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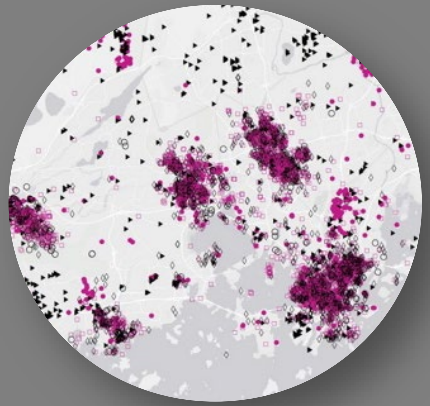

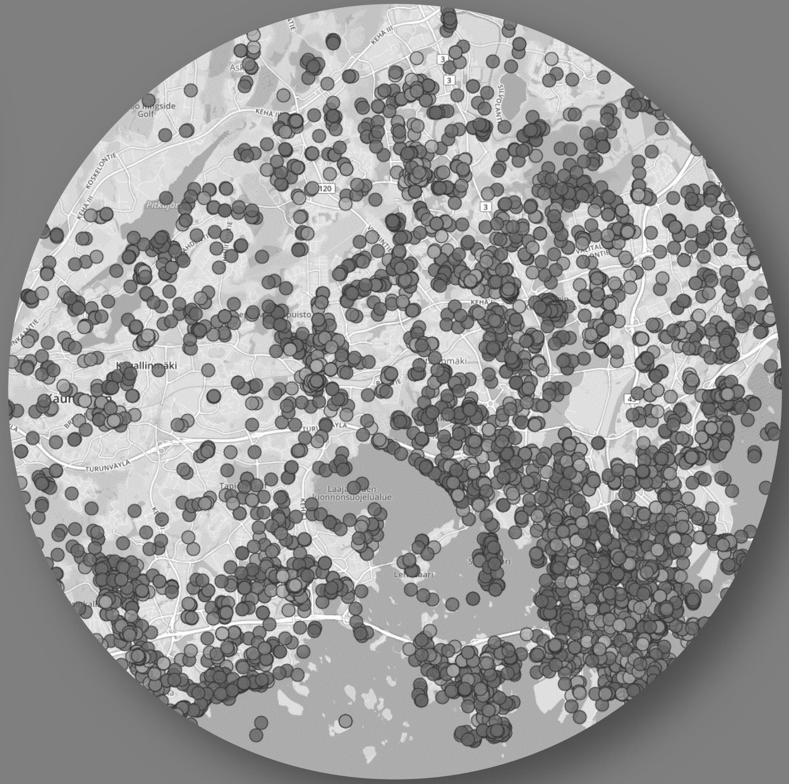

PPGIS data and analysis methods

Urban Experience 2023
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Today we will…

- **First take a closer look to PPGIS data: the nature and structure**
- **Then we dive into the PPGIS analysis methods**
    - Explore
    - Explain
    - Predict

PPGIS survey elements

BACKGROUND INFORMATION
- Age
- Gender
- Tenure
- Education
- Income
- Etc.

1
NON-SPATIAL KNOWLEDGE about individual preferences, lifestyles, attitudes or values

2
SPATIAL KNOWLEDGE:
- individual preferences, attitudes or values
- individual behavior, lifestyles and everyday practices
- environmental phenomenon and problems (citizen science)

3
SPATIAL KNOWLEDGE: individual future wishes, visions and preferences

OUTCOME VARIABLES
- Neigh-bourhood satisfaction
- Quality of Life
- Perceived Heath
- Happiness
- Physical activity levels
- etc.

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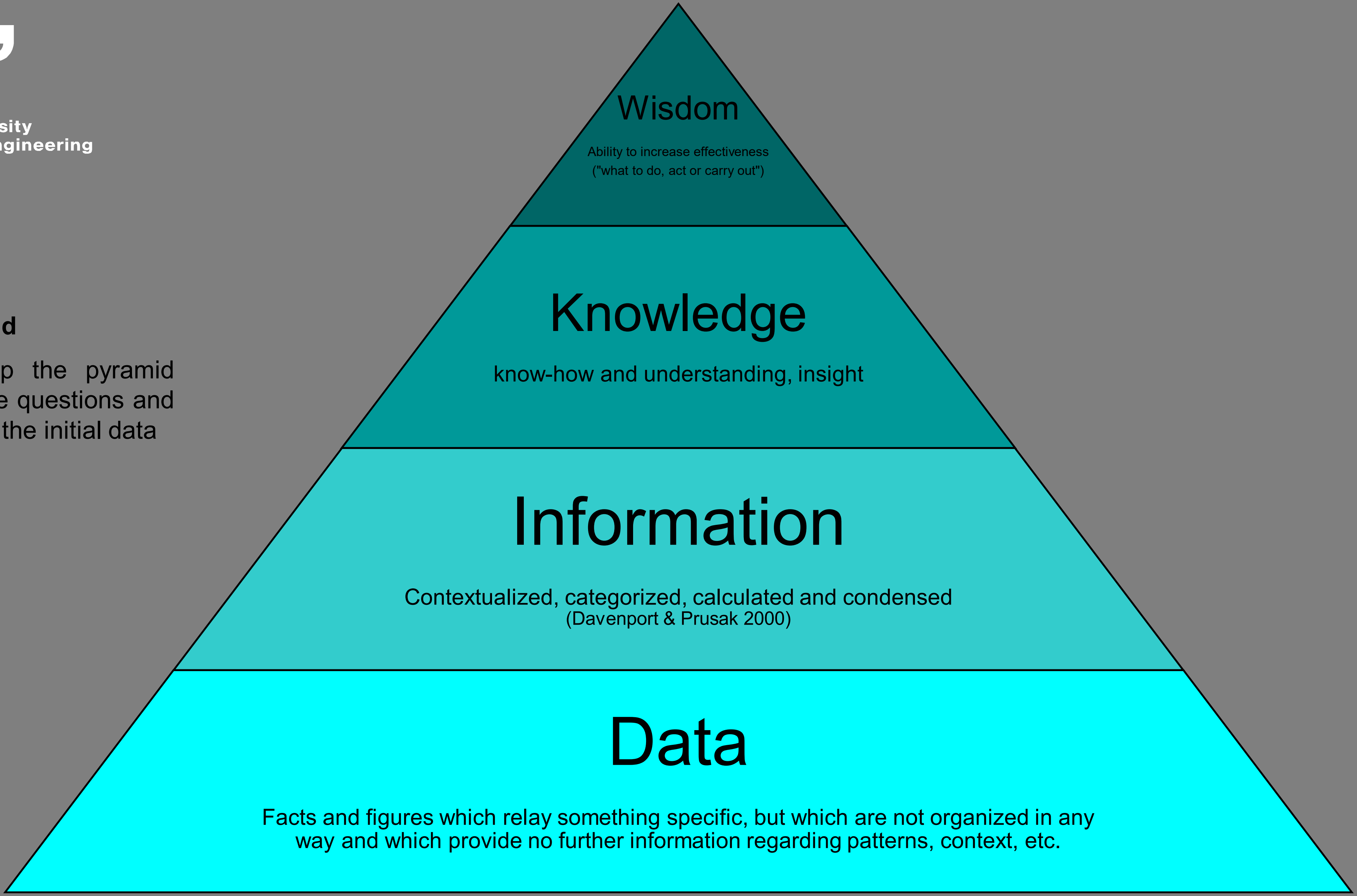
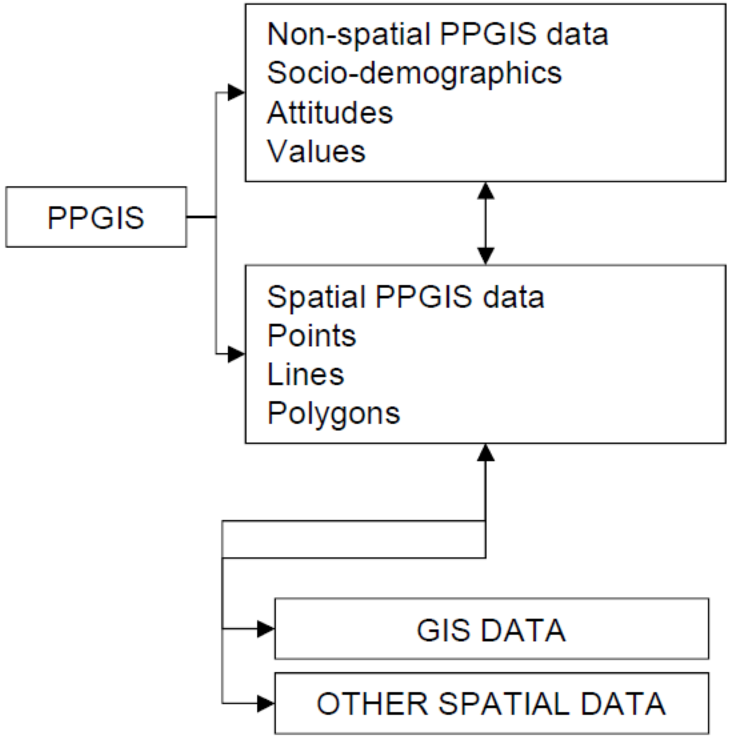
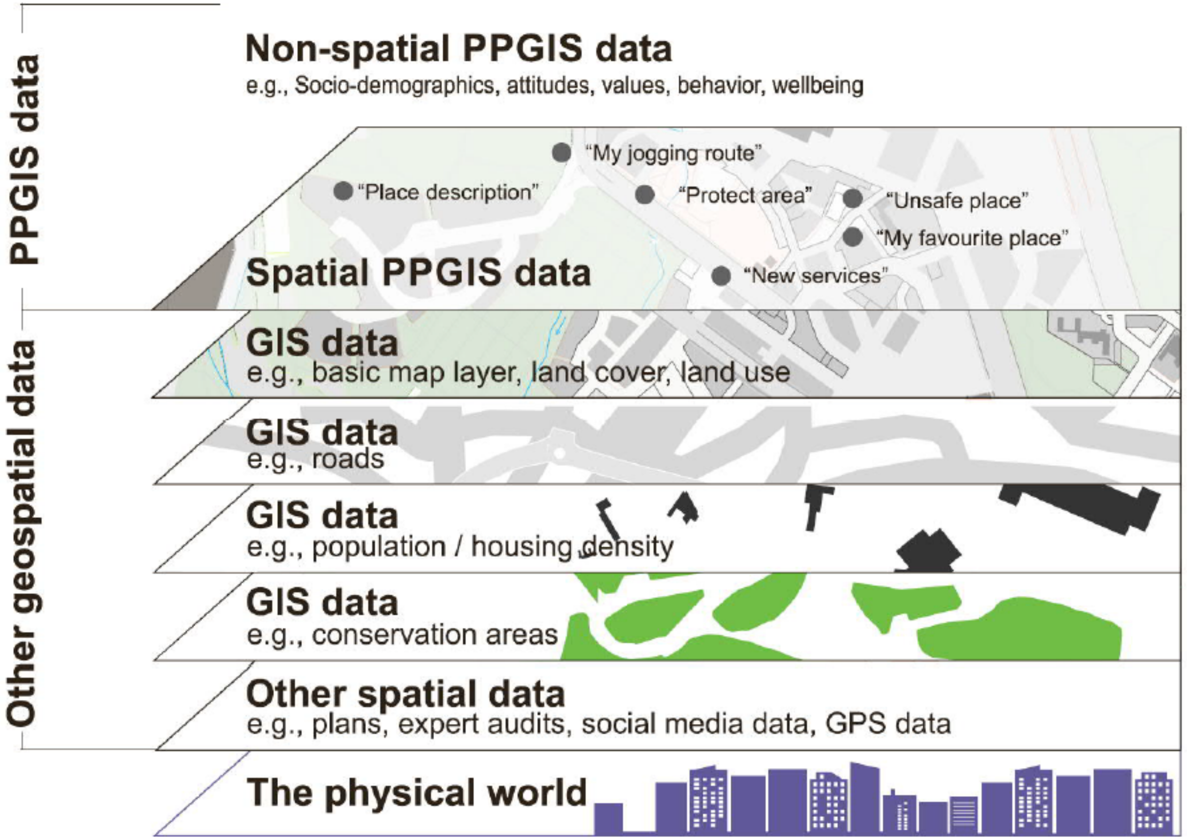
DIKW pyramid

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



About the nature of PPGIS data





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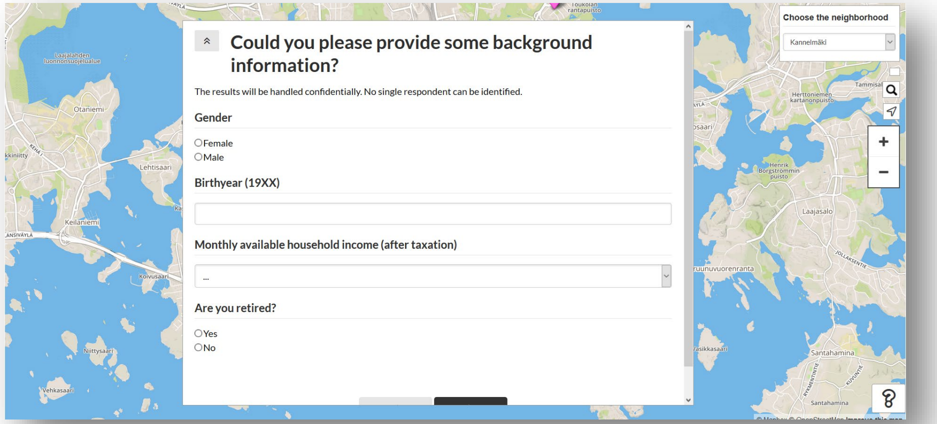
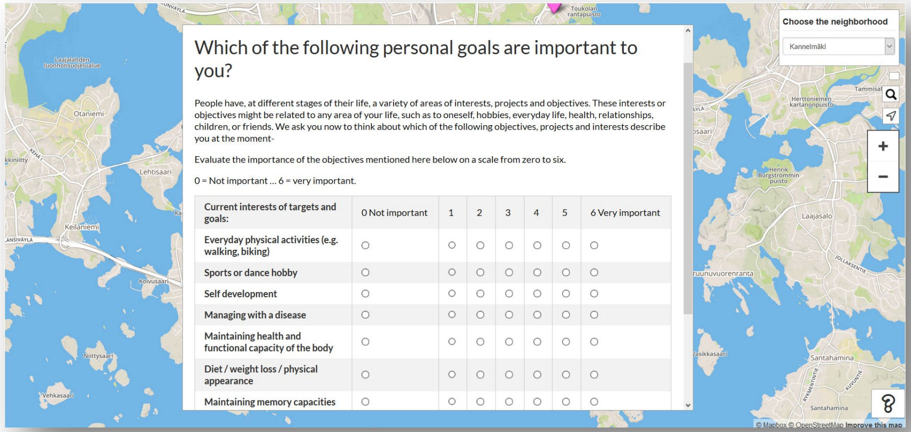
Non-spatial PPGIS data

PPGIS → Non-spatial PPGIS data
- Socio-demographics
- Attitudes
- Values

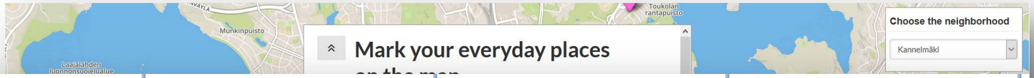
respondent	lang_code	scr_width	Your grade_5th gra	Your grade_9th gra	Your grade	Gender_girl	Gender_boy	Gender
17	fi	1280	1	0	5. grade	0	1	boy
18	fi	1920	1	0	5. grade	0	1	boy
19	fi	1920	1	0	5. grade	0	1	boy
20	fi	1920	1	0	5. grade	0	1	boy
21	fi	1280	1	0	5. grade	0	1	boy
22	fi	1280	1	0	5. grade	1	0	girl
23	fi	1920	1	0	5. grade	0	1	boy
24	fi	1920	1	0	5. grade	0	1	boy
25	fi	1034	1	0	5. grade	1	0	girl
26	fi	1920	1	0	5. grade	0	1	boy
27	fi	1173	1	0	5. grade	1	0	girl
29	fi	1920	1	0	5. grade	1	0	girl
30	fi	1280	1	0	5. grade	1	0	girl
31	fi	1280	1	0	5. grade	1	0	girl
33	fi	1280	1	0	5. grade	0	1	boy
34	fi	1034	1	0	5. grade	0	1	boy
36	fi	1280	1	0	5. grade	1	0	girl
37	fi	1280	1	0	5. grade	1	0	girl
38	fi	768	1	0	5. grade	0	1	boy
39	fi	1920	1	0	5. grade	0	1	boy
40	fi	1920	1	0	5. grade	1	0	girl
42	fi	1280	1	0	5. grade	1	0	girl
45	fi	1280	1	0	5. grade	1	0	girl
47	fi	1920	1	0	5. grade	0	1	boy
51	fi	1173	1	0	5. grade	1	0	girl
52	fi	1280	1	0	5. grade	1	0	girl





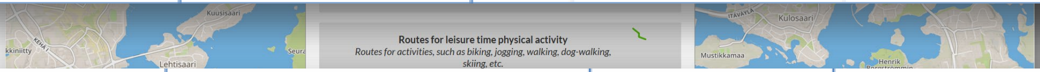
Spatial PPGIS data

PPGIS



respondent	createtime	id	buttonname	visibleLayers	zoomLevel	wkt	What makes the place nice?
18	2016-10-17T05:27:17.0	1	My school	MapBox	17	POINT (24.630575 60.153104)	
21	2016-10-17T05:27:58.0	2	My school	MapBox	17	POINT (24.630575 60.153104)	
17	2016-10-17T05:28:05.4	3	My home	MapBox	17	POINT (24.655970 60.197308)	
20	2016-10-17T05:28:22.4	4	My school	MapBox	17	POINT (24.630575 60.153104)	
20	2016-10-17T05:28:32.4	5	My home	MapBox	17	POINT (24.630758 60.151999)	
17	2016-10-17T05:28:55.5	6	My school	Google Hybrid	16	POINT (24.630833 60.152976)	
19	2016-10-17T05:29:11.3	7	My school	MapBox	18	POINT (24.630677 60.153048)	
20	2016-10-17T05:29:17.1	8	Safe place	MapBox	17	POINT (24.630843 60.152010)	

respondent	createtime	id	buttonname	visibleLayers	zoomLevel	wkt	What makes the place nice?
18	2016-10-17T05:27:17.0	1	My school	MapBox	17	POINT (24.630575 60.153104)	



espondent	createtime	id	buttonname	visibleLayers	zoomLevel	wkt	How to you most often travel your school journeys?	Other transport mode, what?
17	2016-10-17T05:29:41.3	10	My school journey	Google Hybrid	16	LINESTRING (24.631004 60.153136, 24.6	By bus	
19	2016-10-17T05:30:10.2	13	My school journey	MapBox	18	LINESTRING (24.634266 60.153991, 24.6	By scooter	
23	2016-10-17T05:31:43.9	28	My school journey	MapBox	17	LINESTRING (24.629674 60.152181, 24.6	By foot	
24	2016-10-17T05:31:52.0	30	My school journey	MapBox	17	LINESTRING (24.634309 60.154364, 24.6	By foot	
25	2016-10-17T05:32:51.6	42	My school journey	MapBox	17	LINESTRING (24.633504 60.152223, 24.632131 60.152346)		
18	2016-10-17T05:34:01.6	52	My school journey	MapBox	18	LINESTRING (24.637181 60.148752, 24.6	By scooter	
25	2016-10-17T05:34:47.9	58	My school journey	MapBox	17	LINESTRING (24.633558 60.152245, 24.6	By foot	
27	2016-10-17T05:34:58.0	59	My school journey	MapBox	17	LINESTRING (24.633290 60.152026, 24.6	By foot	
25	2016-10-17T05:35:38.0	62	My school journey	MapBox	17	LINESTRING (24.634577 60.151871, 24.6	By foot	
34	2016-10-17T05:37:19.4	83	My school journey	MapBox	17	LINESTRING (24.632024 60.154994, 24.6	By foot	

31	2016-10-17T05:31:59.2	31	My school	MapBox				
64	2016-10-17T07:48:43.9	303	My school journey	MapBox	15	LINESTRING (24.743915 60.157696, 24.743528 60.157888, 24.743056 60.158315, 24.74		
64	2016-10-17T07:49:44.9	305	My school journey	MapBox	15	LINESTRING (24.735503 60.159020, 24.734387 60.158764, 24.731255 60.158038, 24.72		
64	2016-10-17T07:50:03.0	306	My school journey	MapBox	15	LINESTRING (24.711514 60.147743, 24.7	Other mode	By taxi
67	2016-10-17T07:50:09.8	307	My school journey	MapBox	17	LINESTRING (24.649179 60.149131, 24.648868 60.149436, 24.648814 60.149628, 24.64		
68	2016-10-17T07:51:09.9	309	My school journey	MapBox	11	LINESTRING (24.719238 60.212533, 24.6	By car	By taxi

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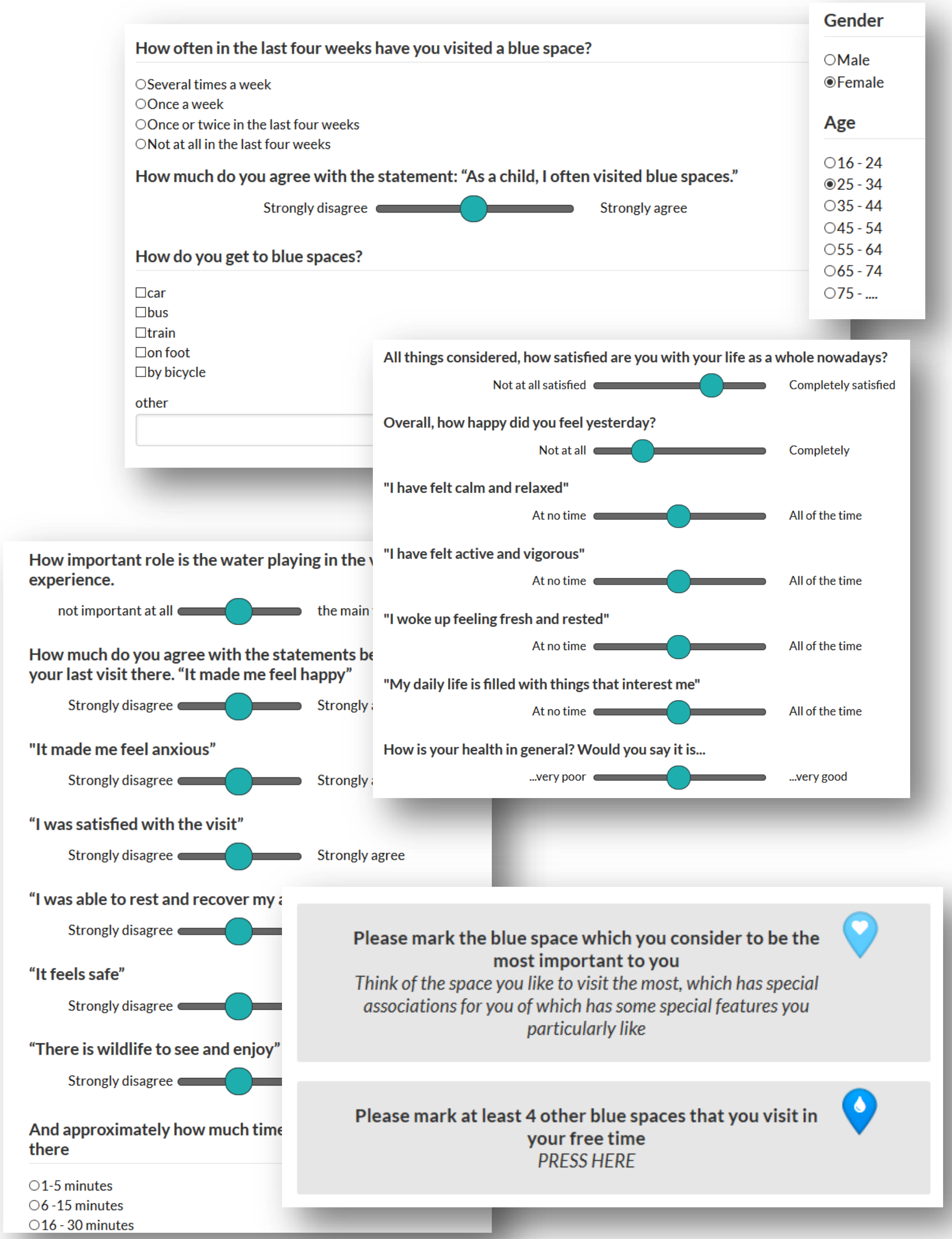
Data preparation

Prior to further analysis the collected data needs to go through preparatory procedures that include but are not limited to:

- **Downloading the data**
- **Cleaning the data/removal of invalid data**
- **Dataset setup: e.g. renaming variables, transforming variables**
- **Additional preparatory steps**



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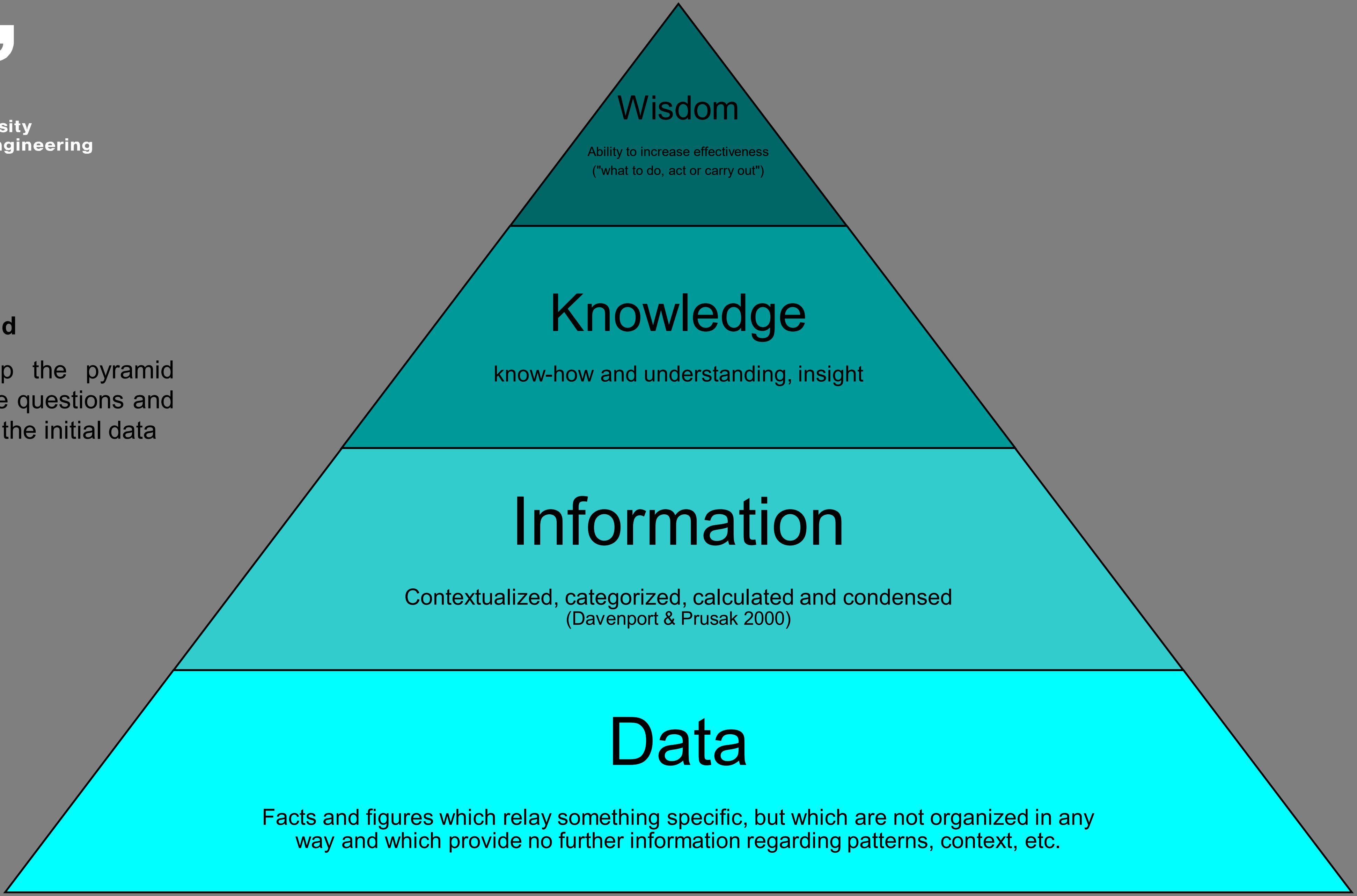
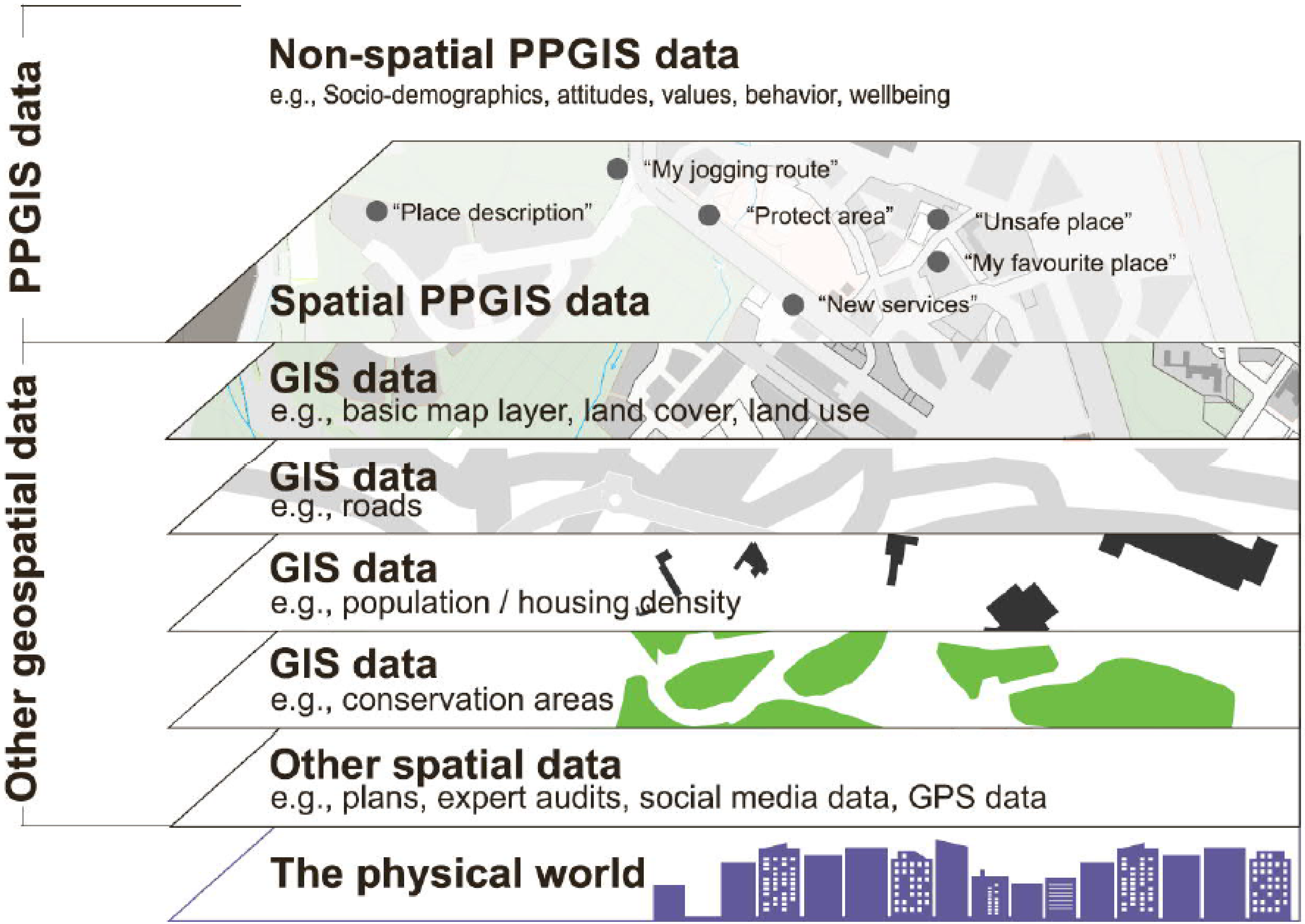
DIKW pyramid

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





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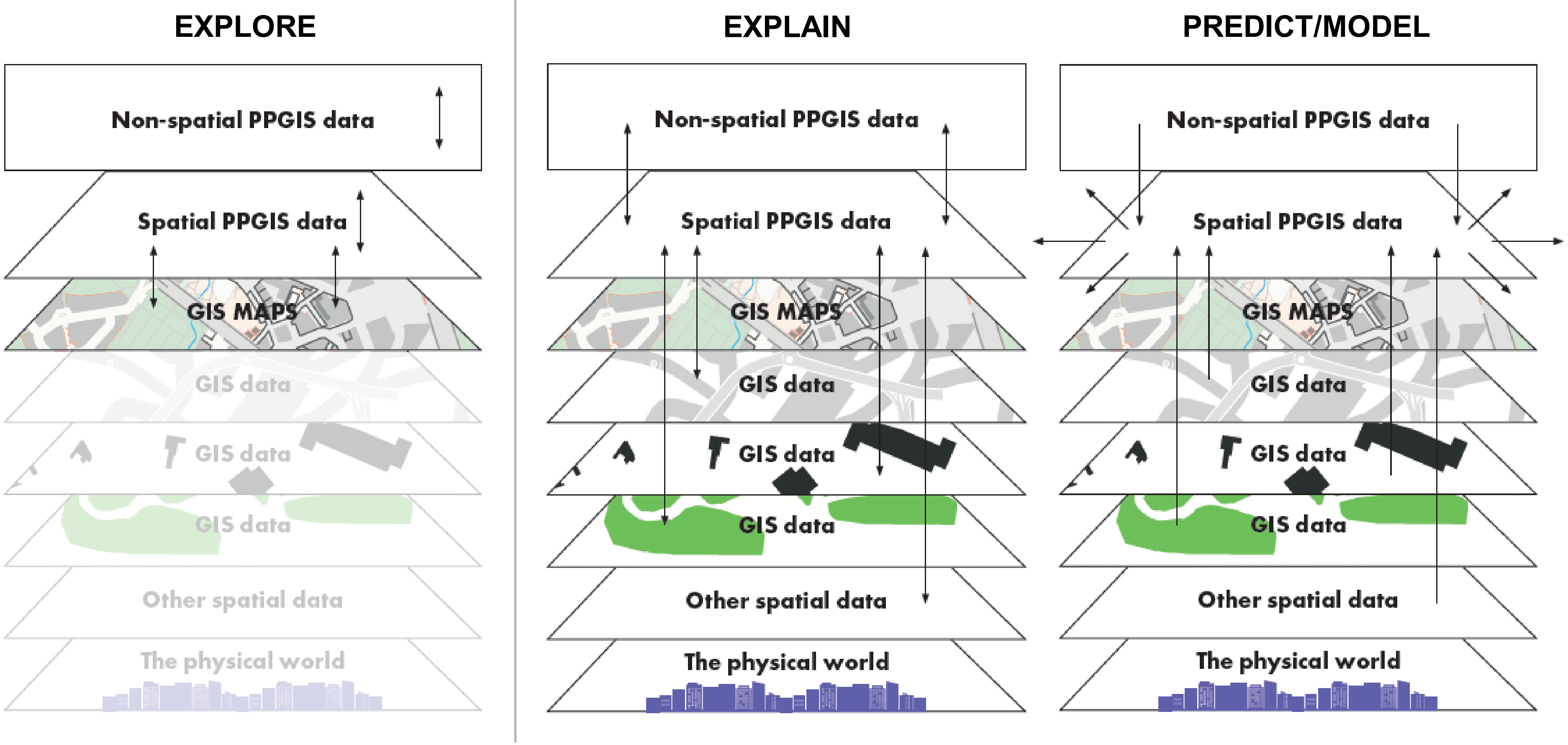

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Explore

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

Explain

- Looking further into data
- Looking more closely at observations from 'Explain'
- 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

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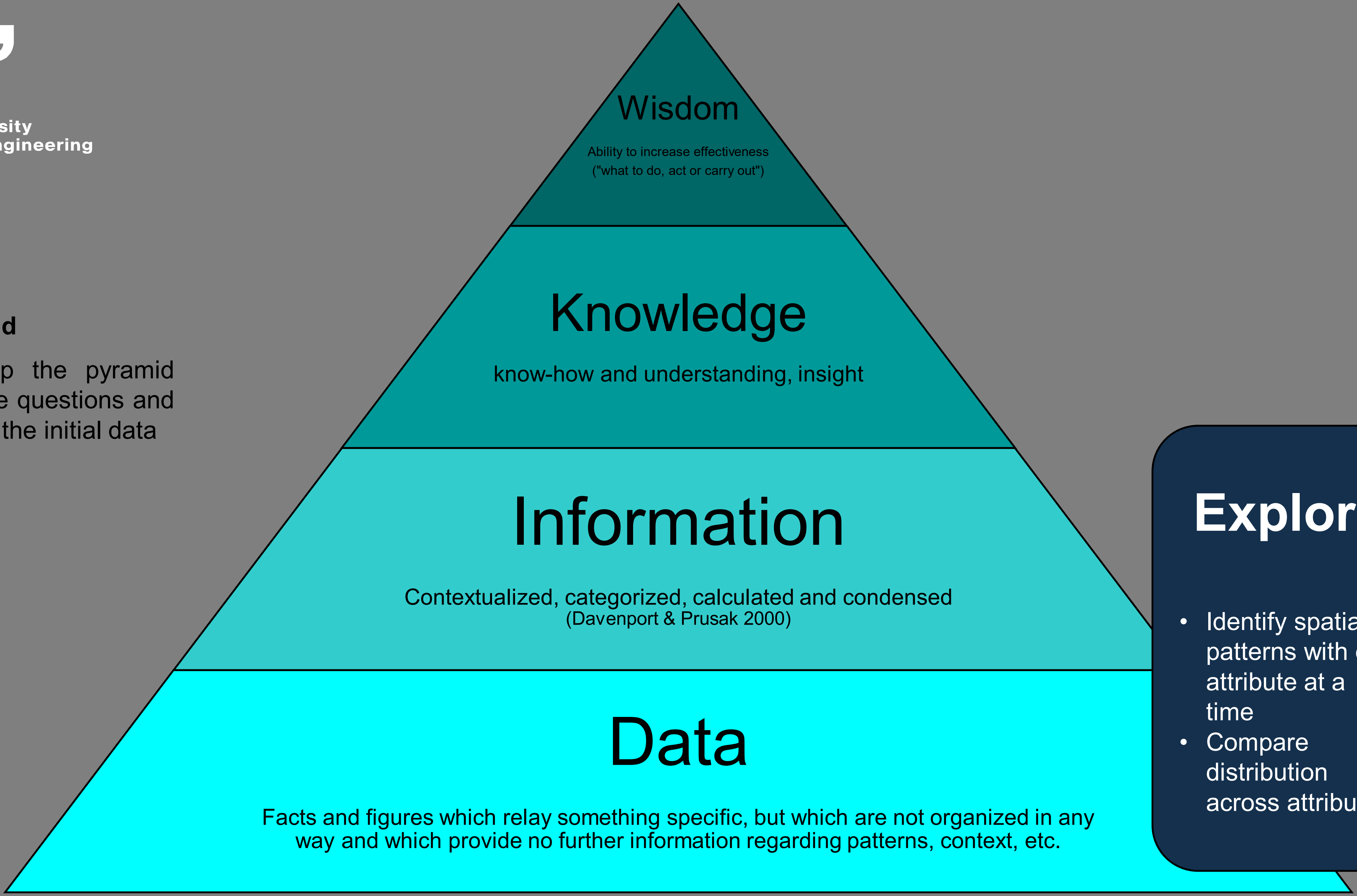
DIKW pyramid

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



Explore

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

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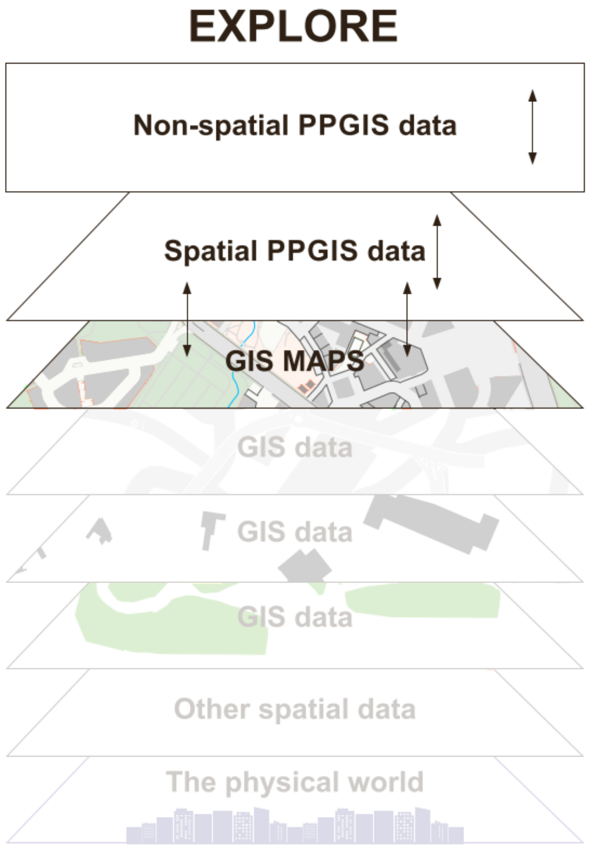
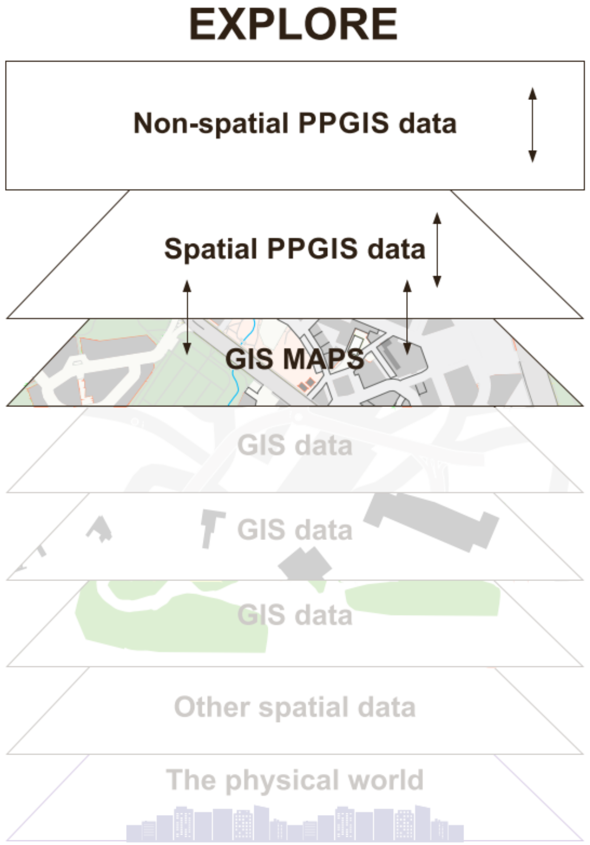
Explore

- The first analytical phase
- *Explore* typically involves descriptive and univariate analysis of PPGIS data and generation of visual outputs.
- Spatial patterns are identified with one attribute at one time (univariate analysis) and compared across attributes.



Explore

- *Explore* phase typically focus on spatial and non-spatial PPGIS data but incorporate other geospatial data only as cartographic background information.
- 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.



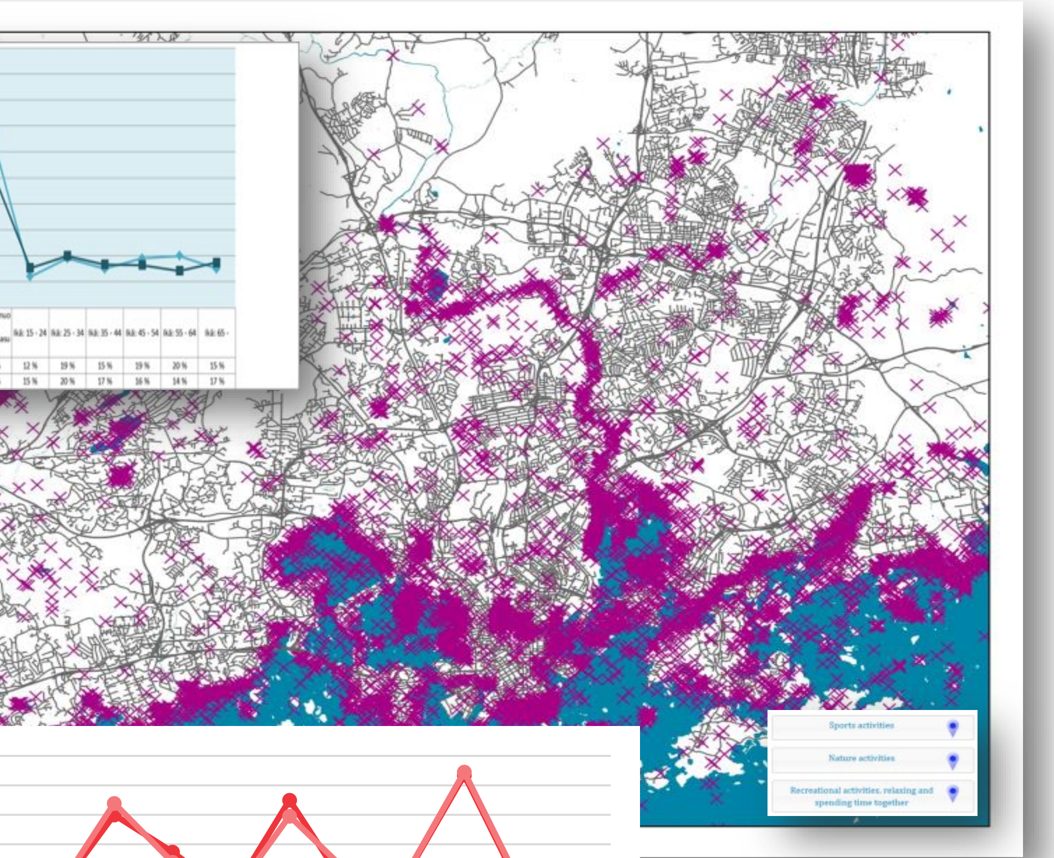
Explore:

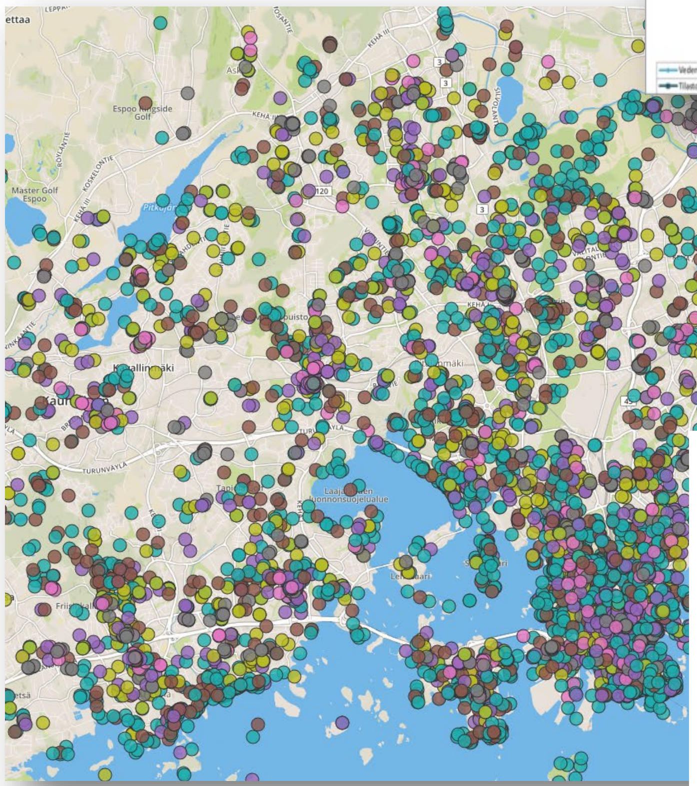
Method categories

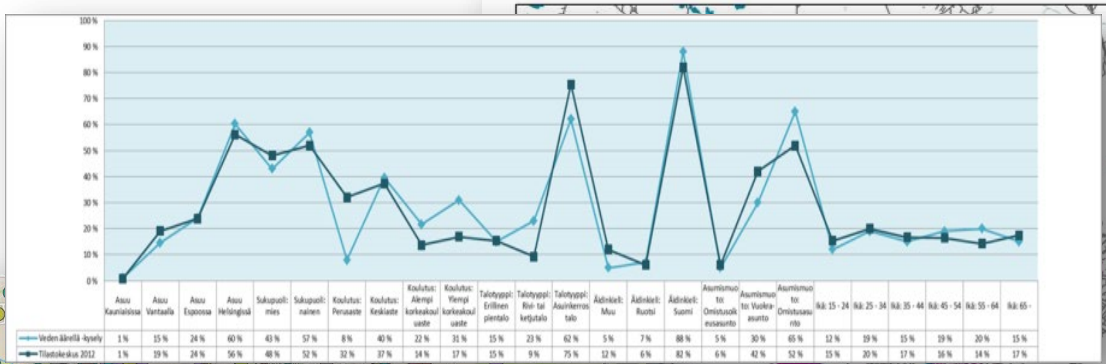
- External and internal validation
- Descriptive and visual analysis

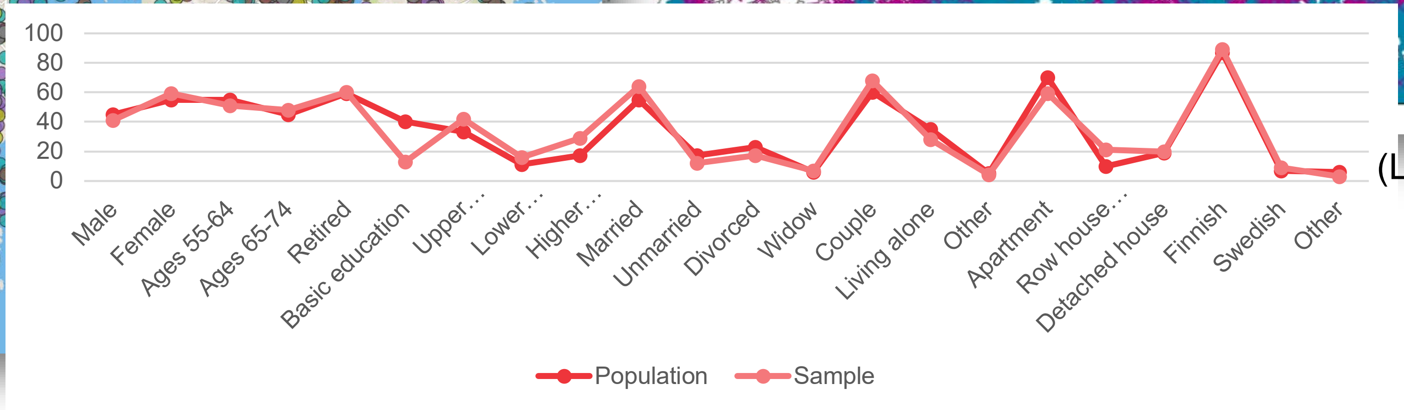
Explore: Examples

Internal and external validation: checking the inclusiveness







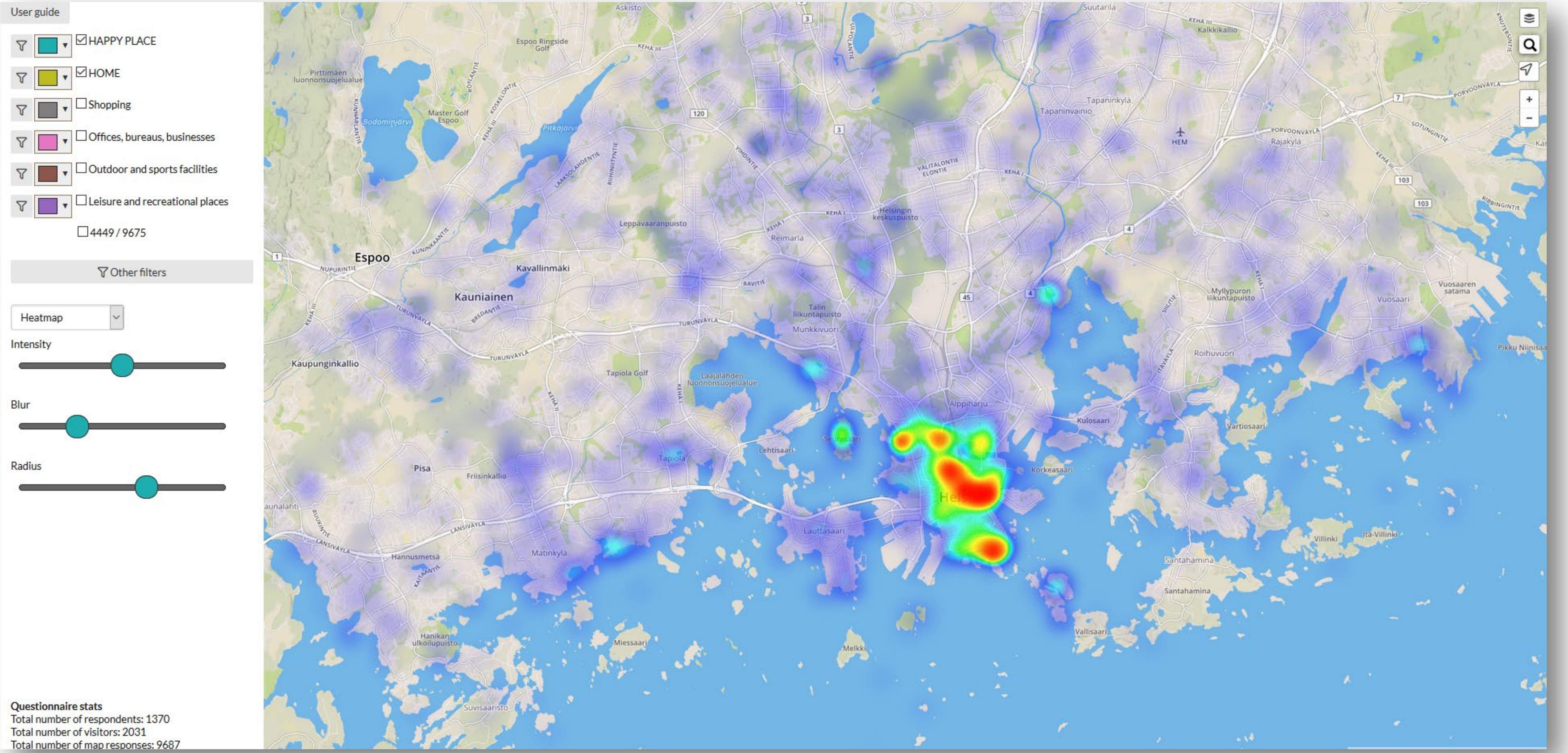


(Laatikainen et al., 2015)

(Laatikainen et al., 2019)

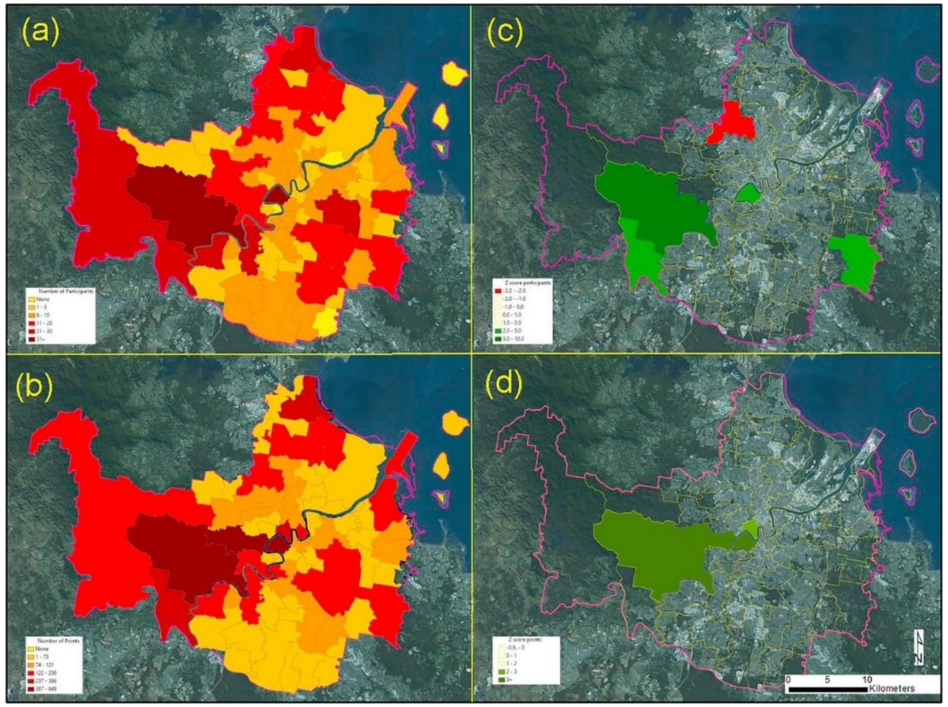
Explore: Examples

Visual analysis

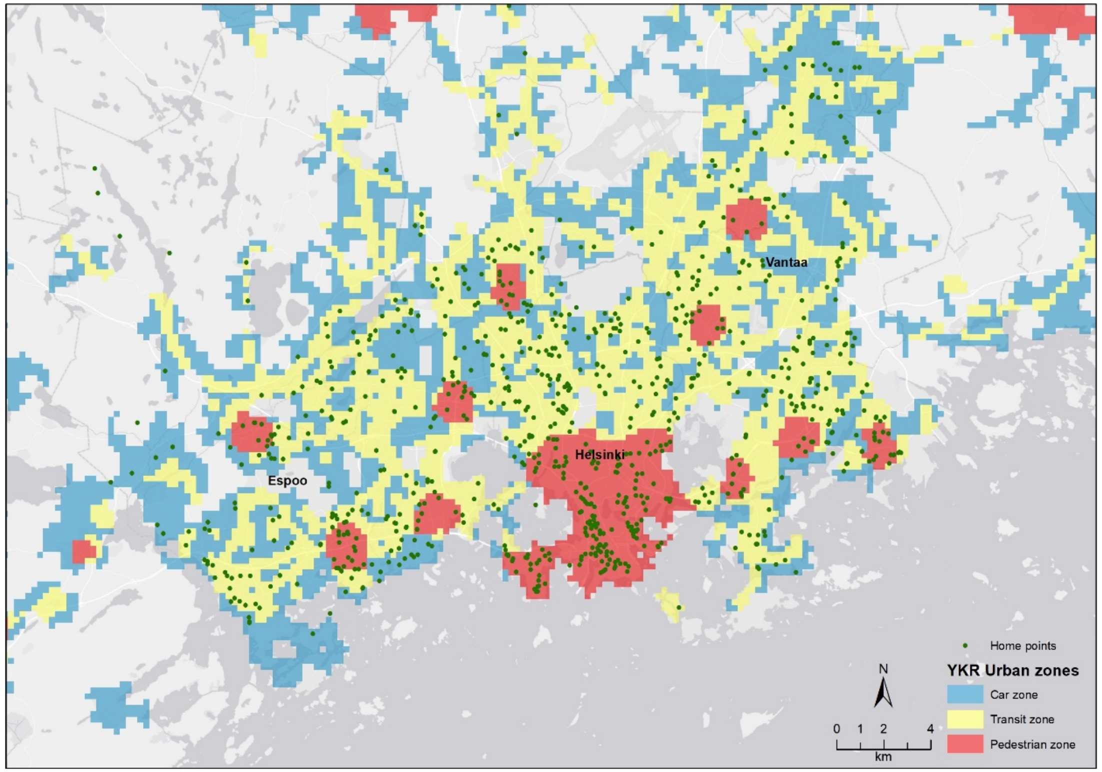


Explore: Examples

Thematic maps



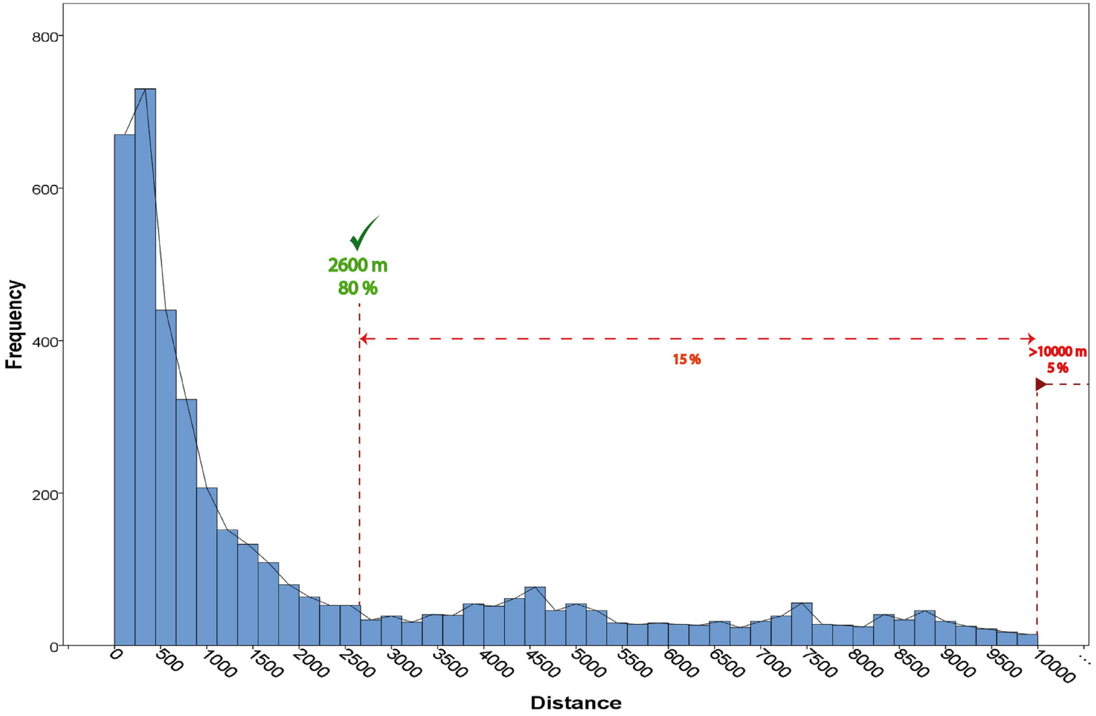
(Brown et al., 2018)



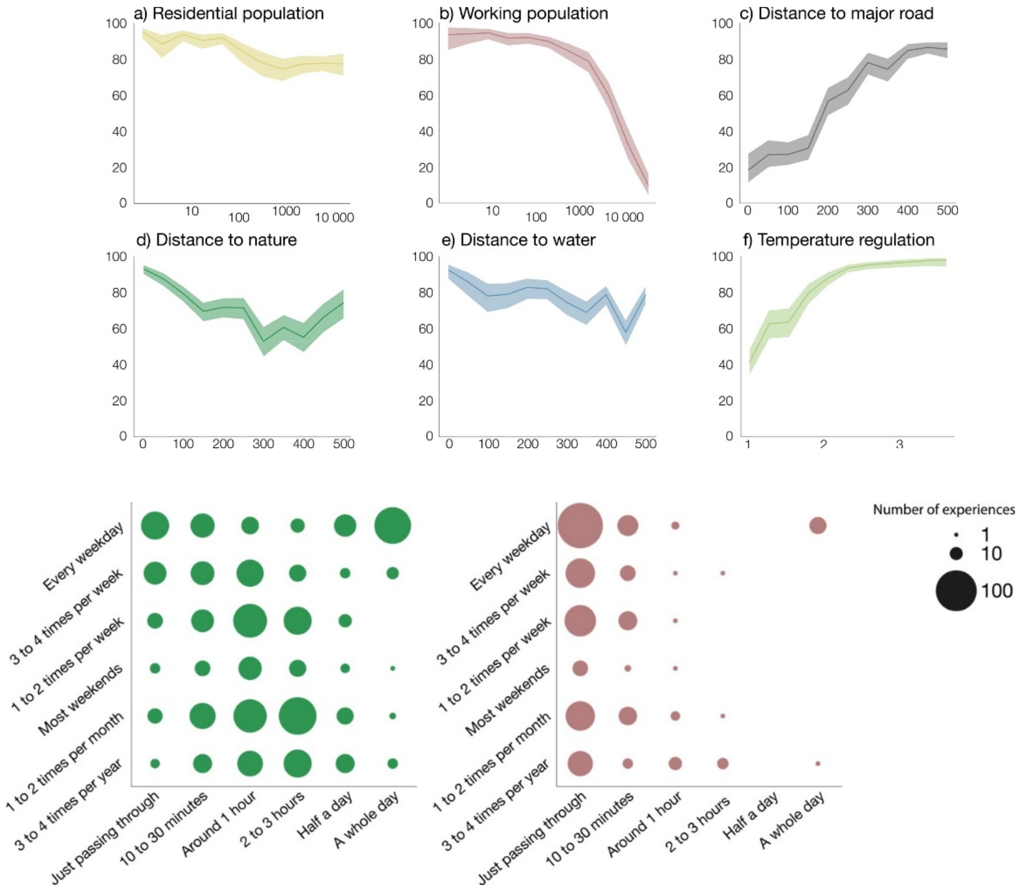
(Hasanzadeh et al., 2019)

Explore: examples

Charts



(Hasanzadeh et al., 2017)



(Samuelsson et al., 2018)

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 ‘Explain’
- 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

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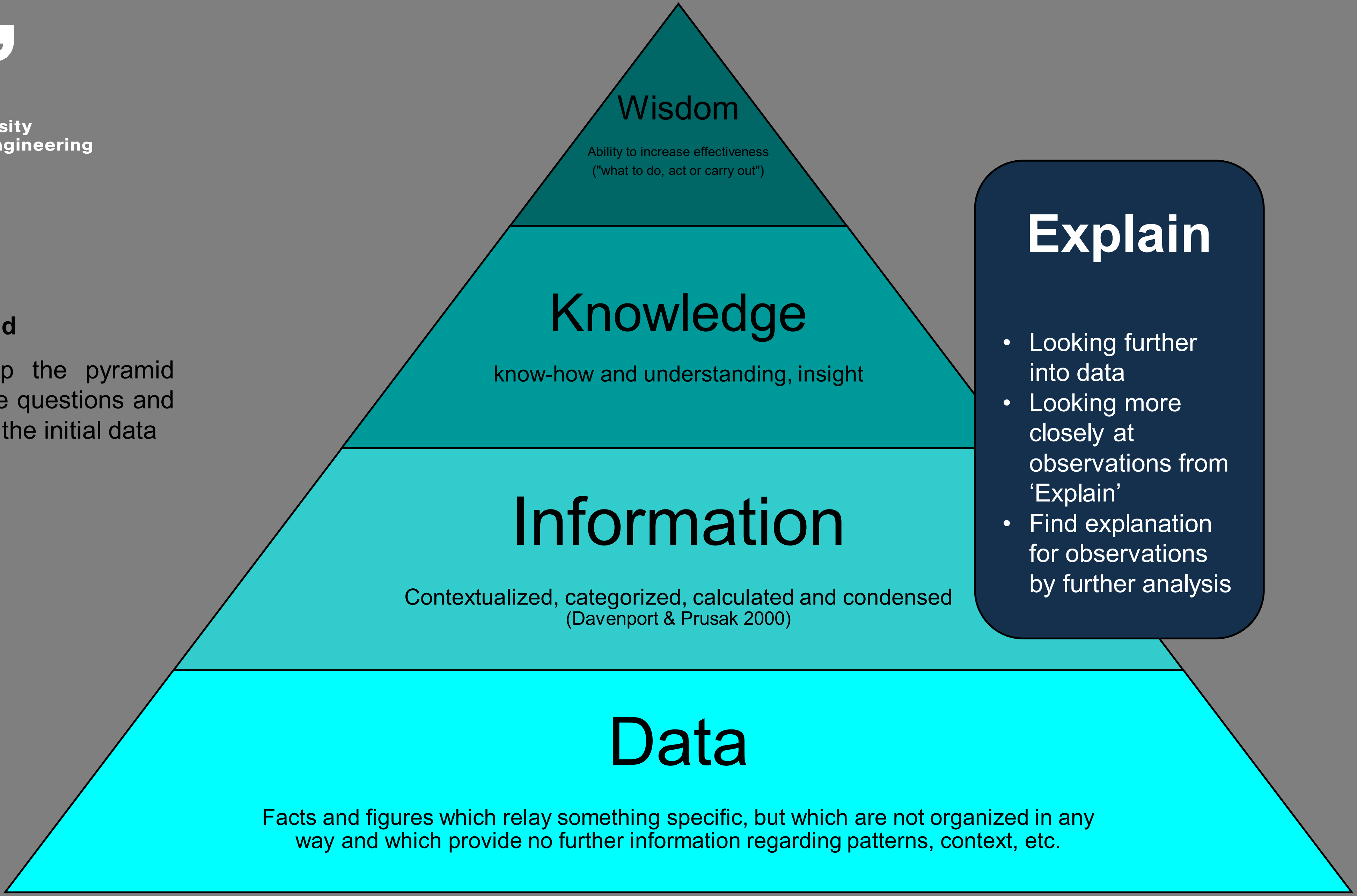
DIKW pyramid

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



Explain

- Looking further into data
- Looking more closely at observations from 'Explain'
- Find explanation for observations by further analysis

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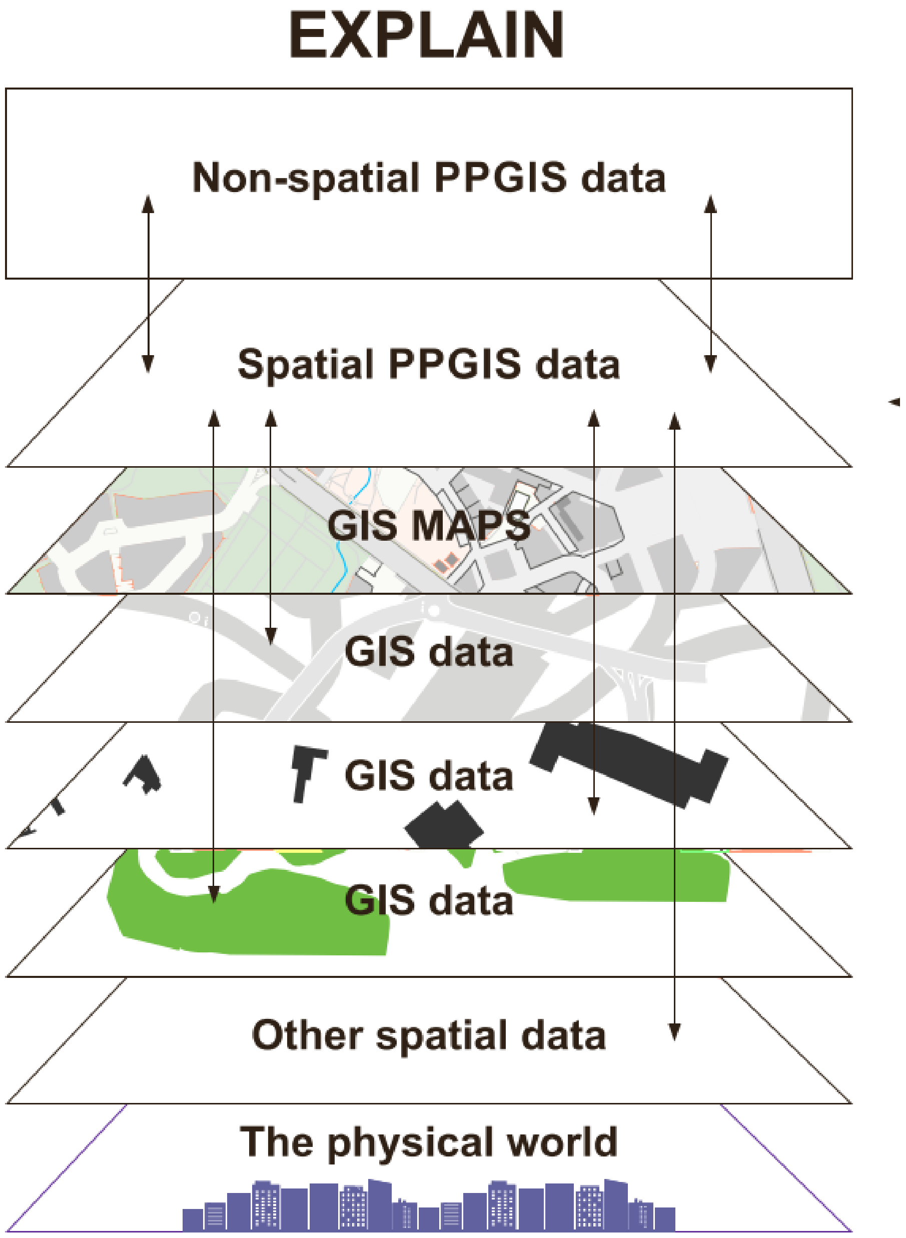
Explain phase

- The aim is to look more closely at observations from the *Explore* phase to explain observations by further analysis
- The *Explain* phase combines spatial and non-spatial PPGIS data with other GIS spatial data.
- Methods include inferential and multivariate statistics in addition to GIS software.



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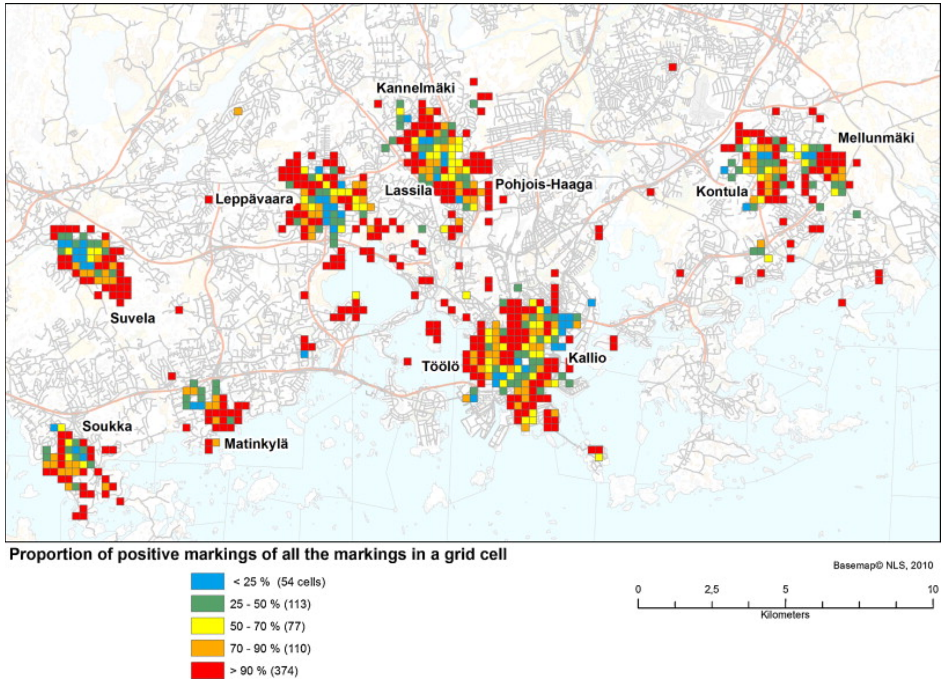
Explain: Method categories

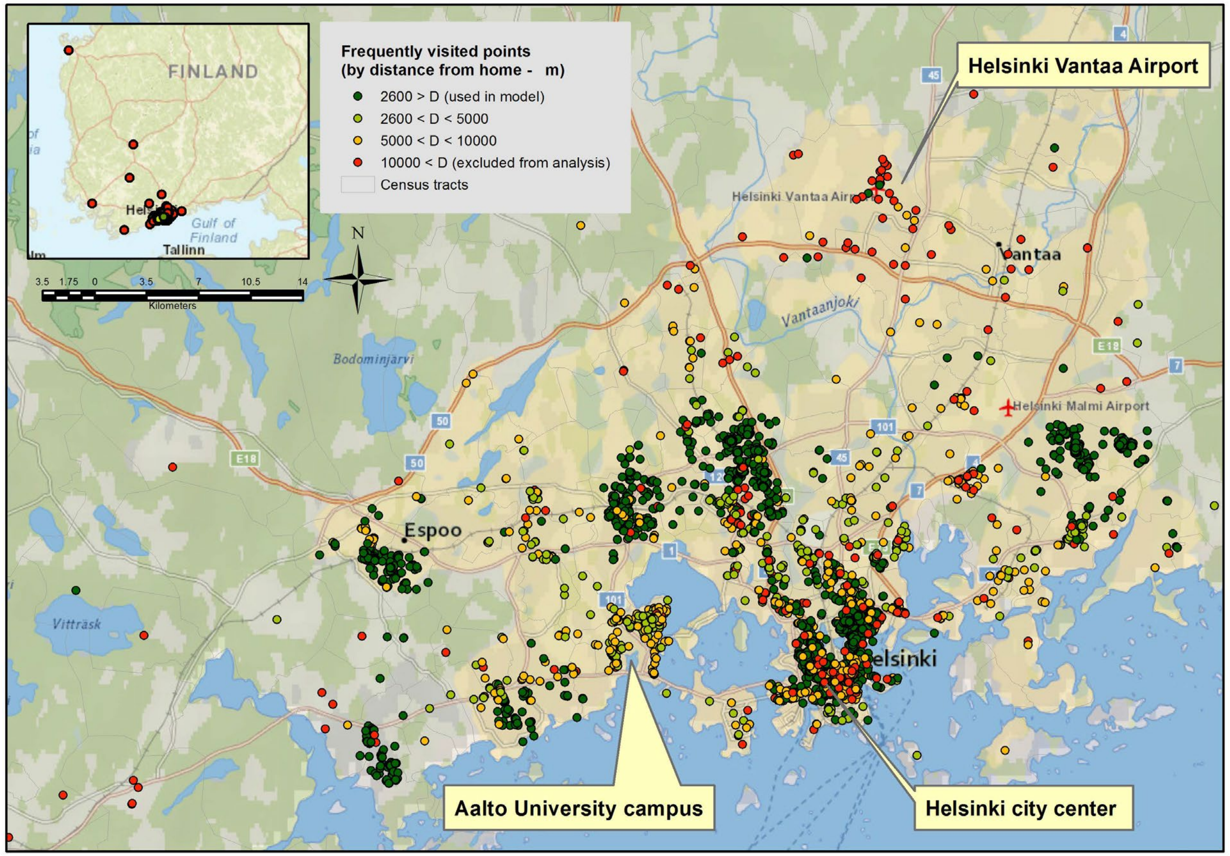
- **Visual and overlay analysis**
- **Spatial pattern analysis**
- **Proximity and coexistence analysis**
- **Calculation of indices/measures across spatial units**
- **Association analysis**
- **Cluster and multivariate analysis**

Explain: examples

Thematic maps



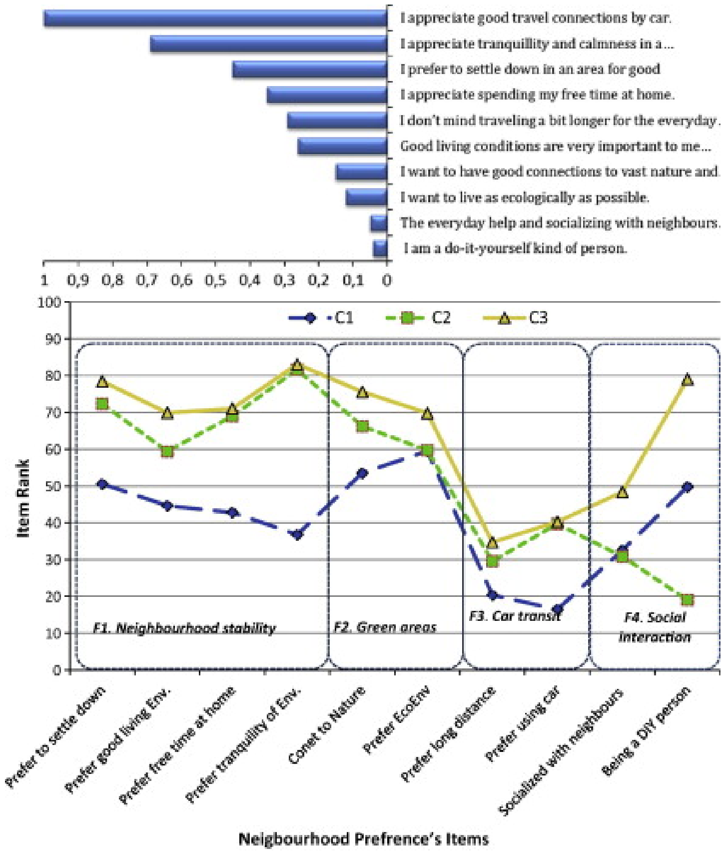
(Kyttä et al., 2013)



(Hasanzadeh et al., 2017)

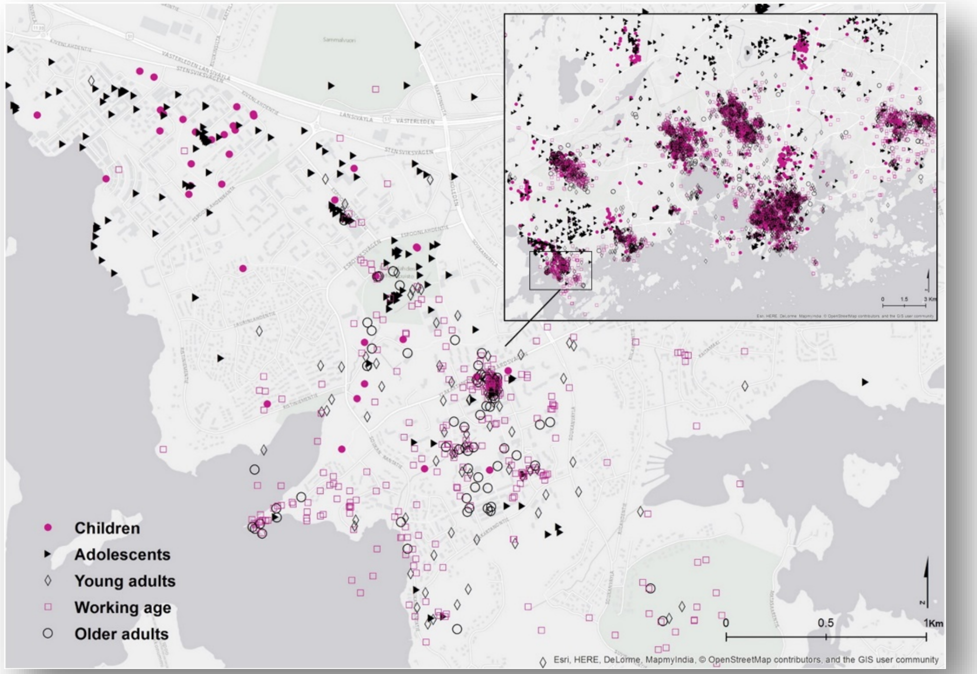
Explain:

Clustering analysis



(Haybatollahi et al., 2015)

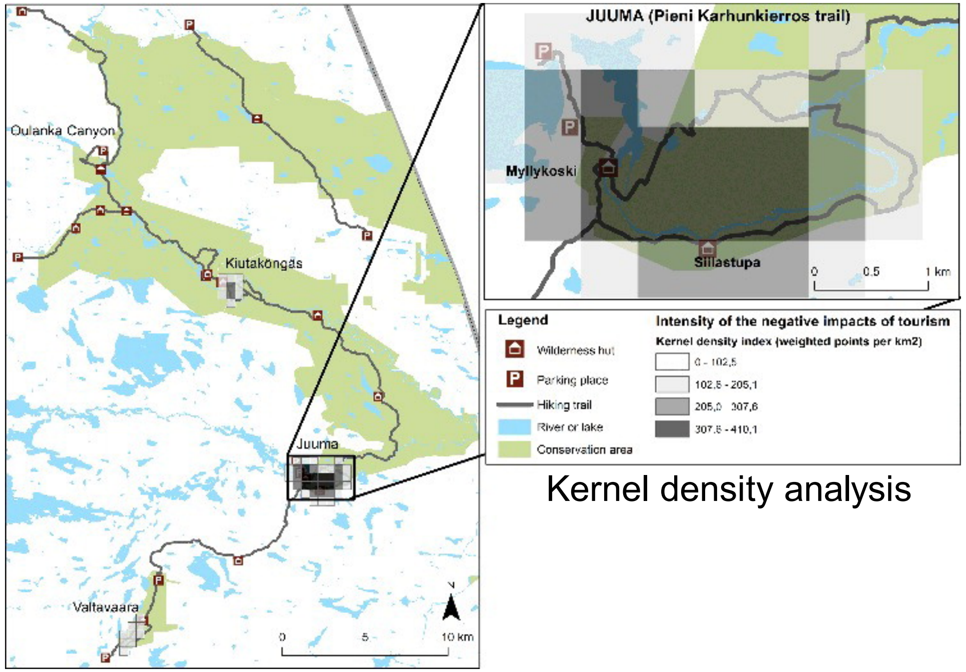
Spatial pattern analysis



(Laatikainen et al., 2017)

Explain: examples

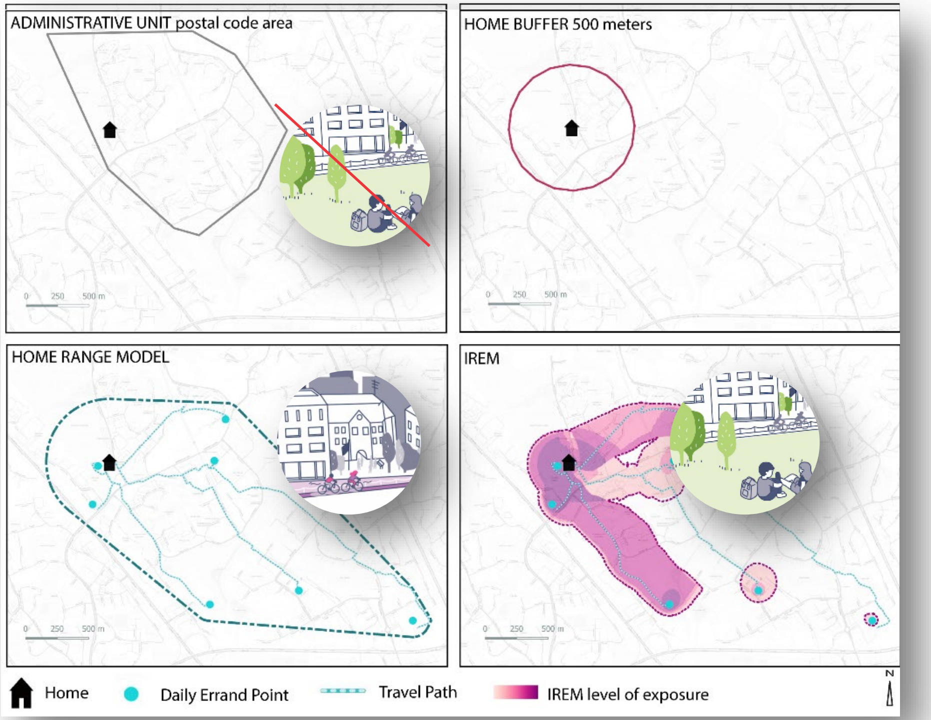
Spatial pattern analysis



Kernel density analysis

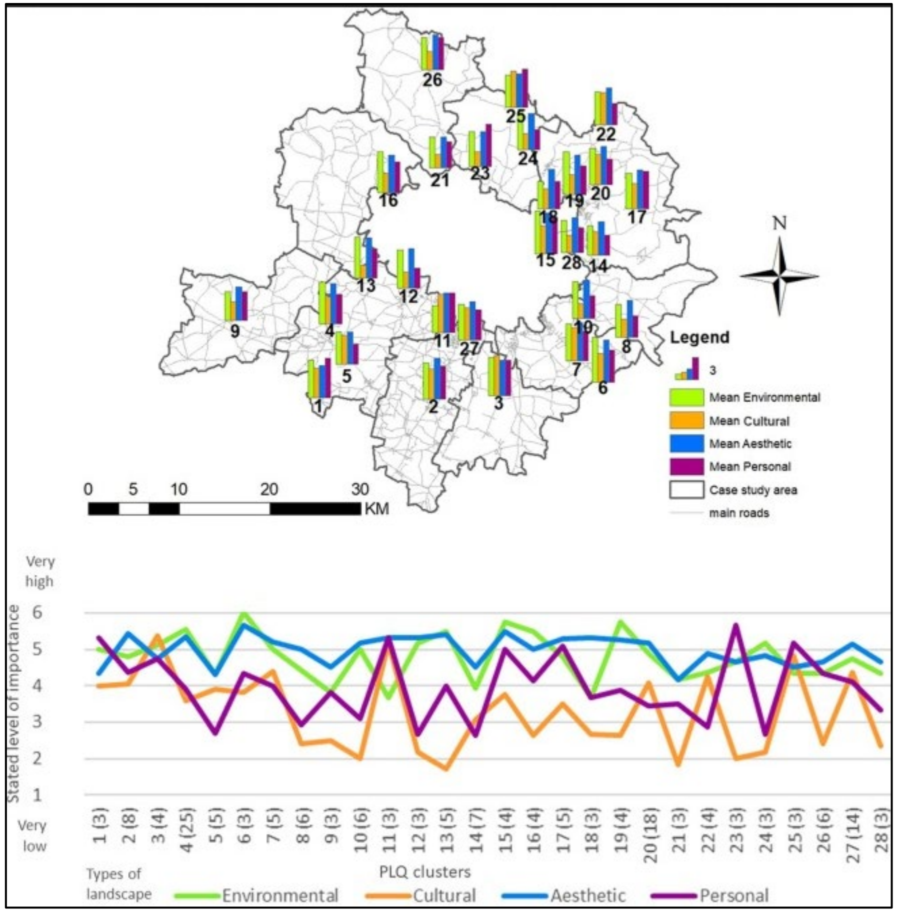
(Pietilä & Fagerholm, 2016)

Association analysis

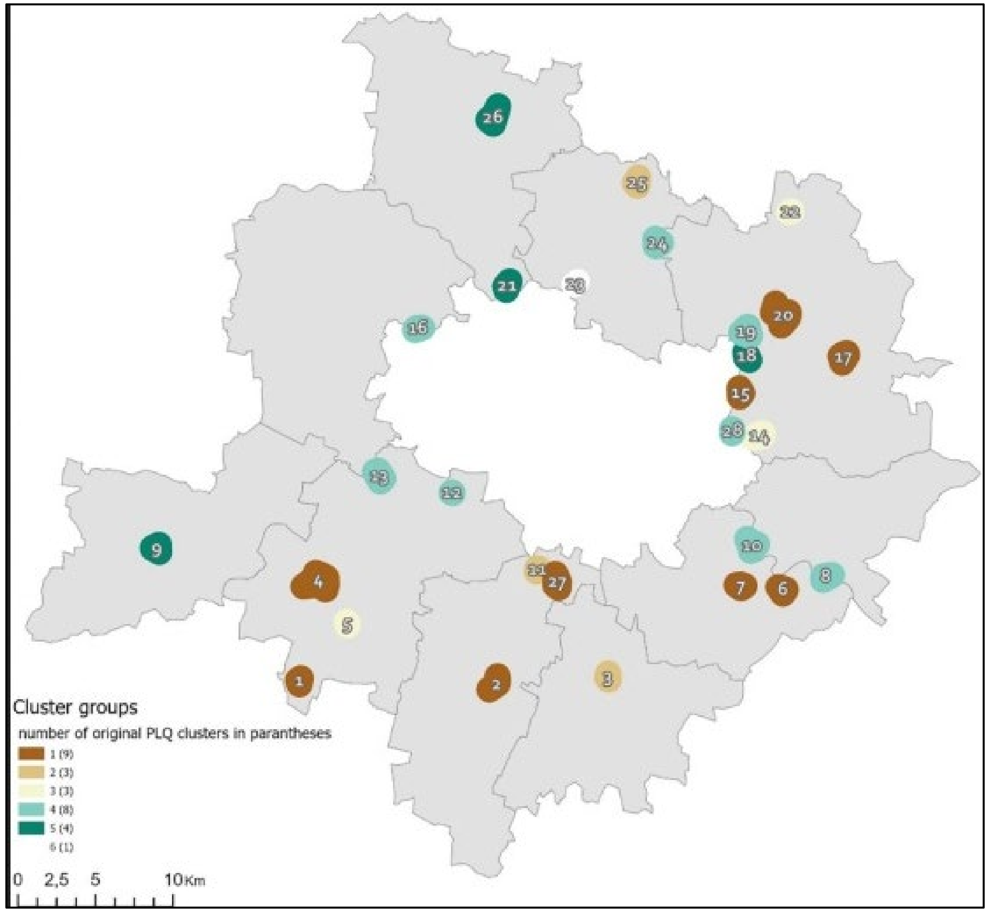


(Laatikainen et al., 2018)

Explain: examples



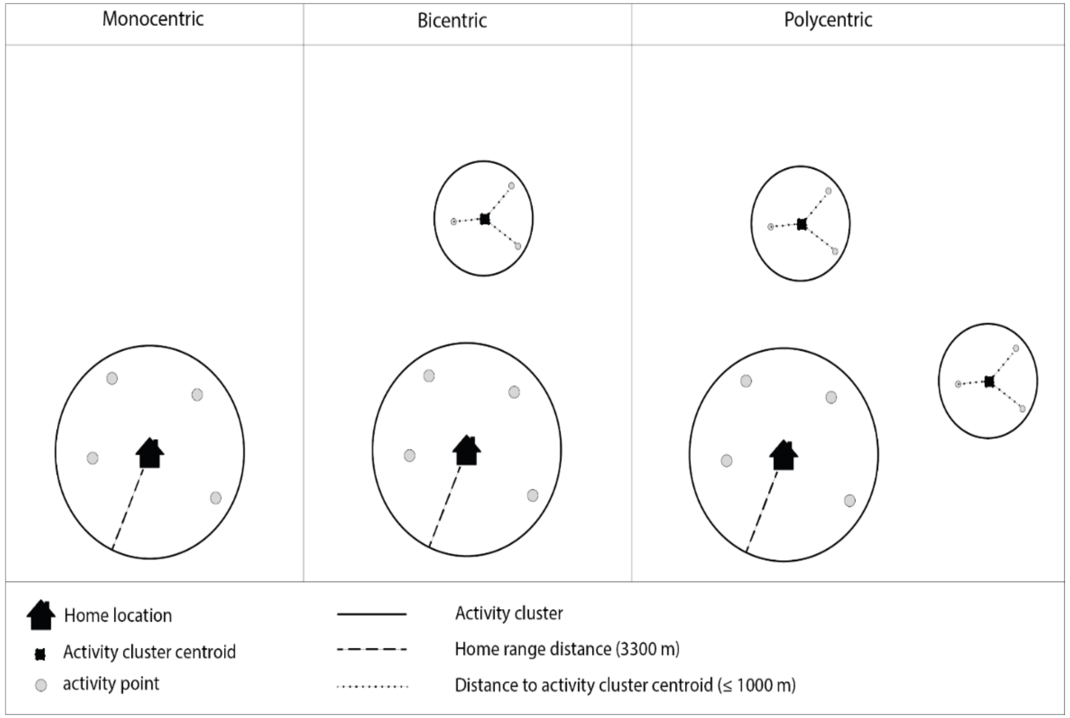
Calculation of indices and Spatial cluster analysis



(Solecka et al., 2021)

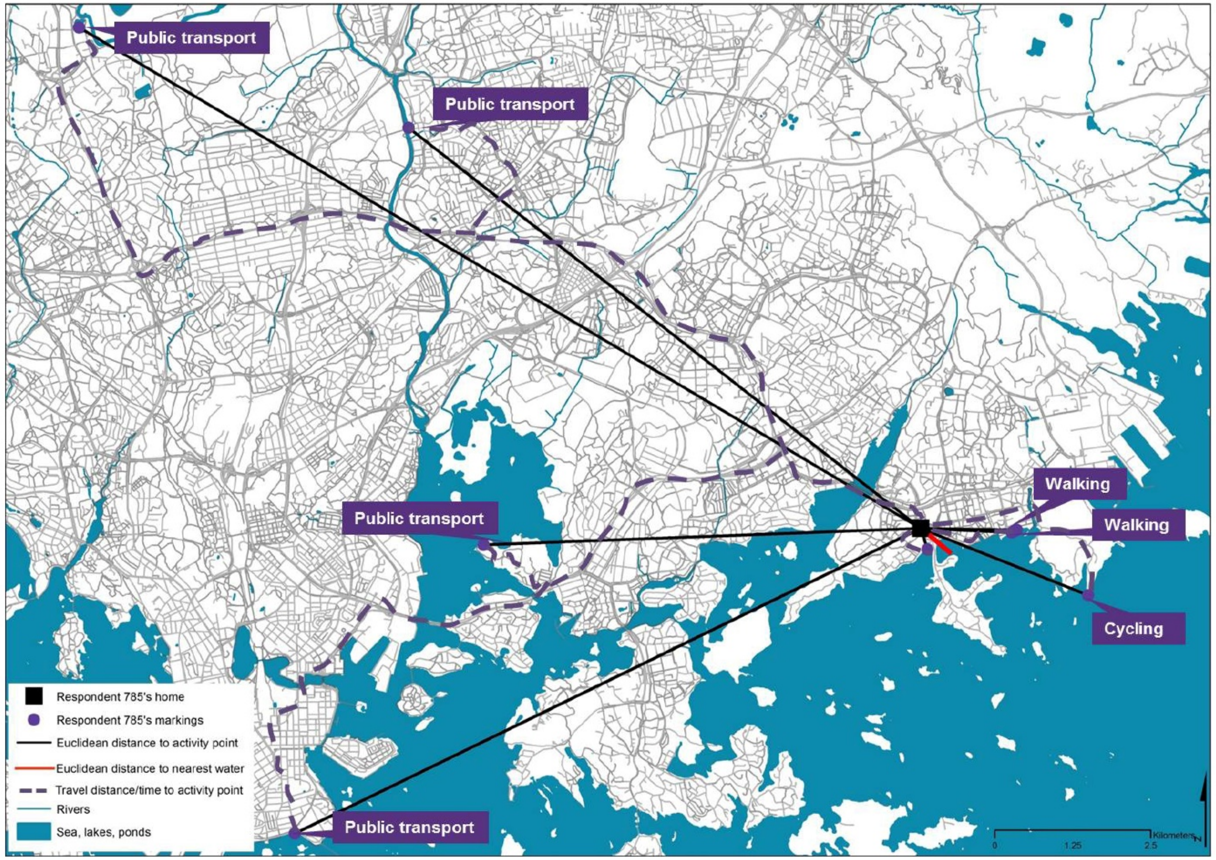
Explain: examples

Cluster analysis



(Hasanzadeh et al., 2021)

Proximity and accessibility analysis



(Laatikainen et al., 2015)

Explain: examples

Association analysis (spatial and non-spatial)

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	0.82	1.08	0.97	0.98	0.91
	(0.61–1.25)	(0.57–1.18)	(0.75–1.54)	(0.68–1.39)	(0.66–1.44)	(0.61–1.34)
Age (years)	1.00	1.01	1.02	1.02	0.96	0.97
	(0.96–1.04)	(0.97–1.05)	(0.98–1.07)	(0.98–1.07)	(0.92–1.01)	(0.93–1.02)
Household income (ref. < 3,000 €)						
3,000–6,500 €	1.14	0.98	1.06	0.87	0.77	0.69
	(0.66–1.98)	(0.56–1.69)	(0.61–1.84)	(0.50–1.52)	(0.43–1.4)	(0.38–1.25)
> 6,500 €	1.18	1.17	0.93	0.87	1.22	1.17
	(0.76–1.81)	(0.76–1.80)	(0.60–1.43)	(0.56–1.35)	(0.77–1.95)	(0.73–1.86)
Employed (ref. no)	**0.59**	**0.53**	0.71	0.74	0.77	0.76
	(0.38–0.93)	**(0.33–0.82)**	(0.45–1.11)	(0.47–1.16)	(0.48–1.25)	(0.47–1.23)
University degree (ref. no)[a]	1.29	**1.55**	1.29	**1.54**	1.05	1.10
	(0.86–1.95)	**(1.02–2.34)**	(0.85–1.96)	**(1.01–2.34)**	(0.67–1.63)	(0.71–1.72)
Children in household (ref. no)	1.12	1.19	**1.71**	**1.76**	1.06	1.01
	(0.74–1.68)	(0.79–1.80)	**(1.13–2.58)**	**(1.16–2.67)**	(0.69–1.64)	(0.66–1.56)
Dissonance (ref. high-walkability consonant)						
Low-walkability consonant	**0.15**	**0.12**	**0.34**	**0.25**	**0.10**	**0.10**
	(0.09–0.26)	**(0.07–0.22)**	**(0.20–0.58)**	**(0.15–0.44)**	**(0.06–0.19)**	**(0.05–0.19)**
Low-walkability, no strong preference	**0.28**	**0.23**	**0.40**	**0.30**	**0.21**	**0.19**
	(0.17–0.47)	**(0.14–0.39)**	**(0.24–0.66)**	**(0.18–0.50)**	**(0.12–0.36)**	**(0.11–0.33)**
Low-walkability dissonant	**0.44**	**0.41**	**0.50**	**0.44**	**0.36**	**0.35**
	(0.24–0.83)	**(0.22–0.77)**	**(0.26–0.93)**	**(0.23–0.83)**	**(0.19–0.70)**	**(0.18–0.67)**
High-walkability dissonant	**0.49**	**0.40**	**0.43**	**0.39**	**0.47**	**0.43**
	(0.24–0.98)	**(0.20–0.81)**	**(0.20–0.90)**	**(0.18–0.82)**	**(0.23–0.99)**	**(0.21–0.90)**
High-walkability, no strong preference	**0.51**	**0.43**	**0.53**	**0.45**	0.57	0.57
	(0.30–0.87)	**(0.25–0.73)**	**(0.31–0.91)**	**(0.26–0.77)**	(0.32–1.02)	(0.32–1.03)
BIC[b]	1188.54	1179.68	1181.54	1171.30	1056.73	1048.85
– Log likelihood	−548.27	−543.84	−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.

Logistic regression

(Kajosaari et al., 2019)

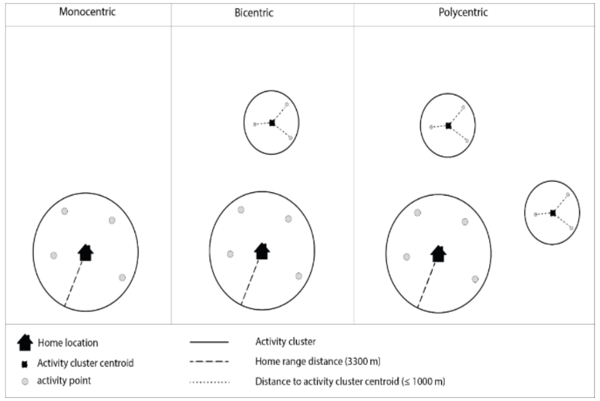


Table 3
Correlations between different measures of activity space dispersion. (AS: activity space).

	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).

Pearson's correlation

(Hasanzadeh, 2019)

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 'Explain'
- 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

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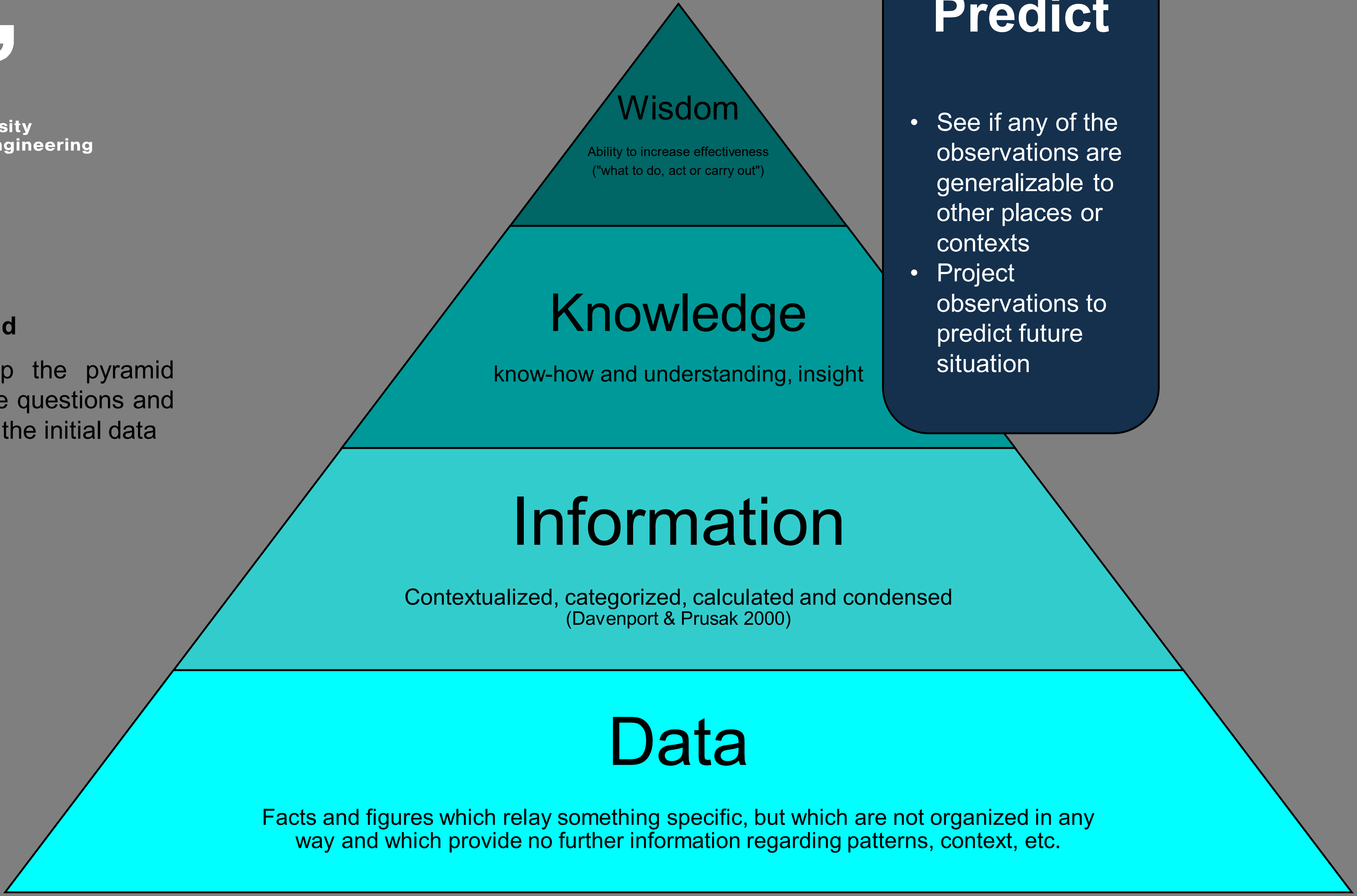
DIKW pyramid

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



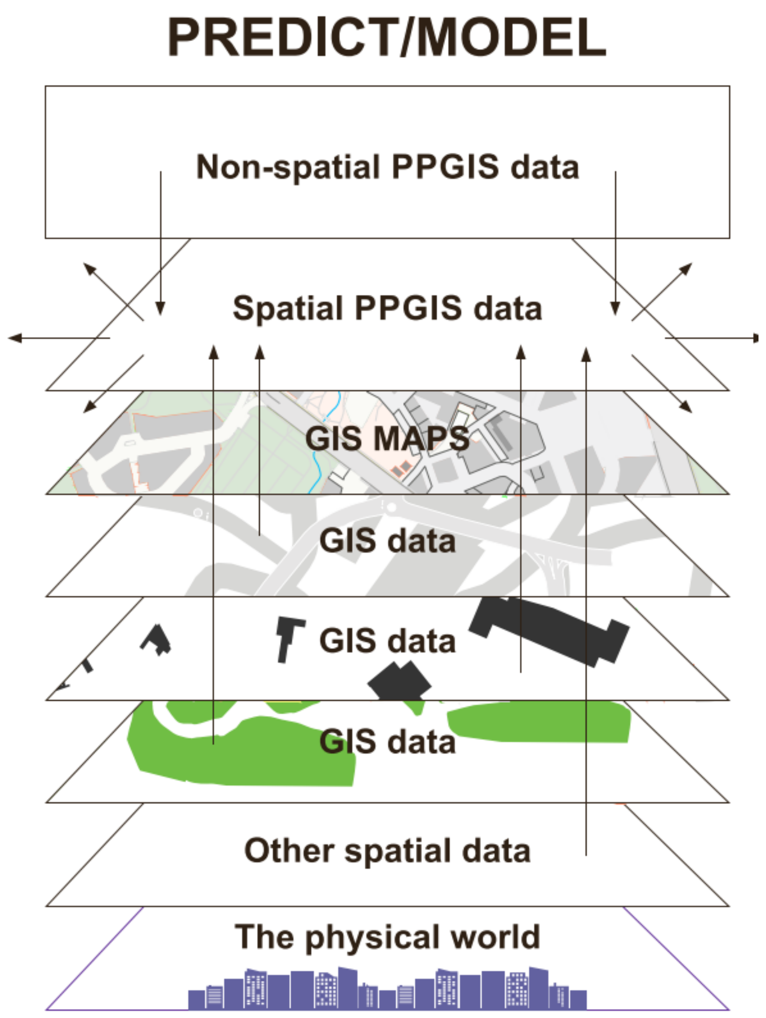
Predict

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

Fagerholm, N., Raymond, C. M., Olafsson, A. S., Brown, G., Rinne, T., Hasanzadeh, K., ... & Kyttä, M. (2021). A methodological framework for analysis of participatory mapping data in research, planning, and management. *International Journal of Geographical Information Science*, 1-28.

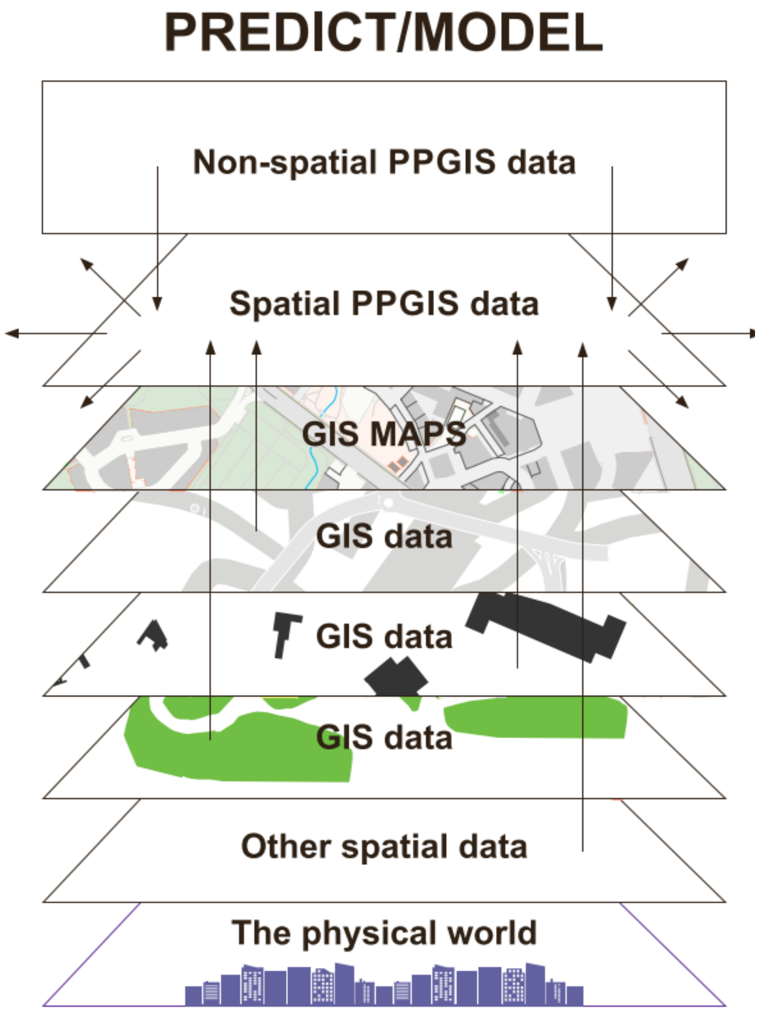
Predict phase

- **The aim is to generalize and predict mapped attributes to other places and contexts (prediction) or produce a representation of a system to make inferences (model)**



Predict phase

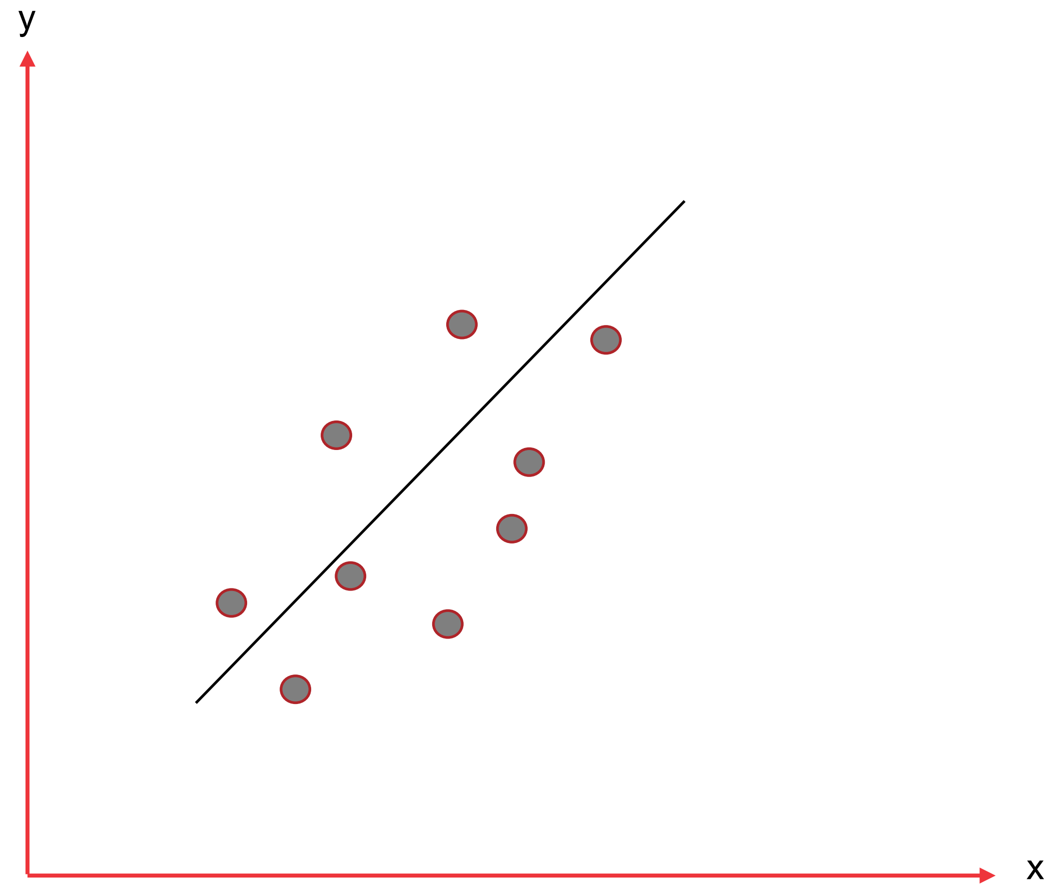
- This phase typically requires multiple data sources with PPGIS data and involve multivariate modelling.
- Performing analysis in *Predict/Model* phase requires in-depth expertise in applying GIS and statistical software. Skills in computer coding may also be necessary.



Predict:

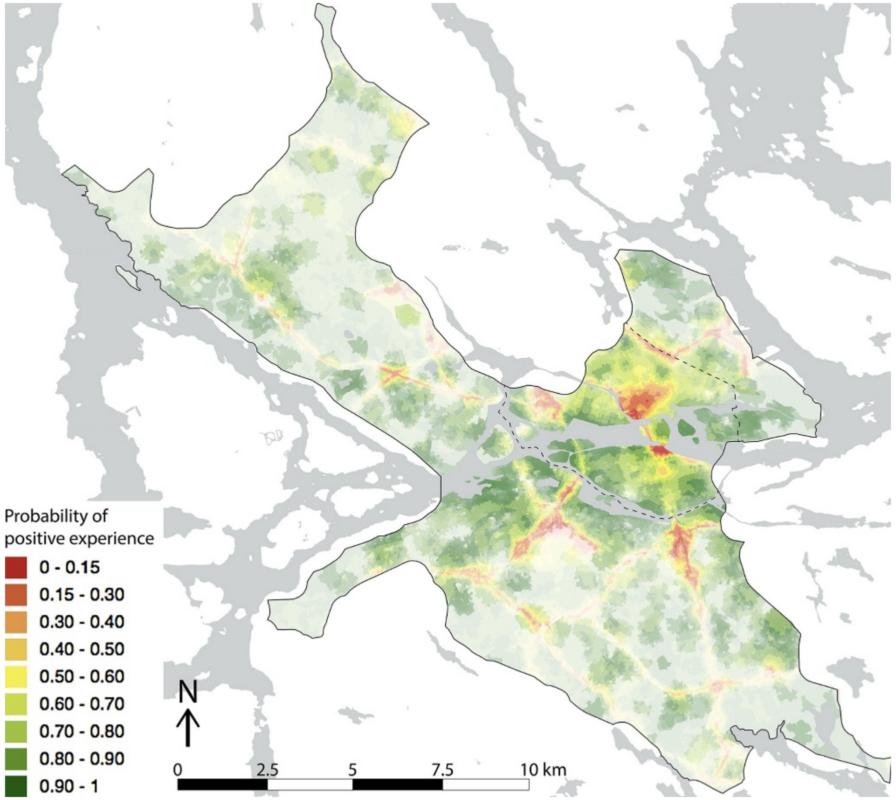
Method categories

- Data modelling



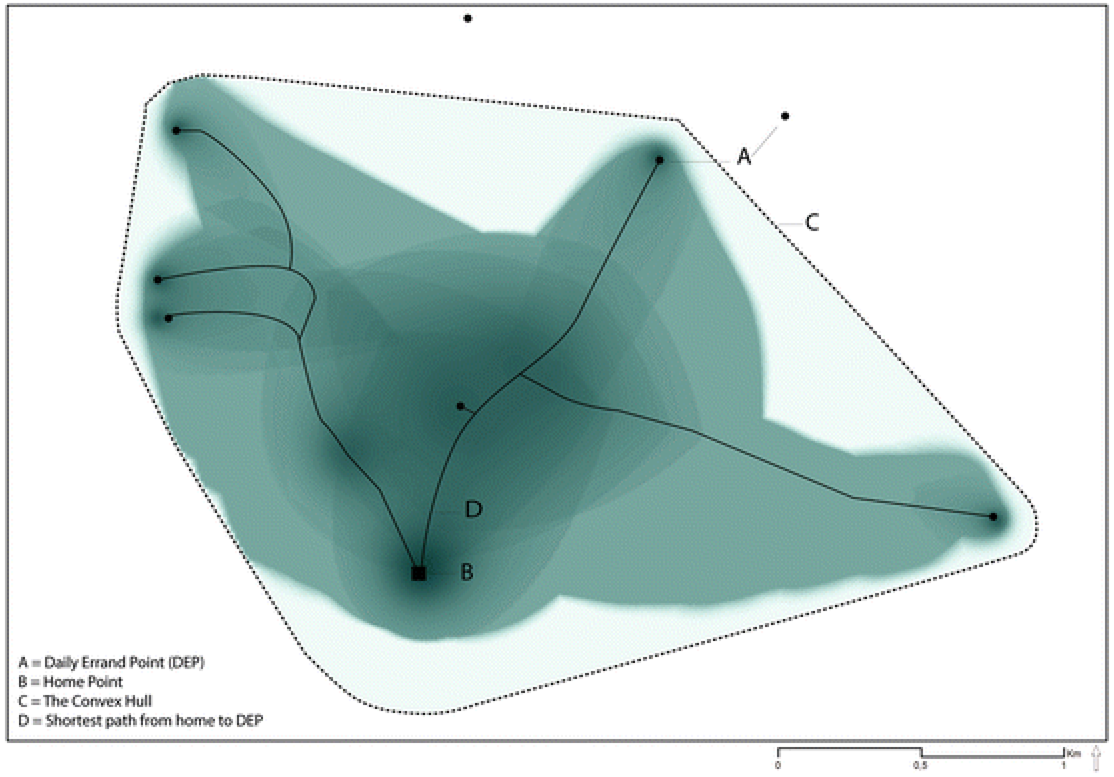
Predict: examples

Spatial regression model



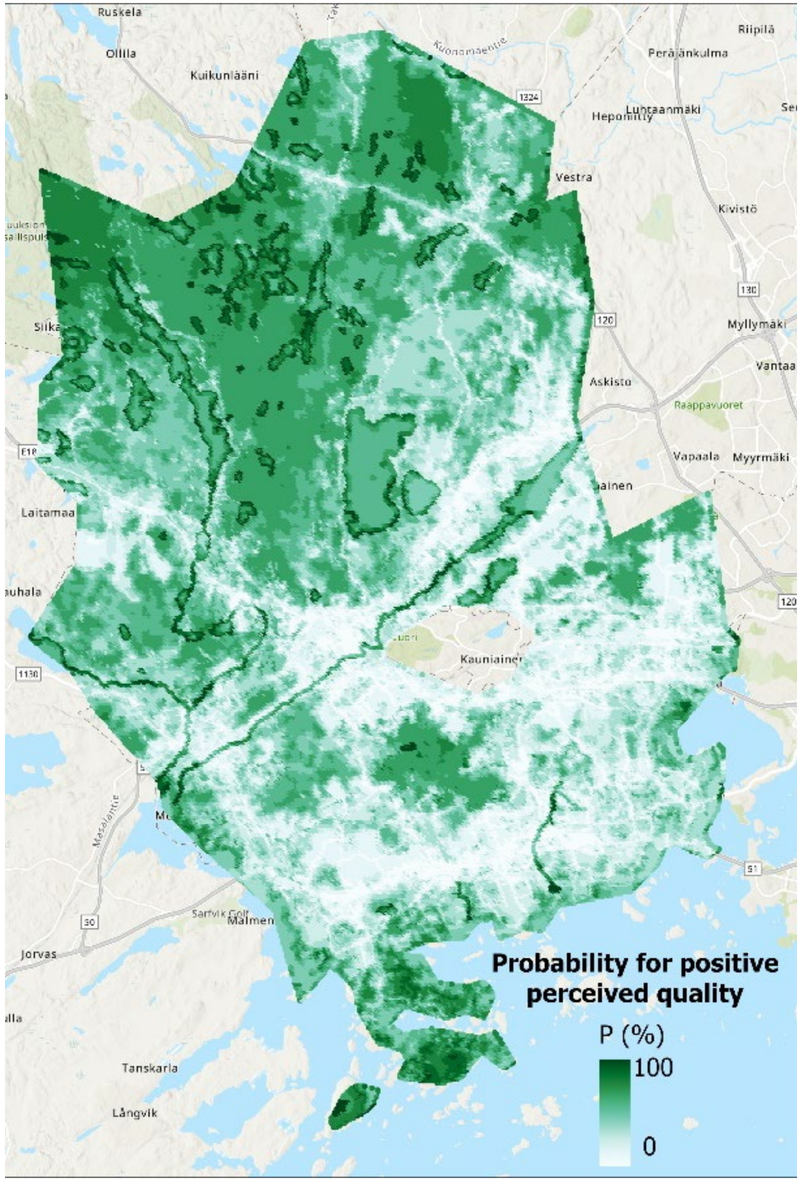
(Samuelsson et al., 2018)

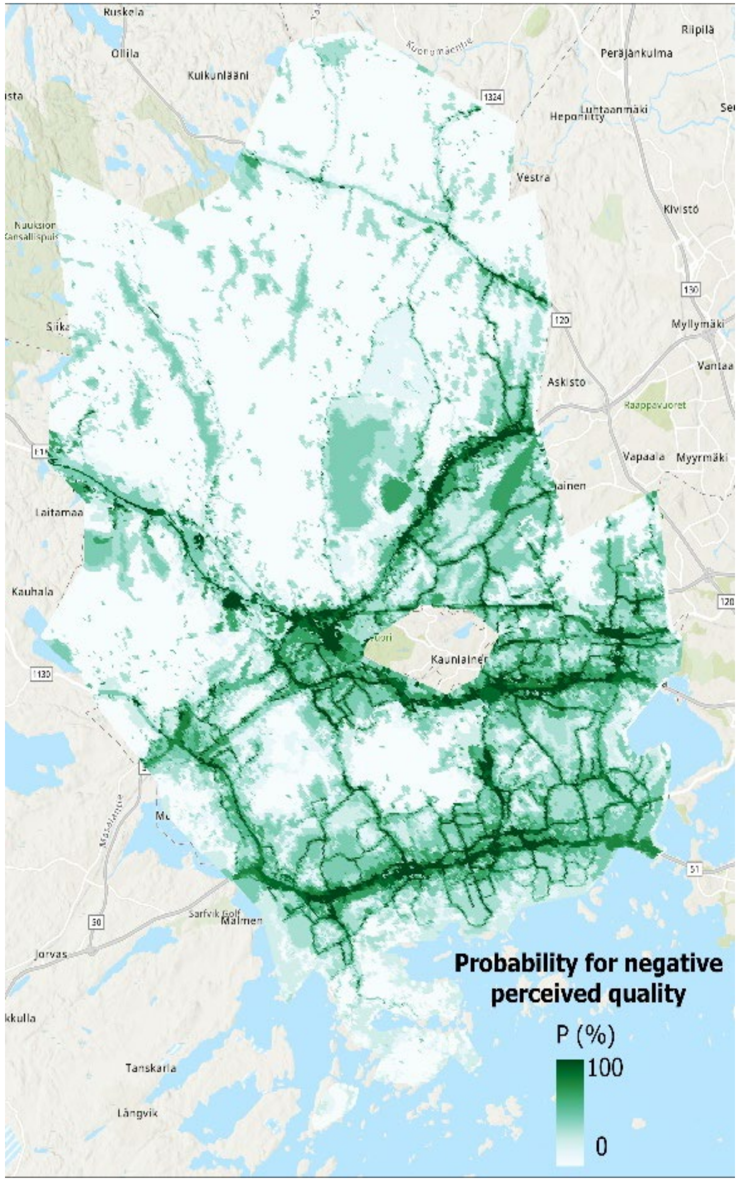
Exposure estimation (IREM)



(Hasanzadeh et al., 2018)

Predict: Examples

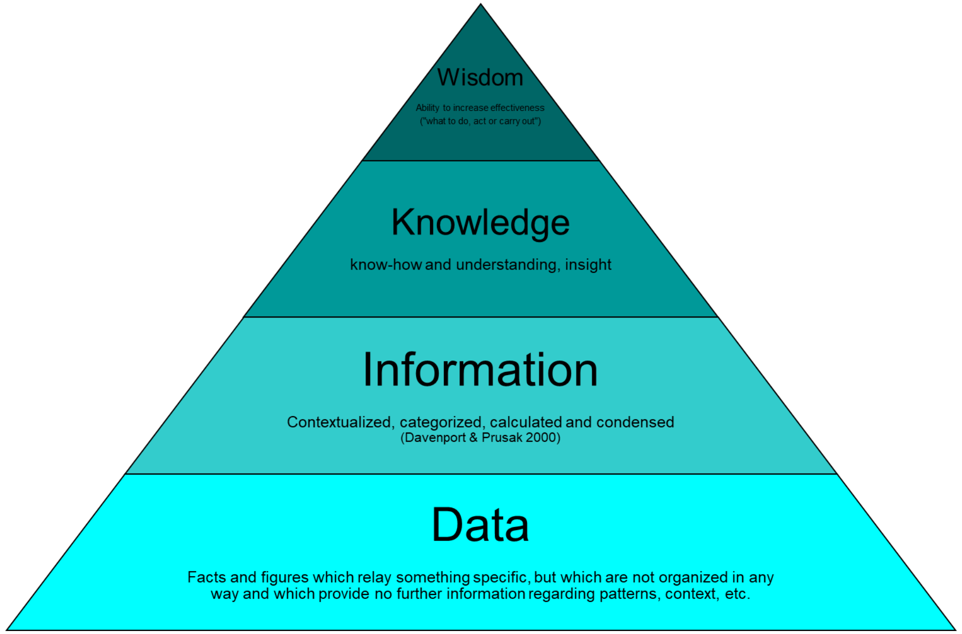


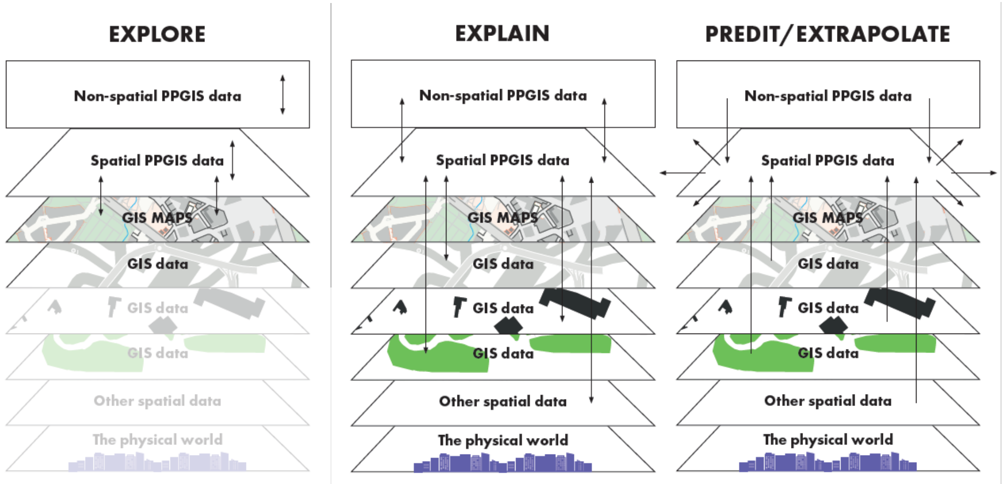


Kajosaari & Hasanzadeh 2022, forthcoming

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!

Also, big thanks to my colleague Kamyar Hasanzadeh for some of the materials used in this presentation.

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