

1 **Multiscale regression model to infer historical**
2 **temperatures in a central Mediterranean Sub-regional**
3 **Area**

4

5 **N. Diodato¹, G. Bellocchi^{1,2}, C. Bertolin³, and D. Camuffo³**

6

7 ¹MetEROBS – Met European Research Observatory, GEWEX-CEOP Network, World Climate Research
8 Programme, via Monte Pino snc, 82100 Benevento, Italy

9 ²Grassland Ecosystem Research Unit, French National Institute of Agricultural Research, avenue du Brézet
10 234, 63000 Clermont-Ferrand, France

11 ³Atmosphere and Ocean Science Institute, National Research Council of Italy, corso Stati Uniti 4, 35127
12 Padua, Italy

13 **Abstract**

14

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

28

29 1 Introduction

30
31 Modelling can be described as an art because it involves experience and intuition as well as
32 the development of a set of mathematical skills.

33
34 Mark Mulligan and John Wainwright (eds.), 2004. *Environmental Modelling*, Wiley, Chichester, p. 8.

35
36 The Mediterranean is one of the few regions in the world holding a large volume of
37 weather documentary proxies for the past 500-1000 years (Camuffo and Enzi, 1992;
38 Jones et al., 2009). However, such large amounts of documents and archives have not yet
39 been fully explored to reproduce with high spatio-temporal resolution the different
40 climates of Mediterranean (García-Herrera et al., 2007). Determining the climatic history
41 in these unrepresented places of the world is a challenging and complex issue at both
42 theoretical and applicative levels.

43 Modelling is an ideal trial to test the environmental processes over extensive space and
44 time domains. In the recent decades, considerable progress has been made in pre-
45 instrumental temperature modelling at both hemispheric and regional scales (e.g. Mitchell
46 et al., 2005; Rutherford et al., 2005). Luterbacher et al. (2004) and Xoplaki et al. (2005)
47 were able to map seasonally resolved temperature reconstructions across European land
48 areas back to 1500. In particular, Luterbacher et al. (2004) developed separate multiple
49 regression equations between each principal component (PC) of the instrumental data and
50 all leading PC of the proxy records. In this way, they assimilated proxy records into
51 reconstructions of the underlying spatial patterns of past climate changes. The
52 reconstructed climate field allows for a special assessment of the spatial coherence of past
53 annual-to-decadal temperature changes at sub-continental scale, thus providing insight
54 into the mechanisms or forcing underlying observed variability. In hemispheric,
55 continental and regional reconstructions, however, multi-proxy coverage is often irregular
56 and heterogeneous (Esper et al., 2002). Temperature and precipitation reconstructions,
57 although well developed over large geographical areas, may become poorly accurate at
58 sub-regional and local scales, or over particular periods (Mann et al., 2000; Ogilvie and
59 Jónsson, 2001; Diodato et al., 2008). On the other hand, it is not surprising if Mann
60 (2007), comparing estimated regional temperatures at different locations over the past
61 1000 years, found that the cold and warm periods were considerably different from region
62 to region. Then, the issue of sub-regional reconstructions should attract the attention of
63 scientists as it may exhibit unexpected results, especially regarding some temperature
64 extremes (Bhatnagar et al., 2002). The issue of downscaling to small spatial and temporal

65 scales must be made a priority in order to achieve a better understanding of sub-regional
66 climates (Riedwyl et al., 2009). Documentary proxies' investigation remains a reliable
67 approach to trace back the temperature extremes before the advent of instrumental
68 recording of meteorological data (Brázdil et al., 2005; Jones et al., 2009). Brewer et al.
69 (2007) investigated tree-ring sites to support the reconstruction of historical droughts in
70 Mediterranean areas during the last 500 years. However, temperature series have not been
71 modelled for this region so far. Moreover, continuous and homogeneous instrumental
72 series cannot be extended before the 19th century (Camuffo et al., 2010). On the other
73 hand, high-resolution climate information is increasingly needed for the study of past, present
74 and future climate changes (Vrac et al., 2007).

75 Several authors such as Luterbacher and Xoplaki, (2003), Pauling et al. (2003), and Ge
76 et al. (2005) suggested that pre-modern instrumental weather indices might be promising
77 to enrich climate reconstructions. Different sets of proxy-variables have indeed been used
78 to find out relationships between predictors and predictands in high-resolution climate
79 time reconstructions (e.g. Wang et al., 1991; Briffa et al., 2002; Larocque and Smith,
80 2005; Moberg et al., 2005; Diodato, 2007; Davi et al., 2008). Many of these
81 reconstructions depend on empirical relationships between proxy records and climate
82 data. Comparing linear algorithms and neural networks, Helama et al. (2009) proved that
83 both the approaches are reliable for temperature reconstruction. Although regression-
84 based techniques have been used with considerable success for climate reconstructions,
85 they can engender bias in the estimates if not employed with care (Robertson et al., 1999;
86 Moberg et al., 2005; von Storch et al., 2005). Moreover, these relationships are seldom
87 based on a training process capable to capture all the possible data combinations that
88 occur when extrapolation is performed (i.e. reconstruction period). With reference to
89 dendroclimatological studies, correlation between tree-ring proxies and temperature data
90 was found to only explain about 50% of the variance (Liang et al., 2008; Helama et al.,
91 2009; Tan et al., 2009). Documentary data series are expected to better correlate with
92 temperature, the overall explained variance being of about 70% (Leijonhufvud et al.,
93 2008; Dobrovlný et al., 2010). However, there are few estimates of uncertainty in
94 documentary based climate reconstructions (Moberg et al., 2009).

95 In this study, we have considered an alternative approach to address the statistical
96 modelling of temperature variability, based on documentary records and previous large-
97 scale reconstructions. In particular, a documentary-based technique was developed based
98 on multiscale temperature regression (MTR)–model at sub-regional level. An area

99 covering Southern and Central Italy and named in this paper Mediterranean Sub-regional
100 Area (MSA) is the focus of the investigation. The goal was to produce a relatively
101 simplified multiscaled model acceptable and verifiable by scientists as well as
102 knowledgeable people. (MTR)–model has a multiscale spatial structure because it
103 combines documentary proxy-based local-scale weather anomalies with large-scale
104 temperature data to adapt regional temperature data to specific sites and seasons. The
105 selected sub-region, centrally located in the Mediterranean region, is an interesting test
106 area rich in documentary proxy data and modern weather records useful to improve the
107 spatial resolution of past climate. The next section describes the geographical
108 environment, the datasets and the developed methods. Section 3 illustrates the novel
109 mixed-model approach in detail. Its results on temperature series estimation were evaluated
110 over the MSA. Conclusions (Section 4) point out the main results and look at horizons for
111 future research.

112

113 **2 Environmental setting, data and methods**

114

115 **2.1 Study area and datasets**

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

122 Regional temperature data (hereafter called T_R) were derived from Luterbacher et al.
123 (2004) for Europe over 1500-2002. The data, upscaled at about 0.5-degree grid resolution
124 (~50 km) from historical instrumental series and multi-proxy data
125 (<http://www.ncdc.noaa.gov/cgi-bin/paleo/eurotemp.pl>), covers an area extending from 25°
126 West to 40° East and from 35° to 70° North (Fig. 1a). From this map and from that
127 depicted in Fig. 1b, it is also possible to observe the temperature-data missing over
128 Southern Europe (including the MSA), as suggested by both data-density and correlation
129 pattern.

130 In order to fill this deficiency in the data available, a new documentary-dataset was
131 derived from chronicles found in two main sources, *Moio and Susanna Manuscript*

132 (Ferrari, 1977) and *Corradi's Annals* (Corradi, 1972). It is in *Moio and Susanna*
133 *Manuscript* (Ferrari, 1977) that a continuous temperature series is supplied for Catanzaro
134 (38° 54' North, 16° 36' East) from 1461 to 1768. More recent weather information is
135 available from different sources at sparse sites, which are suitable for reconstruction of
136 primitive series (Camuffo et al., 2010). The Italian scientist Alfonso Corradi (1833-1892)
137 carried out pioneering works in documentary research on the environmental and
138 climatological extreme conditions that occurred in Italian regions through time. He
139 collected the historical documents from 5 to 1850 A.C., related to meteorology and
140 epidemics into a five-volume book (Corradi, 1972). More recently, the historian Umberto
141 Ferrari published the chronicles of Giovanni Battista Moio and Gregorio Susanna quoting
142 climate extremes, famines from 1710 to 1769 and weather information over the 16th and
143 17th centuries for the Calabrian region (Ferrari, 1977). A data bank (Catalogue EVA –
144 Environmental Events of the ENEA – Italian National Agency of for New Technologies,
145 Energy and the Environment, Clemente and Margottini, 1991) was also referred to and
146 used when necessary.

147

148 **2.2 Monthly temperature anomaly scaled index**

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

160 Based on the above criteria, monthly indices were calculated, thus gaining more than
161 seven possible classes to preserve the variability described by the written sources similar
162 to the natural variability, and over a longer period than the calibration interval. These
163 classes were allocated to their respective index by an asymmetric look-up table in order to
164 take into account temporal shifts between proxy and actual anomalies in different seasons
165 of the year. In fact, as an example, a river freezing on March or April is a more negative

166 anomaly than a frozen river on January. Based on these new classification principles,
167 temperature anomalies were coded for winter and summer by means of a monthly-based
168 Temperature Anomaly Scaled Index (*TASI*), according to the look-up table scheme (Table
169 1a). The geometric interpretation of the classification process is shown in Fig. 2. The
170 asymmetric profile for winter and summer seasons is a bi-dimensional simplification based
171 on observations and documentary-proxy data. For the study-area, positive (red line) and
172 negative (blue line) temperature anomalies result asymmetrically arranged around the mean
173 seasonal values (black line). The latter are long-term average temperatures calculated, for
174 the study-area, from the European database of Luterbacher et al. (2004). In the case of
175 negative anomalies, the baseline is the freezing point of water (0 °C). A baseline for all
176 seasons was not set to reproduce positive anomalies. In this case, in fact, temperature
177 extremes are dictated by the Mediterranean latitudes. Although this region presents a
178 twofold climate regime, where both tropical and mid-latitude aspects play a role, the
179 latitudinal radiative flux stands out as the main factor determining the temperature.
180 Advective transport off northern Africa can also occasionally affect the Mediterranean, but
181 the seasonal variations are well marked (e.g. Schiano et al., 2000; Lionello et al., 2006) and,
182 notably, temperatures in winter are never as high as summer values. Negative anomalies
183 were assigned to cover the gap between the mean value and the freezing point, which is
184 only sporadically (or never) approached in summertime (N/A). In winter (December,
185 January, and February), values of -1 (cold) / +1 (warm) and -2 (very cold) / +2 (very
186 warm) are consistent with temperature values deviating up to three and four times the
187 standard deviation, respectively. Abrupt jumps from “very cold” (-2) to “freezing” (-4) in
188 winter are due to the lack of appreciative intermediate states during the calibration period.
189 In the case of positive anomalies, a similar scheme is reproduced for summer season
190 (June, July and August). Negative anomalies are instead doubled (July-August) or tripled
191 (June) compared to winter, because most evidence of “cold” and “very cold” conditions
192 in the historical sources only refers to cooling to temperatures well below the seasonal
193 mean.

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

199

200 **2.3 Model parameterization and evaluation**

201 For the purposes of modelling, the split-samples approach was used to segregate the
202 available temperature data into a calibration set and a validation set. Particular attention
203 was paid to the calibration procedure in order to ensure that the resulting model could
204 produce reliable outcomes (i.e. time-series reconstruction). Two distinct climate periods
205 (1867-1903 and 1972-2002) were included in the calibration dataset (68 years in total) for
206 two main reasons. The first was to ensure model calibration accuracy by accounting for
207 both cold and warm intervals, and the second to ensure that the model was able to
208 simulate air temperature on periods with either accurate (as in recent times) or inaccurate
209 data (as in historical times). The validation dataset contained instrumental temperature
210 reconstruction for the MSA (as performed by Camuffo et al., 2010). In particular, the
211 periods 1742-1754 and 1792-1818 were selected for model validation. Measured data are
212 available for these two intervals in Central-Southern Italy, which are therefore considered
213 reliable records in the historical time for this area.

214 The entire workflow was executed interactively using a spreadsheet of MS Excel 2003,
215 for data collection, model development and graphical assembling, with the support of
216 STATGRAPHICS online statistical package (<http://www.statgraphics.com>) and Statistics
217 Library–R modules (Wessa, 2009) for statistics performance (e.g. autocorrelation) and
218 graphical outputs (e.g. confidence intervals of regression lines), respectively. The
219 agreement between estimates and observations was evaluated using a set of statistics,
220 including the modelling efficiency by Nash and Sutcliffe (1970), ranging from negative
221 infinity to positive unity (the latter being the optimum value). In order to have a visual
222 inspection of the quality of results, a set of comparative scatterplots and histograms are
223 also presented.

224

225 **3 Modelling of sub-regional winter temperatures**

226

227 In this study, regional temperatures (*case*) from Luterbacher et al. (2004) are the basis for
228 modelling sub-regional temperatures (*response*). In this situation, it is possible to have
229 more than one response for each case. Thus, a central problem in the analysis of
230 multiresponse situations, is finding a function that combines several responses to
231 determine more realistic estimates. This is also the case of air temperature, for which
232 multi-scale predictors are needed to model over different space- and time-domains (after
233 Bates and Watts, 2007). In this way, the information collected (regional temperature data)

234 was downscaled to reasonably approximate the behaviour of the disturbance terms (or
 235 stimulus variables) driving the temperature measurements at sub-regional scale. These
 236 approximations reside on the general assumption that sub-regional air temperature
 237 depends on two disturbance terms: regional-synoptic forcing and local weather
 238 conditions. The regional scale can drive the general temperature trend, while area-specific
 239 temperatures are met by local conditions. Weather variables and climate indices were
 240 both used as predictors as basis of the multi-scale regression model.

241

242 **3.1 Inferences for multi-scale temperature estimation**

243 A statistical model of sub-regional temperature estimation was created with aims of
 244 prediction and explanation. For prediction, the model structure was generated based on
 245 Box and Draper (1972). In particular, a determinant parameter-estimation criterion for
 246 multiresponse data was derived upon the primary assumption that the disturbance terms
 247 of different cases are uncorrelated. A corollary assumption was that, in a single case, the
 248 disturbance terms have a fixed, unknown variance-covariance matrix for different
 249 responses. A model was written along this path, assuming multiple responses and
 250 dependence on a set of parameters, as referred to by Bates and Watts (2007): the
 251 temperature random variable is a function depending on some predictors by a set of
 252 parameters, and assuming the sum of the errors equal to zero.

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

262

$$263 \quad y(T_{MTR}) = k \cdot \sqrt{T_R} + \beta \cdot (T_R + \Omega_S + \sum TASI_S) \quad (1)$$

264

265 where the first term, $y(T_{MTR})$, is the seasonal mean temperature output ($^{\circ}\text{C}$) of the (MTR)-
 266 model; T_R is the regional component of temperature ($^{\circ}\text{C}$) supplied as a boundary

267 condition; the part in brackets is the sub-regional component of temperature (°C) supplied
268 as a local constraint.

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

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

272
273
274
275 where the first condition is to set null intercept (a), the second is to approximate the unit
276 slope (b) of the straight line that would minimize the bias, and the third is to maximize the
277 goodness-of-fit (R^2) of the linear function. Since the different assumptions cannot be
278 guaranteed *a priori*, the parameters were estimated using an iterative, knowledge-driven
279 approach to bias correction steps (after Box et al., 1978). For instance, after a first run, it
280 was found that regional temperatures (T_R) introduced increasingly biased and imprecise
281 estimates over historical times. Likewise, earliest regional inferences in Mann et al.
282 (2000) tended to be associated with decreased performance. To account for this non-
283 invariance over the historical time-scale, a power law was assigned to T_R with the
284 exponent forced to be lower than one (and finally set equal to 0.5) to rebalance internally
285 the quality of calibration. Such iterative fitting of the data allowed for correcting the bias
286 initially observed and capturing the full range of sub-regional scale variability.

287 The scale parameter k (°C²) was initially set equal to one and, for reasons of parsimony
288 as by Grace (2004), not treated as a free parameter because the initial value resulted in a
289 fit that satisfied the criteria outlined above (Eq. 2). T_R appears in both the square root
290 (power of 0.5) and linear term. In the first case, it returns a direct, non-linear effect, while
291 in the brackets it crosses the sub-regional anomalies identified by the *TASI* to correct the
292 bias observed in the historical times. The square root of T_R and parameter β are mainly to
293 define the order of magnitude of the process used to downscale the (MTR)–model to the
294 sub-regional scale. The other two terms into the brackets are seasonally-varying (index S)
295 shift parameters (°C) of T_R , which force the model with meteorological ($\Sigma TASI_s$, sum of
296 monthly values of the Temperature Anomaly Scaled Index defined above) and
297 climatological (Ω_s , hereafter indicated as Ω_w and Ω_s for winter and summer, respectively)
298 boundary conditions.

300 **3.2 Model parameterization and evaluation**

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

305 In the temperature series supplied by Luterbacher *et al.* (2004), standard deviation (sd)
306 for winter increases in more recent years, i.e. after the LIA (sd=0.96 against 0.74 for
307 1739-1783). This contrasts with the instrumental observations, for instance those
308 performed by Domenico Cirillo in the 18th century (sd=1.1) and documented by the
309 Meteorological Diaries of the Royal Society of London for the Kingdom of Naples
310 (Derham, 1733-1734). The reconstructed series based on Eq. (1) gives sd~1.0 for both
311 recent and historical times. For summertime, sd~0.6 was registered for 1739-1783 in the
312 regional dataset, also approached by the reconstructed series.

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

332 Gaussian trend (Fig. 6a, b), with the QQ-plots reflecting theoretical values (Fig. 6a₁, b₁) in
333 both seasons.

334 Independence-of-errors due to the possible presence of significant autocorrelations
335 among the residuals was also tested. Strong temporal dependence may in fact induce
336 spurious relations according to standard inference in an ordinary regression model (see
337 Granger et al., 2001), and the same problem is further increased in the context of
338 nonlinear models (Stenseth et al., 2003). The Durbin-Watson (Durbin and Watson, 1950,
339 1951) d statistic in the following form was calculated to verify the presence of
340 autocorrelation in the residuals e (the index t indicating the t^{th} year):

341

$$342 \quad d = \frac{\sum_{t=1}^T (e_t - e_{t-1})^2}{\sum_{t=1}^T e_t^2} \quad (3)$$

343

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

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

367

368 **3.3 Limitations of the study**

369 The scope of our modelling approach and model parameterization was restricted to
370 capturing the temporal variability of seasonal temperature data in the study-area, and
371 some limitations of the methodology should be acknowledged.

372 Historical climate in the MSA and the modelling background of the authors
373 represented the basis of this study. Indeed, there may be other ways to assess temperature
374 series at sub-regional scale. This implies that the proposed multiscale model is an applied
375 model with a sufficient degree of reliability, but more rigorous and robust analytic
376 techniques could be applied to better precisely define and evaluate the same problem. For
377 instance, structural equation modelling accounts for correlations among predictors and
378 can estimate indirect effects of predictors on other predictor variables that taken together
379 affect the outcome (Hair et al., 1998).

380 To determine an appropriate balance between computation, complexity and
381 uncertainty, we have relied on *ad-hoc* model development and trial-and-error assignment
382 of model parameter values via spreadsheet utility. The use of MS Office Excel 2003
383 solver to minimize the square error of estimation is indeed a common solution, as in
384 previous papers (e.g. Diodato and Bellocchi, 2007, 2010), although other products are
385 available which offer algorithmic improvements (e.g. Menascé et al., 2008).

386 Uncertainty ranges in the estimation of parameters were not formally accounted
387 because parameter estimation was achieved in more steps, which makes confidence
388 bounds for model parameters not easily quantifiable. The model error (mismatch between
389 the observed and the modelled value) is however an indication of total model uncertainty
390 (e.g. Shrestha and Solomatine, 2008), and Nash-Sutcliffe efficiency values of 0.6 can
391 discriminate between bad and good performances (e.g. Lim et al., 2006). The efficiency
392 values obtained in the validation stage (>0.8) thus indicate limited model uncertainty;
393 likely associated with narrow parameter uncertainty. Since the results of model
394 calibration were satisfactory, the robustness of the solution was relied on and sensitivity
395 analysis was not added to the study. The reconstruction of temperatures series has thus
396 used generic optimized parameters, which are crude estimates over multiple years. This

397 ensures a generic representation for the MSA, with evidence of improved performance
398 compared to previous estimates. Since geographical locations have characteristics that
399 require specific model structures and local optimization, then the application of the model
400 to other sub-regions may be limited by the ability to provide representative drivers and
401 parameter values.

402

403 **4 Conclusions**

404

405 The main novelty of this paper is the introduction of a relatively simple model to
406 reconstruct past seasonal (winter and summer) temperature variability at sub-regional
407 scale based on proxy and simulated datasets. In general, the use of data deriving from
408 different spotted sources is not straightforward to reconstruct climate in Southern Europe.
409 Data used in the previous seasonal temperature reconstruction over Europe, especially
410 over the Mediterranean areas, are from few and early instrumental series (data before
411 1850) that, for their nature, are difficult to find, evaluate, correct and convert or present in
412 a Celsius scale in terms of temperature anomalies.

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

431 additional insight into the implications for the production of valuable knowledge from
432 proxy documentary data and can be considered the natural evolution of this study. The
433 temperature series analysis itself is also an issue, which could be the subject of a future
434 paper.

435

436 **References**

437

438 Barriendos Vallve, M., and Martin-Vide, J.: Secular climatic oscillations as indicated by
439 catastrophic floods in the Spanish Mediterranean coastal area (14th-19th centuries),
440 *Climatic Change*, 38, 473-491, 1998.

441 Bates, D.M., and Watts D.G. (Eds.): *Nonlinear regression analysis and its applications*,
442 John Wiley & Sons, Little Falls, NJ, USA, 2007.

443 Bhatnagar, A., Jain, K., and Tripathy, S.C.: Variation of solar irradiance and mode
444 frequencies during Maunder minimum, *Astrophys.Space Sci.*, 281, 761–764, 2002.

445 Box, M.J., and Draper, N.R. (Eds.): *Estimation and design criteria for multiresponse*
446 *nonlinear models with non-homogeneous variance*, *Applied Statistics*, 21, 13-24, 1972.

447 Box, G.E.P., Hunter, W.G., and Hunter, J.S.: *Statistics for experimenters: an introduction*,
448 John Wiley and Sons, New York, NY, USA, 1978.

449 Brázdil, R., Pfister, C., Wanner, H., von Storch, H., and Luterbacher, J.: Historical
450 climatology in Europe – The state of the art, *Climatic Change*, 70, 363-430, 2005.

451 Brewer, S., Alleaume, S., Guiot, J., and Nicault, A.: Historical droughts in Mediterranean
452 regions during the last 500 years: a data/model approach, *Clim. Past*, 3, 355-366, 2007.

453 Briffa, K.R., Osborn, T.J., Schweingruber, F.H., Jones, P.D., Shiyatov, S.G., and
454 Vaganov, E.A.: Tree-ring width and density data around the Northern Hemisphere:
455 Part 1, local and regional climate signals, *Holocene* 12, 737–757, 2002.

456 Camuffo D., Bertolin, C., Barriendos, M., Dominguez-Castro, F., Cocheo, C., Enzi, S.,
457 Sghedoni, M., della Valle, A., Garnier, E., Alcoforado, M.J., Xoplaki, E., Luterbacher,
458 J., Diodato, N., Maugeri, M., Nunes, M.F., and Rodriguez, R.: 500-year temperature
459 reconstruction in the Mediterranean Basin by means of documentary data and
460 instrumental observations, *Climatic Change*, 101, 169-199, 2010.

461 Camuffo, D., and Enzi, S.: Reconstructing the climate of northern Italy from archive
462 sources, in: *Climate since A.D. 1500*, Routledge, London, United Kingdom, 143-154,
463 1992.

464 Clemente, G.F., and Margottini, C.: Sistema EVA: una biblioteca di dischi ottici per le
465 catastrofi naturali del passato, *Prometeo*, 9, 22-29, 1991 (in Italian).

466 Corradi, A.: Corradi Alfonso: Annali delle epidemie occorse in Italia dalle prime
467 memorie fino al 1850, five volumes, Società medico-chirurgica di Bologna (Ed.),
468 Forni, Bologna, Italy, 1972 (in Italian).

469 Davi, N.K., Jacoby, G.C., D'Arrigo, R.D., Baatarbileg, N., Jinbao, L., and Curtis, A.E.: A
470 tree-ring-based drought index reconstruction for far-western Mongolia: 1565-2004, *Int.*
471 *J. Climatol.*, 29, 1508-1514, 2008.

472 Derham, W. 1733-1734. An abstract of the Meteorological Diaries, communicated to the
473 Royal Society, with re-marks upon them, by W. Derham, D. D. Canon of Windsor, F.
474 R. S. [Vide Part III. In *Transact.* No 433.] Part IV. *Philosophical Transactions* (1683-
475 1775), 38, 405-412.

476 Diodato N.: Climatic fluctuations in Southern Italy since 17th century: reconstruction
477 with precipitation records at Benevento, *Climatic Change*, 80, 411-431, 2007.

478 Diodato, N., and Bellocchi, G.: Estimating monthly (R)USLE climate input in a Mediterranean
479 region using limited data, *J. Hydrol.*, 345, 224-236, 2007

480 Diodato, N., and Bellocchi, G.: MedREM, a rainfall erosivity model for the Mediterranean
481 region, *J. Hydrol.*, 387, 119-127, 2010

482 Diodato, N., Ceccarelli, M., and Bellocchi, G.: Decadal and century-long changes in the
483 reconstruction of erosive rainfall anomalies at a Mediterranean fluvial basin, *Earth*
484 *Surf. Proc. Land.*, 33, 2078–2093, 2008.

485 Dobrovolný, P., Moberg, A., Brázdil, R., Pfister, C., Glaser, R., Wilson, R., van Engelen,
486 A., Limanówka, D., Kiss, A., Halíčková, M., Macková, J., Riemann, D., Luterbacher,
487 J., and Böhm, R.: Monthly, seasonal and annual temperature reconstructions for
488 Central Europe derived from documentary evidence and instrumental records since AD
489 1500, *Climatic Change* 101, 69-107, 2010.

490 Durbin, J., and Watson, G.S.: Testing for serial correlation in least squares regression, I,
491 *Biometrika* 37, 409-428, 1950.

492 Durbin, J., and Watson, G.S.: Testing for serial correlation in least squares regression, II,
493 *Biometrika* 38, 159-179, 1951.

494 Esper, J., Cook, E.R., and Schweingruber, F.H.: Low frequency signals in long tree-ring
495 chronologies for reconstructing past temperature variability, *Science*, 295, 2250-2253,
496 2002.

497 Ferrari, U. (Ed.): Giovan Battista Moio, Gregorio Susanna: Diario di quanto successe in
498 Catanzaro dal 1710 al 1769, Edizioni Effe Emme, Chiaravalle Centrale, 1977 (in Italian).

499 García-Herrera, R., Luterbacher, J., Lionello, P., González-Rouco, F., Ribera, P., Rodó,
500 X., Kull, P., and Zerefos, C.: Reconstruction of past Mediterranean climate, *Eos*
501 *Transaction of the American Geophysical Union*, 88, doi:10.1029/2007EO090010,
502 2007.

503 Ge, Q-S, Zheng, J-Y, Hao, Z-X, Zhang, P-Y, and Wang, WC.: Reconstruction of
504 historical climate in China: high-resolution precipitation data from Qing Dynasty
505 Archives, *B. Am. Meteorol. Soc.*, 86, 671-679, 2005.

506 Glaser, R., and Riemann, D.: A thousand-year record of temperature variations for
507 Germany and Central Europe based on documentary data, *J. Quaternary Sci.*, 24, 437-
508 449, 2009.

509 Grace, R.C.: Temporal context in concurrent chains : I. Terminal-link duration, *Journal of*
510 *the Experimental Analysis of Behaviour*, 81, 215-237.

511 Granger, C.W.J., Hyung, N., and Jeon, Y.: Spurious regressions with stationary series,
512 *Applied Economics*, 33, 899–904, 2001.

513 Green, W.: *Econometric analysis*, New York University, 5th Edition, Prentice Hall, New
514 York, 2003.

515 Hair, J.F., Anderson, R.E., Tatham, R.L., and Black, W.C.: *Multivariate data analysis*, 5th
516 Edition, Prentice-Hall, Upper Saddle River, 1998.

517 Helama, S., Makarenko, N.G., Karimova, L.M., Kruglun, O.A., Timonen, M.,
518 Holopainen, J. Meriläinen, J., and Eronen, M.: Dendroclimatic transfer functions
519 revisited: Little Ice Age and Medieval Warm Period summer temperatures
520 reconstructed using artificial neural networks and linear algorithms, *Annales*
521 *Geophysicae*, 27, 1097–1111, 2009.

522 Jones, P.D., Briffa, K.R., Osborn, T.J., Lough, J.M., van Ommen, T.D., Vinther, B.M.,
523 Luterbacher, J., Wahl, E.R., Zwiers, F.W., Mann, M.E., Schmidt, G.A., Ammann,
524 C.M., Buckley, B.M., Cobb, K.M., Esper, J., Goosse, H., Graham, N., Jansen, E.,
525 Kiefer, T., Kull, C., Küttel, M., Mosley-Thompson, E., Overpeck, J.T., Riedwyl, N.,
526 Schulz, M., Tudhope, A.W., Villalba, R., Wanner, H., Wolff, E., and Xoplaki, E.:
527 High-resolution palaeoclimatology of the last millennium: a review of current status
528 and future prospects, *Holocene* 19, 3-49, 2009.

529 Larocque, S.J., and Smith, D.J.: A dendroclimatological reconstruction of climate since
530 AD 1700 in the Mt. Waddington area, British Columbia Coast Mountains, Canada,
531 *Dendrochronologia* 22 , 93-106, 2005.

532 Leijonhufvud, L., Wilson, R., and Moberg, A.: Documentary data provide evidence of
533 Stockholm average winter to spring temperatures in the eighteenth and nineteenth
534 centuries, *Holocene*, 18, 333-343, 2008.

535 Liang, E., Shao, X., and Qin, N.: Tree-ring based summer temperature reconstruction for
536 the source region of the Yangtze River on the Tibetan Plateau, *Global Planet. Change*,
537 61, 313-320, 2008.

538 Lim, K.J., Engel, B.A., Zang, T., Muthukrishnan, S., Choi, J., and Kim, K.: Effects of
539 calibration on L-THIA GIS runoff and pollutant estimation, *J. Environ. Manage.*, 78,
540 35-43, 2006.

541 Lionello, P., Malanotte-Rizzoli, P., and Boscolo, R.: Mediterranean climate variability,
542 *Developments in Earth and Environmental Sciences*, Vol. 4, Elsevier, Amsterdam,
543 2006.

544 Luterbacher, J., Dietrich, D., Xoplaki, E., Grosjean, M., and Wanner, H.: European
545 seasonal and annual temperature variability, trends and extremes since 1500, *Science*,
546 303, 1499-1503, 2004.

547 Luterbacher, J, and Xoplaki, E.: 500-year winter temperature and precipitation variability
548 over the Mediterranean area and its connection to the large-scale atmospheric
549 circulation, in: *Mediterranean climate variability and trends*, Springer-Verlag, Berlin,
550 Germany, 133-153, 2003.

551 Mann, M.E.: Climate over the past two millennia, *Annual Rev. Earth Pl. Sc.*, 35, 111-136,
552 2007.

553 Mann, M.E., Gille, E., Bradley, R.S., Hughes, M.K., Overpeck, J., Keimig, F.T., and
554 Gross, W.: Global temperature patterns in past centuries: an interactive presentation,
555 *Earth Interact.*, 4, 1-29, 2000.

556 Menascé, D.A.: Computing missing service demand parameters for performance models, *Computer*
557 *Measurement Group Conference*, 7-12 December, Las Vegas, 2008.

558 Mitchell, T., and Jones, P.D., An improved method of constructing a database of monthly
559 climate observations and associated high-resolution grids, *Int. J. Climatol.*, 25, 693–
560 712, 2005.

561 Moberg, A., Dobrovolny, P., Wilson, R., Brázdil, R., Pfister, C., Glaser, R.,
562 Leijonhufvud, L., and Zorita, E.: Quantifying uncertainty in documentary-data based
563 climate reconstructions?, *Geophysical Research Abstracts*, 11, EGU2009-1177, 2009.

564 Moberg, A., Sonechkin, D.M., Holmgren, K., Datsenko, N.M., and Karlén, W.: Highly
565 variable Northern Hemisphere temperatures reconstructed from low- and high-
566 resolution proxy data, *Nature*, 433, 613–617, 2005.

567 Nash, J.E., and Sutcliffe, J.V.: River flow forecasting through conceptual models part I -
568 A discussion of principles, *J. Hydrol.*, 10, 282–290, 1970.

569 Ogilvie, A.E.J., and Jonsson, T.: Little Ice Age research: a perspective from Iceland,
570 *Climatic Change*, 48, 9-52, 2001.

571 Pauling, A, Luterbacher, J, and Wanner, H.: Evaluation of proxies for European and
572 North Atlantic temperature field reconstructions, *Geophys. Res. Lett.*, 30, 1787,
573 doi:10.1029/2003GL017589, 2003.

574 Pfister, C.: *Wetternachhersage. 500 Jahre Klimavariationen und Naturkatastrophen (1496-*
575 *1995)*, Haupt, Bern, Switzerland, 1999 (in German).

576 Pfister, C.: I cambiamenti climatici nella storia dell'Europa. Sviluppi e potenzialità della
577 climatologia storica, in: *Che tempo faceva. Variazioni del clima e conseguenze sul*
578 *popolamento umano. Fonti, Metodologie e Prospettive*, Angeli, Milan, Italy, 19-60, 2001
579 (in Italian).

580 Ramsey, E.W., III, Hodgson, M.E., Sapkota, S.K., and Nelson, G.A.: Forest impact estimated
581 with NOAA AVHRR and Landsat TM data related to an empirical hurricane wind-field
582 distribution. *Remote Sens. Environ.*, 77, 279-292, 2001.

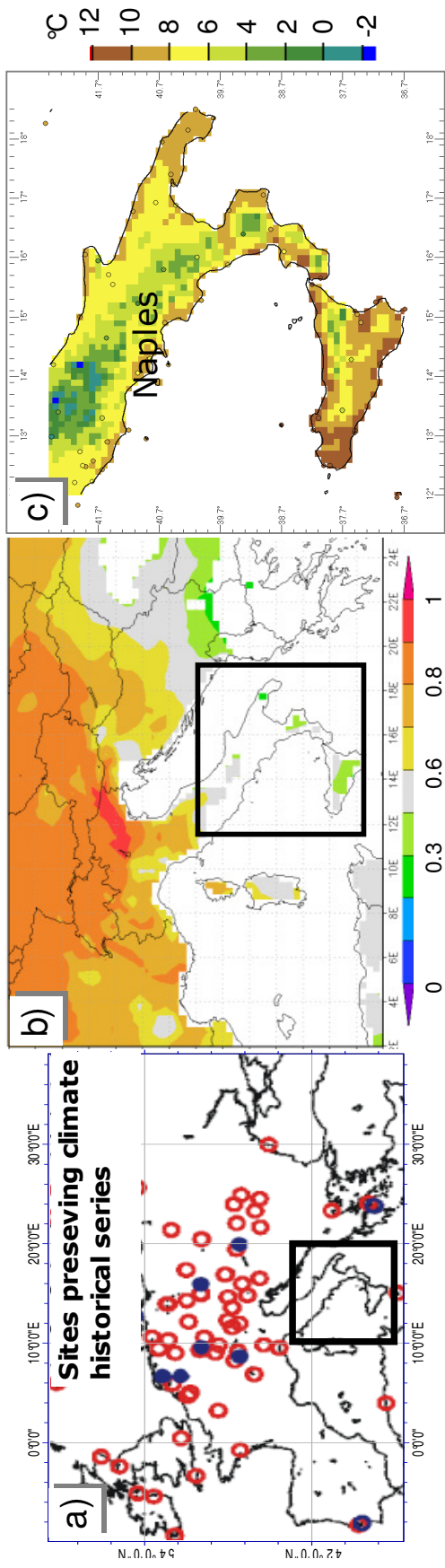
583 Riedwyl, N., Küttel, M., Luterbacher, J., and Wanner, H.: Comparison of climate field
584 reconstruction techniques: application to Europe, *Clim. Dynam.*, 32, 381-395, 2009.

585 Robertson, I, Lucy, D., Baxter, L., Pollard, A.M., Aykroyd, R.G., Barker, A.C., Carter,
586 A.H.C., Switsur, V.R., and Waterhouse, J.S.: A kernel-based Bayesian approach to
587 climatic reconstruction, *Holocene*, 9, 495–500, 1999.

588 Rutherford, S., Mann, M.E., Osborn, T.J., Bradley, R.S., Briffa, K.R., Highes, M.K., and
589 Jones, P.D.: Proxy-based northern hemisphere surface temperature reconstructions:
590 sensitivity to method, predictor network, target season, and target domain, *J. Climate*,
591 18, 2308-2329, 2005.

592 Schiano, M.E., Borghini, M., Castellari, S., and Luttazzi, C.: Climatic features of the
593 Mediterranean Sea detected by the analysis of the longwave radiative bulk formulae,
594 *Ann. Geophysicae*, 18, 1482-1487, 2000.

- 595 Shrestha, D.L., and Solomatine, D.P.: Data-driven approaches for estimating uncertainty
596 in rainfall-runoff modelling, *International Journal of River Basin Management*, 6, 109-
597 122, 2008.
- 598 Stenseth, N.C., Ottersen, G., Hurrell, J.W., Mysterud, A., Lima, M., Chan, K.-S., Yoccoz,
599 N.G., and Ådlandsvik, B.: Studying climate effects on ecology through the use of
600 climate indices: the North Atlantic Oscillation, El Niño Southern Oscillation and
601 beyond, *P. Roy. Soc. B-Biol. Sci.*, 270, 2087-2096, 2003.
- 602 Tan, M., Shao, X., Liu, J., and Cai, B.: Comparative analysis between a proxy-based
603 climate reconstruction and GCM-based simulation of temperatures over the last
604 millennium in China, *J. Quaternary Sci.*, 24, 547–551, 2009.
- 605 Von Storch, H., Zorita, E., Jones, J., Dimitirev, Y., Gonzalez-Rouco, F., and Tett, S.:
606 Reconstructing past climate from noisy data, *Science*, 306, 679-682, 2005.
- 607 Vrac, M., Marbaix, P., Paillard, D., Caveau, P.: Non-linear statistical downscaling of present
608 and LGM precipitation and temperatures over Europe, *Clim. Past*, 3, 669–682, 2007.
- 609 Xoplaki, E., Luterbacher, J., Paeth, H., Dietrich, D., Steiner, N., Grosjean, M., and
610 Wanner, H.: European spring and autumn temperature variability and change of
611 extremes over the last half millennium, *Geophys. Res. Lett.*, 32, L15713,
612 doi:10.1029/2005GL023424, 2005.
- 613 Wang, R., Wang, S., and Fraedrich, K.: An approach to reconstruction of temperature on
614 a seasonal basis using historical documents from China, *Int. J. Climatol.*, 11, 381-392,
615 1991.
- 616 Wessa P.: A framework for statistical software development, maintenance, and publishing
617 within an open-access business model, *Computational Stat.*, 24, 183-193, 2009.
- 618 Wigley, T.M.L.: Future climate of the Mediterranean Basin with particular emphasis in
619 changes in precipitation, in: *Climate change in the Mediterranean*, Edward Arnold,
620 London, United Kingdom, 15-44.



621

622

623

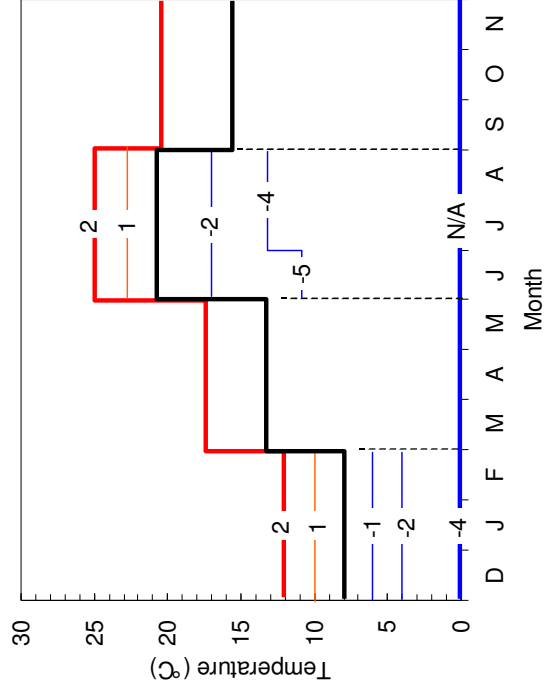
624

625

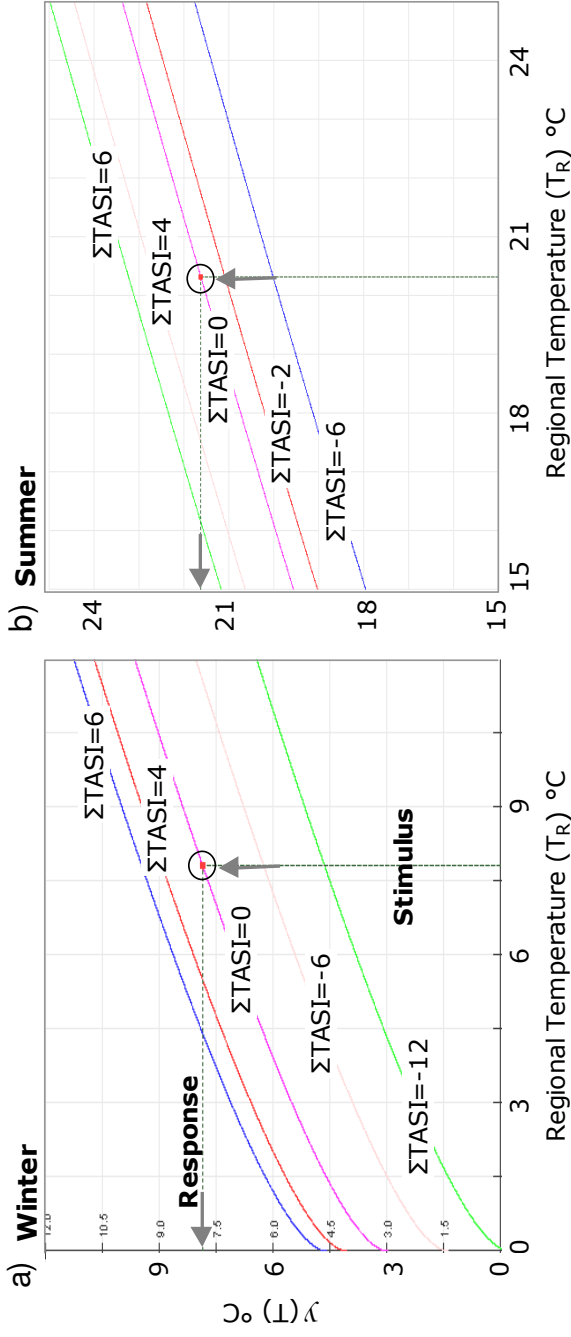
626

627

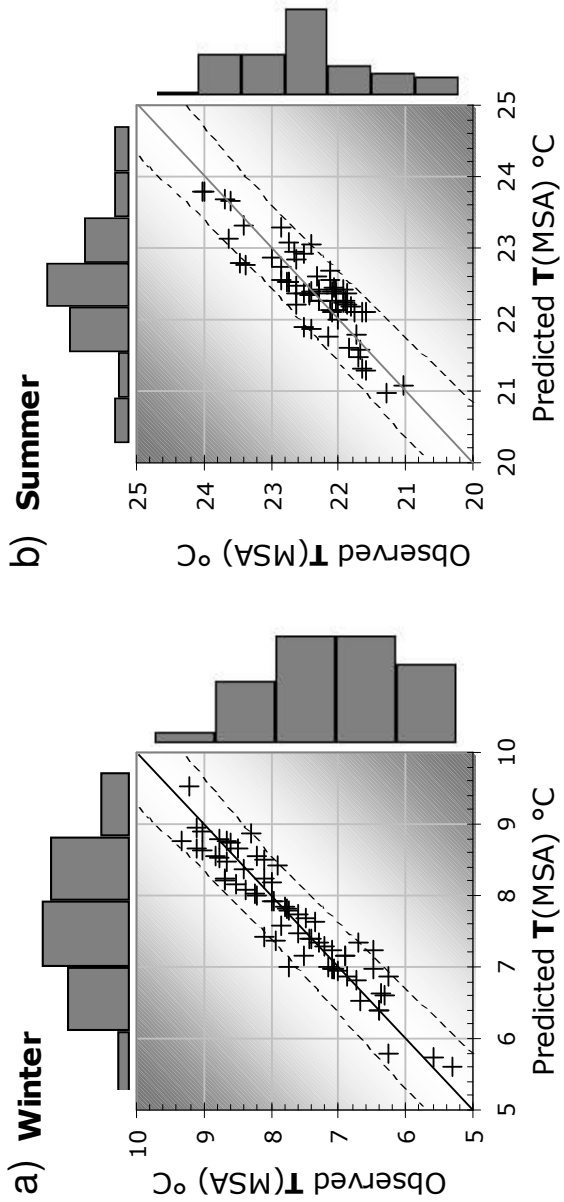
Fig. 1. a): Geographical setting of the Mediterranean Sub-regional Area (MSA, squared) with the location of temperature sites (red circles), and documentary monthly-resolved data (blue dots) used by Luterbacher et al. (2004) to reconstruct the regional seasonal temperatures over Europe since 1500 AD; **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).



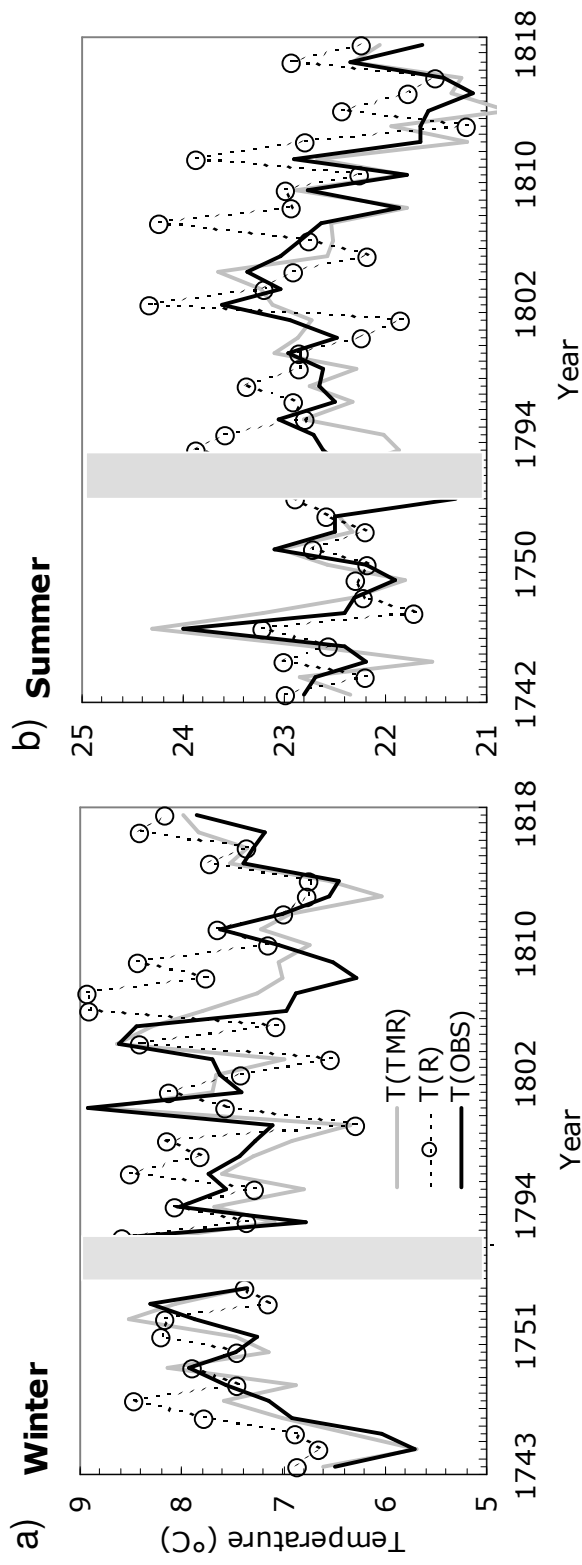
629 **Fig. 2.** Geometric interpretation of monthly values of the Temperature Anomalies Scale Index (*TASI*) for winter and summer (see Table 1a for
630 details). Black line: mean seasonal temperatures; red lines: reference values for positive temperature anomalies; blue lines: reference values for
631 negative temperature anomalies.
632
633



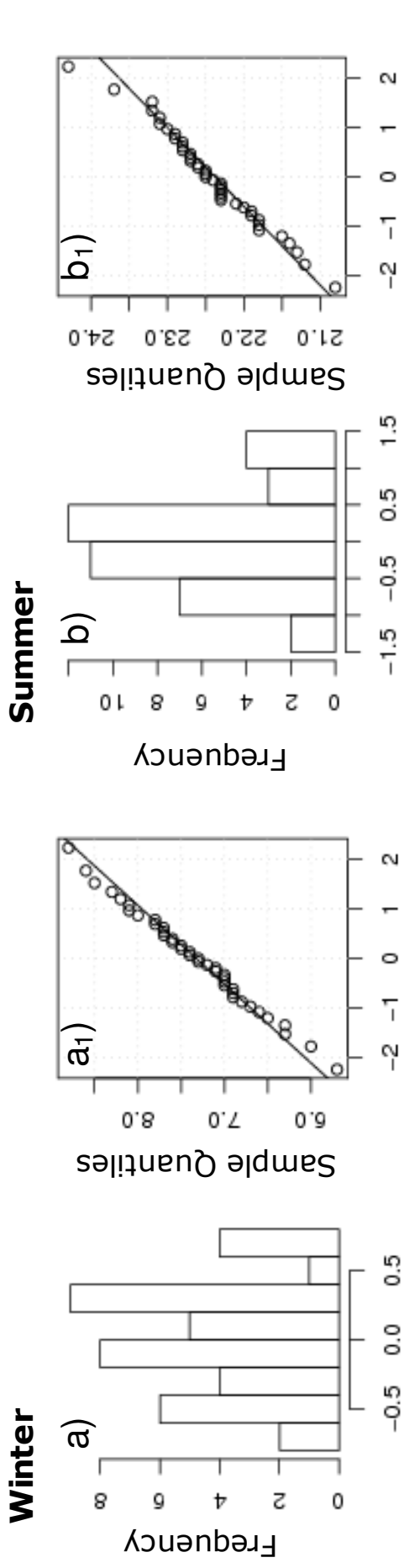
634 **Fig. 3.** Nomogram chart illustrating the multiresponse for different $\Sigma TASI$'s-values originating from regional temperature (T_R) in (MTR)-model
 635 for winter (a) and summer (b) (mathematical functions graphed using provisions supplied by GraphFunc-tool,
 636 http://www.seriesmathstudy.com/sms/graphfunc1_4x).
 637



638 **Fig. 4.** Scatterplots between observed and predicted mean temperatures (°C) for Mediterranean Sub-regional Area (MSA) in winter (a) and in
 639 summer (b) by (MTR)-model (Eq. 1). Diagonal lines 1:1 and outer dashed bounds at 95% prediction limits are drawn too.
 640



642 **Fig. 5.** Trend of observed (black line: Camuffo et al., 2010), predicted by (MTR)–model (grey line), and by the regional model (circles:
 643 Luterbacher et al., 2004) mean temperatures (°C) during 1742–1754 and 1772–1818, for winter (a) and summer (b), at validation stage.
 644



645 **Fig. 6.** Histograms of residuals and QQ-plots of (MTR)–model (Eq. 1), during 1742-1754 and 1772-1818, for winter (**a**, **a₁**) and summer (**b**, **b₁**),
 646 respectively, at validation stage.
 647

a) Month	Categorical anomalies						b) Year	Monthly TASI						Source	
	Freezing	Very cold	Cold	Normal	Warm	Vary warm		Dec	Jan	Feb	Jun	Jul	Aug		Winter
Dec	-4	-2	-1	0	1	2	...	1	1	0	0	0	2	0	(A) (M)
Jan	-4	-2	-1	0	1	2	1752	1	0	0	-2	0	1	-2	(A) (M)
Feb	-4	-2	-1	0	1	2	1753	0	-1	0	0	-1	-1	-1	(A) (M)
Jun	N/A	-4	-2	0	1	2	1754	0	-3	-1	-2	-2	-4	-5	(A) (M)
Jul	N/A	-5	-2	0	1	2	1755	0	0	-1	0	0	-1	0	(A) (M)
Aug	N/A	-5	-2	0	1	2	1756	0	0	-1	-2	-2	-1	0	(A) (M)
							1757	0	0	-1	-2	-2	-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 ($\Sigma TASI$) 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).

Scale of the estimation	Dataset	Performance statistics			Autocorrelation statistics		
		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)							
	Winter	-0.43	0.26	-	-	-	
	Summer	-0.30	0.50	-	-	-	

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