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Modelling the impact of green solutions upon the urban heat island phenomenon by means of satellite data

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Abstract. Climate change causes a critical increase of temperature and frequency of heat waves, whose impact is particularly sensitive within the urban environment. Here, the loss of natural areas, beside morphological and thermal properties, makes urban temperature to be significantly higher compared to peri-urban and rural areas. This phenomenon is commonly known as urban heat island (UHI). Because green infrastructure provides an effective strategy for reducing the UHI effect, we explore the feasibility of remotely sensed data and statistical modelling for assessing the effectiveness of green measures. We simulated how implementing green roofs over the city of Milan could affect temperature. Geographically weighted regression has been used to model the correlation among satellite-derived vegetation map and near-surface air temperature.

1. Introduction and research context

The current increase of temperature and frequency of heat waves in urban areas threaten the health and wellbeing of citizens. The loss of natural areas, beside morphological and thermal properties of materials within the built environment, has a significant impact on urban climate, causing critical differences compared to rural and peri-urban areas. This phenomenon, known as urban heat island (UHI), is characterized by strong daytime absorption of solar radiation, which is released back at nighttime [1].

Mitigating the effect of the UHI requires undertaking both urban design actions and policy design strategies. For instance, incrementing green infrastructure provides an effective solution for reducing the impact of heat waves at local level. However, suitable tools for quantifying, assessing and monitoring the effectiveness of urban greening measures over time are lacking.

Nowadays, satellite-based optical and thermal imagery provides key resources for investigating those features that can effectively reduce the UHI effect. Based on satellite data, the spatial distribution of urban surface temperatures and tree cover [2], urban-rural heating and cooling differences [3] and temperature patterns associated with land use change [4] have been explored. Besides, statistical modelling has been widley investigated for estimating spatial correlation among vegetation and temperature [5], or to analyse the relationship between UHI and land cover changes based on spectral indices [6,7]. In fact, the (negative) correlation among Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) has been estimated at different spatial resolutions [8,9].

In particular, the use of the Multiple Linear Regression (MLR) has been broadly explored either to assess the correlation and relevanace of different variables with respect to UHI, as well as for modelling urban climate based on the combination of remotely sensed data with ground measurements [10–13]. Nonetheless, although standard MLR effectively explains the land-use background of the UHI, it causes inaccurate results when modelling non-stationary phenomena as is the case of temperature [8,14].

In order to compensate for such a limitation, Geographically Weighted Regression (GWR) models have been experimented as an effective statistical approach to account for spatial non-stationarity [15]. Actually, GWR enables site-specific investigation based on local statistics thus showing more clearly the relationship occurring between temperature and land cover.

Here we experiment a GWR model based on NDVI as the independent variable (predictor), and near surface air temperature as the dependent variable. The objective is to explore the effectiveness of remotely sensed data and statistical modelling for assessing urban greenery measures for reducing the UHI. In particular, we simulated the impact of implementing green roofs over the city of Milan, at both day- and night-time. Besides, both global linear regression and GWR model have been tested. For instance, because the non-stationarity of the phenomenon under investigation, the GWR shows widely improved results. However, we emphasize that the reduction of urban temperatures is locally sensitive.

2. Data and study area

For this study, we employed optical and thermal data provided by Landsat 7, acquired on August the 4th, 2017. Landsat 7 (launched in 1999, and still operating) carries an improved passive sensor, termed Enhanced Thematic Mapper Plus (ETM+), which provides multispectral data at spatial resolution of 30 meters, and a spectral resolution that relies on six bands in visible, near-infrared, and short wave infrared (SWIR). In addition, thermal infrared is available.

The study area is the Municipality of Milan, which covers an area of approximately 181.7 km^2, with a population of around 1.370 million. From the climatic point of view, and according to the scenarios provided by the National Plan of Adaptation to Climate Change, the CdM is included in one of the regions of Italy that is most affected by heat waves.

In order to measure the UHI, we used the regional land use classification provided by the DUSAF database (*Destinazione d'Uso dei Suoli Agricoli e Forestali*) updated in 2015 from aerial photos. The classification, which relies on several classes according to different levels of detail, has been generalized into two classes, i.e. urban and non-urban areas. Based on these classes, the UHI has been measured as a difference of mean temperatures between urbanized and rural areas ($\Delta T_{urban\text{-}rural}$).

3. Methodology

The work uses medium resolution satellite imagery to analyse the spatial variation of temperature in relation to vegetation (assessed by means of the NDVI). Temperature refers to the urban layer between the soil surface and 2 meters in height (canopy layer). Based on this, both day- and night-time UHI on August the 4th 2017 have been taken into account. In fact, August the 4th was the hottest day in 2017, in Milan, according to data collected by the weather station in the city centre.

A GWR model has been designed, where vegetation is the predictor, and temperature is the dependent variable. Based on the model, the actual NDVI was replaced with a theoretical NDVI based on the hypothesis to implement a relevant number of green roofs, evenly distributed throughout the town. Therefore, the approach allows simulating the effect of green measures, upon the UHI. A global linear regression model has been also provided, and both models have been compared.

3.1. Estimating the UHI for the City of Milan

Generally, the UHI phenomenon is assessed by means of air temperature obtained through fixed weather stations and/or traverse observations, either for the Urban Canopy Layer (UCL) as well as for the Urban Boundary Layer (UBL), or based on remotely sensed Land Surface Temperatures (LST), in the case of the Surface Urban Heat Island (SUHI) [16,17]. However, while satellite imagery provides continuous distribution LST data (raster format); weather stations provide a punctual, but unevenly distributed data.

Since the work requires continuously distributed air temperature data (raster format), we previously estimated near-surface air temperature (canopy layer) by combining optical and thermal data from MODIS and Landsat satellites (normally provide LST), with air temperature measured by weather stations. In particular, through a statistical model, we get air temperature (raster format) for a critical event (warmest day), both daytime (10:30 am) and nighttime (09:30 pm), as shown in Figure 1.

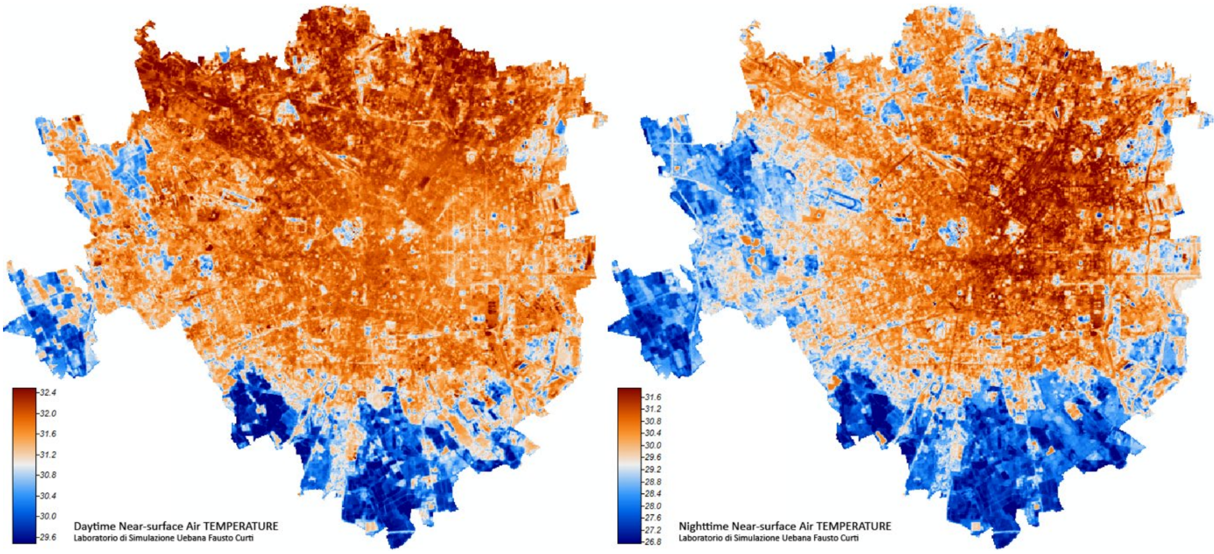

Figure 1. Near-surface air temperature (°C) estimated for the day August the 4th, 2017. (Left side) Daytime temperature, at 10:30 am; (Right side) Nighttime temperature, at 09:30 pm.

Based on the near-surface air temperatures, and the urban/rural classification obtained from DUSAF, the UHI intensity for August the 4th, 2017 was quantified. Both daytime and nighttime averages, and maximum temperatures, have been calculated for urban areas (T_u) and non-urbanized - or rural - areas (T_r). Hence, the UHI intensity is given by the difference among urban temperatures minus rural temperatures (ΔT_{u-r}). Because the pixel-based maximum value is not representative for the whole city, we took into account the UHI estimated by means of average temperatures. Daytime UHI resulted to be of about 1.1° C (10:30 am), and nighttime UHI of about 2.1° C (09:30 pm) as reported in Table 1.

Table 1. Near-surface air temperature derived UHI, both daytime and nighttime, for the City of Milan at August the 4th 2017.

		Daytime (10:30 am)		**Nighttime** (09:30 pm)	
		T_{mean} °C	T_{max} °C	T_{mean} °C	T_{max} °C
Urban	T_u	**31.6**	34.6	**30.0**	35.0
Rural	T_r	**30.5**	32.7	**27.9**	32.0
UHI	ΔT_{u-r}	**1.1**	1.9	**2.1**	3.0

3.2. Current NDVI and green roofs-based simulated NDVI

The NDVI, introduced by Rouse et al. in 1974 [18], is among the most known satellite derived Vegetation Indices (VIs). It is derived combining red and near-infrared spectral bands, and ranges from -1 to 1, where, values close to 0, and lower, means no vegetation, while vegetation normally ranges from 0.2 upwards. To obtain NDVI, Landsat imagery has been firstly calibrated and atmospherically corrected. The latter process is fundamental to remove, or at least greatly reduce, signal distortions. Moreover, because the ETM+ sensor suffered a fault in 2003, a gap-fill algorithm has been applied.

NDVI for August the 4th 2017 has been computed. Hence, we assumed to extensively implement green roofs over the City of Milan, as a measure of adaptation. Potential green roofs have been estimated by the European project Decumanus[1], for different cities including Milan. The algorithm relies on a very-high resolution Digital Surface Model (DSM) to get roof slope, Colour-Infrared (CIR) imagery and imperviousness map to separate actual green and not-green roofs. The GIS database as provided by Decumanus has been used to clip the current NDVI (Figure 2, left side), and then to simulate a theoretical NDVI by increasing per-pixel values upon potential green roofs (Figure 2, right side).

[1] Available at: http://www.decumanus-fp7.eu/home/

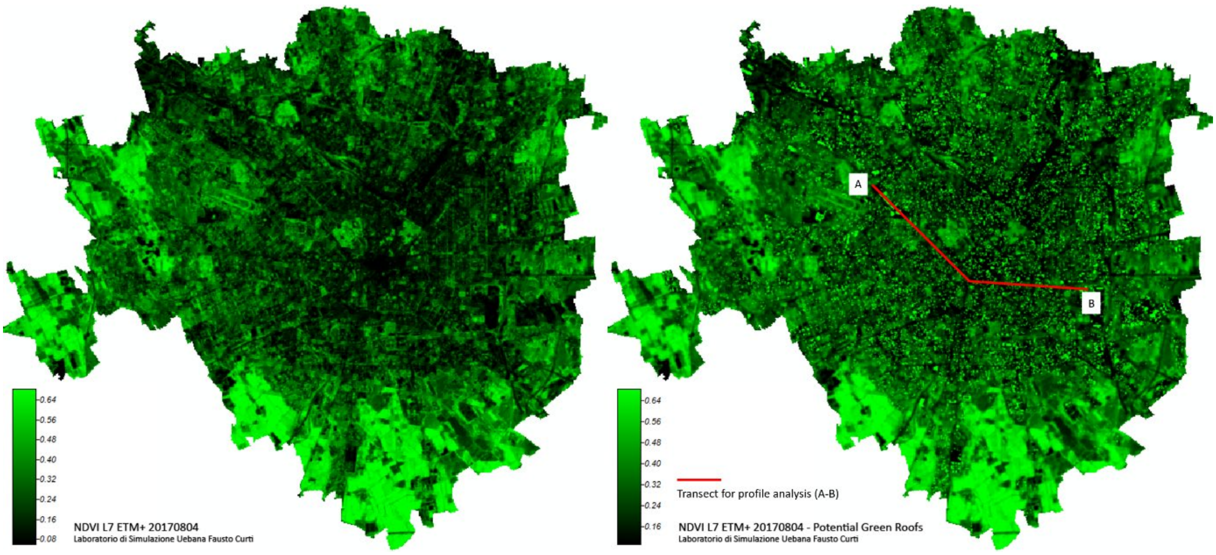

Figure 2. NDVI from Landsat 7 ETM+ multispectral data for the City of Milan at August the 4th 2017. (Left side) Current NDVI. (Right side) Green roofs-based simulated NDVI, and transect (A-B) for profile analysis.

3.3. GWR model to assess the effect of green measures

Spatial phenomena are intrinsically affected by geographical location; hence, they strongly vary across the landscape. This causes spatial heterogeneity that global models are not capable to address. Instead, GWR provides a powerful tool to address spatial heterogeneity based on local calibrated regressions at each geographical position along the landscape. Hence, either the model as well as coefficients are estimated depending on a neighbouring region, or bandwidth, around the target feature. Coefficients are then given in gridded format to account for the spatial distribution of the heterogeneity along the area [19,20]. Weights (expressed in matrix form) also depend on the observed location in relation to the other observations in the dataset; hence, they change at each location.

For this study, we defined a GWR model based on NDVI as predictor and near-surface air temperature as dependent variable. The model has been processed in GRASS GIS, which allows estimating optimal bandwidth and different weighting kernel functions. In particular, we used a Gauss weighting function with bandwidth of seven. In order to test the effectiveness of prediction performance, and to validate the model, a number of fitting measures have been assessed (Table 2). In addition, we compared the goodness of the GWR model with the global model based on same measures.

Table 2. Analysis of model goodness, daytime and nighttime, and comparison of the GWR model with the linear regression model based on NDVI as predictor and air temperature as dependent variable.

	Daytime (10:30 am)		**Nighttime** (09:30 pm)	
	Linear Regression	**GWR** Bandwidth 7	**Linear Regression**	**GWR** Bandwidth 7
Observations (*n*)	201,991	201,991	201,991	201,991
R^2	0.77	0.97	0.74	0.95
F	693,500.37	8,496,120.00	580,738.58	3,899,040.00
AIC	- 459,602.91	- 918,828.00	- 182,505.42	- 517,044.00
BIC	- 459,582.48	- 918,807.00	- 182,484.99	- 517,024.00
RMSE	0.32	0.10	0.64	0.28
MAE	0.26	0.07	0.49	0.19

Coefficient of determination (R^2), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), F-statistic, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are provided. In particular, R^2, RMSE, and MAE provide absolute measures, where R^2 expresses the capability of the independent variable to predict the dependent one, while RMSE and MAE report about the magnitude of the error. On the other hand, AIC, BIC, and F-statistic are relative measures of goodness, hence the meaning is expressed in comparison to another model. All fitting measures for linear regression model and GWR, both daytime and nighttime.

Due to the spatial heterogeneity of the phenomenon, the use of a GWR model provides a significant increase of effectiveness of the model to predict temperatures. Actually, the GWR widely increases R^2, while both RMSE and MAE are dramatically reduced at either daytime or nighttime.

Based on the GWR model we investigated the possibility of assessing the impact of increasing green coverage upon urban temperatures and UHI magnitude. To do so, we simulated a theoretical NDVI by changing pixel values for all potential green roofs. Besides, in order to assess the impact of different degrees of green vigour, three theoretical NDVI are provided using 0.6, 0.7, and 0.8 as constant values for green roofs. Table 3 summarizes the average temperatures (ºC) for urban and rural areas, daytime and nighttime, and the UHI intensity. Current, as well as predicted temperatures and UHI for NDVI 0.6, 0.7, and 0.8 are displayed. Besides, the UHI lowering resulting from the simulation is reported.

Table 3. Daytime and nighttime current average urban (T_u) and rural (T_r) temperatures, and UHI (ΔT_{u-r}), as well as predicted temperatures and UHI for NDVIs 0.6, 0.7, and 0.8.

		Daytime (10:30 am)				**Nighttime** (09:30 pm)			
		T_{mean} ºC				T_{mean} ºC			
		Actual	NDVI 0.6	NDVI 0.7	NDVI 0.8	**Actual**	NDVI 0.6	NDVI 0.7	NDVI 0.8
Urban	T_u	**31.6**	31.5	31.5	31.5	**30.0**	29.8	29.8	29.7
Rural	T_r	**30.5**	30.5	30.5	30.5	**27.9**	28.0	28.0	28.0
UHI	ΔT_{u-r}	**1.1**	**1.0**	**1.0**	**1.0**	**2.1**	**1.8**	**1.8**	**1.7**
UHI lowering			0.1	0.1	0.1		0.3	0.3	0.4

The impact of greening is actually more sensitive at night. Moreover, we emphasize that the impact on temperature reduction through implementing green roofs is much more sensitive at the local scale. For instance, if we outline a profile about the trends of NDVI and temperature values, either current and estimated, for a transect through the city (see Figure 2), as provided in Figure 3, we observe that, at some points, temperature difference is reaching around one degree at daytime and, in some cases, well beyond one degree at nighttime.

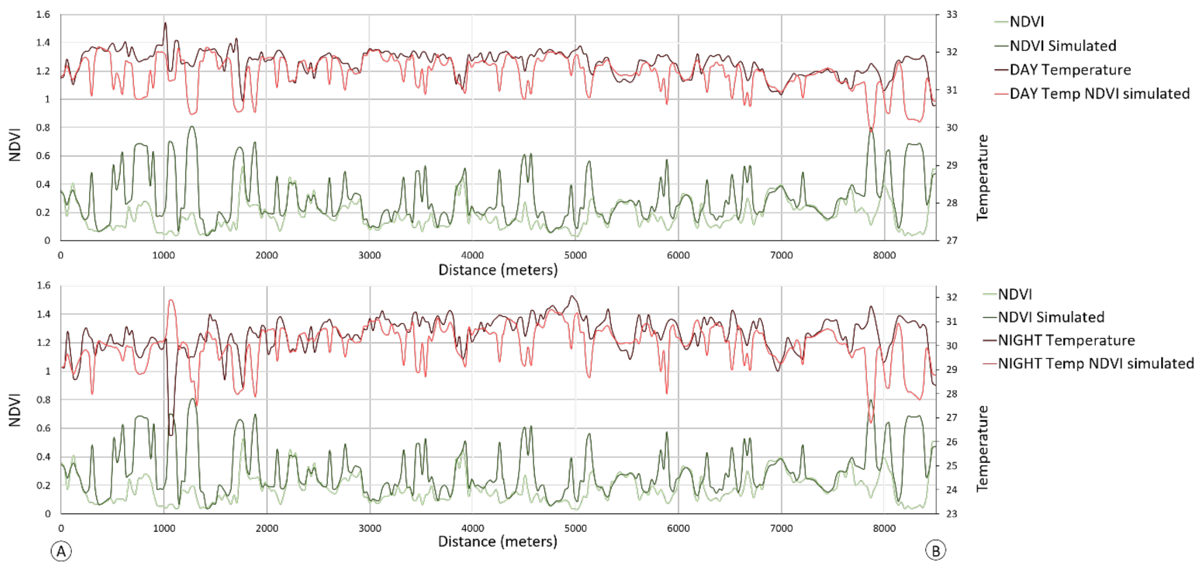

Figure 3. Profile (A-B) as identified on Figure 2, of current and simulated NDVI and temperatures. (Upward) NDVI versus daytime temperature. (Beneath) NDVI versus nighttime temperature.

4. Conclusions

The capability of quantifying different spatial patterns of temperature as vegetation changes, allows the evaluation and monitoring of the impacts induced by greening projects upon urban comfort. Even if the effect of urban greening strategies will not contrast global warming, results show that a massive implementation of green infrastructure in cities can decrease temperatures of about one degree at the local level during heat waves, with evident benefits on wellbeing and the reduction of energy demand.

Moreover, the availability of assessment tools provides the opportunity of weighting the benefits of different greening measures. Here the case study was based on assessing the implementation of green roofs, but actually the work aims at demonstrating that the approach is suitable for assessing and monitoring further adaptation actions, like for instance tree planting or replacing urban materials. In fact, although we set a GWR model based on vegetation as the lone predictor, the model could be improved by introducing further variables that affect urban climate such as the colour of materials (i.e. the albedo) and morphological features (i.e. urban sky roughness, porosity, street canyon geometry etc.).

The ultimate goal of this spatial analysis approach is to better inform decision-makers on urban resilience strategies and the meaning of an effective climate-proof urban planning, by considering the complex interactions and the cost-benefit evaluation of different adaptation solutions in cities.

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