Multiscale regression model to infer historical temperatures in a central Mediterranean Sub-regional Area

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Abstract

This paper has exploited, for Southern and Central Italy (Mediterranean Sub-Regional Area), an unprecedented historical dataset as an attempt to model seasonal (winter and summer) air temperatures in pre-instrumental time (back to 1500). Combining information derived from proxy documentary data and large-scale simulation, a statistical downscaling approach in the form of multiscale–temperature regression (MTR)–model was developed to adapt larger-scale estimations (regional component) to the sub-regional temperature pattern (local component). It interprets local temperature anomalies by means of monthly-based Temperature Anomaly Scaled Index in the range -5 (very cold conditions in June) to 2 (very warm conditions). The modelled response agrees well with the independent data from the validation sample (Nash-Sutcliffe efficiency coefficient >0.60). The advantage of the approach is not merely increased accuracy in estimation. Rather, it relies on the ability to extract (and exploit) the right information to replicate coherent temperature series in historical times.

1 Introduction

> Modelling can be described as an art because it involves experience and intuition as well as the development of a set of – mathematical - skills.
>
> Mark Mulligan and John Wainwright (eds.), 2004. *Environmental Modelling*, Wiley, Chichester, p. 8.

The Mediterranean is one of the few regions in the world holding a large volume of weather documentary proxies for the past 500-1000 years (Camuffo and Enzi, 1992; Jones et al., 2009). However, such large amounts of documents and archives have not yet been fully explored to reproduce with high spatio-temporal resolution the different climates of Mediterranean (García-Herrera et al., 2007). Determining the climatic history in these unrepresented places of the world is a challenging and complex issue at both theoretical and applicative levels.

Modelling is an ideal trial to test the environmental processes over extensive space and time domains. In the recent decades, considerable progress has been made in pre-instrumental temperature modelling at both hemispheric and regional scales (e.g. Mitchell et al., 2005; Rutherford et a., 2005). Luterbacher et al. (2004) and Xoplaki et al. (2005) were able to map seasonally resolved temperature reconstructions across European land areas back to 1500. In particular, Luterbacher et al. (2004) developed separate multiple regression equations between each principal component (PC) of the instrumental data and all leading PC of the proxy records. In this way, they assimilated proxy records into reconstructions of the underlying spatial patterns of past climate changes. The reconstructed climate field allows for a special assessment of the spatial coherence of past annual-to-decadal temperature changes at sub-continental scale, thus providing insight into the mechanisms or forcing underlying observed variability. In hemispheric, continental and regional reconstructions, however, multi-proxy coverage is often irregular and heterogeneous (Esper et al., 2002). Temperature and precipitation reconstructions, although well developed over large geographical areas, may become poorly accurate at sub-regional and local scales, or over particular periods (Mann et al., 2000; Ogilvie and Jónsson, 2001; Diodato et al., 2008). On the other hand, it is not surprising if Mann (2007), comparing estimated regional temperatures at different locations over the past 1000 years, found that the cold and warm periods were considerably different from region to region. Then, the issue of sub-regional reconstructions should attract the attention of scientists as it may exhibit unexpected results, especially regarding some temperature extremes (Bhatnagar et al., 2002). The issue of downscaling to small spatial and temporal scales must be made a priority in order to achieve a better understanding of sub-regional climates (Riedwyl et al., 2009). Documentary proxies' investigation remains a reliable approach to trace back the temperature extremes before the advent of instrumental recording of meteorological data (Brázdil et al., 2005; Jones et al., 2009). Brewer et al. (2007) investigated tree-ring sites to support the reconstruction of historical droughts in Mediterranean areas during the last 500 years. However, temperature series have not been modelled for this region so far. Moreover, continuous and homogeneous instrumental series cannot be extended before the 19th century (Camuffo et al., 2010). On the other hand, high-resolution climate information is increasingly needed for the study of past, present and future climate changes (Vrac et al., 2007).

Several authors such as Luterbacher and Xoplaki, (2003), Pauling et al. (2003), and Ge et al. (2005) suggested that pre-modern instrumental weather indices may be promising to enrich climate reconstructions. Different sets of proxy-variables have indeed been used to find out relationships between predictors and predictands in high-resolution climate time reconstructions (e.g. Wang et al., 1991; Briffa et al., 2002; Larocque and Smith, 2005; Moberg et al., 2005; Diodato, 2007; Davi et al., 2008). Many of these reconstructions depend on empirical relationships between proxy records and climate data. Comparing linear algorithms and neural networks, Helama et al. (2009) proved that both the approaches are reliable for temperature reconstruction. Although regression-based techniques have been used with considerable success for climate reconstructions, they can engender bias in the estimates if not employed with care (Robertson et al., 1999; Moberg et al., 2005; von Storch et al., 2005). Moreover, these relationships are seldom based on a training process capable to capture all the possible data combinations that occur when extrapolation is performed (i.e. reconstruction period). With reference to dendroclimatological studies, correlation between tree-ring proxies and temperature data was found to only explain about 50% of the (Liang et al., 2008; Helama et al., 2009; Tan et al., 2009). Documentary data series are expected to better correlate with temperature, the overall explained variance being of about 70% (Leijonhufvud et al., 2008; Dobrovolný et al., 2010). However, there are few estimates of uncertainty in documentary based climate reconstructions (Moberg et al., 2009).

In this study, we have considered an alternative approach to address the statistical modelling of temperature variability, based on documentary records and previous large-scale reconstructions. In particular, a documentary-based technique was developed based on multiscale temperature regression (MTR)–model at sub-regional level. An area covering Southern and Central Italy and named in this paper Mediterranean Sub-regional Area (MSA) is the focus of the investigation. The goal was to produce a relatively simplified multiscaled model acceptable and verifiable by scientists as well as knowledgeable people. (MTR)–model combines documentary proxy-based local weather anomalies with large-scale temperature data to adapt regional temperature data to specific sites and seasons. The selected sub-region, centrally located in the Mediterranean region, is an interesting test area rich in documentary proxy data and modern weather records useful to improve the spatial resolution of past climate. The next section describes the geographical environment, the datasets and the developed methods. Section 3 illustrates the novel mixed-model approach in detail. Its results on temperature series estimation were evaluated over the MSA. Conclusions (Section 4) point out the main results and look at horizons for future research.

2 Environmental setting, data and methods

2.1 Study area, datasets and method of analysis

The study is based on a set of both monthly-modelled regional temperatures and documentary proxy data at a typical Mediterranean area of Central and Southern Italy (MSA in Fig. 1). This sub-region is frequently crossed by depressions generating over the Mediterranean Sea (Wigley, 1992) that, reinforced by continental North easterly airflows, produce important fluctuations in temperature and precipitation and large-scale atmospheric oscillations (Barriendos Vallve and Martin-Vide, 1998).

Regional temperature data (hereafter called T_R) were derived from Luterbacher et al. (2004) for Europe over 1500-2002. The data, upscaled at about 0.5-degree grid resolution (~50 km) from historical instrumental series and multi-proxy data (http://www.ncdc.noaa.gov/cgi-bin/paleo/eurotemp.pl), covers an area extending from 25° West to 40° East and from 35° to 70° North (Fig. 1a). From this map and from that depicted in Fig. 1b, it is also possible to observe the temperature-data missing over Southern Europe (including the MSA), as suggested by both data-density and correlation pattern.

In order to fill this deficiency in the data available, a new documentary-dataset was derived from chronicles found in two main sources, *Moio and Susanna Manuscript* (Ferrari, 1977) and *Corradi's Annals* (Corradi, 1972). A data bank (Catalogue EVA –

Environmental Events of the ENEA – Italian National Agency of for New Technologies, Energy and the Environment, Clemente and Margottini, 1991) was also referred to and used when necessary. The Italian scientist Alfonso Corradi (1833-1892) carried out pioneering works in documentary research on the environmental and climatological extreme conditions that occurred in Italian regions through time. He collected the historical documents from 5 to 1850 A.C., related to meteorology and epidemics into a five-volume book (Corradi, 1972). More recently, the historian Umberto Ferrari published the chronicles of Giovanni Battista Moio and Gregorio Susanna quoting climate extremes, famines from 1710 to 1769 and weather information over the 16th and 17th centuries for the Calabrian region (Ferrari, 1977).

For the purposes of modelling, the split-samples approach was used to segregate the available data into a calibration set and a validation set. Particular attention was paid to the calibration procedure in order to ensure that the resulting model could produce reliable outcomes (i.e. time-series reconstruction). Two distinct climate periods (1867-1903 and 1972-2002) were included in the calibration dataset (68 years in total) for two main reasons. The first was to ensure model calibration accuracy by accounting for both cold and warm intervals, and the second to ensure that the model was able to simulate air temperature on periods with either accurate (as in recent times) or inaccurate data (as in historical times). The validation dataset contained instrumental temperature reconstruction for the MSA (as performed by Camuffo et al., 2010), including the periods 1742-1754 and 1792-1818. These two intervals are considered the only reliable records in the historical time for this area. The entire workflow was executed interactively using a spreadsheet of MS Excel 2003, for data collection, model development and graphical assembling, with the support of STATGRAPHICS online statistical package (http://www.statgraphics.com) and Statistics Library–R modules (Wessa, 2009) for statistics performance and graphical outputs, respectively. The agreement between estimates and observations was evaluated using a set of statistics, including the modelling efficiency by Nash and Sutcliffe (1970), ranging from negative infinity to positive unity (the latter being the optimum value). In order to have a visual inspection of the quality of results, a set of comparative scatterplots and histograms are also presented.

2.2 Monthly temperature anomaly scaled index

Information held in the written documentary sources was extracted to derive temperature related indices. Different types of indices have been proposed in historical climatology studies (Pfister, 1999, 2001; Brázdil et al, 2005). As a general reference, a seven-point scale was employed, ranging from –3 for 'extreme coldness' to +3 for 'extreme hotness', with 0 indicating 'normal' conditions. However, this ordinal scale bears the limitation of a limited discrimination across the full range of extremes, since it tends to assign all events above a certain level to the same extreme class (Glaser and Riemann, 2009). To obtain a more realistic degree of variability in the temperature modelling, we used a simplified scaled-index for a more accurate estimate of extreme anomalies. Examples of such events are recorded only during the Little Ice Age (e.g. rivers freezing), when no instrumental data could overlap the calibration period.

Based on the above criteria, monthly indices were calculated, thus gaining more than seven possible classes to preserve the variability described by the written sources similar to the natural variability, and over a longer period than the calibration interval. These classes were allocated to their respective index by an asymmetric look-up table in order to take into account temporal shifts between proxy and actual anomalies in different seasons of the year. In fact, as an example, a river freezing on March or April is a more negative anomaly than a frozen river on January. Based on these new classification principles, temperature anomalies were coded for winter and summer by means of a monthly-based Temperature Anomaly Scaled Index (*TASI*), according to the look-up table scheme (Table 1a). The geometric interpretation of the classification process is shown in Fig. 2. The asymmetric profile for winter and summer seasons is a bi-dimensional simplification based on observations and documentary-proxy data. For the study-area, positive (red line) and negative (blue line) temperature anomalies result asymmetrically arranged around the mean seasonal values (black line). The latter are long-term average temperatures calculated, for the study-area, from the European database of Luterbacher et al. (2004). In the case of negative anomalies, the baseline is the freezing point of water (0 °C). A baseline for all seasons was not set to reproduce positive anomalies. In this case, in fact, temperature extremes are dictated by the Mediterranean latitudes. Although this region presents a twofold climate regime, where both tropical and mid-latitude aspects play a role, the latitudinal radiative flux stands out as the main factor determining the temperature. Advective transport off northern Africa can also occasionally affect the Mediterranean, but the seasonal variations are well marked (e.g. Schiano et al., 2000; Lionello et al., 2006) and, notably, temperatures in winter are never as high as summer values. Negative anomalies were assigned to cover the gap between the mean value and the freezing point, which is only sporadically (or never) approached in summertime (N/A). In winter (December, January, and February), values of -1 (cold) / +1 (warm) and -2 (very cold) / +2 (very warm) are consistent with temperature values deviating up to three and four times the standard deviation, respectively. Abrupt jumps from “very cold” (-2) to “freezing” (-4) in winter are due to the lack of appreciative intermediate states during the calibration period. In the case of positive anomalies, a similar scheme is reproduced for summer season (June, July and August). Negative anomalies are instead doubled (July-August) or tripled (June) compared to winter, because most evidence of “cold” and “very cold” conditions in the historical sources only refers to cooling to temperatures well below the seasonal mean.

Once the magnitude of the indices array was defined, then the proxies were transformed into a time series with a clearly defined temporal resolution. This kind of understanding is offered in the form of an exemplary table layout (Table 1b), incorporating monthly and seasonal values of the *TASI*, and the relative sources for the period 1752-1757.

3 Modelling of sub-regional winter temperatures

In this study, regional temperatures (*case*) from Luterbacher et al. (2004) are the basis for modelling sub-regional temperatures (*response*). In this situation, it is possible to have more than one response for each case. Thus, a central problem in the analysis of multiresponse situations, is finding a function that combines several responses to determine more realistic estimates. This is also the case of air temperature, for which multi-scale predictors are needed to model over different space- and time-domains (after Bates and Watts, 2007). In this way, the information collected (regional temperature data) was downscaled to reasonably approximate the behaviour of the disturbance terms (or stimulus variables) driving the temperature measurements at sub-regional scale. These approximations reside on the general assumption that sub-regional air temperature depends on two disturbance terms: regional-synoptic forcing and local weather conditions. The regional scale can drive the general temperature trend, while area-specific temperatures are met by local conditions. Weather variables and climate indices were both used as predictors as basis of the multi-scale regression model.

3.1 Inferences for multi-scale temperature estimation

A statistical model of sub-regional temperature estimation was created with aims of prediction and explanation. For prediction, the model structure was generated based on

Box and Draper (1972). In particular, a determinant parameter-estimation criterion for multiresponse data was derived upon the primary assumption that the disturbance terms of different cases are uncorrelated. A corollary assumption was that, in a single case, the disturbance terms have a fixed, unknown variance-covariance matrix for different responses. A model was written along this path, assuming multiple responses and dependence on a set of parameters, as referred to by Bates and Watts (2007): the temperature random variable is a function depending on some predictors by a set of parameters, and assuming the sum of the errors equal to zero.

To contribute to the aim of explanation, influential predictors were identified and insight gained into the relationship between the predictors and the outcome based on climate history and modelling background. In this path, the temperature random variable comprises predicting variables at regional, $(.)_{\mathrm{R}}$, and sub-regional, $(.)_{\mathrm{SR}}$, scales (Fig. 3). Once regional and sub-regional components are identified, one can estimate the relationship between expected temperature and predictors. To extend the procedure for extrapolations outside the range represented by the calibration sample, the model was iteratively rearranged towards a robust solution whereby two additive components are used (non-linear regional component, linear-and-local component):

$$y(T_{\mathrm{MTR}}) = k \cdot \sqrt{T_{\mathrm{R}}} + \beta \cdot \left(T_{\mathrm{R}} + \Omega_{\mathrm{S}} + \sum TASI_S\right) \qquad (1)$$

where the first term, $y(T_{\mathrm{MTR}})$, is the seasonal mean temperature output (°C) of the (MTR)–model; T_{R} is the regional component of temperature (°C) supplied as a boundary condition; the part in brackets is the sub-regional component of temperature (°C) supplied as a local constraint.

A recursive procedure was performed in order to obtain the best fit of a regression equation $Y=a+b\cdot X$, where Y=model estimates and X=actual data, according to the following criteria:

$$\begin{cases} a = 0 \\ |b-1| = \min \\ R^2 = \max \end{cases} \qquad (2)$$

where the first condition is to set null intercept (a), the second is to approximate the unit slope (b) of the straight line that would minimize the bias, and the third is to maximize the goodness-of-fit (R^2) of the linear function. Since the different assumptions cannot be guaranteed *a priori*, the parameters were estimated using an iterative, knowledge-driven approach to bias correction steps (after Box et al., 1978). For instance, after a first run, it was found that regional temperatures (T_R) introduced increasingly biased and imprecise estimates over historical times. Likewise, earliest regional inferences in Mann et al. (2000) tended to be associated with decreased performance. To account for this non-invariance over the historical time-scale, a power law was assigned to T_R with the exponent forced to be lower than one (and finally set equal to 0.5) to rebalance internally the quality of calibration. Such iterative fitting of the data allowed for correcting the bias initially observed and capturing the full range of sub-regional scale variability.

The scale parameter k (°C^2) was initially set equal to one and, for reasons of parsimony as by Grace (2004), not treated as a free parameter because the initial value resulted in a fit that satisfied the criteria outlined above (Eq. 2). T_R appears in both the square root (power of 0.5) and linear term. In the first case, it returns a direct, non-linear effect, while in the brackets it crosses the sub-regional anomalies identified by the *TASI* to correct the bias observed in the historical times. The square root of T_R and parameter β are mainly to define the order of magnitude of the process used to downscale the (MTR)–model to the sub-regional scale. The other two terms into the brackets are seasonally-varying (index *S*) shift parameters (°C) of T_R, which force the model with meteorological ($\Sigma TASI_S$, sum of monthly values of the Temperature Anomaly Scaled Index defined above) and climatological (Ω_S, hereafter indicated as Ω_w and Ω_s for winter and summer, respectively) boundary conditions.

3.2 Model parameterization and evaluation

For (MTR)–model (Eq. 1), the values of the parameters obtained from a particular set of observations with a recursive procedure are: β=0.268, Ω_w=11.0 °C, Ω_s=43.5 °C. Using the estimated parameter values, the non-linear response to T_R is depicted in Fig. 3, as translated into Eq. 1 for different values of $\Sigma TASI_S$.

In the temperature series supplied by Luterbacher *et al.* (2004), standard deviation (sd) for winter increases in more recent years, i.e. after the LIA (sd=0.96 against 0.74 for 1739-1783). This contrasts with the instrumental observations, for instance those performed by Domenico Cirillo in the 18th century (sd=1.1) and documented by the Meteorological Diaries of the Royal Society of London for the Kingdom of Naples (Derham, 1733-1734). The reconstructed series based on Eq. (1) gives sd~1.0 for both recent and historical times. For summertime, sd~0.6 was registered for 1739-1783 in the regional dataset, also approached by the reconstructed series.

The parameter values estimated from the data roughly matched the observations. In Fig. 4, negligible departures of the data-points from the 1:1 line (observed versus predicted values) indicate the presence of limited bias in the residuals with both winter (graph a) and summer (graph b) calibration datasets. The Nash-Sutcliffe efficiency index and the correlation coefficient, equal to 0.88 and 0.94 for winter and 0.87 and 0.88 for summer (Table 2), are also satisfactory. Fig. 5 shows the results of model validation against independent time-series data. In general, fluctuations of observed and (MTR)–model predicted temperatures compare well in both seasons. In particular, absolute minimum and maximum observed values are both reflected in the predictions (black lines in Fig. 5a, b). The Nash-Sutcliffe efficiency values, equal to 0.66 (winter) and 0.63 (summer) are also satisfactory (Table 2). In contrast, the regional model by Luterbacher et al. (2004) poorly reflects the variability of actual winter temperature in both seasons (circles in Fig. 5a), as also confirmed by the correlation coefficient and the Nash-Sutcliffe efficiency values (equal to 0.26 and –0.43, for winter, and 0.50 and –0.30 for summer, Table 2, validation dataset). In wintertime, regional estimates suffer from reduced precision in Southern Europe where temperatures are more variable than Central Europe. In summertime, when estimated and observed variances are similar, most assessments of the poor performance of regional estimates focus on the weak correlation with observations (Fig. 1b). For (MTR)–model, the residuals distribution denote a quasi-Gaussian trend (Fig. 6a, b), with the QQ-plots reflecting theoretical values (Fig. 6a_1, b_1) in both seasons.

Independence-of-errors due to the possible presence of significant autocorrelations among the residuals was also tested. Strong temporal dependence may in fact induce spurious relations according to standard inference in an ordinary regression model (see Granger et al., 2001), and the same problem is further increased in the context of nonlinear models (Stenseth et al., 2003). The Durbin-Watson (Durbin and Watson, 1950, 1951) d statistic in the following form was calculated to verify the presence of autocorrelation in the residuals e (the index t indicating the t^{th} year):

$$d = \frac{\sum_{t=1}^{T}\left(e_t - e_{t-1}\right)^2}{\sum_{t=1}^{T} e_t^2} \tag{3}$$

Two critical values, $d_{L,\alpha}$ and $d_{U,\alpha}$, vary depending on the level of significance (α), the number of observations, and the number of predictors in the regression equation. In the calibration dataset, indication of possible correlation is produced at $0.01<\alpha<0.05$ significance level for winter only (Table 2). The existence of the autocorrelation can be understood as the result of a functional misspecification problem (e.g. Green, 2003). This aspect is similar to the multicollinearity problem in linear regression, usually dealt with separately from autocorrelation, but also examined by its autocorrelation effect in the error term (e.g. Ramsey III et al., 2001). In our case, autocorrelation may be due to some internal constraint in the calibration stage, probably related to the fact that winter temperatures in the regional dataset and model outputs are more similar in recent times (the period of years used for calibration) than it was in historical times. The calibration dataset is from recent times (covering periods around the 20^{th} century), when estimates from Luterbacher et al. (2004) better approach observed temperatures. Under such conditions, the model likely represents some redundancy in the explanatory variables that means, other predictors than the regional temperature component might not be effective in improving upon the sub-regional estimates. However, both calibration results in summer and the results of data validation in both seasons assume statistical independence of the residuals, with type-I error probability of 0.09 and 0.36 of Durbin-Watson test statistic (Table 2).

The mean absolute error (0.24-0.33), similar between calibration and validation and between seasons, and the other statistics of Table 2 indicate for the validation set a satisfactory performance. This suggests that the proposed approach is a promising tool for future applications in temperature estimation.

The scope of our modelling approach and model parameterization was restricted to capturing the temporal variability of seasonal temperature data in the study-area, and some limitations of the methodology should be acknowledged. Uncertainty ranges in the estimation of parameters were not formally accounted because parameter estimation was achieved in more steps, which makes confidence bounds for model parameters not easily quantifiable. The model error (mismatch between the observed and the modelled value) is however an indication of total model uncertainty (e.g. Shrestha and Solomatine, 2008), and Nash-Sutcliffe efficiency values of 0.6 can discriminate between bad and good performances (e.g. Lim et al., 2006). The efficiency values obtained in the validation stage (>0.8) thus indicate limited model uncertainty; likely associated with narrow parameter uncertainty. Since the results of model calibration were satisfactory, the robustness of the solution was relied on and sensitivity analysis was not added to the study. The reconstruction of temperatures series has thus used generic optimized parameters, which are crude estimates over multiple years. This ensures a generic representation for the MSA, with evidence of improved performance compared to previous estimates. Since geographical locations have characteristics that require specific model structures and local optimization, then the application of the model to other sub-regions may be limited by the ability to provide representative drivers and parameter values.

4 Conclusions

The main novelty of this paper is the introduction of a relatively simple model to reconstruct past seasonal (winter and summer) temperature variability at sub-regional scale based on proxy and simulated datasets. In general, the use of data deriving from different spotted sources is not straightforward to reconstruct climate in Southern Europe. Data used in the previous seasonal temperature reconstruction over Europe, especially over the Mediterranean areas, are from few and early instrumental series (data before 1850) that, for their nature, are difficult to find, evaluate, correct and convert or present in a Celsius scale in terms of temperature anomalies.

The multi-scale regression approached here overcomes the inherent loss of variance in both early instrumental records and univariate least-squares calibration equations. In general, multi-scale, process-based climate models can be accurate. However, the authors argue that improvements in model sophistication may not be as profitable as the ability to reconstruct confidently the overall picture of temperature-related events (and therefore temperature data) over historical times and in different geographical places. Validation, from this point of view, is a major statistical instrument to develop a reliable model to add robustness to past temperature reconstructions. Furthermore, in this paper, we took advantage of the (MTR)-model versatility to evaluate, through proxy-documentary data, how the sub-regional temperatures signal is driven by local and boundary conditions. The accuracy of these signals depends not only on the intrinsic properties of the model itself, but also from the possibility to recover homogeneous documentary records able to maintain unchanged the climate information and to replicate, through the model application, the actual temperature series. Once such conditions are satisfied, the modelling approach may potentially be suitable for applications elsewhere in the Mediterranean basin, provided that model parameters will be documented for other sub-regions than the one investigated here. Further research extending the modelling approach developed here towards other sub-regions of the Mediterranean area would provide additional insight into the implications for the production of valuable knowledge from proxy documentary data and can be considered the natural evolution of this study.

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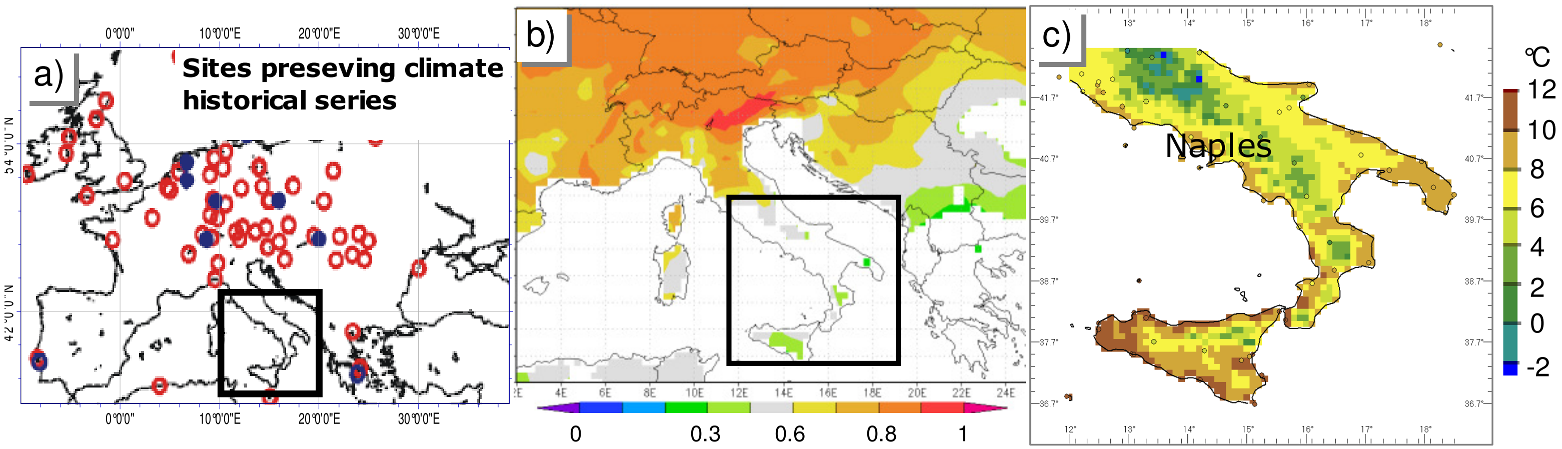

Fig. 1. a): Geographical setting of the Mediterranean Sub-regional Area (MSA, squared) with the location of temperature sites (red circles), and documentary monthly-resolved data (blue dots) used by Luterbacher et al. (2004) to reconstruct the regional seasonal temperatures over Europe since 1500 AD; **b**): Winter temperature correlation patterns (values rendered in white are not significant, $p>0.05$) between one grid-point of Northern Italy (46° North, 12° East) and grid-points over central Mediterranean Europe (the MSA is squared), as processing by Climate Explorer with E-OBS version 3.0 gridded dataset (http://eca.knmi.nl/download/ensembles/ensembles.php) for the period 1950-2010; **c**); Winter temperature pattern averaged over 1961-1990 in the MSA, as arranged by LocClim FAO software at 10-km resolution (http://www.fao.org/sd/2002/EN1203a_en.htm).

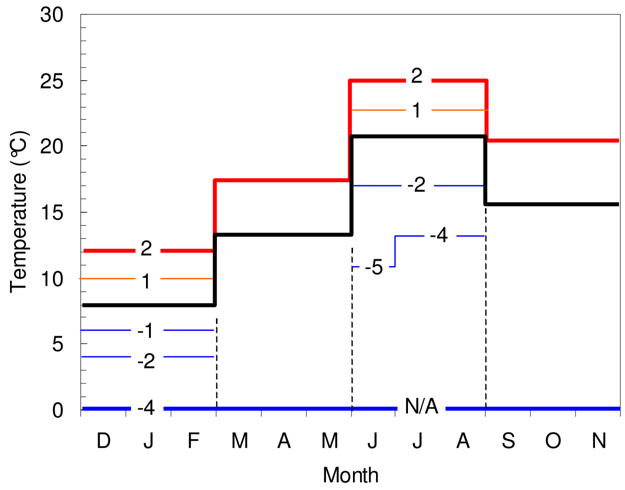

Fig. 2. Geometric interpretation of monthly values of the Temperature Anomalies Scale Index (*TASI*) for winter and summer (see Table 1a for details). Black line: mean seasonal temperatures; red lines: reference values for positive temperature anomalies; blue lines: references values for negative temperature anomalies.

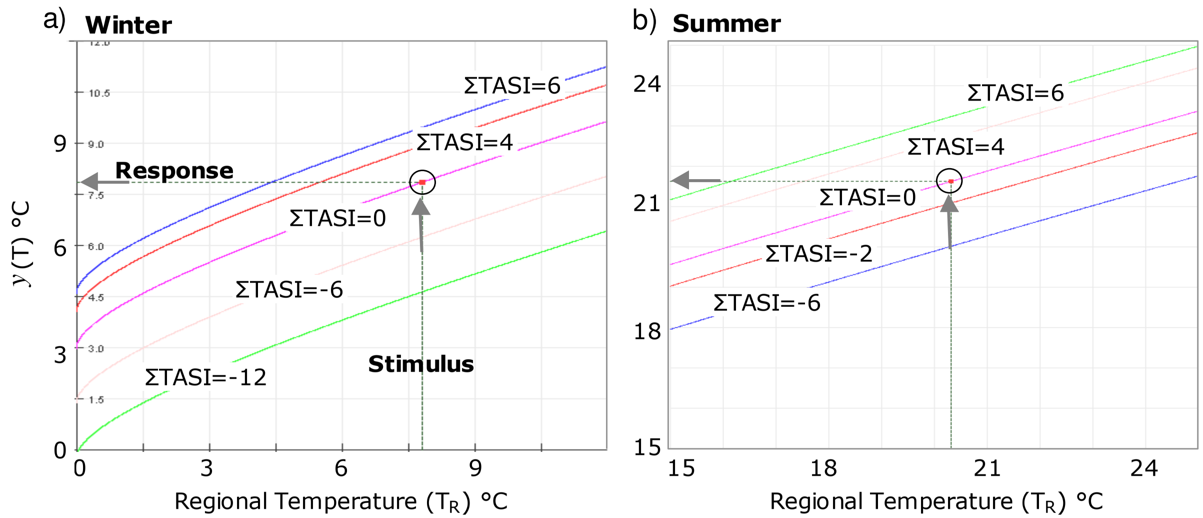

Fig. 3. Nomogram chart illustrating the multiresponse for different $\Sigma TASI_S$-values originating from regional temperature (T_R) in (MTR)–model for winter (a) and summer (b) (mathematical functions graphed using provisions supplied by GraphFunc-tool, http://www.seriesmathstudy.com/sms/graphfunc1_4x).

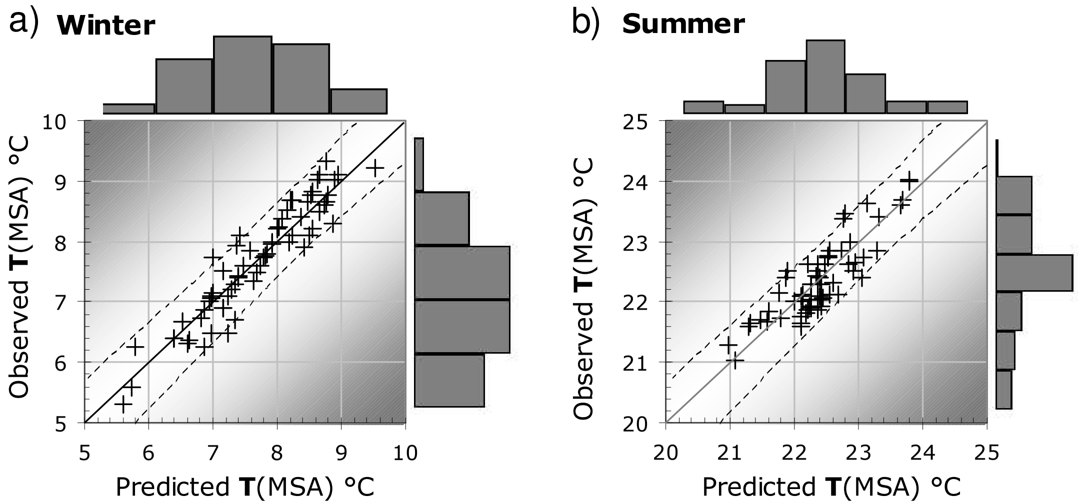

Fig. 4. Scatterplots between observed and predicted mean temperatures (°C) for Mediterranean Sub-regional Area (MSA) in winter (**a**) and in summer (**b**) by (MTR)–model (Eq. 1). Diagonal lines 1:1 and outer dashed bounds at 95% prediction limits are drawn too.

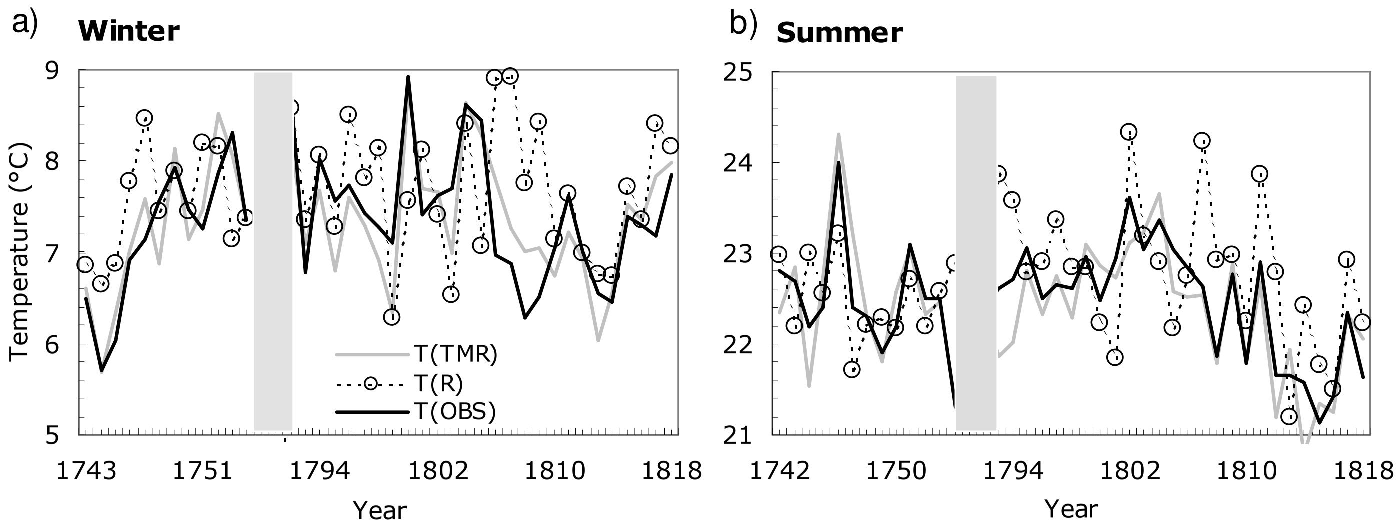

Fig. 5. Trend of observed (black line: Camuffo et al., 2010), predicted by (MTR)–model (grey line), and by the regional model (circles: Luterbacher et al., 2004) mean temperatures (°C) during 1742-1754 and 1772-1818, for winter (**a**) and summer (**b**), at validation stage.

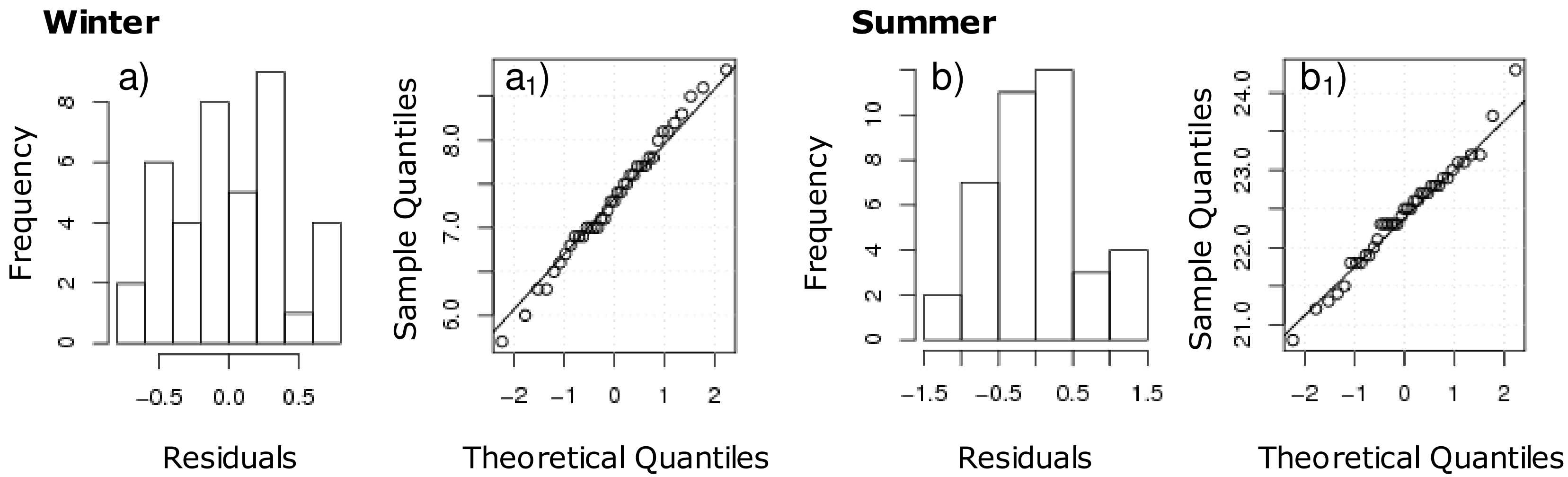

Fig. 6. Histograms of residuals and QQ-plots of (MTR)–model (Eq. 1), during 1742-1754 and 1772-1818, for winter (**a**, **a**$_1$) and summer (**b**, **b**$_1$), respectively, at validation stage.

a) Month	Categorical anomalies					
	Freezing	**Very cold**	**Cold**	**Normal**	**Warm**	**Vary warm**
Dec	-4	-2	-1	0	1	2
Jan	-4	-2	-1	0	1	2
Feb	-4	-2	-1	0	1	2
Jun	N/A	-4	-2	0	1	2
Jul	N/A	-5	-2	0	1	2
Aug	N/A	-5	-2	0	1	2

b) Year	Monthly *TASI*						Σ*TASI*		Source
	Dec	**Jan**	**Feb**	**Jun**	**Jul**	**Aug**	**Winter**	**Summer**	
...									
1752	1	1	0	0	0	0	2	0	(A) (M)
1753	1	0	0	-2	0	0	1	-2	(A) (M)
1754	0	-1	0	0	0	-1	-1	-1	(A) (M)
1755	0	-3	-1	-2	-2	-1	-4	-5	(A) (M)
1756	0	0	-1	0	0	0	-1	0	(A) (M)
1757	0	0	-1	-2	-2	0	-1	-4	(A) (M) (EVA)

Table 1. Monthly-scaled index for decoding temperature anomalies from documentary proxy data (**a**) and temperature anomalies reconstruction for a selected number of years (**b**). Monthly values of the Temperature Anomalies Scale Index (*TASI*) are reported together with the seasonal sums (Σ*TASI*) for winter (Win) and summer (Sum). Sources: A = *Corradi's Annals* (Corradi, 1850); M = *Moio and Susanna Manuscript* (Ferrari, 1977); EVA = Catalogue EVA (Clemente and Margottini, 1991).

		Performance statistics			Autocorrelation statistics	
Scale of the estimation	**Dataset**	**Nash-Sutcliffe efficiency coefficient**	**Correlation coefficient**	**Mean absolute error (°C)**	**Lag-1 residual correlation**	**Durbin Watson Statistic**
Sub-regional (Eq. 1)	**Calibration**					
	Winter	0.88	0.94	0.24	0.27	1.45 (p=0.02)
	Summer	0.87	0.88	0.24	0.04	1.83 (p=0.23)
	Validation					
	Winter	0.66	0.82	0.33	0.19	1.59 (p=0.09)
	Summer	0.63	0.74	0.24	0.03	1.92 (p=0.36)
Regional (Luterbacher et al., 2004)	**Validation**					
	Winter	-0.43	0.26	-	-	-
	Summer	-0.30	0.50	-	-	-

Table 2. Performance and autocorrelation statistics for (MTR)–model (Eq. 1) at the calibration and validation stages. Performance values over the validation set are also reported for the regional simulations.