Prediction models of macro-nutrient content in plant organs of *Cucumis melo* in response to soil elements using support vector regression (#77486)

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Prediction models of macro-nutrient content in plant organs of *Cucumis melo* in response to soil elements using support vector regression

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Background. Undoubtedly, the importance of food and food security as one of the present and future challenges are not invisible to anyone. Nowadays, development methods for monitoring the nutrient content and their status in crop products is a ministerial issue for implementing reasonable and logical soil properties management. Modeling as a new method has the capability of evaluating the soil properties of fields so could study the subject of crop yield through soil management. **Methodology.** In the spring of 2020, this study was down as a factorial test in the form of a randomized complete block design with three replications. The first factor was the use of fertilizers in six levels: no fertilizer (control), cow manure (30 t ha^{-1}), sheep manure (30 t ha^{-1}), nanobiomic foliar application (2 l ha^{-1}), silicone foliar application (3 l ha^{-1}), and chemical fertilizer from urea, triple superphosphate, and potassium sulfate sources (200, 100, and 150 kg ha^{-1}). In addition, four levels of vermicompost were considered as the second factor: no vermicompost (control), 5, 10, and 15 t ha^{-1}. Input data sets such as nitrogen, phosphorus, and potassium levels in seeds, fruits, leaves, and roots were calibrated using the SVR structure. **Results.** According to the results, when the data sets of nitrogen, phosphorus, and potassium in fruit, were used as input, the accuracy of these models was higher than 80.0% (R^2= 0.807 for predicting fruit nitrogen; R^2= 0.999 for fruit phosphorus; R^2= 0.968 for fruit potassium). Likewise, the ratio of prediction performance to deviation (RPD) obtained from the models ranged from 2.017 for predicting fruit nitrogen and 5.17 for fruit potassium to 27.95 for fruit phosphorus content. According to the results of the prediction models in response to soil elements, the best soil nitrogen content ranged from 0.05 to 1.1%, soil phosphorus from 10 to 59 mg kg^{-1}, and soil potassium from 180 to 320 mg kg^{-1}, which offers a better content in the prediction models. Likewise, the best fruit nitrogen content ranged from 1.27 to 4.33%, fruit phosphorus from 15.74 to 26.19%, and fruit potassium from 15.19 to 19.67% obtained by 15 t ha^{-1} of vermicompost using NPK chemical fertilizers. **Conclusions.** Because the macro-nutrient content in fruit had the highest contribution in prediction than actual values, thus identified as the best model compared to other models in response to soil elements. Based on our findings, the importance of fruit phosphorus was identified as a determinant that strongly influenced melon prediction models. More significant values of soil elements do not affect increasing macro-nutrient content in plant organs, and excessive application may not be economical. Therefore, our studies provide an efficient approach with potentially high accuracy to estimate macro-nutrient content in fruits of *Cucumis melo* in response to soil elements and hence caused a saving in the amount of fertilizer during the growing season.

Prediction models of macro-nutrient content in plant organs of *Cucumis melo* in response to soil elements using support vector regression

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Abstract

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Results. According to the results, when the data sets of nitrogen, phosphorus, and potassium in fruit, were used as input, the accuracy of these models was higher than 80.0% (R^2= 0.807 for predicting fruit nitrogen; R^2= 0.999 for fruit phosphorus; R^2= 0.968 for fruit potassium). Likewise, the ratio of prediction performance to deviation (RPD) obtained from the models ranged from 2.017 for predicting fruit nitrogen and 5.17 for fruit potassium to 27.95 for fruit phosphorus content. According to the results of the prediction models in response to soil elements, the best soil nitrogen content ranged from 0.05 to 1.1%, soil phosphorus from 10 to 59 mg kg^{-1}, and soil potassium from 180 to 320 mg kg^{-1}, which offers a better content in the prediction models. Likewise, the best fruit nitrogen content ranged from 1.27 to 4.33%, fruit phosphorus from 15.74 to 26.19%, and fruit potassium from 15.19 to 19.67% obtained by 15 t ha^{-1} of vermicompost using NPK chemical fertilizers.

Conclusions. Because the macro-nutrient content in fruit had the highest contribution in prediction than actual values, thus identified as the best model compared to other models in response to soil elements. Based on our findings, the importance of fruit phosphorus was identified as a determinant that strongly influenced melon prediction models. More significant values of soil elements do not affect increasing macro-nutrient content in plant organs, and excessive application may not be economical. Therefore, our studies provide an efficient approach with potentially high accuracy to estimate macro-nutrient content in fruits of *Cucumis melo* in response to soil elements and hence caused a saving in the amount of fertilizer during the growing season.

Key words Macro-nutrients, Melon, Prediction model, Soil elements, Support vector regression

Introduction

Melon (*Cucumis melo* L.), a member of the *Cucurbitaceae* family, is one of the most important vegetable crops worldwide. The major melon producers are China, Turkey, Iran, India, Kazakhstan, and the United States (FAO, 2018). *Cucumis melo* L. (2n=2x=24) has grown in various geographical areas of Iran from historical times (Munger & Robinson, 1991). Based on archaeological evidence, Iran has been an important center of domestication since 5000 years ago (Bisognin, 2002). It is a common crop consumed by many Iranians, especially during the hot summer. Melon is the most polymorphic species of the cucurbit family, which is particularly true for fruit-related traits (Luan *et al.,* 2010).

In most melons that belong to the *Cucurbitaceae* family, nutrient requirements and NPK ratio vary significantly, depending on the melon type and cultivar, soil mineral status, and the crop developmental stage (Deus *et al.,* 2015; Chen *et al.,* 2019). Nitrogen is the most needed mineral nutrient in all cropping systems due to its ministerial role in the biochemical and physiological processes of the plant (Pourranjbari Saghaiesh, Souri & Moghaddam, 2019). Nitrogen is essential during the vegetative phase for the buildup of the adequate canopy and leaf area to ensure yield capacity. However, excess nitrogen availability during the reproductive phase promotes undesired competition between fruit and vegetation that might reduce produce quality (Ferrante *et al.,* 2008). Likewise, phosphorus is another ministerial mineral nutrient that has different roles in plant functional metabolism (Pourranjbari Saghaiesh, Souri & Moghaddam, 2019). Thus, phosphorus is mainly required for seedling establishment (root growth) and then at early reproductive steps (bloom and seed development) (Martuscelli *et al.,* 2016; Chen *et al.,* 2019). It is a fact that under poor soil conditions, nitrogen and phosphorus fertilizers at low rates can develop plant root growth and BNF efficiency (Pourranjbari Saghaiesh, Souri & Moghaddam, 2019). Also, potassium is most efficient during the later stages of fruit development, supporting sugar translocation and accumulation (Deus *et al.,* 2015; Tränkner, Tavakol & Jákli, 2018).

Pourranjbari Saghaiesh, Souri & Moghaddam (2019) investigated the effects of nitrogen (N), phosphorus (P), and potassium (K) levels in the nutrient solution on leaf mineral content and enzyme activity in Khatouni melon (*Cucumis melo* var. inodorus) seedlings. According to the findings, the leaf's highest N, P, and K were found at the highest levels in the nutrient solution.

Modeling as a new strategy in farm management can improve performance and economic returns by optimizing crop inputs (fertilizers and chemicals) and preserving the environment and energy resources (water resources, etc.). The modeling technique has many benefits, including the capacity to predict numerous soil parameters and perform measurements in labs (Viscarra Rossel *et al.,* 2006) and farms, as well as the absence of chemicals needed (Stenberg *et al.,* 2007). Farming product monitoring also allows farmers to carry out proper farming operations throughout the growing season.

Accordingly, data-driven models are needed to efficiently link input data to the desired output (Adeyemi *et al.,* 2018). The benefits of the support vector machine identified over artificial neural networks in many types of research, which has attracted much research attention (Jiang *et al.,* 2019). The structure and performance of support vector machines have been the main target of many studies (Roodposhti, Safarrad & Shahabi, 2017).

Some researchers have used models such as support vector regression to estimate crop yield in response to soil properties. Zhang *et al.* (2021) suggested a method for organ classification and fruit counting on pomegranate trees based on multi-features fusion and support vector machine. Their experiment results showed that the support vector machine classifier based on color and shape features had an accuracy of 0.75 for fruit and 0.99 for non-fruit.

The study of Esfandiarpour-Boroujeni *et al.* (2019) aimed to evaluate the performance of a hybrid particle swarm optimization-imperialist competitive algorithm-support vector regression (PSO-ICA-SVR) method to predict apricot yield and identify important factors in the Abarkuh, Yazd, Iran. The validation results showed that the hybrid algorithm estimated apricot yield with relatively high accuracy (RMSE= 1.737 for training data and RMSE= 2.329 for testing data). Likewise, Jeong *et al.* (2017) estimated the amount of organic matter, available potassium, and soil available phosphorus using support vector machine models. They found that the predicted and actual parameters had a strong correlation.

In the investigation of the data mining approach based on the chemical composition of grape skin for quality evaluation and traceability prediction of grapes, a data mining algorithms comparison study of grape-skin samples from five regions of Mendoza, Argentina, and builds classification models capable of predicting provenance based on multi-elemental composition, were developed. Support vector machines (SVM) and random forests (RF) were classifier techniques. The best results were achieved for SVM and RF models, with 84% and 88.9% prediction accuracy, respectively, on the 10-fold cross-validation. The RF variable importance showed that Rb (rubidium) was the most relevant component for prediction (Canizo *et al.,* 2019).

Tu *et al.* (2018) investigated tea cultivar classification and biochemical parameter estimation from hyperspectral imagery obtained by UAV. Tea cultivars were classified according to the spectral characteristics of the tea canopies. Furthermore, two major components influencing the taste of tea, tea polyphenols (TP) and amino acids (AA), were predicted. The results showed that the overall accuracy of tea cultivar classification achieved by the support vector machine is higher than 95% with the proper spectral pre-processing method. The best results to predict the TP and AA were achieved by partial least squares regression with standard normal variant normalized spectra, and the ratio of TP to AA-which is one proven index for tea taste-achieved the highest accuracy (R_{CV}= 0.66, $RMSE_{CV}$= 13.27) followed by AA (R_{CV}= 0.62, $RMSE_{CV}$= 1.16) and TP (R_{CV}= 0.58, $RMSE_{CV}$= 10.01).

Prediction of active ingredients in *Salvia miltiorrhiza* Bunge. based on soil elements and artificial neural network was performed by Liu *et al.* (2022). This study measured the active ingredients in the roots of *S. miltiorrhiza* and the contents of rhizosphere soil elements from 25 production areas in eight provinces in China and used the data to develop a prediction model based on BP (back propagation) neural network. The results showed that the active ingredients had different degrees of correlation with soil macronutrients and trace elements, and the prediction model had the best performance (MSE= 0.0203, 0.0164; R^2= 0.93, 0.94).

Mohamed *et al.* (2021) performed a field experiment to investigate the use of phosphorus fertilizer source in common bean (*Phaseolus vulgaris* L.) cultivated under salinity stress. The response curve of total dry weight to different rates of phosphorus proved that the quadratic model fit better than the linear model for phosphorus sources. The total dry weight was predicted at 1.675 t ha^{-1} for superphosphate and 1.875 t ha^{-1} for urea phosphate when phosphorus using at 51.5 kg ha^{-1}, and 42.5 kg ha^{-1}, respectively. In conclusion, the 35.0 kg ha^{-1} phosphorus could be considered the most efficient phosphorus level.

According to the studies accomplished is recognized small information on support vector regression models to predict macro-nutrient content in *Cucumis melo* plant organs in response to soil elements. Therefore, the present study aimed to determine: i) regression models to predict macro-nutrient content in *Cucumis melo* plant organs in response to soil elements; ii) determinants of macro-nutrient prediction; iii) the effect of soil elements on macro-nutrient content in plant organs, and iv) optimization of the fertilizer used in a cropping system, taking into account the levels of macro-nutrients in the plant organs and soil elements.

Materials and methods

Geographical location and meteorological information of the test site. In the spring of 2020, this study was conducted in two Fariman and Zahak counties. Fariman county is situated in Northeastern Iran at 35°70'N and 59°85'E, at an altitude of 1403 meters above sea level, in the hot and dry Mediterranean climates based on the Köppen classification (www.razavimet.ir). Zahak County, too, is situated in Southeastern Iran at 30°89'N and 61°70'E, at an altitude of 483 meters above sea level in the hot and dry climates based on the Köppen classification (www.irimo.ir).

Preparation of soil samples. Before starting the experiment, ten samples were randomly collected from 0 to 30 centimeters in depth to explore the chemical characteristics and composition of the soil components. Table 1 shows the results of the soil sample test.

Experimental design. This study used the support vector regression (SVR) to predict models of macro-nutrient content in *Cucumis melo* plant organs in response to soil elements affected by different fertilizers as a factorial test in the form of a randomized complete block design with three replications. The first factor was the use of fertilizers in six levels: no fertilizer (control), cow manure (30 t ha^{-1}), sheep manure (30 t ha^{-1}), nanobiomic foliar application (2 l ha^{-1}), silicone foliar application (3 l ha^{-1}), and chemical fertilizer from urea, triple superphosphate, and potassium sulfate sources (200, 100, and 150 kg ha^{-1}). In addition, four levels of vermicompost were considered as the second factor: no vermicompost (control), 5, 10, and 15 t ha^{-1}.

Cultivation operation. Before cultivation and in the fall, 30 t ha^{-1} cow manure and 30 t ha^{-1} rotted sheep manure were distributed on the field and mixed with soil via disk. To accelerate and complete the decay process portion of 100 kg ha^{-1} urea was added to livestock manure. Then, vermicompost was distributed and mixed with soil. Vermicompost was prepared using livestock manure and earthworm species in Zahak (Southeastern Iran) from the research farm of Zabol University, Iran, and in Fariman (Northeastern Iran) from the Kaveh Support Services Company in Mashhad, Iran. Table 1 shows the chemical properties and composition of elements in the vermicompost fertilizer and livestock manure samples.

Field preparation and sowing occurred in the second half of February when the soil temperature was sufficient (over 20 °C at both locations). The field was immediately laid out as a lister planting so that the depth and width of the furrows were 50 and 60 centimeters. Planting was done on both sides of the ridges. The width of the ridges was 3 meters, and the distance between the rows was 70 centimeters. Then, a portion of 100 kg ha^{-1} urea, 100 kg ha^{-1} triple superphosphate, and 150 kg ha^{-1} potassium sulfate were distributed and mixed with soil. Native melon seeds of the Khatouni variety were used for sowing. 3 kg ha^{-1} seed was required.

The first irrigation was carried out before seed sowing. The irrigation was gravity-leaky. The seeds germinated using soil moisture and turned green within one week. At this time, the soil was dried, and the second irrigation was carried out. The irrigation was done every five days, except under certain conditions such as high temperatures for several days, which reduced the irrigation distance every three days.

In the four-leaf stage, nanobiomic and silicone foliar applications were performed. Acetobacter, bacillus, pseudomonas, azosprolium, 32% humic acid, 2% folic acid, 0.1% molybdenum, 12% potassium, 0.36% magnesium, 4.3% manganese, 0.36% calcium, 10% zinc, 5.9% iron, and a variety of acids were included in the nanobiomic biofertilizer. The silicon oxide formula is employed as silica acid (H_4SiO_4) in a 30% weight and 36% by volume silicon foliar treatment.

Harvesting operation. On June 26 in Southeastern Iran (Zahak county) and August 7 in Northeastern Iran (Fariman county), fruit harvesting operations were conducted for one week following physiological ripening and detecting changes in color or latticing on fruits. The samples were put in an Avon Digital (PTN 55, manufactured by Pars Teb Novin, Iran) at 70°C for 48 hours to determine nitrogen, phosphorus, and potassium content, and their dry ash was provided. In the laboratory, nitrogen was investigated using Kjeldahl's (1883) method, phosphorus using Olsen *et al.* (1954) method via spectrophotometer (UV-2100S spectrophotometer, manufactured by Unico Company of America), and potassium using a flame detector (PFP7 spectrophotometer, manufactured by Geno Company of United Kingdom).

Modeling methods

Support vector machine (SVM). Boser, Guyon & Vapnik (1992) presented the support vector machine as a learning tool for both regression and classification. Over the next few years, they offered an optimum superficial theory as a linear classifier and used kernel functions to develop non-linear classifiers. Boser, Guyon & Vapnik (1992) developed the fundamental ideas that are now known as the SVM. Finally, in 1995, Vapnik enhanced regression (Vapnik, 1995). The SVR derives from statistical training theory for minimizing the risk structure (Vapnik, 1998). Data classification issues are solved using the SVM classification model, while prediction problems are solved using the SVR model.

Support vector regression (SVR). The accuracy of the performance function is a ministerial issue in probabilistic modeling approaches-based reliability analysis. The SVR is applied successfully in structural reliability analysis (Dai *et al.,* 2012) using the simulation reliability approaches (Sun *et al.,* 2017) and impotence sampling due to their efficiency and accuracy. Consequently, the hybrid SVR and conjugate form can provide efficient and accurate results of reliability analysis-based spermophagy, thus, the SVR modeling approach to build the structure of the nonlinear relation may be improved the accuracy in predicting the probabilistic model by the input random variables *X*. The SVR is structured as the below model in equation 1:

$$SP = b + \sum_{i=1}^{N} w_i K(x, x_i) \quad \text{(Eq. 1)}$$

Where b is bias and $K(x, x_i)$ represents the kernel function for transferring the input variables from real- space into *N*-dimensional feature space. Generally, the Gaussian kernel function uses for transferring the input data as follows in equation 2 (Brereton & Lloyd, 2010):

$$K(x, x_i) = \exp(-0.5\|x - x_i\|^2 / \sigma^2) \quad \text{(Eq. 2)}$$

Where σ is the kernel parameter that provides the smoothness of the kernel function, given as σ =0.5. w_i is the weight to connect the input random data points in feature space and spermophagy for computing by use of two slack variables ξ_i, ξ_i^* by the following optimization problem in equation 3 (Lu, 2014):

$$\begin{aligned} &\textit{Minimise} \quad \frac{\|\boldsymbol{w}\|^2}{2} + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \\ &\textit{Subjected to} \begin{cases} y_i - < \boldsymbol{w}.K(\boldsymbol{x}, \boldsymbol{x}_i) > -b \le \varepsilon + \xi_i \\ < \boldsymbol{w}.K(\boldsymbol{x}, \boldsymbol{x}_i) > +b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \end{aligned} \quad \text{(Eq. 3)}$$

In which factor $C \ge 0$ is the regularization coefficient given as C=500 and ε is the insensitive loss function given as $\varepsilon = 0.01$ in this study. The ε- insensitive loss function uses to neglect the calibrating process-based SVR when differences between the predicted and observed spermophagy are less than ε schematically shown in Fig. 1-A. The structure of SVR is presented in Fig. 1-B that the input data set (x) such as nitrogen, phosphorus, and potassium in seeds, fruits, leaves, and roots are uses to calibrate the probabilistic model of spermophagy (SP) using SVR.

Identification accuracy. The means of standard deviation (SD), coefficient of variation (CV), the root of mean square error (RMSE), mean absolute percentage error (MAPE), the ratio of prediction performance to deviation (RPD), Pearson correlation coefficient (R), and coefficient of determination (R^2) used to determine the accuracy of prediction models in this study.

Used software. Matlab V7.1 software (The Mathworks Inc., Natick, Massachusetts, USA) was used for regression analysis and prediction models of macro-nutrient content in *Cucumis melo* plant organs in response to soil elements. Also, excel software was used for drawing figures of the above-described parameters.

Results and discussion

Investigation of the model predicting plant nitrogen values. Based on the results, the statistical parameters of actual values input to the model are described in Table 2, and the predicted values obtained from the model are presented in Table 3. In Table 4, the results of fitting the predicted values of nitrogen in seed, fruit, leaf, and the root of the melon compared to actual values in response to soil nitrogen are presented based on the SVR model.

According to the estimated parameters, the predicted fruit nitrogen values have the highest accuracy (RMSE= 0.122; MAPE= 7.01) in the model fitting, while the predicted leaf nitrogen values have the lowest accuracy (RMSE= 1.061; MAPE= 31.85). The RPD statistic evaluates the model's performance. Values less than 1.4, between 1.4 and 2, and greater than 2, respectively, show weak, acceptable, and excellent modeling performance (Chang *et al.,* 2001). Accordingly, the fruit nitrogen had an excellent performance (RPD= 2.017) in the model prediction, and the leaf nitrogen had a weak performance (RPD= 0.710). However, it is observed that the regression model obtained from leaf nitrogen values (R^2= 0.832; Adjusted R^2= 0.831; Beta= 0.912) was the most suitable prediction model followed by fruit nitrogen values (R^2= 0.807; Adjusted R^2= 0.805; Beta= 0.898). In contrast, the model obtained from root nitrogen (R^2= 0.542; Adjusted R^2= 0.539; Beta= 0.736) had the weakest performance in prediction. The closer these values are to number one, the model indicates the stronger correlation between the predicted values and the actual values. In other words, the regression model obtained from the prediction of leaf and fruit nitrogen can cover or express a higher percentage of actual values. It is also known that the coefficients of each variable are positive, and due to the significant value of each variable being smaller than 0.05 (Sig= 0.000 $<$ 0.05), this is proof of the appropriateness of the obtained models. Any variable with a larger Beta is more important in the regression model. In this way, it is found that leaf nitrogen (Beta= 0.912) followed by fruit nitrogen (Beta= 0.898) will be the best variables for predicting plant nitrogen changes in response to soil nitrogen (Table 4). Seidel *et al.* (2019) used spectrometry to evaluate organic carbon and nitrogen of whole rangeland soils in Germany; these researchers used a simple regression model to estimate these soil properties and assessed organic carbon and total nitrogen with acceptable accuracy (R^2= 0.65 and RPD= 2.7) and excellent accuracy (R^2= 0.87 and RPD= 2.7), respectively.

Table 4 presents the correlation between the actual values in plant organs and their predicted values using the support vector regression method. The results show the high potential of the support vector regression algorithm in predicting the actual values in plant organs. The predictive performance of the support vector regression algorithm for leaf and fruit nitrogen values is better than seed and root nitrogen values.

Fitting diagrams for predicted seed, fruit, leaf, and root nitrogen values compared to actual values in response to soil nitrogen are presented in Fig. 2, respectively. The regression line slope of diagrams for investigated plant nitrogen values in the SVR model is presented in these figures. The predicted nitrogen values in leaf and fruit had the lowest distance from the 1:1 line and the best fitting based on these results. The predicted nitrogen values in seed and root had the highest relative distance from the 1:1 line and the lowest accuracy. The scatter of dots in the figures indicates the models' accuracy in predicting the values of nitrogen output. Consequently, it can be found that there is a positive correlation between the data and the model having acceptable accuracy (Fig. 2).

Figure 3 presents the diagrams for plant nitrogen changes in response to soil nitrogen values. In general, by increasing soil nitrogen, the nitrogen content of different organs increases to maximize plants' growth. According to the results, the best soil nitrogen ranged between 0.05 and 1.1% to obtain the most accurate predictions of the crop's nitrogen content. According to the results of the predictions, the highest increase in crop nitrogen content in response to soil nitrogen content ranged from 3.04 to 9.18% for leaf nitrogen and from 1.27 to 4.33% for fruit nitrogen under NPK chemical fertilizers by using 15 t ha^{-1} of vermicompost. Then, changes in root nitrogen content were predicted in the range of 1.017 to 2.90 % under NPK chemical fertilizers by 5 t ha^{-1} of vermicompost. Also, changes in seed nitrogen content ranged from 1.93 to 7.39% under cow manure using 15 t ha^{-1} of vermicompost (Fig. 3).

According to the performance evaluation of predicted models, the nitrogen content in leaves and fruits is better than that in seeds and roots, so they were found to be more suitable for crop monitoring. The predictions show that despite the error in soil measurements and the effectiveness of nitrogen values from a combination of different parameters related to the crop, there is a high linear correlation between the crop's nitrogen content and the soil nitrogen values. According to the diagrams, there was a slight difference between the predicted and the actual values. Since the crop's nitrogen content is closely related to soil nitrogen values, the actual values are approximately equal to the estimated nitrogen values. The observed incremental relationship between the crop's nitrogen content and soil nitrogen values is calculated by regression equations as shown in Fig. 3. The results of this study are consistent with those of Dotto *et al.* (2018).

Nitrogen is one of the macro-nutrients for plant growth, so determining its amount and changes in organic compounds is critical for evaluating the final fertilizer's value. Fertilization seems to have increased the nitrogen content in seeds, fruits, leaves, and roots. Due to the similar trend of leaf and fruit nitrogen changes, this result indicates that under NPK chemical fertilizers by using 15 t ha^{-1} of vermicompost, followed decomposition process of organic matter by microorganisms and earthworms, thus the nitrogen content of the plant vegetative body has increased, which by improving photosynthesis and retransfer of photosynthetic materials, more nitrogenous compounds have been transferred to the fruit and has increased the percentage of fruit nitrogen.

This result is consistent with other research findings. Tang *et al.* (2013) reported that the amount of nitrogen in citrus leaves was significantly related to the amount in the soil. In addition, increasing the yield of bitter cucumber with the application of nitrogen, phosphorus, and potassium fertilizers by Baset Mia *et al.* (2014) has been reported. The findings of other researchers also show the positive effect of vermicompost fertilizer on plant characteristics (Simon & Bababbo, 2015).

Investigation of the model predicting plant phosphorus values. The statistical parameters of the actual values input to the model are reported in Table 5 and the predicted values obtained from the model as reported in Table 6. Table 7 shows the results of fitting the predicted values of phosphorus in seed, fruit, leaf, and the root of the melon compared to actual values in response to soil phosphorus presented based on the SVR model.

The term "regression" refers to obtaining a hyperplane that fits the data. The distance of each dot from this hyperplane indicates the error of that particular dot. According to the predicted results, fruit phosphorus had the lowest error (RMSE= 0.228; MAPE= 0.38%); and leaf phosphorus the highest error values (RMSE= 22.98; MAPE= 90.57%) in the model's fitting. Based on the ratio of performance to deviation results, fruit phosphorous had excellent performance (RPD= 27.95), and leaf phosphorus had weak performance (RPD= 0.208) in model prediction.

As can be seen, the regression coefficients calculated for the models obtained from phosphorous in seed, fruit, leaf, and root were 0.997, 0.999, 0.981, and 0.995, respectively. According to the obtained regression coefficients, fruit phosphorous (R^2= 0.999) had the highest contribution in prediction than actual values, thus identified as the best model compared to other models. Also, based on the regression coefficients obtained from seed, fruit, leaf, and root phosphorous (0.998, 0.999, 0.991, 0.997, respectively), observed that there is a positive and significant linear correlation between the predicted and the actual values, indicating the success of the SVR model in predicting the changes in plant phosphorus compared to the actual values in response to soil phosphorus (Table 7).

After investigating the SVR models' accuracy and determining the general correlations between the data, the diagrams for the actual and predicted values of plant organs' phosphorus values were drawn (Fig. 4). The results show reliable modeling for support vector regression in predicting the content of the measured crop elements. The predicting models' performance of the fruit phosphorus is better than leaf, root, and seed phosphorus. The results of the scatter diagram for each feature are presented in Fig. 4. Depending on the figures, actual and predicted values are scattered close to the 1:1 line. Consequently, it found a positive and strong correlation between the data by the high models' accuracy.

Figure 5 presents the diagram for changes in plant organs' phosphorus values in response to soil phosphorus. To achieve the optimum results in predicting the crop phosphorus, the most suitable soil phosphorus content was estimated between 10 to 59 mg kg^{-1}. According to the results obtained from the model's prediction, at first, the rate of the release of phosphorus from different fertilizer treatments was slow. However, gradually, after the decomposition of fertilizers used in the experiment by releasing nutrients and increasing the soil phosphorus content up to 38 mg kg^{-1}, the plant organs' phosphorus values increased to their maximum, then slightly decreased and followed at a constant rate. This pattern of changes is almost the same in all fertilizer and vermicompost treatments. Soil phosphorus content of up to 38 mg kg^{-1} will be suitable and sufficient to supply the plant's agronomic needs. More soil phosphorus values do not affect increasing phosphorus content in plant organs, and more applications may not be economical.

According to the results, the highest increase in crop phosphorus content in response to soil phosphorus was predicted in the range of 15.74 to 26.19% for fruit phosphorus and 19.44 to 27.97% for leaf phosphorus under NPK chemical fertilizers by using 15 t ha^{-1} of vermicompost. After that, changes in root phosphorus were predicted in the range of 15.47 to 25.67% under NPK chemical fertilizers by using 5 t ha^{-1} of vermicompost. Also, changes related to the seed phosphorus were predicted in the range of 18.80 to 28.04% underuse of cow manure by use of 15 t ha^{-1} of vermicompost (Fig. 5).

It can be found that the amount of soil phosphorus has caused the adjustment and reduction of the error in estimating the predicted values of phosphorus in the model compared to the actual values of plant organs.

Phosphorus is also another macro-nutrient that has different roles in plant metabolism (Pourranjbari Saghaiesh, Souri & Moghaddam, 2019). Thus, phosphorus is especially required for seedling establishment (root growth) and later on at early reproductive steps (bloom and seed development) (Martuscelli *et al.,* 2016; Chen *et al.,* 2019).

It seems that chemical fertilizers have increased the storage of phosphorus in the soil by providing soil phosphorus. Also, the use of 15 t ha^{-1} of vermicompost in the field has increased the availability of phosphorus in the plant by increasing the decomposition of organic matter and mineralization of phosphorus in organic matter and their conversion into plant usable form. Vermicompost increases phosphorus uptake by increasing phosphorus solubility by activating microorganisms by secreting organic acids or stimulating phosphatase activity (Busato *et al.,* 2012). Kakraliya *et al.* (2017), in the study of the nutritional and biological effects of vermicompost on rice, stated that vermicompost increased the availability of nitrogen, phosphorus, and potassium. Vermicompost can also increase the amount of absorbed phosphorus (Jumadi *et al.,* 2014).

Investigation of the model predicting plant potassium values. The statistical parameters of the actual values input to the model are presented in Table 8, and the predicted values obtained from the model as reported in Table 9. In Table 10, the results of fitting the predicted values of potassium in seed, fruit, leaf, and the root of the melon compared to actual values in response to soil potassium are presented based on the SVR model.

The results obtained from the output of the regression models showed that leaf potassium with a coefficient of 0.984 and fruit potassium with a coefficient of 0.968 had the highest coefficient of determination (R^2), respectively, more accurately than other coefficients of determination. The coefficients of determination in root and seed potassium were 0.952 and 0.940, respectively.

Accordingly, fruit potassium with the highest ratio of prediction performance to deviation (RPD= 5.174) showed better performance than other potassium values in the root (RPD= 4.420), seed (RPD= 3.577), and leaf (RPD= 0.148), respectively. In addition, in the model fitting, the root of mean square error and the mean absolute percentage error in fruit potassium (RMSE= 0.465; MAPE= 1.77%) are less than the leaf potassium (RMSE= 12.148; MAPE= 132.11%). Based on these results, the regression model obtained from fruit potassium compared to leaf potassium minimized the error coefficients and performed better in estimating the coefficient of determination. It leads to more accuracy of the output models obtained from actual values in the plant organs in response to soil potassium (Table 10).

Figure 6 shows the actual values compared to the predicted values around the 1:1 line using the SVR model. As shown in Fig. 6, the data around the 1:1 line are well placed. The significance of the coefficient of determination for the regression line between actual and predicted values in leaf, fruit, root, and seed potassium with coefficients of 0.984, 0.968, 0.952, and 0.940 indicates the appropriate efficiency of this model to describe the trend of crop potassium changes in response to soil potassium (Fig. 6).

Figure 7 shows the diagram for changes in crop potassium values in response to soil potassium. To achieve the optimum results in predicting the crop potassium, the most suitable soil potassium ranged from 180 to 320 mg kg^{-1}. According to the obtained results, at the beginning of growth, because of potassium uptake by the plant, soil potassium decreased and showed a downward trend. However, gradually, after the decomposition of fertilizers used in the experiment by releasing nutrients and increasing the soil potassium up to 260-280 mg kg^{-1}, the plant organs' potassium values increased to their maximum, then slightly decreased due to the consumption by plant organs. The potassium increased again and reached its maximum in response to 320 mg kg^{-1} of soil potassium. Only the amount of leaf potassium continued to decrease, which was probably due to the transfer of nutrients to the fruits and seeds (Fig. 7).

Because the potassium in leaf and fruit plays a ministerial role in estimating the crop's potassium content, they identified as the best features in the final prediction of crop potassium values in response to soil potassium. According to the prediction results, the highest increase in crop potassium in response to soil potassium ranged from 15.19 to 19.67% for fruit potassium and 1.18 to 11.60% for leaf potassium under the NPK chemical fertilizer and the use of 15 t ha^{-1} vermicompost. After that, changes related to the root potassium values ranged from 9.37 to 15.78% under NPK chemical fertilizers and using 5 t ha^{-1} of vermicompost. Also, the changes related to the seed potassium can be predicted in the range of 14.09 to 18.22% under cow manure and using 15 t ha^{-1} of vermicompost (Fig. 7).

In a study by Xu *et al.* (2016) on the response of rice yield to potassium uptake, these researchers attributed the high yield changes to differences in climatic conditions and soil nutrient supply.

One of the main functions of potassium is to activate certain enzymes. Potassium acts more as a soluble ion to maintain cell turgescence in guard cells (Obreza & Morgan, 2011). The use of NPK chemical fertilizer by 15 t ha^{-1} vermicompost improved the physical and chemical soil properties, improved plant nutritional status, and increased the amount of absorbable potassium in soil and plants. In this regard, researchers such as Sabir *et al.* (2013), as well as Aruda *et al.* (2013), reported that inoculation of corn seeds with growth-promoting bacteria (*Aztobacter*, *Azpirillium*, and *Pseudomonas*) increased phosphorus, nitrogen, and potassium content in roots and shoots of the plant.

Researchers have stated that available potassium is one of the most important soil factors affecting the yield and quality of Novell orange fruit (Cheng *et al.,* 2016). In this regard, some researchers reported that the use of organic and integrated fertilizers, due to improving the physical and chemical properties of soil and availability and simultaneous release of essential elements with plant needs leads to improved vegetative and reproductive features, which ultimately enhances the crop yield (Fallah, Ghalavand & Raisi, 2013).

Conclusions

This study investigates the prediction models of macro-nutrient content in plant organs of *Cucumis melo* in response to soil elements affected by different fertilizers using support vector regression (SVR). Support vector regression can effectively calibrate input data sets such as nitrogen, phosphorus, and potassium in seeds, fruits, leaves, and roots to model (Fig. 1). The results show reliable modeling for support vector regression in predicting the macro-nutrient content in plant organs.

According to the results, when the data sets of nitrogen, phosphorus, and potassium in fruit, were used as input, the accuracy of these models was higher than 80.0% (R^2= 0.807 for predicting fruit nitrogen; R^2= 0.999 for fruit phosphorus; R^2= 0.968 for fruit potassium) (Tables 4, 7, 10, respectively). Likewise, the ratio of prediction performance to deviation (RPD) obtained from the models ranged from 2.017 for predicting fruit nitrogen (Table 4) and 5.17 for fruit potassium (Table 10) to 27.95 for fruit phosphorus (Table 7) content. Because the macro-nutrient content in fruit had the highest contribution in prediction than actual values, thus identified as the best model compared to other models in response to soil elements. Based on our findings, the importance of fruit phosphorus was identified as a determinant that strongly influenced melon prediction models.

According to the results of the prediction models in response to soil elements, the best soil nitrogen content ranged from 0.05 to 1.1%, soil phosphorus from 10 to 59 mg kg^{-1}, and soil potassium from 180 to 320 mg kg^{-1}, which offers a better content in the prediction models. Likewise, the best fruit nitrogen content ranged from 1.27 to 4.33%, fruit phosphorus from 15.74 to 26.19%, and fruit potassium from 15.19 to 19.67% obtained by 15 t ha^{-1} of vermicompost using NPK chemical fertilizers. More significant values of soil elements do not affect increasing macro-nutrient content in plant organs, and excessive application may not be economical. Therefore, the prediction of macro-nutrient content in fruits of *Cucumis melo* in response to soil elements could have caused a saving in the amount of fertilizer utilized and provided for the possibility of proper farming activities during the growing season.

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Table 1(on next page)

Chemical properties and composition of elements in the soil, vermicompost fertilizer and livestock manure samples used in the study.

* The values of phosphorus and potassium in the soil are expressed in mg kg^{-1}.

Chemical properties and composition of elements in the soil, vermicompost fertilizer and livestock manure samples used in the study were presented according to the methodology described in Methods. The final data is presented in Table 1.

Table 1:

Chemical properties and composition of elements in the soil, vermicompost fertilizer and livestock manure samples used in the study.

Features	Southeastern Iran (Zahak county)					Northeastern Iran (Fariman county)				
	N (%)	P (%)	K (%)	pH -	EC (dS m^{-1})	N (%)	P (%)	K (%)	pH -	EC (dS m^{-1})
Soil	0.03	16.6*	170*	8.12	3.2	0.058	39.5*	193*	7.62	5.02
Cow manure	1.14	0.71	1.10	8.02	3.50	1.33	0.65	1.01	7.50	3.26
Sheep manure	0.94	0.48	0.98	8.05	3.47	1.09	0.79	1.33	7.90	3.20
Vermicompost	1.40	1.02	1.10	8.25	7.5	1.50	1.30	1.20	7.30	6.40

*The values of phosphorus and potassium in the soil are expressed in mg kg^{-1}.

Table 2(on next page)

The statistical description of observed values of nitrogen in seeds, fruits, leaves, and roots.

The statistical description of observed values of nitrogen in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 2.

Table 2:

The statistical description of observed values of nitrogen in seeds, fruits, leaves, and roots.

Observed N	NO.	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	1.44	2.94	2.151	0.407	0.1893
Fruit	144	0.79	1.99	1.233	0.278	0.2258
Leaf	144	2.17	5.48	3.182	0.799	0.2512
Root	144	0.71	1.88	1.043	0.315	0.3023

Table 3(on next page)

The statistical description of the predicted values of nitrogen in seeds, fruits, leaves, and roots.

The statistical description of the predicted values of nitrogen in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 3.

Table 3:

The statistical description of the predicted values of nitrogen in seeds, fruits, leaves, and roots.

Predicted N	NO.	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	1.39	2.83	2.136	0.337	0. 1576
Fruit	144	0.68	1.94	1.228	0.247	0.2008
Leaf	144	2.13	5.50	3.215	0.753	0.2343
Root	144	0.66	1.85	1.025	0.268	0.2612

Table 4(on next page)

Evaluating the performance function in predicting nitrogen content in seeds, fruits, leaves, and roots.

Evaluating the performance function in predicting nitrogen content in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 4.

Table 4:

Evaluating the performance function in predicting nitrogen content in seeds, fruits, leaves, and roots.

Model N	RMSE	MAPE	RPD	R	R^2	Adjusted R^2	Standardized Beta	t	Sig.
Seed	0.224	6.73%	1.504	0.835^{**}	0.697	0.695	0.835	18.060	0.000
Fruit	0.122	7.01%	2.017	0.898^{**}	0.807	0.805	0.898	24.345	0.000
Leaf	1.061	31.85%	0.710	0.912^{**}	0.832	0.831	0.912	26.519	0.000
Root	0.216	14.02%	1.239	0.736^{**}	0.542	0.539	0.736	12.970	0.000

Table 5(on next page)

The statistical description of the observed values of phosphorus in seeds, fruits, leaves, and roots.

The statistical description of the observed values of phosphorus in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 5.

Table 5:

The statistical description of the observed values of phosphorus in seeds, fruits, leaves, and roots.

Observed P	N	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	15.21	46.80	23.916	5.875	0.2456
Fruit	144	10.29	40.88	22.968	6.382	0.2778
Leaf	144	14.60	34.39	24.004	4.818	0.2007
Root	144	9.72	56.55	21.684	7.890	0.3638

Table 6(on next page)

The statistical description of the predicted values of phosphorus in seeds, fruits, leaves, and roots.

The statistical description of the predicted values of phosphorus in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 6.

Table 6:

The statistical description of the predicted values of phosphorus in seeds, fruits, leaves, and roots.

Predicted P	N	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	15.18	44.55	23.915	5.822	0.2434
Fruit	144	10.34	40.83	22.955	6.375	0.2777
Leaf	144	14.55	32.85	23.966	4.782	0.1995
Root	144	9.77	55.49	21.705	7.816	0.3601

Table 7(on next page)

Evaluating the performance function in predicting phosphorus content in seeds, fruits, leaves, and roots.

Evaluating the performance function in predicting phosphorus content in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 7.

Table 7:

Evaluating the performance function in predicting phosphorus content in seeds, fruits, leaves, and roots.

Model P	RMSE	MAPE	RPD	R	R^2	Adjusted R^2	Standardized Beta	t	Sig.
Seed	0.334	0.46%	17.455	0.998^{**}	0.997	0.997	0.998	210.486	0.000
Fruit	0.228	0.38%	27.957	0.999^{**}	0.999	0.999	0.999	333.189	0.000
Leaf	22.98	90.57%	0.208	0.991^{**}	0.981	0.981	0.991	86.679	0.000
Root	0.579	0.82%	13.493	0.997^{**}	0.995	0.995	0.997	162.203	0.000

Table 8(on next page)

The statistical description of the observed values of potassium in seeds, fruits, leaves, and roots.

The statistical description of the observed values of potassium in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 8.

Table 8:

The statistical description of the observed values of potassium in seeds, fruits, leaves, and roots.

Observed K	N	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	9.62	22.93	14.345	2.686	0.1872
Fruit	144	12.23	22.84	16.831	2.540	0.1509
Leaf	144	5.75	13.80	9.099	1.833	0.2014
Root	144	5.42	19.02	11.916	3.182	0.2670

Table 9(on next page)

The statistical description of the predicted values of potassium in seeds, fruits, leaves, and roots.

The statistical description of the predicted values of potassium in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 9.

Table 9:

The statistical description of the predicted values of potassium in seeds, fruits, leaves, and roots.

Predicted K	N	Minimum (%)	Maximum (%)	Mean (%)	S.D	C.V
Seed	144	9.82	22.73	14.274	2.434	0.1705
Fruit	144	12.43	22.62	16.784	2.406	0.1433
Leaf	144	5.80	13.75	9.096	1.792	0.1970
Root	144	5.47	18.89	11.806	3.106	0.2630

Table 10(on next page)

Evaluating the performance function in predicting potassium content in seeds, fruits, leaves, and roots.

Evaluating the performance function in predicting potassium content in seeds, fruits, leaves, and roots in the study were presented according to the methodology described in Methods. The final data is presented in Table 10.

Table 10:

Evaluating the performance function in predicting potassium content in seeds, fruits, leaves, and roots.

Model K	RMSE	MAPE	RPD	R	R^2	Adjusted R^2	Standardized Beta	t	Sig.
Seed	0.681	2.39%	3.577	0.970^{**}	0.940	0.940	0.970	47.209	0.000
Fruit	0.465	1.77%	5.174	0.984^{**}	0.968	0.968	0.984	65.425	0.000
Leaf	12.148	132.11%	0.148	0.992^{**}	0.984	0.984	0.992	94.761	0.000
Root	0.703	1.97%	4.420	0.976^{**}	0.952	0.952	0.976	53.122	0.000

Figure 1

Schematic view of probabilistic model-based SVR. A) Calibrating data with the *ε*-insensitive loss function. B) Structure of SVR for predictions of spermophagy.

SVR for evaluating the performance function uses to calibrate the probabilistic model of spermophagy (SP) according to the methodology described in Methods. The *ε*- insensitive loss function uses to neglect the calibrating process-based SVR when differences between the predicted and observed spermophagy are less than <!--[if !vml]--> <!--[endif]--> schematically shown in Fig. 1-A. The structure of SVR is presented in Fig. 1-B that the input data set (*x*) such as nitrogen, phosphorus, and potassium in roots, leaves, seeds, and fruits are used to calibrate the probabilistic model of spermophagy (SP) using SVR.

SVR for evaluating the performance function uses to calibrate the probabilistic model of spermophagy (SP) according to the methodology described in Methods. The ε- insensitive loss function uses to neglect the calibrating process-based SVR when differences between the predicted and observed spermophagy are less than ε schematically shown in Fig. 1-A. The structure of SVR is presented in Fig. 1-B that the input data set (x) such as nitrogen, phosphorus, and potassium in roots, leaves, seeds, and fruits are used to calibrate the probabilistic model of spermophagy (SP) using SVR.

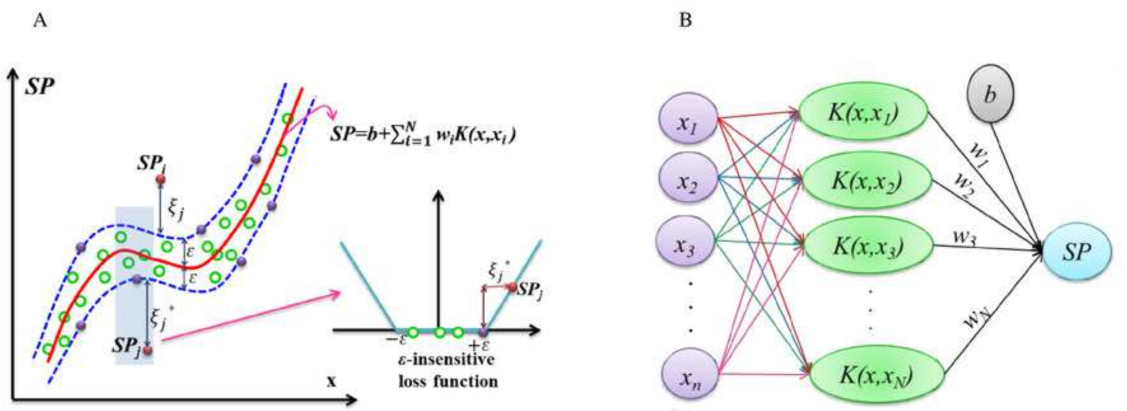

Figure 1: Schematic view of probabilistic model-based SVR.

A) Calibrating data with the ε-insensitive loss function. B) Structure of SVR for predictions of spermophagy.

Figure 2(on next page)

Scatter diagrams of observed and predicted values of nitrogen in response to soil nitrogen.

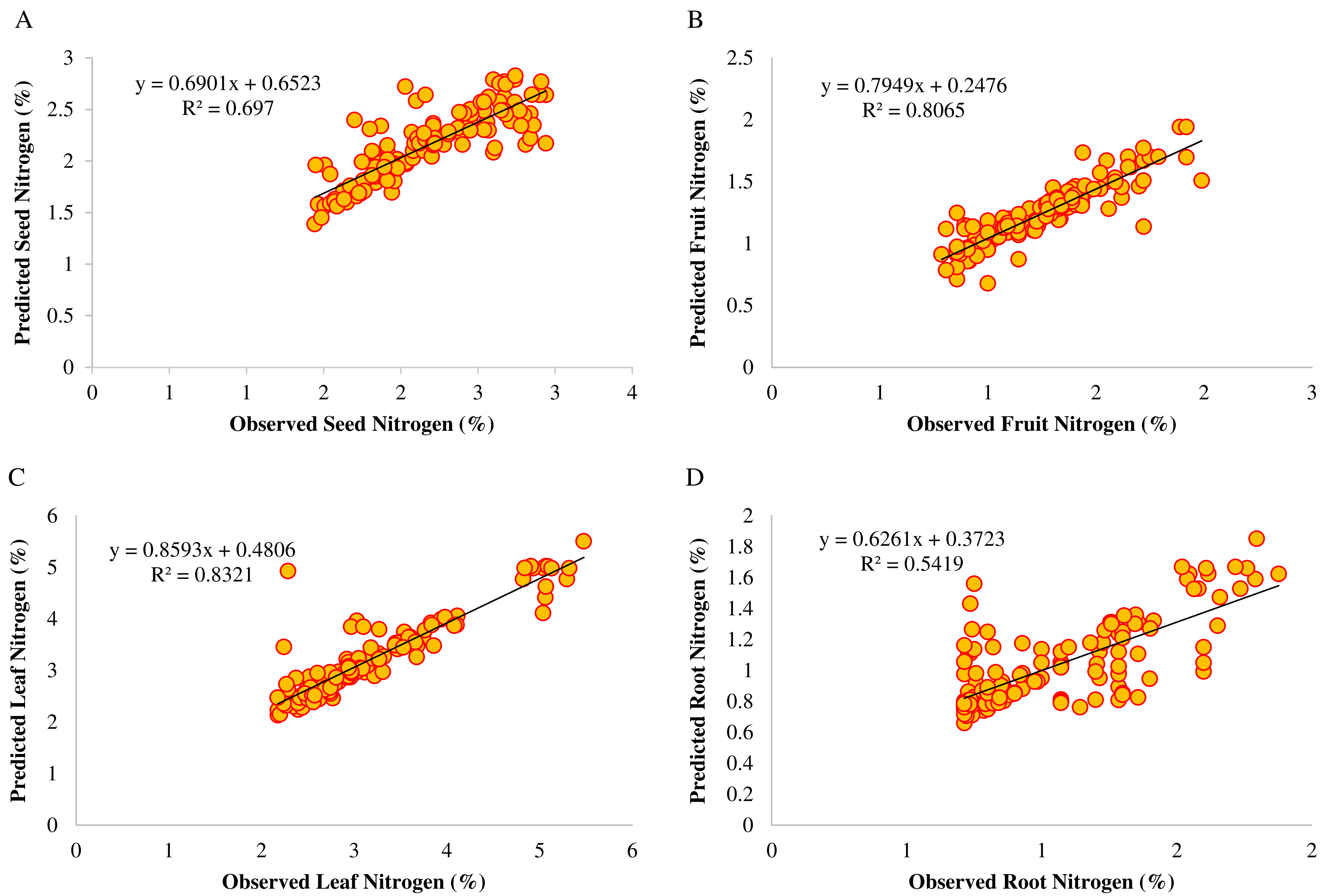

Figure 2: Scatter diagrams of observed and predicted values of nitrogen in response to soil nitrogen.

Fitting diagrams for predicted nitrogen content in plant organs of *Cucumis melo* in response to soil nitrogen using support vector regression investigated according to the methodology described in Methods. Fitting diagrams are presented in Fig. 2, respectively. The regression line slope of diagrams for investigated plant nitrogen values in the SVR model is presented in these figures.

Figure 3(on next page)

Patterns of changes in the predicted nitrogen values of plant organs in response to soil nitrogen under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

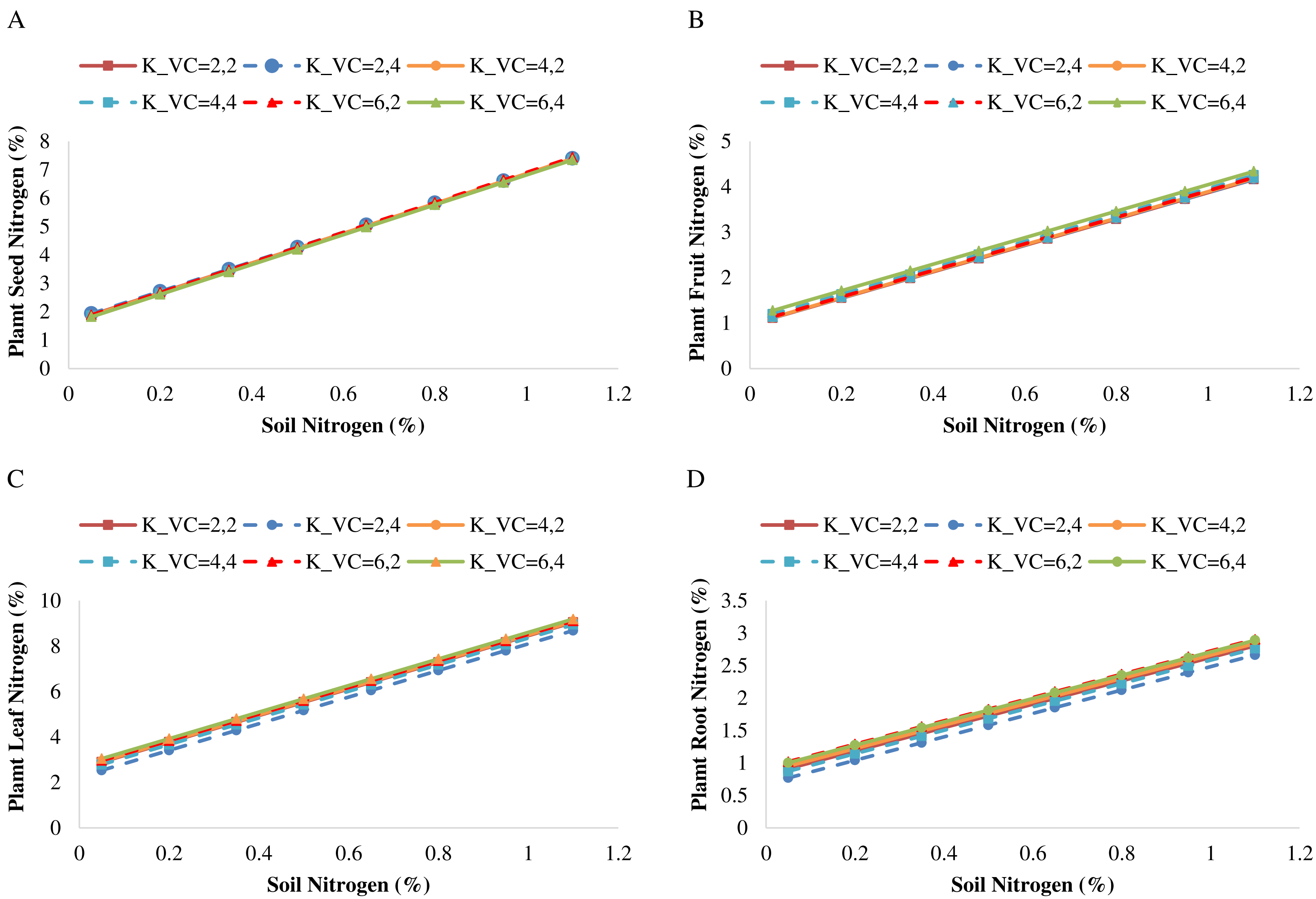

Figure 3: Patterns of changes in the predicted nitrogen values of plant organs in response to soil nitrogen under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

Changes of nitrogen content in plant organs of *Cucumis melo* in response to soil nitrogen using support vector regression investigated according to the methodology described in Methods. Figure 3 presents the diagrams for plant nitrogen changes in response to soil nitrogen values.

Figure 4 (on next page)

Scatter diagrams of observed and predicted values of phosphorus in response to soil phosphorus.

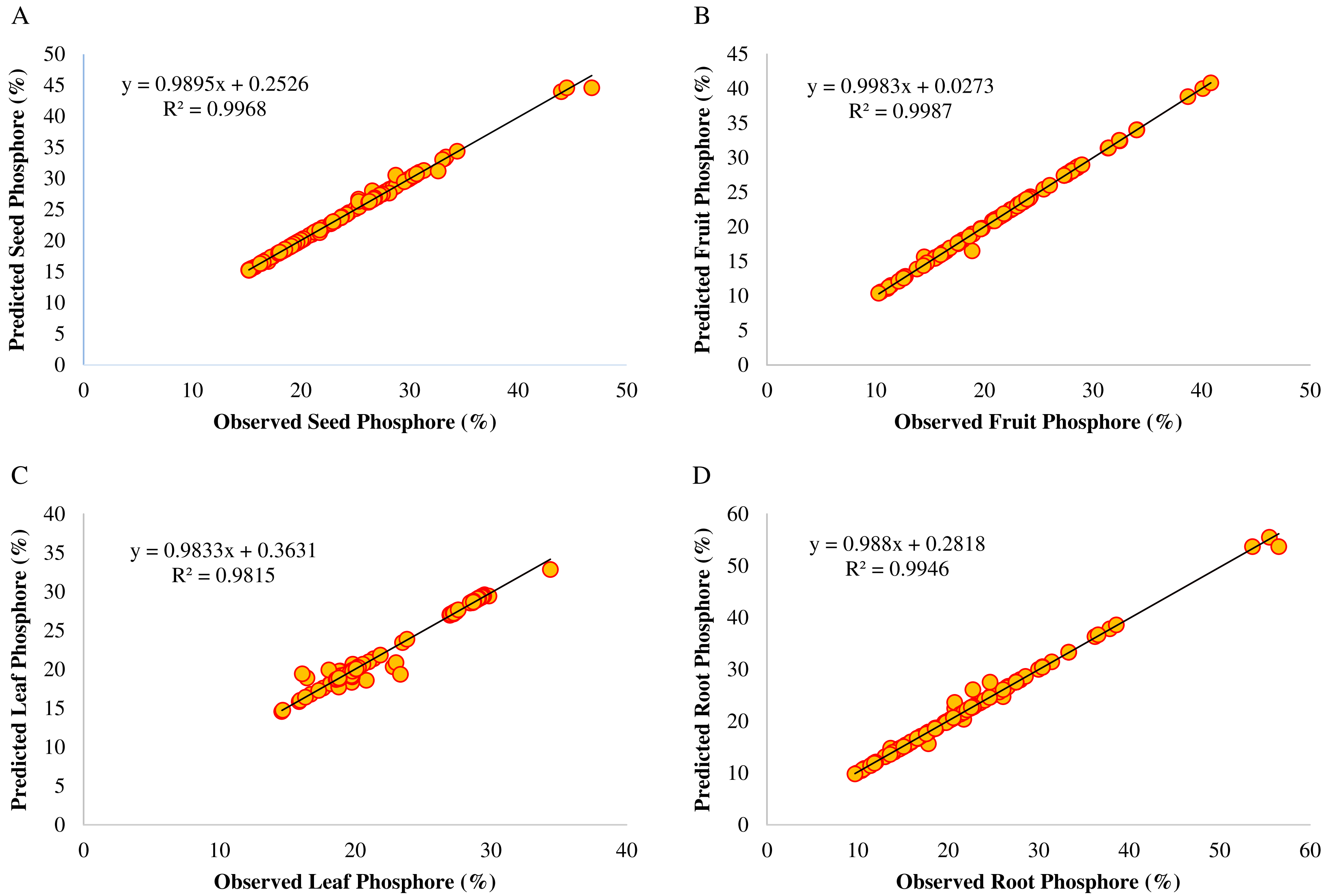

Figure 4: Scatter diagrams of observed and predicted values of phosphorus in response to soil phosphorus.

Fitting diagrams for predicted phosphorus content in plant organs of *Cucumis melo* in response to soil phosphorus using support vector regression investigated according to the methodology described in Methods. Fitting diagrams are presented in Fig. 4, respectively. The regression line slope of diagrams for investigated plant phosphorus values in the SVR model is presented in these figures.

Figure 5 (on next page)

Patterns of changes in the predicted phosphorus values of plant organs in response to soil phosphorus under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

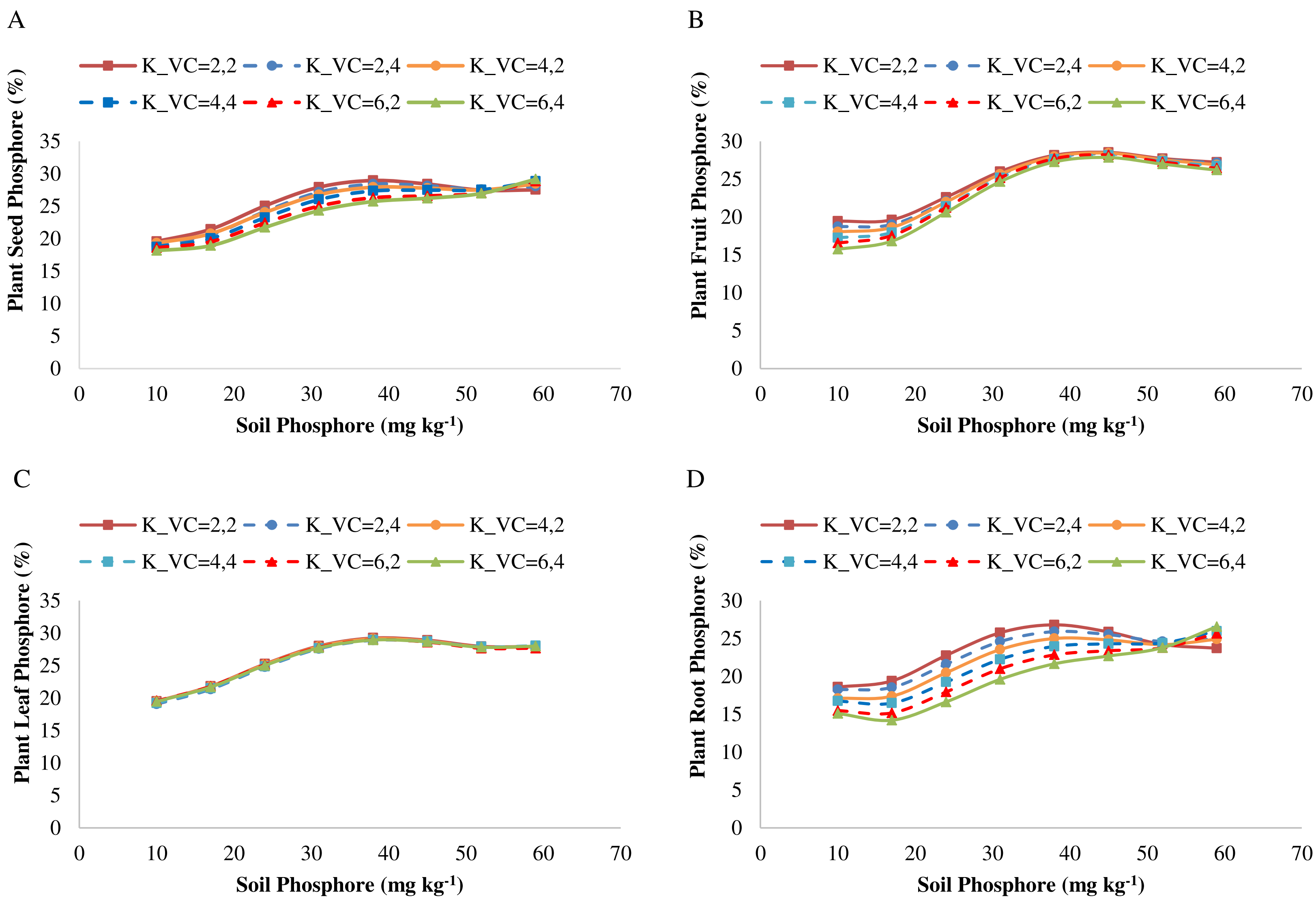

Figure 5: Patterns of changes in the predicted phosphorus values of plant organs in response to soil phosphorus under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

Changes of phosphorus content in plant organs of *Cucumis melo* in response to soil phosphorus using support vector regression investigated according to the methodology described in Methods. Figure 5 presents the diagrams for plant phosphorus changes in response to soil phosphorus values.

Figure 6 (on next page)

Scatter diagrams of observed and predicted values of potassium in response to soil potassium.

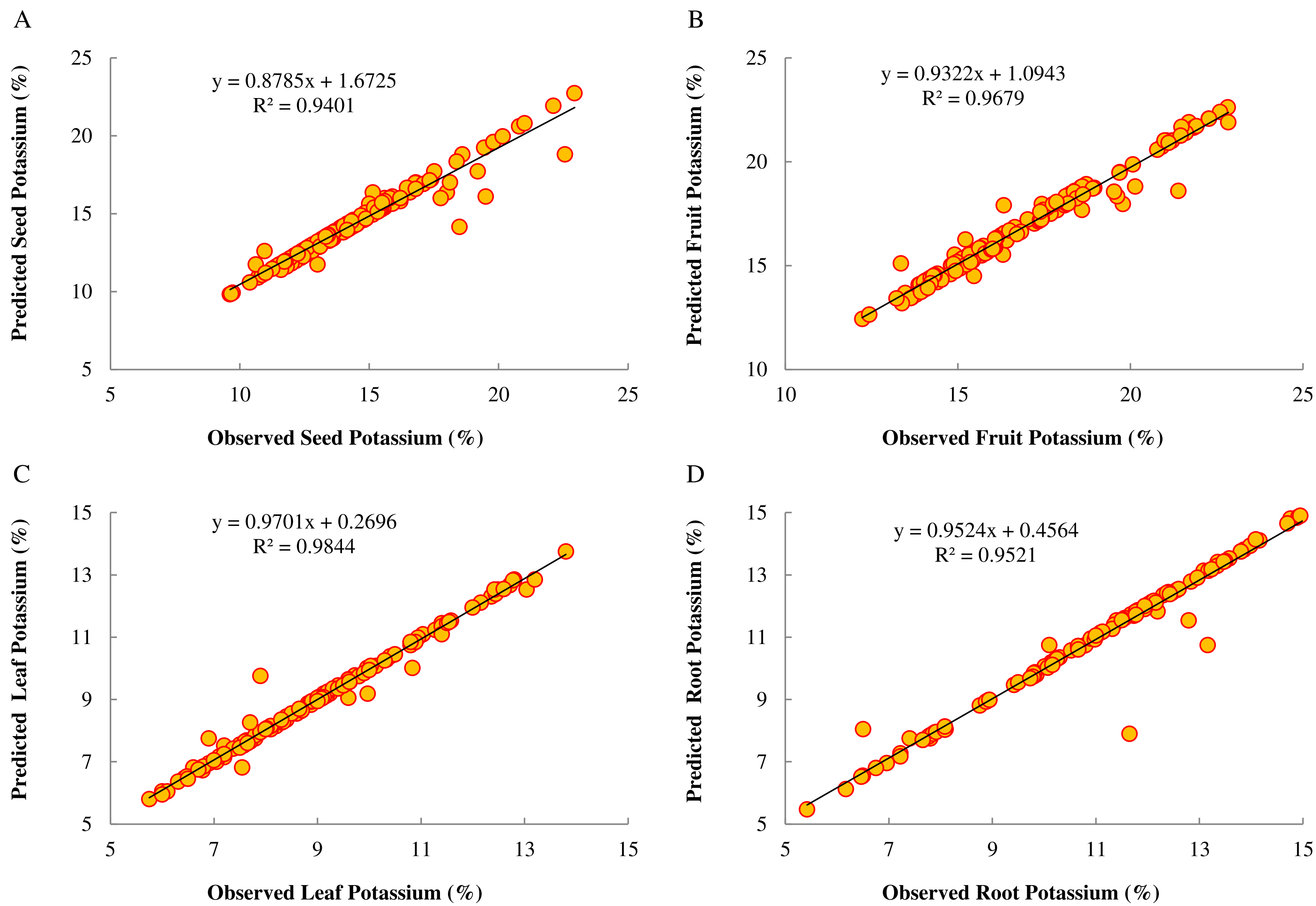

Figure 6: Scatter diagrams of observed and predicted values of potassium in response to soil potassium.

Fitting diagrams for predicted potassium content in plant organs of *Cucumis melo* in response to soil potassium using support vector regression investigated according to the methodology described in Methods. Fitting diagrams are presented in Fig. 6, respectively. The regression line slope of diagrams for investigated plant potassium values in the SVR model is presented in these figures.

Figure 7 (on next page)

Patterns of changes in the predicted potassium values of plant organs in response to soil potassium under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

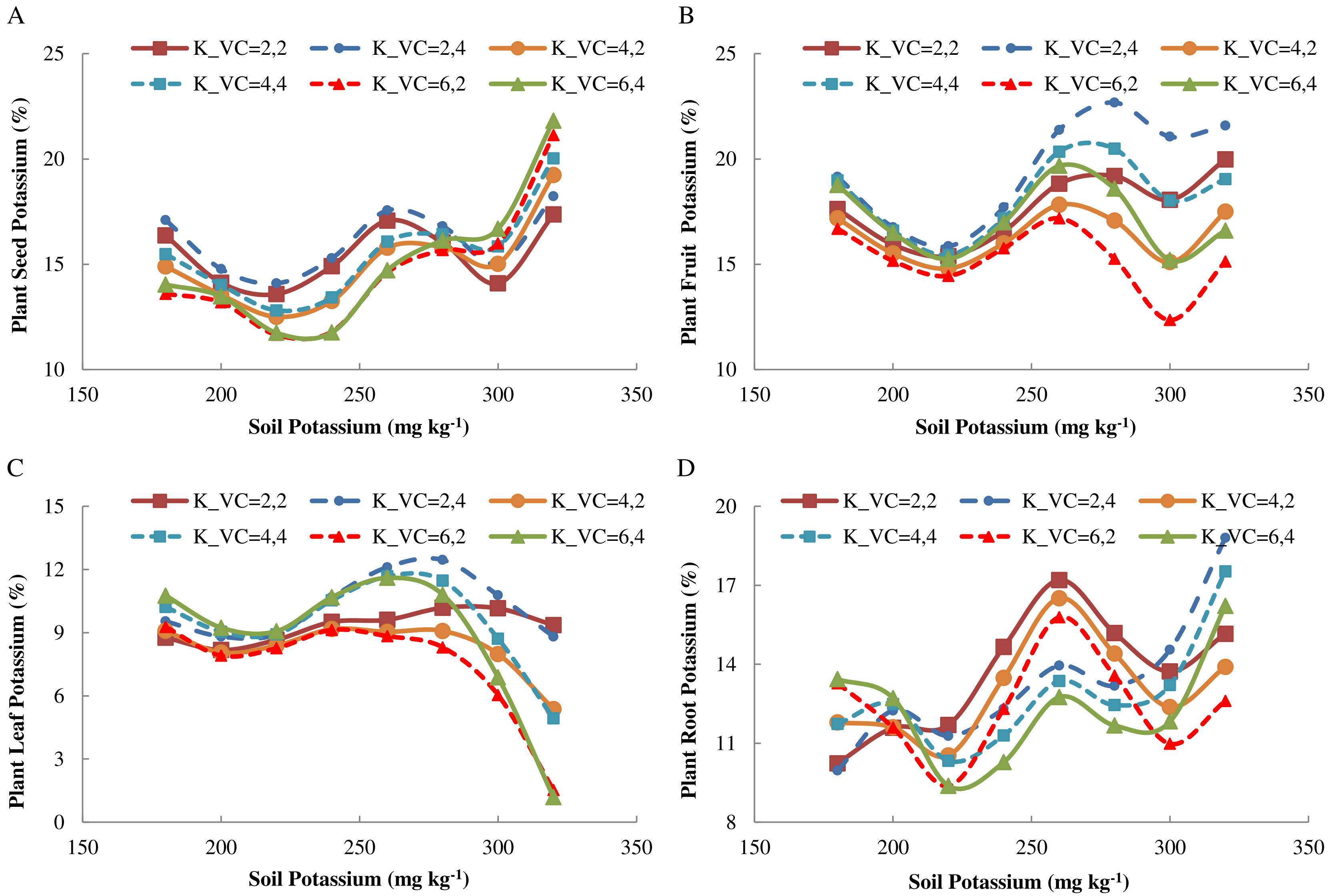

Figure 7: Patterns of changes in the predicted potassium values of plant organs in response to soil potassium under different fertilizer and vermicompost levels according to the SVR model.

The use of cow manure + 5 t ha^{-1} of vermicompost (F_VC= 2,2); cow manure + 15 t ha^{-1} of vermicompost (F_VC= 2,4); Nanobiomic foliar application + 5 t ha^{-1} of vermicompost (F_VC= 4.2); Nanobiomic foliar application + 15 t ha^{-1} of vermicompost (F_VC= 4.4); use of chemical fertilizer + 5 t ha^{-1} of vermicompost (F_VC= 6,2); the use of chemical fertilizer + 15 t ha^{-1} of vermicompost (F_VC= 6,4).

Changes of potassium content in plant organs of *Cucumis melo* in response to soil potassium using support vector regression investigated according to the methodology described in Methods. Figure 7 presents the diagrams for plant potassium changes in response to soil potassium values.