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Article

Hybrid neural network with genetic algorithms for predicting distribution pattern of *Tetranychus urticae* (Acari: Tetranychidae) in cucumbers field of Ramhormoz, Iran

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ABSTRACT
Today, with the advanced statistical techniques and neural networks, predictive models of distribution have been rapidly developed in Ecology. Purpose of this research is to predict and map the distribution of *Tetranychus urticae* Koch (Acari: Tetranychidae) using MLP neural networks combined with genetic algorithm in surface of farm. Population data of pest was obtained in 2016 by sampling in 100 fixed points in cucumber field in Ramhormoz city, Khuzestan province, Iran. To evaluate the ability of neural networks combined with genetic algorithm to predict the distribution, statistical comparison between the predicted and actual values of some parameters such as variance, statistical distribution and linear regression coefficient was performed. Results showed that in training and test phases of neural network combined genetic algorithm, there was no significant difference between variance and statistical distribution of actual values and predicted values, but distribution was no significant. Our map showed that patchy pest distribution offers a large potential for using site-specific pest control on this field.

KEY WORDS: Genetic algorithms; Khuzestan province; neural network; spatial distribution; *Tetranychus urticae*.

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INTRODUCTION

Precision farming is the newest technology in agriculture, which is based on increasing performance, increasing economic profit, and decreasing adverse effects on environment. The most important orientation of precision farming is recognizing farm precisely such that we can detect problems and take actions for management with regard to conditions at different points of farm (Searcy 2008). Precision farming provides powerful instruments for increasing farm management performance. In this approach, by employing information technology, the farm is divided into similar units and after realizing characteristics of each unit, farm managers use inputs to achieve maximum economic profit based on the required amount (Cardina and Doohan 2008). Using inputs appropriately based on correct and precise maps is the key factor in applying precision farming successfully. Realizing dispersion patterns of pests and controlling them with regard to place can result in decrease of costs and entrance of chemicals to environment, and better control of pests in farm (Williams *et al*. 1999).

Cucumber is native to India and as the most economic plant of cucurbits is one of the valuable crops in Middle East (Nario 2010). Cucumber has many pests and diseases which one of them is two-spotted spider mite which in addition to cucumber, causes damage to crops in most parts of the world, especially in warm and temperate regions. Two-spotted spider mite by feeding leaves decreases the level of plant photosynthetic activity destroys chlorophyll, and in the case that damage is severe, results in falling leaves (Gorman *et al*. 2001). Huge amounts of artificial pesticides are used for controlling this tick annually. This pest has become resistant to artificial compounds due to short life cycle and quick reproduction, and using acaridae only results in crop infection and increase of their harmful side effects on non-subject creatures and environment (Isman 1999).

Today, many researches are conducting on preparing and using distribution maps of pests by using pest population dynamicity modeling in order to employing in management. However, what makes possible achieving to these goals is increasing accuracy and precision of methods of interpolation and preparing practical maps (Dille *et al*. 2003). Kriging is one of the interpolation methods that use in biological studies. Kriging calculates the amount of error related to predicted values using semi-variograms by combining given weights to adjacent data points (Gotway *et al*. 1996). One of the problems in common methods of classic statistics is lack of attention to profitability of information related to geographical location of observations (Makarian *et al*. 2007).

Zhang *et al*. (2008) used Learning Vector Quantization Neural Network for studying spatial distribution of insects in pasture lands, and it showed desirable performance. Now, many researches are conducting in order to predict and prepare precise maps of vegetation, changes of pests' population and so on with different interpolation methods. In the current study, we aim to assess the ability of Multi-layer Perceptron neural network hybrid with genetic algorithm as a smart alternative method in predicting and classifying distribution of two-spotted spider mite in non-sampled points based on data from sampled points of a cucumber farm.

MATERIALS AND METHODS

In order to conduct this research, a one-hectare cucumber farm around Ramhormoz with longitude 30° 33' N and 49.36 E′ with 150, meter above sea level was selected. This farm was divided into 10 m networks, and a total of 100 points was determined on it. In all sampling points, a 2×2 m2 block was selected, and 4 bushes were selected randomly as sampling units in it and number of insects in the back of plant leaf was calculated and recorded.

Pre-processing data

First, data were divided randomly to the instruction group with 70 members (70% of data) and test group with 30 members (30% of data). Of course, if this classification doesn't make desirable results, we can repeat this step (Zhang *et al*. 1998).

Before using initial raw data in instructing network, data should be normalized in a good range since learning algorithm with raw data can't have a good performance and due to changes of output of sigmoid activity function, which was used in middle layer, this task seems necessary. Otherwise, network will not be convergent during instruction phase. Consequently, desirable results will not obtain (Yuxin *et al*. 2006). When sigmoid activity function is used, the best range of data conversion is between 0.1 and 0.9 (Vakil-Baghmisheh and Pavešic 2003). In order to convert data, linear normalization equation (1) was used:

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

Where X is initial raw data, X_n is normalized data, X_{max} and X_{min} are maximum and minimum initial data, respectively, and r_{max} and r_{min} are upper and lower limits of change range of converted data, respectively.

MLP neural network with genetic algorithm was used in order to classify farm surface to two classes for three different modes. First mode is when the farm classified as two regions of existence and non-existence of pests, and second and third modes are when pest density for some points of farm is less than or equal, or more than 4 and 8, respectively. First class for first, second and third modes includes 35, 71, and 92 sampled points, respectively and second class for first, second and third modes includes 65, 29, and 8 sampled points, respectively. Seventy percent of data was selected for instructing network and remained 30% was selected for testing network in order to classification.

Multi-layer Perceptron (MLP) Neural Network

Multi-layer Perceptron neural networks are composed of one or more middle layers. Input signals are normalized by normal coefficients and after calculations, output is returned to real values (Kim 2006). Calculated values for output are compared with their real values, and the amount of error is calculated. If the amount of error, be different from desirable error which was previously considered, we go back and by changing communication coefficients and repeating previous steps, calculating new outputs, and in these networks instruction is based on the propagation algorithm (Choudhury and Bartarya 2003).

Despite general successes of the propagation algorithm, there are some problems: low converging rate of this algorithm, and convergent of this algorithm is dependent on selecting initial values of network weights, bias vectors and parameters in algorithm like learning rate (Freeman and Sakura 2005). With regard to disadvantages of this algorithm, smart algorithms are used for increasing converging rate and determining good network weights. Thus, genetic algorithm is used in this research.

Neural Network Architecture

In designing structure and architecture of neural networks, number of input vector elements is determined from the studied problems; however, determining the number of hidden layers, number of neurons, kind of relation among neurons, kind of activation function, and number of iterations are in control of designer and therefore, an optimal design seems necessary in neural network (Vellido *et al.* 2010).

For selecting model parameters and optimal designing, 8-step process presented by Kaastra and Boyd (1996) was used which hidden layer and 3 neurons in hidden layer had the best performance. Activation function which was used is sigmoid function in hidden layer and linear function in output layer was used. Number of iterations was considered 10000 in all steps.

Setting neural network weights by using genetic algorithm

Genetic algorithm is one of the searching algorithms, which is based on living organisms genetic. This algorithm merges Darwin's principle (selecting or survival of superior) with some structured random information and makes a searching algorithm with natural evolution method characteristics. In other words, in each generation a new set of strand is created using the most appropriate elements of previous generation, and new elements are tested for appropriateness (Shu-Heng 2002). One of the capabilities of genetic algorithm which is used in combination with neural network is setting weights of network connection. In the next section, we describe how to employ genetic algorithm in order to determine weights of developed neural network in current research.

Coding chromosomes

Each chromosome of genetic algorithm chromosomes is composed of sum of weights and biases corresponding to neural network architecture (Lohn *et al*. 2002). In this network, the weights which connect first and second layers are equal to 6. Also, the weights which connect second and third layers are equal to 3. On the other hand, 2 biases are considered for two neurons of second layer, and one bias is determined for one neuron in third layer. Sum of these biases is equal to sum of weights and biases of this network, which is 13.

Fitness function

Initial weights corresponding to neural network inputs (genetic algorithm chromosomes) are selected randomly in the first iteration. Also, mean square error relation is considered as fitness function of each chromosome of genetic algorithm and thus employing the instruction operator becomes possible (Paredis 1995). In the end of each iteration, 10% of the best chromosomes with 90% of new random produced chromosome is transferred to the next generation. The above process continues to reach to stop condition of the algorithm. At the end, the best chromosome is put as initial weights to artificial neural network.

Crossover and mutation operators

In order to intersect selected parent chromosome and produce child chromosomes, one-point crossover operator was used. Crossover operator is used for reproduction in each iteration and main purpose of using this operator is producing a generation with better fitness, provided that each child inherits desirable characteristics of its parents (Kumar *et al*. 2006). For selecting parent chromosome, Roulette wheel approach was used (Goldberg 1999). After using crossover operator, mutation operator is used in order to examine problem space more comprehensively such that in it, one place of each chromosome is selected randomly and the amount of gen corresponding to 0.5 possibility, increases (decreases) by 10%.

Stop condition

Number of all iterations of genetic algorithm was considered equal to 100 and if an improvement in the amount of fitness doesn't make after 30 iterations, algorithm stops.

Neural network and genetic algorithm codes were written in Matlab software version 8.1, and SPSS software version 19 were used for conducting statistical comparisons.

RESULTS AND DISCUSSION

In order to select genetic algorithm parameters like number of initial population, Crossover and mutation possibility, algorithms were conducted several times. According to Table 1, results of trial and error method showed that the best genetic algorithm output becomes possible with an assumption of initial population of 100 chromosomes, Crossover possibility of 0.9 and mutation possibility of 0.1. In fact, for mentioned parameters, relative error absolute mean becomes the minimum for recommended neural network output component.

Realization error of MLP artificial neural network in learning and test steps are shown in Table 2 which network error is different in varoius densities. In the study of dispersion patterns of insects (Zhang *et al*. 2008), realization error for specific insect density was equal to zero, because pasture insects have more mobility for earning enough food and have an almost uniform dispersion. However, mature ticks don't have mobility in farms, and this results in the increase of realization error of neural network.

Table 1. Error percentage of proposed neural network with different parameters of genetic algorithms.

AARE percentage for the third class (%)	AARE percentage for the second class (%)	AARE percentage for the first class (%)	Mutation rate	Crossover rate	Population
2.64	3.51	4.43	0.4	0.6	50
2.53	2.01	6.30	0.3	0.7	50
2.65	3.18	5.60	0.2	0.8	50
2.31	2.91	3.85	0.1	0.9	50
2.22	2.72	5.69	0.4	0.6	100
2.19	2.68	7.68	0.3	0.7	100
2.01	2.52	3.53	0.2	0.8	100
1.99	2.51	4.19	0.1	0.9	100
1.99	2.49	5.65	0.4	0.6	150
1.99	2.43	6.65	0.3	0.7	150
1.97	2.32	4.57	0.2	0.8	150
1.96	2.24	5.05	0.1	0.9	150

Table 2. Recognition error of MLP neural network in training and test phases.

Network goals for classification	Members of class 1	Members of class 2	Recognition error in training phase (%)	Recognition error in test phase (%)
TD = 0, TD < 4	35	65	25	29
TD ≥ 4, TD < 8	71	29	13	17
TD ≥ 8, TD > 12	92	8	10.07	12

In order to be sure from learning instructed neural network for predicting two-spotted spider mite dispersion pattern, real data and predicted data by network were compared statistically. Here, null assumption is equity of mean, variance and statistical distribution. Each hypothesis was tested at 95% confidence level by using p parameter. For comparing mean, variance and statistical distribution, t-test, F-test, and Kolmogorov and Asmyrnov test were used, respectively. Calculated p-values for each case are shown in Table 3. The mean and variance of results didn't show a significant difference for artificial neural network ($p < 0.001$) and there is no significant difference between statistical distribution of real data and predicted data by neural network at 95% confidence level ($p > 0.89$). Existence of $p > 0.73$ in case of statistical distribution between real and predicted values of two-spotted spider mite density at the farm surface show high accuracy and ability of MLP artificial neural network in order to classify farm surface in terms of density of this pest with any critical density.

Table 3. Statistical comparisons between the observed and estimated to *T. urticae* by MLP neural networks.

Classification	Utilization phase	Comparisons of means	Comparisons of variance	Comparisons of distribution
TD = 0, TD < 4	Training phase	0.893	0.778	0.75
	Test phase	0.006	0.689	0.61
TD ≥ 4, TD < 8	Training phase	0.681	0.324	0.73
	Test phase	0.008	0.009	0.70
TD ≥ 8, TD > 12	Training phase	0.776	0.594	0.89
	Test phase	0.653	0.006	0.70

Specification coefficients and linear regression relation between real values of each class against predicted values by neural networks are shown in Table 4. The best results based on these two criteria obtain when linear relation between pest density and predicted pest density by neural network, in addition to having specification coefficients, has been low intercept and a slop near to one. Results of Table 4 reveal generalizability of neural network in estimating density of two-spotted spider mite in farm. In a research which was done in order to determine dispersion patterns of insects in a pasture land by using neural networks, it is stated that MLP, LVQ, and linear neural networks can realize distribution patterns of insects very well (Zhang *et al*. 2008). However, among mentioned networks, MLP networks had the most powerful algorithm in realizing patterns, and Chon *et al*. (2000) research revealed high efficiency of MLP artificial neural networks in predicting dynamicity of dipertan Cecidomyiida in needle forests of U.S. Results obtained from these two researches are consistent with results from current research.

Table 4. Linear regression relationship and coefficient of determination between dv (actual value) and pv (predicted value by model).

Network goals for classification	Network Utilization phase	Linear regression relationship	R2
TD = 0, TD < 4	Training Phase	pv = 0.601 av + 0.025	0.650
	Test Phase	pv = 0.564 dv + 0.046	0.598
TD ≥ 4 , TD < 8	Training Phase	pv = 0.778 av + 0.186	0.797
	Test Phase	pv = 0.675 av +0.162	0.683
TD ≥ 8 , TD > 12	Training Phase	pv = 0.890 av + 0.090	0.880
	Test Phase	pv = 0.756 av + 0.047	0.701

Spatial distribution maps of two-spotted spider mite

Spatial distribution maps of two-spotted spider mite were separated and drawn by neural network and are shown in Fig. 1. In this figure, first, population of this pest was divided to non-pest and pest classes, and their maps were drawn (Figs. 1a and 1b). In Figs. 1c and 1d and also in Figs. 1e and 1f, pest population is drawn based on two thresholds of 4 and 8, respectively. Selected 0, 4, and 8 bushes limits can be a hypothetical threshold for this pest to show capability of neural network. Although we achieved lack of significance difference in statistical distribution of pest based on statistical comparisons, realization error and regression equation between real and predicted values, now, by comparison between maps resulted from real values and predicted values by network, we understand that there are some differences between corresponding points in map in some places which origin from neural network model error. However, we can't judge about accuracy of a model only by comparing one or more points (Zhang and Fuh 1998).

In comparing maps separated by neural network model and real maps, northern and south-eastern parts of farm had pests which were not predictable by neural network. Zhang *et al.* (1998) in comparing three neural network models for determining the dispersion patterns of pest at a meadow, argued that MLP neural network was a more powerful algorithm in realizing dispersion patterns of insect. They considered ecologic behavior of insect to be affective. Therefore, it is affective for increasing efficiency of a neural network for realizing dispersion of the number of hidden layers, mobility functions and even life cycle of insect (Filippi and Jensen 2006; Zhang *et al*. 2008). In another research which was done by using LVQ neural network, researchers classified amount of rice panicle infection to Blythe disease to healthy level, low infection level, medium infection level, and high infection level. Then, they tried to control this disease based on the considered infection threshold (Liu *et al*. 2010). Economic threshold is defined as density of pest at which cost of controlling pest is equal to profit of controlling it (Seraj 2011). Clearly points with density more than the threshold are spraying and other points, which are below the threshold don't need to spray. Prepared maps by neural network if have high accuracy can help the farm manager in controlling pesticides. Moreover, if maps are prepared based on coordinates of each place, can be a good guidance to active nozzles in points, which are above the pest threshold in variable-rate sprayers. Drawn maps reveal cumulative distribution.

CONCLUSION

This research showed that one of the other methods for modeling mite behavior is artificial neural networks. In this type of models, without considering non-linear complex equations, we can understand dynamicity in system and predict model outputs. In this research, a neural network combined with genetic algorithm could predict and draw dispersion of two-spotted spider mite with high accuracy. The resulted map reveals cumulative dispersion of this pest. Therefore, only by spraying points with high density, we can achieve good management of farm and decrease of using poisons.

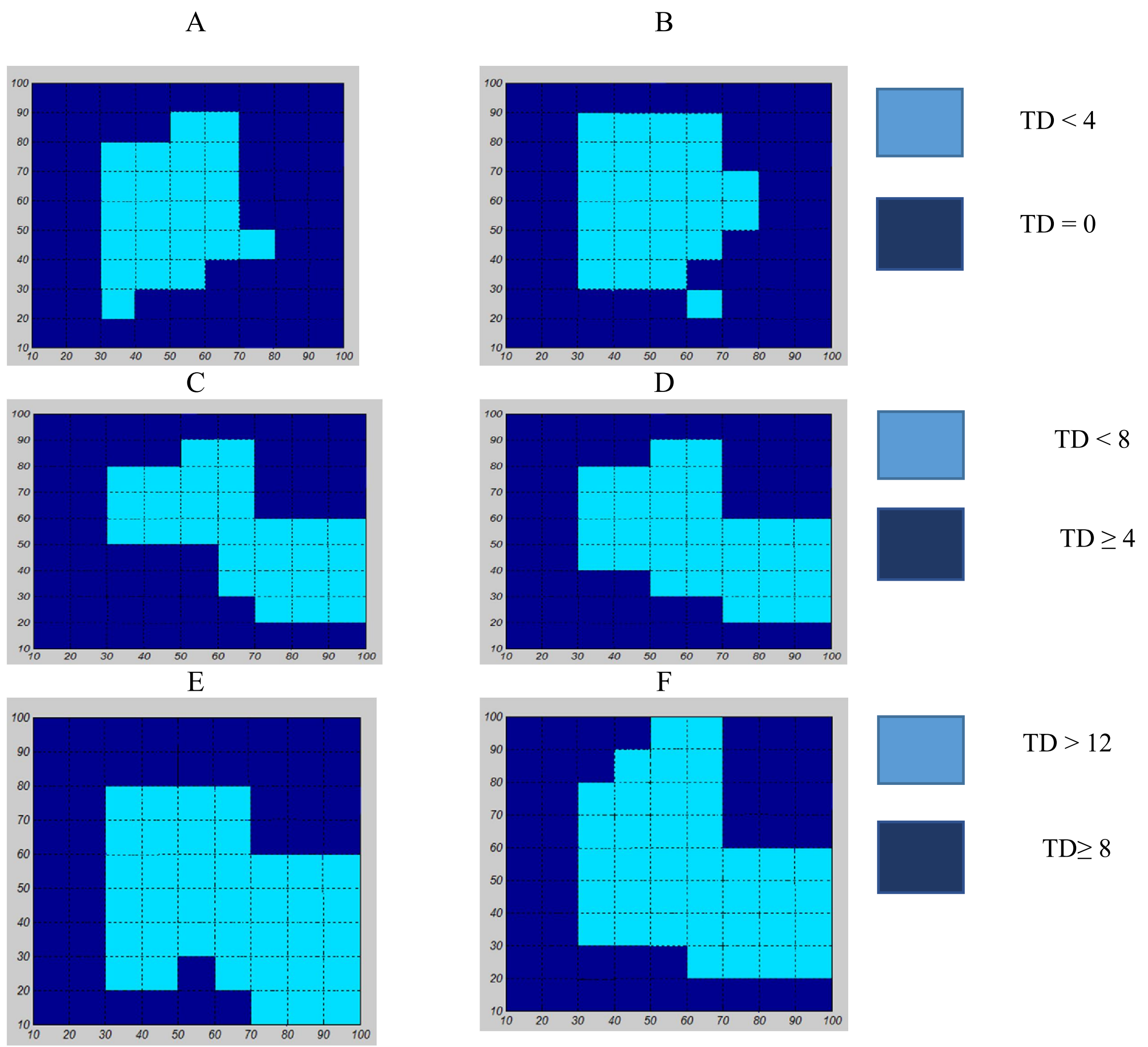

Figure 5. *Tetranychus urticae* distribution maps in actual (b, d and f) and classified conditions by MLPNN (c, e and a). The maps of a, c, e and b, d, f have been drawn according to economic threshold of 4, 8 and 12, respectively.

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ترکیب شبکه عصبی مصنوعی و الگوریتم ژنتیک در پیش‌بینی الگوی توزیع کنهٔ تارتن دولکه‌ای *Tetranychus urticae* (Acari: Tetranychidae) در مزرعه خیار شهرستان رامهرمز، ایران

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چکیده

با پدید آمدن تکنیک‌های آماری قوی و شبکه‌های عصبی، مدل‌های پیش بینی کننده پراکنش موجودات به سرعت در اکولوژی توسعه پیدا کرده است. این پژوهش به منظور پیش‌بینی و ترسیم نقشه توزیع جمعیت *Tetranychus urticae* Koch (Acari: Tetranychidae) با استفاده از شبکه‌های عصبی پرسپترون چندلایه (MLP) ترکیب شده با الگوریتم ژنتیک در سطح مزرعه انجام شد. داده‌های مربوط به جمعیت این آفت از راه نمونه برداری از ۱۰۰ نقطه از سطح یک مزرعه در شهرستان رامهرمز در سال ۱۳۹۵ به دست آمد. برای ارزیابی توانایی شبکه‌های عصبی مورد استفاده در پیش‌بینی توزیع از مقایسه آماری پارامترهایی مانند واریانس، توزیع آماری و ضریب تبیین رگرسیونی خطی بین مقادیر پیش‌بینی شده مکانی با شبکه عصبی و مقادیر واقعی آن‌ها استفاده شد. نتایج نشان داد که در مراحل آموزش و آزمایش بین مقادیر ویژگی‌های آماری واریانس و توزیع آماری مجموعه داده‌های واقعی و پیش‌بینی شده مکانی این آفت توسط شبکه عصبی ترکیب شده، تفاوت معنی‌داری وجود نداشت ولی توزیع آماری هم معنی‌دار نشد. نقشه‌های ترسیم شده نشان داد که توزیع آفت تجمعی است و امکان کنترل متناسب با مکان را در مزرعه مورد مطالعه دارد.

واژگان کلیدی: الگوریتم‌های ژنتیک؛ استان خوزستان؛ شبکه عصبی؛ پراکندگی مکانی؛ *Tetranychus urticae*.

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