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Predicting Spatial Distribution of Redroot Pigweed (*Amaranthus retroflexus* L.) using the RBF Neural Network Model

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ABSTRACT

Estimating the spatial distribution of weeds for site-specific control is essential. Therefore, this research was conducted to predict and interpolate the spatial distribution of *Amaranthus retroflexus* L. populations using a Radial Basis Function Neural Network (RBF-NN) in two potato fields. Weed population data were collected from sampling 200 and 36 points, respectively, in two commercial potato fields in Jolge Rokh, of Torbat Heidarieh in Khorasan Razavi and Mojen of Shahroud in Semnan Provinces, Iran, in 2012. Some statistical tests, such as comparisons of the means, variance and statistical distribution, as well as linear regression, were used for the observed point sample data and the estimated weed seedling density surfaces to evaluate the neural network capability for predicting the spatial distribution of the weed. The results showed that the trained RBF-NN had high capability in the spatial prediction in points that were not sampled with 100% output, 0.999 coefficients, and an average error of less than 0.04 and 0.07 in the Mojen and Jolge Rokh Regions, respectively. Test results also showed that there was no significant difference between the statistical characteristics of actual data and the values predicted by the RBF-NN. According to the experimental results, the RBF-NN can be used as an alternative method to estimate the spatial changes function of annual weeds with random dispersion, such as Redroot Pigweed.

Keywords: Density estimation, Patchy distribution, Precision management, Radial Basis Function.

INTRODUCTION

In the site-specific management system, the first step is to collect information on weed spatial distribution in order to prepare detailed maps (Grundy *et al.*, 2005) as variable-rate applicators need precise maps for accurate herbicide application (Kiani and Jafari, 2012). Although, at the present time, herbicides are often used to kill weeds in agricultural fields, the fact is that the weeds still appear as patchy within fields (Heijeting *et al.*, 2007). On the other hand, weeds are considered as one of the factors responsible for decreasing the output of crops in agricultural fields, so, weed control is one of the most important aspects of production in the agricultural systems (Barberi, 2002). Today, chemical-dependent fielding systems have been increasingly reviewed because of concerns over environmental pollution, human health, and economic costs. In this

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regard, the studies show that predictions of weeds distribution and spot herbicide spraying in comparison with broadcast spraying reduces herbicide consumption and environmental pollution. Furthermore, it is economically beneficial for farmers (Jurado-Exposito *et al.,* 2004; Mohammadi, 2010). For example, patchy control of weeds in wheat in a five-year period reported that 39 and 44% of the total field area needed to be sprayed for controlling, respectively, narrow-leaved and broad-leaved weeds (Nordmeyer, 2006). Forecasting and preparing accurate maps of weed distribution in order to apply spot management has been assessed by different methods (Lamb and Brown, 2001). Today, in many fields such as classification, pattern recognition, prediction and modelling processes, neural networks are used in various sciences (Vakil-Baghmisheh and Pavešic, 2003). The advantage of the neural network method is direct learning by data without the need to estimate the statistical specifications (Gholipoor *et al.,* 2013).

A neural network, regardless of any initial hypothesis and prior knowledge of the relationships between the studied parameters, is able to identify the relationship between a set of inputs and outputs in order to forecast every corresponding output with an arbitrary input (Kaul *et al.,* 2005; Torrecilla *et al.,* 2004). Another feature of the neural network is tolerance against error (Rohani *et al.,* 2011). These advantages clarify the reasons of using a neural network to predict weed density. Nowadays, neural network models are considered as well-known tools for estimating functions in ecological and environmental research, and they can accurately distinguish weeds from crops in the fields (Zhang *et al.,* 2008). Torra *et al.* (2016) developed an Artificial Neural Network (ANN) model for emergence prediction of ripgut brome (*Bromus diandrus* Roth) and comparison of their predictive capability against already-developed Non-Linear Regression (NLR) models. Both ANN and NLR were able to predict satisfactorily *B. diandrus* Roth emergence patterns. However, the ANN improved the fitting accuracy with *RMSE* estimates 46% lower compared to NLR models. These results confirm that ANNs are powerful tools for modeling weed emergence, thus they could help improve IWM decision support systems. Dyrmann and Christiansen (2014) demonstrated a framework that was able to distinguish 22 weed and crop species at early growth stages by fusing a shape based classification of leaves and whole plants. For these 22 species, the network was able to achieve a classification accuracy of 86.2%. Irmak *et al.* (2006) predicted spatial patterns of soybean yields by using an artificial neural network in the field and they examined factors causing spatial changes in function, such as topography and soil fertility. *A. retroflexus* L. is one of the most dominant dicotyledonous weeds in the world (Rafael *et al.,* 2001), and on a competitive index in a scale from zero to one, it is close to one (Cowan *et al.,* 1998). Corn and soybean yield losses due to high redroot pigweed densities (more than 30 plants per square meter) have been reported at about 90% (Costea *et al.,* 2004). Vangessel and Renner (1990) reported that one redroot pigweed per meter of row reduced marketable tuber yield 19-33%. Thus, regarding the significant effects of this weed species on potato production, knowledge about its reproduction, dispersal and distribution can play an effective role in better managing the impacts of the weed. Wyse-pester *et al.* (2002) reported that the spatial distribution of *A. retroflexus* L. population appeared almost in fixed patches during two successive years. Thus, these researchers concluded that sampling for preparing maps of this type of weed pollution may not be necessary every year, especially considering that the most important principle in examining the density and spatial distribution of weeds in the fields is providing a way for accurate and detailed prediction of weed location. In this regard, several studies have been conducted by various interpolation techniques in order to predict, classify, and prepare accurate maps of vegetation, biomass, and function changes etc., and their main objective is to prepare reliable maps for accurate management in the fields (Zhang *et al.*, 2008; Wiles, 2005). Therefore, our main objective in this study was to examine the ability of the Radial Basis Function Neural Network (RBF-NN) model for predicting the spatial distribution function and interpolation of *A. retroflexus* L. in areas not sampled, based on data obtained from samples of two potato fields in two areas with different climate conditions.

MATERIALS AND METHODS

Two field experiments were carried out in two potato fields of two different agricultural sites including Mojen of Shahroud, in Semnan Province (36° 26' N, 54° 39' E), and Jolge Rokh of Torbat Heidarieh, in Khorasan Razavi Province (36° 35' N, 28° 59' E), Iran, in July 2012. The Jolge Rokh and Mojen fields were 100×200 and 35.5×70 m in size, respectively. In Mojen and Jolge Rokh Regions, the soil texture was silt loam and loam, respectively (Table 1). A 3- year rotation of wheat-potato-potato was implemented in the Mojen field, and in the Jolge Rokh field, a steady rotation of cereal-fallow–potato had been done. Paraquat (1, 10-dimethyl-4, 40-bipyridinium) (Gramoxone 20% SL) was applied to the Mojen field at a rate of 480 gai ha^{-1} during the third week after planting, to control annual weeds. However, in the Jolge Rokh field, metribuzin (4-Amino-6-tert-butyl-3-methylsulfanyl-1, 2, 4-triazin-5-one) (Sencor, 70% WP) was used at a rate of 500 gai ha^{-1} as pre-plant soil incorporation. Sampling was done on square grids in dimensions of 10×10 m in September, 2012. At each node of the grid pattern, the numbers of weed seedlings were counted in the two fields within a permanent 0.5×0.5 m^2 quadrate, perpendicular to crop rows, giving a total of 36 and 200 sampling units on the first (Mojen) and second (Jolge Rokh) fields, respectively.

Data Preprocessing

Firstly, the data were divided randomly into two groups: 80% training data and 20% test data. If this classification did not lead to the desirable results, this step would be repeated again (Zarifneshat *et al.*, 2012). Prior to any ANN training process with the trend free data, the data must be normalized over the range of [0, 1]. The most commonly employed method of normalization involves mapping the data linearly over a specified range, whereby each value of a variable x is transformed as follows:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (r_{\max} - r_{\min}) + r_{\min} \qquad (1)$$

Where, x is the original data, x_n the normalized input or output values, x_{max} and x_{min}, are the maximum and minimum values of the concerned variable, respectively. r_{max} and r_{max} correspond to the desired values of the transformed variable range. A range of 0.1–0.9 is appropriate for the transformation of the variable on to the sensitive range of the sigmoid transfer function (Rohani *et al.*, 2011).

RBF Neural Network

The RBF network structure has been

Table 1. Some physicochemical characteristics of the field soil at the two study regions.

Region	pH	Ec (dS m^{-1})	Nitrogen (mg kg^{-1})	Phosphorous (mg kg^{-1})	Potassium (mg kg^{-1})	Organic matter (%)	Sand (%)	Clay (%)	Loam (%)
Mojen	7.2	0.94	0.041	46.4	604	0.31	20	18	62
Jolge Rokh	7.7	3.4	0.063	9.6	427	0.67	42	14	44

shown by a hidden layer in Figure 1. The network inputs and outputs are the spatial coordinates and the density of weeds, respectively. The input layer of the network includes three neurons as the network inputs include the bias factor and spatial coordinates. Coordinates are pairs (X, Y) in a two-dimensional space referenced to location of sampling points. The output layer includes only one neuron that indicates the density value of *A. retroflexus* L. The optimized values of learning parameters $\eta 1$, $\eta 2$, and $\eta 3$ were selected by trial and error, and based on the method explained by Rohani *et al.* (2011). The network is in charge of vector mapping, i.e., by inserting the input vector, X^q the network will answer through the vector Z^q in its output (for q= 1,...,Q). The aim is to adapt the parameters of the network in order to bring the actual output Z^q close to corresponding with the desired output dq (for q= 1,...,Q). For network training, Back propagation with a Declining Learning-Rate Factor (BDLRF) algorithm is employed. The computer code of this algorithm was also developed in MATLAB software.

BDLRF Algorithm

We also used a modified version of the back-propagation original algorithm (Vakil-Baghmisheh, 2002). This training algorithm was initiated with a relatively constant large step size of learning rate and momentum term. Before destabilizing the network or when the convergence was slowed down, for every T repetition (3≤ T ≤5), these values were decreased monotonically by means of arithmetic progression, until they reached x% (equals to 5) of their initial values. Learning parameter (η) was decreased using the following equations:

$$\eta_n = \eta_\circ + (x-1)\frac{n\eta_\circ T}{Q-n_1} \quad (2)$$

Here, n_1, η_n and η_0 are the start point of BDLRF, the learning rate in n^{th} term of arithmetic progression, and the initial learning rate, respectively.

The cost function used in this algorithm is the Total Sum-Squared Error (TSSE) and it is calculated as follows:

$$q = 1,\ldots,Q$$

$$TSSE = \sum_q \sum_k \left(d_k^q - z_k^q\right)^2 \quad (3)$$

Where, d_k^q and $z_k^q X$ are the k^{th} components of desired and actual out-put vectors of the q^{th} input, respectively. Network learning occurs in two phases: forward pass and backward pass. The weights of each layer of the network are calculated as follows:

$$u_{mj}(n+1) = u_{mj}(n) - \eta_3 \frac{\partial E}{\partial u_{mj}} \quad (4)$$

$$v_{im}(n+1) = v_{im}(n) - \eta_2 \frac{\partial E}{\partial v_{im}} \quad (5)$$

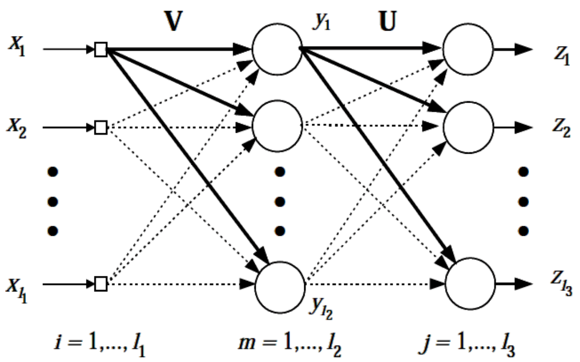


Figure1. The structure of the RBF network with one hidden layer (Vakil-Baghmisheh, 2002).

$$\sigma_m^2(n+1) = \sigma_m^2(n) - \eta_1 \frac{\partial E}{\partial \sigma_m^2} \tag{6}$$

i=1,...,l_1، m=1,...,l_2,j=1,...,l_3

Where, u_{mj} is the weight connection between nodes j and m, v_{im} is the weight connection between nodes i and m, and $\sigma_m$is the dispersion parameter for *m* nodes. The initial values of these weights are randomly selected from values range [-0.1 0.1]. L_1 ،L_2 and L_3 are the number of neurons in the input layer, hidden layer, and output layer, respectively. η_1, η_2 and η_3 are learning momentum for σ_m ،v_{im} and u_{mj}, respectively, and their values are between [0-1] and n is the number of algorithm repetition ($n=1,...,N$). When *TSSE* is lower than the threshold value, the algorithm is stopped (0.0001 is the threshold value for this study).

Performance Evaluation Criteria of the Network

To evaluate the capability of the RBF neural network for predicting the distribution and density of weeds, some criteria were applied, which included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and linear regression coefficient values predicted by the neural network and the actual values and model Efficiency (EF). These statistical parameters are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(d_i - p_i)^2}{n}} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| d_i - p_i | \tag{7}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(d_i - p_i)^2}{\sum_{i=1}^{n}(d_i + \bar{d})^2} \tag{8}$$

Where, d_i is the component of actual output, p_i is the component of the predicted output (fitted) by the network and $\bar{d}$ is the average of the actual outputs and *n* is the number of variable outputs (Rohani *et al.*, 2017). *RMSE* is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are (Jadhav *et al.*, 2017). A model with the smallest *RMSE*, *MAE*, and largest *EF* is considered to be the best (Das *et al*., 2015; Rohani *et al.*, 2017). Here, the null hypothesis implicates the equality of mean and variance of the two data series. Each hypothesis was tested at the probability level of 95% by *P* parameter. For the comparison of mean and variance, the *t* and *F* tests were used, respectively (Rohani *et al.*, 2017).

RESULTS AND DISCUSSION

The results showed that the network's best performance is achieved in $\eta_1 = \eta_2 = 10^{-12}$ and $\eta_3 =$ 0.95. It resulted in 150 optimums of the repetitions required for the network with the starting point (n_1) in seven. Makarian and Rohani (2012) reported that the Multi Layer Perceptron (MLP) neural network for learning the distribution pattern of the *Acroptilon repense* based on the threshold in order to divide the field, in terms of the existence or nonexistence of the weed, requires 1000 repetitions. Therefore, the repetition number of the RBF-NN is much less and about 0.01% of the repetition number of the MLP-NN for interpolation and prediction of the spatial distribution of weeds. The comparison of the results obtained by applying the linear normalization method showed better performance than in non-normalization method. Therefore, this method was used in order to normalize the data, and this result is in accordance with the results of other studies (Gholipoor *et al.*, 2013). Figure 2 demonstrates the convergence diagram of the RBF-NN. The initial value of TSSE for *A. retroflexus* L. was found to be much higher in the Jolge Rokh Region than in the Mojen Region (around five-fold). This is due to the more drastic local changes of *A.*

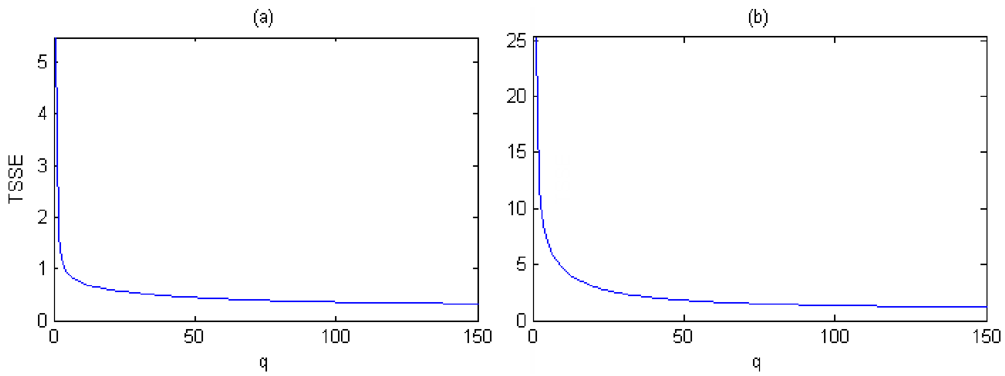


Figure 2. The convergence diagram of the RBF-NN during the training stage for the data of the two regions (a) Mojen and (b) Jolge Rokh. *q* shows repetition number and *TSSE* the Total Sum of Square Errors of training stage for normalized data.

retroflexus L. Probably, it may be related to the greater variance of weed density and distribution in Jolge Rokh than Mojen Region. As seen in Figures 4 and 5, patches in Jolge Rokh Region are small and abundant but in Mojen field they are low and widespread. At the end of the learning process, the *SSE* obtained for both the Jolge Rokh and Mojen Regions was 1.173 and 0.325, respectively. Makarian *et al.* (2007) also reported that, because of lower relative variance in seed bank than seedling, the difference between observations was greater at seedling level compared to seed bank.

Table 2 shows the mean and variance values, as well as the comparison between mean and variance values of actual density data of *A. retroflexus* L. and the values predicted by the network at the two stages of training and testing of the RBF-NN for both the Jolge Rokh and Mojen Regions. According to reports by Rohani *et al.* (2011) and Gholipoor *et al.* (2013), in order to achieve better performance, the division of data into two sets of training and testing can be different in each case. No significant difference is observed between the statistical features of the predicted values and their actual values for the trained neural network. The results show that the mean and variance of actual and predicted values of *A. retroflexus* L. density in the two regions have no significant difference with each other (in all cases P> 0.49). The result related to the training stage of the network shows that learning parameters and other parameters of the network have been well optimized. Furthermore, based on the results obtained from the testing of the network with a data collection separated from the training data collection, it can be claimed that the network can have a good prediction

Table 2. Statistical comparison of the actual and predicted values of *A. retroflexus* L. density by RBF-NN.

Region	Performing stage of network	Statistical analysis					
		Mean		*P*-Value	Variance		*P*-Value
		Avd [a]	*Pv* [b]		*Avd*	*Pv*	
Mojen	Training	4.48	4.65	0.92	39.09	35.28	0.80
	Testing	2.91	2.95	0.98	19.49	19.03	0.97
Rokh	Training	3.68	3.81	0.78	19.00	17.01	0.49
	Testing	5.44	5.46	0.99	29.04	28.22	0.93

[a] The Actual values of the data, [b] The Predicted values by the neural network RBF.

in the new conditions (generalizability capability).

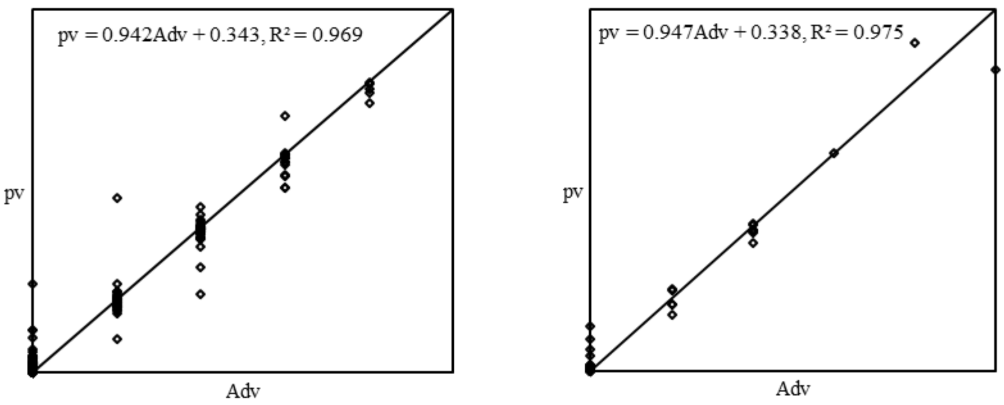
The performances of the RBF-NN planned at both the data training and testing stages were compared with each other (Table 3). It was quite evident that *RMSE* and *MAE* at the training and testing stages were very limited, indicative of a high capability of the artificial RBF-NN in interpolation of the distribution and density of *A. retroflexus* L.. As the data of the testing stage seemed new to the neural network, the error value at the testing stage was lower than at the training stage. As the results show (Table 3), *RMSE* and *MAE* values derived from both the training and testing stages for the Mojen are greater than Jolge Rokh Region. The reason for this may be due to the variability and pattern of weed distribution in the two regions such that the inherent function of weed distribution in the Mojen Region is more complex compared to the Jolge Rokh. Therefore, the values of neural network errors in the fitting of distribution function for Mojen Region are more than Jolge Rokh. The efficiency value of the RBF model for all the data in each of the two regions was 0.99, so, the neural network model was successful in the prediction of patterns of *A. retroflexus* L. density in the field.

Figure 3 demonstrates the coefficients of determination and also the relationship of linear regression between the actual density of the weed and densities predicted by the RBF-NN. If the linear equation of actual and predicted values by the neural network have high coefficients of determination (R^2), low y-intercept (near to zero) and a slope near to 1 (pv= 1.000 Adv+0.000), the best result is attained (Rohani *et al.*, 2011). The coefficients of determination between the actual and predicted data are very high (R^2> 0.96). Furthermore, the linear regression equation between them has slopes near to 1 and low *y*-intercepts. Therefore, such networks can be trusted. As the variability of

Table 3. Performance of the RBF-NN in prediction of *A. retroflexus* L. distribution in the two stages of training and testing.

Region	*MAE* [a]			*RMSE* [b]			*EF* [c]
	Training	Testing	Total data	Training	Testing	Total data	
Mojen	51.0	48.0	51.0	93.0	85.0	92.0	99.0
Jolge Rokh	47.0	15.0	41.0	91.0	22.0	82.0	99.0

[a] Mean Absolute Error; [b] Root Mean Square Error, [c] is model Efficiency.



(a) (b)

Figure 3. Linear regression relationship and coefficient of determination between the Actual data (Adv) and Predicted data (Pv) for the sum of the data of the two regions (a) Jolge Rokh and (b) Mojen.

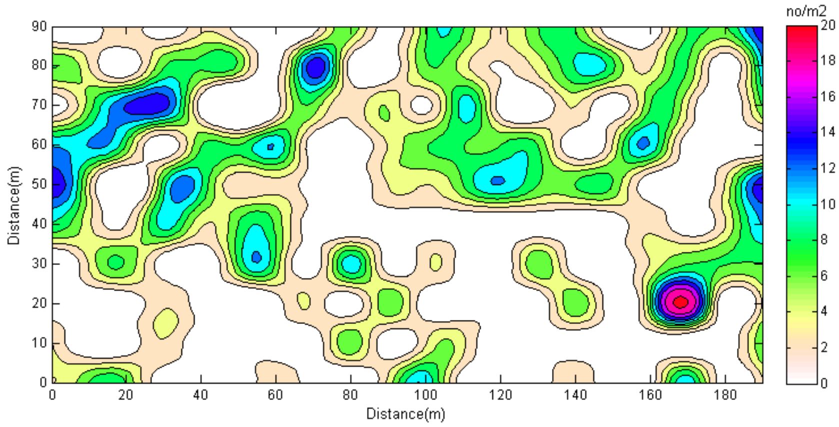


Figure 4. Map of population distribution and density of *A. retroflexus* L. seedling in interpolated mode by the RBF-NN model for the Jolge Rokh Region. Legend shows the number of weeds per square meter.

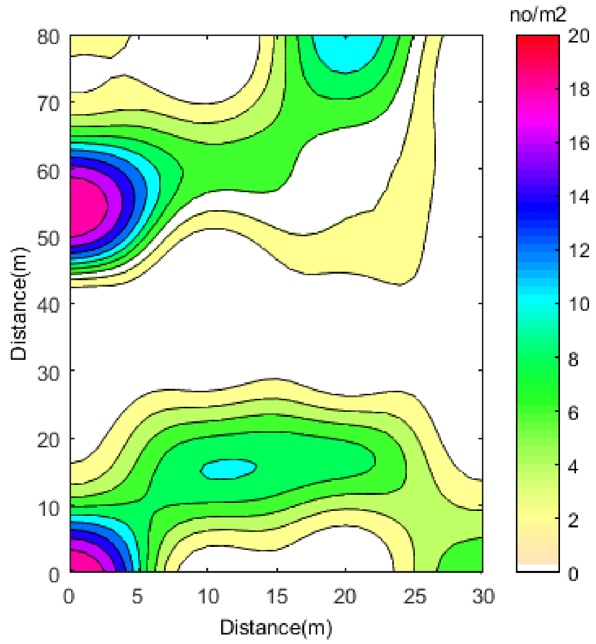


Figure 5. Interpolated map of population distribution and density of *A. retroflexus* L. in interpolated mode by the RBF neural network model for the Mojen Region. (no m^{-2}) in legend refer to the number of weed per square meter.

A. retroflexus L. density in the Mojen Region is higher than in the Jolge Rokh Region, y-intercept and the slope of regression line for the Mojen Region toward the Jolge Rokh Region are nearer to 1 and zero, respectively.

Zhang *et al.* (2008) studied the distribution patterns of insects on the surface of a grassland using means of artificial neural networks. The same researchers mentioned that recognition performance of neural networks depended upon not only the ecological scale but also the criterion for classification, because under the uniform criterion, recognition efficiency of linear methods became weaker as ecological scale became coarser. Also, in the output of the neural network, the number of available data for training the network and finding the optimal values of their weights and the degree of complexity inherent functions can be effective (Vakil-Baghmisheh, 2002; Zhang *et al.*, 2008). Therefore, it seems that differences in management practices and, probably, the environmental conditions of the two regions under study affected the ecological behaviors of *A. retroflexus* L. and, besides the difference in the number of available data for training the network and feature of inherent functions, resulted in different behaviors of this weed in both regions. As we observed, these differences influence the network's function. Tang *et al.* (2016) state that weed density can influence the accuracy of weed distribution algorithms, such that the accuracy of algorithm decreases when there are fewer weeds in corn fields. But, when there are a lot of weeds in corn fields, the accuracy of this paper algorithm decreases, and the algorithm can still correctly identify the center line of the crop rows. Therefore, our results confirm that the neural network can be a useful tool in the field of ecological behavior studies.

Weed Spatial Distribution

Figures 4 and 5 demonstrate the interpolated map of *A. retroflexus* L. in the Jolge Rokh and Mojen Regions, respectively, and show that the *A. retroflexus* L. has a heterogeneous distribution pattern in the two fields. In other words, numerous small and large weed patches were observed in the Jolge Rokh field, which does not follow a specific pattern. In the Mojen field, two spots of *A. retroflexus* L. were observed, which had infested a large part of the field. Distribution patterns of the population of the weeds demonstrate the proliferation method (sexual or asexual), the mechanism of seed distribution (by means of wind for small seeds or seeds having umbellate, water for small or winged seeds, machinery, predators activity etc.), seed size, existence or nonexistence of dormancy in seeds, soil-related factors (moisture, nitrogen, and other fertilizers, as well as texture and organic matters of the soil), and field management (Shaukat and Siddiqui, 2004; Streibig *et al.*, 1984). Burks *et al.*, (2005) stated that *A. retroflexus* L. seeds, along with dried inflorescence, are easily displaced on the fields by the wind in winter. *A. retroflexus* L. is an annual species that proliferates by seed; its seeds do not have a specific distribution mechanism but the large number of seeds may result in the success of this species in agricultural ecosystems (Costea *et al.*, 2004). Although the seeds of this weed are tiny, they are not adjusted for distribution by wind, therefore, a large part of the seeds of this weed are scattered in a distance of 0.2 to 2 meters from the mother plant (Costea *et al.*, 2004). According to Goslee *et al.* (2006), interactions among rainfall, temperature, soil texture, and management methods result in heterogeneous distribution of weeds in the fields, while, actually, a large part of this heterogeneity in the distribution of weeds populations, seed banks, and biomass of crops on the fields results from management practices (Makarian *et al.*, 2007). However, annual proliferous species can have patchy distribution by means of seed, and even preserve the stability of their patches for several years. Therefore, population predictions of these weed species in agricultural fields for site specific management purposes would be useful (Heijeting *et al.*, 2007). Therefore, it seems that due to the effective factors in distribution of this weed and its biological features, its different distribution in the fields under our study, obtained by application of neural network models, can be expected.

CONCLUSIONS

Accurate weeds identification, classification, and precision spraying are the main trend of modern agricultural development. This study demonstrated that the RBF neural network with a high precision (99% efficiency, 0.97coefficient of determination, average error less than 0.51, and 0.41 for the Mojen and Jolge Rokh Regions, respectively) was successful in the prediction and interpolation of distribution patterns of *A. retroflexus* L. In other words, the network was successful in the prediction of the weed status at other points, by means of 80% of sample point data. Furthermore, the maps obtained from the interpolation of the weed population demonstrated that *A. retroflexus* in the Mojen field had an array of spots. However, in the Jolge Rokh Region, numerous small and big spots of the weed were observed in the field, which indicated that these different distribution patterns resulted from the difference in management practices at the two fields. One of the problems of site-specific management is a lack of diagnosis of patches on the fields, or a lack of detailed practical maps and the large costs of sampling (Dille *et al.*, 2003). It seems that the RBF neural network can resolve these problems by proper prediction. In particular, when the weed has spot distribution, it becomes possible to conduct site-specific management of the weeds, in which time and costs can be saved, and the pollution that results from overall use of herbicides in the field will abate.

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پیش بینی توزیع مکانی علف هرز تاج خروس با استفاده از مدل شبکه عصبی مصنوعی تابع پایه شعاعی (RBF)

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چکیده

تخمین توزیع مکانی علف های هرز به منظور کنترل متناسب با مکان آنها امری ضروری است. بنابراین این پژوهش به منظور پیش بینی و درونیابی توزیع مکانی جمعیت علف هرز تاج خروس با استفاده از شبکه عصبی مصنوعی تابع پایه شعاعی (RBF) در سطح دو مزرعه زیر کشت سیب زمینی انجام شد. داده های مربوط به جمعیت علف هرز از طریق نمونه برداری از ۲۰۰ و ۳۶ نقطه بترتیب از سطح دو مزرعه تجاری سیب زمینی در منطقه جلگه رخ تربت حیدریه و مجن شاهرود در سال ۱۳۹۱ بدست آمد. برای ارزیابی قابلیت شبکه عصبی در پیش بینی توزیع مکانی علف هرز از مقایسه آماری و ضریب تبیین رگرسیونی خطی بین مقادیر پیش بینی شده مکانی توسط شبکه عصبی و مقادیر واقعی آنها و نیز معیارهای خطا و بازده مدل استفاده شد. نتایج نشان داد که شبکه عصبی آموزش دیده RBF، دارای قابلیت بالایی در پیش بینی مکانی علف هرز در نقاط نمونه برداری نشده با بازده ۱۰۰٪، ضریب تبیین ۰/۹۹۹ و متوسط خطای کمتر از ۰/۰۴ و ۰/۰۷ به ترتیب برای منطقه مجن و جلگه رخ بود. همچنین، نتایج نشان داد که در مرحله آزمایش بین مقادیر ویژگی های آماری مجموعه داده های واقعی و پیش بینی شده مکانی علف هرز توسط شبکه عصبی RBF تفاوت معنی داری وجود نداشت. بر اساس نتایج آزمایش، شبکه عصبی RBF می تواند به عنوان یک روش جایگزین برای تخمین تابع تغییرات مکانی علف هرز یکساله ای با پراکنش تقریبا تصادفی مانند تاج خروس استفاده شود.