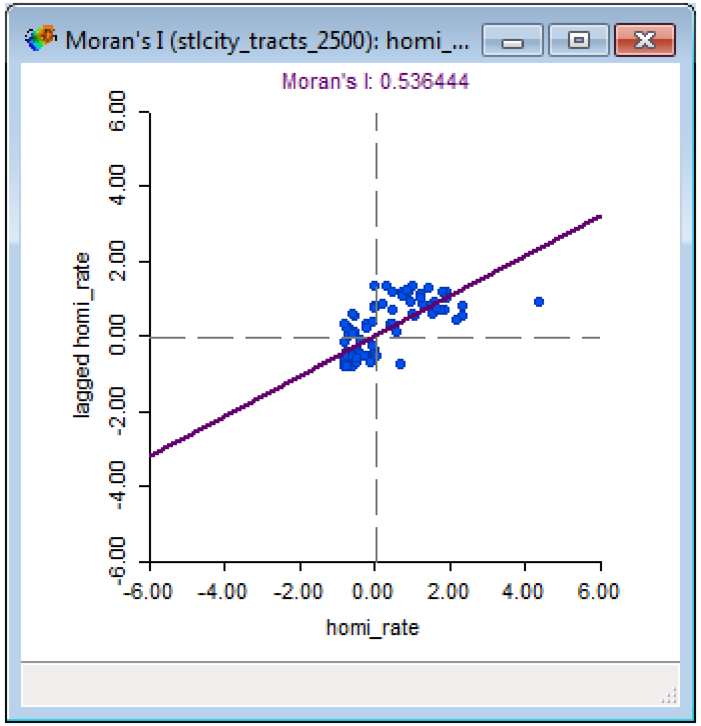
	A	B	C	D	E	F
A	0	10	30	11.2	22.4	28.3
B	10	0	20	11.2	14.1	22.4
C	30	20	0	26.9	14.1	22.4
D	11.2	11.2	26.9	0	15.0	18.0
E	22.4	14.1	14.1	15.0	0	10.0
F	28.3	22.4	22.4	18.0	10.0	0

Asymmetric

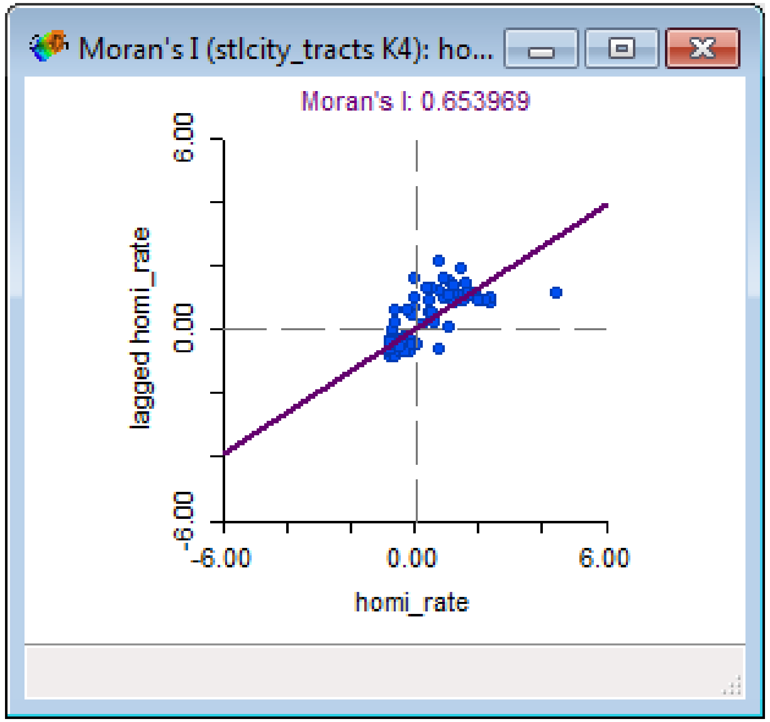
	A	B	C	D	E	F
A	0	1	0	1	1*	0
B	1	0	0	1	1	0
C	0	1	0	0	1	1
D	1	1	0	0	1	0
E	0	1	1	0	0	1
F	0	1	1	0	1	0



Queen Contiguity



Distance

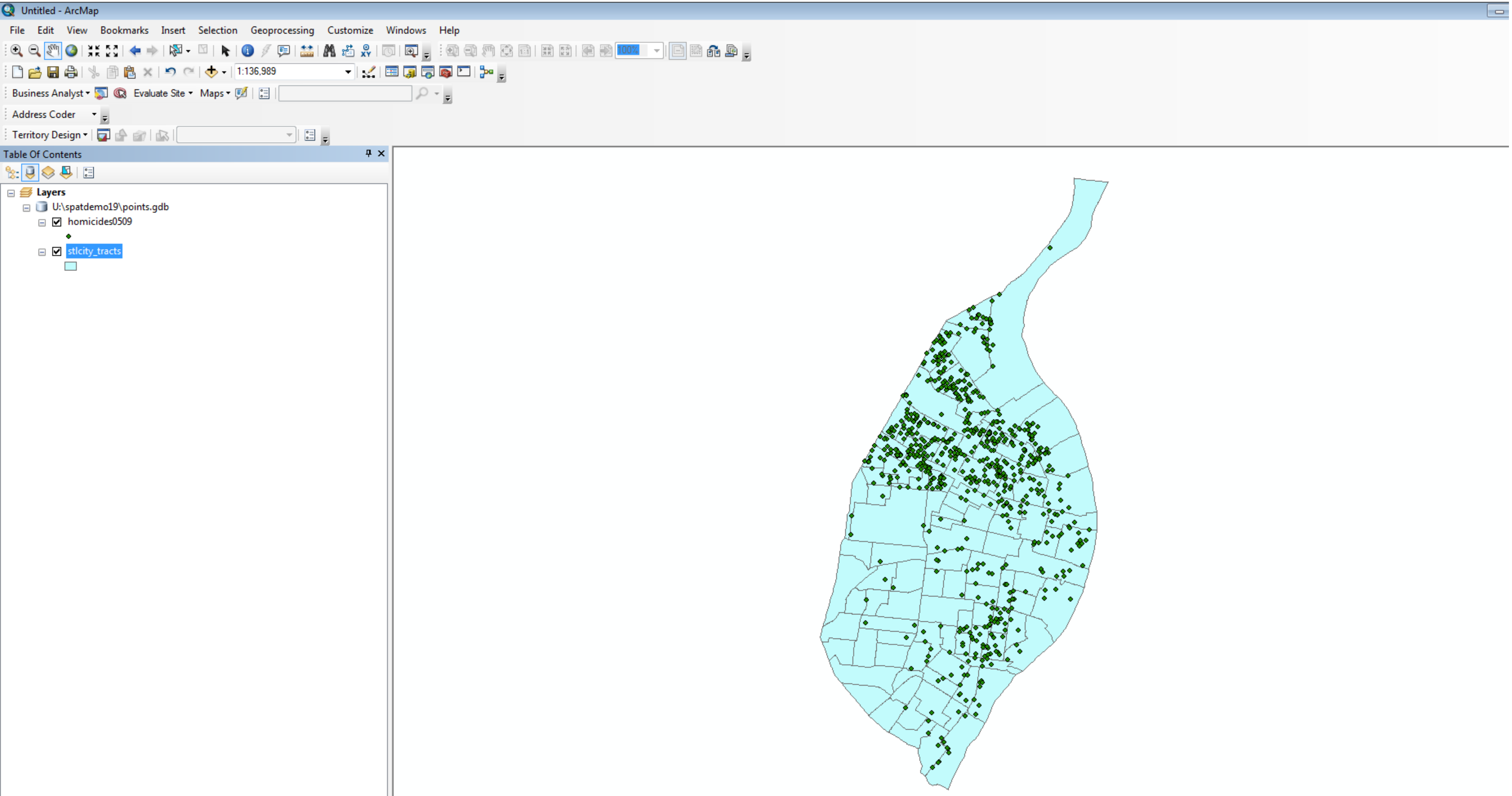


KNN

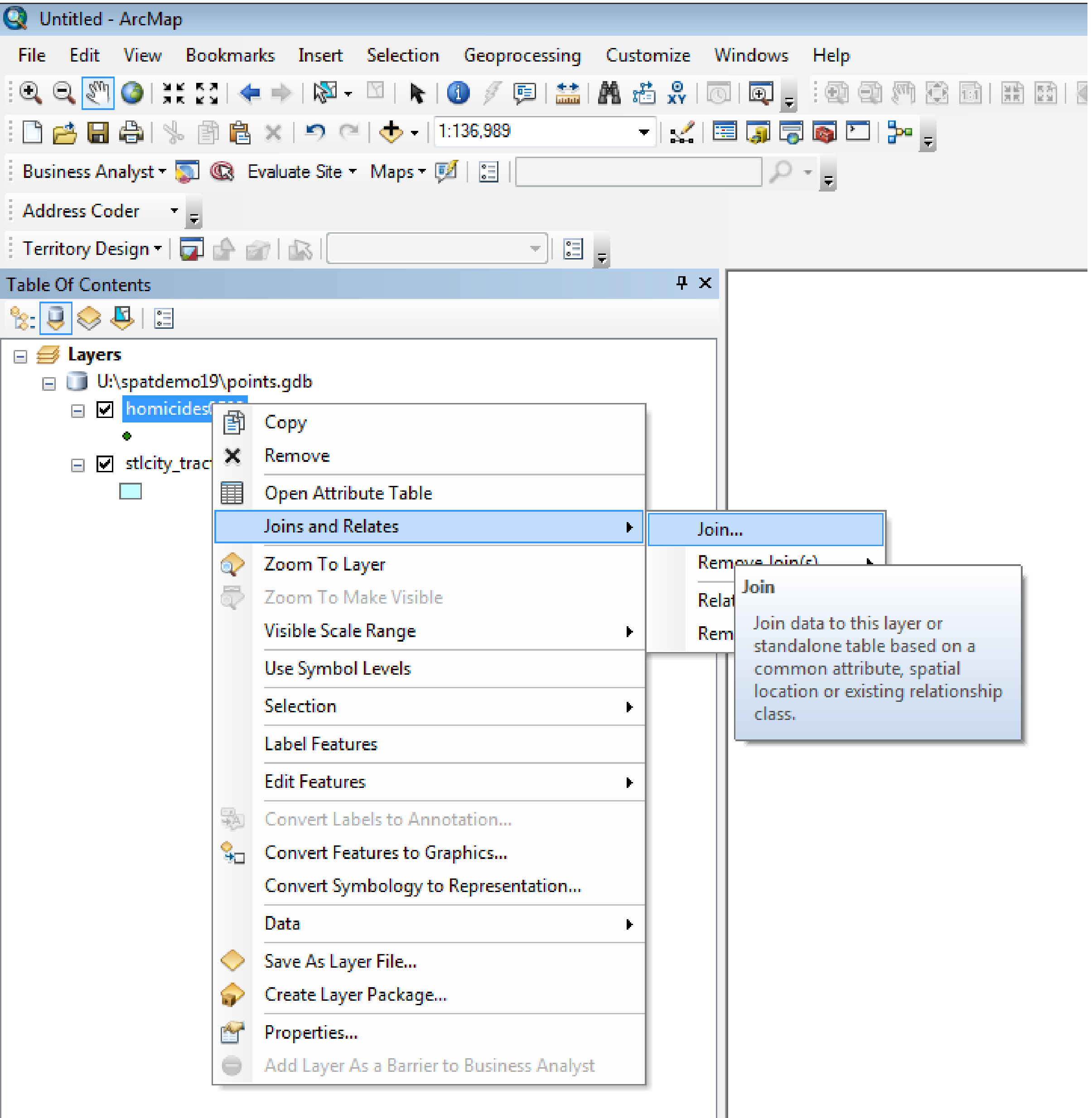
Example

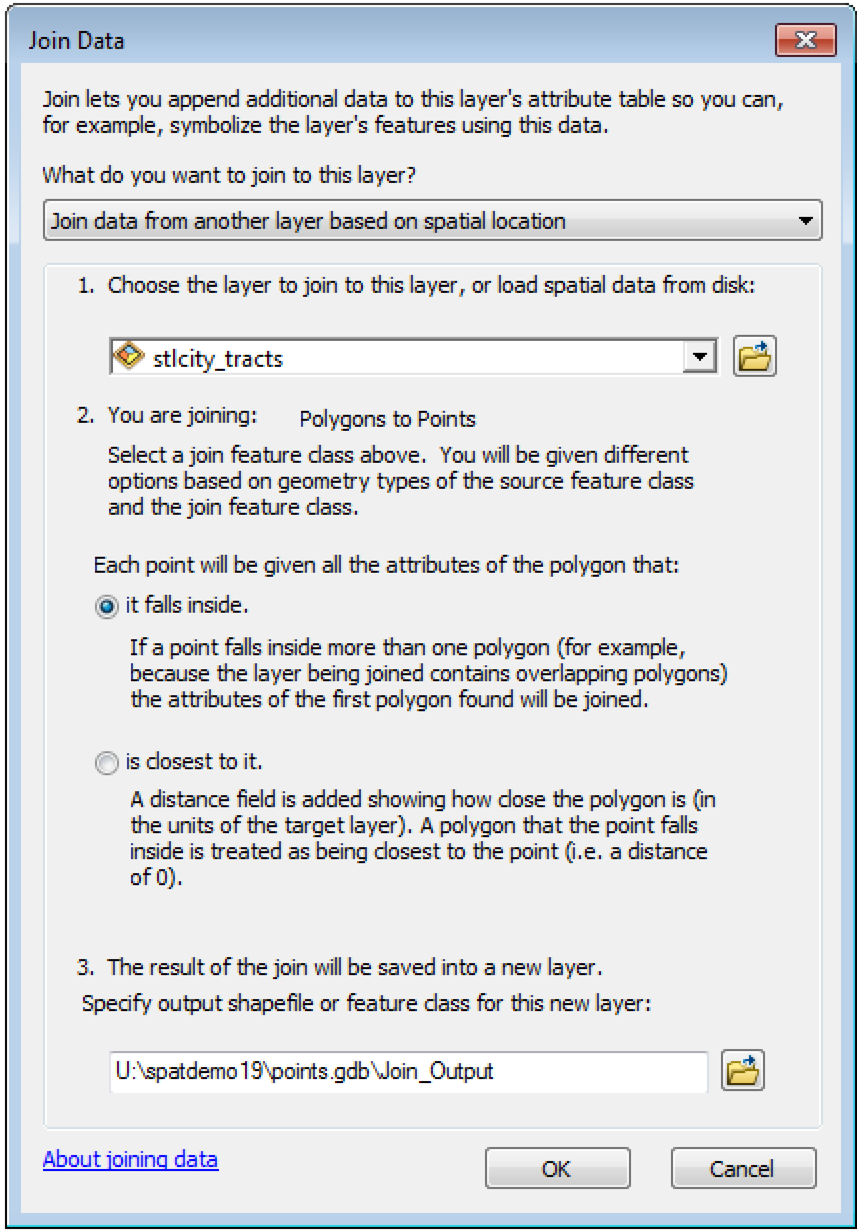
Create Crime Rate using Spatial Join

1. Load your crime data and tract data for city from the point geodatabase



2. Select Join Data and make sure you selected the point shapefile
3. Make sure you select “Joint data from another layer based on spatial location





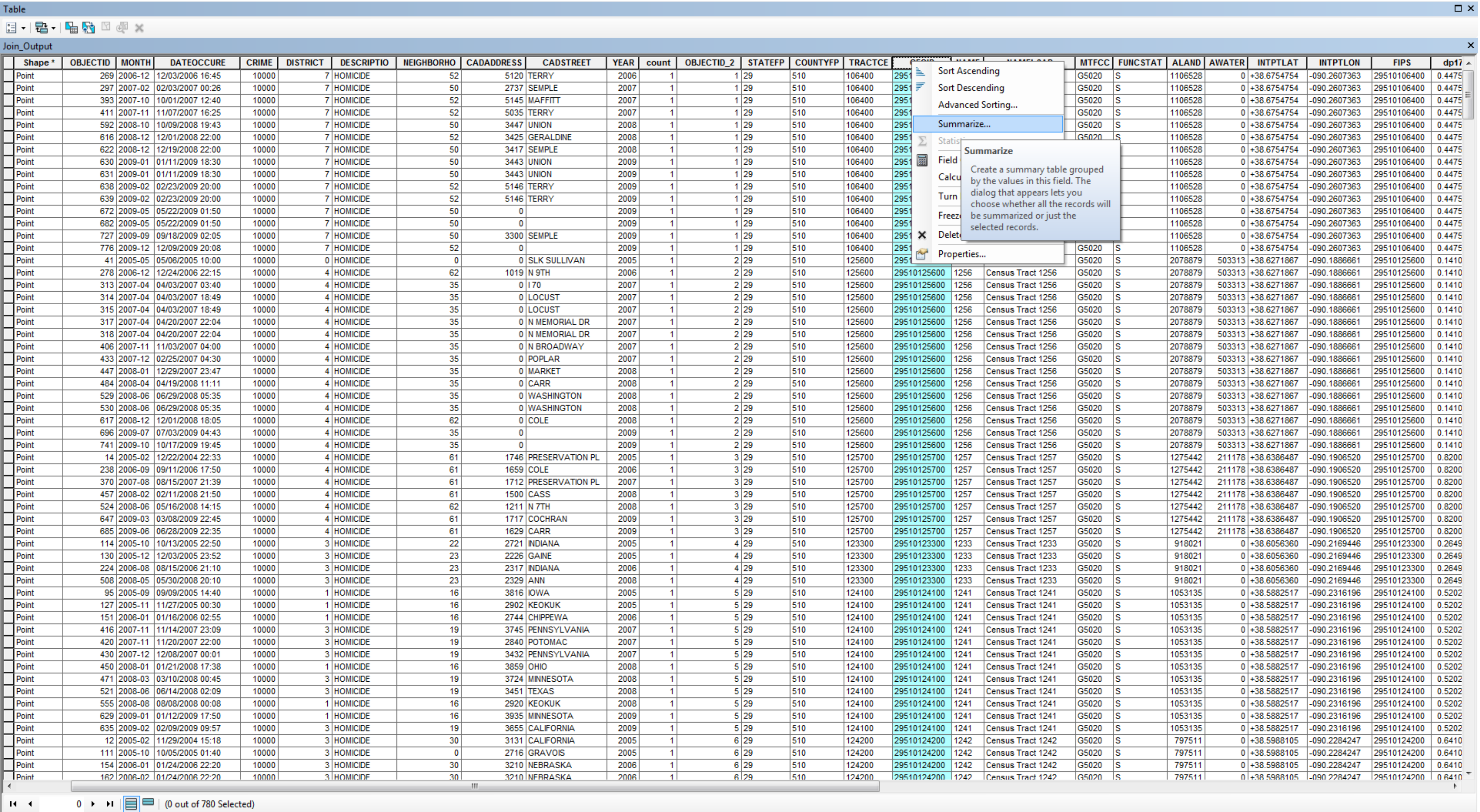
4. Each point has the attribute of the census tract

Table

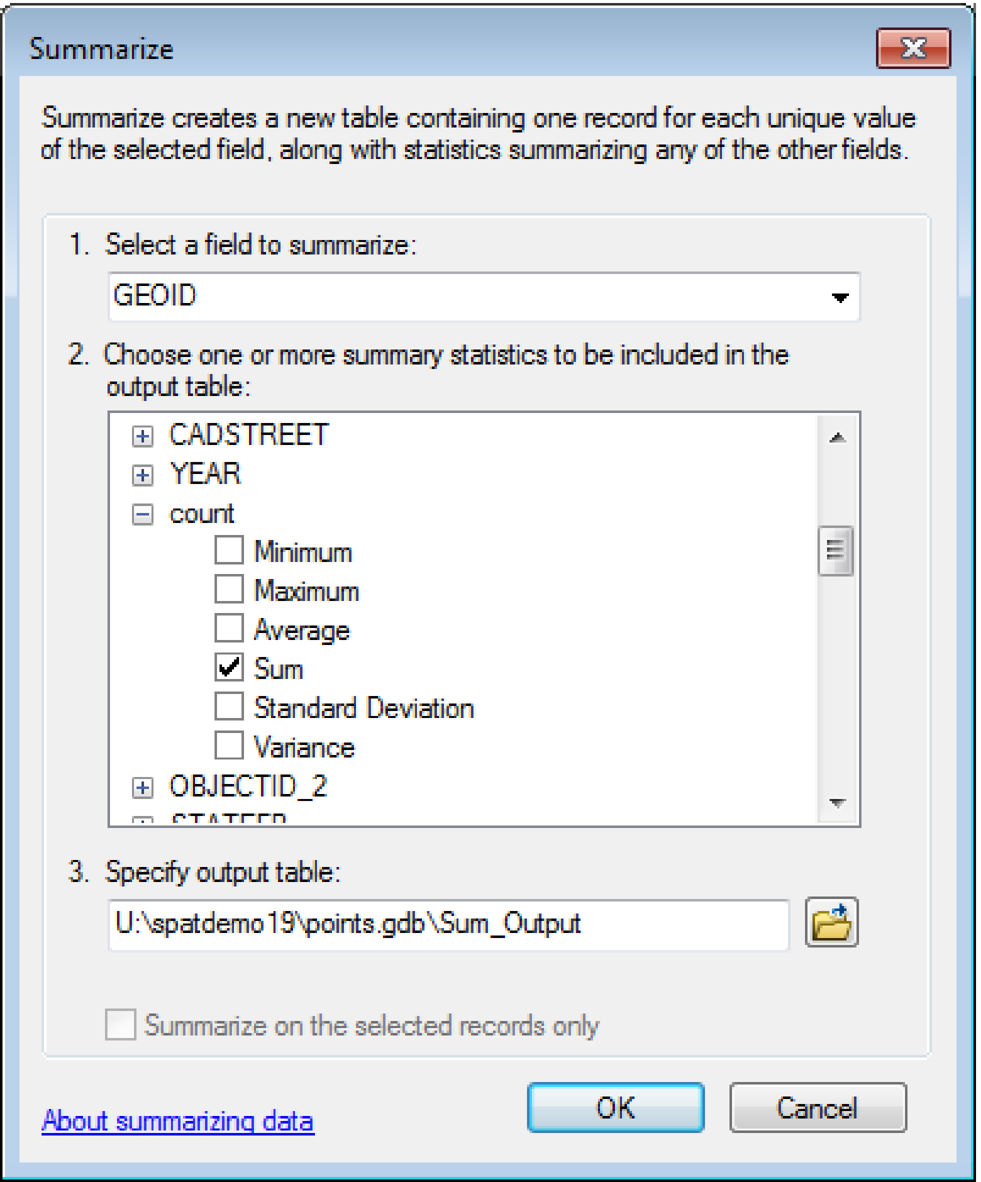
Join_Output

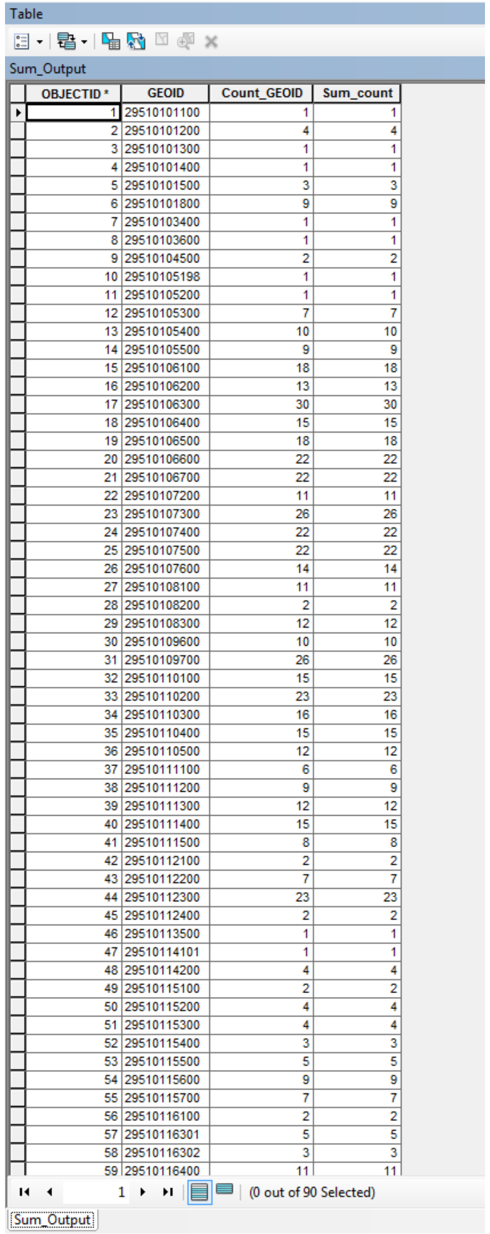
OBJECTID_2	STATEFP	COUNTYFP	TRACTCE	GEOID	NAME	NAMELSAD	MTFCC	FUNCSTAT	ALAND	AWATER	INTPTLAT	INTPTLON	FIPS	dp17	cdp17	sdp17	ai17	e17	wht17	blk17	lat17	oth17	tot17	pwht17	pblk17	keep	GEOID10	theil17	ED_TOT17
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
1	29	510	106400	29510106400	1064	Census Tract 1064	G5020	S	1106528	0	+38.6754754	-090.2607363	29510106400	0.447522	0.240525	0.206997	0.860606	0.074276	21	1950	0	15	1986	0.010574	0.981873	1	29510106400	0.314531	0.892136
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
2	29	510	125600	29510125600	1256	Census Tract 1256	G5020	S	2078879	503313	+38.6271867	-090.1886661	29510125600	0.141032	0.098843	0.042189	0.426829	0.750076	2033	2118	109	473	4733	0.429537	0.447496	1	29510125600	0.341027	1.709605
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
3	29	510	125700	29510125700	1257	Census Tract 1257	G5020	S	1275442	211178	+38.6386487	-090.1906520	29510125700	0.820058	0.599328	0.220729	0.368295	0.02739	13	3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652
4	29	510	123300	29510123300	1233	Census Tract 1233	G5020	S	918021	0	+38.6056360	-090.2169446	29510123300	0.264998	0.193785	0.071213	0.367483	0.58376	1912	889	71	59	2931	0.652337	0.303309	1	29510123300	0.411635	1.715804
4	29	510	123300	29510123300	1233	Census Tract 1233	G5020	S	918021	0	+38.6056360	-090.2169446	29510123300	0.264998	0.193785	0.071213	0.367483	0.58376	1912	889	71	59	2931	0.652337	0.303309	1	29510123300	0.411635	1.715804
4	29	510	123300	29510123300	1233	Census Tract 1233	G5020	S	918021	0	+38.6056360	-090.2169446	29510123300	0.264998	0.193785	0.071213	0.367483	0.58376	1912	889	71	59	2931	0.652337	0.303309	1	29510123300	0.411635	1.715804
4	29	510	123300	29510123300	1233	Census Tract 1233	G5020	S	918021	0	+38.6056360	-090.2169446	29510123300	0.264998	0.193785	0.071213	0.367483	0.58376	1912	889	71	59	2931	0.652337	0.303309	1	29510123300	0.411635	1.715804
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
5	29	510	124100	29510124100	1241	Census Tract 1241	G5020	S	1053135	0	+38.5882517	-090.2316196	29510124100	0.520231	0.409492	0.110739	0.270431	0.707162	1138	3157	533	169	4997	0.227737	0.631779	1	29510124100	0.511292	0.891857
6	29	510	124200	29510124200	1242	Census Tract 1242	G5020	S	797511	0	+38.5988105	-090.2284247	29510124200	0.641095	0.536115	0.10498	0.195816	0.736704	872	2244	347	195	3658	0.238382	0.61345	1	29510124200	0.361009	1.023155
6	29	510	124200	29510124200	1242	Census Tract 1242	G5020	S	797511	0	+38.5988105	-090.2284247	29510124200	0.641095	0.536115	0.10498	0.195816	0.736704	872	2244	347	195	3658	0.238382	0.61345	1	29510124200	0.361009	1.023155
6	29	510	124200	29510124200	1242	Census Tract 1242	G5020	S	797511	0	+38.5988105	-090.2284247	29510124200	0.641095	0.536115	0.10498	0.195816	0.736704	872	2244	347	195	3658	0.238382	0.61345	1	29510124200	0.361009	1.023155
6	29	510	124200	29510124200	1242	Census Tract 1242	G5020	S	797511	0	+38.5988105	-090.2284247	29510124200	0.641095	0.536115	0.10498	0.195816	0.736704	872	2244	347	195	3658	0.238382	0.61345	1	29510124200	0.361009	1.023155

5. Select GEOID and then select Summarize



6. Select Count and then click on “Sum” – This will create a database of the number of homicides per census tract





Table

Sum_Output

OBJECTID *	GEOID	Count_GEOID	Sum_count
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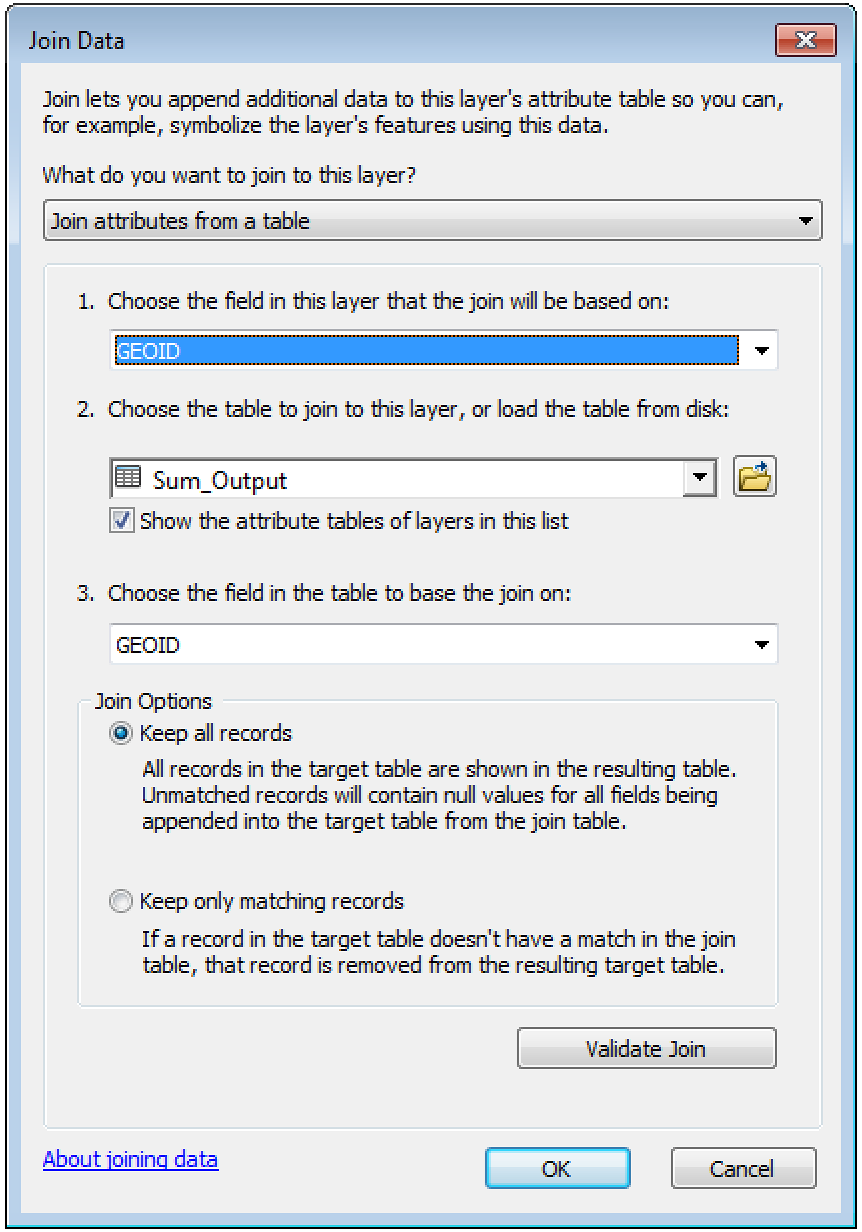
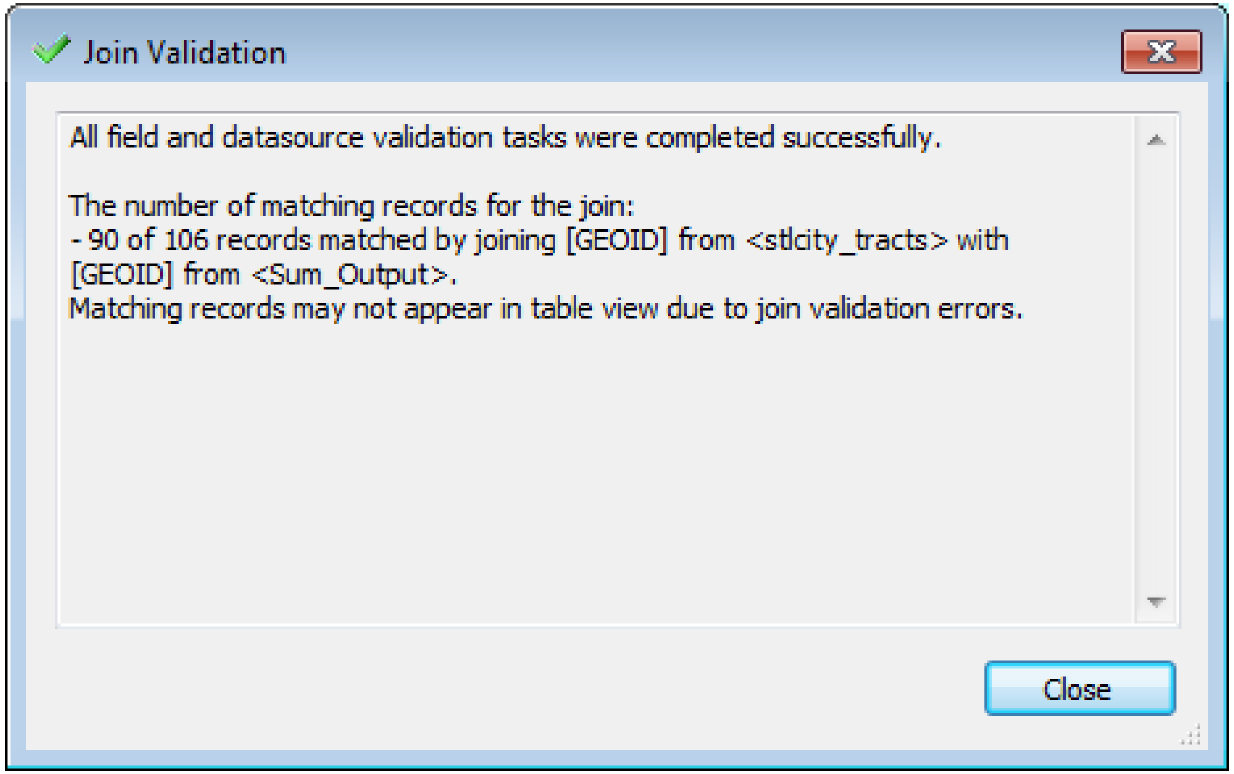
3	29510101300	1	1
4	29510101400	1	1
5	29510101500	3	3
6	29510101800	9	9
7	29510103400	1	1
8	29510103600	1	1
9	29510104500	2	2
10	29510105198	1	1
11	29510105200	1	1
12	29510105300	7	7
13	29510105400	10	10
14	29510105500	9	9
15	29510106100	18	18
16	29510106200	13	13
17	29510106300	30	30
18	29510106400	15	15
19	29510106500	18	18
20	29510106600	22	22
21	29510106700	22	22
22	29510107200	11	11
23	29510107300	26	26
24	29510107400	22	22
25	29510107500	22	22
26	29510107600	14	14
27	29510108100	11	11
28	29510108200	2	2
29	29510108300	12	12
30	29510109600	10	10
31	29510109700	26	26
32	29510110100	15	15
33	29510110200	23	23
34	29510110300	16	16
35	29510110400	15	15
36	29510110500	12	12
37	29510111100	6	6
38	29510111200	9	9
39	29510111300	12	12
40	29510111400	15	15
41	29510111500	8	8
42	29510112100	2	2
43	29510112200	7	7
44	29510112300	23	23
45	29510112400	2	2
46	29510113500	1	1
47	29510114101	1	1
48	29510114200	4	4
49	29510115100	2	2
50	29510115200	4	4
51	29510115300	4	4
52	29510115400	3	3
53	29510115500	5	5
54	29510115600	9	9
55	29510115700	7	7
56	29510116100	2	2
57	29510116301	5	5
58	29510116302	3	3
59	29510116400	11	11

(0 out of 90 Selected)

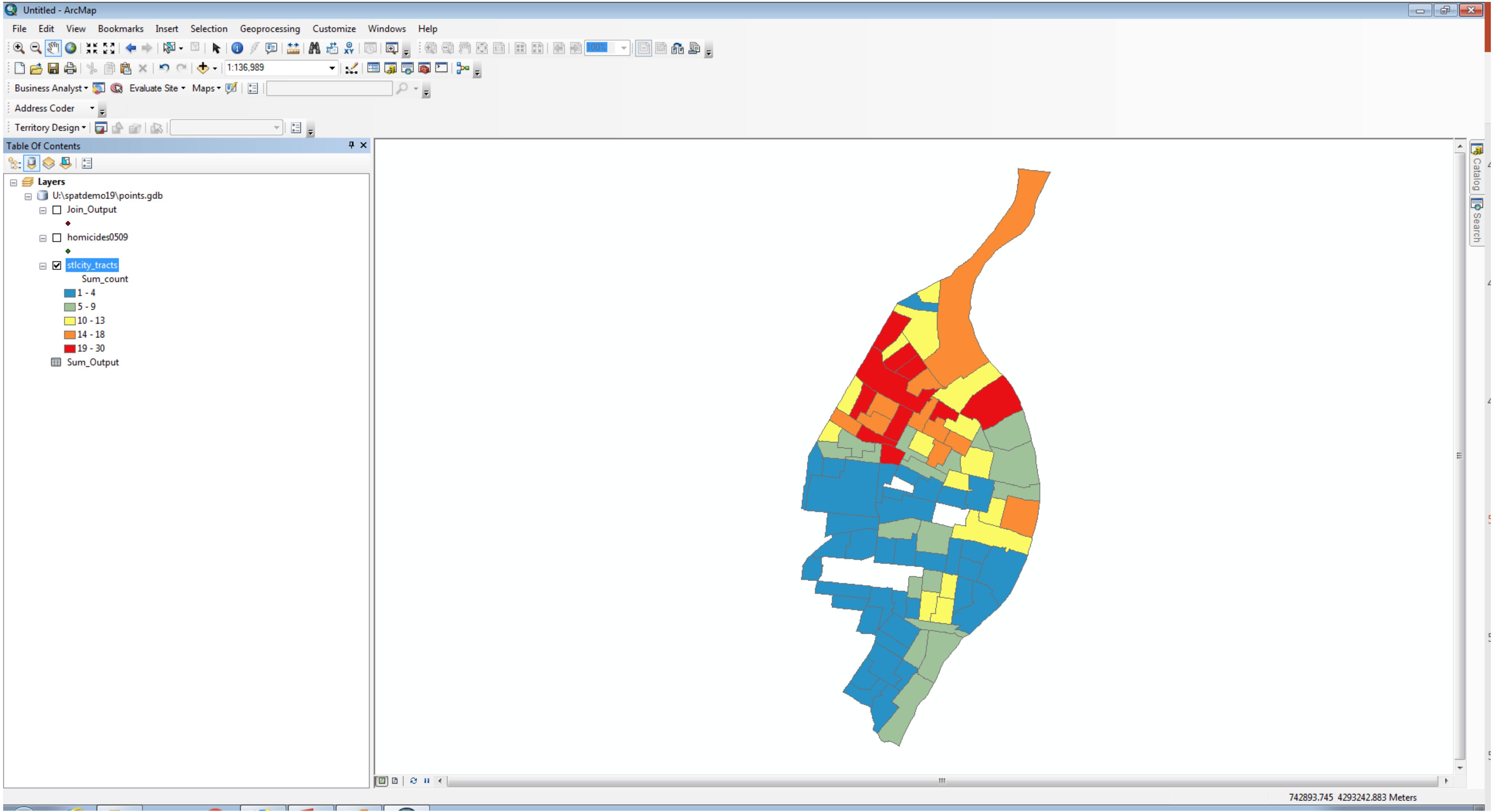
Sum_Output

7. Join the Homicide database with the STL –Census Tract shapefile and make it a permanent joint

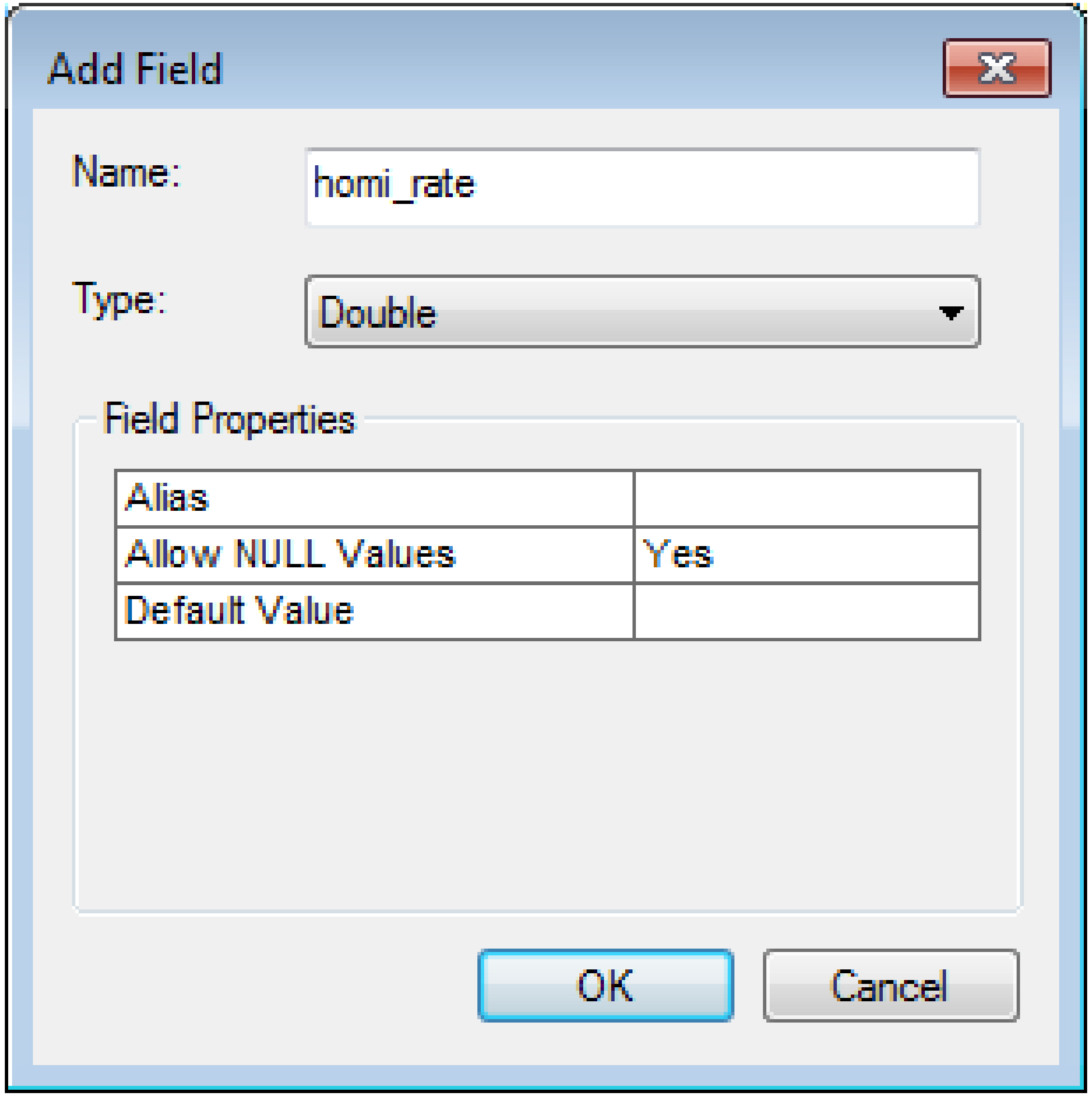


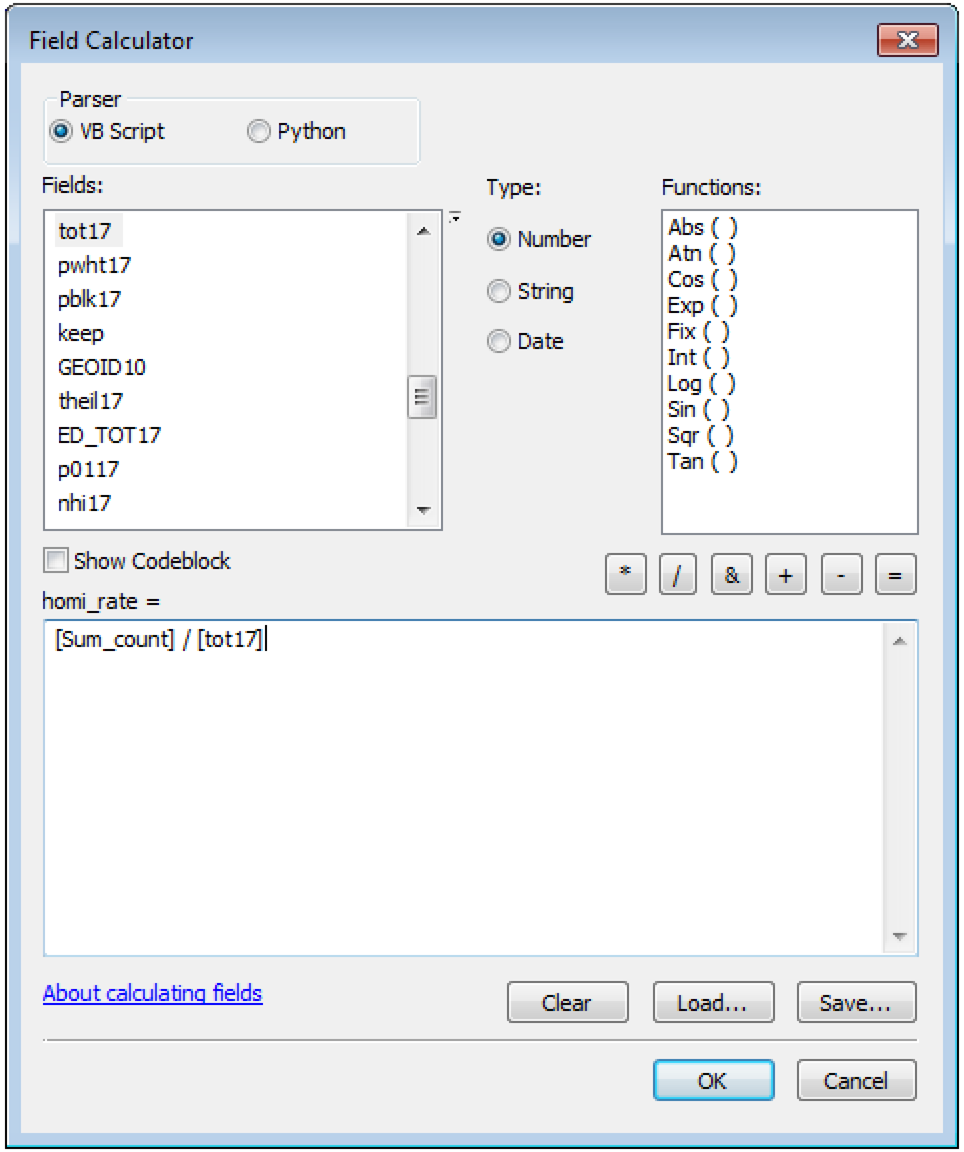


8. Example of the number of homicides by census tracts.



9. Create a homicide rate variable - add field and then use field calculator –
Note: check your database you may have some cases where it is <Null>





10. Note: check your database you may have some cases where it is <Null>. Convert those values to zero

Table

stl_tracts02

blk17	lat17	oth17	tot17	pwht17	pblk17	keep	GEOID10	theil17	ED_TOT17	p0117	nhi17	mhi17	GEOID10_1	index01	index02	x_coord	y_coord	cc	OBJECTID_1	GEOID	Count_GEOID	Sum_count	Shape_Length	Shape_Area	homi_rate
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90	84	71	1949	0.874295	0.046178	1	29510102500	0.280117	1.271293	0.132437	0.107748	44507	29510102500	0.545587	0.501418	737226.886781	4272798.02052	1	<Null>	<Null>	<Null>	<Null>	4167.375505	954613.372923	<Null>
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74	243	146	5857	0.920949	0.012634	1	29510102200	0.268645	1.720444	0.043708	0.039099	70596	29510102200	0.685557	0.667779	735389.358473	4273467.33702	1	<Null>	<Null>	<Null>	<Null>	8572.250255	2607490.777502	<Null>
122	69	100	2406	0.879052	0.050707	1	29510103700	0.343532	1.543391	0.064007	0.092685	50565	29510103700	0.575511	0.561047	735808.21854	4276760.564285	1	<Null>	<Null>	<Null>	<Null>	4412.847178	911486.797359	<Null>
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602	47	595	3203	0.611614	0.187949	1	29510119102	0.447863	2.023238	0.281496	0.048885	47736	29510119102	0.600472	0.645347	739091.841769	4280637.05867	1	<Null>	<Null>	<Null>	<Null>	3821.854522	582107.282211	<Null>
200	206	245	3515	0.814794	0.056899	1	29510126800	0.296938	1.44993	0.082788	0.092461	51759	29510126800	0.586115	0.556228	734514.586924	4277514.581155	1	<Null>	<Null>	<Null>	<Null>	9385.981033	2795760.795143	<Null>
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981	76	369	4332	0.670822	0.226454	1	29510127200	0.458711	1.50907	0.151893	0.049631	40679	29510127200	0.482936	0.486926	736987.476996	4276550.216833	1	<Null>	<Null>	<Null>	<Null>	6366.500637	2020197.637588	<Null>
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44	31	92	1860	0.910215	0.023656	1	29510103400	0.251956	1.586481	0.047849	0.083333	66509	29510103400	0.663384	0.632841	734965.828089	4276702.458033	1	7	29510103400	1	1	3918.135544	909792.352668	0.000538
176	221	212	2510	0.757371	0.07012	1	29510101100	0.184065	1.133758	0.122311	0.156972	57036	29510101100	0.600016	0.523443	737488.53046	4270908.681295	1	1	29510101100	1	1	6143.22599	1258502.093032	0.000398
489	25	113	4017	0.843913	0.121733	1	29510101300	0.330073	1.592207	0.039333	0.049788	58387	29510101300	0.607832	0.59196	738355.647663	4272228.23722	1	3	29510101300	1	1	6581.446836	1975239.282872	0.000249
896	115	209	2717	0.550975	0.329775	1	29510101400	0.330434	1.209096	0.261318	0.113611	39107	29510101400	0.492679	0.453237	739301.476469	4271776.912455	1	4	29510101400	1	1	4461.516745	860519.13647	0.000368
1528	34	355	2981	0.356927	0.51258	1	29510105200	0.393966	1.857766	0.107155	0.034552	60938	29510105200	0.62675	0.642441	735936.350366	4281487.553295	1	11	29510105200	1	1	3908.071761	831471.669612	0.000335
41	4	68	1298	0.912943	0.031587	1	29510103600	0.370173	1.505933	0.195686	0.083975	48929	29510103600	0.550683	0.537307	736002.989174	4277749.696824	1	8	29510103600	1	1	5478.281664	1373211.988339	0.00077
461	141	354	3120	0.69359	0.147756	1	29510105198	0.408099	2.258488	0.180707	0.027244	57222	29510105198	0.685098	0.740967	734987.857579	4281347.192408	1	10	29510105198	1	1	7469.296214	1176494.511445	0.000321
1212	190	827	4119	0.458849	0.294246	1	29510119300	0.579736	1.451338	0.393522	0.09894	22056	29510119300	0.338509	0.370716	740380.236858	4280448.96763	1	68	29510119300	1	1	4556.306503	1180499.964657	0.000243
32	74	21	2389	0.94684	0.013395	1	29510113500	0.353701	1.421025	0.131854	0.069904	41436	29510113500	0.525326	0.506686	737304.945618	4277855.382854	1	46	29510113500	1	1	5412.654497	1798251.288294	0.000419
1829	105	157	5110	0.590802	0.357926	1	29510117200	0.343792	1.752461	0.14513	0.049315	63094	29510117200	0.638405	0.636791	739353.942856	4277525.928429	1	62	29510117200	1	1	4994.157072	1268265.847714	0.000196
1041	62	229	2800	0.524286	0.371786	1	29510119101	0.600654	1.776938	0.27964	0.075109	37417	29510119101	0.446154	0.495947	738845.022317	4280242.536322	1	66	29510119101	1	1	3689.609763	506681.55008	0.000357
821	137	358	4162	0.683806	0.197261	1	29510114101	0.384234	1.462638	0.159961	0.09851	42843	29510114101	0.520284	0.508591	736705.285672	4275115.706024	1	47	29510114101	1	1	4438.670895	950092.453159	0.00024
675	70	127	3003	0.709624	0.224775	1	29510124300	0.380279	1.612747	0.147852	0.149816	62500	29510124300	0.592299	0.583117	742042.075358	4275515.993251	1	77	29510124300	2	2	5187.84264	1168645.777583	0.000666
1147	109	249	4253	0.646132	0.269692	1	29510112100	0.457876	2.072886	0.135265	0.101987	56118	29510112100	0.622368	0.668554	736555.602807	4280379.252256	1	42	29510112100	2	2	11897.102971	6941014.275569	0.00047
162	35	336	1990	0.732161	0.081407	1	29510104500	0.431062	1.778043	0.139769	0.125126	54286	29510104500	0.579293	0.595953	736706.849567	4278844.247574	1	9	29510104500	2	2	6818.338273	1940836.784673	0.001005
1302	22	51	2019	0.31897	0.644874	1	29510119200	0.517423	1.560127	0.201302	0.08663	49219	29510119200	0.482198	0.49335	739478.824307	4281110.304673	1	67	29510119200	2	2	4361.245463	734108.90835	0.000991
660	391	183	4519	0.726931	0.14605	1	29510115100	0.423917	1.006744	0.285052	0.180301	30432	29510115100	0.377382	0.33911	737681.426364	4274296.845401	1	49	29510115100	2	2	4313.925641	1146017.920623	0.000443
579	231	656	2888	0.492382	0.200485	1	29510116100	0.361884	1.255054	0.214261	0.151662	38021	29510116100	0.481002	0.45076	739067.686351	4275103.222049	1	56	29510116100	2	2	4019.217576	765638.413567	0.000693
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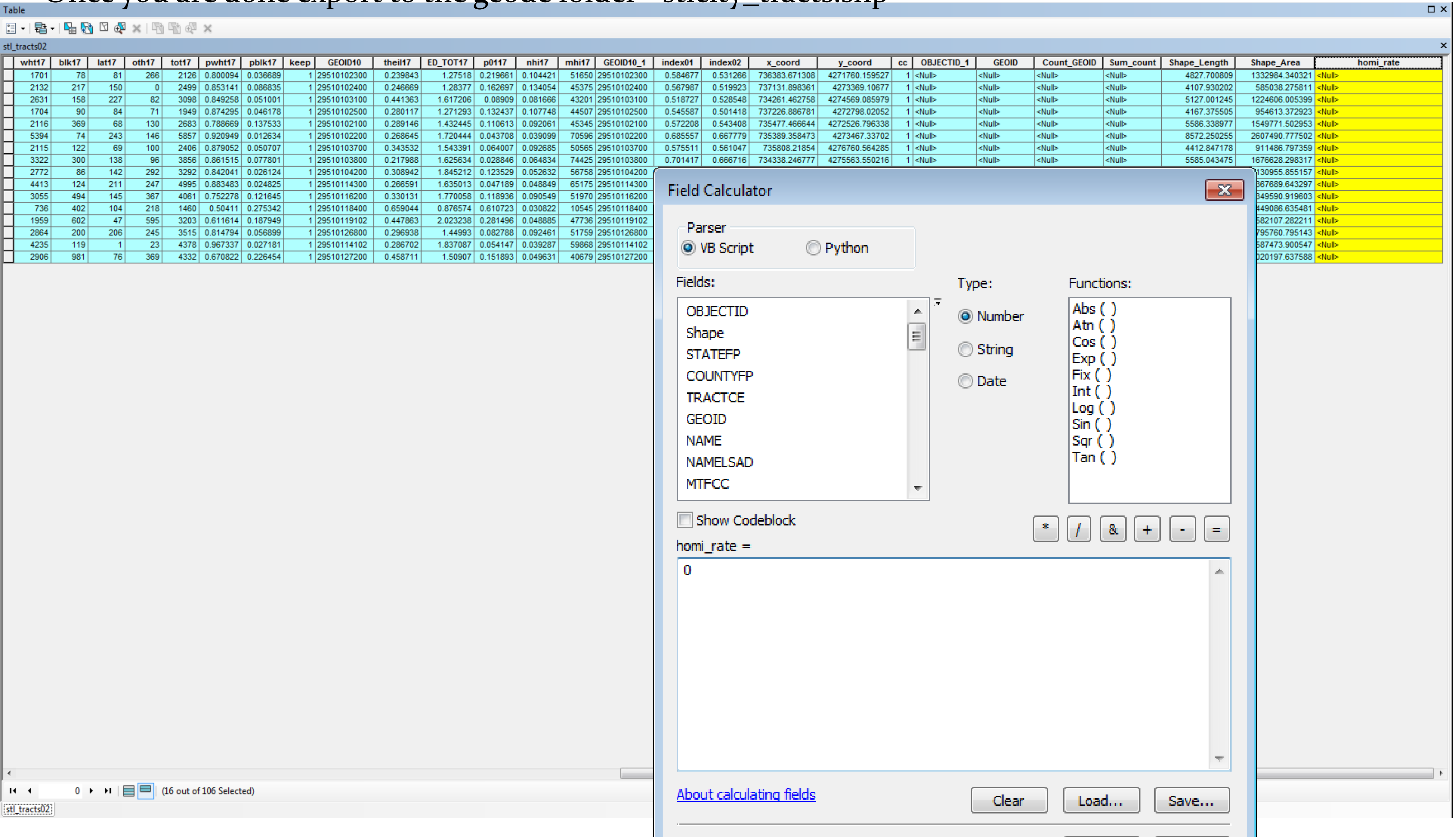
1885	221	408	4590	0.452288	0.410675	1	29510116500	0.332459	1.562422	0.201961	0.15207	43913	29510116500	0.569032	0.558789	740588.469354	4276141.148258	1	60	29510116500	6	6	3776.474916	904478.257254	0.001307
1921	7	20	2001	0.026487	0.96002	1	29510111100	0.456138	1.108865	0.391166	0.216131	29315	29510111100	0.374486	0.350894	740210.049699	4281385.251115	1	37	29510111100	6	6	5629.843797	1091538.842539	0.002999
3772	0	8	3793	0.003427	0.994464	1	29510125700	0.498373	0.826652	0.587925	0.182178	13200	29510125700	0.210513	0.189345	744543.420152	4280333.936847	1	81	29510125700	7	7	6415.529301	1487620.342645	0.001846

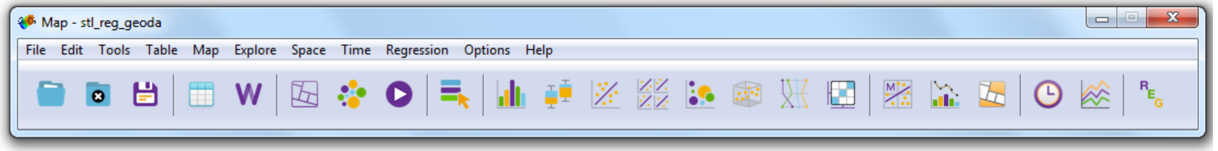
18 (16 out of 106 Selected)

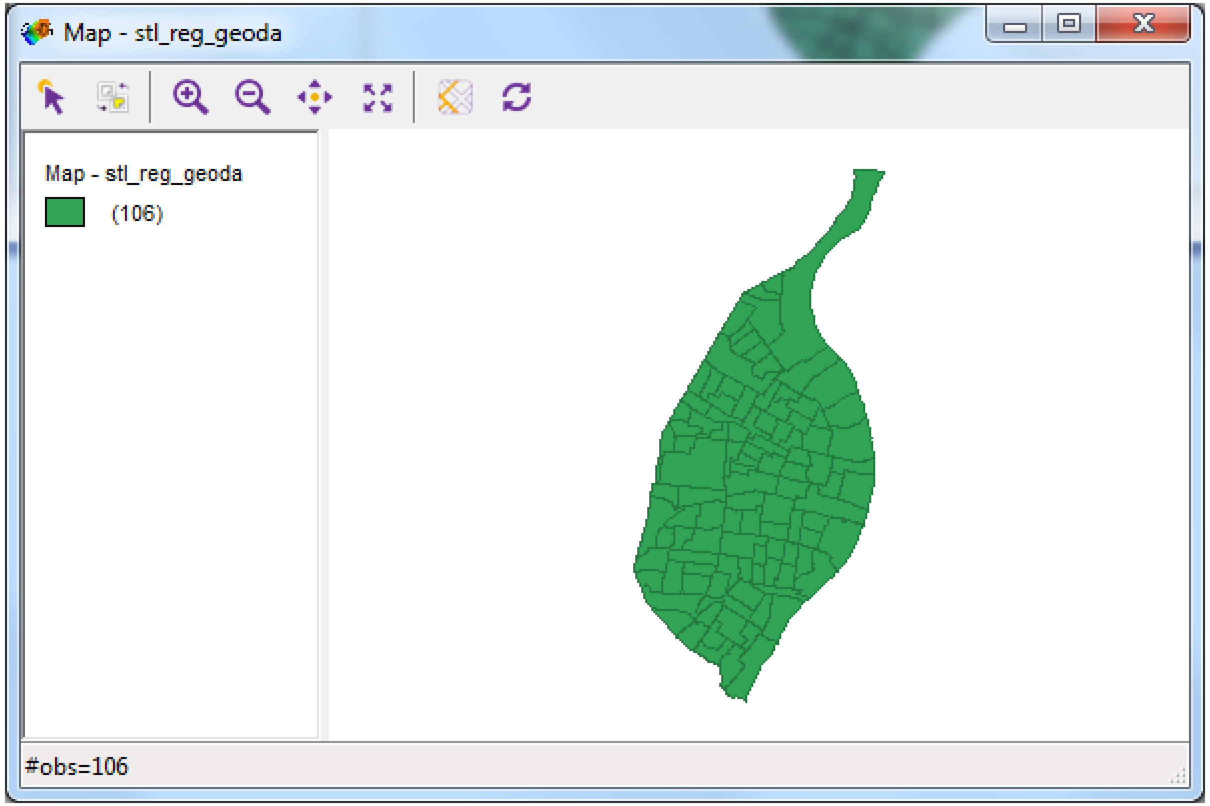
stl_tracts02

11. Select the cases and use field calculator to make the value equal to 0.
Once you are done export to the geode folder - stlcity_tracts.shp

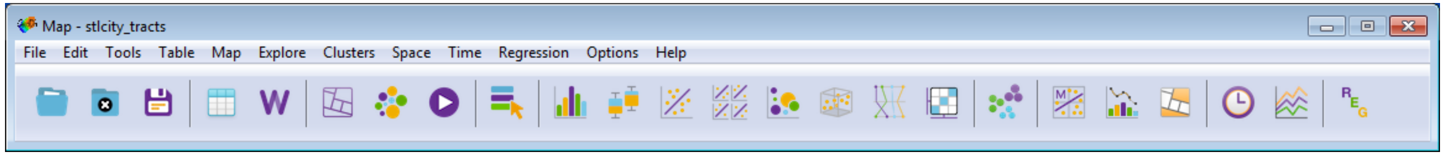


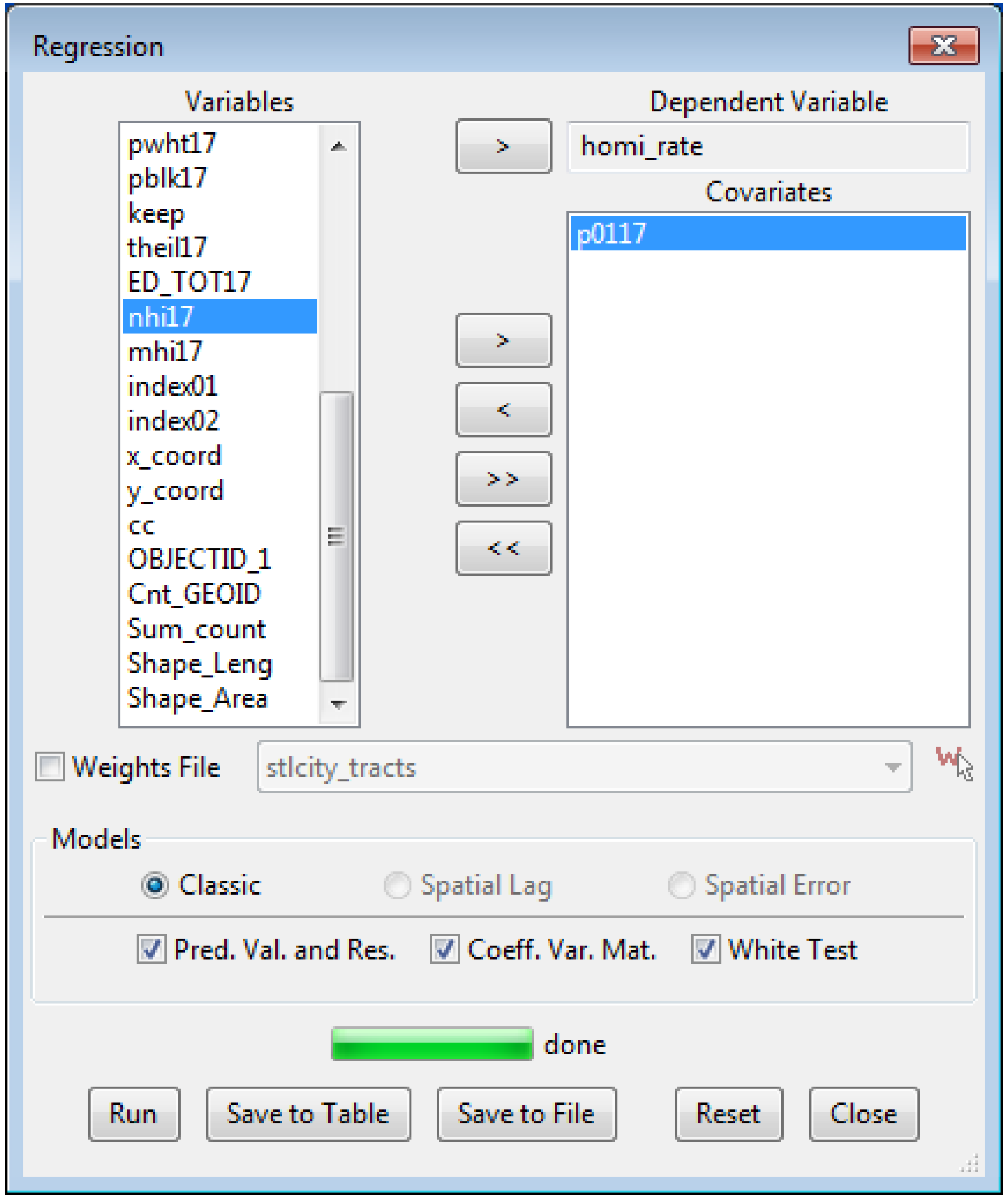
Start with OLS





1. Open the shapefile
2. Create a weight matrix
3. Compute your Spatial Autocorrelation Statistic for crime rate and poverty
4. If you find you have positive spatial autocorrelation, then some evidence that OLS might not be appropriate.
5. To be on the conservative side, we will start with OLS





1. To run OLS go to Methods and select Regression.
2. Check the box predicted value, coefficient variance matrix and Moran's I Z-value
3. Select your dependent variable
4. Select your poverty rate.
5. Click the Run Button
6. Click the View Result Button.

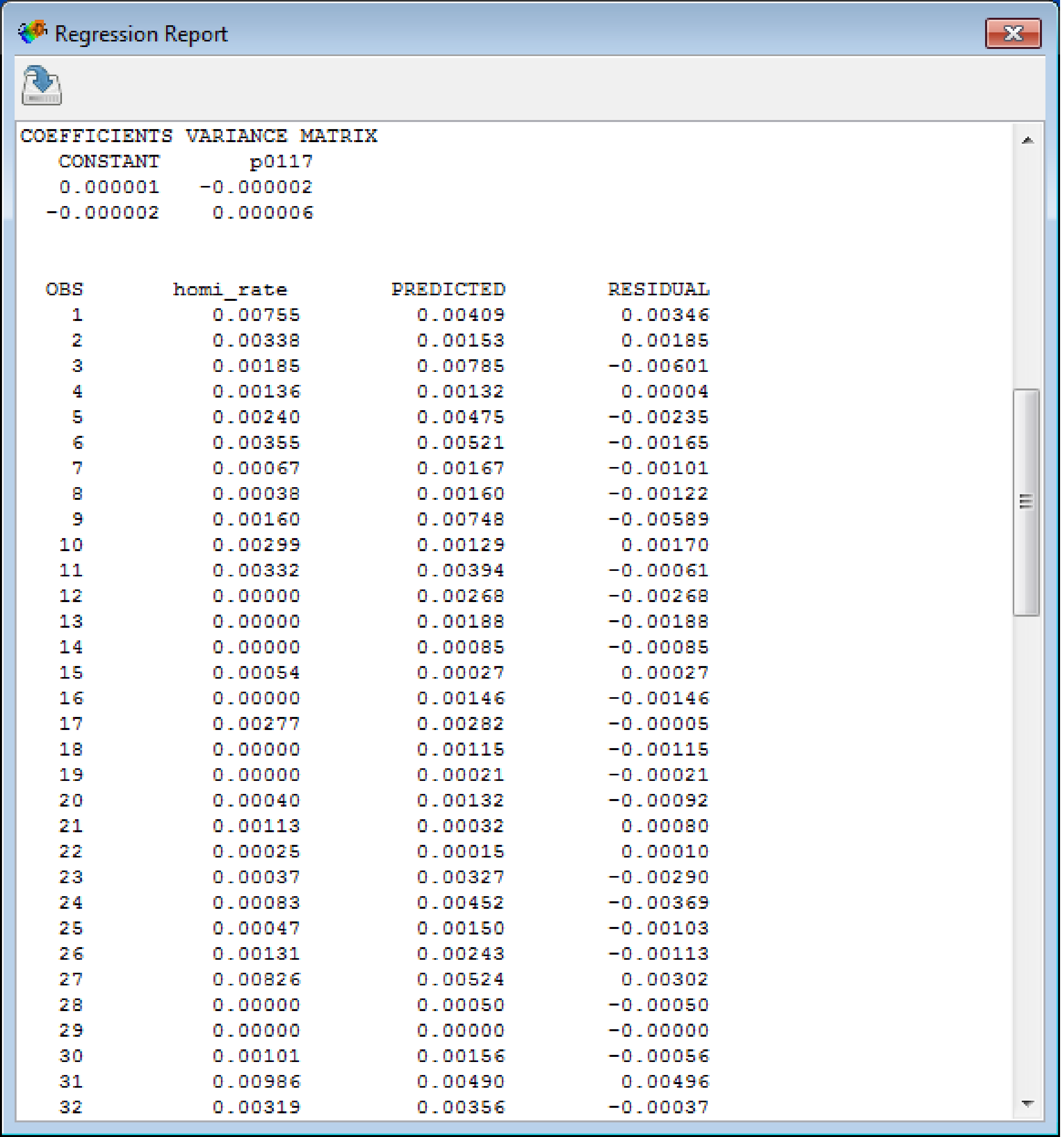
Note: at this point do not click the weights file box.

Regression Report

```
>>03/20/19 11:33:39
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set             :  stlcity_tracts
Dependent Variable   :   homi_rate  Number of Observations:  106
Mean dependent var   :  0.00340081  Number of Variables   :    2
S.D. dependent var   :  0.00407594  Degrees of Freedom    :  104

R-squared            :    0.240954  F-statistic           :     33.0141
Adjusted R-squared   :    0.233655  Prob(F-statistic)     :9.18912e-008
Sum squared residual:   0.00133669  Log likelihood        :     447.486
Sigma-square         :1.28528e-005  Akaike info criterion :    -890.971
S.E. of regression   :  0.00358507  Schwarz criterion     :    -885.644
Sigma-square ML      :1.26103e-005
S.E of regression ML:   0.00355109

-----------------------------------------------------------------------------
       Variable       Coefficient        Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT  -0.000400913      0.000747688      -0.536204      0.59296
             p0117   0.0140372        0.00244304        5.74579       0.00000
-----------------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.047352
TEST ON NORMALITY OF ERRORS
TEST                     DF            VALUE              PROB
Jarque-Bera               2            224.9842           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF            VALUE              PROB
Breusch-Pagan test        1              8.4759           0.00360
Koenker-Bassett test      1              2.0447           0.15274
SPECIFICATION ROBUST TEST
TEST                     DF            VALUE              PROB
White                     2              2.7658           0.25085
```

1. Review the Output
2. Good of Fit Statistics
3. Is poverty rate significant?
4. What is Multicollienarity?
   Note: this is not a test statistic.
   Looks for numbers greater than 20, numbers greater than 30 are problematic.
5. What is Heteroskedasticity?

   We may have a problem…

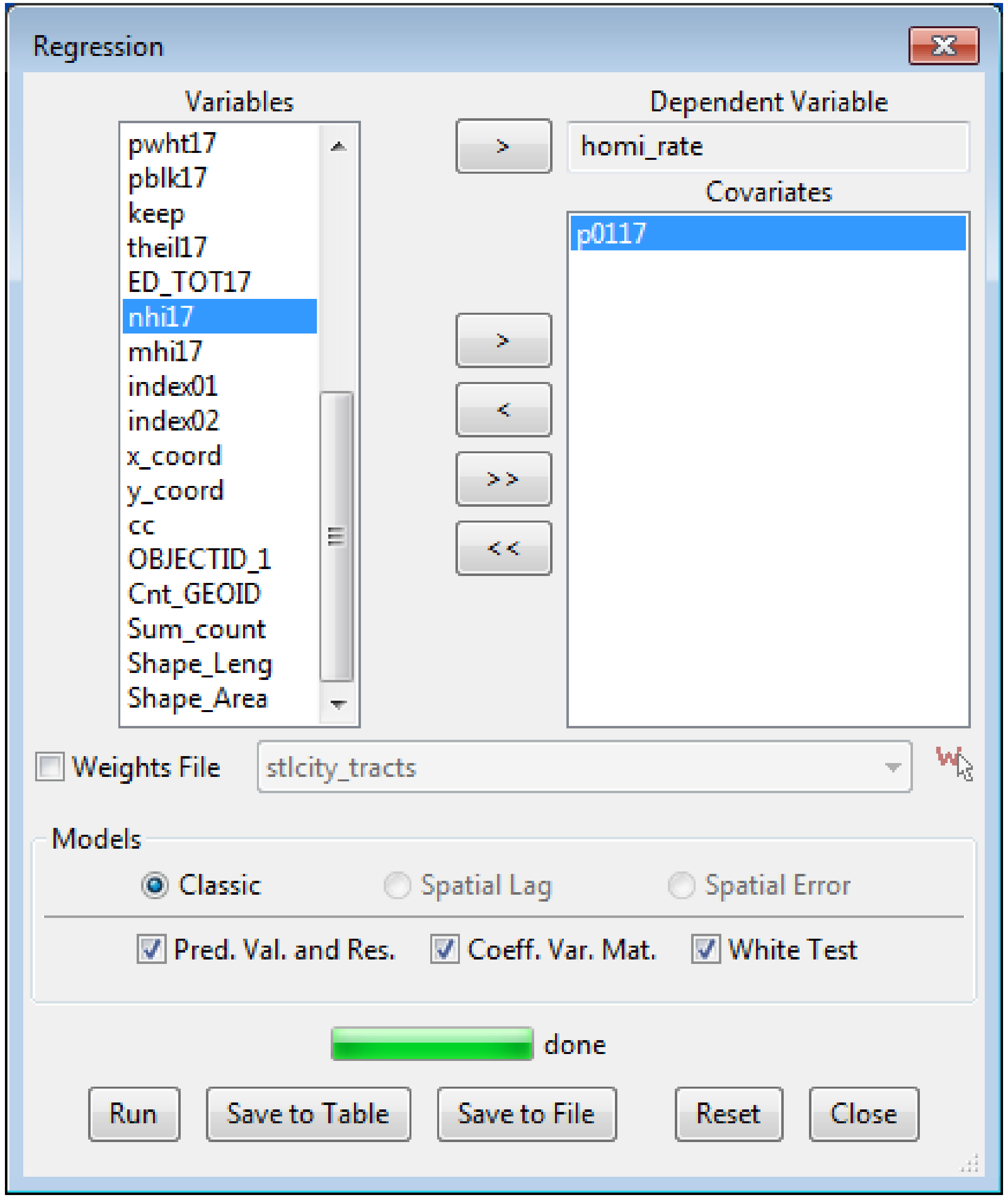

Regression Report

COEFFICIENTS VARIANCE MATRIX

CONSTANT	p0117
0.000001	-0.000002
-0.000002	0.000006

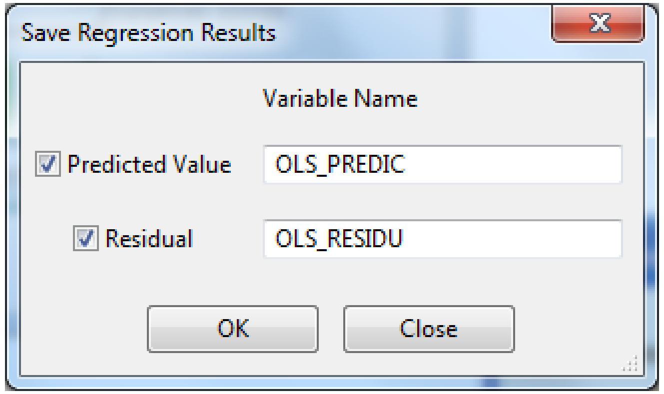
OBS	homi_rate	PREDICTED	RESIDUAL
1	0.00755	0.00409	0.00346
2	0.00338	0.00153	0.00185
3	0.00185	0.00785	-0.00601
4	0.00136	0.00132	0.00004
5	0.00240	0.00475	-0.00235
6	0.00355	0.00521	-0.00165
7	0.00067	0.00167	-0.00101
8	0.00038	0.00160	-0.00122
9	0.00160	0.00748	-0.00589
10	0.00299	0.00129	0.00170
11	0.00332	0.00394	-0.00061
12	0.00000	0.00268	-0.00268
13	0.00000	0.00188	-0.00188
14	0.00000	0.00085	-0.00085
15	0.00054	0.00027	0.00027
16	0.00000	0.00146	-0.00146
17	0.00277	0.00282	-0.00005
18	0.00000	0.00115	-0.00115
19	0.00000	0.00021	-0.00021
20	0.00040	0.00132	-0.00092
21	0.00113	0.00032	0.00080
22	0.00025	0.00015	0.00010
23	0.00037	0.00327	-0.00290
24	0.00083	0.00452	-0.00369
25	0.00047	0.00150	-0.00103
26	0.00131	0.00243	-0.00113
27	0.00826	0.00524	0.00302
28	0.00000	0.00050	-0.00050
29	0.00000	0.00000	-0.00000
30	0.00101	0.00156	-0.00056
31	0.00986	0.00490	0.00496
32	0.00319	0.00356	-0.00037

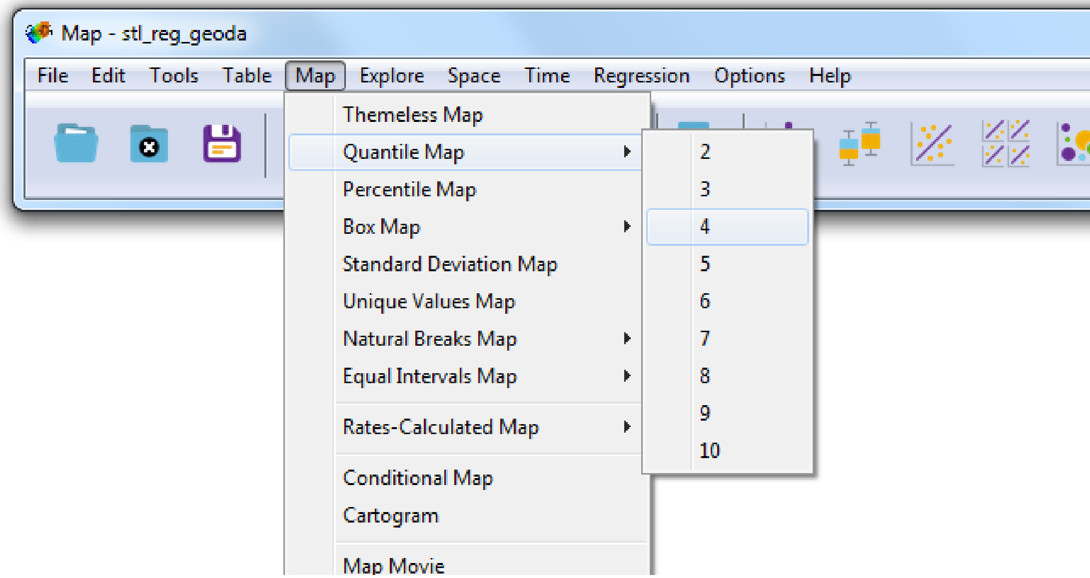
1. Review the Coefficient Variance Matrix
2. Review the Predicated values and Residuals

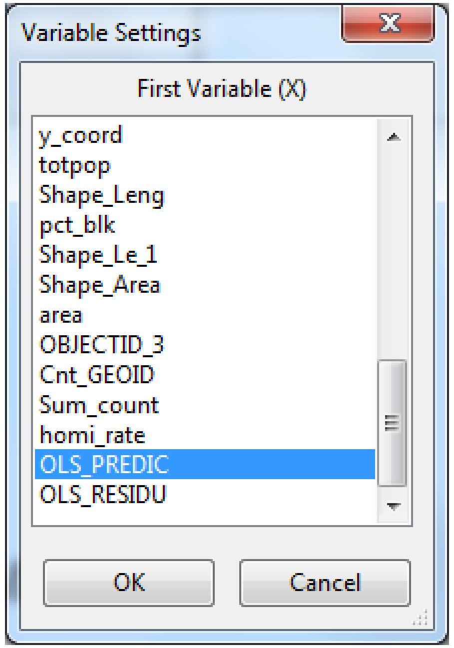


1. If you want the predicted values and residuals click the save to table button.

2. You will need to add the variables.





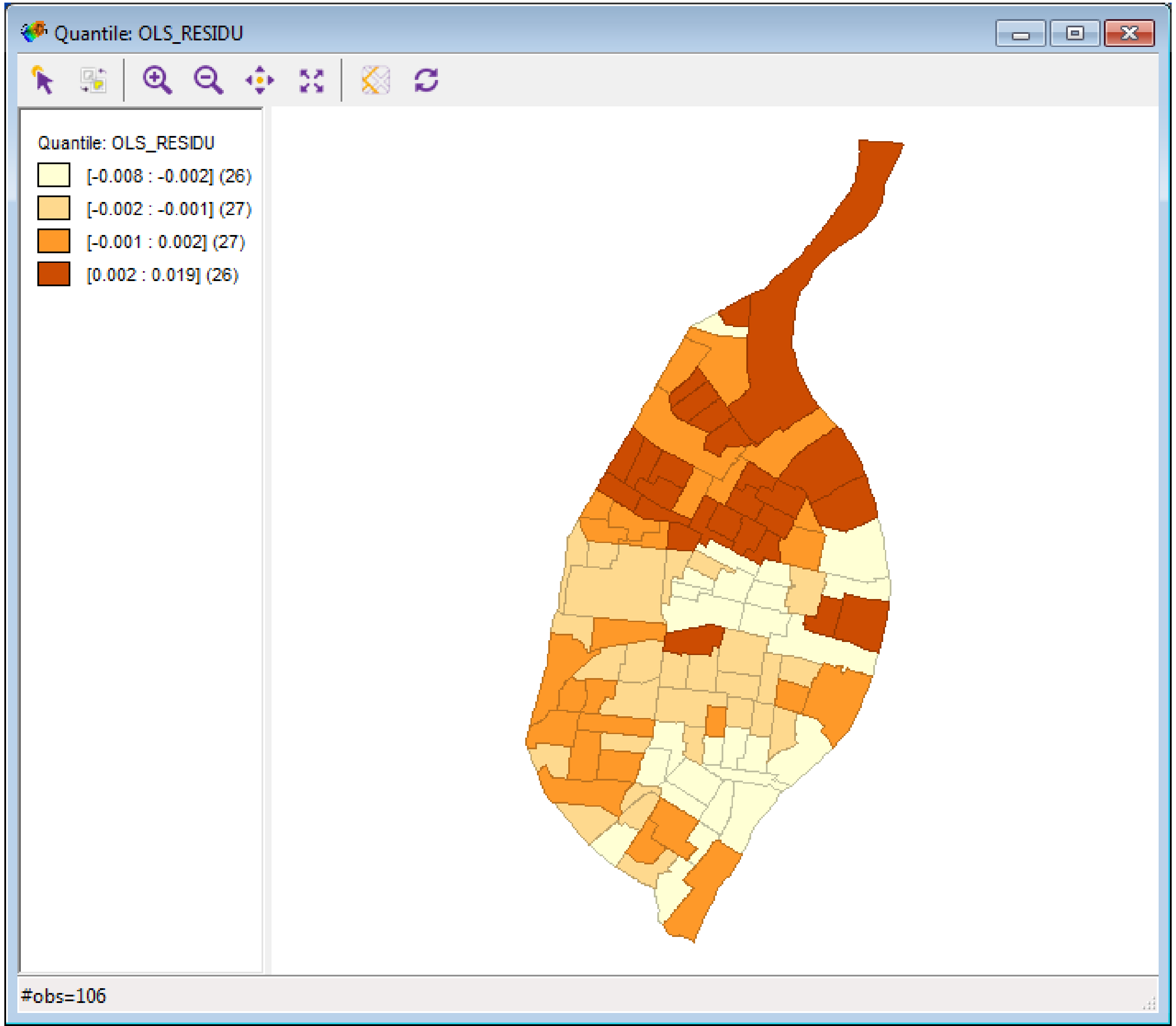


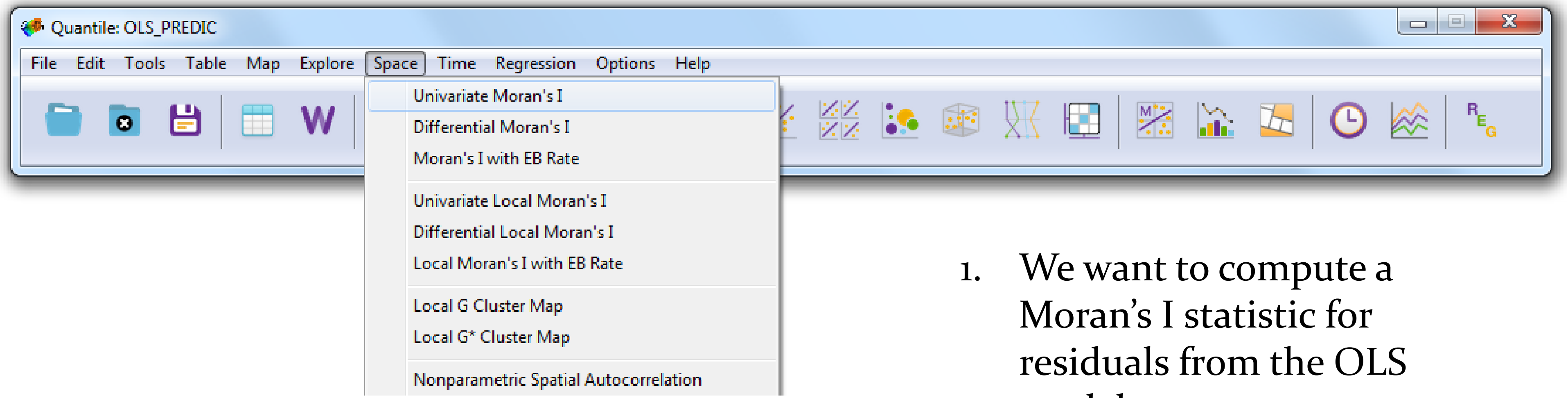
1. Let's examine the residuals.

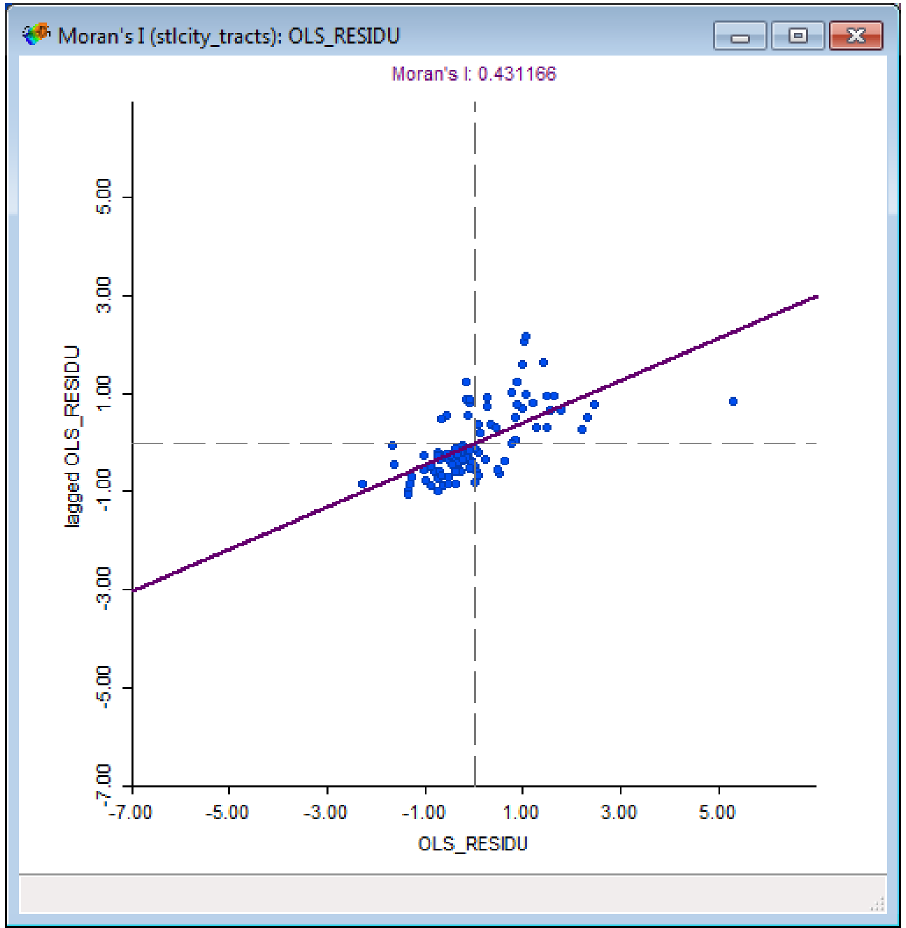
2. Create a Quantile Map

1. The map show spatial clustering

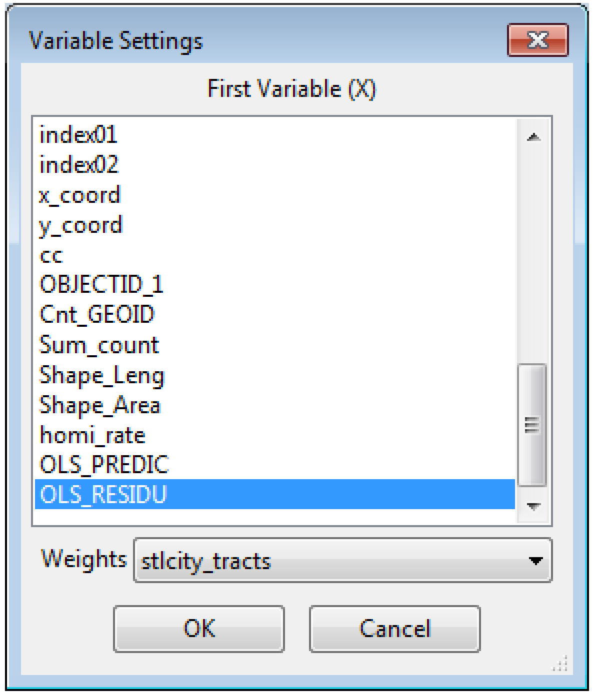
2. Let's compute a spatial autocorrelation statistics for the residuals



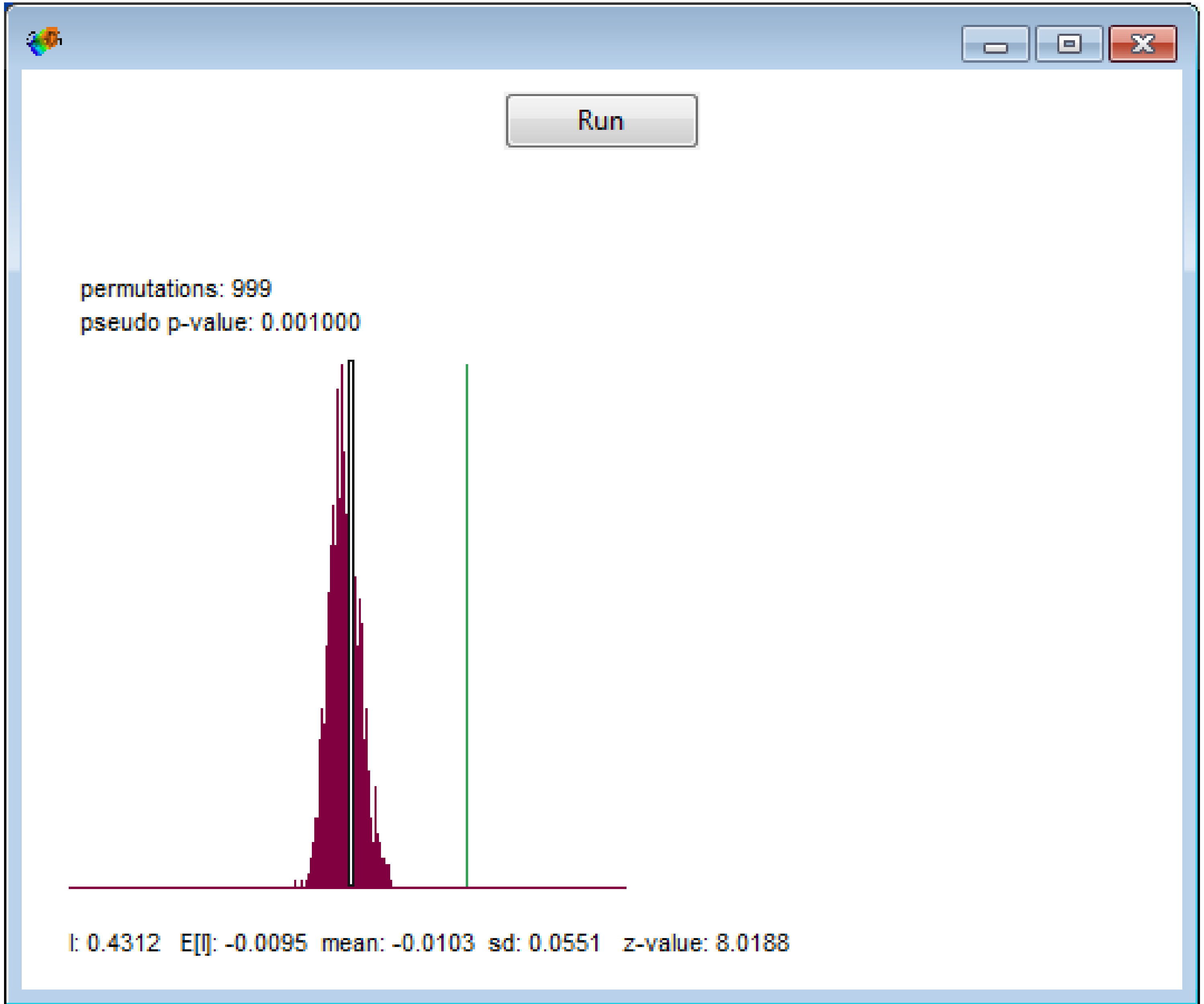




1. We want to compute a Moran's I statistic for residuals from the OLS model.



1. The accumulation of evidence suggest we have a problem of spatial autocorrelation.

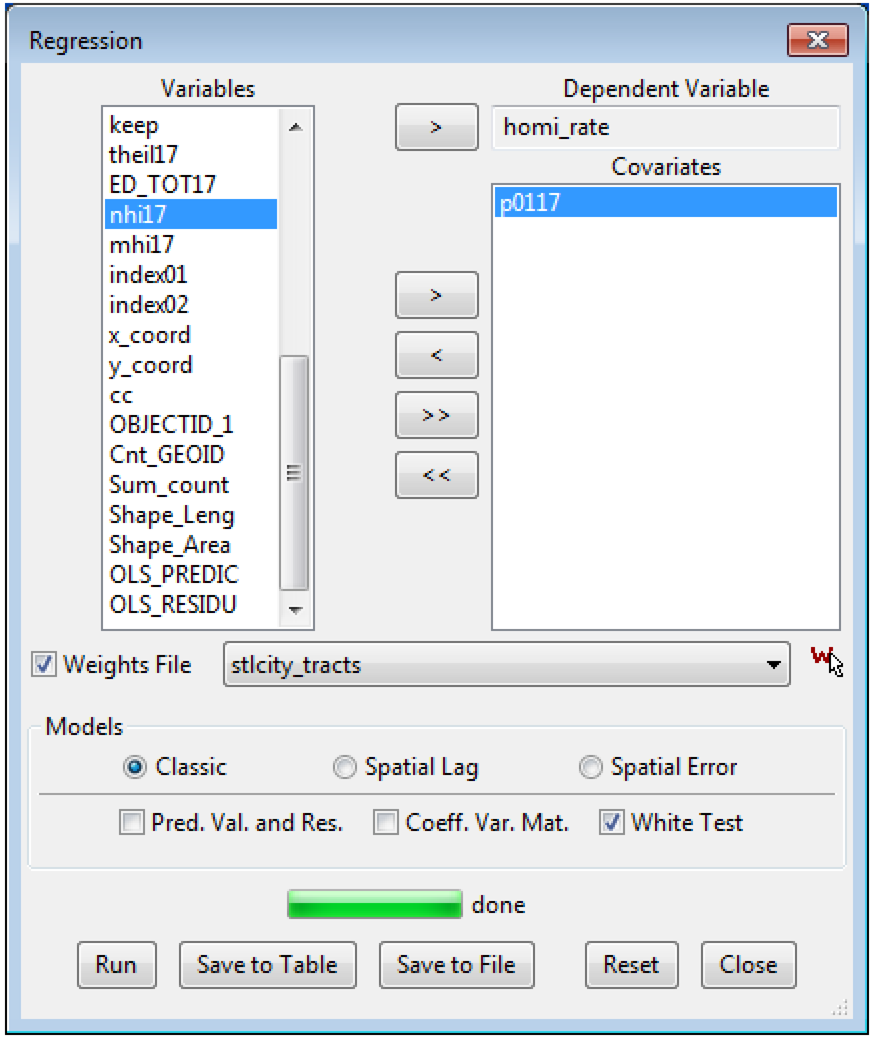


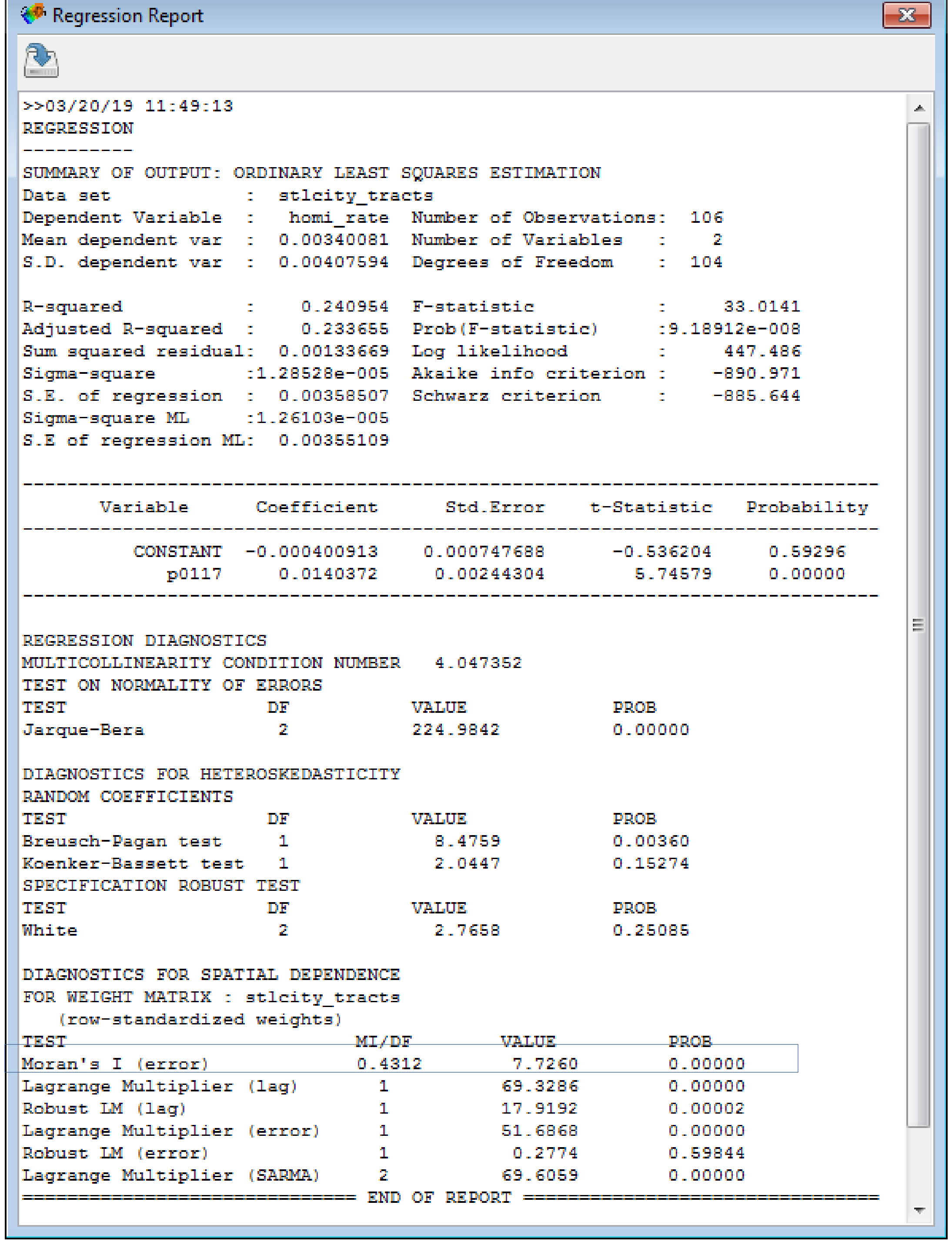
Variable	OLS
Poverty	.0140372 (.00244)***
Constant	-0.0004 (0.0007)
r-square	0.240954
Log likelihood	447.486
AIC	-890.971
Moran's I Residual	.431166***
N	106

$* \leq .05, ** \leq .01, *** \leq .001$

Standard Errors in Parentheses

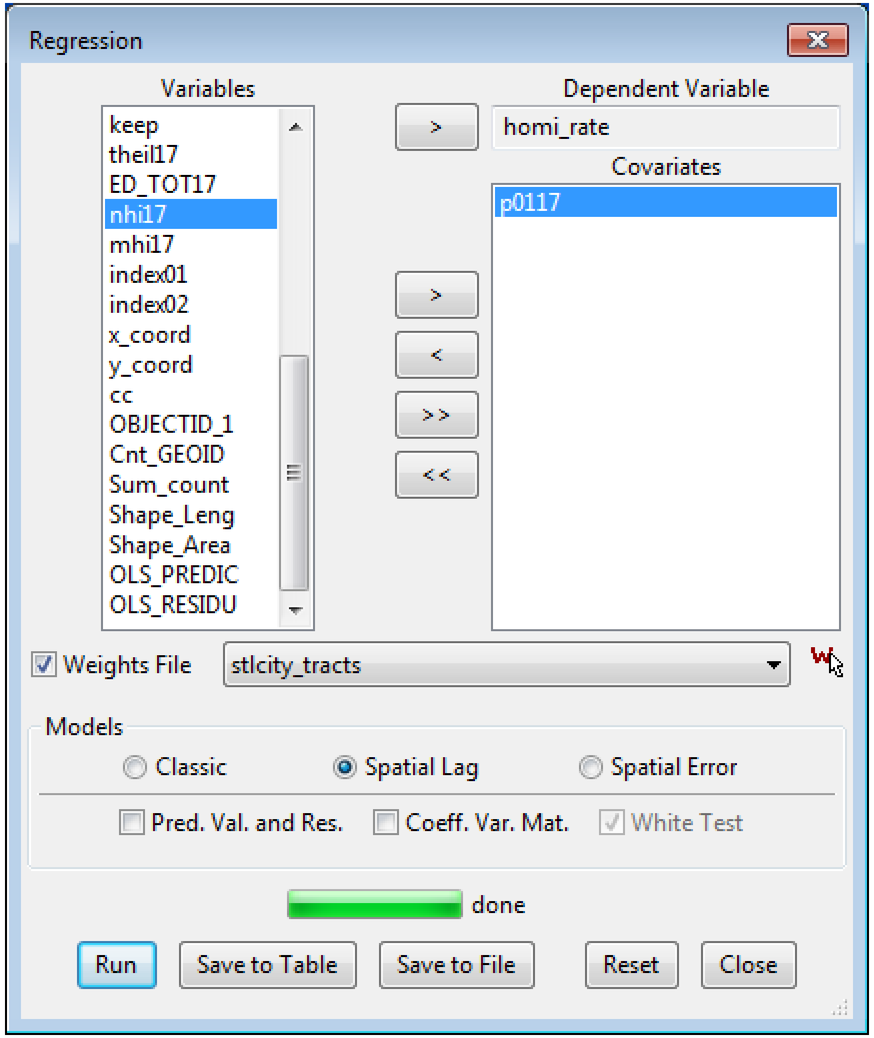
Move to Spatial Lag

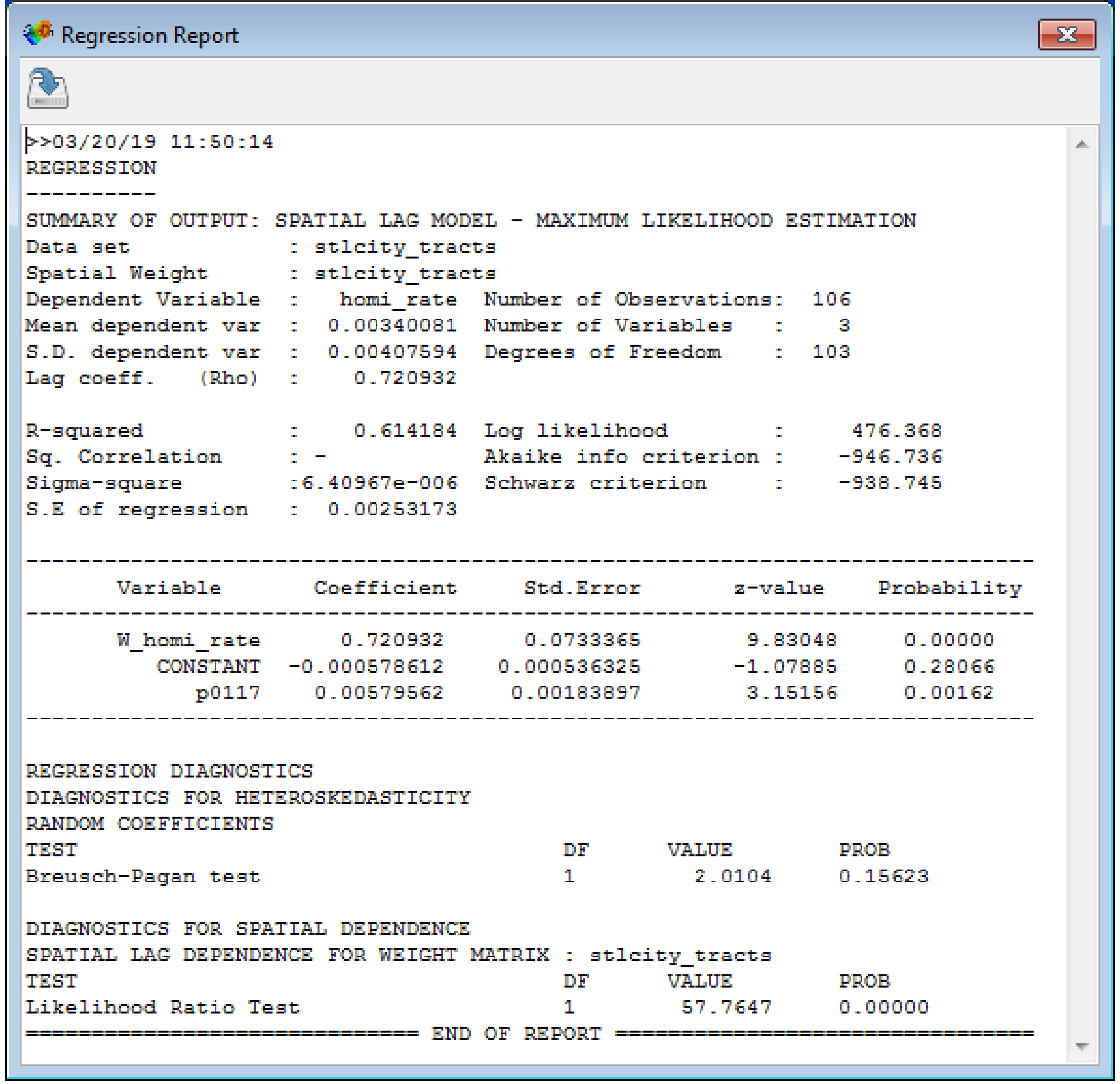




Regression Report

```
>>03/20/19 11:49:13
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  stlcity_tracts
Dependent Variable  :   homi_rate  Number of Observations:  106
Mean dependent var  :  0.00340081  Number of Variables   :    2
S.D. dependent var  :  0.00407594  Degrees of Freedom    :  104

R-squared           :    0.240954  F-statistic           :     33.0141
Adjusted R-squared  :    0.233655  Prob(F-statistic)     :9.18912e-008
Sum squared residual:  0.00133669  Log likelihood        :     447.486
Sigma-square        :1.28528e-005  Akaike info criterion :    -890.971
S.E. of regression  :  0.00358507  Schwarz criterion     :    -885.644
Sigma-square ML     :1.26103e-005
S.E of regression ML:  0.00355109

-----------------------------------------------------------------------------
       Variable      Coefficient       Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT  -0.000400913     0.000747688      -0.536204     0.59296
             p0117     0.0140372      0.00244304        5.74579     0.00000
-----------------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.047352
TEST ON NORMALITY OF ERRORS
TEST                     DF           VALUE              PROB
Jarque-Bera               2           224.9842           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF           VALUE              PROB
Breusch-Pagan test        1             8.4759           0.00360
Koenker-Bassett test      1             2.0447           0.15274
SPECIFICATION ROBUST TEST
TEST                     DF           VALUE              PROB
White                     2             2.7658           0.25085

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : stlcity_tracts
   (row-standardized weights)
TEST                           MI/DF        VALUE          PROB
Moran's I (error)              0.4312       7.7260         0.00000
Lagrange Multiplier (lag)        1         69.3286         0.00000
Robust LM (lag)                  1         17.9192         0.00002
Lagrange Multiplier (error)      1         51.6868         0.00000
Robust LM (error)                1          0.2774         0.59844
Lagrange Multiplier (SARMA)      2         69.6059         0.00000
============================== END OF REPORT ================================
```



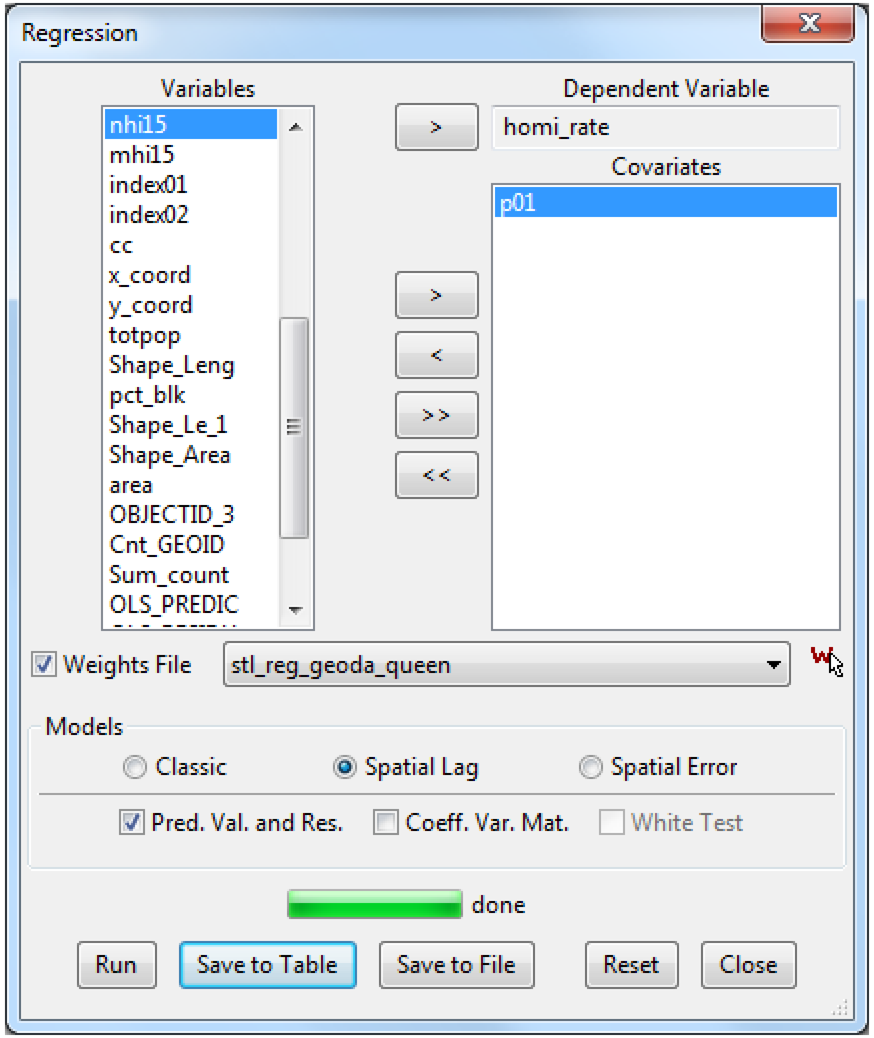

Regression Report

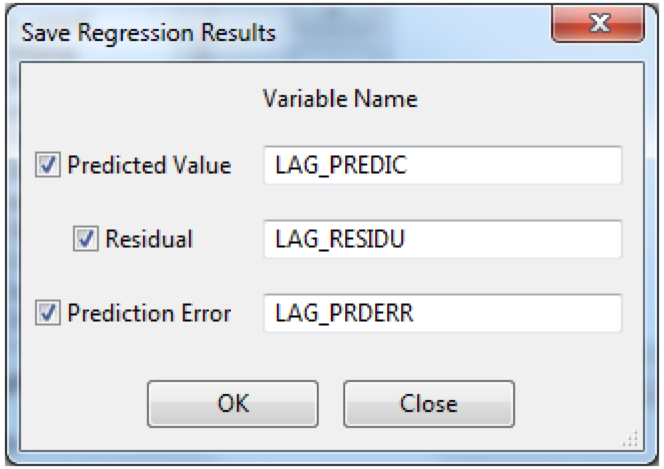
```
>>03/20/19 11:50:14
REGRESSION
----------
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : stlcity_tracts
Spatial Weight      : stlcity_tracts
Dependent Variable  :   homi_rate  Number of Observations:  106
Mean dependent var  :  0.00340081  Number of Variables   :    3
S.D. dependent var  :  0.00407594  Degrees of Freedom    :  103
Lag coeff.   (Rho)  :    0.720932

R-squared           :    0.614184  Log likelihood        :     476.368
Sq. Correlation     : -            Akaike info criterion :    -946.736
Sigma-square        :6.40967e-006  Schwarz criterion     :    -938.745
S.E of regression   :  0.00253173

-----------------------------------------------------------------------------
       Variable       Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------------
       W_homi_rate      0.720932       0.0733365       9.83048     0.00000
          CONSTANT  -0.000578612     0.000536325      -1.07885     0.28066
             p0117    0.00579562      0.00183897       3.15156     0.00162
-----------------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                     DF      VALUE        PROB
Breusch-Pagan test                       1         2.0104     0.15623

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : stlcity_tracts
TEST                                     DF      VALUE        PROB
Likelihood Ratio Test                    1        57.7647     0.00000
============================== END OF REPORT ================================
```

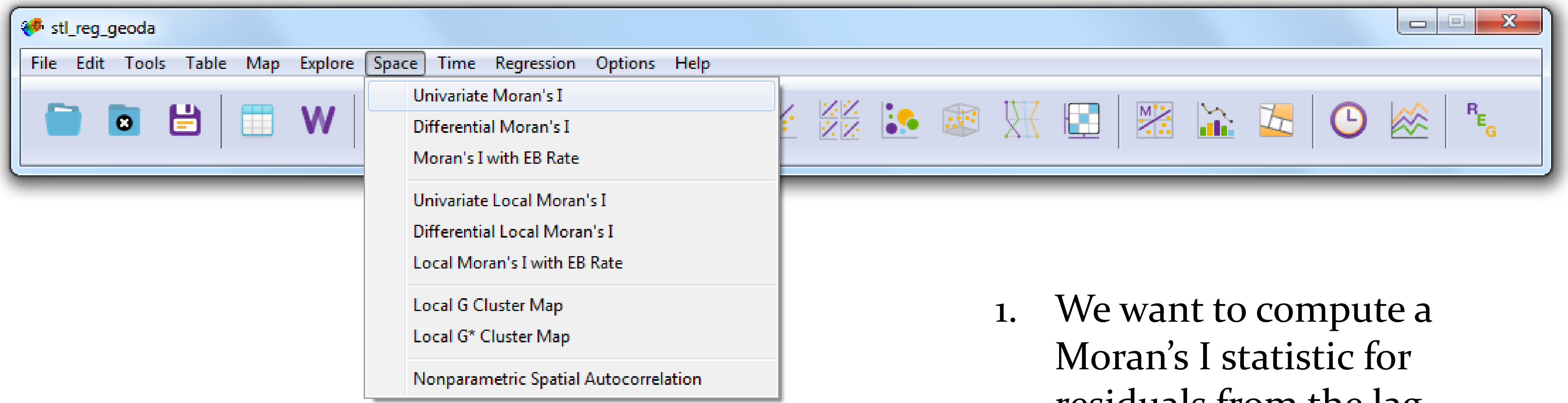
1. The Likelihood Ratio Test tell us this model is better than the OLS model.

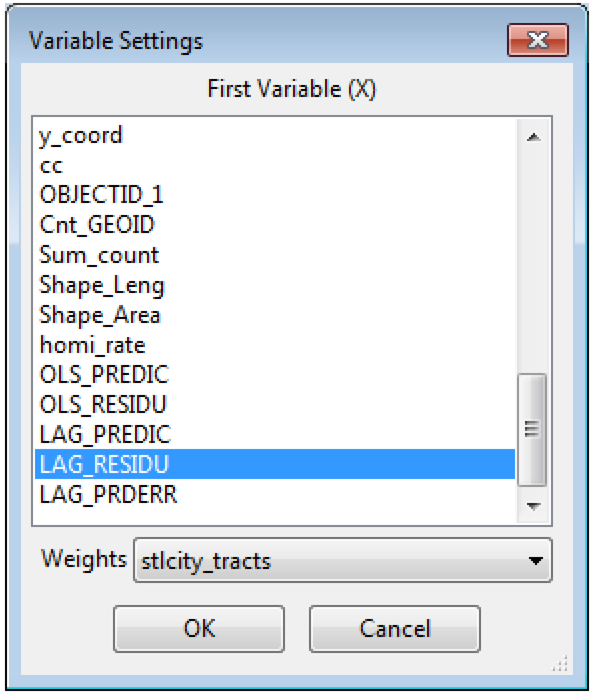
2. Our spatial lag variable *W_homi_rat* is significant

1. We want to save the predicted values, residual and prediction error



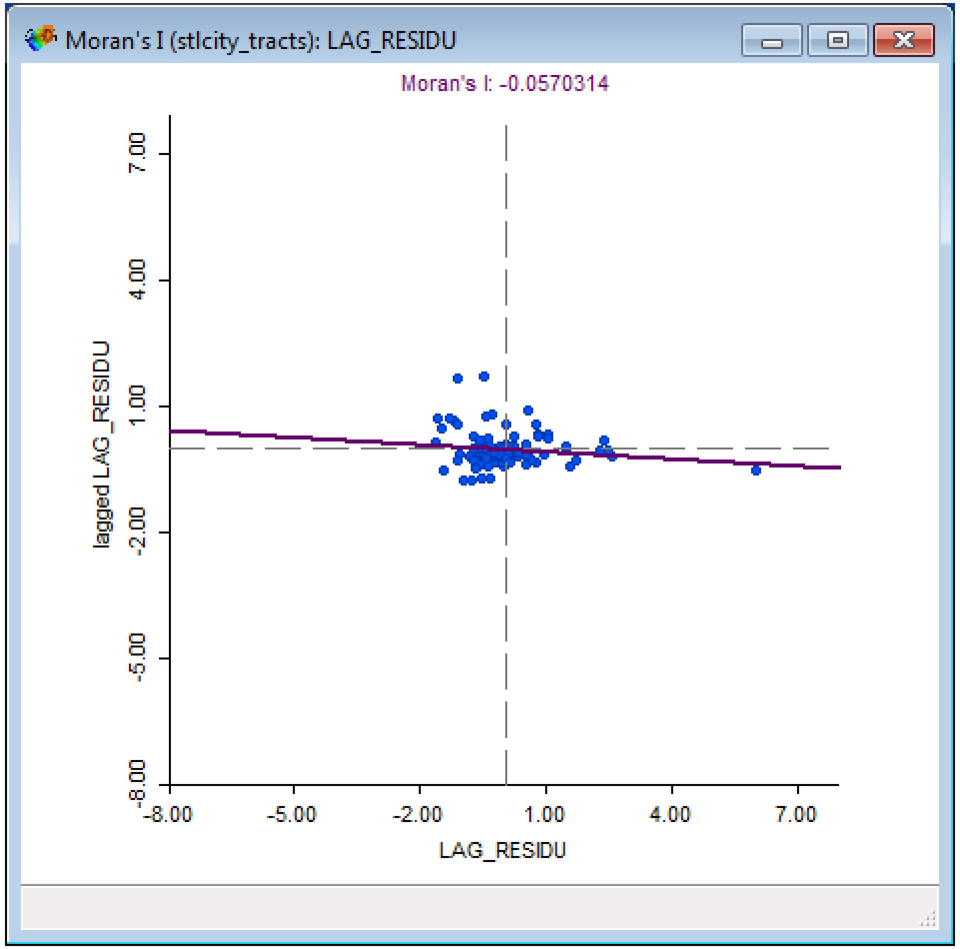


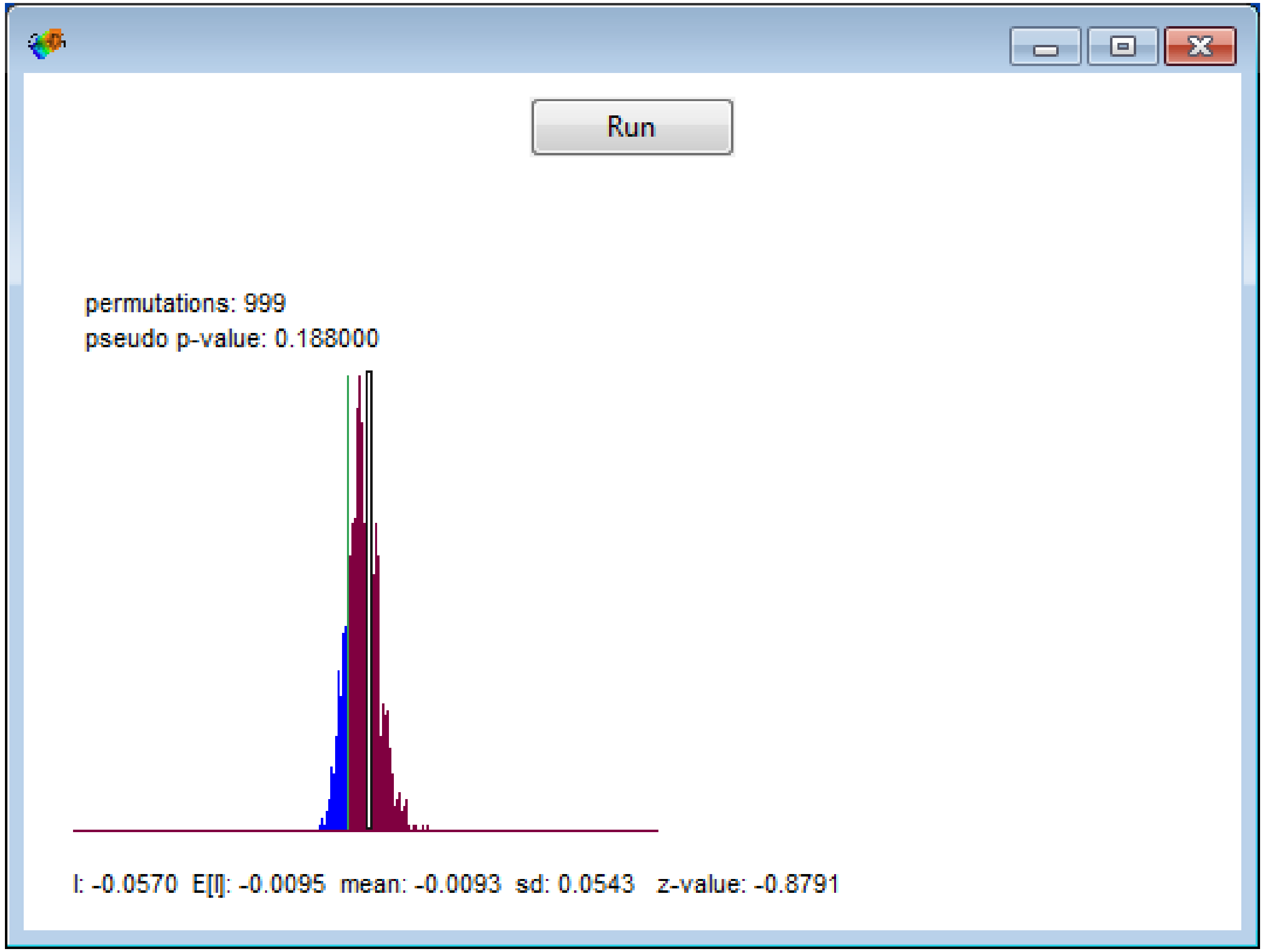




1. We want to compute a Moran's I statistic for residuals from the lag model.

1. We no longer have a problem with spatial autocorrelation





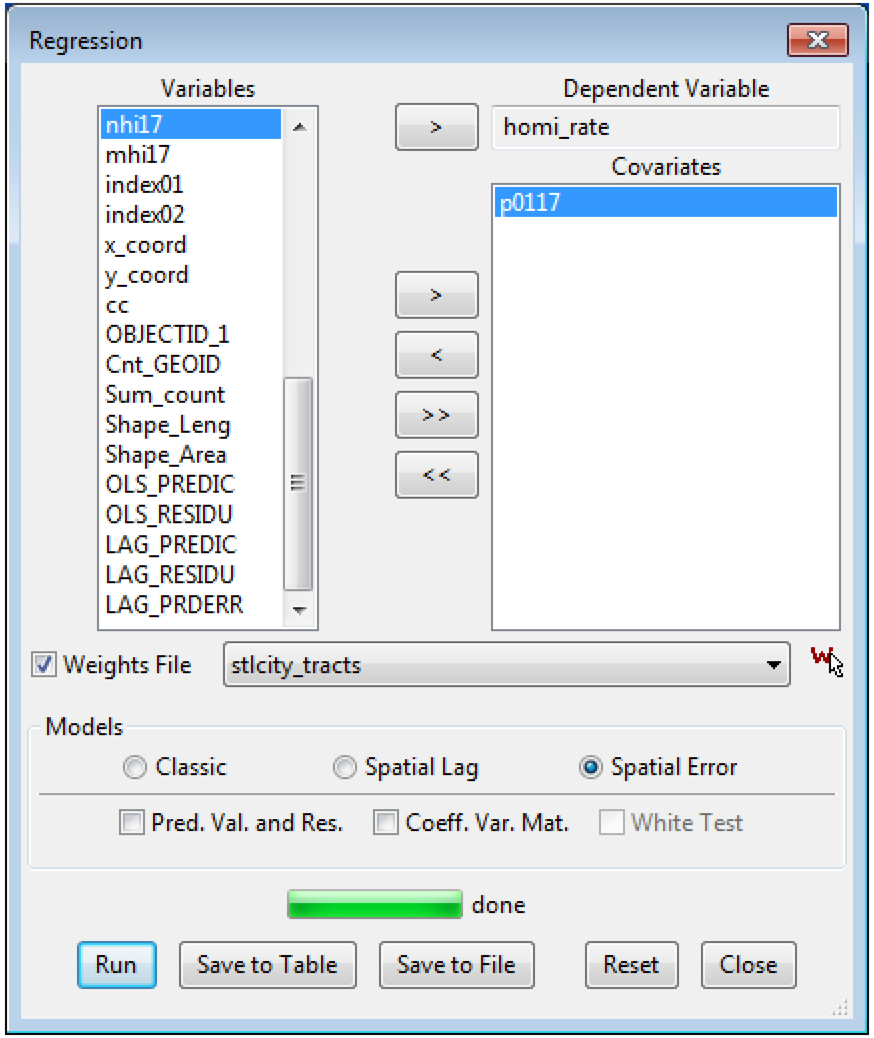
Variable	OLS	SLM
Poverty	.0140372 (.00244)***	0.00579562 (0.00183897) **
Constant	-0.0004 (0.0007)	-0.000578612 0.000536325
ρ		0.720932 (0.0733365) ***
r-square	0.240954	0.614184
Log likelihood	447.486	476.368
AIC	-890.971	-946.736
Moran's I Residual	.431166***	-0.0570314
N	106	106

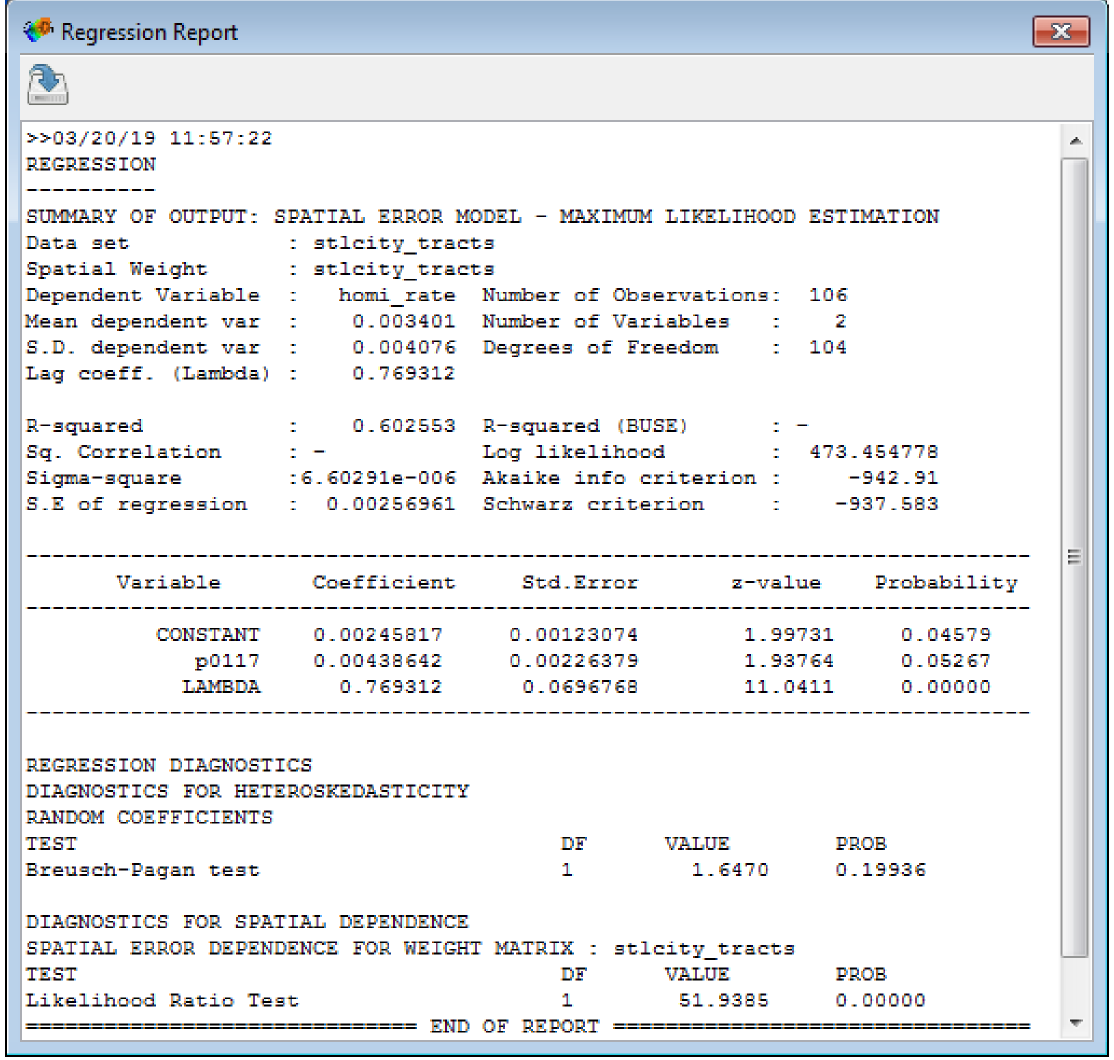
$* \leq .05, ** \leq .01, *** \leq .001$

Standard Errors in Parentheses

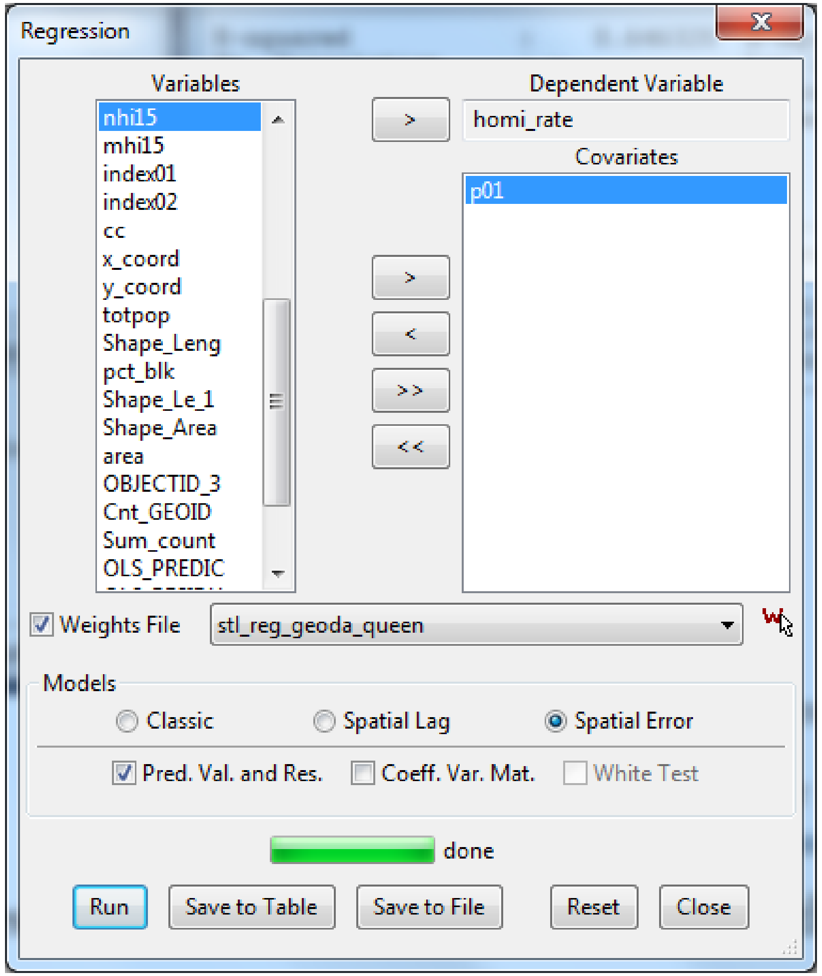
The ρ coefficient is positive and highly significant, indicating strong spatial autocorrelation in the dependent variable. The Moran's I statistic indicates that the residuals are no longer spatially clustered.

Move to Spatial Error

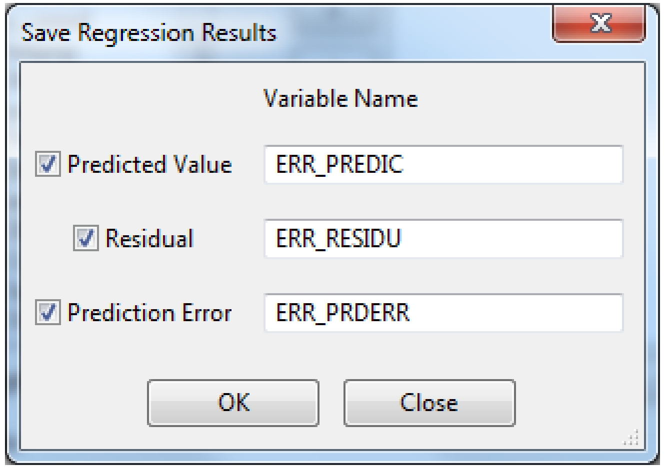


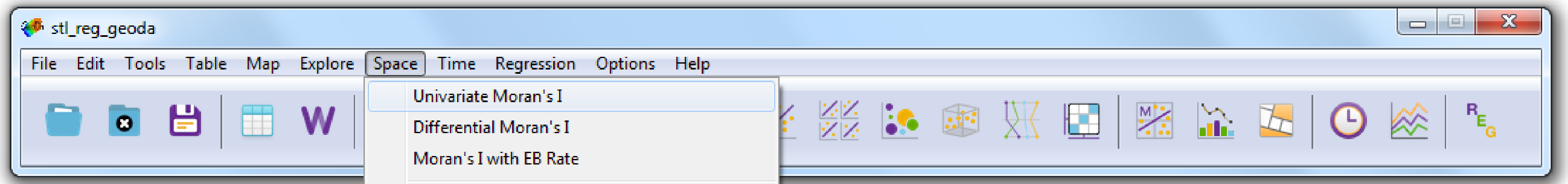


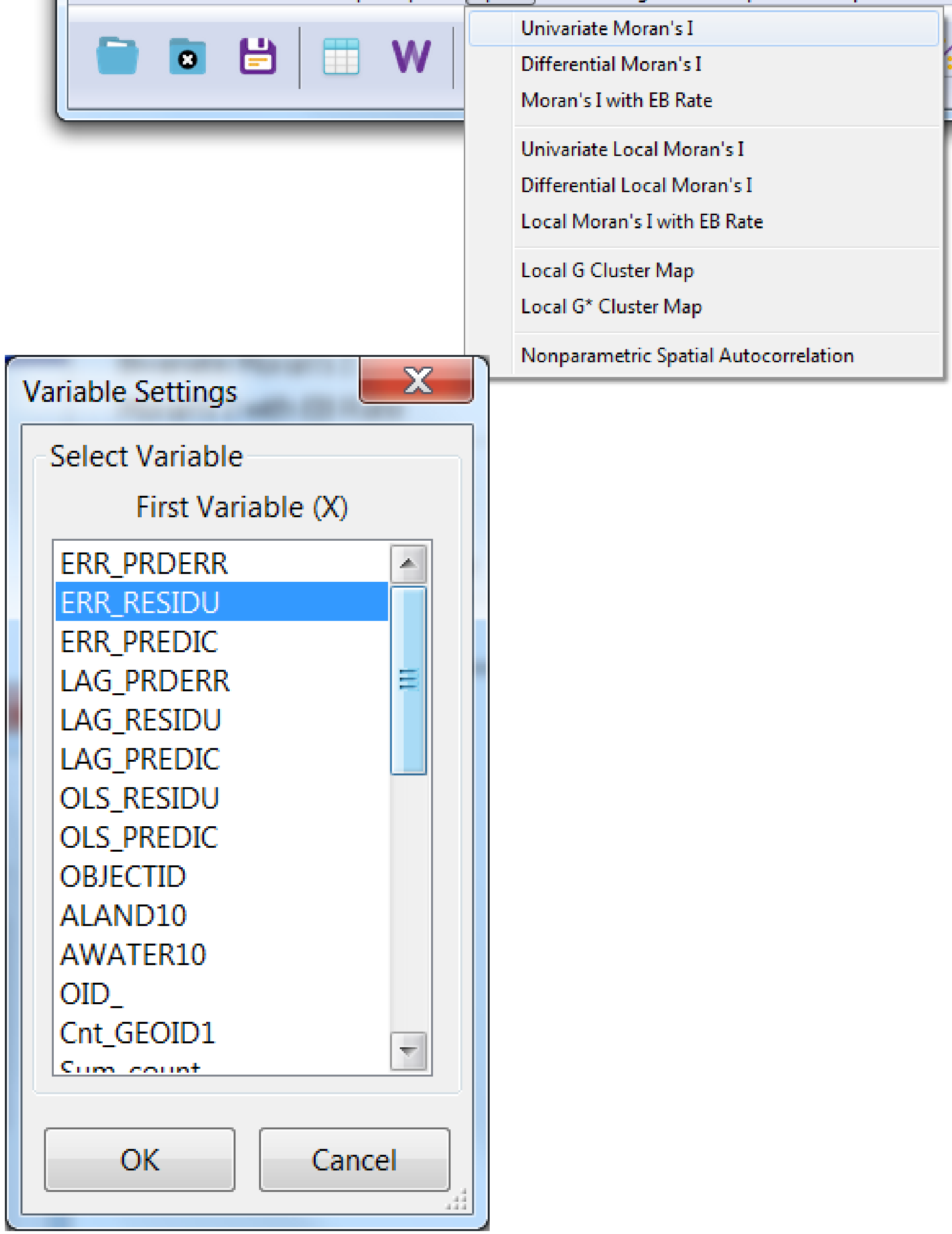
1. The Likelihood Ratio Test tell us this model is better than the OLS model.
2. Our spatial error variable Lambda is significant



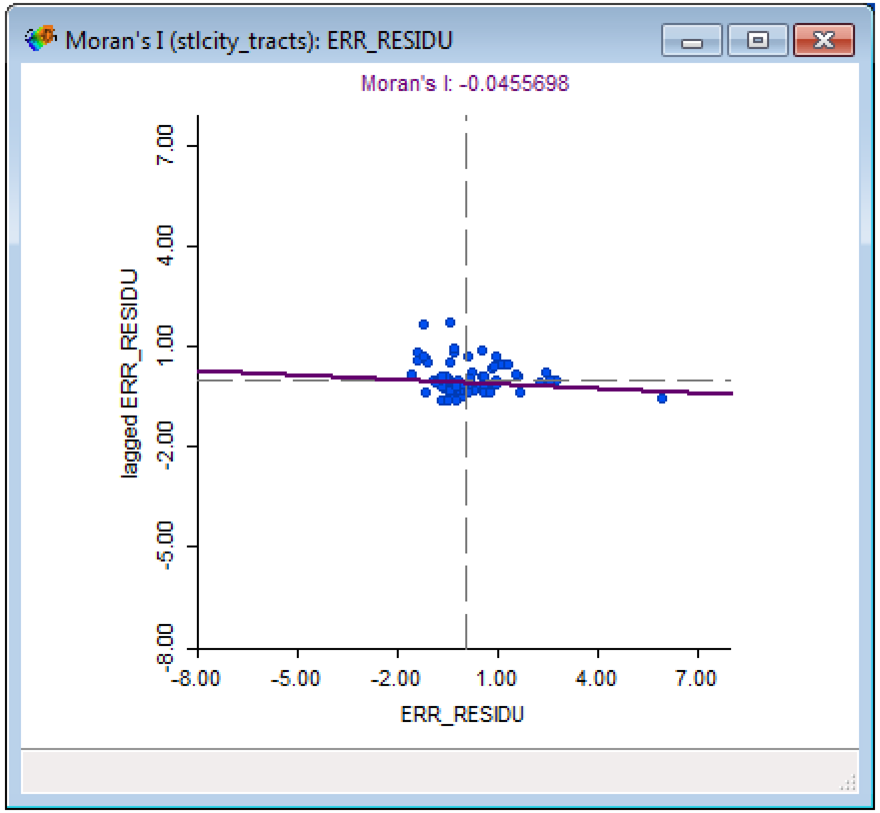
1. We want to save the predicted values, residual and prediction error



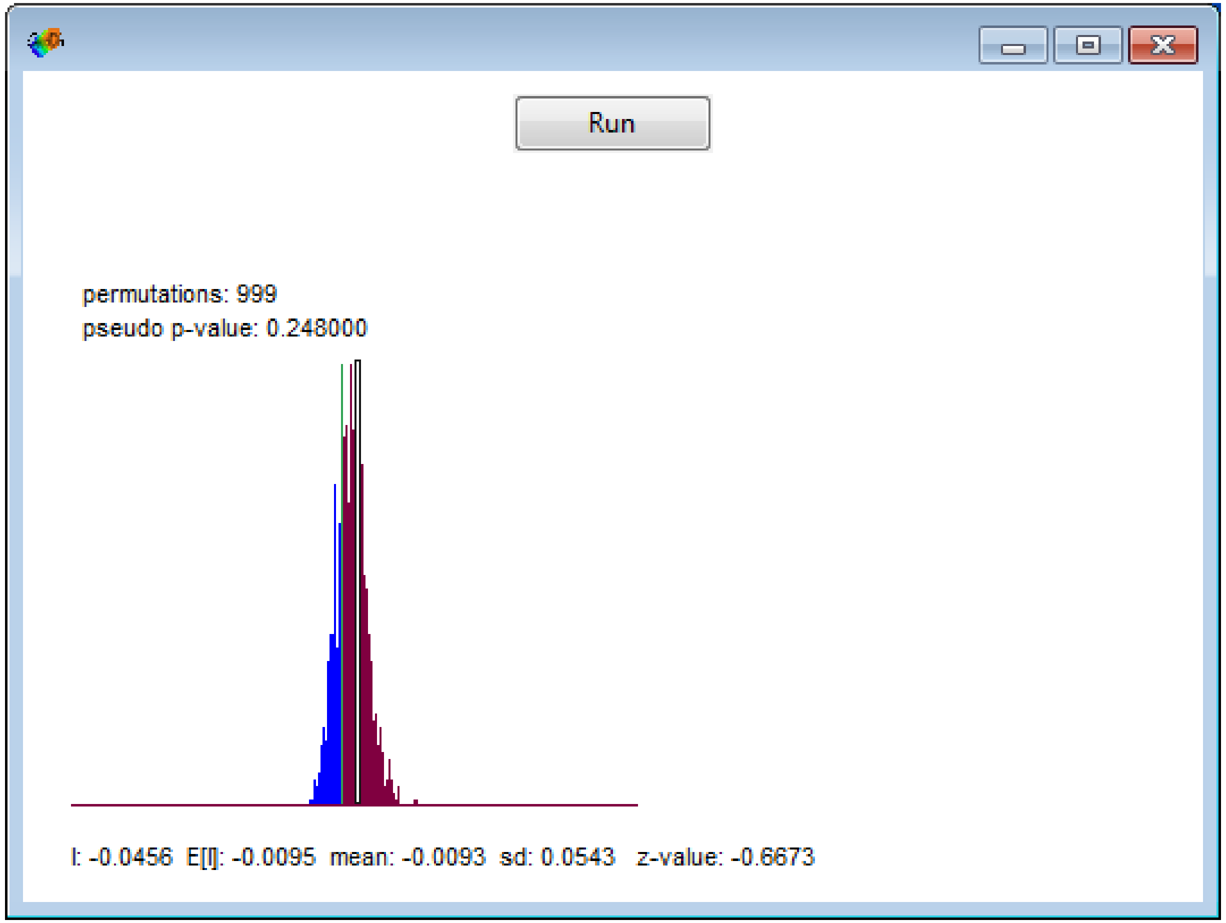




1. We want to compute a Moran's I statistic for residuals from the error model.



1. We no longer have a problem with spatial autocorrelation



Variable	OLS	SLM	SEM
Poverty	.0140372 (.00244)***	0.00579562 (0.00183897) **	0.00438642 (0.00226379)*
Constant	-0.0004 (0.0007)	-0.000578612 0.000536325	0.00245817 (0.00123074)
ρ		0.720932 (0.0733365) ***	
λ			0.769312 (0.0696768)***
r-square	0.240954	0.614184	0.602553
Log likelihood	447.486	476.368	473.454
AIC	-890.971	-946.736	-942.91
Moran's I Residual	.431166***	-0.0570314	-0.0455698
N	106	106	106

$* \leq .05, ** \leq .01, *** \leq .001$

Standard Errors in Parentheses

The λ coefficient is positive and highly significant, indicating strong spatial autocorrelation in the dependent variable. The Moran's I statistic indicates that the residuals are no longer spatially clustered.

Final Decision

	OLS	SLM	SEM	Conclusion	Why?
Log likelihood	447.486	476.368	473.454	SLM is better	SLM>SEM> OLS
AIC	-890.971	-946.736	-942.91	SLM is better	SLM<SEM< OLS
Moran's I Residual	.431166***	-0.0570314	-0.0455698	SLM and SEM better	Fail to reject Ho

Log Likelihood - The higher the value the better the fit
AIC - The lower the value the better the fit

Spatial Regression by Method

Note: These tables are use the crime rate by 1000 using 2015 ACS data

Queen Weight Matrix

Variable	OLS	SLM	SEM
Poverty	12.2057 (2.16)***	5.11771 (1.66671) **	4.19772 (2.13146)*
Constant	-0.251479 (0.713962)	-0.46838 0.526285	2.20829 (1.13544)
ρ		0.69895 (.0776769) ***	
λ			0.74083 (0.0751734)***
r-square	0.234909	0.591147	0.578692
Log likelihood	-280.986	-254.216	-256.872
AIC	565.973	514.432	517.744
Moran's I Residual	.4414***	-0.0701	-0.605
N	106	106	106

$* \le .05, ** \le .01, *** \le .001$

Standard Errors in Parentheses

Distance Weight Matrix

Variable	OLS	SLM	SEM
Poverty	12.2057 (2.16)***	4.98793 (1.74544)**	4.43687 (2.13167)*
Constant	-0.251479 (0.713962)	-0.539434 (0.553934)	1.84796 (1.26047)
ρ		0.71194 (0.0852352)***	
λ			0.765561 (0.0798896)***
r-square	0.234909	0.547679	0.542255
Log likelihood	-280.986	-257.915	-259.597582
AIC	565.973	521.83	523.195
Moran's I Residual	.4414***	0.0257	-0.0230
N	106	106	106

$* \leq .05, ** \leq .01, *** \leq .001$

Standard Errors in Parentheses

K-Nearest Neighbor (n=4)

Variable	OLS	SLM	SEM
Poverty	12.2057 (2.16)***	5.0658213 (1.6571861)**	4.4759007 (2.0709449)*
Constant	-0.251479 (0.713962)	-0.4149546 90.5243832)	1.9617256 (1.1007548)
ρ		0.6809633 (0.0730158)***	
λ			0.7265326 (0.0697611)***
r-square	0.234909	0.5993	0.2349
Log likelihood	-280.986	-254.462	-256.588
AIC	565.973	514.924	517.177
Moran's I Residual	.4414***	Not sig	Not sig
N	106	106	106

$* \leq .05, ** \leq .01, *** \leq .001$

Standard Errors in Parentheses