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NEURAL NETWORK MODELING AS A TOOL FOR CLIMATIC ANALYSES OF FORCINGS/TEMPERATURES RELATIONSHIPS AT GLOBAL AND REGIONAL SCALES

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1. INTRODUCTION

The climate system, characterized by the interactions of many sub-systems (atmosphere, oceans, ices, biosphere, etc.), can be considered as the prototype of a complex system. Here, processes and phenomena interact each other in a very complex manner and with many feedbacks. In this framework, a dynamical approach to the reconstruction of the system's behavior is itself very complex.

As well known, Atmosphere-Ocean General Circulation Models (AOGCMs) have been developed in order to possibly grasp this complexity in a dynamical way. By means of theoretical descriptions of the single main phenomena and processes in the climate system and their inclusion inside a system of equations and parameterization routines, these models are able to simulate the behavior of the climate system itself, even though in a simplified manner. In this context, one is able to recognize the role of some cause-effect relationships in the system and to relate them with the underlying causes of the major changes in the behavior of some important variables, like the annual global temperature (Houghton et al. 2001).

At present, AOGCMs represent the standard tool for the investigation of the climate system, even if they show some limits in the simulations at regional and local scales. Furthermore, their results can be crucially affected by different choices in the delicate balance among the relative strength of feedbacks and the various parameterization routines.

In this framework, here we consider a non-dynamical approach to the problem of catching nonlinear relationships in the climate system, with the aim of performing an independent analysis of influence/causality and "weighting" the magnitude of different causes on the temperature variations in the past 140 years at both global and regional scales. More precisely, we use neural network modeling as a tool for climatic analyses of the relationships between forcings/circulation patterns and temperatures. In particular, the application of a fully nonlinear neural network model allows us to estimate the amount of variance explained by various forcings/circulation patterns in the reconstruction of temperature records at global and regional scales.

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In what follows we will describe the neural network tool developed by our group during the last years (section 2) and the data available for the present study (section 3). Then we apply our methodology to the reconstruction of annual mean temperatures at global level (section 4). At this stage we show the distinct roles of natural and anthropogenic forcings in driving global temperatures and we are also able to investigate the combined effect of the dynamics here not considered, by analysis of residuals (section 5). A case study about the influence of global forcings and a regional circulation pattern on winter temperatures in Europe is presented in section 6. Finally, brief conclusions are drawn and perspectives of further study are envisaged in the last section.

2. THE NEURAL NETWORK TOOL

A neural network tool for both diagnostic characterization and forecast in complex systems has been developed some years ago (Pasini and Potestà 1995). Since that date it has been applied to diagnostic and prognostic problems in the boundary layer (Pasini and Potestà 1995, Pasini et al. 2001, 2003a,b,d, Pasini and Ameli 2003) and recently also to attempts at analyzing climatic data (Pasini et al. 2003c, 2004).

As far as the kernel of our neural models is concerned, this tool has been extensively described elsewhere (see, for instance, Pasini et al. 2003a). Here, we just remind that our neural networks are feedforward and characterized by a backpropagation training endowed with gradient descent and momentum terms in the rules for weights update. Furthermore, an early stopping method is also available.

We would like to stress, however, that, together with these quite standard features (see Hertz et al. (1991) and Bishop (1995) for two reviews on these topics), this tool provides us many training facilities, useful for handling historical data from complex systems. One of these facilities, the so called "moving window" training, has been explicitly described in Pasini et al. (2001). Here, we briefly present what we call "all frame" training, a method to perform an optimal training in cases of a limited statistics available.

As we will see, our problem is to find a fully nonlinear correlative law between forcings/circulation patterns and temperatures at global or regional scales. In order to do so, we use data with a typical record length of about 140. In this situation characterized by short records, we need a training set as large as possible, but of course, for the correct estimation of a target, we have to exclude the correspondent inputs-target patterns from the training set on which we build the correlative law.

For these cases, an iterative procedure of training + validation/test cycles has been developed in our tool: it is sketched in the following Fig. 1. Here our total set of patterns is divided in two subsets. The white squares represent the elements (patterns) of the training set, while the gray square (one single element) represents the validation/test set. The relative composition of training and validation/test sets changes at each step of our iterative procedure, so that a gray "hole" moves across the total set of patterns, thus permitting the estimation of all targets at the end of iterations.

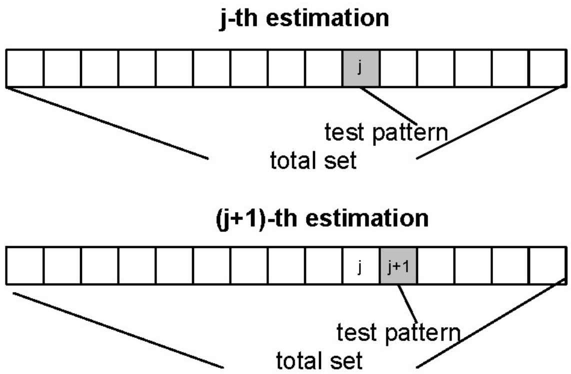


Fig. 1. "All frame" training as an iterative procedure.

In the present study the topology of our neural networks consists of one input layer, one hidden layer and one output layer. In what follows the inputs (up to 5) will come from data about circulation patterns, natural and anthropogenic forcings, while the target will be related to observed values of temperature at global or regional scale in the same year.

3. AVAILABLE RECORDS OF DATA

In the climate community many data about global and regional meteorological parameters, as well as data about physical-chemical forcings, are available from papers or web sites. Here we consider the following data:

- global temperature anomalies since 1856, related to the average value of 1961-1990 (from http://www.cru.uea.ac.uk);
- Central England Temperatures (CET) during extended winters (December to March) since 1659 (from http://badc.nerc.ac.uk/data/cet);
- solar irradiance anomalies, representative of the solar activity, since 1700 (from Hoyt and Schatten (1993) and from http://daac.gsfc.nasa.gov);
- stratospheric aerosol optical thickness at 550 nm since 1850 (from Sato et al. (1993) and from http://www.giss.nasa.gov/data/strataer): this series is representative of the past volcanic activity in terms of the optical properties of low stratosphere;
- global concentration of carbon dioxide (CO_2) since 1860 (from http://cdiac.esd.ornl.gov);
- global emissions of sulfates (SO_x) since 1850 (from http://www.rpi.edu/~sternd/datasite.html);
- Southern Oscillation Index (SOI), related to El Niño Southern Oscillation (ENSO), since 1866 (from http://www.cru.uea.ac.uk);
- monthly index of the North Atlantic Oscillation (NAO) since 1821 (from http://www.cru.uea.ac.uk).

As far as the global climate forcings are concerned, we will consider solar irradiance and stratospheric optical thickness as indices of natural forcings to the climate system. On the other hand, CO_2 concentration and sulfate emissions will be considered as mainly due to human activities and therefore labelled as anthropogenic forcings.

4. INFLUENCE ANALYSIS AT GLOBAL SCALE

A pioneeristic attempt at attribution and detection of anthropogenic climate change at global level by means of neural networks is due to Walter and coworkers (Walter et al. 1998, Walter and Schönwiese 2002). Our present investigation is quite different from their attempt, for several reasons. Among them, we can cite the use of neural networks endowed with some well founded features, like a momentum term in the weight updating rules, few hidden neurons as prescribed for short time series analysis, and the adoption of the "all frame" training presented above. Furthermore, in this paper we discuss the role of both anthropogenic and natural forcings, together with the contributions of circulation patterns, both at global and regional scales.

Thus, in the present global case study our aim is to investigate the influence of both natural and anthropogenic forcings on the behavior of global temperature since 1866. Moreover, data about SOI are used, because this oscillation in the Pacific Ocean between warming and cooling periods directly affects a large part of sea surface and also shows teleconnections with other regions of the world (see, for instance, a recent paper by Brönnimann et al. (2004)), so that it could contribute in a sensible manner to determine the values of annual mean temperature over the world.

Here we find the best linear and nonlinear reconstructions of the global temperature record when a multivariate linear model and a neural network model are fed by the following data for independent variables or inputs:

a) natural forcings only;
b) anthropogenic forcings only;
c) natural + anthropogenic forcings;
d) natural + anthropogenic forcings + ENSO.

The results are presented in Table 1 and Figs. 2a-d. Note that in Table 1 the models' performance is expressed in terms of the linear correlation coefficient R and that the error bars associated to the results by neural modeling come from ensemble runs with different random initial weights, so that the networks are able to widely explore the landscapes of the cost functions: they indicate ± 2 standard deviations. Furthermore, in this study an "all frame" procedure is adopted for both the neural model and the multi-linear regression.

Some fundamental pieces of information can be deduced from this analysis and summarized as follows:

- neural network modeling allows us to better reconstruct the temperature record in the last 3 cases of Table 1, if compared with the multi-linear regression, and the increase in performance is statistically significant (that is to say, outside the error bars);
- taking into account only the natural forcings (Fig. 2a), we are not able to reconstruct the temperature record (strong failure in the period 1900 -1960 and in the last decade);
- when anthropogenic forcings are considered as inputs to the network (Fig. 2b), a very evident increase in performance is obtained, even if the absolute minimum is overstimated and the relative maximum during the 2nd World War is underestimated;
- when anthropogenic and natural forcings are considered together as inputs to the neural model (Fig. 2c), the performance results are quite the same as in the previous case: anyway, now it seems to us that the amount of variance not explained is almost completely due to interannual variability;
- finally, when also data about SOI are added in input (Fig. 2d), we obtain the best results: here the interannual variability is better catched.

Now it is worthwhile to do some remarks and further considerations.

First of all, with reference to Table 1, we can say that a neural network model shows its usefulness in catching nonlinearities hidden in the data, at least when anthropogenic forcings are taken into account.

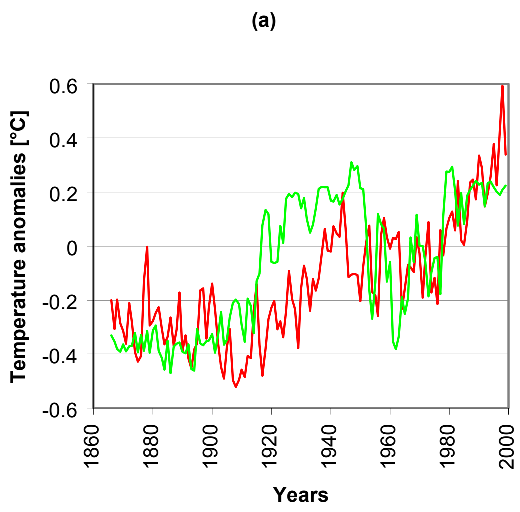
Secondly, the failure in reconstructing the temperature record by considering only the real behavior of natural inputs has been recovered also in AOGCMs' runs (see, for instance, Houghton et al. 2001, p. 710). In these latter cases big discrepancies have been observed in simulating the warming of the last 30 years, so that this evidence (and many others) leads to consider anthropogenic forcings as fundamental for reconstructing this recent warming. In the present purely correlative study, instead, we cannot infer a so precise dynamical conclusion, because the neural model simply found the best of a set of erroneous global correlative laws.

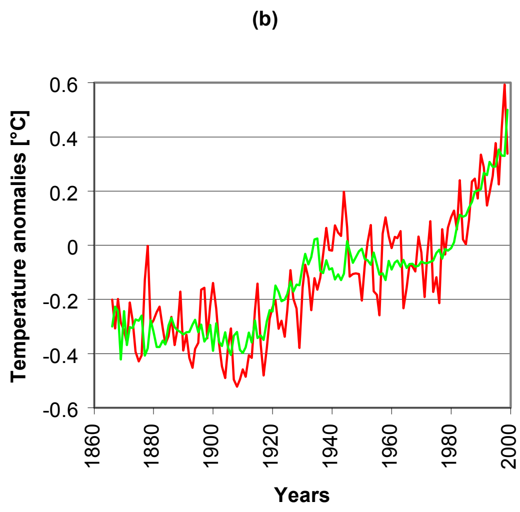
Anyway, the further insertion of data about anthropogenic forcings in our model and the consequent good performance results hint that these forcings can actually be fundamental causes of temperature variations in the whole period during the last 135 years.

Finally, we would like to stress that the insertion of ENSO data as inputs to our model leads to better catch the interannual variability in the temperature record. The reconstruction results obtained by considering the most complete inputs set (natural + anthropogenic forcings + ENSO) in our neural model are very satisfying.

Case	Linear model	Neural model
(a)	0.661	0.622 ± 0.014
(b)	0.818	0.847 ± 0.005
(c)	0.828	0.852 ± 0.005
(d)	0.844	0.877 ± 0.004

Table 1. Reconstruction performance in terms of R.





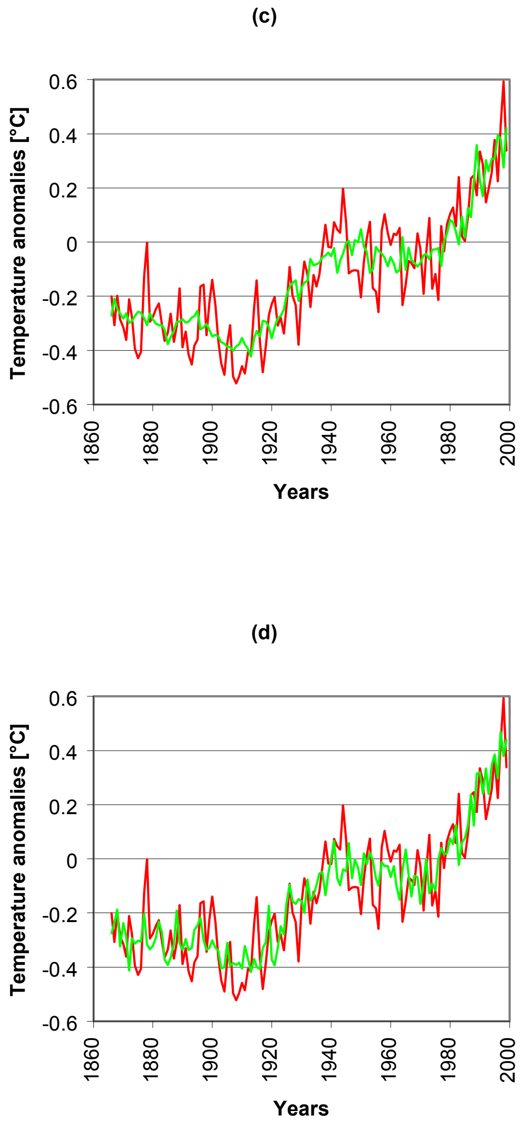


Fig. 2. Observed annual global temperature (red curve) vs. estimated annual global temperature by neural modeling (green curve) for different inputs (the 4 cases cited above).

The main forcings to the climate system have been probably considered in our analysis, so that it is worthwhile to test if the variance not explained by our final model can be due to a natural random variability of the climate system, or to the dynamical action of other forcings here neglected. This analysis will be done in the next section.

5. ANALYSIS OF THE RESIDUALS

When a dynamical or a correlative model reconstructs the behavior of a certain variable in a system, it is worthwhile to wonder whether the differences between the simulated and the observed signals are due to a natural random variability of the system or to the action of some variables not included in the model. This question is particularly important in a complex system like the Earth climate, where many variables can influence the behavior of temperature at global scale.

In order to perform a preliminary analysis, we study the record of residuals (estimated T - observed T) for the previous case (d). In particular, we search for a test which can allow us to discriminate between white noise due to a random process and some kind of periodicity or dynamical signal in the residuals.

As well known by statistics (see, for instance, von Storch and Zwiers (1999) for a general reference), two useful tools for this purpose are the Fourier spectrum and the AutoCorrelation Function (ACF). From the analysis of their graphs one is usually able to discriminate between white noise and the signs of some dynamics.

In Figs. 3,4 the Fourier spectrum and the ACF are presented for our record of residuals coming from the neural network reconstruction due to the insertion of inputs related to natural + anthropogenic forcings and ENSO.

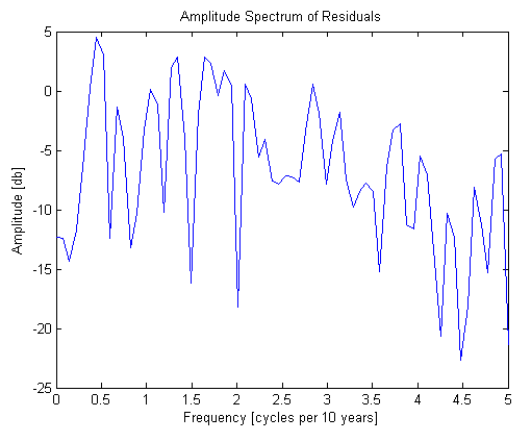


Fig. 3. Fourier spectrum of our residual time series.

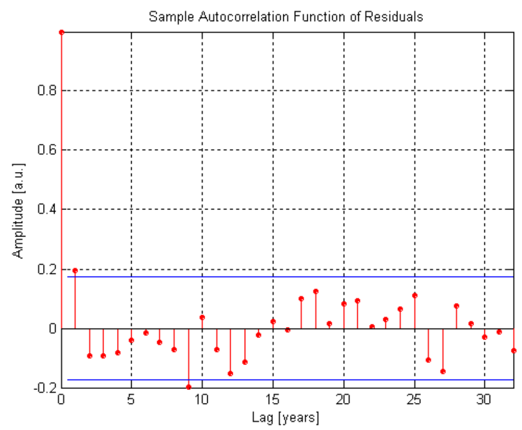


Fig. 4. Autocorrelation function of our residual time series.

In Fig. 3, the Fourier spectrum shows no particular peak or periodicity, like in the case of a random process of white noise. Nevertheless, some decrease in the amplitude is visible at frequencies higher than 3 cycles per 10 years. This fact can lead to think that we are not able to exclude the possibility that red or pink noise is hidden in our residual time series.

In Fig. 4, the ACF is almost completely confined inside the limits of white noise (represented by the two horizontal lines at values of about ± 0.18). Furthermore, even if some oscillations are detectable in the graph, these are more uncoupled than in previous results (Walter and Schönwiese 2002).

Thus, from these analyses, the behavior of our time series of residuals seems quite similar to that of series due to a random process, so that we can be confident that the major causes of temperature variations have been considered in our reconstruction and only second-order dynamics has been neglected.

Nevertheless, a word of caution about the application of these analysis methods for our case is necessary. First of all, these statistical analyses are usually applied to longer time series in order to have a significant response. In this framework, our residual record seems too short for drawing an undoubted conclusion. Furthermore, these methods can allow us to distinguish between white noise and periodic/dinamic signals, when, instead, in geophysical time series the most frequent feature is the fingerprint of red noise.

Thus, we would like to apply a more specific tool for analysis of short geophysical records. At present, work is in progress in order to analyze our residual time series by means of the so called Monte Carlo Singular Spectrum Analysis (MCSSA): see Allen and Smith (1996) for a specific reference and Ghil et al. (2002) for a more general review. This tool seems particularly useful in order to distinguish between colored noise and dynamical signals in very short geophysical time series.

6. INFLUENCE ANALYSIS AT REGIONAL SCALE

It is well known that climate on specific regions of the world is driven by the position of the main centers of meteorological action, like thermal cyclones and anticyclones, and by particular circulation patterns influencing the regions themselves. For the Central-Northern Europe a peculiar teleconnection has been recognized between the NAO and patterns of temperature/precipitation during extended winters (December to March).

Here, adopting the same strategy as in section 4, we want to analyze the fundamental elements that drive the temperature behavior in a region called Central England, approximatively enclosed by the towns of Preston, London and Bristol. More specifically, we use neural networks for reconstructing temperatures in this area during extended winters since 1860, when inputs to the model are given as in the following 3 cases:

a) natural + anthropogenic forcings;
b) NAO only;
c) natural + anthropogenic forcings + NAO.

As previously done in the global case study, we adopt again an "all frame" training, because of the few data available. The time series of CET during extended winters is shown in Fig. 5, where one can appreciate the high interannual variability of this regional record. Here no evident climate trend is visible, except for a slightly increasing linear tendency, especially due to data of the last decades.

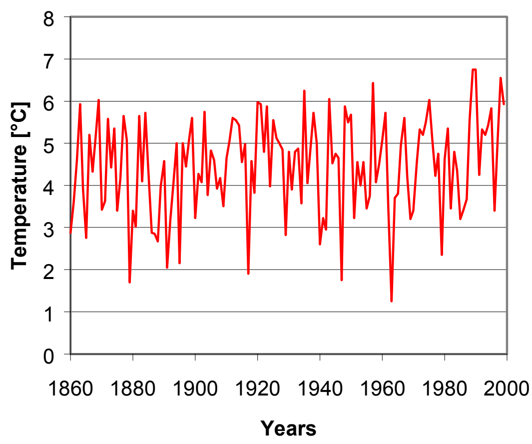


Fig. 5. CET time series during extended winters.

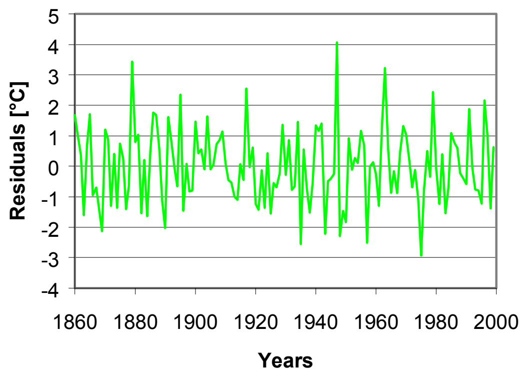
The results obtained by this modelling activity are presented in Table 2, where the values of Bias and Mean Absolute Error (MAE) for these 3 cases of reconstruction are shown, and in Figs. 6a-c, where the three time series of residuals (estimated T - observed T) are graphed.

The first clear result concerns the very little influence that global forcings have on the behavior of winter temperatures in Central England. On the other hand, the results of cases (b) and (c) show the good reconstruction performance of the two neural models that use NAO data as inputs. These latter results are very similar and the linear correlation coefficients (estimated T vs. observed T) are both around 0.72 ÷ 0.75. We stress that these values are lower than in the analogous situations of global case studies, but this is not surprising if we take the enhanced interannual variability of climate at a regional scale into account. Finally, in the present regional case study, some dynamics has been surely neglected, like the influence of the Artic Oscillation (AO) at these latitudes.

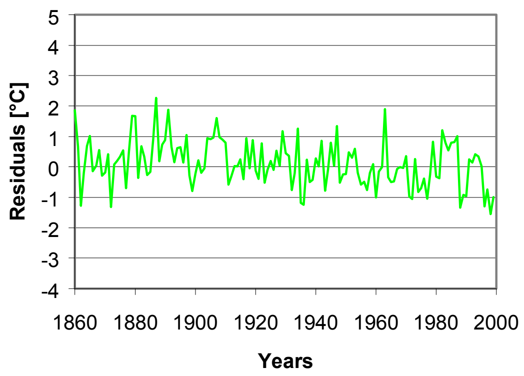
In short, this analysis shows that we have to consider NAO as the driving force of temperature time pattern in Central England. This information is very important and must be considered if we want to achieve a correct estimation of climate in this zone. In particular, only regional dynamical models which correctly describe the NAO phenomenon can have a chance to achieve reliable reconstructions of climate in the past and satisfying predictions for the future.

Furthermore, any statistical downscaling model has to take NAO into account for determining its regional climate scenarios.

(a)



(b)



(c)

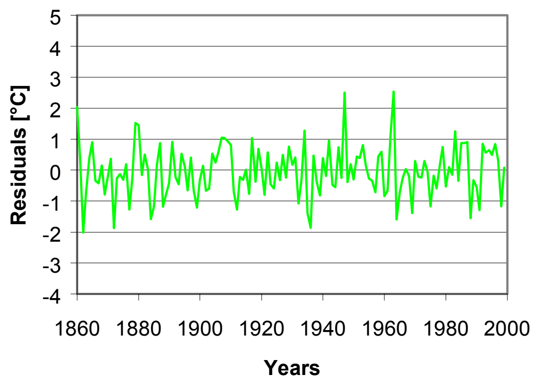


Fig. 6. Time series of residuals (neural estimations - CET observations during extended winters) for different inputs (the 3 cases cited above).

Case	Bias	MAE
(a)	-0.002	0.995
(b)	0.117	0.601
(c)	-0.037	0.651

Table 2. Systematic error and mean absolute error (in °C) for the 3 cases of this regional case study.

7. CONCLUSIONS AND PERSPECTIVES

In this paper we have applied a non-dynamical approach (neural network modeling) to the analysis of forcings/temperatures relationships at different scales in the climate system.

As already shown by some AOGCMs' simulations, here we recognize the importance of anthropogenic forcings in order to successfully reconstruct the annual temperature record at global scale. In this framework, we also achieve the evidence that the consideration of ENSO data leads to a better catching of interannual variability.

The analysis of residuals gives us no undoubtable conclusion, but shows that a large part of the dynamics of the climate system has been considered.

At regional scale, we obtain a clear recognition of the NAO importance, as far as its role in driving the winter temperature behavior in central England is concerned. This must be kept in mind if one wants to achieve successful reconstructions or predictions either by regional dynamical models or statistical downscaling of AOGCMs.

Finally, this paper opens perspectives of further work, too. For example, the non-conclusive results of section 5 hint to explore other statistical tests in order to assess if a fingerprint of neglected dynamics can be discovered in the signal of residuals, or if we can assume this signal as the manifestation of a random noise, eventually a red one. In any case, we think that it is worthwhile to extend our inputs and take other forcings and circulation patterns into account.

Other possible developments of this work concern the application of our neural network tool and methodology to data about other regions of the world. In this future activity we do not want to neglect the possibility of reconstructing some different and very important meteo-climatic records and fields, like regional precipitation regimes.

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