Quantifying the Predictability of Winter River Flow in Iberia. Part I: Interannual Predictability

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ABSTRACT

The interannual variability and predictability of the winter streamflow of the main Iberian Peninsula international rivers (Douro, Tejo, and Guadiana) are examined for the period 1923–2004. In the first part of this paper, a singular spectral analysis was carried out to isolate the main oscillatory components of the streamflow series. Results showed a similar model structure for the three rivers, including the following components: (i) a nonlinear trend that contains variability at periods of 20–30 yr, (ii) modulated amplitude oscillations with associated periods in the bands 2–3, 4–5, and 6–8 yr, and (iii) a red noise process. These models accounts for the bulk of winter river flow variance, ranging between 64% (Guadiana) and 96% (Douro). In general, the amount of variability associated with the low-frequency component is similar to that associated with the interannual variability. The analysis of the association between the North Atlantic Oscillation (NAO) and the streamflow variability proved this relationship to be complex and nonstationary. In particular, it is found that only when the NAO presents high amplitude oscillations is this mode capable of dominating the streamflow variability.

In Part II, autoregressive-moving-average (ARMA) models were fitted to the filtered streamflow series and an interannual forecasting experiment was conducted. Results were tested against the raw streamflow series. The percentage of variance explained by the models ranged from 25% to 62%. Additionally, the ARMA models presented useful one-year-ahead forecasting skills. Particularly during the validation period (1986–2004) the models performed between 51% and 53% better than climatology. The skill against persistence proved to be much greater, indicating that the climatology is a better benchmark than persistence for streamflow forecasting in Iberia. Finally, the developed models were, in most cases, able to accurately predict the phase of the streamflow, with a percentage of agreement that ranged from 54% to 90% throughout the validation period.

1. Introduction

The ability to forecast unusual climate conditions several months in advance is arguably one of the most relevant developments in the atmospheric sciences over the last decade. There is a broad consensus nowadays of the large economic added value associated with these forecasts (Katz and Murphy 1997). It is a well known fact that countries located within the tropical belt are characterized by a climate easier to predict, while midlatitude regions (such as the United States, Europe, and Japan) present a much less reliable picture (Goddard et al. 2001). Nevertheless, in the last decade, the increment on the skill obtained by both dynamical and statistical forecasting models over midlatitudes (Rodwell

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and Folland 2002; Czaja and Frankignoul 2002; Saunders and Qian 2002; Saunders et al. 2003; Doblas-Reyes et al. 2005) has prompted a number of groups to apply the seasonal forecasts to different socioeconomic contexts such as water resources management (Hartmann et al. 2002), agriculture (Hansen 2002; Schneider and Garbrecht 2003; Atkinson et al. 2005), fire hazard (Pereira et al. 2005; Gedalof et al. 2005; Hessl et al. 2004; McKenzie et al. 2004a,b, 2006), and human diseases (Ellner et al. 1998; Shaman et al. 2003, 2006; McGregor et al. 2004). In many cases, the statistical models offer better results since there are still some unaccounted physical mechanisms in most coupled dynamical models, particularly those that include the extratropics (Anderson et al. 1999).

Seasonal and interannual streamflow variability plays an important role in the development and management of water resources in most regions of the world (Houghton et al. 2001). The hydrological system acts as a sensible spatial and temporal integrator of precipitation (rain and snow), temperature, and related evapotranspiration over a specific region. Therefore, seasonal to interannual streamflow variability in many large river basins can be controlled by corresponding changes in large-scale atmospheric circulation patterns. The relationship between these climatic regimes and its hydrological response, through its streamflow, presents different grades of complexity according to the physical characteristics of the basin. Nevertheless, streamflow can be better related with important patterns of climate teleconnections than precipitation or temperature fields since variations in precipitation are amplified in streamflow and, in general, it is easier to detect a change in discharge than directly in the basic climatic variables (Cayan et al. 1999; Dettinger and Diaz 2000; Trigo et al. 2004). This high sensitivity of the streamflow to climate variability has been used even for climate change studies (e.g., Kiely 1999). Additionally, Scarsbrook et al. (2003) showed that the climate variability has an impact not only on the river streamflow, but also in the quality of the water (temperature, oxidized nitrogen, etc.).

This work focuses on variability and predictability of Iberian rivers because, for this southern European region, present and future water resources management presents a considerable number of challenges, namely:

- Most Iberian rivers show relatively high coefficients of interannual streamflow variation, decreasing from rivers located in the north (~50% for Douro) to those in the southern sector (~100% for Guadiana) (e.g., Trigo et al. 2004). These high values of variability can be explained based on the strong interannual precipitation variability observed throughout the whole Western Mediterranean region (Goossens 1985; Barry and Chorley 1998; Esteban-Parra et al. 1998; Serrano et al. 1999).
- The Iberian Peninsula precipitation is strongly influenced by the North Atlantic Oscillation (NAO) phenomenon (Trigo et al. 2004; Goodess and Jones 2002). Around 40% of the winter precipitation can be related to the NAO index, and this large-scale atmospheric circulation phenomenon is characterized by a marked interannual variability. In fact, the significant and steady decline of Iberian precipitation, observed for March since the 1960s, has been shown to be correlated with latitudinal shifts of storm tracks over the Atlantic and that these shifts are associated with an increasing trend of the NAO index for March (Paredes et al. 2006). This trend is important because the winter tends to be shorter than previously observed, diminishing the soil water moisture available in the following spring and summer seasons.
- Both Portugal and Spain show an increasing demand of water supply not only for domestic use, but also for the tourist and agricultural sectors, two main economic activities accounting for more than 10% of gross national product (GNP) in both countries. The strong socioeconomic impacts of the recent extreme drought observed during the 2004/05 hydrological year further emphasizes the necessity to develop long-term planning tools (Garcia-Herrera et al. 2007).
- In a recent report (Houghton et al. 2001), the Intergovernmental Panel on Climate Change stated that the entire Mediterranean region (including the Iberian sector) is already presenting broadly consistent decreases in precipitation and streamflow. Moreover, climate change scenarios developed for the Iberian Peninsula for the twenty-first century point to a general increase in the risk of summer droughts with increasing uncertainty in the reliability of water supplies (Parry 2000; González-Rouco et al. 2000; Santos et al. 2002).

The purpose of this paper (Part I hereinafter) and the work presented in a companion paper (Gámiz-Fortis et al. 2008, hereinafter Part II) is twofold: first, we study the interannual variability of the winter streamflow of the three most important international rivers in the Iberian Peninsula, namely, Douro, Tejo, and Guadiana, particularly in relation to trends and quasi-oscillatory modes of variability; and second, we explore the feasibility for seasonal to interanual forecasts of the streamflows.

While in Part I we study the winter interannual vari-

ability and explore the interannual predictability, in the companion paper (Part II), we analyze the seasonal predictability. Particularly we explore the role of the Atlantic Ocean summer and autumn SST in forecasting the following winter streamflow. Additionally, in Part II the relative importance of the interannual and seasonal predictability of the winter streamflow is analyzed. The provision of these simple forecast models may help to alleviate some of the negative effects that the strong interannual Iberian climate variability has on the water resources, principally through increased preparedness. Additionally, given that the water resources planning and management are carried out on time horizons of about 30–40 yr, the analysis of the multidecadal streamflow variability is particularly relevant for long-term planning and operation strategies (Jain et al. 2002).

Part I is divided into two parts. In the first part, we use singular spectral analysis (SSA) to determine and isolate the significant temporal modes of variability of the three river streamflows. SSA acts as a data-adaptive filter, removing the background noise and retaining the leading statistically significant signals (Ghil and Vautard 1991; Vautard et al. 1992). The filtered signal is composed of modulated oscillatory signals and trends. The near-cyclic nature of the modulated oscillatory signals, resulting from the SSA, implies predictability. Consequently, in the second part of this paper, an interannual linear prediction of the reconstructed streamflow series is carried out. To this end, autoregressive-moving-average (ARMA) models (Box and Jenkins 1976) are fitted to the streamflow time series. ARMA models can be regarded as a special case of general linear stochastic processes and provide a linear representative structure of the temporal evolution of the data. We assume that the filtered streamflow data series provides the predictable signal contained in the raw streamflow series.

The methodology employed in this work, concerning SSA and ARMA modeling, was extensively used in a previous work by several of the authors (Gámiz-Fortis et al. 2002) to analyze the temporal variability and predictability of the NAO pattern. Additionally, a similar approach was used by Robertson and Mechoso (2001) and Krepper et al. (2003) to analyze the interannual variability and predictability of, respectively, the Paraná and Uruguay river flow.

The paper is organized as follows: section 2 describes the data used. Section 3 explains the SSA and ARMA methodologies. Section 4 deals with the results obtained with the SSA, while section 5 shows the results of the ARMA modeling and forecasting experiments.

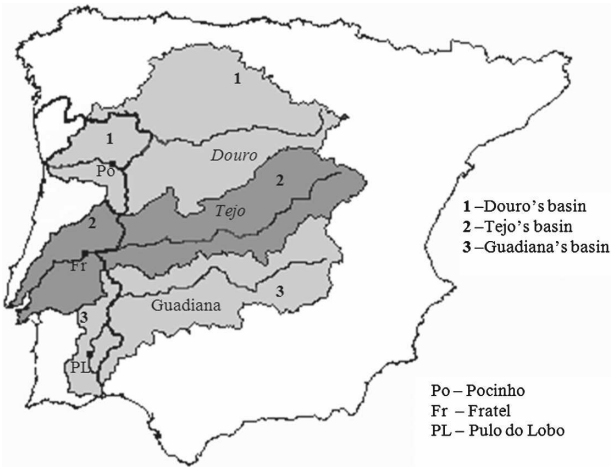

FIG. 1. Location of the three main international rivers in Iberia and their catchment boundaries. Small black dots show the location of river flow gauges used in each basin.

Finally, a discussion of the results and some conclusions are provided in section 6.

2. Data

The entire central Iberian plateau is dominated by three large river basins that cover more than half of the whole peninsula and are roughly oriented in a northeast–southwest direction, confined by mountain ranges. These three river basins, the Douro (north), Tejo (center), and Guadiana (south), are shown in Fig. 1. River flow data from both Douro (at Pocinho) and Tejo (at Fratel) spans between 1923 and 2004 (82 hydrological years), while data for the Guadiana River (at Pulo do Lobo) are restricted to the shorter period, between 1947 and 2004 (58 hydrological years). These data series were kindly provided, in a monthly basis, by the Portuguese National Electrical Supply Company (REN).

The international character of these three rivers, with the Spanish section considerably longer than the Portuguese counterpart, is immediately striking. This is a natural consequence of Iberian geography wherein almost 80% of the combined basin area of these three transnational rivers is located inside Spain (Fig. 1). Therefore, taking into account their location, the volume of water that passes the above-mentioned river gauges corresponds mostly to precipitation fallen over the Spanish territory. Under natural conditions, that is, without artificial water transfers, about 70% of the total outlet flow of these three rivers has its origin in Spain (INAG 2001). The location of the river gauges within the Portuguese section of the rivers is also depicted in

TABLE 1. Main characteristics of the three river basins considered. Average and standard deviation values correspond to annual river flow and were obtained using the full available period. Storage volumes for Portugal and Spain were obtained from the recently released Portuguese National Plan for Water (INAG 2001).

River (gauging station)	Total basin area ($\times 10^3$ km^2)	Basin area upstream gauging station ($\times 10^3$ km^2)	Period	Annual average ($\times 10^3$ hm^3)	Annual std dev ($\times 10^3$ hm^3)	Max/ min	JFM average ($\times 10^3$ hm^3)
Douro (Pocinho)	98.4	83.0	1923–2004	11.36	4.02	9	4.24
Tejo (Fratel)	80.1	59.0	1923–2004	8.96	6.17	31	3.68
Guadiana (Pulo do Lobo)	66.9	60.9	1947–2004	3.90	3.51	54	2.54

Fig. 1, and the main characteristics of the flow measured at these gauges can be seen in Table 1.

In previous work the authors have shown the highly irregular regime of both precipitation (Trigo and Da-Camara 2000) and river flow (Trigo et al. 2004) for the Iberian Peninsula. This fact can be appreciated in Fig. 2, which presents the seasonal variability of the mean monthly flow for the three rivers along the entire period of available data. As expected for this region, winter and springtime river flow account for the majority of runoff, being followed by a relatively long and dry summer period (Dettinger and Diaz 2000; Trigo et al. 2004). The Douro (Guadiana) presents the highest (lowest) average values of annual and winter flow (Table 1), while the extreme maximum values for the wet winter season can be observed for Tejo (Fig. 2).

In this work, we have used a normalized series of the January trough March mean flow (JFM flow hereinafter). To this end, first, the monthly January, February, and March streamflow series were normalized separately, using the normalization period 1961–90. Second, the average of these three monthly normalized series was computed. As shown in Fig. 2 and in the last row in Table 1, this JFM mean flow is partially representative of the annual river flow, since during these months a large amount of the total annual flow takes place (around 60% for the Tejo and Guadiana and 40% for the Douro).

3. Methodology

There is a basic problem when dealing with most annual-averaged climatic time series: namely, that these time series present an almost white noise spectrum. As a consequence, linear models, as in the case of ARMA models, tend to achieve poor results when applied—for forecasting purposes—to this kind of time series, even though some predictability is present in the series.

To overcome this problem, a two-stage methodology has been applied in this work for forecasting the streamflow series. Instead of directly obtaining the ARMA model of a series, an SSA filter was first applied to the "raw" series, obtaining a new "filtered" series. Then, an ARMA model is obtained for the filtered series. Finally, this ARMA model is used to forecast the filtered series, and results, for the sake of clearness, are compared not against the filtered series, but against the original "raw" series.

This methodology, widely explained in a previous work (Gámiz-Fortis et al. 2002) and also applied by Robertson and Mechoso (2001) and Krepper et al. (2003), provides considerably better results, in terms of forecasting skills, than the results that can be obtained when ARMA models are directly applied to climatic time series. The rationale behind this improvement appears to be related to the fact that the SSA filters are able to partially remove the background noise of some climatic time series, retaining the leading statistically significant (and predictable) components of these series.

In the following sections, a brief discussion of the SSA and ARMA methodologies are presented, including the procedures employed for evaluating the skills of the forecasts.

a. Singular spectral analysis

We use SSA to determine and isolate the significant temporal modes of variability of the three rivers' streamflow. SSA is a powerful form of the standard principal component analysis (PCA) based on the extensive use of the lag correlation structure of a time series (Vautard et al. 1992), which is particularly successful in isolating multiple-period components with fluctuating amplitudes and trends in short and noisy series. A comprehensive review, explaining in detail the mathematical foundations of SSA, can be found in Vautard et al. (1992) and Plaut et al. (1995).

SSA is based on the diagonalization of the lagged-autocovariance matrix of a time series. As in the case of PCA, the eigenvectors or empirical orthogonal functions (EOFs) represent patterns of temporal behavior, and the principal component series (PCs) are charac-

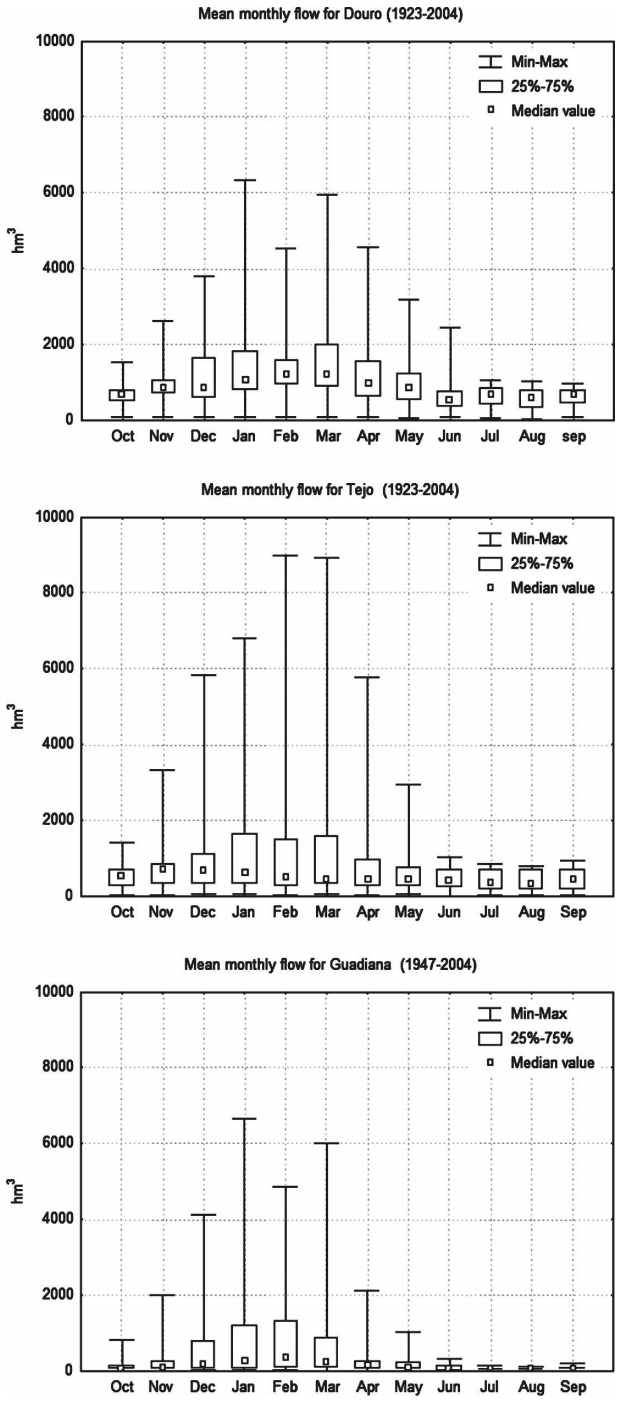

FIG. 2. Box plots showing the annual cycle of the variability of average monthly river flow for (top) Douro, (middle) Tejo, and (bottom) Guadiana.

teristic time series containing a very limited number of harmonic components. The detailed reconstruction of a set of significant components, called SSA-filtered components or reconstructed components (RCs) of the time series, is carried out by an optimal linear square fitting between the corresponding PCs and the original data. Each RC represents the contribution of its associated EOF to the variance of the time series; additionally, the RCs are additive and their sum provides the original time series. When two eigenvalues of the lagged-covariance matrix are nearly equal and their corresponding eigenvectors are orthogonal, they represent an oscillation. Therefore, we can consider SSA an eigenvalue technique that is particularly efficient for extracting and reconstructing periodic components from noisy time series. To determine the corresponding frequencies requires, however, estimations of power spectra. The maximum entropy method (MEM) is used to evaluate the spectral contents of the PC time series corresponding to the EOFs. We have evaluated the statistical significance of the SSA results by means of the Monte Carlo method, following the indications of Allen (1992) and Allen and Smith (1994).

Once a component of the series has been identified as a signal, the rest of the spectrum can be examined to determine whether or not it is simply noise. In this study, the noise analysis was performed based on the method described in Allen and Smith (1996, p. 3387).

b. ARMA modeling and forecasting

1) ARMA MODELING

ARMA models can be regarded as a special case of general linear stochastic processes and provide a linear representative structure of the temporal evolution of the data.

A stochastic process $\{X_t\}$, with mean zero, has an ARMA(p, q) representation if it can be expressed in the form:

$$X_t - \phi_1 X_{t-1} - \phi_2 X_{t-2} - \cdots - \phi_p X_{t-p} = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \cdots - \theta_q a_{t-q}, \quad (1)$$

where $\{a_t\}$ is a white noise Gaussian process with variance σ_a^2 and zero mean; p and q are nonnegative integers; $\{\phi_1, \cdots, \phi_p\}$ are the autoregressive (AR) coefficients; and $\{\theta_1, \cdots, \theta_q\}$ are the moving average (MA) coefficients.

The order of the model is selected, in a preliminary approach, studying the autocorrelation function (ACF) and partial autocorrelation function (PACF). In physical terms, the best model has as few parameters as possible. We have used the Akaike information criterion (AIC) (Akaike 1974) to select the final model among all the candidates. The AIC is based on information theory and represents a compromise between the goodness of the fit and the number of parameters of the model. A comprehensive review, explaining in detail

how to fit ARMA models to datasets following the identification, estimation, and diagnostic check stages, can be found in Brockwell and Davis (1996) and Hipel and Mcleod (1994).

Given an ARMA(p, q) model, the forecast with the minimum mean-squared-error $\hat{x}_t(L)$ for a leading time L is the conditional expectation $E_t[x_{t+L}]$ of x_{t+L} at origin "t":

$$\begin{aligned}\hat{x}_t(L) = E_t[x_{t+L}] &= \phi_1 E_t[x_{t+L-1}] + \phi_2 E_t[x_{t+L-2}] + \cdots \\ &+ \phi_p E_t[x_{t+L-p}] + \cdots + E_t[a_{t+L}] \\ &- \theta_1 E_t[a_{t+L-1}] - \theta_2 E_t[a_{t+L-2}] - \cdots \\ &- \theta_q E_t[a_{t+L-q}]. \end{aligned} \quad (2)$$

The one-step-ahead forecast error is

$$e_t(1) = x_{x+1} - \hat{x}_t(1) = a_{t+1}. \quad (3)$$

The variance of this $\{e_t: t = 1, \cdots, n\}$ series is called the innovations variance $\hat{\sigma}_e^2$ and gives a measure of the variance of the modeled series not accounted for by the ARMA model.

We should be aware of the fact that forecasts projected with ARMA models are influenced not only by the goodness of the fit but also by the assumptions that the underlying physical process related to the series does not change during the forecasting time. However, this latter assumption is hardly ever true in a complex dynamical system such as climate.

2) Separate calibration, validation intervals, and cross validation

The separation of calibration and validation periods is fundamental for reliable skill assessment (Wilks 1995, chapter 7). We employ data from 1923 to 1985 to calibrate the Douro and Tejo models (1947–85 for the Guadiana) while data from 1986 to 2004 are used for validation purposes for all three rivers. The forecasting experiments consist of computing the one-step-ahead forecast; that is, the streamflow values are forecasted for the following winter. Note that the initial conditions to forecast the 1986 winter streamflow were set up based on the state of the streamflow value until the previous winter (1985), including this previous winter value; for the forecast of the 1987 winter streamflow value, we use the information up to the previous winter (1986) and so on.

Additionally, a cross-validation procedure of the model is applied to validate the model. Commonly, the cross-validation of a regression model is carried out using a development dataset of size $n - 1$ and verification dataset containing the remaining single observation of the predictand, which leads to n partitions of the dataset. The model is then calculated for each of these partitions, resulting in n similar forecast equations, each one computed without one of the observations of the predictand.

Unfortunately, this procedure cannot be applied in our case for several reasons. Usually, in the regression models, some variables are used to predict another variable; in our case, we must obtain the potentially predictable signal from the times series own history. When fitting ARMA models, the temporal location of each data is significant: that is, the "history" of the series is very important. When removing one single data in the middle of the dataset, the remaining data are not useful to fit the model because the temporal structure of the data is then broken (Gámiz-Fortis et al. 2002). Furthermore, in a regression model we know a priori the temporal dependence between the predictand and the predictors. This allows one to properly remove some samples from the dataset and fit the model using the rest of the sample. Note that the temporal dependence of the ARMA models is unknown a priori (Gámiz-Fortis et al. 2002).

To cross-validate these models, and taking into account these pitfalls of the ARMA models, we have divided the Douro and Tejo development period 1923–85 into two subperiods of equal duration, 1923–49 and 1950–74. We have then fitted different ARMA models in these two subperiods and have carried out one-step-ahead forecasts between 1950 and 1965 for the first subperiod model and between 1975 and 1990 for the second subperiod model. Results are compared with those obtained for the whole period 1923–85. Owing to the short available streamflow record for the Guadiana, no cross-validation was carried out for this river model.

3) Accuracy and skill scores

To asses the extent to which the SSA models are able to reproduce the river flow series and the performance of the ARMA model forecasting experiments, a set of commonly used scores are used:

(i) The Pearson correlation coefficient is used to measure the relationship between the modeled/forecasted series and the original/expected series.
(ii) The percentage of phase agreement, that is, the percentage of cases in which the modeled/forecasted values has the same sign as the original values.
(iii) As accuracy measures, the mean absolute error (MAE) and the mean square error (MSE) are employed.
(iv) To assess the skill of the ARMA model-based forecasts, we first computed the MSE when climatology (MSE_{cl}) and persistence (MSE_{pe}) are used

TABLE 2. Comparative results of the SSA and ARMA model flow data for the three rivers.

	Douro	Tejo	Guadiana
Variance explained by the SSA filter (%)	96	82	64
Reduction in variance by the ARMA model (%)	44	76	39
Total variance explained by the ARMA model (%)	42	62	25

for forecasting; then, we have obtained the percentage improvement in MSE forecast over a climatological forecast ($SMSE_{cl}$) and the percentage improvement in MSE forecast over a persistence forecast ($SMSE_{pe}$). Climatology is taken as the 30-values average prior to each value being forecasted, and persistence value is taken from the previous value to those being forecasted.

4. SSA applied to the river flow series

a. Oscillatory modes, significance, and reconstruction

1) DOURO RIVER

The SSA was applied on the lagged-covariance matrix based on the Vautard and Ghil (1989) algorithm, using an $M = 15$ window length. The oscillatory modes derived from the SSA correspond to the following five pairs of eigenvalues; 4 and 5, 6 and 7, 8 and 9, 10 and 11, and 12 and 13, each one in quadrature. On the other hand, the general trend is characterized by eigenvalues 1 and 2.

The MEM has been used to evaluate the spectral contents of the PC time series corresponding to the EOFs. Results show that EOF pairs 4–5, 6–7, 8–9, 10–11, and 12–13 contain oscillations associated with periods around 5.3, 4, 3.3, 8, and 2.7 yr, respectively. The extent to which this hypothesis can be considered true was assessed through the use of the Monte Carlo technique. First, the results obtained by SSA were tested against the hypothesis of the winter Douro series to be the result of a pure AR(1) process with a lag 1 autocorrelation value corresponding to that of the winter Douro series. To this end, we use the data-adaptive basis, projecting each surrogate Monte Carlo realization onto the EOFs of the data and comparing the results with those of the original data. Then the test procedure is continued until a final null hypothesis cannot be rejected (see Gámiz-Fortis et al. 2002 for further details).

Using this methodology, we concluded that the winter Douro series can be represented by the following model: a nonlinear trend that contains decadal variability with period of 30 yr (EOFs 1 and 2), a set of oscillations with associated periods of 5.3 yr (EOFs 4–5), 4 yr (EOFs 6–7), 3.3 yr (EOFs 8–9), 8 yr (EOFs 10–11), and 2.7 yr (EOFs 12–13), and a red noise process with lag 1 autocorrelation 0.043 and variance 0.49.

Based on this model, we carried out a reconstruction of the winter Douro series, called the SSA-filtered Douro series. The raw series has a variance value of 0.54, while the SSA-filtered Douro has a variance of 0.52; thus, the variance explained by the model is 96% (see first column in Table 2). Over the period 1923–2004, the correlation between the original and the SSA-filtered series is 0.95 (significant at 95% confidence level); see first column in Table 3.

Figure 3a shows the raw and SSA-filtered river flow Douro series plus the trend component. The high value of the explained variance by the SSA model is reflected in Fig. 3a; the model reproduces most of the Douro streamflow variability, including extreme positive and negative values. It is interesting to notice that the model is particularly reliable in capturing the Douro river flow series behavior between 1935 and 1980. Extreme positive values are correctly modeled in most cases. Some

TABLE 3. Statistical results for the raw winter Douro (RWD) streamflow analysis. The first RWD shows the results related to the SSA modeling, while the second and third are related to the ARMA modeling and forecasting experiment over the calibration and validation period, respectively. Correlation coefficients (r) with an asterisk are statistically significant at the 95% confidence level.

	RWD vs SSA-filtered winter Douro (1923–2004)	RWD vs one-step-ahead forecast (1930–85)	RWD vs one-step-ahead forecast (1986–2004)
MSE	0.06	0.48	0.38
MAE	0.20	0.52	0.47
r	0.95*	0.60*	0.73*
MSE_{cli}		0.77	0.77
MSE_{per}		1.35	1.88
$SMSE_{cli}$ (%)		37	51
$SMSE_{per}$ (%)		61	75
Phase accordance (%)	93	80	90

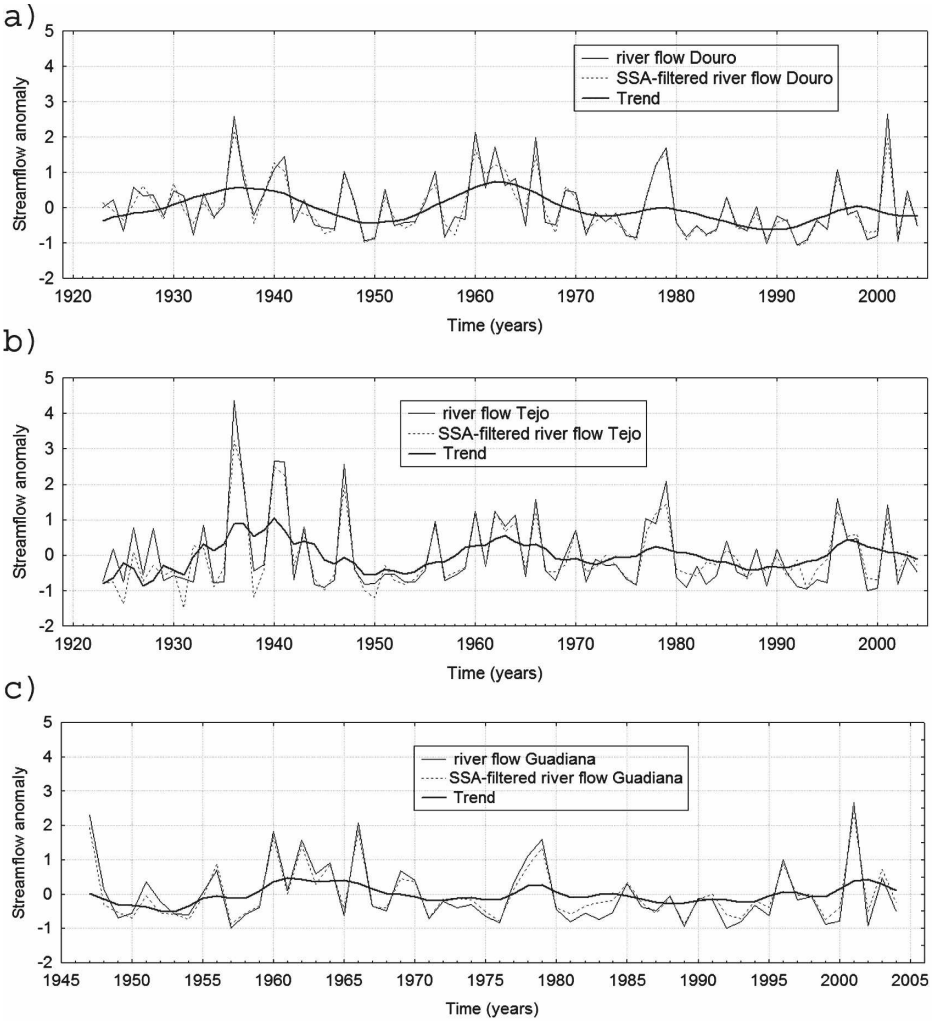

FIG. 3. Raw (continuous line) and SSA-filtered (dashed line) streamflow series. The trend components are also shown (continuous thick line) for the (a) Douro, (b) Tejo, and (c) Guadiana Rivers.

periods with trends can be also observed. The most prominent positive trend can be seen during the periods 1923–37 and 1951–61, while the periods 1972–78 and 1990–98 have slight trends. The remaining periods correspond to negative trends. A more detailed discussion about the trend modes in the three rivers will be produced later in the paper.

2) TEJO RIVER

A similar analysis was conducted for the winter Tejo river flow data. The first 10 eigenvalues were considered for the remaining analysis. The oscillatory modes are represented by four pairs of consecutive eigenvalues, namely, 2–3, 5–6, 7–8, and 9–10, each one in quadrature. In this case, eigenvalues 1 and 4 reflect the general decadal variability of the data. The MEM analysis reveals that EOF pairs 2–3, 5–6, 7–8, and 9–10 contain oscillations associated with periods around 3.6, 5.3, 2, and 7.5 yr, respectively, suggesting the existence of oscillatory components in the winter Tejo series. The application of the Monte Carlo technique to study the significance of these oscillations shows that the winter Tejo series can be represented by the following model: a nonlinear trend that contains decadal variability centered at the 23-yr period (EOFs 1 and 4), a set of oscillations with associated periods of 2 yr (EOFs 7–8), 3.6 yr (EOFs 2–3), and 5.3 yr (EOFs 5–6), an oscillation associated with a broadband peak of period around 7.5 yr (EOFs 9–10), and a red noise process with lag 1 autocorrelation 0.17 and variance 0.76.

Figure 3b shows both the raw and SSA-filtered river flow Tejo series along with the trend component. The raw series has a variance value of 1.07, while the SSA-filtered Tejo has a variance of 0.87. Over the period

TABLE 4. As in Table 3 but for the Tejo River (RWT).

	RWT vs SSA-filtered winter Tejo (1923–2004)	RWT vs one-step-ahead forecast (1931–85)	RWT vs one-step-ahead forecast (1986–2004)
MSE	0.16	0.43	0.26
MAE	0.29	0.47	0.43
r	0.93*	0.83*	0.85*
MSE_{cli}		0.69	0.59
MSE_{per}		1.43	1.28
$SMSE_{cli}$ (%)		38	53
$SMSE_{per}$ (%)		67	68
Phase accordance (%)	90	89	90

1923–2004, the correlation between the original and SSA-filtered series is 0.93 (also statistically significant at the 95% confidence level) (see second column in Table 2 and first column in Table 4). Thus, the variance explained by the model is 82%. Note the similitude between this series and the previous one corresponding to the Douro River. Years with maximum river flow are coincident in most of the series. Also, the trend for the Tejo River presents similar periods of positive and negative compared to the Douro trend. On the other hand, during the early period 1923–35, the model tends to provide lower than the actual values. This might be related to the poor quality of the river flow data from the earliest decade, a pitfall in the data that has been communicated to the authors by data providers. In any case, the vast majority of the time series seems to be well reproduced and, in particular, extreme values are correctly modeled in most cases.

3) GUADIANA

We have considered only 10 eigenvalues, as a result of the application of the SSA methodology to the Guadiana river flow. The eigenvalue pairs 1 and 2, 3 and 5, 7 and 8, and 9 and 10 represent oscillatory modes. The MEM shows that the former pairs contain oscillations associated with periods around 2, 4.5, 6.5, and 3.4 yr, respectively. Finally, eigenvalues 4 and 6 reflect the general trend of the data.

The application of the Monte Carlo technique to study of the significance of the former results shows that the winter Guadiana series can be represented by the following model: a nonlinear trend that contains decadal variability with a periodicity of 20 yr (EOFs 4–6), a set of oscillations with associated periods of 2 yr (EOFs 1–2), 4.5 yr (EOFs 3–5), 6.5 yr (EOFs 7–8), and 3.4 yr (EOFs 9–10), and a red noise process with lag 1 autocorrelation 0.02 and variance 0.35.

Based on this model, a reconstruction of the winter Guadiana series was performed. The raw series has a variance of 0.77, a value larger than the variance of the SSA-filtered Guadiana series, which is 0.49 (64% of explained variance). Over the period 1947–2004, the correlation between the original and SSA-filtered series is 0.95, significant at the 95% confidence level (see Tables 2 and 5). Figure 3c shows the raw and SSA-filtered series along with the trend component for the Guadiana River. As in the previous two cases, the model properly reproduces the extreme cases of the series. However, the associated trend is slightly weaker than for the Tejo and Douro Rivers.

b. Analysis of the interannual modes of variability

Streamflow at the monthly/seasonal time scales integrates influences of precipitation, evapotranspiration, temperature, and soil moisture, as well as other factors associated with river basin variables. Therefore, the year-to-year variability in the streamflow is bound to be associated with the large-scale climatic fluctuations that affect the region under study. Additionally, as shown in Cayan et al. (1999) and Dettinger and Diaz (2000), streamflow can be better related with strong patterns of climate teleconnections than precipitation and temperature. Over the northern Atlantic and western Europe sector, the most important of these phenomena is the NAO (Qian et al. 2000; Trigo et al. 2002). The ENSO phenomenon has also been related to interannual climate variability in southern Europe and, in particular, over Iberia (Fraedrich and Müller 1992; Pozo-Vázquez et al. 2001; Mariotti et al. 2002; Wu and Hsieh 2004). However, the relationship seems to be very complex and nonstationary and the eventual influence of the ENSO index on the Iberian streamflow is not attempted here.

In a previous work we assessed the impact of the NAO on the river Douro, Tejo, and Guadiana catchment rainfall during winter (Trigo et al. 2004). Results showed that the large interannual variability of precipitation in these catchments is largely modulated by the

TABLE 5. As in Table 3, but for the Guadiana River (RWG).

	RWG vs SSA-filtered winter Guadiana (1947–2004)	RWG vs one-step-ahead forecast (1953–85)	RWG vs one-step-ahead forecast (1986–2004)
MSE	0.10	0.36	0.34
MAE	0.25	0.41	0.41
r	0.95*	0.48*	0.47*
MSE_{cli}		0.68	0.72
MSE_{per}		0.67	1.82
$SMSE_{cli}$ (%)		47	52
$SMSE_{per}$ (%)		46	81
Phase accordance (%)	89	52	54

NAO phenomenon. Other works also support these results. Particularly, Goodess and Jones (2002) analyzed the link between circulation types and Iberian rainfall, finding that, for the central and southern part of Iberia where these catchments are located, the influence of the NAO is dominant. Additionally, in Gámiz-Fortis et al. (2002) we analyzed the main oscillatory modes of variability of the winter NAO index [December–February (DJF)]. Results showed that the winter NAO index is dominated by variability centered at periods of around 7.7, 4.8, and between 2.3 and 2.4 yr. It should be stressed that these frequencies have been detected previously by other authors; in particular, the leading 7.7-yr oscillation has been comprehensively described (e.g., Da Costa and Colin de Verdiere 2002).

Naturally, it is promising to raise the possibility on the existence of preferred common modes of NAO and streamflow variability, that is, resonance modes. To answer this question, we have compared some of the oscillations present in both the winter NAO and river flow time series. Figure 4a shows the 7.7-yr period oscillation of the winter NAO index simultaneously with the oscillatory modes, which possess similar periods, found for Douro, Tejo, and Guadiana river flows. Similarly, Fig. 4b shows the 4.8-yr period oscillation of the NAO along with the corresponding oscillatory modes of river flow for the considered three rivers. Figure 4a shows a general tendency toward an out-of-phase relationship between the 7.7-yr oscillation in the NAO and those present in the river flows. This makes sense since a negative NAO index means more precipitation over the Iberian Peninsula. The behavior is more clearly seen from 1950 onward, when the 7.7-yr NAO oscillations show larger amplitude, while during the period 1923–40 the NAO–river flow relationship seems to be more complex. Regarding the 4.8-yr oscillation (Fig. 4b), the out-of-phase relationship is clearly seen during the periods 1923–50 and 1970–1980, while over the rest of the time the relationship is more variable. Interestingly, the early period between 1923 and 1950 is also the period when the 7.7-yr oscillation shows the lowest amplitude. The results are in agreement with those found by other authors. Particularly, Rodríguez-Puebla et al. (1998) found strong covariability between the NAO and the Iberian Peninsula precipitation at periods 4–6 and 7–9 yr. Rimbu et al. (2002) analyzed the decadal (>5 yr) variability of the Danube River flow and its relationship with the NAO, finding an overall out-of-phase relationship throughout the period 1931–95. Interestingly, these NAO–river flow relationships are not restricted to the European sector. In a recent work Coulibaly and Burn (2005) investigated the relationship between Canadian streamflows and large climate variability patterns [NAO, ENSO, and Pacific–North American (PNA)]. The authors have identified a strong correlation between the NAO and the eastern Canada streamflow centered in the 2–6-yr band, which presents values of up to $r = 0.5$ during autumn and winter seasons.

To sum up, we have found that, although the precipitation in the Douro, Tejo, and Guadiana catchments are largely modulated by the NAO, the relationship between the NAO and these river streamflows is complex and nonstationary. This result can be justified if we take into account that the JFM streamflow is representative of both precipitation and snowmelt processes. Therefore, the streamflow reflects not only the precipitation regime but also the temperature and wind fields, which are not so clearly influenced by the NAO in the study area (Trigo et al. 2002). Particularly, the relationship between temperature and the NAO in southern Europe (including Iberia) is strongly nonlinear (Pozo-Vázquez et al. 2001; Sáez et al. 2001; Castro-Díez et al. 2002). It could be argued that only when the NAO presents high amplitude oscillations is the influence of the rainfall on the streamflow capable of overriding other influences.

c. *Analysis of the trend modes*

In the three analyzed streamflow series, a low-frequency or nonlinear trend component has been found;

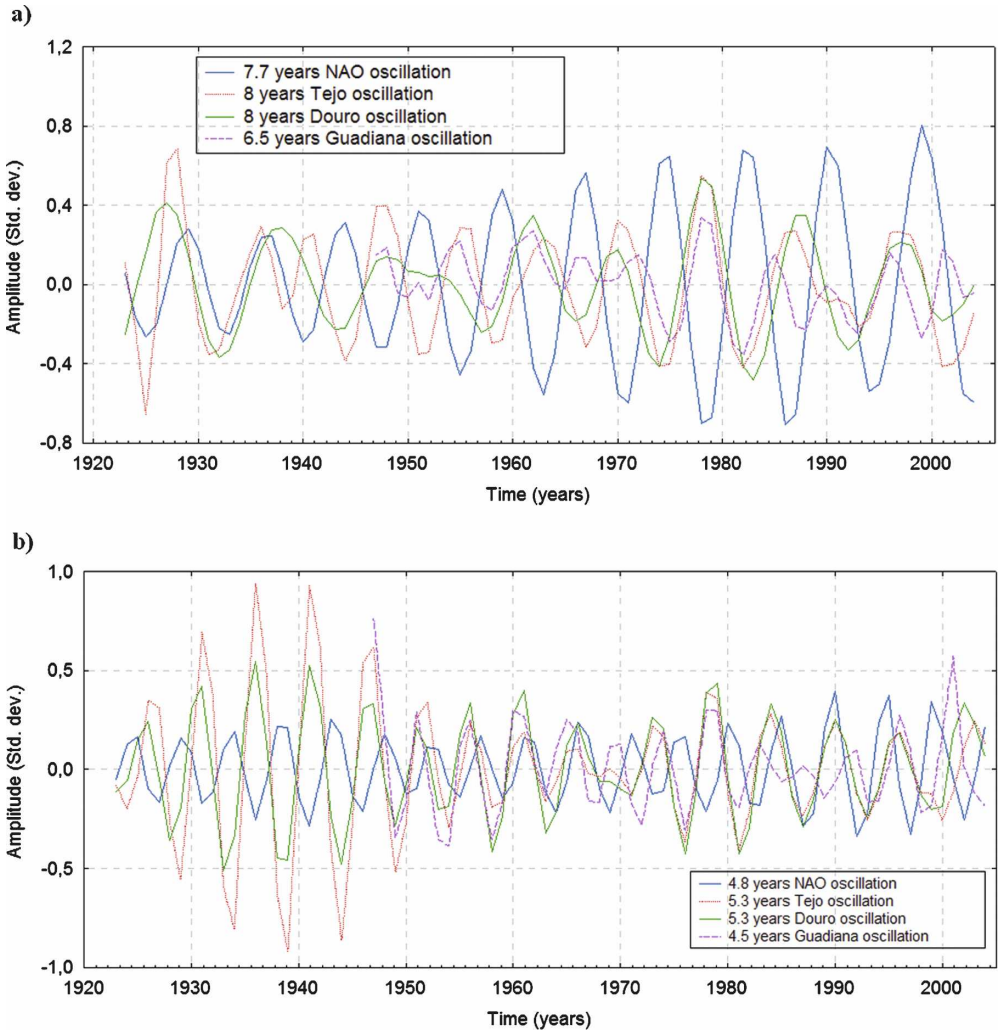

FIG. 4. (a) NAO, Tejo, Douro, and Guadiana oscillations in the 6–8-yr period band resulting from the SSA and over the period 1920–2000. (b) As in (a), but for the 4–6-yr period band.

in Fig. 3 these trend components are displayed. These three low-frequency components have similar long-term decadal variability (around 30 yr for Douro, 23 for Tejo, and 20 for Guadiana). Overall, this long-term variability is related to some slightly positive (1923–37, 1950–63, 1972–78, and 1990–98) and negative trends (1940–50, 1963–72, and 1980–90). The steepness of the trends is similar for Douro and Tejo and slightly lower for the Guadiana.

Two questions arise when studying the low frequency variability in the river flow. First, what is the relative importance of these low frequency components regarding the total river flow variability and, second, what is the possible origin of these oscillations? There is a scarce number of studies dealing with interdecadal streamflow variability, mainly due to the generally short time series available for streamflow records.

Results of the SSA proved that the variance associated with the trend mode is 24% for the Douro, 20% for the Tejo, and 15% for the Guadiana (see Table 6). Additionally, the trend component is the most important, explaining the total variance for the Douro and Tejo. Overall, the variability associated with the low frequency component of the streamflow is similar to that associated with the individual oscillatory modes that drive the interannual variability. These results are in agreement with those from Dettinger and Diaz (2000) for our study region. This means that the low frequency variability must be taken into account and not only the interannual variability.

Regarding the second question, interdecadal natural climate variability is usually associated with slow-varying oceanic processes. The integration effect of other climatic variables (precipitation and tempera-

TABLE 6. Explained variance (%) for each oscillatory mode.

	Trend	2–2.7 yr	3.3–3.6 yr	4–4.5 yr	5.3–6.5 yr	7.5–8 yr	Total
Douro	24	9	13	14	15	11	85
Tejo	20	—	21	—	15	12	68
Guadiana	15	19	16	16	13	—	75

ture) that the streamflow provides should be considered. Low frequency modes for precipitation in the region have been described before (e.g., Dai et al. 1997). Particularly, over the study area they have found two principal components: the first one shows interdecadal variability and is associated with ocean–atmosphere processes in the Atlantic Ocean (see their Fig. 11). The low frequency variability of this second pattern roughly agrees with that found here concerning the trend component of the river flow. In the study region, there are different results concerning the interdecadal streamflow variability. For instance, Kiely (1999) analyzed 50 years (from 1950 onward) of streamflow data in Ireland, finding a steady increment in streamflow from 1975 onward associated with the tendency toward positive values of the NAO. Additionally, Cullan and deMenocal (2000) have found, analyzing the impact of the NAO on the Tigris–Eufrates streamflow, an important influence of NAO on the precipitation of this area and tendency to decreasing streamflow values, particularly steep from 1970 onward. Note that this is in agreement with Kiely's (1999) results for Ireland since the positive phase of the NAO gives rise to positive precipitation anomalies in Ireland and, simultaneously, negative anomalies over Turkey (where the main sources of the Tigris–Eufrates are located). Regarding the precipitation, Goodess and Jones (2002) found a general tendency toward decreasing seasonal rainfall in our study region (central and southern Iberia), although this tendency is clearer for spring than for winter. In particular, western and central Iberia (the location of the three river basins) have been affected by a significant negative trend in March (Paredes et al. 2006) but this has been compensated, at least partially, by positive trends that took place in late autumn (October and November). This contradictory behavior helps to explain that, when results are averaged for the entire year (or even for the wet half of the year, i.e., October–March), negative (but statistically not significant) trends of precipitation over this part of Iberia exist (Rodrigo and Trigo 2007). We have conducted an additional analysis trying to test for the presence of significant trends in the three streamflow series. The analysis was carried out both on a seasonal and annual basis. No statistically significant trends, positive or negative, were found. The absence of statistically significant trends in seasonal river flow may reflect the large capacity of major dams for the three rivers (particularly in Spain), as described in detail in Trigo et al. (2004). This allows the accumulation of the water from late autumn (when it is raining more) to early spring (when it is raining less), therefore maintaining artificially the same seasonal cycle or river flow as in previous decades. Nevertheless, there are decades showing positive and negative trends; in particular, the short-term positive and negative trends in the 1970s and 1980s [previously described by Cullan and deMenocal (2000) and Kiely (1999)] were also found in our data.

5. ARMA modeling and forecasting

In the previous sections, SSA has been applied to isolate the "climate" signal contained in the winter river flow. As previously highlighted, SSA acts as a data-adaptive filter, removing the background noise and retaining the statistically significant signals.

In this section we carry out an ARMA modeling of the SSA-filtered winter river flow. The ARMA models are then used in a forecasting experiment where it is assumed, on the one hand, that the filtered winter streamflow series contains the interannual predictable signal present in the raw series, and on the other hand, that the ARMA models are able to represent this predictable signal based only on the "history" of the series.

a. ARMA modeling

Data from 1923 to 1985 were used for calibrating the Douro and Tejo models, while the shorter 1947–85 period was used for Guadiana. Similar to the division employed previously for the SSA models, data from 1986 to 2004 was used for validation purposes only.

The ARMA modeling process begins by analyzing the sample autocorrelation and partial autocorrelation functions for the different SSA-filtered river flow series. Additionally, the stationarity of the series (both in terms of mean and variance) was also evaluated. Based on these analyses and following a process fully explained in Gámiz-Fortis et al. (2002), we used the AIC to select an ARMA(7, 3) model for the Douro, an ARMA(8, 4) model for the Tejo, and an ARMA(6, 4) model for the Guadiana, containing the following parameters:

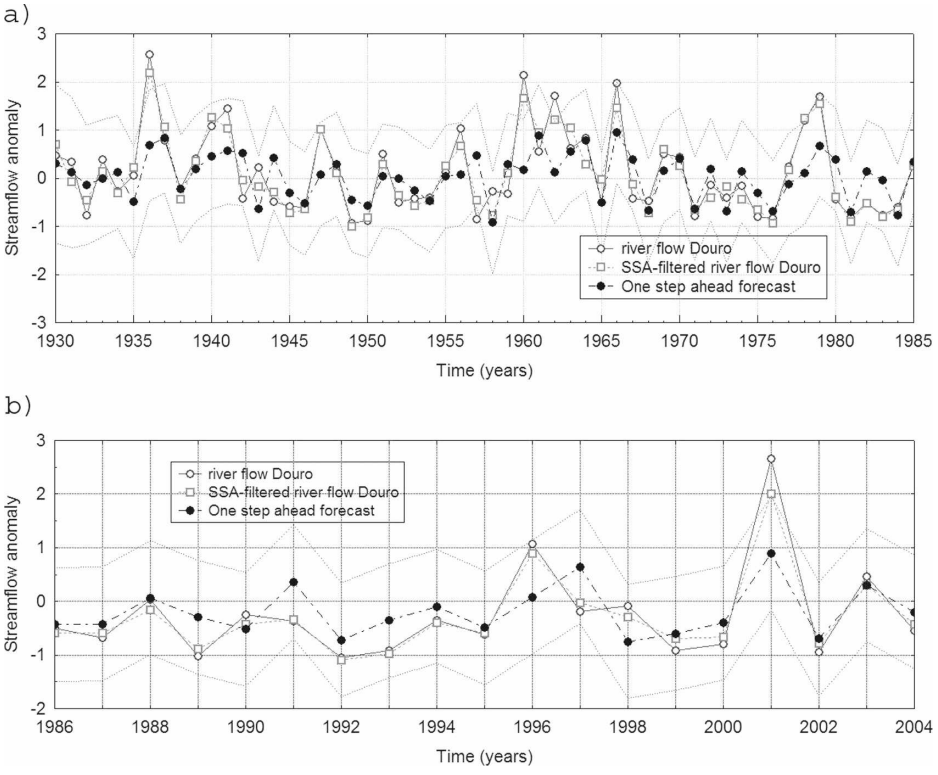

FIG. 5. (a) Results of the forecasting experiment of the Douro river flow. The one-step-ahead forecast for the SSA-filtered Douro streamflow is shown for the period 1931–85. Raw (unfiltered) streamflow data, filtered streamflow data, and the one-step-ahead forecasts along with the 95% confidence intervals are displayed. (b) As in (a), but during the validation period 1986–2004.

$$\text{Douro: AR} = (\Phi_1 = 0, \Phi_2 = 0.34^*, \Phi_3 = 0.41^*, \Phi_4 = 0^*, \Phi_5 = -0.13, \Phi_6 = 0.14, \Phi_7 = -0.25^*),$$
$$\text{MA} = (\theta_1 = -0.74^*, \theta_2 = 0.50^*, \theta_3 = 0.78^*).$$
$$\text{Tejo: AR} = (\Phi_1 = 0.42^*, \Phi_2 = 0.27^*, \Phi_3 = -0.31^*, \Phi_4 = 0.80^*, \Phi_5 = -0.44^*, \Phi_6 = 0^*, \Phi_7 = 0.31^*, \Phi_8 = -0.61^*),$$
$$\text{MA} = (\theta_2 = -0.47^*, \theta_2 = 0.76^*, \theta_3 = 0.76^*, \theta_4 = -0.18^*).$$
$$\text{Guadiana: AR} = (\Phi_1 = 0.38^*, \Phi_2 = 0, \Phi_3 = 0, \Phi_4 = 0.15^*, \Phi_5 = -0.25^*, \Phi_6 = 0.21^*).$$
$$\text{MA} = (\theta_1 = 0.18^*, \theta_2 = 0^*, \theta_3 = 0.36^*, \theta_4 = -0.67^*).$$

The significance of the parameters was computed using approximate t values, derived from the parameter standard errors. Parameters highlighted with an asterisk are statistically significant at the 95% confidence level.

The estimated innovation variances are $\sigma^2_{e\text{Douro}} = 0.29$, $\sigma^2_{e\text{Tejo}} = 0.21$, and $\sigma^2_{e\text{Guadiana}} = 0.29$, which means that the models provide around 44%, 76%, and 39% reduction in the variance (respectively for the Douro, Tejo, and Guadiana) from that of an uncorrelated process (Table 2). Finally the combined variance explained by the SSA filter and the ARMA models is 42% for the raw Douro River flow, 62% for the Tejo, and 25% for the Guadiana (Table 2).

b. Forecasting experiment

A forecasting experiment was conducted for each SSA-filtered winter river flow based on its ARMA model. Results were tested against the raw winter river flow.

Figures 5, 6, and 7 present the results of the forecasting experiments, while Tables 3, 4, and 5 show a summary of the model performance for, respectively, the Douro, Tejo, and Guadiana data. Figures 5a, 6a, and 7a show the one-step-ahead forecasts, that is, the prediction made for one year into the future, during the calibration period and Figs. 5b, 6b, and 7b for the validation period (1986–2004). For the sake of comparison, the raw winter river flow values are also shown.

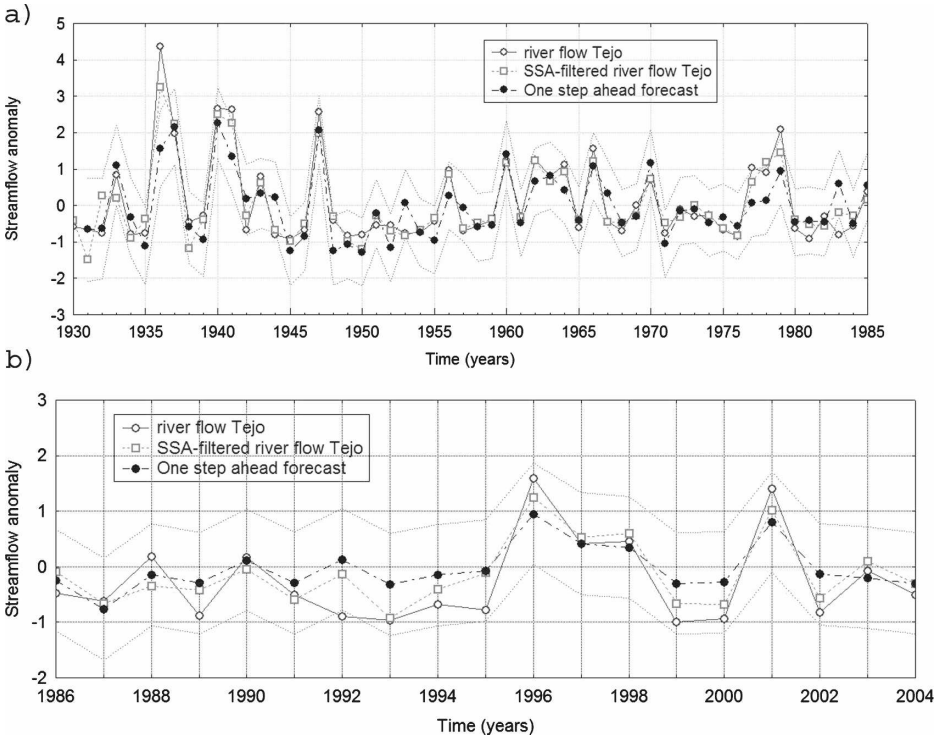

FIG. 6. As in Figs. 5a,b, but for the Tejo River.

Overall, the actual filtered winter river flow values are always within the 95% confidence intervals, indicating that the ARMA models properly represent the main characteristics of the SSA-filtered winter river flows. Additionally, and although the raw data show a considerably higher variability than the filtered one, the observed values fall within the forecasted confidence range. Only in very few cases (both during the calibration and validation period) are the observed values outside of the ARMA forecasting 95% confidence levels.

Results for the Douro River show considerable skill of the ARMA model. Particularly, during the validation period 1986–2004, with the MSE value of 0.38 and the MAE = 0.47, the correlation coefficient is 0.73 (Table 3). As can be observed in Fig. 5b, the model provides a fairly good one-step-ahead forecast; in particular, the raw values are always within the one-step-ahead forecast 95% confidence levels (except 2001). Furthermore, the percentage of cases in which the phase of the river flow was accurately predicted is 90%, which means that the model is able, for the vast majority of cases, to predict a phase change in the river flow. Additionally, the skill against climatology (persistence) is 51% (75%). Results during the calibration period are similar. Particularly, outside the period 1955–65 and the year 1936, the raw values are within the one-step-ahead forecast 95% confidence levels (see Fig. 5a).

The Tejo model presents broadly similar results to those achieved for the Douro. During the validation period, with a MSE of 0.26 and MAE reaching 0.43, the correlation coefficient is 0.85 (Table 4). Moreover, according to Fig. 6b and during the validation period, the raw streamflow values are always within the one-step-ahead 95% confidence intervals. The phase agreement is, as for the Douro case, 90%. The skill against climatology is 53% and 68% against persistence. Results of the calibration period 1931–85 are similar; only in four cases are the raw values outside the 95% confidence intervals (see Fig. 6a).

The Guadiana ARMA forecast results are not as good when compared to the corresponding model performance attained for the Tejo and Douro. Particularly, during the validation period, the MSE is 0.34, the MAE is 0.41, the correlation coefficient drops to 0.47, and the percentage of phase accordance is only 54% (Table 5). Unlike for the Tejo and Douro models, there are several cases in which the raw series falls outside the one-step-ahead forecasting 95% confidence intervals (1992, 1996, 2001, and 2002; Fig. 7b). Nevertheless, the skill improving against climatology is 52%, very similar to the values achieved for the Tejo and Douro cases, and 81% against persistence. The calibration period 1947–85 shows similar results compared to the validation one, in terms of skill and phase agreement, while from Fig.

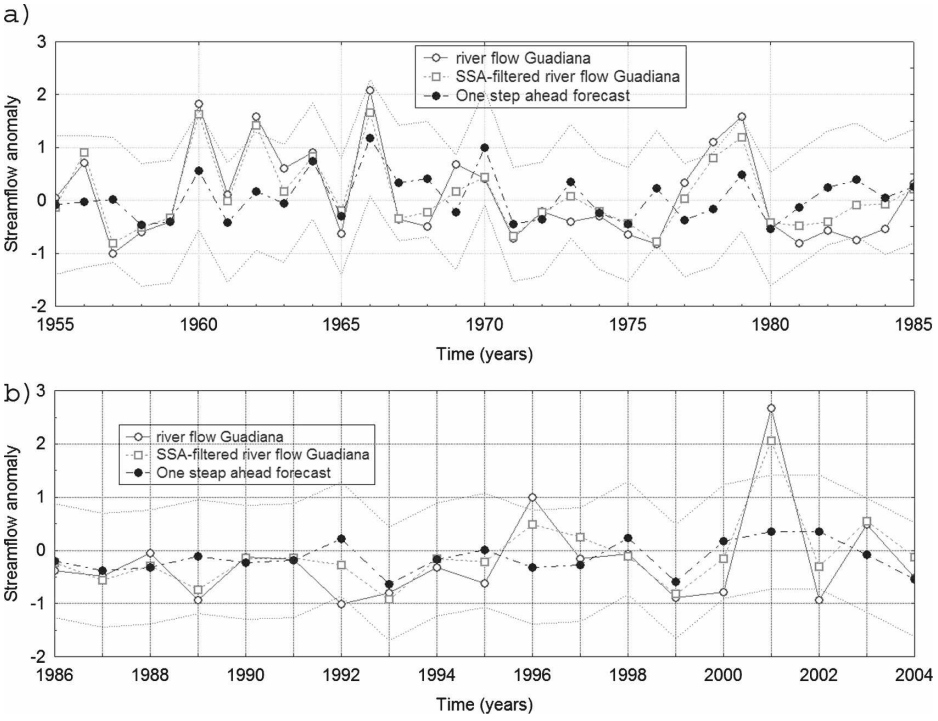

FIG. 7. As in Figs. 5a,b, but for the Guadiana River.

7a we again see several years (1960, 1962, 1979, and 1983) whene the raw values are outside the 95% confidence intervals.

c. Cross validation

As mentioned earlier, the cross-validation schemes for the Douro and Tejo models had to be adapted to the harsh constrains imposed by the ARMA models. Therefore this cross-validation was performed dividing the calibration period 1923–85 into two subperiods, 1923–49 and 1950–74 and then fitting the ARMA models to these two subseries. The unused decades of 1950–60 and 1975–85 were employed for validation.

For the Tejo River and the first subperiod (1923–49), an ARMA(8, 4) model was selected with the following parameters:

$$\mathrm{AR} = (\Phi_1 = 0.45^*, \Phi_2 = 0.10, \Phi_3 = -0.26^*, \Phi_4 = 0.88^*,$$
$$\Phi_5 = -0.44^*, \Phi_6 = 0^*, \Phi_7 = 0.29^*, \Phi_8 = -0.70^*),$$
$$\mathrm{MA} = (\theta_1 = -0.26^*, \theta_2 = 0.74^*, \theta_3 = 0.62^*, \theta_4 = -0.32^*).$$

For the second subperiod (1950–74), the fitted model was also an ARMA(8, 4) having the following parameters:

$$\mathrm{AR} = (\Phi_1 = 0.31^*, \Phi_2 = 0.27^*, \Phi_3 = -0.20^*, \Phi_4 = 0.43^*,$$
$$\Phi_5 = -0.45^*, \Phi_6 = 0.22^*, \Phi_7 = 0.22^*, \Phi_8 = -0.42^*),$$
$$\mathrm{MA} = (\theta_1 = -0.41^*, \theta_2 = 0.47^*, \theta_3 = 0.89^*, \theta_4 = -0.02^*).$$

Tables 7 and 8 summarize the results of the performance test for these two models. A one-to-one comparison of obtained parameters denotes strong similarities between these two models and the model developed for the whole period (see Table 4). Only slight differences for some coefficients can be appreciated, but the order of the models remains unchanged. During the calibration periods, the estimated reduction in variance from that of an uncorrelated process is 64% for the 1923–49 model and 84% for the 1950–1974 model. The value obtained for the total model, 76%, falls in between. Correlation coefficients and phase agreement percentages are also similar to that of the total period model. Regarding the validation period, values in all parameters are similar for the first model validation period, 1950–60. On the other hand, results for the sec-

TABLE 7. Statistical results for the validation ARMA model developed over the period 1923–49 for the Tejo River. Correlation coefficients (r) with an asterisk are statistically significant at the 95% confidence level.

	Raw Tejo vs one-step-ahead forecast (1923–49)	Raw Tejo vs one-step-ahead forecast (1950–60)
MSE	0.69	0.23
MAE	0.60	0.38
r	0.88*	0.76*
Phase accordance (%)	89	81

TABLE 8. As in Table 7, but over the period 1950–74.

	Raw Tejo vs one-step-ahead forecast (1950–74)	Raw Tejo vs one-step-ahead forecast (1975–85)
MSE	0.20	0.50
MAE	0.35	0.60
r	0.81*	0.67*
Phase accordance (%)	76	54

ond model along the period 1975–85 are slightly worse. Particularly, the percentage of phase accordance is only 54% during this period, while the corresponding values are 81% during the 1950–60 decade and 90% over the period 1986–2004. This result is consistent with the fact that the model performance is worse for the 1975–85 decade than for 1950–60 and the whole period model (1923–49). Considering Fig. 6a, there are several years in the 1975–85 decade when the raw values are outside the 95% confidence intervals (1976, 1978, and 1983), while all of the raw values are inside these intervals in the 1950–60 decade.

For the river Douro similar results (not shown) were obtained: thus, it could be concluded that the ARMA models obtained in section 5a can be reasonably considered independent of the period of calibration, providing this period is sufficiently long.

d. ARMA raw-streamflow modeling

For comparison, we conducted an additional ARMA analysis and forecasting experiment similar to those presented in previous sections but using the raw streamflow series with no SSA filter applied. Results were compared against those obtained using the SSA methodology. Results showed that the order of the models were similar for the three rivers to that obtained using the SSA filter, although the magnitude of the parameters retained by the model do change. Nevertheless, the variance explained by the models was considerably lower: 8%, 17%, and 5% respectively for the Douro, Tejo, and Guadina instead of the 42%, 62%, and 25% obtained using the SSA filter approach. Regarding the forecasting skill, these models performed considerably worse than the models obtained based on the SSA filter. Particular, for the validation period 1986–2004 the improvement against climatology in one-step-ahead forecasts was only 3% for the Douro, while the Tejo and Guadian raw streamflow models do not show skill at all (compared to the 51%, 45%, and 52% improvement obtained with the SSA filtered series).

It is concluded that the application of SSA filtering prior to deriving the ARMA models considerably improves the forecasting skill of these ARMA models. The reason for this improvement in the forecasting skill may be partially related to the fact that the SSA acts as a data-adaptive filter, therefore removing the background noise and retaining the leading statistically significant signals. Then, the filtered signal is composed by modulated oscillatory signals and trends and the near-cyclic nature of the modulated oscillatory signals implies predictability. It may be the case that the autocorrelation patterns of the raw climatic time series are hidden by other random signals and that the SSA filtering was successful in removing the influence of these other signals. That is, the SSA filter is able to partially remove background noise, retaining the leading statistically significant (and predictable) components.

6. Summary and concluding remarks

The interannual variability and predictability of the January through March streamflow series of the three major Iberian Peninsula international rivers (Douro, Tejo, and Guadiana) has been studied using SSA and ARMA models. The period of study was 1923–2004 for Douro and Tejo and 1947–2004 for Guadiana.

First, we applied a SSA algorithm to isolate the main characteristics of the streamflow series. Results show a relatively similar model structure for the three rivers that include the following components: 1) a nonlinear trend dominated by decadal variability with periods of 20 to 30 yr; 2) modulated amplitude oscillations with associated periods in the bands 2–3, 4–5, and 6–8 yr; and 3) a red noise process. The resulting model accounts for the 96% variance of the Douro, 82% of the Tejo, and 64% of the Guadiana. If we consider the entire period (calibration and validation) the percentage of cases in which the actual phase of the streamflow series was accurately reproduced was 93%, 90%, and 89% for the Douro, Tejo, and Guadiana, respectively. Results from the SSA analysis also show that the variability associated with the low frequency component (20 to 30 yr) of the streamflow is similar to that associated with the individual components driving the interannual variability. Finally, the analysis of the series does not show the presence of significant trends when we consider the whole record. Nevertheless, there are short-term positive and negative trends in the 1970s and 1980s.

Since interannual winter precipitation variability in the Douro, Tejo, and Guadiana catchments is largely modulated by the NAO mode (Trigo et al. 2004), a study was undertaken to evaluate potential common oscillations present in both the winter NAO and river-flow time series. Results showed the existence of two significant oscillations with periods 7.7 and 4.8 yr

present in both the NAO index and the streamflow series. These oscillations show a general tendency toward an out-of-phase relationship. This out-of-phase evolution makes sense since a negative NAO index is usually related with higher-than-usual precipitation over the Iberian Peninsula. Nevertheless, overall the relationship between the NAO and the river streamflows is complex and nonstationary. We believe that this complexity is associated with the role played by other climate fields such as temperature and wind (variables that influence the evapotranspiration) that are, therefore, also involved in the precipitation–streamflow relationship. It is possible that, only when the NAO is characterized by large amplitude oscillations, is the impact of the NAO rainfall on the streamflow capable of overriding other influences.

In the second part of this paper, an ARMA model was obtained for each SSA-filtered streamflow series and a forecasting experiment was conducted for each winter river flow based on its ARMA model. The models were calibrated for the period 1923–85 (1947–85 for the Guadiana) while the period 1986–2004 was used for validation in all the three cases. Finally, results were tested against the raw (observed) values. An ARMA(7, 3) model, with constrained parameters, was fitted for the Douro, while ARMA(8, 4) and ARMA(6, 4) models were found, respectively, for the Tejo and Guadiana. The percentage of explained variance (in respect to the raw streamflow series) obtained by the ARMA models are 42%, 62%, and 25% for the Douro, Tejo, and Guadiana, respectively. Results of the forecasting experiment proved that the ARMA models possess considerable forecasting skill with one-step-ahead (i.e., to predict the following winter flow based on the models developed until the preceding winter). Although the raw data shows a considerably higher variability than the filtered time series for the vast majority of the cases, the observed values fall within the one-step-ahead 95% forecasting confidence levels. Additionally, during the validation period, the skill of the models against climatology (measured using the MSE) is on the order of 52% for the three rivers, while the skill against persistence is considerably higher, ranging from 68% for the Tejo to 75% and 81% for the Douro and Guadiana, respectively. This indicates that the climatology is a better benchmark than persistence for streamflow forecasting in Iberia. Finally, the models are able in most cases to predict a phase change since phase agreement during the validation period is 90% for the Douro and Tejo and 54% for the Guadiana.

We also conducted an ARMA analysis and forecasting experiment for the raw streamflow series. Results showed that these models performed considerably worse than the models obtained based on the SSA filter technique. It is concluded that the SSA filtering prior to obtaining the ARMA models considerably improves the forecasting skill of these ARMA models. The reason for this improvement in the forecasting skill appears to be related to the fact that the SSA filter is able to partially remove background noise, retaining the leading statistically significant (and predictable) components.

In summary, we believe that we have shown the existence of a valuable interannual predictability of the winter streamflow for the Iberian Peninsula, a result that may be useful to water resources management. We acknowledge that this is a pure time series method that, whatever the quality of results achieved, still lacks predictors with relevant physical information (e.g., SST). Nevertheless, this analysis allows assessing the extent of the interannual predictability of the streamflow. In Part II, we intend to explore explicitly the role of the Atlantic Ocean summer and autumn SST in forecasting the following winter streamflow.

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REFERENCES

Akaike, H., 1974: A new look at the statistical model identification. *IEEE Trans. Automat. Control,* **19,** 716–723.

Allen, M. R., 1992: Interactions between the atmosphere and oceans on time-scales of weeks to years. Ph.D. thesis, University of Oxford, 202 pp.

——, and L. A. Smith, 1994: Investigating the origins and significance of low-frequency modes of climate variability. *Geophys. Res. Lett.,* **21,** 883–886.

——, and ——, 1996: Monte Carlo SSA: Detecting irregular oscillations in the presence of colored noise. *J. Climate,* **9,** 3373–3404.

Anderson, J., H. Van den Dool, A. G. Barnston, and W. C. C. Stern, 1999: Present-day capabilities of numerical and statistical models for extratropical seasonal simulation and prediction. *Bull. Amer. Meteor. Soc.,* **80,** 1349–1361.

Atkinson, D., K. E. Black, L. A. Dawson, Z. Dunsiger, C. A. Watson, and S. A. Wilson, 2005: Prospects, advantages and limitations of future crop production systems dependent upon

the management of soil processes. *Ann. Appl. Biol.,* **146,** 203–215.

Barry, R. G., and R. J. Chorley, 1998: *Atmosphere, Weather and Climate*. Routledge, 409 pp.

Box, G. E. P., and G. M. Jenkins, 1976: *Time Series Analysis: Forecasting and Control*. Holden-Day, 543 pp.

Brockwell, P. J., and R. A. Davis, 1996: *Introduction to Time Series and Forecasting*. Springer-Verlag, 420 pp.

Castro-Díez, Y., D. Pozo-Vázquez, F. S. Rodrigo, and M. J. Esteban-Parra, 2002: NAO and winter temperature variability in southern Europe. *Geophys. Res. Lett.,* **29,** 1160, doi:10.1029/2001GL014042.

Cayan, D. R., K. T. Redmond, and L. G. Riddle, 1999: ENSO and hydrologic extremes in the western United States. *J. Climate,* **12,** 2881–2893.

Coulibaly, P., and D. H. Burn, 2005: Spatial and temporal variability of the Canadian seasonal streamflows. *J. Climate,* **18,** 191–210.

Cullan, H. M., and P. B. deMenocal, 2000: North Atlantic influence on Tigris-Euphrates streamflow. *Int. J. Climatol.,* **20,** 853–863.

Czaja, A., and C. Frankignoul, 2002: Observed impact of Atlantic SST anomalies on the North Atlantic Oscillation. *J. Climate,* **15,** 606–623.

Da Costa, E. D., and A. Colin de Verdiere, 2002: The 7.7 year North Atlantic Oscillation. *Quart. J. Roy. Meteor. Soc.,* **128,** 797–817.

Dai, A., I. Y. Fung, and A. D. Del Genio, 1997: Surface observed global land precipitation variations during 1900–1988. *J. Climate,* **10,** 2943–2962.

Dettinger, M. D., and H. F. Diaz, 2000: Global characteristics of stream flow seasonality and variability. *J. Hydrometeor.,* **1,** 289–310.

Doblas-Reyes, F. J., R. Hagedorn, and T. N. Palmer, 2005: The rationale behind the success of multi-model ensembles in seasonal forecasting. Part II: Calibration and combination. *Tellus,* **57A,** 234–252.

Ellner, S. P., B. A. Bailey, G. V. Bobashev, A. R. Gallant, B. T. Grenfell, and D. W. Nychka, 1998: Noise and nonlinearity in measles epidemics: Combining mechanistic and statistical approaches to population modeling. *Amer. Nat.,* **151,** 425–440.

Esteban-Parra, M. J., F. S. Rodrigo, and Y. Castro-Díez, 1998: Spatial and temporal patterns of precipitation in Spain for the period 1880-1992. *Int. J. Climatol.,* **18,** 1557–1574.

Fraedrich, K., and K. Müller, 1992: Climate anomalies in Europe associated with ENSO extremes. *Int. J. Climatol.,* **12,** 25–31.

Gámiz-Fortis, S. R., D. Pozo-Vázquez, M. J. Esteban-Parra, and Y. Castro-Díez, 2002: Spectral characteristics and predictability of the NAO assessed through singular spectral analysis. *J. Geophys. Res.,* **107,** 4685, doi:10.1029/2001JD001436.

——, ——, R. M. Trigo, and Y. Castro-Díez, 2008: Quantifying the predictability of winter river flow in Iberia. Part II: Seasonal predictability. *J. Climate,* **21,** 2503–2518.

Garcia-Herrera, R., D. Paredes, R. M. Trigo, I. F. Trigo, H. Hernández, D. Barriopedro, and M. T. Mendes, 2007: The outstanding 2004–05 drought in the Iberian Peninsula: Impacts and atmospheric circulation associated. *J. Hydrometeor.,* **8,** 483–498.

Gedalof, Z. M., D. L. Peterson, and N. J. Mantua, 2005: Atmospheric, climatic and ecological controls on extreme wildfire years in the northwestern United States. *Ecol. Appl.,* **15,** 154–174.

Ghil, M., and R. Vautard, 1991: Interdecadal oscillations and the warming trend in global temperature series. *Nature,* **310,** 324–327.

Goddard, L., S. Mason, S. Zebiak, C. Ropelewski, R. Basher, and M. A. Cane, 2001: Current approaches to seasonal-to-interannual climate predictions. *Int. J. Climatol.,* **21,** 1111–1152.

González-Rouco, F., E. Zorita, H. Heyen, and F. Valero, 2000: Agreement between observed rainfall trends and climate change simulations in the southwest of Europe. *J. Climate,* **13,** 3057–3065.

Goodess, C. M., and P. D. Jones, 2002: Links between circulation and changes in the characteristics of Iberian rainfall. *Int. J. Climatol.,* **22,** 1593–1615.

Goossens, C., 1985: Principal component analysis of the Mediterranean rainfall. *Int. J. Climatol.,* **5,** 379–388.

Hansen, J. W., 2002: Realizing the potential benefits of climate prediction to agriculture: Issues, approaches, challenges. *Agric. Syst.,* **74,** 309–330.

Hartmann, H. C., T. C. Pagano, S. Sorooshian, and R. Bales, 2002: Confidence builders: Evaluating seasonal climate forecasts from user perspectives. *Bull. Amer. Meteor. Soc.,* **83,** 683–698.

Hessl, A. E., D. McKenzie, and R. Schellhaas, 2004: Drought and Pacific decadal oscillation linked to fire occurrence in the inland Pacific Northwest. *Ecol. Appl.,* **14,** 425–442.

Hipel, K. W., and A. I. Mcleod, 1994: *Time Series Modelling of Water Resources and Environmental Systems*. Elsevier, 1013 pp.

Houghton, J. T., Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell, and C. A. Johnson, Eds., 2001: *Climate Change 2001: The Scientific Basis*. Cambridge University Press, 881 pp.

INAG, 2001: Plano Nacional da Água. Instituto da Água, Lisbon, Portugal, 800 pp.

Jain, S., C. A. Woodhouse, and M. P. Hoerling, 2002: Multidecadal streamflow regimes in the interior western United States: Implications for the vulnerability of water resources. *Geophys. Res. Lett.,* **29,** 2036–2039.

Katz, R. W., and A. H. Murphy, Eds., 1997: *Economic Value of Weather and Climate Forecasts*. Cambridge University Press, 222 pp.

Kiely, G., 1999: Climate change in Ireland from precipitation and streamflow observations. *Adv. Water Resour.,* **23,** 141–151.

Krepper, C. M., N. O. Garcia, and P. D. Jones, 2003: Interannual variability in the Uruguay River basin. *Int. J. Climatol.,* **23,** 103–115.

Mariotti, A., N. Zeng, and K. M. Lau, 2002: Euro–Mediterranean rainfall and ENSO—A seasonally varying relationship. *Geophys. Res. Lett.,* **29,** 1621, doi:10.1029/2001GL014248.

McGregor, G. R., H. Watkins, and M. L. Cox, 2004: The relationship of the seasonality of temperature and Ischaemic heart disease mortality: Implications for climate based health forecasting. *Climate Res.,* **25,** 253–263.

McKenzie, D., Z. M. Gedalof, D. L. Peterson, and P. W. Mote, 2004a: Climatic change, wildfire, and conservation. *Conserv. Biol.,* **18,** 890–902.

——, S. J. Prichard, A. E. Hessl, and D. L. Peterson, 2004b: Empirical approaches to modeling wildland fire in the Pacific Northwest: Methods and applications to landscape simulations. *Emulating Natural Forest Landscape Disturbances,* A. J. Perera and L. Buse, Eds., Columbia University Press, 85–97.

——, S. O'Neill, N. Larkin, and R. A. Norheim, 2006: Integrating

models to predict regional haze from wildland fire. *Ecol. Modell.,* **199,** 278–288.

Paredes, D., R. M. Trigo, R. Garcia-Herrera, and I. F. Trigo, 2006: Understanding precipitation changes in Iberia in early Spring: Weather typing and storm-tracking approaches. *J. Hydrometeor.,* **7,** 101–113.

Parry, M. L., 2000: Assessment of potential effects and adaptation for climate change in Europe: The ACACIA Project. Jackson Environmental Institute, University of East Anglia, Norwich, United Kingdom, 320 pp.

Pereira, M. G., R. M. Trigo, C. C. Dacamara, J. M. C. Pereira, and S. M. Leite, 2005: Synoptic patterns associated with large summer forest fires in Portugal. *Agric. For. Meteor.,* **129,** 11–25.

Plaut, G., M. Ghil, and R. Vautard, 1995: Interannual and interdecadal variability in 335 years of central England temperatures. *Science,* **268,** 710–713.

Pozo-Vázquez, D., M. J. Esteban-Parra, F. S. Rodrigo, and Y. Castro-Díez, 2001: The association between ENSO and winter atmospheric circulation and temperature in the North Atlantic region. *J. Climate,* **16,** 3408–3420.

Qian, B., J. Corte-Real, and H. Xu, 2000: Is the North Atlantic Oscillation the most important atmospheric pattern for precipitation in Europe? *J. Geophys. Res.,* **105,** 11 901–11 910.

Rimbu, N., C. Boroneant, C. Buta, and M. Dima, 2002: Decadal variability of the Danube River flow in the lower basin and its relation with the North Atlantic Oscillation. *Int. J. Climatol.,* **22,** 1160–1179.

Robertson, A., and C. Mechoso, 2001: Interannual prediction of the Paraná River. *Geophys. Res. Lett.,* **28,** 4235–4238.

Rodrigo, F. S., and R. M. Trigo, 2007: Trends in daily rainfall in the Iberian Peninsula from 1951 to 2002. *Int. J. Climatol.,* **27,** 513–529.

Rodríguez-Puebla, C., A. H. Encinas, S. Nieto, and J. Garmendia, 1998: Spatial and temporal patterns of annual precipitation variability over the Iberian Peninsula. *Int. J. Climatol.,* **18,** 299–316.

Rodwell, M. J., and C. K. Folland, 2002: Atlantic air-sea interaction and seasonal predictability. *Quart. J. Roy. Meteor. Soc.,* **128,** 1413–1443.

Sáez, J., C. Rodriguez-Puebla, J. Fernández, and J. Zubillaga, 2001: Interpretation of interannual winter temperature variations over southwestern Europe. *J. Geophys. Res.,* **106,** 20 641–20 651.

Santos, F. D., K. Forbes, and R. Moita, 2002: *Climate Change in Portugal. Scenarios, Impacts and Adaptation Measures—SIAM Project.* Gradiva, 454 pp.

Saunders, M. A., and B. Qian, 2002: Seasonal predictability of the winter NAO from North Atlantic sea surface temperatures. *Geophys. Res. Lett.,* **29,** 2049, doi:10.1029/2002GL014952.

——, ——, and B. Lloyd-Hughes, 2003: Summer snow extent heralding of the winter North Atlantic Oscillation. *Geophys. Res. Lett.,* **30,** 1378, doi:10.1029/2002GL016832.

Scarsbrook, M. R., C. G. BcBride, G. B. McBride, and G. C. Bryers, 2003: Effects of climate variability on rivers: Consequences for long term water quality analysis. *J. Amer. Water Resour. Assoc.,* **39,** 1435–1447.

Schneider, J. M., and J. D. Garbrecht, 2003: A measure of the usefulness of seasonal precipitation forecasts for agricultural applications. *Trans. ASAE,* **46,** 257–267.

Serrano, A., A. J. Garcia, V. L. Mateos, M. L. Cancillo, and J. Garrido, 1999: Monthly modes of variation of precipitation over the Iberian Peninsula. *J. Climate,* **12,** 2894–2919.

Shaman, J., M. Stieglitz, S. Zebiak, and M. Cane, 2003: A local forecast of land surface wetness conditions derived from seasonal climate predictions. *J. Hydrometeor.,* **4,** 611–626.

——, J. F. Day, M. Stieglitz, S. Zebiak, and M. Cane, 2006: An ensemble seasonal forecast of human cases of St. Louis encephalitis in Florida based on seasonal hydrologic forecasts. *Climatic Change,* **75,** 495–511.

Trigo, R. M., and C. C. DaCamara, 2000: Circulation weather types and their impact on the precipitation regime in Portugal. *Int. J. Climatol.,* **20,** 1559–1581.

——, T. J. Osborn, and J. Corte-Real, 2002: The North Atlantic Oscillation influence on Europe: Climate impacts and associated physical mechanisms. *Climate Res.,* **20,** 9–17.

——, D. Pozo-Vázquez, T. J. Osborn, Y. Castro-Díez, S. Gámiz-Fortis, and M. J. Esteban-Parra, 2004: North Atlantic Oscillation influence on precipitation, river flow and water resources in the Iberian Peninsula. *Int. J. Climatol.,* **24,** 925–944.

Vautard, R., and M. Ghil, 1989: Singular spectrum analysis in non-linear dynamics with applications to paleoclimatic time series. *Physica D,* **35,** 395–424.

——, P. Yiou, and M. Ghil, 1992: Singular spectrum analysis: A toolkit for short, noisy chaotic signal. *Physica D,* **58,** 95–126.

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences: An Introduction*. Academic Press, 467 pp.

Wu, A., and W. Hsieh, 2004: The nonlinear Northern Hemisphere winter atmospheric response to ENSO. *Geophys. Res. Lett.,* **31,** L02203, doi:10.1029/2003GL018885.