



Cartography M.Sc.

Refining Spatial Autocorrelation Analysis for Dasymetrically Disaggregated Spatial Data

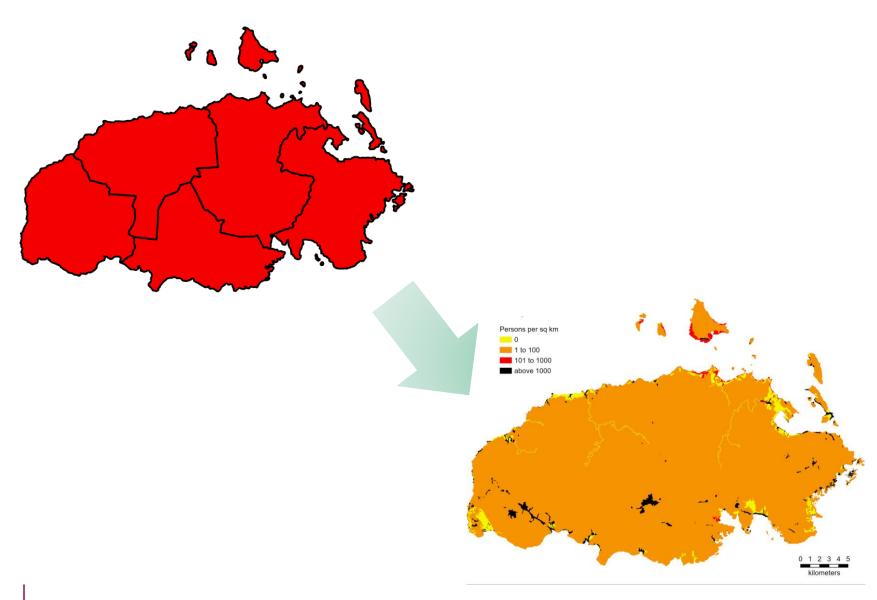
Dennis P. Dizon

Candidate, MSc Cartography

The agenda

- Introduction
 - The research problem
 - Objectives and questions
- Central concepts, related studies
- Methodology
 - Conceptual framework
 - Analysis parameters and workflow
 - Case study areas
- Results
- Discussion, conclusion

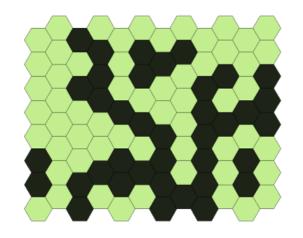
Dasymetric mapping?



Spatial outliers?

Overall pattern of values?

Spatial dispersion?

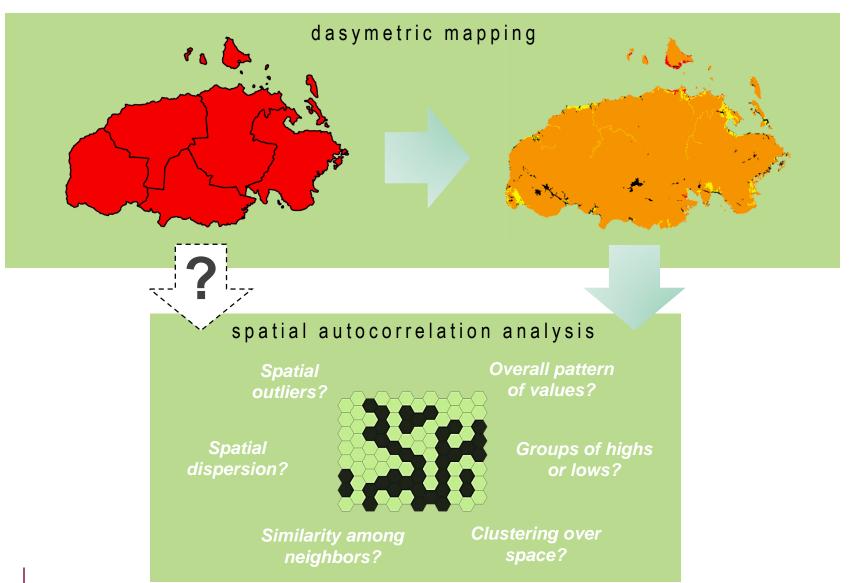


Groups of highs or lows?

Similarity among neighbors?

Clustering over space?

The research problem



What to refine

Which **spatial autocorrelation measures** can utilize dasymetrically disaggregated spatial data?

Which **parameter(s)** in spatial autocorrelation analysis can be modified when using dasymetrically disaggregated data?

How to refine?

What **modification(s)** in spatial autocorrelation analysis can be made when using dasymetrically disaggregated data?

Are there differences

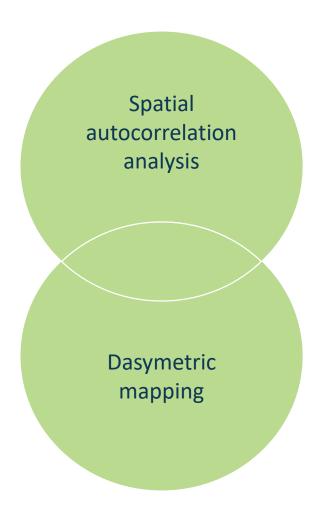
How do these modifications **differ from each other** in terms of results in the spatial autocorrelation analysis?

How do the results differ from the original spatial autocorrelation analysis?

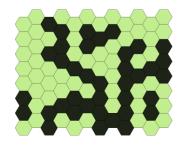
Let's talk about...

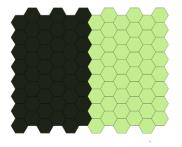
- Introduction
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The central concepts

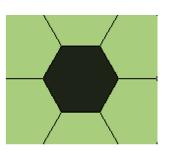


Global





Local







Global

$$I = \left(\frac{N}{\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W z_{i} z_{j}}{\sum_{i=1}^{N} z_{i}^{2}}\right)$$

Global Moran's 1

$$I = \left(\frac{N}{\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W z_{i} z_{j}}{\sum_{i=1}^{N} z_{i}^{2}}\right) \qquad C = \left(\frac{N-1}{2\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W (x_{i} - x_{j})}{\sum_{i=1}^{N} z_{i}^{2}}\right)$$

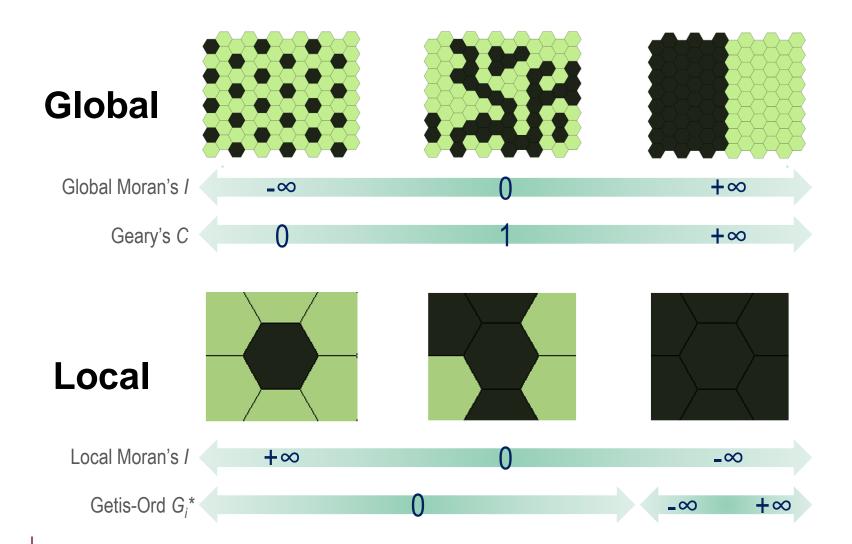
Geary's C

Local

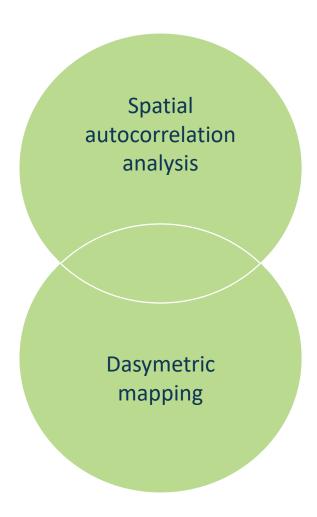
$$I_i = \left(\frac{z_i}{\sum_{i=1}^{N} (z_j)^2 / N - 1}\right) \left(\sum_{j=1}^{N} W z_j\right)$$

Local Moran's 1

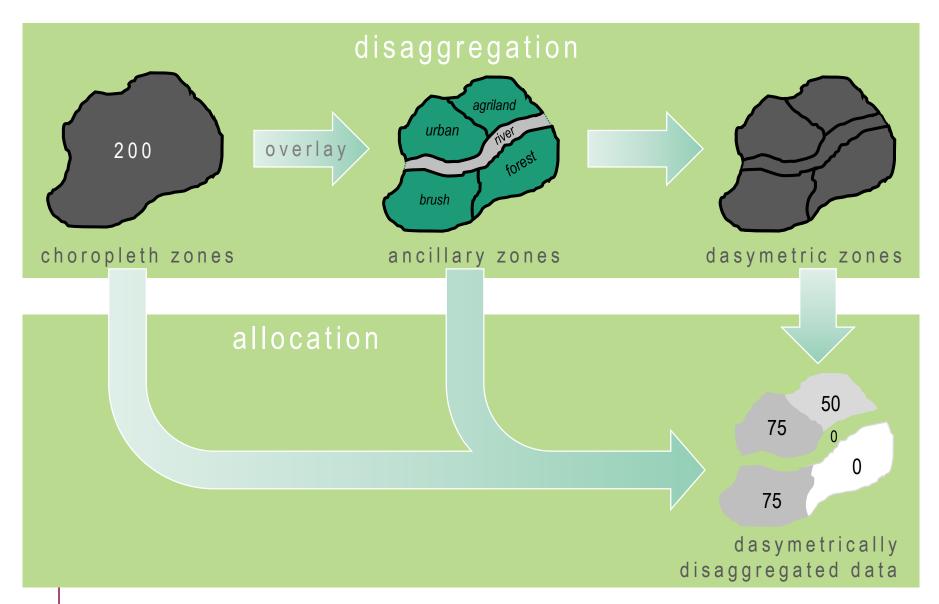
$$I_{i} = \left(\frac{z_{i}}{\sum_{i=1}^{N}(z_{j})^{2}/N - 1}\right) \left(\sum_{j=1}^{N}Wz_{j}\right) \qquad G_{i}^{*} = \frac{\sum_{j=1}^{N}Wx_{j} - \frac{\sum_{j=1}^{N}x_{j}}{N - 1}\left(\sum_{j=1}^{N}W\right)}{\sqrt{\left(\frac{\sum_{j=1}^{N}x_{j}^{2}}{N - 1} - \frac{\sum_{j=1}^{N}x_{j}}{N - 1}\right) \left(\frac{\left[N\sum_{j=1}^{N}W^{2} - \left(\sum_{j=1}^{N}W\right)^{2}\right]}{N - 1}\right)}}$$
Local Moran's /
$$Getis-Ord\ G_{i}^{*}$$



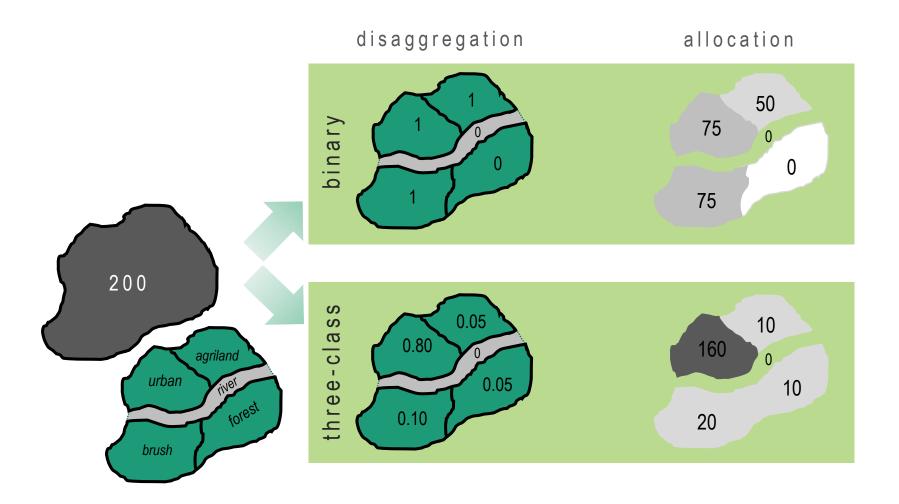
The central concepts

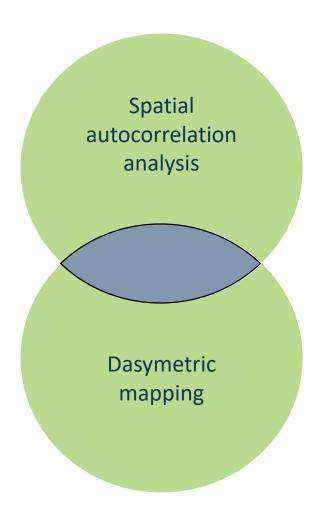


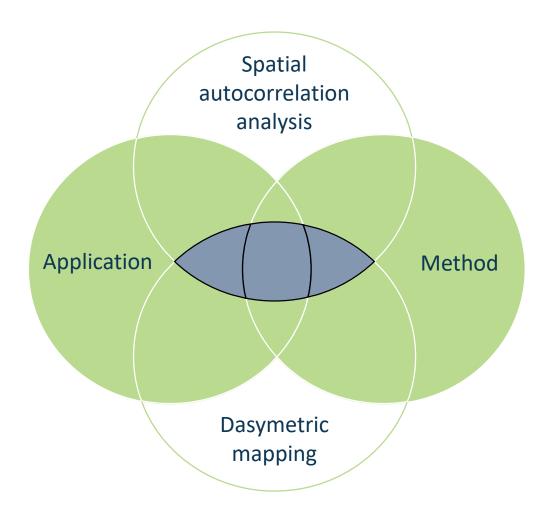
Dasymetric mapping

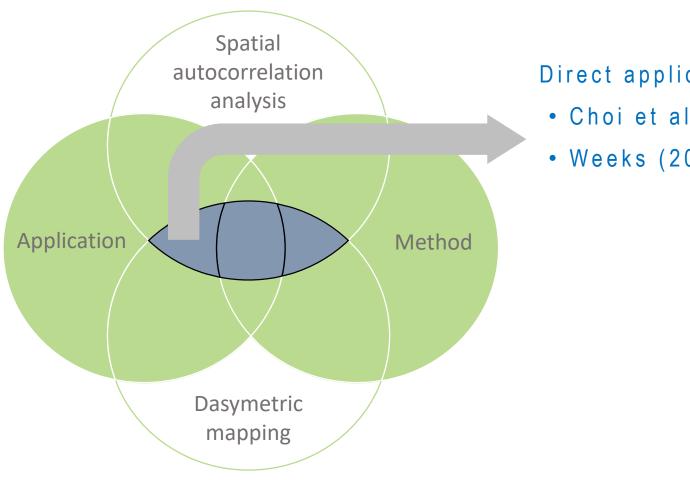


Dasymetric methods



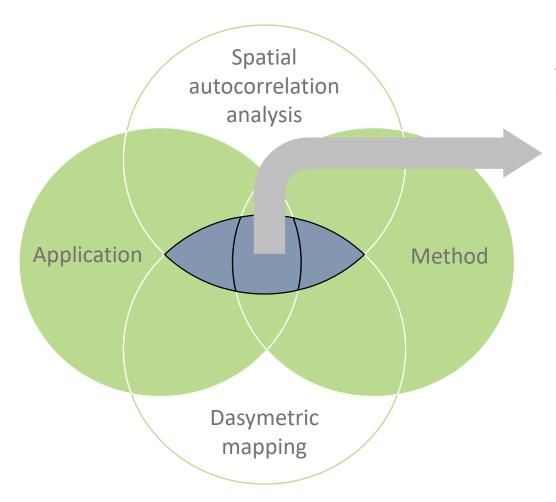






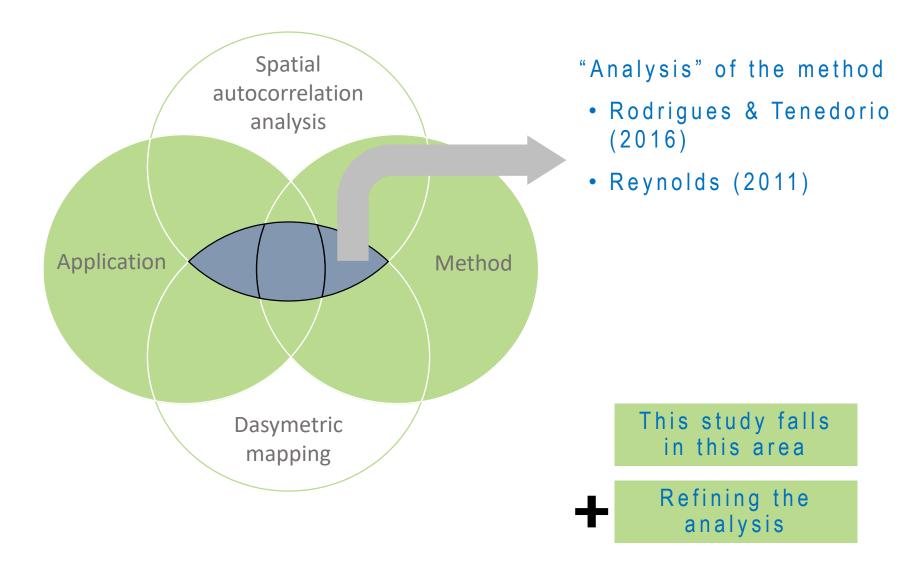
Direct application

- Choi et al. (2011)
- Weeks (2010)



Application to improve an existing analysis method

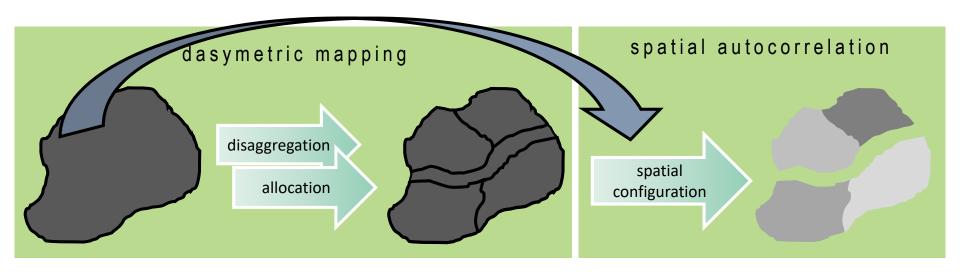
- Boo et al. (2015)
- Mosley (2012)
- Parenteau & Sawada (2012)
- Hu et al. (2007)



Let's talk about...

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The conceptual framework



Global

$$I = \left(\frac{N}{\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{i} z_{j}}{\sum_{i=1}^{N} z_{i}^{2}}\right)$$

Global Moran's 1

$$I = \left(\frac{N}{\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{i} z_{j}}{\sum_{i=1}^{N} z_{i}^{2}}\right) \qquad C = \left(\frac{N-1}{2\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W(x_{i} - x_{j})}{\sum_{i=1}^{N} z_{i}^{2}}\right)$$

Geary's C

Local

$$I_i = \left(\frac{z_i}{\sum_{i=1}^{N} (z_j)^2 / N - 1}\right) \left(\sum_{j=1}^{N} W_j\right)$$

Local Moran's /

$$I_{i} = \left(\frac{z_{i}}{\sum_{i=1}^{N}(z_{j})^{2}/N - 1}\right) \left(\sum_{j=1}^{N} W_{j}\right) \qquad G_{i}^{*} = \frac{\sum_{j=1}^{N} W_{j}}{\sqrt{\left(\frac{\sum_{j=1}^{N} x_{j}^{2}}{N - 1} - \frac{\sum_{j=1}^{N} x_{j}}{N - 1}\right) \left(\frac{\left[N \sum_{j=1}^{N} W^{2} - \left(\sum_{j=1}^{N} W\right)^{2}\right]}{N - 1}\right)}}{\operatorname{Getis-Ord} G_{i}^{*}}$$
Local Moran's /

Spatial weight matrices

$$I = \left(\frac{N}{\sum_{i=1}^{N} \sum_{j=1}^{N} W}\right) \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{i}}{\sum_{i=1}^{N} z_{i}^{2}}\right)$$



\int_0	1	1	0	0	0
1	0	1	1	0	0
1	1	0	1	1	1
0	1	1	0	0	1
0	0	1	0	0	1
l_0	0	1	1	1	0
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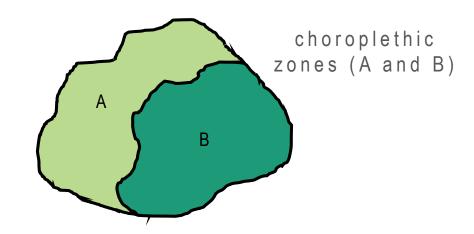
\int_0	1	1	1	0	0
1	0	1	1	0	0
1	1	0	0	1	0
$\begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$	1	0	0	1	0 0 0 1 1
0	0	1	1	0	1
\lfloor_0	0	1	1	1	0

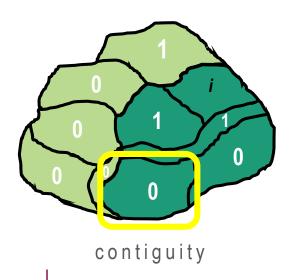
nearest neighbors

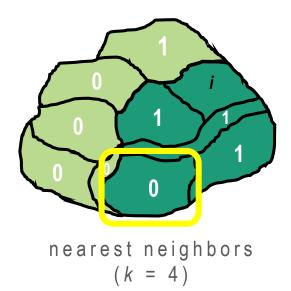
0	0,004	0,010	0	0,003	0]
0,004	0	0,004	0,005	0,002	0,002
0,010	0,004	0	0	0	0,003
0	0,005	0	0	0,,003	0,007
0,003	0,002	0	0,003	0	0,007
[₀	0,002	0,003	0,007	0,007	0

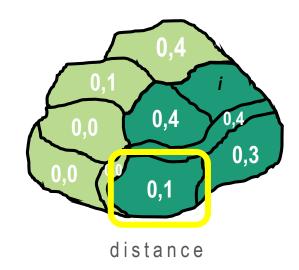
distance

Spatial weight matrices

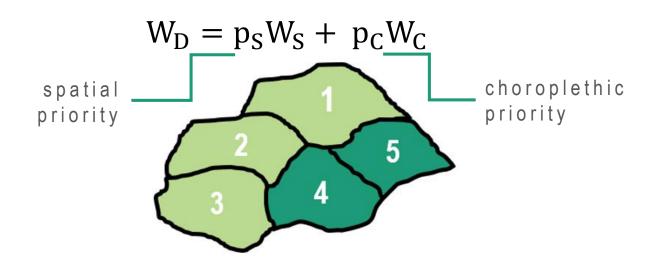








A revised spatial weight matrix



$$W_D = 0.70W_S + 0.30W_C$$

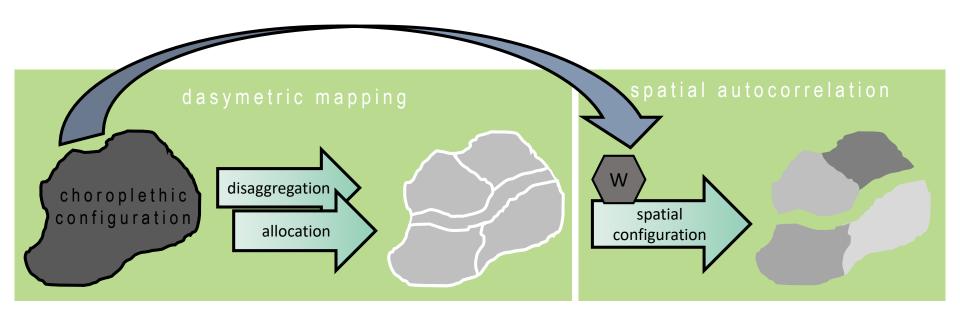
$$\begin{bmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0.3 & 0.7 & 0.7 \\ 1 & 0 & 1 & 0.7 & 0 \\ 0.3 & 1 & 0 & 0.7 & 0 \\ 0.7 & 0.7 & 0.7 & 0 & 1 \\ 0.7 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$W_{S}$$

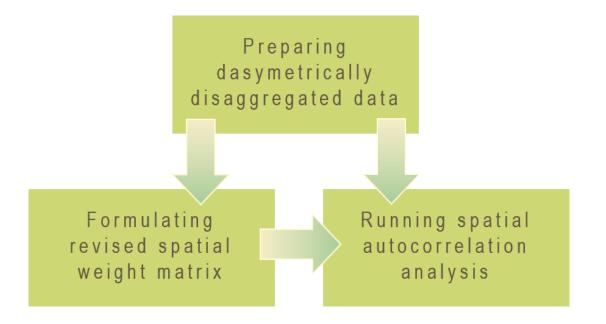
$$W_{C}$$

$$W_{D}$$

The conceptual framework



Analysis workflow



Spatial weight matrices				
	W _{D1}			
Revised	W _{D2}			
Revised	W _{D3}			

$$W_{D1} = 0.70W_S + 0.30W_C$$

$$W_{D2} = 0.50W_S + 0.50W_C$$

$$W_{D3} = 0.30W_S + 0.70W_C$$



Spatial weight matrices			Spatial autocorr	elation measures				
		Glob	pal	Loc	cal			
		Global Moran's I	Geary's C	Local Moran's I	Getis-Ord G _i *			
	W _{D1}							
Revised	W _{D2}							
	W _{D3}							



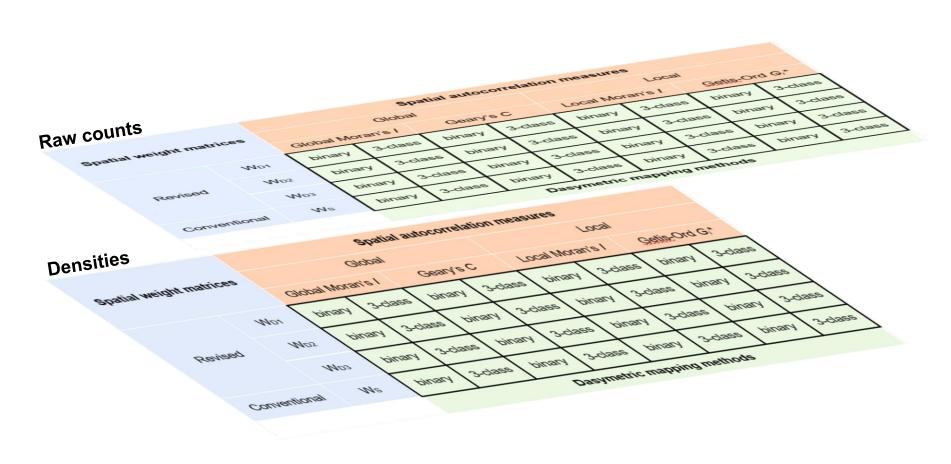
Spatial weight matrices		Spatial autocorrelation measures							
			Glo	bal		Local			
		Global N	/loran's /	Geary's C		Local Moran's I		Getis-Ord G _i *	
Revised	W _{D1}	binary	3-class	binary	3-class	binary	3-class	binary	3-class
	W_{D2}	binary	3-class	binary	3-class	binary	3-class	binary	3-class
	W _{D3}	binary	3-class	binary	3-class	binary	3-class	binary	3-class



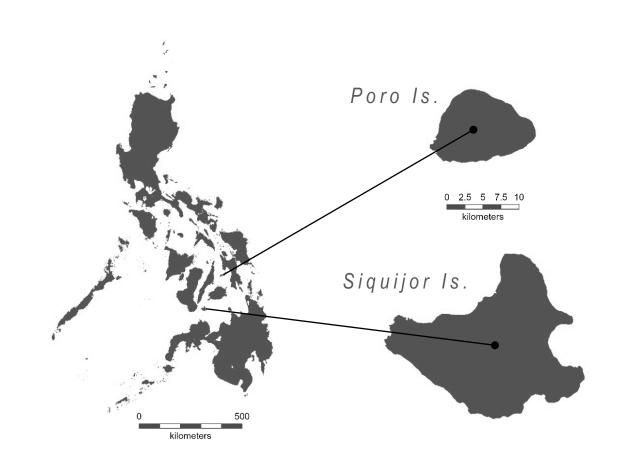
Spatial weight matrices		Spatial autocorrelation measures								
		Global					Lo	cal		
		Global N	/loran's /	Geary's C		Local Moran's I		Getis-Ord Gi*		
Revised	W _{D1}	binary	3-class	binary	3-class	binary	3-class	binary	3-class	
	W _{D2}	binary	3-class	binary	3-class	binary	3-class	binary	3-class	
	W _{D3}	binary	3-class	binary	3-class	binary	3-class	binary	3-class	
Conventional	Ws	binary	3-class	binary	3-class	binary	3-class	binary	3-class	

Dasymetric mapping methods

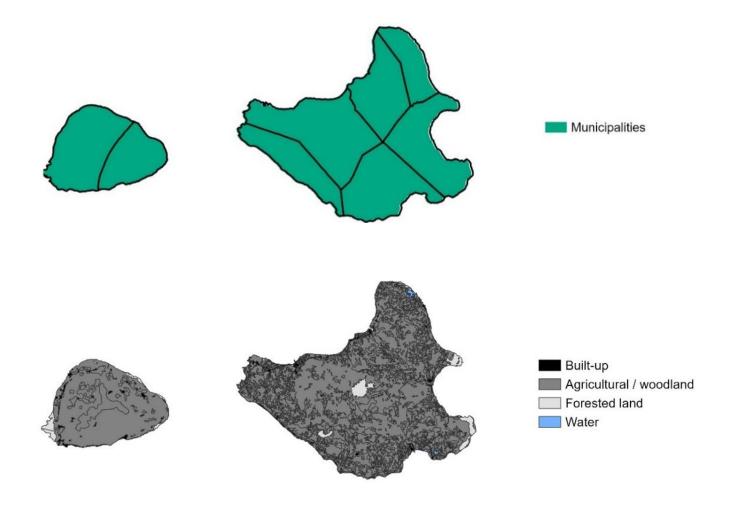




Case study areas



Case study areas



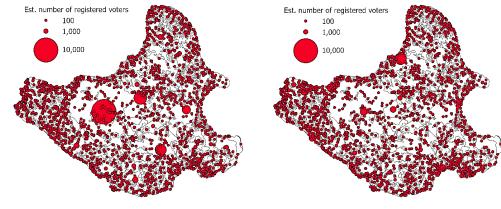
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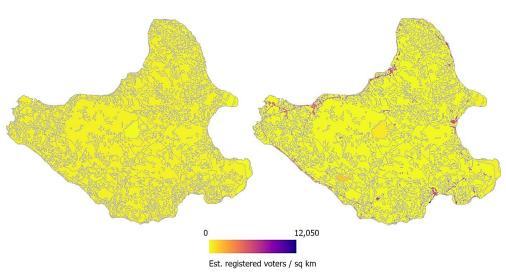
Dasymetric disaggregation



Raw counts



Densities



Spatial weight matrix construction

Preparing dasymetrically disaggregated data

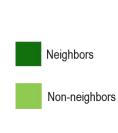
Formulating revised spatial weight matrix

Running spatial autocorrelation analysis

No. of dasymetric zones: 1 885

No. of matrix elements: $1 \ 885^2 = 3 \ 553 \ 225$





Spatial weight matrix construction

Preparing dasymetrically disaggregated data

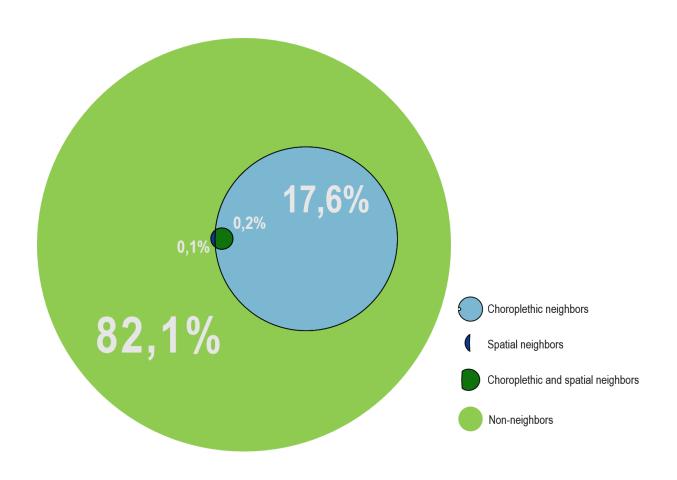
Formulating revised spatial weight matrix

Running spatial

autocorrelation
analysis

No. of dasymetric zones: 1 885

No. of matrix elements: $1.885^2 = 3.553.225$





Global Moran's I

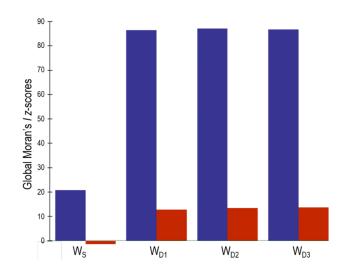
Raw counts

Saloss 15

Three-class

When the state of th

Densities

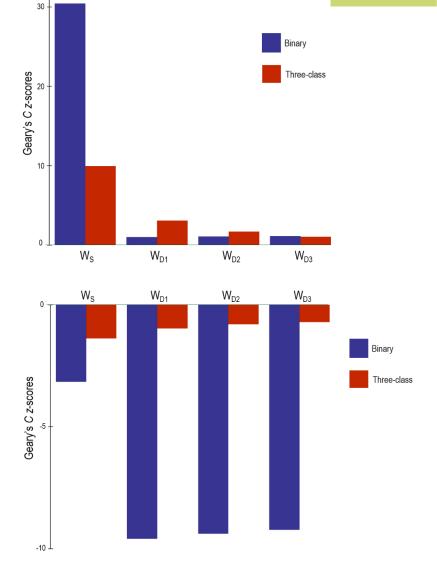




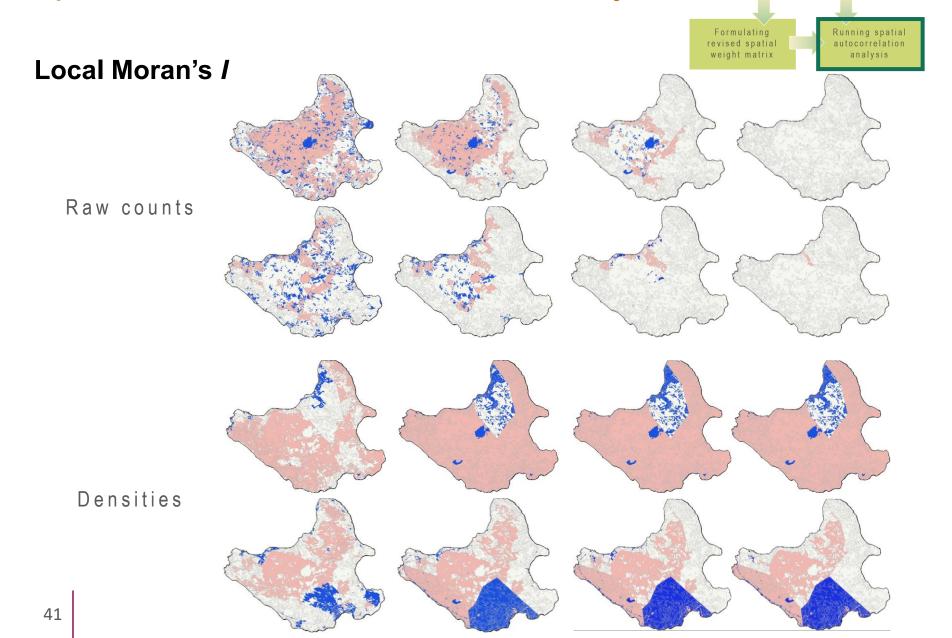
Geary's C

Raw counts

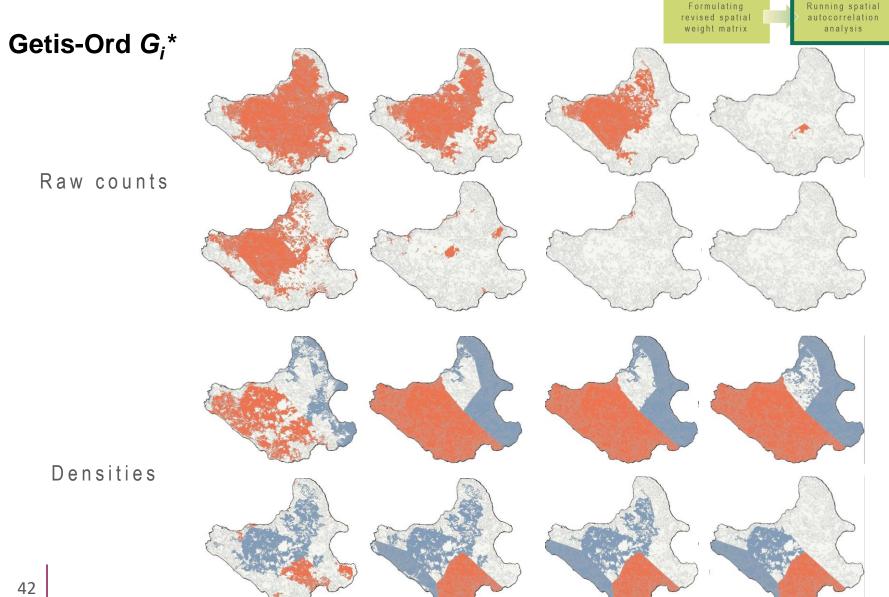
Densities











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What to refine?

Which spatial autocorrelation measures can utilize dasymetrically disaggregated spatial data?

Which parameter(s) in spatial autocorrelation analysis can be modified when using dasymetrically disaggregated data?

- All global and local spatial autocorrelation measures
 - Global Moran's I
 - Geary's C
 - Local Moran's 1
 - Getis-Ord G_i*
- The spatial weight matrix

How to refine?

What **modification(s)** in spatial autocorrelation analysis can be made when using dasymetrically disaggregated data?

- A priority-based spatial weight assignment method
 - Spatial weights are jointly based on their spatial and choroplethic configurations, and;
 - Relative weighting of the two configurations

Are there differences

How do these modifications **differ from each other** in terms of results in the spatial autocorrelation analysis?

How do the results differ from the original spatial autocorrelation analysis?

- With increasing choroplethic priority, the refined method gives two effects:
 - A dampening effect spatial autocorrelation decreases
 - An amplifying effect spatial autocorrelation increases
- Two aspects
 - An increase in degree of neighborhood of the spatial data
 - An increase/decrease in degree of detected spatial autocorrelation





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