Modelling the Atmospheric Urban Heat Island and its Contributing Spatial Characteristics

The Case of The Hague, the Netherlands

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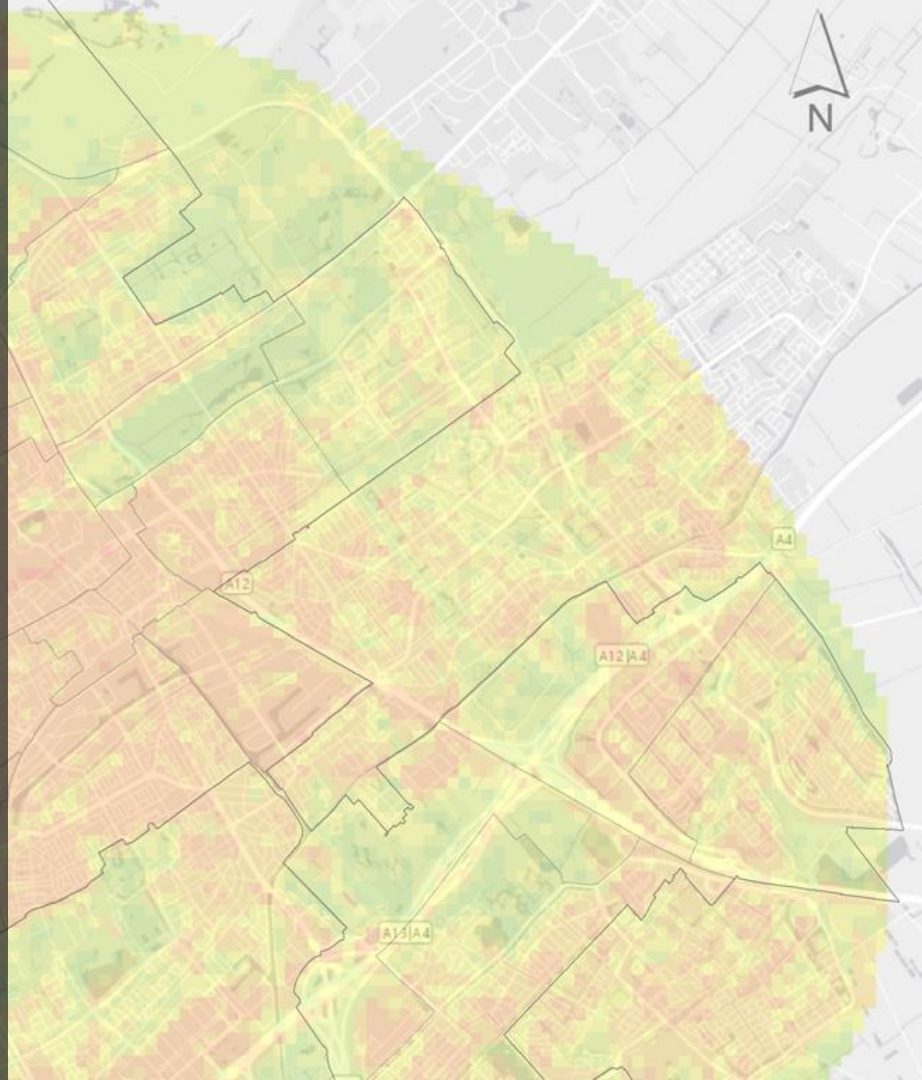
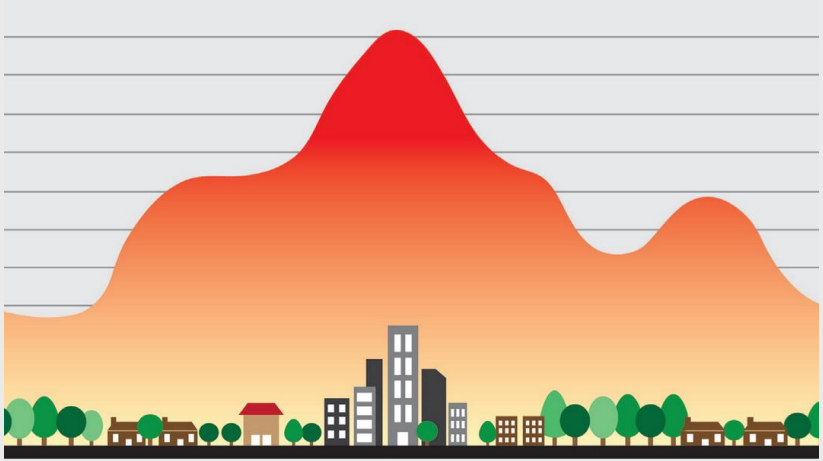


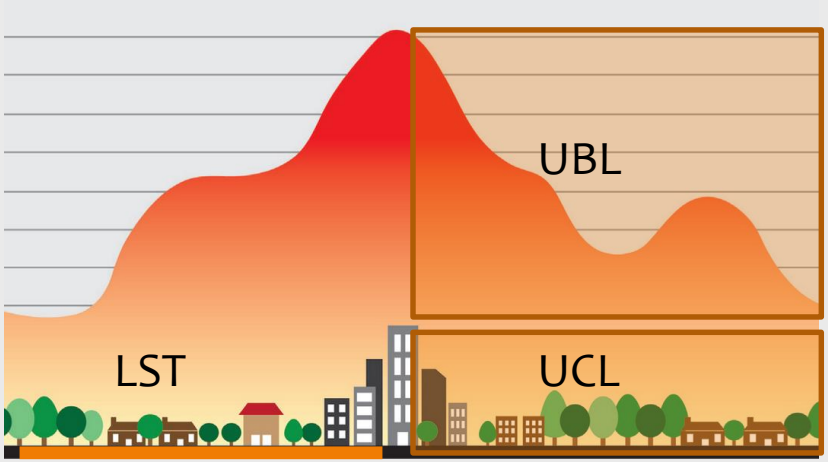
- **Urban Heat Island** (UHI) is a phenomenon in which a city forms microclimates which heat-up quicker than its rural surroundings.

$\Delta T(u\text{-}r) = Tu - Tr$



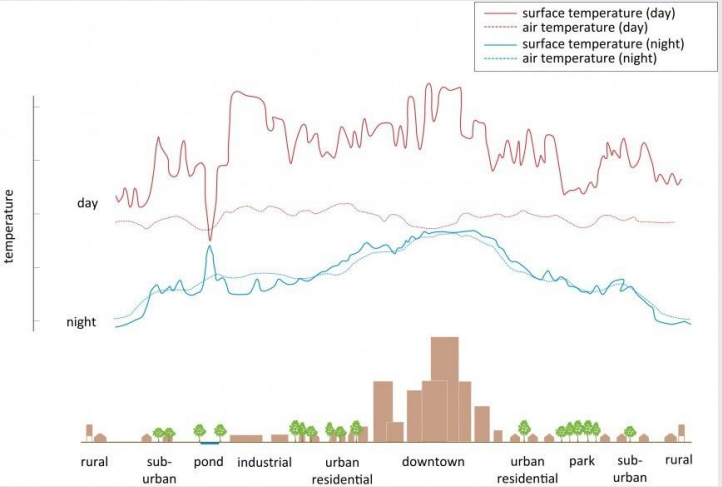
(Oke ,1982; , Johnson & Wilson ,2009; Arnfield, 2003; Taha et al.,1997; van der Hoeven & Wandl, 2015; Li et al., 2011; Steeneveld et al., 2011)

- There are different **UHI types** depending on the layer in which the temperature is measured
  - Surface UHI
  - Atmospheric UHI
  - Upper Atmospheric UHI



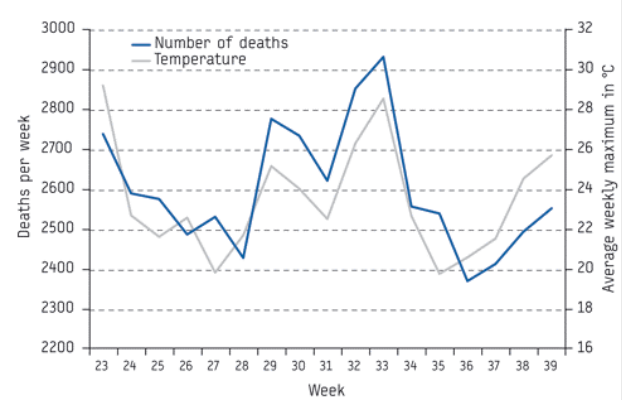
(EPA, 2008)

- The UHI types share different characteristics in terms of
  - temporal development,
  - intensity and
  - spatial distribution



(EPA, 2008)

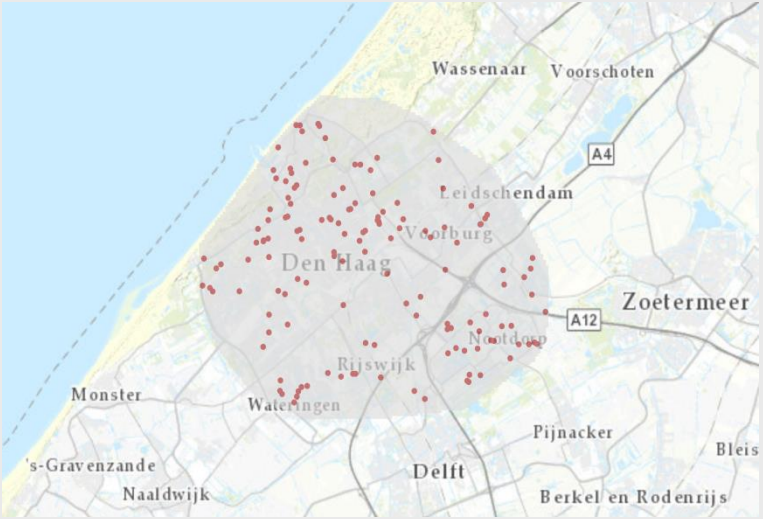
- The UHI was assumed to have minor **effects** in The Netherlands till the first major heat-wave (2003)
  - Unhealthiness
  - Mortality
  - Discomfort
  - Respiratory disorders



(Garssen, 2005; Hoeven & Wandl, 2015; Mavrogianni, 2011)

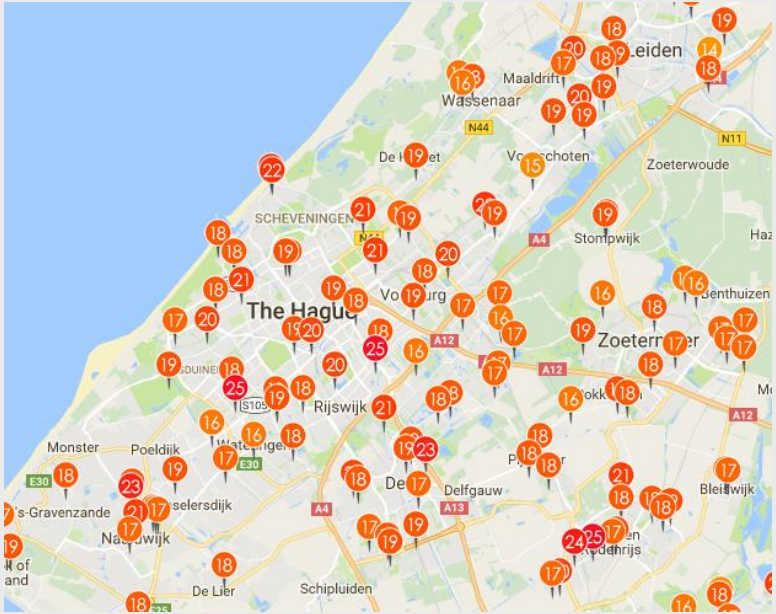
- The **aim** of this research is to estimate the air temperature for the entire area of interest dynamically, constructing a model
- The **scope** of this research is to bridge the gap between the ‘raw’ data and the qualitative research capabilities of planners and designers → enable them design more livable cities

The Municipality of The Hague



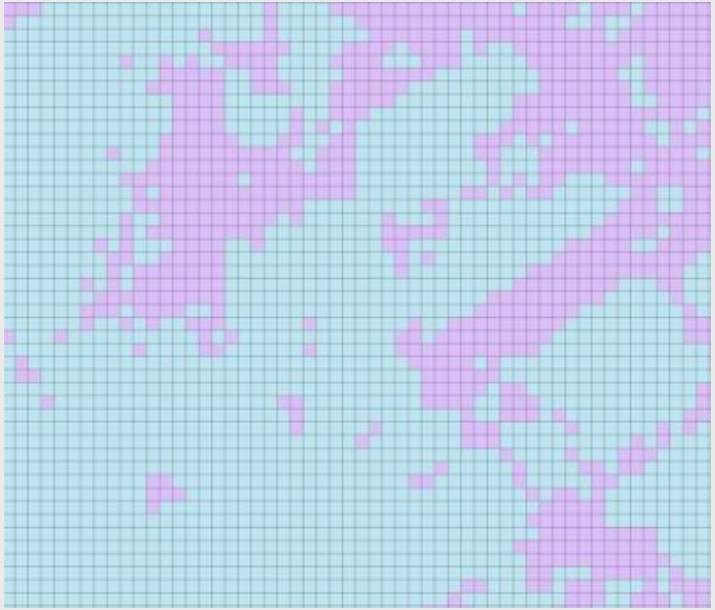
The Area of Interest

Netatmo weather station



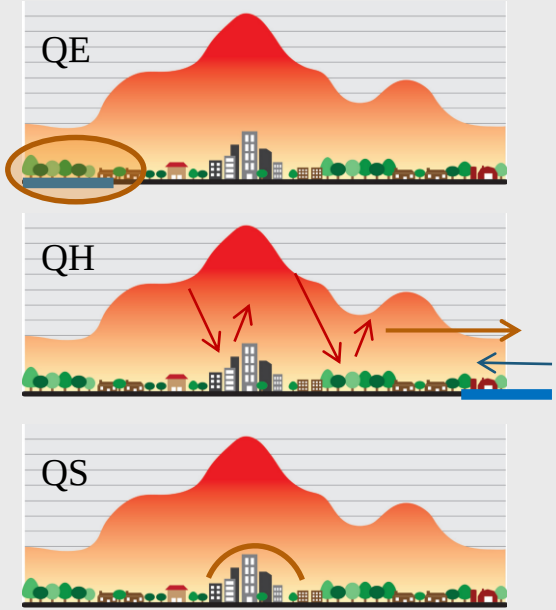
Netatmo weather map

- Define the **spatial unit**
  - CBS 100m*100m grid



CBS grid, 100*100 combined with a fishnet

- $Q^* = QE + QH + QS$



- Datasets derived:
  - Vegetation Index
  - Water Surfaces
  - Imperviousness
  - Albedo
  - Distance from the Coastline
  - Building Footprint
  - Height of the buildings
  - Building Volume
  - Sky View Factor

Organize all data into the grid

- A certain methodology was applied in ArcGIS
- Values for each spatial variable were assigned to all grid-cells
- Example: Footprints, Values: 0 -100
- Example: Coastline Proximity, Values: 0 – max. distance

Footprints

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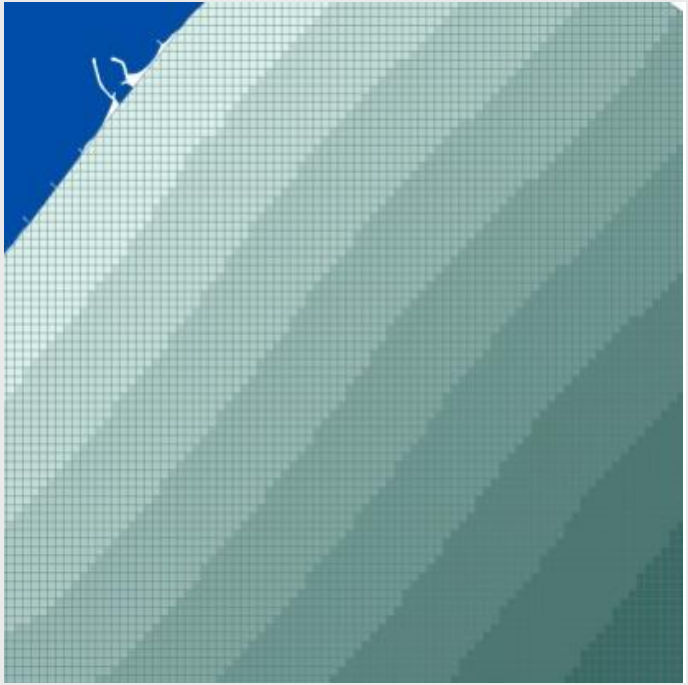
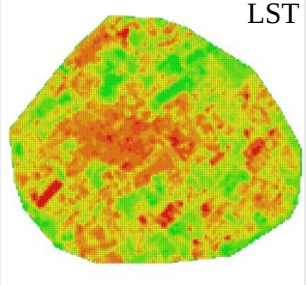
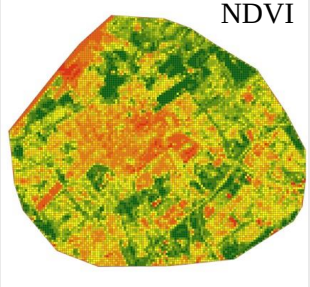
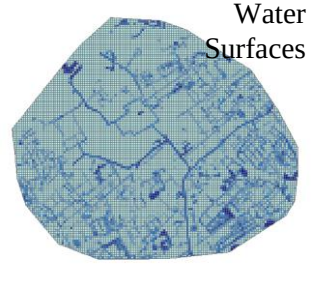
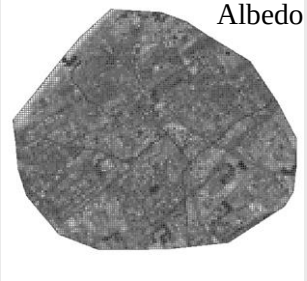


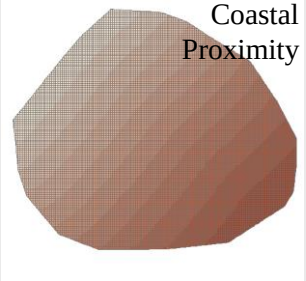
Coastline Proximity

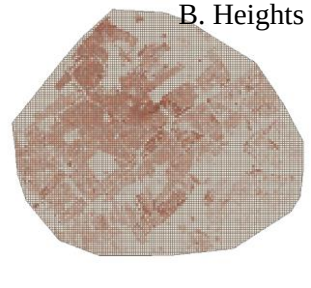

LST

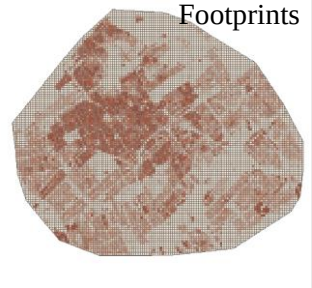

NDVI


Water Surfaces

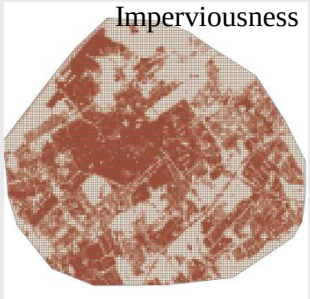

Albedo

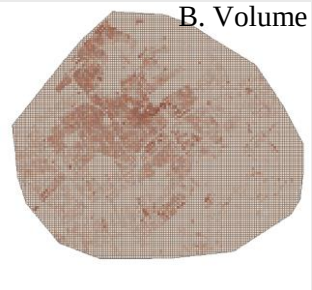

Coastal Proximity


B. Heights

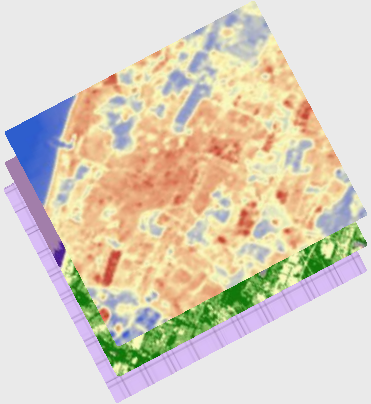

Footprints

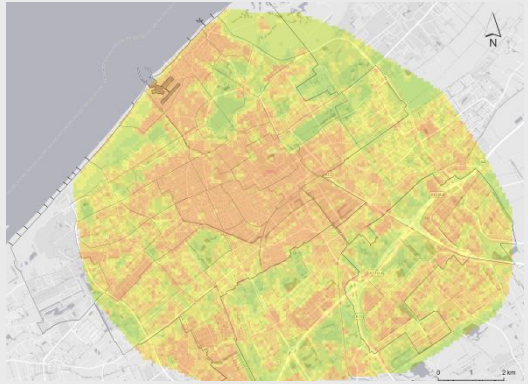

SVF


Imperviousness

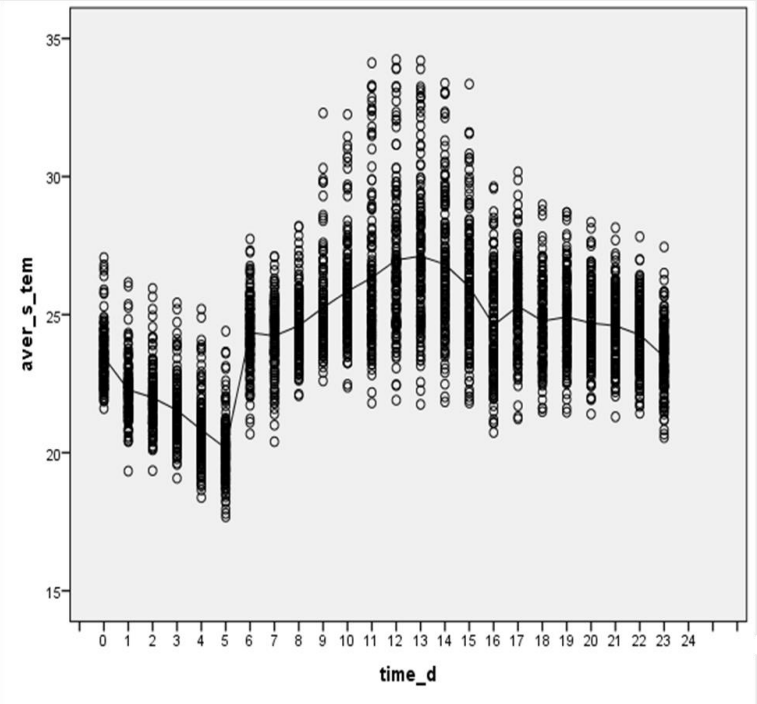

B. Volume


Leidschendam
Voorburg
Den Haag
Rijswijk
Wateringen





- The spatial variables have different behavior during day and night
- Air temperature, has smaller heat capacity → temperature changes quicker
- Day division based on the inflection points



Temperature-time graph

$$y_i = \beta_0 + \beta_1 * x_{i1} + \beta_2 * x_{i2} + \ldots + \beta_v * x_{iv}$$

$$y_{22-06} = 9.223 + 0.073 * [KNMI\_344] - 0.067 * [Albedo] + 0.0000827 * [Coastline\ Proximity] + 0.071 * [Footprint] - 0.003 * [SVF]$$

$$y_{05-13} = 7.302 + 0.072 * [KNMI\_344] - 0.006 * [NDVI] - 0.036 * [Albedo] + 0.004 * [Imperviousness]$$

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
Night	.639[a]	.408	.404	1.33161179238	.408	120.290	6	1048

a. Predictors: (Constant), SVF, KNMI_344, Coastline Proximity, Albedo, Footprint

b. Dependent Variable: aver_s_tem

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
05_13	.717[a]	.514	.513	1.87286233870	.514	271.503	4	1025

a. Predictors: (Constant), Imperviousness Copern, KNMI_344, Albedo, NDVI

b. Dependent Variable: aver_s_tem

$$y_{22-06} = 9.223 + 0.073 * [KNMI\_344] - 0.067 * [Albedo] + 0.0000827 * [Coastline\ Proximity] + 0.071 * [Footprint] - 0.003 * [SVF]$$

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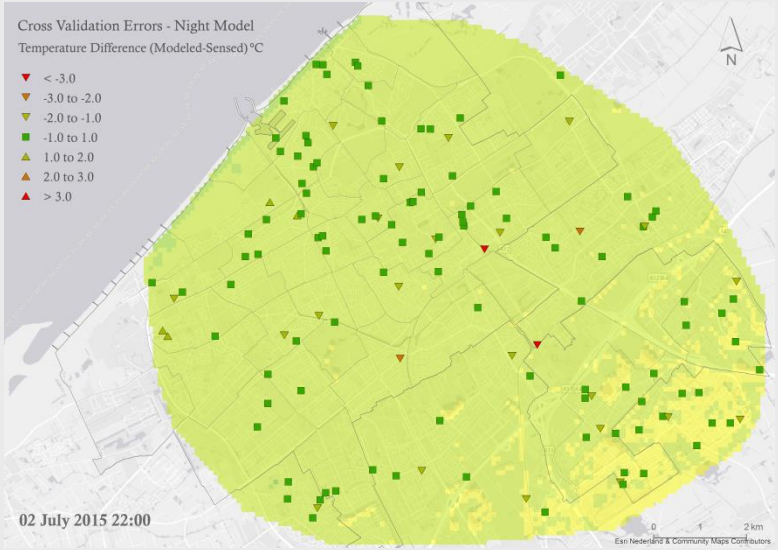

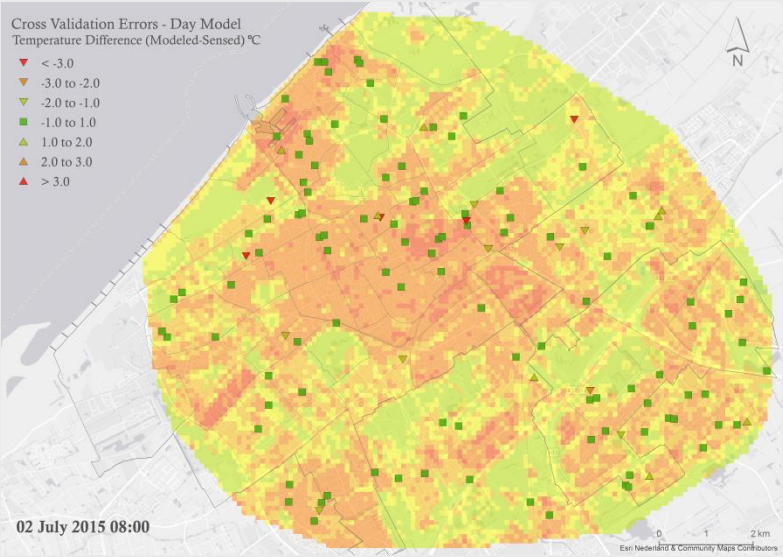

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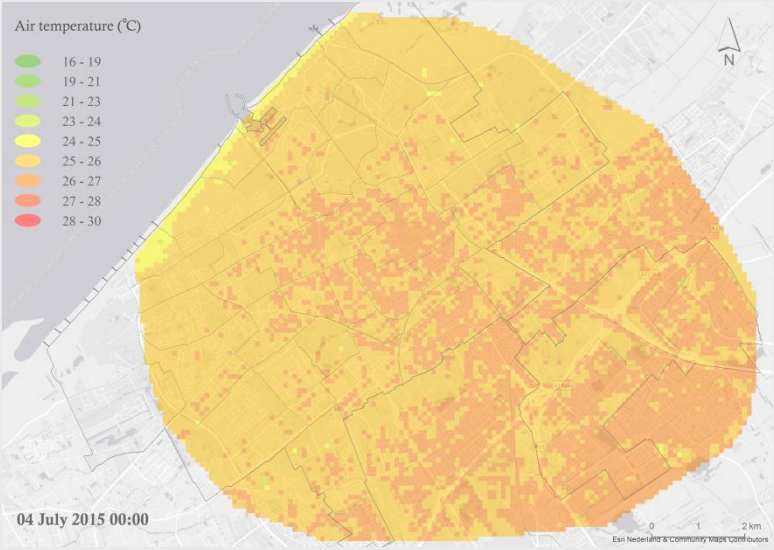
Cooling-down model (22:00 – 06:00)



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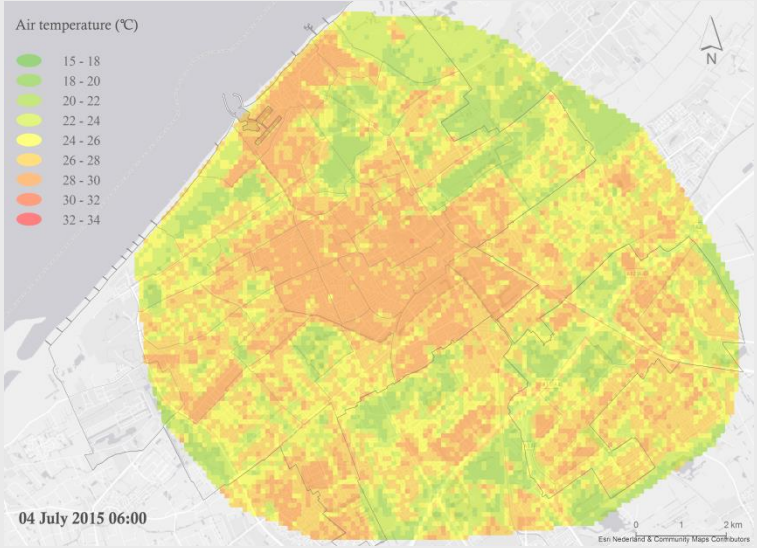
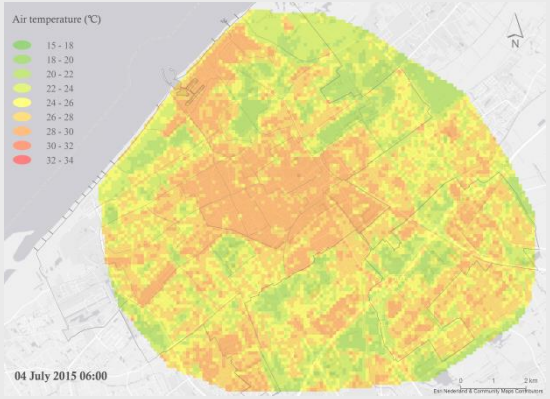
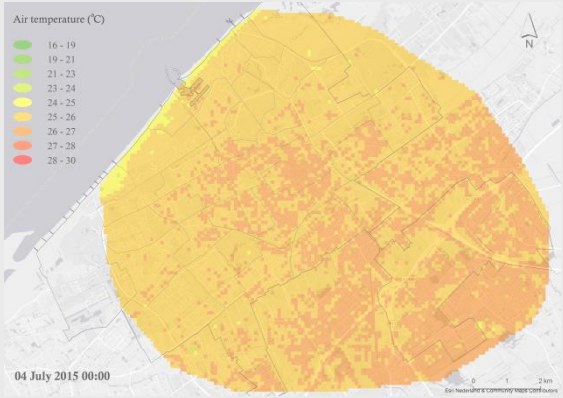
Heating-up model (06:00 – 13:00)



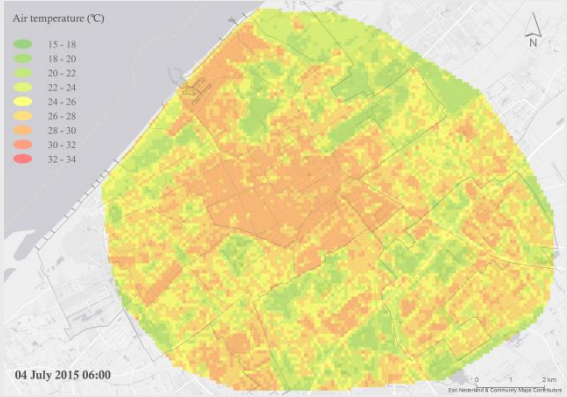
- Dynamic Visualization
  - Time is used as input data
  - Animated maps enable large data-series visualization
  - More perceivable
  - Easy pattern and trend detection

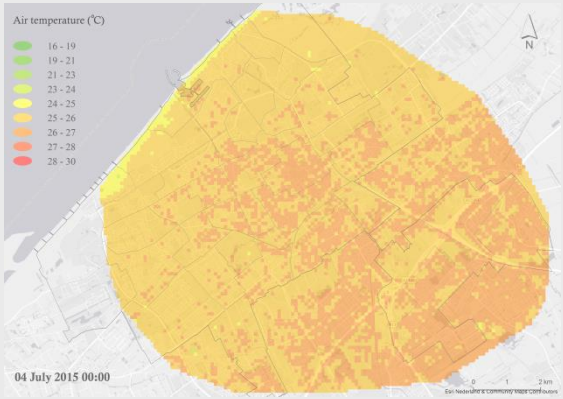
…If animated visualization was not utilized in this study, 80 different maps would have been presented instead of concise videos





- The day and night models are affected from different indicators
  - Both models follow the built-environment pattern
  - The nocturnal model is mostly affected by the Coastline Proximity
  - Thus, there are densely urbanized areas with low temperature by the sea





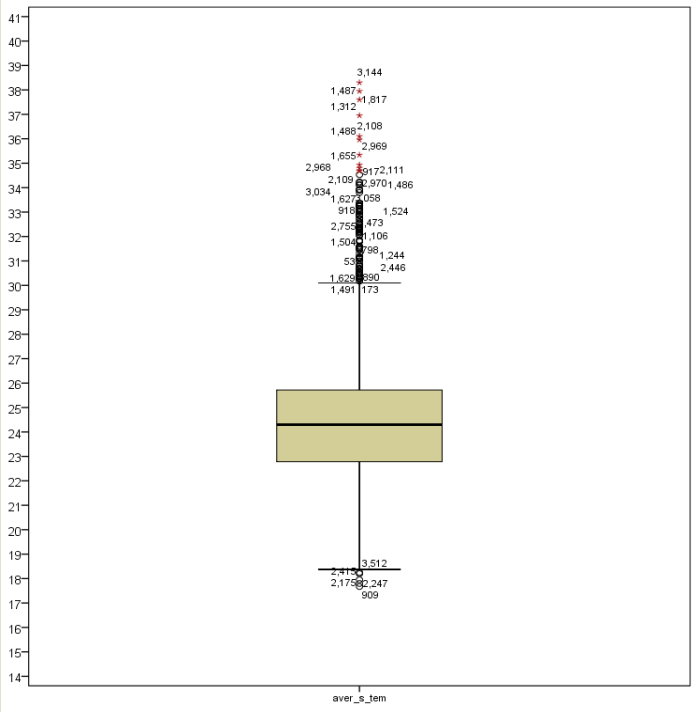
- Limitations
  - Uncertainty of the sensor data quality
  - Sensor orientation leads to different results
  - Biased sensor sample
  - T_a is highly affected by air movements and circulation
- Recommendations
  - Use more sensors
  - Acquire information about the sensor orientation
  - Model the air movements (CFD)

Sensor installation

- Adaption
  - Use lighter colors (increase albedo)
  - Use less impervious materials
  - Increase Vegetation
  - Street orientation (vertical to the coastline) to maximize the see breeze effect
  - Lower building coefficient close to sea.

… Thank you for the attention

… Questions



Box-plot

- The extreme outliers were excluded from the datasets
- The mild outliers were kept since they follow logical time development

- Test for normality
- Correlation analysis
- Multi-collinearity analysis
- Regression analysis

- Surface temperature and atmospheric temperature behave differently
  - T_s has strong and significant relation with most indicators
  - T_s is not related with the T_a
  - T_a, due to the small heat capacity and air movements, is more prone to temporal changes → greater day division is needed

Correlations

	Day		Night	
	aver_s_tem	LST	aver_s_tem	LST
aver_s_tem	1	.023	1	-.002
KNMI_344	.250**	-.002	.612**	-.001
KNMI_330	.025	-.005	.674**	-.003
LST	.023	1	-.002	1
NDVI	.001	-.635**	.007	-.619**
Albedo	-.021	.254**	-.088**	.244**
Water	-.007	-.318**	.036	-.326**
Coastline Proximity	.154**	-.103**	.166**	-.102**
Footprint	-.050*	.460**	-.071*	.452**
Buildings Height	-.108**	.171**	-.056*	.177**
Building Density	-.095**	.211**	-.054*	.214**
SVF	.063**	.173**	-.036	.168**
Imperviousness	.013	.701**	-.045	.692**

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

- **KNMI** weather stations are located in the rural area
- It is a valuable dataset to model UHI
- Provides hourly temperature updates which enable the dynamic representation

KNMI weather stations

- Datasets used:
  - Sensor data
  - Top10NL
  - AHN3
  - Imperviousness (Copernicus)
  - Satellite images
  - KNMI 330 and 344 temperatures
  - CBS grid

- Datasets derived:
  - Land Surface Temperature
  - Vegetation Index
  - Water Surfaces
  - Albedo
  - Distance from the Coastline
  - Building Footprint
  - Height of the buildings
  - Building Volume
  - Sky View Factor
  - Imperviousness

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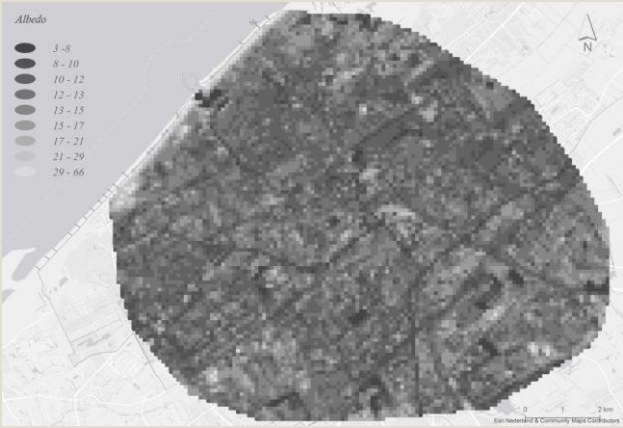

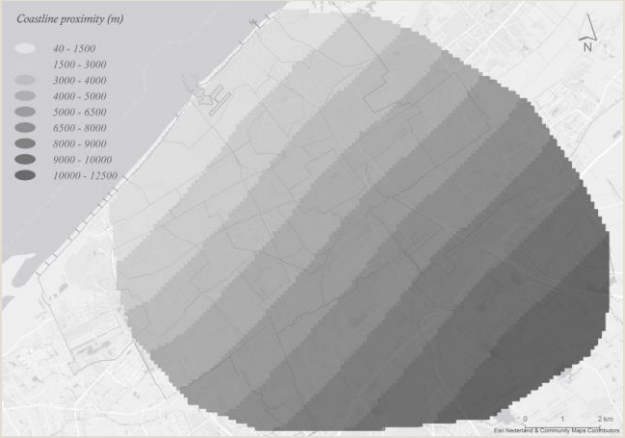

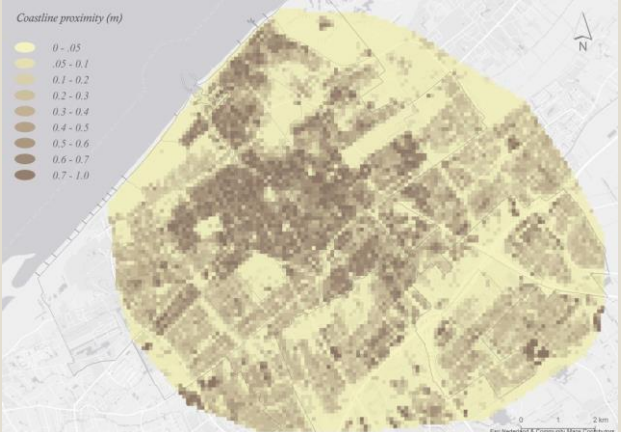

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