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Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies

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Abstract:

Two downscaling methods designed for the study of the hydrological impact of climate change on the Seine basin in France are tested for present climate. First, a multivariate statistical downscaling (SD) methodology based on weather typing and conditional resampling is described. Then, a bias correction technique for dynamical downscaling based on quantile–quantile mapping is introduced. To evaluate the end-to-end SD methodology, the atmospheric forcing derived from the large-scale circulation (LSC) of the ERA40 reanalysis by SD is used to force a hydrological model. Simulated discharges reproduce historical values reasonably well. Next, the dynamical and statistical approaches are compared using the Météo–France ARPEGE general circulation model in a variable resolution configuration (resolution around 60 km over France). The ARPEGE simulation is downscaled using the two methodologies, and hydrological simulations are performed. Regarding downscaled temperature and precipitation, the statistical approach is more efficient in reproducing the temporal and spatial autocorrelation properties. The simulated river discharges from the two approaches are nevertheless very similar: the two methods reproduce well the seasonal cycle and the daily distribution of streamflows. Finally, the results of the study are discussed from a practical impact study perspective. Copyright © 2007 Royal Meteorological Society

KEY WORDS statistical downscaling; dynamical downscaling; hydrological impacts; climate change; regional climate; bias correction

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INTRODUCTION

Climate change may have important impacts on the hydrological cycle at the regional scale (Etchevers *et al.*, 2002; Arnell, 2003), raising important issues concerning water management, linked for example, to flood risk, irrigation, water storage or hydroelectricity. In order to quantify and anticipate the consequences of anthropogenic climate change on river discharge or groundwater recharge, reliable regional climate scenarios are needed as input data for hydrological modelling. Whereas coupled atmospheric-oceanic general circulation models (AOGCM) are suitable to provide global climate scenarios, their coarse spatial resolution is irrelevant for most of the impact studies (Zorita and von Storch, 1999).

A typical resolution for an AOGCM is 250 km, whereas hydrological models often need input meteorological variables at a resolution lower than 10 km. Downscaling is then a necessary step to derive the high-resolution information needed by the impact model from the coarse scale resolution of the AOGCM.

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During the past few decades, many downscaling methodologies have been described and tested. They can be classified into two main families (Mearns *et al.*, 1999). The first approach, dynamical downscaling (DD), is a model-based methodology intended to lead to sub-AOGCM grid scale features by an increase of the spatial resolution of a physical model. In the regional climate model (RCM) approach, a finer-scale model is nested within an atmospheric general circulation model (AGCM) (Giorgi *et al.*, 1990). Another possibility exists in using a global AGCM with a variable resolution grid to obtain a high resolution on a domain of particular interest (Gibelin and Déqué, 2003).

The second approach, statistical downscaling (SD), is based on the view that the regional climate is conditioned by two factors: the large-scale circulation (LSC) which is well resolved by the models, and small-scale features like land-use, topography, land-sea contrast that are not adequately described in the models (von Storch, 1995, 1999). Following this approach, an empirical relationship linking large-scale information (or predictor(s)) and local variables (or predictands) is first established for current climate and then applied to derive the regional climate scenario from the LSC simulated by a low-resolution model.

To date many of the published studies on downscaling have been mainly theoretical and not related to specific applications like hydrology. They have been mainly focussed on variables like precipitation and/or temperature at particular points. As many impact models need to be forced by several spatially distributed variables, a practical end-to-end impact study has often to cope with additional difficulties. The realism of river discharges obtained from hydrological modelling with downscaled meteorological forcing is much less frequently examined (Wilby *et al*., 2000; Hay and Clark, 2003; Salathé, 2003; Wood *et al*., 2004; Diaz–Nieto and Wilby, 2005). Nevertheless, ultimately, the validity of a downscaling technique dedicated to the study of the hydrological impacts of climate change should be examined principally on secondary variables like river discharges or evolution of water table levels. Hydrological simulations provide an integrated view of the performance of the downscaling methodology, and can reveal unexpected problems regarding, for example, the coherency between variables and/or their spatial autocorrelation.

In this paper, two downscaling approaches designed to study the impact of climate change on the hydrological cycle of the Seine basin in France are compared for present climate. The first approach is based on a multivariate SD methodology described in Boé *et al*. (2006). The second approach is based on DD with a bias correction technique based on quantile–quantile mapping. The study area, data and models used in the study are introduced in Section on Study Area,Data and Model.The two downscaling methods are described in Section on Downscaling Methods.The SD methodology is then evaluated by performing a hydrological simulation driven by atmospheric forcing derived from the SD of the ERA40 reanalysis. Simulated river discharges are then compared to observations (Section on Statistical Downscaling of ERA40 Reanalysis). In Section on Comparison of Statistical and Dynamical Downscaling Approaches, a variable resolution AGCM is statistically and dynamically downscaled to force a hydro-meteorological model. The two downscaling methods are compared to observations. Finally, the main conclusions of the study are given in Section on Conclusion and Discussion and different practical issues arising in the context of climate change impact studies are discussed.

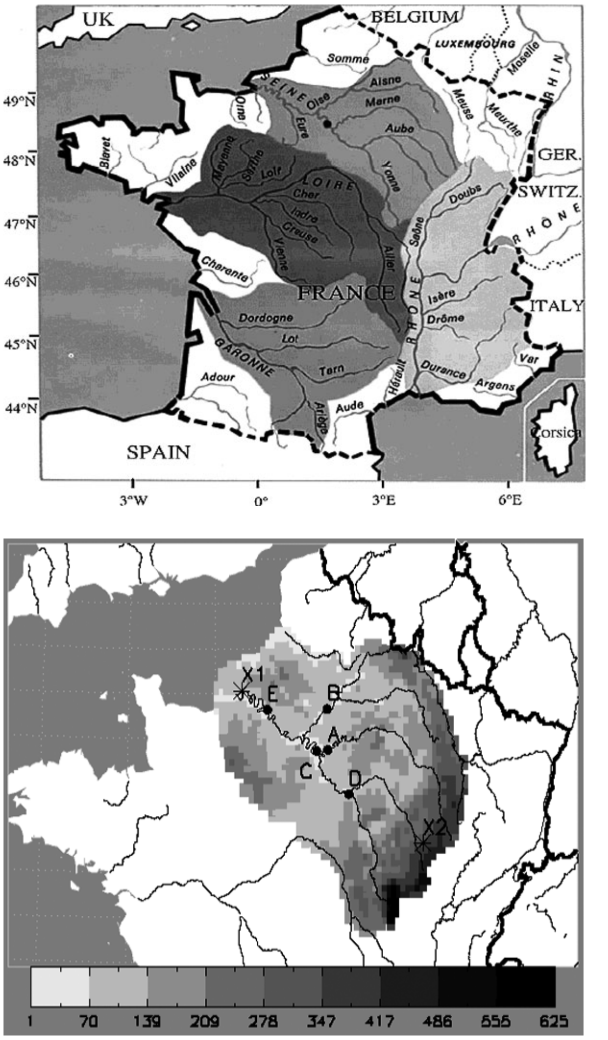

Figure 1. Location of the Seine basin in France (top) and details (bottom). The shading stands for the altitudes (meter). The location of the five main gauging stations used in the following is indicated by a letter (A: Marne at Noisiel, B: Oise at Pont-Sainte-Maxence, C: Seine at Paris, D: Yonne at Courlon-sur-Yonne, E Seine at Poses). X1 and X2 are two grid points used in Section on Comparison of Statistical and Dynamical Downscaling.

STUDY AREA, DATA AND MODEL

Study area: the Seine basin

The Seine is a major river of northwestern France that flows into the English Channel (Atlantic Ocean) (Figure 1, top). Its basin covers around 12% of the French territory (78 600 km^2). The length of the Seine is 776 km. Its main tributaries are the Oise, the Marne, the Yonne, the Eure and the Aube rivers. The altitude is lower than 300 m over most of the domain, except in the southeast of the basin where it reaches 900 m (Figure 1, bottom). The influence of snowmelt on river discharges is thus limited. The seasonal flow pattern exhibits a peak in winter and a minimum at the end of summer. The seasonal cycle of precipitation over the Seine basin is weak and the main driver of the streamflow seasonality is evapotranspiration.

Hydro-meteorological system

The SAFRAN-ISBA-MODCOU hydro-meteorological coupled system used in this study is composed of three different parts (Habets *et al*., 1999a,b). SAFRAN (Durand *et al*., 1993) analyses the seven atmospheric variables at the hourly time step needed by the soil-vegetation-atmosphere transfer (SVAT) scheme ISBA. These variables are liquid and solid precipitation, incoming long-wave and short-wave radiation fluxes, 10 m wind speed, 2 m specific humidity and temperature. The analysis takes into account all the available observations collected by Météo–France, as well as the operational analyses of the weather prediction model of

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Météo–France, and some climatological data. Over the Seine basin, about 1000 rain gauges and 200 synoptic stations are available. The SAFRAN analyses are performed in homogeneous climatic zones and then interpolated onto a regular 8-km grid given the altitude of the grid points (a vertical gradient of the variables is assumed). Here, SAFRAN analysis results available from August 1981 to July 2005 are used as observations to develop the downscaling schemes.

The SVAT scheme ISBA (Noilhan and Planton, 1989) computes the surface water and energy budgets on the 8-km grid. The fluxes are averaged over the cell according to the fraction of each land cover. In this study, the force-restore version of ISBA is used, with three soil layers (Boone *et al.*, 1998). MODCOU (Ledoux *et al.*, 1984; Gomez, 2002) is the last component of the modelling system. It uses the information provided by ISBA to simulate river flow and the evolution of the aquifers. MODCOU routes the surface runoff to the hydrographic network, while the gravitational drainage computed by ISBA is transferred to the aquifers. The ability of the SAFRAN-ISBA-MODCOU system to simulate the hydrological functioning of the Seine basin has already been demonstrated by Rousset *et al.* (2004).

Atmospheric general circulation model

In this study, the Météo–France Action de Recherche Petite Echelle Grande Echelle (ARPEGE) global AGCM (Déqué *et al.*, 1994) is used in a variable resolution configuration (Gibelin and Déqué, 2003). This model has a T106 spectral truncation, uses semi-Lagrangian advection, and a two-time-level discretization. Vertical discretization uses hybrid coordinates with 31 vertical levels. The variable resolution allows the spectral and grid-point resolution over a region of interest to be increased. The centre of the high-resolution region is located in the Mediterranean Sea, allowing for a resolution on the European sector of about 60 km. A current climate simulation for the 1950–1999 period has been performed. The model is forced by monthly mean observed sea surface temperature (Smith and Reynolds, 2004), historical greenhouse gas (GHG) and sulfate aerosol concentrations.

DOWNSCALING METHODS

Statistical downscaling scheme

The statistical downscaling model (SDM) used in this study is described in detail in Boé *et al.* (2006). This SDM is suitable for the downscaling of several spatially distributed variables at the daily time step. It is mainly based on weather typing. Originally, the SDM used two variables as predictors: the 500 hPa geopotential height (Z500) and the air surface temperature. For this study, a vorticity index is used as an additional predictor as it can be a useful variable to catch within-type dynamical variability (Jacobeit *et al.*, 2003). This index is simply defined as the values at the grid point which exhibits the highest correlation with averaged precipitation over the Seine basin.

The downscaling algorithm starts from regional climate properties in order to establish discriminative daily weather types on Z500 for the chosen local variable, precipitation in this case. As shown, for example, in Boé *et al.* (2006), it is also necessary to take into account the within-type variability of precipitation. To do this, a second step, based on multivariate regression is used. In this regression, the predictand is daily precipitation spatially averaged over the Seine basin, and the predictors are the vorticity index and the distances between the Z500 pattern on a given day and the weather types. The regression equation allows us to compute a daily precipitation index over the Seine basin that only depends on the LSC. This index is well correlated with the observed precipitation (correlation between 0.7 and 0.8 depending on the season).

The temperature as predictor is used in the final step of the SDM. This step involves the conditional resampling of the days of the learning period, given three conditions: the decile of the reconstructed precipitation index described above, the decile of the averaged temperature over the domain and the weather type.

Each day, the 24-hourly values of the seven spatially-distributed variables needed by ISBA-MODCOU are taken altogether, ensuring a good reproduction of the inter-variables' coherency. The learning period for the SDM is 1985–2002. The validation of the downscaling scheme in Boé *et al.* (2006) is focused on precipitation and temperature. As the final objective is to study the impact of climate change on the hydrological cycle of the Seine basin, hydrological simulations forced by downscaled forcing are performed to compare simulated and observed discharges. It is an integrated way to ensure that the input variables and their coherency are sufficiently well reproduced to simulate flow properties reasonably. Nevertheless, as some biases in downscaled variables might have a weak impact on flow properties, all the forcing variables will also be briefly examined.

The major drawback of the SDM is that the greatest observed value can never be exceeded in the regional climate scenario. It could be problematic for extreme high temperature but less for precipitation or mean temperature. Indeed, in the SRES-A2 climate scenario used in Boé *et al.* (2006) that shows a strong increase of mean precipitation in winter, the greatest value of precipitation in the control simulation is very rarely exceeded, even at the end of the 21st century. Moreover, as the greatest accumulated amount of precipitation over N days can be exceeded, the greatest observed discharge can also be exceeded in the scenario. The limitation of the resampling strategy for extreme discharges thus depends on the size of the gauged area and its concentration time. In our case, the objective is not to study flash floods on small watersheds for which it would be very important to be able to consider changes in extreme daily and sub-daily precipitation.

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Quantile–quantile bias correction for dynamical downscaling

Even if DD improves the realism of simulated regional climate properties, some important biases may still exist, especially concerning precipitation. To simulate realistically the regional hydrology after DD, raw RCM model results have thus to be corrected (Wood *et al*., 2004). Different bias correction techniques may be used. The simplest methods consist of adding the climatological difference between a climate scenario and a control simulation to an observed baseline (the 'delta' method) or to unbias the regional climate scenario given the climatological differences between the observations and a control simulation (the unbiasing method) (Déqué, 2007). These methods are straightforward, but implicitly assume that the variability in the climate scenario is unchanged (delta method) or that the RCM variability is perfect (unbiasing method). A quantile–quantile mapping transformation (the empirical transformation of Panofsky and Brier, 1968) may be used to overcome these limitations. For a given variable, the cumulative density function (cdf) of a control simulation is first matched with the cdf of the observations, generating a correction function depending on the quantile. Then, this correction function is used to unbias the variable from the climate scenario quantile by quantile. A simple principle scheme of the bias correction technique is shown in Figure 2.

This method has already been applied, for example, by Reichle and Koster (2004) and Déqué (2007). In the downscaling context, Wood *et al*. (2004) use this technique to correct simulated variables at the monthly time-step to force a hydrological model. Here, the quantile–quantile correction is applied at the daily level. From a practical point of view, a correction table with the 99 percentiles of the two distributions (control simulation and observation) is built. A linear interpolation is applied between two percentiles.

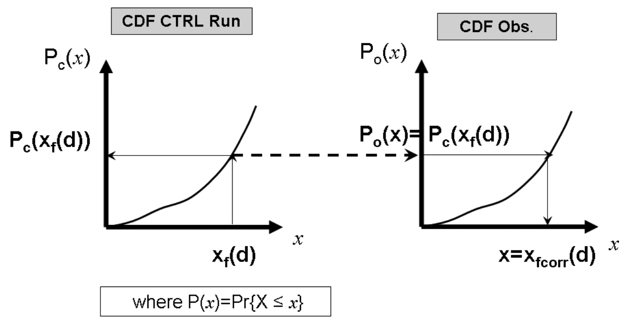

Figure 2. Principle scheme of bias correction using quantile–quantile mapping technique. cdf is empirical Cumulative Distribution Function. The subscript f, c, o stand for the climate scenario, the control simulation and the observations respectively. For the value xf(d) of the variable x for the day d in the climate scenario, the corresponding seasonal cumulative frequency Pc(xf(d)) where $P(x) = Pr\{X \leq x\}$ is searched on the empirical cdf of the present climate control simulation. Then, the value of x such as Po (x) = Pc(xf(d)) is searched on the cdf of the observations. This value, named *xfcorr(d)*, is finally used as the corrected value of xf(d) in the climate scenario.

A difficulty arises for the variables bounded by zero, such as precipitation. As the model tends to drizzle, the probability of precipitation in the model is greater than that observed. When model precipitation is zero, an observed value is randomly chosen in the interval where the observed cumulative frequency is less than or equal to the probability of no precipitation in the model. This procedure ensures that the probability of precipitation after correction is equal to that observed. Nevertheless, biases in precipitation inter-arrival time and duration statistics may still exist after bias correction. This point will be tested in the following pages (Section on Comparison of Statistical and Dynamical Downscaling Approaches, Table II).

Some values in the climate scenario may exceed the greatest value found in the control simulation. In this case, a simple extrapolation is used: outside the range of the correction function, a constant correction is applied. For example, if the last quantile of temperature in the present climate simulation is corrected by +1.5 K, all the superior values in the climate scenario will be corrected by +1.5 K. This choice may have implications in the context of climate change, in particular, regarding extreme discharges. In principle, it would be possible to fit the tails of the modelled and observed distribution with a theoretical statistical distribution in order to extrapolate better the correction function. In our case, the length of observations is too limited to use this approach. The implication of this choice should, nevertheless, be considered when dealing with climate scenarios.

For practical purposes, the daily variables from the variable resolution model are first interpolated on the SAFRAN grid (8×8 km) and then corrected at each point using SAFRAN values as reference. As the bias in the model distribution depends on the season, the correction is applied independently for each season (winter: December–February, spring: March–May, summer: June–August, autumn: September–November). Using an independent correction function for each month would also be possible, but it would result in fewer values to provide a robust estimate of the correction function. As an hourly time-step is needed to force the surface scheme ISBA, a simple hourly interpolation is applied, based on monthly climatological hourly fraction derived from the SAFRAN dataset. It would be, in theory, possible to work with sub-daily RCM outputs. Nevertheless, the ability of the RCMs to simulate accurately the diurnal variations of the climate variables is questionable, in particular, when convection occurs (Dai *et al*., 1999). Moreover, the hourly values of SAFRAN variables also result from a temporal interpolation. Finally, all the methodology – DD with bias correction, hydro-meteorological model – is better adapted to the study of large gauged areas, where the impact of diurnal variations of the climate variables on flows is arguably less important.

The quantile–quantile bias correction methodology has three main limitations. The temporal autocorrelation properties of the series are not corrected. For example too short wet spells or precipitation inter-arrival time in the

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regional model may still exist after the correction. Secondly, each variable is corrected independently, whereas bias in precipitation might not be independent of bias in temperature for example. This may be an important issue in the context of climate change. Finally, the spatial autocorrelation of the different variables is given by the regional model, and thus, may be biased.

Summary of downscaling experiments

The main downscaling experiments performed in this study are summarized in Figure 3. CTRL is a control simulation in which the hydro-meteorological system is directly forced by the SAFRAN analysis, designed to evaluate the performance of the hydro-meteorological system. ERA40 is a hydrological simulation forced by the SD of the ERA40 reanalysis: the time evolution of the simulated discharges may be compared to observations. The hydrological simulations forced by the SD and the DD with bias correction of the ARPEGE simulation enable the comparison of the two approaches.

STATISTICAL DOWNSCALING OF ERA40 REANALYSIS

In order to evaluate the SDM, the ERA40 reanalysis is statistically downscaled to force the ISBA-MODCOU hydro-meteorological system (hereafter, this hydrological simulation is simply named *ERA40*). First, the downscaled variables necessary to force ISBA-MODCOU are compared to the observations (Table I). At the daily level, the smallest area-averaged correlations are obtained for precipitation and wind. For precipitation, the value is, nevertheless, comparable to other SD studies (for example Wilby *et al*., 2004 or Timbal *et al*., 2003). Among the different variables, the best daily correlations are obtained for temperature and humidity. It is not surprising as a temperature index is used as predictor in the SDM. At the monthly scale, good correlations (greater than 0.70) are obtained for all the variables. The values of the mean bias and the ratio of variance between observed and downscaled variables indicate that the SDM reasonably reproduces the first two moments of all the variables. Even if the SDM has been developed focusing on precipitation and temperature, all the variables are correctly reproduced. In particular, incoming solar and long-wave radiation fluxes, rarely examined in downscaling studies, are well captured.

Table I. Area-averaged daily and monthly correlation, mean bias, and ratio of variance between observations and downscaled ERA40 for the different forcing variables (PR: total precipitation, TA: 2 m temperature, QA: 2 m specific humidity, UA: 10 m wind speed, ILR: incoming long-wave radiation at surface, ISR: incoming short-wave radiation at surface).

	Daily correlation	Monthly correlation	Mean bias	Variance ratio
PR	0.41	0.72	1.7 (%)	1.03
TA	0.95	0.99	0.02 (°C)	0.99
QA	0.87	0.97	−0.10 (%)	0.99
UA	0.41	0.74	0.43 (%)	1.01
ILR	0.62	0.95	−0.011 (W/m^2)	0.98
ISR	0.71	0.91	0.19 (W/m^2)	1.01

Downscaled variables are then used to force the ISBA-MODCOU system. The hydrological simulation starts on 1 August 1958 and ends on 31 July 2002. Figure 4 shows daily observed and simulated river discharges from the CTRL and ERA40 experiments. Four gauging stations are considered on the 1982–1991 sub-period: the Yonne

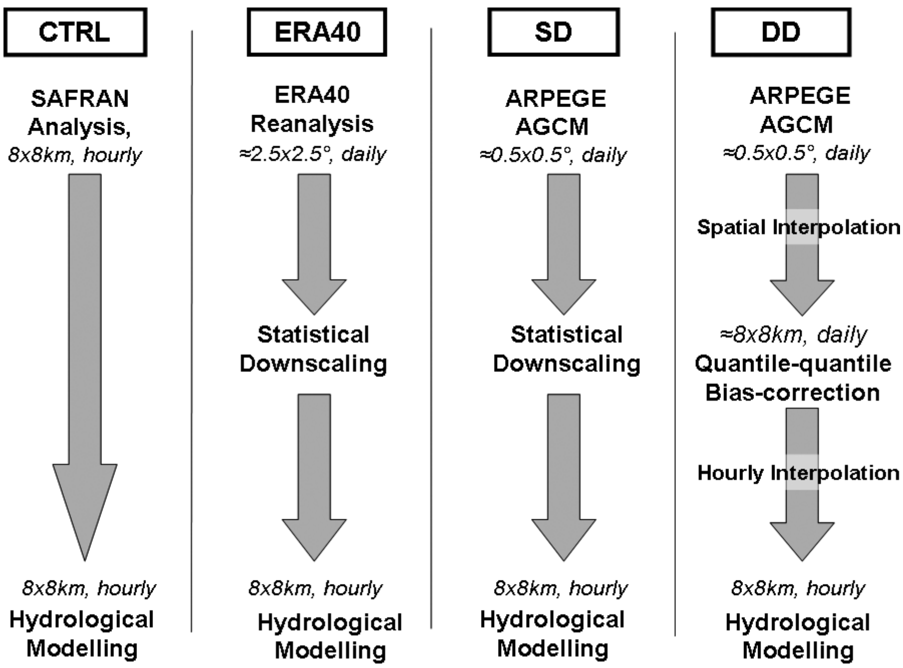

Figure 3. Summary of the different downscaling experiments. The spatial resolution and the time step are given at each step.

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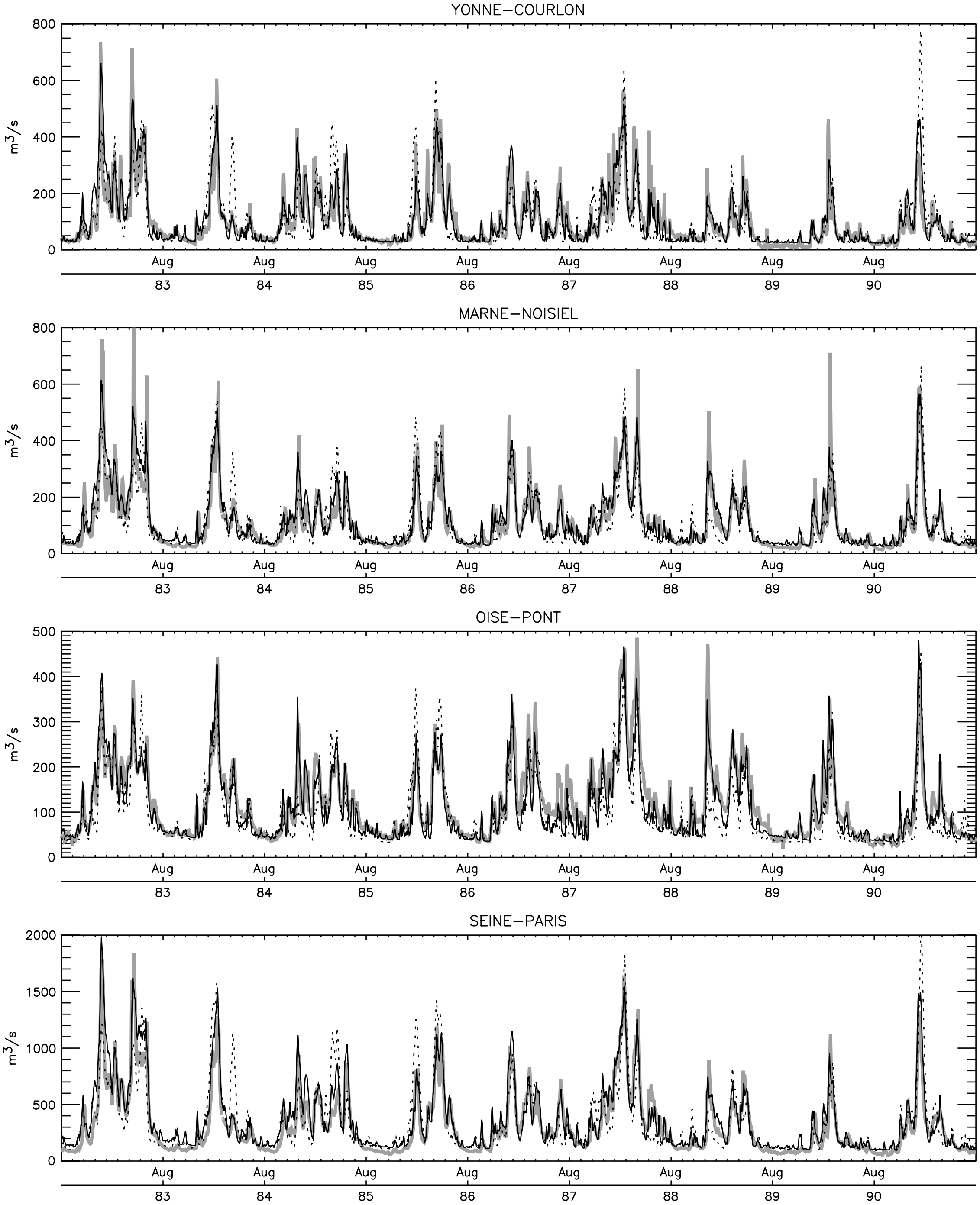

Figure 4. Daily discharges for selected stations on the Seine Basin for the 1982–1991 period as simulated with SAFRAN analysis (CTRL, thin black line), downscaled ERA40 forcing (ERA40, black dotted line) and as observed (grey).

at Courlon-sur-Yonne (gauged area of 10 669 km^2) the Marne at Noisiel (12 443 km^2), the Oise at Pont-Sainte-Maxence (13 632 km^2), the Seine at Paris (43 509 km^2).

Some systematic discrepancies between observed and simulated discharges are observed. For example, the low flows for the Seine at Paris are slightly overestimated in the two simulations, indicating that it is an intrinsic bias of the hydrological modelling system. Some high flows are present in the ERA40 simulation but not in the observations and CTRL simulation and vice versa. For example, in the winter of 1984, for the Yonne and the Marne a peak discharge is greatly overestimated in the ERA40 simulation. As expected, the CTRL simulation performs better than the ERA40 hydrological simulations. Nevertheless, the time variations of the ERA40 simulated discharges are overall in reasonable agreement with the observations for the four stations (daily correlations around 0.80), considering that only the LSC and temperature are used as predictors in the SDM.

A more synthetic view of the performance of the SDM is displayed on Figure 5. The correlation, the Nash efficiency and the mean ratio between simulated and

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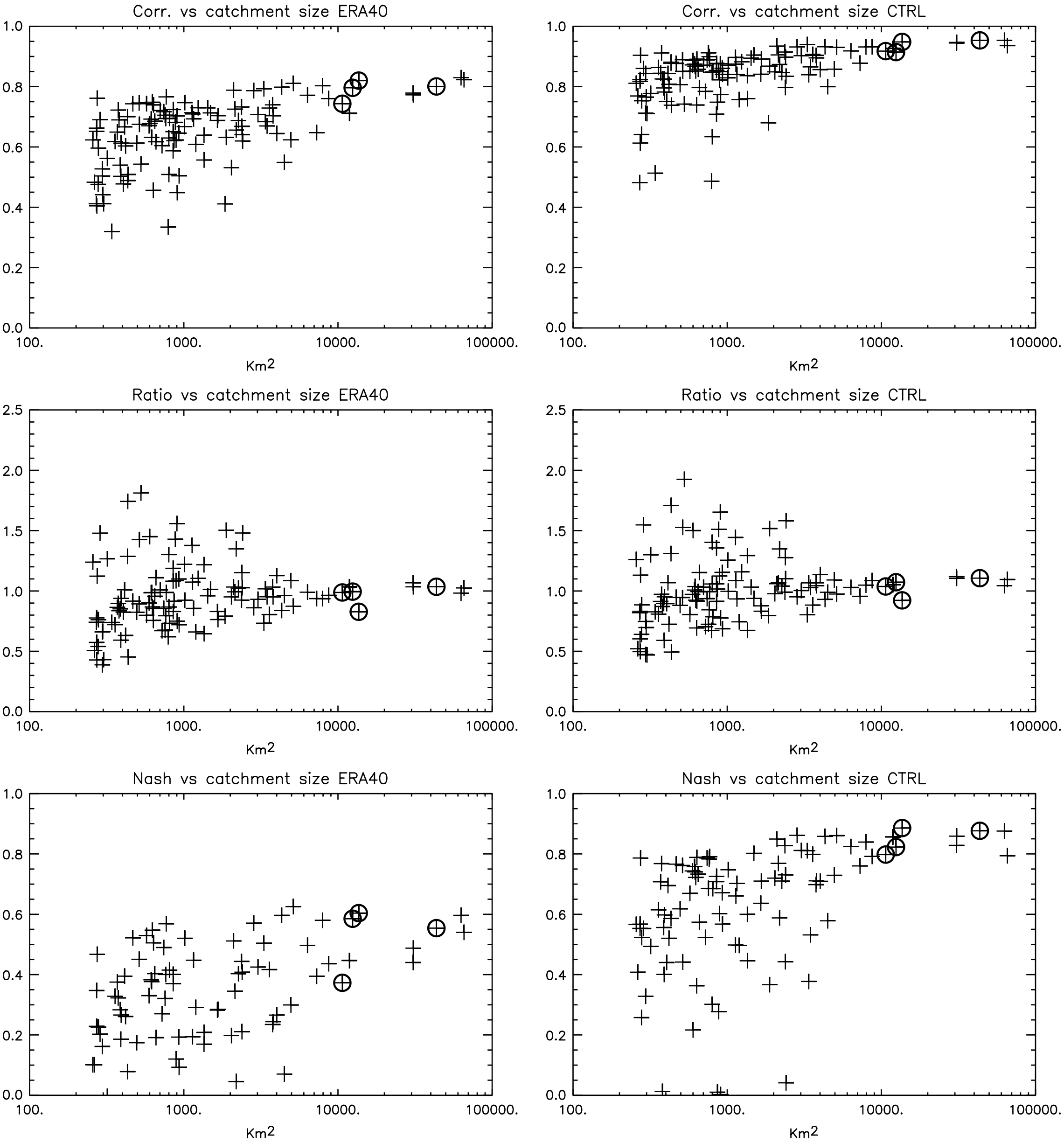

Figure 5. Diagnostics for rivers discharges on the 1981–2002 period. The daily correlation (Corr., top), the mean ratio (Ratio, middle) and the daily Nash efficiency (Nash, bottom) between observed and simulated discharges as a function of the catchment size are shown for the ERA40 (left) and CTRL (right) hydrological simulations. The circles highlight the stations previously shown on Figure 4 (From left to right: Yonne at Courlon, Marne at Noisiel, Oise at Pont Ste Maxence, Seine at Paris).

observed daily discharges as a function of the gauged area are computed. To illustrate the biases that directly results from the hydrological model, the results from the CTRL are also shown. The period considered (1981–2002) is the same in the two cases. The results obtained from the CTRL simulation demonstrate the ability of the SAFRAN-ISBA-MODCOU hydrological system to simulate realistically stream flow over the Seine basin where the gauged area is not too small.

Indeed, a strong relationship relating the quality of the simulated discharges to the catchment size is observed, both for the CTRL and the ERA40 hydrological simulations. Good scores are obtained in the ERA40 hydrological simulation where the hydrological model forced by SAFRAN performs well and vice versa. The lowest quality of simulated discharges for small-gauged areas is thus an intrinsic characteristic of the hydrological modelling framework and not a result of the SD. Rousset *et al.* (2004) discuss the probable causes of the weak quality of simulated discharges for small-gauged areas: errors in the spatial and temporal representation of the atmospheric forcing as well as in the description of the land cover, approximation of the resolved physics and local effect of the water management.

The results for ERA40 reanalysis and CTRL are similar concerning the ratio of simulated over observed mean annual discharges: no biases are introduced by the downscaled forcing. The two other scores are weaker for ERA40. It is particularly true for the Nash efficiency. The occasional overestimation or underestimation of peak

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discharges noted on Figure 4 for ERA40 may explain the more limited efficiency. However, Figure 5 indicates that skill exists in simulating daily flows when using LSC plus an area-averaged temperature index as predictors. It is important to note that the objective is not to obtain the best reproduction of observed daily discharges using downscaled forcing. Other predictors from reanalysis may improve the simulation of discharges, but their use when coming from a climate model is more questionable. Indeed, in the context of climate change, the predictors have to be realistically reproduced by the climate model.

Some of the diagnoses previously shown are computed for a period that includes the learning period of the downscaling scheme (1985–2002). The period was chosen to allow for a comparison with the CTRL simulation that only covers the 1981–2005 period and to limit the amount of missing values in the observations. As the inclusion of the learning period in the diagnoses computation might lead to spurious results, the temporal stability of the SDM performance is now tested. The daily correlations between simulated and observed daily flows computed for each year and for five gauged stations are shown on Figure 6.

For the Marne and the Oise, an important drop in correlation is seen in 1972 and 1973 respectively. Although this drop also exists for the Seine at Paris and at Poses (as the Marne and the Oise are tributaries of the Seine), it is less pronounced. Our metadata does not explain the lower correlations seen in 1973 and 1972. Temporary problems concerning the measurements of the discharges or the impacts of water management for these years may be envisaged. Except for these years, even if some interannual variability exists, relatively stable correlations are seen for the whole period. In particular no rupture is seen at the beginning of the learning period in 1981.

COMPARISON OF STATISTICAL AND DYNAMICAL DOWNSCALING APPROACHES

The two downscaling techniques described in Section on Downscaling Methods are used to downscale the ARPEGE variable resolution model present climate simulation (1950–1999 period). Two hydrological simulations are then performed. The simulation SD is forced by the results from SD and the simulation DD is forced by ARPEGE results after bias correction with the quantile–quantile mapping technique (Figure 3).

First, the comparison of the two downscaling approaches is performed on downscaled temperature and precipitation. The properties linked to the statistical distribution (as mean, variance, value of extreme quantiles for example) cannot be used to compare the two methods. Indeed, the quantile–quantile bias correction method is designed to correct the pdf of simulated variables in order to match the pdf of the observations. Properties linked to the distribution shape are thus perfectly reproduced by construction in the quantile–quantile mapping approach. Concerning the SDM, it has already been shown that it is able to correctly represent these properties (Section on Statistical Downscaling of ERA40 Reanalysis for ERA40 downscaling, Boé *et al*., 2006 for a detailed study with both ERA40 and ARPEGE).

As previously said, the quantile–quantile mapping does not correct the model temporal properties. For example, if the simulated wet spells are too short, they remain too short after correction. The cross-correlations between the different variables and the spatial autocorrelation of each variable may also be biased. The first comparison is based on the temporal properties of precipitation. Table II shows the area-averaged mean relative absolute errors concerning the probability to have a dry (wet) day conditioned by the previous day being dry (wet) and the mean dry (wet) spell length. The SDM performs better than the bias correction method for all the diagnoses, confirming

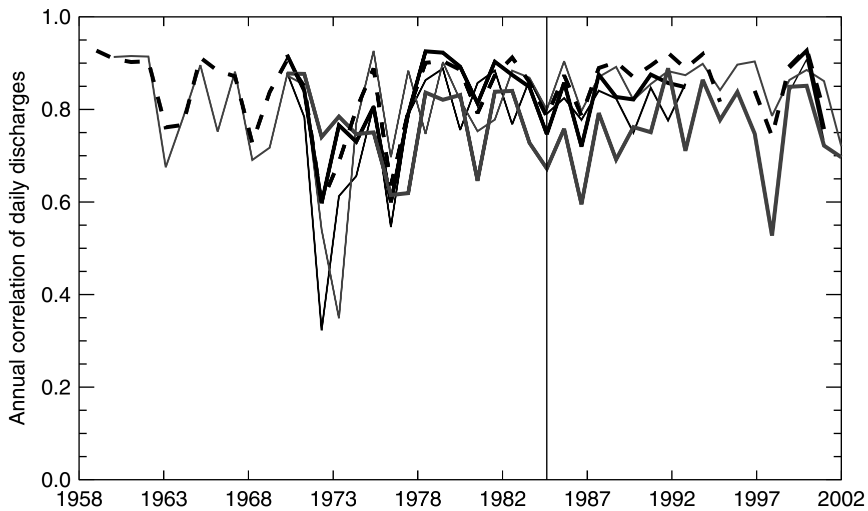

Figure 6. Annual correlations between simulated (downscaled ERA40) and observed daily discharges for five gauging stations (Grey: thick line: Yonne at Courlon, thin line: Oise at Pont-Sainte-Maxence. Black: thick line: Seine at Paris, thin line: Marne at Noisiel, dotted line: Seine at Poses).

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the possible matters of concern mentioned in Section on Quantile–quantile Bias Correction for Dynamical Downscaling.

Next, the spatial autocorrelation properties of precipitation and temperature are examined. Two points on the Seine basin characterized by different climate properties are selected: X1 is located on the coast and X2 is situated inland in a mountainous area (Figure 1). The spatial autocorrelation between temperature and precipitation at X1 or X2 and all the other points of the domain are computed. Results are encapsulated in Figure 7. For both the variables, the SDM very well captures the spatial autocorrelation of precipitation and temperature, whereas the performance of the bias correction method is more limited. For precipitation, DD with bias correction tends to overestimate the spatial autocorrelation. The overestimation is more pronounced where the observed spatial autocorrelation is maximal, i.e. for the neighbouring points. For temperature, the spatial autocorrelation tends to be underestimated for the furthest points with the DD approach. Note that the poorest representation of the spatial autocorrelation with DD is general over the domain and not related to the particular choice of X1 and X2.

Table II. Area-averaged absolute relative errors for different precipitation diagnoses. Pd/d (Pw/w) is the probability of a dry (wet) day conditional on the previous day being dry (wet). Ld (Lw) is the mean dry (wet) spell length. The diagnoses are computed at each grid point for the four seasons before the mean absolute relative error is computed.

	SD (%)	DD (%)
Pd/d	2.3	5.5
Pw/w	3.3	5.4
Ld	9.4	12.1
Lw	6.7	9.1

Next, the results of the DD and SD hydrological simulations are used to compare the two methods. The mean annual cycle of rivers discharges at selected stations for these two simulations, and the observations are displayed in Figure 8. The mean annual cycle of ERA40 and CTRL hydrological simulations are also shown (due to the limited length of the CTRL simulation the comparison of the CTRL results with the others should be taken with caution).

At the four selected gauged stations, the annual variations of simulated discharges are well reproduced even if some small biases exist. The most important biases are seen in winter for the four stations, with a general overestimation of discharges. The biases are generally more pronounced in December and January. The overestimation of winter discharges is probably due to the hydrological model itself as it is also seen in the CTRL simulation. The annual cycles of the different hydrological simulations are very similar whatever the origin of the forcing. In particular, results from the DD and SD of the ARPEGE simulation are very close.

Figure 9 shows the cdf of daily discharges for the same simulations and for observations at the four gauged stations used previously. The results from the different simulations are once again very similar. A slight overestimation of discharges corresponding to cumulative frequencies between approximately 0.5 and 0.99 is generally seen. A slight overestimation of very frequently exceeded discharges (cumulative frequencies lower than 0.1) also exists (although it is not very visible with this

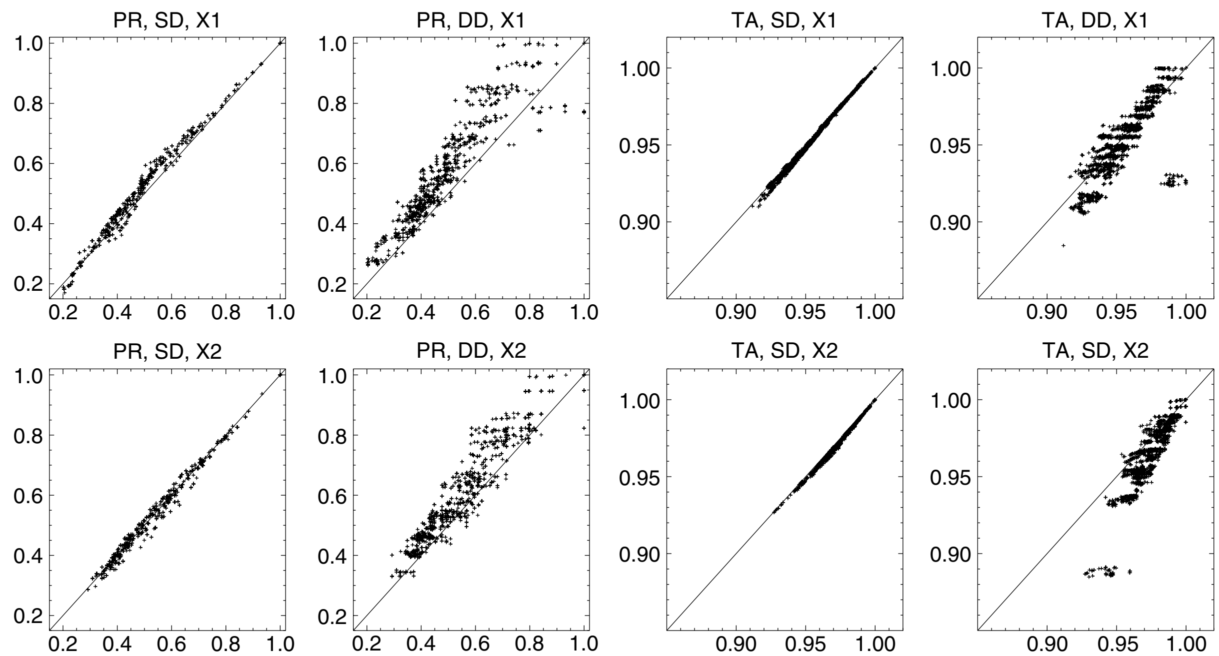

Figure 7. Scatter plot of spatial autocorrelation: observations (x-axis) *versus* downscaling (y-axis). See text for details. PR is precipitation and TA is temperature.

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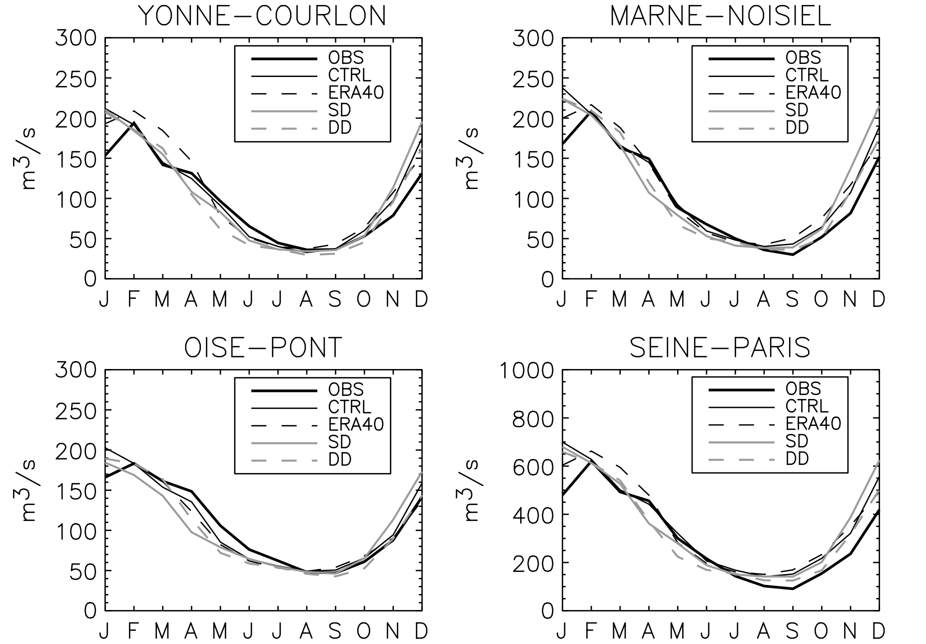

Figure 8. Mean annual cycle of discharges for selected gauged stations. The different acronyms are defined in the text. For the ERA40, SD, DD hydrological simulations and the observations (OBS) the period considered is 1958–1999. For the CTRL simulation, due to limited data availability, the period considered is only.

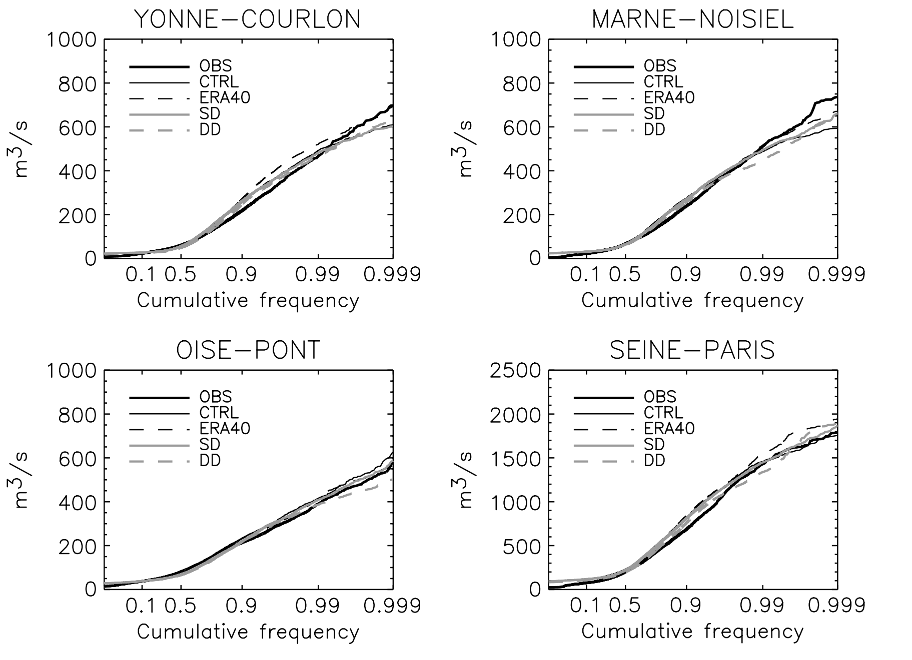

Figure 9. Cumulated density function of discharges for selected gauged stations. The different acronyms are defined in the text. For the ERA40, SD, DD hydrological simulations and the observations (OBS) the period considered is 1958–1999. For the CTRL simulation, due to limited data availability, the period considered is only 1981–2005. A Gumbel transformation defined as $u = -\log(-\log(P(x)))$ where P(x) is the cumulative frequency is applied on the horizontal axis.

graph). For cumulative frequencies greater than 0.99, the relative performance of the methods is not clear as it depends on the station and simulation. Nevertheless, an overall good agreement between simulated and observed cdf exists for all the simulations. These results give confidence in the use of the two downscaling approaches concerning changes in the daily variability and flooding in future climate.

To conclude the comparison of the dynamical and statistical approaches, the daily correlations between DD and SD simulated discharges are shown in Figure 10 as a function of the catchment size.

The strongest correlations are obtained for the largest areas (correlations up to 0.75), whereas a larger range of correlations are obtained for the smallest domain. This was expected since a large gauged area provides a

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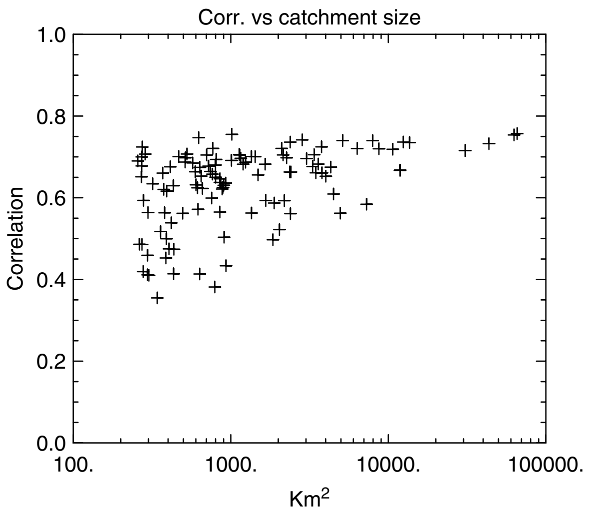

Figure 10. Correlation between SD and DD simulated discharges for the 1950–1999 period as a function of the catchment size.

kind of spatial and temporal integration of meteorological forcing. Figure 10 shows that at the daily level, simulated discharges from DD and SD also present important similarities.

In this section, the two downscaling approaches have been compared using the ARPEGE AGCM. Regarding precipitation and temperature temporal properties and spatial autocorrelations, the SDM outperforms DD with bias correction. For river discharges, the two methods give rather similar results. Realistic river discharges properties (seasonal cycle, daily distribution) are obtained after hydrological modelling in the two approaches where the hydrological model forced by SAFRAN performs well. The similarity of simulated discharges for present climate does not imply that the two approaches will give identical results for climate scenarios. The Seine basin has homogeneous physiographic characteristics with a simple orography and is thus well adapted to the DD approach. In less homogeneous areas, DD would probably be less suitable. Small-scale spatial variability – at scales lower than the model resolution – is not resolved, which could be an important matter of concern in mountainous areas and small watersheds. It is also mainly for this reason that the bias correction technique is not applicable to low-resolution model outputs. Moreover, biases in the spatial autocorrelation of precipitation and temperature have been highlighted after the correction step. The main advantage of the SDM is the possibility to directly downscale the results of a low-resolution climate model.

CONCLUSION AND DISCUSSION

After having introduced a SD scheme based on weather typing and conditional re-sampling, a bias correction technique for DD outputs using quantile–quantile mapping has been described. The two methods have been compared, using direct downscaled variables and river discharges after hydrological modelling.

Both DD with bias correction and SD rely on the availability of high-resolution daily observations. In the two approaches, the idea is to correct the model results given our knowledge of the observed properties of regional climate. In the quantile–quantile correction approach the implicit hypothesis made is that the high-resolution model is able to correctly represent ranked categories of the regional climate variable, i.e. that the prediction 'very high precipitation' by the model can be qualitatively trusted. The bias correction algorithm only corrects quantitatively the value of 'very high precipitation' in the model world (Déqué, 2007). The implicit hypothesis of SD is more restrictive as it is supposed that some climate variables at the regional scale are poorly simulated by the model, and that only the LSC can be regarded with confidence.

The statistical downscaling approach is initially the more complex of the two approaches to set-up. As a SDM is based on the relationship that exists between LSC and regional climate, it is first necessary to physically understand and then to statistically describe this relationship. On the contrary, the bias correction method based on quantile–quantile mapping is easy to implement. It is, nevertheless, worth noting that the work on weather typing that is necessary to develop the SDM may be very useful when it comes to understanding the physical mechanisms underlying regional climate change or past regional climate variability (Philipp *et al.*, 2006).

The major drawback of all the statistical downscaling methods is that they rely on the assumption that the relationship between predictors and regional climate is unchanged in future climate conditions. This hypothesis cannot be totally verified even if it can be partly tested (for example, Frías *et al.* (2006) develops an interesting approach). Two kinds of 'stationarity assumptions' also underlie the DD approach. It is first assumed that the physical parameterizations of the RCM remain applicable to climate change conditions. Then, the bias correction supposes that the correction function established for present climate is still applicable to the altered climate. The dynamical approach with quantile–quantile correction suffers from other limitations. First, the sub-grid variability is not resolved. It may be a problem, given the resolution of the regional model and the resolution needed by the impact model. Moreover, it is implicitly assumed that the temporal properties of the simulated variables as well as their spatial autocorrelations and cross-correlations are represented well. We have seen in this study that the DD with bias correction is less skillful than SD in reproducing precipitation persistence properties and the spatial autocorrelation of precipitation and temperature. Concerning river discharges, the two downscaling methods give rather similar results and perform well for the analysed diagnoses (daily distribution, seasonal cycle).

It is important to note that the SDM can be directly applied to a low-resolution climate model. Moreover, preliminary results show that the differences between the downscaling of the variable resolution version of

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ARPEGE and a standard low resolution version with a regular grid (2.80° × 2.80° resolution) are very limited (not shown). The great advantage of SD is its low computational cost. It is thus possible to consider many climate scenarios, allowing multi-model and/or ensemble approaches. DD is comparatively much more computationally expensive. Running multiple ensembles of regional simulations with multiple RCMs forced by boundary conditions from multiple coupled climate models is far beyond current computational limits (Leung *et al*., 2003).

The uncertainty analysis is a major step of any impact study. It is even truer, since today, the principal societal demand for impact studies concerns the first decades of the 21st century. For this period, the emerging climate change signal-to-noise ratio is weaker than at the end of the 21st century. The quantification of uncertainties is thus a necessity for the impact assessments to be really useful for policy-making decision. Among the different levels of uncertainty involved by a climate change impact assessment study (Wilby *et al*., 2006), the greatest uncertainty likely comes from the formulation of the climate model (Rowell, 2006). The quantification of the uncertainties thus requires the use of multiple models or alternative approaches like perturbed physics (Murphy *et al*., 2004) or stochastic parameterization (Palmer, 2001). In this perspective, given its low computational cost, the SD approach is far more appropriate. Nevertheless, the use and the comparison of both the dynamical and the statistical approaches for the downscaling of climate scenario, at least for one model, should be very valuable. A RCM accounts for the main physical processes that may be involved in climate change, whereas a SDM is only based on partial relationships established for present climate. The comparison of the two methodologies, driven by the same high-resolution model, may give indication on the validity of the SD method in altered climate. Moreover, DD allows for a deeper analysis of the physical mechanisms underlying regional climate change. A better understanding of the relevant physical processes may help to understand the involved uncertainties and thus to mitigate the projections spread.

In a future study, the SDM will be extended over the entire French territory. Models from the IPCC AR4 archive and the ARPEGE variable resolution will be statistically downscaled to force the ISBA-MODCOU hydro-meteorological system, in order to study the impact of climate change on the main French watersheds. The DD methodology described in this paper will also be used with the ARPEGE variable resolution model in order to compare the two downscaling approaches in the future climate and thus to assess the robustness of the results obtained.

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