Handout for Presentation: Issues in Spatial Analysis

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1) Selected spatial elements of data (Carl Amrhein)

a) Point-assigned information vs. areal information

Figure 1 – point and area geographical objects



b) Continuous vs. discrete spatial phenomena

Figure 2 – Vector and raster GIS data models

Discrete phenomena can be well	Continuous phenomena can be well	
represented by points, lines and polygons	represented by raster	
Vector Model - good for discrete features like	Raster Model - good for continuously varying	
locations or paths	features like temperature	

c) The time element in data

d) Spatial objects of the study area: 'block face (BF)', 'postal codes (PC's)', 'enumeration areas (EA's)', 'census tracts (CT's)', 'forward sortation areas (FSA's)'
 Figure 3 - Statistics Canada 2001 geographic divisions (source: Statistics Canada)



Figure 4 – Three levels of statistical spatial units

Enumeration areas	Census tracts	Forward sortation areas	
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2) Selected spatial topics: spatial autocorrelation; aggregation of spatial data for (health) analysis (Carl Amrhein)

a) Spatial autocorrelation of data.

(See Appendix 1)

- b) Why data need to be aggregated spatially?
 - i) Matching available data sets to the smallest common spatial denominator
 - ii) Making spatial units compatible with units used in other studies
 - iii) Removing small cells problem
 - iv) Creating meaningful areal units for analysis
- c) Basic methods of spatial aggregations
 - i) Aggregation of several smaller areas to one larger zone
 - ii) Spatial-weighting during aggregation in case of boundary misalignments at different levels of aggregation

Figure 5 – Area-weighting during data transfers between polygon layers



- iii) Point-to-polygon data aggregation (e.g.: BF to EA)
 - Aggregation of point data to areas **★**177 *****168 61 +442 ★148 463 *****359 *153 *****221 *15 *****193 444 +223 4160 109 436 **★**720 *****21
 - Figure 6 Point-to-polygon data transfers

iv) Hierarchical vs. non-hierarchical aggregations

Figure 7 - Hierarchical vs. non-hierarchical spatial units aggregation



- d) Consequences of spatial data aggregation
 - i) Loss of homogeneity within larger units
 - ii) Loss of positional accuracy of count/frequency data summed up in areal units (See Appendix 2)
 - iii) Changed statistical characteristics of data (MAUP: scale and zoning effects; several examples of the impacts of spatial aggregations on means, averages, correlation coefficients etc)
 - iv) Guidelines for choosing the most appropriate spatial units

3) Selected issues in data mapping (Peter Gozdyra)

- a) Thematic maps
 - i) Types of thematic maps and variable types best shown by these maps



Figure 8 – Various types of thematic maps

ii) Strengths and weaknesses of various map types

Table 1 – Pros and cons of using various types of thematic maps

Choropleth (shaded) map	Dot density map
<u>Variables types:</u> rates_ratios_density_per areal_unit	Variables types: counts/frequencies
Shows well:	Shows well:
value ranges for specific areas, overall	spatial distribution, clusters
pattern	Shortcomings:
Shortcomings:	deceptive impression of accurate locations of
small areas are visually overpowered	dots in randomly distributed dot maps
by large areas	

Proportional symbol map	Interpolated grid map
Variables types:	Variables types:
rates, ratios, counts/frequencies	rates, ratios, density per areal unit
Shows well:	Shows well:
magnitude of phenomenon, comparison of	gradual change of continuous-type
areas of different sizes	phenomenon over space
Shortcomings:	Shortcomings:
overlaps of symbols on each other and on	values interpolated between known data
other map layers	points, centroids etc., pattern depends on
	a chosen algorithm

iii) Defining limits and the number of ranges on choropleth maps (map patterns)

Natural breaks Equal count (equal number of areas in each category) Choropleth Map Of ousehold Income 1996 By Census Tract Choropleth Map Of ousehold Income 199 By Census Tract (Equal C Lake Ontario Lake Ontario Мар Map § Equal range (equal data ranges in each Standard division category) Choropleth Map Of usehold Income 199 By Census Tract ropleth Map Of sehold Income 19 By Census Tract Ma

Figure 9 – Different ways of data classification on choropleth maps



Figure 10 – Number of ranges on choropleth maps (map pattern)

iv) Ways of scaling symbols on proportional symbol maps

Figure 11 – Scaling schemes of proportional symbols



- b) Map's elements
 - i) Basic map elements





ii) Map colours

Figure 13 – Use of colours on 'Average Household Income' choropleth map



iii) Map scale





c) Overlaying of variables

i) Contents and stacking of layers





d) Basic model for utilization of GIS and maps in health care

Defining questions -> Identification and Selection of Variables -> Mapping -> Map Interpretation -> Decision Making

Appendix 1 - Spatial autocorrelation (source: P. Gozdyra)

When examining spatial data the values tend to either cluster together showing groupings of regions with similar characteristics or they demonstrate less ordered patterns within the area of study. In the latter case regions show weaker data patterns or even a patchwork indicating that regions with relatively different values tend to neighbour with each other. The two most common ways of measuring the clustering of similar values in two-dimensional space are the Moran Coefficient [MC] and Geary Ratio [GR] defined as:

$$MC = \left(\frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}}\right) \left(\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}(x_{i} - \overline{x})(x_{j} - \overline{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}}\right)$$
(1)
$$GR = \left(\frac{n-1}{2\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}}\right) \left(\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}(x_{i} - \overline{x}_{j})^{2}}{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}}\right)$$
(2)

where: *n* is the number of regions, x_i and x_j , are the attribute values of the neighbouring spatial units, c_{ij} is the weighting component from the connectivity matrix for neighbouring units x_i and x_j , \overline{x} is the mean attribute value of a whole region

As shown, formulas (1) and (2) utilize a weighting scheme, which in both cases is usually a binary connectivity matrix based on the adjacency of regions. The interpretation of the values of MC and GR is shown in Table 1. Later sections of this paper describe some relationships between spatial autocorrelation and MAUP.

Statistic\Value	-1.0	0.0	1.0	2.0
Moran	Strong	Random	Strong	
Coefficient	negative	distribution	positive	
	autocorrelati	of values	autocorrelati	
	on		on	
Geary Ratio		Strong	Random	Strong
		positive	distribution	negative
		autocorrelati	of values	autocorrelati
		on		on

 Table 2: Value ranges for Moran Coefficient and Geary Ratio

Figure 16 - Sample visual patterns of spatial autocorrelations (source: Practical Handbook of Spatial Statistics, Edited by: Sandra Lach Arlinghaus)



<u>Appendix 2</u> - Loss of spatial accuracy due to aggregation of point data to areas (source: P.

Gozdyra)

Use of point-define data vs. polygon-summed data.

In the table below (column A) the points in the higher-located polygon are spread out more evenly than in the lower-located polygon. Upon aggregation of point data to polygons (column B) only one number represents the whole data in each polygon. The higher-located polygon may be thought of as well representing the distribution of the original point data, while the lower-located polygon conceals the true distribution of highly concentrated point data (loss of positional accuracy of data)



Figure 17 – Appropriateness of areas to represent point data

Representation of count data within areas by random points (dot density map).

In the table below data points are in reality located close to the line (e.g. population living close to a street). When a polygon-summed data is represented by random points (e.g.: one dot representing 100 persons) a use of a smaller polygon (column A) makes the points fall closer to the true physical location of the population. An aggregation of population to larger polygon (column B) causes the random points to be located further away from the true physical location of data (column C).

Figure 18 – Loss of spatial proximity of point data to its sources during their aggregation to larger areal units

