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LALEH PARVIZ

Faculty of Agriculture, Azarbaijan Shahid Madani University, Tabriz, Iran
Correspondence to: e-mail: laleh_parviz@yahoo.com

Assessing accuracy of barley yield forecasting with integration of climate variables and support vector regression

SUMMARY

Investigations of the relation between crop yield and climate variables are crucial for agricultural studies and decision making related to crop monitoring. Multiple linear regression (MLR) and support vector regression (SVR) are used to identify and model the impact of climate variables on barley yield. The climate variables of 36 years (1982–2017) are gathered from three provinces of Iran with different climate: Yazd (arid), Zanjan (semi-arid), Gilan (very humid). Air temperature by high correlation coefficient with barley yield was introduced as the dominant climate variable. According to evaluation criteria, SVR provided accurate estimation of crop yield in comparison with MLR. The diversity of climate impressed the estimated yield in which UI, decreasing from Gilan to Yazd provinces, was 47.77%. Support vector machine (SVM) with capturing the nonlinearity of time series, could improve barley yield estimation, with the minimum UI for Yazd province. Also, the minimum correlation coefficient between the observed and simulated yield was found in Gilan province. Based on GMER calculations, SVM forecasts were underestimated in three provinces. All findings show that SVM is able to have high efficiency to model the climate effect on crop yield.

Keywords: yield, climate, MLR, SVM

INTRODUCTION

Forecasting of crop yield has a growing importance to ensure food security, optimize agro-management practices and resource use. Crop yield monitoring and forecasting are conducted with several sources of information such as field observation, climate data, satellite images and crop growth simulation models (20). In this regard, weather and climate have the main role on crop yield and productions. Climate extremes with intensity and frequency increasing can have an effect on crop yield, security and safety (29). There are many confirmations about global warming, increasing of global temperature by 0.8˚C from 1880 and the increase by 3° to 7°C in 2100 (15, 16, 17). The climate variables changes can affect global socio-economic and agricultural systems. The climate variables, for example temperature and precipitation, serve as direct inputs of agriculture whose changes have a significant impact on crop yield and related variation (3). Crop growth and development are affected by climate variables in different times related to growth cycle (17). The effect of climate variables on crop yield and modeling of their relationship are verified in many studies (8, 9, 20, 34). Therefore, forecasting and modeling of crop yield seems to benefit with considering climate aspect. Also, related studies indicated that some factors such as quantities of climate variables relation and variability of crop yield have an effect on accurate crop yield forecasting. The relationship between past climate variables and yield data are derived from statistical models. Therefore, several statistical approaches to different nature of the modeling process have a great role in this regard (10, 30). The useful regression models can be served in this case, and can be classified from linear to more sophisticated nonlinear regression models such as support vector machine analysis (25). Simple linear regression which is used to model crop yield and climate variables such as temperature and precipitation has a long history (2, 6, 17).

In order to assess the climate impacts on crop yields of winter wheat and silage maize, statistical regression was applied in Germany. The used climate variables were solar radiation, precipitation, potential evapotranspiration (1991–2010). Accurate regression model could improve the Nash–Sutcliffe efficiency (18%). In addition to the type of used models, the kind of time series is more important whereas the correlation between the goodness of fit and yield variability for silage maize was stronger than winter wheat (11). Different regression models such as linear, also ridge, and SVR regression (with linear, polynomial, and RBF) were used to forecast rice yield with regard to climatological aspect (22). Comparison of classical and fuzzy regression has been conducted for wheat and oil seeds yield forecasting (26). Also, satellite indices such as NDVI, EVI have been used for wheat and barley crop production in arid and semi-arid regions (27) and satellite rainfall estimation was applied to forecast maize yield (21). The importance of artificial neural network (ANN) and support vector machines (SVM) to model nonlinear processes has been proved in many studies (12, 24, 28). The methodology which incorporates statistics and neural networks was proposed for wheat yield forecasting (13). The effect of pan evaporation, solar radiation and wind speed on rice crop were investigated with linear regression, principle component analysis and support vector machine in southwest Nigeria. Solar radiation had the most important effect on rice yield. The scores explanation of first principle component using SVM had high percent compared to linear regression. The exhibition of long-term trend of rice yield was the first component of the principle analysis (25). The performance of SVM is found to be more successful compared to ANN (5, 23). SVM (18, 32) provides a contemporary pattern-recognition technique (based on statistical learning theory) which has provided highly accurate estimates compared to ANN (31).

The goal of this study was to investigate the applicability of Nu support vector regression (SVR) and multiple linear regression (MLR) for barley yield estimation. The effect of climate data during 36 years (1982–2017) was assessed in different climate conditions (arid, semi-arid, very humid). The correlation coefficient analysis was applied to find the dominant climate variable. SVR sensitivity analysis related to kernel function was emphasized strongly.

MATERIALS AND METHODS

Case study

Climate data were obtained from three provinces: Gilan, Yazd, and Zajan. Their location in Iran is illustrated in Figure 1. The reason for selection of the mentioned provinces is related to investigation of SVR performances for barley yield estimation in different climate conditions. The climate types of Gilan, Yazd, and Zanjan provinces based on De Martonne *climate classification* method are: very humid, arid, and semi-arid. Climate data: precipitation, mean air temperature, maximum air temperature, minimum air temperature, and mean wind speed for the period 1982–2017, were utilized as inputs of model which were gathered from the meteorological organization.

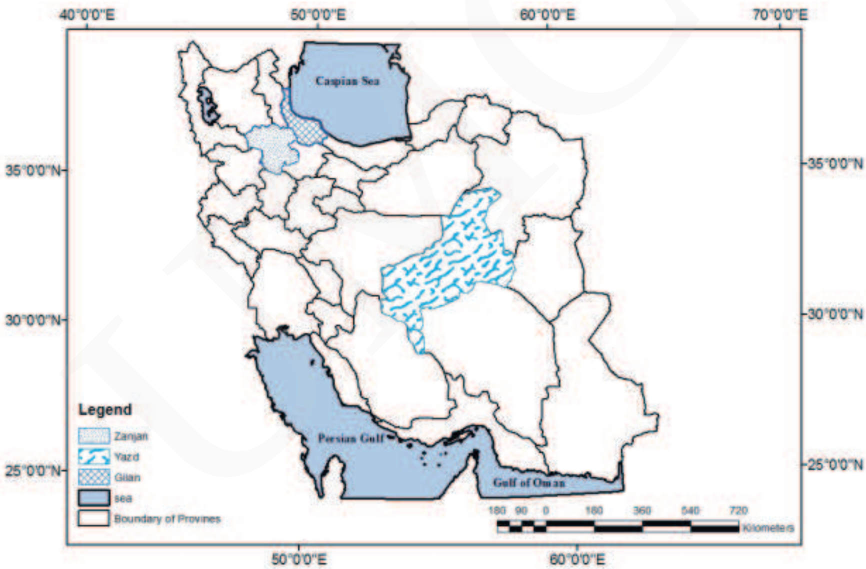

Fig. 1. The location of three provinces in Iran which are selected for barley yield estimation.

The average of barley yield in Yazd, Zanjan, and Gilan provinces (studied cultivars are Afzal, Jolghe and Sahra, respectively) are 3722.15, 5595.93, and 6453.06 kg/ha. The maximum and minimum values of barley yield were found in Gilan and Yazd provinces, respectively. Barley is one of the strategic crops in each province, therefore its estimation with an efficient method is necessary.

Multiple linear regressions

In order to estimate the relationship between a dependent variable and one or more independent variables, regression analysis is a useful and efficient technique. Linear regression (equation 1) has been used for definition of the variables relations.

$$y = X\beta + \varepsilon, \quad (1)$$

where y is the dependent variables, X is the predictor variables, β is parameters vector, and ε is residual vector (25).

Support Vector Regression

One of the robust and strong multivariate models for non-linear time series is SVR. The idea of the method is related to how complex non-linear relations are ascribed to linear ones with higher dimensional space. With some fixed mapping (non-linear), the inputs of the model are mapped to high dimensional feature space and in this space a linear model is constructed. The prediction of y_i in SVM was conducted for x. The SVR definition can be given as equation 2 and the function in equation 2 can be defined as equation 3.

$$y = f(x) + \varepsilon \tag{2}$$

$$f(x) = \sum_{i=1}^{n} y_i \, \alpha_i \, K(x_i, x) + b, \tag{3}$$

where $K(x_i, x)$ is a kernel function, ε is error term and b is constant scalar.

In order to find the parameters of equation 3, optimization of the problem was proposed whose structure is illustrated in equation 4.

$$\min_{\alpha,\beta} \quad \sum_{i=1}^{n} \alpha_i + \frac{1}{2} \sum_{i,j=1}^{n} y_i \, \alpha_i \, y_j \, \alpha_j \, K(x_i, x) \tag{4}$$

$$\text{subject to} \quad \begin{cases} 0 \le \alpha_i \le C, \quad i = 1,2,..,n \\ \sum_i y_i \, \alpha_i = 0. \end{cases}$$

C is the pre-specific term which can control the penalty values related to errors outside the error margin (23) and can be named penalty parameter.

Often, the relation between dependent and independent variables is non-linear. This kind of relation in SVR can be defined with mapping the input space onto some higher dimensional space with a non-linear mapping function which is named kernel function. With kernel function, working in a higher dimensional feature space is possible and can dominate. The common kernel functions are linear, polynomial, Gaussian radial basis, and sigmoid kernel function. A special case of the Gaussian radial basis is linear kernel and the behavior of sigmoid kernel is similar to Gaussian radial kernel in certain parameters (19, 23).

Evaluation criteria

In order to compare the efficiency of SVR and MLR models, GMER (geometric mean error ratio), MAE (mean absolute error), RRMSE (relative root mean square error), UI were used as evolution criteria, whose structure is brought in equations 5 to 8.

$$UI = \frac{\left[\sum_{i=1}^{N}(P_i - O_i)^2\right]^{0.5}}{\left[\sum_{i=1}^{N}(O_i)^2\right]^{0.5} + \left[\sum_{i=1}^{N}(p_i)^2\right]} \tag{5}$$

$$GMER = \exp\left[\frac{1}{N}\sum_{i=1}^{N}\ln(\frac{P_i}{O_i})\right] \tag{6}$$

$$RRMSE = \frac{\frac{1}{N}\sqrt{\sum_{i=1}^{N}(O_i - P_i)^2}}{\overline{O}} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i|\ , \tag{8}$$

where P_i is the predicted value, O_i is the observed value, $\overline{O}$ is the mean of the observed value.

GMER >1 indicates overestimation and GMER <1 shows underestimation. The error criteria, UI = 0 is indicative of perfect forecast, and the minimum values of RRMSE and MAE are the desired situation (35).

RESULTS

Time series of precipitation, mean air temperature, minimum air temperature, maximum air temperature and wind speed during 1982–2017 were used as climate variables which were the average of stations in each province as climate variables of provinces. The climate data are divided to training, 26, and verification, 10, periods; verification data were utilized for model evaluation. MLR and SVR are the models used for barley yield estimation. In order to find the impact of climate variable on barley yield, the correlation coefficient between crop yield and climate variables is calculated. Some statistics of climate variables and correlation coefficient are brought in Table 1.

According to Table 1, the dominant climate variable is temperature, whereas the correlation coefficient between the climate variables and barley yield has the significant values with high number. The correlation coefficient of precipitation and barley yield is negative and the coefficient of wind speed, mean air temperature, maximum air temperature, and barley yield is positive in all provinces. The maximum number of significant correlation coefficient was observed in Zanjan province. Generally, the maximum values of air temperature and precipitation were related to Yazd and Gilan. Also, precipitation and wind speed showed the highest variability according to the calculated CV. It must be said that the empty cell of CV for minimum air temperature in Zanjan was related to the negative values of temperature. The maximum value of CV average for precipitation, mean air temperature, maximum temperature and wind speed was related to Gilan prov-

Table 1. Some statistics of climate variables and crop yield with correlation coefficient between crop yield and climate variables

Climate variables	Mean			CV			Correlation coefficient		
	Yazd	Zanjan	Gilan	Yazd	Zanjan	Gilan	Yazd	Zanjan	Gilan
Mean air temperature (˚C)	20.79	12.14	16.37	0.068	0.126	0.042	0.15	0.46**	0.39
Precipitation (mm)	56.03	290.76	1250.11	0.43	0.23	0.26	-0.17	-0.26	-0.2
Wind speed (KNOTS)	2.5	2.6	2.6	0.21	0.19	0.34	0.24	0.17	0.3
Maximum air temperature (˚C)	33.72	25.21	63.45	0.034	0.065	0.38	0.44**	0.53**	0.26
Minimum air temperature (˚C)	6.76	-1.07	8.2	0.105		0.08	-0.3	0.41**	0.23

inces. CV values (%) related to mean air temperature in Yazd, Gilan provinces and maximum air temperature in Yazd, Zanjan and minimum air temperature in Gilan provinces are less than 10%. Many studies suggested temperature increasing and precipitation decreasing due to climate changes in recent years (15, 16, 17). Therefore, the slope of trend line for some climate variables time series was calculated and the results are brought in Table 2.

Table 2. Slope of trend line for precipitation and temperature time series in the studied provinces.

Climate variables	Yazd	Zanjan	Gilan
Mean air temperature	0.091	0.12	0.053
Maximum air temperature	0.08	0.13	1.89
Precipitation	-0. 78	-1.56	-19.54

Positive slope of mean air temperature and maximum air temperature time series is indicative of temperature increasing and negative slope of precipitation implies the precipitation decreasing during 36 years.

Evaluation of the performance of regression models

The regression techniques which are used for barley yield forecasting are MLR and SVR. The parameters of SVR were selected in a trial-and error producer. Kernel functions have a greater role for modeling nonlinearity of time series in SVR. Therefore, the sensitivity analysis of kernel function must be considered in the SVR modeling. The used kernel functions are linear, polynomial, Gaussian radial basis, and sigmoid functions. The result of SVR sensitivity analysis is illustrated in Figure 2, where the penalty parameter is equal to 2.

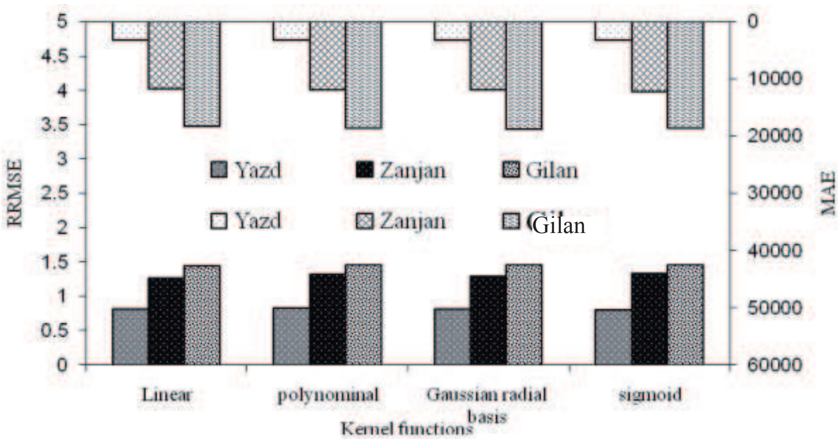

Fig. 2. SVR sensitivity analysis related to kernel function for three provinces of the study.

The RRMSE decreasing from polynominal to sigmoid kernal function in Yazd was 3.6%, from sigmoid to linear kernel function in Zanjan was 4.5%, from polynominal to linear kernel function in Gilan was 2%. The linear kernel function in Zanjan and Gilan provinces had the minumum error (RRMSE, MAE) and the minimum error of Yazd provinces belonged to sigmoid kernel function. It must be said that another SVR sensitivity analysis has been conducted with regard to penalty parameter, where the penalty parameter equal to 2 had the minimum error. After construction of structure model, the performance of MLR and SVR was evaluated using some evaluation criteria which are shown in Figure 3.

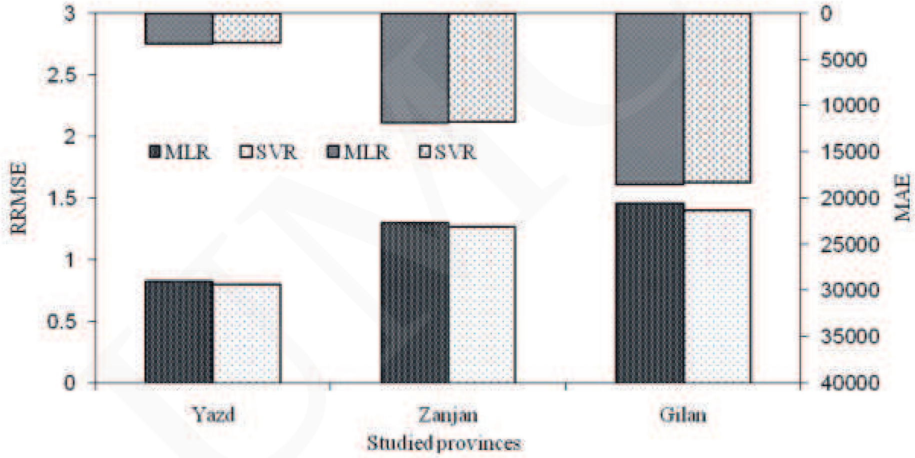

Fig. 3. Comparison of the efficiency of MLR and SVR for barley yield estimation in the validation period.

The error criteria of Figure 3 were decreased from MLR to SVR, which indicates the efficiency of SVR in barley yield estimation. The RRMSE decreasing from MLR to SVR in Yazd, Zanjan, and Gilan was 3.6%, 2.3% and 5.25%, respectively. The MAE decreasing from MLR to SVR in Yazd, Zanjan, and Gilan was 2.1%, 1% and 2%, respectively. The minimum error was found in Yazd province. The minimum correlation coefficient between the observed and forecasted barley yield concerned Gilan province, whereas the decreasing of correlation coefficient from Gilan to Zanjan was 61.91%. For better investigation, UI and GMER were calculated and the results are shown in Figure 4.

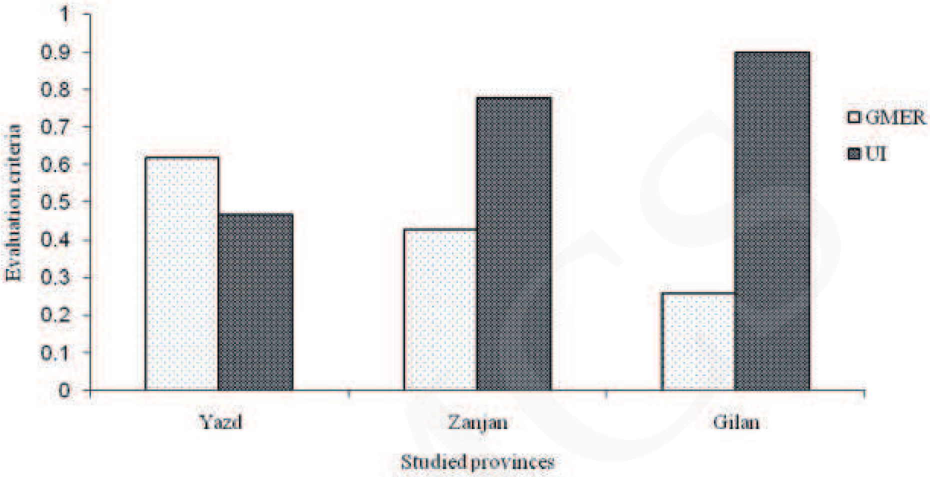

Fig. 4. Investigation of the performance of SVR for barley yield estimation in three provinces of Iran.

The UI values of provinces indicate that Yazd and Zanjan are better than Gilan and the performance of Yazd is in optimum case for simulation of barley yield. GMER values in Yazd, Gilan and Zanjan provinces are less than 1, which indicates underestimation of SVR model in barley yield estimation.

DISCUSSION

The main aim of this study was investigation of the climate effect on crop yield such as temperature, precipitation, and wind speed. According to the calculated correlation coefficient, the dominant climate variables were related to temperature, especially mean air temperature and maximum air temperature. The effect of temperature on crop yield was verified in many studies (1, 26). The correlation coefficient between precipitation and barley yield was not significant in the studied province. The study of Zhang et al. (36) indicated that in regions with water supply, rainfall has not significant effect on rice yield. Wind speed was one of the climate variables with highest variability according to the calculated CV. In the study of Oguntunde et al. (25) for rice yield estimation, wind speed had high variability. During the period of 36 years, temperature and precipitation increased and decreased, which is matching with climate changes (15, 16).

The sensitivity analysis is one of the major processes of SVR modeling where the variation of error criteria with variation of kernel function was observed in the result of SVR simulation. The optimum kernel function of Yazd, Gilan, and Zanjan was selected sigmoid and linear based on error criteria. Based on Keerthi and Lin (19), the kernel function of the provinces is not the same. In the study of Mishra et al. (22) for crop yield estimation, in many cases linear kernel function had a minimum error. Also, in this study, the kernel function and penalty parameter are investigated for sensitivity analysis.

Comparison of the efficiency of MLR and SVR indicated that SVR had high efficiency for barley yield estimation. The better performance of SVR has been proved in many studies (5, 23) and the performance of SVM regression function for rice yield forecasting in Nigeria had acceptable results with regard to the climatological aspect (25). Structural risk minimization principle has been used by SVM, which is the strong point of model rather to ANN model with empirical risk minimization principle (23). SVM with introducing an alternative loss function can lead to encouraging simulation on regression problems (4, 32). Also, SVM has high ability to relate input to the desired output (14). High accessibility of SVM is related to their excellent generalization capacity (7).

The UI of Yazd and Zanjan was better in relation to Gilan province. It is indicative of climate effect on barley yield and it may lead to nonlinearity of time series. With increasing the nonlinearity of time series, the performance of SVR has increased (23). The poor performance of Gilan province can be related to climate variables values, for example the average of precipitation in Gilan province is higher than in the other provinces.

CONCLUSION

The climate changes in recent years indicate the need for comprehensive modeling of climate variables and crop yield. Therefore, the relation of climate variables on barley yield was investigated with robust SVR model. Air temperature was the dominant variable on barley yield based on correlation of the coefficient analysis. Sensitivity analysis was introduced as the major step in SVR modeling process. SVR relative to MLR provided better estimation because of its optimization structure. The results of SVR in different climate types have not similar results, which indicates the effect of climate and variation of time series relation. SVR with power structure can capture this matter. The comparison of observed and forecasted values of barley yield has underestimated values.

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