Assessing the relationship between urban parameters and the LST derived by satellite and aerial imageries in a GIS environment: the case of Bari (Italy)

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Introduction & Motivations

A large number of researches were recently focused on the relationship between the land surface temperature and several urban physical factors. The remote sensing data are recognized as the most appropriate to study the thermal behavior at the urban or meso-scale. Within such studies various indicators representative of the urban environment have been used to describe their influence on the different urban thermal patterns. For this purpose several correlation techniques were applied. Altought global multivariate regression relationships are relatively well established, the statistical analysis used are very often aspatial, not representative of the spatial nature of the relationship among the involved factors. In order to highlight the spatial nature and scale dependencies of the thermal processes occurring within urban areas used as case study, we established the existing relationships between satellite-derived Land Surface Temperatures (LST) and the physical-geometrical parameters of the urban environment. A better knowledge on the effect of increasing spatial resolution of thermal data from space on the overall analysis was achieved by using thermal data from Terra-ASTER and Landsat platforms.

Methodology

In order to explore the relationship between the LST and the urban physical parameters we have:

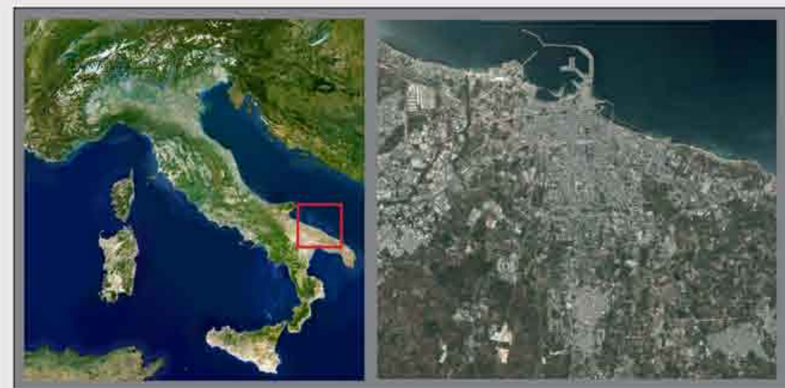
- enhanced the estimation of the LST through the methodology suggested by Sobrino et al. (2004), as an alternative to the widely used method such as the TES and ERC;

- oversampled the LST ground resolution to 15 m for the thermal data from ASTER image, and 30m for the thermal data form Landsat 8 image;

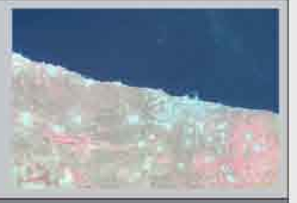
- applied an aspatial multiple regression analysis (i.e. no geographical location is considered in the estimation of the model parameters);

- applied a spatial multiple regression analysis

Study Area & Dataset



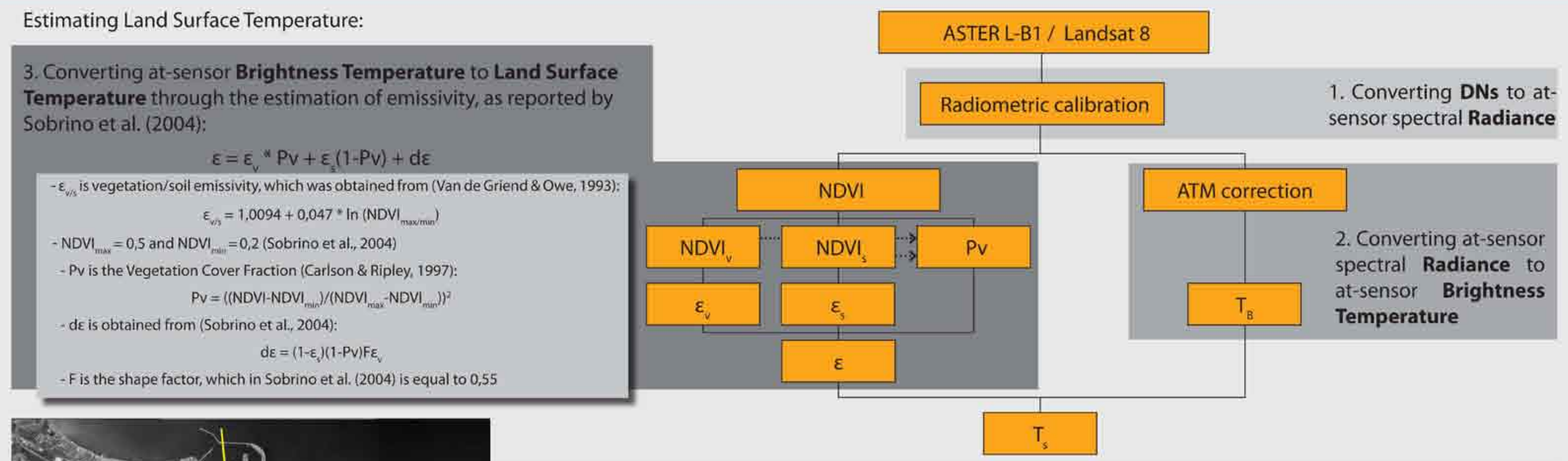
STUDY AREA:
Bari, Apulia Region, Italy;
(41°7'N, 16°51'E);
DIMENSION:
116,20 km²; 326.915 habitants.
CLIMATE:
mediterranean with mild winter and hot dry summer.

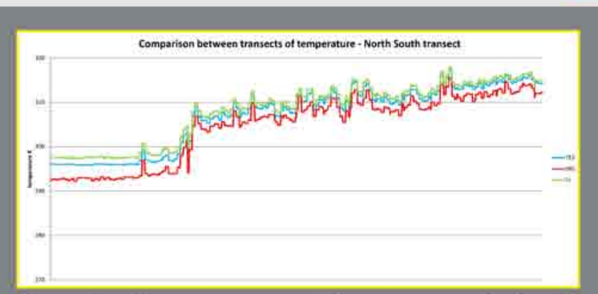


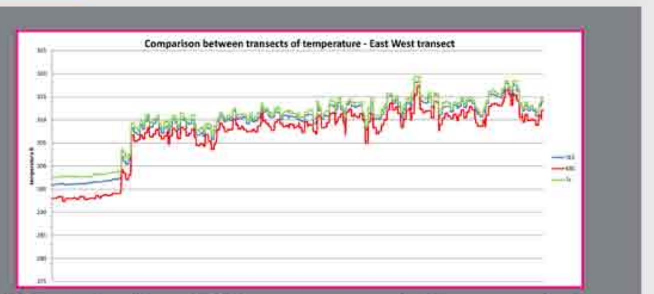
ASTER Level-1B
DATE OF ACQUISITION: 06 July 2001; (approx.10:00 a.m.)
GROUND RESOLUTION: 15 m (Vis & Vnir) and 90 m (TIR)
SPECTRAL RESOLUTION: 15 bands (5 TIRs)

LANDSAT 8
DATE OF ACQUISITION: 19 May 2013 (09:36 a.m.)
GROUND RESOLUTION: 30 m (Vis & Nir) and 60 m (TIR)
SPECTRAL RESOLUTION: 11 bands (2 TIRs)

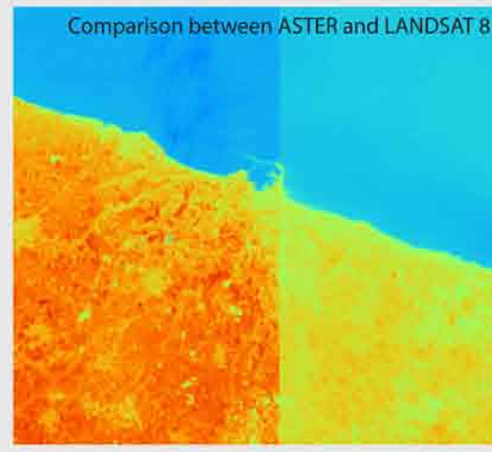
Thermal analysis



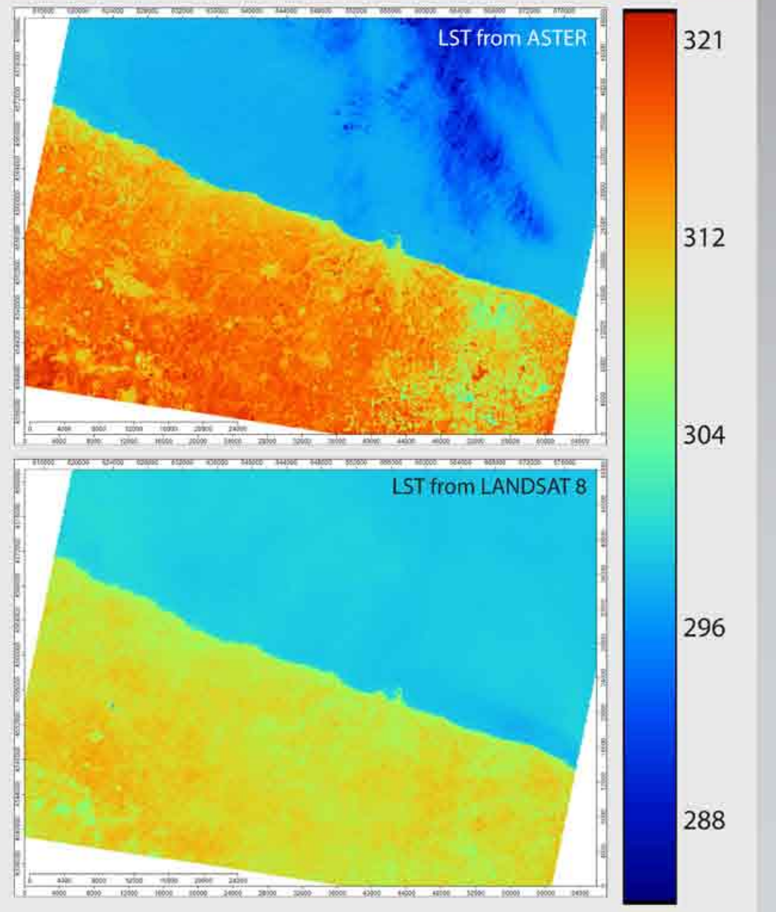




Comparison between transects of temperature obtained from different algorithms: TES (temperature-emissivity separation), ERC (Reference Channel Emissivity) and Ts (used in this work).



	ASTER L-1B	LANDSAT 8
NDVI	$(\rho_{nir}-\rho_r)/(\rho_{nir}+\rho_r)$	
NDVImin	0,2	0,2
Pv	0,5	0,5
NDVImax	$((NDVI-NDVI_{min})/(NDVI_{max}-NDVI_{min}))^2$	
ε_v	$1,0094+0,047*\ln(NDVI)$	
ε_s	$1,0094+0,047*\ln(NDVI)$	
ε	$\varepsilon=\varepsilon_v*Pv+\varepsilon_s(1-Pv)+d\varepsilon$	
ATM correction	ISAC (Johnson & Young, 1998)	(Coll et al., 2010)
$T_b = k_2/\ln(k_1/B_\lambda+1)$	$k_1=641,326$ $k_2=1271,21$	$k_1=477,607$ $k_2=1198,41$
T_s	$T_b/\varepsilon^{1/4}$	



Multiple Regression Analysis

NAME	DATA_CELLS	NODATA_CELL	CELLSIZE	MEAN	MIN	MAX	RANGE	VARIANCE
LST LANDSAT	4441863	51437688	30,000	303,073	295,794	315,366	19,572	25,954
NDVI LANDSAT	55879551	0	30,000	-0,455	-1,000	1,000	2,000	0,162
PV LANDSAT	55879551	0	30,000	0,114	0,000	1,000	1,000	0,013
LST ASTER	18016147	9372195	14,896	303,294	268,783	323,882	55,099	82,895
NDVI ASTER	24371679	3138370	14,984	-0,087	-1,000	1,000	2,000	0,023
PV ASTER	27547170	0	14,995	0,129	0,000	1,000	1,000	0,013
SKY VIEW FACTOR	1539705	606579	10,000	0,985	0,106	1,000	0,894	0,002
MORPHOMETRIC PROTECTION INDEX	1437265	709019	10,000	0,026	0,000	0,723	0,723	0,002
LST ASTER AOI	2146284	0	14,896	307,566	293,010	322,220	29,211	54,184
PV ASTER AOI	2146284	0	10,000	0,219	0,075	0,597	0,521	0,003
NDVI ASTER AOI	2146284	0	10,000	-0,067	-0,450	0,546	0,996	0,014
LST LANDSAT AOI	2146284	0	30,000	305,370	298,087	313,732	15,645	21,458
NDVI LANDSAT AOI	2146284	0	10,000	-0,099	-0,321	0,310	0,631	0,017
PV LANSAT AOI	2146284	0	10,000	0,205	0,114	0,429	0,315	0,003

In the table above are presented descriptive statistics of parameters used in the two models: ASTER and Landsat 8 LST; the Normalized Difference Vegetation Index (NDVI) and Vegetation Fraction (Pv) obtained as described before; Sky View Factor (SVF) and Morphometric Protection Index (MPI) as variables descriptives of the urban settlement derived by two different digital elevation model available for the Apulia Region. The showed data are referred to the whole data extension and to study area named Area of Interest (AOI).

MULTIPLE REGRESSION - LANDSAT			
PARAMETER	VALUE	PARAMETER	VALUE
R2	0,808	R2	0,826
R2_ADJ	0,808	R2_ADJ	0,826
STD_ERROR	1,420	STD_ERROR	1,426

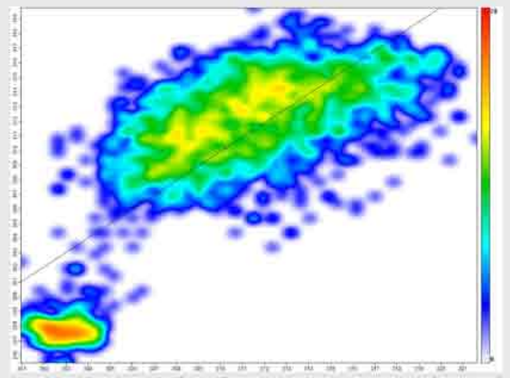
MULTIPLE REGRESSION - ASTER			
PARAMETER	VALUE	PARAMETER	VALUE
R2	0,286	R2	0,028
R2_ADJ	0,286	R2_ADJ	0,028
STD_ERROR	4,631	STD_ERROR	2,598

Parameter used:
- NDVI;
- Morphometric protection index;
- Sky View Factor;
- Vegetation Fraction.

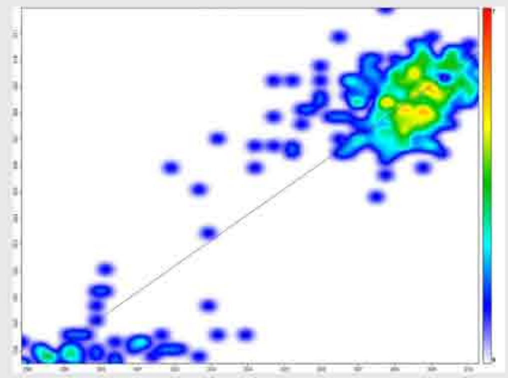
MULTIPLE SPATIAL REGRESSION - LANDSAT			
PARAMETER	VALUE	PARAMETER	VALUE
R2	0,835	R2	0,851
R2_ADJ	0,834	R2_ADJ	0,851
STD_ERROR	1,317	STD_ERROR	1,323

MULTIPLE SPATIAL REGRESSION - ASTER			
PARAMETER	VALUE	PARAMETER	VALUE
R2	0,581	R2	0,605
R2_ADJ	0,581	R2_ADJ	0,605
STD_ERROR	3,545	STD_ERROR	3,592

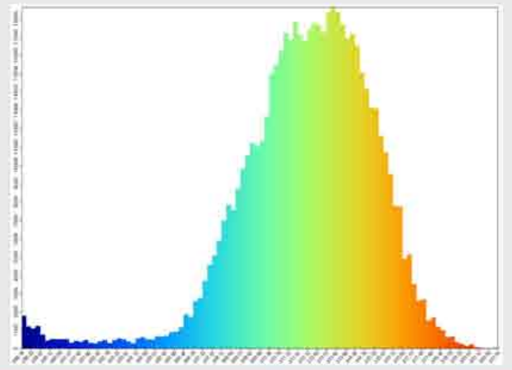
Parameter used:
- NDVI;
- Sky View Factor;
- Vegetation Fraction.

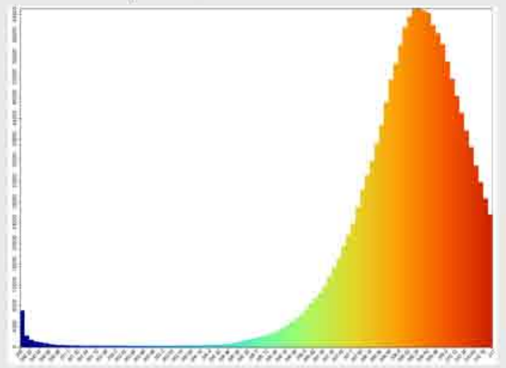


ASTER: x-axis = predicted temperature; y-axis = observed temperature (ASTER LST histogram is shown in the bottom picture).



LANDSAT: x-axis = predicted temperature; y-axis = observed temperature (LANDSAT LST histogram is shown in the bottom picture).



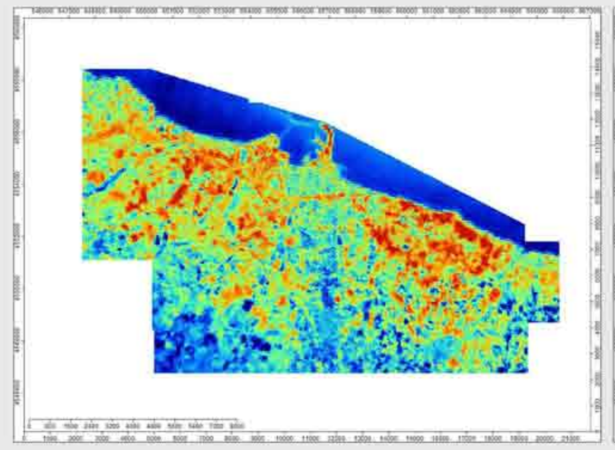


Results

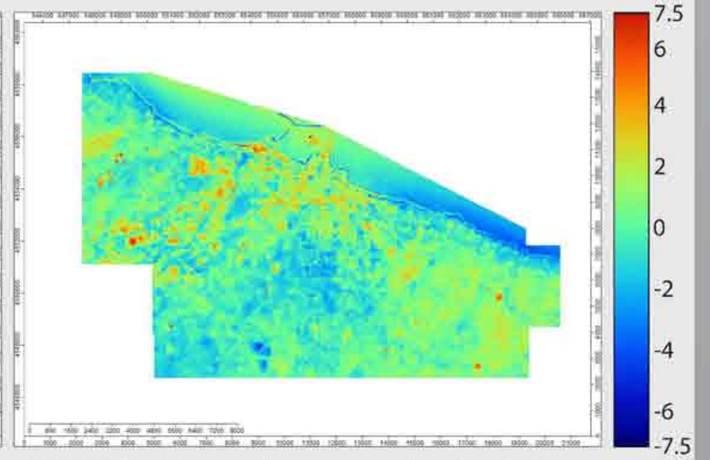
Regression analysis applied to the thermal imaging highlighted the relationship between LST and parameters included in the analysis. From the initial dataset the morphometric protection index (MPI) was excluded due to the very high value of statistical significance (p-value). Subsequently, both models, aspatial and spatial, used with thermal data with dual spatial resolution, showed a better overall result. This can be probably explained by the strong inverse correlation that this parameter exhibits with respect to the Sky View Factor (SVF) variable. This value is about 0.6.
However, the SVF, seems to show a greater predictive power with respect to the MPI. By substituting such a factor in place of the MPI in the model, the predicted value is lowered substantially.
The analysis of the coefficients shows that the most important predictor variables are those from the spectral analysis, rather than the SVF with an inverse correlation, as expected. The greater influence of the parameters derived from remote sensing with respect to the morphometric ones could be related to their common origin while the morphometric data could not be a more faithful picture of the context.
The geographic variables (x, y) help to improve the predictive power of the analysis, but the regression coefficients are not significant, perhaps to explain the spatial behavior is necessary to apply a local spatial analysis.

Conclusions

The global behavior of the regression analysis, both aspatial and spatial, demonstrates the strong effect of spatial resolution on the thermal processes occurring at urban extent.
This was demonstrated by inspecting the values of the determination coefficient and residuals provided as outcomes for the two thermal images.
In particular, the analysis of residuals shows the need to integrate the explanatory variables with variables more descriptive of the urban environment, such as the analysis of Impervious surfaces.
The overall results of the analysis are rather satisfactory and could allow to predict the variations of surface temperature with respect to variation of the urban parameters, such as the introduction of vegetated surfaces, which would produce an increase of factors NDVI and PV.



ASTER: Residues map between predicted and observed temperature.



LANDSAT: Residues map between predicted and observed temperature.

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