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# Nocturnal cooling in Local Climate Zone: statistical approach using mobile measurements

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## Abstract

Up-to-date climate scenarios warn that the frequency and intensity of heat waves are likely to increase in Europe during the twenty first century. In these circumstances, urban climate is progressively taken into account in urban planning processes, for instance using terrain classifications. The developed methodology involves the Local Climate Zone scheme (LCZ), which has been applied to Nancy, France. Mobile measurements campaigns have been performed using an instrumented vehicle in order to record daily air temperature dynamics, with a focus on the daily cooling period. So as to quantify LCZ cooling before and after sunset over several days, a climatic indicator called Normalized Cooling Rate (NCR) has been used. This study presents statistical regressions that have been performed between normalized cooling rate values calculated from field measurements and urban indicators. Results indicate that normalized cooling rates and most of the studied urban features are correlated. Regression model using sky view factor and distance

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to the city center seems enough accurate to estimate nocturnal cooling at the district scale.

*Key words:* Urban Heat Island, Air temperature, Mobile measurements, Nocturnal cooling, Local Climate Zone, Urban indicators, Regression analysis

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## 1. Introduction

Urban Heat Island, that could be described as the increased air temperature in the city centers canopies compared to their surrounding rural spaces, has been recognized since the 1970s (Oke, 1973) and is now a well studied anthropic climatic phenomenon (Arnfield, 2003) (Gartland, 2008). Indeed, it has been identified as a major concern for public policies to mitigate it or to build up adaptation strategies facing it (Rizwan et al., 2008), for now and for the next decades when heat waves would be more frequent. UHI need to be more documented and understood by stakeholders and planners to better integrate it in their projects and applications, especially at the district scale (Grimmond et al., 2010) (Baklanov et al., 2018).

The UHI magnitude is both influenced by regional climatic and geographical parameters and instant meteorological data - that can be qualified as uncontrollable variables - and by city morphology, materials, land use and anthropogenic sources - that can be qualified as controllable variables (Rizwan et al., 2008).

In order to perform accurate city climate diagnosis, modelling approaches are improving continuously (Mirzaei, 2015). Surface Energy Balance in meteorological meso-scale models is the more relevant technique to deal with

20 physical processes both from the district to the city scale (Grimmond et al.,  
21 2010) (Grimmond et al., 2011). But, these kind of model require at least  
22 a high level of expertise held by researchers or technical engineers with a  
23 strong background in climatology, or even, depending on the accuracy of  
24 model parametrisation, well-supplied urban databases.

25 To take into account climate processes in a first approach, many empiri-  
26 cal and statistical modelling of UHI have been investigated. Firstly Oke  
27 proposed a method to link UHI maximum intensity with population and  
28 incident wind, and due to the impact of city morphology, improve it by a  
29 function of aspect ratio parameter (Oke, 1987). This approach has been  
30 pursued by several studies involving sky view factor (Unger, 2004) (Svens-  
31 son, 2004), a combination of urban indicators (Balázs et al., 2009) or hybrid  
32 method between meteorological data and urban indicators (Bernard et al.,  
33 2017).

34 Other researches tend to discriminate urban features using terrain clas-  
35 sification such as the Urban Climate Zone (Oke, 2006) and more recently  
36 the Local Climate Zone (LCZ) scheme (Stewart and Oke, 2012) to describe  
37 inner urban climate. Measurements campaigns have highlighted that LCZ  
38 demonstrate a homogeneous thermal behavior (Leconte et al., 2015) (Stewart  
39 et al., 2013).

40 Decision makers are looking for models involving urban indicators that  
41 provide quantitative information about thermal behavior of districts. This  
42 work aims to develop correlations between LCZ indicators and UHI climatic  
43 descriptors. This paper addresses specifically the methodology of statistical  
44 analysis and the limits associated to the consistency of LCZ indicators.

## 45 **2. Materials and methods**

### 46 *2.1. Mobile measurements within Local Climate Zone*

#### 47 *2.1.1. Climate classification in Nancy*

48 The conurbation of Nancy is located North East of France and numbers  
49 286,000 inhabitants. It has an area of approximately 270 km<sup>2</sup> and its ele-  
50 vation ranges between 190 meters and 420 meters. Regarding its geographic  
51 features, Nancy is surrounded by two plateaus located West and North East  
52 of the conurbation, and crossed by two water bodies from South East to  
53 North. The Great Nancy Area is located in the center of the Lorraine re-  
54 gion, which exhibits an temperate climate without dry season (Class Cfb  
55 according to the Köppen-Geiger classification (Peel et al., 2007)).

56 The Local Climate Zones (LCZ) classification has been applied for the  
57 area of interest. The determination of LCZ is organized following a three-  
58 steps method. The contours of the LCZ have been determined based on  
59 land use and building height information as well as global knowledge of the  
60 experimental field. Over the conurbation of Nancy, 82 urbanized LCZ have  
61 been identified.

#### 62 *2.1.2. LCZ selection for the field experiment*

63 Thirteen LCZ of similar elevation have been selected, representing five  
64 different LCZ types. Within these areas, seven urban indicators have been  
65 calculated, namely sky view factor, aspect ratio, mean building height, ter-  
66 rain roughness class, building surface fraction, impervious surface fraction  
67 and pervious surface fraction. Contours have been corrected and a LCZ type  
68 has been assigned to each of these thirteen LCZ regarding urban indicators

69 values (Table 1). Residential areas of Nancy presents urban features at the  
70 edge between two LCZ types, namely "Open Lowrise" and "Sparsely Built".  
71 It appears that urban indicators calculations did not allow to choose between  
72 these two LCZ types, therefore three residential areas have been classified as  
73 dual type "Open Lowrise / Sparsely Built".

### 74 *2.1.3. Field survey with instrumented vehicle*

75 On the basis of this LCZ map, screen-height air temperature has been  
76 recorded within these thirteen LCZ during summer 2013 and 2015 (Figure  
77 1). Mobile measurements have been performed using an instrumented vehicle  
78 that records air temperature every three meters. A PT100 probe has been  
79 placed within a ventilated cylinder, which has been mounted on the roof of  
80 the car. This probe has an elevation of two meters above the ground, and  
81 an accuracy of 0.2 °C. Data corresponding to very low speed measurements  
82 may be influenced by heat release from other vehicles, therefore measures  
83 carrier out below 15 km.h<sup>-1</sup> are dismissed. Since the itinerary is mostly  
84 urban, the maximum vehicle speed is around 60 km.h<sup>-1</sup>. A sensitivity test  
85 has been performed in order to study the impact of vehicle speed on air  
86 temperature. Results demonstrate that mean air temperature values are  
87 marginally impacted by vehicle speed.

88 The chosen meteorological conditions are low wind speed (below 9 m.s<sup>-1</sup>,  
89 wind speed at 10 m high), clear sky (from 0 to 2 octas), anticyclonic condi-  
90 tions, dry road and absence of precipitation during the previous twenty-four  
91 hours. Regarding these requirements, seven measurements days have been  
92 selected. Two measurements hours have been set, which correspond approx-  
93 imately to the beginning of the cooling phase (5 PM local time) and to the

94 expected urban heat island amplitude maximum (three to five hours after  
95 sunset, 0 PM local time) (Oke, 1987). A measurement takes approximately  
96 two hours and thirty minutes, and during this time the regional temperature  
97 can decrease up to 2 °C at night. A linear time-correction scheme has been  
98 applied in order to balance the temperature evolution between the beginning  
99 and the end of the measure session. The scheme consists in correcting the  
100 measured air temperature proportionally to the elapsed time between the  
101 beginning of the session and the measurement.

## 102 *2.2. Nocturnal cooling indicator at district scale*

103 This study focuses on the air temperature behavior at the individual Local  
104 Climate Zones unit, which means that spatially averaged air temperature  
105 is considered. The spatial homogeneity inside LCZ has been analyzed in  
106 previous study (Leconte et al., 2015). The daily air temperature cycle is  
107 specially investigated. The air temperature difference between two Local  
108 Climate Zones is often used to characterize their thermal pattern. However,  
109 temperature difference only provides information at a given time of the day.  
110 In order to analyse the evolution throughout the time, heating rates or cooling  
111 rates can be implemented. These rates are calculated as the derivative of air  
112 temperature by the time.

113 Heating and cooling rates can be considered as urban climatic indica-  
114 tors to examine the urban heat island phenomenon. For city located in the  
115 same climate than Nancy, the urban heat island amplitude is generally weak  
116 during daytime and strong during nighttime. This phenomenon starts to  
117 develop before sunset and reach a maximum at night. Therefore, the cooling  
118 period is the relevant period to study the urban heat island. For low cloud

119 cover and low wind speed, Holmer has observed that the cooling of neigh-  
 120 borhoods is divided into two different phases (Holmer et al., 2007). During  
 121 a first phase, urban areas show different cooling dynamics while during the  
 122 second phase, the air temperature dynamics tend to be uniform between ur-  
 123 ban zones. The first phase coincides with a time period between one to two  
 124 hours before sunset and three to five hours after sunset (P1 on Figure 2),  
 125 while the second phase covers a period between three to five hours after sun-  
 126 set to sunrise (P2 on Figure 2). This two-phases cooling has been observed  
 127 for several locations, namely in Singapore (Chow and Roth, 2006), Adelaide,  
 128 Australia (Erell and Williamson, 2007), Athens, Greece (Giannopoulou et al.,  
 129 2010), Ouagadougou, Burkina Faso (Holmer et al., 2013), Novi Sad, Serbia  
 130 (Milosevic et al., 2019), and Nancy, France (Leconte et al., 2017). These  
 131 previous results highlight that the amplitude of the urban heat island rises  
 132 during phase 1 and remains stable during phase 2. Neighborhoods demon-  
 133 strate different cooling rates during phase 1 and similar cooling rates during  
 134 phase 2. In order to explicit the thermal behavior of Local Climate Zones  
 135 during the development of the urban heat island, cooling rates during phase  
 136 1 are examined. The cooling rate are calculated between the daytime mea-  
 137 sure (character D on Figure 2) and the nighttime measures (character N on  
 138 Figure 2). They are defined as :

$$\chi_{DN} = \frac{\Delta T_{air,DN}}{\Delta t_{DN}} \quad (1)$$

139 With  $\Delta t_{DN}$  the elapsed time between the two measures and  $\Delta T_{air,DN}$  the air  
 140 temperature decrease between the two measures for a given LCZ.

141 The diurnal temperature range (DTR) is expressed as the temperature  
 142 difference between daily maximum and daily minimum temperature. It ap-



143 pears that cooling rates are not identical from one day to another due to  
 144 diurnal temperature range variation. Thus, cooling rates during phase 1  
 145 have been normalized in order to be able to compare them when several days  
 146 show dissimilar DTR values. When several Local Climate Zones are studied,  
 147 the cooling rates are divided by the temperature drop observed in the coolest  
 148 Local Climate Zone during phase 1 ( $\Delta T_{air,DN,max}$ ). In this way, all cooling  
 149 rates – named normalized cooling rates (NCR) – are expressed relatively to  
 150 an identified reference, namely the coolest studied area :

$$NCR = \frac{\chi_{DN}}{\Delta T_{air,DN,max}} \quad (2)$$

### 151 2.3. Statistical approach

152 In order to question the existence of a linear relationship between normal-  
 153 ized cooling rate and urban indicators (UI), a regression analysis (ordinary  
 154 least squares method) has been carried out. The regression model is evalu-  
 155 ated by using both the regression coefficient to estimate the linearity and the  
 156 Breusch-Pagan test to check if the variance around the regression line is the  
 157 same for all values of the predictor (homoscedasticity) (Breusch and Pagan,  
 158 1979).

159 Nine urban indicators have been selected. Seven of them belong to the  
 160 LCZ scheme, namely sky view factor (SVF), aspect ratio (AR), mean build-  
 161 ing height (H), terrain roughness class (R), building surface fraction (Built),  
 162 impervious surface fraction (Imper), pervious surface fraction (Per). In ad-  
 163 dition, the distance to the center of the conurbation (Pos) and the elevation  
 164 (Elev) have also been examined, as they may impact the thermal behavior  
 165 of the districts. The statistical results have been evaluated according three  
 166 criteria:

- 167 • The regression coefficient of the linear regression between NCR and one  
 168 (or more) urban indicator is used to evaluate the regression quality. A  
 169 correlation coefficient close to one corresponds to an accurate regression  
 170 model.
- 171 • Akaike Information Criteria (AIC) is applied on regression equations  
 172 in order to compare them. This criterion is defined as equation (3).  
 173 (Akaike, 1981) (Akaike, 1998)

$$\text{AIC} = 2K - 2 \log(\ell(\hat{\theta}|y)) \quad (3)$$

174 Where  $K$  is the number of parameters to be estimated and  $\log(\ell(\hat{\theta}|y))$   
 175 is the log likelihood at its maximum likelihood estimator  $\hat{\theta}$  based on  $y$   
 176 observations. The most effective model is the model with the lowest  
 177 AIC score. This approach has been used in previous studies for statis-  
 178 tical model selection, including in the geosciences field (Gopalan et al.,  
 179 2018) (Bernard et al., 2017).

- 180 • Student's t-test has been performed for each UI's coefficient of the lin-  
 181 ear regression in order to evaluate their contribution. The significance  
 182 threshold chosen for the P-value is 0.05.

183 Regression calculations have been completed over a sample representing  
 184 75% of the normalized cooling rate values which has been chosen randomly.  
 185 The remaining values (25% of the experimental data set) have been used to  
 186 examine the quality of the regression equation. Thus, NCR estimations from  
 187 empirical models are compared with independent NCR observations. The  
 188 goodness of fit is estimated with the Chi-Square statistic (eq 4). As depicted

189 in this equation, the Chi-Square statistic ( $\chi^2$ ) is based on the difference be-  
190 tween the NCR observed during field measurements and the NCR estimated  
191 using the statistical models.

$$\chi^2 = \sum \frac{(NCR_{Obs.} - NCR_{Est.})^2}{NCR_{Est.}} \quad (4)$$

192 The lower the Chi-Square value, the better the NCR estimated value.

### 193 **3. Results and discussion**

#### 194 *3.1. Single urban indicator approach*

195 Regressions have been performed between NCR and each of the nine  
196 studied urban indicator  $UI_i$  ( $i \in \llbracket 1, 9 \rrbracket$ ), according to equation (5).

$$NCR = \beta_0 + UI_i \cdot \beta_1 \quad (5)$$

197 The constants  $\beta_0$  and  $\beta_1$  are the intercept and the slope of the linear regression  
198 respectively.

199 The relationship between NCR and urban indicators have been investi-  
200 gated based on 75% of the 90 experimental data set which has been chosen  
201 randomly. Initial dataset included measurements performed during seven  
202 days within thirteen LCZ (91 NCR values). One NCR value has been re-  
203 moved from the dataset due to experimental dysfunction. In order to as-  
204 sess the accuracy of this approach, the impact of the sample selection on  
205 regression results have been analysed. Multiple samples have been chosen  
206 randomly and then used to perform regression between NCR and urban in-  
207 dicators. The number of random samples is twice larger than the amount of  
208 field observations.

209 Figure 3 highlights that terrain roughness class, sky view factor, mean  
210 building height and the distance to the center of the conurbation achieve the  
211 lowest AIC values. The box plots for each urban indicator tend to be similar  
212 in terms of interquartile range and distance between extremum values.

213 Overall, it seems that indicators related to the urban morphology perform  
214 better than land use indicators. Indeed, urban morphology indicators are  
215 ranked in 1<sup>st</sup>, 2<sup>nd</sup>, 4<sup>th</sup> and 7<sup>th</sup> positions in terms of AIC values, while land  
216 use indicators are ranked in 5<sup>th</sup>, 6<sup>th</sup> and 8<sup>th</sup> positions.

217 After this step, one of the 180 random samples is selected, a regression  
218 is performed and it confirms the results of Figure 3 in terms of ranking.  
219 Table 2 summarizes the values of  $\beta_0$  and  $\beta_1$  coefficients as well as P-values,  
220 AIC and  $R^2$  for one random sample. Thus, this sample will be used for  
221 following analysis. Results show that all Breusch-Pagan values are positives,  
222 which demonstrate the homoscedasticity of the data. All coefficients pass  
223 the Student's t-test, except in the case of the elevation. Based on AIC and  
224  $R^2$  values, the terrain roughness class is the indicator that leads to the best  
225 correlation with normalized cooling rate values (AIC =  $-362.4$ ,  $R^2 = 0.48$ ),  
226 followed by the sky view factor (AIC =  $-359.2$ ,  $R^2 = 0.45$ ) and the distance  
227 to the center of the conurbation (AIC =  $-358.1$ ,  $R^2 = 0.45$ ). The model that  
228 achieves the best results is presented in equation (6).

$$\text{NCR} = 0.17 \cdot \text{R} - 0.001 \quad (6)$$

229 Scatter plots of experimental data including regression lines are presented  
230 (Figure 4). Each graph presents NCR values, in relation to urban indicators  
231 calculated within the each of the thirteen identified LCZ, for seven days of  
232 measurements. First, a significant dispersion of NCR values can be noticed

233 for each of the urban indicators, between 0.04 and 0.06 h<sup>-1</sup>. Nonetheless, all  
234 the scattered charts show trends of monotonic increase or decrease, except  
235 for the elevation indicator ( $R^2 = 0.09$ ) mostly because the measurement  
236 surveys have been carried out at almost constant elevation. This allows us to  
237 elaborate basic conclusions confirming previous studies which express local  
238 intensity of heat island as a linear function of the SVF (Svensson, 2004). The  
239 graphs show patterns of vertical alignments of dots corresponding to the seven  
240 days of measurements in each of thirteen LCZ. For several indicators such as  
241 AR, SVF or Imper, clusters can be perceived because same LCZ typologies  
242 lead to very close indicator values (cf. Table 1). This is even more obvious  
243 for R that shows only four distinct values of terrain roughness class. Indeed,  
244 R is calculated using the Davenport classification (Davenport et al., 2000),  
245 which implies that R values are integers (cf. Table 1). The thirteen studied  
246 LCZ in Nancy belong to only four roughness class. On the other hand, for the  
247 position indicator, a slightly more homogeneous horizontal distribution can  
248 be observed, except for the two LCZ D (Low plants) located at the outskirts  
249 of the city.

250 In order to evaluate the regression equation related to the urban indica-  
251 tors, NCR computed from statistical regressions has been confronted with  
252 NCR obtained from the measurement validation data set (Figure 5).  $\chi^2$  val-  
253 ues are also calculated. The lower the  $\chi^2$  value, the closer the points from  
254 the first bisector. For the nine models,  $\chi^2$  values range from 0.02 to 0.065.  
255 The best results are obtained for the Sky View Factor (0.02), the distance to  
256 the center (0.02), the mean building height (0.022) and the terrain roughness  
257 class (0.022). Results presented in Figure 5 are consistent with AIC and  $R^2$

258 values. Indeed, urban indicators with the lowest AIC values and the highest  
259  $R^2$  show the lowest  $\chi^2$  values. The elevation of all the studied LCZ is quite  
260 similar. Since the NCR varies depending on the LCZ, the regression between  
261 NCR and Elev leads to poor results. Thus, the parameter Elev will not be  
262 taken into account for the following section.

263 Finally, the single urban indicator approach allows to identify urban in-  
264 dicators that explain best the NCR variations. However, nocturnal cooling  
265 of LCZ is led by multiple factors. Therefore, a multiple urban indicators  
266 approach have to be investigated in order to propose a more comprehensive  
267 model.

### 268 *3.2. Multiple urban indicators approach*

269 Multiple linear regression are investigated between NCR and several ur-  
270 ban indicators (Eq. (7)).

$$\text{NCR} = \beta_0 + \sum_{p=1}^{p=n} UI_p \cdot \beta_p \quad (7)$$

271 A collinearity analysis of the urban indicators is carried out. A strong  
272 level of collinearity between independent variables can lower the performance  
273 of the statistical model. Correlation matrix between the eight urban indica-  
274 tors has been calculated (Figure 6). 82% of the correlation coefficients are  
275 above 0.7, which highlights that many indicators are strongly correlated.

276 The high level of correlation observed in Figure 6 is explained by the  
277 morphological and layout patterns of the neighborhoods. Indeed, an increase  
278 of sky view factor value may be linked to a decrease of built surface fraction  
279 and mean building height. The LCZ position in the conurbation (Pos) is also

280 correlated with morphological and land use indicators. This result may be  
281 due to the specific spatial distribution of the LCZ types for the studied area.  
282 Within the Nancy conurbation, the most dense areas with highest building  
283 height and built surface fraction are located in the center, while the less  
284 dense areas with moderate building height and low built surface fraction can  
285 be found close to the conurbation's boundaries. Therefore, an increase of  
286 the radial distance from the center of the conurbation can correspond to an  
287 urbanisation gradient.

288 Explanatory variables can be considered as weakly correlated if the cor-  
289 relation coefficient ranges between  $-0.5$  and  $+0.5$ . It appears that only one  
290 pair of urban indicators reaches this criteria, namely the impervious surface  
291 fraction with the aspect ratio. However, regarding the single indicator ap-  
292 proach (cf. Section 3.1 and Table 2), these two indicators demonstrate poorer  
293 correlation with NCR (higher AIC and lower  $R^2$ ) than other indicators. As  
294 a result, this pair (i.e. impervious surface fraction and aspect ratio) seems  
295 to be not relevant for a regression involving two indicators.

296 This analysis suggests that in the case of multi indicator regression, only  
297 a small number of urban indicators can be selected in order to lower the  
298 negative effects of the collinearity. The choice of these urban indicators is  
299 based on urban and statistical criteria.

300 First, it appears that urban indicators can be sorted depending on their  
301 nature. Sky view factor, aspect ratio, mean building height and terrain  
302 roughness class are related to the urban morphology, while the built, imper-  
303 vious and pervious surface fraction refer to the urban land use. The distance  
304 to the center of the conurbation can be considered as independent geograph-

305 ical indicator. If the two urban indicators selected for the regression belong  
306 to the same group, the model may be redundant and the other group will  
307 not be represented. Therefore, the two selected indicator should be chosen  
308 in different groups.

309 Second, indicators that demonstrate low AIC values for single indicator  
310 regression can be selected for multiple variables regression. For the land use  
311 group, the pervious surface fraction has been selected. Unlike the built and  
312 impervious surface fraction, this indicator provides an indirect information  
313 regarding the vegetation. Regarding the urban morphology group, R and  
314 SVF show the best AIC values. The later is selected for the multiple indica-  
315 tor regressions because it describes the urban geometry in a more detailed  
316 way than the terrain roughness class, which is based on the Davenport clas-  
317 sification. The distance to the center has been selected due to its low AIC  
318 value.

319 Three urban indicators – namely SVF, Per and Pos – are then selected  
320 to carry out regressions. Four regressions are presented, namely:

- 321 • Three regressions between NCR and two explanatory variables (conbi-  
322 nations of SVF, Per and Pos)
- 323 • One regression between NCR and three explanatory variables

324 Models are discussed regarding their  $\chi^2$  value (cf. section 2.3). Figure 7  
325 presents NCR calculated from the observations in function of NCR estimated  
326 by regressions in the multiple variables regression case.  $\chi^2$  ranges from 0.016  
327 to 0.02. Among the two indicators model, the pair SVF and Pos obtains the  
328 lowest  $\chi^2$  value (0.016). This can be considered as an improvement regarding



329 the single variable regression approach, which only reach a  $\chi^2$  value of 0.02.  
330 Finally, the two indicators model which leads to the better estimation of the  
331 normalized cooling rate is expressed in equation (8).

$$NCR = 4.7 \times 10^{-3} \cdot Pos + 4.4 \times 10^{-5} \cdot Per + 8.8 \times 10^{-2} \quad (8)$$

332 In addition, a model involving these three indicators is proposed. Regres-  
333 sion model involving three urban indicators – namely SVF, Per and Pos –  
334 do not achieve better performance ( $\chi^2 = 0.016$ ).

#### 335 4. Conclusion

336 This paper questions the relationship between the cooling pattern of dis-  
337 tricts and several urban indicators. This study has required the application  
338 of the Local Climate Zone scheme in Nancy. During this stage, nine urban in-  
339 dicators have been determined within a selection of thirteen LCZ. Nocturnal  
340 cooling information has been gathered throughout measurement campaigns,  
341 and normalized cooling rate have been calculated based on these field data.

342 The statistical connection between NCR and the chosen urban indicators  
343 have been investigated using regression analysis. The statistical models are  
344 built using 75% of the total experiments. The overall performance of the  
345 urban indicators (i.e. AIC values) is independent from the sample. Nine  
346 single variable regressions are presented. Terrain roughness class, the sky  
347 view factor, the mean building height and the distance to the center of the  
348 conurbation achieve best results in terms of AIC,  $R^2$  and  $\chi^2$ .

349 Multi indicator regressions have been investigated in order to take into  
350 account multiple drivers of the LCZ nocturnal cooling. Correlations appear

351 to be generally strong between urban indicators, which limits the number of  
352 explanatory variables for the regression. Three urban indicators are selected  
353 for the multiple indicator regression. The best results are obtained with  
354 the pair SVF and Pos. The addition of a third explanatory variable do not  
355 improve the performance of the model.

356 Regression analysis underlines the general trends regarding the relation-  
357 ship between normalized cooling rate and the nine selected urban indicators.  
358 Overall, it looks like NCR and most of the studied urban features are corre-  
359 lated. However, morphological indicators seems to perform better than land  
360 use indicators.

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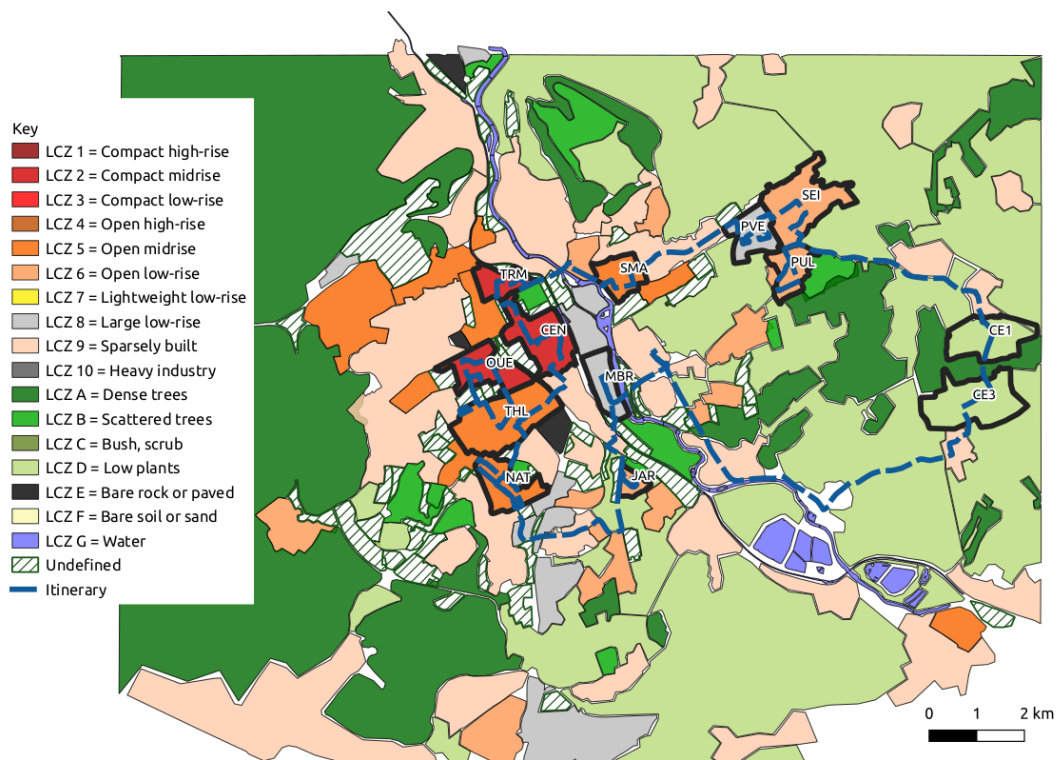


Figure 1: LCZ map of the Great Nancy Area. The itinerary is displayed in blue. The thirteen selected LCZ for the field experiment are circled in black.

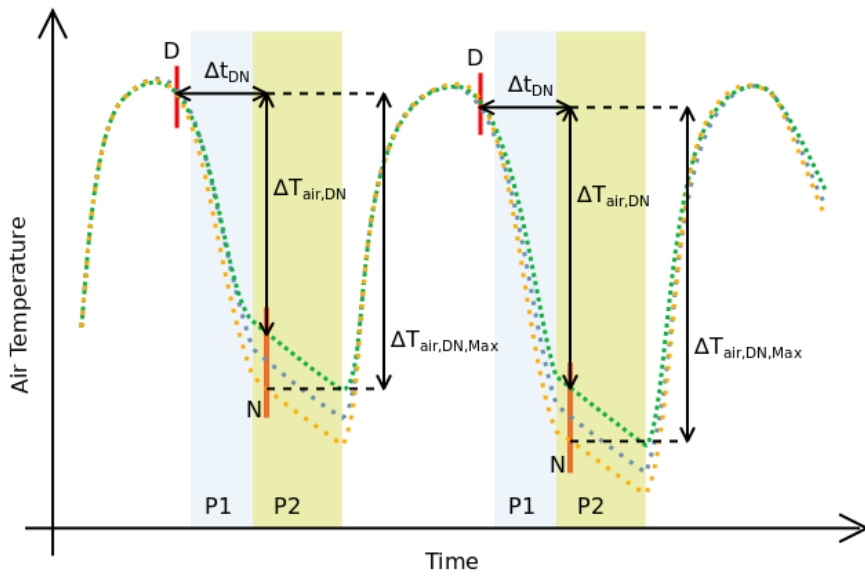


Figure 2: Theoretical nocturnal cooling phases for three LCZ of different types. Phase 1 (P1, blue area) is between 1 to 3 h before sunset and 3 to 5 h after sunset. Phase 2 (P2, green area) is between 3 and 5 h after sunset and sunrise. The letter D refers to the sessions performed in the middle of the afternoon, letter N refers to the sessions carried out around 3 h after sunset.



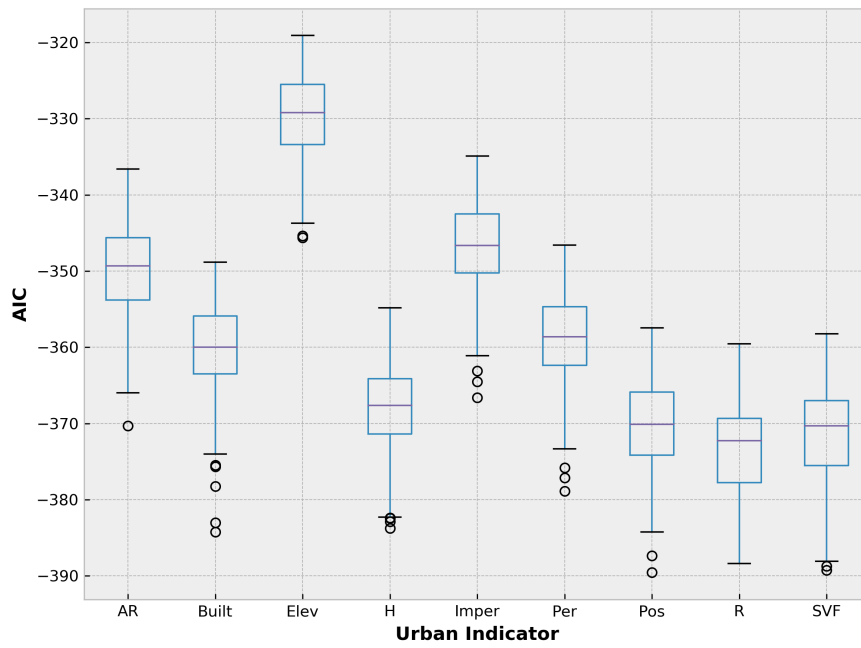


Figure 3: AIC values calculated from 180 different models for each urban indicator. Each model is based on 75% of the experimental data set which has been chosen randomly.

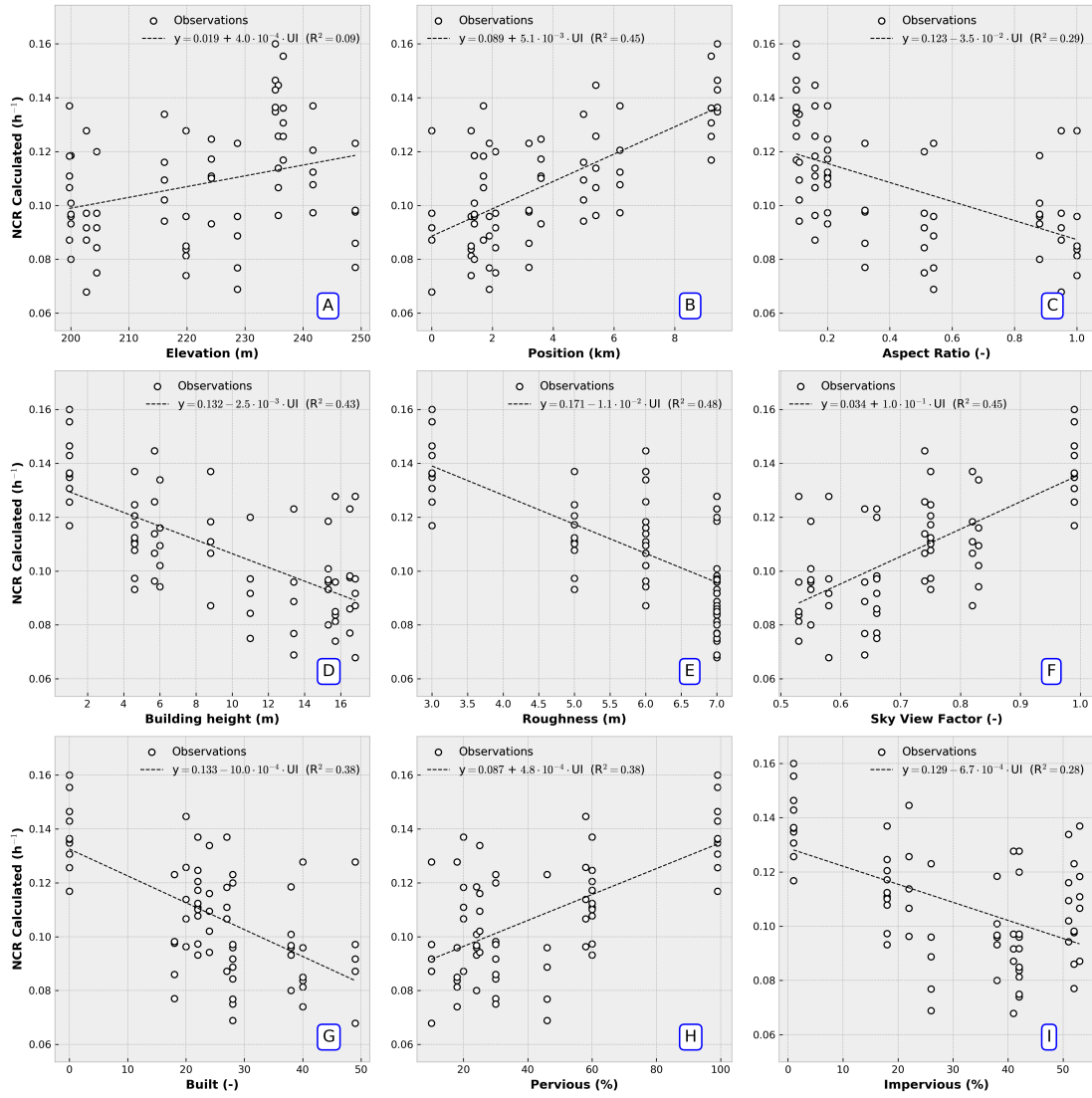


Figure 4: Scatter plots of experimental data including regression lines. Each observation correspond to a particular day for a given LCZ. Values with identical abscissa refer to a specific LCZ.

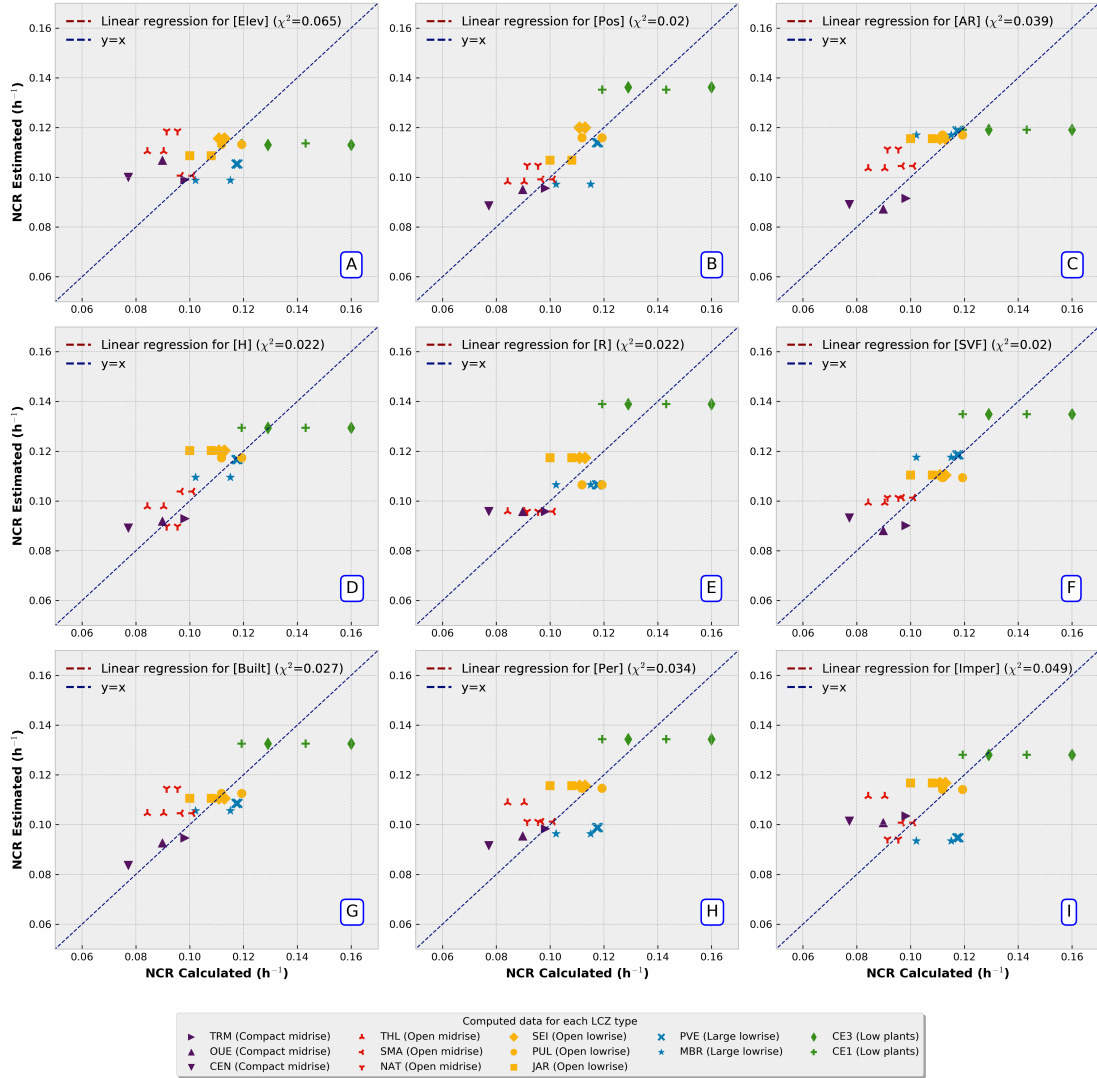


Figure 5: NCR from statistical regressions compared with NCR from the validation data set for single indicator regression. If the models would estimate perfectly the NCR from the validation data set, all the points would be on the first bisector (blue dashed line).

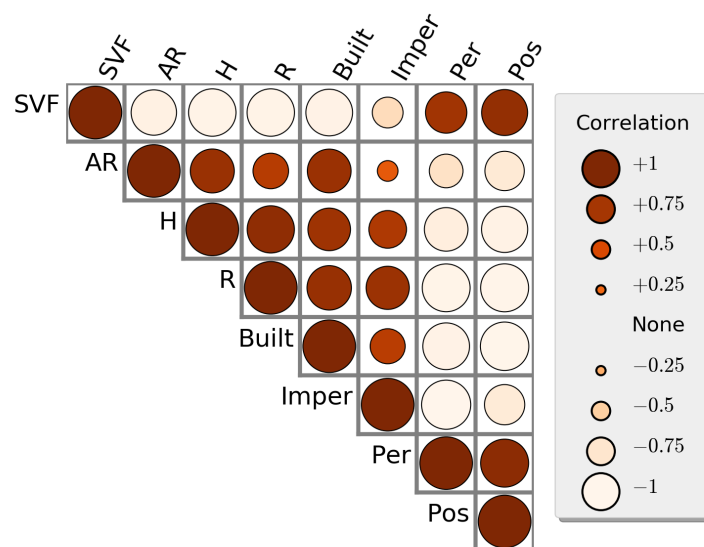


Figure 6: Correlation matrix of the explanatory variables, namely the urban indicators. The bigger the dot, the larger the correlation coefficient. The color indicates the sign of the correlation (positive/negative).

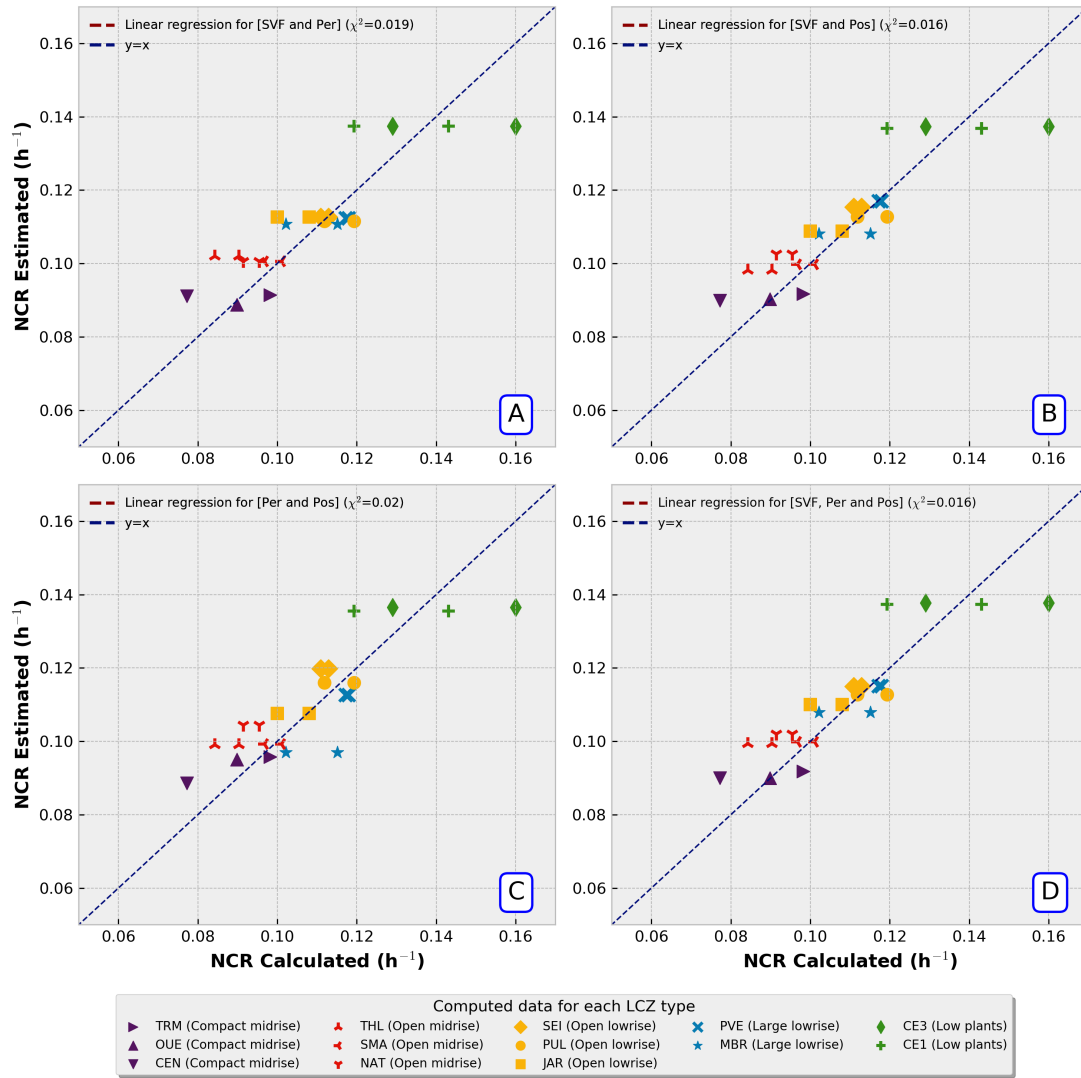


Figure 7: NCR from statistical regressions compared with NCR from the validation data set for multiple indicator regression. If the models would estimate perfectly the NCR from the validation data set, all the points would be on the first bisector (blue dashed line).

LCZ code	SVF (-)	AR (-)	H (m)	R (-)	Built (%)	Imper (%)	Per (%)	LCZ type (-)
OUE	0.53	1.00	15.7	7	40	42	18	2 (Compact Midrise)
CEN	0.58	0.95	16.8	7	49	41	10	2 (Compact Midrise)
TRM	0.55	0.88	15.3	7	38	38	24	2 (Compact Midrise)
NAT	0.66	0.32	16.5	7	18	52	30	5 (Open Midrise)
THL	0.64	0.54	13.4	7	28	26	46	5 (Open Midrise)
SMA	0.66	0.51	11.0	7	28	42	30	5 (Open Midrise)
MBR	0.82	0.16	8.8	6	27	53	20	8 (Large Lowrise)
PVE	0.83	0.11	6.0	6	24	51	25	8 (Large Lowrise)
JAR	0.75	0.20	4.8	5	22	18	60	6 / 9 (Open Lowrise / Sparsely Built)
SEI	0.75	0.16	5.0	6	19	22	59	6 / 9 (Open Lowrise / Sparsely Built)
PUL	0.74	0.16	5.7	6	20	22	58	6 / 9 (Open Lowrise / Sparsely Built)
CE1	> 0.9	< 0.1	< 1	3	0	1	99	D (Low Plants)
CE3	> 0.9	< 0.1	< 1	3	0	1	99	D (Low Plants)

Table 1: Urban indicators values for the thirteen selected LCZ. SVF: Sky view factor, AR: Aspect ratio, H: Mean building height, R: Terrain roughness class, Built: Built surface fraction, Imper: Impervious surface fraction, Per: Pervious surface fraction.

Urban Indicator	$\beta_0$	$P >  t $	$\beta_1$	$P >  t $	AIC	$R^2$	$P_{BP}$
R	0.17	$< 10^{-3}$	-0.01	$< 10^{-3}$	-362.43	0.48	0.21
SVF	0.03	$< 10^{-3}$	0.10	$< 10^{-3}$	-359.22	0.45	0.31
Pos	0.09	$< 10^{-3}$	0.01	$< 10^{-3}$	-358.13	0.45	0.12
H	0.13	$< 10^{-3}$	-0.00	$< 10^{-3}$	-356.79	0.43	0.42
Per	0.09	$< 10^{-3}$	0.00	$< 10^{-3}$	-350.83	0.38	0.20
Built	0.13	$< 10^{-3}$	-0.00	$< 10^{-3}$	-350.24	0.38	0.38
AR	0.12	$< 10^{-3}$	-0.04	$< 10^{-3}$	-341.93	0.29	0.85
Imper	0.13	$< 10^{-3}$	-0.00	$< 10^{-3}$	-340.39	0.28	0.28
Elev	0.02	0.59	0.00	0.01	-324.80	0.09	0.07

Table 2: Coefficients ( $\beta_0$  and  $\beta_1$ ), Student's t-test ( $P > |t|$ ), Akaike Information Criteria and  $R^2$  regarding regressions between normalized cooling rate and nine explanatory variables. Student's t-test results need to be under the chosen threshold of 0.05, whereas Breusch-Pagan values must be different from zero.