

# 11 –Analyzing Spatial Patterns

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# Outline

Average Nearest Neighbor

Ripley's K function

Kernel Density Estimation

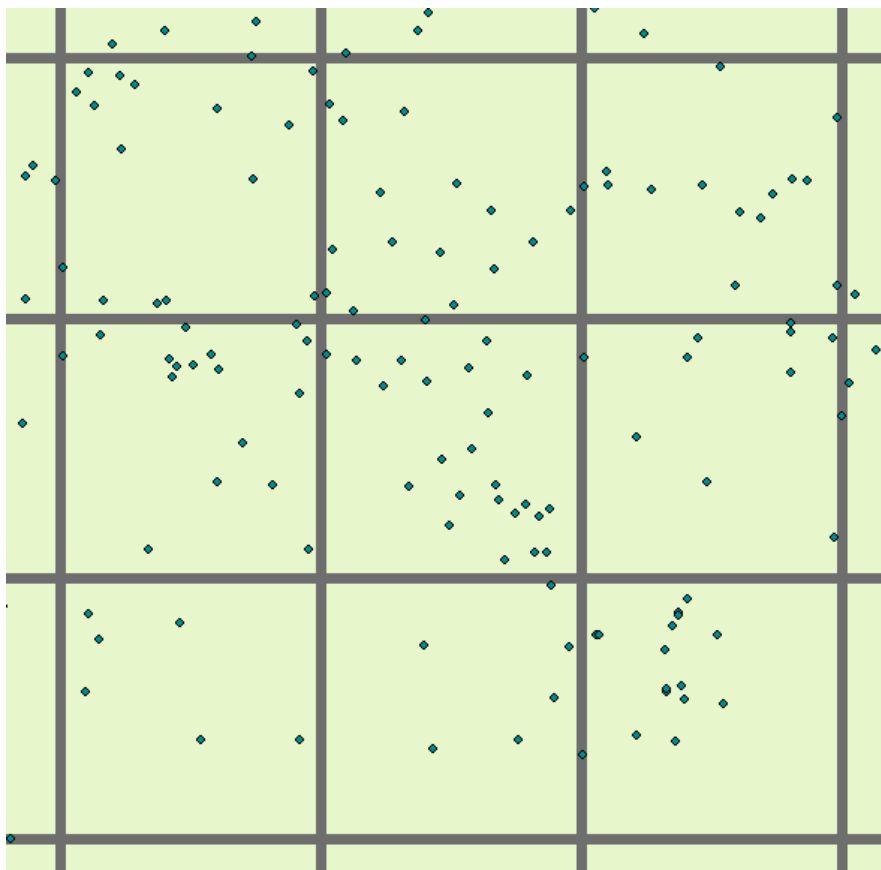
General G Statistic

Hot-Spot Analysis  $G_i^*$

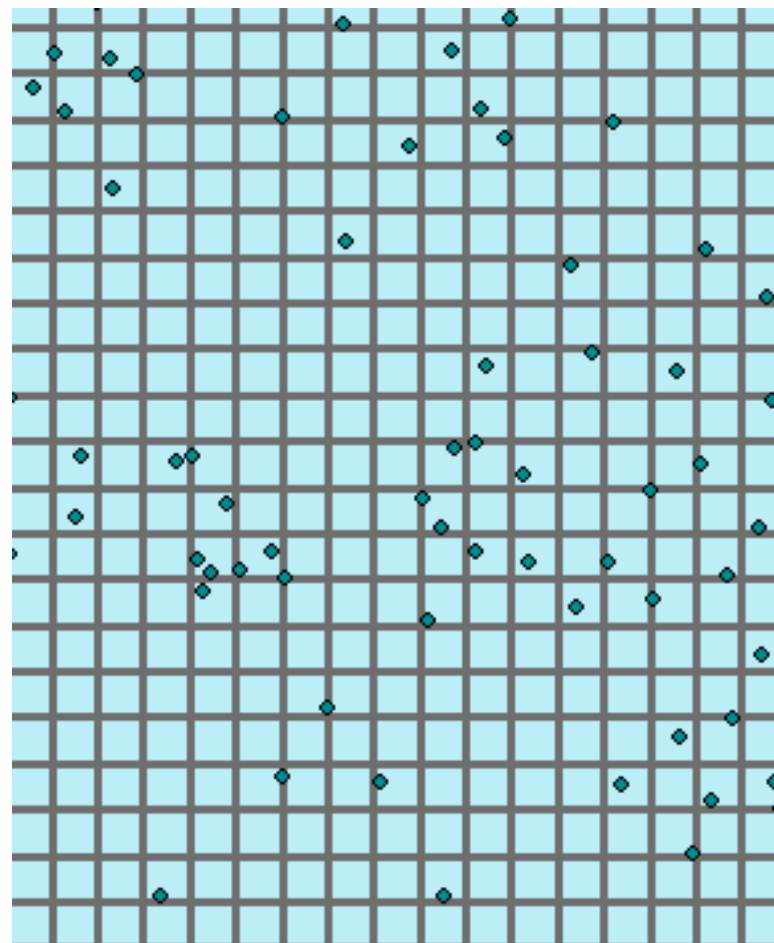
Lab Exercise

# Point Pattern Analysis

- Point Association
  - Nearest Neighbor Analysis
- Point Density
  - Quadrat Analysis
  - Modifiable Areal Unit Problem



May be too big  
1000 meters



May be too small  
100 meters

# Average Nearest Neighbor

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Cluster or Dispersion

Calculates a  
mathematical  
index

Degree of  
clustering

Are physical  
locations closer  
together than a  
random  
distribution?

Point vs.  
Polygon Data

ANN

```
graph TD; A[Calculates a mathematical index] --> ANN((ANN)); B[Degree of clustering] --> ANN; C[Are physical locations closer together than a random distribution?] --> ANN; D[Point vs. Polygon Data] --> ANN;
```

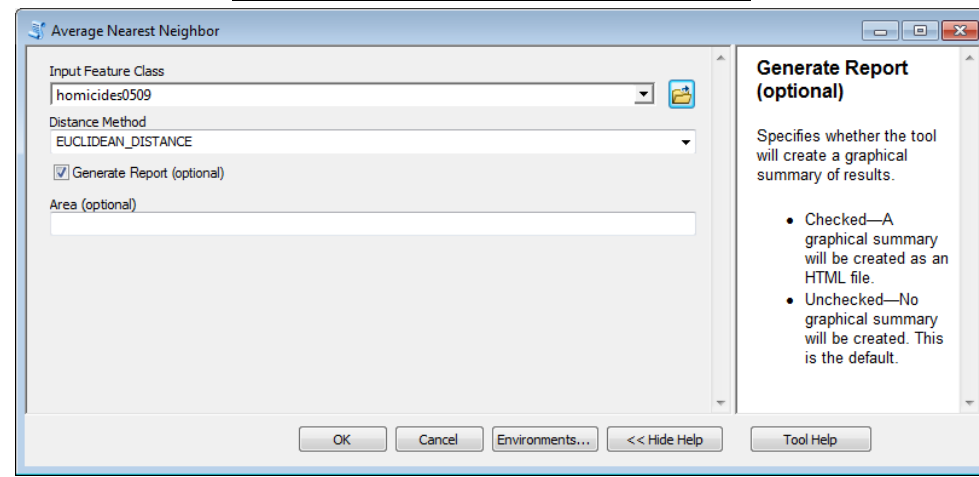
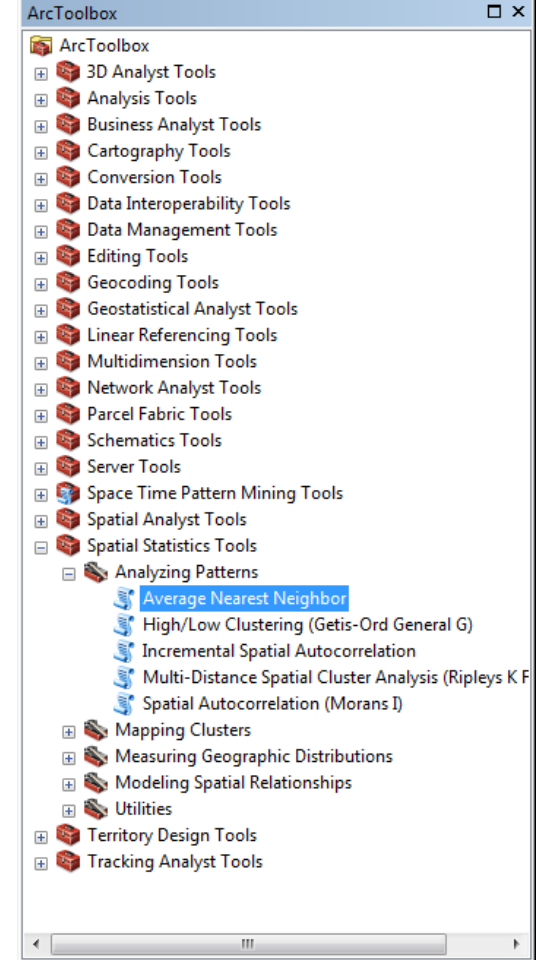
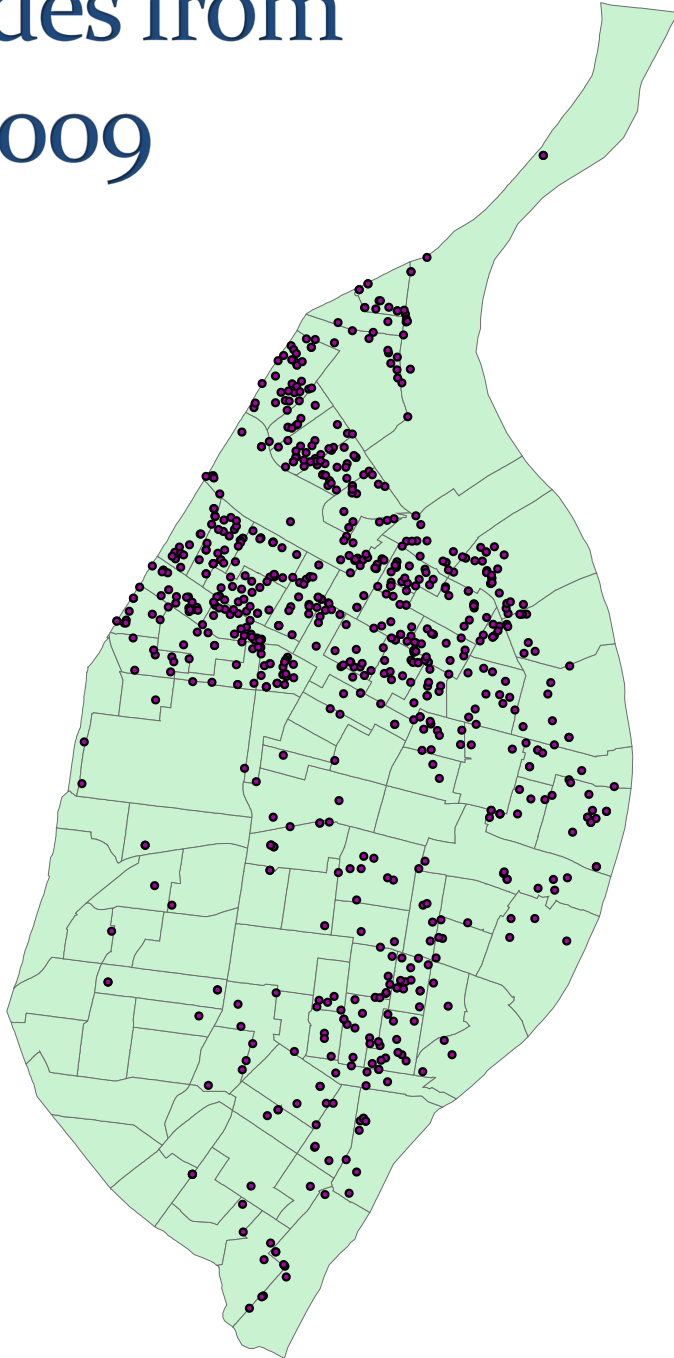
The diagram illustrates the inputs to an Artificial Neural Network (ANN). A central blue circle labeled 'ANN' is the target of four arrows. A green arrow points from the top-left box 'Calculates a mathematical index'. A purple arrow points from the top-right box 'Degree of clustering'. A red arrow points from the bottom-left box 'Are physical locations closer together than a random distribution?'. A teal arrow points from the bottom-right box 'Point vs. Polygon Data'.

# Average nearest neighbor (ANN)

The ANN index tool will calculate a z-score which can be used to reject or fail to reject  $H_0$ .

- $H_0$ = There is no pattern
- $H_1$ =There is a pattern

# Homicides from 2005 - 2009





## Results



Current Session



Average Nearest Neighbor [114405\_03062019]



NNRatio: 0.491702



NNZScore: -27.157948



PValue: 0



NNExpected: 272.901598



NNObserved: 134.186143



Report File: NearestNeighbor\_Result\_9764\_4036\_.ht



Inputs



Environments



Messages



Shared

Click on the  
Report File

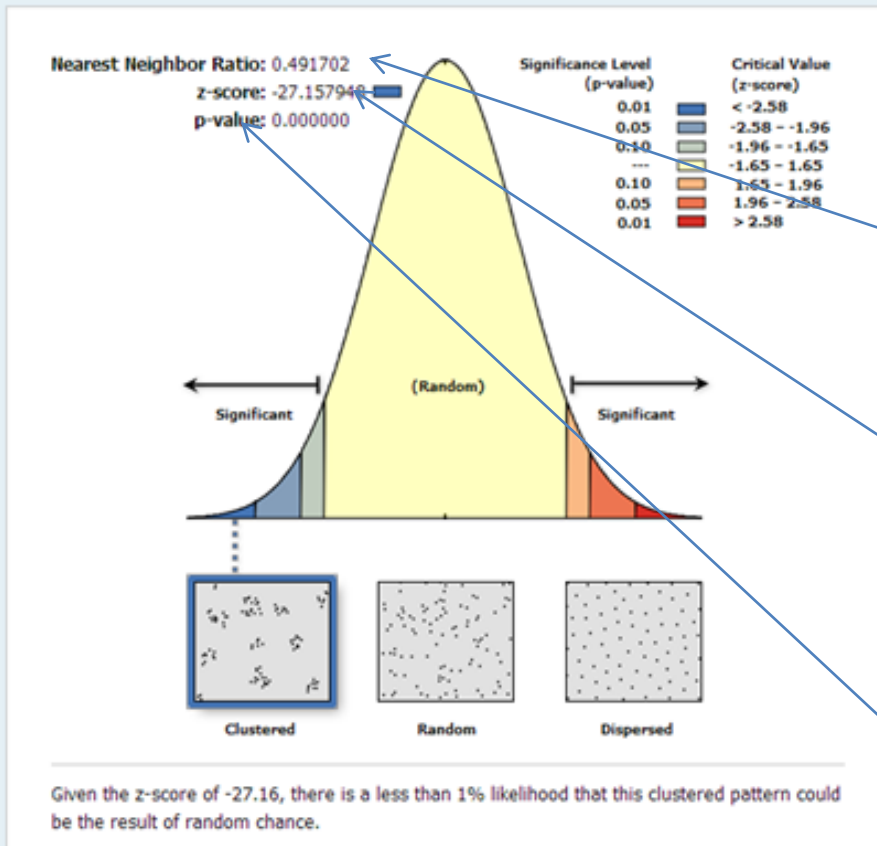


ArcToolbox



Results

## Average Nearest Neighbor Summary



## Average Nearest Neighbor Summary

Observed Mean Distance:	134.186143 Meters
Expected Mean Distance:	272.901598 Meters
Nearest Neighbor Ratio:	0.491702
z-score:	-27.157948
p-value:	0.000000

## Dataset Information

Input Feature Class:	homicides
Distance Method:	EUCLIDEAN
Study Area:	232362880.085246
Selection Set:	False

## Important Points for observation

- The dataset returned an index of .49
- This tells us that the features are trending toward clustering
- The z-score is -27.16 with a significance level of 0.01. This score gives us the confidence level of rejecting the null hypothesis.

# Ripley's K function

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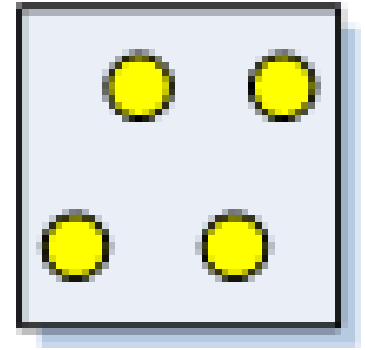
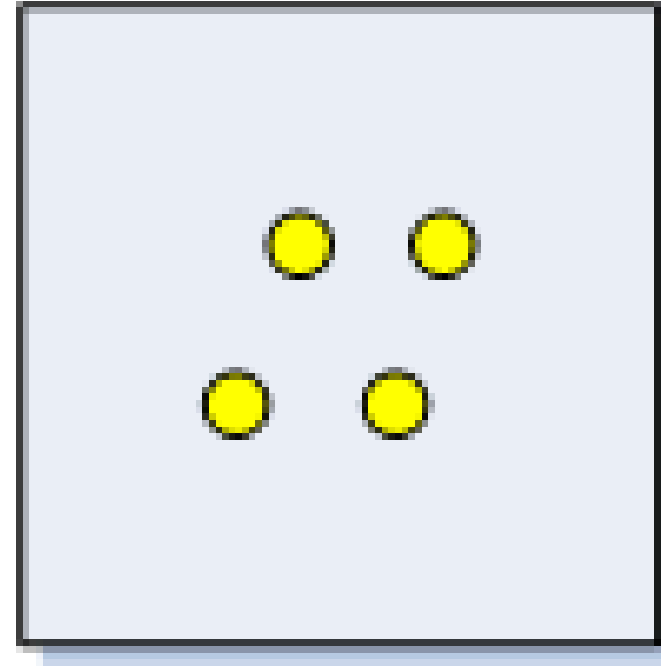
Multi-distance clustering

# Ripley's K function Part 1

- Ripley's K function is a method of pattern analysis.
  - Always uses points
  - Determines if there spatial pattern that is statistically significant clustering or dispersion over a range of distances.
  - The difference between ANN, is that Ripley's K function includes all the neighboring features in the calculation, not the just the nearest one.
- The index is calculated by measuring the distance from ach feature to all the other features in the dataset.
- Points at the edge of the study may have few neighbors
- Our goal is to find the point of most clustering.

# Challenges – Part 1

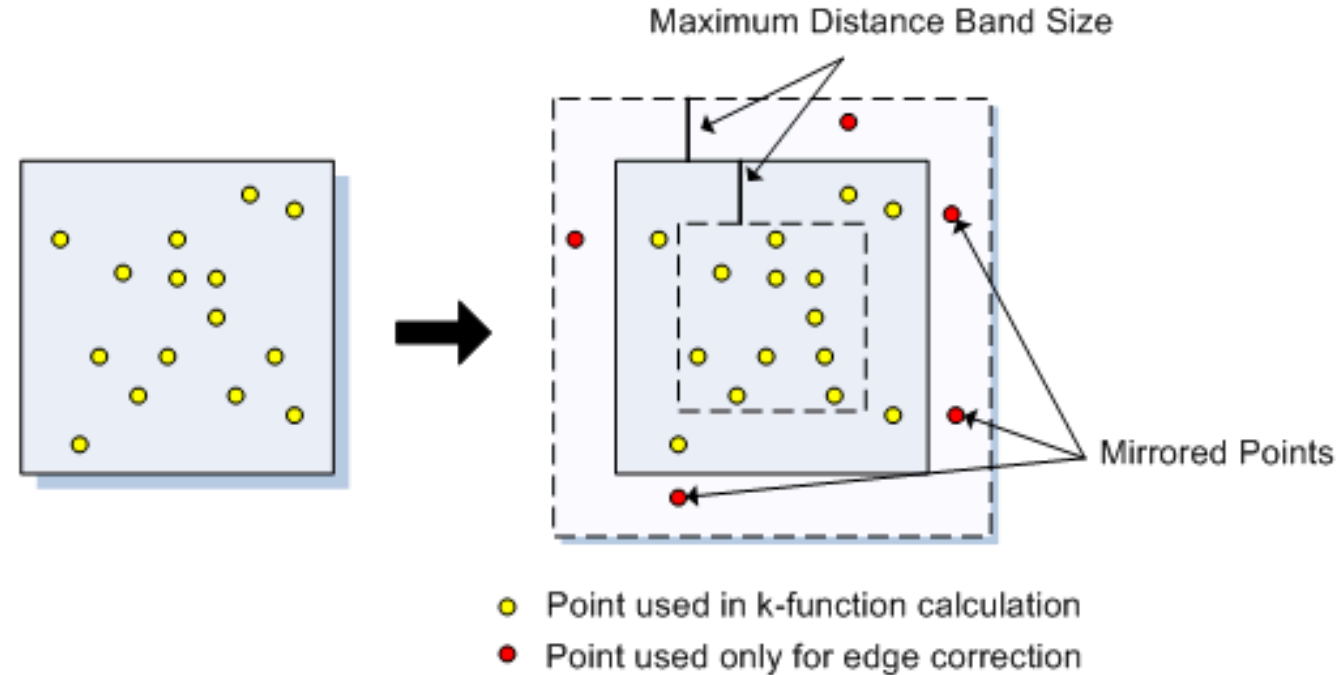
- The k-function statistic is very sensitive to the size of the study area.
- Identical arrangements of points can exhibit clustering or dispersion depending on the size of the study area enclosing them.
- Therefore, it is imperative that the study area boundaries are carefully considered.
- The picture to the right is a classic example of how identical feature distributions can be dispersed or clustered depending on the study area specified.



# Solutions – Part 1

## SIMULATE OUTER BOUNDARY VALUES

- This method creates points outside the study area boundary that mirror those found inside the boundary in order to correct for underestimates near the edges.
- Points that are within a distance equal to the maximum distance band of an edge of the study area are mirrored.
- The mirrored points are used so that edge points will have more accurate neighbor estimates.



This diagram illustrates what points will be used in the calculation and which will be used only for edge correction.

# Solutions – Part 2

## REDUCE ANALYSIS AREA

- This method shrinks the study area such that some points are found outside of the study area boundary.
- Points found outside the study area are used to calculate neighbor counts but are not used in the cluster analysis itself.

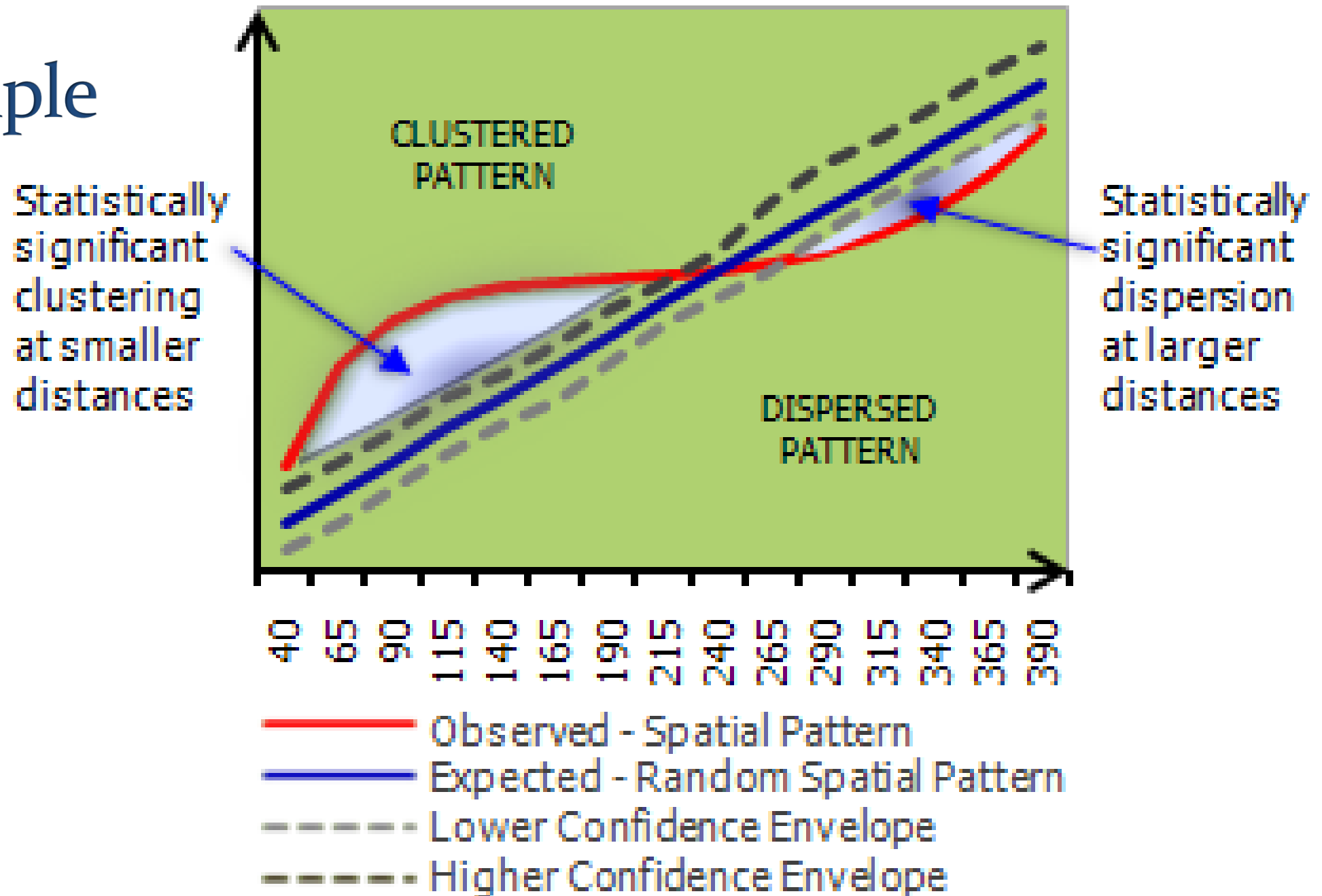
# Solutions – Part 3

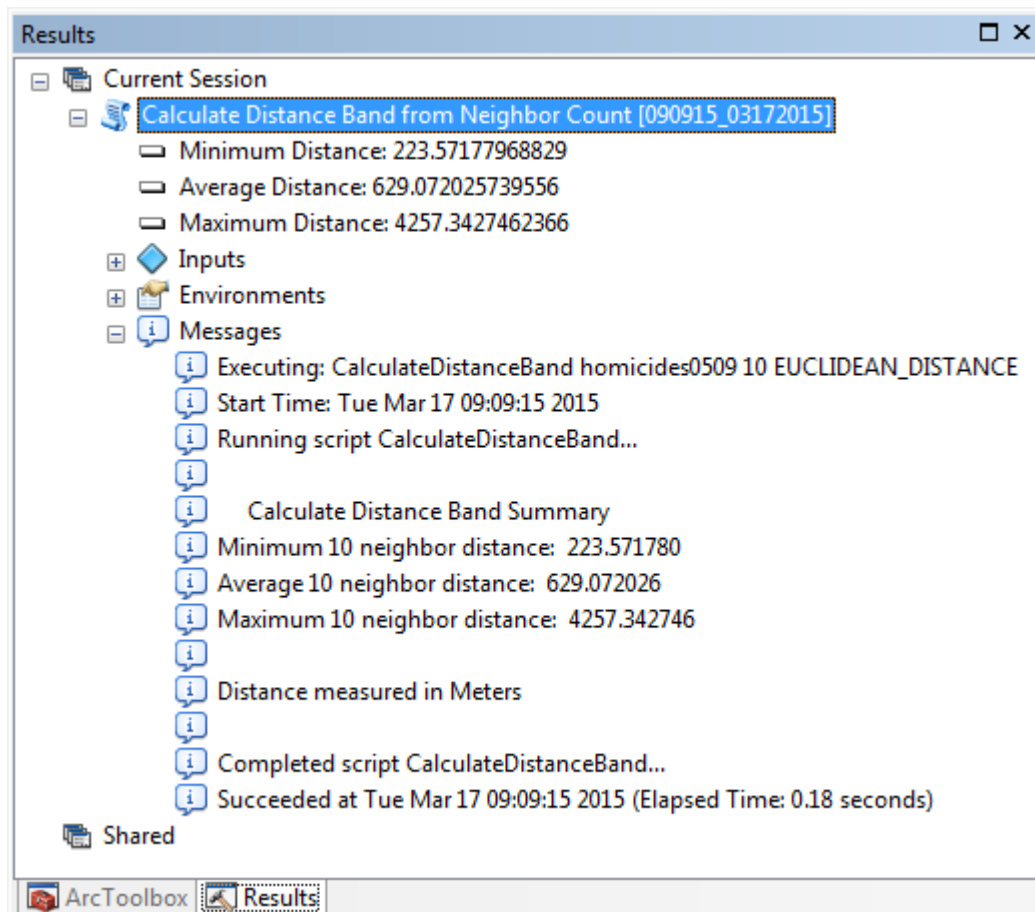
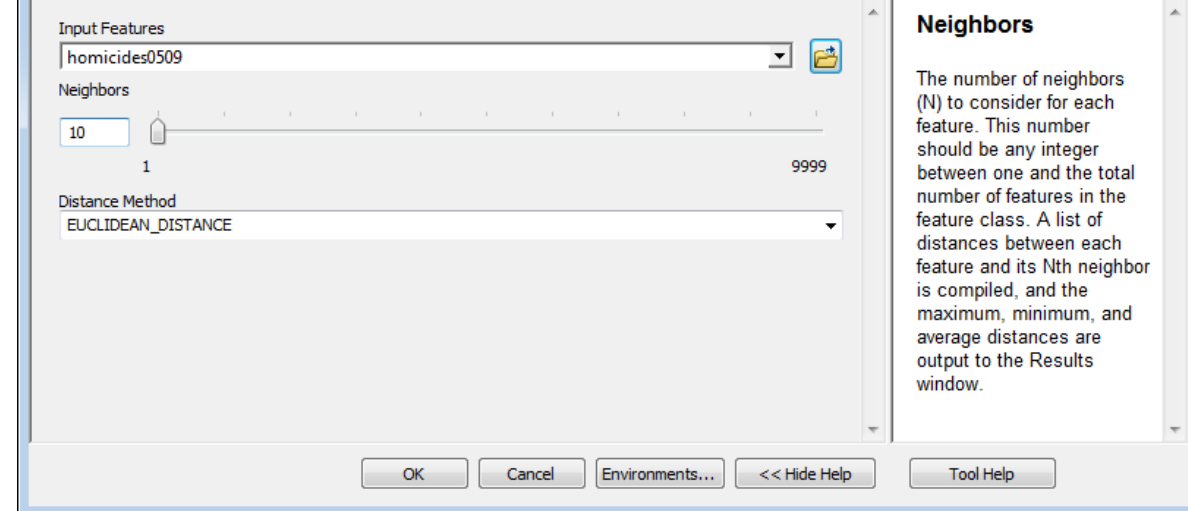
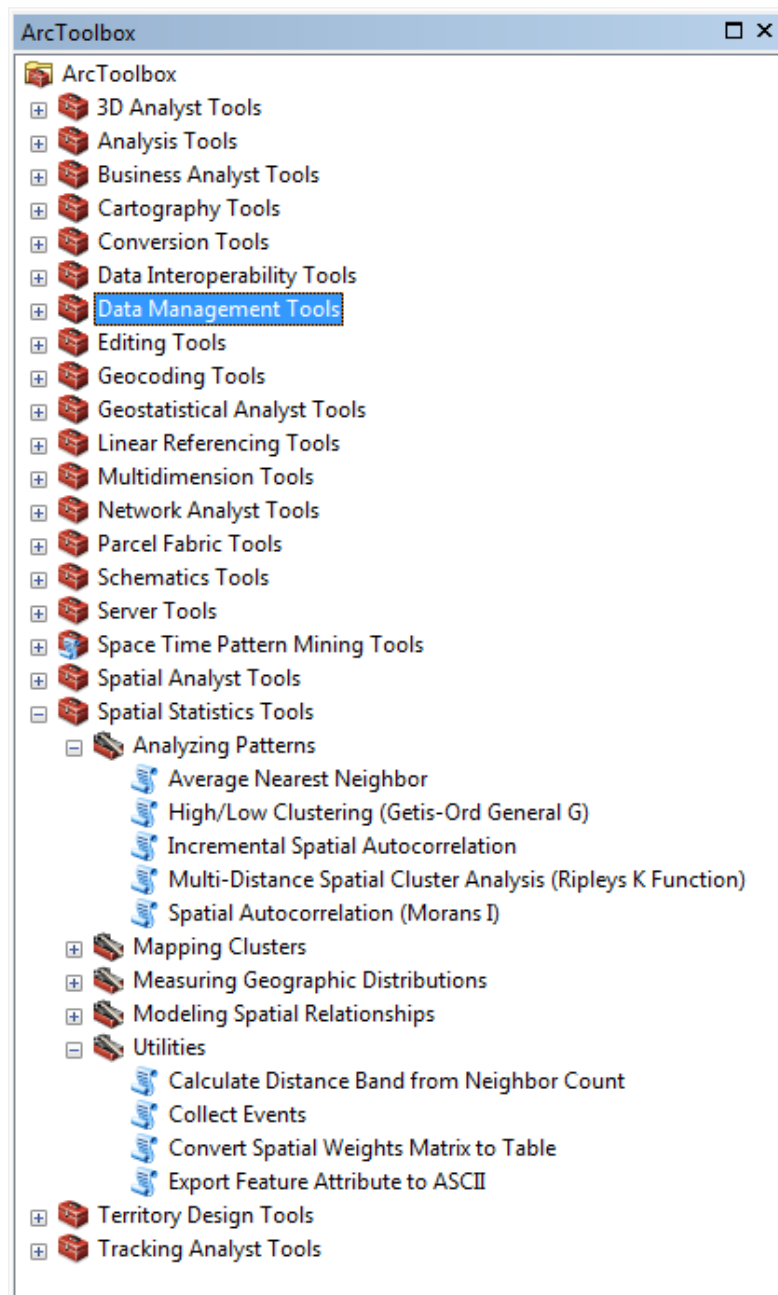
## RIPLEY EDGE CORRECTION FORMULA

- This method checks each point's distance from the edge of the study area and its distance to each of its neighbors.
- All neighbors that are further away from the point in question than the edge of the study area are given extra weighting.
- This edge correction method is only appropriate for square or rectangular shaped study areas, or when you select `MINIMUM_ENCLOSING_RECTANGLE` for the Study Area Method parameter.

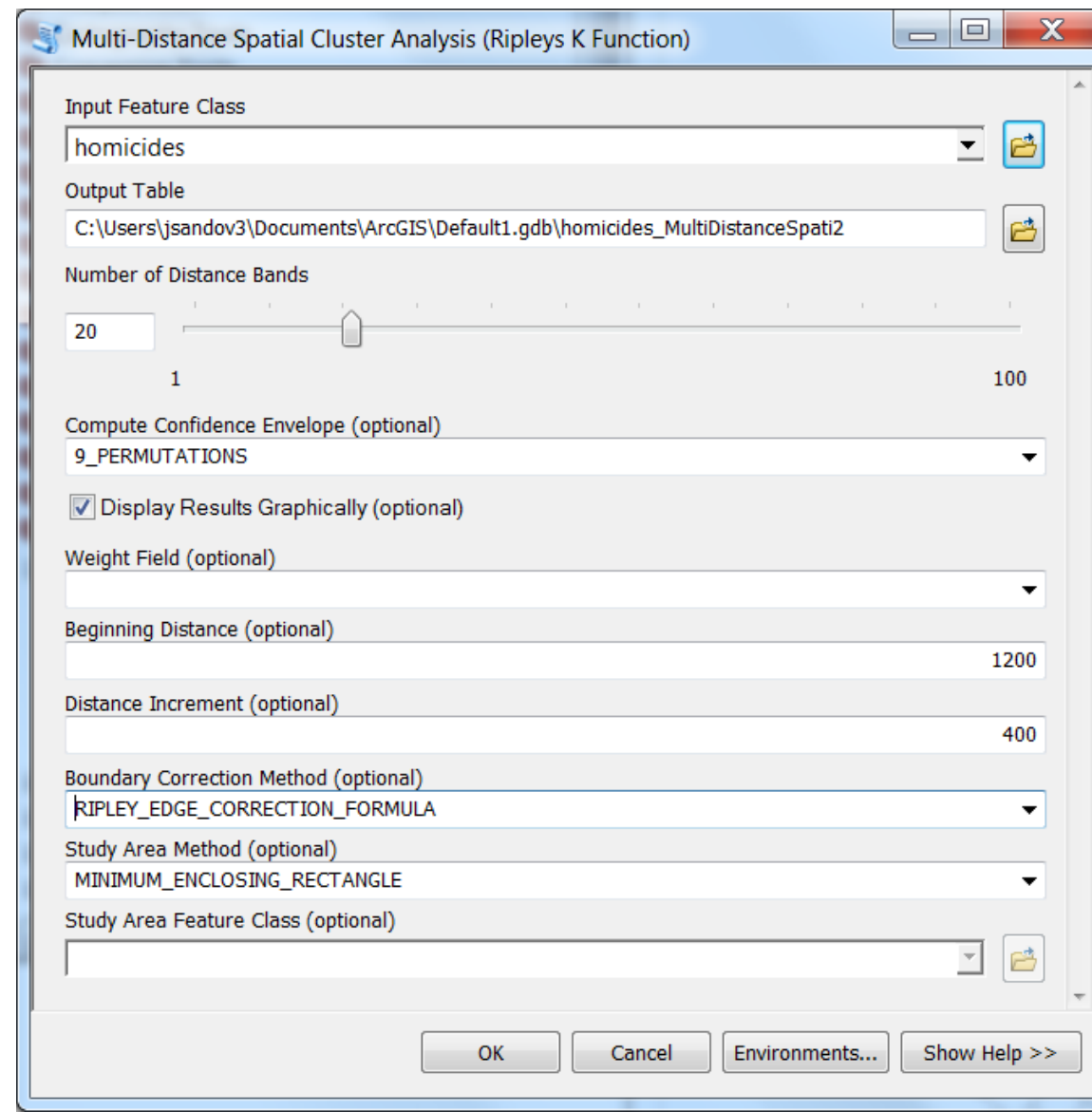
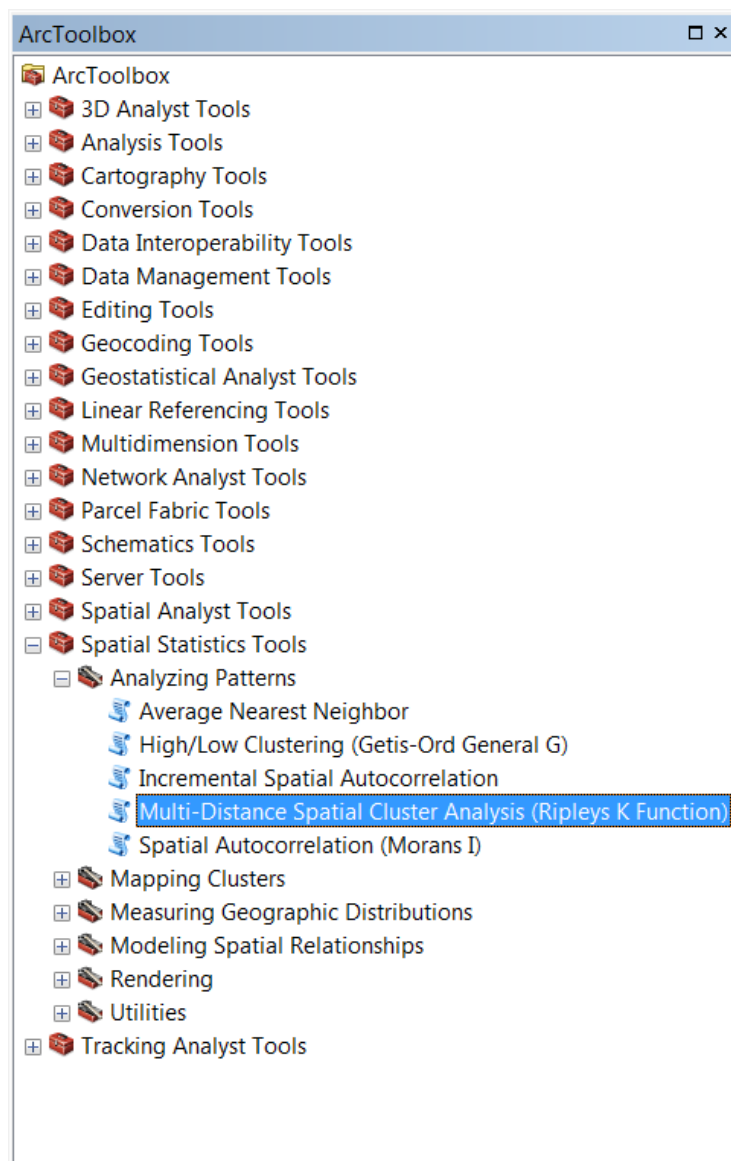


# Example



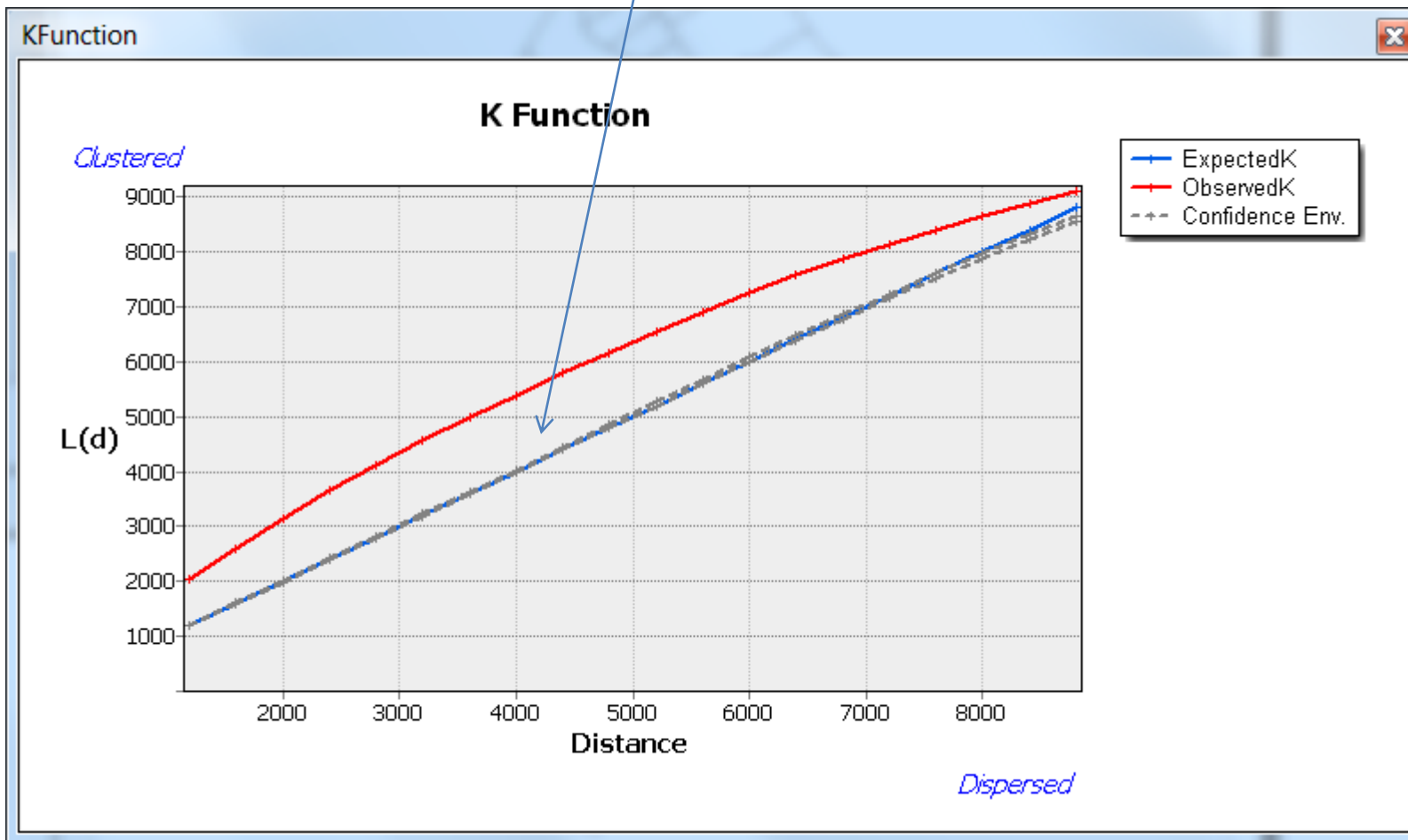


# Ripley's K function Part 2



Current Session
Multi-Distance Spatial Cluster Analysis (Ripley's K Function) [111347_03192013]
Output Table: homicides_MultiDistanceSpati2
Result Image: KFunction
Inputs
Environments
Messages
Executing: MultiDistanceSpatialClustering homicides C:\Users\jsandov3\Docum
Start Time: Tue Mar 19 11:11:55 2013
Running script MultiDistanceSpatialClustering...
k-Function Summary
Distance* L(d) Diff Min L(d) Max L(d)
1200.00 2053.28 853.28 1188.79 1209.47
1600.00 2607.33 1007.33 1584.51 1615.62
2000.00 3144.11 1144.11 1992.46 2014.46
2400.00 3651.42 1251.42 2382.43 2416.56
2800.00 4126.07 1326.07 2785.48 2824.00
3200.00 4568.52 1368.52 3187.59 3228.80
3600.00 4985.87 1385.87 3591.00 3625.34
4000.00 5389.41 1389.41 3993.20 4030.00
4400.00 5787.18 1387.18 4393.66 4446.06
4800.00 6170.67 1370.67 4787.49 4855.39
5200.00 6548.96 1348.96 5189.05 5271.81
5600.00 6916.30 1316.30 5591.01 5683.29
6000.00 7258.97 1258.97 5994.19 6087.33
6400.00 7574.18 1174.18 6381.11 6482.89
6800.00 7869.03 1069.03 6770.46 6862.96
7200.00 8141.70 941.70 7159.09 7239.24
7600.00 8397.39 797.39 7530.34 7609.23
8000.00 8644.50 644.50 7888.28 7970.84
8400.00 8882.61 482.61 8231.66 8325.83
8800.00 9104.41 304.41 8560.40 8664.53
* Measured in Meters
Completed script MultiDistanceSpatialClustering...
Succeeded at Tue Mar 19 11:13:47 2013 (Elapsed Time: 1 minutes 52 seconds)

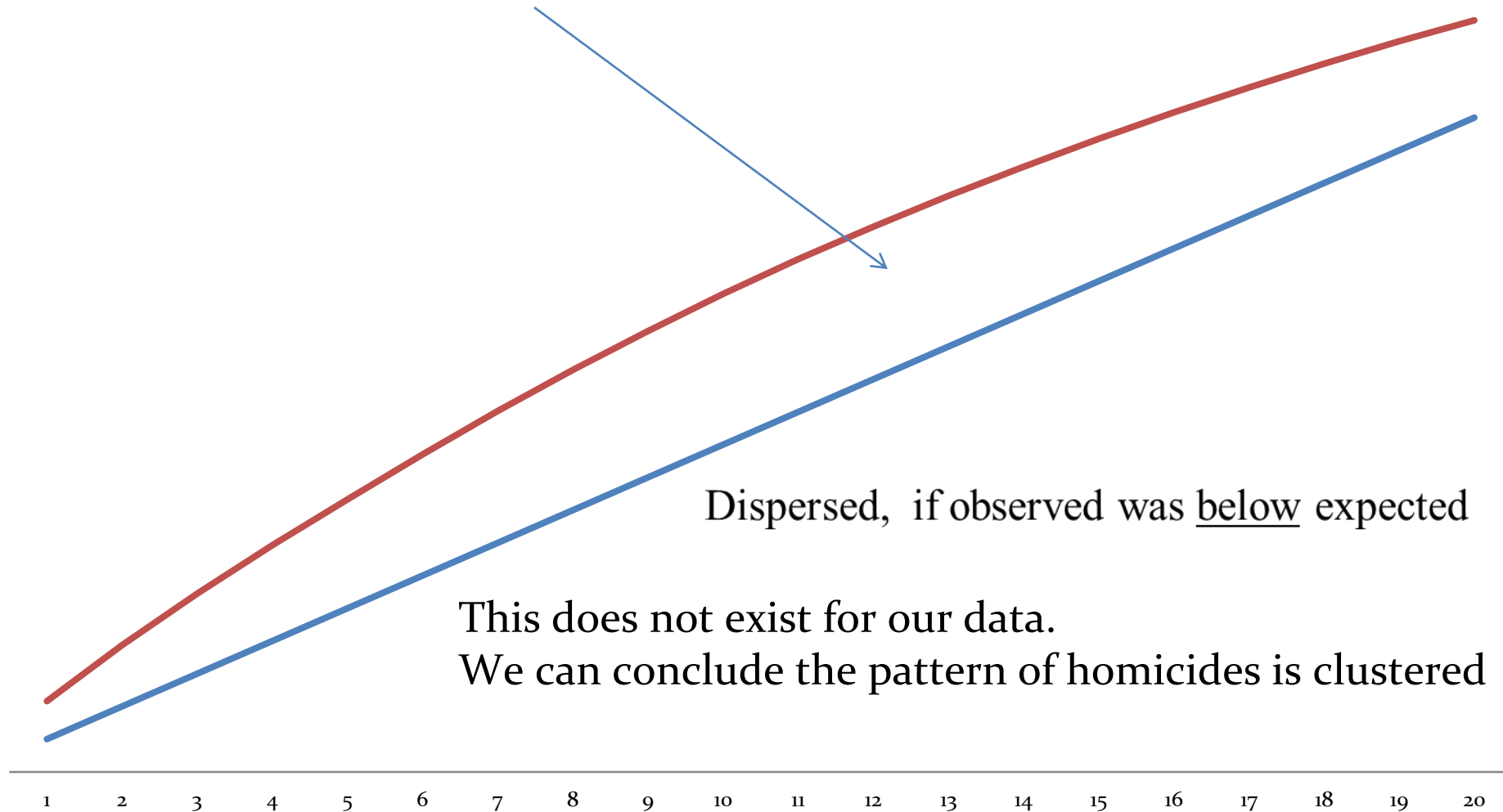
This indicates clustering at the low and high end



# Homicides o 2005-2009

ExpectedK ObservedK

**Clustered**, since observed is above expected



We can create a second graph – we may want to plot the difference between observed and expected k, versus distance

Table						
homicides_MultiDistanceSpati2						
	OBJECTID *	ExpectedK	ObservedK	DiffK	LwConfEnv	HiConfEnv
▶	1	1200	2053.275681	853.275681	1188.792758	1209.467028
	2	1600	2607.326824	1007.326824	1584.514082	1615.619258
	3	2000	3144.11243	1144.11243	1992.46456	2014.458375
	4	2400	3651.415352	1251.415352	2382.433714	2416.563197
	5	2800	4126.072445	1326.072445	2785.478101	2823.998785
	6	3200	4568.515832	1368.515832	3187.591722	3228.803123
	7	3600	4985.871149	1385.871149	3590.997587	3625.335765
	8	4000	5389.411307	1389.411307	3993.196352	4030.003285
	9	4400	5787.175936	1387.175936	4393.65688	4446.055105
	10	4800	6170.673691	1370.673691	4787.492673	4855.389063
	11	5200	6548.964993	1348.964993	5189.053218	5271.811653
	12	5600	6916.30149	1316.30149	5591.010102	5683.290435
	13	6000	7258.96974	1258.96974	5994.189858	6087.328332
	14	6400	7574.179736	1174.179736	6381.108861	6482.886514
	15	6800	7869.028549	1069.028549	6770.461896	6862.956986
	16	7200	8141.697796	941.697796	7159.090915	7239.236183
	17	7600	8397.385465	797.385465	7530.337775	7609.234845
	18	8000	8644.500928	644.500928	7888.277819	7970.844929
	19	8400	8882.606477	482.606477	8231.663018	8325.825861
	20	8800	9104.413103	304.413103	8560.399041	8664.527144

Table						
homicides_MultiDistanceSpati2						
	ExpectedK	DiffK				
	93638	849.93638				
	25968	889.425968				
	75086	926.675086				
	30473	964.430473				
	27444	1000.927444				
	11011	1038.711011				
	54064	1077.554064				
	83171	1105.183171				
	29274	1130.29274				
	82459	1158.482459				

- Find and Replace...
- Select By Attributes...
- Clear Selection
- Switch Selection
- Select All
- Add Field...
- Turn All Fields On
- ☒ Show Field Aliases
- Arrange Tables
- Restore Default Column Widths
- Restore Default Field Order
- Joins and Relates
- Related Tables
- Create Graph...**
- Add Table to Layout
- Reload Cache
- Print...
- Reports
- Export...
- Appearance...

#### Create Graph

Creates a graph from the table.

Graph type:

Vertical Line

Layer/Table:

homicides0509\_MultiDistances

Y field:

DiffK

X field (optional):

ExpectedK

None

X label field:

&lt;None&gt;

Vertical axis:

Left

Horizontal axis:

Bottom

☒ Add to legend☐ Show labels (marks)

Color:

Custom

Stairs mode:

Off

Line

Symbol

Width:

2

Style:

Solid

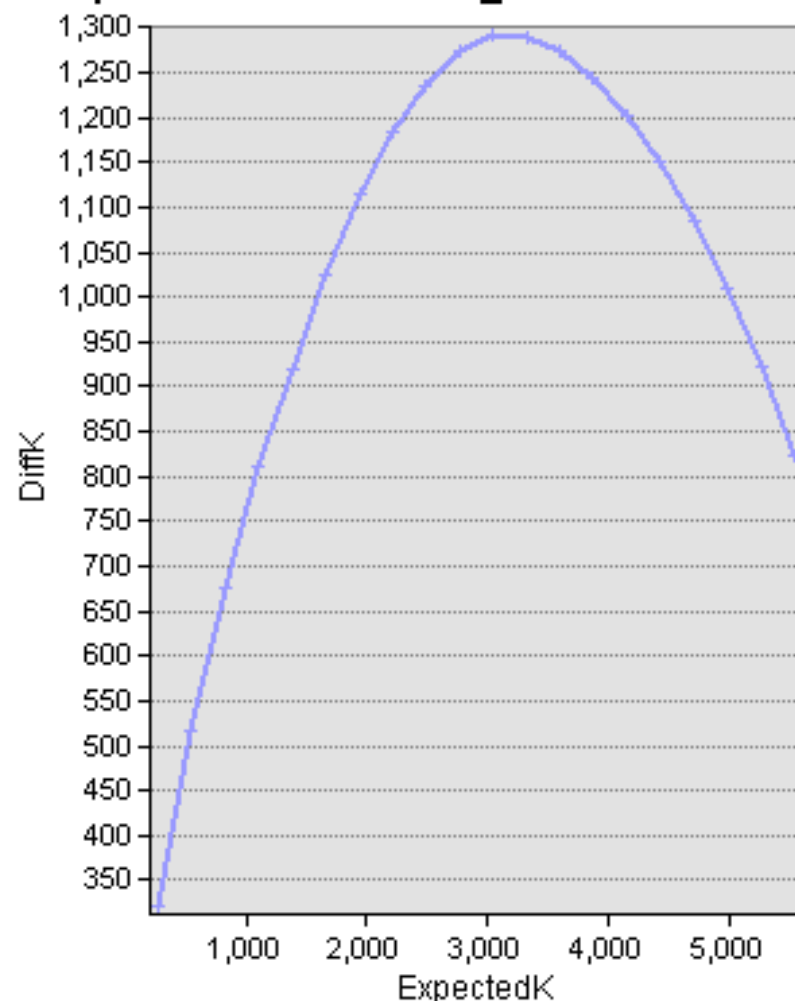
Vertical Line

Add

Load Template

[About graphs](#)

Graph of homicides0509\_MultiDistances



+	321.355
+	517.346
+	676.455
+	809.884
+	920.346
+	1,024.454
+	1,115.651
+	1,184.98
+	1,236.277
+	1,273.693
+	1,292.236
+	1,288.764
+	1,273.548
+	1,244.15
+	1,203.171
+	1,150.048
+	1,084.924
+	1,009.375
+	922.269
+	823.316

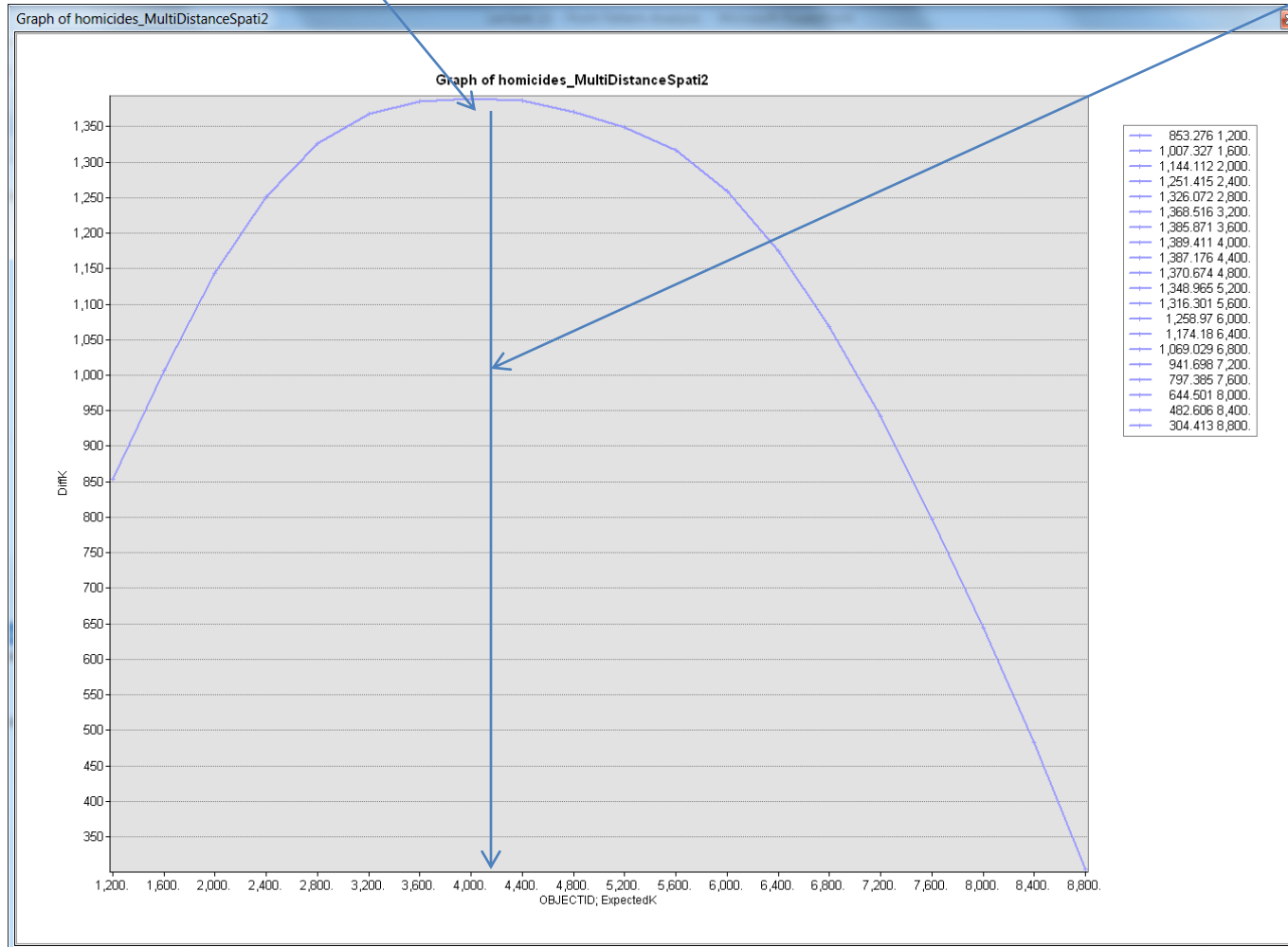
&lt; Back

Next &gt;

Cancel

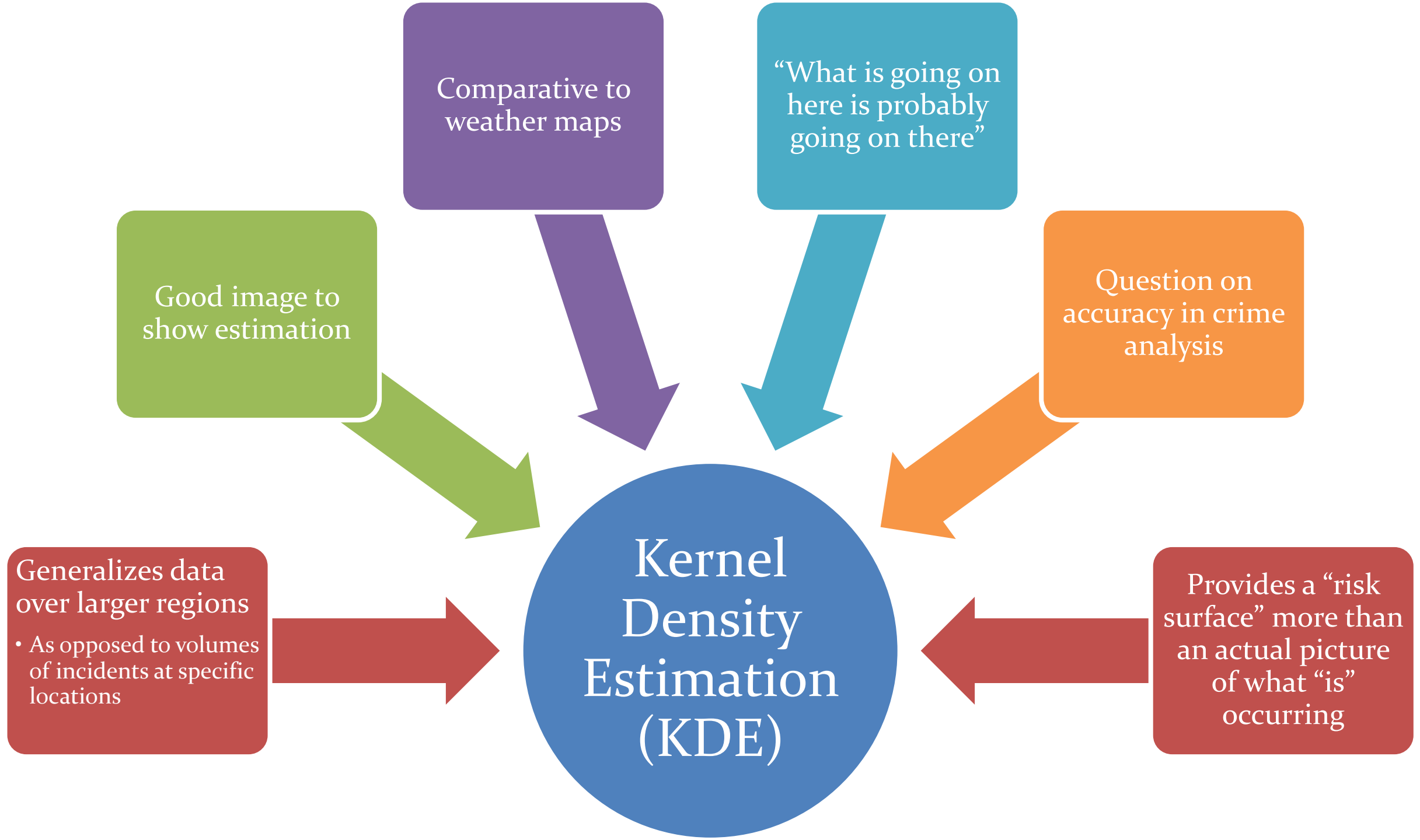


Look for the peak for most pronounced clustering  
After the peak, we get less clustering



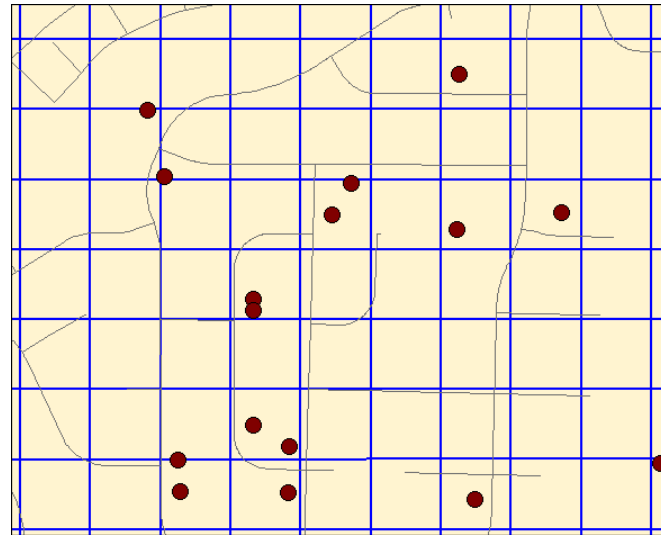
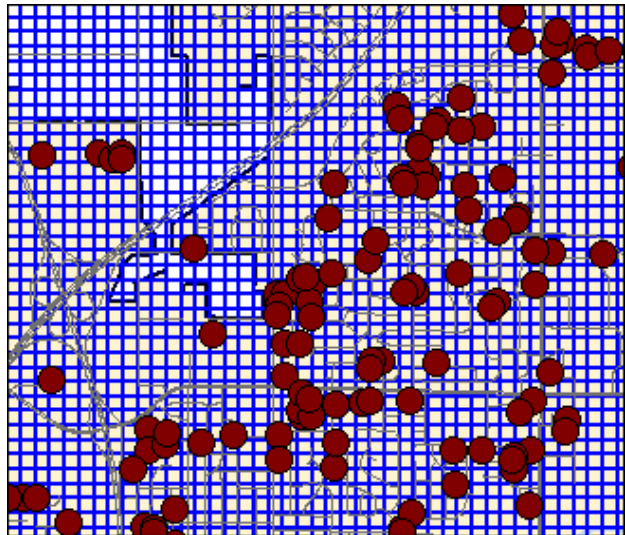
# Kernel Density Estimation (KDE)

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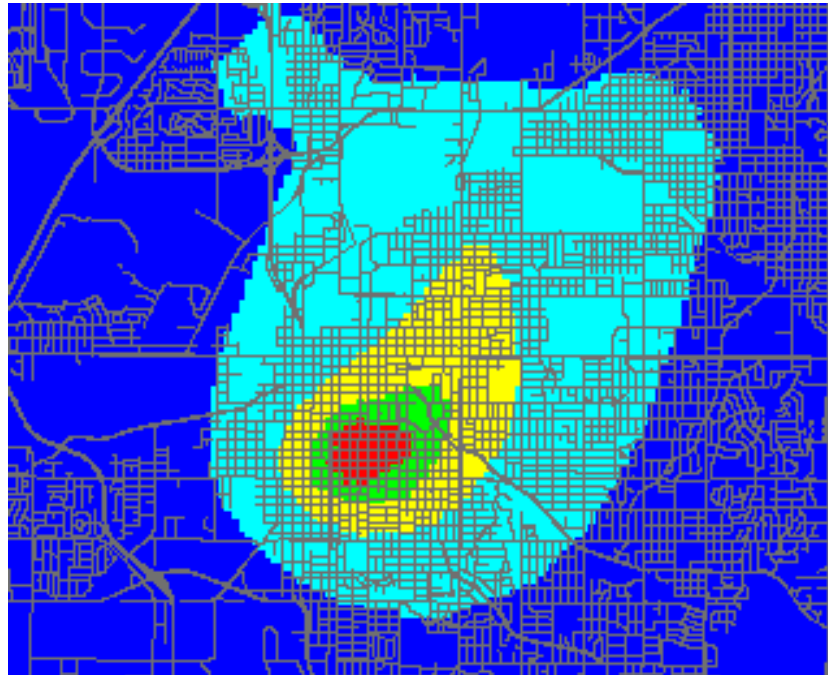
# How KDE Works

- Every point on the map has a density estimate based on its proximity to crime incidents
- Done by overlaying a grid on top of the map
  - Calculates the density estimate for the centerpoint of each grid cell
  - Number of cells in the grid is defined by the user



# How KDE Works

- In a map, the grid cells are color-coded based on the density
  - Often reds for hottest area and blues for coolest
  - When making comparisons standard deviation is typically used



Analyst must use  
experience & judgment

Single versus dual kernel  
density estimates

- Single is usually used in crime analysis
- Dual can help normalize data for population or other risk factors or calculate change from one time to the next

Many parameters  
involved

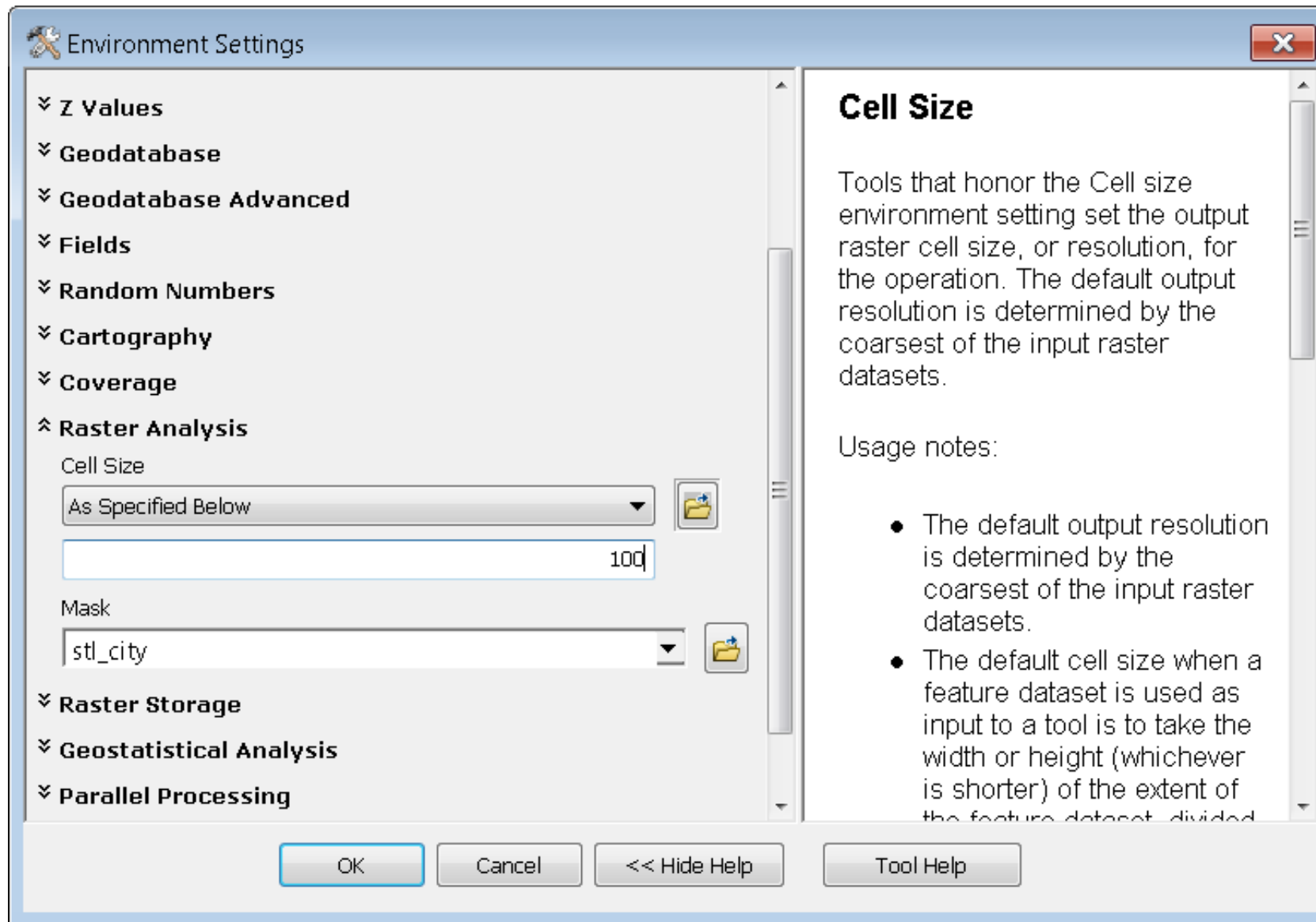
Bandwidth

- Refers to the size of the cone; specified by user

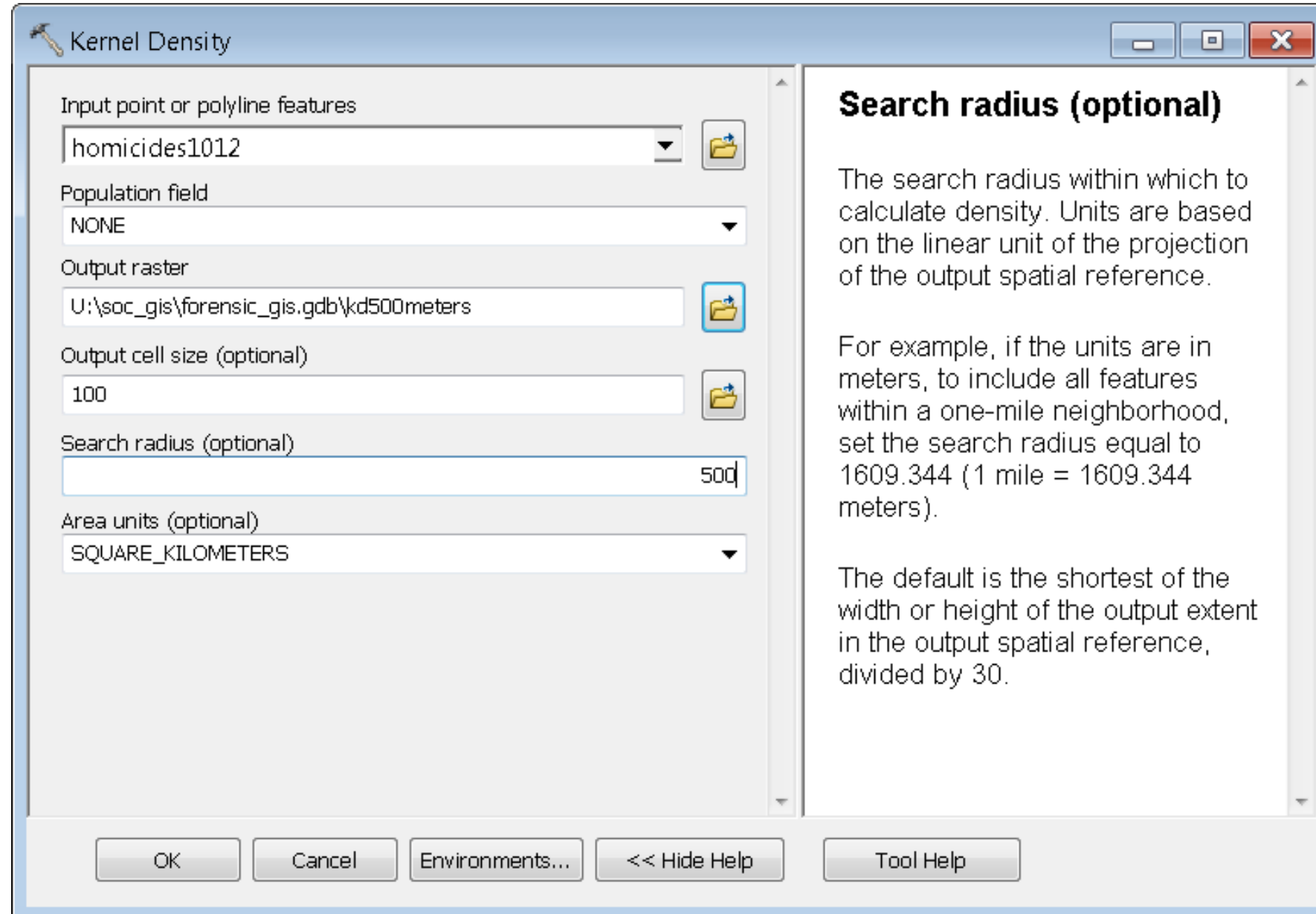
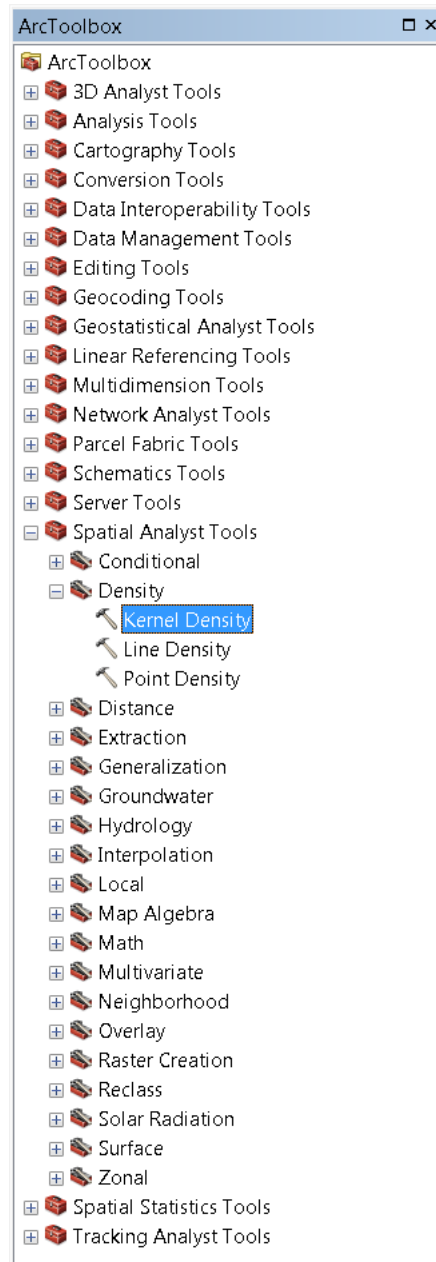
KDE  
Parameters

```
graph TD; A[Analyst must use experience & judgment] --> E((KDE Parameters)); B[Single versus dual kernel density estimates] --> E; C[Many parameters involved] --> E; D[Bandwidth] --> E;
```

1. Geoprocessing-> Environmental Setting->Raster Analysis->select “As specified Below  
->Mask should be the city of Saint Louis. I will use 100 meters for the grid cells.

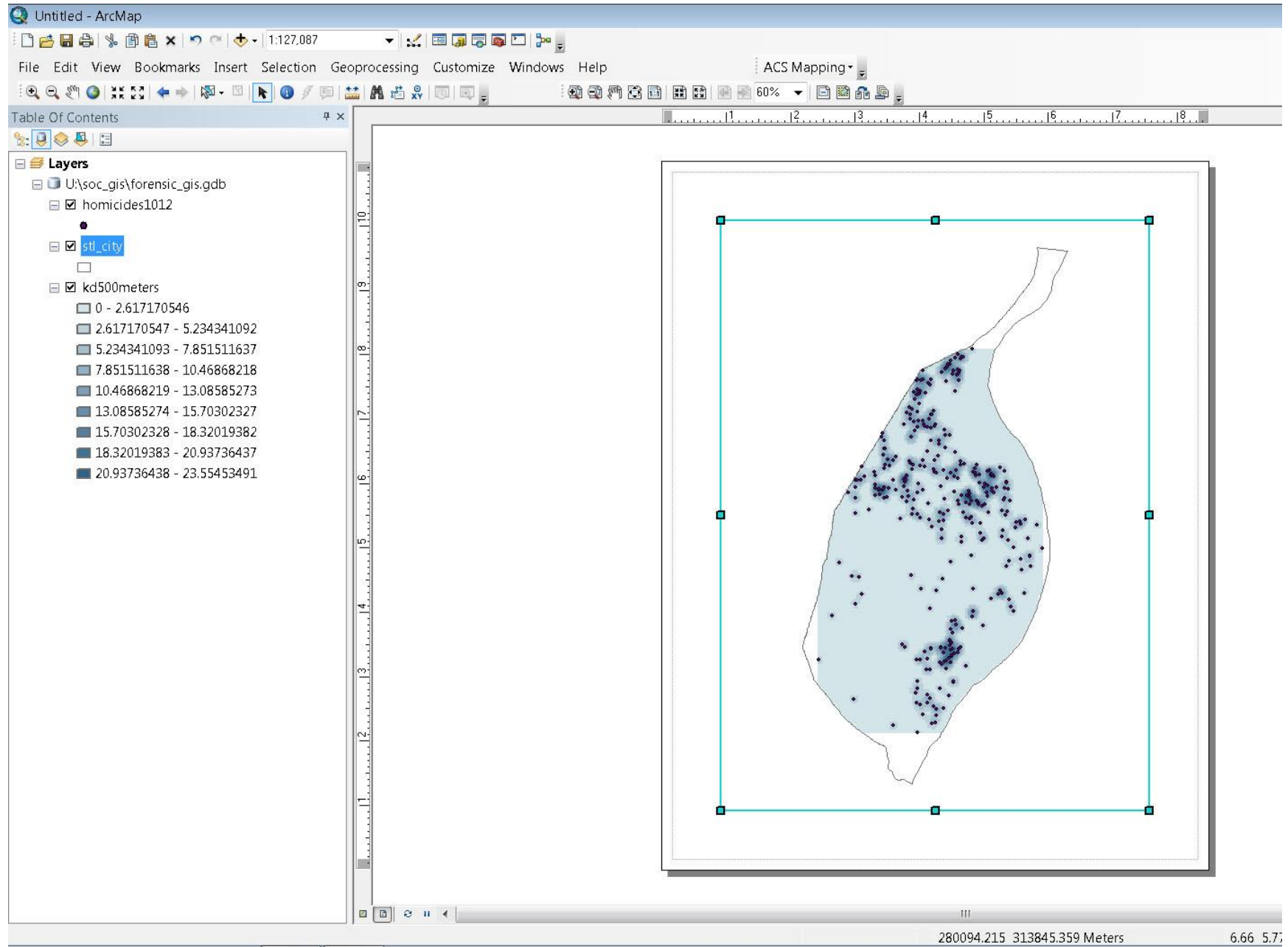


## 2. ArcToolbox->Spatial Analyst Tools->Density-> Kernel Density

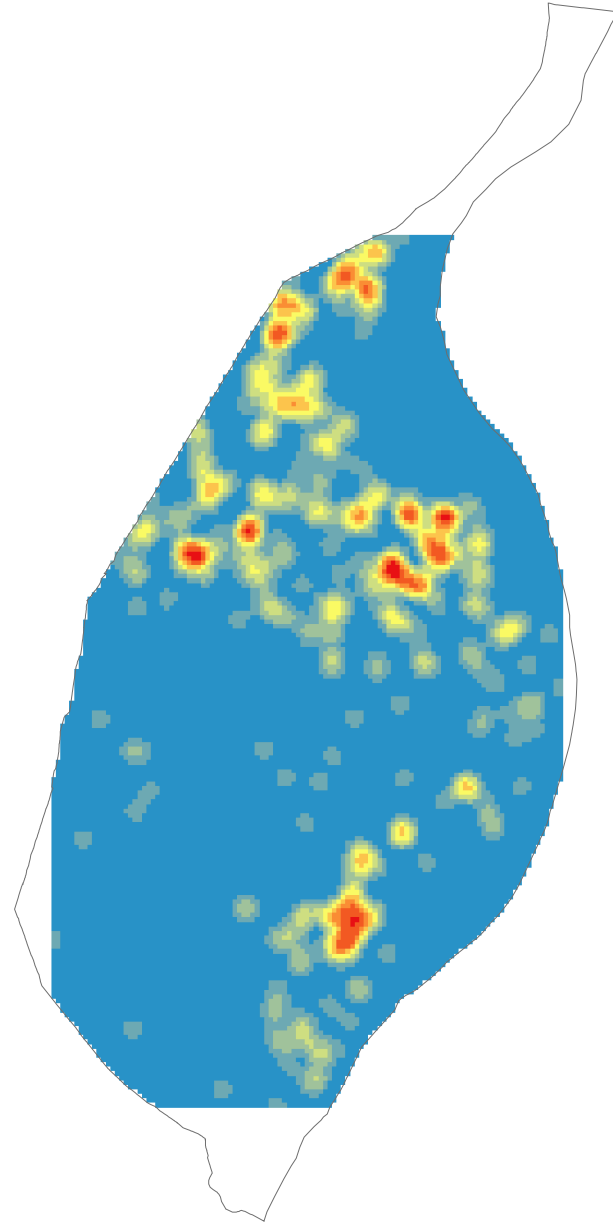
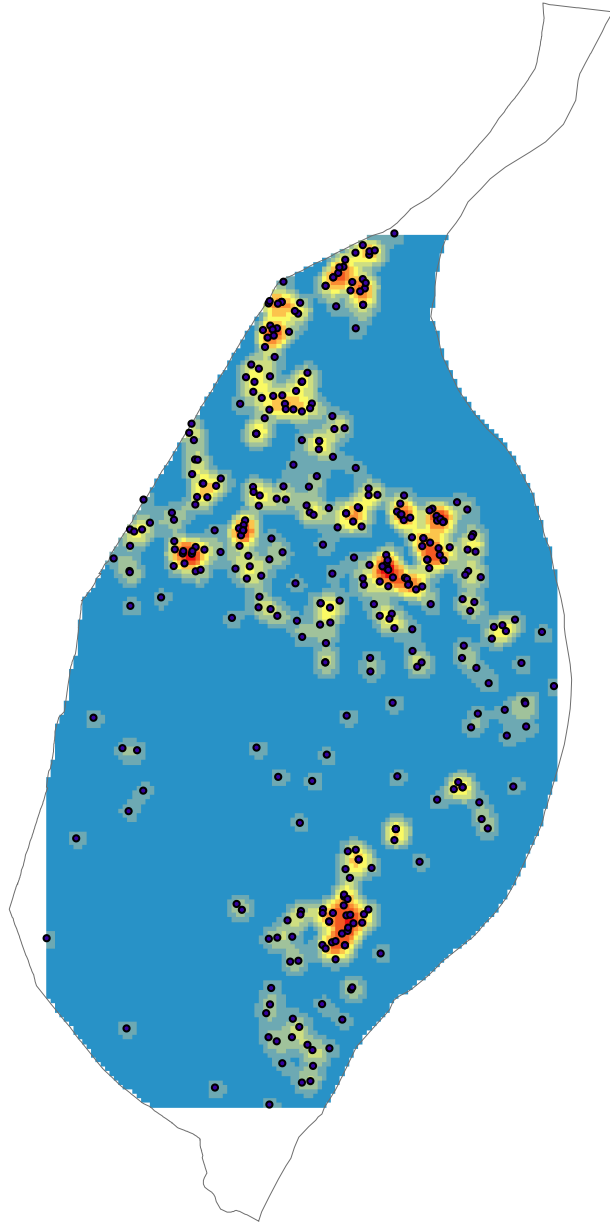




3. You should have a map that looks like this map.



4. Let's change the color ramp and remove the points.



# General G Statistic

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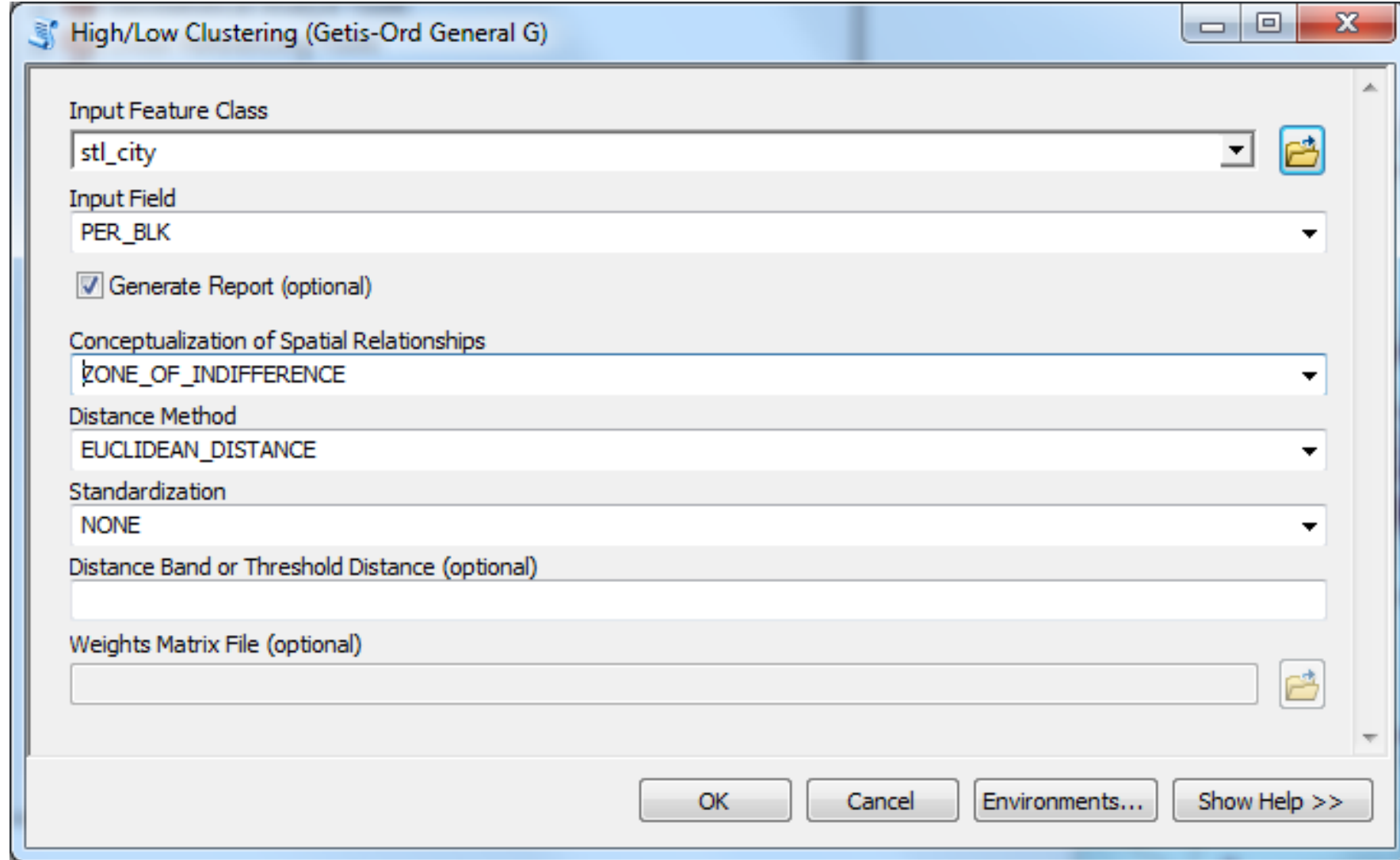
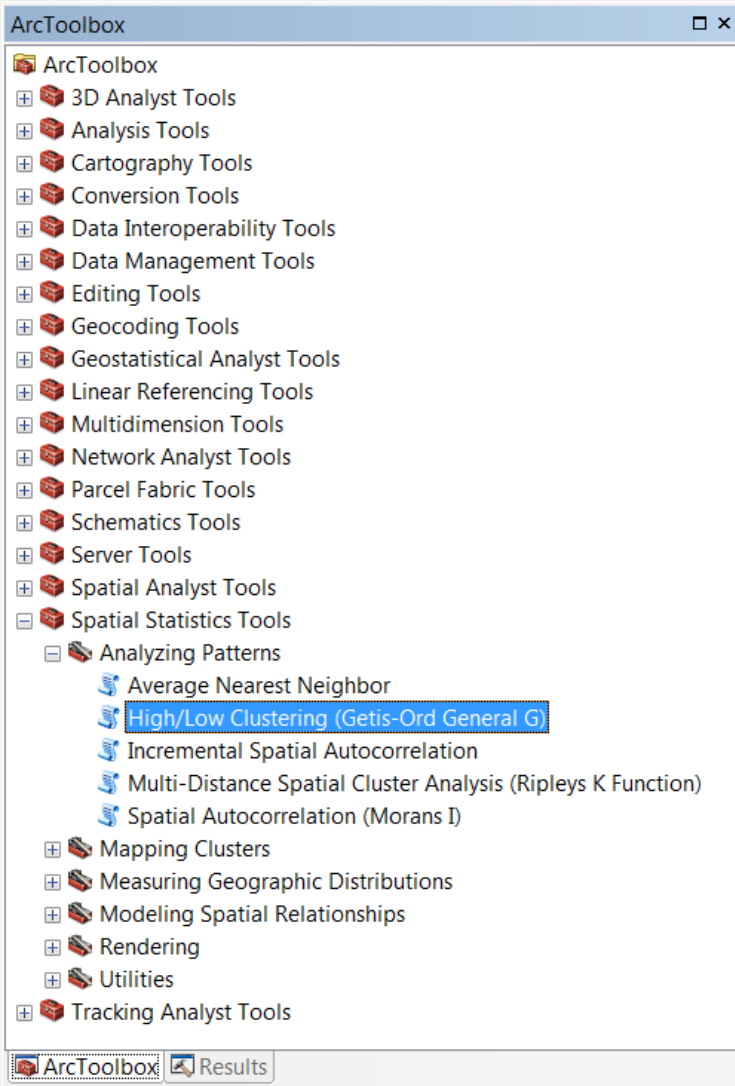
Identifying the clustering of values

# General G Statistic – Part 1

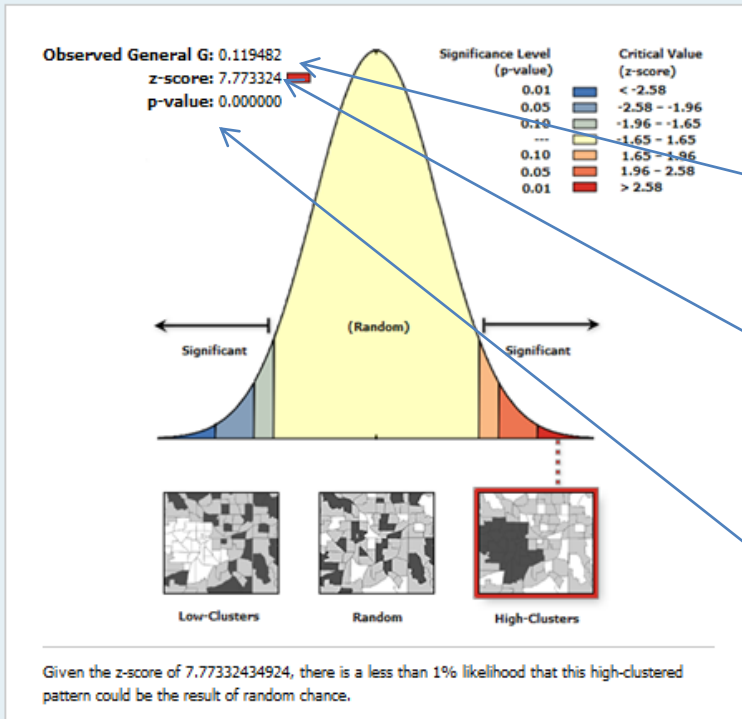
- The General G (aka Getis-Ord General G) statistic looks at the similarity of the values associated with the features within a critical distance of each other. The value is excluded in the calculation – only neighbors
- The General G measures concentrations of high and low values over the entire study area.
- General G = Global Moran's I
- The input feature should have an attribute demonstrating some characteristic or value associated with the location.

# General G Statistic – Part 2

- The results will determine if the values are clustered, not the locations.
- It will distinguish between clustering of high values and low values.
- $H_0$ =Data are randomly distributed across the study area.
- $H_1$  = There is clustering.



## High-Low Clustering Report



## Important Points for observation

- The dataset returned an index of .119482
- This tells us that there is little clustering in the features
- The z-score is 7.773324 with a significance level of 0.000. This score does gives us the confidence level of rejecting the null hypothesis.

### General G Summary

Observed General G:	0.119482
Expected General G:	0.085662
Variance:	0.000019
z-score:	7.773324
p-value:	0.000000

### Dataset Information

Input Feature Class:	stl_city
Input Field:	PER_BLK
Conceptualization:	ZONE_OF_INDIFFERENCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	2189.7355 Meters
Weights Matrix File:	None
Selection Set:	False

Gi\*

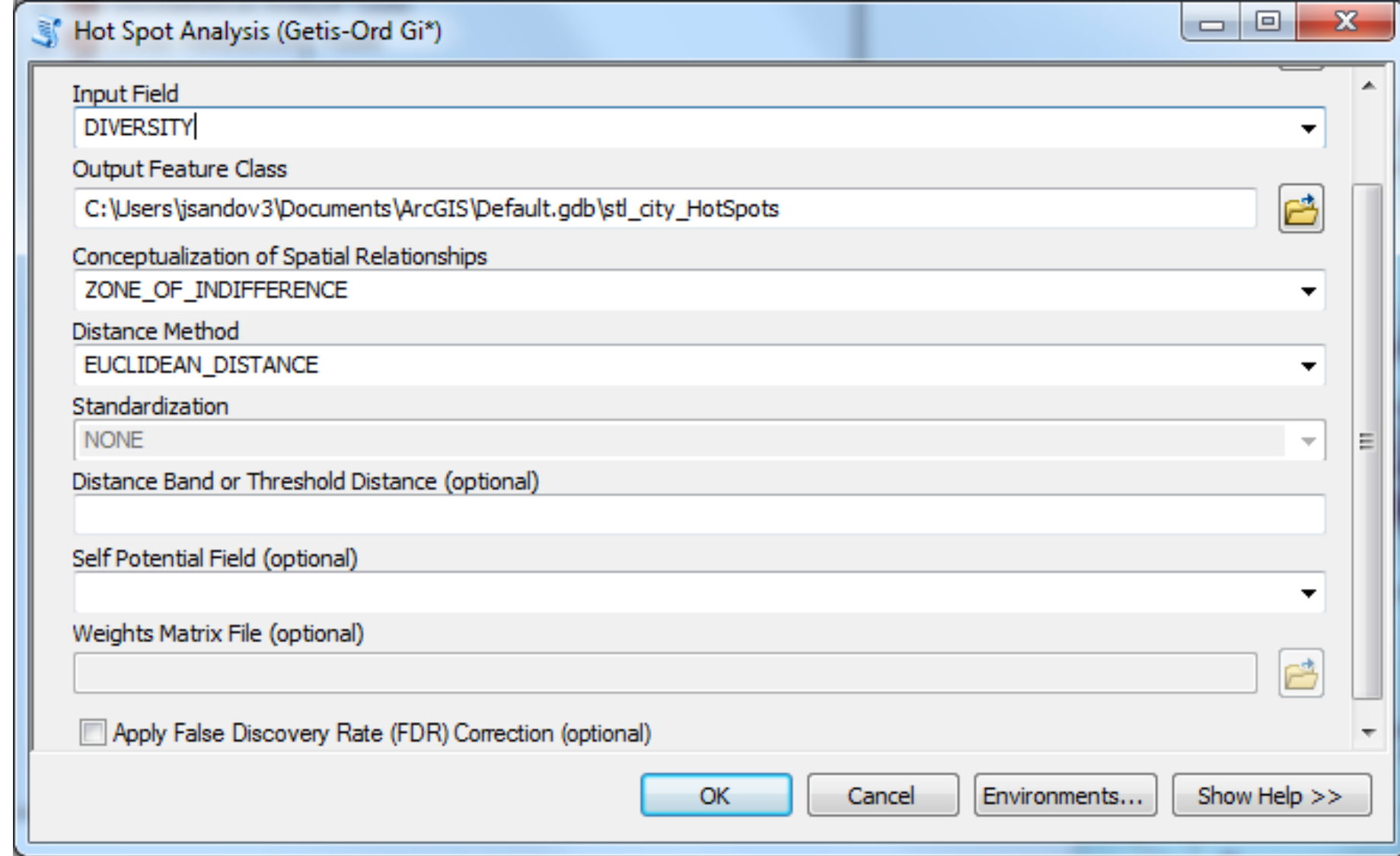
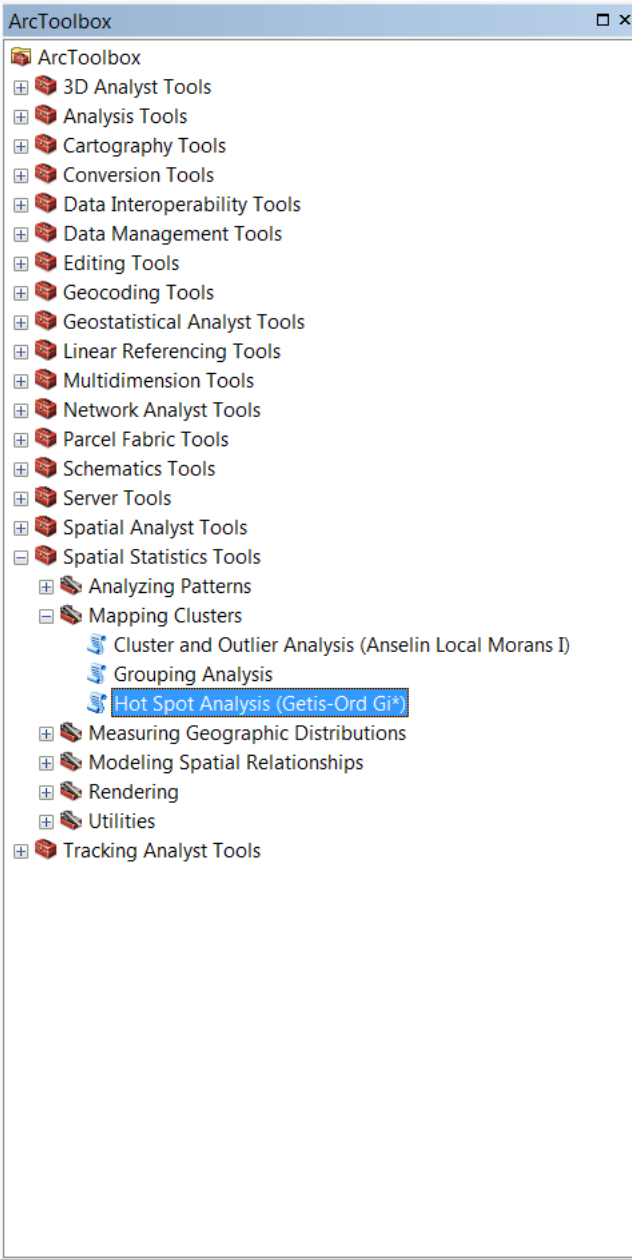
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Hot-Spot Analysis



# $G_i^*$

- $G_i^*$  (aka as the  $G_i$  statistic) uses both the location and the value in the pattern calculations. (i.e., more information)
- $G_i^*$  is used to see the effect of the value field on the clustering.
- The user must select distance or neighbors.
- $G_i^*$  is similar to LISA

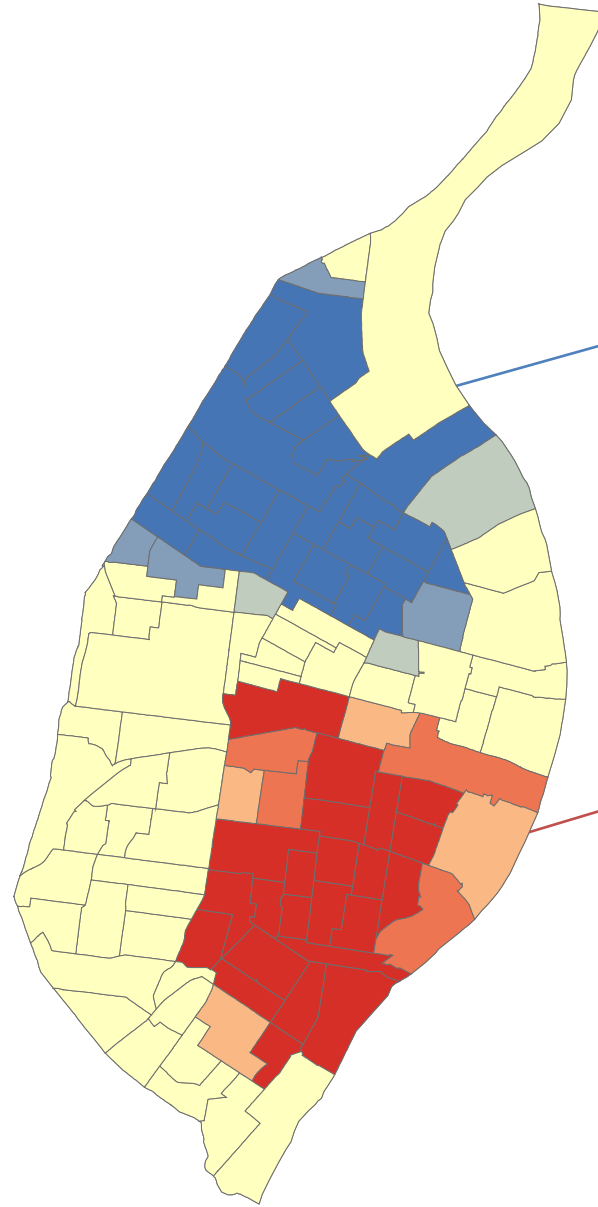


### Legend

#### stl\_city\_HotSpots

#### Gi\_Bin

- Cold Spot - 99% Confidence
- Cold Spot - 95% Confidence
- Cold Spot - 90% Confidence
- Not Significant
- Hot Spot - 90% Confidence
- Hot Spot - 95% Confidence
- Hot Spot - 99% Confidence
- stl\_city



The blue areas  
represent clusters  
of low values

The red areas  
represent clusters  
of high values

OBJECTID *	Shape *	SOURCE_ID	DIVERSITY	Shape_Length	Shape_Area	GiZScore ZOI 2189	GiPValue ZOI 2189	Gi_Bin ZOI 2189
1	Polygon	1	0.38	4414.988191	910998.865291	-0.603176	0.546392	0
2	Polygon	2	0.3	5588.341372	1676106.950701	-0.836114	0.403091	0
3	Polygon	3	0.42	4921.136188	1121010.777144	-0.580329	0.569133	0
4	Polygon	4	0.58	6815.936063	1939468.736939	0.367454	0.71328	0
5	Polygon	5	0.66	7487.708625	1162116.258634	1.269412	0.204294	0
6	Polygon	6	0.75	3906.691794	831167.208584	0.243179	0.807867	0
7	Polygon	7	0.29	4563.260523	957507.968608	-0.61976	0.535416	0
8	Polygon	8	0.55	3533.487207	706853.680582	-2.018662	0.043522	-2
9	Polygon	9	0.21	5516.324536	1195404.478612	-1.967682	0.049105	-2
10	Polygon	10	0.12	4210.86845	956129.855259	-3.104829	0.001904	-3
11	Polygon	11	0.13	4663.067288	1064700.001989	-2.837626	0.004545	-3
12	Polygon	12	0.12	4819.317517	1017014.684177	-3.468963	0.000522	-3
13	Polygon	13	0.15	4744.724148	1106265.984888	-4.325905	0.000015	-3
14	Polygon	14	0.18	4575.541138	1064254.682802	-4.010201	0.000061	-3
15	Polygon	15	0.11	4779.71489	854742.901107	-3.212202	0.001317	-3
16	Polygon	16	0.15	4842.663499	1238223.189551	-4.549113	0.000005	-3
17	Polygon	17	0.12	3957.156068	655316.033691	-3.493338	0.000477	-3
18	Polygon	18	0.11	5608.171999	1587503.95767	-3.040845	0.002359	-3
19	Polygon	19	0.15	4397.149981	1084963.927742	-3.493067	0.000478	-3
20	Polygon	20	0.11	4112.381738	911653.601148	-3.50506	0.000457	-3
21	Polygon	21	0.06	5237.164963	1164873.072028	-4.011125	0.00006	-3
22	Polygon	22	0.21	8515.906679	3214040.746895	-3.149188	0.001637	-3
23	Polygon	23	0.16	4775.556512	827201.840957	-2.1675	0.030197	-2
24	Polygon	24	0.24	3652.334986	750387.253438	-1.41605	0.156761	0
25	Polygon	25	0.11	9047.384795	3151770.078188	-2.724892	0.006432	-3
26	Polygon	26	0.26	8342.14083	4043350.956623	-1.707945	0.087646	-1
27	Polygon	27	0.15	5104.659371	993870.611148	-4.528333	0.000006	-3
28	Polygon	28	0.17	4277.247926	777647.756911	-4.242388	0.000022	-3
29	Polygon	29	0.13	4271.38562	938175.793142	-4.110302	0.00004	-3
30	Polygon	30	0.14	3923.110437	885105.582724	-4.187916	0.000028	-3
31	Polygon	31	0.14	5034.345313	1246970.64096	-3.946875	0.000079	-3

Here is your  
value

Here is the  
score

Here is the  
significance

Here is your  
cluster

# Lab

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