Integrated method for cities air temperature estimation

J. Bernard[1,2,3], M. Musy[1,2], I. Calmet[4], E. Bocher[5], P. Kéravec[4]

[1] Institut de Recherche en Sciences et Techniques de la Ville, FR CNRS 2488, France
[2] Centre de recherche méthodologique d'architecture, UMR CNRS 1563, France
[3] ADEME, France
[4] Laboratoire de recherche en Hydrodynamique, Énergétique et Environnement Atmosphérique, UMR CNRS 6598, France
[5] Laboratoire Lab-STICC – UMR CNRS 6285, Frahce

Corresponding author : Jérémy Bernard (jeremy.bernard@crenau.archi.fr)

Abstract :

Urban Heat Island (UHI) is defined as the air temperature difference between the city and its surrounding areas. This phenomenon varies spatially (depending on the type of urban fabric constituting each neighborhood) and temporally (depending on the time of the day, on the season and on the weather conditions). This contribution proposes a methodology to model the UHI spatially and temporally using simple models built with free and open sources softwares (orbisGIS and python language). Ten air temperature sensors have been implemented in several neighborhoods of the Nantes urban area (a west coast french conurbation). The difference of UHI is observed and modeled for each of those sites. Spatial differences are modeled according to geographical indicators characterizing the urban surroundings of each temperature station. Temporal variations are modeled according to weather conditions (such as wind speed, solar radiations, etc.) for different time scales : diurnal and nocturnal differences, daily variations and seasonal variations. The objective is to create a method which may be applied for any city in France. Geographical indicators are then calculated with OrbisGIS software from geographical data which are homogeneous and available at the french territory scale. Wheather conditions are recorded by MeteoFrance stations, which follow the same standard for the measurement of climatic parameters all around France. Climatic data analysis and modeling are performed with Python language using libraries such as Pandas and StatsModels. Modeled established according to the Nantes temperature dataset are verificated according to new air temperature networks implemented in the city of Nantes as well as other cities of west France (Angers, La Roche-sur-Yon).

Introduction :

Urban Heat Island (UHI) is defined as the air temperature difference between the city and its surrounding areas. Combined with global warming, this phenomenon may be a source of vulnerability for future cities. In order to diagnose existing urban temperature differences, energy balance simulation tools are often used. This formal approach is complex and makes the relations between urban fabric and climate difficult to identify. In order to make the relationship easier to interpret, empirical modeling can be used (McKendry, 2003). Two main problems are related to such modeling methods : the UHI is modeled either spatially, either temporally but never both at once. Geographical databases used for modeling are rarely homogenous at country scale. Thereby, models developed can not be extrapolated to other cities. The objective of this study is to propose a

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.2240v1 | CC BY 4.0 Open Access | rec: 5 Jul 2016, publ: 5 Jul 2016

methodology to overcome those problems.

Study area :

Ten air temperature sensors have been implemented in several neighborhoods of the Nantes urban area (a west coast french conurbation of about 600 000 inhabitants and 500 kms²). This network recorded temperature measurement during four years, used for model calibration purpose.

Methodology :

The study is composed by a calibration phase and a verification phase :

a) <u>Calibration</u>

The whole calibration methodology is based on the following steps and illustrated figure 1 :

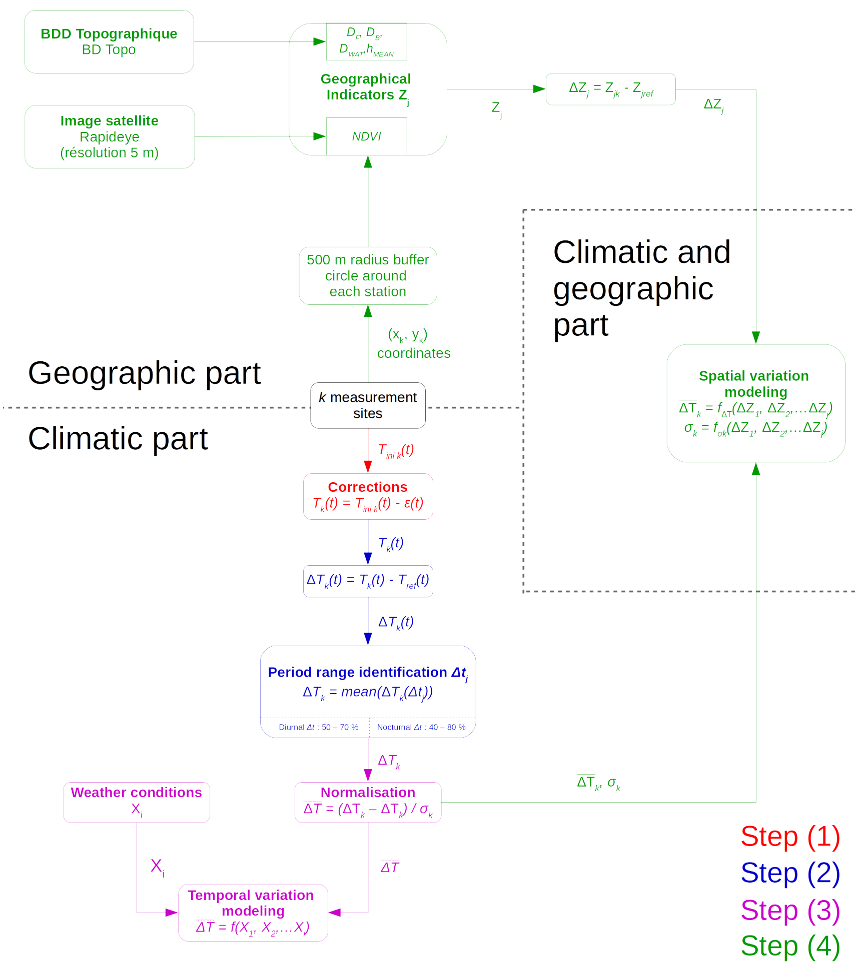

Figure 1: Scheme of the different steps used in the global methodology

(1) the equipment used to measure air temperature may lead to bias, due to their lack of ventilation or their sensibility to solar radiation. In order to correct this bias, the equipment is compared to reference equipment under different solar radiations (*K*) and wind speed (*U*) conditions. The error ε is modeled according to weather conditions ($\varepsilon = f(K, U)$) in order to correct datasets.

(2) the dispersion of the temperature measured between stations is maximum at certain times of the day. The UHI is calculated for each station k at those time range Δt_j :

$$\Delta T_k(\Delta t_j) = T_k(\Delta t_j) - T_{ref}(\Delta t_j)$$

with ΔT_k the temperature difference between the station *k* and a station taken as reference *ref* averaged during the period Δt_j.

(3) the indicator ΔT_{kj}, when it is normalized ($\widetilde{\Delta T_{kj}}$) by its mean value ($\overline{\Delta T_{kj}}$) and standard deviation

($\sigma_{\Delta Tj}$), reacts similarly to weather conditions for any station *k* and for any time period *j*. A model to explain the variations of $\widetilde{\Delta T}_{kj}$ is calibrated using weather conditions as the explicative variables.

$$\widetilde{\Delta T}_{kj} = (\Delta T_{kj} - \overline{\Delta T}_{kj}) / \sigma_{\Delta Tj} = f_j(X_{1j}, X_{2j},..., X_{ij})$$

where X_{ij} are the value taken by explicative variables *j* such as solar radiation, wind speed and air temperature averaged during T_j

(4) Main interactions between geographical objects and climate are identified according to literature. Geographical indicators which highlights the best those interactions are used to model spatial differences observed between air temperature stations :

- facade density (D_F) water density (D_{WAT}), building density (D_B), mean building height (h_{MEAN}) are calculated in a buffer circle of 500 meters around each station from the topographic database of the french National Institute of Geography (IGN) : they are calculated from basic parameters described figure 2. Most of them are representative of solar trapping and energy storage;

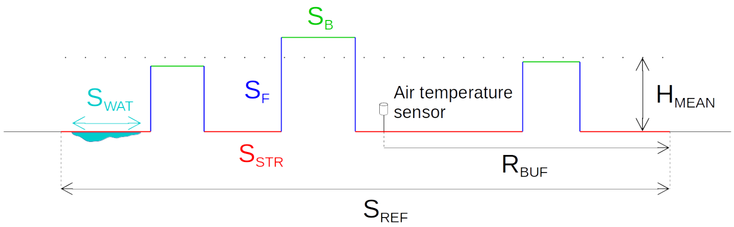

Figure 2: Basic geographical variables calculated from BD Topo

- Normalised Difference Vegetation Index is calculated in a buffer circle of 500 meters around each station from a satellite image (RAPIDEYE – 5 m resolution) (see figure 3). This indicator is used to estimate the amount of vegetation present in each pixel. The vegetation density is representative of the potential of cooling by evaporation.

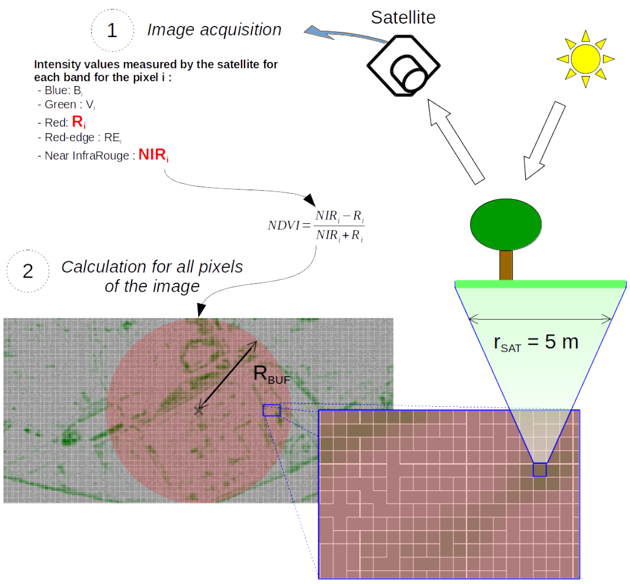

Figure 3: NDVI calculation method from a RAPIDEYE satellite image

- Distance from the city peripheral. Buildings are one of the main characteristic of the city which make the energy balance differs from rural to urban areas. Balazs et al. (2009) showed empirically that a close relation exists between UHI and the logarithm of the distance to city peripheral. The urban peripheral is calculated according to a fractal method using building footprint as input and the free software Morpholim (Tannier et al, 2011).

Both $\overline{\Delta T}_j$ and $\sigma_{\Delta Tj}$ used to normalize ΔT_j are estimated for all stations k from a linear combination of geographical indicators. Similarly to the temperature indicator, geographical indicators Z_l are calculated from the value taken by the reference site $(\Delta Z_{lk} = \Delta Z_{lk} - Z_{lref})$ for all stations k.

$\Delta T_l = f(\Delta Z_1, \Delta Z_2, \ldots \Delta Z_l)$

b) <u>Verification</u>

For verification purpose, new air temperature measurements are acquired in some other parts of Nantes and for several neighborhood of two other cities located in west France. Models established in previous steps are used to estimate the temperature that should be measured by those new stations. Estimations and observations are confronted to verify model performances. A root mean square error indicator ($RMSE_{norm}$) is proposed to consider whether or not the performances are satisfactory (true if $RMSE_{norm} < 1$) for each time range Δt_j of the day :

$$RMSE_{norm} = \frac{\sqrt{\sum_k \sum_i (\Delta T_{ki_{obs}} - \Delta T_{ki_{est}})^2}}{\sqrt{\sum_k \sum_i (\Delta T_{ki_{obs}} - \Delta T_{refi_{obs}})^2}}$$

where k the stations and i the day of the year

Results

From our dataset, two main periods of the day are identified as important regarding urban climate (step (1)) : the beginning of the afternoon (from 50% to 70% of the diurnal period) and the middle of the night (from 40% to 80% of the night period). Wind speed and solar radiation are the major variables explaining the temporal variation of the UHI along the days. NDVI is the major variable which explains the temperature heterogeneity in a city. Estimations for Nantes, La Roche-sur-Yon and Angers give always RMSE lower than one for nocturnal indicator and always higher than zero for diurnal indicator. Figure 4 is an example of results of the regression. Estimation performances is not equal for all stations. Closer a station is from the reference stations in terms of geographical context, harder it is to estimate its temperature.

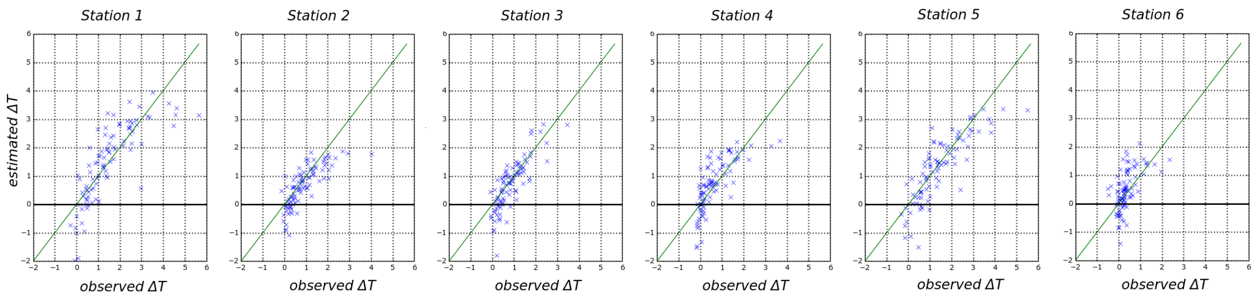

Figure 4: Example of results for the verification dataset of Angers (6 stations + a reference station) : estimated values against observed values for each station

Conclusions

According to the indicator calculated in step (4), performances are always satisfactory ($RMSE_{norm} < 1$) for the nocturnal indicator model and never satisfactory for the diurnal. This is understandable since the diurnal temperature differences are really low, thereby make the variance of the uncertainty high compared with the total variance. The nocturnal values, which are of the most importance and give good results for all cities, make the whole methodology reproducible for any city of France, unless major geographical components such as big mountains or oceans are found to be near the city. In this case, local climate should be studied and the methodology may be applied using new sensors to recalibrate models.

References

Balázs, B., Unger, J., Gál, T., Sümeghy, Z., Geiger, J., & Szegedi, S. (2009). Simulation of the mean urban heat island using 2D surface parameters: empirical modelling, verification and extension. *Meteorological Applications*, *16*(3), 275-287.

McKendry, I. G. (2003). Applied climatology. *Progress in Physical Geography*, *27*(4), 597-606.

Tannier, C., Thomas, I., Vuidel, G., & Frankhauser, P. (2011). A Fractal Approach to Identifying Urban Boundaries. 城市边界识别的分形方法. *Geographical Analysis*, *43*(2), 211-227.