Assessment and Mapping of the Urban Heat Island Effect: A Preliminary Analysis on the Impact on Urban Morphology for the City of Turin, Italy

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Abstract

Urban Heat Island (UHI) effects, intensified by growing urbanization, significantly impact thermal comfort and energy demand in cities. To accurately model these effects in building performance and urban energy simulations, precise weather data and boundary conditions are essential. Although weather stations in city centers are increasingly used to develop typical meteorological years, they often fail to capture the microclimate variations across urban areas. New tools and methods are thus needed to help building professionals and municipalities assess UHI severity, use more representative weather data, and evaluate the impact of buildings on the urban microclimate. Among available tools for UHI impact assessment, Computational Fluid Dynamics (CFD) models offer detailed analysis but are computationally intensive and impractical for large-scale, year-round studies. Conversely, equivalent RC networks are more computationally efficient but still require extensive inputs, limiting their widespread use in large cities. This research introduces a new workflow using correlations to estimate UHI effects from rural weather data. The MIT Urban Weather Generator (UWG) was used to simulate UHI in representative districts, with the results employed to develop correlations for mapping local microclimates across urban areas. The proposed methodology is preliminary applied to the Italian city of Turin, focusing primarily on the correlation between urban morphology and the UHI phenomena (i.e., paying attention to those variables with the most significant effects on the local urban microclimate, according to the literature). The UHI impact has been quantified in terms of differential heating and cooling degree-days with respect to the rural environment. Results prove that with a training set of about 5 % of the city, modelled in detail with UWG, developed correlations appear robust enough to describe the phenomenon for residential districts of Turin.

1. Introduction

The increasing urbanisation process has led to a notable intensification of the Urban Heat Island (UHI) phenomenon, which is affecting both indoor and outdoor thermal comfort, as well as the energy demand of neighbourhoods and cities (Li et al., 2019). This phenomenon is driven by several factors, including urban morphology, material albedos, anthropogenic heat, and the lack of evapotranspiration due to the absence or limited presence of vegetation. The interaction of these factors, along with their spatial variability within urban contexts, results in a multitude of microclimates within urban areas.
In this context, the use of representative weather data and boundary conditions must be considered to increase the accuracy of the simulation at building and district scale. In the past, weather data were typically obtained from rural areas or external locations such as airports. Nevertheless, data from urban locations have been recently incorporated in building simulations towards a more accurate definition of climatic conditions. However, this solution is not able to entirely capture the microclimate variability within a city. For this reasons, different tools have been developed to assist policymakers in mapping the UHI and formulate mitigation strategies. These tools can be classified in two different categories: Urban Energy Balance (UEB) models and Computational Fluid Dynamics (CFD) models. CFD

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models, as ENVI-MET (Bruse & Fleer, 1998), solve the governing equations of fluid motion, allowing for high spatial resolution and precision. However, they necessitate substantial simulation and computational time, as well as advanced expertise and knowledge for model definition. Consequently, CFD applications at the district scale are typically confined to selected case studies over specific periods of the year. In contrast, UEB models use urban metrics to simplify and accelerate the description and calculation of the urban energy balance. The most used and spread tool in this category is the Urban Weather Generator (UWG) (Bueno et al., 2013). The UWG is an RC (resistance-capacitance) model comprising four sub-models: the Rural Station Model (RSM), the Vertical Diffusion Model (VDM), the Urban Boundary-Layer Model (UBL), and the Urban Canopy and Building Energy Model (UC-BEM). This model provides air temperature and humidity data for urban contexts starting from a rural weather data. The advantages of UEB models like the UWG include a faster computational speed compared to CFD models and the ability to generate weather data with UHI effects that can be directly used in urban and building simulation tools. Additionally, these models require less data and expertise for their definition.

However, UHI mapping and weather files still require a significant amount of data to cover both local and entire urban areas. Among the several factors that influence both simulations and real-world scenarios, urban layout has the most significant impact (Salvati et al., 2019). Urban geometry can vary significantly between cities and urban areas, making the definition of representative districts a powerful way to reduce data needs and extend analysis to the entire city. Different methods exist for clustering urban layouts. Among them, the most widely used is the Local Climate Zone (LCZ) classification (Stewart & Oke, 2012). However, other techniques and workflow have been developed to improve the LCZ classification, usually characterized by excessively broad classes. These alternative procedures, such as the one proposed by Joshi et al. (2022) or Boccalatte et al. (2023), integrate additional urban metrics and clustering techniques to obtain more representative districts archetypes that can be used for climate analysis.

Considering this context, a novel workflow is proposed in this study in order to map the UHI and weather data in the cities by the definition of representative district. The proposed methodology is preliminary tested on a case study, considering only urban morphology metrics for the definition of representative districts.

2. Methods

This paper presents a methodology to map the UHI and urban climate. The workflow (Figure 1) is structured in five steps: i) Metrics calculation, ii) Cases selection, iii) Microclimate simulation, iv) Correlation and validation and v) Mapping.

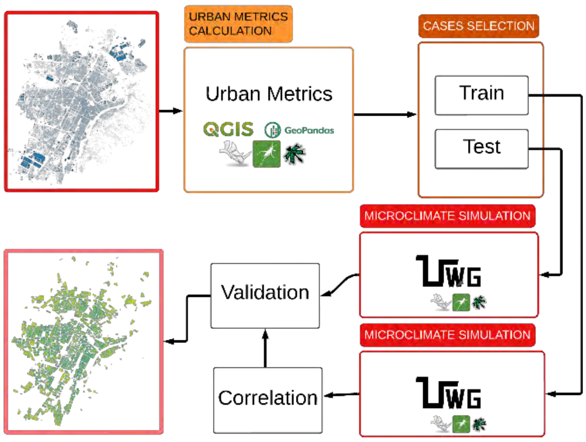

Fig. 1 – Methodology scheme

The main scope of this preliminary analysis is to assess possible correlations between urban parameters and microclimate metrics. To that purpose, different cases are selected according to the urban metrics. The microclimate effect is acknowledged to be significant at neighbourhoods' level. Therefore, the buildings in the city are grouped into urban blocks by clustering all the buildings with adjacent parcels area. The blocks with fewer buildings, irregular shape, or large area (mainly composed by industrial area and factory) are no object of the analysis and so were removed. For each filtered block, 10 urban metrics (Table 1) are defined among the most used metrics in literature (Javanroodi et al., 2023) and among the ones used by Joshi et al. (2022).

Table 1 – Urban Metrics

Metrics	Formula
Floor Area Ratio (FAR)	$FAR = \frac{\sum A_i * n_i}{A_{block}}$
Volume Area Ratio (VAR)	$VAR = \frac{\sum V_i}{A_{block}}$
Relative Compactness (REC)	$REC = \frac{\sum \frac{6V_i^{\frac{2}{3}}}{A_{i_{frontal}}}}{n}$
Shape Factor (SF)	$SF = \frac{A_{block}}{\pi r_{minbounding}^2}$
Surface Coverage (SC)	$SC = \frac{\sum A_i}{A_{block}}$
Green Ratio (GR)	$GR = \frac{A_{veg}}{A_{block}}$
Average Building Height (ABH)	$ABH = \frac{\sum_i^n h_i}{n}$
Sky View Factor (SVF)	$Qgis\ plugin$
Average Building Distance (ABD)	$ABD = \frac{\sum_i^n \sum d_i}{n^2}$
Vertical to Horizontal (VtH)	$Vth = \frac{\sum A_{vert}}{A_{block}}$

The metrics calculation process requires different software, such as QGIS and Rhinoceros, and python libraries, such as Geopandas. The Sky View Factor (SVF) is calculated using the QGIS plug in Relief Visualization Toolbox (Zakšek et al., 2011) that requires a digital surface model (DSM) as input data and produces the same raster vector with the calculated metrics. From the image raster the SVF for the building block is calculated as the average value on a virtual block positioned at half of the minimum distance to the closest block. This results in assigning to each building block the SVF value that corresponds to the one calculated in the middle of the streets. This approach is used in order to take into account the surrounding street canyon.

To proper select the urban metrics, a Spearman correlation analysis is performed to consider more independent metrics and sample the blocks population. The main statistical values for the selected metrics (e.g., Q_1, median, Q_3) are combined to define a representative population of districts. The blocks with the closest morphological features to each combination are selected as train subset for the correlation definition. The cases selected are modelled and simulated with the Urban Weather Generator (UWG) to create the urban weather file and data of interest (e.g., Heating Degree Days HDD, Cooling Degree Days CDD, Mean temperature, UHI index). On the selected outcome, different techniques can be adopted and implemented in order to correlate the input variable with the climate metrics and weather data.

The defined correlations are tested and verified on the result of an urban block subset randomly chosen. The outcome of the validation process gives information concerning the possibility to extend the metrics to all the city mapping and extracting information.

3. Case Study

The methodology proposed is tested and applied to the city of Turin, which has an estimated population of 848,000. The data used in this study is provided by the Municipality of Turin and includes a GIS model of the city and a digital surface model (DSM) input for the SVF calculation. The city is composed of 128,144 buildings, which are grouped into 4,518 blocks based on their cadastral parcel area. The filtering criteria are selected as follows: each block must have (1) a minimum of four buildings, (2) a SF higher than 0.1, and (3) an area lower than 0.1 km^2. Those criteria allow for the removal of uncommon blocks geometry, single or few building blocks, as well as removing huge industrial area in outside parts of the city. The final population is composed of 2,804 blocks. All the metrics selected are then calculated. The results of the correlation analysis using the Spearman method are reported in Table 2.

According to the results, the variables selected for the analysis and significant to the representative blocks definition are: i) Green ratio, ii) Surface coverage, iii) Average building height, iv) Vertical to horizontal, which are reported in Figure 2.

Table 2 - Spearman correlation

	SF	SVF	GR	SC	Abh	FAR	VAR	REC	Abd	Vth
SF	1	-0.095	-0.037	0.059	0.063	0.058	0.064	-0.023	-0.21	0.24
SVF	-0.095	1	0.2	-0.17	-0.25	-0.26	-0.29	0.32	0.27	-0.34
GR	-0.037	0.2	1	-0.37	-0.099	-0.27	-0.3	0.13	0.5	-0.34
SC	0.059	-0.17	-0.37	1	0.08	0.54	0.61	0.013	-0.032	0.19
Abh	0.063	-0.25	-0.099	0.08	1	0.6	0.73	-0.71	-0.084	0.61
FAR	0.058	-0.26	-0.27	0.54	0.6	1	0.85	-0.4	-0.16	0.63
VAR	0.064	-0.29	-0.3	0.61	0.73	0.85	1	-0.51	-0.13	0.64
REC	-0.023	0.32	0.13	0.013	-0.71	-0.4	-0.51	1	0.22	-0.53
Abd	-0.21	0.27	0.5	-0.032	-0.084	-0.16	-0.13	0.22	1	-0.59
Vth	0.24	-0.34	-0.34	0.19	0.61	0.63	0.64	-0.53	-0.59	1

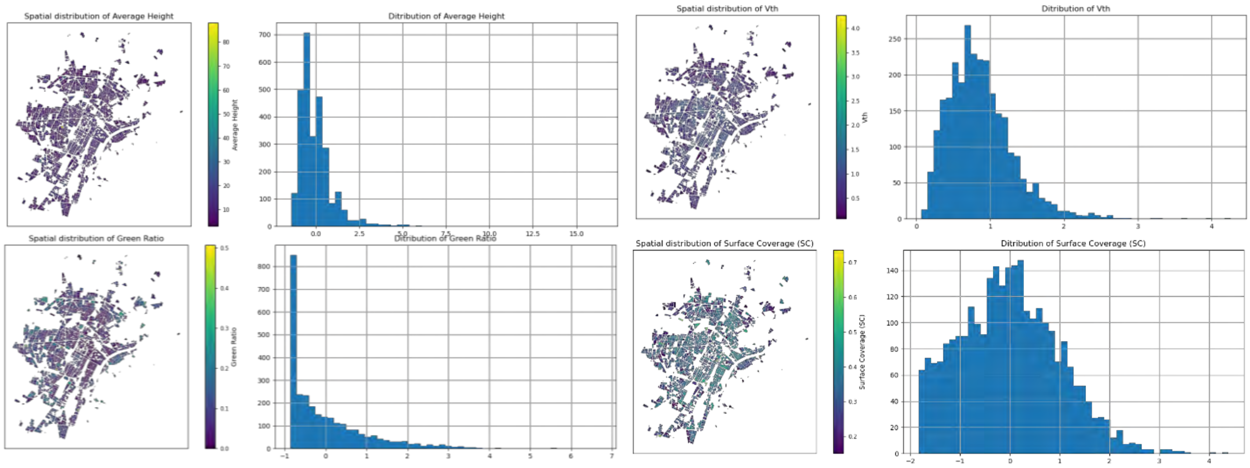

Fig. 2 – Distribution of metrics selected

The relevant statistical points, combined for the representative cases, are the minimum, the 10th percentile, Q_1, median, Q_3, the 90th percentile, and maximum value of the distribution. This approach ensures a complete spatial sample, including the extreme cases. The total train sample, after removing duplicates, is composed of 171 blocks, which represent 6 % of the total sample. The blocks, shown in Figure 3, are uniformly distributed across the city. The test sample is composed of 20 cases chosen randomly (Figure 3).

The geometry property of the selected blocks is employed as input for the UWG, combined with the vegetation information present in GIS data. The other parameters (e.g., the anthropic heat and building archetype) are taken as default values, given the morphological aspect focus of this preliminary analysis. Due to their strong correlation with the building energy demand, the selected metrics are the Heating and the Cooling Degree Days variations between the simulated values and the ones resulting from the rural weather station (TORINO 160590 IWEC), characterized by CDD_{18} equal to 381 K d and HHD_{18} equal to 2505 K d. As a first trial, a simple linear correlation is performed on both the metrics investigated.

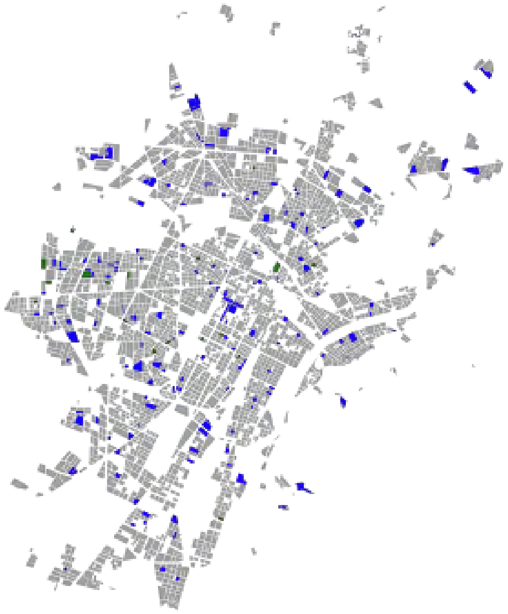

Fig. 3 – Spatial disposition of Train sample (Blue) and Test sample (Green)

4. Results

The linear correlation carried out on the datasets provides a positive outcome for both the metrics. The cooling degree days correlation is reported in Figure 4.

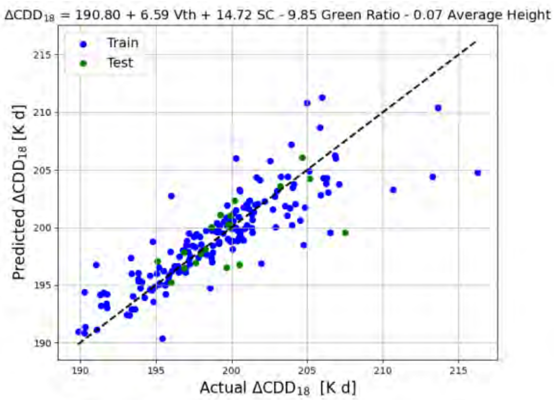

Fig. 4 – Cooling degree-days correlation

The trained sample shows a good correlation, as confirmed by a R^2 value of 0.73 and a RMSE value of 2.39 K d. On the test sample, an RMSE value 2.31 K d is considered acceptable for the validation of the correlation, being lower than the RMSE of the training sample. Among the different metrics, the vertical to horizontal (Vth) is the one with the biggest influence, followed by the surface coverage (SC) and green ratio (GR), which has a counter effect on the CDD variation. The average building height shows a very low impact. Similar results for the heating degree days correlation are reported in Figure 5, with a R^2 of 0.74 a RSME on the train sample of 4.98 K d. The RMSE of 4.63 K d on the test sample is higher than the one found for the Cooling Degree Days analysis but again acceptable for the validation purpose. The trends for the different variables are similar in absolute value and opposite in sign compared to the Cooling Degree Day.

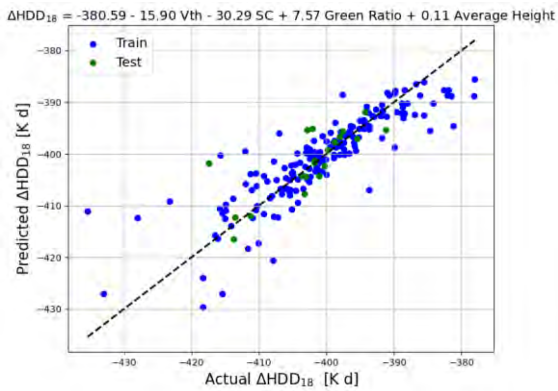

Fig. 5 – Heating degree-days correlation

These correlations allow us to map the metrics variation inside the cities, as shown in Figures 6 and 7. The average variation of the metrics inside the cities are -402 K d for the Heating Degree Days, corresponding to a reduction of 16 %, and a significative increase of 200 K d (+52 %) for Cooling Degree Days. The variation range inside the different blocks configurations is 66 K d for the HDD that correspond to the 3 % of the average urban HDD value. More important is the variation range of the CDD. It corresponds to 30 K d, resulting in 5 % of the average CDD value inside the urban area.

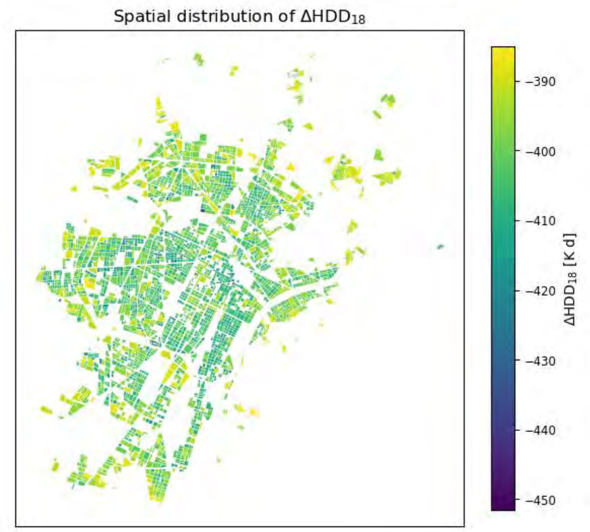

Fig. 6 – Heating degree days spatial distribution

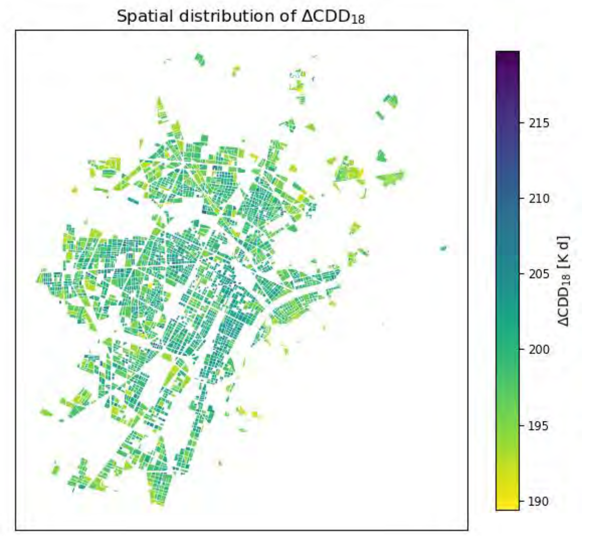

Fig. 7 – Cooling degree days spatial distribution

5. Conclusion

This study introduces a novel methodology for mapping urban microclimates and establishing boundary conditions for urban and building simulations. The approach adopted emphasises the identification of correlations between environmental variables and urban morphological metrics, thereby reducing the computational time and data requirements by a significant extent. By calculating a range of metrics within an urban context, a small, representative subset of districts is identified for the purpose of training the correlation model.

Subsequently, the selected districts are modelled using the Urban Weather Generator (UWG) to produce urban microclimate data and extract urban heat island (UHI) metrics based on the established correlations. The methodology is initially evaluated in the case study of Turin, with a primary focus on morphological parameters. By simulating a mere 6 % of the total urban blocks, a clear correlation is identified between urban metrics and variations in Heating Degree Days (HDD) and Cooling Degree Days (CDD) in comparison to a rural climate baseline.

The results demonstrate the considerable impact of urban morphology on climate variations, with vertical-to-horizontal metrics and surface coverage identified as the most influential factors. Furthermore, the study demonstrates that the mean discrepancy in HDD and CDD is considerable, with CDD exhibiting notable disparities across diverse urban zones. The results validate the effectiveness of the proposed methodology in mapping urban heat islands using urban metrics, reducing both the data requirements and the computational time.

The workflow is adaptable and can be readily applied to other contexts and metrics. However, the principal limitation of this approach is its narrow focus on urban morphology, without accounting for other crucial factors such as anthropogenic heat, building archetypes, and wind patterns. Future research should seek to incorporate these additional variables and conduct a real case validation to enhance the precision and applicability of the methodology.

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