# Investigating the potential of NAO index to forecast droughts in Sicily

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**Abstract.** Drought monitoring and forecasting is essential for an effective drought preparedness and mitigation. The use of large-scale climatic patterns, such as El Nino Southern Oscillation (ENSO), North Atlantic Oscillation (NAO ) or European Blocking (EB), can potentially improve the forecasting of drought evolution in time and space, provided the influence of such indices on the climatic variability in a region is verified.

In the present paper, a stochastic model for the seasonal forecasting of the Standardized Precipitation Index (SPI), developed in previous works, is extended in order to include information from NAO index. In particular SPI forecasts at a generic time horizon *M* are analytically determined, in terms of conditional expectation, as a function of a finite number of past observations of SPI and NAO, assuming a multivariate normal as the underlying distribution. In addition, an expression of the Mean Square Error (MSE) of prediction is also derived, which allows confidence intervals of prediction to be estimated. The forecasting performance of the model is verified by hindcasting observed SPI values computed on monthly areal average precipitation series observed in Sicily and validation is carried out by repeatedly applying a jackknife scheme.

Preliminary results of the comparison between the model based only on the past observations of SPI values and the one that includes also the NAO index, seem to indicate a slight improvement of the latter model. Such results however cannot be considered conclusive and further analyses are needed in order to better assess the use of NAO as a predictor for droughts in Sicily.

## 1. Introduction

It is largely recognized that an effective mitigation of the most adverse drought impacts is possible, more than in the case of other extreme hydrological events such as floods, earthquakes, hurricanes, etc., due to the fact that drought is a phenomenon whose consequences take a significant amount of time with respect to its inception in order to be perceived by the socio-economic systems. Within this context, an accurate monitoring and forecasting of drought, able to promptly warn of the onset of a drought and to follow its evolution in space and time, represents the prerequisite for a successful mitigation strategy (Rossi, 2003).

Among the several drought indices that have been proposed for drought monitoring (Heim, 2000) the Standardized Precipitation Index (SPI) (McKee et al., 1993) and the Palmer Index (Palmer, 1965) have probably found the most widespread application. Although most of the proposed indices have been developed with the objective to monitor current drought conditions, nevertheless some of them can find application to forecast the possible evolution of an ongoing drought, in order to adopt appropriate mitigation measures and drought policies for water resources management. Attempts in this direction have been made, with reference to the Palmer index (Karl et al., 1986, Cancelliere et al., 1996, Lohani et al., 1998) or SPI (Cancelliere et al., 2005; Bordi et al. 2005). Recently, Cancelliere et al. (2006) have proposed a stochastic model to forecast SPI values at short-medium term as well as to estimate transition probabilities of SPI classes corresponding to drought of different severities.

Despite such efforts, forecasting when a drought is likely to begin or to come to an end remains a difficult task (Cordery and McCall, 2000). Recently, important progress is being made in relation to the possibilities of using information provided by large-scale climatic indices, such as the North Atlantic Oscillation (NAO), as a support to forecast drought evolution. Indeed, use of such indices to forecast droughts, could allow for an improved forecasting ability of the models, as well as for a longer time horizon of forecasting, provided they exert some influence on the climatic variability in a region.

The aim of the present paper is to assess whether taking into account information from a large scale climatic index leads to improvements in the forecasting of SPI drought index in Sicily, Italy. In particular, a previously developed methodology that enables to estimate seasonal forecast of the SPI by means of non-parametric stochastic techniques, is extended in order to include information provided by an exogenous variable such as NAO index. Analytical expressions of short-medium term forecasts of the Standardized Precipitation Index are derived as the expectation of future SPI values conditioned on past SPI and NAO values.

Following a preliminary correlation analysis between SPI series computed on areal precipitation in Sicily and NAO series in the same or previous time intervals, the model is applied and tested with reference to the same SPI series, making use of NAO as exogenous variable. Validation of the models, based on the historical areal precipitation series observed in 40 precipitation stations in Sicily, is carried out by iteratively applying a jackknife scheme, namely by repeatedly dividing the observations into two sets, one for parameter estimation and one for evaluating the forecasting accuracy of the model. Moreover, MSE between the values derived by jackknife and the corresponding observed values is computed, in order to evaluate the accuracy of the model. Such performance indicator allows confidence intervals for forecasted values to be computed.

## 2. The North Atlantic Oscillation and its effects on precipitation and drought in Europe

The North Atlantic Oscillation has been recognized more than 70 years ago as one of the major patterns of atmospheric variability in the Northern Hemisphere. However, only recently it has become the subject of a wider interest. Historically, the NAO has been defined as a simple index that measures the difference of normalized surface pressure between Ponta Delgada in the Azores and Stykkisholmur in Iceland. Recently, researchers have proposed that, during the winter season, stations located in the Iberian peninsula could be used with some advantages over Ponta Delgada. Hurrel (1995) started to use Lisbon and Jones et al. (1997) opted for Gibraltar. However, it should be stressed that all of those indices are highly correlated, presenting correlation coefficients values higher than 0.9 between them.

Several studies have established links between the NAO phase and precipitation in western Europe and the Mediterranean basin (Hurrell, 1995; Qian et al., 2000). The correlation between NAO index and precipitation observed in Europe shows a significant dependence between the two variables. Such control exerted by NAO on the precipitation regime is related to corresponding changes in the associated activity of North-Atlantic storm tracks that affect the western European border (Goodess and Jones, 2002).

Over the past decade the Oscillation has remained in one extreme phase during the winters, contributing significantly to the recent wintertime warmth across Europe and to cold conditions in the northwest Atlantic (Hurrell et al., 2001). For example, NAO has a major role in controlling European climate and appears to exert a strong influence in modulating North Atlantic ecosystems. During the positive phases of NAO, the North Atlantic westerlies, which provide much of the atmospheric moisture to north Africa and Europe, shift northward. This, in turn, results in drier conditions over southern Europe, the Mediterranean Sea and northern Africa (Hurrell, 1995).

Other correlation analyses (Wedgbrow et al., 2002) have demonstrated that positive winter anomalies of NAO index are associated with negative PDSI (i.e. drought) across eastern parts of the British Isles in summer ($r < 0.51$).

## 3. Preliminary correlation analysis between SPI series in Sicily and NAO index series

A preliminary correlation analysis between SPI series in Sicily and NAO index series has been carried out by means of Pearson correlation coefficient. The choice of such correlation coefficient is justified by the fact that SPI series are normally distributed by definition, and that an analysis of the investigated NAO series showed that it can be considered normally distributed as well.

SPI series have been computed on areal monthly precipitation series from 1921 until 2003, obtained by applying Thiessen polygons method on 40 precipitation stations in Sicily. The selected stations are included in the drought monitoring bulletin published on the web-site of the Sicilian Regional Agency for Waste and Water - Water Observatory, formerly Hydrographic Service (Rossi and Cancelliere, 2002, http://www.uirsicilia.it ). Regarding the NAO series, following Jones et al. (1997), it was decided to adopt the Gibraltar–Iceland NAO index developed by the Climatic Research Unit of the University of East Anglia, UK.

According to the characteristics of SPI index and of NAO index and his influence on meteorological variables, a time scale of 4 months has been adopted for the SPI series, whereas NAO series have been averaged on a 4 months period which end in the same month of the SPI.

For both series fall-winter months have been selected, since they account for most of annual precipitation in Sicily, and furthermore they generally present the highest (negative) values of correlation between NAO and precipitation (Hurrell, 1995).

In Figure 1 correlation values between the considered series are shown, for three periods of observation of different length (i.e., 1923-2003, 1974-2003 and 1984-2003). In order to investigate possible lead times, the correlations have been computed also by shifting 1, 2 and 3 months ahead the SPI series. It is evident how the correlation significantly increases as the period considered coincides with the last three or two decades. Besides, the highest values of correlation generally correspond to the periods from November to February and from December to March.

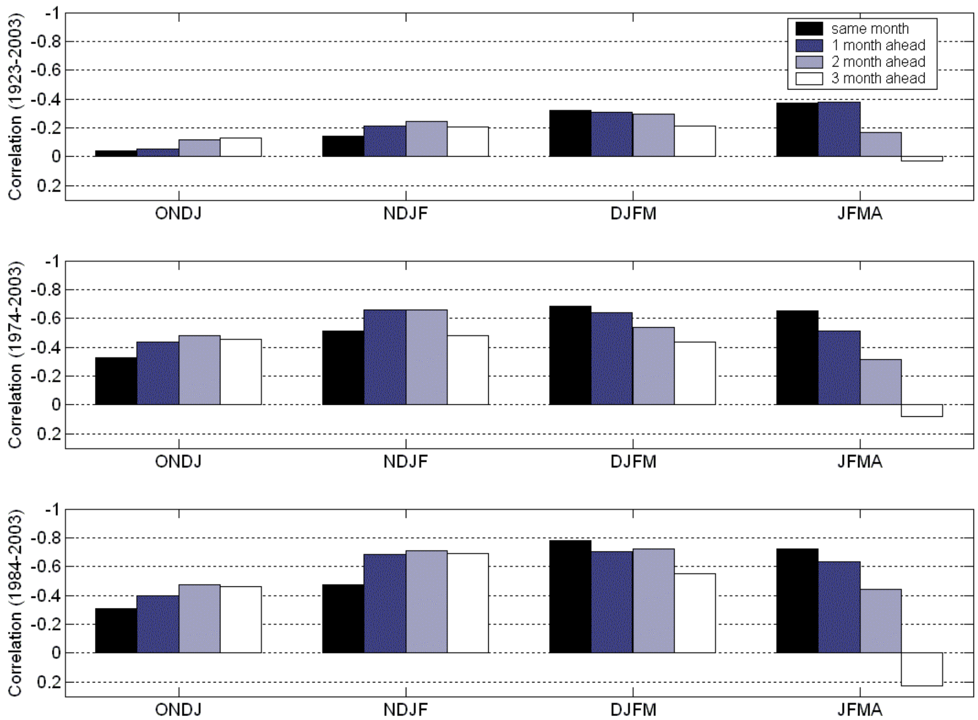


**Figure 1.** Pearson correlation coefficients between NAO series (averaged on 4 months) and SPI series (k=4 months) simultaneous and shifted 1, 2 or 3 months ahead.

Figure 2 shows the NAO series averaged on the months from December to March (DJFM) and three different SPI series (with an aggregation time scale $k$= 4 months) corresponding to March, April and May (respectively 0, 1 and 2 months ahead), for the last 20 years. The plot seems to confirm from a qualitatively point of view the significant negative correlations shown in Table 2, and therefore NAO appears as a potential candidate to be included as an exogenous variable within a forecasting model for SPI series.

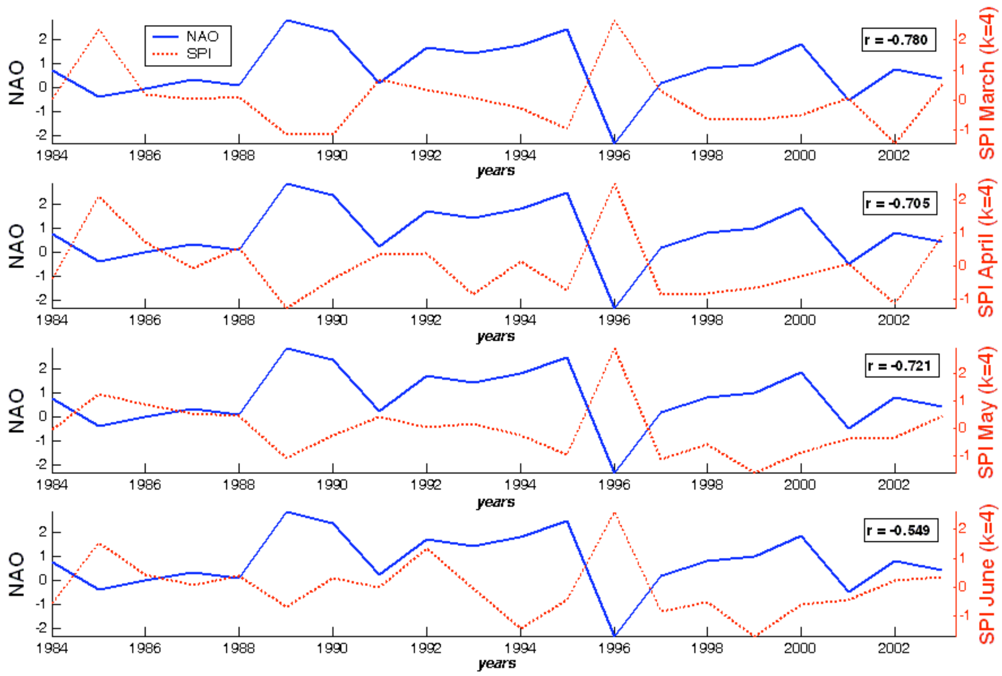


**Figure 2.** Comparison among NAO averaged on DJFM months and SPI time series (*k*=4) corresponding to March, April, May and June, on the period 1984-2003.

## 4. SPI forecasting

From a stochastic point of view, the problem of forecasting future values of a random variable can be pursued by fitting a parametric model (e.g. ARMA, FARMA, etc.) to an observed sample, and by deriving, either analytically or by means of a Montecarlo approach, best forecasts, according to a predefined criterion. Such an approach however requires the preliminary selection of an appropriate model, as well as the estimation of its parameters. Alternatively, in some cases the problem can also be addressed by deriving the probability density function of future values conditioned by past observations. Indeed, it can be shown that the expected value of such a conditional distribution yields a forecast with minimum Mean Square Error (MSE) (Brockwell and Davis, 1996). Furthermore, knowledge of the conditional distribution allows confidence intervals of prediction to be computed. Here the latter approach will be followed to forecast future values of SPI, capitalizing on the intrinsic normality of the index.

Let's define $Z_{\nu,\tau}$ as the SPI value at year $\nu$ and month $\tau = 1, 2, \ldots 12$, for an aggregation time scale $k$ of monthly precipitation. The interest here lies in determining the conditional distribution (and the expectation) of a future value $M$ months ahead $Z_1 = Z_{\nu,\tau+M}$, conditioned on the vector of $\theta$ past observations $\mathbf{Z}_2 = \left[Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots Z_{\nu,\tau-\theta+1}\right]$, i.e. the distribution of the variable:

$$Z_{1|2} = Z_{\nu,\tau+M} \left| Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots Z_{\nu,\tau-\theta+1} \right. .$$

The conditional density function of $Z_{1|2}$ is defined as:

$$f_{\mathbf{Z}_{1|2}}(z) = \frac{f_{\mathbf{Z}}(\mathbf{z})}{f_{\mathbf{Z}_2}(\mathbf{z_2})} \tag{1}$$

where $f_{\mathbf{Z}}(\mathbf{z})$ is the multivariate pdf of the random vector $\mathbf{Z} = \left[Z_{\nu,\tau+M}, Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots Z_{\nu,\tau-\theta+1}\right]^T$ and $f_{\mathbf{Z}_2}(\mathbf{z_2})$ is the joint density function of $\mathbf{Z_2}$.

Since, by definition, the SPI is marginally distributed as a standard normal variable, it is fair to assume that both vectors $\mathbf{Z}$ and $\mathbf{Z_2}$ are multivariate normal with zero mean. The variance-covariance matrix $\boldsymbol{\Sigma}$ of $\mathbf{Z}$ can be partitioned as follows:

$$\mathbf{Ó} = \begin{bmatrix} \mathbf{Ó}_{11} & \mathbf{Ó}_{12} \\ \mathbf{Ó}_{21} & \mathbf{Ó}_{22} \end{bmatrix} \tag{2}$$

where:

$$\Sigma_{11} = Var\left[Z_1\right] = 1 \tag{3}$$

$$\mathbf{Ó}_{12} = \mathbf{Ó}_{21}^{\mathrm{T}} = Cov\left[\mathbf{Z_1}, \mathbf{Z_2}\right] \tag{4}$$

$$\mathbf{Ó}_{22} = Cov\left[\mathbf{Z_2}, \mathbf{Z_2}\right] \tag{5}$$

According to a well known statistical property of multivariate normal distributions the conditional density function of $Z_{1|2}$ is normal itself (Kotz et al., 2000). Besides, reminding that the SPI has zero mean, it can be shown that the expected value of $Z_{1|2}$ is (Kotz et al., 2000):

$$\mathrm{E}\left[Z_{1|2}\right] = \mathbf{Ó}_{12} \cdot \mathbf{Ó}_{22}^{-1} \cdot \mathbf{z} \tag{6}$$

where $\mathbf{z} = \left[z_{\nu,\tau}, z_{\nu,\tau-1}, \ldots z_{\nu,\tau-\theta+1}\right]^T$ is the vector of past observations. Equation (6) yields the best forecast (in MSE sense) of a future value $\tilde{Z}_{\nu,\tau+M}$ given $\theta$ past observations. Furthermore, it is easy to see that the above forecast is unbiased and therefore the Mean Square Error of forecast coincides with the variance of $Z_{1|2}$, which is given by (Kotz et al., 2000):

$$MSE = \mathrm{Var}\left[Z_{1|2}\right] = 1 - \mathbf{Ó}_{12} \cdot \mathbf{Ó}_{22}^{-1} \cdot \mathbf{Ó}_{21} \tag{7}$$

Obviously, if $Z_{\nu,\tau+M}$ is uncorrelated with $Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots, Z_{\nu,\tau-\theta}$, the best forecast of $Z_{\nu,\tau+M}$ is its expected value, and furthermore, the MSE of prediction is just the variance of $Z_{\nu,\tau+M}$.

If $\theta$=1, i.e. the forecast is based only on the present value, eq. (6) simplifies as:

$$\tilde{Z}_{\nu,\tau+M} = \mathrm{E}\left[Z_{\nu,\tau+M} \mid Z_{\nu,\tau} = z_{\nu,\tau}\right] = \rho \cdot z_{\nu,\tau} \tag{8}$$

while the Mean Square Error becomes:

$$MSE = \mathrm{Var}\left[Z_{\nu,\tau+M} \middle| Z_{\nu,\tau} = z_{\nu,\tau}\right] = 1-\rho^2 \tag{9}$$

where $\rho$ is the correlation coefficient between $Z_{\nu,\tau}$ and $Z_{\nu,\tau+M}$

The previous methodology can be extended in order to include also an exogenous variable. With reference to a variable $W_{\nu,\tau}$, let's consider the vector of past observations $\mathbf{Z_2}$:

$$\mathbf{Z}_2 = \left[Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots Z_{\nu,\tau-\theta+1}, W_{\nu,\tau}\right]^T \tag{10}$$

The conditioned variable will be:

$$Z_{1|2} = Z_{\nu,\tau+M} \middle| Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots, Z_{\nu,\tau-\theta+1}, W_{\nu,\tau} \tag{11}$$

while the random vector $\mathbf{Z}$:

$$\mathbf{Z} = \left[Z_{\nu,\tau+M}, Z_{\nu,\tau}, Z_{\nu,\tau-1}, \ldots, Z_{\nu,\tau-\theta+1}, W_{\nu,\tau}\right]^T \tag{12}$$

Assuming the exogenous variable normally distributed, it is correct to assume the vector $\mathbf{Z}$ as normal multivariate with zero mean and variance-covariance matrix $\mathbf{\Sigma}$, partitioned like the previous case (eqs. 2-5).

In order to compute the expected value of the conditioned distribution and the related MSE, previous expressions can be used (eqs. 6-7), by taking into account the vector of past observations:

$$\mathbf{z} = \left[z_{\nu,\tau}, z_{\nu,\tau-1}, \ldots, z_{\nu,\tau-\theta+1}, w_{\nu,\tau}\right]^T \tag{13}$$

Besides MSE, a practical way of quantifying the accuracy of the forecast is by estimating the confidence interval of prediction, i.e. an interval that contains the future observed value with a fixed probability $p$. Obviously, the wider the interval, the less is the accuracy of the forecast and vice-versa. Confidence intervals of prediction for SPI can be estimated by capitalizing on the intrinsic normality of the index and by observing that, since the predictor is unbiased, its variance coincides with the MSE. Thus, the upper and lower confidence limits $B_{1,2}$ of fixed probability $\gamma$ can be computed as:

$$B_{1,2} = \tilde{Z}_{\nu,\tau+M} \mp \sqrt{MSE} \cdot u\left(\frac{1-\gamma}{2}\right) \tag{14}$$

where $u\left(\frac{1-\gamma}{2}\right)$ is a standard normal variate with non-exceeding probability $\left(\frac{1-\gamma}{2}\right)$.

## 5. Application of the model

In according to the correlation analysis presented in section 3, the proposed forecasting methodology has been applied with reference to the months from October to April. These months account for about 80% of the annual rainfall in Sicily and the influence of NAO on the Mediterranean pluviometric regime seems more significant during this period of the year.

Different combinations of starting months $\tau$ (January, February, March and April) and time horizons $M$ (1, 2 and 3 months) have been considered during the investigation. In all cases, a time scale equal to 4 months for both SPI and NAO (average) series has been adopted.

Following the results of the correlation analysis previously reported (see Figure 1), as well as by taking into account the need of a proper sample size for a reliable statistical analysis, the period 1974-2003 has been selected as the period on which to test the forecasting model.

First, the model has been verified with reference to the whole observation period 1974-2003. As an example, Figure 3 illustrates time series of observed SPI and forecasted SPI referred to February as starting month ($\tau$=2) and April as forecasting month ($M$=2). Forecasted SPI values have been hereafter derived either by considering only the SPI value at month $\tau$ (namely, eq. 8) or by also including the contemporary NAO value. From the figure, no clear-cut improvement in the forecasts can be inferred when NAO is included in the model (blue dashed-dotted line), although in some years (e.g. 1983, 1989, 1996, 1999), the forecasts computed by considering NAO appear closer to the observed values than in the other case.

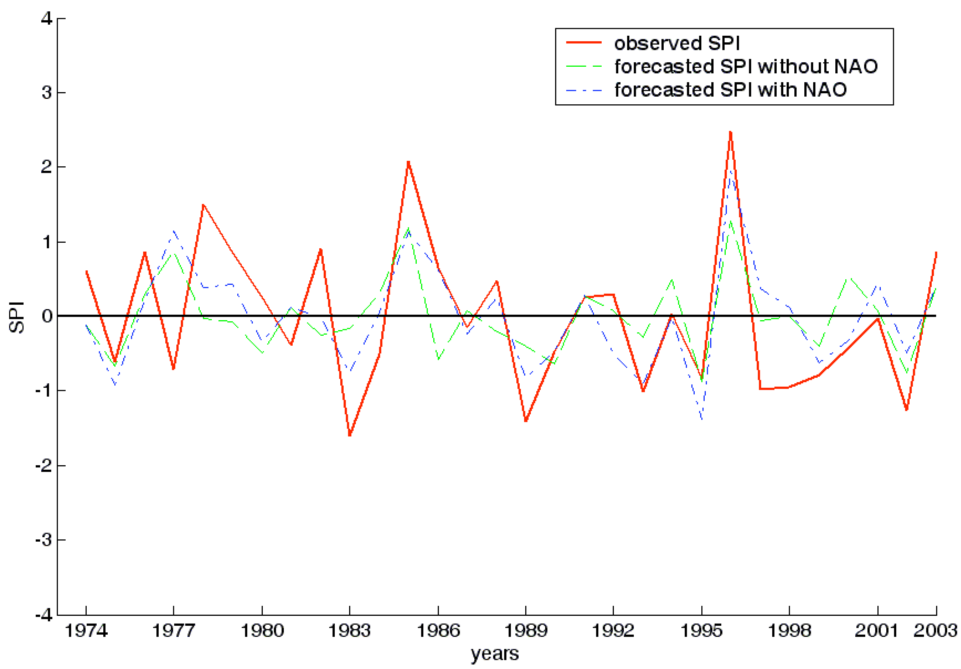


**Figure 3.** SPI observed and SPI forecasted with or without NAO (starting month: February, $M$=2 months, $k$=4 months, verification period: 1974-2003).

In order to assess from a quantitative point of view the performance of the proposed forecasting model, MSEs computed by not considering NAO (i.e. eq. 7) have been compared with those obtained by including the NAO index.

Results for different starting months and time horizons $M$ are reported in Figure 4 with respect to the verification period 1974-2003. As it can be observed, the use of NAO index within the forecasting model leads to some reduction of corresponding MSEs in all considered cases, with special reference to January and February.

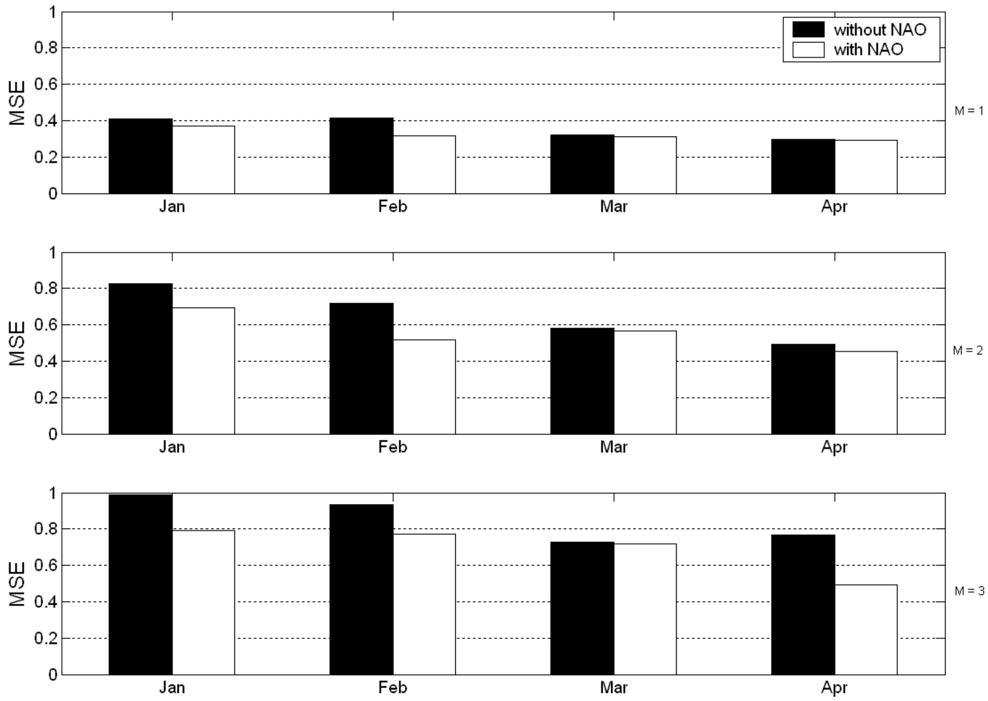


**Figure 4.** Comparison between MSEs computed on the observed series for the two forecasting models (with and without NAO), for different time horizon (M = 1, 2 and 3 months) and different starting month (verification period: 1974-1993).

Then, the forecasting model has been validated by means of repeatedly applying a jackknife scheme. This has been done by excluding the generic $i^{th}$ observation from the calibration set and by hindcasting its value. By repeating such procedure for each of the observations in the available sample, a validation set of 30 hindcasted values has been computed.

In Figure 5 observed and forecasted SPI values are shown with reference to February as starting month ($\tau$=2) and March ($M$=1), April ($M$=2) and May ($M$=3) as forecasting months, for the validation period 1974-2003. Furthermore, confidence limits for $\gamma$= 95% have been computed by eq. (14) only for the case of forecasting also including the NAO index.

Figure 5, which refers to the validation of the model, seems to confirm the considerations already done with reference to the verification of the model (Figure 3). In particular, including NAO in the model apparently improves the forecasts in some years, although a general improvement cannot be inferred. A general good accuracy of both forecasting models can be inferred for all the analyzed cases, since almost all the observed SPI values lie within the confidence limits. As expected, the agreement between observed and forecasted values gets worse as the time horizon increases.

Finally, a comparison between MSEs computed on the observed series corresponding to the forecasting model either with NAO and without NAO, has been carried out in order to quantify whether taking into account the NAO index within the model yields an effective improvement.

As it can be observed from Figure 6, a general reduction of MSEs is obtained when the information provided by NAO values is included in the forecasting model. In particular, a reduction of about 9 % is obtained for $M$=1 month, while for $M$=2 months and $M$=3 months the reduction is respectively about 20 % and 16 %. Similar results have been obtained by considering different starting months, such January, March or April.

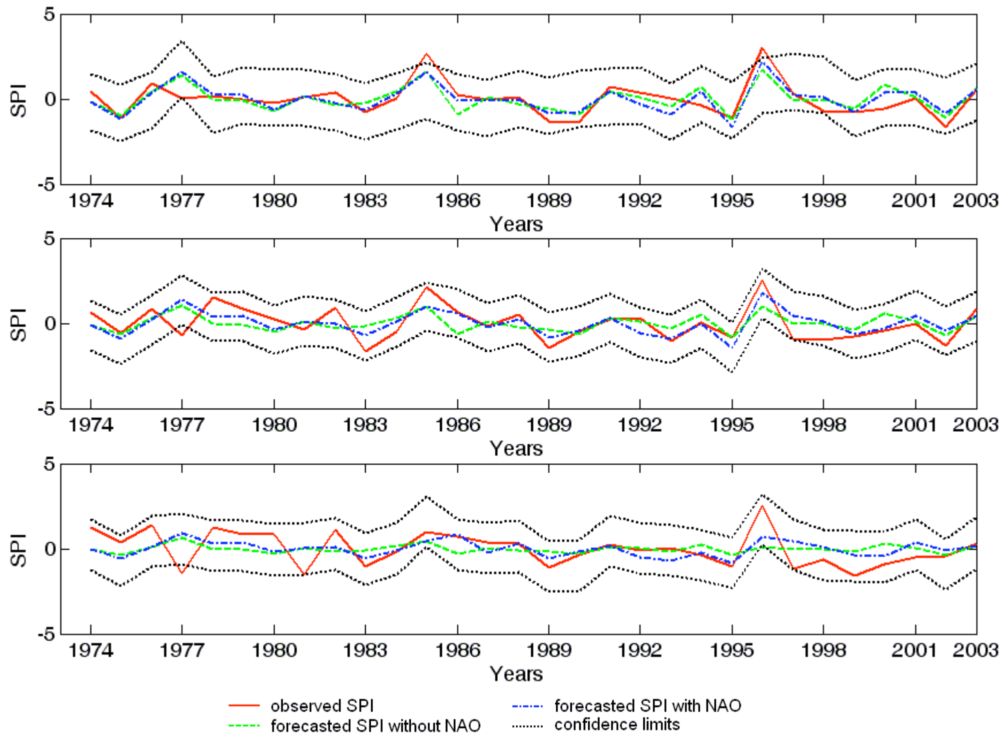


**Figure 5.** SPI observed and SPI forecasted with or without NAO for different time horizons $M$ (starting month February, $k$=4 months, validation period: 1974-2003).

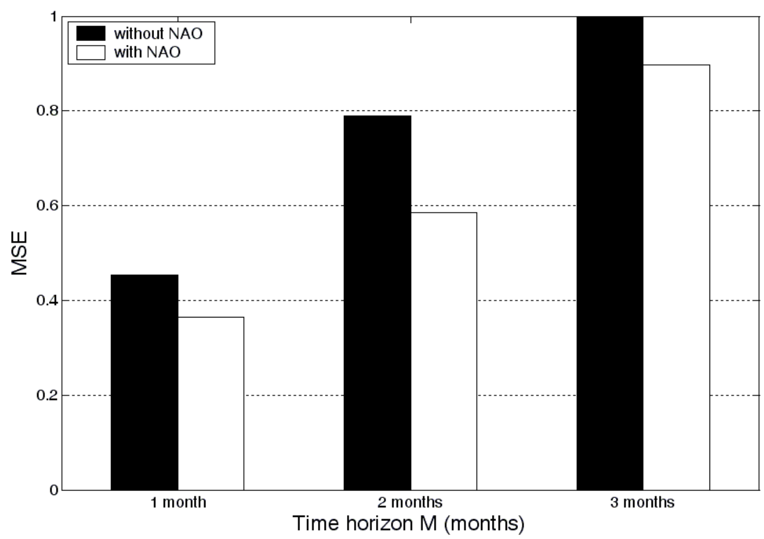


**Figure 6.** Comparison between MSEs computed on the observed series for the two forecasting models (with and without NAO) for different time horizon $M$ (starting month: February, validation period: 1974-2003).

## 6. Conclusions

Advances in understanding the influence of large-scale climatic patterns on the climate in a region can potentially contribute to a better forecast of drought conditions. In the present paper an attempt is made to verify whether the use of the NAO index could improve drought forecasting, with special reference to Sicily region.

First the NAO influence on SPI series computed on areal monthly precipitation from 1921 until 2003 in Sicily, has been investigated by means of a correlation analysis. Results indicate that the NAO series are significantly anti-correlated with SPI series for winter months and especially on the last decades.

Then, the information provided by NAO index has been included within a previously developed forecasting model for SPI, under the assumption of multivariate normal as the underlying distribution.

The comparison between the winter forecast obtained by either including or not the NAO values within the model, indicates some improvements in the forecast when the NAO is considered, especially in terms of MSE. Such preliminary results however are not conclusive, and further research is being carried out in order to investigate non-linear dependencies between SPI and NAO, as well as to consider different time scales and number of past observations for both series in the forecasting model.

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