Modelling the Atmospheric Urban Heat Island and its Contributing Spatial Characteristics

The Case of The Hague, the Netherlands

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02/11/2016
Urban Heat Island (UHI) is a phenomenon in which a city forms microclimates which heat-up quicker than its rural surroundings.

\[ \Delta T(u-r) = T_u - T_r \]

(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 Area of Interest

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
Organize all data into the grid

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Spatial Analysis

- LST
- NDVI
- Water Surfaces
- Albedo
- Coastal Proximity
- B. Heights
- SVF
- Imperviousness
- B. Volume
- Footprints
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
\[ y_{i} = \beta_{0} + \beta_{1} \times x_{i1} + \beta_{2} \times x_{i2} + \ldots + \beta_{v} \times x_{iv} \]

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

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

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>R Square Change</th>
<th>F Change</th>
<th>df1</th>
<th>df2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Night</td>
<td>0.639</td>
<td>0.408</td>
<td>0.404</td>
<td>1.33161179238</td>
<td>0.408</td>
<td>120.290</td>
<td>6</td>
<td>1048</td>
</tr>
<tr>
<td>05_13</td>
<td>0.717</td>
<td>0.514</td>
<td>0.513</td>
<td>1.87286233870</td>
<td>0.514</td>
<td>271.503</td>
<td>4</td>
<td>1025</td>
</tr>
</tbody>
</table>

- a. Predictors: (Constant), SVF, KNMI_344, Coastline Proximity, Albedo, Footprint
- b. Dependent Variable: aver_s_tem
\[ Y_{\text{22-05}} = 9.223 + 0.073 \times [\text{KNMI \, 344}] - 0.067 \times [\text{Albedo}] + 0.0000827 \times [\text{Coastline Proximity}] + 0.071 \times [\text{Footprint}] - 0.003 \times [\text{SVF}] \]

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

Cooling-down model (22:00 – 06:00)
\[ Y_{06-13} = 7.302 + 0.072 \cdot [RNMI_{344}] - 0.006 \cdot [NDVI] - 0.036 \cdot [Albedo] + 0.004 \cdot [Imperviousness] \]

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)
### Conclusions

- **Adaption**
  - Use lighter colors (increase albedo)
  - Use less impervious materials
  - Increase vegetation
  - Street orientation (vertical to the coastline) to maximize the sea breeze effect
  - Lower building coefficient close to sea.
... Thank you for the attention
... Questions
- 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

<table>
<thead>
<tr>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day Night</td>
</tr>
<tr>
<td>aver_s_tem</td>
</tr>
<tr>
<td>aver_s_tem</td>
</tr>
<tr>
<td>KNMI_344</td>
</tr>
<tr>
<td>KNMI_330</td>
</tr>
<tr>
<td>LST</td>
</tr>
<tr>
<td>NDVI</td>
</tr>
<tr>
<td>Albedo</td>
</tr>
<tr>
<td>Water</td>
</tr>
<tr>
<td>Coastline Proximity</td>
</tr>
<tr>
<td>Footprint</td>
</tr>
<tr>
<td>Buildings Height</td>
</tr>
<tr>
<td>Building Density</td>
</tr>
<tr>
<td>SVF</td>
</tr>
<tr>
<td>Imperviousness</td>
</tr>
</tbody>
</table>

**. 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
\[ Y_{22-06} = 9.223 + 0.073 \times [KNMI\_344] - 0.067 \times [Albedo] + 0.0000827 \times [Coastline\ Proximity] + 0.071 \times [Footprint] - 0.003 \times [SVF] \]
\[ Y\text{NIR}_{13} = 7.302 + 0.072 \times [\text{RWMI}_344] - 0.006 \times [\text{NDVI}] - 0.036 \times [\text{Albedo}] + 0.004 \times [\text{Imperviousness}] \]