Effects of transient climate change on basin hydrology.  
1. Precipitation scenarios for the Arno River, central Italy

Paolo Burlando1* and Renzo Rosso2

1 Institute of Hydromechanics and Water Resources Management, ETH Zurich, ETH Hönggerberg, CH-8093 Zurich, Switzerland  
2 Department of Hydraulic, Environmental and Surveying Engineering, Politecnico di Milano, Leonardo da Vinci 32, I-20133 Milan, Italy

Abstract:
Long-term simulations of temporal rainfall and temperature under transient global climate conditions are discussed to give an insight into potential modifications of atmospheric inputs at the basin scale in the Arno River in central Italy. The outputs from a global circulation model (GCM), simulating climate changes due to an increase in the greenhouse effect resulting from a continuous trend in the growth of CO2 atmospheric concentration and accounting for the influence of both CO2 and sulphate aerosols, are downscaled using a stochastic approach based on the observed non-stationarity of precipitation and temperature patterns. By using the historical joint variability of the internal structure of storm events, one can infer future changes in storm duration and depth from GCM trend variables, thus indicating the extent of changes in the occurrence of wet and dry periods and in the daily rates, including those of distributional properties at the monthly and annual scales. Because the changes detected mainly affect the tails of the distributions, one can conclude that modifications can occur in both low and high values of rainfall at the monthly and annual scales, with a shift of the storm patterns towards shorter and more intense convective rainfall, especially in the summer season. Stochastic simulation also shows that the distributional and scaling properties of rainfall extremes may progressively change, thus indicating that some revision of current practices to estimate extreme storms is needed to account for possible effects of non-stationary climate conditions. This approach provides local precipitation that, together with temperature scenarios, can be used for hydrological simulation of basin water fluxes in the Arno River, as reported in a companion paper (Burlando P, Rosso R. Hydrological Processes this issue). Copyright © 2002 John Wiley & Sons, Ltd.

KEY WORDS precipitation scenarios; climate change; stochastic downscaling

INTRODUCTION
It is widely recognized that the natural and anthropogenic production of greenhouse gases might induce many changes in the natural environment. The most investigated of these changes are those relevant to climate—specifically to the potential increase of global and local temperatures—and to the resulting modification of rainfall space–time distribution. These primary effects could generate a number of direct and indirect impacts on the environment and the society, such as changes in water resources, increased desertification, loss of biodiversity, sea-level rise, and changes in agricultural productivity, as summarized for instance, by the Special Reports of the Intergovernmental Panel on Climate Change (IPCC, 1995a–c, 1997).

During the 1980s a major focus was on global and large-scale effects of anthropogenic climate change (e.g. Manabe and Stouffer, 1980; Manabe and Wetherald, 1987), whereas attention given to regional and local impacts was only emphasized in the 1990s. In this respect, the study performed by Nemec and Schaake (1982) was pioneering work, in which the effect of changes in temperature and precipitation on river flows and reservoir operation in several test catchments in North America were simulated. Since then, there has been an increasing degree of research interest in both global and local effects of a potential climate change.

* Correspondence to: Professor P. Burlando, Institute of Hydromechanics and Water Resources Management, ETH Zurich, ETH Hönggerberg, CH-8093, Zurich, Switzerland. E-mail: paolo.burlando@ethz.ch

Received 19 September 2001
Accepted 15 October 2001
(e.g. Cohen, 1986; Askew, 1987; Gleick, 1987; Manabe and Wetherald, 1987; Mimikou and Kouvopoulos, 1991; Burlando et al., 1997, Dvorak et al., 1997; Strzepek and Yates, 1997). One should notice, however, that great attention has been directed towards understanding the impact of changes of the mean climate, whereas only a limited number of contributions assessing the variability of changes, including extreme value analysis, can be found in the literature (e.g. Burlando and Rosso, 1991; Boorman and Sefton, 1997; Mearns et al., 1997).

One can approach climate-induced non-stationarity in hydrological processes using different methods, including the analysis of palaeo-climate analogues, and that of proxy and historical data. An alternative route is the development of hydrological simulations at the basin scale using meteorological data inputs retrieved from global climate scenarios, which are provided by global circulation models (GCMs). Unfortunately, the structure of GCMs is such that their space resolution is too coarse and not adequate to describe the variability at the basin scale. Moreover, most of the models use rough representations to describe hydrologic processes, despite the large effort that has been made in recent years to improve the GCM components of the soil–vegetation–atmosphere interaction (e.g. Koster and Suarez, 1994; Blyth et al., 1999). For these reasons there is a serious restriction in the direct use of GCM-based scenarios for investigating the possible impacts of climate change.

Identifying local climate scenarios for impact analysis, therefore, implies the definition of more detailed local scenarios by ‘downscaling’ GCMs results. This can be done by approaching the problem according to several techniques (Giorgi and Mearns, 1991). For instance, the improvement of high-resolution climate models, the so-called regional Climate Models (ReCMs) or limited-area models (LAMs), which use boundary conditions obtained from the global prediction to drive a nested regional climate model, may improve the quality of the hydrological variables generated (Giorgi et al., 1994; Mearns et al., 1995; Ohmura et al., 1996). Nested models can provide useful information on day-to-day variability and can account for forcing due to increased greenhouse gas concentrations. However, the reliability of this approach to analyse the local variability of the processes is nowadays still questionable, especially with respect to the description of precipitation and its variability at such small scales. Models belonging to this class are still a considerable way from providing a tool for engineering and impact analysis because of several problems. Recent contributions in the relevant literature indeed report on systematic errors similar to those of GCMs, which increase as the LAM domain is reduced (Machenhauer et al., 1996), let alone the relatively large errors in the fundamental near-surface climate parameters, surface air temperature and precipitation (Christensen et al., 1997). Similarly, Cubasch et al. (1996) note that regional nested models exhibit problems connected with the boundary conditions, so that it is difficult to obtain sufficiently long runs, which are necessary to have a high statistical confidence in predictions. Despite the progress achieved in recent years and active ongoing research, LAMs still need to improve with respect to the inadequacy of the model physics. In view of climate reproduction, it is generally agreed that winter-time simulations are satisfactory (although on a 50 km grid-scale), whereas more serious problems occur in summer-time, essentially related to the correct representation of energy fluxes and radiation balance driving the convective activity.

Two alternative routes are represented by statistical and stochastic downscaling. The literature reports a number of contributions dealing with statistical downscaling (e.g. Huth and Kysely, 2000; Wilby, 1998, Wilby et al., 1998). Statistical downscaling methods are often criticized because of their fundamental postulate that assumes statistical relationships between climatic and hydrological variables—often a multiple regression—to be invariant in the observed and in the modified (predicted) climate. This problem is overcome by stochastic downscaling methodologies, like those described by Burlando and Rosso (1991), Matyasovszky et al. (1993), Katz (1996), Semenov and Barrow (1997), Dubrovský (1997) and Corte-Real et al. (1998), among others. These techniques, in essence, allow modelling of future climate conditions based on stochastic models that are able to model the present climate; satisfactorily the parameters of such models are modified to account for the changing climate according to different techniques, often linked to predictions given by GCMs simulations.

This is the case, for instance, in the analytical framework introduced by Burlando and Rosso (1991), and further used by Burlando et al. (1997). These authors make use of the ratio between the mean daily
precipitation in GCM control simulations and the same variable in GCM simulations under changed climate as a driving variable for the re-parameterization of a stochastic model of temporal rainfall, which is then used to simulate the continuous temporal process of rainfall at a point in space, corresponding to a raingauge station. The re-parameterization under climate change is obtained by means of an analytical framework based on observed properties of rainfall and on the structure of the stochastic model of the temporal rainfall process. It is worth noticing that this downscaling framework allows analysis of changes in the internal structures of the storm events. It is thus capable of accounting for changes in the variance of the process, which is generally not the case for most of the downscaling procedures available in the literature. It is well recognized that analysing the variance of the process is of great importance, when dealing with water resources analysis, in order to capture the variability of the process and perform a correct frequency analysis. The importance of this aspect of the analysis and of how extreme values of precipitation may change has been widely recognized in the literature (e.g. Giorgi and Mearns, 1991; Beniston, 1994; IPCC, 1996), because of their larger impact on natural and socio-economic systems in relation to changes in mean climate (Beniston, 1998). This indicates that changes in extreme properties of precipitation—for instance, the enhancement of 'dry' or 'wet' conditions—may have impacts, the severity of which could be more significant than a change in temperature extremes alone.

Moving from the downscaling technique introduced by Burlando and Rosso (1991), the present study—and its related companion paper; see Burlando and Rosso (2002)—illustrates an extensive analysis of the effects of a potential climate change on hydrological processes at the basin scale, especially addressing changes in the variability of rainfall process and at a space–time scale of interest for engineering design problems in mesoscale catchments. Moreover, unlike previous studies, the analysis presented hereafter makes use of a transient climate-change scenario as a starting point for the generation of local scenarios. The GCM scenarios forming the basis for downscaling have been generated (Mitchell et al., 1995) by assuming that the doubling of CO$_2$ atmospheric concentration is reached by a continuous, time-dependent increase in the percentage of greenhouse gases, thus generating a transient scenario, which looks more realistic than the steady-state 2 × CO$_2$ often adopted by impact studies. Furthermore, the GCM scenario adopted also accounts for the action of sulphate aerosols, the cooling mechanism of which has been recognized to be the second most influential anthropogenic forcing component in the atmosphere after greenhouse gases (Mitchell et al., 1995).

Long-term simulations of temporal rainfall under transient conditions have, therefore, been performed to investigate the modification of rainfall, and rainfall-driven processes, as illustrated by Burlando and Rosso (2002), due to non-stationarities that might be caused by a progressively changing climate. First, the parameters of the rainfall model have been investigated, as they reflect the internal structure of storm events, hence allowing detection of any change in storm duration and depth. Secondly, a number of statistical properties have been analysed in order to outline the extent of changes in the occurrence of wet and dry periods and in the mean daily amounts, including frequency analysis, to point out any change in the distributional properties at the monthly and yearly scales. Finally, simulated rainfall extremes have been examined in the search for modifications in distributional and scaling properties, which might affect the estimates obtained by means of the current techniques, as well as the technique itself.

The results of the investigation provide interesting clues, indicating, for instance, that some changes might occur in the tail of the distributions, hence affecting both the low and the high values of rainfall at the monthly and annual scales, as further outlined below. A shift of the patterns of storms towards shorter and more intense convective rainfall also seems more likely, especially in the summer season. The latter change has also been detected by analysing alterations in the scaling properties of rainfall extremes, that denoted changes from scaling to multiscaling behaviour (see below), and, more generally, in the sense of an increased variability of the process. Accordingly, noticeable modifications potentially induced by non-stationarity indicate that more attention should be paid to design storm estimation procedures, and indicate the need for a revision of the techniques currently in use in order to account for both natural and man-induced climatic fluctuations.
DOWNSCALING OF GCM PRECIPITATION SCENARIOS VIA STOCHASTIC MODELLING OF TEMPORAL RAINFALL

General

The approach used by Burlando and Rosso (1991) to derive precipitation scenarios at the local and basin scales from GCM outputs is based on stochastic modelling of temporal precipitation using a physically based representation of the major features of the underlying process. Poisson cluster models give a representation of these features as reflected by storm cell dynamics, the statistical properties of which are represented by model variates, such as the duration, temporal displacement and rain rate of a cell, and the rate of occurrence of cell clusters and their temporal displacement. An example of cluster model is the Neyman–Scott rectangular pulses (NSRP) model illustrated in Figure 1, which has been shown capable of capturing the observed statistical properties of both continuous rainfall and rainfall extremes for a wide range of climate conditions (e.g. Burlando, 1989; Cowpertwait, 1991, 1994, 1995; Burlando and Rosso, 1993; Cowpertwait et al., 1996a, b).

For the specific area analysed by the present investigation, the NSRP model has been shown to match the main rainfall characteristics, thereby including statistical, scaling and extreme properties over the period 1962–86 (Burlando and Rosso, 1993; Olsson and Burlando, 2002). Under the assumption of a stationary rainfall process, one can then derive model parameters using the observed precipitation series and matching the model-computed statistics with the observed. These are often derived by aggregating the process at different temporal scales in order to achieve a robust model, which is capable of representing the statistical properties of precipitation processes over a range of temporal scales. Because cluster dependence should reflect seasonal variability, one must introduce a time-dependent (periodic) model parameterization, which makes use of statistics on a monthly basis, in order to capture the annual precipitation patterns (e.g. Burlando and Rosso, 1993). The persistence of wet and dry periods may affect the statistical properties of the observed process, thus resulting in different parameter estimates, which then reflect the non-stationary character of precipitation rates. In this respect, the NSRP model used in the analysis is briefly reviewed below.

The NSRP model of temporal rainfall

Let $X(t)$ denote rainfall rate at a point in space and time $t$. The NSRP model is based on Poisson arrivals of storms, a cluster of rectangular pulses or cells of random height and duration that are randomly displaced.

Figure 1. Sketch of the NSRP model of point precipitation

$w_i = \text{interarrival time of events (pulses)}$
$t_j^{(1)} = \text{displacement of the } j \text{-th cell from the cluster center}$
$t_i = \text{duration of the } i \text{-th pulse}$
$c_i = \text{intensity of the } i \text{-th pulse}$
from the cluster origin being associated with each arrival. The superposition of these pulses provides the description of the storm profile. It is often assumed that both the intensity and the duration of a pulse are independent and identically distributed with exponential marginals, being displaced from the cluster origin according to an exponential distribution, and the number of cells assumed to follow a geometric distribution. The second-order properties of the aggregated process \( X_T(t) \) at scale \( T \) were derived under these assumptions by Rodriguez-Iturbe (1986), resulting in

\[
E[X_T(t)] = \lambda \mu \delta T
\]

\[
\text{var}[X_T(t)] = 2\lambda \mu^2 \delta^3 v \left( \frac{T}{\delta} - 1 + \exp \left( -\frac{T}{\delta} \right) \right) \left[ 2 - \frac{\beta^2 \delta^2 (v-1)}{1 - \beta^2 \delta^2} \right]
\]

\[
\text{cov}[X_T^i, X_T^{i+k}] = \lambda \mu^2 \delta^3 v \left[ 2 - \frac{\beta^2 \delta^2 (v-1)}{1 - \beta^2 \delta^2} \right] \left[ 1 - \exp \left( -\frac{T}{\delta} \right) \right]^2 \exp \left[ -\frac{T(k-1)}{\delta} \right]
\]

where \( \lambda \) is the Poisson rate of storm arrival, \( \mu \) and \( \delta \) are respectively the mean intensity and the mean duration of a pulse, \( v \) is the mean number of cells in a cluster, and \( \beta\delta \) is the mean displacement of a cell from the cluster origin. The scale of fluctuation \( \theta \) of the process \( X(t) \), which provides the time interval required to obtain stable (low variance) estimates of the mean of the fluctuating process of rainfall intensity, can be expressed as

\[
\theta = 2\delta \frac{(v+1)}{2 + \frac{(v-1)\beta\delta}{1 + \beta\delta}}
\]

One notes that the scale of fluctuation is independent of the Poisson rate and of the rain rate of a cell, but it is almost equal to twice the average pulse duration for the range of values of \( \delta, \beta, \) and \( v \) usually found in nature.

**Downscaling of GCM precipitation outputs using the NSRP model**

The non-stationary behaviour of precipitation processes is reflected by the statistical properties observed in different periods. For example, the second-order statistics of rain rate are expected to vary from one month to the next. Therefore, one can assume that the process is second-order periodic-stationary, i.e. stationary in a month. However, the average rain rate and its second-order moments in a month of a certain year, e.g. July 1998, differ from those observed in the same month of another year, e.g. July 1999. This variability is shown in Figure 2, where the estimated standard deviation \( s_{X_T}(t) \) is plotted against the estimated mean \( m_{X_T}(t) \), of the daily precipitation rate at Firenze Ximeniano station in the study area. One can assume that

\[
s_{X_T(t; \tau)}^2 = b \left[ m_{X_T(t; \tau)} \right]^{2\alpha}
\]

where the scaling exponent \( \alpha \) and the constant \( b \) can be estimated from the aggregated data of precipitation rate. Here, \( X_T(t; \tau) \) denotes aggregated precipitation rate at time \( t \) of the \( \tau \)th period of the year, with \( T \) denoting the length of the aggregation window. Figure 2 shows that Equation (5) can reasonably fit the joint variability of the observed second-order statistics for the station examined. This assumption is also supported by a large amount of daily precipitation data in the Arno River basin, as shown in Table I for two stations of the study area. The estimated values of the monthly scaling exponent of Equation (5) are found to range from 0.73
Figure 2. Mutual variability of first- and second-order central moments in February and July for one station in the study area (Firenze Ximeniano), based on daily data.

Table I. Exponents of Equation (5) for Firenze Ximeniano and Borgo S. Lorenzo stations

<table>
<thead>
<tr>
<th>Month</th>
<th>Firenze Ximeniano</th>
<th>Borgo S. Lorenzo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scaling exponent</td>
<td>$R^2$</td>
</tr>
<tr>
<td>January</td>
<td>0.779</td>
<td>0.866</td>
</tr>
<tr>
<td>February</td>
<td>0.775</td>
<td>0.936</td>
</tr>
<tr>
<td>March</td>
<td>0.630</td>
<td>0.732</td>
</tr>
<tr>
<td>April</td>
<td>0.809</td>
<td>0.940</td>
</tr>
<tr>
<td>May</td>
<td>0.750</td>
<td>0.776</td>
</tr>
<tr>
<td>June</td>
<td>0.794</td>
<td>0.874</td>
</tr>
<tr>
<td>July</td>
<td>0.887</td>
<td>0.975</td>
</tr>
<tr>
<td>August</td>
<td>0.840</td>
<td>0.856</td>
</tr>
<tr>
<td>September</td>
<td>0.826</td>
<td>0.973</td>
</tr>
<tr>
<td>October</td>
<td>0.638</td>
<td>0.843</td>
</tr>
<tr>
<td>November</td>
<td>0.726</td>
<td>0.885</td>
</tr>
<tr>
<td>December</td>
<td>0.760</td>
<td>0.850</td>
</tr>
</tbody>
</table>

to 0.88, with $R^2$ values ranging from 0.83 to 0.97. One can observe that Equation (5) holds for ‘wide-sense simple-scaling’ hydrological processes (e.g. Gupta and Waymire, 1990) if the value taken by exponent $\alpha$ is independent of the scale of aggregation $T$. Investigations at smaller aggregation scales have shown that, at smaller scales, Equation (5) still holds, although a broader range of $R^2$ values are obtained, largely depending on the strong seasonal patterns that become more evident at smaller temporal scales.
If one assumes that the modification in the trend variate is expressed by the ratio $K_m$ between the mean daily precipitation of the enhanced CO$_2$ scenario $m_{(n\times CO_2)}$ and the present climate mean daily precipitation $m_{(control)}$ corresponding to the control scenario:

$$\frac{m_{(n\times CO_2)}}{m_{(control)}} = K_m$$  \hspace{1cm} (6)

the conjecture that the shape and parameters of Equation (5) do not change under the modified scenario yields

$$\frac{\sigma_Y^2}{\sigma_X^2} = K_\sigma = K_m^{2\alpha}$$  \hspace{1cm} (7)

where, for the sake of simplicity, the index $Y$ stands for the enhanced CO$_2$ scenario and $X$ for the control one. This implies that the standard deviation of the precipitation rate will be modified by a factor of $K_m^{2\alpha}$ if the trend of precipitation changes by a factor of $K_m$.

One can obtain a similar relationship to investigate the variability in the scale of fluctuation. Under the further assumption of system linearity, one gets (Vanmarcke, 1983)

$$\frac{\sigma_Y^2 \theta_Y}{m_Y^2} = \frac{\sigma_X^2 \theta_X}{m_X^2}$$  \hspace{1cm} (8)

which can be used to derive the ratio $K_\theta$ of the scales of fluctuation under modified and control conditions, i.e.

$$K_\theta = K_m^{2(1-\alpha)}$$  \hspace{1cm} (9)

Accordingly, Equations (6), (7) and (9) provide the framework for rescaling the second-order statistics of the precipitation rate as a function of the ratio $K_m$, representing the change in the precipitation trend. Because the second-order statistics of the NSRP model are a function of the five parameters of the model, one can use these equations to derive analytical relationships for rescaling three out of five parameters of the stochastic model. To this purpose, relationships similar to Equation (5) can be written to relate the changes of some of the NSRP model parameters between the present (control) and the enhanced CO$_2$ scenario, thus obtaining

$$\frac{\lambda_Y}{\lambda_X} = K_\lambda; \frac{\mu_Y}{\mu_X} = K_\mu; \frac{\delta_Y}{\delta_X} = K_\delta$$  \hspace{1cm} (10)

For the two remaining parameters, $\upsilon$ and $\beta$, it is assumed that the number of cells per cluster is unmodified under the enhanced CO$_2$ scenarios, i.e. $K_\upsilon = 1$, and that the mean displacement of cells from the cluster origin is rescaled with respect to the cell duration, namely according to the power law

$$\frac{\beta_Y}{\beta_X} = K_\beta = (K_\delta)^s$$  \hspace{1cm} (11)

where $s$ is a scaling exponent to be evaluated on the basis of the parameter estimated for the control scenario.

By combining the NSRP model second-order statistics, i.e. Equations (1)–(3), with Equations (6), (7) and (9) one finally obtains, after a few manipulations, the ratios $K_\lambda$, $K_\mu$, and $K_\delta$ as functions of $K_m$, which is the factor of change in the trend of precipitation as provided by GCMs outputs, in the form

$$K_\lambda = \frac{K_m}{K_\mu K_\delta}$$  \hspace{1cm} (12)

$$K_\mu = \frac{K_m^{2\mu-1} (\Phi_1 + \Phi_2)}{K_\delta (\Phi_3 + \Phi_4)}$$  \hspace{1cm} (13)

$$K_\delta = \frac{1 + K_\delta^{(s+1)} \beta_X \delta_X}{2 + K_\delta^{(s+1)} \beta_X \delta_X (\nu + 1)} \frac{(1 + \beta_X \delta_X)}{2 + \beta_X \delta_X (\nu + 1)}$$  \hspace{1cm} (14)
where the mean pulse duration computed for the present scenario $\delta_X$, the scale of temporal aggregation $T$, and the scaling factor $\alpha$ are the parameters used for model rescaling, and $\Phi_1$, $\Phi_2$, $\Phi_3$ and $\Phi_4$ are functions of $\delta_X$, $\nu$, $\beta_X$ and $T$. These are given by

$$\Phi_1 = \left\{ \delta_X \left[ 2 - \frac{\beta_X^2 \delta_X^2 (\nu - 1)}{(1 - \beta_X^2 \delta_X^2)} \right] \left[ \frac{T}{\delta_X} - 1 + \exp \left( -\frac{T}{\delta_X} \right) \right] \right\}$$

$$\Phi_2 = \frac{(\nu - 1)}{\beta_X (1 - \beta_X \delta_X)} \left[ \beta_X - 1 + \exp(-\beta_X T) \right]$$

$$\Phi_3 = \left\{ K_\delta \delta_X \left[ 2 - \frac{K_\delta^2 (\nu - 1)}{(1 - K_\delta^2 (\nu - 1)) \beta_X^2 \delta_X^2} \right] \left[ \frac{T}{K_\delta \delta_X} - 1 + \exp \left( -\frac{T}{K_\delta \delta_X} \right) \right] \right\}$$

$$\Phi_4 = \frac{(\nu - 1)}{K_\delta^m \beta_X (1 - K_\delta^m \beta_X \delta_X)} \left[ K_\delta^m \beta_X T - 1 - \exp(-K_\delta^m \beta_X T) \right]$$

After the ratio of change in the precipitation trend $K_m$ is obtained from the analysis of the GCM mean daily precipitation totals as averaged on a monthly basis, it is straightforward to estimate the new NSRP parameterization for the $n \times$ CO$_2$ scenario from Equations (11)–(14).

One can observe that this technique limits to the minimum the propagation of GCM errors, which are well recognized to be affected by substantial problems with respect to direct simulation of hydrological variables, as clarified in the above sections. This is as a result of the ratio being computed between two homogeneous variables that are affected by the same bias because they have been computed by the same model. This ratio, and not the mean daily rainfall predicted by GCMs, is used to rescale the historical mean daily rainfall as computed from an observed series into a value that is assumed to represent the mean daily rainfall potentially ‘measured’ in a changed climate. In other words, it is assumed that the ratio between the observed mean daily rainfall and the mean daily rainfall that is expected to occur under climate change is characterized by the same ratio computed on the basis of the values predicted by GCMs in the control simulation and in the CO$_2$-enhanced simulation respectively. Although it is recognized that this is an assumption, it must also be observed that, in practice, the assessment of its validity, and of the validity of any other assumption based on GCM simulation of the recent climate, is not particularly easy because of the uncertainties associated with the emission scenarios that underlie GCMs predictions.

**PRECIPITATION SCENARIOS FOR THE ARNO RIVER BASIN**

The geographical area selected to perform the analysis of the impact of a potential climate change on precipitation, and then on rainfall-driven processes (Burlando and Rosso, 2002), is the Arno River basin. A large set of historical data is available for the Arno River basin, including both fine resolution and daily rainfall records and daily temperature data for a considerable number of stations (Figure 3). Also, daily streamflow and peak flood discharge records are available, thus allowing a detailed simulation of the hydrologic process at different space and time scales.

The basin is representative of a Mediterranean climate, with a total annual precipitation from about 700 to 1700 mm (Figure 4), and is therefore located in one of the regions that are expected to suffer significantly from a global change. Heavy storms mainly occur in autumn, following dry summers. The mixture of mountainous and flat areas offers a good opportunity to test global-change effects at different elevations and for different local climatic patterns. The mean monthly distribution for summer and autumn precipitation clearly denotes that the analysis of the potential climate-change impacts is important not only for floods, but also in view of the potential increase in summer dryness leading to a water shortage, which is already sometimes a problem in the current climate. A broader description of the Arno River basin is provided in Burlando and Rosso (2002).
Precipitation data are available for two different temporal resolutions over a large number of stations. A 20 min rainfall data set covering a period of 25 years (1962–86) is available for 14 stations, as reported in Table II. This can be used to investigate the effects of climate change on rainfall patterns, and to test the above-mentioned downscaling methodology.

**GCM and precipitation scenarios**

A number of transient climate GCM simulations available from the Hadley Centre for Climate Prediction and Research have been examined; these show increasing reliability in reproducing the climate of the Earth, and increasing complexity of the global-change scenarios (Table III).

In detail, the HADCM2GHG and the HADCM2SUL runs (which stand for Hadley Centre Coupled Ocean–Atmosphere Model 2 Greenhouse Gases simulation and for Hadley Centre Coupled Ocean–Atmosphere Model 2 Sulphate simulation respectively) provide predictions for transient scenarios that account for increasing concentrations of greenhouse gases (all being considered as equivalent CO$_2$ concentrations), and of greenhouse gases plus sulphate aerosols respectively. The latter models probably represent the first attempt to reproduce adequately the climate that has been observed in the last century, and should therefore be able to produce more realistic control and modified scenarios (Mitchell et al., 1995). Although simulations of most of the hydrologic variables are available from these models (e.g. Jones and Conway, 1996), only temperature and precipitation outputs are used to generate downscaled scenarios for analysis of global-change impact at the catchment scale. The two gridboxes covering the area where the Arno basin is located are highlighted in Figure 5.
Two different assumptions have been made concerning the derivation of the key parameter to produce basin-scale scenarios from GCM transient simulations. First, the $K_{nm}$ ratio has been evaluated on a decade basis; a set of $K_{nm}$ values has thus been obtained, each one referring to a specific decade of the transient simulation. This assumption stems from the conjecture that climate may evolve as a sequence of successive stationary states, each covering a time span of 10 years. It is thus speculated that an average time span of 10 years has to pass before a significant change in climate pattern prevails. The corresponding scenario is referred to as 'not smoothed', hence the ‘/ns’ suffix labelling the related scenarios. The $K_{nm}$ values have thus been obtained for each 10 year period from the beginning of the transient run. The year 1990 was selected as the starting year for the forcing run based on the experiment by Mitchell et al. (1995), who followed the use of 1990 as the starting year for forcing in the IPCC-IS92a scenario (Houghton et al., 1992), which also assumes an increase in CO$_{2}$ of about 1% per year.

Alternatively, another set of values of $K_{nm}$ was obtained by computing its values for increasing windows, always starting with the beginning of the transient simulation and augmenting the window by a 10 year interval. Accordingly, assuming the start of the transient simulation to be 1990, the $K_{nm}$ values have been
Table II. Rainfall stations with fine-resolution data in the Arno basin and neighbouring catchments

<table>
<thead>
<tr>
<th>Station</th>
<th>Latitude (°N)</th>
<th>Longitude (°E)</th>
<th>Time resolution (min)</th>
<th>Data record length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arezzo</td>
<td>43° 28’N</td>
<td>11° 53’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Borgo S.L.</td>
<td>43° 57’N</td>
<td>11° 23’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Camaldoli</td>
<td>43° 48’N</td>
<td>11° 49’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Castelfiorentino</td>
<td>43° 36’N</td>
<td>10° 57’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Empoli</td>
<td>43° 43’N</td>
<td>10° 57’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Firenze Ximeniano</td>
<td>43° 47’N</td>
<td>11° 15’E</td>
<td>5</td>
<td>1962–86</td>
</tr>
<tr>
<td>Foiano d. Chiana</td>
<td>43° 15’N</td>
<td>11° 49’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Monsummano</td>
<td>43° 52’N</td>
<td>10° 49’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Larderello</td>
<td>43° 14’N</td>
<td>10° 53’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>La Verna</td>
<td>43° 43’N</td>
<td>11° 56’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Livorno</td>
<td>43° 33’N</td>
<td>10° 18’E</td>
<td>5</td>
<td>1962–86</td>
</tr>
<tr>
<td>Pisa</td>
<td>43° 42’N</td>
<td>10° 24’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Siena</td>
<td>43° 19’N</td>
<td>11° 20’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
<tr>
<td>Vallombrosa</td>
<td>43° 44’N</td>
<td>11° 33’E</td>
<td>20</td>
<td>1962–86</td>
</tr>
</tbody>
</table>

Table III. Summary of the outputs of HADCM2 GCM

<table>
<thead>
<tr>
<th>Scenario</th>
<th>GCM experiment</th>
<th>Run Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>HADCM2CON</td>
<td>HadCM2CON</td>
<td>control integration</td>
</tr>
<tr>
<td>HADCM2GHG/ns</td>
<td>HadCM2GHG</td>
<td>greenhouse gas forcing</td>
</tr>
<tr>
<td>HADCM2SUL/ns</td>
<td>HadCM2SUL</td>
<td>greenhouse gas and sulphate aerosols forcing</td>
</tr>
</tbody>
</table>

Figure 5. HADCM2 model gridboxes covering the Arno basin area
obtained for the periods 1990–99, 1990–2009, and so on up to the last 10 year increase, yielding an averaging period from 1990 to 2099. This second criterion provides a smoothing of the fluctuations determined by this forcing (hence, the suffix ‘/s’, standing for ‘smoothed’, that labels the corresponding scenarios). Although this may be questionable, it is conjectured that nature will partially smooth the forcing due to climate change, for instance, by compensating the richer CO₂ atmosphere with the enhancement of vegetation activity and, therefore, increasing the magnitude of CO₂ sinks.

Both formulations accordingly yield a value of \( K_m \) for each month and for each decade starting with 1990–99, and ending with 2090–99, as shown by the plot illustrated in Figure 6a for one decade out of ten computed and in Figure 6b for the traditionally flood-prone month of November. Based on the available GCM outputs and on the two scenario options, ‘/ns’ and ‘/s’, a 110 year simulated scenario of local precipitation has been generated, as summarized by Table IV.

![Figure 6. Sample plots of the anomaly of mean daily rainfall \( K_m \) for both the non-smoothed and smoothed scenarios. Plot (a) reports the monthly variation of the anomaly for the a specific decade (2020–29) of the transient simulations, whereas (b) illustrates the decadal variability for the specific month of November](image)

<table>
<thead>
<tr>
<th>Precipitation Scenario</th>
<th>‘/ns’</th>
<th>‘/ns’</th>
</tr>
</thead>
<tbody>
<tr>
<td>HADCM2GHG and HADCM2SUL</td>
<td>(1990–99; 2000–09; ...)</td>
<td>(1990–99; 1990–09; ...)</td>
</tr>
<tr>
<td>Control</td>
<td>110 years continuous simulation</td>
<td>110 years continuous simulation</td>
</tr>
</tbody>
</table>

Table IV. Summary of local precipitation scenarios

Internal structure of rainfall events

One of the advantages of the NSRP model technique for the downscaling of GCM precipitation outputs stems from the capability of the stochastic model to perform continuous simulations of the temporal rainfall process. This makes an investigation of the internal structure of rainfall events possible, thereby providing an insight into possible structural changes involved in the modification of rainfall patterns. These modifications are described by the changes detected in the component variates under the new scenario, as reflected by modified parameters of the NSRP model.

The results obtained for the transient scenarios benefit from GCM predictions that provide control simulations closer to the actual climate than those of the previous generation of models (e.g. Mitchell et al., 1995). Accordingly, the re-parameterization for both the HADCM2GHG and the HADCM2SUL scenarios, and for both the '/ns' and '/s' schemes, provides a heterogeneous impact on rainfall pattern, rather than a generalized reduction of rainfall amounts and occurrences as usually retrieved from climate models and predicted by most steady-state ($2\times CO_2$) simulations. As expected, rainfall patterns under the HADCM2GHG/s and HADCM2SUL/s scenarios generally display a smoother response to climate change than under the '/ns' scenarios, thereby somehow limiting the quantitative impact of climate change, but not modifying its general trend.

In detail, the mean number of events $\lambda$ displays a decrease in the summer and autumn seasons in all of the transient scenarios, ranging from a few percent in late spring and early autumn to about 25% reduction in July and August (Figure 7a). The number of storm arrivals conversely increases in the winter season (January to March). Only under the HADCM2SUL/s scenario does $\lambda$ exhibit a weak fluctuation around the no-change line. A reduction of the frequency of the events should therefore be expected, similar to what is foreseen according to many predictions referring to stationary $2\times CO_2$ scenarios.

The average rainfall rate $\mu$ of a storm cell and its duration $\delta$ are affected by a dual impact, as shown in Figure 7b and c, illustrating that $\mu$ increases and $\delta$ decreases in spring, summer and autumn, thereby strengthening the hypothesis of an increase in the frequency of short but intense rainfall events throughout most of the year, including those seasons that are already characterized by a proneness to flood events. Winter events should conversely be characterized by a strengthening of the frontal activities with persistent rainfall, as indicated by the increase in the event arrival rate and of the mean cell duration. This behaviour is more detectable when the '/ns' scenarios are examined, and when the effect of the greenhouse gases is considered without accounting for the sulphate aerosols influence. The latter will contribute to local short-term cooling of the atmosphere and, therefore, to a weakening of convective gradients. It is only under the HADCM2SUL/s scenario that the re-parameterization results in a weak and less significant fluctuation in the mean intensity of cells around the no-change line. Less significant variations are finally observed for the mean displacement of cells from the cluster origin $\beta$, which increases in spring, summer and early autumn, and decreases in winter (Figure 7d). These anomalies also exhibit a tendency to consolidate the outlined patterns for summer months throughout all of the 110 years of the simulation under transient scenarios. As shown in Figure 8, this effect is stronger for greenhouse gas forcing, and weaker when sulphate aerosols are also considered. Similarly, the tendency is more visible if the '/ns' scenarios are considered. The dual case has been observed for winter and autumn months.

As a result of the above changes in NSRP parameters, the long-term simulations of the downscaled precipitation process from the transient scenarios examined indicate that, for all of the four scenarios examined, one should expect that both the cluster duration and the number of clusters will reduce for the summer season (see Figure 9). This is a consequence of the expected reduction in the mean duration of a cell and in the mean number of events. An increase in cluster duration is conversely simulated for the winter season, corresponding to the increase in the cell duration already mentioned, which could lead to an increase in high-frequency flood
Figure 7. Monthly variations in the anomaly of the NSRP model parameters for the Arezzo station.

Figure 8. Variations in the anomaly of the NSRP model parameter $\mu$ throughout the scenario decades for the months of July and November.
events. One can further observe that the reduction in the number of clusters is even more extended than is predictable from the variation in the Poisson rate of storm arrivals, thereby delineating a considerable increase in the frequency of dry periods. Similar to the changes computed for the parameters of the NSRP, the long-term simulation also suggests that a weaker impact should be expected under the scenario that accounts for forcing induced by sulphate aerosols.

**Daily, monthly and annual rainfall**

Long-term simulations of the continuous temporal process provide an insight into the quantitative impact of different GCM scenarios on precipitation patterns, as reflected by daily, monthly and annual precipitation. This impact is represented by changes detected in second-order statistics and the distribution of the aggregated rainfall figures. Accordingly, five statistics of daily precipitation have been examined on a monthly basis to summarize this impact, i.e. the average daily rainfall, its standard deviation, the frequency of dry and wet days, and the frequency of wet days exhibiting a rainfall depth higher than 3 mm. Figure 10 shows, for one representative station, the variations in these statistics as obtained by comparing the statistics of the control simulation with those obtained by NSRP simulation under the transient scenarios. The transient scenario values used for such a comparison correspond to the expected anomaly averaged over the 11 decades of the 'ns' simulations. It is to be noted that, under the HADCM2GHG/ns scenario, generalized severe dry conditions are expected due to reductions in the mean daily rainfall ranging from about 10 to 50%, with the only exception being the values for the winter months, which exhibit an increase up to about 25%. This effect is even more critical due to the non-negligible increase in the frequency of dry days.

Increases in the mean daily rainfall and in the number of wet days, as well as in wet days with rainfall higher than 3 mm, are detected for the winter season (December to February), indicating the growth of
Figure 10. Station Arezzo, HADCM2GHG/ns scenario. Monthly variations averaged over the transient scenarios for the basic statistics of daily rainfall: (a) mean, (b) variance, (c) frequency of dry days, (d) frequency of wet days, (e) frequency of days with rainfall depth >3 mm potentially high-flow periods in the winter season. Figure 10 also suggests that the results from the NSRP model parameterized from the transient scenario HADCM2SUL/ns provide a weaker impact than those coming from HADCM2GHG/ns climate simulations. The impact due to greenhouse gases is weakened if the sulphate aerosols are included (HADCM2SUL/ns), and when the smoothed scenarios (HADCM2GHG/s and HADCM2SUL/s) are considered. In the case of sulphate-aerosol simulations, the modification of the mean daily rainfall, as well as of the frequency of wet days, is distinctly reduced, as shown in Figure 10. Further, it is worth noticing that the predicted variation in the frequency of wet days in November practically equals the increase of the frequency of days characterized by rainfall depths higher than 3 mm; this indicates that a higher frequency of high flows could be expected for this specific season, which is already recognized as a potential flood period for this area in the present climate.
Long-term simulation has also been used to indicate the direction of the expected changes in the distributional properties of monthly and annual precipitation. Water-resources-related problems make considerable use of the probability approach to characterize monthly and annual rainfall for planning and design activities. Accounting for modifications induced by potential climate change will be essential for developing the proper design for future strategies in water resources management. Different transient scenarios yield different impacts, depending on sulphate aerosol influence and the smoothing procedure adopted in the analysis, as shown in Figures 11 to 13. In general, the combined forcing of greenhouse gases and sulphate aerosols mitigates the significant reduction predicted for the annual water yield predicted from greenhouse-gas-dominated scenarios (Figure 11) and by other studies that considered stationary $2 \times CO_2$ scenarios (Burlando et al., 1997). Moreover, it has been observed that the patterns dictated by the sulphate aerosols forcing might also induce some change in the distributional properties, determining a non-symmetric shape of the probability distribution, which departs from the frequently observed Gaussian behaviour, as shown in Figure 11c.

Similar considerations apply to the distributional properties of monthly rainfall. In summer months the reduction of the monthly amount of rainfall occurs jointly with an increase in the asymmetry of the probability distribution that fits the data (see Figure 12). This occurrence is more evident in the values simulated under...
Figure 12. Station Arezzo, July: cumulative distribution function of monthly rainfall for different downscaled scenarios

the HADCM2SUL/ns scenario, which display a considerable increase in the monthly amount for higher non-exceedence frequencies (almost double that of the control simulation). Accordingly, a potential increase in flood risk in the summer season could be expected, also keeping in mind that for the same period an increase in the mean intensity of a cell and a decrease in its duration (see Figure 7) again indicate a shift in the patterns of events towards short and intense convective rainfalls.

A similar, although weaker, increase in the asymmetry of the distribution is also found to hold for November, thus indicating an increase in process variability (see Figure 13). The rainfall amounts under transient scenarios are generally lower than their corresponding control counterparts. Nevertheless, both the lower and upper tails of the distribution display values that are closer to the control values, and are sometimes even higher. This indicates that higher low-flow averages should occur, but also higher values of rare events might be expected, thereby yet again highlighting the possibility of an increase in flood volumes.

**Extreme values of storm rainfall**

The above considerations of the potential increase of flood hazards can be supplemented by the analysis of potential changes in the extreme values of storm rainfall. In this respect, the annual maxima for different
storm durations, ranging from 20 min to 24 h, can be extracted from the simulation runs and then analysed in the depth–duration–frequency (DDF) domain using the scaling/multiscaling approach introduced by Burlando and Rosso (1996). This provides a deeper insight into properties that are directly related to the internal structure of the event, since they represent a description of the variability in the process throughout the continuum of temporal and spatial scales. Accordingly, changes in both distributional and scaling properties have been investigated.

The changes detected mainly concern the scaling properties of rainfall extremes and a general increase in the occurrence of extremes, although the results depend strongly on the climate scenario. As is to be expected, the extremes simulated under the ‘smoothed’ scenarios, HADCM2GHG/s and HADCM2SUL/s, generally display weaker modifications of both scaling and distributional properties, because the levelling of the $K_m$ values by averaging over an increased number of years is reflected by the NSRP model re-parametrization. Accordingly, the order of magnitude of the changes (not reported herein) can be considered statistically non-significant, sometimes leading to an increase or a decrease of the hazard level, and are thus comparable to variability due to natural fluctuations in a stationary climate. Changes are conversely more evident when simulations under
Figure 14. Probability plots for control and climate-change scenarios. Examples of unmodified/modified distributional properties

the ‘not smoothed’ scenarios are considered. Also, changes in the DDF are more meaningful for these two scenarios, as further explained below.

With regard to distributional properties, the plots in Figure 14 show that, in some cases, these are practically unchanged with respect to the control simulation, often resulting only in a shift of the cumulative distribution function (CDF). In other cases, the simulated values display a slightly different CDF, although it can be argued that a clear change in the underlying probability distribution can hardly be demonstrated using traditional statistical goodness-of-fit tests. It is also noted that such changes are more pronounced for durations above 6 h. These results are reflected by changes in scaling patterns, if it is kept in mind that scale-invariance and multiscaling properties have implications with respect to the characterization of the distributional properties at different scales of analysis. In this respect, Figure 15 shows the plots of the scaling exponent as a function of the order of the moment for a station that exhibits a change in the distributional properties. Following the theoretical framework presented by Burlando and Rosso (1996), the plot in Figure 15 describes the wide-sense scaling property, 

\[
E[H^j_T] = \lambda^j E[H^j_T],
\]

where, as introduced by Gupta and Waymire (1990), \(H_T\) is the annual maximum rainfall for the duration \(T\), \(\lambda\) and \(n\) are respectively the scaling factor and the exponent, and \(j\) is the order of the moment.

Such modifications in scaling properties imply that the scale-invariant scheme of DDF holding under the present climate can lead to over/underestimation in a changed climate. As shown in Figure 15, a multiscale model provides the correct estimation of the quartiles simulated in a modified climate, whereas the use of a scale-invariant can lead to significant errors. These errors could produce overestimation of rainfall amounts.
for long durations, and underestimation for short durations. It is quite clear that this could have potential consequences in some specific areas of civil and environmental engineering design activities, such as, for instance, the design of an urban drainage system.

However, it is noted that only two out of the four simulation runs have generated rainfall extremes leading to increased storm hazard, i.e. those corresponding to the HADCM2GHG/ns and HADCM2SUL/ns scenarios. The forcing of greenhouse gases generally provides higher values of the extremes only for stations that are located in areas close to the mountainous limit of the basin. In this respect, it appears that stations located in regions influenced by orographic effects, and therefore subject to higher natural variability, experience larger changes than stations located in the floodplain. An example is illustrated in Figure 16, which shows the changes for the stations of Firenze Ximeniano (~50 m a.s.l.) and Camaldoli (~1100 m a.s.l.). In this example, clear evidence of the modification of extreme properties is also indicated by the best fitting provided by the multiscaling model for extremes under climate change with respect to control simulation. This effect is remarkable, especially for high return periods, thereby indicating that some additional attention should be paid to the estimation of design values for critical rainfall events, which could display rather larger fluctuations than in the control climate. It is noticeable how this result can be connected to, and is consistent with, the high increase in the mean intensity of cells of NSRP found to characterize the summer months (characterized by highly convective events) under both the HADCM2GHG/ns and HADCM2SUL/ns scenarios. Furthermore, the additional forcing of sulphate aerosols, embedded in the values simulated under the HADCM2SUL/ns scenario, indicates an increased risk of extreme rainfall. The enhancement is extended to most of the stations.

Figure 15. Scaling properties for control and climate-change scenarios. Examples of change from scale-invariant (SI) to multiscaling (MS) pattern
Figure 16. The 100 years return period DDF curves for control and HADCM2GHG/ns scenarios

examined, with some exceptions for the stations located in or close to the southern area of the basin. It is worth noting in Figure 16 that a given storm rainfall depth can occur in the enhanced CO₂ scenario over a duration that is, on average, in most of the examined cases, 30% shorter than the corresponding one in the control scenario. The plots in Figure 17 finally show that the increase is observed for a large range of return periods, also indicating that in some cases the greenhouse-gas-only forcing does not lead to an increase, but rather to a decrease in storm hazard.

CONCLUSIONS

The analysis of possible impacts of global change on precipitation patterns at the basin scale requires that appropriate downscaling procedures are applied to derive hydrologically useful information from GCM outputs. Climate models provide trend variates that can be downscaled according to some criterion before they are used to infer changes that will affect hydrological variables at the catchment scale. The stochastic analysis adopted in this study allows investigation not only of the average changes in the rainfall process, but also of its variability, as well as of the internal structure of events and extreme processes. Moreover, this technique can comfortably accommodate the downscaling of transient scenarios and provide long-term simulation for sensitivity and frequency analysis, as required by engineering needs.

The systematic application to the specific case of the Arno River basin, dealing with several trend scenarios based on different GCM outputs, shed some new light on the most meaningful changes to be expected at the basin scale as result of global change. Specifically, the expected modifications to the internal structure of storm events are characterized by future changes in storm duration, depth and clustering of rain cells, as inferred by simulations obtained by running the stochastic rainfall model re-parameterized on the basis of GCM trend variables. These trend variables influence the extent of changes in the occurrence of wet and dry
Figure 17. The 10 and 100 years return period DDF curves for control and HADCM2SUL/ns scenarios

periods, in the daily rates and in the monthly and annual totals, including modifications in the distributional properties of monthly and annual precipitation totals.

The changes detected mainly affect the tails of the distributions, thus suggesting that modifications can occur in both low and high values of rainfall at the monthly and annual scales, with a shift in storm patterns towards shorter and more intense convective rainfall, especially in the summer season. Significant anomalies from the present (stationary) climate have been detected for all of the stations examined, but some extra enhancements have been noted for stations that show pronounced variability due to orographic effects. Stochastic simulation also shows that the distributional and scaling properties of rainfall extremes may change progressively, thereby indicating that some revision of current practices for estimating extreme storms is needed to account for possible effects of non-stationary climate conditions.

Furthermore, the uncertainties due to the choice of different GCM scenarios have also been investigated. The results have shown that the downscaling procedure does not simply propagate the overall pattern of the GCM, but can enhance, in some cases, and smooth, in some others, some peculiar characteristics of a GCM. Accordingly, the GCM predictions that account for sulphate aerosols drive a downscaled scenario that, at the catchment scale, exhibits higher variability and more significant effects on the tail of the distributions than is expected when based on the comparison of the large-scale patterns with the prediction obtained by simulations accounting for greenhouse gases only. This outcome, although based on the use of one GCM model only, underlines the importance of approaching basin impact studies by means of downscaled scenarios when a quantitative impact evaluation comparable to traditional hydrological analyses is required.
Finally, the above approach provides local precipitation scenarios that are also useful for extensive simulation of basin water fluxes in the Arno River, as further reported in a companion paper (Burlando and Rosso, 2002).

ACKNOWLEDGEMENTS

This research work has been supported by the European Union through the POPSICLE project under the IV Framework Programme (contract no. EV5V-CT94-0510). The Hadley Research Centre for Climate Prediction and Research is gratefully acknowledged for allowing the use of the outputs from HADCM2 models. Grateful thanks are due to Alberto Montanari (DISTART, University of Bologna) for his help in data processing.

REFERENCES


Copyright © 2002 John Wiley & Sons, Ltd.


Machenhauer B, Windelband M, Botzet M, Jones RG, Déqué M. 1996. Validation of present-day regional climate simulations over Europe: nested LAM and variable resolution global model simulations with observed mixed layer ocean boundary conditions. Report No. 191, Max Planck Institute for Meteorology, Hamburg, Germany.


