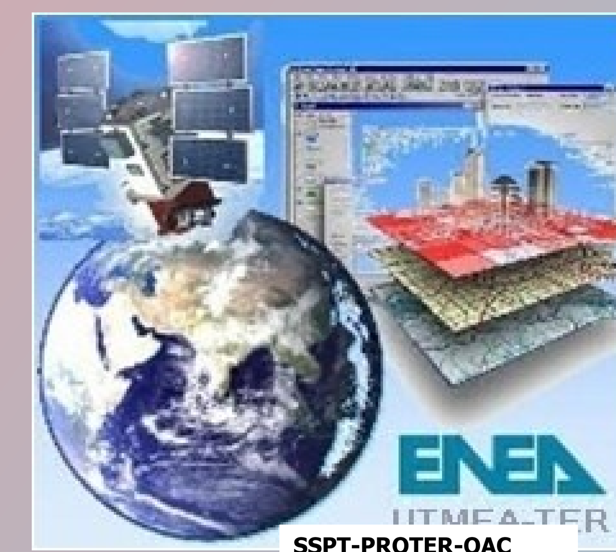
Remote Sensing and Object Classification for assessing the Urban Fabric Vulnerability to Heat Waves and UHI

Borfecchia F. (*), Caiaffa E. (*), Rosato V. (*), Pollino M. (*), De Cecco L. (*), Martini S. (*), La Porta L. (*), Ombuen S. (**), Filpa A. (**)

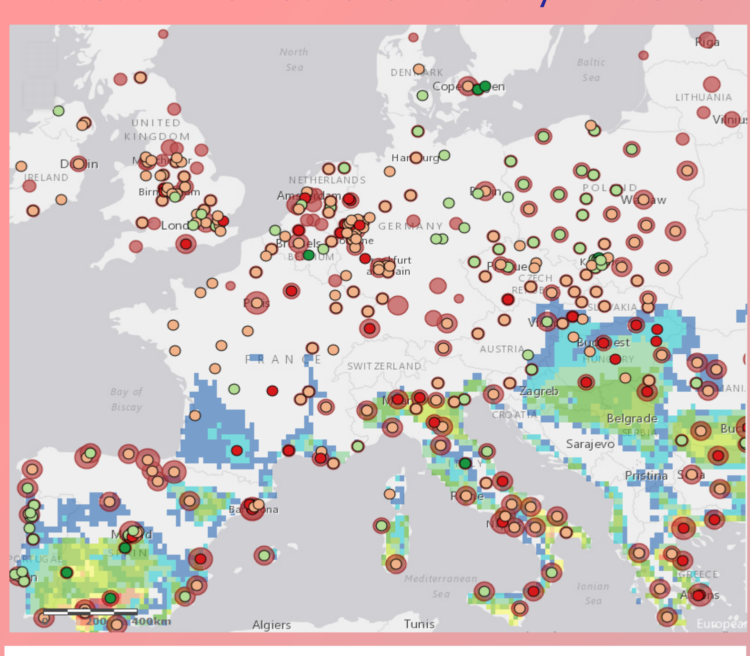
(*) ENEA Italian National Agency for New Technologies, Energy and Sustainable Economic Development. C.R. Casaccia – via Anguillarese, 301 Rome-Italy;
(**) Roma 3 University. Architecture Department - Via della Madonna dei Monti, 40 Rome-Italy.



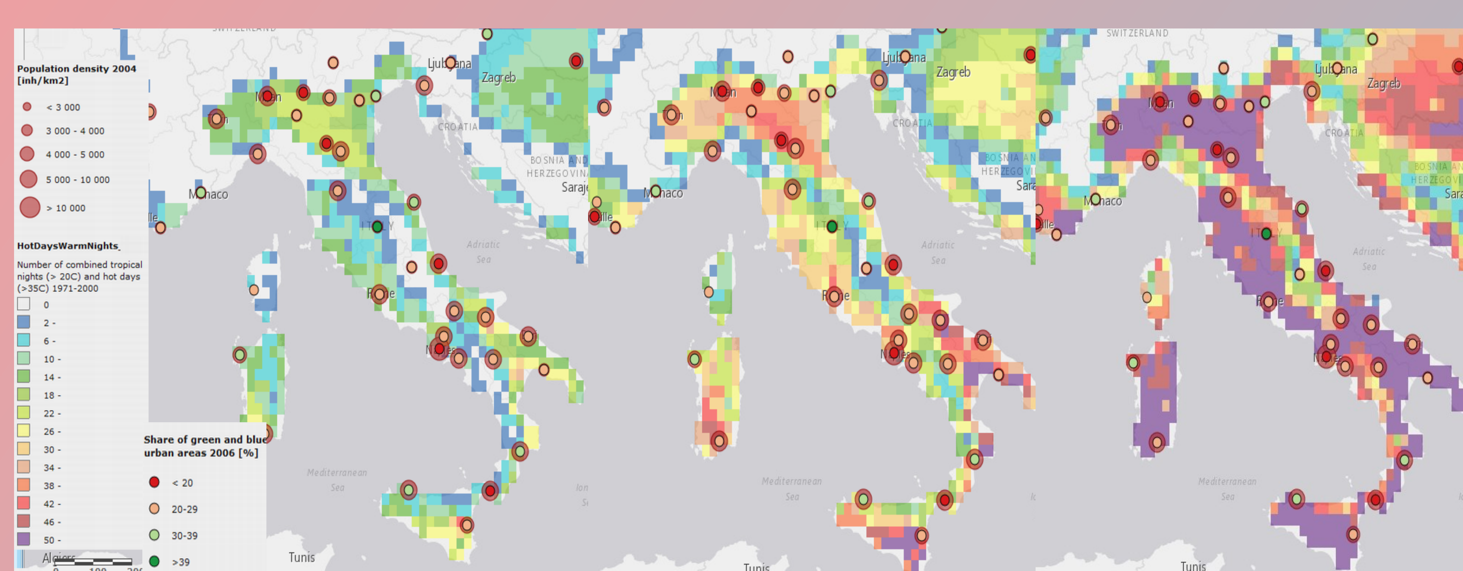
Today more than 50% of the world population lives in urban settlements that are continuously growing their infrastructures and build-up areas, often without appropriate planning, with significant changes in land cover/use and consequent variations in biophysical parameters related to their radiation budget, hydrological cycle and to microclimate. Densely urbanized areas, with a low percentage of green vegetation, are highly exposed to the rise in temperature extremal occurrences phenomena like Heat Waves (HW) which are increasing in terms of frequency and intensity, also in temperate regions, due to ongoing Climate Change (CC). Their negative effects may combine with those of the UHI (Urban Heat Island), a local phenomenon where air temperatures in the compact built up cores of towns increase more than those in the surrounding rural areas, with significant impact on the quality of urban environment, on citizens health and energy consumption, as it has occurred in the summer of 2003 on France and Italian central-northern areas. In this context this work aims at designing and developing a methodology based on aero-spatial remote sensing (EO) at medium-high resolution and on most recent GIS techniques, for the extensive characterization of the urban fabric response to these climatic aspects related to the temperature (within the general framework of supporting local and national strategies and policies of mitigation and adaptation to CC). Due to its extension and variety of built-up typologies, the municipality of Rome was selected as test area for the methodology development and validation. First of all, we started by operating through photointerpretation of cartography at detailed scale (CTR 1: 5000) on a reference area consisting of a transect of about 3x20 km, extending from the downtown to the suburbs (including all the built-up classes of interest). The reference built-up vulnerability classes found inside the transect were exploited as training areas to classify the entire Rome territory. To this end, the satellite EO multispectral data, provided by the new sensor Landsat 8 OLI (with perspective to be duly integrated with those acquired by the ESA Sentinel 2 system), were used within a "supervised" classification automatic procedure, based on data mining and "object-classification" techniques. The classification results were then exploited for developing a calibration method, based on a typical UHI temperature distribution derived from MODIS satellite sensor data (summer 2003), to obtain an analytical expression of the vulnerability model, firstly introduced on a semi-empirical basis.

HW (Heat Waves) and UHI (Urban Heat Islands)

HW Condition: protracted period (> 3-5 days) with high temperature (more than 5 ° above the average) even in the night and often accompanied by high humidity. Common during the summer in areas of the Mediterranean basin, are expected to increase in number and intensity in relation to CC and with significant effects, especially in dense urban areas.

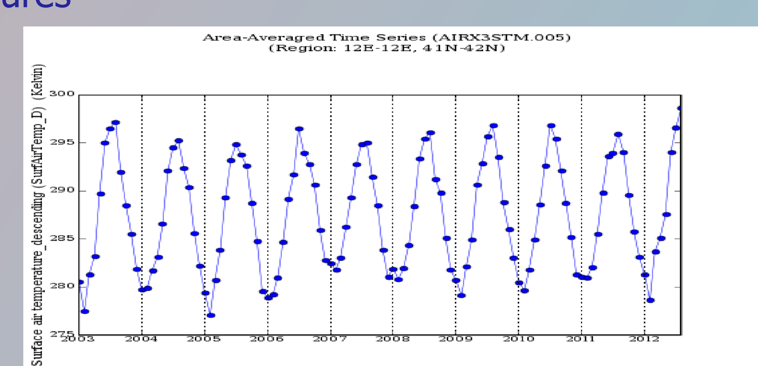


Map of HW number/year days and nights with temperatures respectively over 35° and 20°) from observations relating to the period 1971-2000 and vulnerable cities (population density and % of green/blue areas) E.E.A.



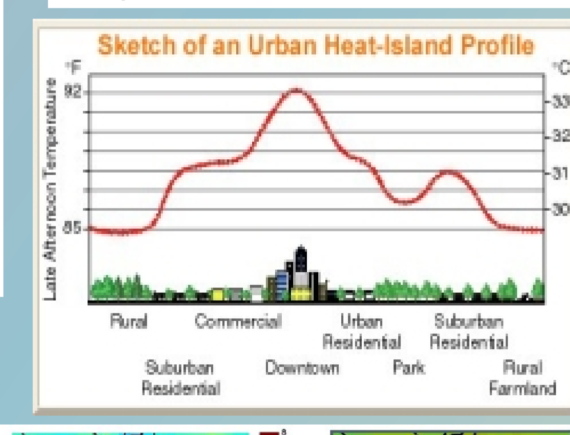
HW measured on Italy from 1971 to 2000 (left) and planned (IPCC scenarios) in the periods from 2021 to 2050 (center) and 2051-2100 (right) by EEA (European Environment Agency)

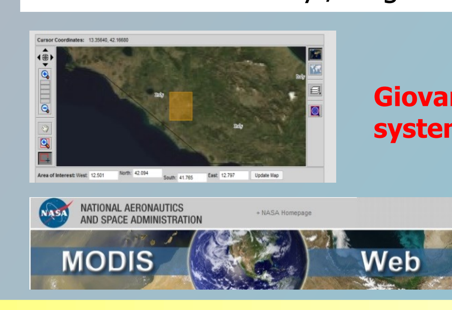
UHI phenomena can occur both day and night, the latter mainly affected by the release of the heat, stored during the day, by low albedo surfaces such as asphalt and urban structures



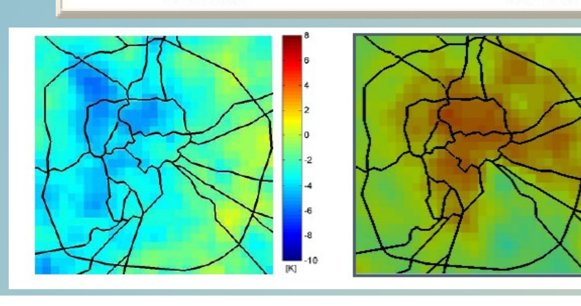
Average monthly temperatures ground detected by the sensor AIRS (Atmospheric Infrared Sounder) aboard the NASA Aqua satellite (MODIS) on the area of Rome, with maximum measured relative to HW in July / August 2003

Typical profile of surface temperature in UHI conditions





Giovanni online data system, NASA GES DISC



Example of UHI on ROME in 2003 July at h:9:00 AM-PM da MODIS

Methodologies

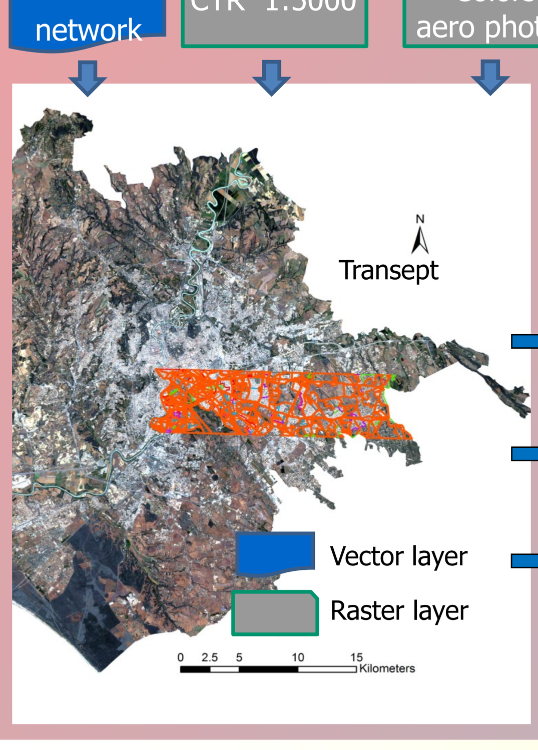
Photointerpretation

Classification of the transept residential areas on the basis of **typology**, urban fabric **compactness** and soils **permeability** parameters by assigning partial increasing levels of vulnerability to estimate INV (Numerical Vulnerability Index)

Input

Road network | CTR 1:5000 | Colors aero photos

Hypothesis: the characteristics of typology and compactness of the urban fabric (M1L) and the soils permeability determine the thermal response to climatic forcing.



290 polygonal, of urban residential fabric, delimited by roads in the transept

11 classes Morfo-type 1° liv. = M1L, on transect

11 building **typology** (T) in 6 levels of partial vulnerability

2	4	6	8	10	20

M1L=T+ C

4 **compactness** levels (C)

5	10	20	35

INV=T+ C + P

3 soil **permeability** levels (P)

1	20	45

Vulnerability Numerical Index INV (0-100)

Photo interpretation attributes polygonal areas with relative levels of partial vulnerability

290 polygonals

M1L

INV

Object Classification

Classification of the urban fabric of the entire municipality on the basis of its typology and compactness parameters (M1L) by EO

Municipality areas segmentation [1] with 3400 polygonal
Extraction of the values of the 51 variables (spectral, textural / GLCM and morphological)

Spectral indices derived from surveys multispectral Landsat 8 OLI :
$NDVI=(R_4-R_3)/(R_4+R_3)$;
$NBUI=(R_6-R_5)/(R_5+R_6)$ [3];
$NDGI=(R_3-R_2)/(R_2+R_3)$.
R_n = banda Landsat n

Identification and characterization of the training areas (40) on the polygonal photo interpreted (290)

Supervised classification per urbanized pixel

Selection of urbanized poligonal (1481) on the basis of the percentage (> 0,15) of pixels available

Data mining algorithms

Algorithims Test
C4.5 (Decision Tree);
BVM (Ball Vector Machine);
C-SVC (Support Vector Machine);
K-NN (K-nearest-neighbors);
RnTr (Random Forest Tree).

		Train/test (70-30)
	O.A.	err.rate
C4.5	0.50	0.92
BVM	0.65	0.92
C-SVC	0.88	0.85
K-NN	0.33	0.85
RnTr	0.98	0.60

Selection algorithm on the basis of accuracy (OA and error-rate) obtained on polygonal training

Classification of polygonal (1481) using the selected algorithm (Random Forest Tree) [2]

11 classes M1L, on Municipal territory

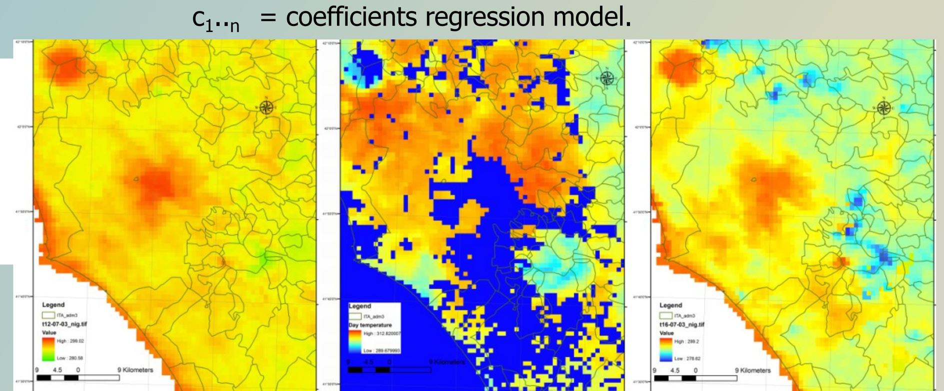
M1L

Calibration

Use of the maps of ground temperature detected by the satellite sensors for calibration/validation of the linear model of INV introduced:

$$T=c_1\ M1L + c_2\ Alt + \sum_{1}^{N} c_n * V_n$$

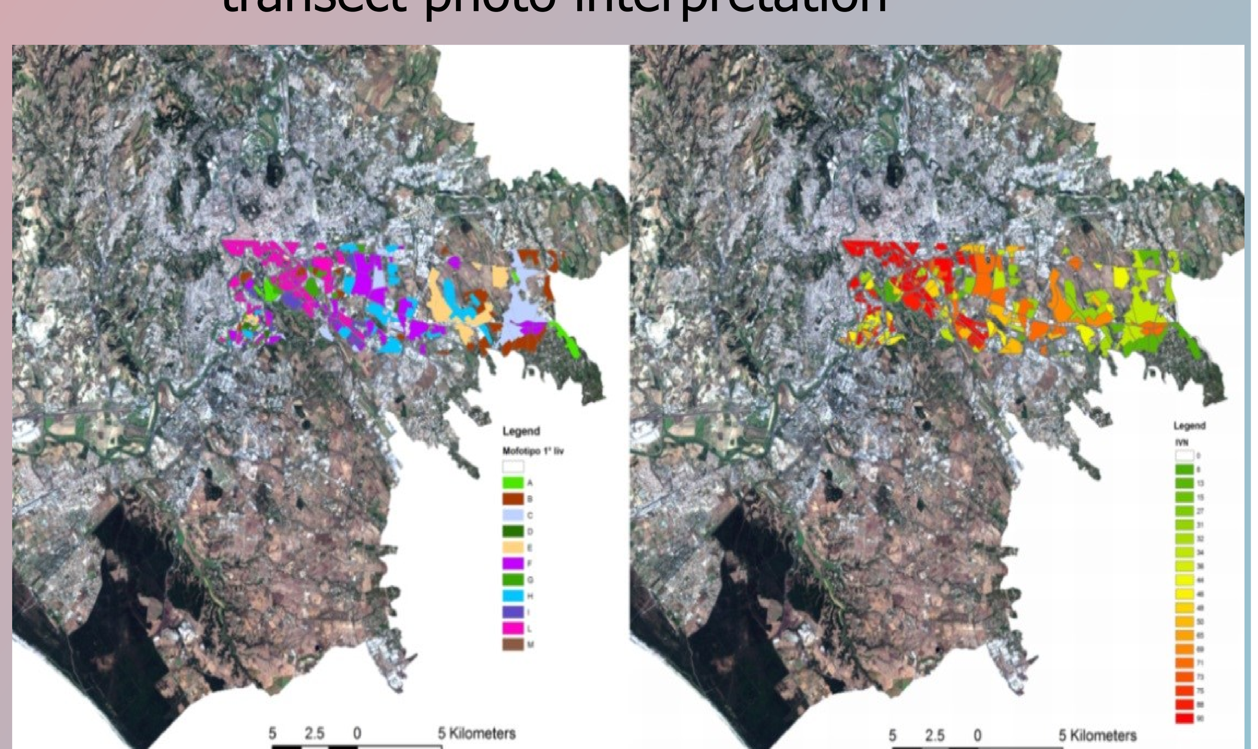
M1L = 1° level morph type;
Alt. = Altimetry;
V_n = Most significant variables (back. Stepwise regression) derived from spectral indices EO;
T = temperature distribution of UHI nighttime;
$c_{1..n}$ = coefficients regression model.



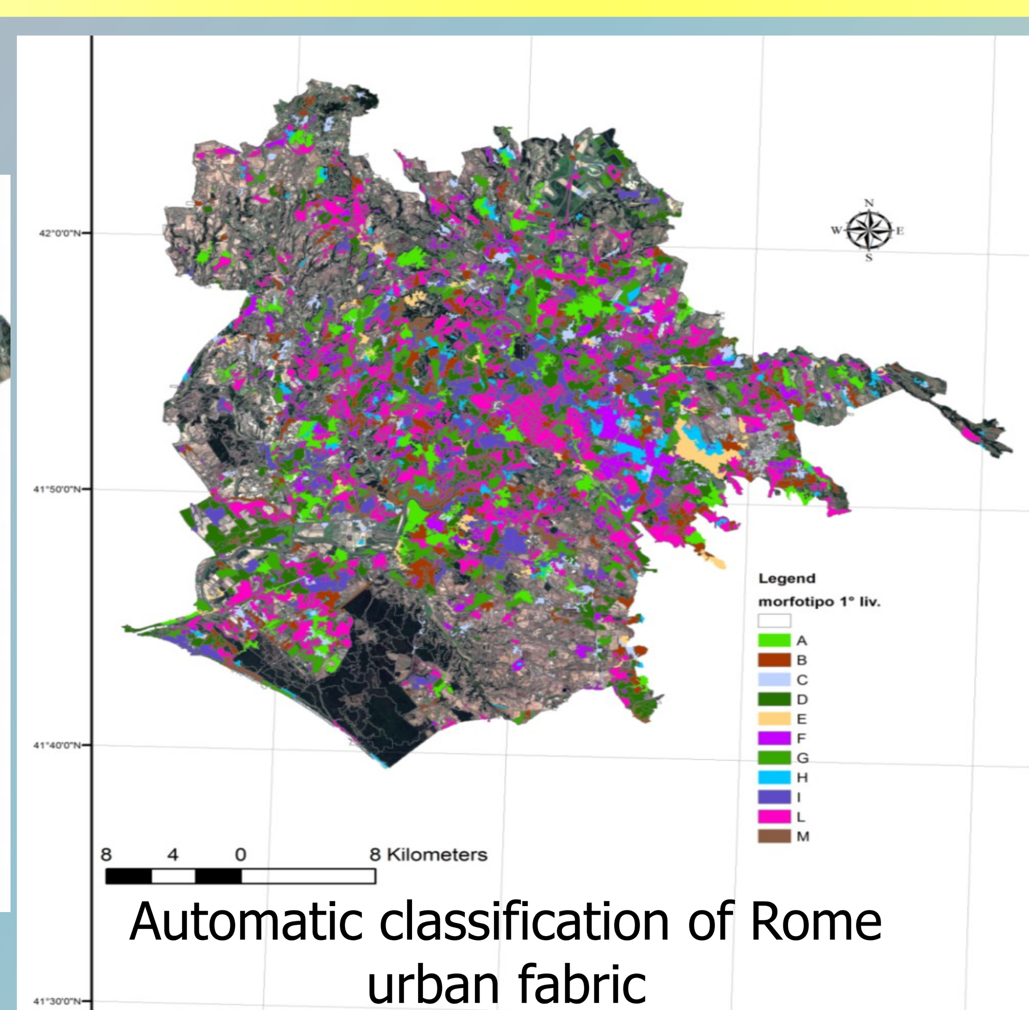
LST (Land Surface Temperature) detected by the MODIS sensor on days 07.12.2003 (left) and 30.9.2003 (center), and 16.7.2003 (right) at 21:30 on the town of Rome. There are visible UHI nocturnal effects (left and right)

Results

M1L and INV distributions obtained by transect photo interpretation



Classification of the urban residential areas on the basis of typological and compactness M1L (left) parameters, INV distribution obtained by adding the permeability contribution (right). It highlights plausibly increased vulnerability going from the periphery to the center city, where prevails the presence of more compact urban fabric, with more scarcity of permeable soils and vegetation.



Automatic classification of Rome urban fabric

Distribution on the entire municipality of M1L classes obtained by the integrated procedure of object classification (algorithm RnTr) and data mining.

Calibrated regression model

LST = 765*M1L -980.66*NDVI -589.74*NBUI -0.0086*Alt. (m.) +1.46*Diss. NBUI + 302.91

Model calibration was based on the nocturnal LST distribution of MODIS on 12-07-2003 (previous picture) that is relative to the HV period and clearly presents the typical form of UHI in contrast to daylight.

Conclusions :

Calibration through LST has allowed estimation of coefficients on physical basis of the INV model, derivable by considering also the altimetry dependency. The five variables included in the final model were the most significant (R^2 = 0.409, P-value $<10^{-5}$). Furthermore it can be seen that variable resulting from photo-interpretation of the urban fabric characteristics, M1L, presents a positive effect compared to a temperature increment, in agreement with the initial hypothesis. The NDVI, assumed like proxy of the percentage of permeable and vegetated areas, together with the elevation, plausibly it demonstrates a mitigating effect (negative coefficients). The contribution of NBUI (Built Up Index) is less easily interpretable together with its texture parameter Diss.NBUI (dissimilarity), obtained through GLCM (Gray Level Occurrence Matrices) and linked to the local contrast and compactness of the urban fabric.

Bibliografia:

1.Baatz, M., Schäpe A.: Object-Oriented and Multi-Scale I age Analysis in Semantic Networks. In: Proc. of the 2nd International Symposium on Operationalization of Remote Sensing August 16th – 20th, 1999. Enschede. ITC.;

2.Breiman, L. (2001). "Random Forests". Machine Learning 45 (1): 5–32. doi:10.1023/A:1010933404324;

3.Hanqiu Xu. Extraction of Urban Built-up Land Features from Landsat Imagery Using a Thematic oriented Index Combination Technique. Photogrammetric Engineering & Remote Sensing Vol. 73, No. 12, December 2007