

Geographically weighted Urban Heat Island modelling using the Netatmo sensors. The case of the Hague.

Lilia Angelova | 4620380

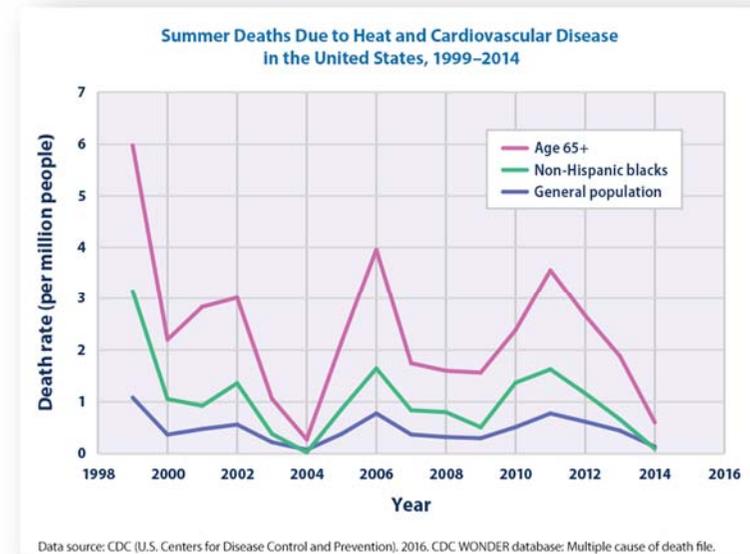
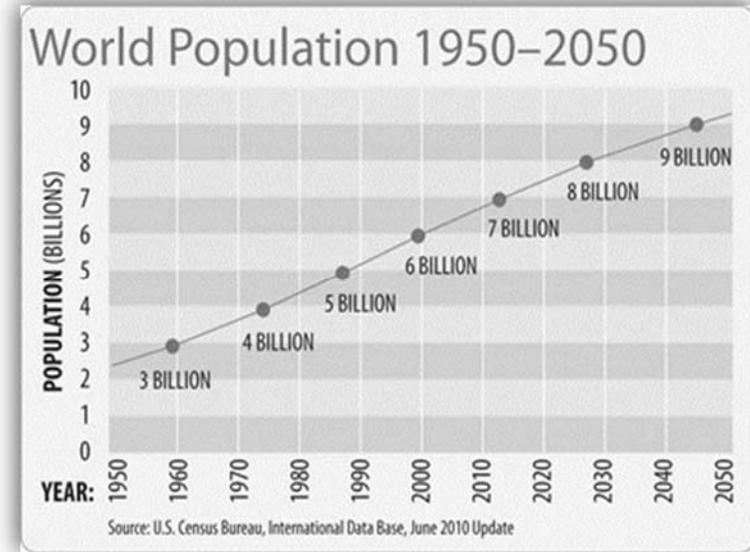
Mentor #1: Jorge Gil

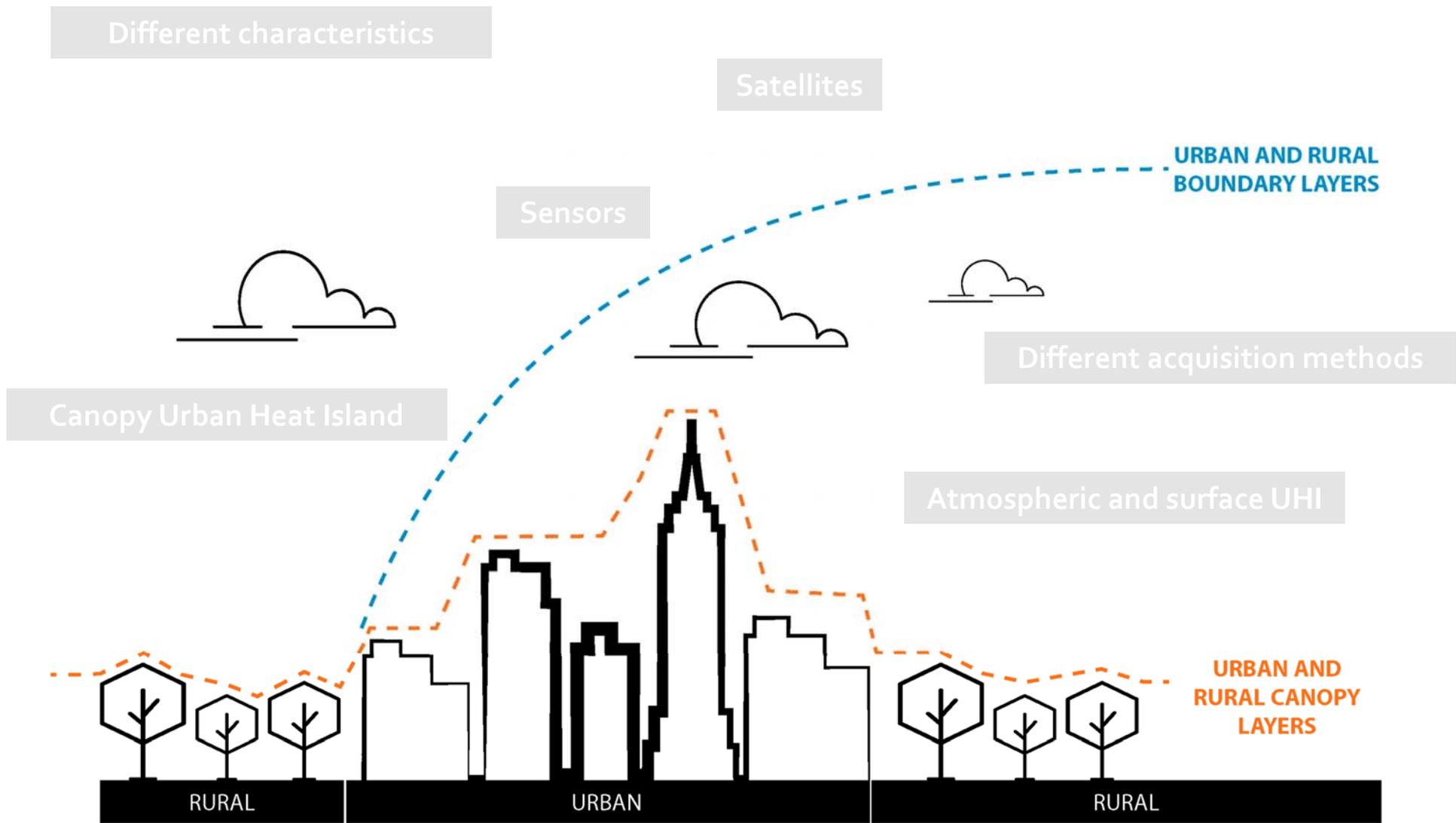
Mentor #2: Alexander Wandl



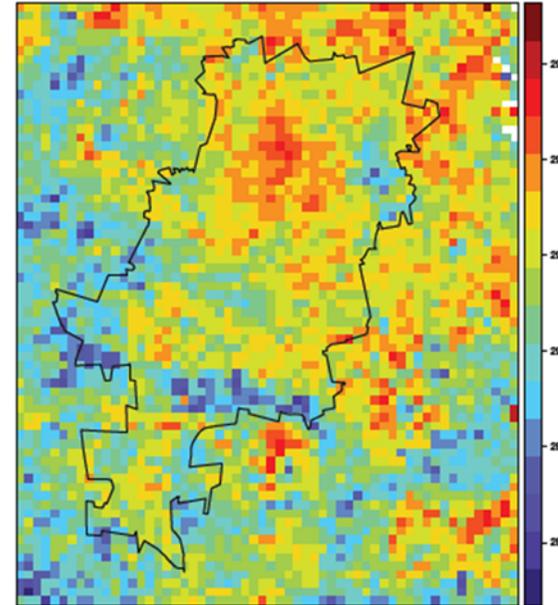
1. Intro
2. Problem
3. Research questions
4. Methodology
5. Analysis of the sensor data
6. Spatial models
7. Statistical models
8. Conclusions

- Increasing population
- More people in the cities
- Sustainable development
- Climate change
- Heat waves
- UHI leads to health-related issues, higher energy demands, economic losses

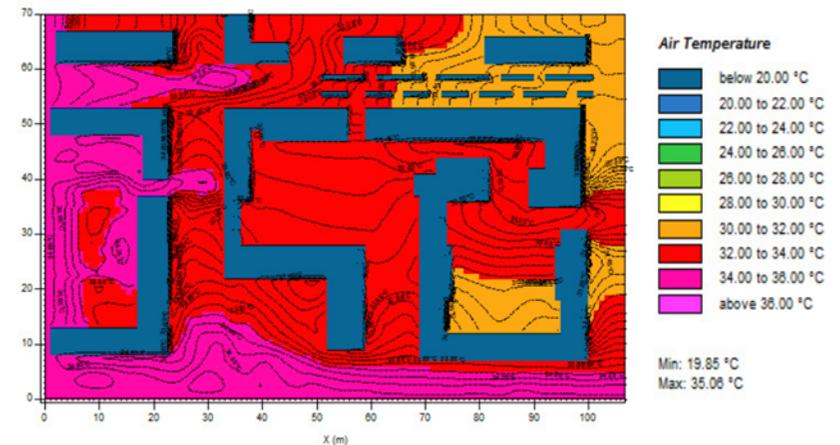




- Understanding the UHI pattern.
 - can be achieved by understanding its variability and the factors that define it.
- Therefore, we need highly detailed UHI models.
- Until now – such models exist but with limited spatial extent.
- City scale models – very coarse – don't provide info about intraurban variability.



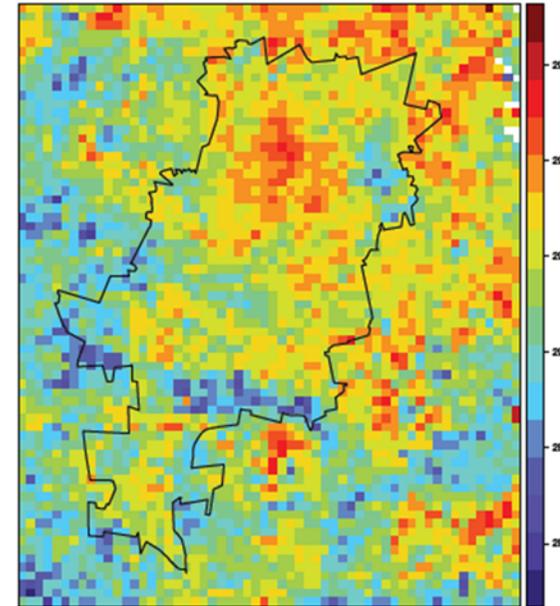
Hardy, C. H., & Nel, A. L. (2015). Data and techniques for studying the urban heat island effect in Johannesburg.



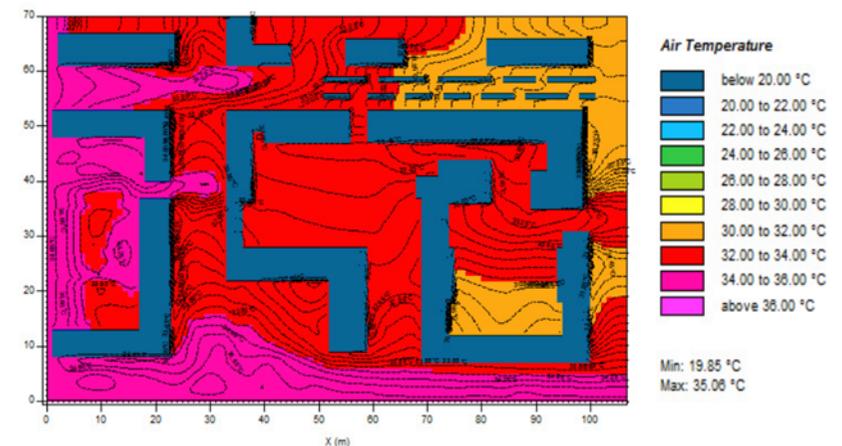
Gaspari, J., & Fabbri, K. (2017). A Study on the Use of Outdoor Microclimate Map to Address Design Solutions for Urban Regeneration.

- Understanding the UHI pattern.
 - can be achieved by understanding its variability and the factors that define it.
- Therefore, we need highly detailed UHI models.
- Until now – such models exist but with limited spatial extent.
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Bridging the gap between the highly detailed small-scale models and the coarse city scale ones.



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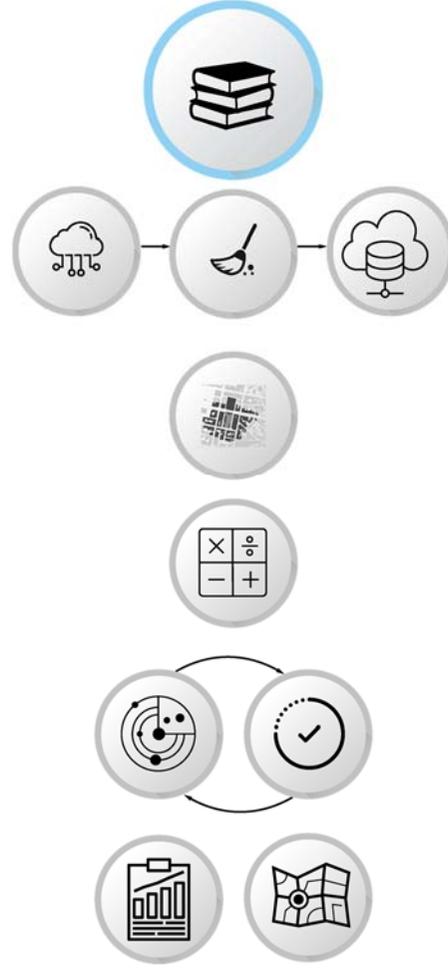
RESEARCH QUESTION

**How to accurately model the spatial and
time variability of the Canopy Urban
Heat Island (CUHI) effect in the city of
The Hague?**

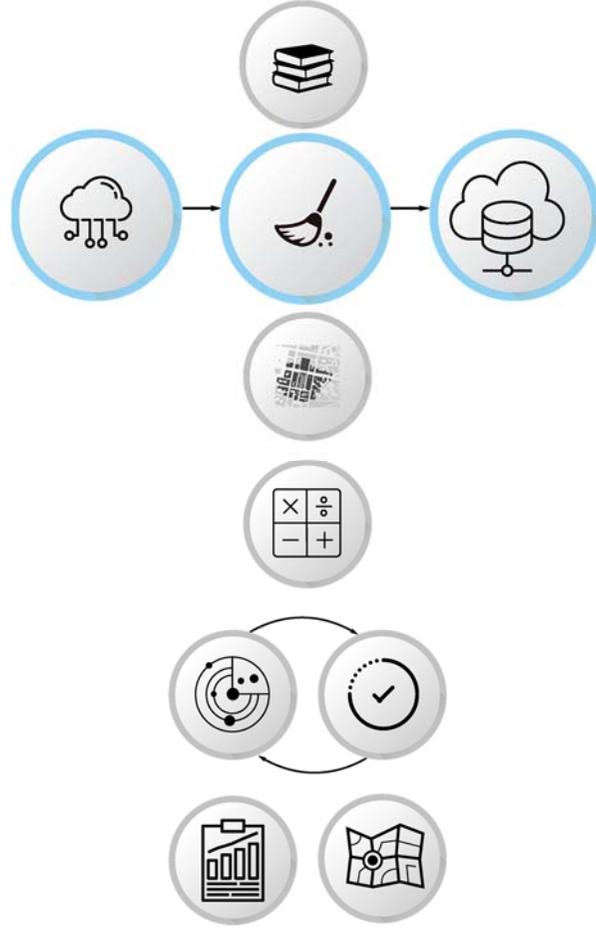
1. How to collect, clean and validate the raw sensor data?
2. Which factors or combination of factors influences the UHI effect at most?
3. What level of detail is needed to model the UHI variability?
4. How does the UHI effect variate in the different parts of the city during the day and night?



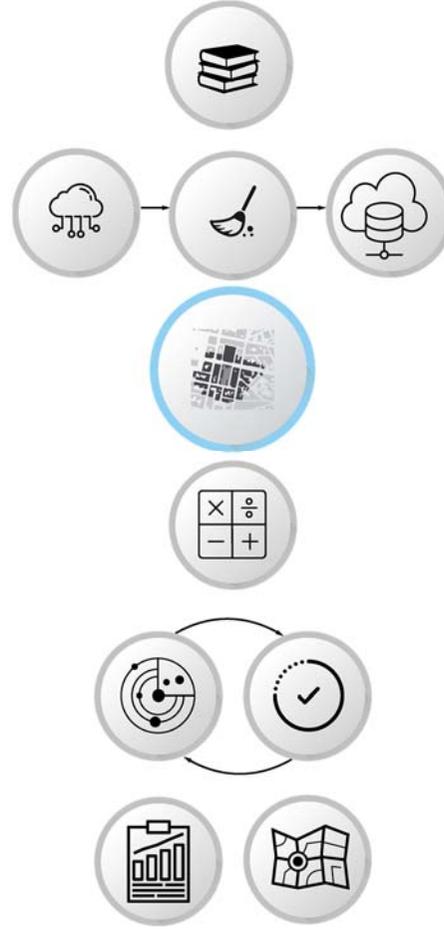
METHODOLOGY



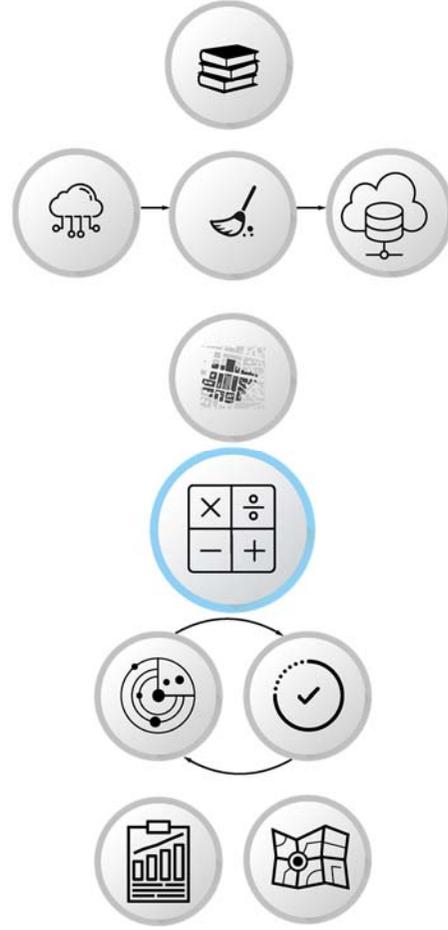
Literature review of the current state of the art in Urban Heat Island studies and models.



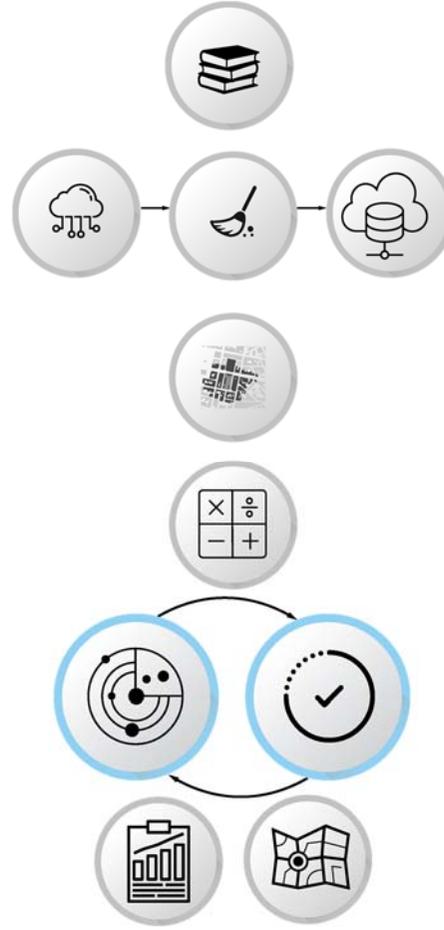
Sensor data retrieval, analysis, cleaning and storage in a spatial data base.



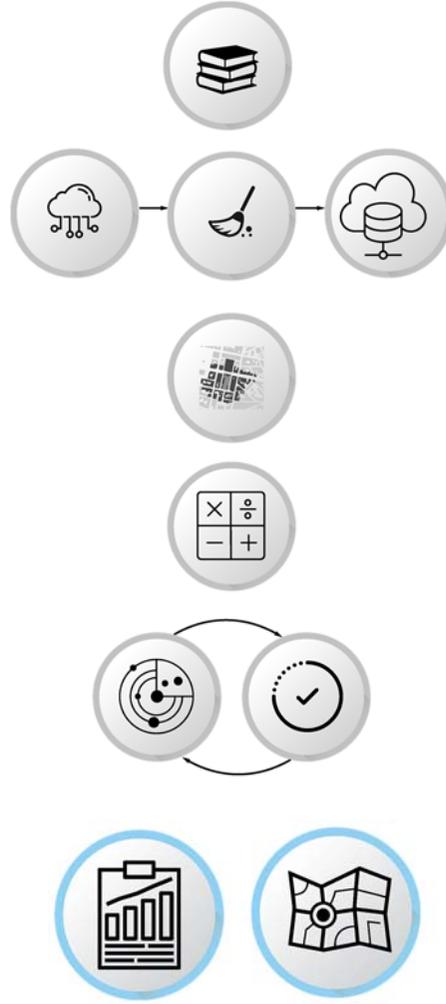
Collection, aggregation and analysis of additional relevant spatial data.



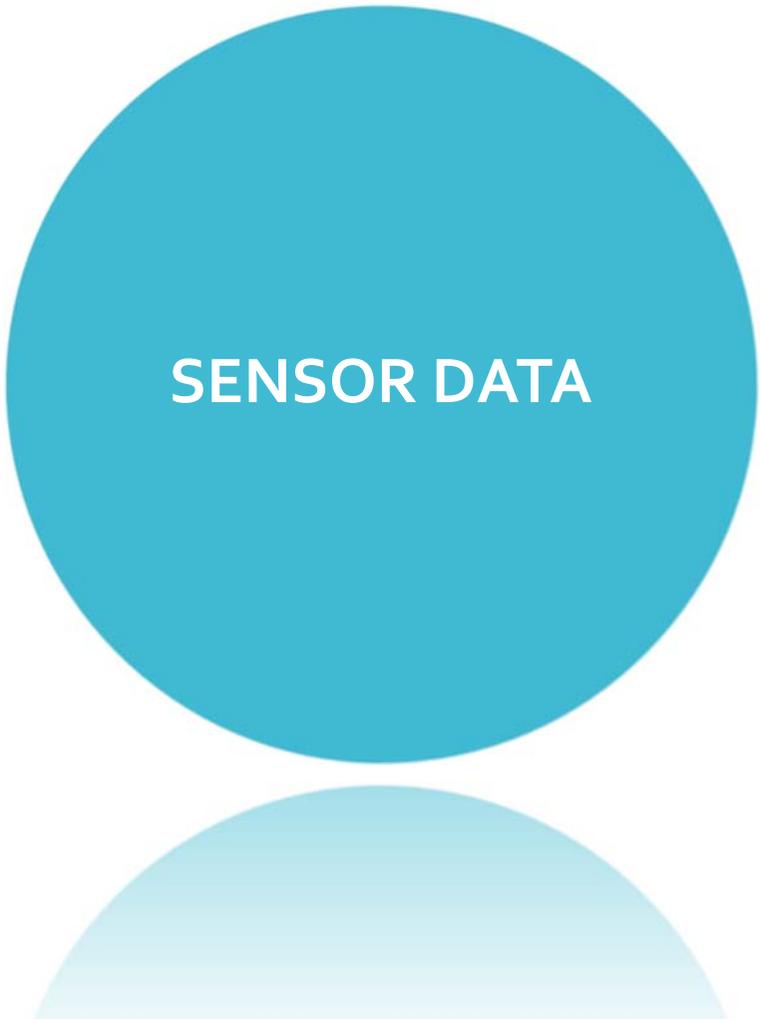
Calculation of the spatial input parameters for the regression models.



Recursive building and validation of the alternative models.



Analysis and comparison of the obtained results from the models.

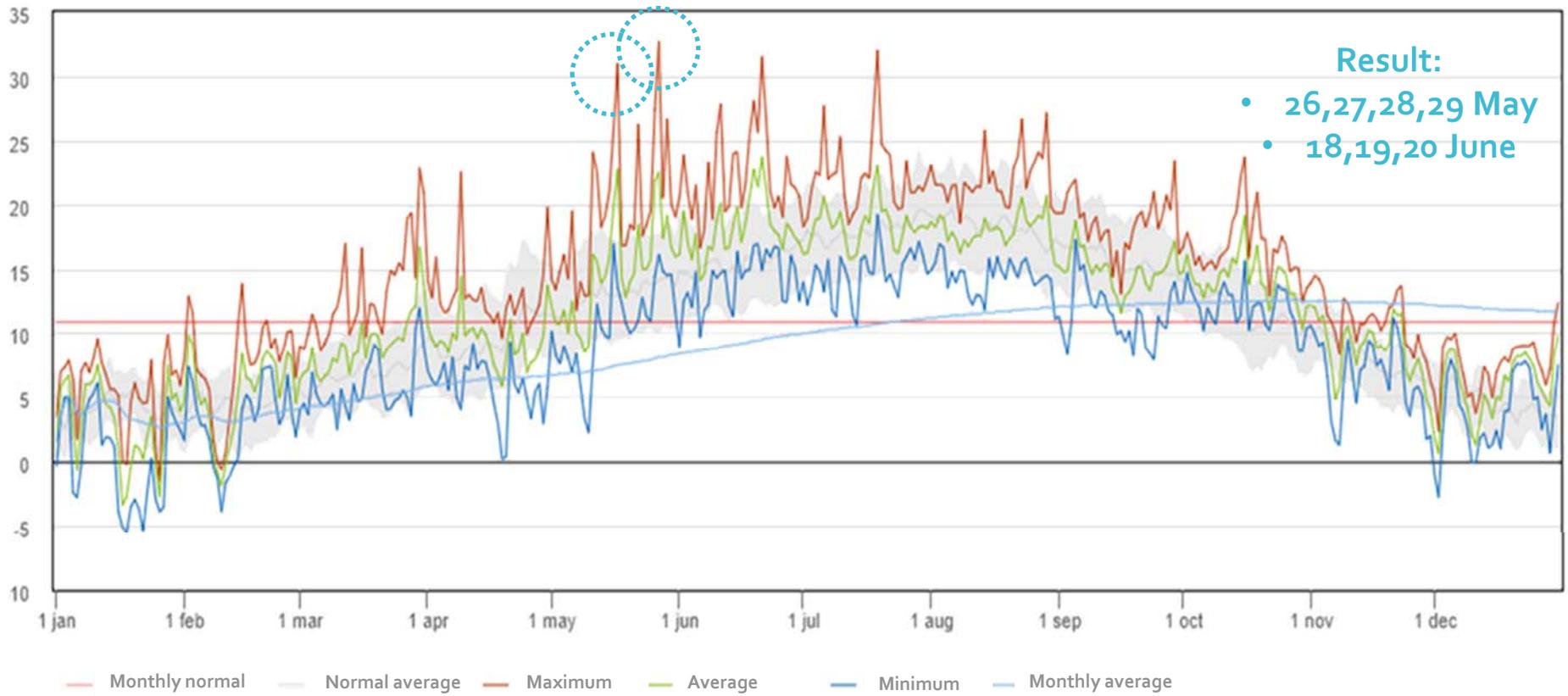


SENSOR DATA

But what is a Heat Wave?

For the Netherlands - **Five consecutive** days in which the maximum temperatures exceed 25° (**at least 3 days** with temperatures higher than 30°).

Hottest days in 2017



Source: <https://weerstatistieken.nl/hoek-van-holland/2017>

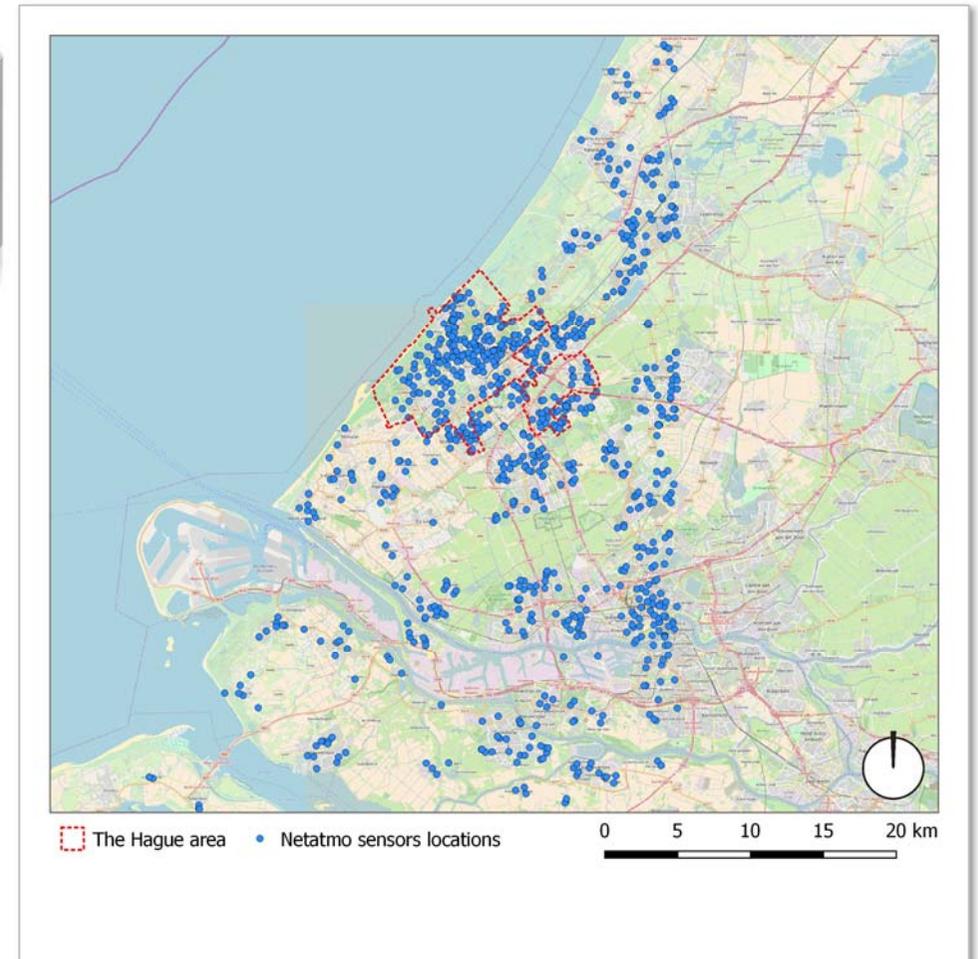
Over 800 Netatmo sensors measuring:

- Temperature
- Humidity
- Rain for the last Hour
- Rain for the last 24 Hours
- Pressure

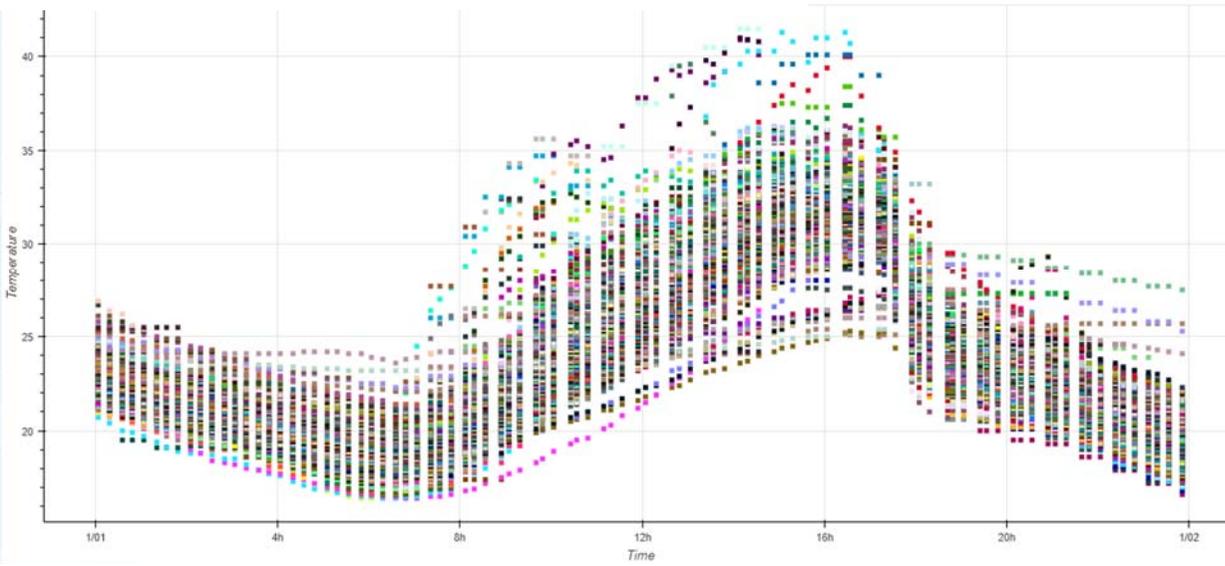


22 271 files for April – December 2017

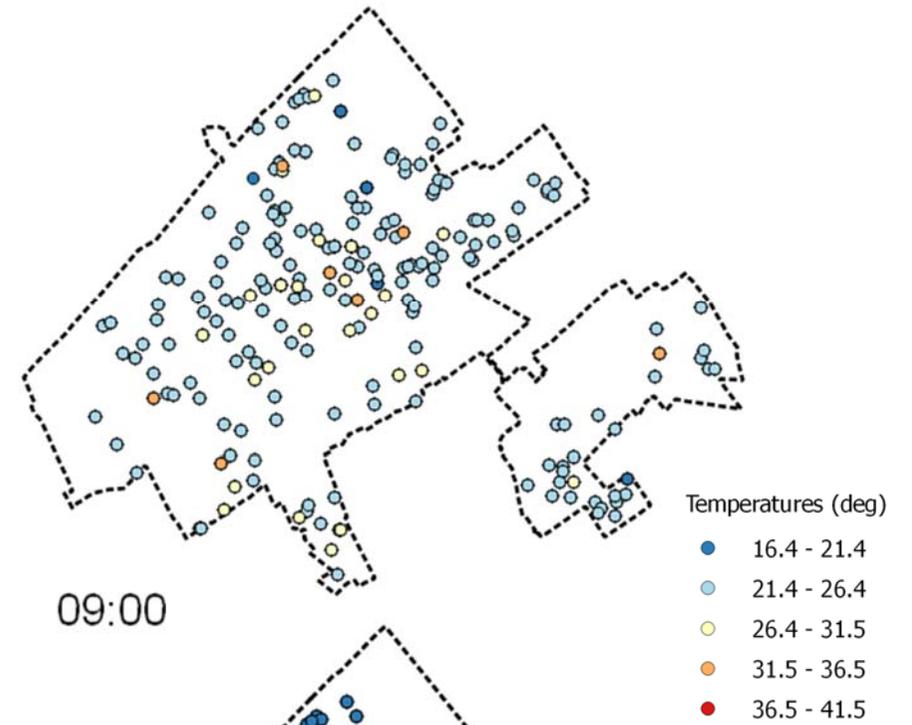
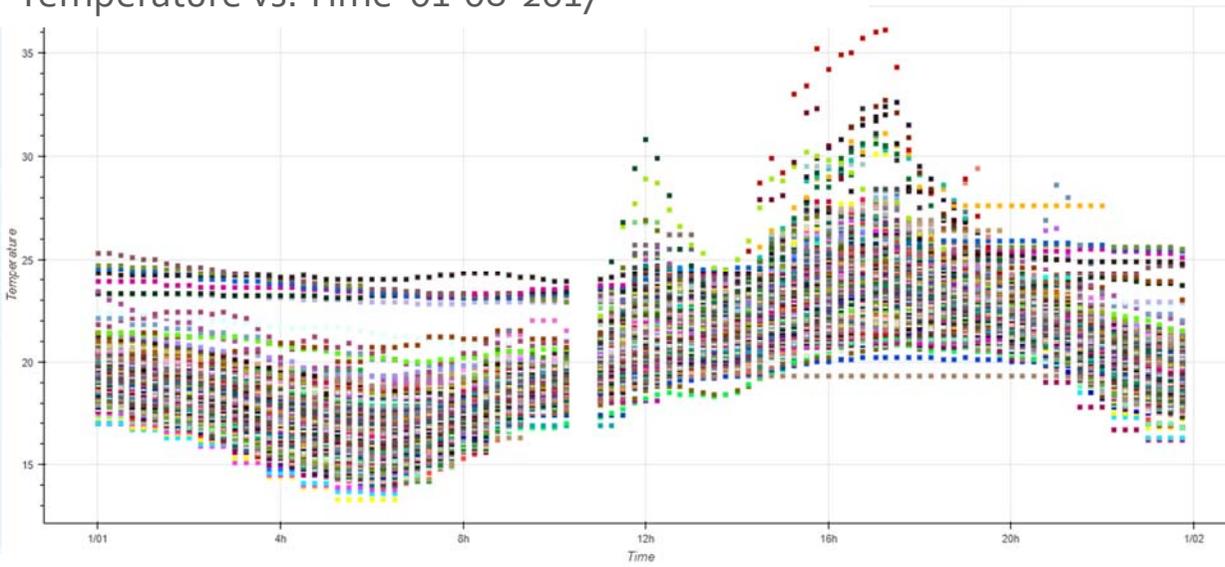
Data Output		Explain	Messages	History							
measure... [PK] dou...	sensor geometry	date date	time time wit...	mac text	altitude double p...	tempera... double p...	humidity double p...	rain_60... double p...	rain_24h double p...	pressure double p...	
<input type="checkbox"/>	1	0101000...	2017-04...	04:36:17	70:ee:50...	3	8.9	92			1020.2
<input type="checkbox"/>	2	0101000...	2017-04...	04:36:17	70:ee:50...	2	8.9	89	0	0	1019
<input type="checkbox"/>	3	0101000...	2017-04...	04:36:17	70:ee:50...	2	9.3	85			1025
<input type="checkbox"/>	4	0101000...	2017-04...	04:36:17	70:ee:50...	4	9	87	0	0	1026.8
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<input type="checkbox"/>	9	0101000...	2017-04...	04:36:17	70:ee:50...	2	9.8	85			1028.5
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<input type="checkbox"/>	13	0101000...	2017-04...	04:36:17	70:ee:50...	0	10.8	78			1027.2
<input type="checkbox"/>	14	0101000...	2017-04...	04:36:17	70:ee:50...	0					1023.9



Temperature vs. Time 27-05-2017



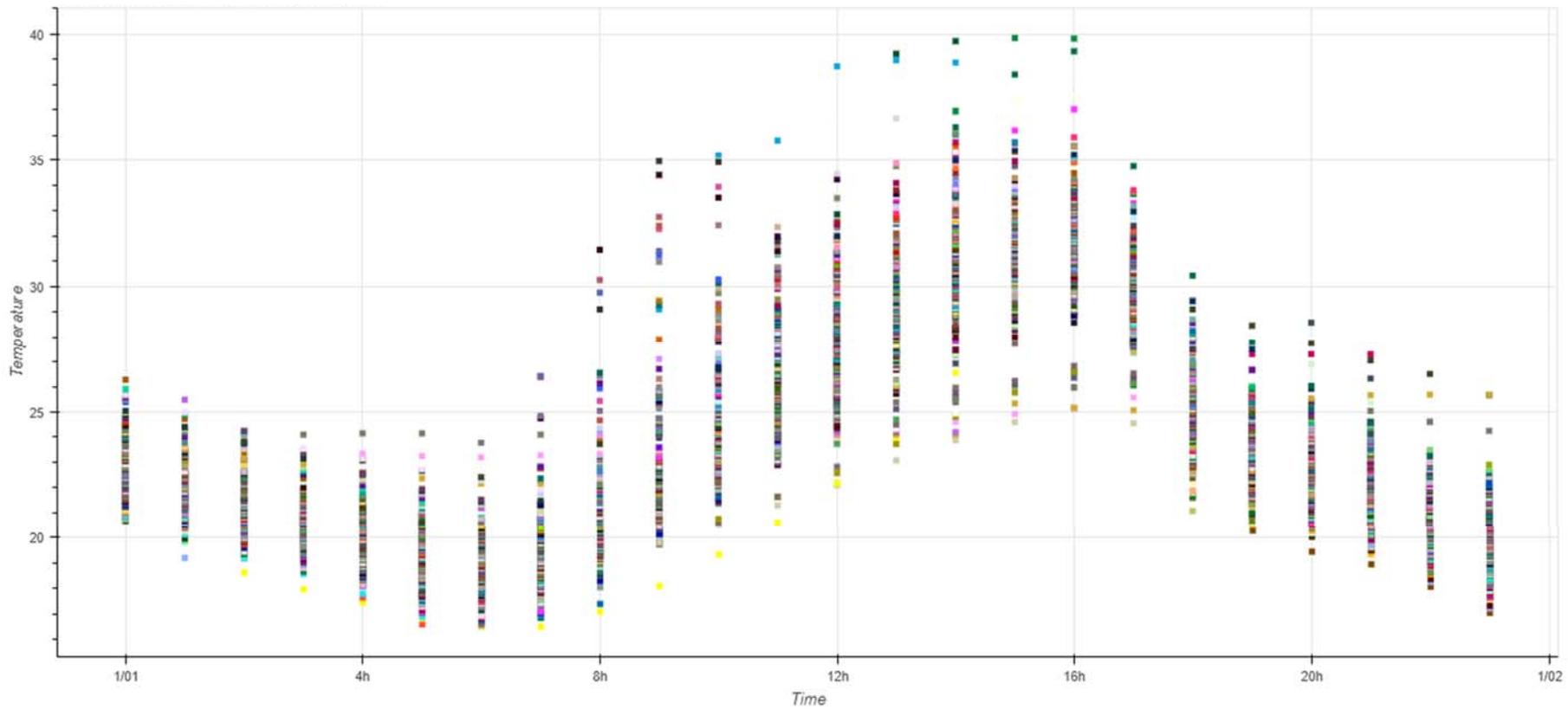
Temperature vs. Time 01-08-2017



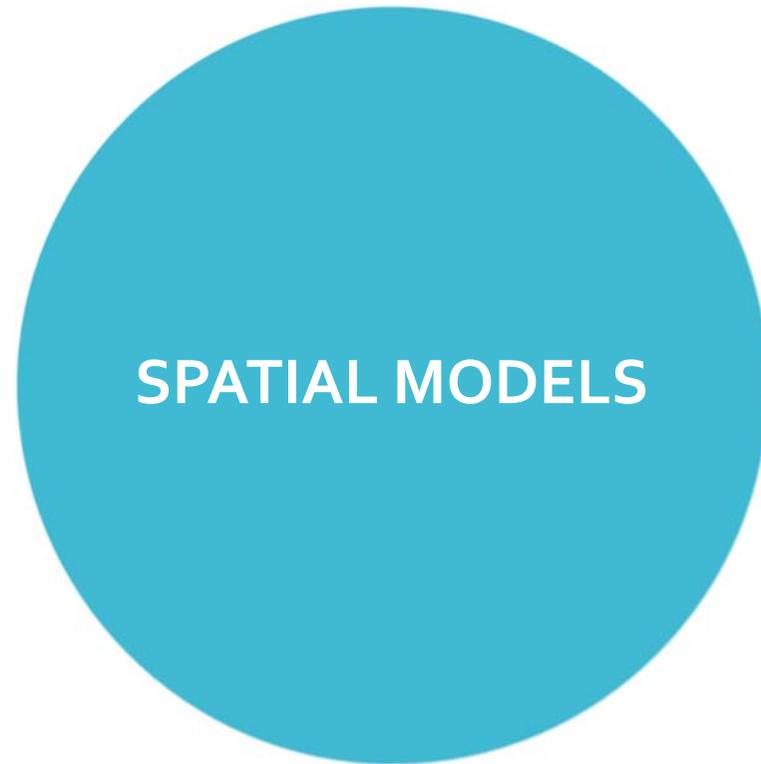
09:00



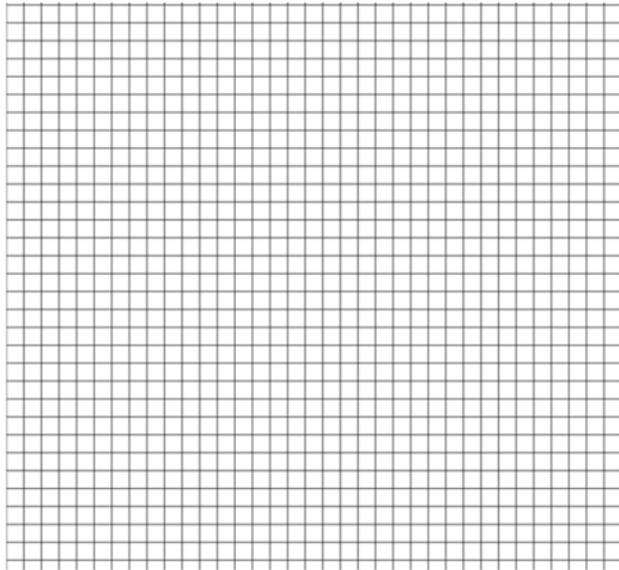
Temperature vs. Time 27-05-2017 (averaged per hour)



Dependent variable - the hour with the highest difference in the temperatures between the urban and rural areas – **1 am**

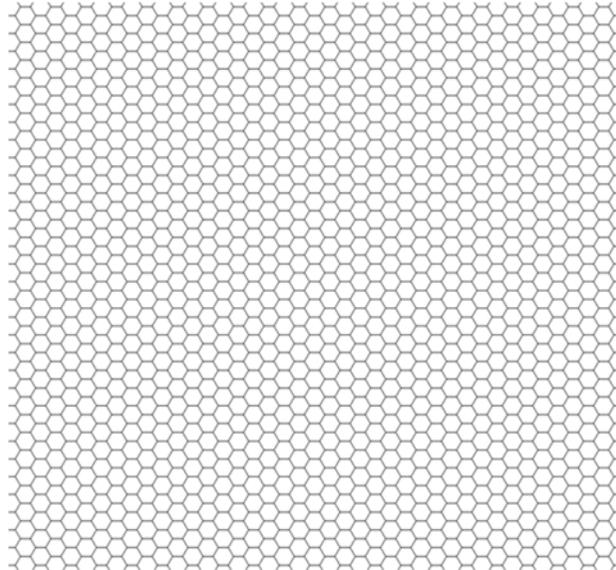


Rectangular grid – 9062 cells
100m side



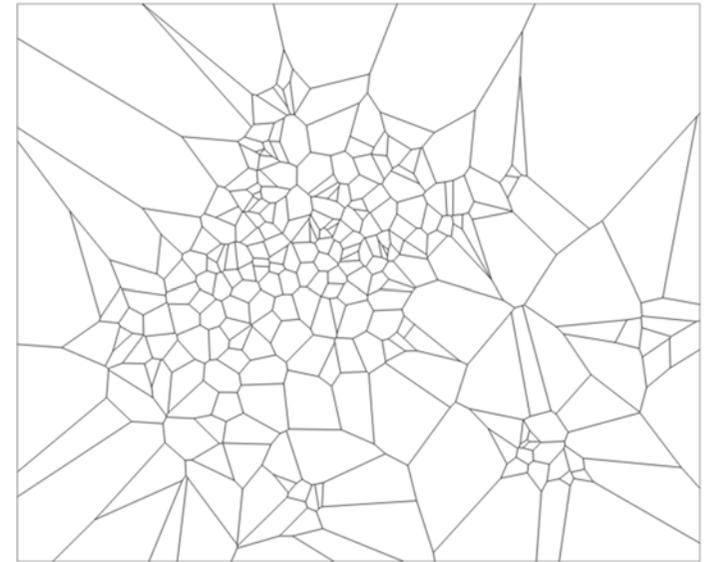
simpler definition, easily scalable,
easier raster operations

Hexagonal grid – 10359 cells
100m side distance

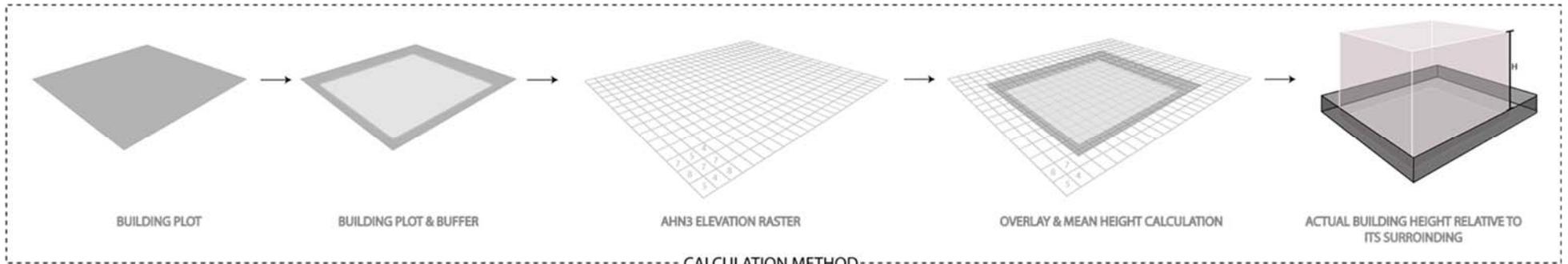
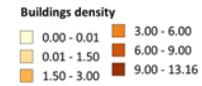
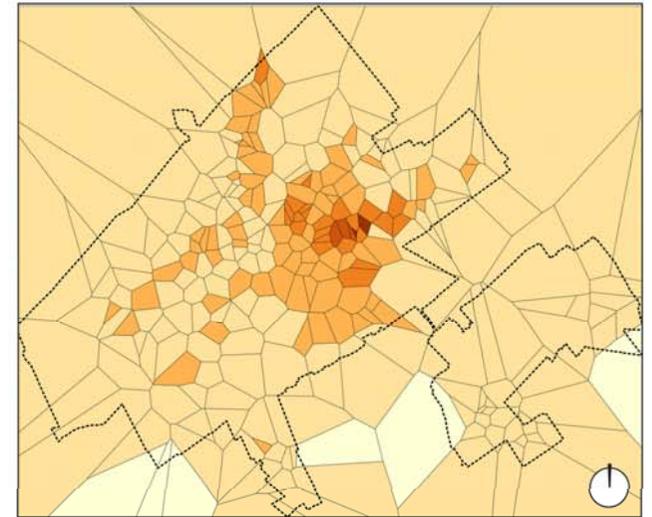
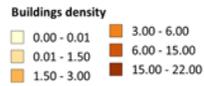
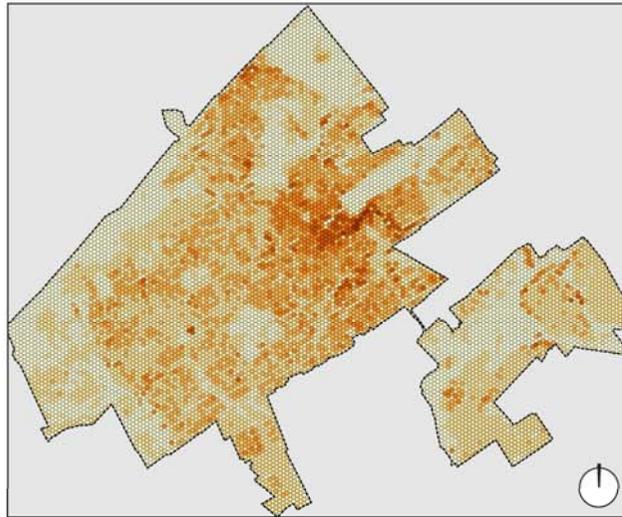
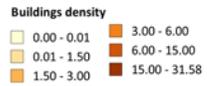
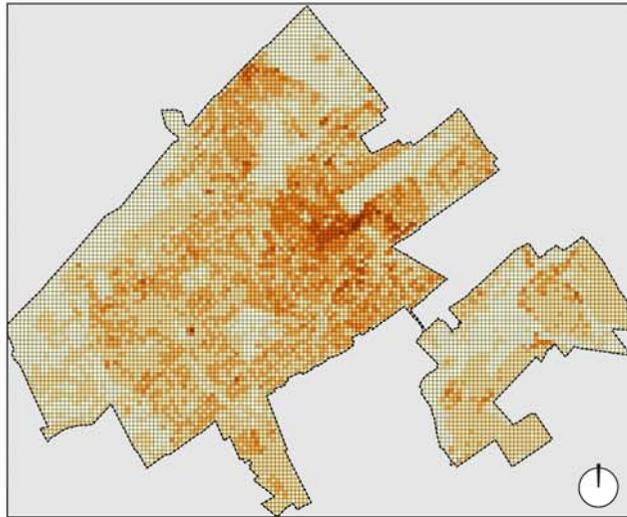


reduce edge effects, more compact,
curvature patterns of data better
visualized

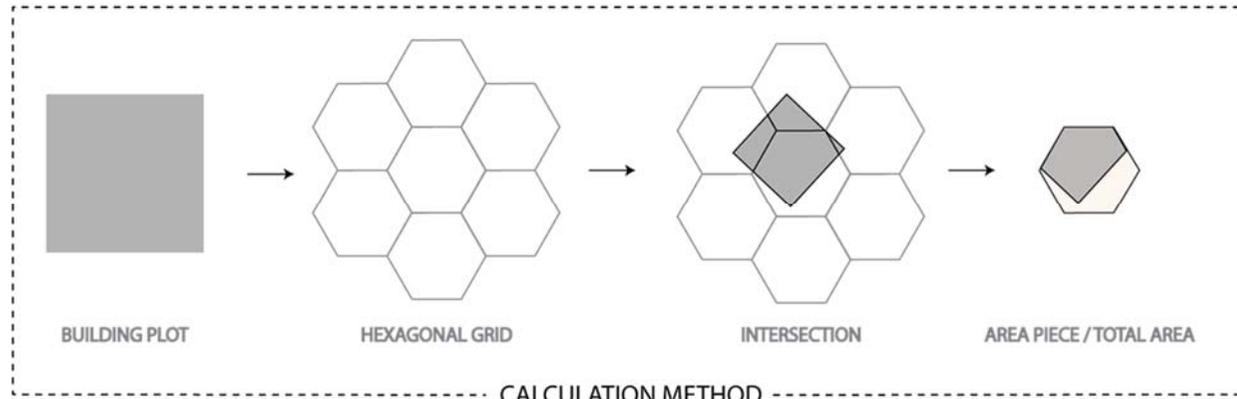
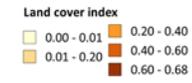
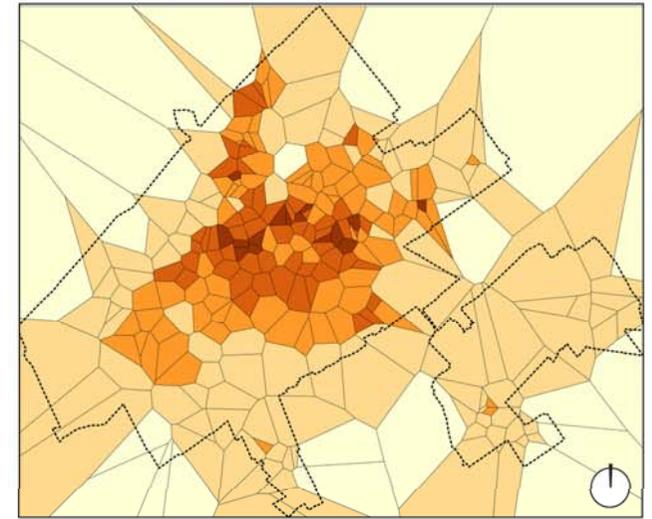
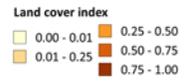
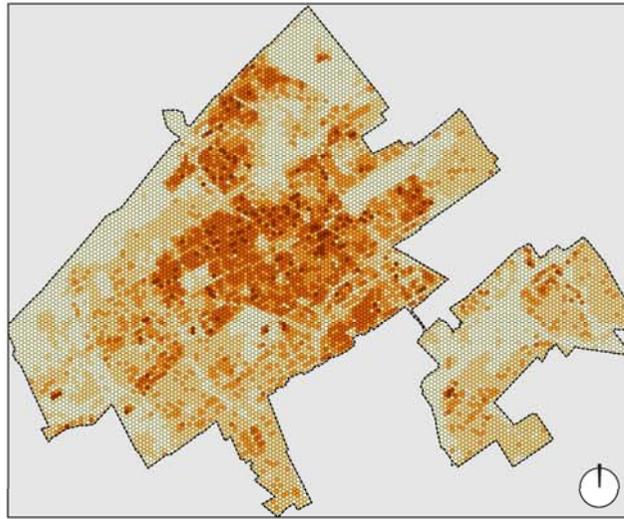
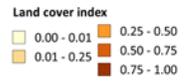
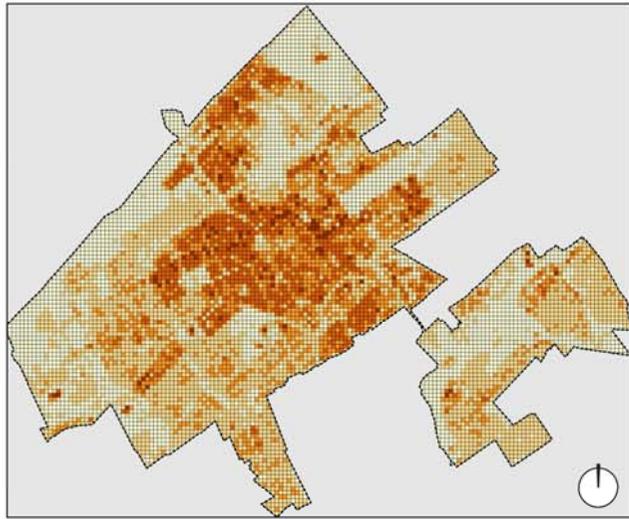
Voronoi tessellation - 273 cells
varying areas



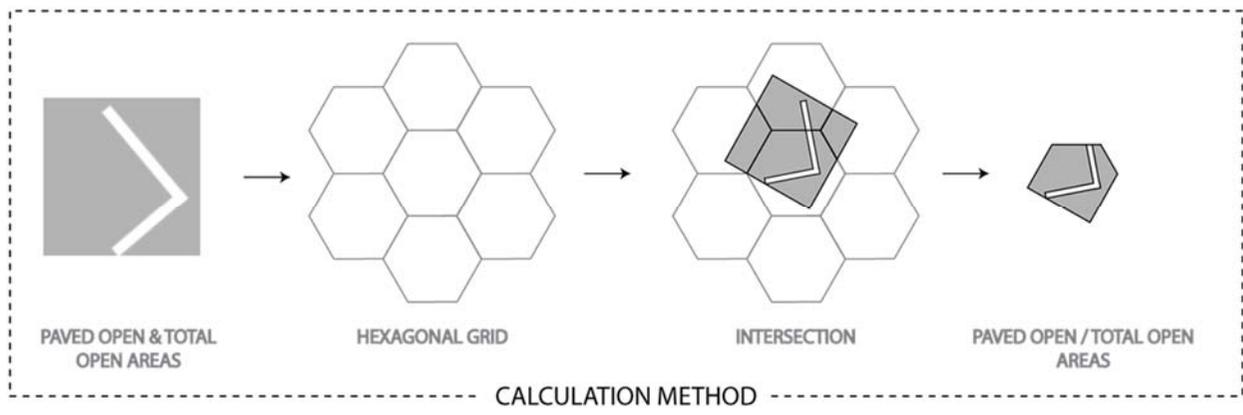
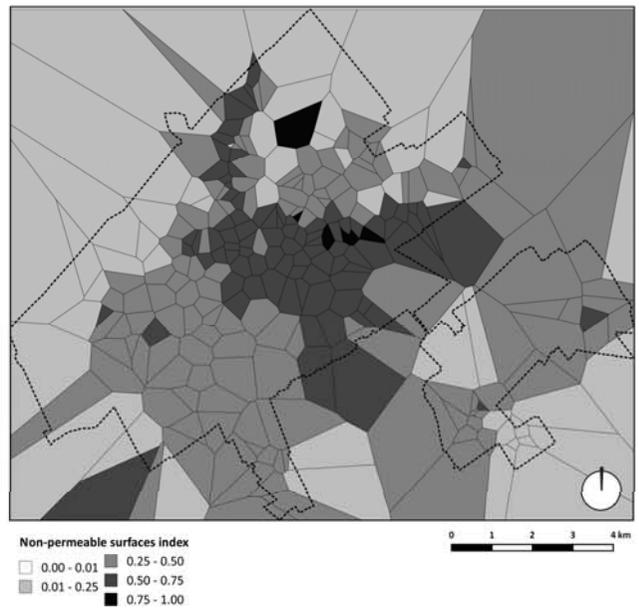
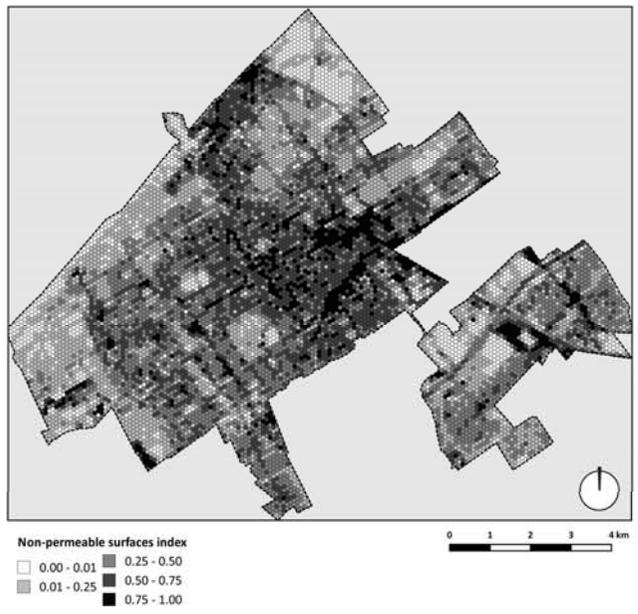
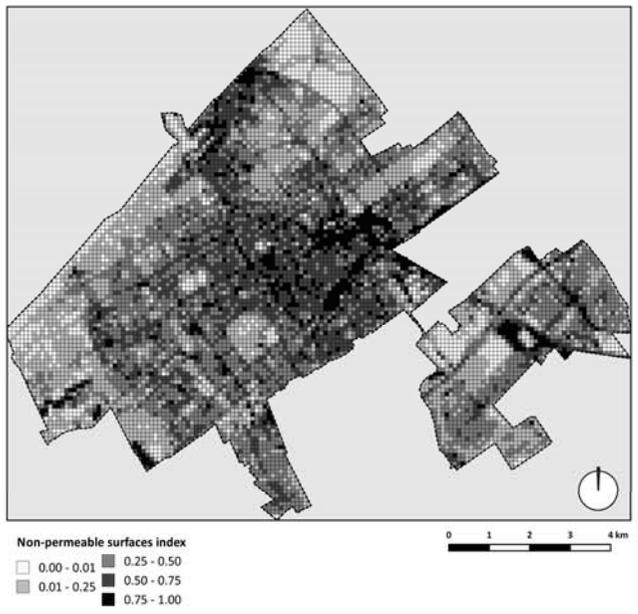
1 to 1 relation with sensor locations,
resembles data spread

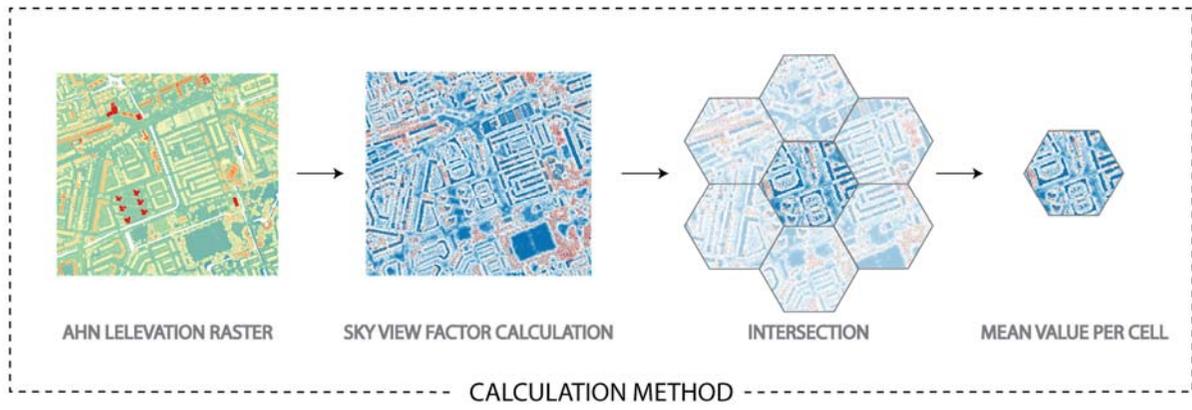
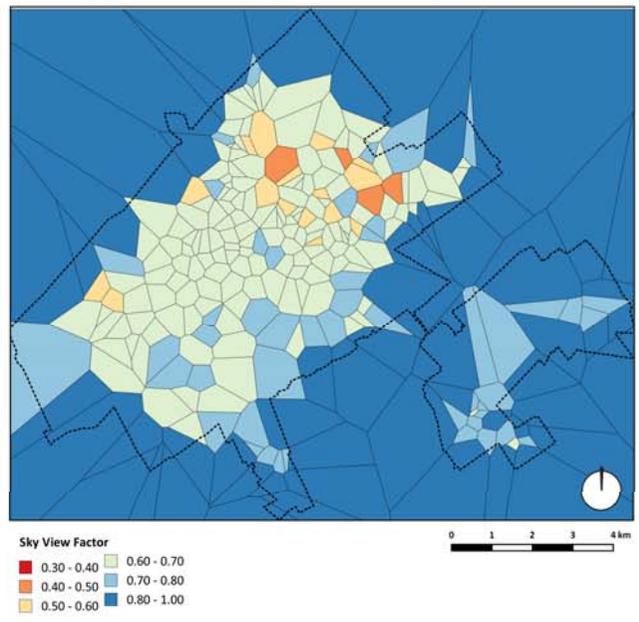
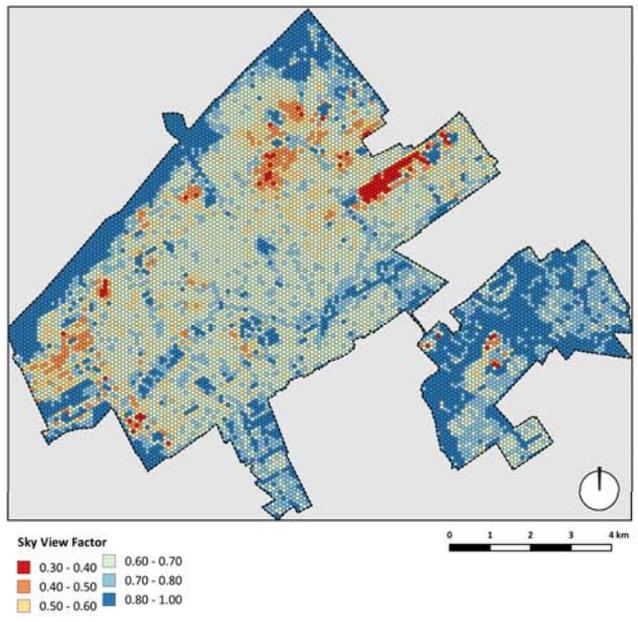
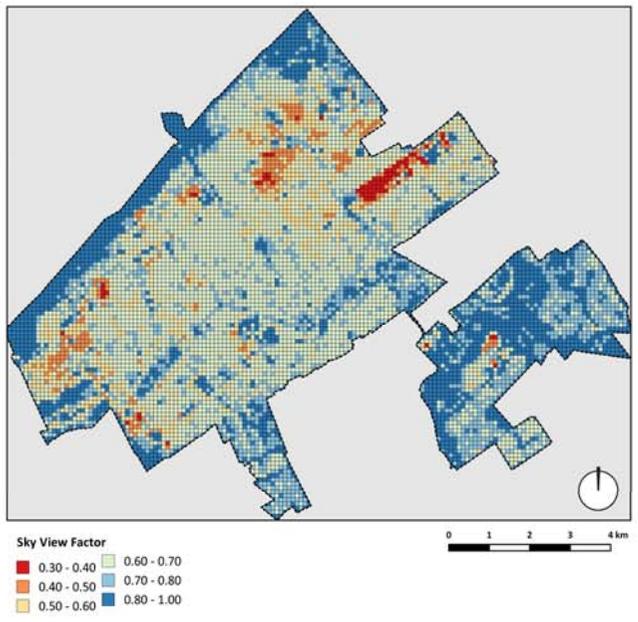


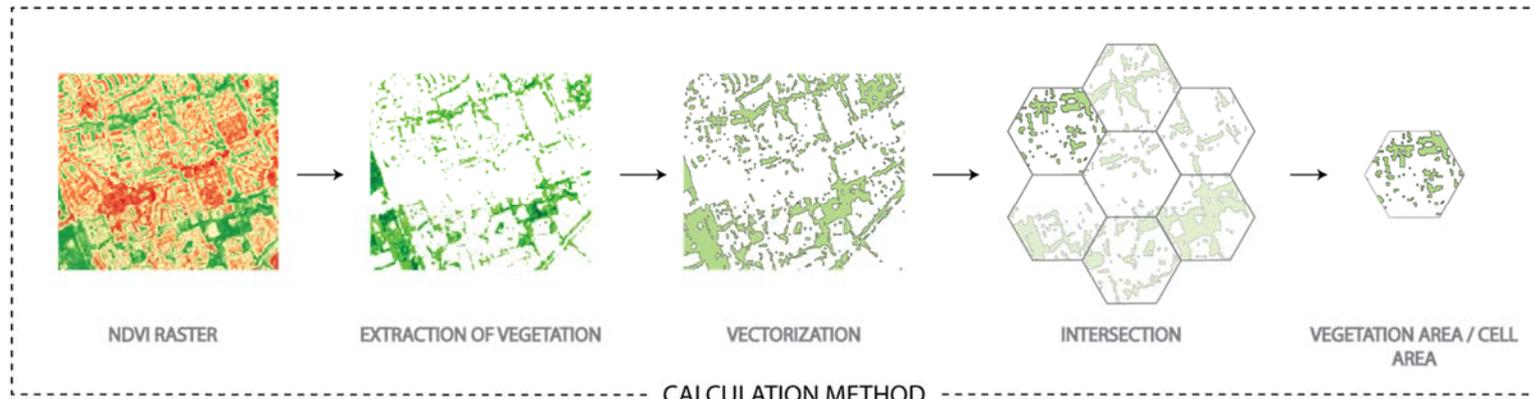
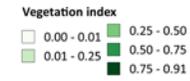
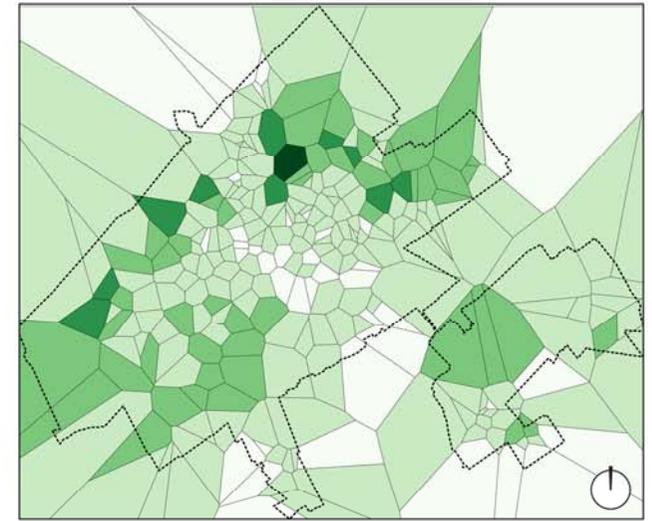
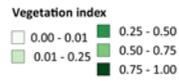
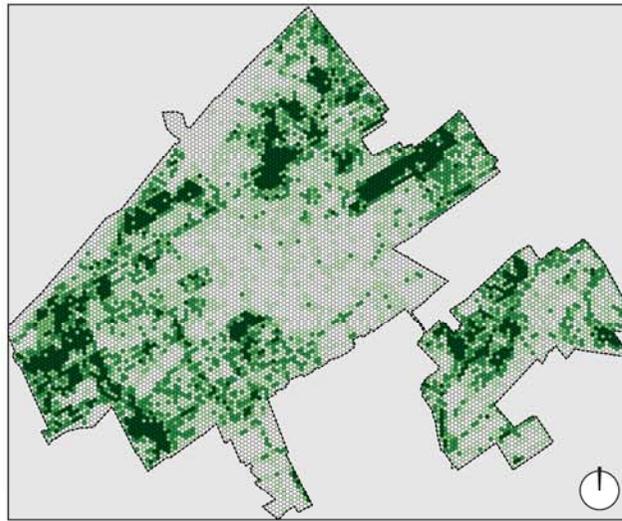
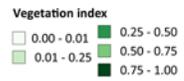
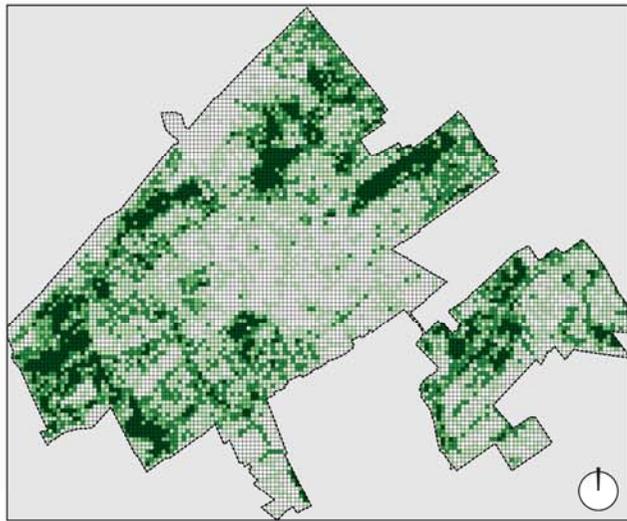
CALCULATION METHOD



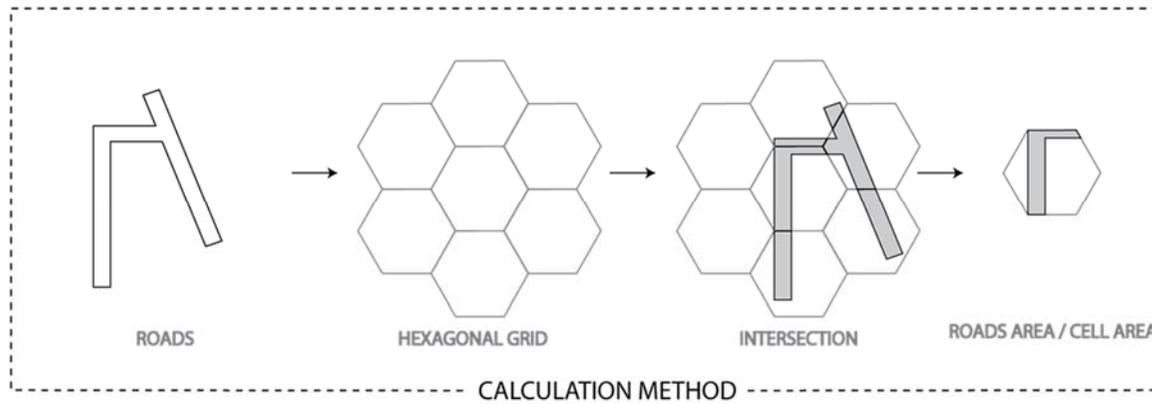
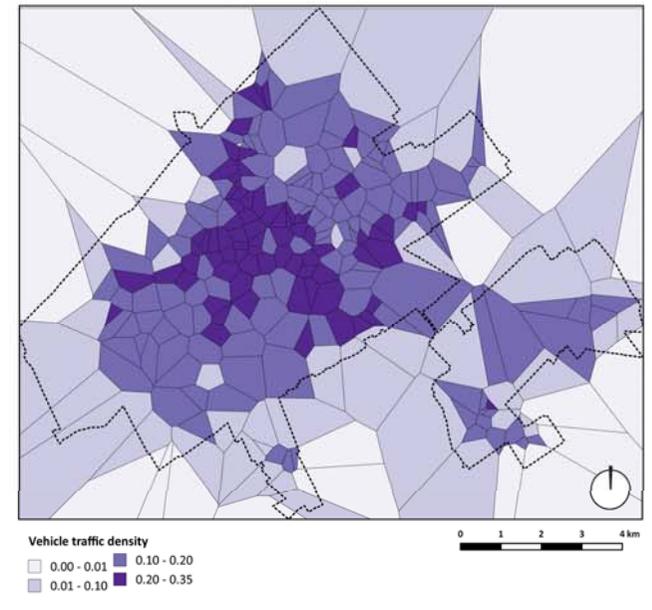
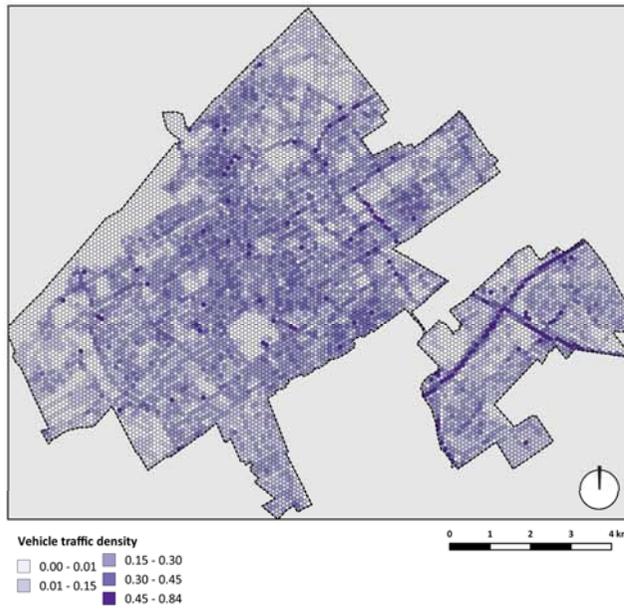
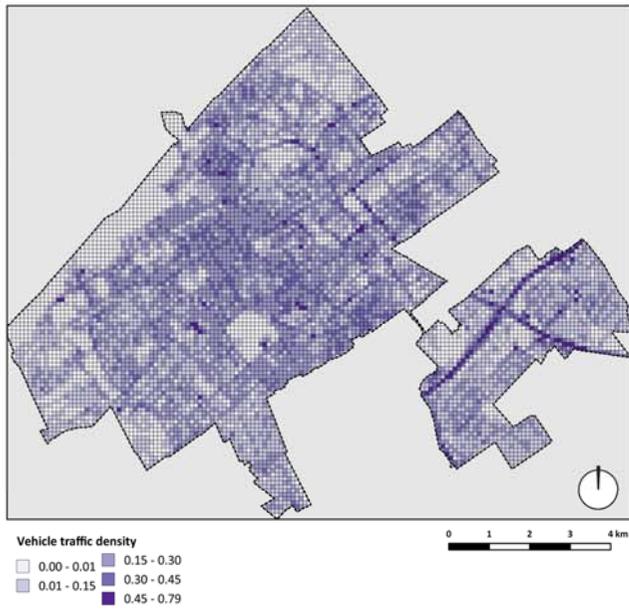
Non-permeable surfaces index

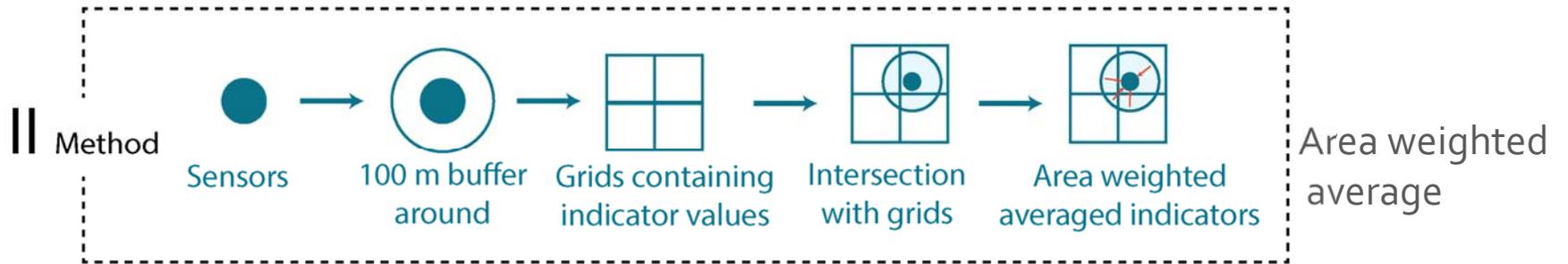
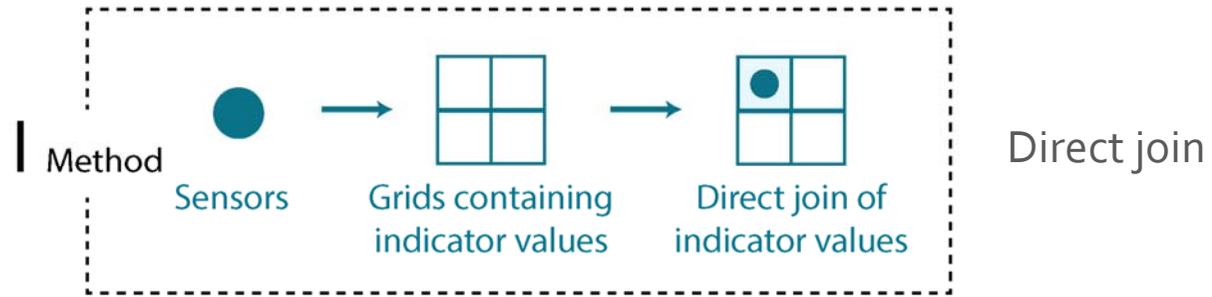


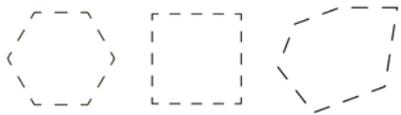




Vehicle traffic density







X 3

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2	2	70:ee:50:00:38:bc	80512.73678	454281.14441	15245	8632.94...	0.73000	1.73000	0.34000	0.61000	0.04000	0.00000	2.58000
3	3	70:ee:50:00:3a:dc	81562.54547	457191.62886	17172	8632.85...	0.60000	1.22000	0.14000	0.37000	0.52000	0.20000	2.78000
4	4	70:ee:50:00:56:6c	81839.22567	454983.42010	17684	8632.94...	0.67000	8.30000	0.46000	0.99000	0.01000	0.27000	2.63000
5	5	70:ee:50:00:5d:42	79179.33785	457483.32328	12605	8632.82...	0.56000	1.64000	0.20000	0.47000	0.52000	0.15000	3.95000
6	6	70:ee:50:00:69:62	75345.43971	451174.73352	5496	8632.98...	0.78000	0.48000	0.08000	0.28000	0.09000	0.17000	3.10000



X 2

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2	2	70:ee:50:00:38:bc	80512.73678	454281.14441	0.72000	1.29000	0.31800	0.68000	0.01000	0.23000	2.58000
3	3	70:ee:50:00:3a:dc	81562.54547	457191.62886	0.63000	1.46000	0.29900	0.39000	0.27000	0.24000	2.78000
4	4	70:ee:50:00:56:6c	81839.22567	454983.42010	0.66000	9.78000	0.43800	0.92000	0.01000	0.15000	2.63000
5	5	70:ee:50:00:5d:42	79179.33785	457483.32328	0.56000	1.56000	0.20900	0.36000	0.39000	0.15000	3.95000
6	6	70:ee:50:00:69:62	75345.43971	451174.73352	0.79000	0.51000	0.10400	0.40000	0.05000	0.12000	3.10000



Ordinary least squares regression – simplest form of linear model

Spatial lag - added spatially lagged dependent variable

Spatial error – added spatially autocorrelated error term

Geographically weighted regression – locally varying spatial model

$$y = \beta_0 + \beta_1 x + u \text{ (OLS)}$$

Dependent variable - t^o

Independent variables – Spatial indicators

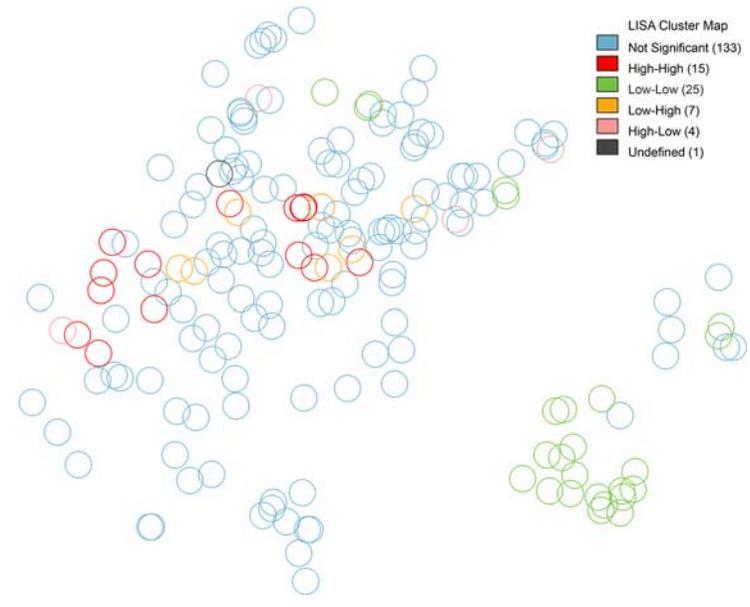
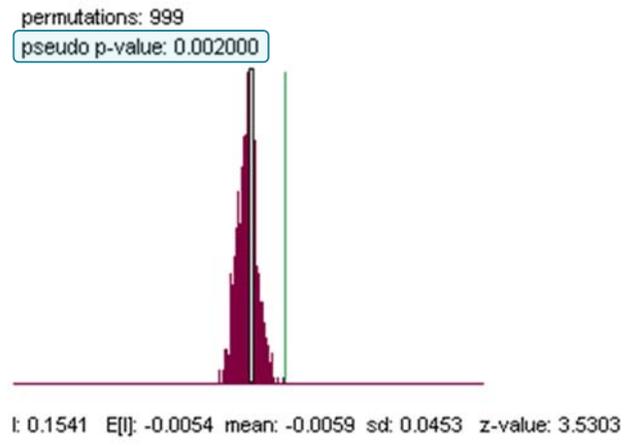
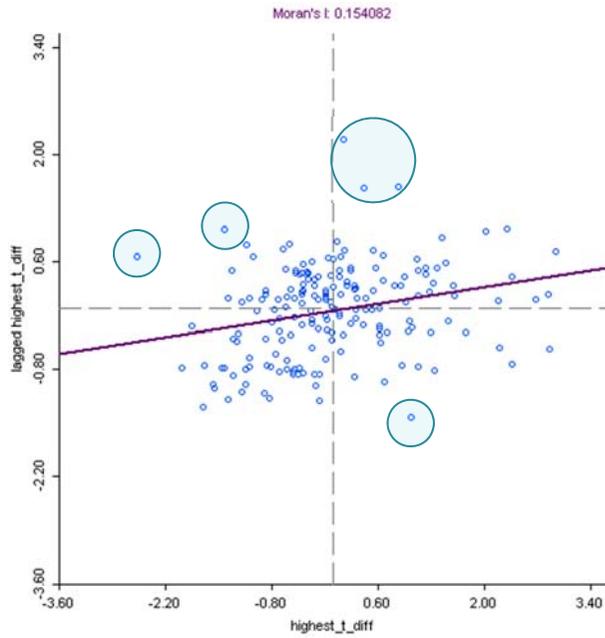
$$y = \rho W y + x + \varepsilon, \text{ (Spatial lag model)}$$

$$y = X\beta + \varepsilon, \text{ (Spatial error model)}$$

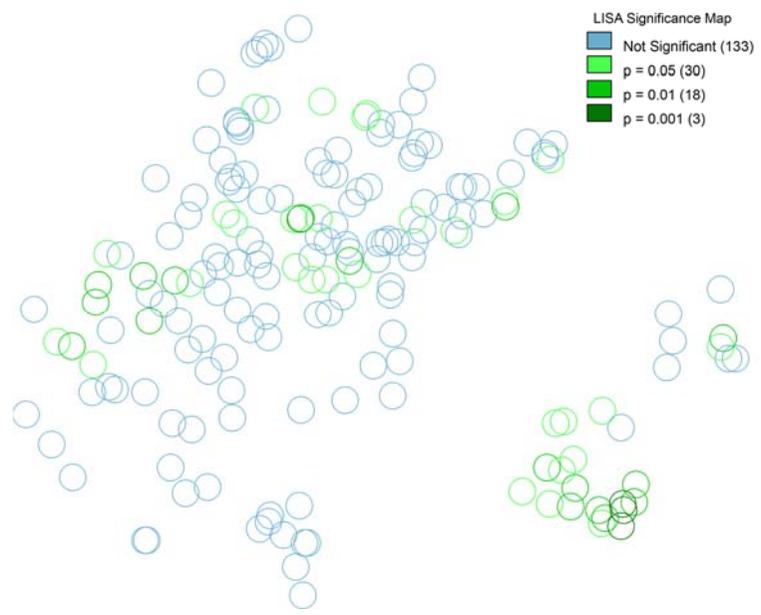
$$y_i = a_{i0} + \sum_{k=1,m} a_{ik} x_{ik} + \varepsilon_i, \text{ (GWR)}$$

- 1) Random data sample representing the general population.
- 2) The random error term has normal distribution (no systematic misspecification or bias in the model).
- 3) The errors have constant variance (homoscedasticity).
- 4) The individual observations are independent.

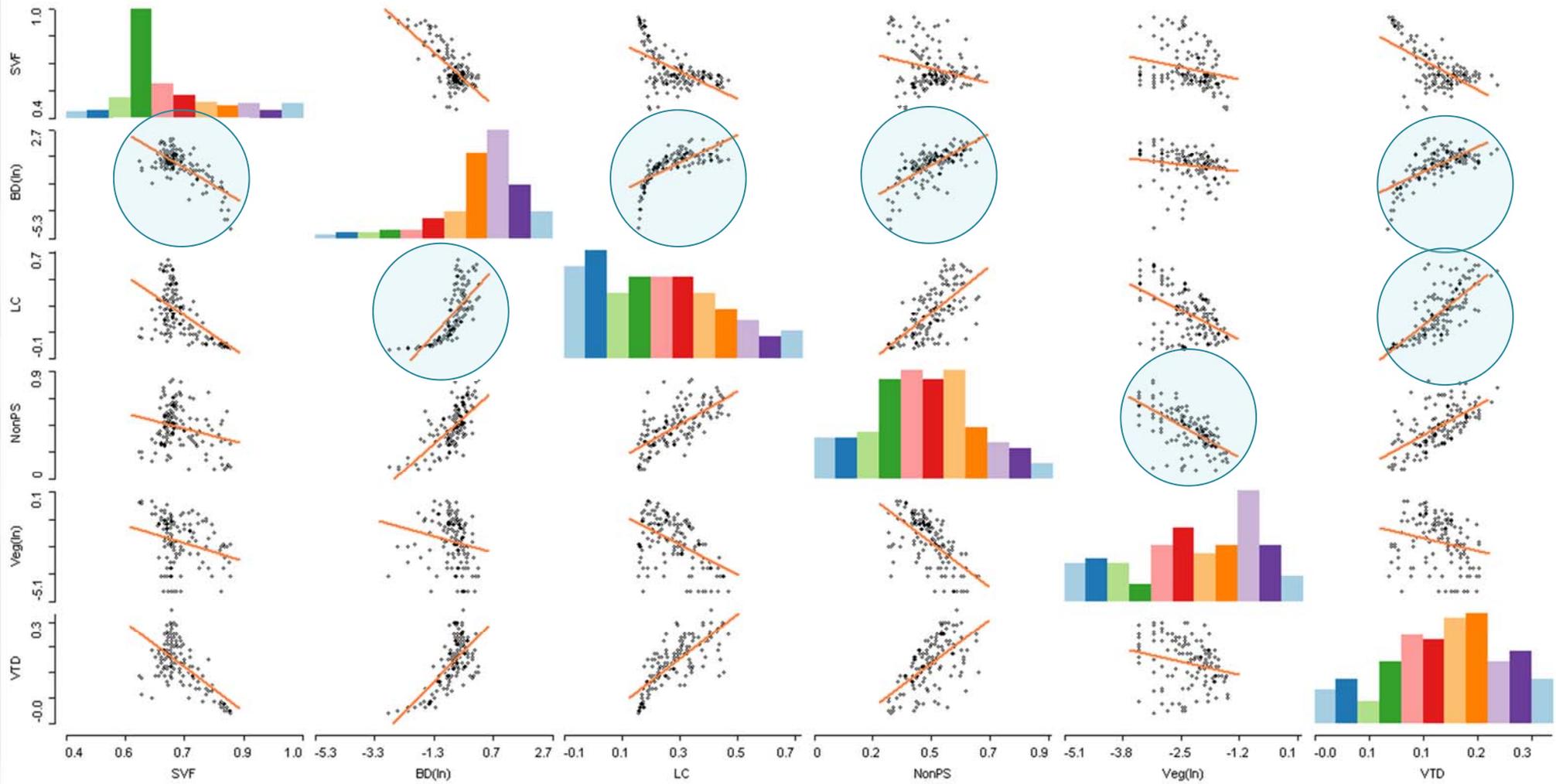
The violation of any of these assumptions can lead to bias, inefficiency in the regression estimates or unreliability of the confidence intervals.



Local indicators of spatial association (LISA) - Cluster map



LISA - significance map



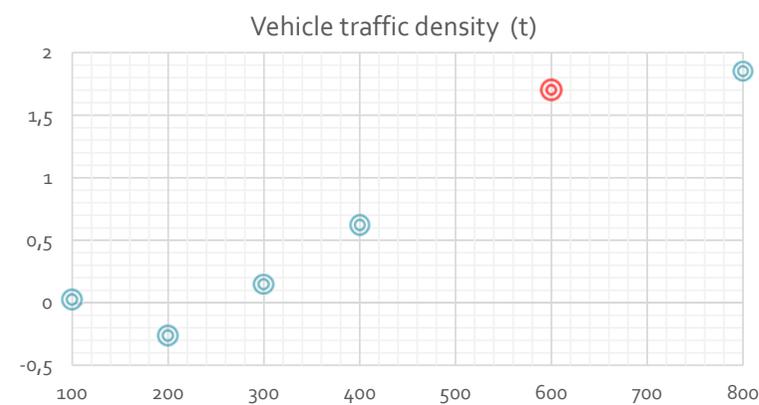
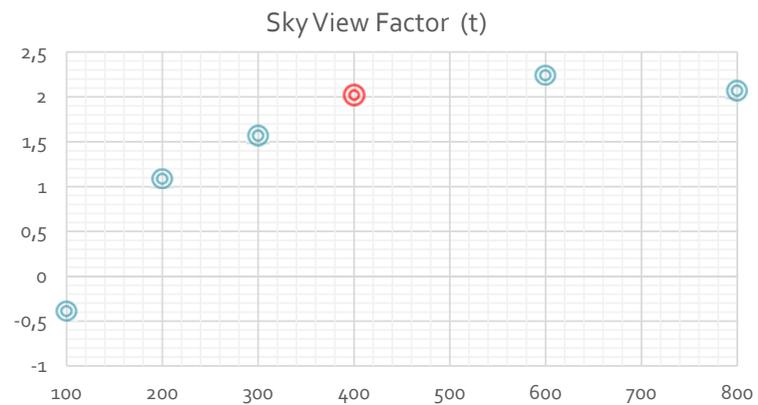
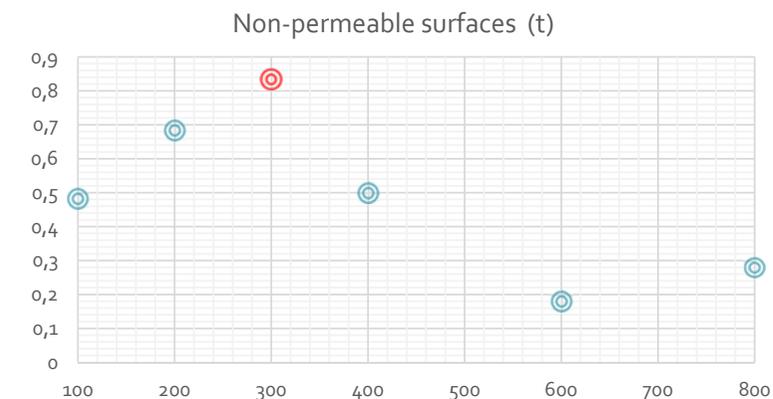
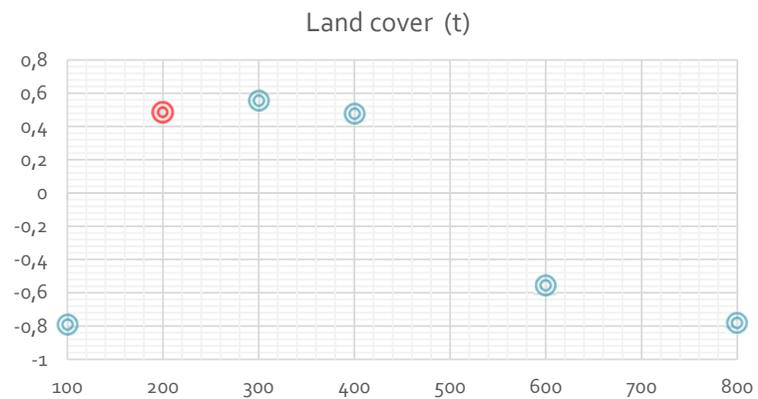
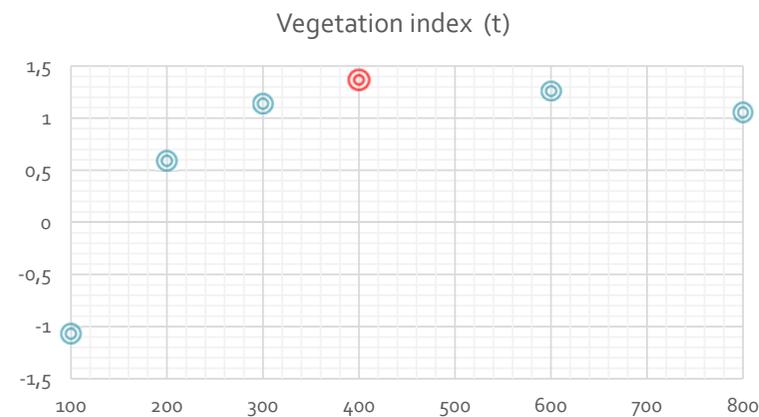
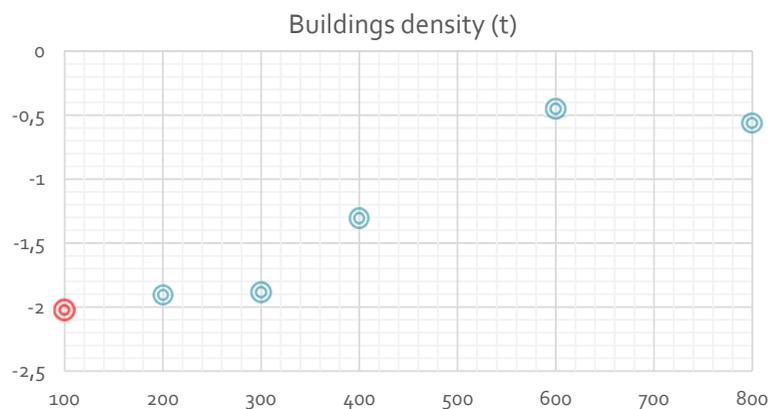
Correlated indicators:
 BD with SVF, LC, NonPS, VTD; Land cover –BD, VTD; NonPS -
 Vegetation

Goodness of fit indicators

MODEL	R ²	R ² -ADJUSTED	AIC	LOG -LIKELIHOOD	MULTICOLL INEARITY CONDITION NUMBER
HEX (DIRECT)	0.03	-0.012	415.682	-200.841	45.70
RECT (DIRECT)	0.03	-0.003	414.425	-200.213	47.92
VORONOI	0.04	0.002	413.592	-199.796	71.12
HEX (AWA)	0.04	0.004	413.283	-199.642	62.81
RECT (AWA)	0.04	0.005	413.051	-199.526	62.50

Variables significance

	SVF	BD	LC	NONPS	VEG	VTD
HEXAGONAL GRID (DIRECT)						
COEFFICIENT	-1.2818	-0.0586	-0.2475	1.3438	-0.2010	-1.0807
T-STATISTIC	-0.7739	-0.9129	-0.4127	1.7952	-0.2506	-0.7489
P-VALUE	0.44039	0.3629	0.6804	0.0748	0.8024	0.4552
RECTANGULAR GRID (DIRECT)						
COEFFICIENT	-0.9518	0.0325	-0.3079	0.6709	-0.1239	0.2965
T-STATISTIC	-0.5621	0.5851	-0.5267	0.8781	-0.1441	0.1898
P-VALUE	0.5749	0.5594	0.5992	0.3814	0.8856	0.8497
VORONOI DIAGRAM						
COEFFICIENT	-2.1701	-0.0334	0.3877	1.0948	-0.6776	-3.4852
T-STATISTIC	-1.0278	-0.2994	0.3308	1.1077	-0.5313	-1.4100
P-VALUE	0.3059	0.7651	0.7412	0.2699	0.5960	0.1608
RECTANGULAR GRID (AWA)						
COEFFICIENT	-2.8955	-0.0784	0.1512	2.0012	-0.0317	-3.4379
T-STATISTIC	-1.3974	-0.9200	0.1687	1.7872	-0.0261	-1.4907
P-VALUE	0.1646	0.3592	0.8662	0.0761	0.9792	0.1384
HEXAGONAL GRID (AWA)						
COEFFICIENT	-2.4328	-0.0751	0.3085	1.9227	0.1071	-3.6976
T-STATISTIC	-1.1616	-0.8635	0.3567	1.7670	0.0898	-1.6608
P-VALUE	0.24747	0.3893	0.7218	0.0795	0.9285	0.0991



Statistical significance against buffer sizes

Improved models by:

- Different areas of influence included
- Removed insignificant variables
- Excluded correlated variables
- Applied spatial models

MODEL	R ²	R ² -ADJUSTED	AIC	LOG - LIKELIHOOD	MULTICOLLINEARITY CONDITION NUMBER
OLS (INITIAL STAGE)	0.04	0.004	413.283	-199.642	62.810
OLS	0.11	0.07	431.275	-207.638	163.427
OLS (REFINED)	0.10	0.09	422.786	-208.393	31.8182
SPATIAL LAG	0.11	-	424	-208	-
SPATIAL ERROR	0.11	-	422.221	-208.110	-
GWR	0.20	0.15	424.767	-	-

Geographically weighted regression has the highest performance.

	SVF (400M)	BD (100M)	LC (200M)	NONPS (300M)	VEG (400M)	VTD (600M)
OLS						
COEFFICIENT	-4.816	-0.012	0.035	2.932	-0.156	-3.121
T-STATISTIC	-1.926	-0.085	0.036	2.126	-0.133	-0.948
P-VALUE	0.0562	0.9326	0.9716	0.0353	0.8947	0.3446
OLS (REFINED)						
COEFFICIENT	-3.934	-	-	2.032	-	-
T-STATISTIC	-2.482	-	-	3.147	-	-
P-VALUE	0.0142	-	-	0.0020	-	-
SPATIAL LAG						
COEFFICIENT	-3.735	-	-	1.889	-	-
T-STATISTIC	-2.325	-	-	2.862	-	-
P-VALUE	0.0200	-	-	0.0042	-	-
SPATIAL ERROR						
COEFFICIENT	-3.974	-	-	2.011	-	-
T-STATISTIC	-2.410	-	-	2.994	-	-
P-VALUE	0.0159	-	-	0.0027	-	-

What?

Model predicting **extreme temperatures in the city**; primarily based on **spatial data**, thus not dependent on weather data.

How?

Based on **spatial and statistical techniques for data modelling**; using **spatial indicators** as independent variables; using Geographically weighted regression model.

Why?

Tool, assisting **different planning strategies** and the development of different **UHI mitigation measurements**; different experts can address the UHI problem by **evaluating the significance of the different spatial indicators** for the temperatures in the city.

Currently the model has limited explanatory power, because of:

- 1) The inconsistent nature of the air – e.g. wind.
- 2) The errors in the sensor data – position, technical characteristics.

Improvement of the model:

- 1) Inclusion of more diverse indicators.
- 2) Improvement of the calculation methods for these indicators – e.g. Vehicle traffic density, Vegetation.
- 3) Statistical analysis of the variables in the selection process.
- 4) Exploration of different non-linear models.



THANK YOU