12.1 Introduction

At present, climate change is a “hot topic”, not only in scientific analyses and papers by researchers, but also in wider discussions among economists and policy-makers.

In whatever area you are, the role of modeling appears crucial in order to understand the behavior of the climate system and to grasp its complexity. Furthermore, once validated on the past, a model represents the only chance to make projections about the future behavior of the climate system.

In this framework, AI methods (more specifically, neural networks – NNs) have recently shown their usefulness in modeling studies dealing with the climate system. Thus, the aim of this paper is to review and discuss the applications of neural network modeling to climate change studies. In doing so, we will meet at least two strategies of application: the first one is “complementary” to the standard dynamical modeling via Global Climate Models (GCMs), due to its substantial nature of NN post-processing of GCM outputs; the second one is more “alternative” to dynamical modeling, because it is founded on the direct modeling of the climate system by NNs in an empirical and data-driven way.

Thus, in the next section we will present studies about GCMs downscaling via neural networks, an activity that has become quite standard in research papers during the last few years, even if not even thoroughly applied. Then, considerations about the application of dynamical modeling to a complex system like climate will lead us to recognize some weaknesses in the simulated reconstruction of the system itself. In particular, as we will see, this can lead us to criticize this kind of modeling (when applied to complex systems) and to not rely on its results.

In this unsatisfactory situation, a more phenomenological approach to the analysis of climate behavior can be applied. In Section 12.3 we will initially show how some modelers used neural network modeling for studying and forecasting the occurrence of specific phenomena, like El Niño. Then, in what follows, a comprehensive analysis of the influence of natural and anthropogenic forcings on global and regional temperature behaviors will be performed by NNs, shedding light on the most important forcings that drove the observed trends in the past.

Furthermore, in Section 12.4, a particular application of neural network modeling to the analysis of predictability on unforced and forced Lorenz attractors, which can mimic present and future climatic conditions, will be presented and discussed.

Finally, in the last section, brief conclusions will be drawn and prospects of future applications will be envisaged.

12.2 Post-processing of GCMs and Downscaling

As discussed in the first chapter of this book, the discovery of deterministic chaos in meteorological models (by Lorenz) led to reconsidering statistical methods for the forecasting activity, like MOS or Perfect Prog
A. Pasini (see Marzban et al. 2005, for a brief discussion of these methods, and for the introduction of a new method that is bias-free and shows lower uncertainty than MOS and Perfect Prog). These methods are usually applied to the post-processing of a meteorological model, too, essentially for achieving a local prediction starting from an area forecast given by the dynamical model, characterized by a finite resolution.

Recently, NNs have been used for this aim, due to their capacity for modeling nonlinear relationships between large-scale variables/patterns and local variables of fundamental importance, like temperature and precipitation. The reader can see Casaioli et al. (2003), Marzban (2003), and Yuval and Hsieh (2003) for further information and examples of applications.

Due to the fact that climate models are generally endowed with coarser resolution than those of meteorological models, one should expect that a kind of post-processing must be applied to GCMs if one wants to achieve high-resolution reconstructions or projections of climate at a regional scale. And this is exactly what happens!

12.2.1 Rationale of Downscaling

As a matter of fact, due to the very large amount of computer time needed for global simulations over several decades even on big and expensive supercomputers, the GCMs are rarely endowed with a horizontal grid spacing less than 100–150 km. This fact leads to spatially averaged reconstructions and projections that do not correctly simulate the influence of mesoscale and microscale features on regional or local climate.

The rationale for downscaling is depicted in Fig. 12.1. Here, given a certain averaged simulation result by a GCM over a grid area (bottom part of the figure), we obtain a unique value for meteo-climatic variables, like temperature and precipitation, in this area. This value should be representative of several places in the area that, on the other hand, are characterized by different physiographic features, like the presence of flat land or mountains, rivers, arid lands or forests, and human-induced changes, like land use, urbanization and the presence of industrial activities (upper part of the figure). Of course, in the past these features led to differences in parameters like the monitored surface air temperature and the amount of precipitation at different sites inside the area.

Thus, the climatic reconstruction of a GCM at regional and local scales cannot be accurate; its projections for the future would be even worse. The problem of downscaling is therefore how to pass from global reconstructions and projections to regional and local ones.

12.2.2 Statistical Downscaling

Following a dynamical paradigm, the basic idea for solving this problem is to enhance resolution, either by using a purely meteorological model driven by lower boundary conditions coming from a complete GCM, or by “nesting” a complete regional climate model (RCM) in a GCM just for a limited area of the globe, with all the boundary conditions coming from the GCM and, possibly, taking the feedbacks of the regional scale on the global one into account. In either method one can run the models at high resolution to obtain a dynamical downscaling. Here we do not discuss features, results, or pros and cons of these methods: we just note that RCMs seem to guarantee a better consistency with the global picture given by GCMs, even in the absence of feedbacks from the regional scale to the global one. The interested reader can see Wang et al. (2004) for a recent review of RCMs.