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Weather drought index prediction using the support vector regression in the Ansegmir Watershed, Upper Moulouya, Morocco

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Abstract: The purpose of this study is to develop mathematical models based on artificial intelligence: Models based on the support vectors regression (SVR) for drought forecast in the Ansegmir watershed (Upper Moulouya, Morocco). This study focuses on the prediction of the temporal aspect of the two drought indices (standardized precipitation index – *SPI* and standardized precipitation-evapotranspiration index – *SPEI*) using six hydro-climatic variables relating to the period 1979–2013.

The model SVR3-SPI: *RBF*, $\varepsilon = 0.004$, $C = 20$ and $\gamma = 1.7$ for the index *SPI*, and the model SVR3-SPEI: *RBF* $\varepsilon = 0.004$, $C = 40$ and $\gamma = 0.167$ for the *SPEI* index are significantly better in comparison to other models SVR1, SVR2 and SVR4. The SVR model for the *SPI* index gave a correlation coefficient of $R = 0.92$, $MSE = 0.17$ and $MAE = 0.329$ for the learning phase and $R = 0.90$, $MSE = 0.18$ and $MAE = 0.313$ for the testing phase. As for the *SPEI* index, the overlay is slightly poorer only in the case of the SPI index between the observed values and the predicted ones by the SVR model. It shows a very small gap between the observed and predicted values. The correlation coefficients $R = 0.88$ for the learning, $R = 0.86$ for testing remain higher and corresponding to a quadratic error average $MSE = 0.21$ and $MAE = 0.351$ for the learning and $MSE = 0.21$ and $MAE = 0.350$ for the testing phase. The prediction of drought by SVR model remain useful and would be extremely important for drought risk management.

Keywords: Ansegmir watershed, drought, forecast, modelling, standardized precipitation index (*SPI*), standardized precipitation-evapotranspiration index (*SPEI*), support vectors regression (SVR)

INTRODUCTION

Morocco is a Mediterranean country facing a shortage of water resources due to arid and semi-arid conditions, exacerbated by global climate changes. Recurrent droughts have occurred in the last five decades, having a significant impact on both surface and ground water resources.

Drought might be defined as a temporary natural disequilibrium, hardly predictable, resulting in a decrease in the availability of water resources [PEREIRA *et al.* 2009]. When lasts for a long time, it affects the natural environment of a region.

Upper Moulouya is ranked among the areas marked by a strong agricultural production. For several years, it has been susceptible of a rainfall deficiency. Indeed, the management of groundwater resources used by various economic sectors is a complicated task and subject to several factors. It is appositely important to better understand and predict drought, since it can have significant impacts on economic, agricultural, and environmental activities as well as water stocks.

Pursuant to these threats, it is important to have efficient tools to detect and follow up drought conditions. It is within this framework we have a research problem raised by the present study, a study which was initiated based on prerequisite motivations.

A variety of measurement methods have been applied for predicting and patterning of the drought level. Among these methods, we can mention, for example, artificial neural network (ANN), support vectors regression (SVR), and wavelet neurons (WN). Support vectors regression models are mathematical models whose architecture is inspired by a biological neuron network. Such networks are strongly adapted to patterning non-linear phenomena. The main advantage of these models versus other classical models is in their ability to solve problems which can be hardly formalized. The advantage of the SVR is that it could transfer a non-linear problem to a linear problem using the kernel function and be effective in solving a higher dimension problem.

The purpose of this study is to monitor consequences of drought through climatic indices, such as standardized precipitation index (*SPI*) and standardized precipitation-evaporation index (*SPEI*) by applying artificial intelligence techniques. The development of such models necessitates efficient modeling and reliable forecasts and simulations.

Hence, the purpose of the present study is to predict the weather drought index for the Ansegmir watershed (Upper Moulouya, Morocco) using *SPI* and *SPEI* through the implementation of SVR data-driven models. As such, the current study proposes to apply new methods of drought forecasting based on artificial intelligence while using of SVR models.

MATERIALS AND METHODS

STUDY AREA

The study is held in the Ansegmir valley situated in the watershed of upper Moulouya. From an administrative point of view, it is a part of the Midelt district (Dra-Tafilalt region), and hydraulically it belongs to the watershed of upper Moulouya. In the north, it is bound by the province of Ifrane, Boulmane and Midelt in the east, Er-Rachidia and Beni Mellal in the south, and Khenifra in the west. It is wedged between the mountain ranges of the middle and high Atlas which geographical position is marked by hilly terrain with an altitude ranging from 1400 to 3000 m a.s.l. (Fig. 1). Its average annual temperature is 14.10°C with a daily minimum 6.02°C on average and daily average maximum of 22.18°C during the study period (1978–1979 and 2012–2013). The climate is arid cold with a mountainous tendency. The rainfall pattern is marked by poor rainfall of 200 mm, combined with an extreme variability and irregularity. Brutal stormy rainfall brings upstream-eroded products, and sometimes, when climate conditions are in its favor, the region experiences snow [CHAHBOUNE *et al.* 2014].

The Ombrothermic diagram of Bagnouls and Gaussen is based on average temperatures and rainfall over the period of 1979–2013. The dry period, longer than the wet period, lasts for six months from April to October (Fig. 2).

The upper Moulouya geology is composed of Paleozoic age sites, cross-linked by Hercynian granitic intrusions, metamorphic granite and shale outcropping in bottomholes of Zaida, Ahouli, to the east of Bou Mia and Kerrouchen to the west on which a dismatchedmesozoic coverage has recently formed [COMBE, SIMONOT 1971; EMBERGER 1965]. In the occidental part of upper Moulouya, triassiclangs are generally made of marls, dolerits, red clay, and basalts laying in dismach on a Hercynian bedrock made up by metamorphic granite and shale (Fig. 3) [COMBE, SIMONOT 1971].

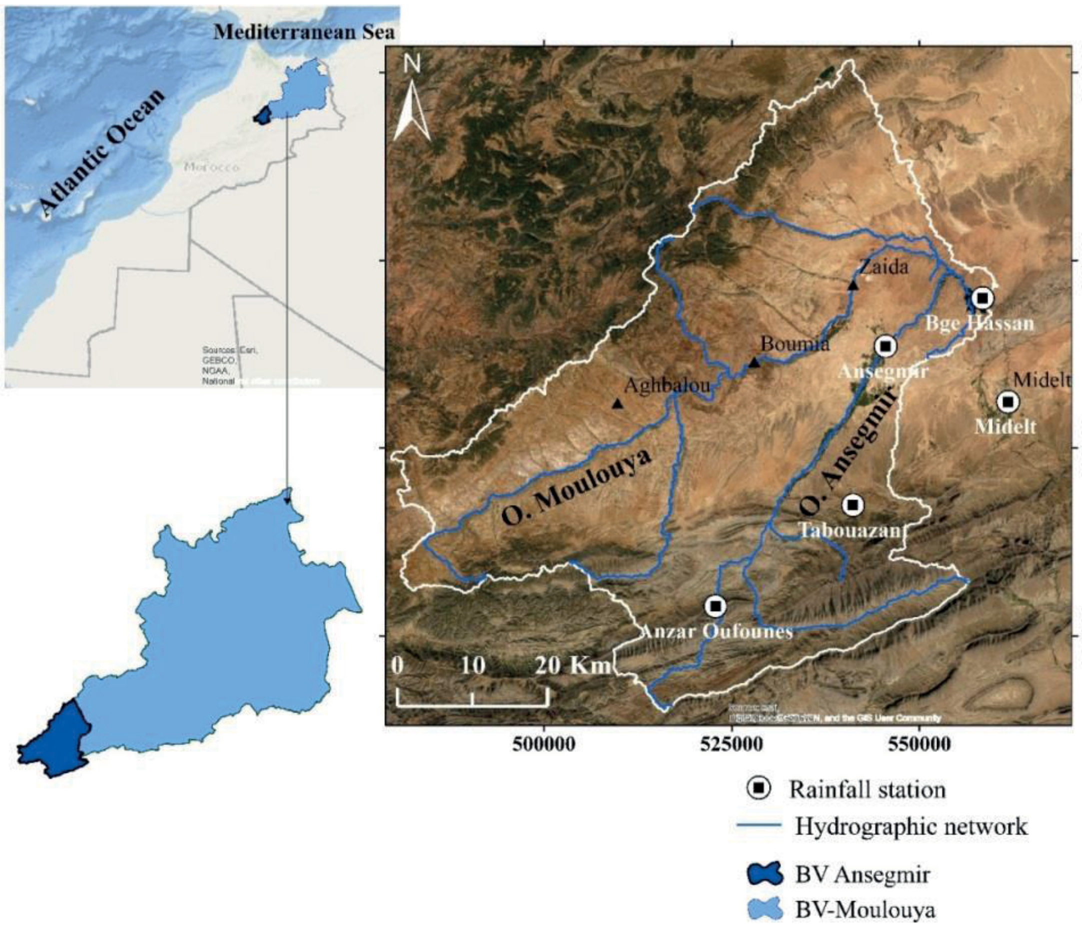

Fig. 1. Geographic location of the study area; source: own elaboration

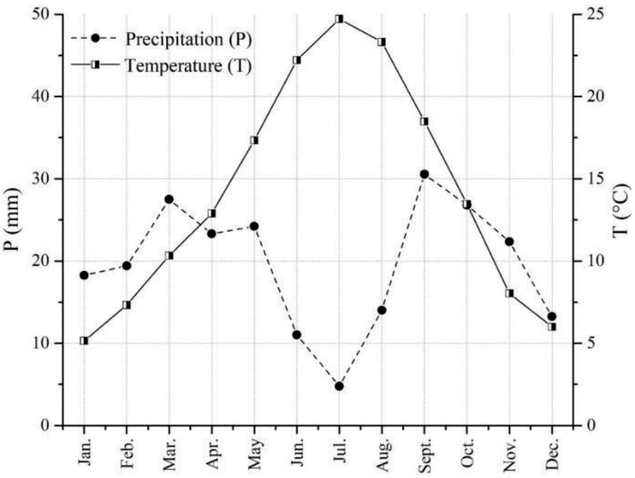

Fig. 2. Bagnouls-Gaussen's diagram of the study area; source: own elaboration

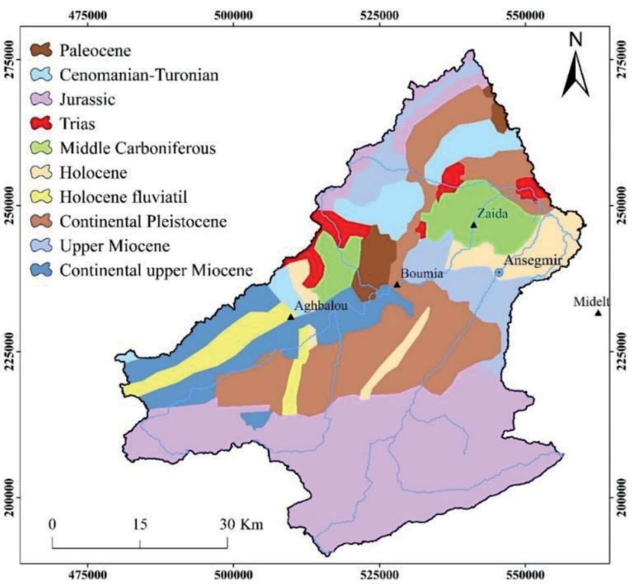

Fig. 3. Extract from the geological map of Morocco (Moroccan geological service 1985, scale 1/1 000 000); source: own elaboration

DATA USED

A monthly rainfall rate database has been set up for the computing of the *SPEI* index in the studied region. The database used covers a period of thirty-five years, from 1978 to 2013 (Tab. 1). The majority of data are received from the Moulouya Basin Hydraulic Agency (Fr. Agence du Bassin Hydraulique de la Moulouya) and the other data are retrieved from the soil and water assessment tool (SWAT).

DROUGHT INDEX

Droughts can be quantified using multiple hydro-meteorological drought indices, of which the most popular are the Palmer index [PALMER 1965], standardised precipitation index [MCKEE *et al.* 1993], index of the surface water supply [SHAFER, DEZMAN 1982], dryness index of flows [NALBANTIS, TSAKIRIS 2009], standard hydrological index [SHARMA, PANU 2010], standard index of maximum evapotranspiration [VICENTE-SERRANO *et al.* 2010], and agricultural drought benchmark index [WOLI *et al.* 2012].

Table 1. The input and output variables considered for developing the forecasting model

Variable – meteorological parameters	Code	Kind of variables
Monthly maximum air temperature (°C)	*TMAX*	independent
Monthly minimum air temperature (°C)	*TMIN*	
Monthly average precipitation (mm)	*PRCP*	
Monthly mean wind speed (m·s^{-1})	*AWND*	
Monthly average relative humidity (%)	*HR*	
Monthly mean solar radiation (MJ·m^{-2})	*TSUN*	
Standardized precipitation index	*SPI*	dependent
Standardized precipitation-evapotranspiration index	*SPEI*	

Source: own elaboration.

Multiple indices have been used to characterize hydrological droughts. These require, in general, a lot of data and calculations, unlike very simple and efficient meteorological drought indices, such as the standardized precipitation index (*SPI*) [NALBANTIS, TSAKIRIS 2009] and the standardized precipitation-evapotranspiration index (*SPEI*) [VICENTE-SERRANO *et al.* 2010].

STANDARDISED PRECIPITATION INDEX (*SPI*)

The standardized precipitation index is a very simple index created by MCKEE *et al.* [1993]. It is a benchmark recommended by the World Meteorological Organization in 2009 to facilitate drought monitoring and climate-related risk management. *SPI* is a standardized monthly indicator, which is based on the probability of precipitation (*P*) occurring regardless the time period considered. It is expressed mathematically as follows:

$$SPI = \frac{P_i - P_m}{\sigma} \tag{1}$$

where: P_i = rain per month or year, P_m = average rainfall of the series on the time scale considered; σ = standard deviation of the series on the considered time scale.

Drought occurs when the *SPI* is consecutively negative and its value reaches an intensity of –1 or less, and ends when the *SPI* becomes positive.

MCKEE *et al.* [1993] uses the classification system to define drought intensities resulting from the *SPI*. Based on the *SPI* values, severity of drought is classified as extremely wet for *SPI* ≥ 2.00, very wet for *SPI* ϵ <1.5; 1.99>, moderately wet for *SPI* ϵ <1.00; 1.49>, near normal for *SPI* ϵ <−0.99; 0.99>, moderately dry for *SPI* ϵ <−1.00; −1.49>, severely dry for *SPI* ϵ <−1.50; −1.99> and extremely dry for *SPI* ≤ −2.00.

STANDARDISED PRECIPITATION-EVAPOTRANSPIRATION INDEX (*SPEI*)

The *SPEI* is calculated using the same method in *SPI*. It is therefore also standardized and can be calculated at different time scales. This index is based on precipitation and potential evapotranspiration (*PET*), while the *SPEI* is based on the difference between precipitation (*P*) and potential evapotranspiration (*PET*). Then, to this cumulative value of (*P* – *PET*) over months, the log-logistic law with three parameters is adjusted [Beguería *et al.* 2014]. The calculation of this index requires potential evapotranspiration (*PET*) as an input parameter.

The data for the *PET* parameter are not available and must therefore be estimated using several methods, such as the Thornthwaite method [Thornthwaite 1948], Hargreaves method [Hargreaves 1994] or the Penman method [Penman 1948]. Each of these methods has its own advantages and disadvantages in terms of data required.

Recent studies, such as the study of Mavromatis [2007], have shown that the use of simple or complex methods to calculate the *PET* could produce similar results when a drought index is calculated. Thus, in this study, we adopt the simplest approach to calculate the *PET* [Thornthwaite 1948], which has the advantage of only requiring data on monthly mean temperature and the latitude of stations studied.

In this study, we adopt the Thornthwaite method that requires the monthly mean temperature and the latitude of stations studied. The *PET* is calculated using following formula:

$$PET = 16K\left(\frac{10T}{I}\right)^{a} \tag{2}$$

where: T = monthly mean temperature (°C), I = heat index, which is calculated as the sum of 12 monthly index values according to (Eq. 3) computed based on mean monthly temperatures:

$$i = \left(\frac{t}{5}\right)^{1.514} \tag{3}$$

where: a = a coefficient depending on I (Eq. 4):

$$a = 6.75 \cdot 10^{-7} I^3 - 7.71 \cdot 10^{-5} I^2 + 1.79 \cdot 10^{-2} I + 0.49 \tag{4}$$

where: K = a correction coefficient derived as a function of the latitude and month.

SUPPORT VECTOR REGRESSION (SVR)

It is difficult to obtain operating models of complex processes and it requires skills and time. The use of wide-margin separators in the case of regression is a promising alternative to the modelling of these systems.

Large margin separators are part of predictive methods that involve neural networks. This method was first introduced in 1995 by Vapnik [1995] and is based on the principle of the structural risk minimization. Theoretically, it minimizes the expected error of a learning machine and thus reduces the problem of overfitting. The SVR have recently been extended to the domain of regression problems [Dibike *et al.* 2001; Liong, Sivapragasam 2002; Vapnik [1999]. Let the set D be the set of N data pairs, having a data vector X_i as input data and the label Y_i of this vector as output data, which can now take any real value.

The goal of the SVR is to find a function $f(x)$ that has at most ε deviation from the obtained target y_i for all training data and meanwhile as flat as possible. In general, the approximating function of the SVR takes the linear form (Eq. 5):

$$f(x) = w\varphi(x) + b \tag{5}$$

where: $\varphi(x)$ represents high dimensional space characteristic which maps the input space vector x, w and b = coefficients to be estimated from input data by minimizing the regularized risk equation.

Training the SVR means solving (Eq. 6):

$$\text{minimizing}\,\frac{1}{2}\|w\|^2 + C\sum\nolimits_{i=1}^{n}\left(\varepsilon_i + \varepsilon_i^*\right) \tag{6}$$

where: $\frac{1}{2}\|w\|^2$ represents the regularization term, C represents the error penalty feature controlling the trade-off between the error and regularization term, ε_i and $\varepsilon_i{}^*$ are positive and negative errors indicating upper and lower excess deviation [Brereton, Lioyd 2010].

The most important feature of the SVR is to establish data correlations by non-linear mapping. There are different types of kernels, such as linear function, sigmoid function, polynomial function and radial basis function (RBF). However, the 'RBF' kernel type has proven to be effective and it is used for the current analysis. In addition to the kernel type, the model is dependent on three different parameters: ε, C and γ which will be explained bellow [Belayneh *et al.* 2016; Chevalier *et al.* 2011; Smola, Schölkopf 2004].

STATISTICAL EVALUATION OF THE SVR MODEL PERFORMANCE

The efficiency of the model in forecasting the monthly *SPI* and *SPEI* is statistically assessed using three different performance metrics for the output during the testing period. Statistical tests include mean square error (*MSE*), mean absolute error (*MAE*), and coefficient of correlation (*R*). Mathematical equations for calculating the efficiency of the model are as follows:

$$MSE = \frac{1}{N}\left(\sum\nolimits_{i=1}^{n}(SPI_m - SPI_{es})\right)^2 \tag{7}$$

$$MAE = \frac{1}{N}\sum\nolimits_{i=1}^{n}|SPI_m - SPI_{es}| \tag{8}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(SPI_m - SPI_{es})}{\sum_{i=1}^{n}\left(SPI_m - \overline{SPI}\right)}} \tag{9}$$

where: SPI_m = measured value, SPI_{es} = predicted (estimated) value and $\overline{SPI}$ is = measured values mean, and n = number of data points.

RESULTS

The total number of samples includes 420 observations covering relative data from the five stations shown in Figure 1 and studied over 35 years (1979–2013). This database includes six explanatory variables (independent), namely maximum temperature, minimum temperature, precipitation, relative humidity, solar radiation, wind and speed, and two dependent variables (to be predicted) represented by the standardized precipitation index (*SPI*) and standardized precipitation-evapotranspiration index (*SPEI*) and drought indices.

In the last step, model development ends with the model validation by examining the model's performance on data that is not used in training. This is done through the performance criteria, the mean square error (*MSE*) and the mean absolute error (*MAE*). The model, which gives the best performance criteria, is chosen for drought forecasting. The data are divided into two parts: learning and testing (Tab. 2).

Table 2. Repartition of data from 1979 to 2013 used for the construction of support vector regression (SVR) models

Start database: 420 observations	
Learning: 315 obs.	Testing: 105 obs.
75% of the data base	25% of the data base

Source: own study.

In the implementation of the SVR for drought modelling through *SPI* and *SPEI* climatic indices, the learning and testing data are monthly weather parameter data. The multiple data (input/outputs/control variables) characterizing the process are retrieved from the program and broken down into two parts. The first part of 315 samples (75% of 420 samples) is used for training and building of the model. The remaining portion of 105 samples (25% of a total of 420) is used for testing. The obtaining of a fairly robust relationship between the input and output variables consists of choosing an input that is sufficiently rich in information. The frequency and amplitude of this input should be chosen to excite the system sufficiently to capture the input/output relationship (which amounts to choosing the input so as to make the system observable). Indeed, this nonlinear system generally depends on the input. The input must enable to follow the trajectory and, at the same time, to be continuously exciting (or persistent excitation) to obtain a good identification that makes it possible to extract the dynamics of the system. Input variables in this system are summarized in Table 1. The values of the *SPI* and *SPEI* indices represent the output variable.

The SVR model was developed using the online-SVR software created by [Parrella 2007]. The Online SVR is a technique used to build support vector machines for regression. The online-SVR partitions divide the database into two parts: one part for learning and the other for testing.

There are different nuclei for regression: linear kernel, Gaussian and a radial kernel. In this study, the SVR model is used with the kernel of the non-linear radial base function. The database has been divided into two parts: 75% for learning, and 25% for testing.

As a result, each SVR model consisted of three parameters that were selected: γ, C and ε. The γ parameter is a constant that reduces the model space and controls the complexity of the solution, whereas C is a positive constant that corresponds to a capacity control parameter, and ε is the loss function that describes the regression vector [Kisi, Cimen 2011]. The C parameter is responsible for the balance between the simplicity of the model and the quantity of error,   is the difference between the desired result and the model result, and it is considered as the level of tolerated error of the model. If the difference is superior to the value of , it will be corrected by the C parameter [Belayneh, Adamowski 2012; Belayneh *et al.* 2016].

Four regression models have been tested for each climatic index (*SPI* and *SPEI*) to predict the degree of drought: the SVR with a radial basis function (RBF), sigmoid, polynomial and linear kernel. The set of these models will be evaluated with a mean square error (*MSE*) and the correlation coefficient (*R*) between the predicted values with the model and the observed values.

To select these three parameters (ε, C and γ), a large number of trials were carried out with different combinations for the four function kernels (linear, polynomial, sigmoid and RBF). To evaluate the performance of the proposed method, experiments were conducted to determine the relative significance of each independent parameter (input SVR) on this index (*SPI* and *SPEI*) (output). The mean squared error (*MSE*) and correlation coefficient (*R*) were used to evaluate differences between the observed and predicted values for SVR1, SVR2, SVR3 and SVR4.

The results of correlations and the *MSE* coefficients obtained for each kernel functions are presented in Table 3. These results show that the experimental values and the output values of the *SVR* model are better linked to each other compared to that modelled by: *SVR* with an *RBF* kernel (Tab. 3). However, the RBF has proved to be effective and was used in this study.

Table 3. Optimization parameters for the support vector regression (SVR) model in the test period

SVR model	Kernel function	ε	C	γ	R	MSE
SVR1-*SPI*	linear	0.100	10	–	0.792	0.354
SVR1-*SPEI*		0.100	10	–	0.799	0.317
SVR2-*SPI*	polynomial	0.100	10	0.167	0.758	0.480
SVR2-*SPEI*		0.100	10	0.167	0.704	0.510
SVR3-*SPI*	RBF	0.004	20	1.70	**0.92**	**0.17**
SVR3-*SPEI*		0.004	40	0.167	**0.88**	**0.213**
SVR4-*SPI*	sigmoid	0.004	10	0.167	0.143	6.037
SVR4-*SPEI*		0.004	10	0.167	0.145	2.927

Explanations: *SPI* = standardized precipitation index, *SPEI* = standardized precipitation-evapotranspiration index, ε = loss function that describes the regression vector, C = positive constant that is a capacity control parameter, γ = constant that reduces the model space and controls the complexity of the solution, and bolded values = best values for R and *MSE*.
Source: own study.

The forecasting results show that the SVR3-*SPI* model: RBF, ε = 0.004, C = 20 and γ = 1.7 for the *SPI* index, and the SVR3-*SPEI* model: RBF, ε = 0.004, C = 40 and γ = 0.167 for the *SPEI* index are sharply the best compared to the other models (SVR1, SVR2 and SVR4) (Tab. 3).

The models are henceforth very accurate because the correlation coefficient which determines the adjustment quality of the model is very high (R must be the closest to 1) for the learning phase and the testing phase.

In the case of prediction, *SPI* and *SPEI* indices are used during the learning and testing phases. The superposition is excellent between the observed and predicted values. (Fig. 7). The

SVR model for the *SPI* index has given a correlation coefficient R = 0.920, *MSE* = 0.17 and *MAE* = 0.329 for the learning phase and R = 0.903, *MSE* = 0.18 and *MAE* = 0.313 for the testing phase (Fig. 8, Tab. 4).

For the *SPEI* index, the overlay is slightly worse than in the case of the *SPI* index between the observed and predicted values in the SVR model. It shows a very small difference between the observed and predicted values (Fig. 7). The correlation coefficients R = 0.88 for the learning, R = 0.86 for the test remain high as well and correspond to *MSE* = 0.21 and *MAE* = 0.351 for the learning phase and *MSE* = 0.21 and *MAE* = 0.350 for the testing phase (Fig. 8, Tab. 4).

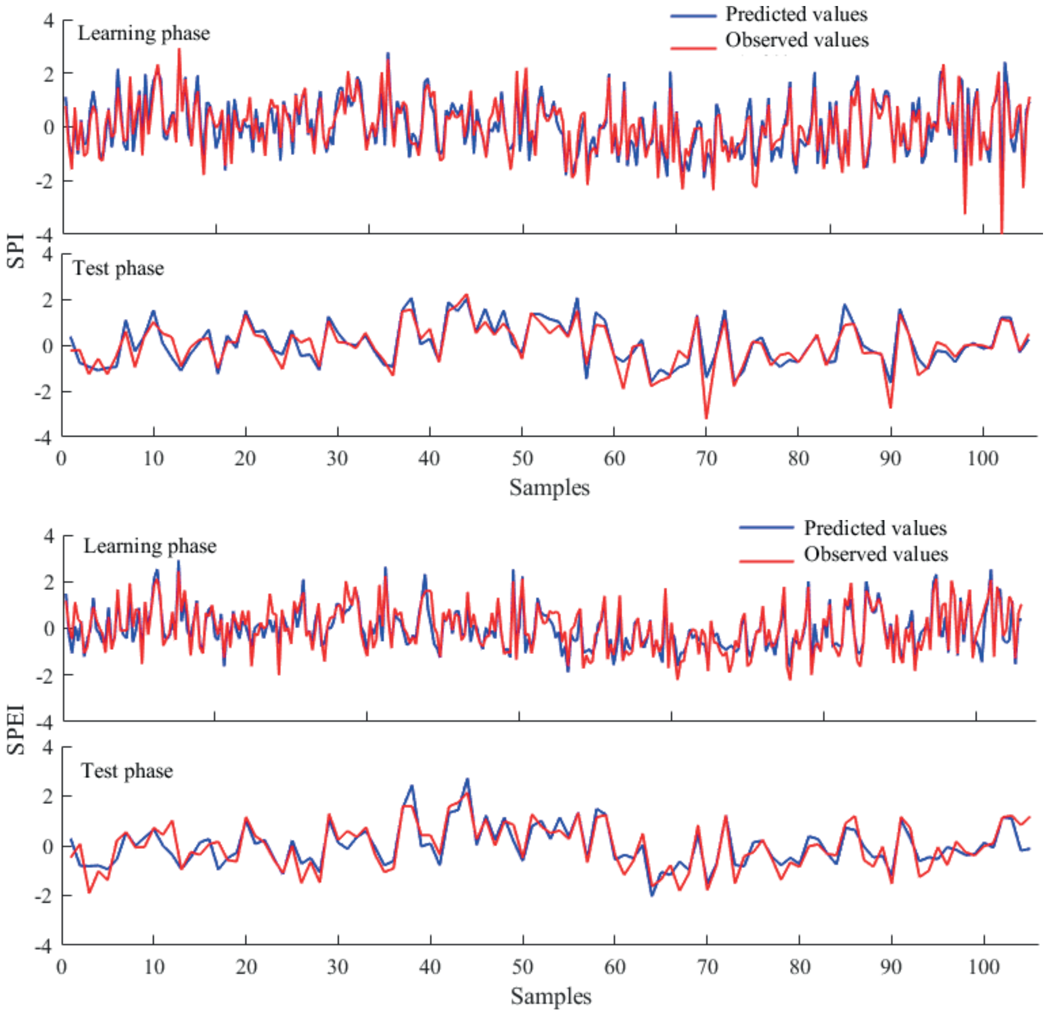

Fig. 7. Observed and predicted standardized precipitation index (*SPI*) and standardized precipitation-evapotranspiration index (*SPEI*) values using the support vector regression model; source: own study

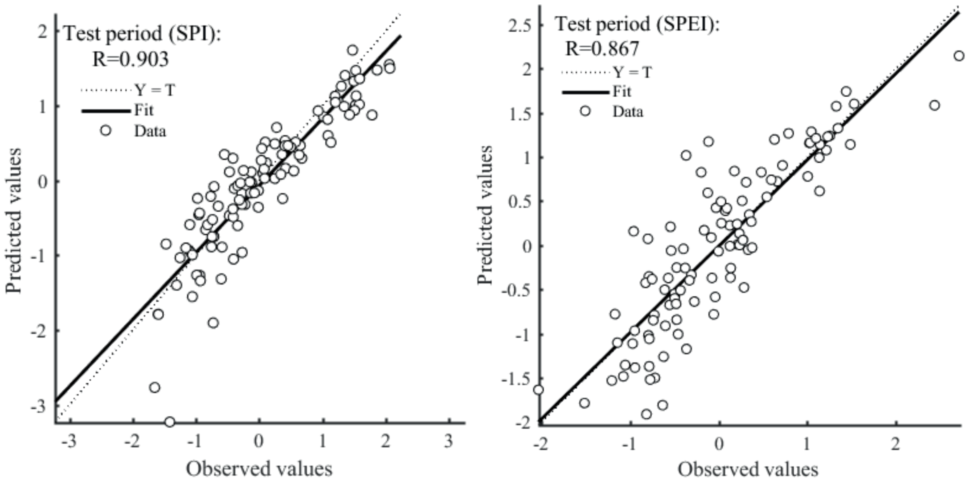

Fig. 8. Correlation between the observed and predicted values of support vector regression model for the prediction of standardized precipitation-evapotranspiration index (*SPEI*) and standardized precipitation index (*SPI*) in the test period; source: own study

Table 4. Support vector regression (SVR) model performance indices for the prediction of drought degree

SVR model	Learning			Testing		
	MSE	*R*	*MAE*	*MSE*	*R*	*MAE*
SVR-*SPI*	0.170	0.92	0.329	0.180	0.90	0.313
SVR-*SPEI*	0.217	0.885	0.351	0.215	0.867	0.350

Explanations: *SPI* = standardized precipitation index, *SPEI* = standardized precipitation-evapotranspiration index, *MSE* = mean square error, *R* = correlation coefficient, *MAE* = mean absolute error.

DISCUSSION

The SVR models are used for the prediction of drought in the region of Upper Moulouya through the *SPI* and *SPEI* indices. They have demonstrated good performance in the prediction model (Tab. 5).

The obtained correlation coefficients in the SVR model are close to 1 with 0.92 for the *SPI* and 0.88 for the *SPEI*, whereas the mean square errors established by the model are relatively very low *MSE* = 0.17 for the *SPI* and *MSE* = 0.22 for the *SPEI*.

Table 5. Comparison between the performance indices established by the support vector regression (SVR) models for the prediction of the degree of drought

SVR model	*R*	*MSE*	*MAE*
SVR-*SPI*	0.915	0.172	0.325
SVR-*SPEI*	0.881	0.216	0.351

Explanations: *SPI* = standardized precipitation index, *SPEI* = standardized precipitation-evapotranspiration index, *MSE* = mean square error, *R* = correlation coefficient, *MAE* = mean absolute error.
Source: own study.

The SVR with RBF kernel had better performance than the three SVR models (linear, polynomial, and sigmoid kernel) in both the training and testing phase; this is compatible with scientific results of Zahraie *et al.* [2011], Lima *et al.* [2013], Ghumman *et al.* [2018] and Tian *et al.* [2018].

In the case of the SVR models, the performances depend on the choice of the kernel and associated parameters. This was done using a trial-and-error approach which increased the calculation time due to the large size of the data set. The uncertainty between parameters increases the number of necessary trials to find the optimal model. In terms of time scales, previous multiple experiments showed that the longest time scales were better predicted than the shortest ones. This may be due to the strong correlation between the climatic indices and drought at the longest time scales [Achour *et al.* 2020; Ali *et al.* 2017; Belyaneh, Adamowski 2012; Dikshit *et al.* 2020; El Ibrahimi, Baali 2017]. Future works should focus on the development of complex ANN models and profound neuron networks, which provide a wide range of information on drought forecasting and its characteristics in the region.

CONCLUSIONS

Drought is a serious and frequent natural risk, which inflicts serious damage to the agricultural production, economy, biodiversity and the environment. The recent increase in the drought impact is linked to the climatic change and its effects are expected to increase in the future.

The objective of this study is to predict the temporal trends of drought in Upper Moulouya, located in the far North-East of Morocco. The region has witnessed several periods of drought during which its severity has been largely influenced by extreme variations of climatic factors.

This study presents a support vector regression (SVR) technique and a model for predicting the weather drought index by using the standardized precipitation index (*SPI*) and standardized precipitation-evapotranspiration index (*SPEI*). One of the main characteristics of the SVR technique in this model is that instead of minimizing the observed training error, the *SVR* attempts to minimize the generalized error bound so as to achieve generalized performance. Four SVR models were investigated: the linear function (SVR1), polynomial function (SVR2), radial basis function (SVR3) and the sigmoid function (SVR4). The result has shown that the SVR3 (RBF) is better than the other models in predicting the weather drought index.

The SVR models have revealed significantly better perform and in the prediction of the two drought indices (*SPI* and *SPEI*). The predictions provided very high correlation coefficients *R* = 0 .92 for the *SPI* and *R* = 0.89 for the *SPEI* and very low errors *MSE* = 0.01 and *MAE* = 0.07. This suggests that these models should be used for forecasting the degree of drought in the region.

The results show that an improvement in predictive accuracy and capability of generalization can be achieved by the proposed approach. In addition, the results show that the *SVR* with Kernel function RBF can serve as a promising alternative to existing prediction models.

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