



Integration of heterogeneous data to high resolution temperature maps for urban planning and management in the ClimaMi project.

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The ClimaMi Project



Objectives:

- Set up of a functional urban climatology for the metropolitan Milano area
- Promote a more effective knowledge and consideration of the local climate in urban planning and management
- Keynote adaptation to climate change in cities consistently with regional and national plans

www.progettoclimami.it

In 2019 (1° year):

- DB of Milan urban climate (Strumento Informativo Clima Urbano: SI-CU)
- First application to a real case: Comune di Melzo
- Capacity building activities for engineers, architects and agronomists

In 2020 (2° year):

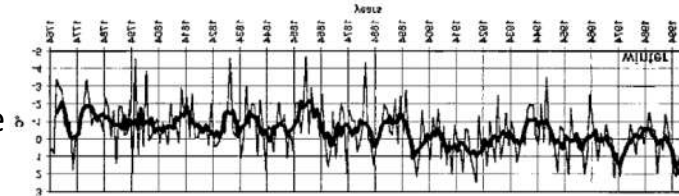
- Extension of SI-CU with Climatic Temperature Atlas
- Functional applications to more projects (Milano and Pavia)
- Further capacity building activities

Stakeholders



Urban Climatology

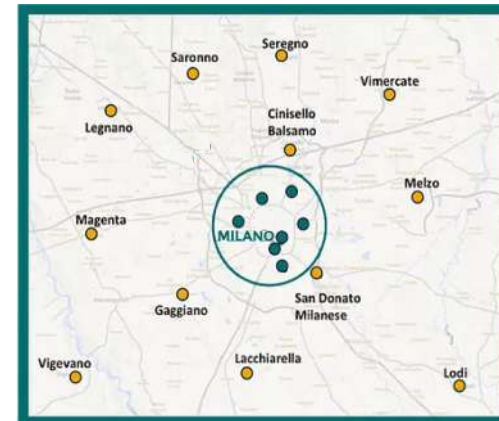
- In general based on long term series by historical observatories
(Milano Brera), or nearby synoptic stations (Linate airport)
but **inadequate** to the emerging needs in evolving cities and climate change



- Strong need** for appropriate measurements
to describe and monitor the complex urban environment,
but
- Missing specialized networks** and climatological procedures



- In Italy only few urban stations, in general for air quality monitoring,
but ...
- OMD has a nationwide urban climatological network since 2011**
with more than 20 stations at top of UCL in and around Milano



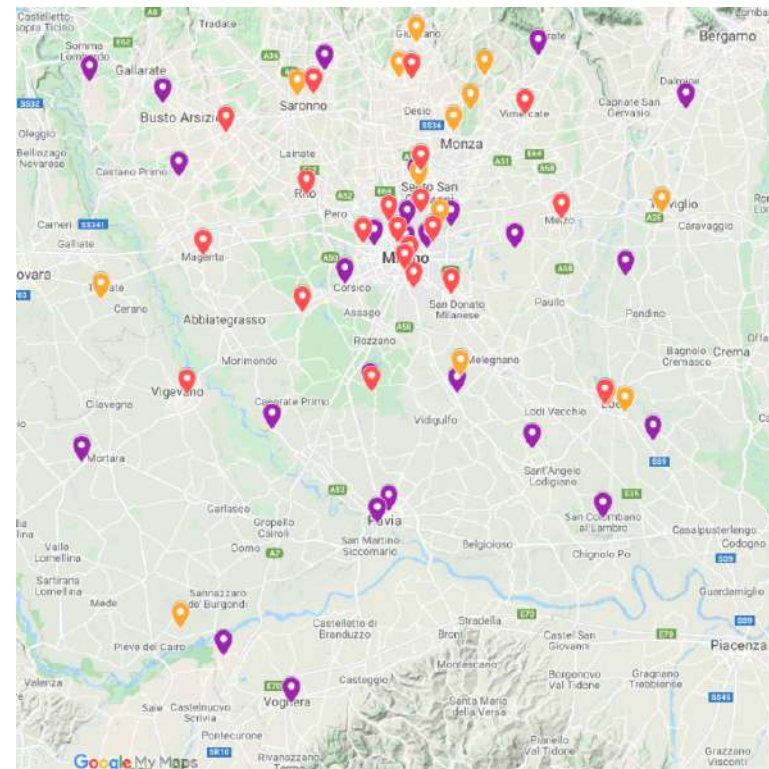
High resolution urban climatology for applications

Given the high variability and complexity of the urban structure,
even the specialized OMD network lacks in accurately describing
and resolving the UCL for a number of important applications:

- therefore, other 40 AWS from third parties have been included in the 2nd year of ClimaMi Project after evaluation of:
 - siting and exposure suitability
 - measurement accuracy
 - sufficient data availability
- but engineers, architects and urbanists often require very high spatial resolution (<100 m)

Several approaches are possible:

- Interpolation of measured air temperatures
- Use of Remote sensing data (LST)
- HR Urban Modelling



A first approach: remote sensing from space

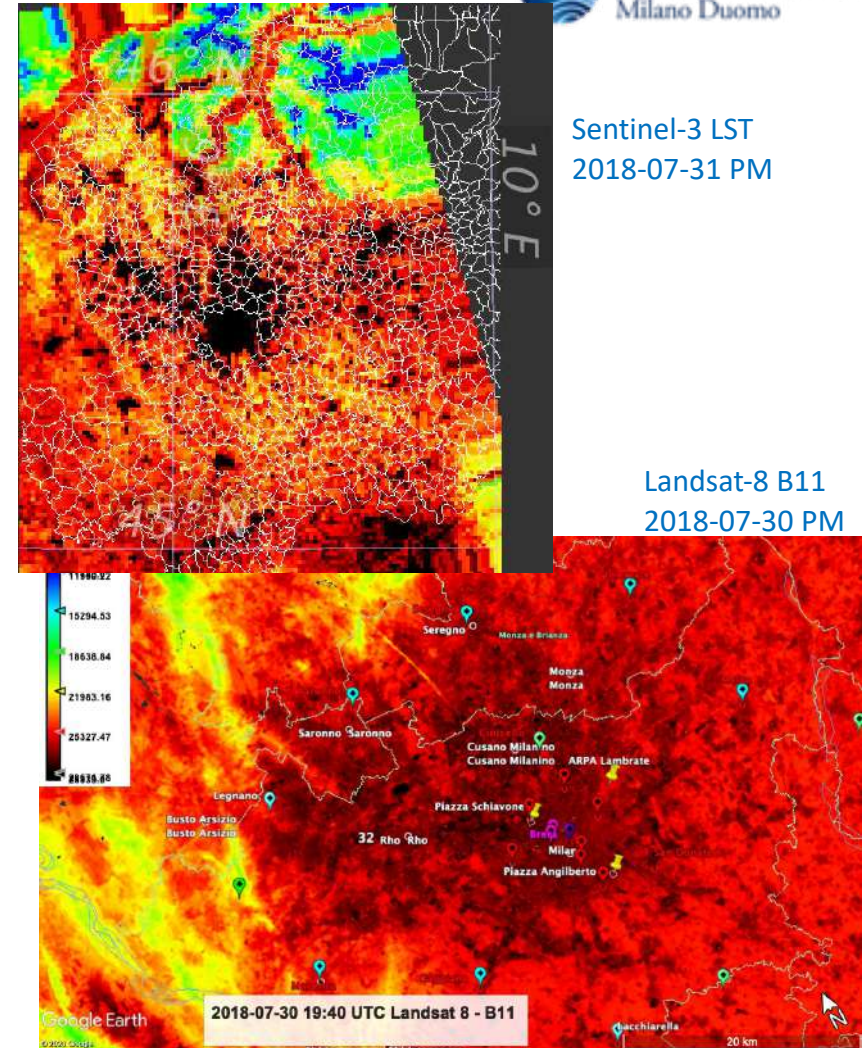
Platform choice:

1. Sentinel-3 (ESA-Copernicus):

- **Pros:** 2 sat. (A & B) since April 2018 (A since 2016), data easy accessible, LST directly provided by ESA
- **Cons:** lower resolution (1 Km)

2. Landsat-8 (NOAA-USGS):

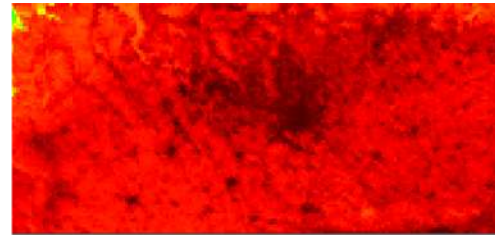
- **Pros:** since 2013, higher resolution (30÷100 m)
- **Cons:** LST (still) not directly provided (but several methods available), some calibration problems in one IR Channel



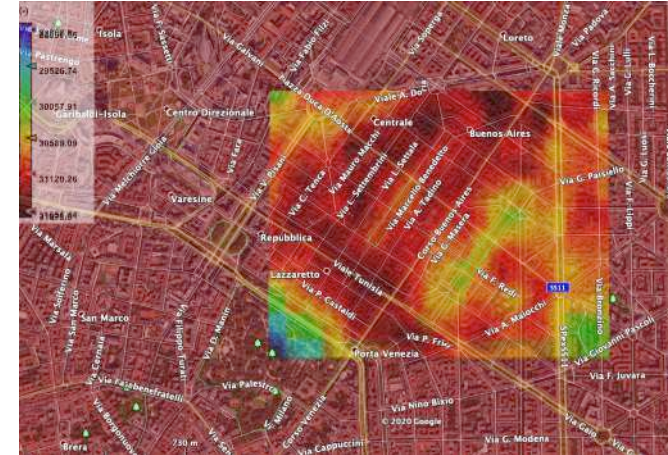
LST: data and algorithms

- Sentinel-3A&B: acceptable number of useful frames in the ClimaMi Project time span
(a total of 54 useful pictures selected)

- Landsat-8:
very few useful frames, used only for single cases and limited urban areas
(ClimaMi experimentations: Melzo, Milano Piazza Angilberto, etc.)



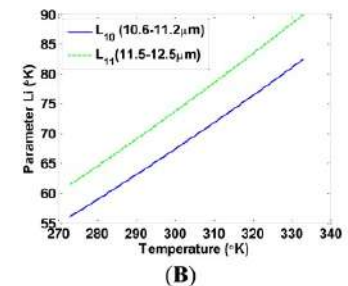
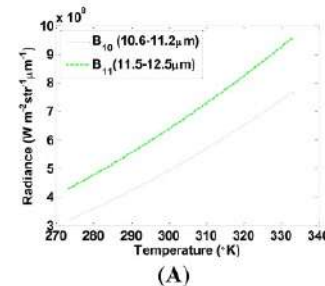
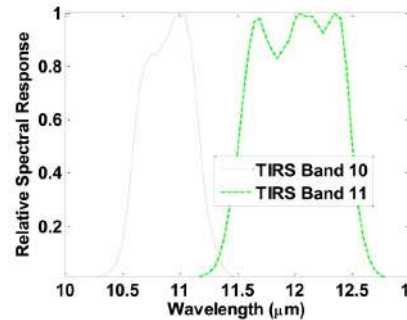
Milan UHI by Sentinel 3 LST Product
2018 07 19 09:25 UTC



Milan Corso Buenos Aires area
Landsat 8 – Band 10
2019-07-30 10:10 UTC

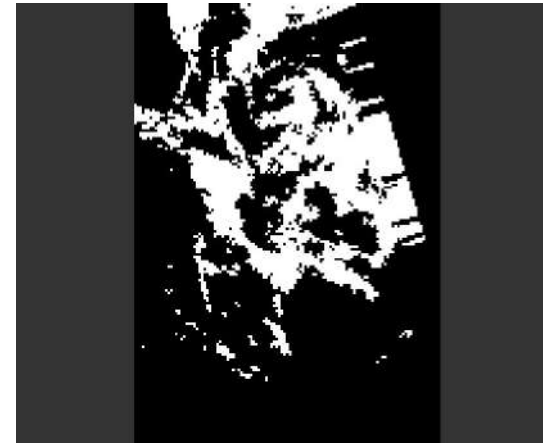
- Split-Window method adopted
for Landsat 8: using 6 channels as in Rozenstein et al. .
Sensors 2014, 14, 5768-5780

$$LST = a + b T_{10} + c T_{11} ; RMSE \approx 1^{\circ}C$$

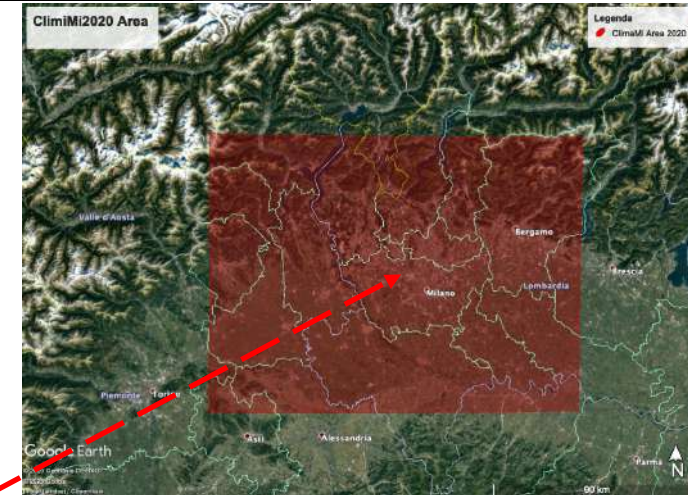


Data Selection Criteria for ClimaMi

- Cloud masks:
Must be **null over the domain**,
but clouds are frequent over the hills in summer
and fog in the Po Valley during winter!
- Full (or almost full) **coverage of the Project area**: 45-46 °N, 8 – 10 °E
Not always satisfied because of orbit geometry
- Meteorology:
Specific (clear sky) weather types based on different
**frequently observed spatial thermal distributions
of interest for practical applications**
(defined by in situ measurements only)



Cloud mask
“thin cirrus” by
Sentinel 3:
2017-08-26-
20:37 UTC



Milan

Project domain used in LST
extraction from Sentinel 3
(at 1 km spatial resolution)

Climatic weather types, UHI and HW

Database : average **hourly data** from 1/7/2015 to 31/08/2019

We considered episodes with:

- atmospheric stability: **high pressure**
- low ventilation: **average wind < 1.3 m/s in Milan**
- intense heat island: **$\text{UHI} \equiv T_u - T_r > 3^\circ\text{C}$** at 11-12 UTC+1 and 22-23 UTC+1 (typical times of satellite passes)

u: OMD urban stations in Milano; **r**: selected stations in the Milan rural neighborhood

- different UHI configurations (**UHI maximum** in one or more the 8 stations downtown Milan):

Station (area)	Frequency of occurrence (%)	Frequency of occurrence (%)	Frequency of occurrence (%)	Frequency of occurrence (%)
	Winter Morning	Winter Night	Summer Morning	Summer Night
Bicocca (NE)	17.8	0.5	0.0	2.3
Bocconi, Centro, Sarpi (downtown)	45.6	79.4	0.0	58.4
Bovisa (NW)	3.3	0.0	0.0	19.7
Città Studi (E)	15.6	18.7	0.0	17.6
San Siro (W)	15.6	1.4	0.0	0.6
Sud (S)	2.2	0.0	0.0	1.4

Separately considered : **Heat Waves** (at least two consecutive days with

minimum and maximum temperatures above a certain threshold)

Sentinel 3 - LST and T_{air} : Correlations?

- Bilinear correlations obtained for some test cases:

$$LST = f(T; NDVI)$$

T_a : near surface Air Temperature

NDVI: Norm. Diff. Vegetation Index

- computed from ≈ 40 in situ independent measurements (OMD + ARPA Lomb.).

- AM episodes:

R^2 up to 0,9

Std. Err. as low as $0,5^\circ\text{C}$

- PM episodes results are generally worse

(use of morning Vis channels to obtain NDVI)

Bilinear		Regression							
AM Episods & NDVI		LST = f(T; NDVI)							
		2	4	6	8	10	11	12a	12b
Regression	R^2	0,03	0,8	0,8	0,8	0,7	0,7	0,6	0,5
	$m(T)$	-0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
	$m(NDVI)$	6,7	-16,5	0,3	-16,5	-7,6	-3,4	0,5	-7,1
	c	2,0	40,0	28,6	26,7	15,9	4,4	0,0	4,7
	Std. Err. (LST)	2,7	1,2	0,8	0,9	1,2	1,2	1,2	0,5
F (sign. if ≥ 40)		1	83	77	99	40	37	28	112
Other info	Missing stations	6	6	5	6	0	5	5	6
	Nr. Flags Nubi	9	0	0	0	1	6	35	9
	$\Delta = [\sum(LST-T)] / n$	4,3	8,1	12,2	6,5	5,0	2,7	-1,0	-1,0
	$\sigma(\Delta)$	3,2	4,4	5,9	3,4	1,9	1,5	1,2	1,2
	T mean	-1,6	24,6	29,6	27,1	19,6	7,3	6,1	8,6

Bilinear		Regression							
PM Episods with AM NDVI		LST = f(T; NDVI) (evening hours and morning NDVI)							
		2	4	6	8	10	11	12a	12b
Regression	R^2	0,3	0,5		0,3	0,4			
	$m(T)$	0,3	0,5		0,2	0,9			
	$m(NDVI)$	-6,7	-7,9		-7,5	-4,0			
	c	-1,4	13,6		18,8	-5,7			
	Std. Err. (LST)	1,4	1,7		1,9	1,2			
F (sign. if ≥ 40)		8,2	17,7		9,2	39,7			
Other info	Missing stations	6	11		6	1			
	Nr. Flags Nubi	2	0		6	88			
	$\Delta = [\sum(LST-T)] / n$	-0,7	-1,4		-1,6	-9,7			
	$\sigma(\Delta)$	1,7	1,9		2,3	2,8			
	T mean	-3,0	20,0		23,1	23,6			

A second approach: Air temperatures via cokriging (COK)

STEP 1

Building of the **empirical semivariogram** γ for both air temperature and LST satellite data

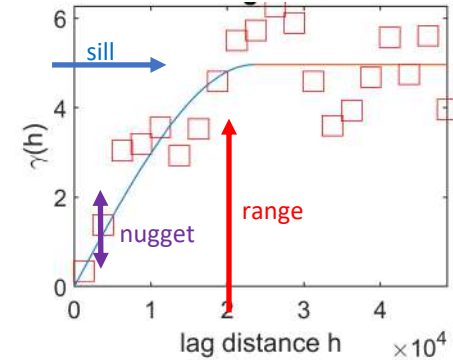
$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2$$

Z is the regionalized variable, x_i the position in the domain, h the separation distance between two points and $N(h)$ the pairs of points separated by h .

STEP 2

Fitting of a model to the empirical semivariogram (*spherical model*).

RANGE, SILL, NUGGET



STEP 4

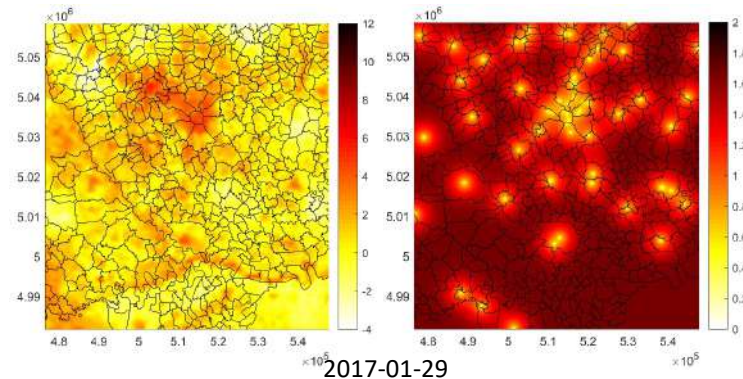
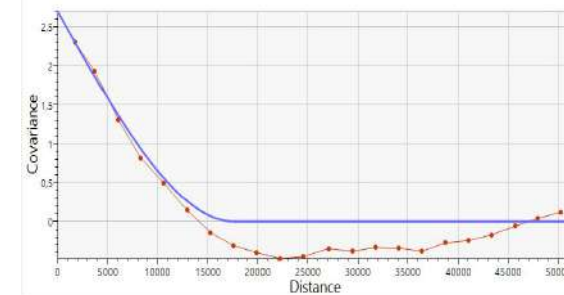
Performing the **cokriging interpolation**

$$z_1^*(x_0) = \sum_{\alpha=1}^{n_1} \lambda_{\alpha} \cdot z_1(x_{\alpha}) + \sum_{\alpha=1}^{n_2} \omega_{\alpha} \cdot z_2(x_{\alpha})$$

where z_1 is air temperature and z_2 is the LST (λ_{α} and ω_{α} are the corresponding weights)

STEP 3

Building and fitting the crossvariogram (covariance)



Estimated air temperature

Error on estimated air temperature

First results for the the ClimaMi Atlas (end 2020)

Land Surface temperature:
remotely sensed twice a day
for selected situations (100 m)
(secondary variable)

Air temperature at top of UCL:
HQ hourly data at low
spatial resolution (> 1000 m)
(primary variable)

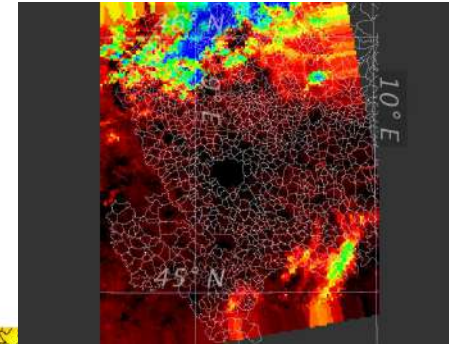
CoKriging

Air Temperature (T_a)

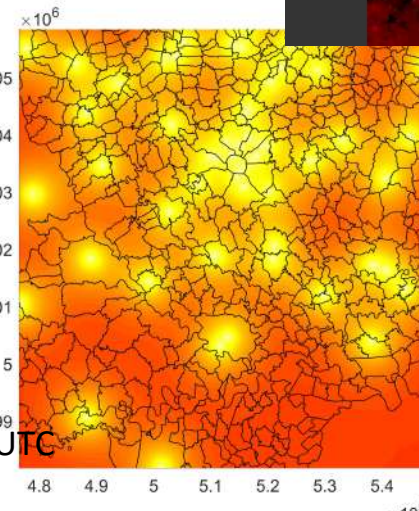
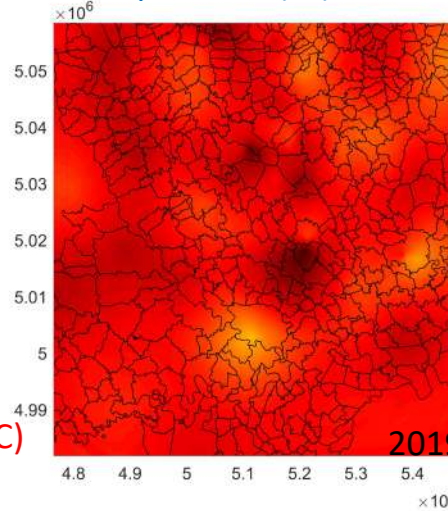
T_a Errors

Air Temperature measured by
the surface network

⇒ High Resolution (100 m) maps
of Air temperature
with Low Uncertainty ($< 1.5^\circ\text{C}$)

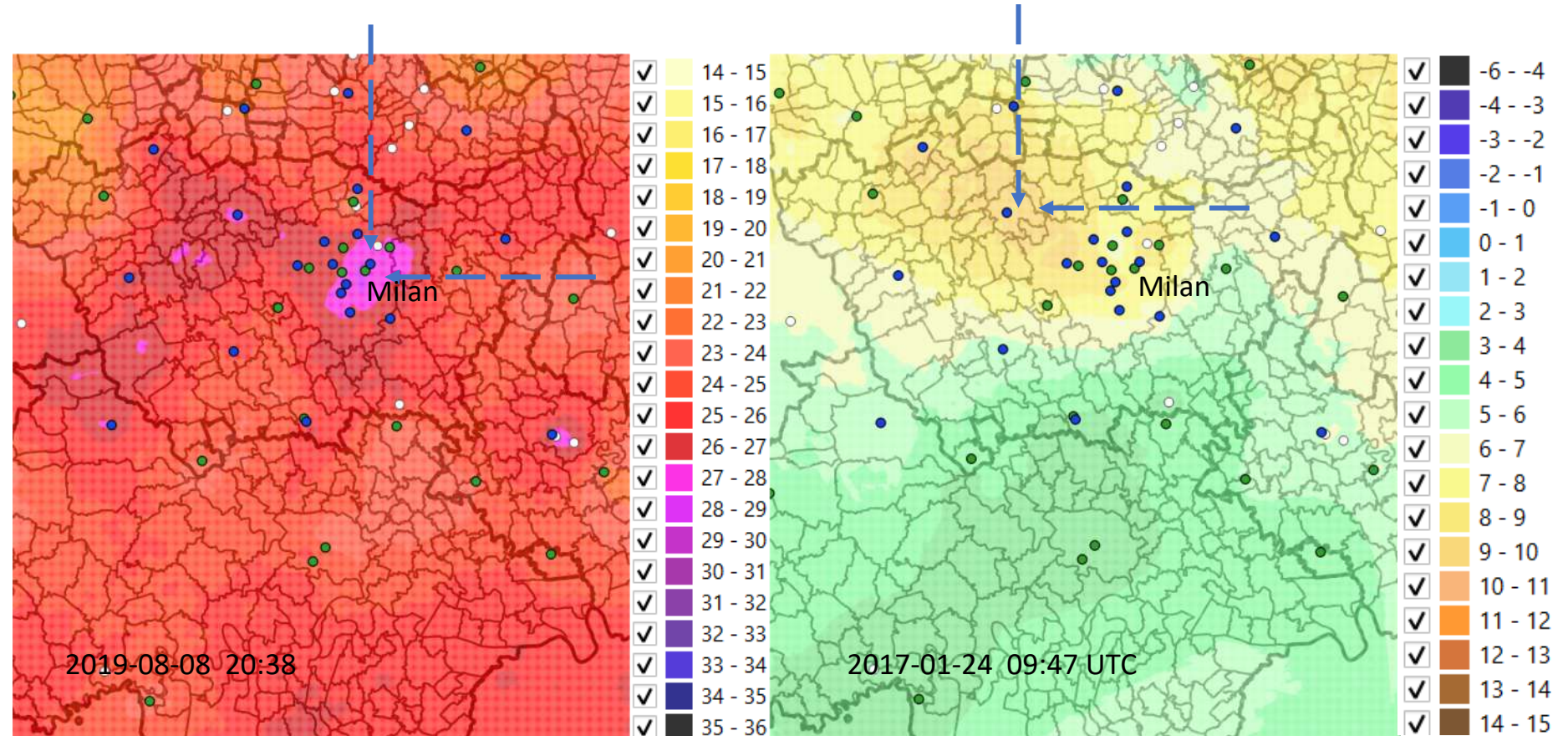


Sentinel 3
Land Surface
Temperature



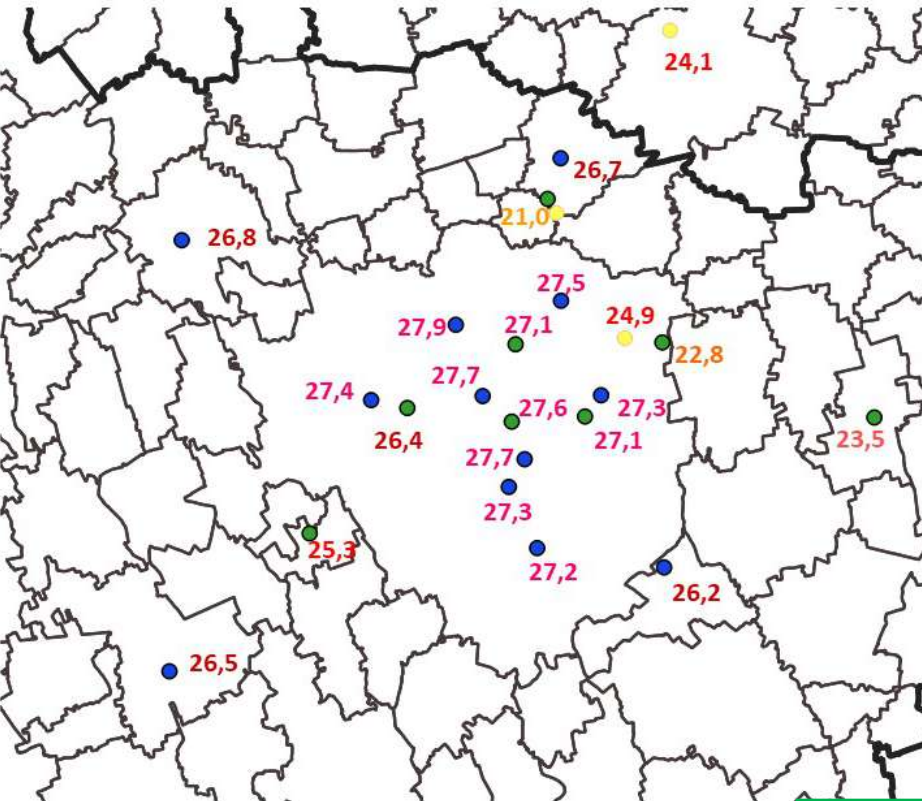
ClimRisk2020-Frustaci

Near surface Air Temperatures: summer and winter cases

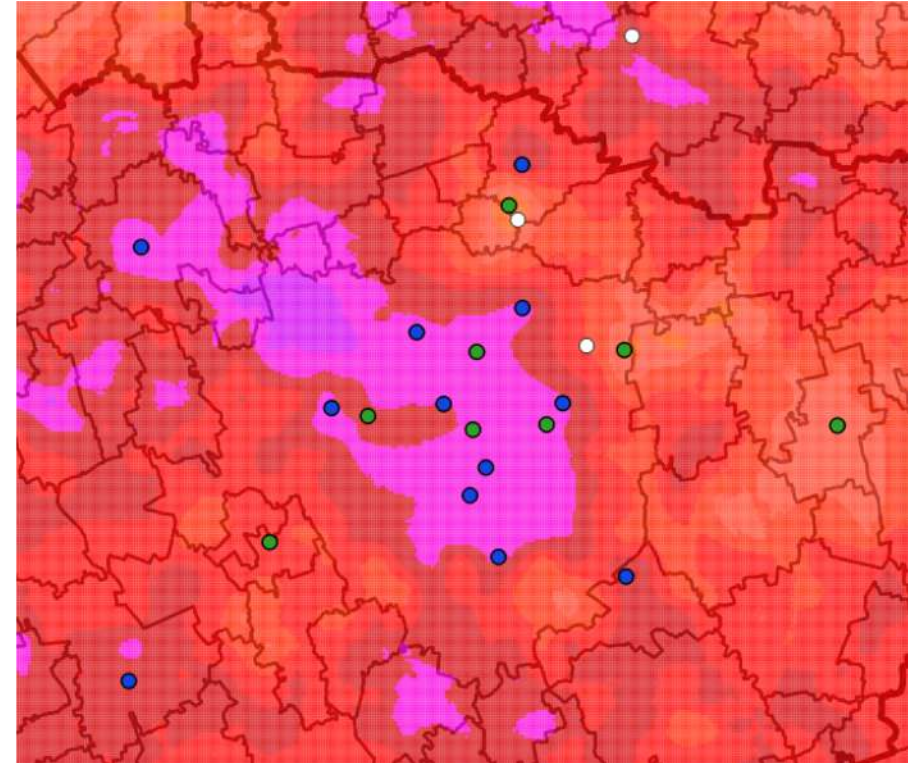


Close up for an evening episode

UCL Air Temperatures by AWS

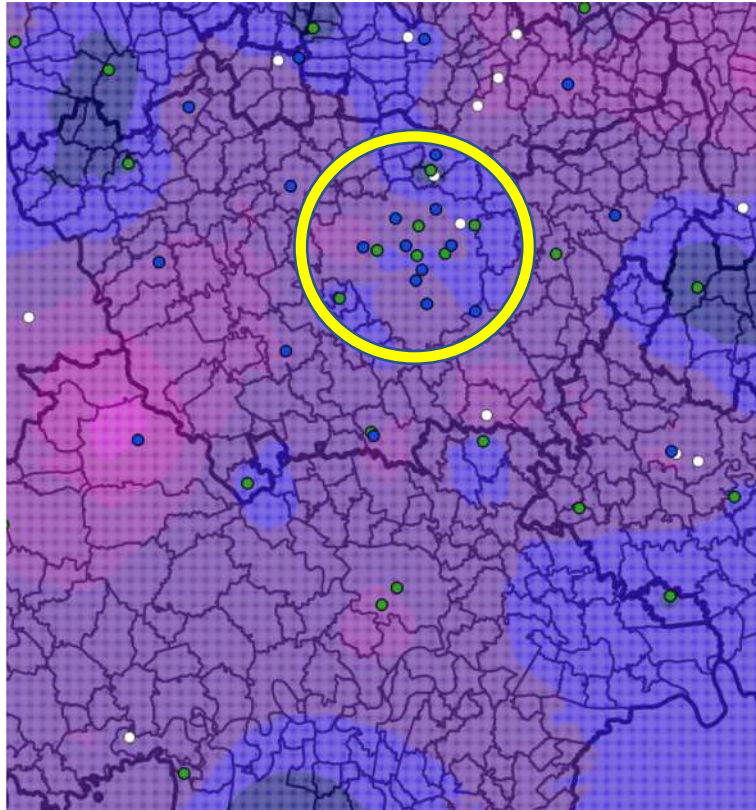


UCL Air Temperature obtained via co-Kriging

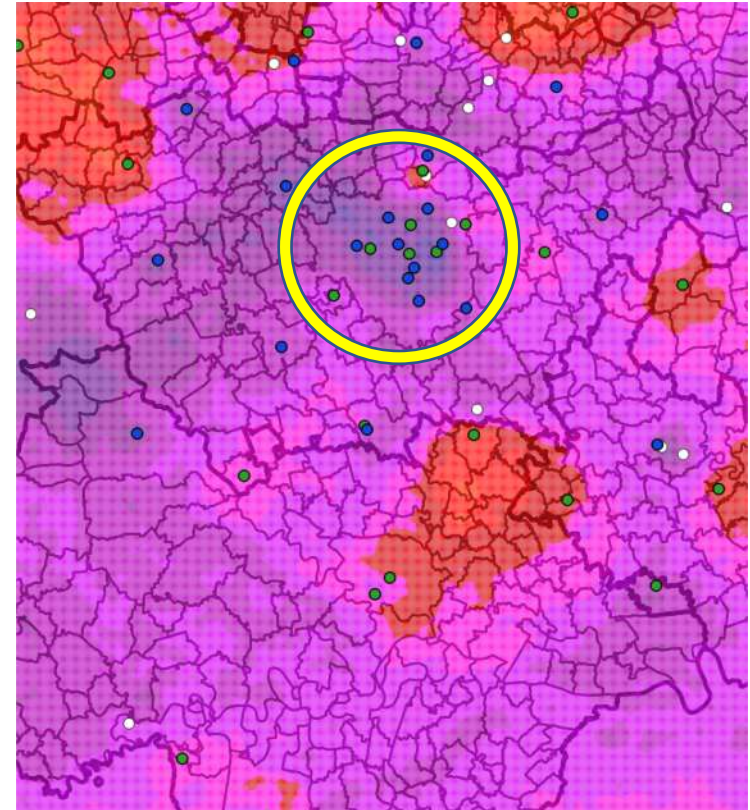
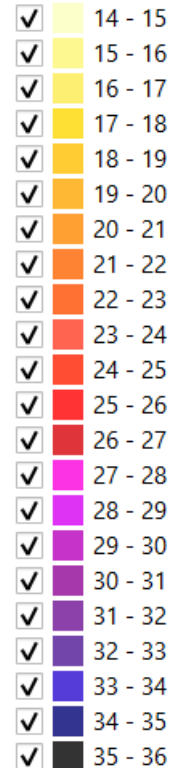


2018 – 07 – 08 21 UTC

Near surface Air Temperatures: Heat Waves



2019-06-26_10 UTC



2019- 06- 26_21 UTC

Summary

- Starting from in situ “ad hoc” **urban measurements** . . .
- Selecting climatic **relevant weather situations** . . .
- Integrating “**remote sensing**” data . . .
- Using an appropriate and efficient **co-Kriging method** . . .

to obtain a

high resolution and climatically representative thermal mapping

for urban adaptation and resilience applications

<https://www.progettoclimami.it/>

<https://www.fondazioneomd.it/>

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Further developments:

- *Time span extension and larger statistics*
- *Future platforms and higher resolution*
- *Improving regression and co-kriging methods*

*Thank you for listening!
Any question?*