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# Zonation of groundwater quality using spatially constrained multivariate clustering

**Fahad Alahmadi**



# Presentation Outline

- Introduction
- Study area description
- Data Set
  - General description, descriptive statistics, histogram, boxplot
- Methodology used
  - Scenarios formulation
- Results & Discussions
- Conclusion



# Introduction

- Urban groundwater (GW) is usually vulnerable to pollution.
- The main sources of GW quality degradation are:
  - Anthropogenic activities
  - Natural processes
  - Atmospheric input
- Subdividing the region into zones based on GW quality is usually undertaken.
- Recently, several methods are used, such as Genetic Algorithm, Model-Based Approach, Bayesian Approach, cluster analysis ... etc.
- In this study, spatially constrained multivariate clustering method (SCMC) is used to subdivide Madina city (West KSA) into several zones based on six GW chemicals.



# Introduction (cluster analysis overview)

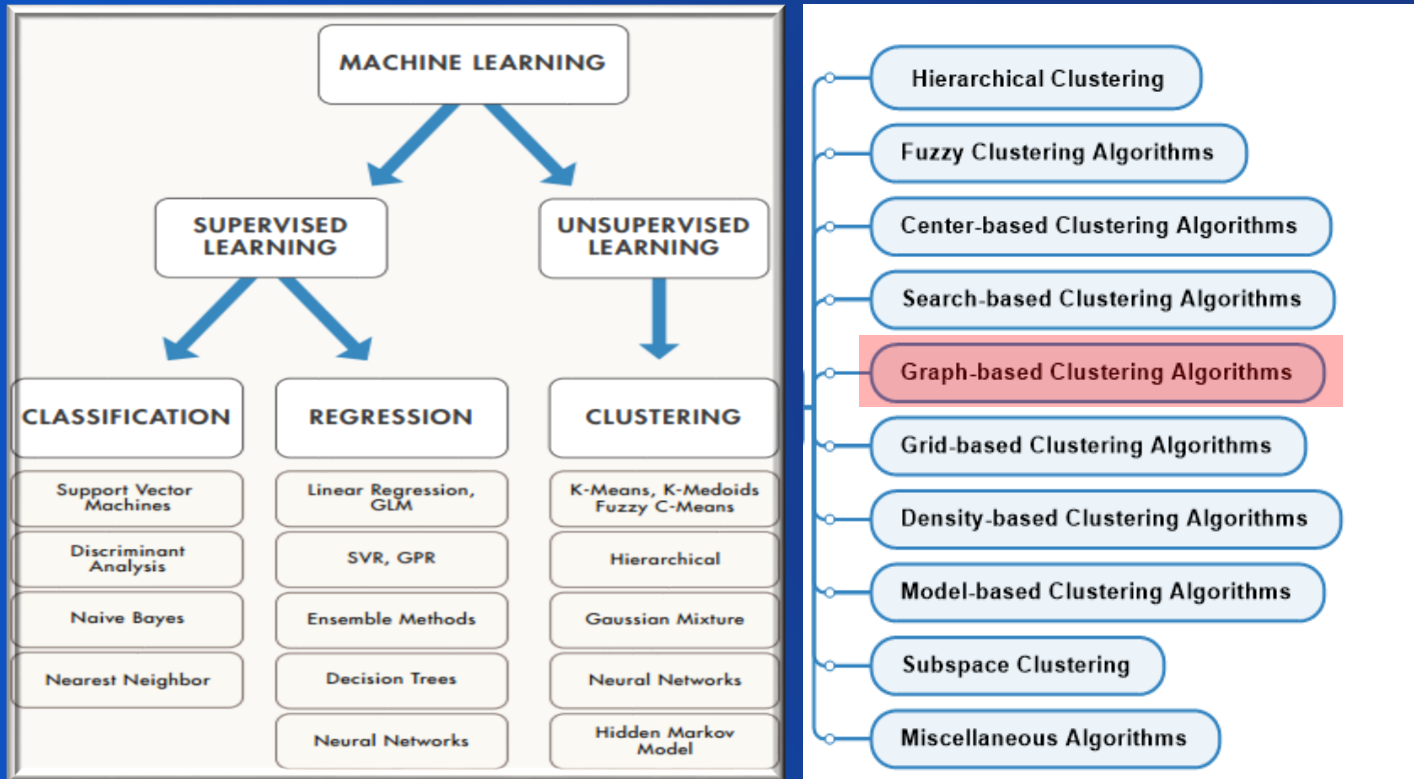
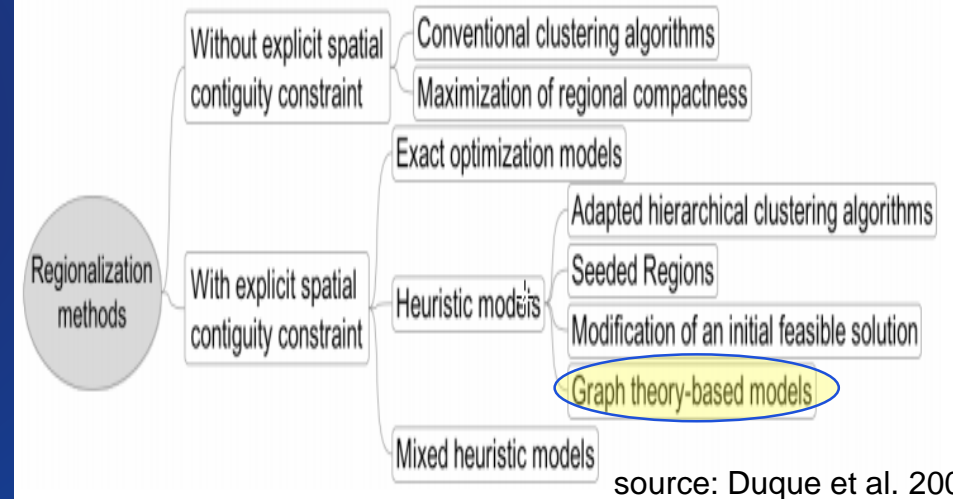


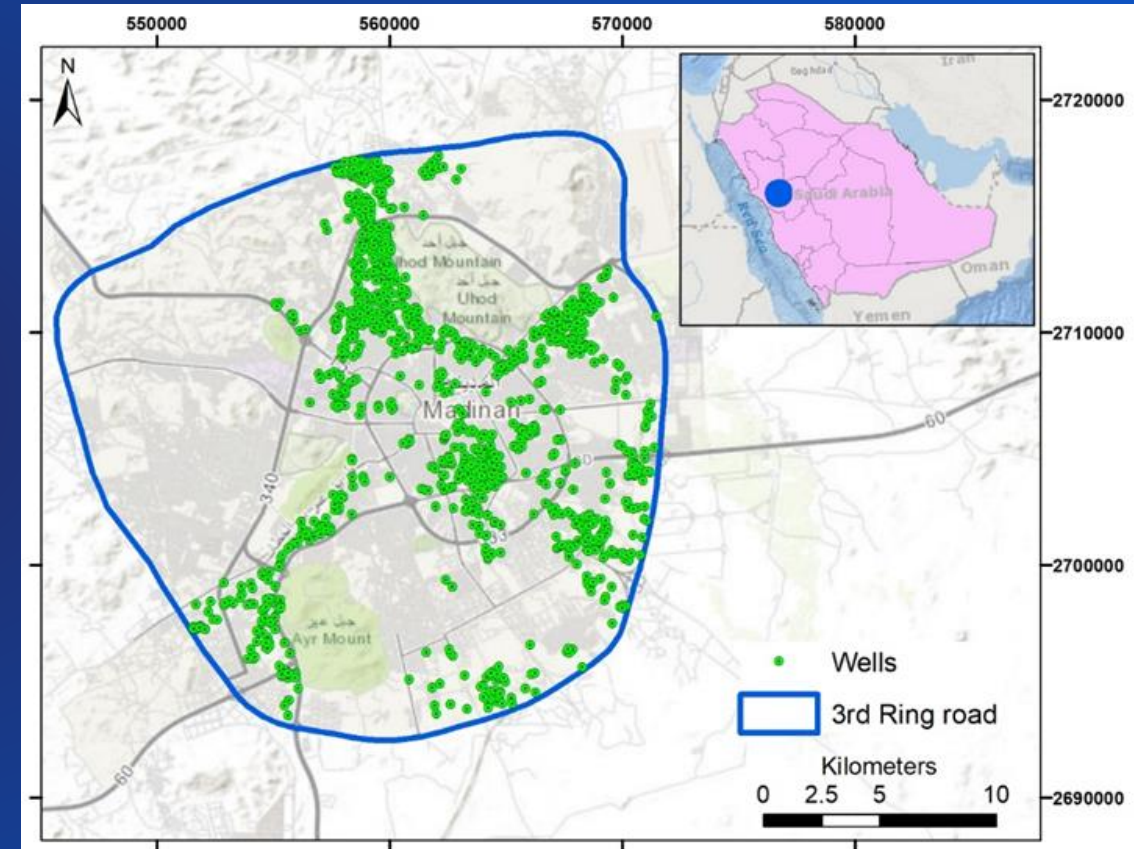
Figure 1. Taxonomy of methods for solving regionalization problems

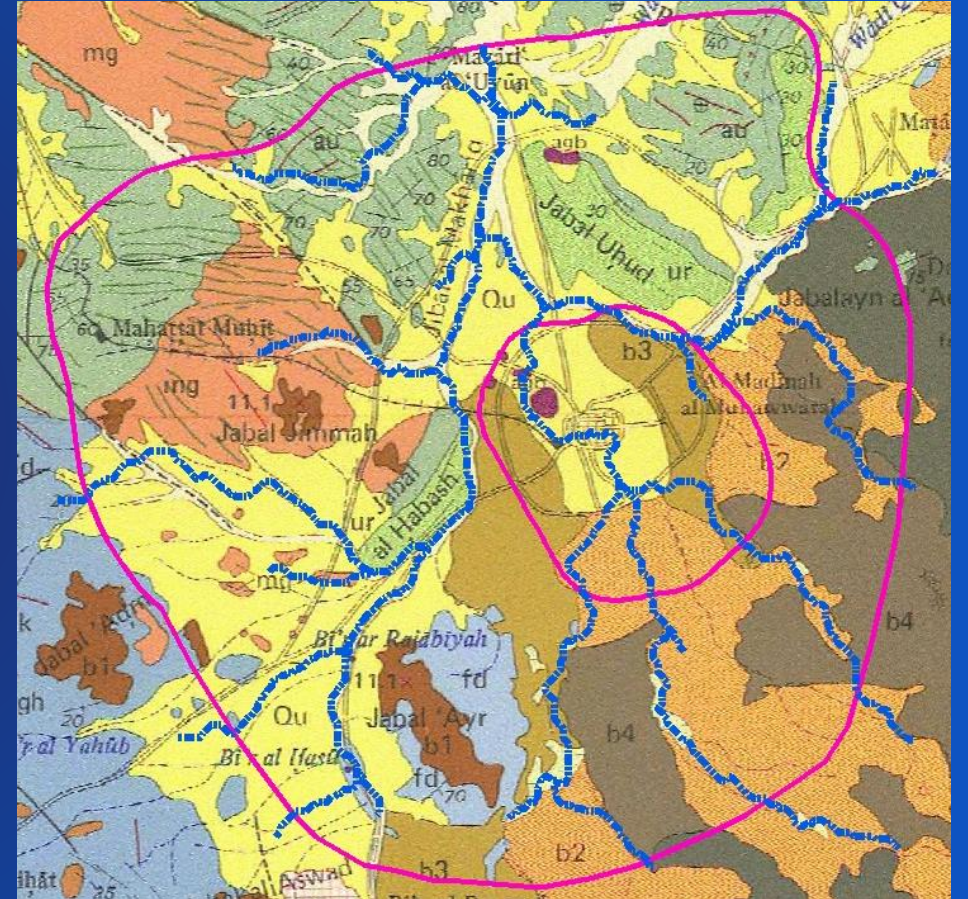


source: Duque et al. 2007

# Study area description (General Location)

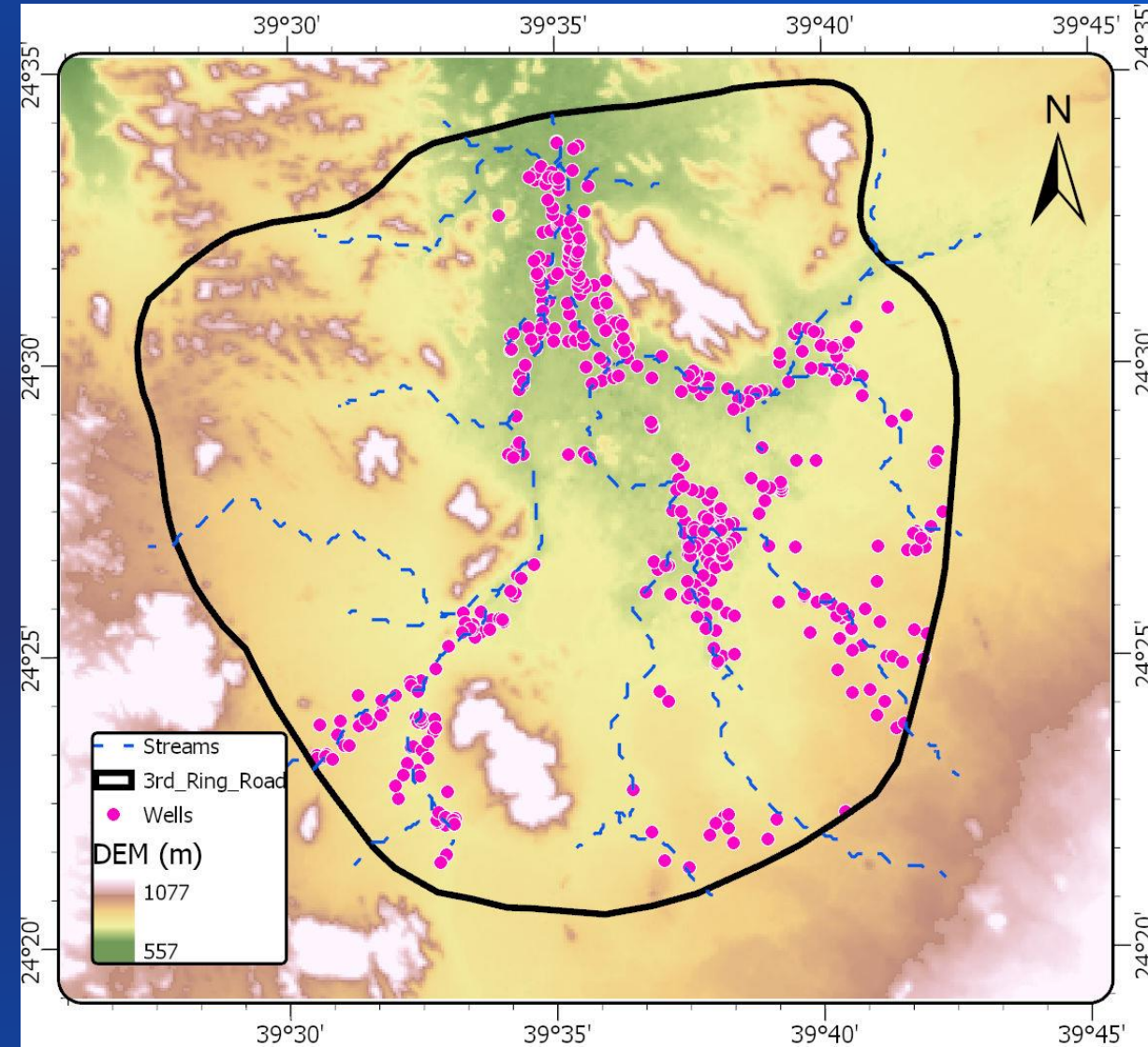
- ❖ Madinah city (West KSA) is selected.
- ❖ The population about 1.25 million + 10 million annual visitors.
- ❖ covering an area of 522 km<sup>2</sup>.
- ❖ In this study, The wells inside the 3rd ring road is selected for analysis.
- ❖ These wells are located in private farms.



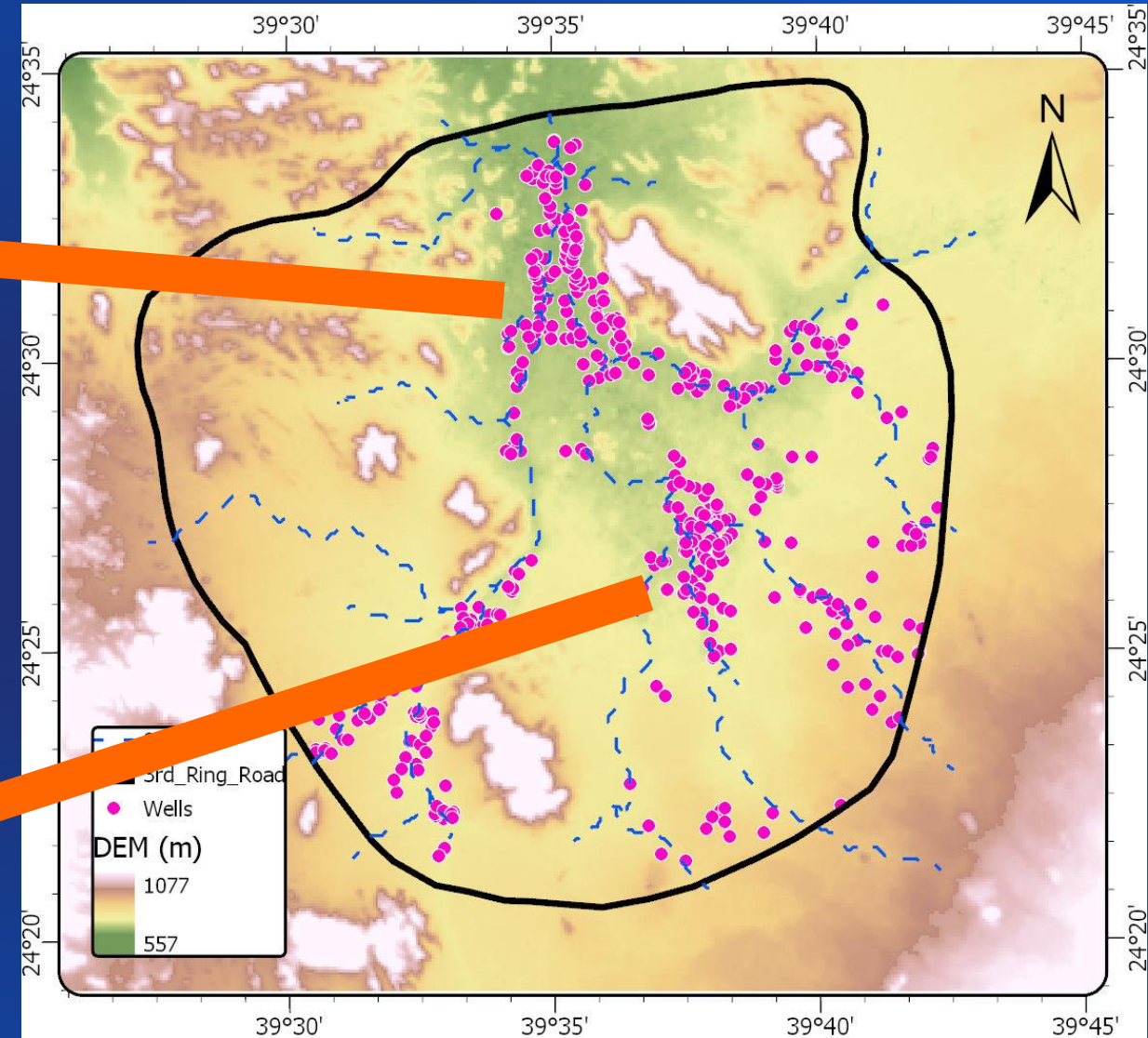
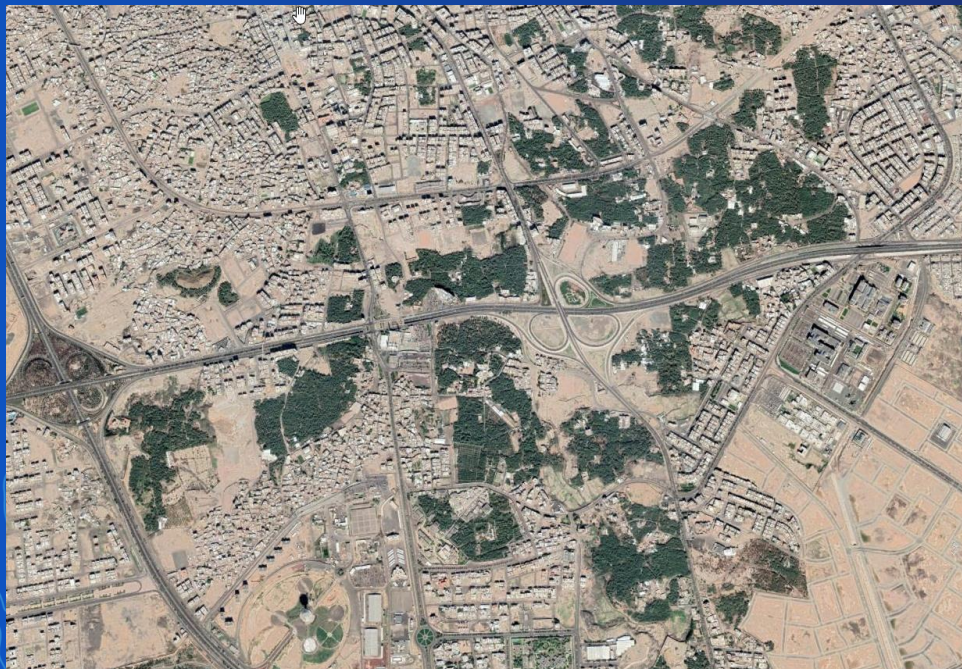


# Study area description (Topography)

- The elevation ranges from 570 m (a.m.s.l.) up to 1,100 m.
- Strong relationship between wells location and watercourses (ephemeral streams)



# Study area description (Wells location)

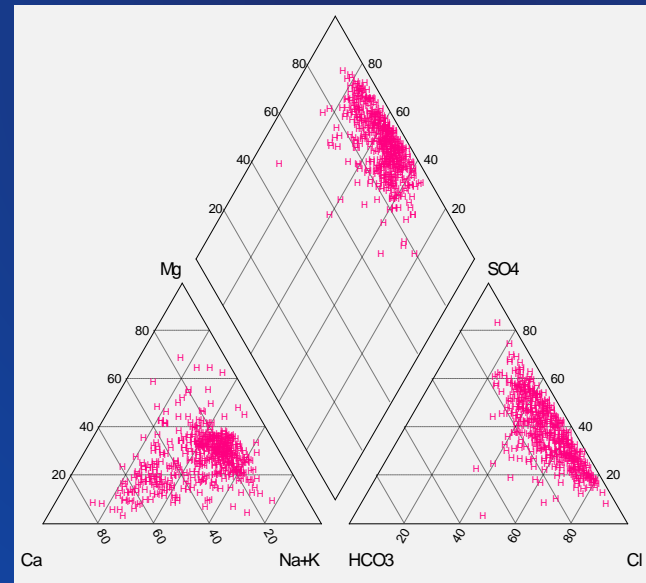
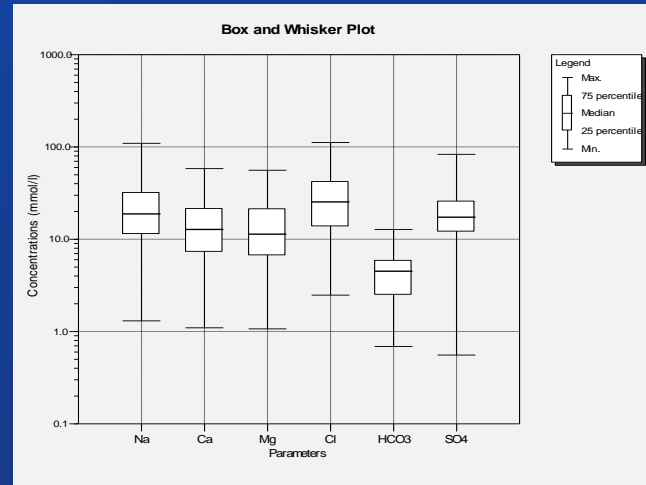
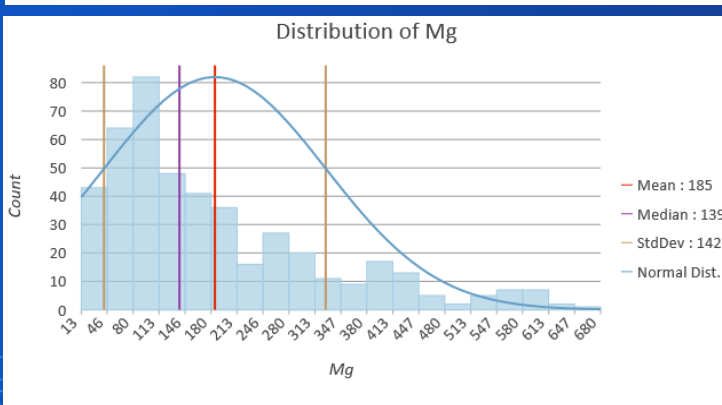
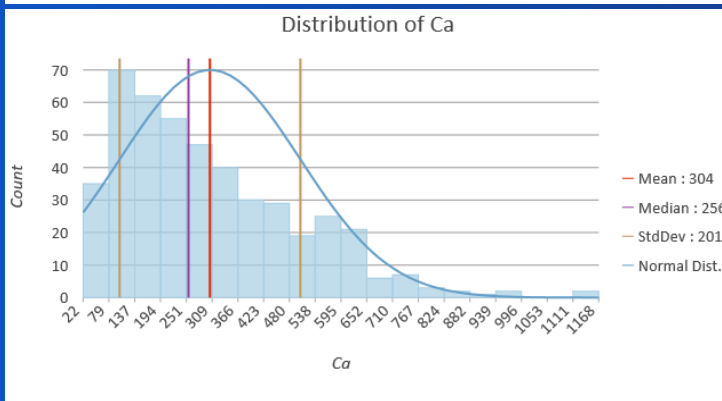
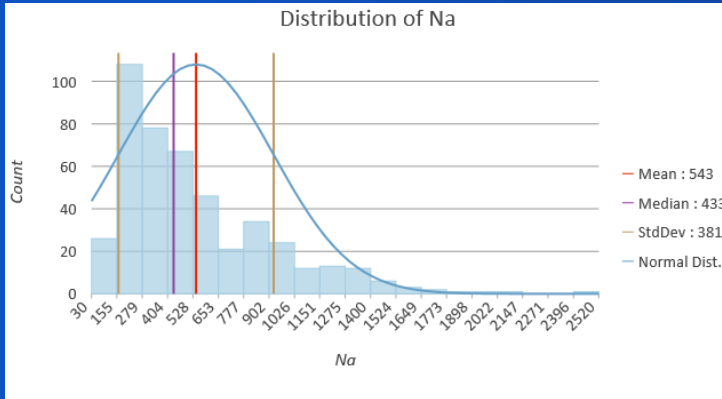


# Data set

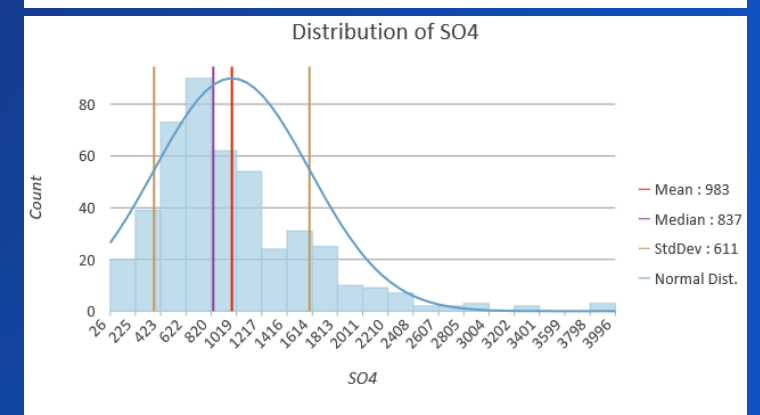
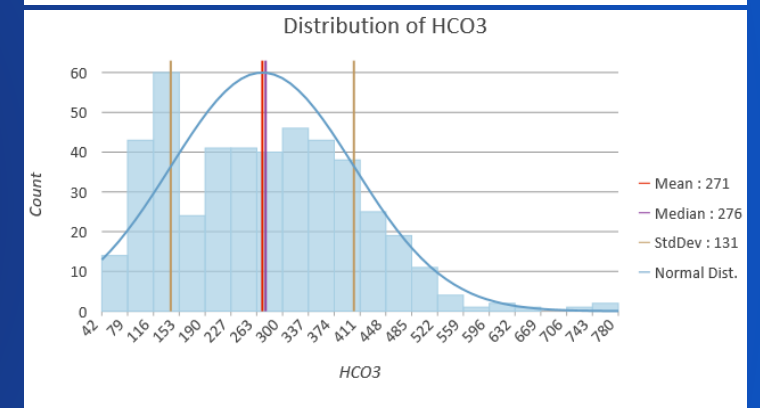
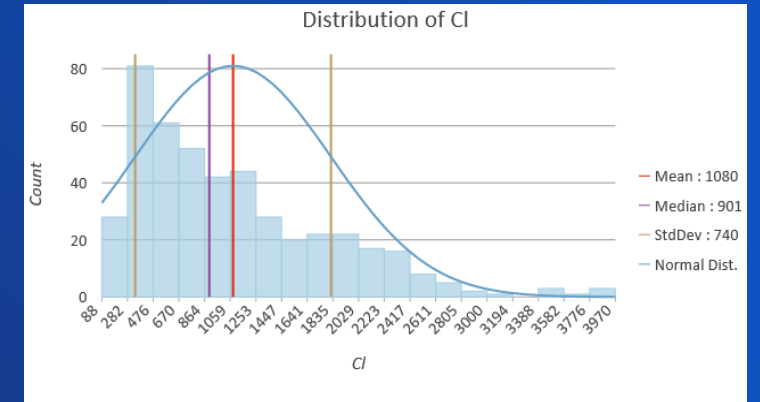
- 456 private farms inside the 3<sup>rd</sup> ring road are visited.
- From each farm, one well location is registered using GPS.
- Water samples from the wells are collected and taken to the laboratory for analysis (pH, TDS, EC, hardness, turbidity, alkalinity, color, ions (*cations and anions*)).
- Three cations (Na, Ca, Mg) and three anions (Cl, HCO<sub>3</sub>, SO<sub>4</sub>) are selected for cluster analysis.

	Na	Ca	Mg	Cl	HCO <sub>3</sub>	SO <sub>4</sub>
Min.	30	22	13	88	42	26
Max.	2520	1168	680	3970	780	3996
Avg.	543	304	185	1080	271	982
Media	433	256	139	901	276	836
STD	381	201	142	740	131	611

# Data set

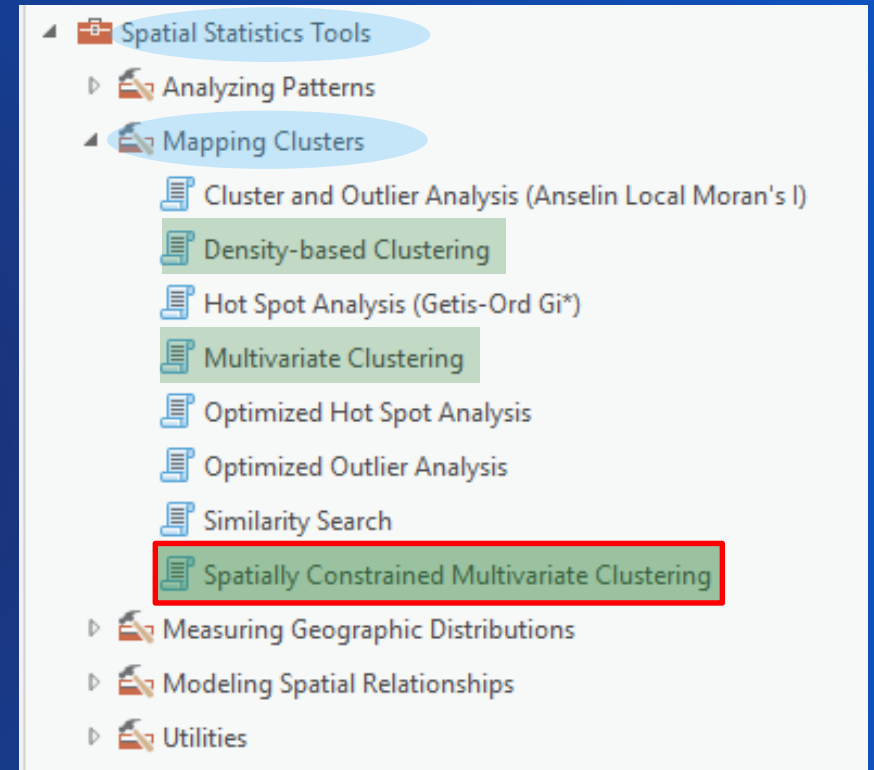


Piper plots (Trilinear diagram)



# Methodology (clustering in ArcGIS Pro)

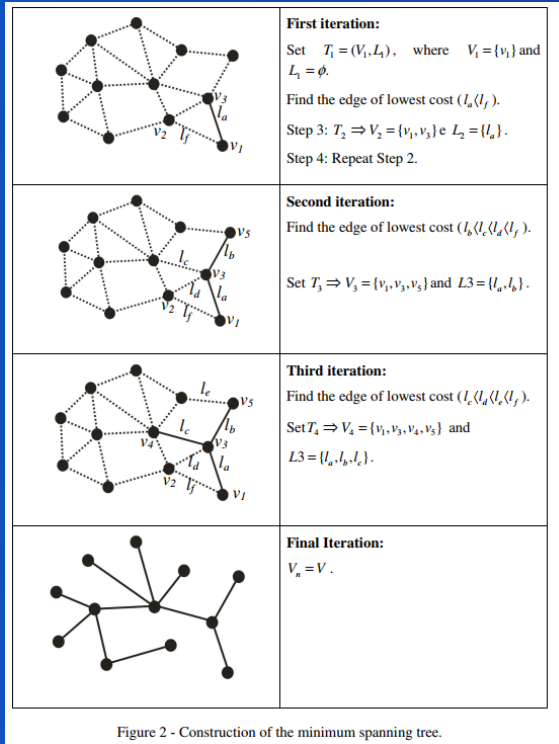
- The Three new cluster methods in ArcGIS Pro are:
  - density-based clustering,
  - multivariate clustering and
  - **spatially constrained multivariate clustering (SCMC).**



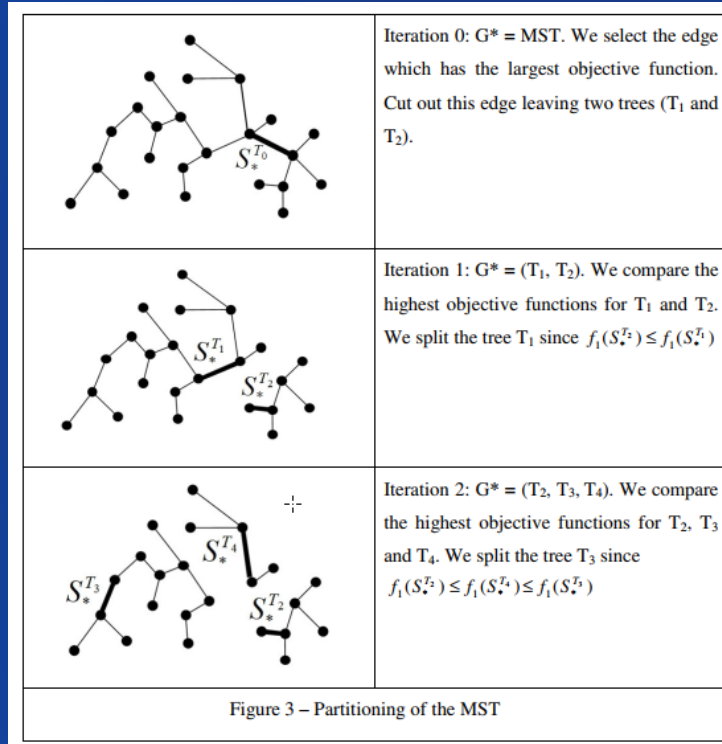
SCMS is the process of grouping of the observations based on the **attributes similarity** and **location similarity** using multiple objective optimization.  
maximizing within-group similarity

# Methodology (theoretical background)

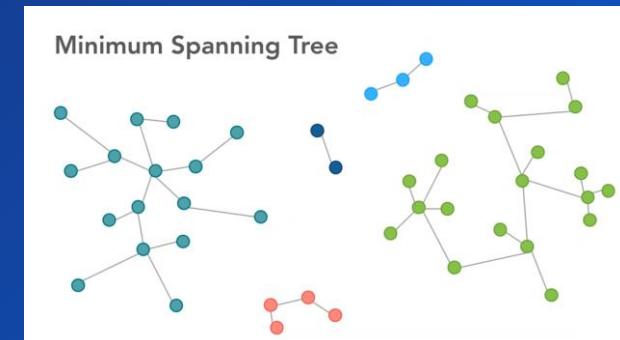
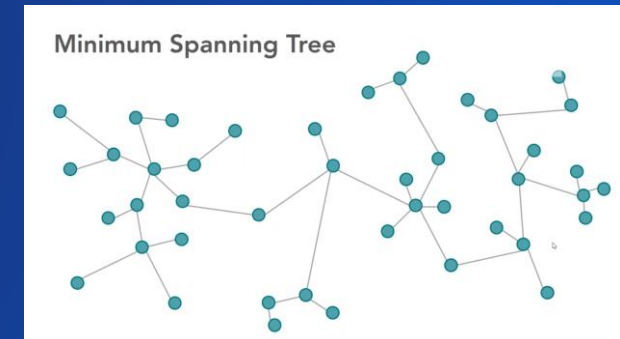
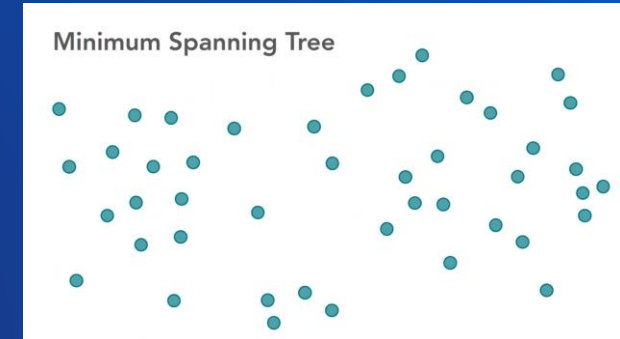
- In ArcGIS Pro, spatially constrained multivariate clustering tool uses Spatial K'cluster Analysis by Tree Edge Removal (SKATER) algorithm which is based on minimum spanning tree (MST) method



construct the network graph by connecting the contiguous nodes with lowest cost.



find the shortest path that minimizes the sum of dissimilarity (or maximizing the sum of similarities) – minimum spanning tree



# Methodology

- Spatially constrained Multivariate Clustering (SCMC) methods in ArcGIS Pro has two main groups of input parameters:
- **Three required input:**
  - Input layer
  - The name of output layer
  - Selected attributes for analysis
- **Five optional input:**
  - **Cluster size constraints** (None, No. of features, Attribute value)
  - Number of clusters
  - **Spatial constraints**
  - Permutations Membership probabilities
  - Output table for evaluating number of clusters

The screenshot displays the 'Geoprocessing' window for the tool 'Spatially Constrained Multivariate Clustering'. The 'Parameters' tab is active, showing the following settings:

- Input Features:** Madinah\_GW
- Output Features:** SpatiallyConstrainedMCA\_3
- Analysis Fields:** A list of chemical parameters with checkboxes. The checked parameters are Na, Ca, Mg, HCO3, SO4, and Cl. The unchecked parameters are Alkalinity, PH, Fe, F, and NO3.
- Cluster Size Constraints:** A dropdown menu set to 'None'.
- Number of Clusters:** An empty text box.
- Spatial Constraints:** A dropdown menu set to 'Trimmed Delaunay tri'.
- Permutations to Calculate Membership Probabilities:** A dropdown menu set to '0'.
- Output Table for Evaluating Number of Clusters:** An empty text box.

The 'Cluster Size Constraints' section is highlighted with a red box and labeled 'Optional input'.

# Methodology (Scenarios formulation)

- Four groups of scenarios are developed based on the optional input parameters:
  - **Group (A) scenario** : no optional input and the optimum number of clusters is computed automatically.
  - **Group (B) scenarios** : three optimum No. of clusters are specified (2, 3 and 7).
  - **Group (C) scenarios**: min. No. of features per cluster is specified (20, 40), with fixed number of cluster (= 7 clusters).
  - **Group (D) scenarios**: min. no. and max. no. of features per clusters are specified (“25, 150” and “50, 100”), the optimum number of clusters is computed automatically.

## Group (A) scenario

Cluster Size Constraints  
None

Number of Clusters

Spatial Constraints  
Trimmed Delaunay triangulation

Permutations to Calculate Membership Probabilities

Output Table for Evaluating Number of Clusters

## Group (B) scenarios

Cluster Size Constraints  
None

Number of Clusters  
3

Spatial Constraints  
Trimmed Delaunay triangulation

Permutations to Calculate Membership Probabilities  
1000

Output Table for Evaluating Number of Clusters

## Group (C) scenarios

Cluster Size Constraints  
Number of features

Minimum per Cluster  
40

Number of Clusters  
7

Spatial Constraints  
Trimmed Delaunay triangulation

Permutations to Calculate Membership Probabilities  
1000

Output Table for Evaluating Number of Clusters

## Group (D) scenarios

Cluster Size Constraints  
Number of features

Minimum per Cluster  
25

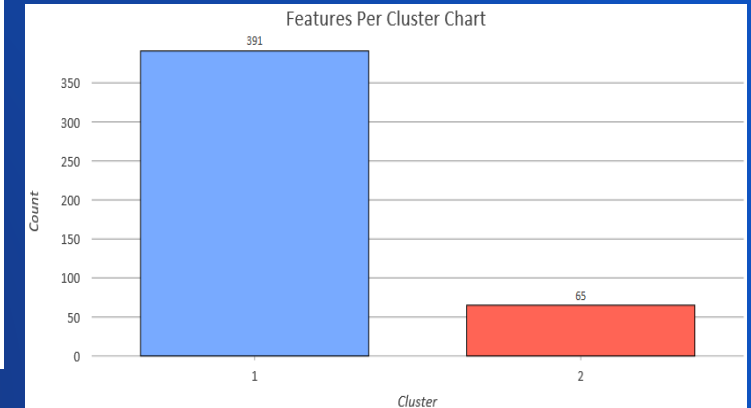
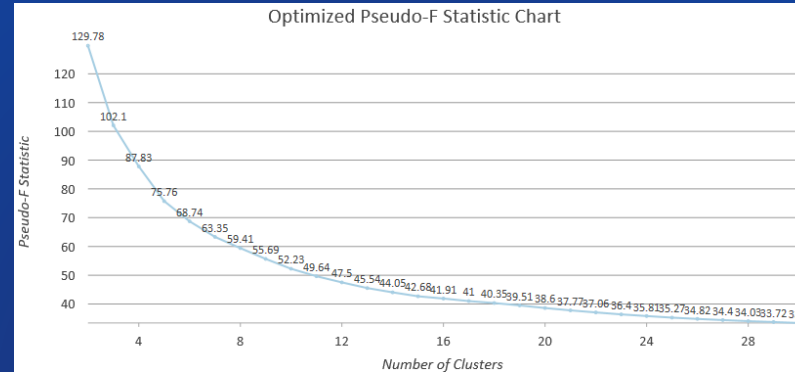
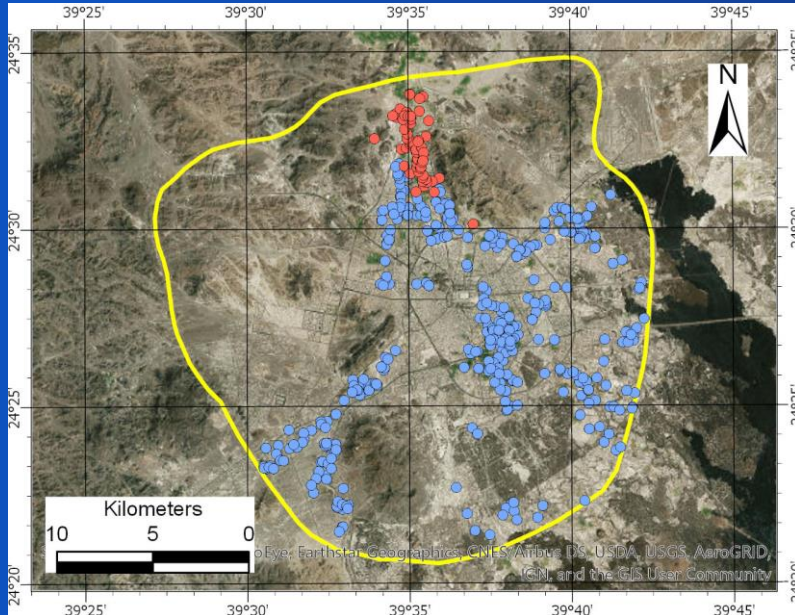
Fill to Limit  
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Spatial Constraints  
Trimmed Delaunay triangulation

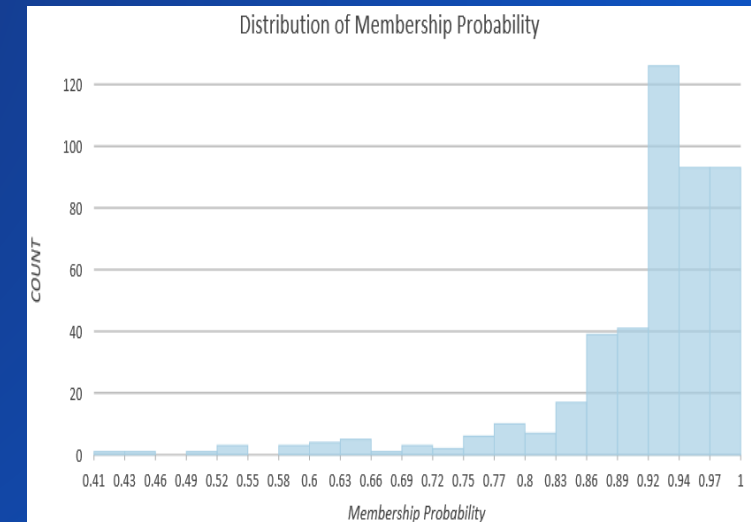
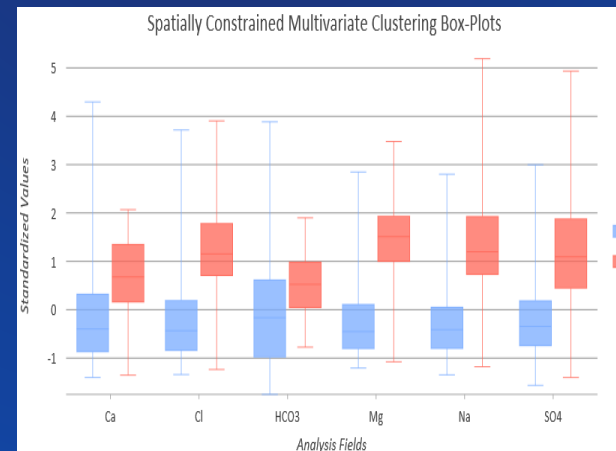
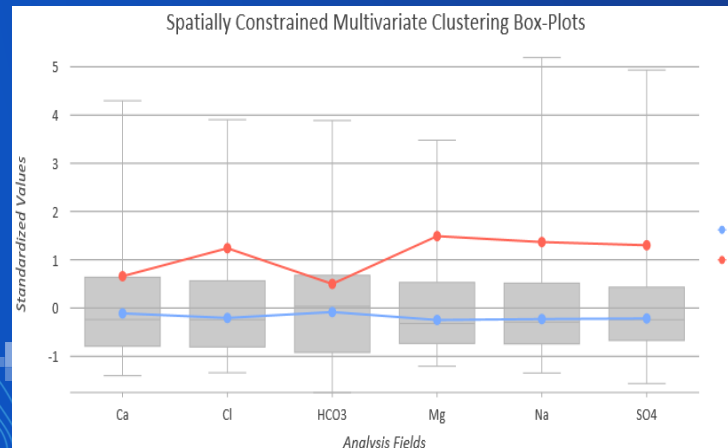
Output Table for Evaluating Number of Clusters

# Results & Discussions (Group (A) scenario)

No optional input and the optimum number of clusters is computed automatically



Variable	Mean	Std. Dev.	Min	Max	R2
MG	184.589912	142.241319	13.000000	680.000000	0.369584
NA	542.953947	380.473044	30.000000	2520.000000	0.311333
SO4	982.528509	610.161313	26.000000	3996.000000	0.282234
CL	1079.949561	739.258629	88.000000	3970.000000	0.256788
CA	303.885965	200.843004	22.000000	1168.000000	0.072334
HCO3	271.379386	130.798051	42.000000	780.000000	0.041548



# Results & Discussions (Group (B) scenarios)

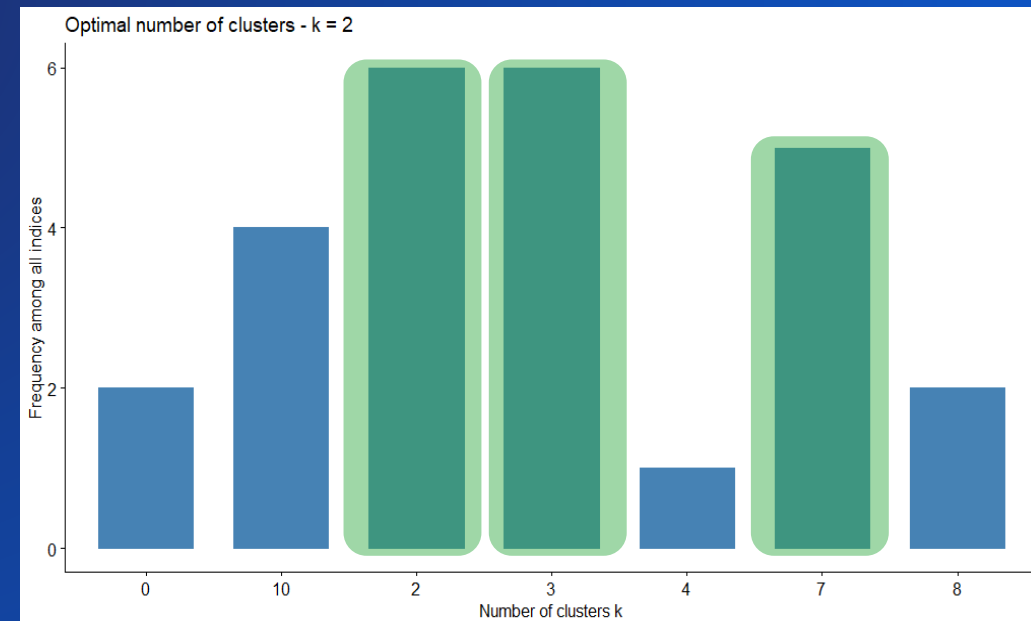
- Most of the clusters methods need from the user to specify the optimum number of clusters
- Unfortunately, this is still unsolved problem and there is no definitive answer to this question.
- Determining the optimal number of clusters is somehow subjective.
- In this study, the optimum number of clusters is determined by evaluating 30 indices using R programming language (NbClust R package).
- Selection of the optimum No. of cluster is based on the “majority rule”.

Among all indices:

=====

```
* 2 proposed 0 as the best number of clusters
* 6 proposed 2 as the best number of clusters
* 6 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 5 proposed 7 as the best number of clusters
* 2 proposed 8 as the best number of clusters
* 4 proposed 10 as the best number of clusters
```

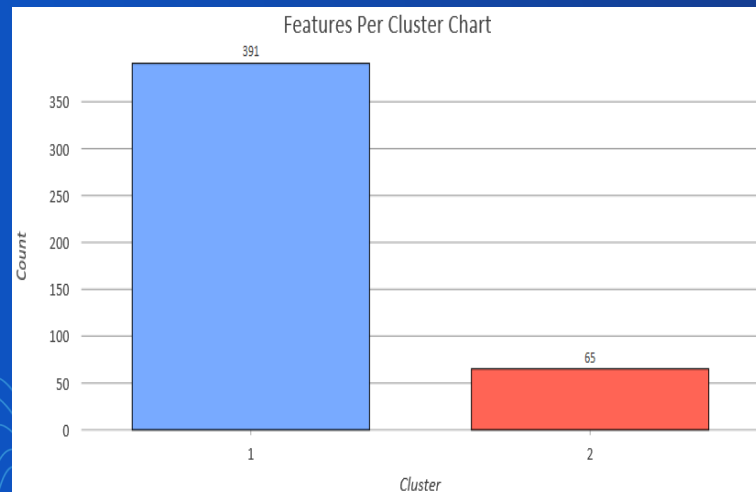
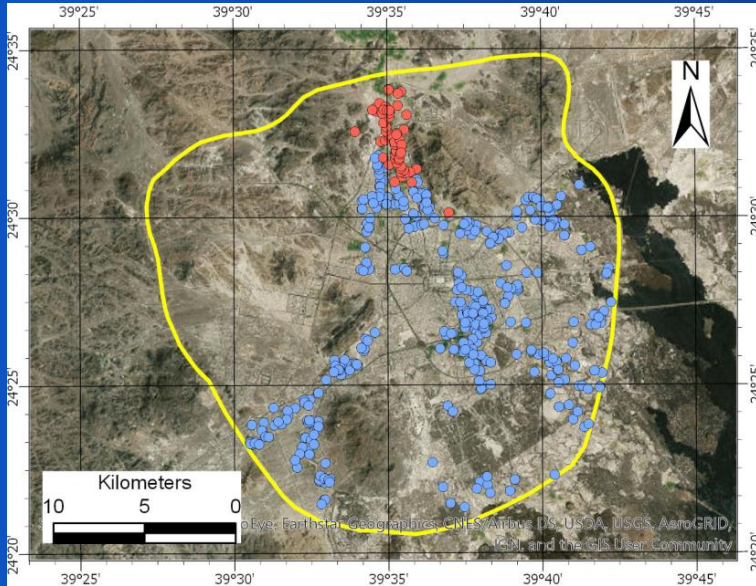
- 2, 3 and 7 are selected as the optimum number of clusters



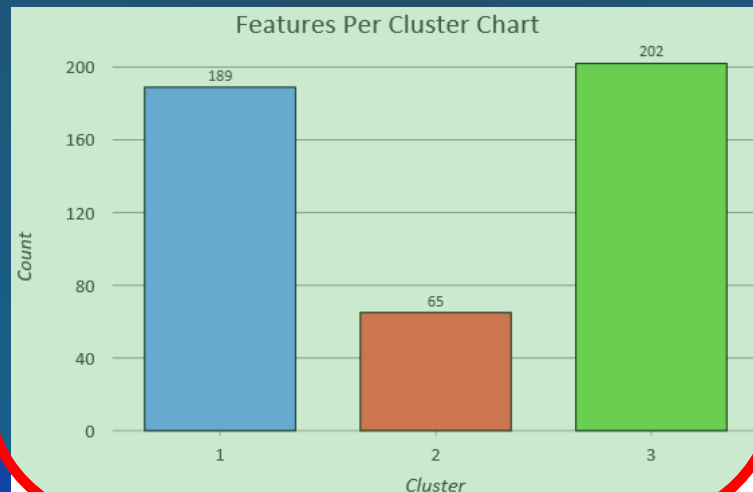
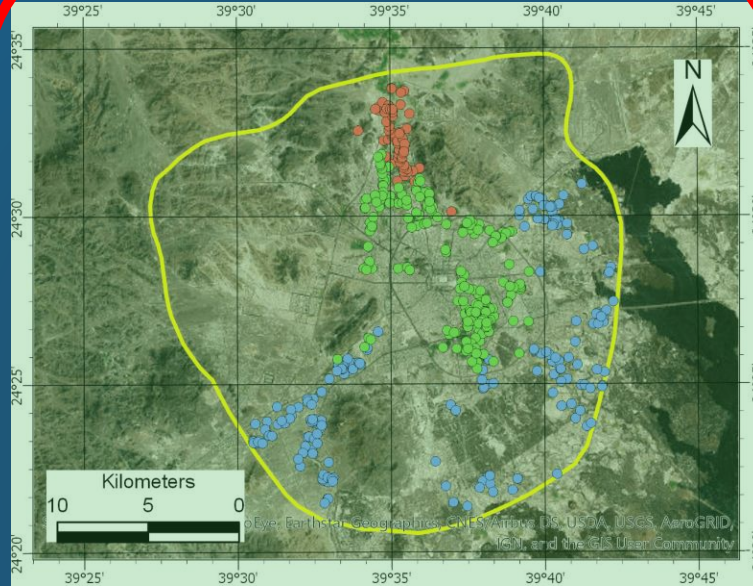
# Results & Discussions (Group (B) scenarios)

Three optimum No. of clusters are specified (2, 3 and 7)

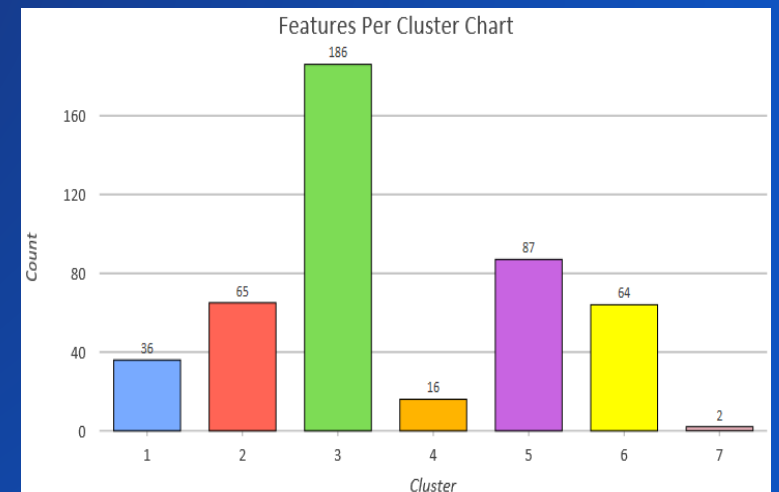
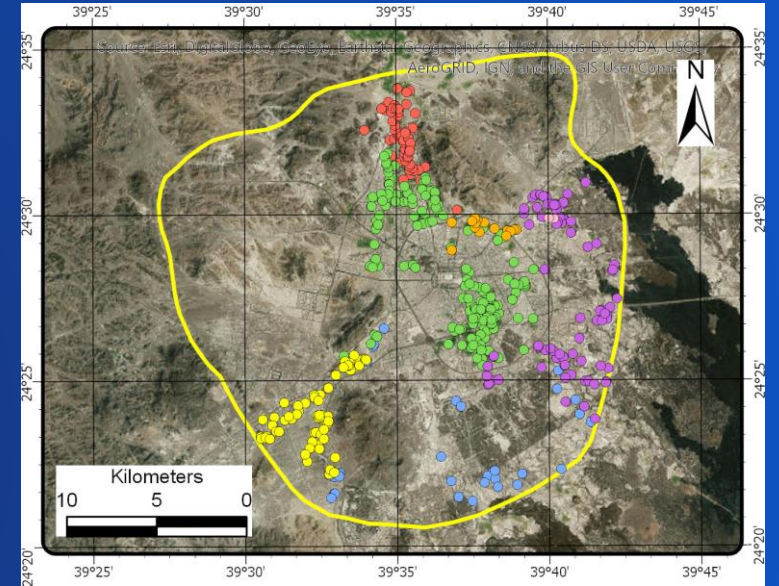
No. of clusters = 2



No. of clusters = 3

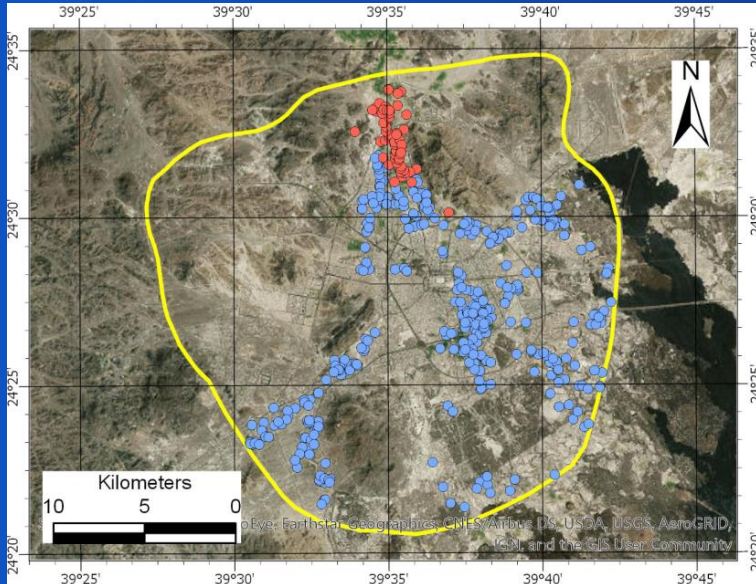


No. of clusters = 7

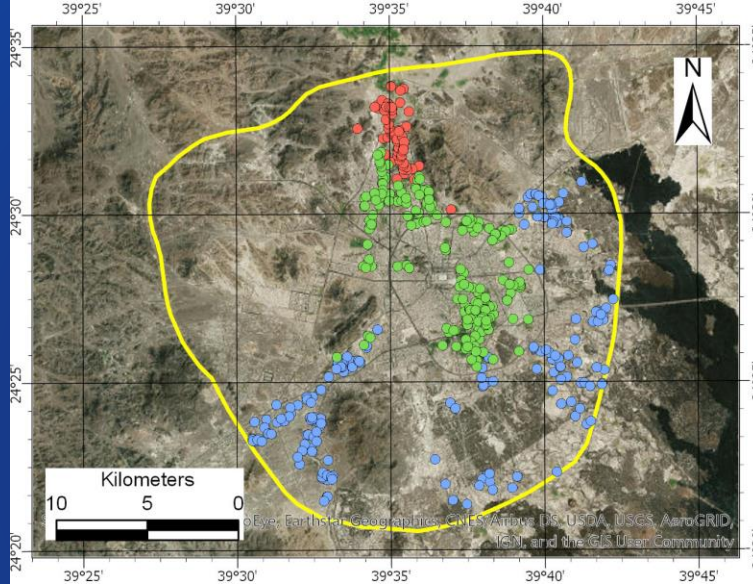


# Results & Discussions (Group (B) scenarios)

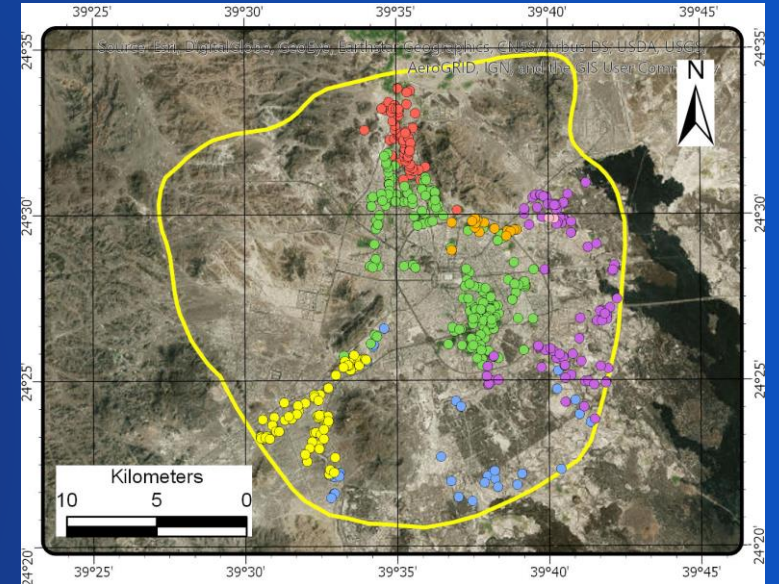
No. of clusters = 2



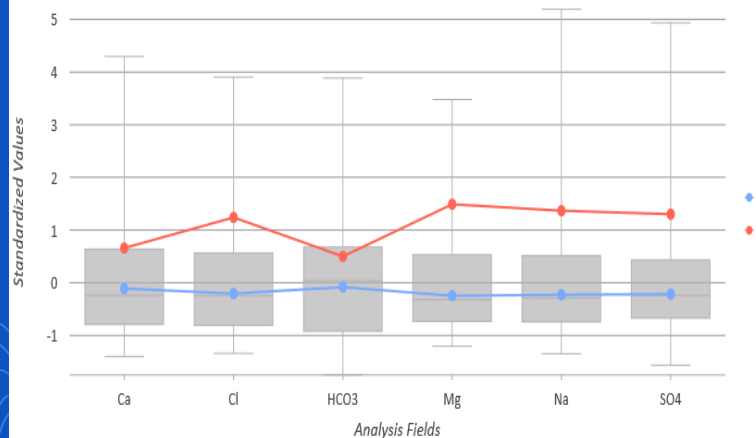
No. of clusters = 3



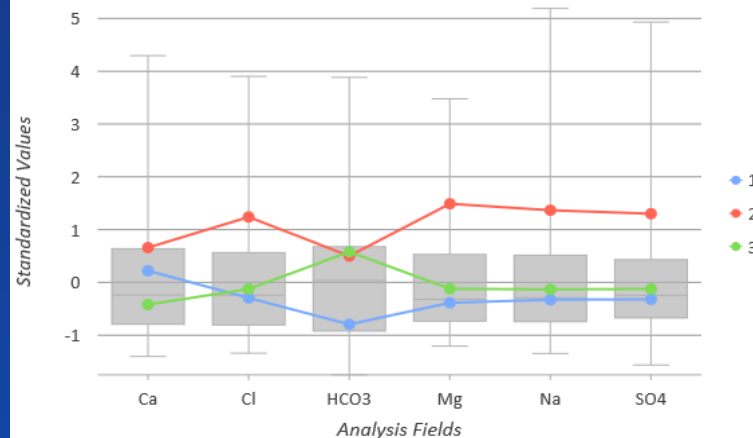
No. of clusters = 7



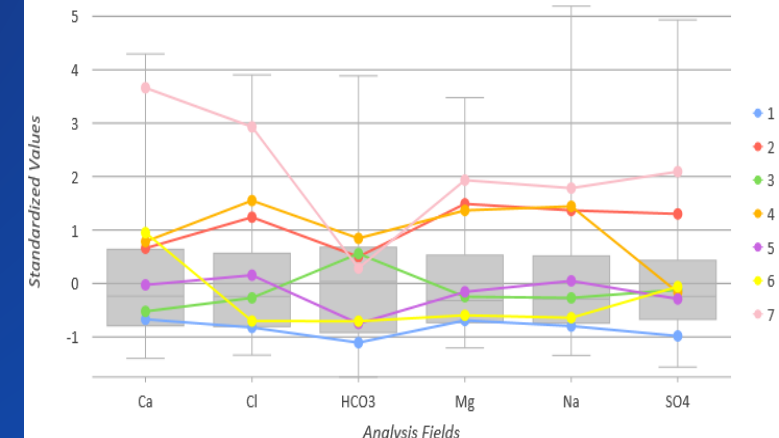
Spatially Constrained Multivariate Clustering Box-Plots



Spatially Constrained Multivariate Clustering Box-Plots

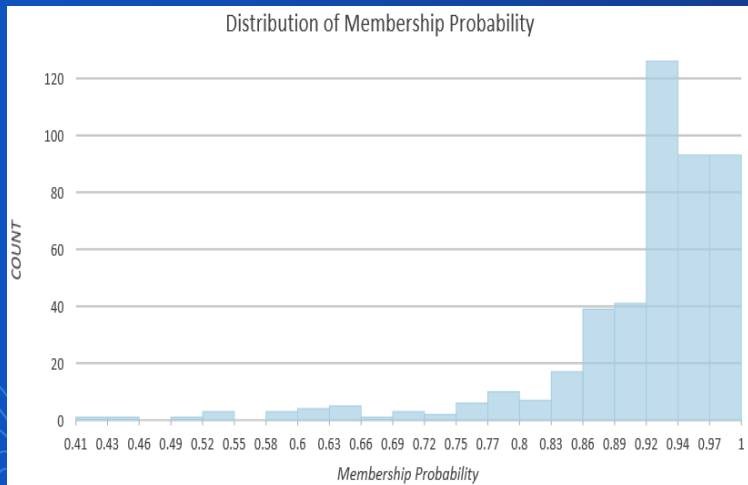
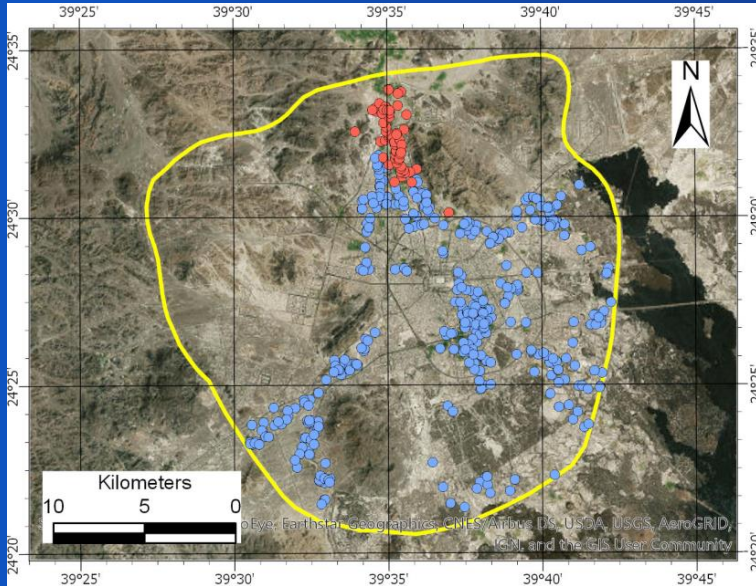


Spatially Constrained Multivariate Clustering Box-Plots

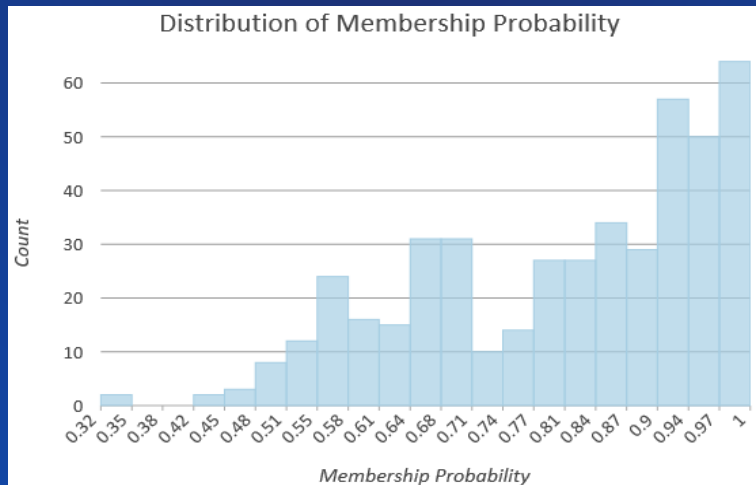
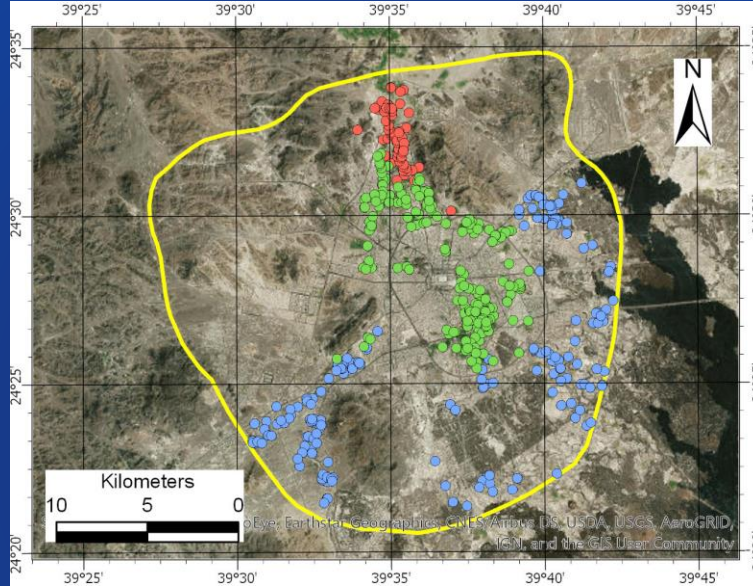


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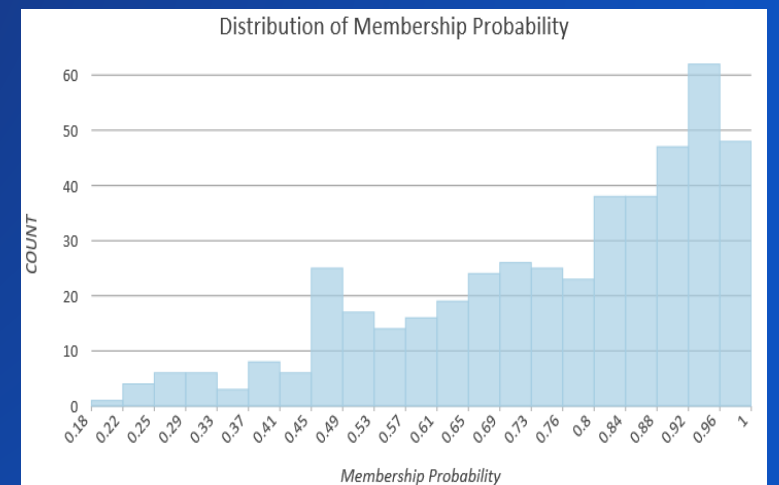
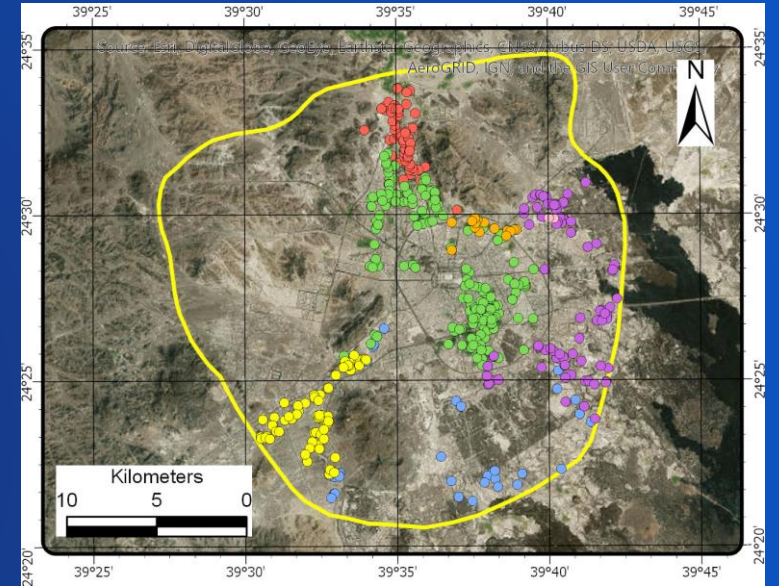
No. of clusters = 2



No. of clusters = 3

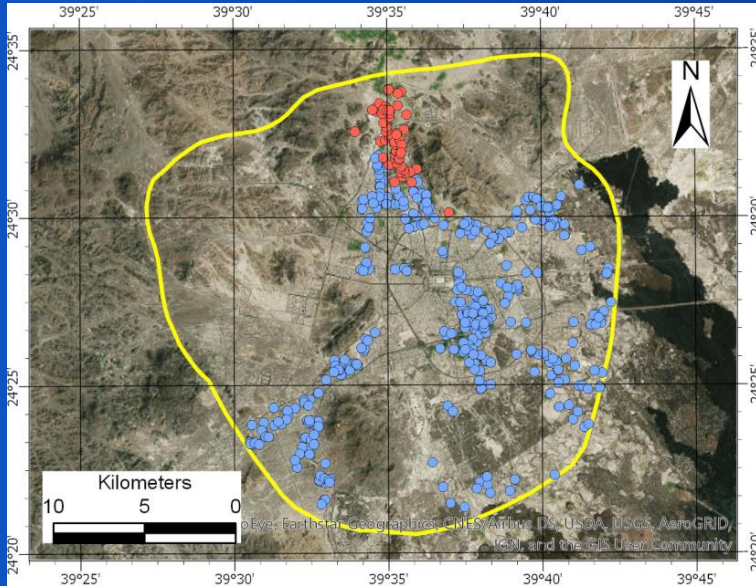


No. of clusters = 7

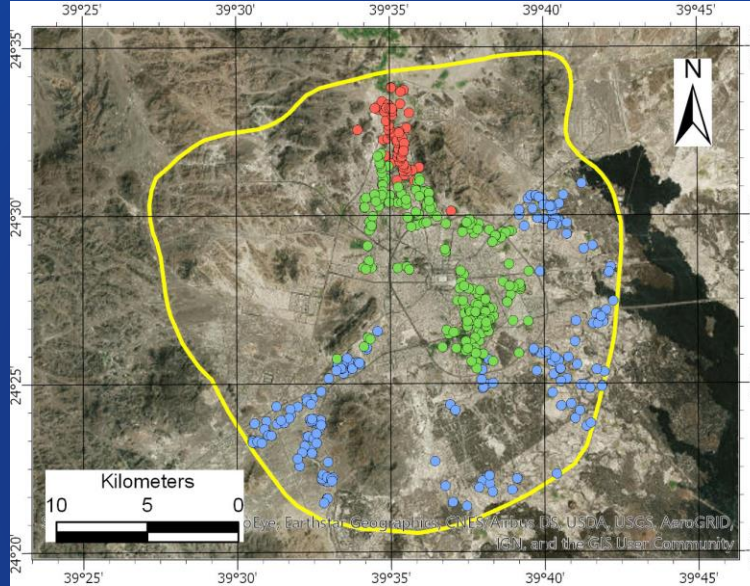


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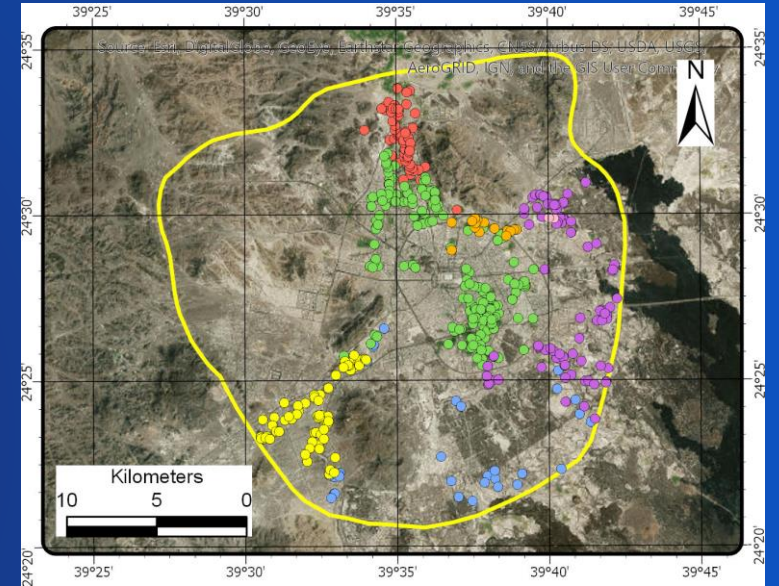
No. of clusters = 2



No. of clusters = 3



No. of clusters = 7



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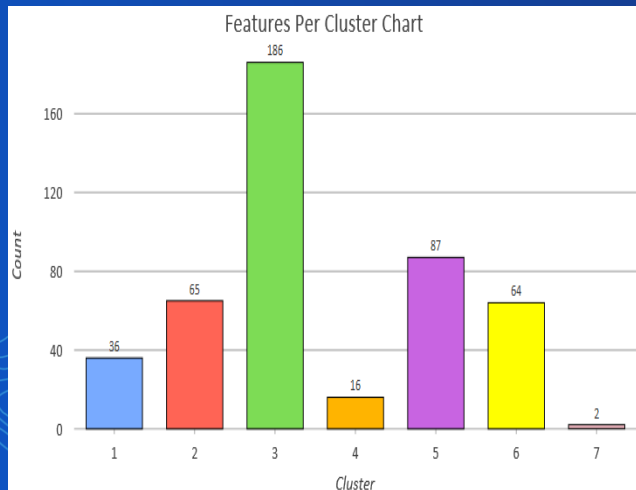
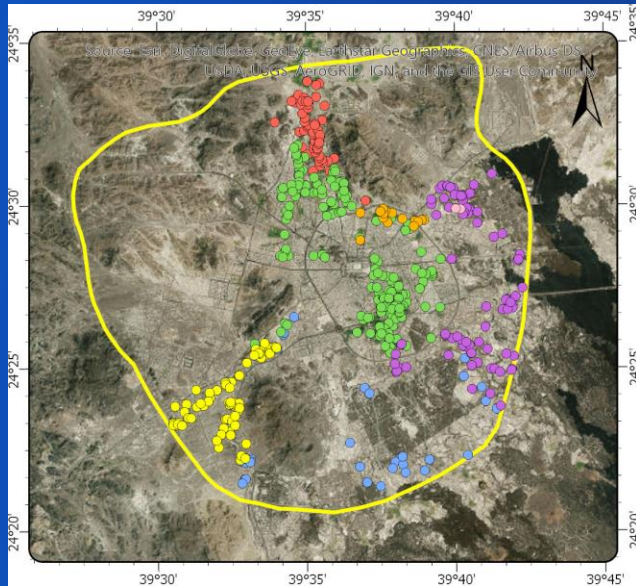
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MG	184.589912	142.241319	13.000000	680.000000	0.384542
NA	542.953947	380.473044	30.000000	2520.000000	0.319470
SO4	982.528509	610.161313	26.000000	3996.000000	0.290497
CL	1079.949561	739.258629	88.000000	3970.000000	0.262823
CA	303.885965	200.843004	22.000000	1168.000000	0.160296

Variable	Mean	Std. Dev.	Min	Max	R2
MG	184.589912	142.241319	13.000000	680.000000	0.516441
CL	1079.949561	739.258629	88.000000	3970.000000	0.500044
NA	542.953947	380.473044	30.000000	2520.000000	0.492381
HCO3	271.379386	130.798051	42.000000	780.000000	0.463728
CA	303.885965	200.843004	22.000000	1168.000000	0.417436
SO4	982.528509	610.161313	26.000000	3996.000000	0.360552

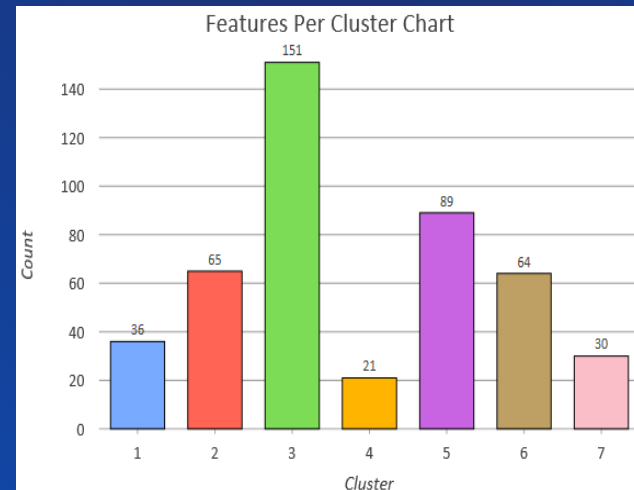
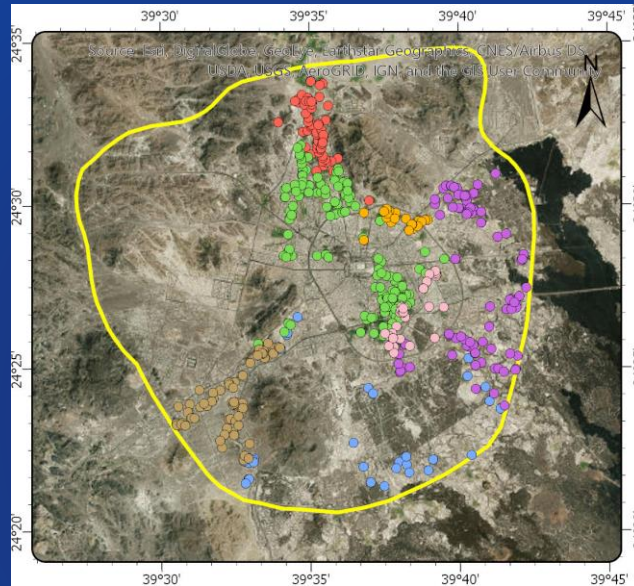
# Results & Discussions (Group (C) scenarios)

Assuming the optimum No. of cluster = 7

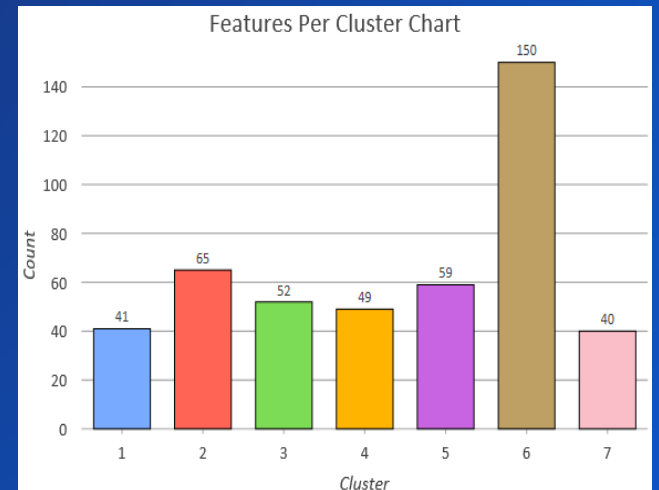
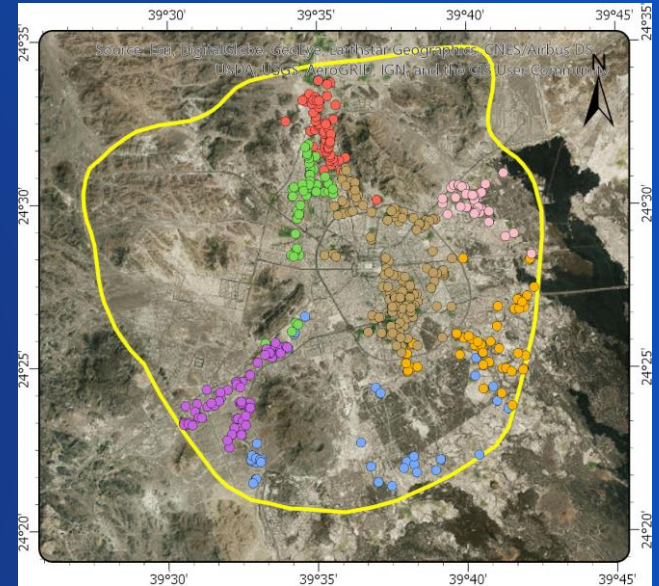
7 clusters, no min. No. of features



7 clusters, min. No. of features = 20

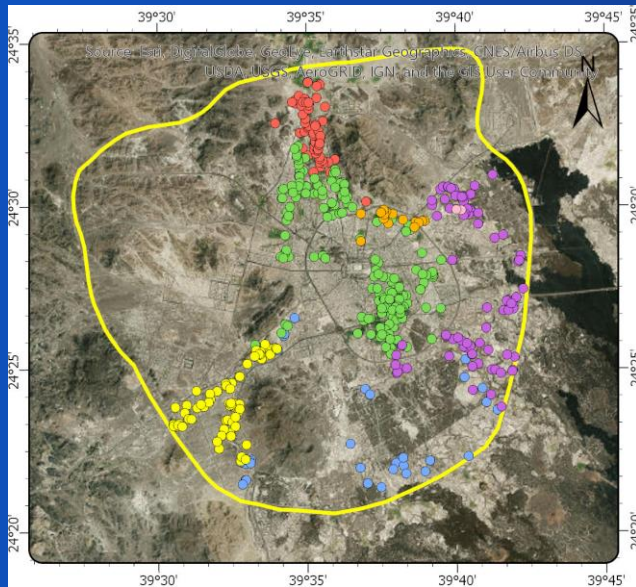


7 clusters, min. No. of features = 40

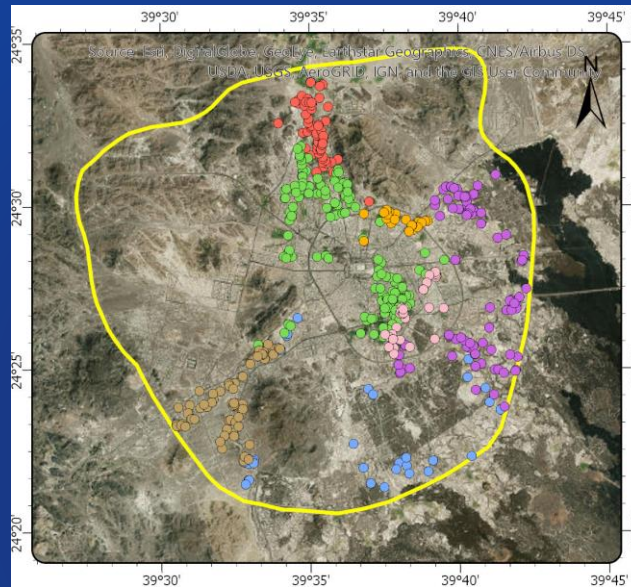


# Results & Discussions (Group (C) scenarios)

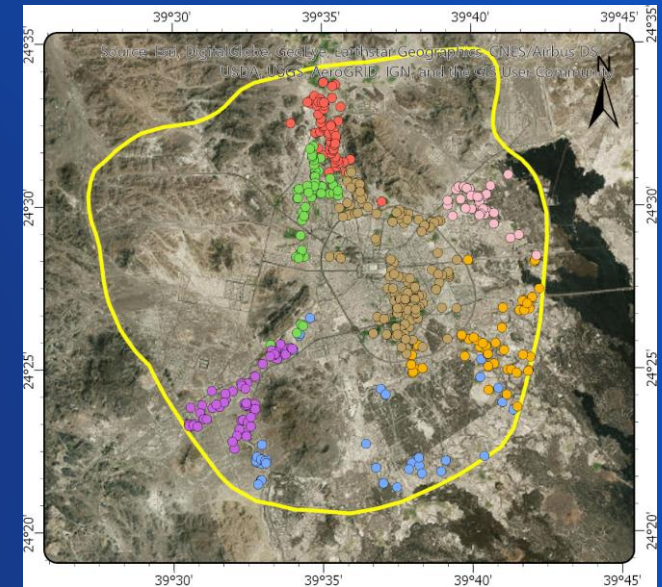
7 clusters, no min. No. of features



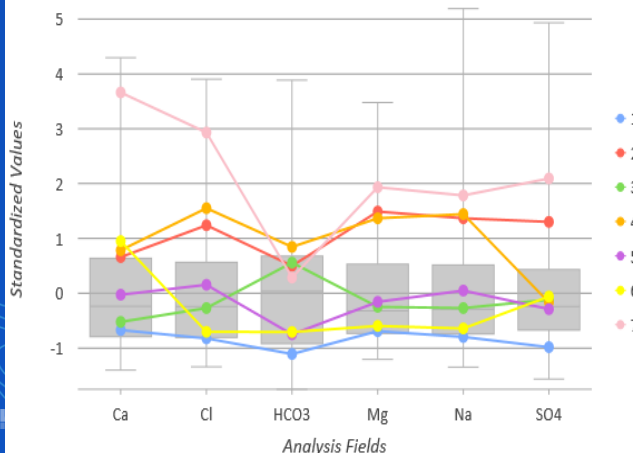
7 clusters, min. No. of features = 20



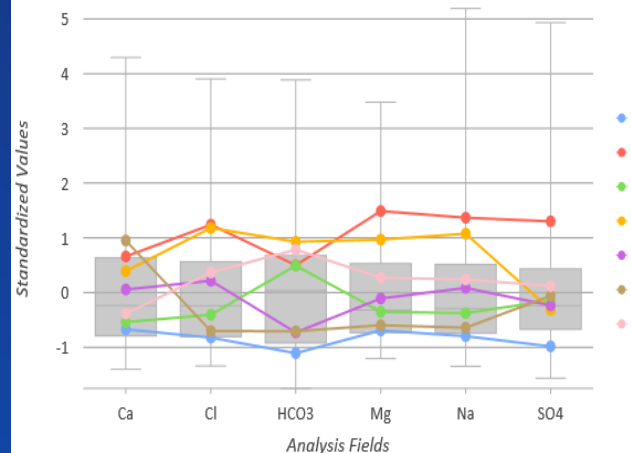
7 clusters, min. No. of features = 40



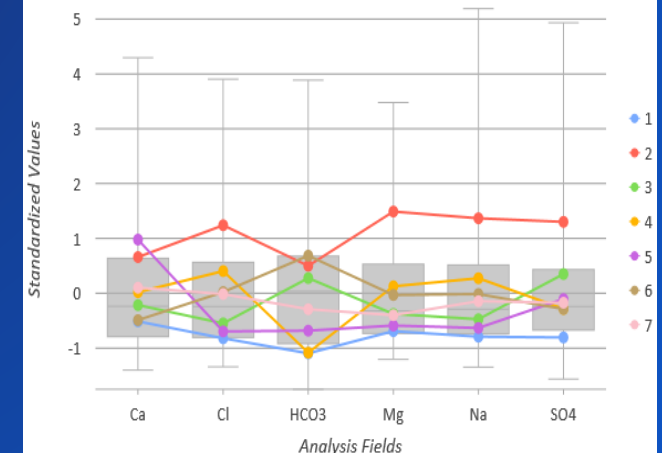
Spatially Constrained Multivariate Clustering Box-Plots



Spatially Constrained Multivariate Clustering Box-Plots

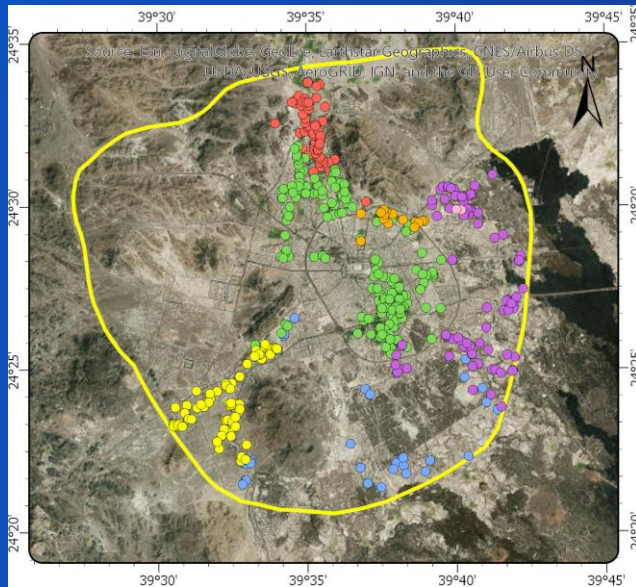


Spatially Constrained Multivariate Clustering Box-Plots



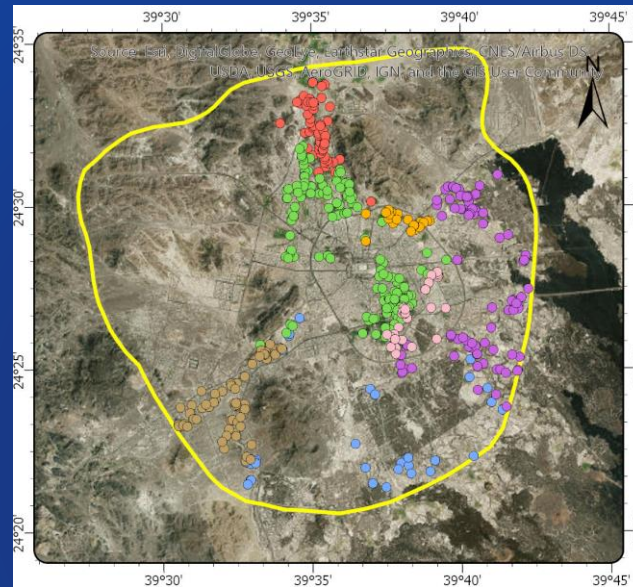
# Results & Discussions (Group (C) scenarios)

7 clusters, no min. No. of features



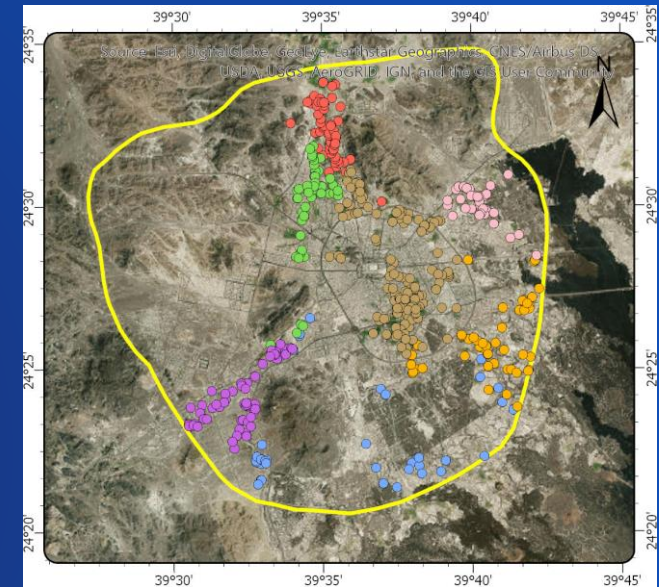
Variable	Mean	Std. Dev.	Min	Max	R2
MG	184.589912	142.241319	13.000000	680.000000	0.516441
CL	1079.949561	739.258629	88.000000	3970.000000	0.500044
NA	542.953947	380.473044	30.000000	2520.000000	0.492381
HC03	271.379386	130.798051	42.000000	780.000000	0.463728
CA	303.885965	200.843004	22.000000	1168.000000	0.417436
S04	982.528509	610.161313	26.000000	3996.000000	0.360552

7 clusters, min. No. of features = 20



Variable	Mean	Std. Dev.	Min	Max	R2
MG	184.589912	142.241319	13.000000	680.000000	0.516441
CL	1079.949561	739.258629	88.000000	3970.000000	0.500044
NA	542.953947	380.473044	30.000000	2520.000000	0.492381
HC03	271.379386	130.798051	42.000000	780.000000	0.463728
CA	303.885965	200.843004	22.000000	1168.000000	0.417436
S04	982.528509	610.161313	26.000000	3996.000000	0.360552

7 clusters, min. No. of features = 40

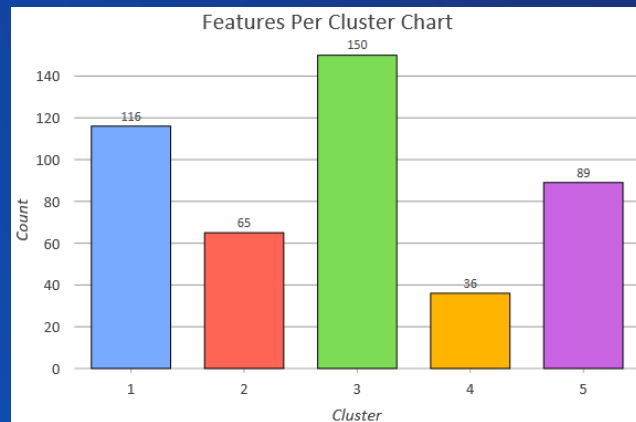
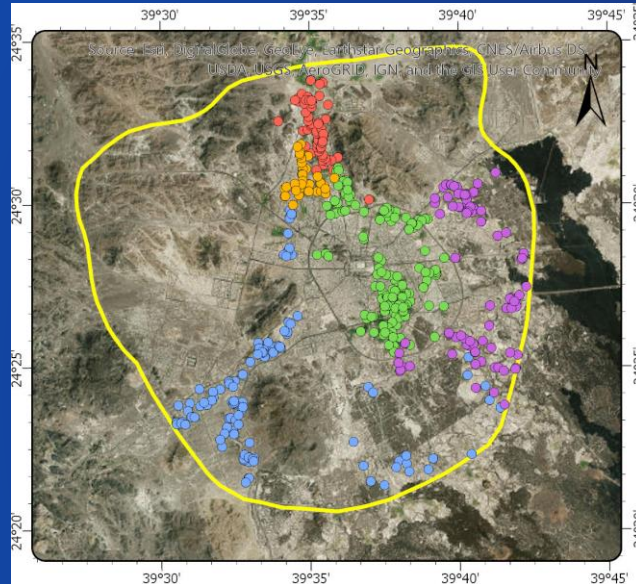


Variable	Mean	Std. Dev.	Min	Max	R2
HC03	271.379386	130.798051	42.000000	780.000000	0.501893
MG	184.589912	142.241319	13.000000	680.000000	0.436772
NA	542.953947	380.473044	30.000000	2520.000000	0.410843
CL	1079.949561	739.258629	88.000000	3970.000000	0.395729
S04	982.528509	610.161313	26.000000	3996.000000	0.354156
CA	303.885965	200.843004	22.000000	1168.000000	0.294929

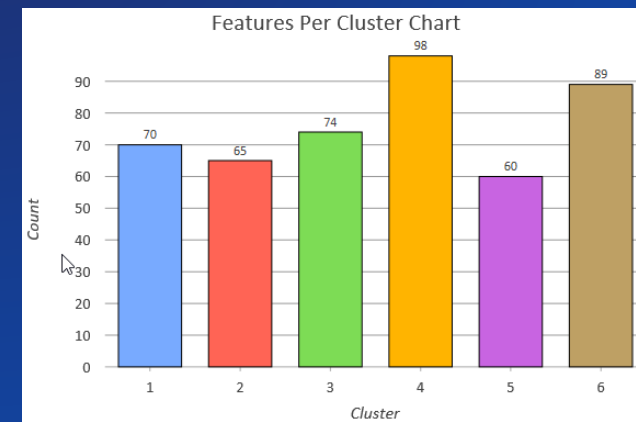
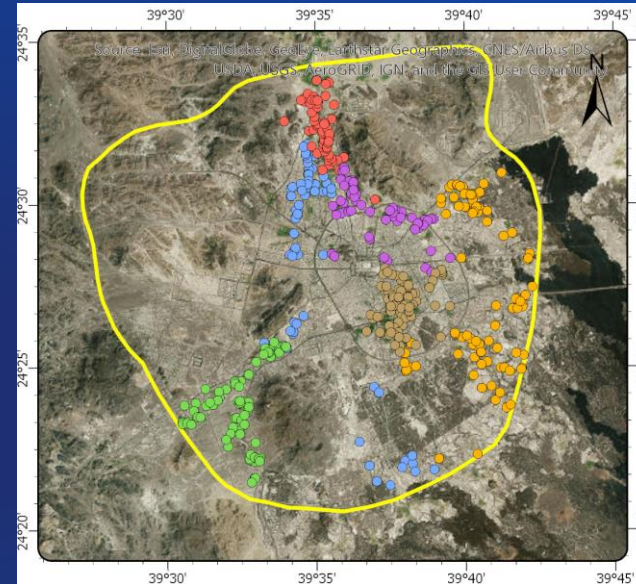
# Results & Discussions (Group (D) scenarios)

Specifying the margins (boundaries) of the No. of features per cluster

Min. No. of features/cluster = 25  
Max. No. of features/cluster = 150

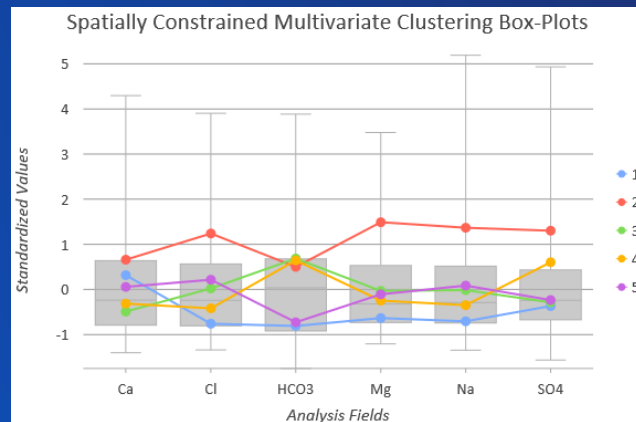
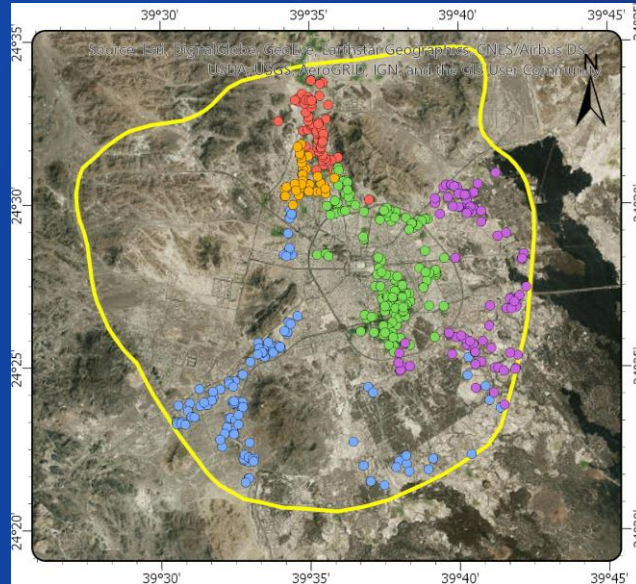


Min. No. of features/cluster = 50  
Max. No. of features/cluster = 100

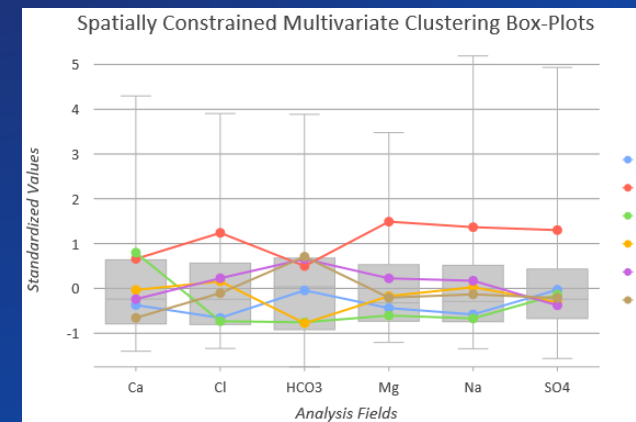
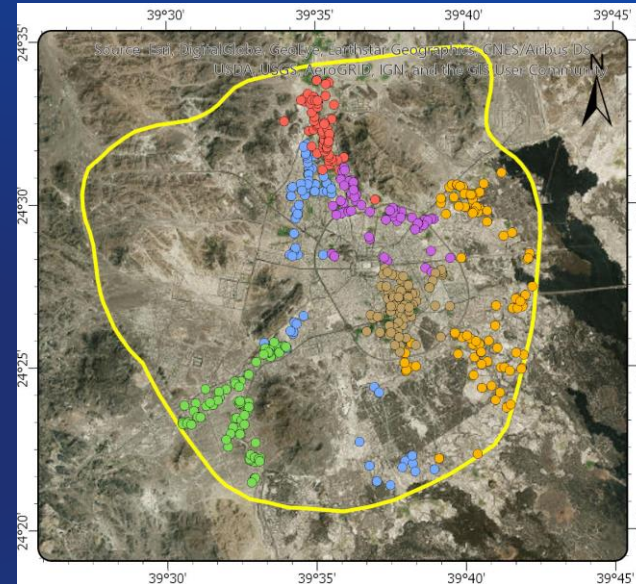


# Results & Discussions (Group (D) scenarios)

Min. No. of features/cluster = 25  
Max. No. of features/cluster = 150

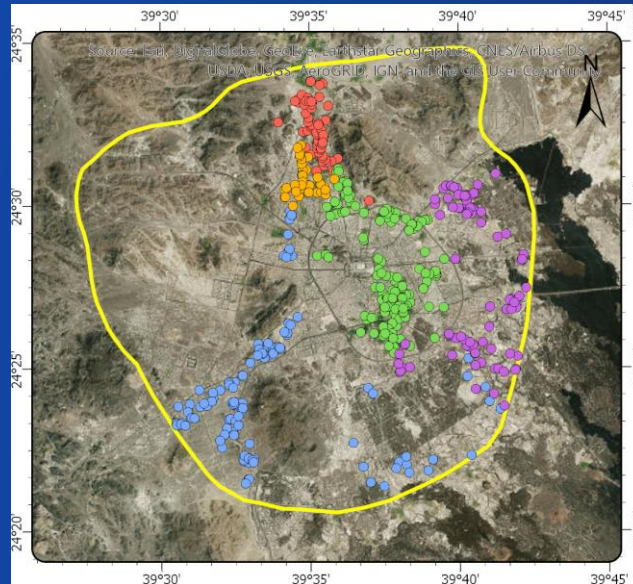


Min. No. of features/cluster = 50  
Max. No. of features/cluster = 100



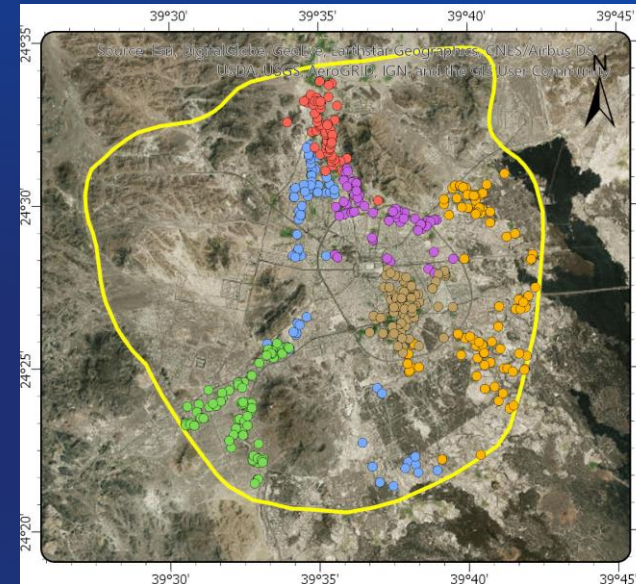
# Results & Discussions (Group (D) scenarios)

Min. No. of features/cluster = 25  
Max. No. of features/cluster = 150



Variable	Mean	Std. Dev.	Min	Max	R2
HCO3	271.379386	130.798051	42.000000	780.000000	0.494480
MG	184.589912	142.241319	13.000000	680.000000	0.427112
NA	542.953947	380.473044	30.000000	2520.000000	0.405020
CL	1079.949561	739.258629	88.000000	3970.000000	0.390493
S04	982.528509	610.161313	26.000000	3996.000000	0.342758
CA	303.885965	200.843004	22.000000	1168.000000	0.174965

Min. No. of features/cluster = 50  
Max. No. of features/cluster = 100



Variable	Mean	Std. Dev.	Min	Max	R2
MG	184.589912	142.241319	13.000000	680.000000	0.426960
HCO3	271.379386	130.798051	42.000000	780.000000	0.412836
NA	542.953947	380.473044	30.000000	2520.000000	0.398952
CL	1079.949561	739.258629	88.000000	3970.000000	0.388360
S04	982.528509	610.161313	26.000000	3996.000000	0.293898
CA	303.885965	200.843004	22.000000	1168.000000	0.278877

# Results & Discussions (more spatial control using spatial weights)

- Weighted Optimization

$w_1(\text{attribute similarity}) + w_2(\text{geometric centroids})$

$$w_1 + w_2 = 1$$

iterate until contiguity constraint is satisfied

bisection method

$w_2$  is weight for centroids,  $w_1 = 1 - w_2$

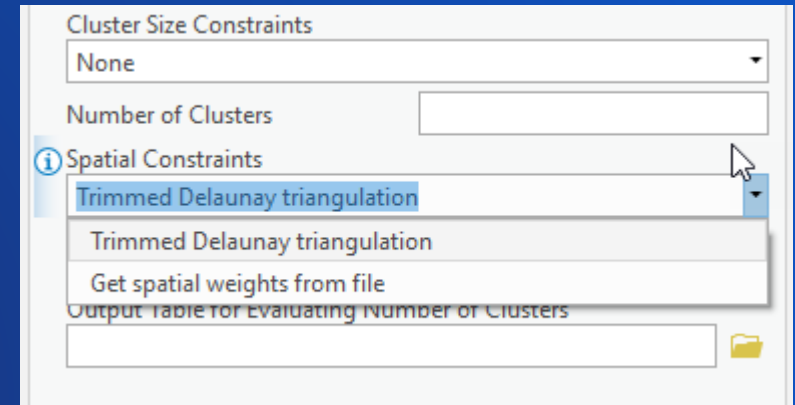
start with 0.0 and 1.0

then move to 0.50 - check contiguity

if contiguous, then to midpoint to the left of 0.50

if not contiguous, then to midpoint to the right of 0.50

etc... until contiguous with the highest bSS/tSS ratio



# Results & Discussions (Cluster results evaluation)

- Higher Goodness of fit index is better
- B = between-cluster sum of square error (SSE) – need to be maximized
- W = within-cluster sum of square error (SSE)
- K = the number of clusters
- N = the number of features (observation)

$$\text{Goodness of fit index} = \frac{B / (k - 1)}{W / (n - k)}$$



# Conclusion

- SCMC method in ArcGIS Pro found to be powerful tool for spatial clustering with many options and functionalities.
- SCMC method as many Clustering methods needs full understanding of the data used.
- One of the best scenarios is sub-dividing the city based on GW quality into three zones which are; **Upper zone** with good quality, **city center zone** with moderate quality, and **lower (downstream) zone** with low quality.
- The results of this study will be beneficial not only for the farmers but also for the local government, environmental agencies and investors in agriculture.

# References and Resources

- **Spatially Constrained Multivariate Clustering**
  - <https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/spatially-constrained-multivariate-clustering.htm>
- **How Spatially Constrained Multivariate Clustering works**
  - <https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/how-spatially-constrained-multivariate-clustering-works.htm>
- **Determining Number of Clusters in One Picture**
  - <https://www.datasciencecentral.com/profiles/blogs/determining-number-of-clusters-in-one-picture>
- Assunção, R. M., Neves, M. C., Câmara, G., & da Costa Freitas, C. (2006). Efficient regionalization techniques for socio-economic geographical units using minimum spanning trees. *International Journal of Geographical Information Science*, 20(7), 797-811.
- Duque, J. C., Ramos, R., & Suriñach, J. (2007). Supervised regionalization methods: A survey. *International Regional Science Review*, 30(3), 195-220.
- *Luc Anselin, (2017), Cluster Analysis (3) Spatially Constrained Clustering Methods,*
  - [https://geodacenter.github.io/workbook/8\\_spatial\\_clusters/lab8.html](https://geodacenter.github.io/workbook/8_spatial_clusters/lab8.html)
- Kassambara, A. (2017). *Practical guide to cluster analysis in R: unsupervised machine learning* (Vol. 1). STHDA.
- Fischer, M. M., & Getis, A. (Eds.). (2009). *Handbook of applied spatial analysis: software tools, methods and applications*. Springer Science & Business Media.

**Thank you**

