ACCADEMIA NAZIONALE DEI LINCEI

Climate variability in Italy during the last two millennia
Italy 2k

HIGH-RESOLUTION TEMPERATURE CLIMATOLOGY FOR ITALY: INTERPOLATION METHOD INTERCOMPARISON

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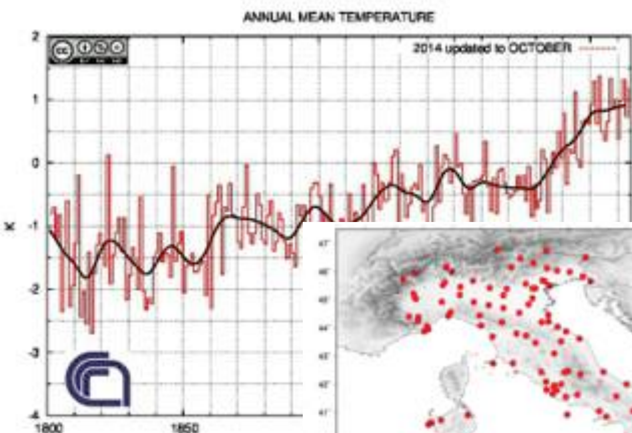
WHY DO WE NEED HIGH RESOLUTION TEMPERATURE CLIMATOLOGIES?

ITALY HAD A VERY IMPORTANT ROLE IN THE DEVELOPMENT OF METEOROLOGICAL OBSERVATIONS AND ACCUMULATED A HUGE HERITAGE OF DATA DURING THE PAST CENTURIES



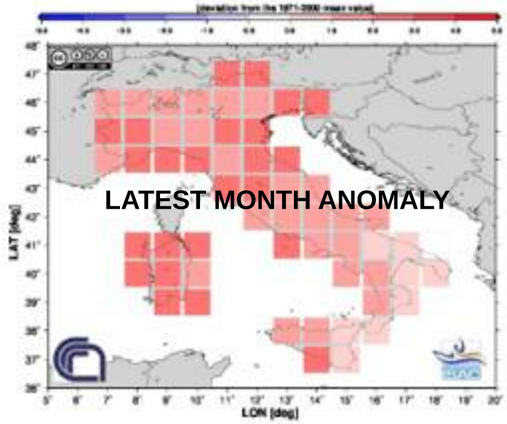
INVENTION OF SOME OF THE MOST IMPORTANT METEOROLOGICAL INSTRUMENTS (THERMOMETER, BAROMETER).

ESTABLISHMENT OF THE FIRST NETWORK OF OBSERVATIONS (ACCADEMIA DEL CIMENTO)

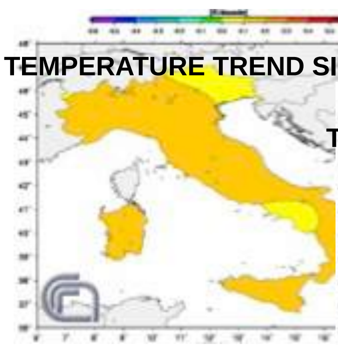
SIX STATIONS HAVE BEEN **ACTIVE SINCE THE EIGHTEENTH CENTURY** (BOLOGNA, MILAN, ROME, PADUA, PALERMO AND TURIN) AND OTHER 15 STATIONS WHERE OBSERVATIONS STARTED IN THE FIRST HALF OF THE NINETEENTH CENTURY (AOSTA, FLORENCE, GENOA, IVREA, LOCOROTONDO, MANTUA, NAPLES, PARMA, PAVIA, PERUGIA, TRENTO, TRIESTE, UDINE, URBINO AND VENICE).

WITH THE PRESENT AVAILABILITY OF LONG-TERM STATION DATA WE CAN PRODUCE GRIDDED DATA SETS EXPRESSED IN TERMS OF ANOMALIES.

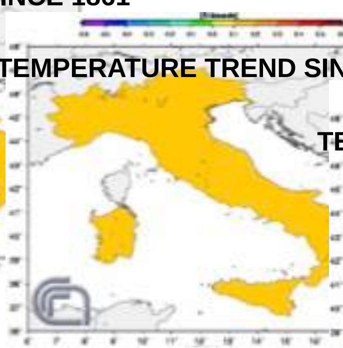
THESE PRODUCTS ARE VERY USEFUL TO STUDY **CLIMATE VARIABILITY AND CHANGES** OVER THE PAST.......



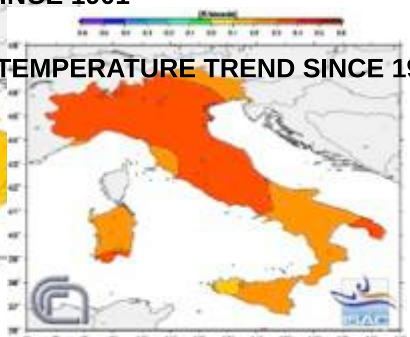
LATEST MONTH ANOMALY



TEMPERATURE TREND SINCE 1861



TEMPERATURE TREND SINCE 1901

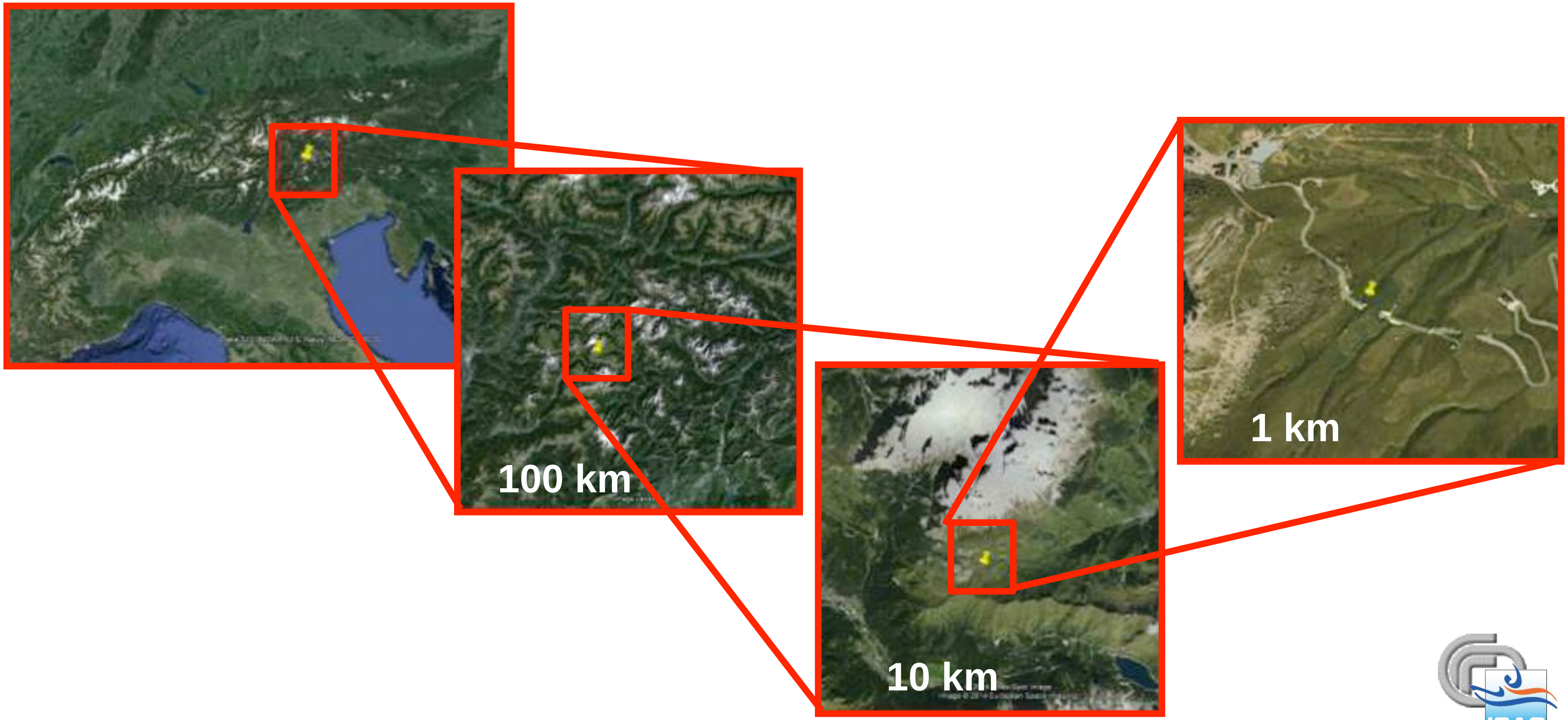


TEMPERATURE TREND SINCE 1961

WHY DO WE NEED HIGH RESOLUTION TEMPERATURE CLIMATOLOGIES?

…HOWEVER, ROUGH RESOLUTION DATA EXPRESSED AS ANOMALIES CANNOT ANSWER TO SPECIFIC QUESTIONS RELEVANT FOR CLIMATE IMPACT-RELATED STUDIES AND FOR MANY APPLICATIONS.

How can I get the climate information (e.g. a monthly temperature series in absolute values) relative to a remote place where a meteorological station is not available?



HOW TO CONSTRUCT HIGH RESOLUTION TEMPERATURE SERIES IN ABSOLUTE VALUES

We can describe the **spatio-temporal structure of the climate signal** over a given area by the superimposition of two fields: the climatic normals over a given reference period (i.e. the **climatologies**) and the departures from them (i.e. the **anomalies**).

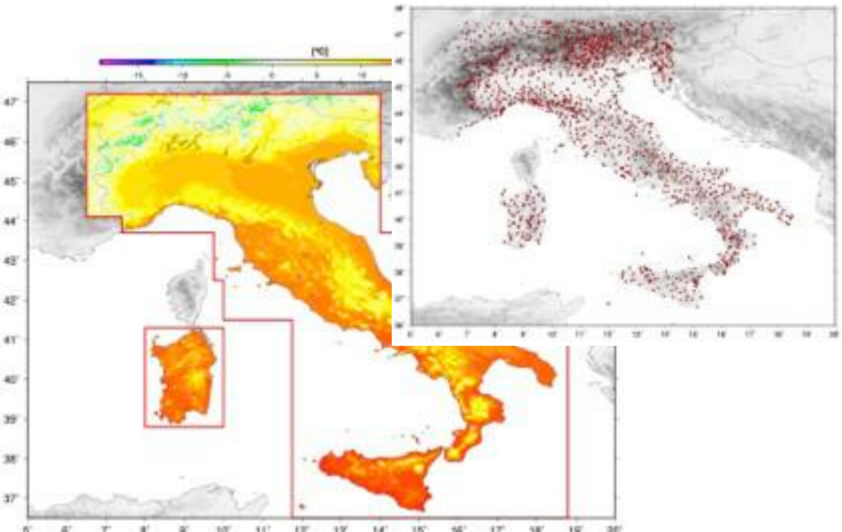
(Mitchell and Jones, 2005. ***Int J Clim***, **25**, 693-712)

Climatologies are basically linked to the geographic features of the territory and they can manifest **remarkable spatial gradients**.

Very high number of station 20-30 years long needed to evaluate the complex orography influences on temperature gradients.

Anomalies are linked to climate variability and change and they are generally characterized by **rather low spatial gradients**.

Sparse but at least 50-100y long station data needed to evaluate the time behavior of temperature over the past.



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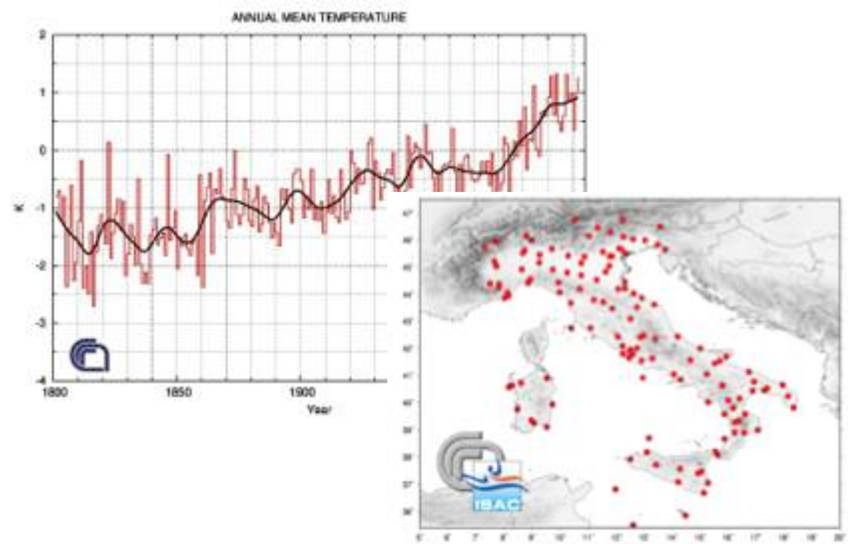


The two fields can be **reconstructed in a completely independent way** and can be **based on completely different databases**.

From the superimposition of climatology and anomaly fields we get temperature series in absolute values at 1kmX1km spatial resolution.

SPATIAL INTERPOLATION OF ANOMALIES

A **radial** and a **vertical** gaussian weighting functions with the following form are used:

$$w_i^{rad}(x,y) = e^{-\left(\frac{d_i^{r^2}(x,y)}{c_r}\right)} \qquad w_i^{h}(x,y) = e^{-\left(\frac{d_i^{h^2}(x,y)}{c_h}\right)}$$

with

$$c_r = -\frac{\overline{d}_r^{\,2}}{\ln 0.5} \qquad c_h = -\frac{\overline{d}_h^{\,2}}{\ln 0.5}$$

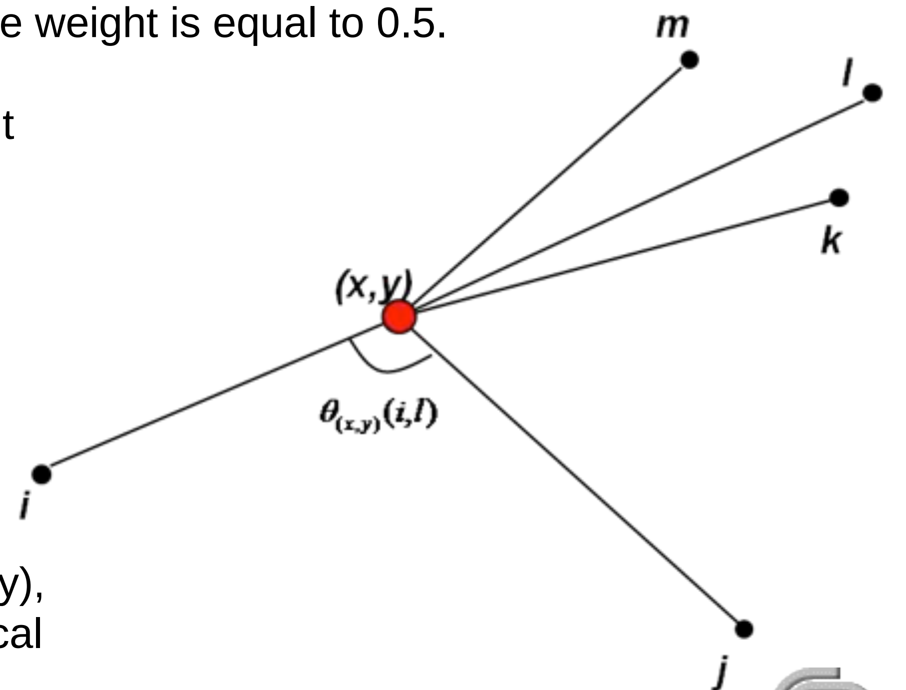
i runs along the stations

$d_i^{r(h)}$ is the horizontal (vertical) distance between the station *i* and the grid point (x,y)

$\overline{d}_{r(h)}$ is the horizontal (vertical) distance at which the weight is equal to 0.5.

An **angular** weight is also used to take into account spatial anisotropy in stations' location:

$$w_i^{ang}(x,y) = 1 + \frac{\sum_{l=1}^{n} w_l^{rad} \cdot w_l^{h} \cdot \left[1 - \cos\theta_{(x,y)}(i,l)\right]}{\sum_{l=1}^{n} w_l^{rad}(x,y) \cdot w_l^{h}(x,y)}$$



$\theta_{(x,y)}(i,l)$ is the angular separation of stations *i* and *l* with the vertex of the angle defined at grid point (x,y), and $w_l^{rad}(x,y)$ and $w_l^{h}(x,y)$ are the radial and vertical weights as defined above.

$$w_i(x,y) = w_i^{rad}(x,y) \cdot w_i^{h}(x,y) \cdot w_i^{ang}(x,y)$$

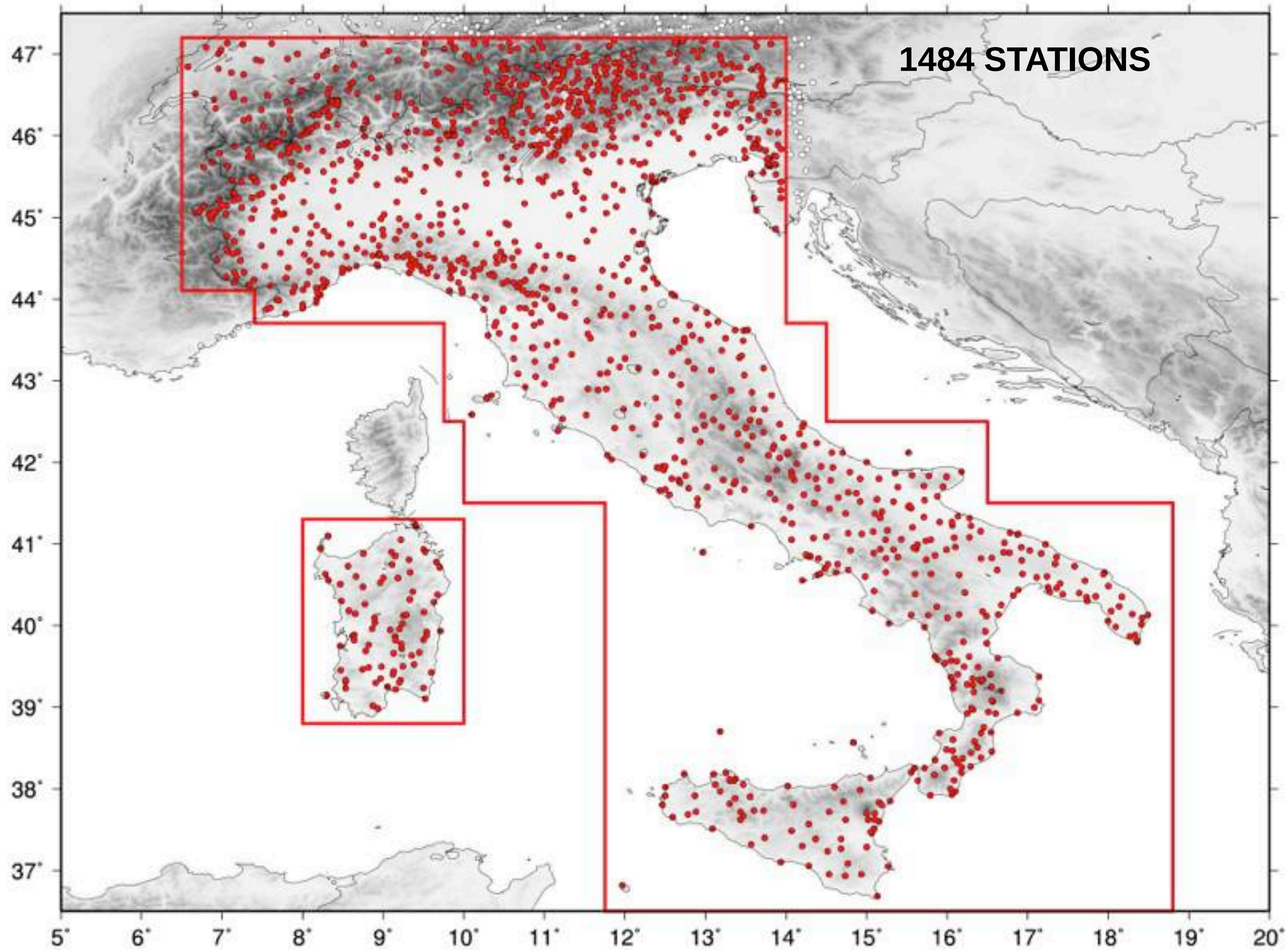
SPATIAL INTERPOLATION OF CLIMATOLOGIES

TO GET THE CLIMATE NORMALS AT HIGH SPATIAL RESOLUTION (**1km^2**).

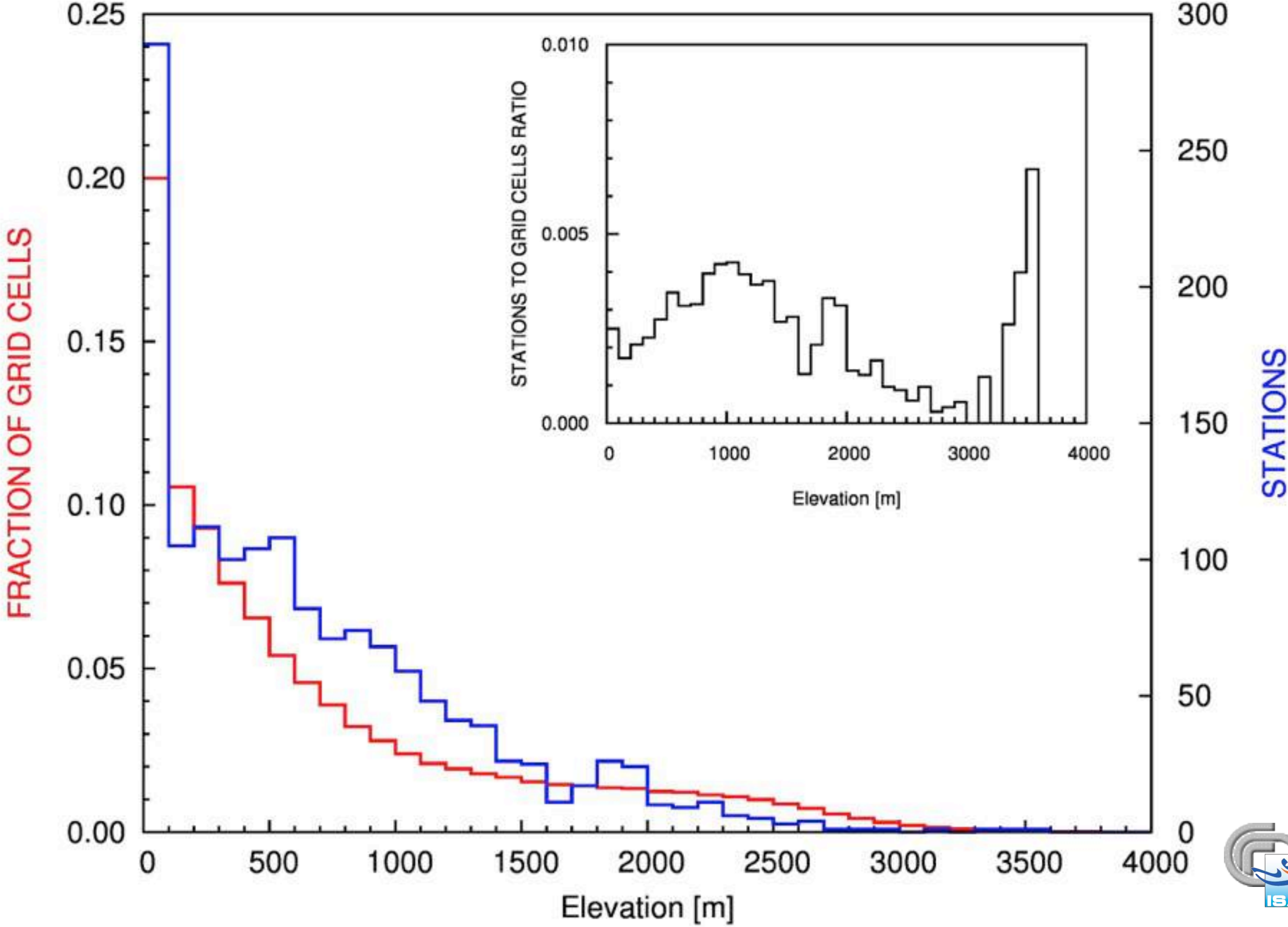
WE NEED:

- **AN ADEQUATE DATA SET** TO DESCRIBE THE CORRECT SPATIAL GRADIENTS AT THE RESOLUTION WE HAVE CHOSEN
- **AN ADEQUATE PROCEDURE** TO CAPTURE THE CORRECT DEPENDENCE OF THE VARIABLE ON GEOGRAPHICAL PARAMETERS

THE DATA (FIRST GUESS)

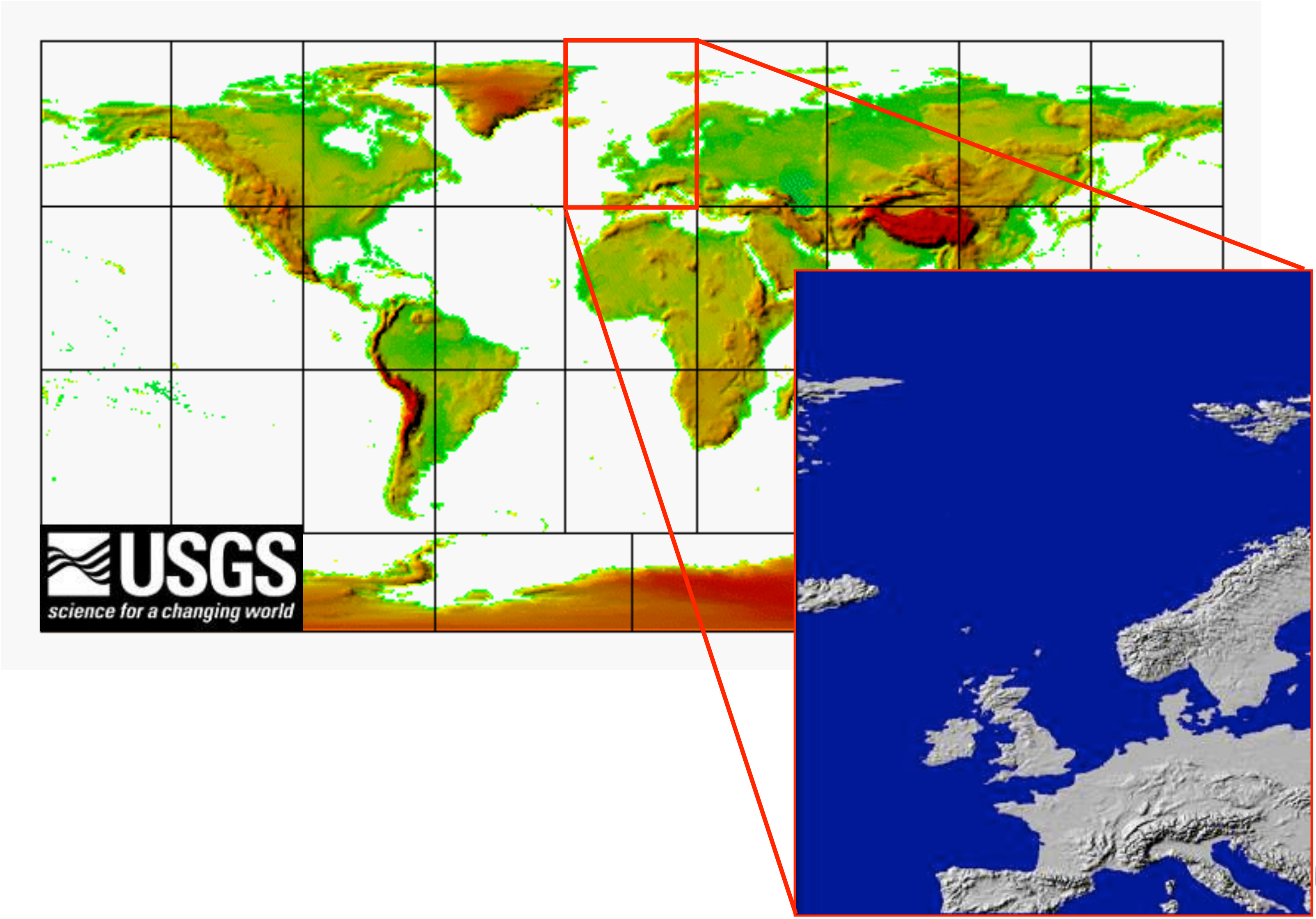


THE DATA (FIRST GUESS)



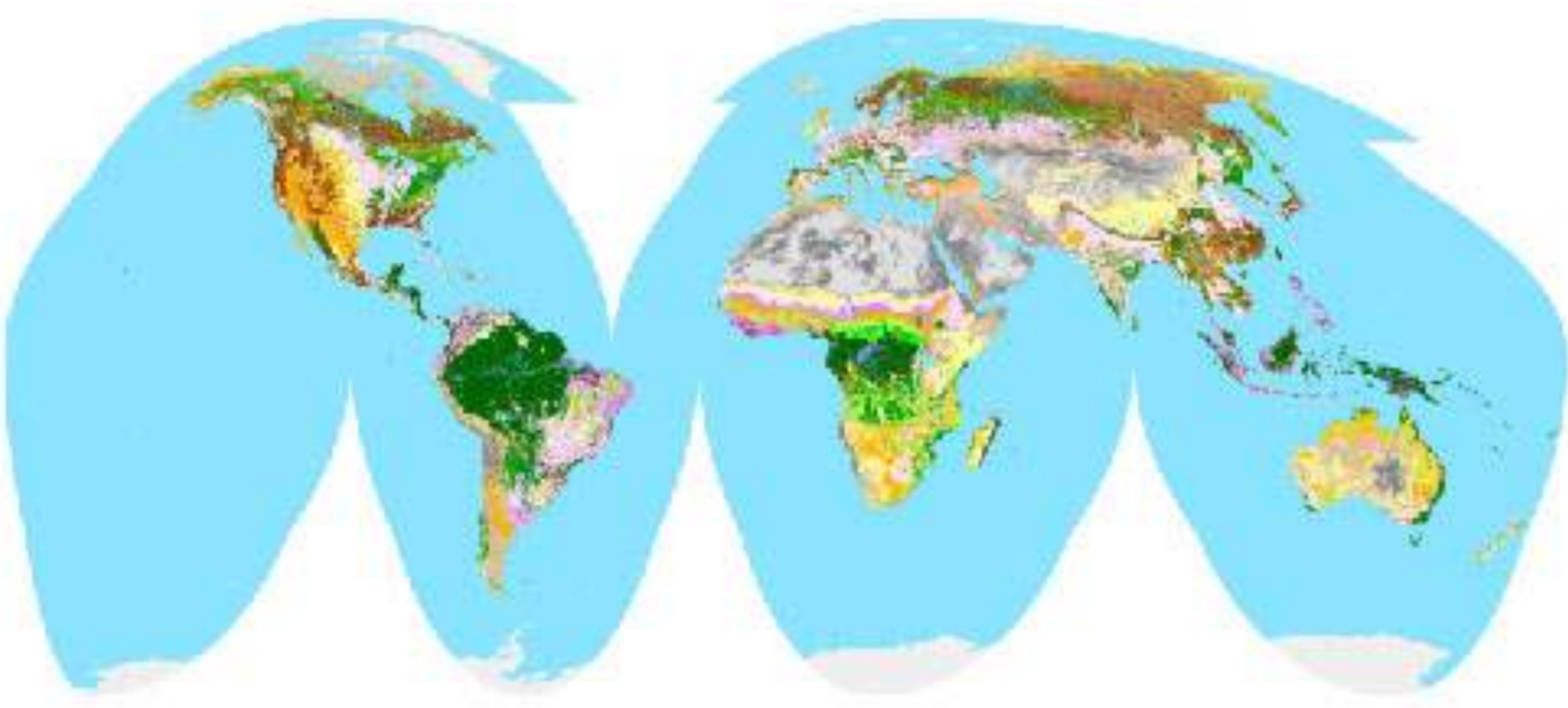
ADDITIONAL DATA

30 arcsecdonds Digital Elevation Model



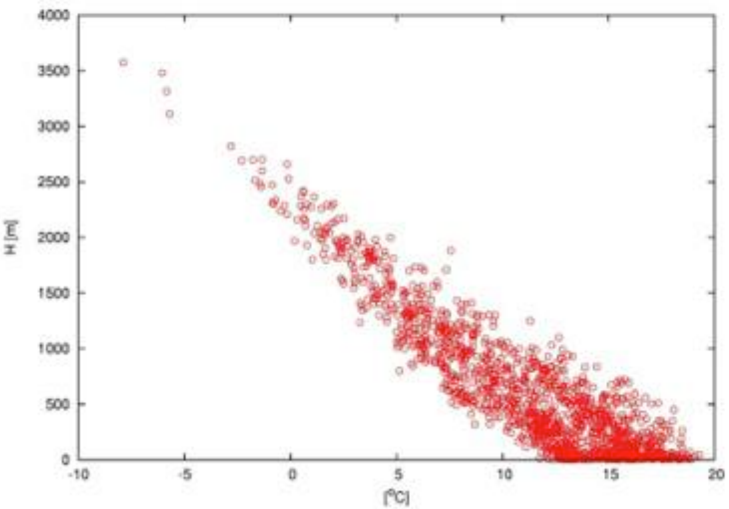
ADDITIONAL DATA

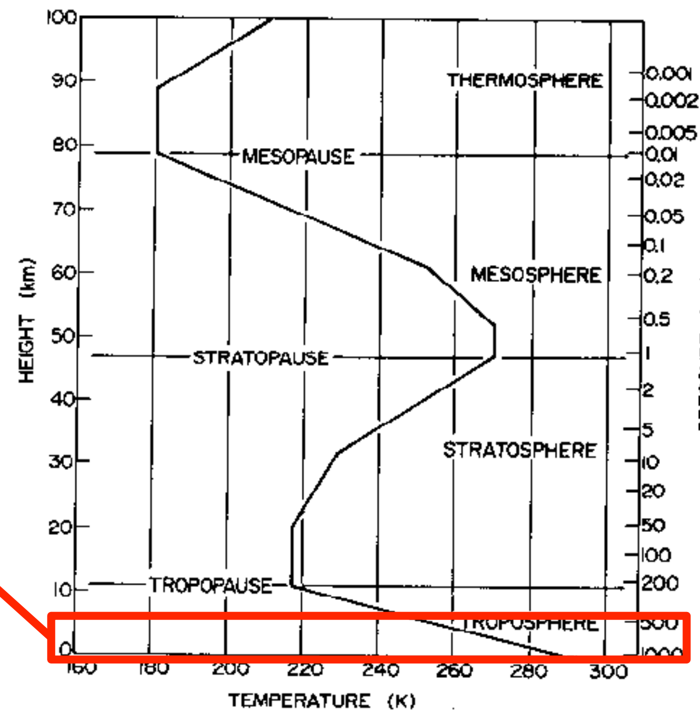
Global Land Cover 2000 (GLC 2000) of the Joint Research Centre



THE INTERPOLATION METHODS

Temperature decrease with elevation in the troposphere





However the **lapse rate is locally different** depending on various factors:

- Total solar radiation received (i.e. slope orientation and steepness)
- Sea mitigating effect
- Pool air cooling (i.e. temperature inversion effect)

FOR THESE REASONS A GLOBAL T vs H RELATIONSHIP IS NOT APPROPRIATE, AND WE MUST TAKE INTO ACCOUNT FURTHER IMPROVEMENTS TO A GLOBAL APPROACH, OR CONSIDER A LOCAL ESTIMATION OF THE LAPSE RATE.

THE INTERPOLATION METHODS

THREE DIFFERENT METHODS TO FACE THIS PROBLEM:

-Multi Linear Regression with Local Improvements (MLRLI)

-Regression Kriging (RK)

-Local Weighted Linear Regression of Temperature versus Elevation (LWLR)

MULTI LINEAR REGRESSION WITH LOCAL IMPROVEMENTS (MLRLI)

MULTI LINEAR REGRESSION WITH LOCAL IMPROVEMENTS (MLRLI)

The first step of this method consists in applying, for each month, a **Multi Linear Regression** (MLR) of temperature versus **elevation** (h), **latitude** (ϕ) and **longitude** (λ) to the entire station normal data set.

$$T = T(\lambda,\phi) = m_0 + m_1 \cdot h(\lambda,\phi) + m_2 \cdot \lambda + m_3 \cdot \phi$$

The monthly residuals (ε) from the MLR are then subjected to further analyses aimed at identifying the most significant relations with additional geographical and physiographical variables.

Step by step, improvement terms are added to the MLR equation and after each step temperature residuals from this new equation are considered.

The final result is an equation expressing temperature as a function of the various variables F(h, λ, ϕ, dsea,....).

This equation can be finally applied to each grid-cell of a DEM to construct, for each month, a high-resolution temperature climatology.

MLRLI – IMPROVEMENT TERMS

The effects producing relevant improvements to the temperature estimation are:

i) Sea effect

ii) Lake effect

iii) Po Plain Continentality Effect

iv) Slope orientation effect for both the non-smoothed and the smoothed DEM

v) Summit/Valley Effect

vi) Urban Heat Island Effect

MLRLI – SEA AND LAKE EFFECTS

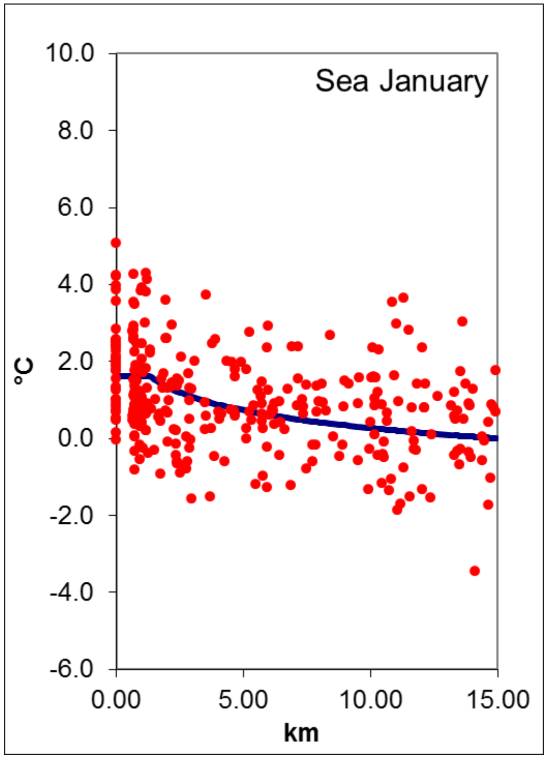
The sea and lake effects account for the sea and, to a less extent, lake water **mitigation effect**.

According to the analysis of scatter plots of temperature residuals versus *dsea*, the **sea effect** was modelled by attributing to the grid-cells with *dsea* ≤ 1.3 km the average residual ($\overline{\varepsilon}_{dsea}$) of the corresponding stations having *dsea* ≤ 1.3 km (excluding the Po Plain stations).

It was also imposed that this effect vanishes when *dsea*≥15 km.

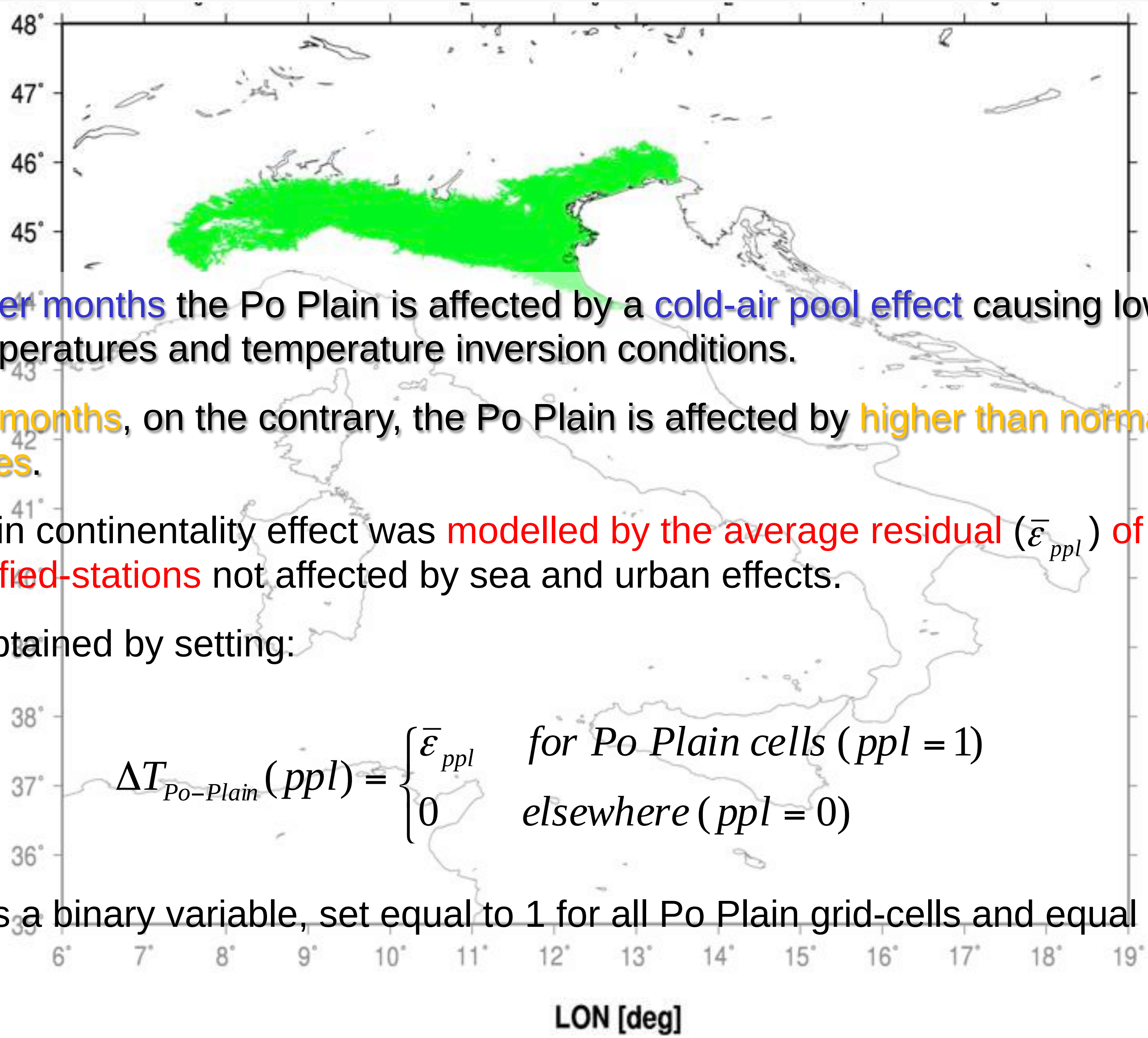
This was obtained by setting:

$$\Delta T_{sea}(dsea) = \begin{cases} \overline{\varepsilon}_{dsea} & if\ dsea \le 1.3km \\ \overline{\varepsilon}_{dsea}\left(1 - \dfrac{\ln(dsea/1.3)}{\ln(15/1.3)}\right) & if\ 1.3km < dsea < 15km \\ 0 \quad if\ dsea \ge 15km \end{cases}$$



The **lake effect** is similar to, but less prominent than, the sea effect and it was taken into account using a similar approach. In this case, however, the number of stations was too small to study the decrease of the effect with the distance from the lake (*dlake*); for this reason we attributed to the grid-cells with *dlake* ≤ 1.3 km the average residual of the corresponding non Po Plain stations within this distance from the lakes and half of this value to grid-cells with 1.3 ≤ *dlake* ≤ 2.6 (km).

MLRLI – PO PLAIN CONTINENTALITY EFFECT



During winter months the Po Plain is affected by a cold-air pool effect causing lower than normal temperatures and temperature inversion conditions.

In summer months, on the contrary, the Po Plain is affected by higher than normal temperatures.

The Po Plain continentality effect was modelled by the average residual ($\bar{\varepsilon}_{ppl}$) of all Po Plain classified-stations not affected by sea and urban effects.

This was obtained by setting:

$$\Delta T_{Po-Plain}(ppl) = \begin{cases} \bar{\varepsilon}_{ppl} & for\ Po\ Plain\ cells\ (ppl = 1) \\ 0 & elsewhere\ (ppl = 0) \end{cases}$$

where *ppl* is a binary variable, set equal to 1 for all Po Plain grid-cells and equal to 0 otherwise.

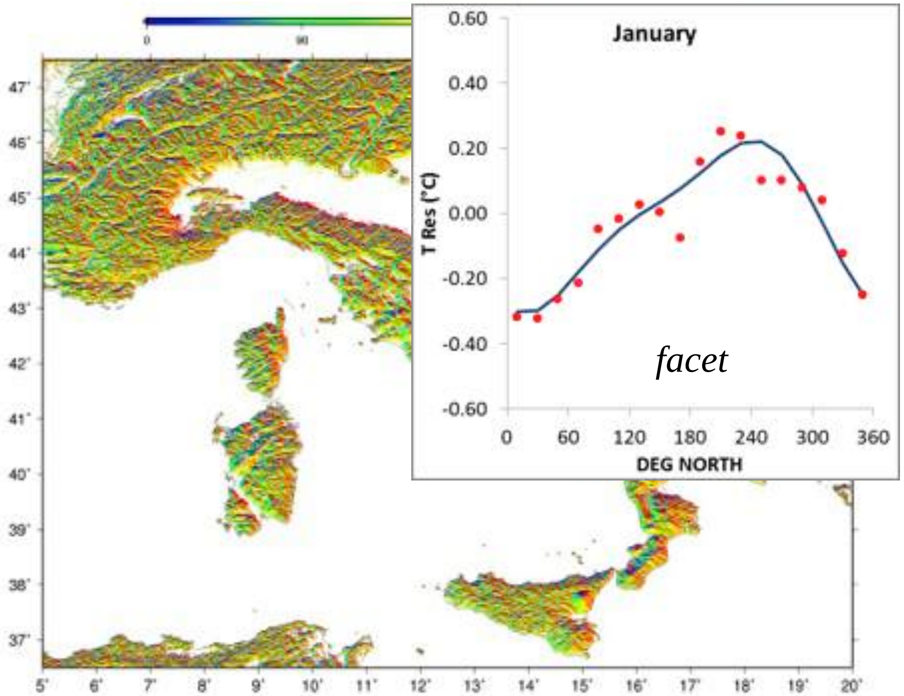
MLRLI – SLOPE ORIENTATION (FACET) EFFECT

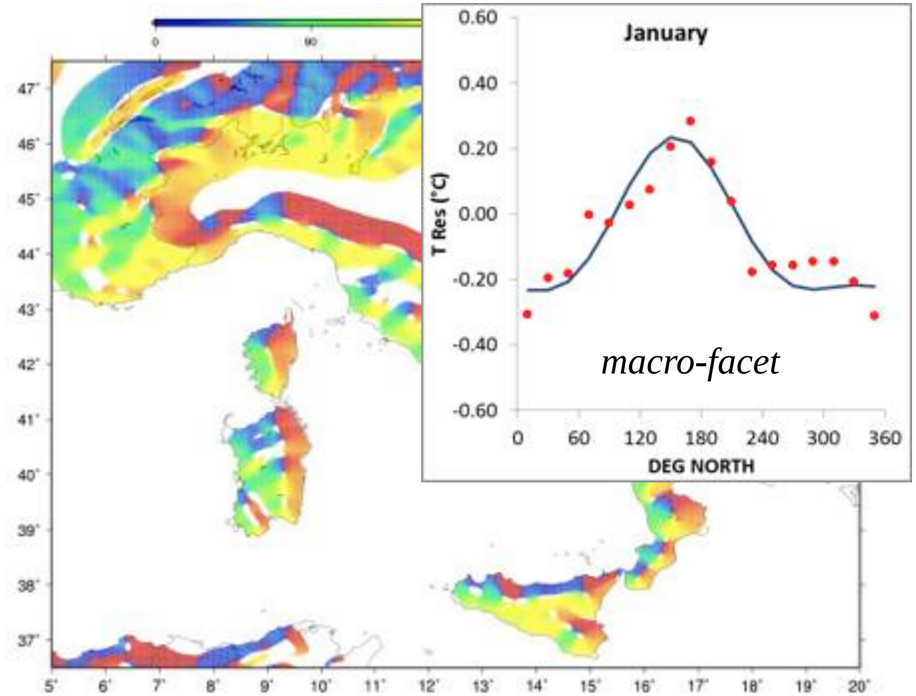
We estimated a *facet effect* and a *macro-facet effect*.

The former accounts for the effect of *exposition to solar radiation*, whereas the latter is aimed to investigate the *effect of large scale topographic barriers* (e.g. the Alpine and Apennines ridges) on the spatial temperature distribution.

These effects were modelled binning the station residuals into **36 exposition intervals** 10 degrees wide and fitting the corresponding values by means of the **first two harmonics of a Fourier series**.

With these fits we got, for any grid-cell, the facet $\Delta T_{facet}(fc, sl)$ and the macro-facet $\Delta T_{macro-facet}(Mfc, Msl)$ effects, where *fc* and *Mfc* are the facet and macro-facet variables (i.e. the slope orientation in the original and smoothed DEM, respectively).





MLRLI – SUMMIT/VALLEY EFFECT

This effect was introduced to take into account the **cold-air pool effect of the valleys** and the **higher exposition to solar radiation of summits and ridges**.

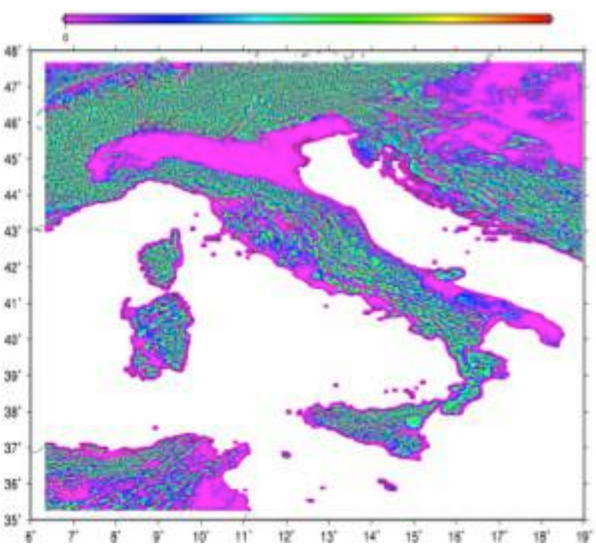
The summit/valley effect was modelled considering a new variable *sv* (the summit-valley variable) defined, for each point (λ,ϕ), as the fraction of the 120 surrounding points (i.e. the grid-points belonging to a 11x11-cell box centred on the grid-point under examination) that satisfy the condition $h(\lambda, \phi) - h(\lambda+i\bullet\Delta\lambda, \phi + j\bullet\Delta\phi) > 50$ m (with *h* indicating the grid-point elevation and *i* and *j* running from -5 to +5 grid-steps).

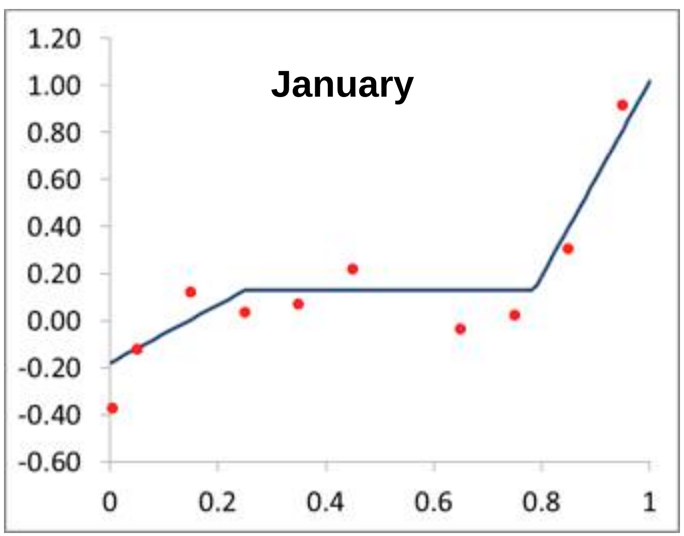
Valleys tend to present *sv* values which are very close to 0, whereas areas on mountain ridges tend to have *sv* values close to 1.

The effect was modelled according to:

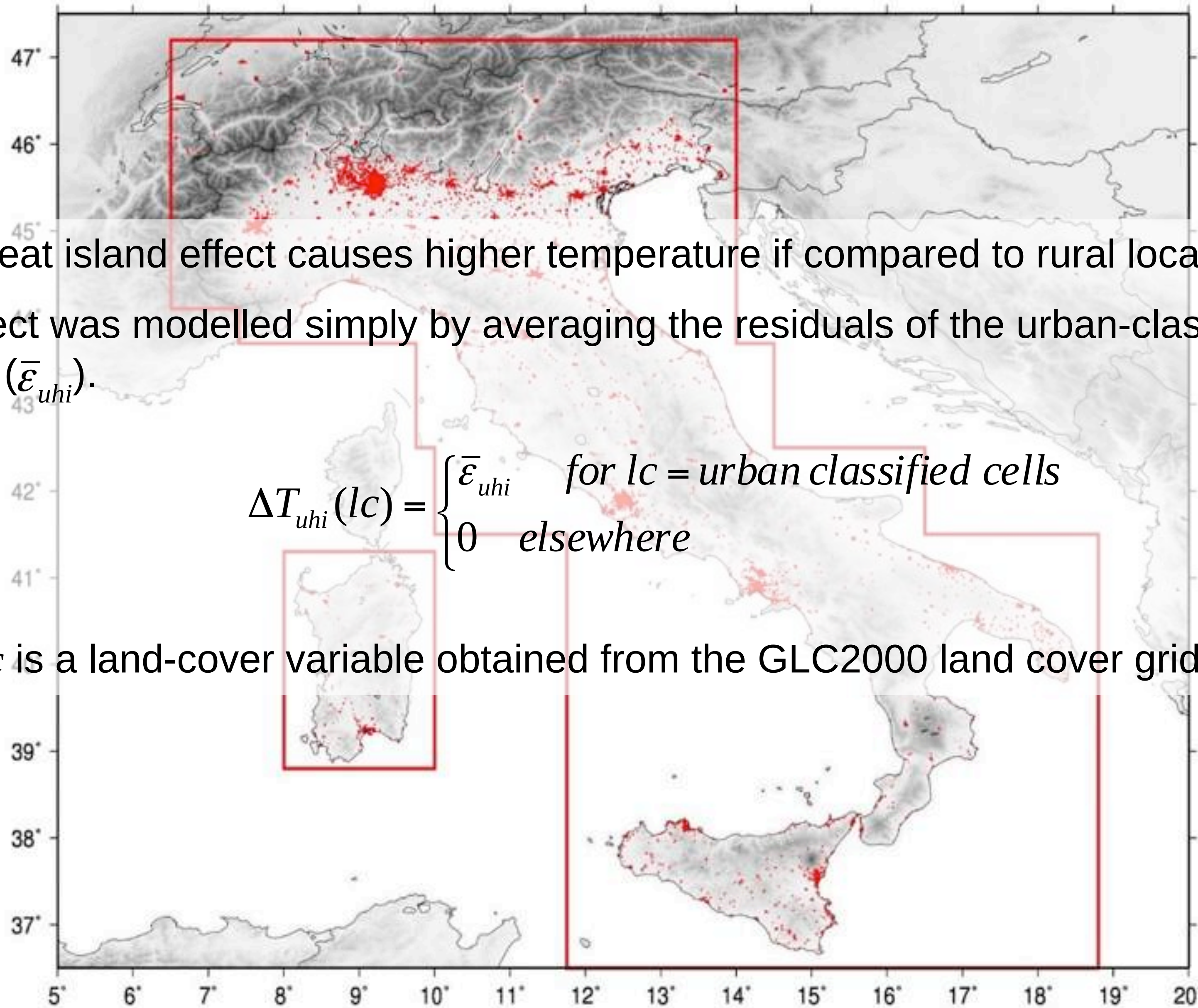
$$\Delta T_{summit-valley}(sv) = \begin{cases} a_0 + a_1 \cdot sv & sv \le sv_a \\ \bar{\varepsilon}_{0.25<sv<0.75} & sv_a < sv \le sv_b \\ b_0 + b_1 \cdot sv & sv > sv_b \end{cases}$$

were a_0 (b_0) and a_1 (b_1) are the coefficients of the linear fit between the station residuals and *sv* for *sv* < 0.25 (> 0.75), $\bar{\varepsilon}_{0.25<sv<0.75}$ is the average of the residuals of the stations with 0.25 < *sv* < 0.75 and sv_a and sv_b are the values of *sv* in which the first and last interpolating lines cross the line $\Delta T_{summit-valley}(sv) = \bar{\varepsilon}_{0.25<sv<0.75}$





MLRLI – URBAN HEAT ISLAND EFFECT



Urban heat island effect causes higher temperature if compared to rural locations.

This effect was modelled simply by averaging the residuals of the urban-classified stations ($\bar{\varepsilon}_{uhi}$).

$$\Delta T_{uhi}(lc) = \begin{cases} \bar{\varepsilon}_{uhi} & for\ lc = urban\ classified\ cells \\ 0 & elsewhere \end{cases}$$

where lc is a land-cover variable obtained from the GLC2000 land cover grid.

MLRLI – THE FINAL MODEL

Once all the above effects have been included in the model, the final result is an equation which estimates the temperature normal of each grid-cell as a function of the previous variables.

$$T = T(\lambda,\phi) =$$

$$= m_0 + m_1 \cdot h(\lambda,\phi) + m_2 \cdot \lambda + m_3 \cdot \phi + \Delta T_{sea}(dsea(\lambda,\phi)) + \Delta T_{lake}(dlake(\lambda,\phi)) + \Delta T_{Po-Plain}(ppl(\lambda,\phi)) +$$

$$+ \Delta T_{facet}(fc(\lambda,\phi)) + \Delta T_{macro-facet}(Mfc(\lambda,\phi)) + \Delta T_{summit-valley}(sv(\lambda,\phi)) + \Delta T_{uhi}(lc(\lambda,\phi))$$

where the only independent variables are λ and ϕ, whereas all other variables are obtained from them by means of the GTOPO30 DEM and the GLG2000 land cover grid.

REGRESSION KRIGING (RK)

REGRESSION KRIGING

An alternative approach to the step-wise local improvements to the MLR estimations of temperature normals is to consider, for each grid-cell, a distance weighted average of the station residuals, with weights calculated by means of a kriging-based approach.

The MLR residual (ε) of each grid-point *(λ,ϕ)* is estimated by

$$\hat{\varepsilon}(\lambda,\phi) = \sum_{i=1}^{n} k_i(\lambda,\phi) \cdot \varepsilon_i = \mathbf{k}^{\mathrm{T}}(\lambda,\phi) \cdot \boldsymbol{\varepsilon}$$

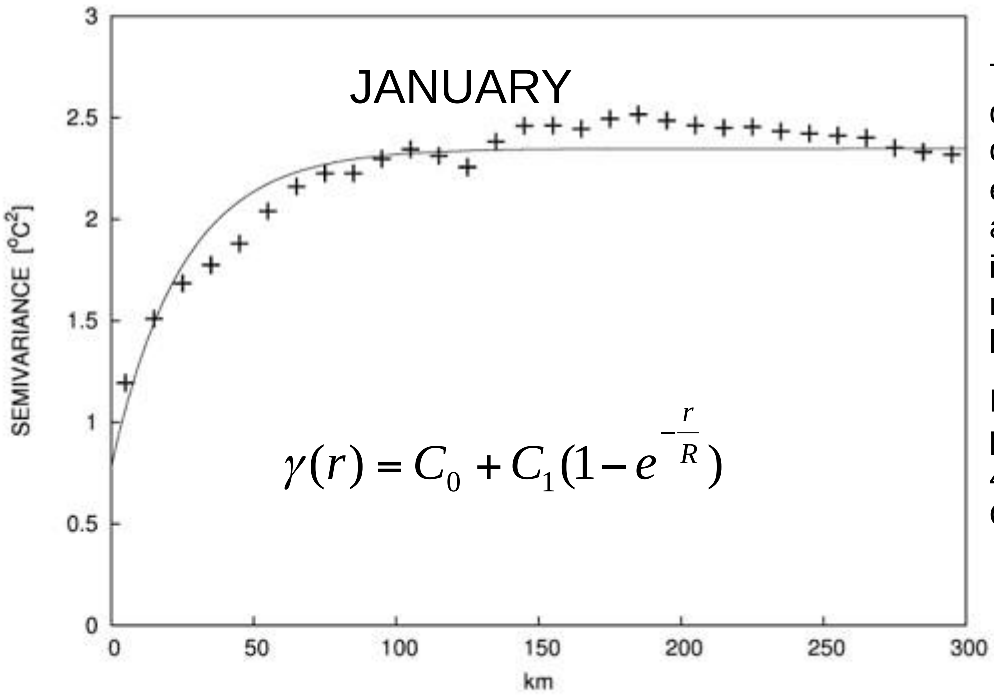
where $\mathbf{k}$ is the vector of the kriging weights (k_i) for the grid-point *(λ,ϕ)*, $\boldsymbol{\varepsilon}$ is the vector of station residuals and *n* is the number of stations.

REGRESSION KRIGING

The first step consists in the definition of the variogram that describes the spatial covariance of the station data. The variogram was determined by i) considering all station pairs within 300 km and clustering them according to station distance, binned into 10 km intervals; ii) calculating, for each distance interval, the semivariance of the differences of temperature residuals of all station pairs within the interval; iii) fitting semivariance versus distance by means of a chosen theoretical variogram.

The ***exponential variogram*** turned out to be the most suitable for our application

It assumes that semivariance tends to C_0 (the nugget parameter) for $r \to 0$, which means that spatial coherence cannot completely explain station temperature residuals. As r increases, the semivariance tends to C_0+C_1 (the sill parameter), which means that for large distances (e.g. r > 3R) there is no more spatial coherence between station temperature residuals.



$$\gamma(r) = C_0 + C_1\left(1 - e^{-\frac{r}{R}}\right)$$

The range parameter (R) was defined as 1/3 of the minimum distance with semivariance equal to at least 95 % of the average semivariance of the intervals from that with maximum semivariance to the last within 300 km.

R ranges from 25 km in the period December-February to 45-50 km in the period May-October.

C_0 ranges from about 0.4 (°C^2) in the period March-July to about 0.8 (° C^2) in the period December-January. C_1 ranges from about 0.3-0.5 (° C^2) in the periods March-May and September-October to about 1.5-1.6 (° C^2) in the period December-January.

This fit was performed using a weighted linear interpolation of γ versus $(1-e^{-r/R})$, with weights given by the ratios between the number of station pairs within each distance interval and the corresponding average distance

REGRESSION KRIGING

The theoretical variogram was then used to obtain the covariance (C) versus the distance ($C(r) = C_1 \cdot e^{-r/R}$) and the covariance matrix $\mathbf{C}$, expressing the covariance of any pair of stations. .

The vector of kriging weights ($\mathbf{k}$) for the grid-point (λ,ϕ) was then obtained as:

$$\mathbf{k}(\lambda,\phi) = \mathbf{C}^{-1} \cdot \mathbf{c_0}(\lambda,\phi)$$

where $\mathbf{c_0}(\lambda,\phi)$ is the vector expressing the covariances of the grid-cell (λ,ϕ) with all the station positions estimated from $C(r) = C_1 \cdot e^{-r/R}$.

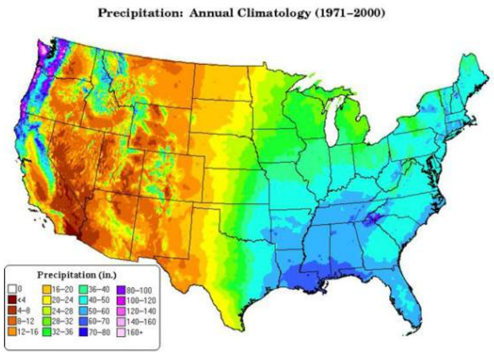
The temperature of each grid-cell is therefore estimated by RK as:

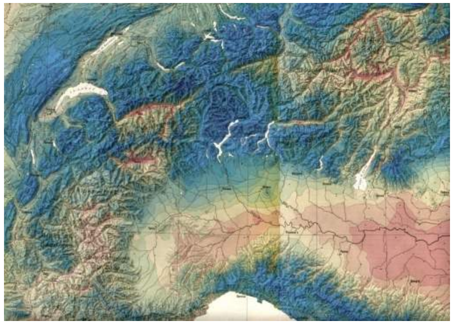
$$T = m_0 + m_1 \cdot h(\lambda,\phi) + m_2 \cdot \lambda + m_3 \cdot \phi + \mathbf{k}^{\mathrm{T}}(\lambda,\phi) \cdot \boldsymbol{\varepsilon}$$

LOCAL WEIGHTED LINEAR REGRESSION (LWLR)

LOCAL WEIGHTED LINEAR REGRESSION – LWLR

THE MODEL IS SIMILAR TO **PRISM** (Parameter-elevation regression on independent slopes model) ALREADY USED FOR **U.S.** TEMPERATURE AND PRECIPITATION (Daly et al., 1994) AND FOR PRECIPITATION IN THE **ALPINE REGION** (Frei and Schär, 1998).





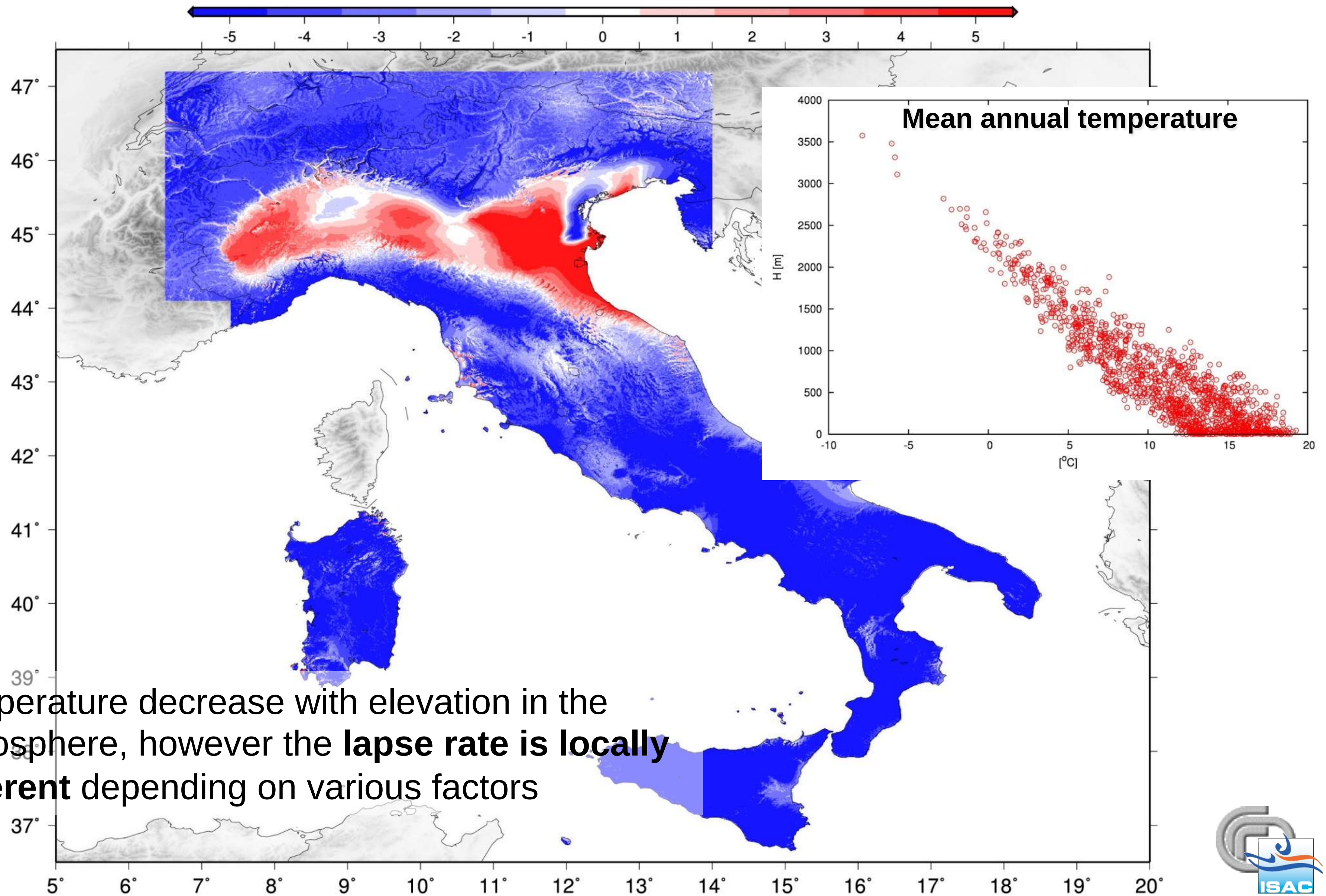
LOCAL PARAMETER vs ELEVATION WEIGHTED LINEAR REGRESSION (LWLR)

Daly C, Neilson RP, Philipps DL. 1994. Journal of Applied Meteorology, 33: 140–158

Frei C., Schär C. 1998. International Journal of climatology, 18: 873-900.

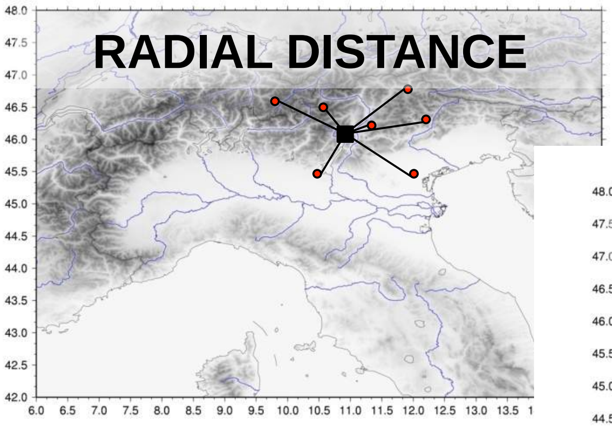
WHY THIS MODEL?

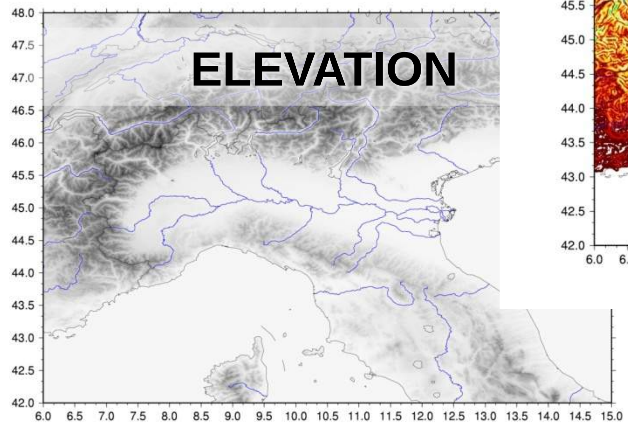
January near-surface temperature lapse rate (K/km)

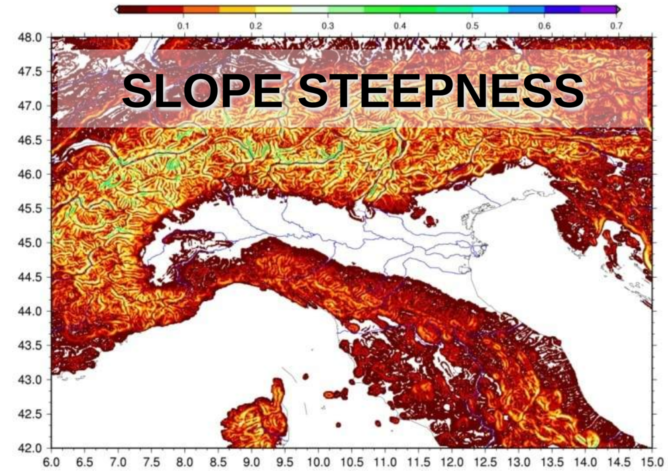


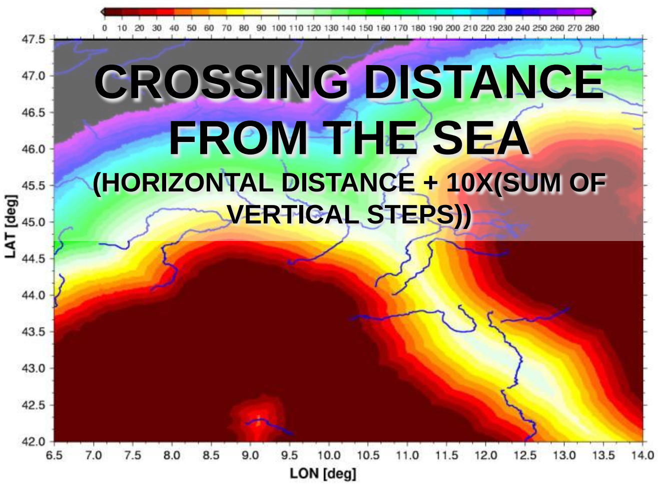
Temperature decrease with elevation in the troposphere, however the **lapse rate is locally different** depending on various factors

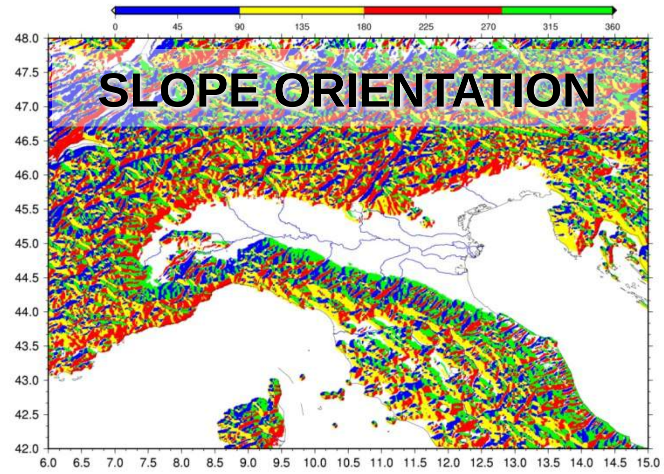
LWLR – THE WEIGHTING FACTORS







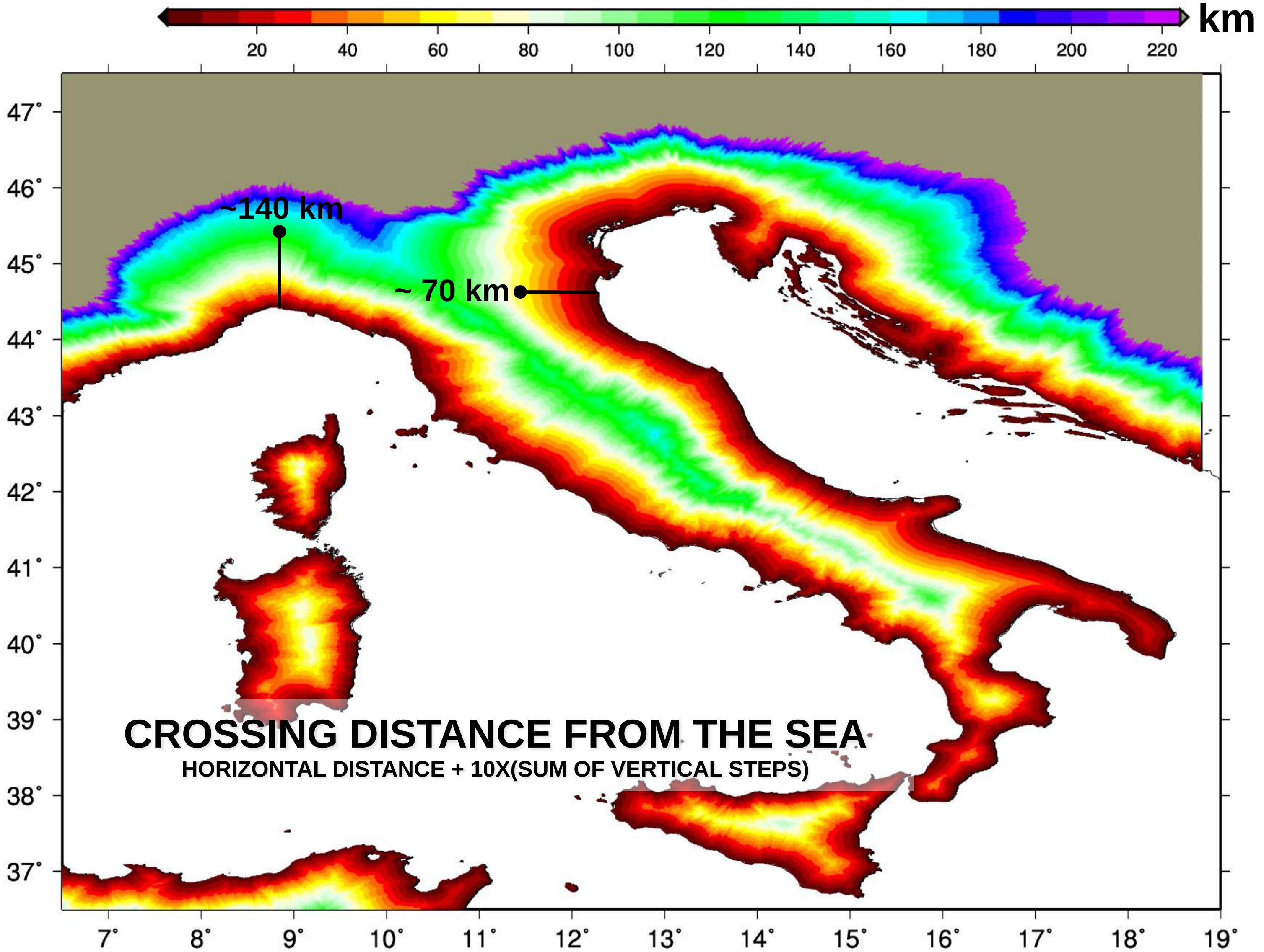




$$w_i(\lambda,\phi) = w_i^r(\lambda,\phi)\cdot w_i^h(\lambda,\phi)\cdot w_i^{dsea}(\lambda,\phi)\cdot w_i^{slope}(\lambda,\phi)\cdot w_i^{facet}(\lambda,\phi)$$

LWLR – THE WEIGHTING FACTORS

TWO POINTS AT THE SAME HORIZONTAL DISTANCE FROM THE SEE CAN PRESENT SIGNIFICSNTLY DIFFERENT CROSSING DISTANCES



LWLR – THE WEIGHTING FACTORS

$$w_i^{\mathrm{var}}(\lambda,\phi) = e^{-\left(\frac{\Delta_i^{\mathrm{var}}(\lambda,\phi)^2}{c_{\mathrm{var}}}\right)}$$

Here *var* is the specific geographical variable which is being considered, Δ_i^{var} is the absolute value of the difference between the value of this variable at the grid-cell point (λ,ϕ) and that at the *i*-th station location, and c_{var} is a coefficient which regulates the decrease of the weighting function with increasing Δ_i^{var}

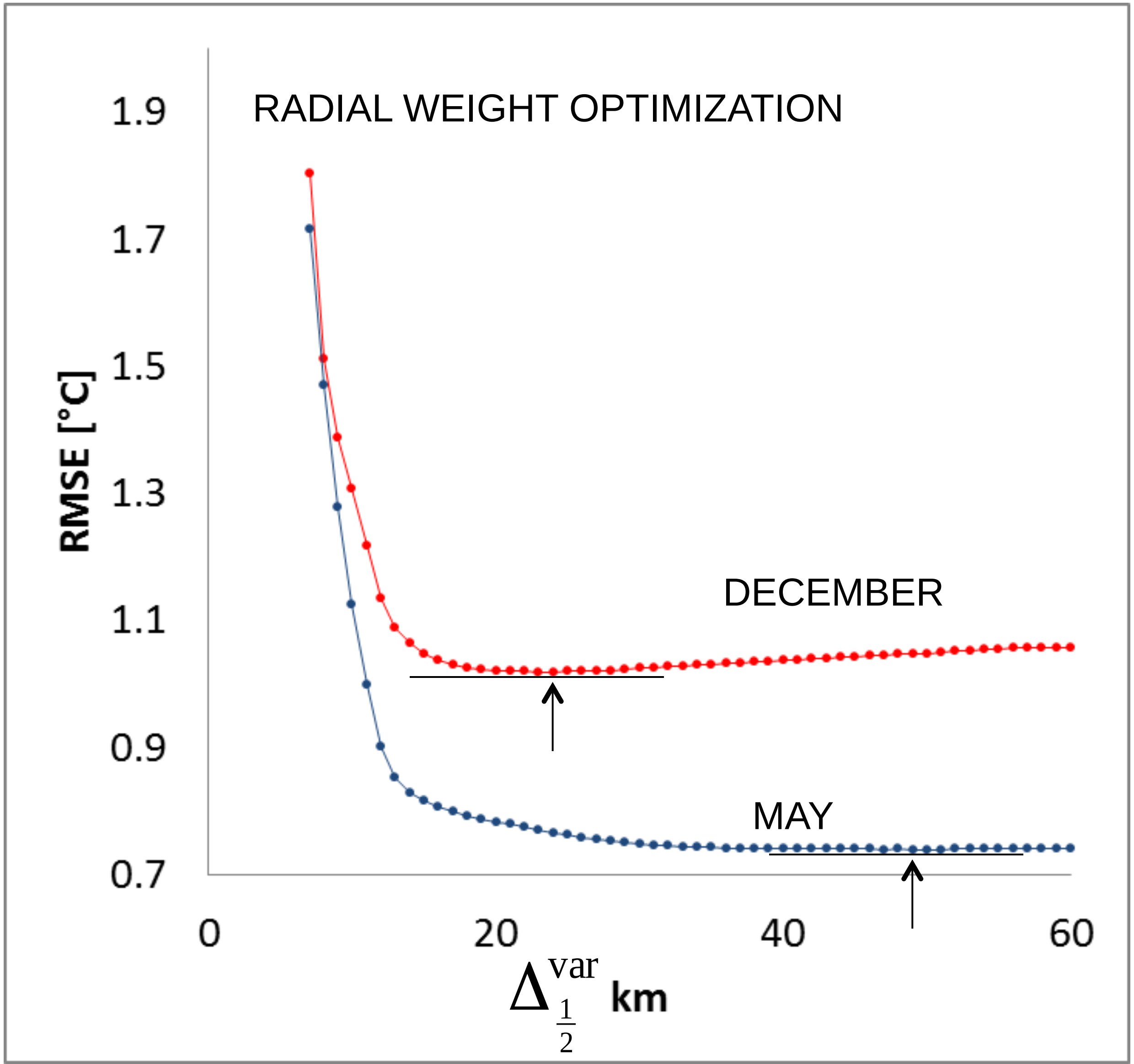
$$c_{\mathrm{var}} = -\frac{(\Delta_{\frac{1}{2}}^{\mathrm{var}})^2}{\ln 2}$$

The selection of the most appropriate $\Delta_{\frac{1}{2}}^{\mathrm{var}}$ values to be used in the weighting factors was performed iteratively, for each month of the year, by searching for the value that gives, for any variable, the lowest possible error at station locations

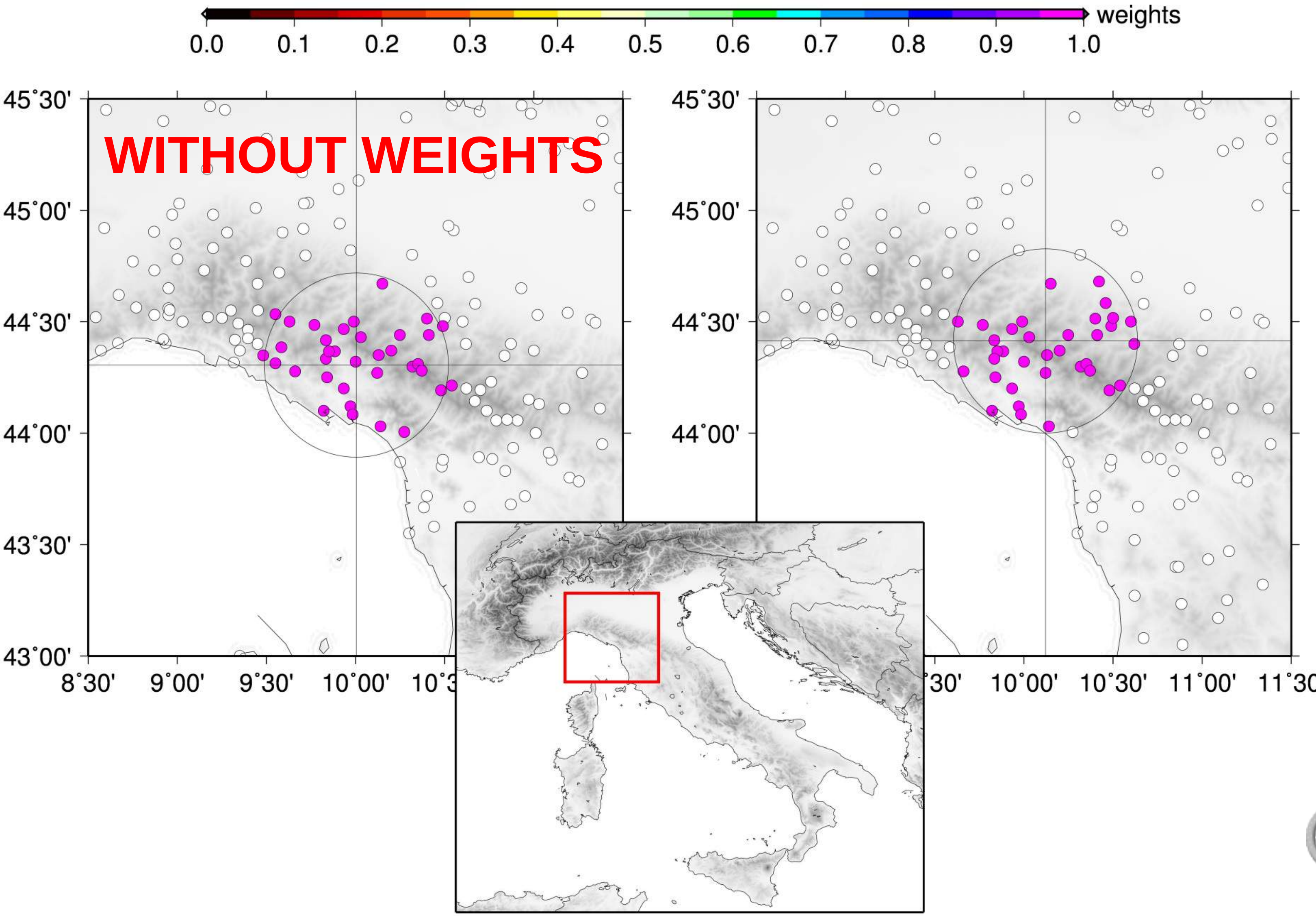
LWLR –WEIGHTING FACTOR OPTIMIZATION

$$c_{\text{var}} = -\frac{(\Delta_{\frac{1}{2}}^{\text{var}})^2}{\ln 2}$$

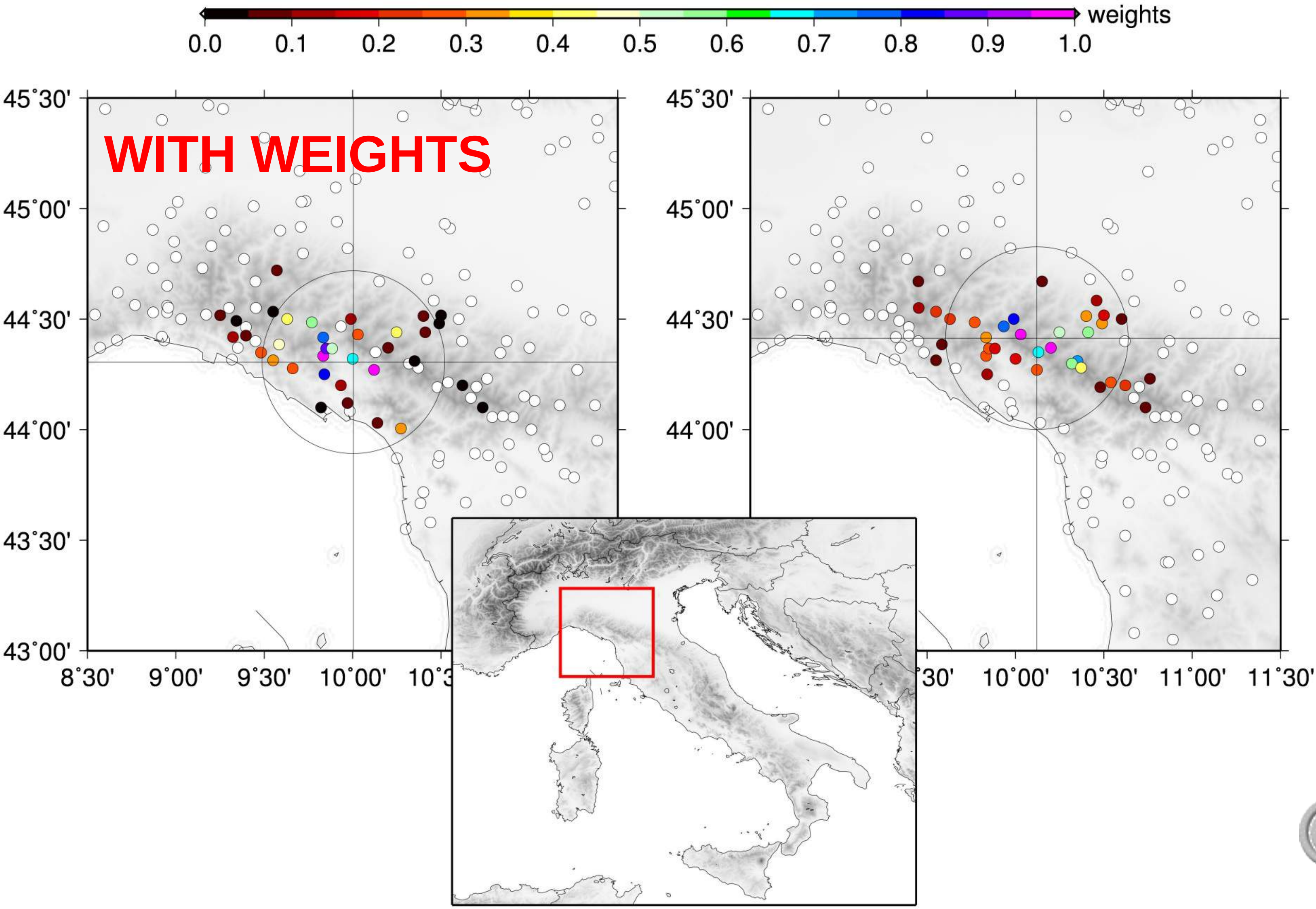
We vary the decay coefficient searching for the minimum RMSE



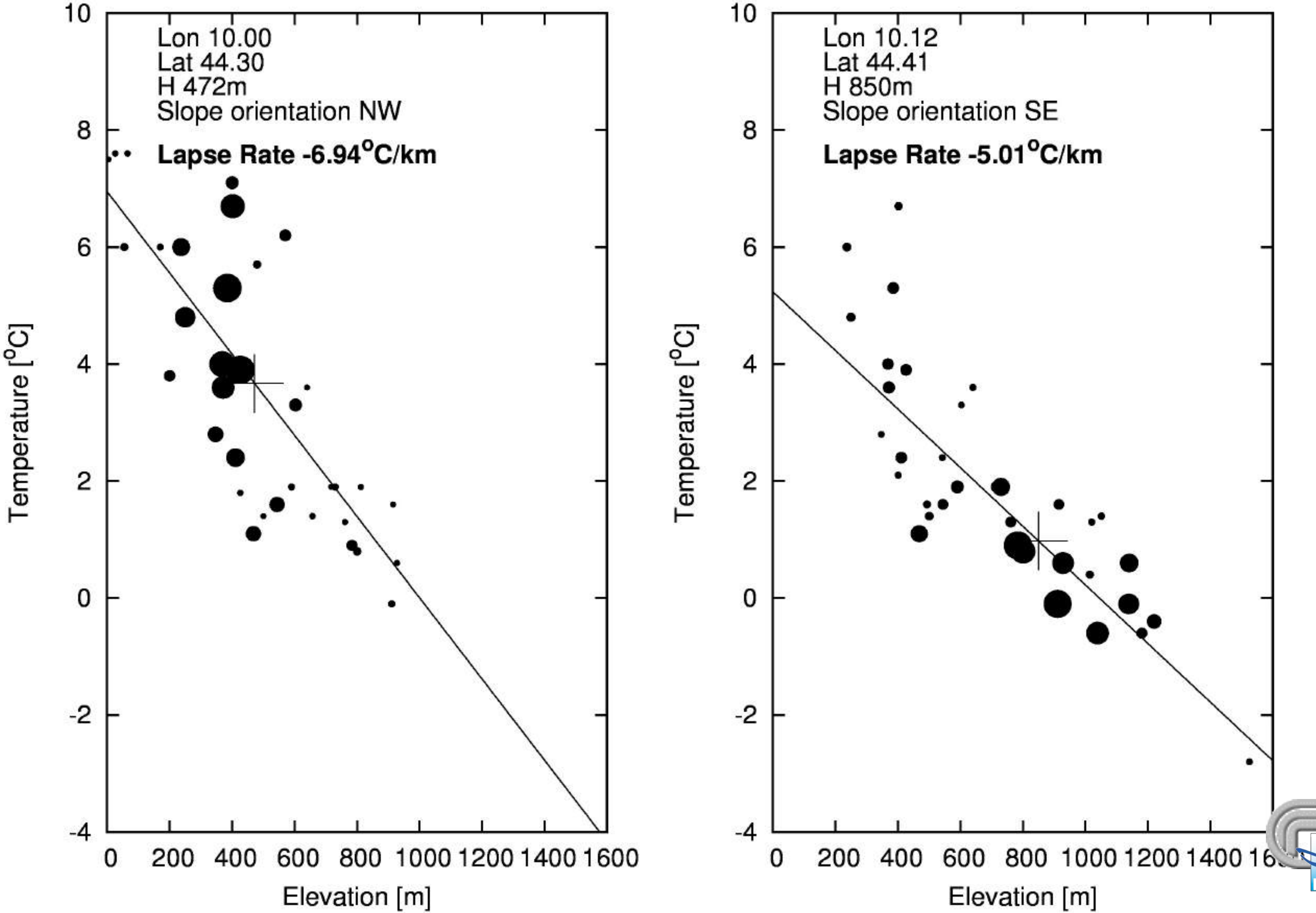
LWLR – THE IMPORTANCE OF WEIGHTING FACTORS



LWLR – THE IMPORTANCE OF WEIGHTING FACTORS



LWLR – THE IMPORTANCE OF WEIGHTING FACTORS



MODEL INTERCOMPARISON

ERROR INTERCOMPARISON

LEAVE-ONE-OUT CROSS-VALIDATION TECHNIQUE

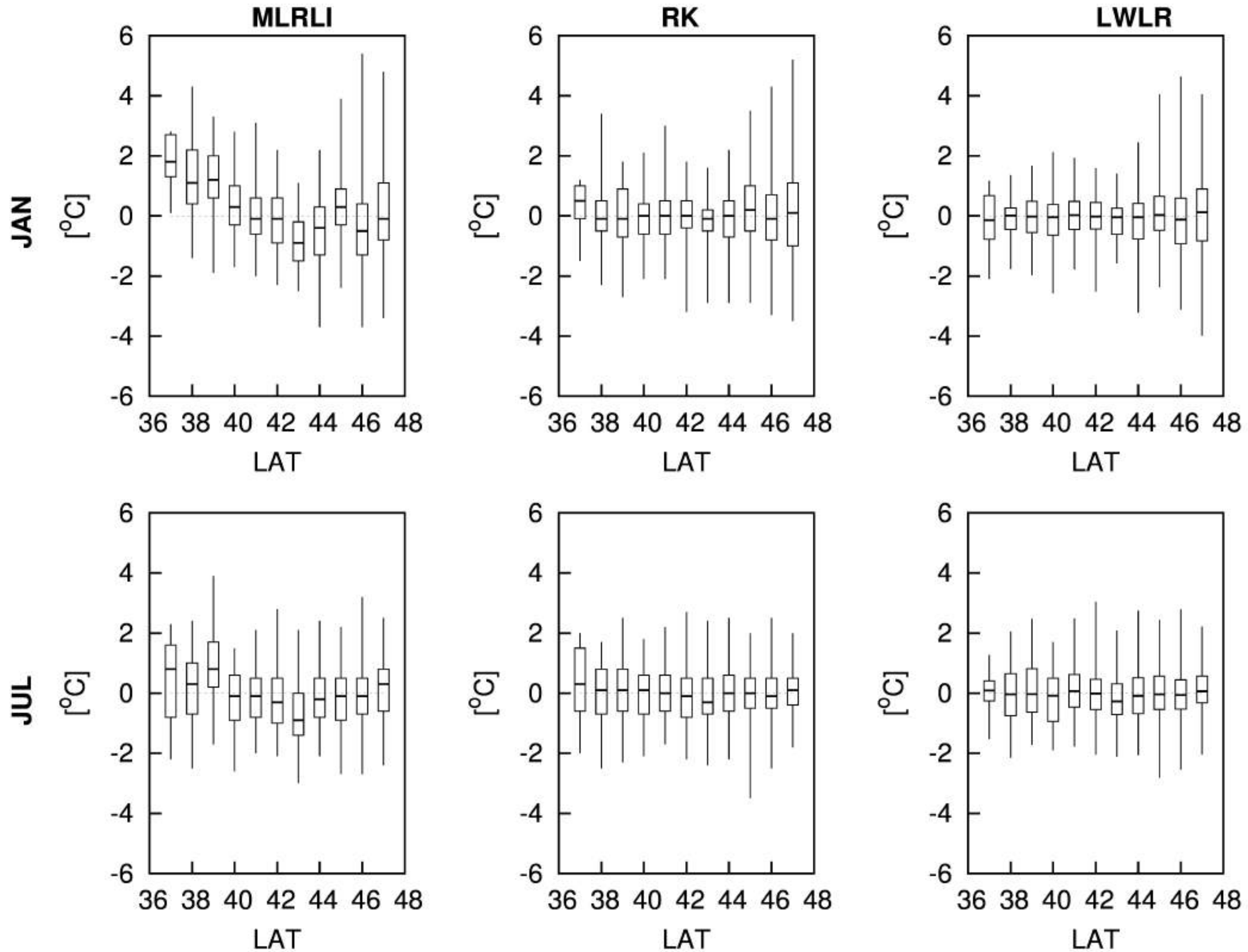
$$BIAS = \frac{\sum_{i=1}^{N} \left(T_i^{est} - T_i^{obs}\right)}{N} \qquad MAE = \frac{\sum_{i=1}^{N} \left|T_i^{est} - T_i^{obs}\right|}{N} \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(T_i^{est} - T_i^{obs}\right)^2}{N}}$$

	MLRLI			RK			LWLR		
	BIAS	MAE	RMSE	BIAS	MAE	RMSE	BIAS	MAE	RMSE
1	0.04	1.02	1.29	0.00	0.84	1.09	-0.04	0.77	1.01
2	0.01	0.82	1.05	0.00	0.73	0.94	-0.04	0.69	0.90
3	-0.02	0.70	0.89	-0.01	0.61	0.79	-0.03	0.60	0.78
4	-0.04	0.70	0.86	-0.01	0.59	0.75	-0.03	0.58	0.74
5	-0.04	0.70	0.86	-0.01	0.61	0.76	-0.02	0.58	0.74
6	-0.05	0.76	0.94	-0.01	0.64	0.81	-0.01	0.62	0.79
7	-0.05	0.83	1.03	-0.01	0.69	0.88	-0.02	0.66	0.85
8	-0.05	0.80	0.99	-0.01	0.67	0.85	-0.02	0.65	0.84
9	-0.03	0.71	0.89	-0.01	0.62	0.80	-0.02	0.62	0.79
10	-0.01	0.72	0.92	-0.01	0.65	0.83	-0.02	0.63	0.81
11	0.01	0.81	1.03	0.00	0.71	0.90	-0.03	0.67	0.86
12	0.03	1.02	1.31	0.00	0.86	1.11	-0.04	0.78	1.03
MEAN	**-0.02**	**0.799**	**1.005**	**-0.01**	**0.685**	**0.876**	**-0.03**	**0.654**	**0.845**

ERROR INTERCOMPARISON – LATITUDINAL DISTRIBUTION OF BIASES

January and July box-plots of the errors of the three methods, clustering the stations within 1 degree latitude belts.

All stations are considered here

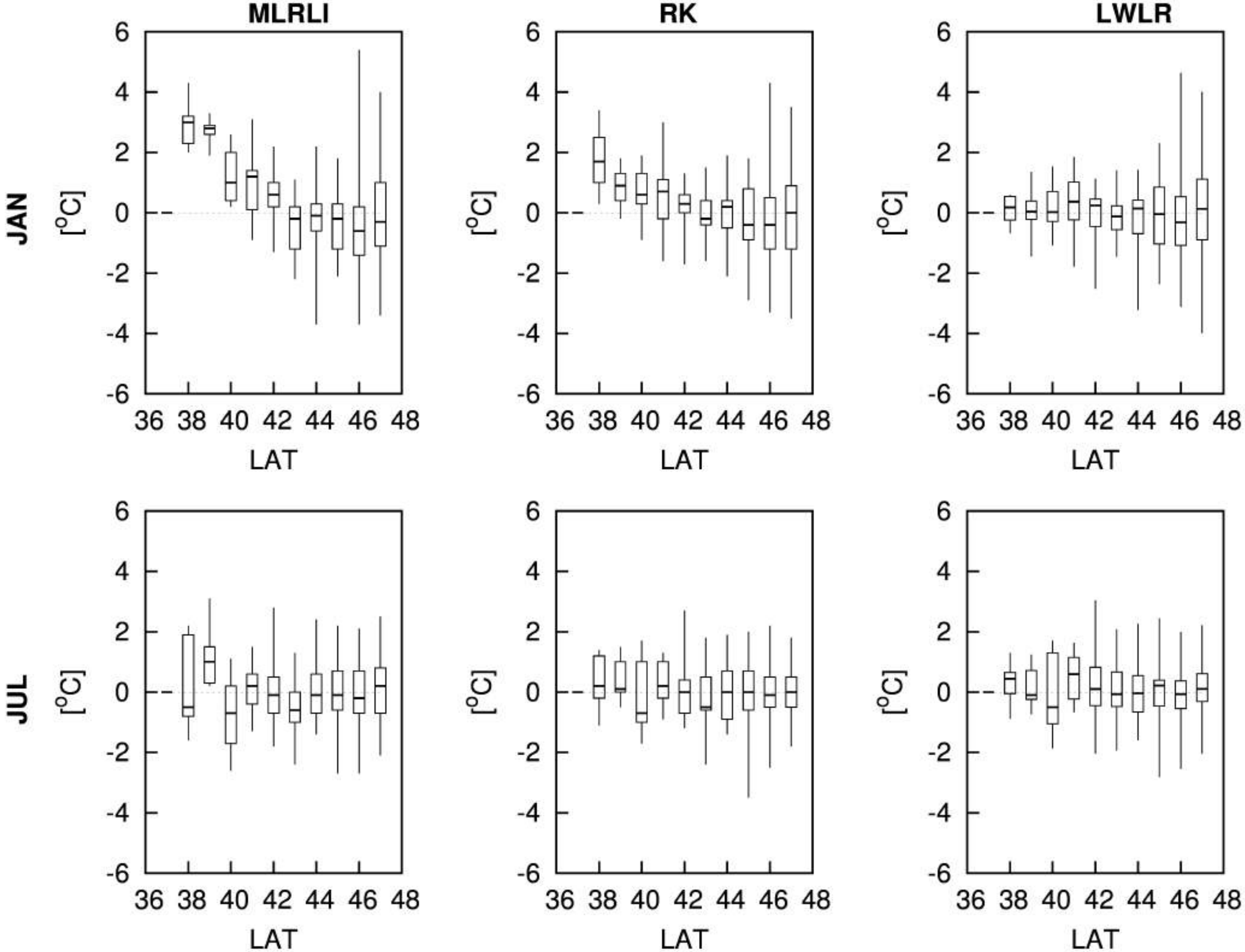


The boxes range from the lowest quartile to the highest one and are centred on the median; whiskers represent the minimum and the maximum errors.

ERROR INTERCOMPARISON – LATITUDINAL DISTRIBUTION OF BIASES

January and July box-plots of the errors of the three methods, clustering the stations within 1 degree latitude belts.

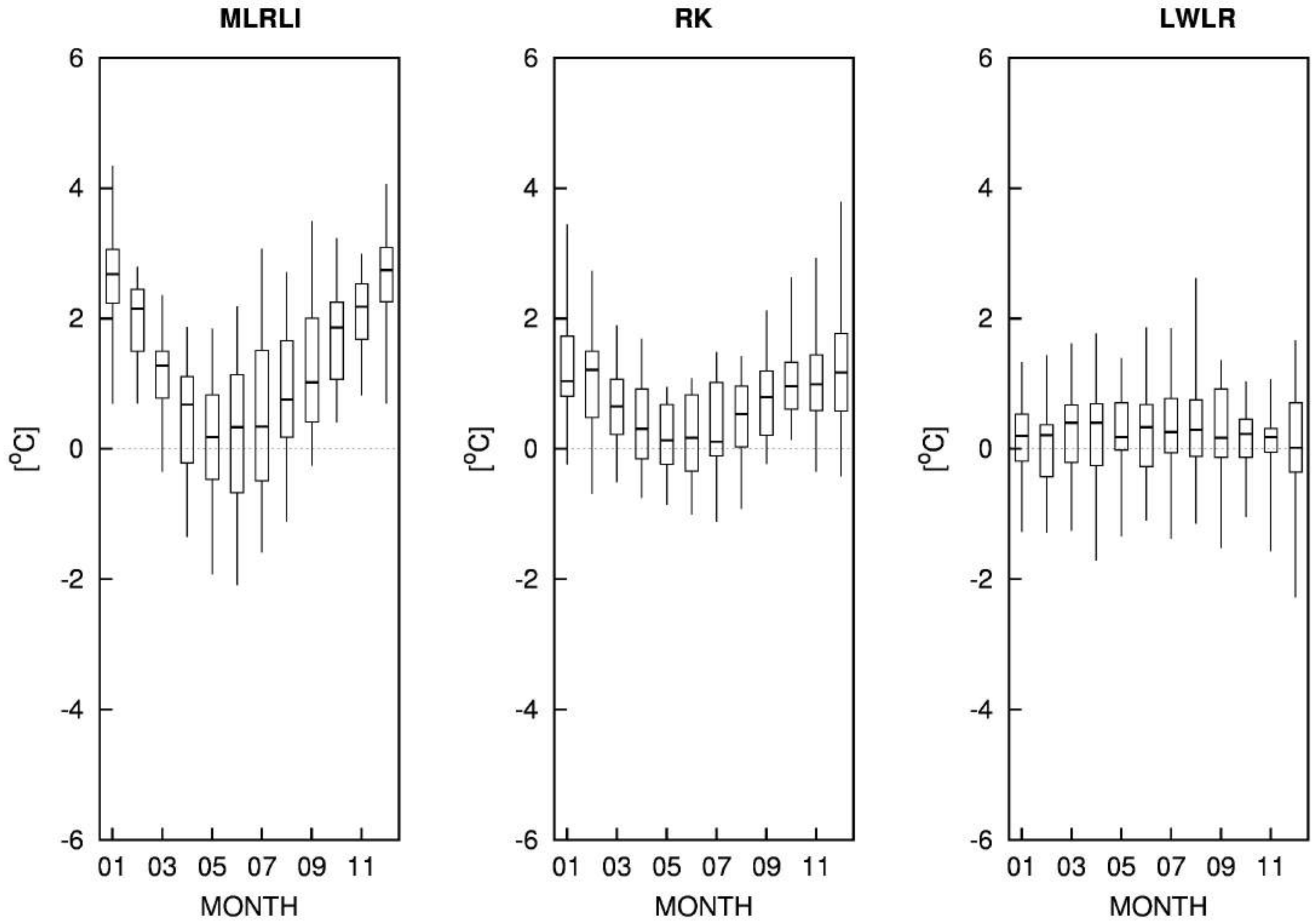
Stations with an elevation above 800 m a.s.l. only



The boxes range from the lowest quartile to the highest one and are centred on the median; whiskers represent the minimum and the maximum errors.

ERROR INTERCOMPARISON – NORTHERN ITALY AND HIGH ELEVATION

Monthly box-plot of the errors of the three methods from stations with **latitude < 40°N** and **elevation > 800m**.



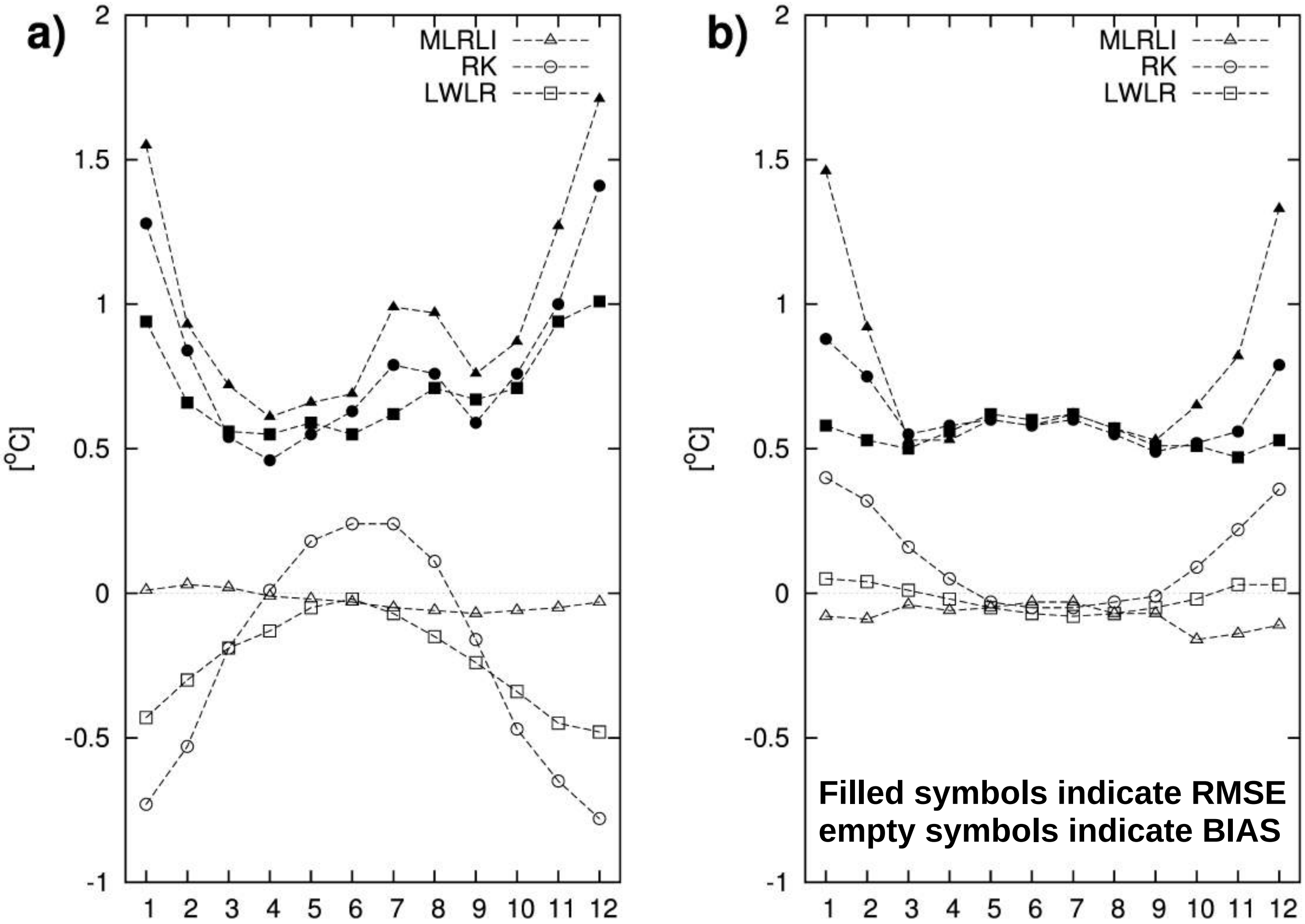
The boxes range from the lowest quartile to the highest one and are centred on the median; whiskers represent the minimum and the maximum errors.

ERROR INTERCOMPARISON – COASTS AND PO PLAIN

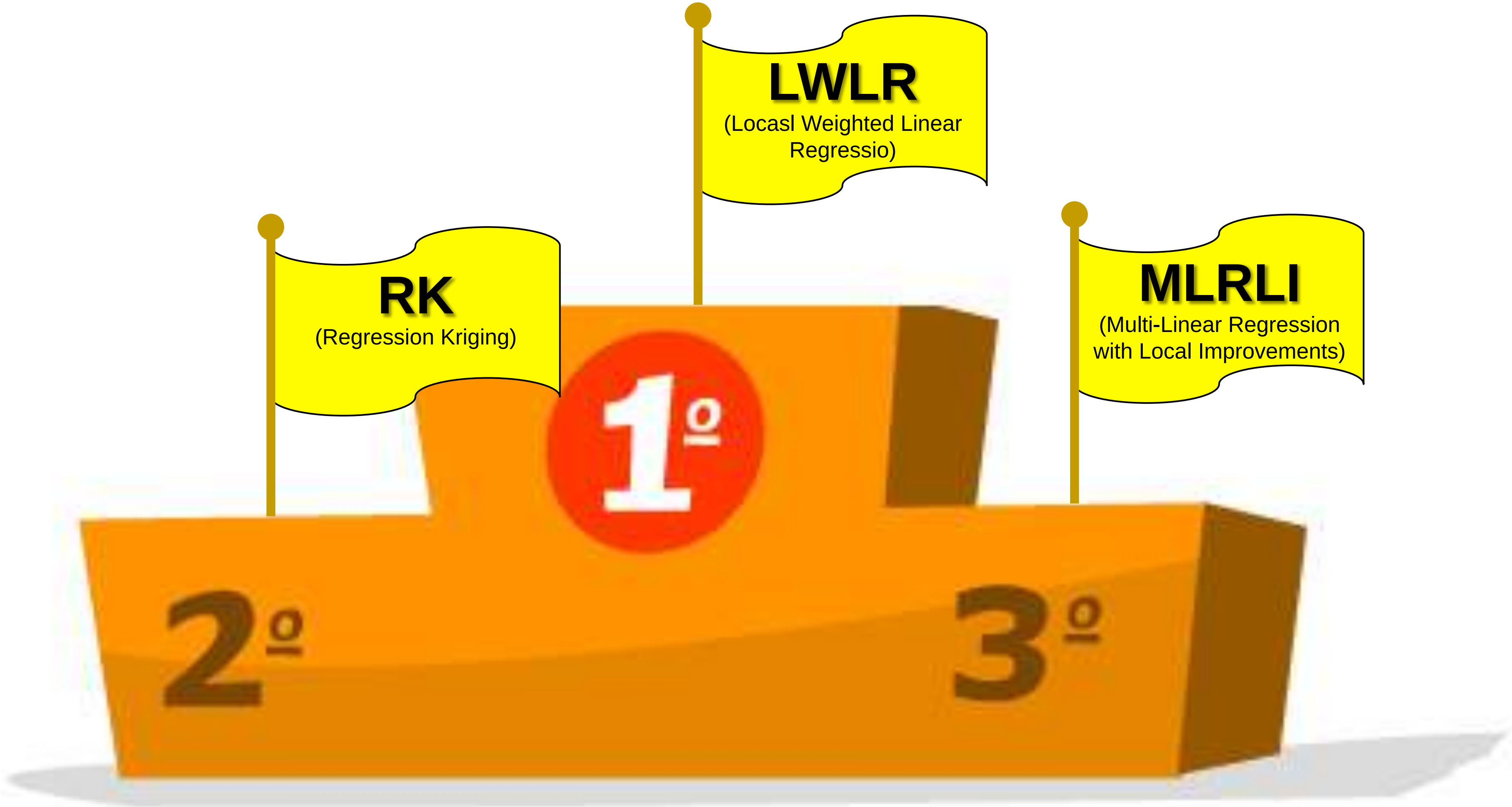
Monthly average errors of the three methods from

a) **coastal stations** (stations within the first 1.3 km from the sea)

b) **Po Plain** stations.



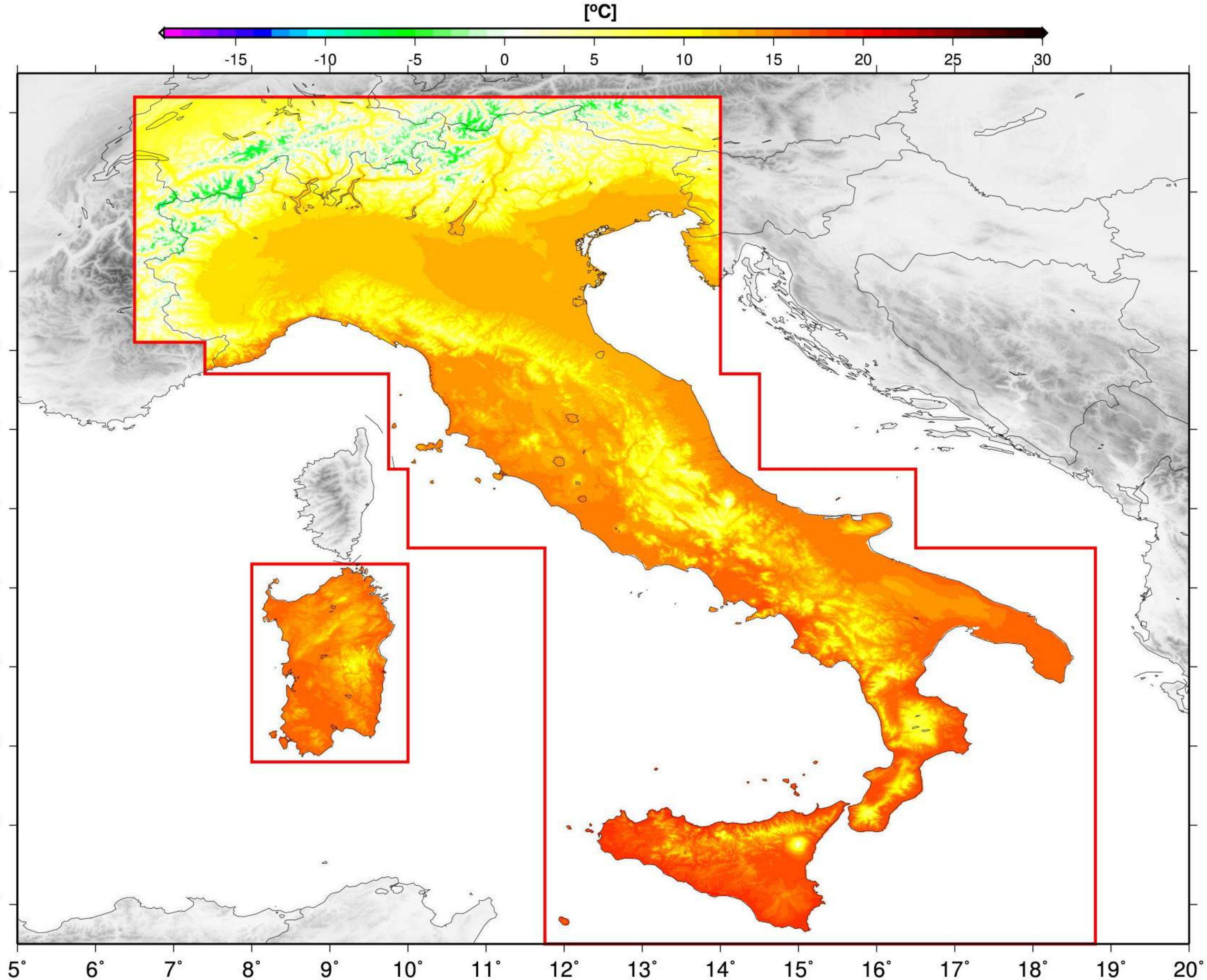
THE WINNER IS….



SOME RESULTS AND APPLICATIONS

TEMPERATURE CLIMATOLOGY

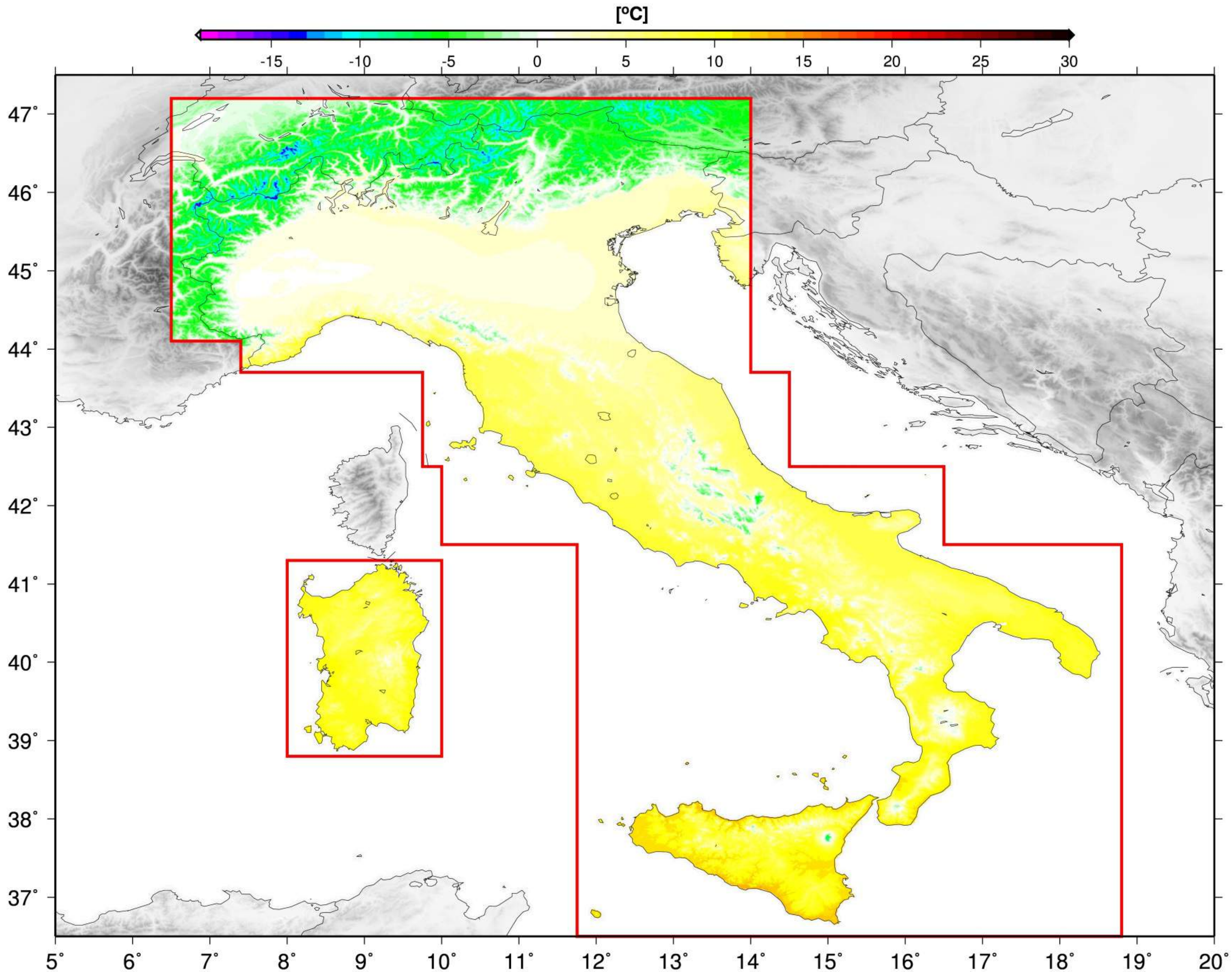
ANNUAL



ISAC

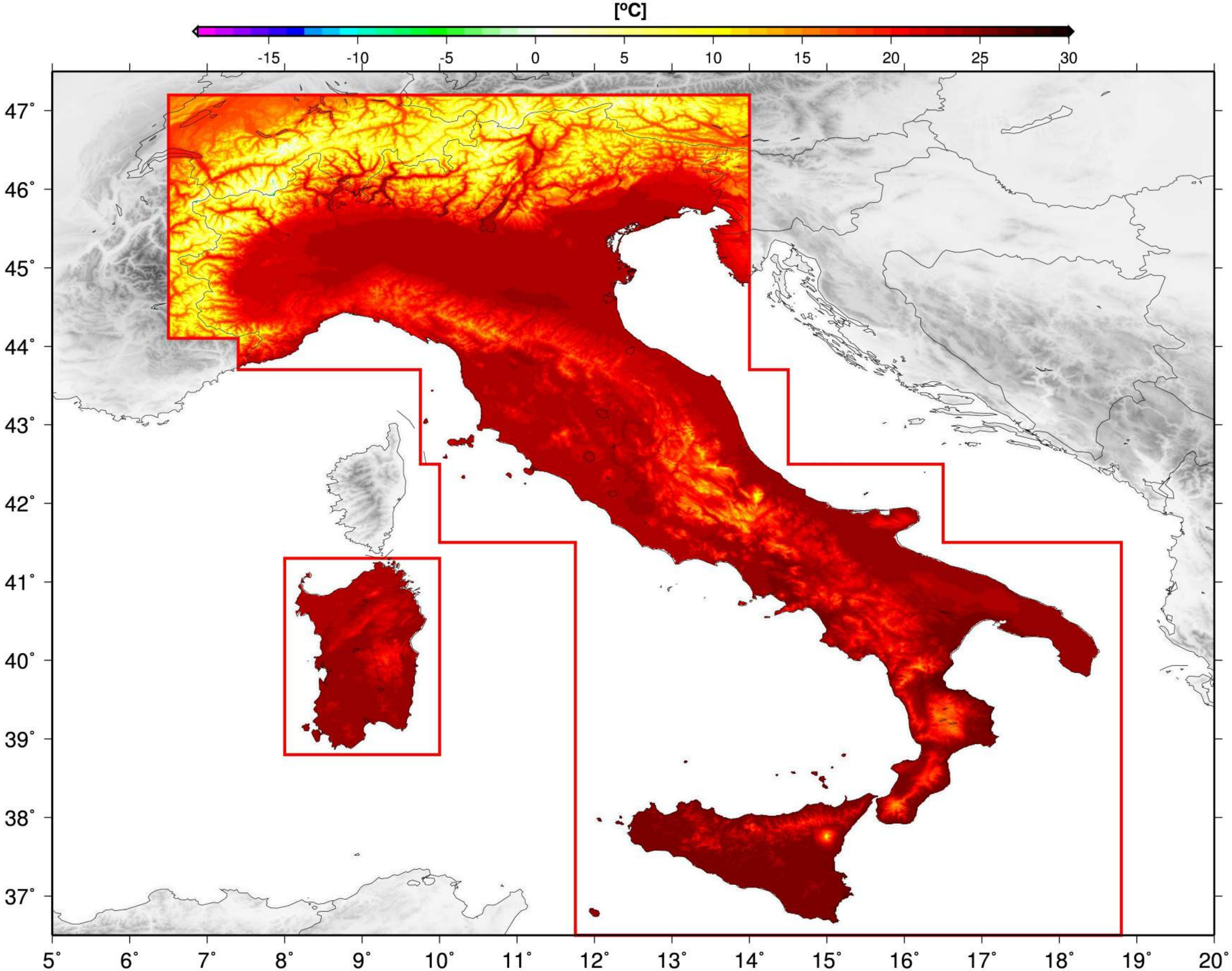
TEMPERATURE CLIMATOLOGY

JANUARY



TEMPERATURE CLIMATOLOGY

JULY



LWLR – CONFIDENCE INTERVAL

IMPORTANT ADVANTAFGE OF **LWLR**: **CONFIDENCE INTERVAL**

$$S^2 = MSE + \frac{MSE}{\sum_{i=1}^{N} w_i} + MSE \frac{\left(h - \bar{h}\right)^2}{\sum_{i=1}^{N} w_i \left(h_i - \bar{h}\right)^2}$$

UNCERTANTY IN THE COEFFICIENT ESTIMATION

MEAN SQUARE ERROR

$$MSE = \frac{\sum_{i=1}^{N} w_i [T_i - T(x,y)]^2}{\sum_{i=1}^{N} w_i} \cdot \frac{N}{N-2}$$

UNCERTANTY IN THE MEAN VALUE ESTIMATION OF THE PREDICTAND FROM A FINITE SAMPLE

w_i WEIGHTS

$\bar{h}$ WEIGHTED MEAN ELEVATION OF THE REGRESSION DATA SET

h ELEVATION AT WHICH THE PARAMETER IS ESTIMATED

h_i ELEVATION OF THE ITH STATION

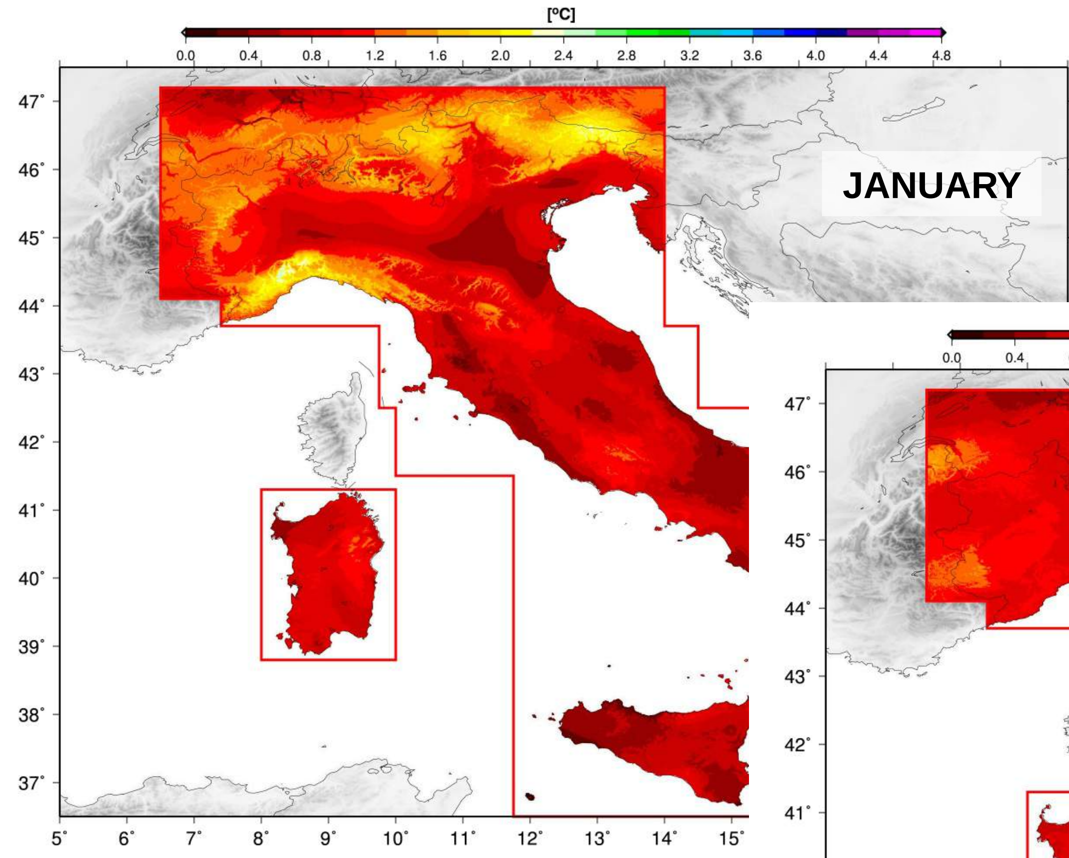
The prediction interval for the grid-point with elevation h is

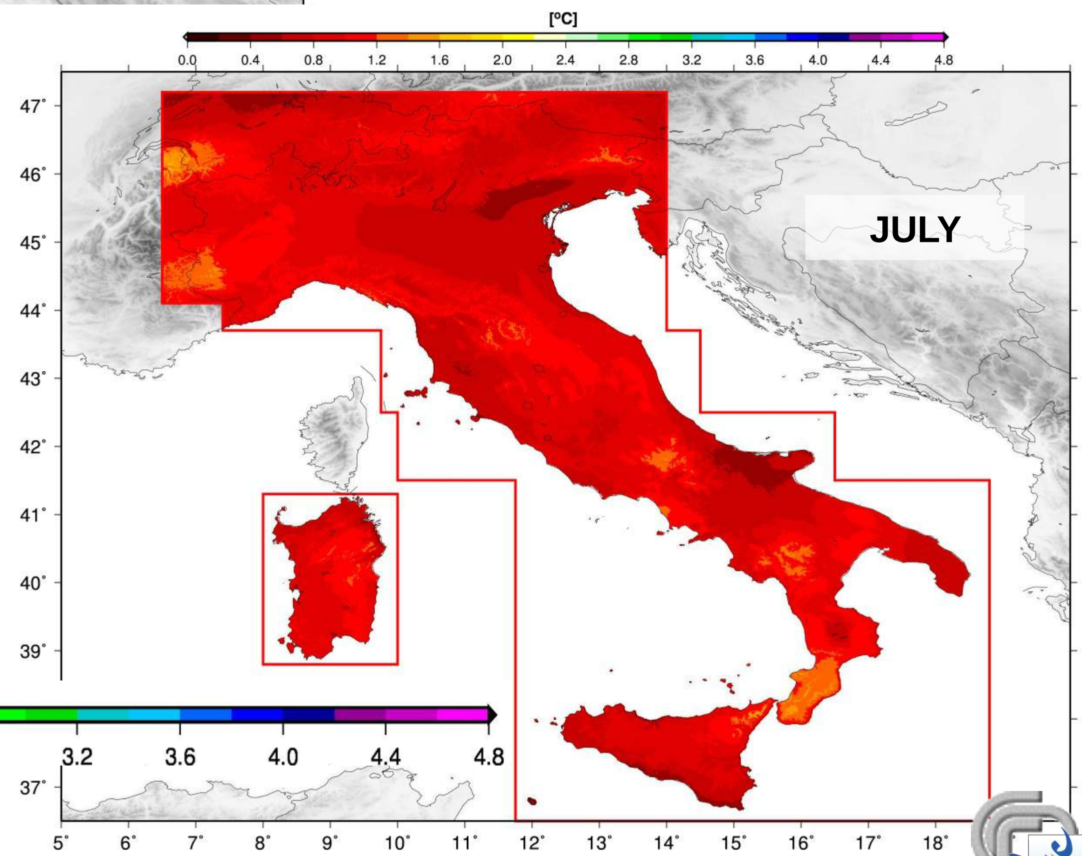
$$T_h \pm t_{\frac{1-\alpha}{2},df} \cdot s\{T_h\}$$

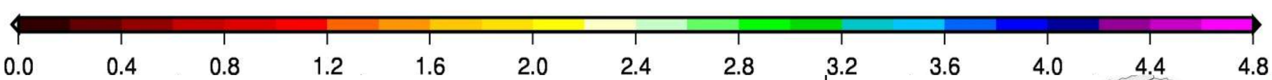
where t is the value of a Student distribution with *df* degrees of freedom corresponding to cumulative probability (1-α)/2.

CONFIDENCE INTERVAL

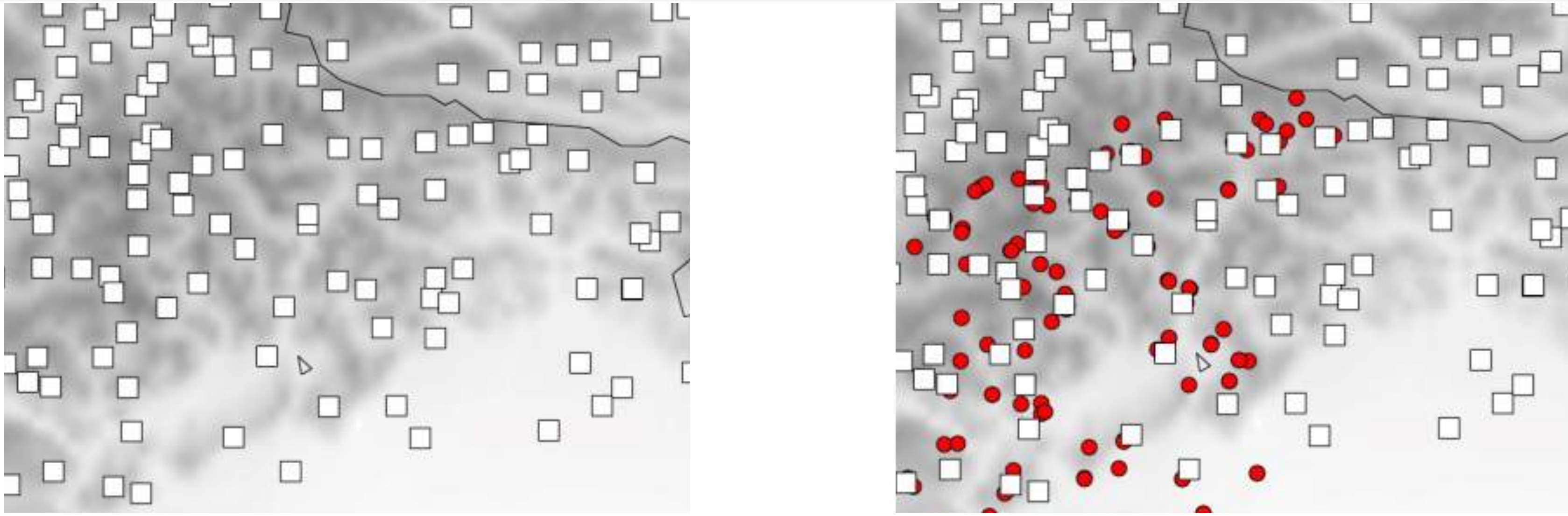
α=0.6827



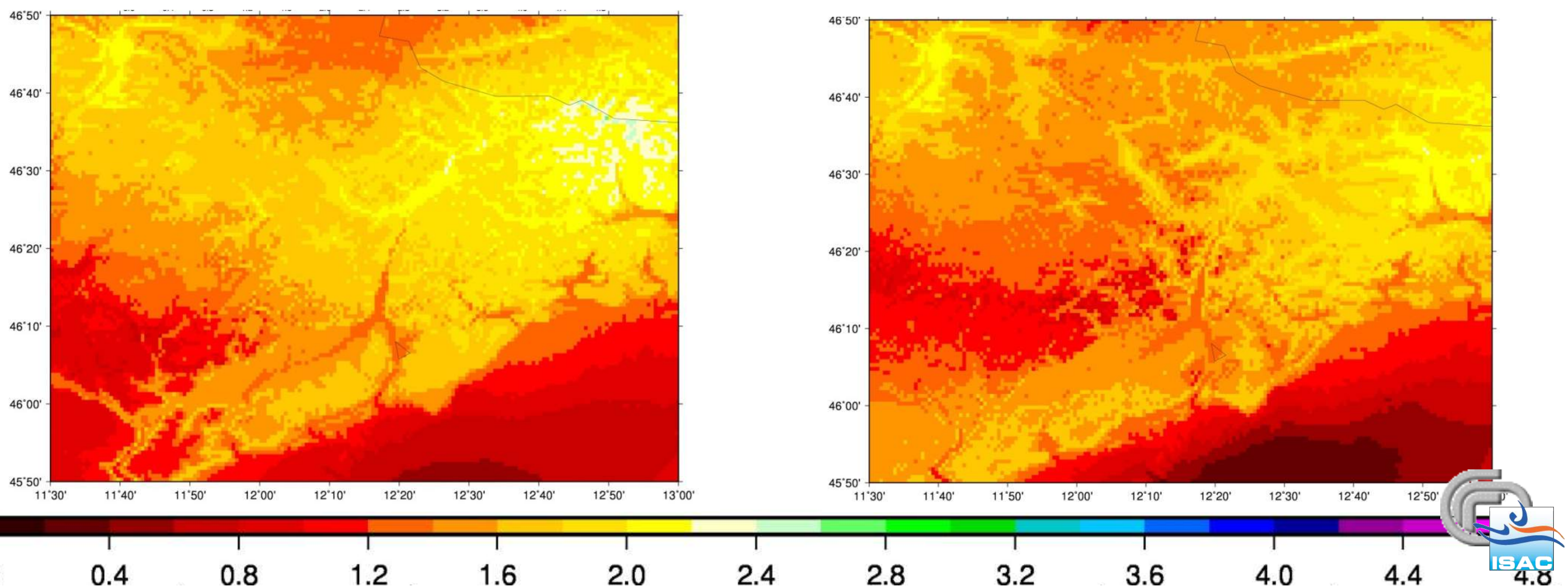




IMPROVING DATA AVAILABILITY



CONFIDENCE INTERVAL REDUCTION



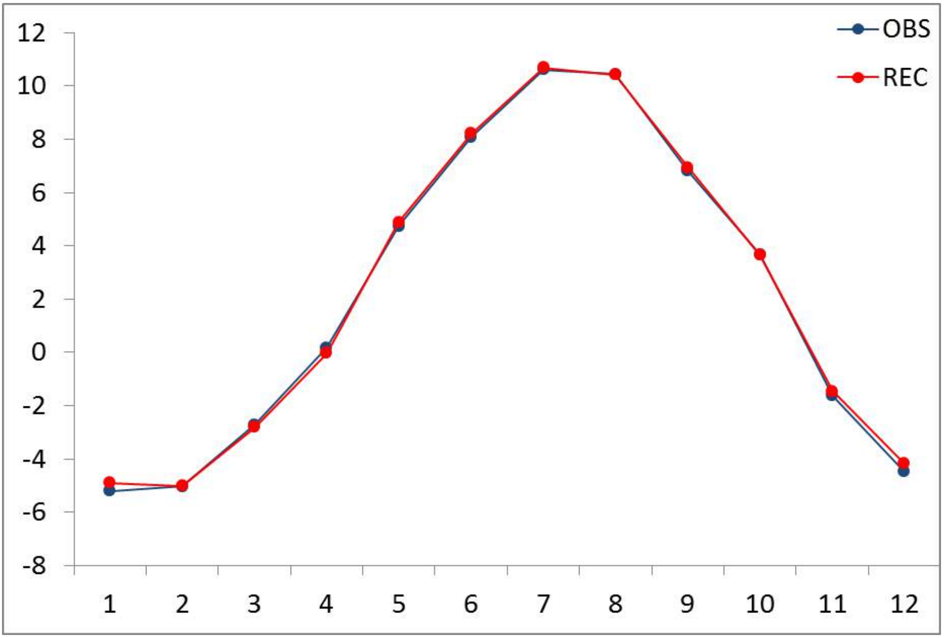
SYNTHETIC SERIES RECONSTRUCTION

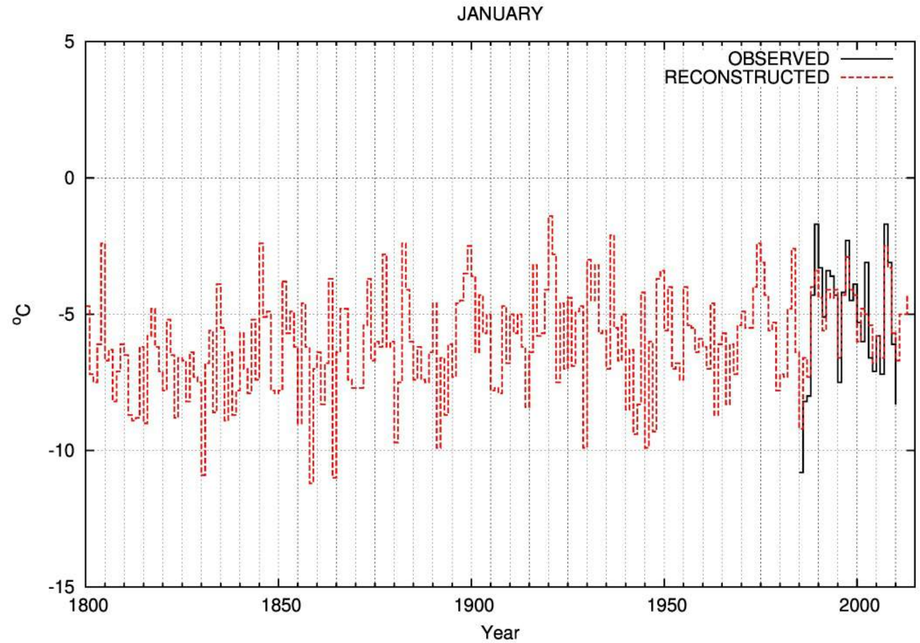
THE EXAMPLE OF TWO REMOTE SITES

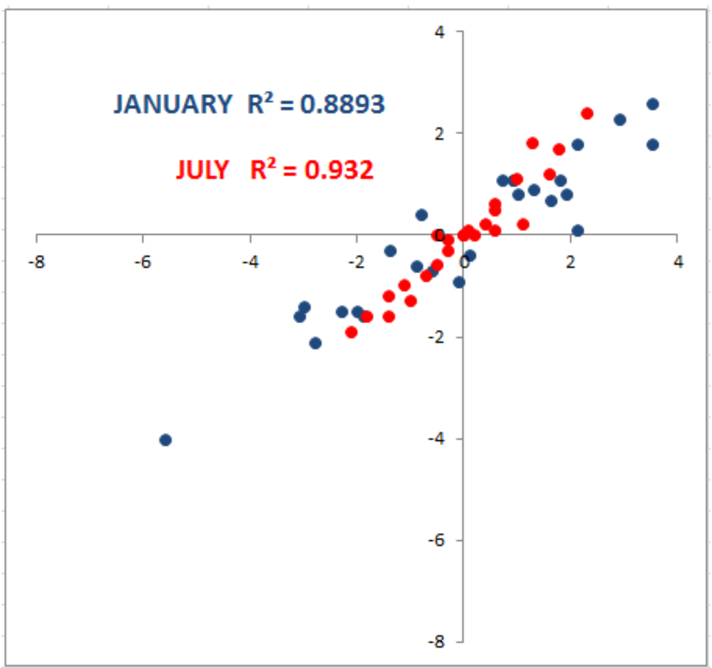
(LEAVE-ONE-OUT APPROACH)

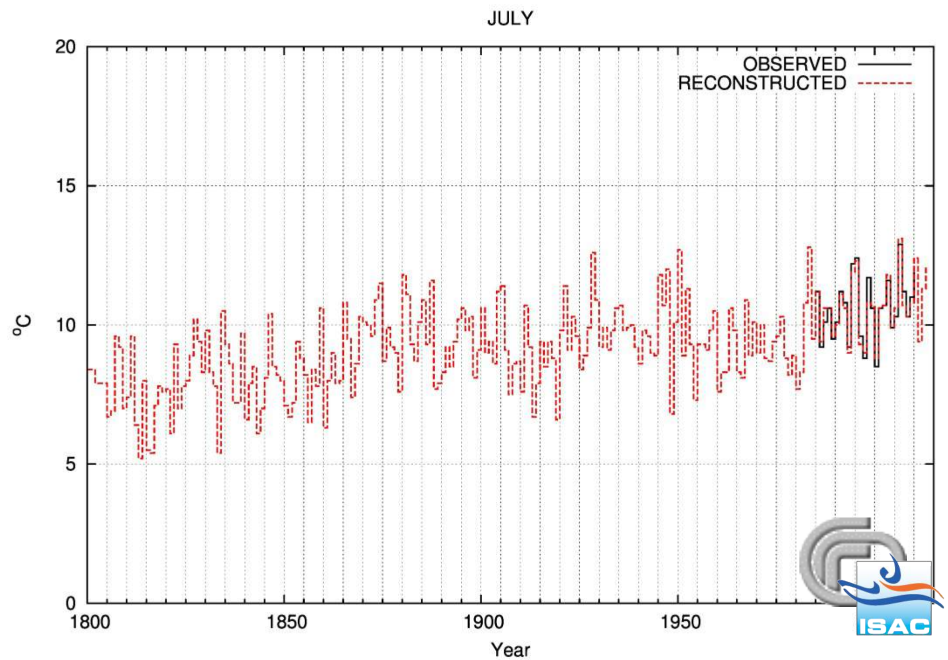
SYNTHETIC SERIES RECONSTRUCTION (PASSO PORDOI 2155m)

SYNTHETIC SERIES RECONSTRUCTION (PASSO PORDOI 2155m)



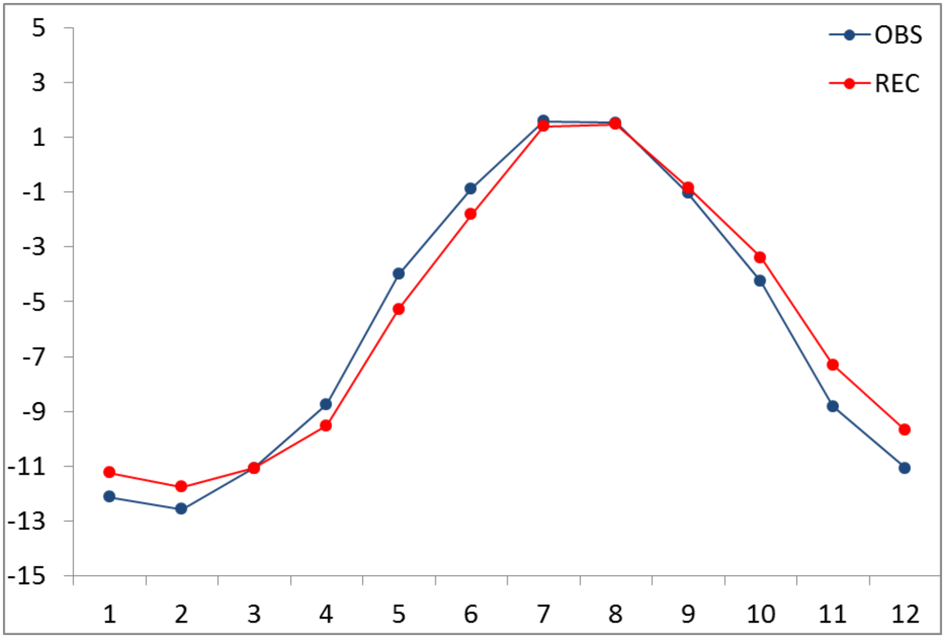


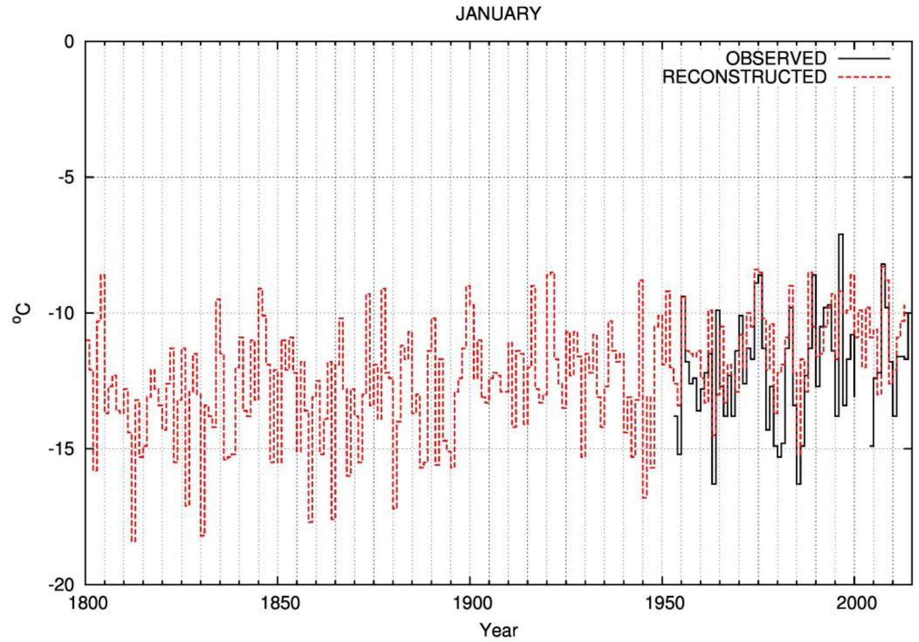


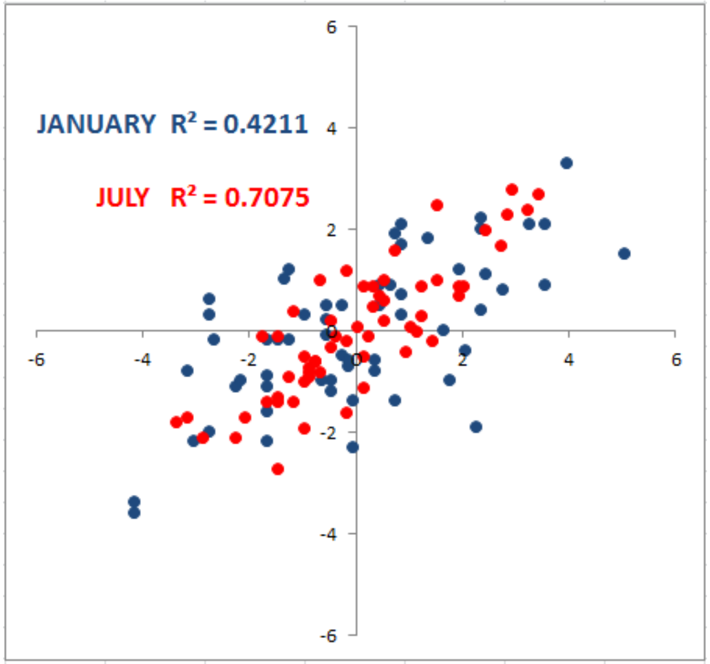


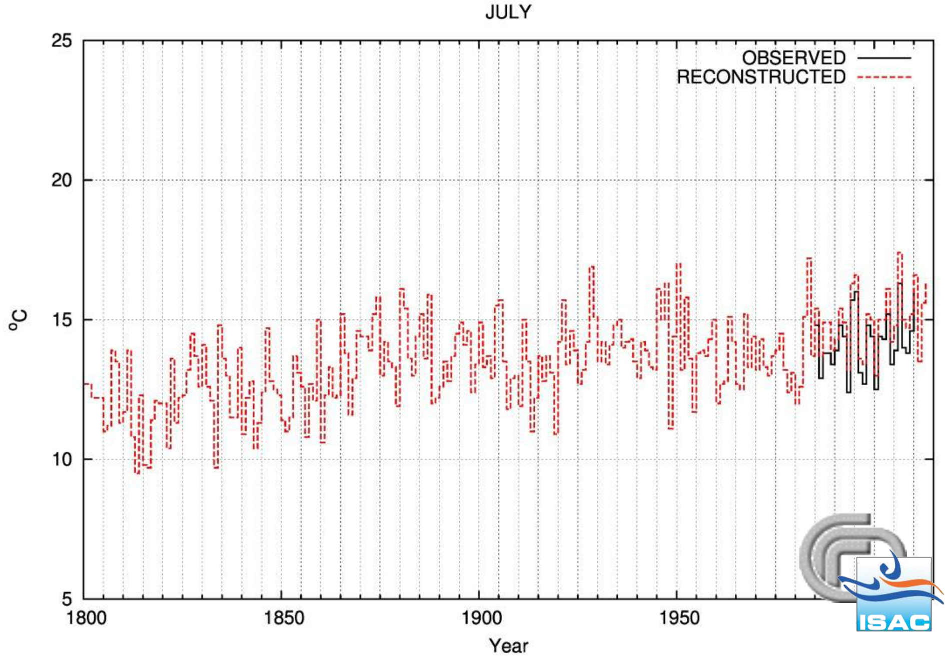
SYNTHETIC SERIES RECONSTRUCTION (PLATEAU ROSA' 3488m)

SYNTHETIC SERIES RECONSTRUCTION (PLATEAU ROSA' 3488m)

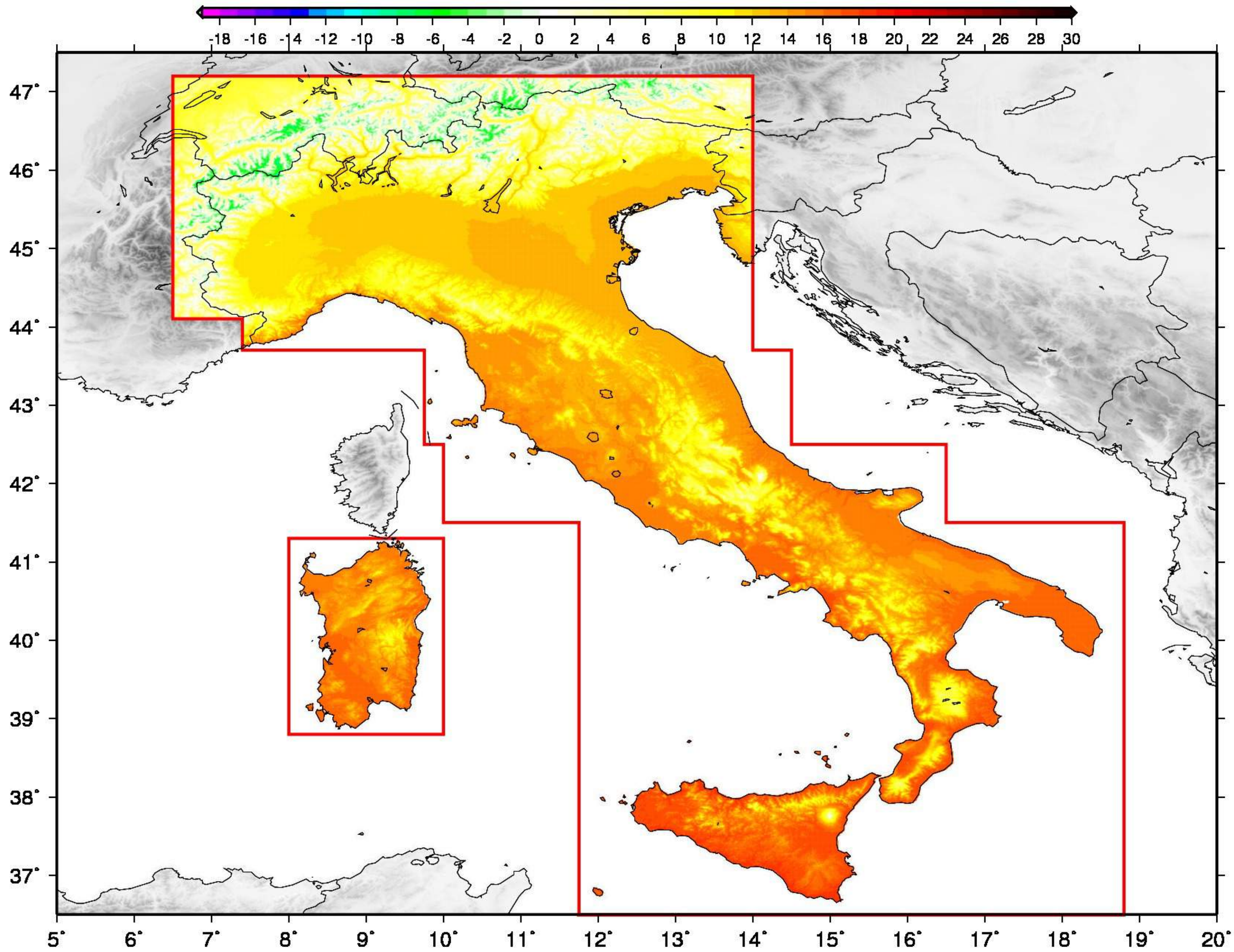








1951-1960



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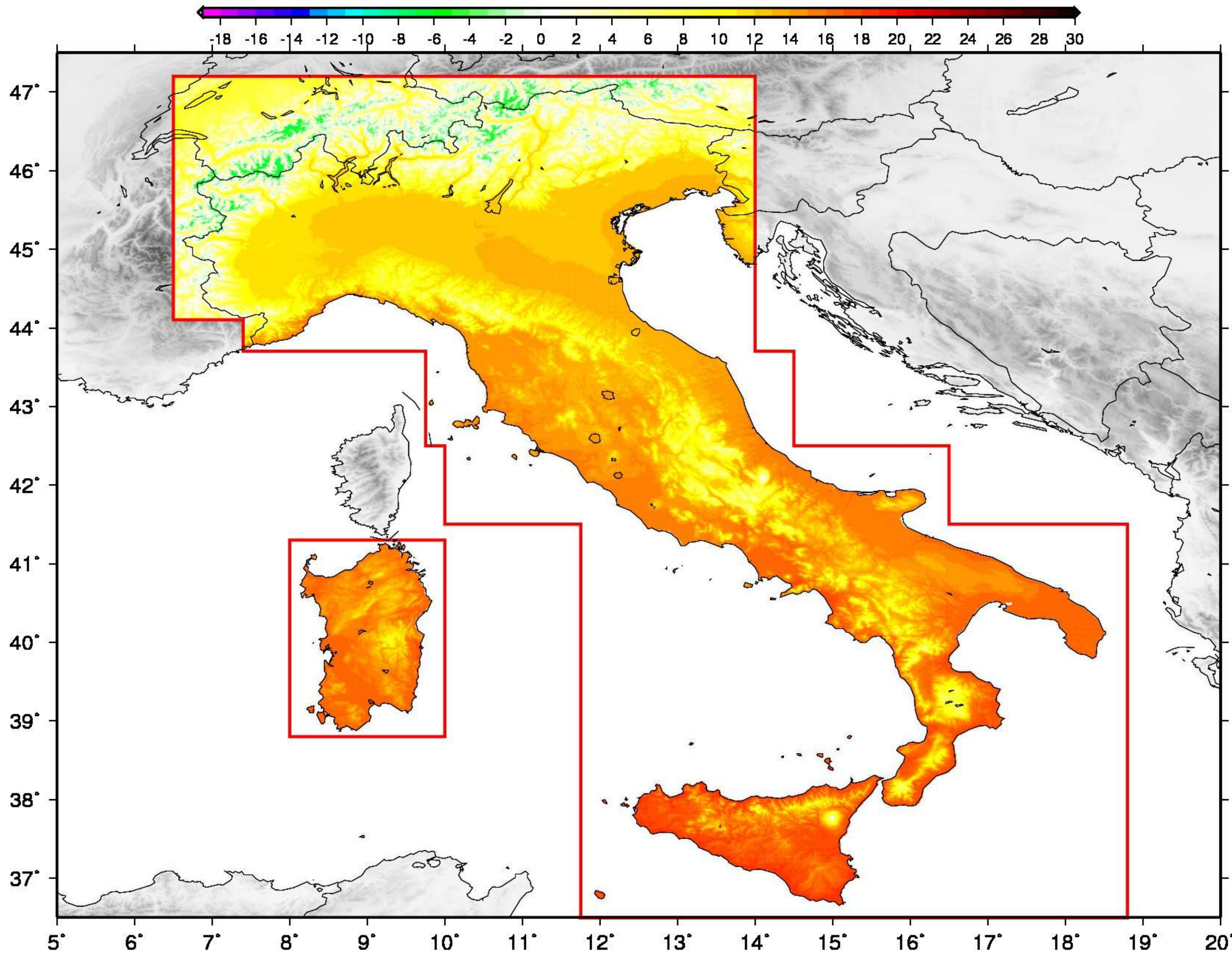
1961-1970



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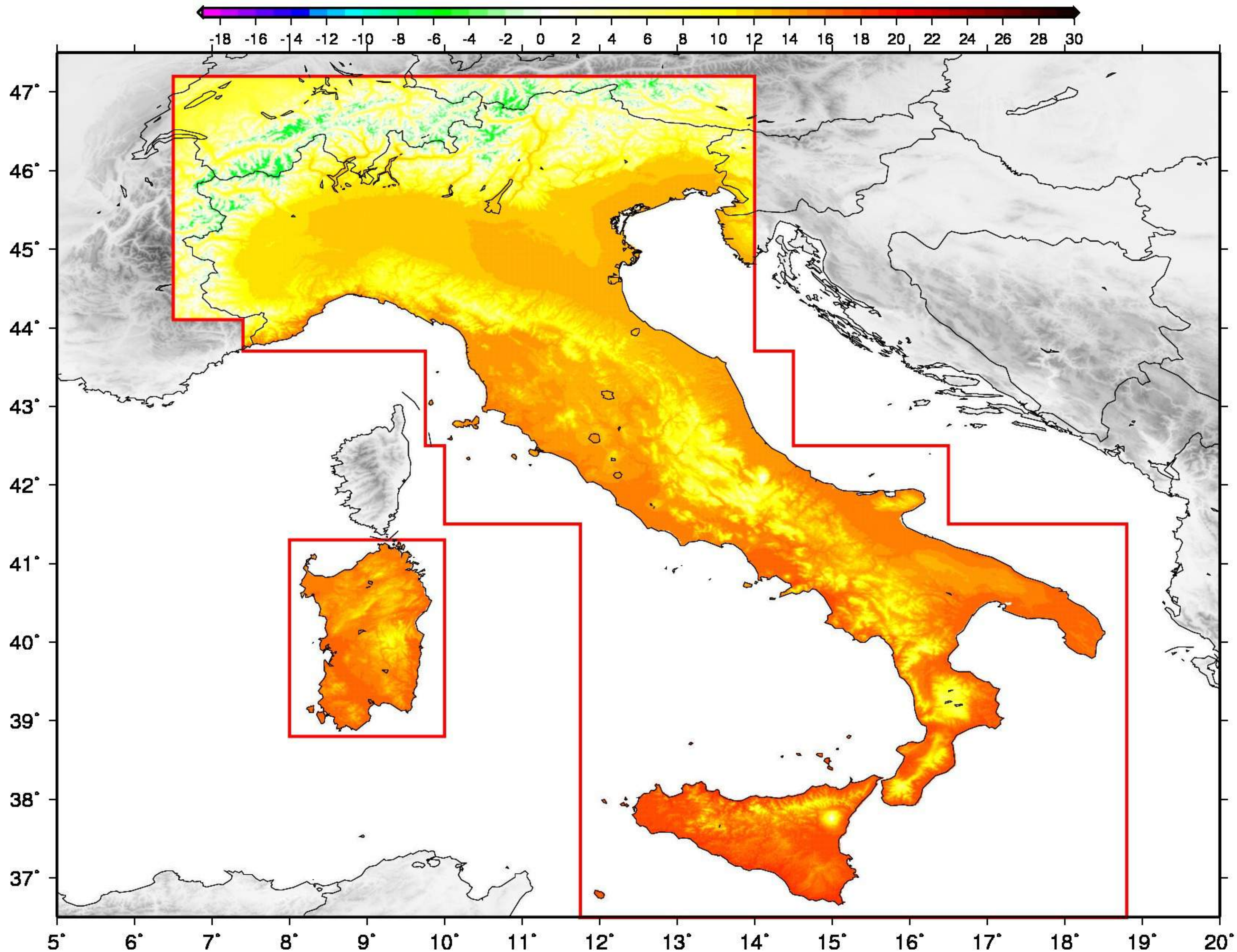
1971-1980



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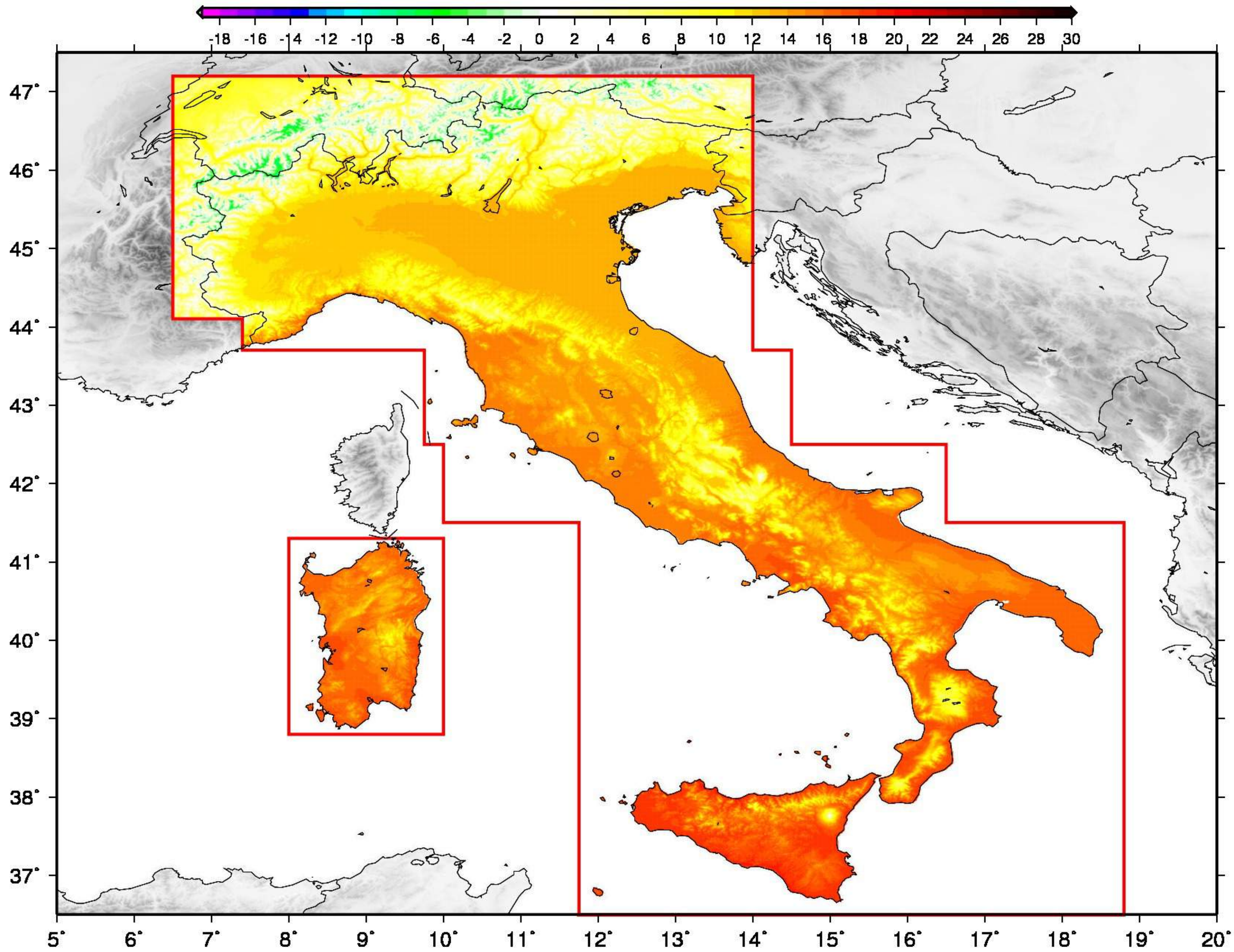
1981-1990



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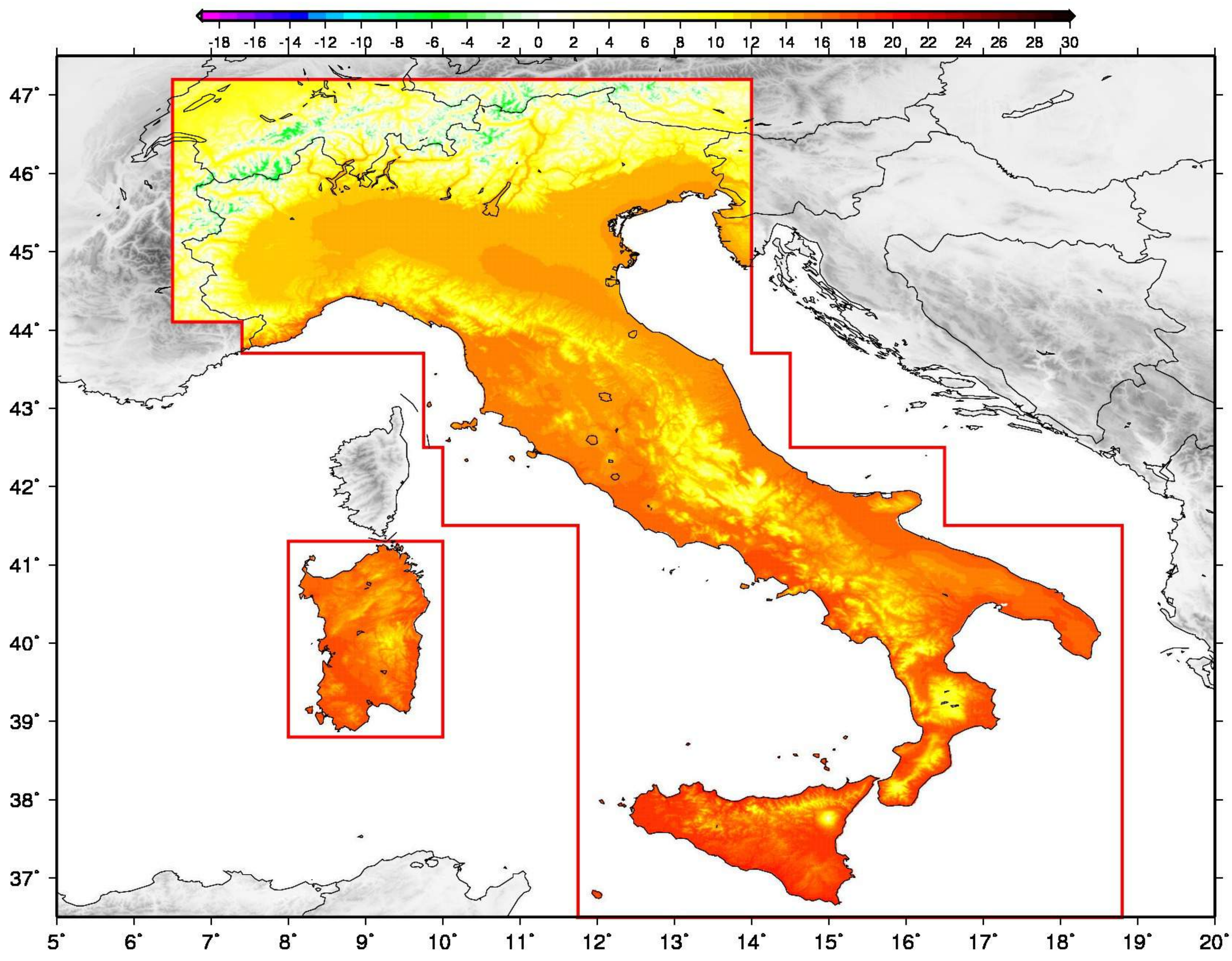
1991-2000



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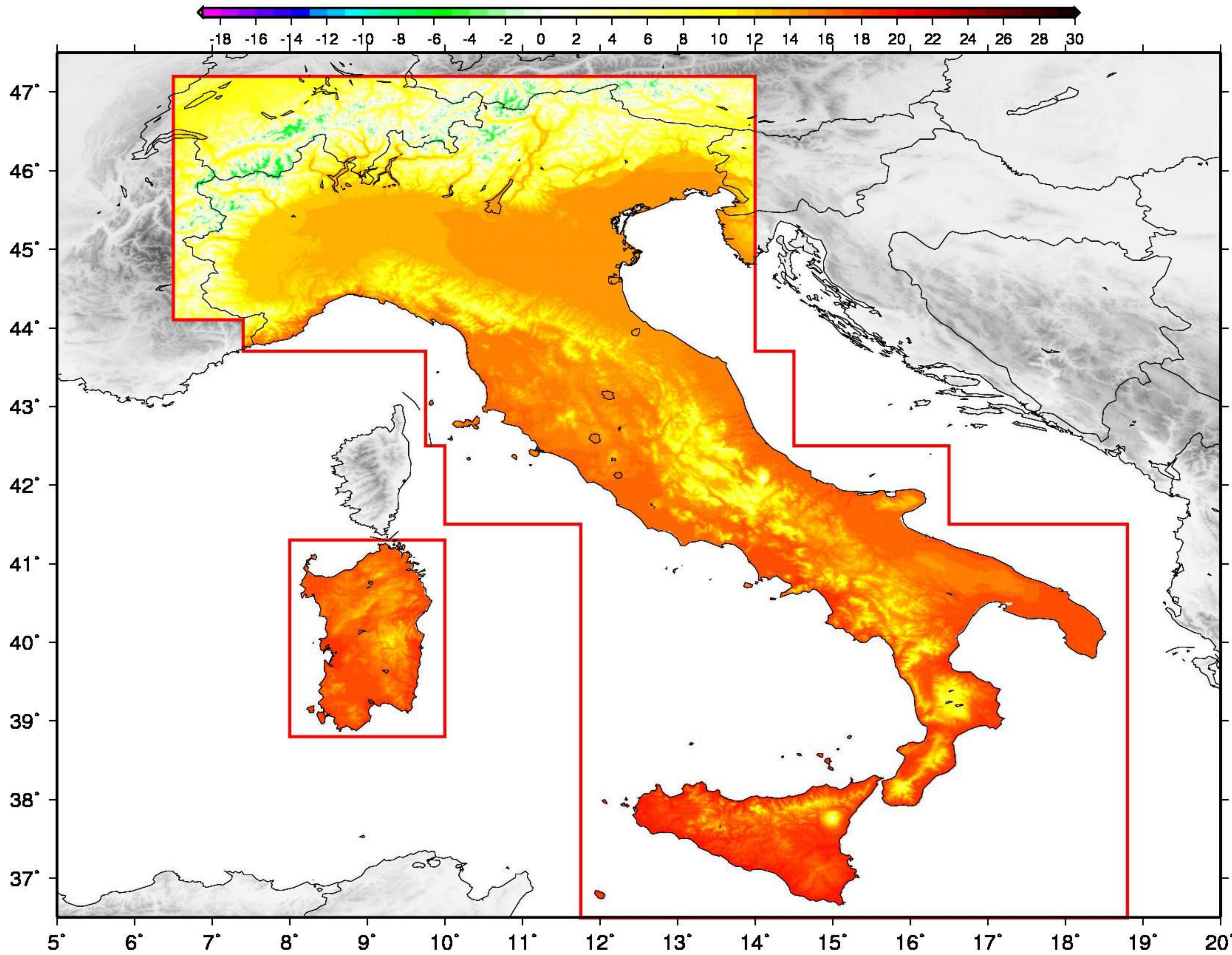
2001-2010



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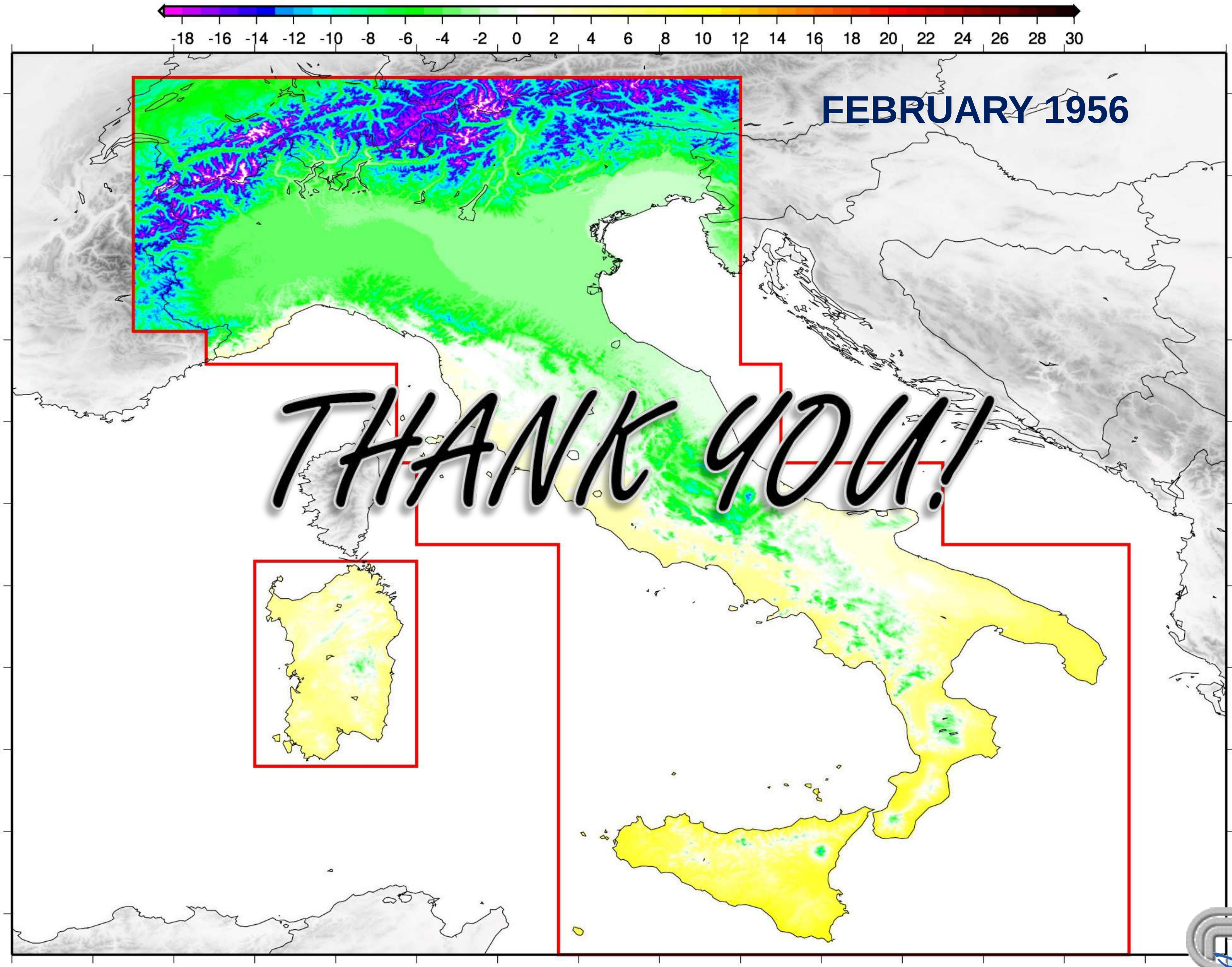
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