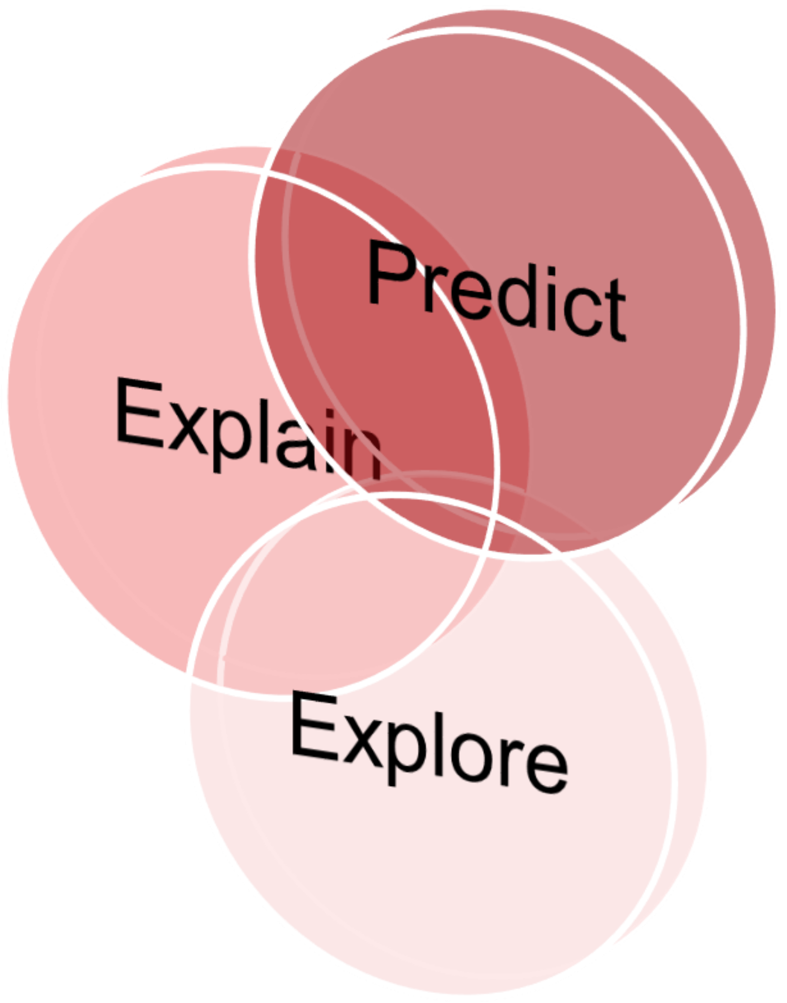
PPGIS analysis methods

A typology for use in research, planning and management



PPGIS analysis methods

A typology for use in research, planning and management

Manhattan skyline, Joseph Pennell

Boulevard des Capucines, Claude Oscar Monet

Kirche in Cassone (Church in Cassone), Gustav Klimt

BETTER LIVING
ENVIRONMENTS

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ENVIRONMENTS

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ENVIRONMENTS

NO SCIENCE ACHIEVES
MATURITY WITHOUT DATA

In this presentation

What is data? & What should we do with it?

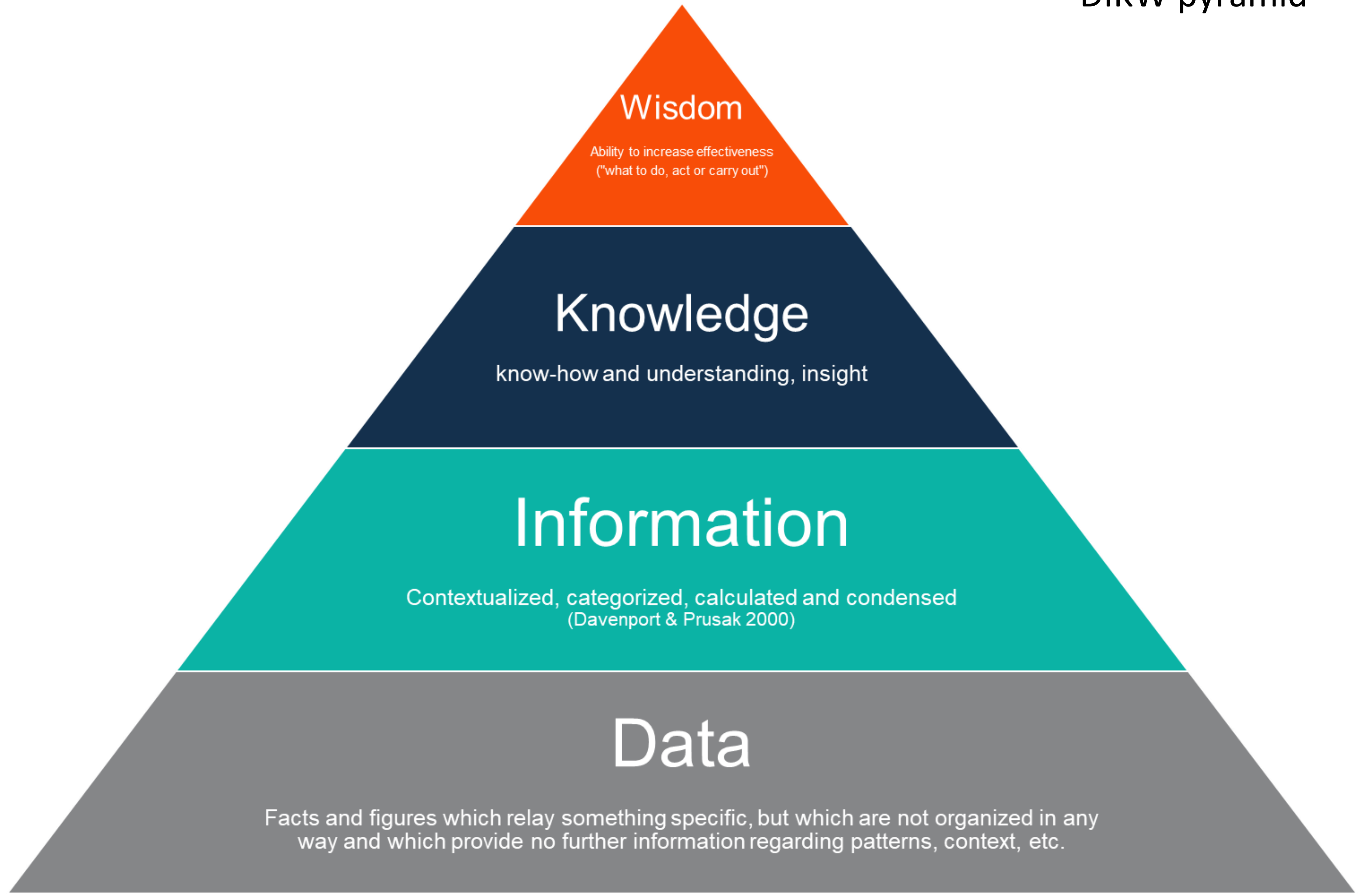
Data:
Factual information (such as measurements or statistics) used as a basis for reasoning, discussion, or calculation (Merriam-Webster)

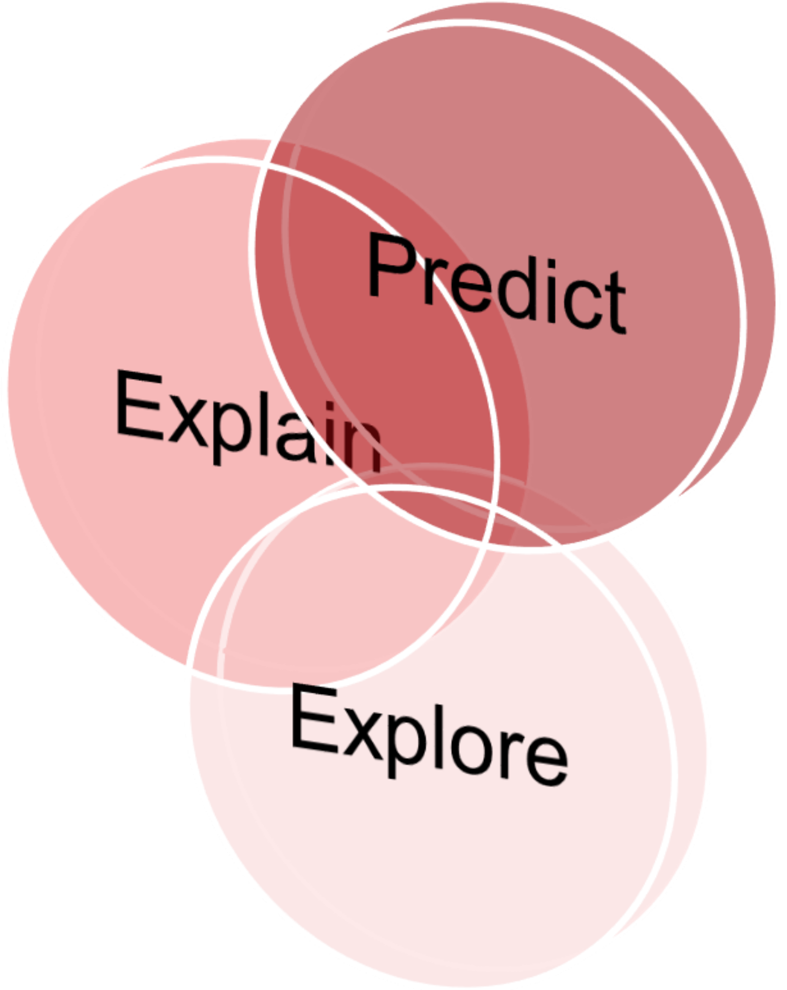
0612 → Finnish independence day
0612 → Rolling Stone's disastrous concert

06121917 → Finnish independence day

DIKW pyramid

Each step up the pyramid answers some questions and adds value to the initial data





(Fagerholm et al., 2021)

Goals:

Explore

- Identify spatial patterns with one attribute at a time
- Compare distribution across attributes

Explain

- Looking further into data
- Looking more closely at observations from ‘Explore’
- Find explanation for observations by further analysis

Predict

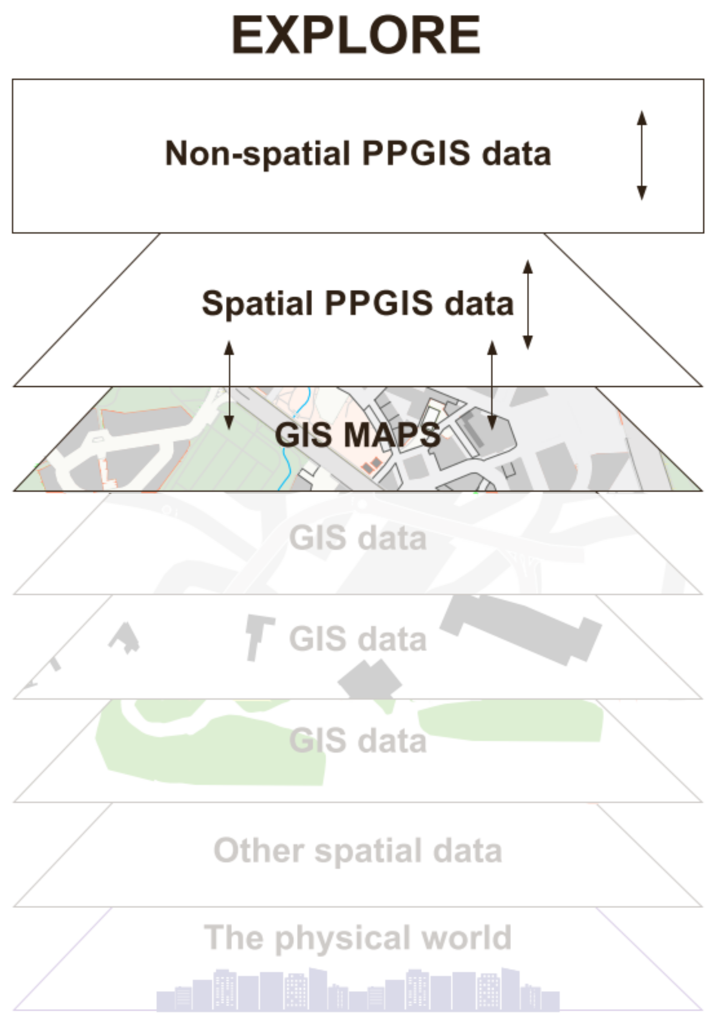
- See if any of the observations are generalizable to other places or contexts
- Project observations to predict future situation

Explore

- The first analytical phase
- *Explore* typically involves descriptive and univariate analysis of PPGIS data and generation of visual outputs.
- The analysis are accomplished with basic GIS software or with the help of the interactive analysis tools provided by some online PPGIS services.
- An important part of *Explore* phase is also assessment of spatial data quality through validation.

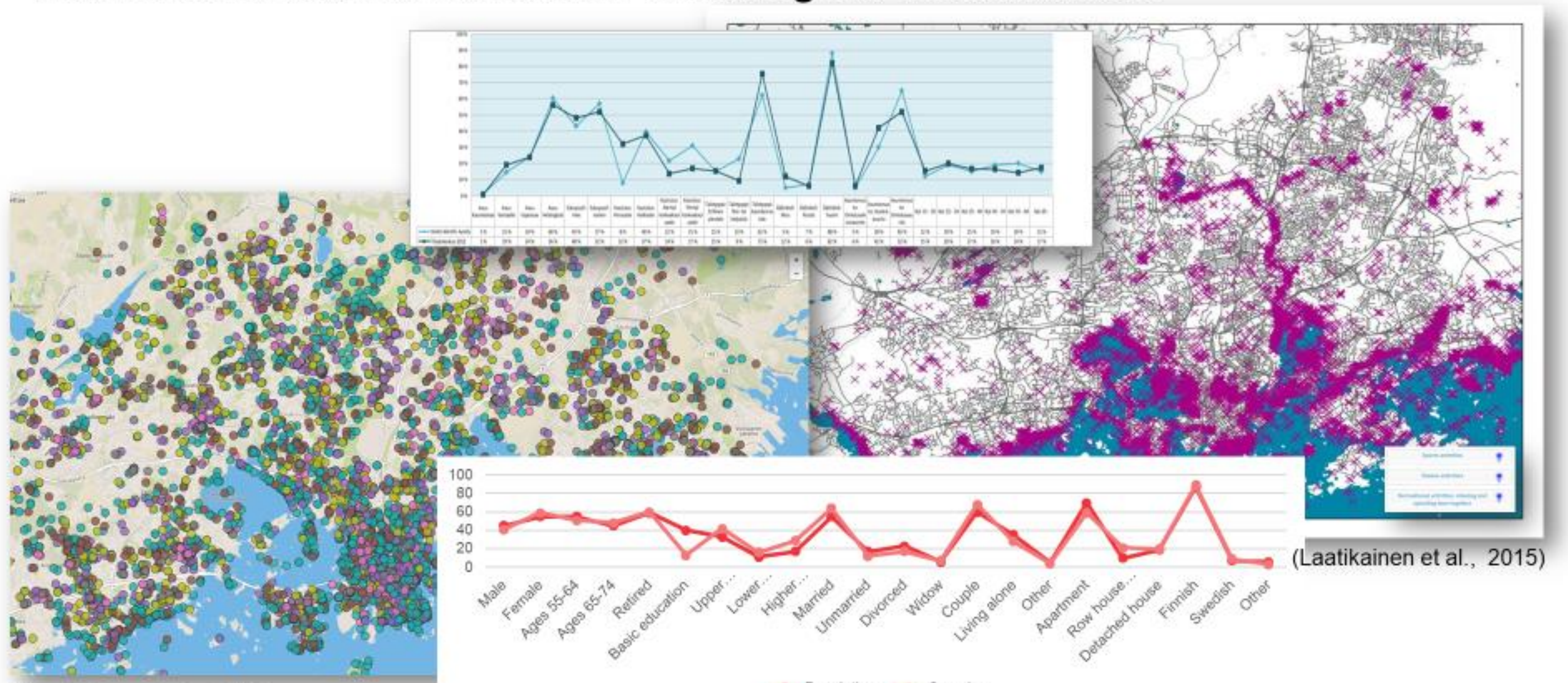
Method categories:

- External and internal validation
- Descriptive and visual analysis



Explore: Examples

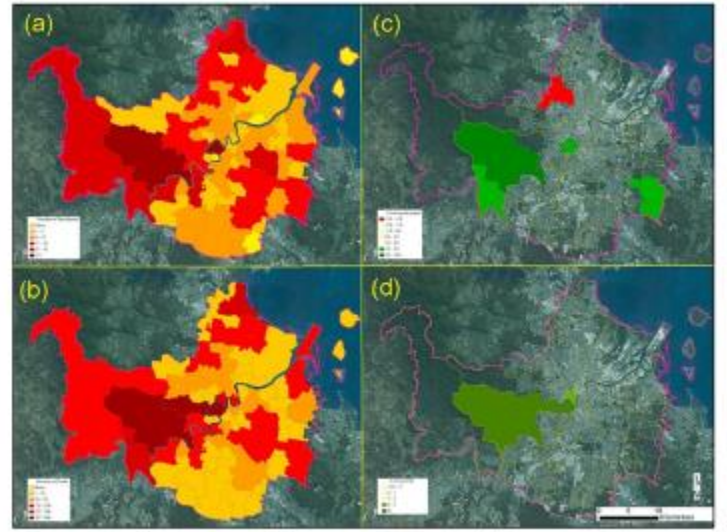
Internal and external validation: checking the inclusiveness



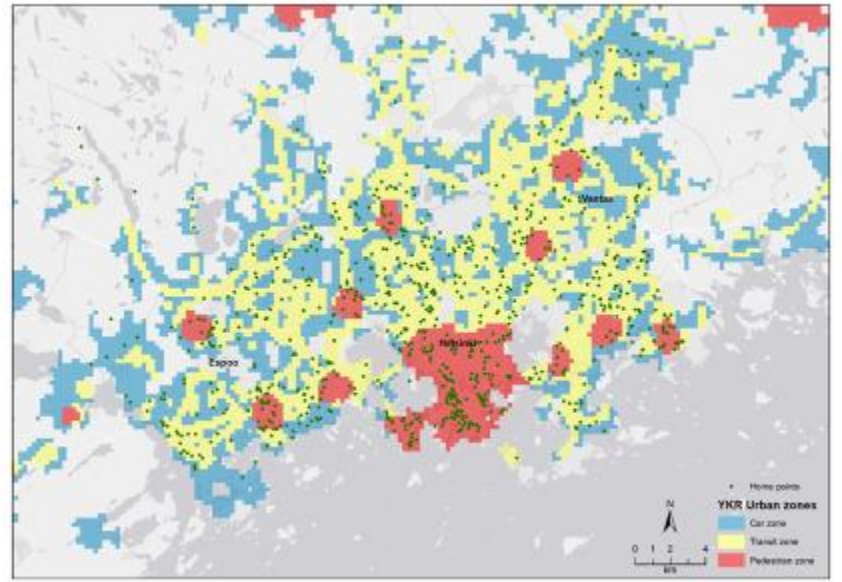
(Laatikainen et al., 2015)

(Laatikainen et al., 2019)

Thematic maps

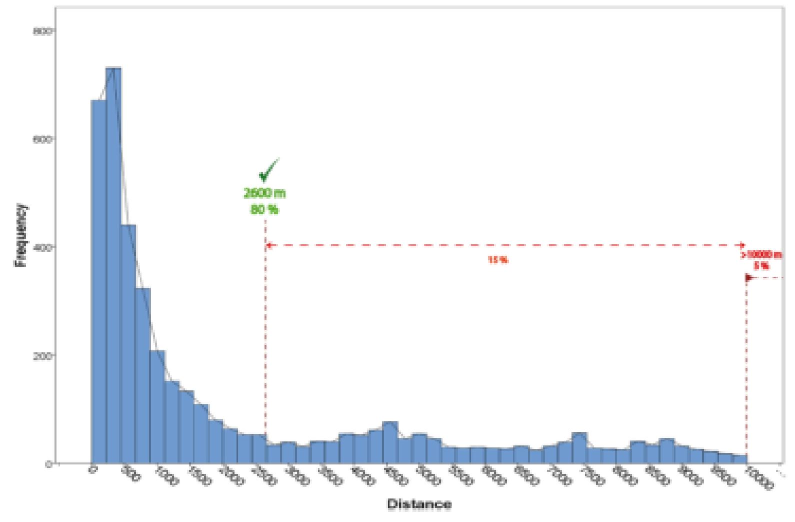


(Brown et al., 2018)

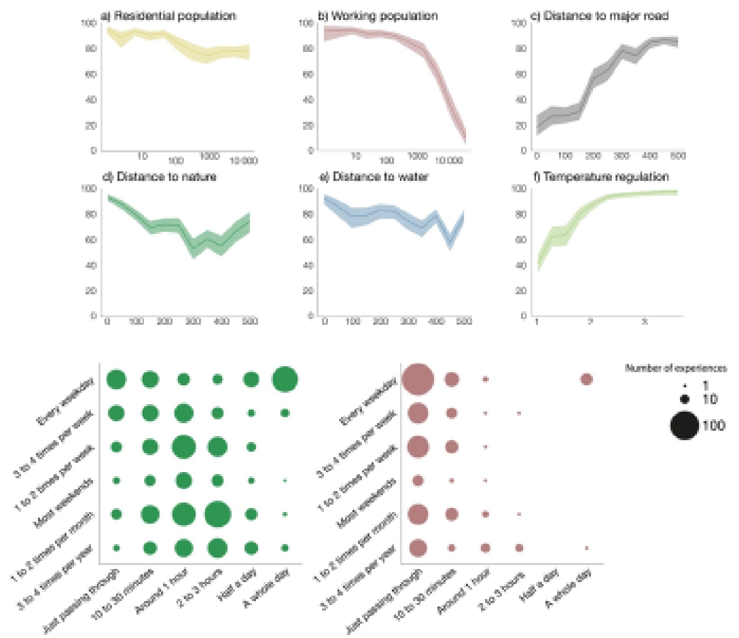


(Hasanzadeh et al., 2019)

Charts



(Hasanzadeh et al., 2017)



(Samuelsson et al., 2018)

Explore: examples

Descriptive statistics

Table 1. Structural variables statistics for the three urban tribes.

		Urban Tribes (Count)		
Urban Structural Variables	Measures	Tribe 1 Urbanist (359)	Tribe 2 *Semi-urbanist* (291)	Tribe 3 Nature lover (353)
Population density (Pop. Per km^2)	Min	75	6	5
	Max	14,748	9125	9152
	Mean	4773	3494	2956
	Median	3886	2497	2021
	SD	2989	2630	2520
	Skewness	0.05	0.73	1.05
Green area coverage (%)	Min	0	2.5	0
	Max	76.5	79.2	88.8
	Mean	19.3	24.6	26.9
	Median	17.3	22.1	22.7
	SD	11.8	12.8	16.9
	Skewness	1.34	0.88	1.34
Service density (service points per km^2) $\times 10^5$	Min	0	0	0
	Max	184	190	214
	Mean	35.2	19.3	14.1
	Median	18	7	5
	SD	43.4	31.6	27.6
	Skewness	1.67	2.9	3.84
Non-motor route density (km of road per km^2) $\times 10^3$	Min	1784	389	489
	Max	34,888	34,475	33,589
	Mean	19,204	15,558	13,329
	Median	19,749	14,535	11,794
	SD	8078	7624	7265
	Skewness	−0.21	0.15	0.33

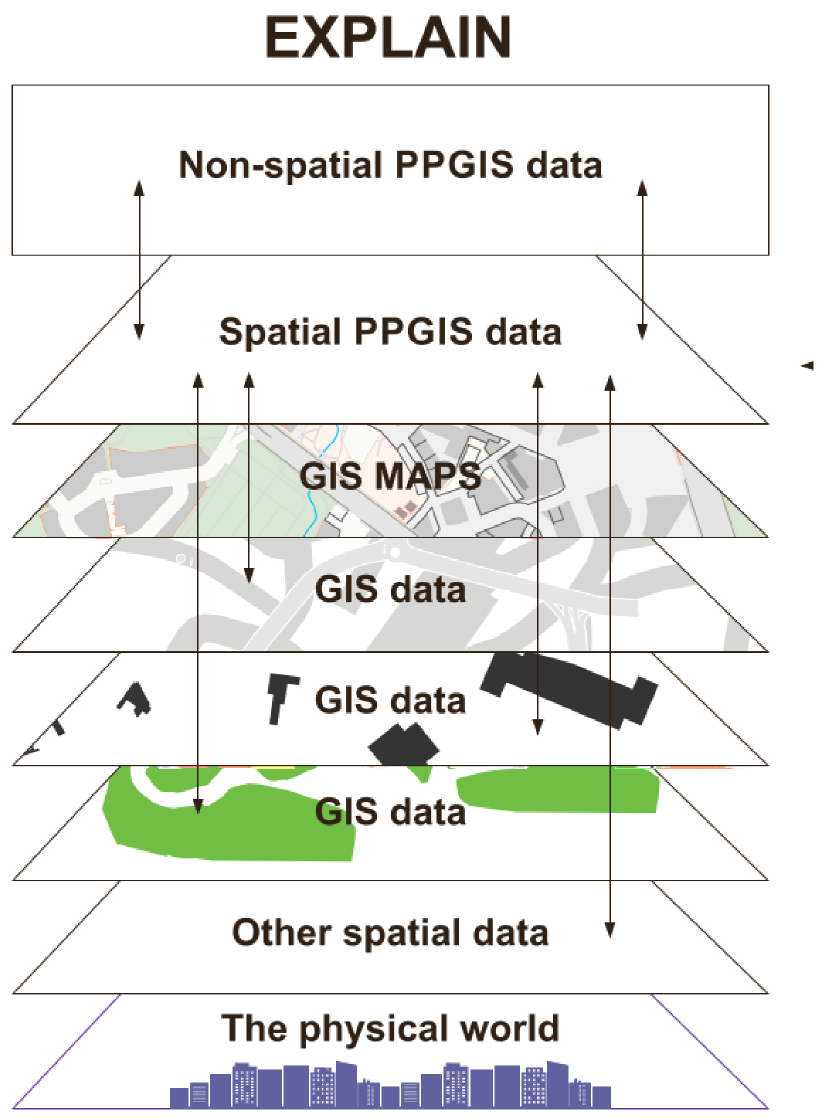
(Hasanzadeh, Kyttä, Brown, 2019)

Explain

- the aim is to look more closely at observations from the Explore phase to explain them by further analysis
- The Explain phase combines spatial and non-spatial PPGIS data with other GIS spatial data.

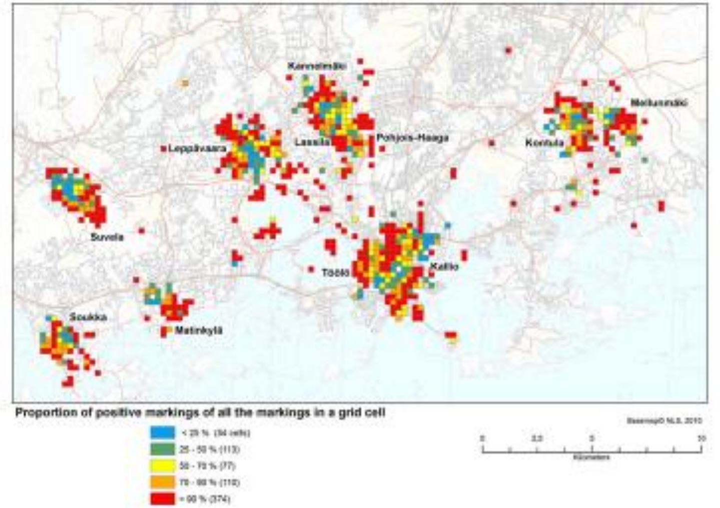
Method categories:

- Visual and overlay analysis
- Spatial pattern analysis
- Proximity and coexistence analysis
- Calculation of indices/measures
- Association analysis
- Cluster analysis

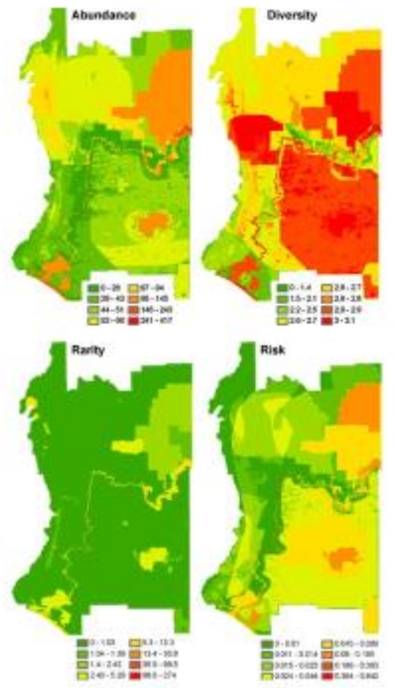


Explain: examples

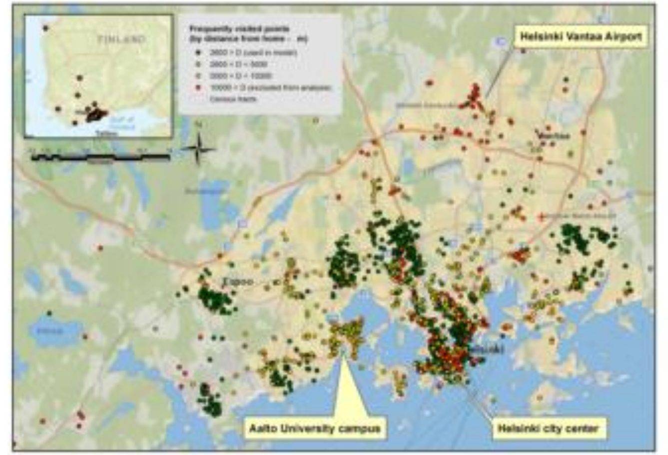
Thematic maps



(Kyttä et al., 2013)



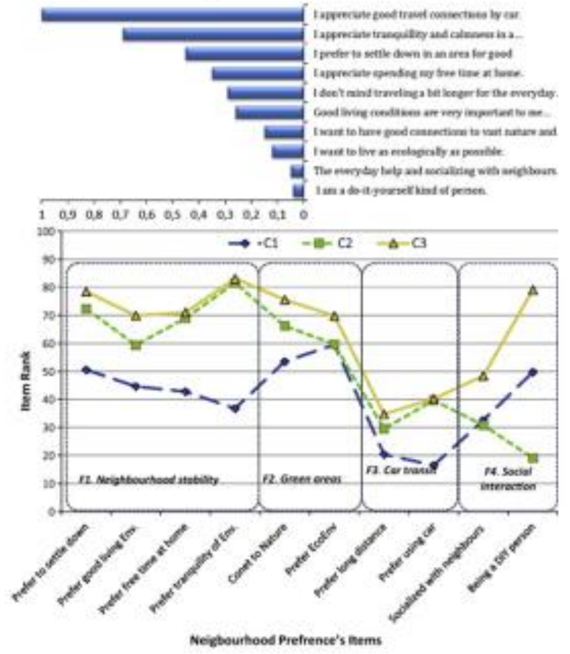
(Bryan et al., 2010)



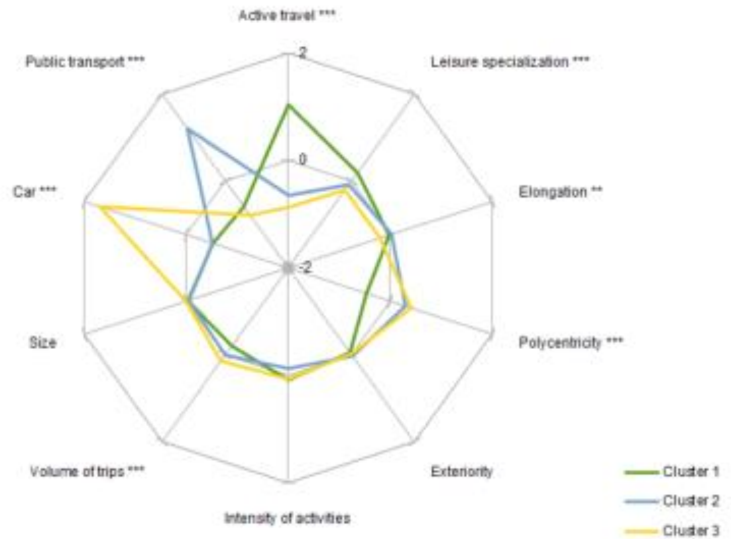
(Hasanzadeh et al., 2017)

examples from PPGIS studies

Clustering analysis

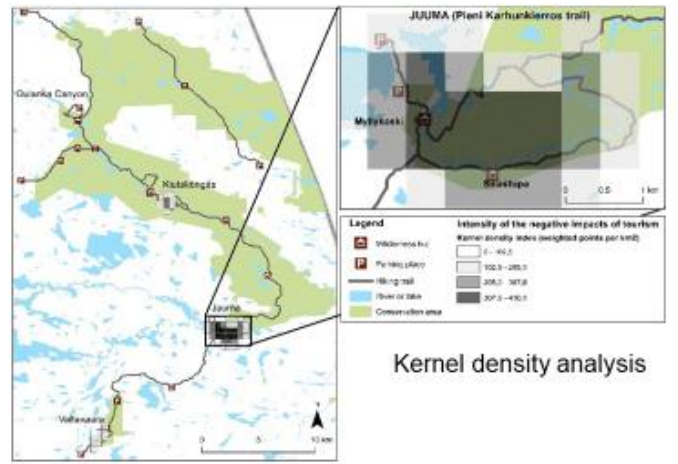


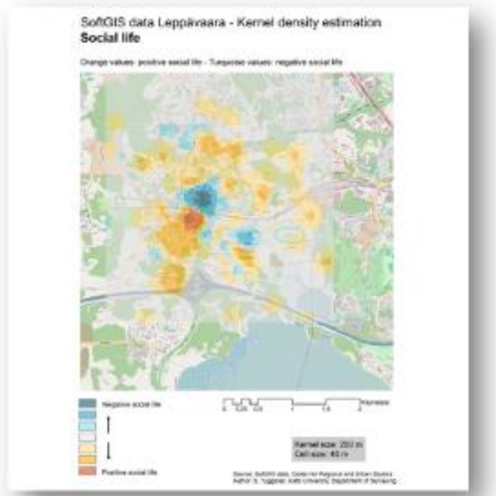
(Haybatollahi et al., 2015)



(Hasanzadeh, 2019)

Spatial pattern analysis





(Pietilä & Fagerholm, 2016)

Explain: examples

Association analysis

Logistic regression

Table 6
Results of ordered logistic regression analyses on associations between the dissonance groups and walking outcomes.

	All destinations		Recreational destinations		Utilitarian destinations	
	Walking trips	Walking distance	Walking trips	Walking distance	Walking trips	Walking distance
	OR	OR	OR	OR	OR	OR
	(95% CI)	(95% CI)	(95% CI)	(95% CI)	(95% CI)	(95% CI)
Gender (ref. female)						
Male	0.87 (0.61–1.25)	0.82 (0.57–1.18)	1.08 (0.75–1.54)	0.97 (0.68–1.39)	0.98 (0.66–1.44)	0.91 (0.61–1.34)
Age (years)	1.00 (0.96–1.04)	1.01 (0.97–1.05)	1.02 (0.98–1.07)	1.02 (0.98–1.07)	0.96 (0.92–1.01)	0.97 (0.93–1.02)
Household income (ref. < 3,000 €)						
3,000–6,500 €	1.14 (0.66–1.98)	0.98 (0.56–1.69)	1.06 (0.61–1.84)	0.87 (0.50–1.52)	0.77 (0.43–1.4)	0.69 (0.38–1.25)
> 6,500 €	1.18 (0.76–1.81)	1.17 (0.76–1.80)	0.93 (0.60–1.43)	0.87 (0.56–1.35)	1.22 (0.77–1.95)	1.17 (0.73–1.86)
Employed (ref. no)	**0.59 (0.38–0.93)**	**0.53 (0.33–0.82)**	0.71 (0.45–1.11)	0.74 (0.47–1.16)	0.77 (0.48–1.25)	0.76 (0.47–1.23)
University degree (ref. no)[a]	1.29 (0.86–1.95)	**1.55 (1.02–2.34)**	1.29 (0.85–1.96)	**1.54 (1.01–2.34)**	1.05 (0.67–1.63)	1.10 (0.71–1.72)
Children in household (ref. no)	1.12 (0.74–1.68)	1.19 (0.79–1.80)	**1.71 (1.13–2.58)**	**1.76 (1.16–2.67)**	1.06 (0.69–1.64)	1.01 (0.66–1.56)
Dissonance (ref. high-walkability consonant)						
Low-walkability consonant	**0.15 (0.09–0.26)**	**0.12 (0.07–0.22)**	**0.34 (0.20–0.58)**	**0.25 (0.15–0.44)**	**0.10 (0.06–0.19)**	**0.10 (0.05–0.19)**
Low-walkability, no strong preference	**0.28 (0.17–0.47)**	**0.23 (0.14–0.39)**	**0.40 (0.24–0.66)**	**0.30 (0.18–0.50)**	**0.21 (0.12–0.36)**	**0.19 (0.11–0.33)**
Low-walkability dissonant	**0.44 (0.24–0.83)**	**0.41 (0.22–0.77)**	**0.50 (0.26–0.93)**	**0.44 (0.23–0.83)**	**0.36 (0.19–0.70)**	**0.35 (0.18–0.67)**
High-walkability dissonant	**0.49 (0.24–0.98)**	**0.40 (0.20–0.81)**	**0.43 (0.20–0.90)**	**0.39 (0.19–0.82)**	**0.47 (0.23–0.99)**	**0.43 (0.21–0.90)**
High-walkability, no strong preference	**0.51 (0.30–0.87)**	**0.43 (0.25–0.73)**	**0.53 (0.31–0.91)**	**0.45 (0.26–0.77)**	0.57 (0.32–1.02)	0.57 (0.32–1.03)
BIC[b]	1180.54	1179.68	1181.54	1171.30	1056.73	1048.85
– Log likelihood	−548.27	−543.64	−544.98	−539.86	−483.39	−479.47
n	461	461	448	448	402	402

All outcome measures have been classified into ordered outcome variables (1 = 1st quartile, 2 = 2nd quartile, 3 = 3rd quartile, 4 = 4th quartile). Bolded values are significant ($p < .05$).
[a] Including undergraduate, graduate and postgraduate degrees.
[b] Bayesian Information Criterion (BIC). Lower values indicate a better model fit.

(Kajosaari et al., 2019)

Pearson's correlation

Table 3
Correlations between different measures of activity space dispersion. (AS: activity space).

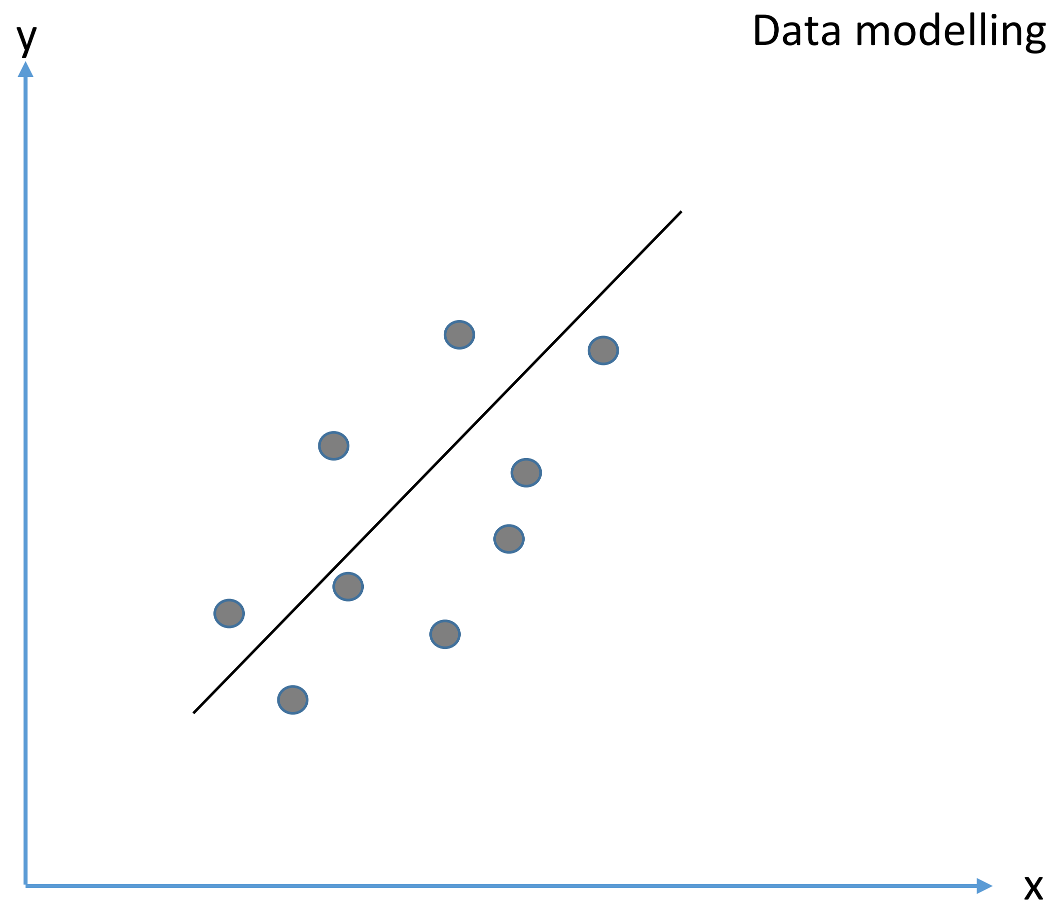
	Perimeter of AS	Area of AS	Average distance to activity places	Elongation	Gravelius	Centricity
Perimeter of AS	1	0.627**	0.415**	0.105**	0.201**	0.282**
Area of AS	0.627**	1	0.263**	−0.013	−0.012	0.136**
Average distance to activity places	0.415**	0.263**	1	0.031	0.025	0.233**
Elongation	0.105**	−0.013	0.031	1	0.901**	−0.054
Gravelius	0.201**	−0.012	0.025	0.901**	1	−0.084*
Centricity	0.282**	0.136**	0.233**	−0.054	−0.084*	1

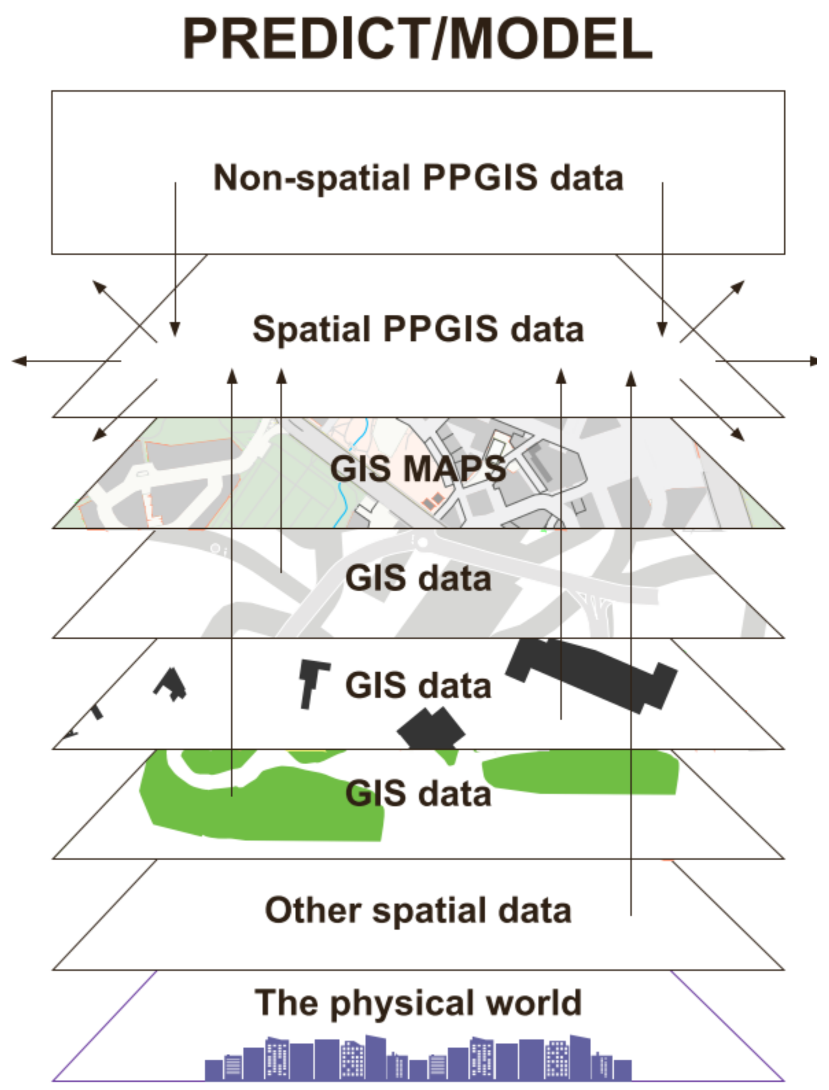
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

(Hasanzadeh, 2019)

Predict

- the aim is to generalize and predict mapped attributes to other places and contexts (prediction) or produce a representation of a system (model)
- this phase typically requires multiple data sources Performing analysis in Predict/Model phase requires in-depth expertise in applying GIS and statistical software. Skills in computer coding may also be necessary.





THE FALLACY TRAP:

A fallacy is a kind of error in reasoning.

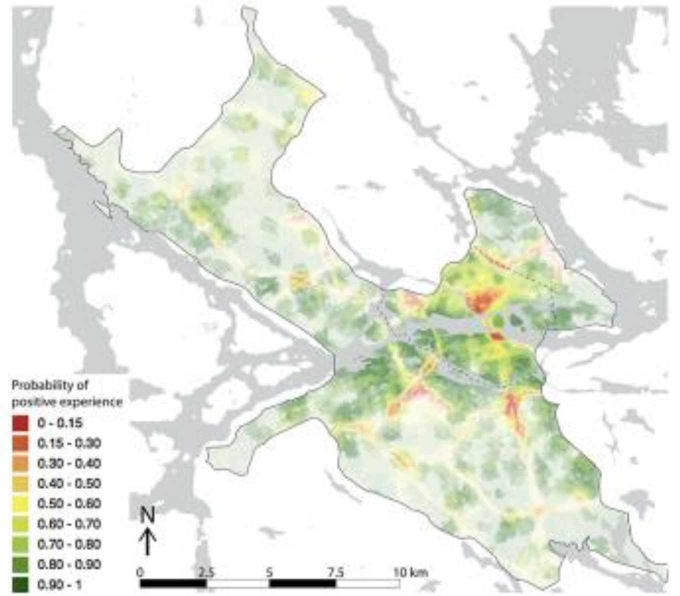
Examples:
Biased Generalizing: Generalizing from a biased sample. Using an unrepresentative sample and overestimating the strength of an argument based on that sample.

Ecological fallacy: failure in reasoning that arises when an inference is made about an individual based on aggregate data for a group

Predict:

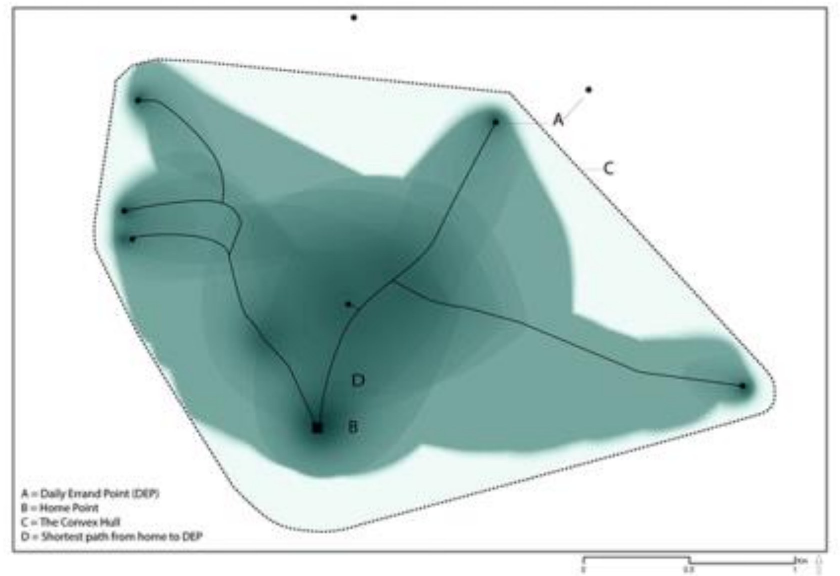
examples from PPGIS studies

Spatial regression model



(Samuelsson et al., 2018)

Exposure estimation (IREM)



(Hasanzadeh et al., 2018)

Remember…

- **The journey up the pyramid is not always a straight one**
  - We might need to move back and forth between analytical stages
- **The stages can overlap**
  - Similar methods may be used for different purposes
- **Mixed approaches are very common**

Thank you!

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Read more:

Nora Fagerholm, Christopher M. Raymond, Anton Stahl Olafsson, Gregory Brown, Tiina Rinne, Kamyar Hasanzadeh, Anna Broberg & Marketta Kyttä (2021) A methodological framework for analysis of participatory mapping data in research, planning, and management, International Journal of Geographical Information Science, DOI: 10.1080/13658816.2020.1869747

References:

Brown, G., Rhodes, J., & Dade, M. (2018). An evaluation of participatory mapping methods to assess urban park benefits. Landscape and Urban Planning, 178, 18-31.

Hasanzadeh, K. (2019). Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors.

Hasanzadeh, K., Kyttä, M., & Brown, G. (2019). Beyond Housing Preferences: Urban Structure and Actualisation of Residential Area Preferences. Urban Science, 3(1), 21.

Laatikainen, T., Haybatollahi, M., & Kyttä, M. (2019). Environmental, individual and personal goal influences on older adults' walking in the Helsinki metropolitan area. International journal of environmental research and public health, 16(1), 58.

Laatikainen, T., Tenkanen, H., Kyttä, M., & Toivonen, T. (2015). Comparing conventional and PPGIS approaches in measuring equality of access to urban aquatic environments. Landscape and Urban Planning, 144, 22-3.

Samuelsson, Karl, et al. "Impact of environment on people's everyday experiences in Stockholm." Landscape and Urban Planning 171 (2018): 7-17.