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Determination of weed intensity in wheat production using image processing techniques

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ABSTRACT

It is of great importance to precisely and carefully apply the minimum amount of chemicals as needed because agricultural chemicals negatively impact the human health, environment and balance in the nature and increase the production costs. In this study, it was aimed at determining the density of broad leaf weeds and contributing to the reduction of herbicide use in wheat grown fields. For this purpose, Image Processing Techniques were used in this study; and Artificial Neural Networks (ANN) and regression models were developed for determination of weeds. In the ANN model, Weed Covered Areas Acquired by Image Processing Techniques (WCAAIPT) was used as input parameter; and Actual Weed Covered Areas (AWCA) as output parameter. In the study, a total of 262 data consisting of 244 data for training and 18 data for test were used. In the ANN model, the structure of the network was designed in the form of 1-(9-5)-1, consisting of 1 input layer, 2 hidden layers and 1 output layer; and the number of neurons in the hidden layer were determined to be 9-5. Also, tansig was used in the first hidden layer, logsig in the second hidden layer; and purelin transfer functions were used in the output layer. In the ANN and Regression models, R^2 value of the ANN model was found to be 99% and the goodness of fit (U^2) to be 0.000436; whereas R^2 and U^2 values of the Regression model were found to be 95% and 0.008431, respectively. It was determined that the results obtained from the ANN model were in agreement with the experimental data. By the developed ANN model, it would be possible to design and manufacture agricultural machinery in order to determine the weed density and reduce the herbicide use.

Anahtar Sözcükler:
Artificial neural networks
Image processing
Weeds
Winter wheat

Buğday üretiminde yabancı ot yoğunluğunun görüntü işleme teknikleri kullanılarak belirlenmesi

ÖZET

Tarımsal ilaçların insan sağlığı, çevre ve doğal dengeyi olumsuz yönde etkilemeleri ve artan üretim maliyetleri nedeniyle hassas, dikkatli, en az ilaç kaybına neden olacak şekilde ve gerektiği kadar uygulanması oldukça önem arz etmektedir. Çalışmada, buğday ekili arazilerde geniş yapraklı yabancı ot yoğunluğunun tespit edilmesi ve herbisit kullanımının azaltılmasına katkıda bulunulması amaçlanmıştır. Bu amaçla araştırmada Görüntü İşleme Teknikleri kullanılmış ve yabancı ot tespitine yönelik olarak Yapay Sinir Ağları (YSA) ve regresyon modelleri geliştirilmiştir. YSA modelinde, Görüntü İşleme Teknikleri ile elde edilen yabancı ot alanları giriş ve gerçek yabancı ot alanları çıkış parametresi olarak değerlendirilmiştir. Çalışmada eğitim için 244 ve test için 18 veri olmak üzere toplam 262 veri kullanılmıştır. Ağın yapısı 1-(9-5)-1 olacak şekilde, 1 giriş katmanı, 2 gizli katman ve 1 çıkış katmanı olarak dizayn edilmiş ve gizli katmanların nöron sayıları 9-5 olarak belirlenmiştir. Ayrıca birinci gizli katmanda tansig, ikinci gizli katmanda logsig, çıkış katmanında ise purelin transfer fonksiyonları kullanılmıştır. YSA ve Regresyon modelleri değerlendirildiğinde, YSA modelinin R^2 değeri %99, uyuşma derecesi (U^2) 0.000436, Regresyon modelinin ise R^2 değeri %95, uyuşma derecesi (U^2) 0.008431 olarak bulunmuştur. YSA modeli ile elde edilen sonuçların gerçek veriler ile uyumluluk içinde olduğu tespit edilmiştir. Geliştirilen YSA modeli ile, yabancı ot yoğunluğunun tespit edilmesi ve herbisit kullanımının azaltılmasına yönelik olarak tarım makinaları sanayisinde makine tasarımı ve üretimi mümkün olabilecektir.

Keywords:
Yapay sinir ağları
Görüntü işleme
Yabancı ot
Kışlık buğday

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1. Introduction

Today, the yield loss in agricultural production is becoming increasingly important because of decrease in agricultural lands as well as the population growth. The most important part of losses in plant production is caused by weeds. Herbicides are commonly used in order to control the weeds. However, common use of herbicides negatively affects human health and environment, and chemical residues are left in the soil, water, air and products.

When pesticide use around the world is analyzed, it is seen that the share of herbicides in the total pesticide expenditures is 26% while the amount of herbicides used constitutes 47% of the total use of pesticides (Öztürk, 1997; Tiryaki et al., 2010). Also in Turkey, herbicides with a share of 24% in pesticide expenditures have a considerably important place in agricultural inputs (Turabi, 2007; Durmuşoğlu et al., 2010). Besides, it is known that pesticides are heavily used especially in the regions where intensive cultivation is highly widespread. Fertile agricultural lands are deteriorating due to pesticide residues caused by the overuse of pesticides and the health of living organisms exposed to the residues, notably production materials, is also threatened (Topal, 2011). Since pesticides affect human health, environment and natural balance negatively and have increasing production costs, it is necessary to apply them in a sensitive and attentive manner that will cause the least pesticide loss (Dursun, 2000).

Considering the herbicide use in agriculture, it is important to reduce the usage of herbicides in the production areas of wheat, the essential nutrient. With the production capacity of 20.1 million tons, Turkey is ranked the 9th country around the world in wheat production. Moreover, wheat is the most cultivated crop in Turkey with around 7.7 million hectares of land in terms of agricultural production activities (FAO, 2012).

Herbicides commonly targeting broad leaf weeds are preferred in chemical application in wheat production. Applying pesticides is generally based on the method of covering the whole land surface with herbicides. Nevertheless, target weed areas can be detected and herbicides can be applied only in these areas instead of covering the whole surface, which will remarkably reduce the use of herbicides (Ramaswamy, 1993). Therefore, it is observed that controlled dosage methods in chemical spraying has recently become more widespread notably in orchards. In this method, sensors used on pesticide application machines function based on stopping the application at sites without trees and cut spraying costs (Balsari and Tamagnone, 1998). Sensors that function similarly but can detect smaller spaces compared to those used in orchards are used for field crops (Doruchowski et al., 1998). Works such as detecting the green portions of plants, perceiving inter-row and intra-row spacing and promoting the separation of weeds and crops have gained speed as well as the detection of blank spaces in the land with the proliferation of precision agriculture applications.

Image Processing Techniques and Artificial Neural Networks are among the methods that can be used to detect weeds (Yang et al., 2003).

Physical properties of agricultural materials such as length, thickness, width, surface area, bulk density, projection area are of considerable importance. However, the structures of mentioned materials including weeds that do not resemble any geometrical figures hamper manual measurement of concerning values notably. Thus, it is necessary to use modern technologies while measuring weed density. Image processing techniques are one of the technologies frequently used in this field. Image processing techniques include the analysis of computerized images via special programs by such means as cameras, scanner, etc. (Demirbas and Dursun, 2007). Image processing systems are often used for the classification, cleaning, quality control and automation of agricultural products like vegetables, fruits, cereals, etc. As such, the productivity increases and production costs decrease. In addition, consumers are provided with healthier products of better quality (Chen et al., 2010).

ANN are used at the phase of model building in most of the works in the field of engineering. ANN are very effective methods in terms of modeling uncertain, nonlinear and complicated structures like distribution of weeds. Most of classical software used in predicting similar structures fail to give a result. ANN models constructed can give faster results (Jarmulak et al., 1997). Also, ANN are capable of solving complicated problems (Zurada, 1992; Haykin, 1994; Öztemel, 2003).

ANN are the systems designed to model the methods used by the human brain. They are realizable with electronic circuits as equipment and with computers as software. In accordance with the data processing method of the brain, ANN can be considered as a parallel processor capable of collecting data after a learning period, keeping these data with connection weights between cells and generalizing. ANN are formed by the reunion of artificial neuron cells. Generally, cells are composed of 3 layers: input, hidden and output, where they come together in these layers to constitute the network (Haykin, 1994).

During the application, ANN are trained by sample data sets primarily shown to them. Afterwards, it is tested whether the network has learned or not with the other part of the data sets. The networks are considered trained if they can recognize the shown samples in these tests with reasonable mistakes (Akkaya, 2007). ANN provide a lot of opportunities in order to control and operate agricultural machinery and apply general-purpose experimental models. With these properties, Artificial Neural Networks draw attention as a quite attractive method in being a model for agricultural mechanization and controlled use.

The purpose of this study is to detect the density of broadleaved weeds in wheat-planted lands and contribute to the diminution of herbicide use. In line with this purpose, the phases below were carried out in this study:

-Determination of image processing parameters to be used in separation of weeds and wheat plant by analyzing image processing techniques

-Detection of weed covered areas acquired by image processing techniques (WCAAIPT) with these parameters,

-Construction of regression models designed to predict detected weed areas and actual weed covered areas (AWCA) on the image.

2. Materials and Methods

2.1. Material

The study was carried out in the 2013-14 growing season in the lands of the Black Sea Agricultural Research Institute. 262 photos of wheat called “Canik 2003” were used as data in the study. These photos were taken with a camera having 12 megapixel resolutions. Adobe Photoshop program and Image Processing Toolbox in MATLAB Package were used for image processing. Neural Network Toolbox in MATLAB Package was used to obtain the model by means of Artificial Neural Networks.

2.2. Method

2.2.1. Imaging

Imagings were carried out in wheat tillering period and on the days when environmental conditions were suitable for pesticide application in the 1st and 2nd weeks of March. Images were taken vertically and from a height of 60 cm that is suitable for spraying. It was observed that the variations among the images taken during imaging were wide. Thereby, each possible image alternative was evaluated.

2.2.2. Image processing

2.2.2.1. Masking

Masking is the application of colored images between the saturations of 0-255 of red, green and blue on a gray image. The upper and lower saturation values were detected for the color green corresponding to green portions in the study. The areas under or above these saturation values on the images were filtered with the color “black” and those remaining between the values were filtered with the color “white”. No filtering was applied to the colors “red” and “blue”. White areas on black and white images in filtering represent green portions. Masking was done by placing the black and white images created at this phase on the original images and featuring green portions (Figure 1).

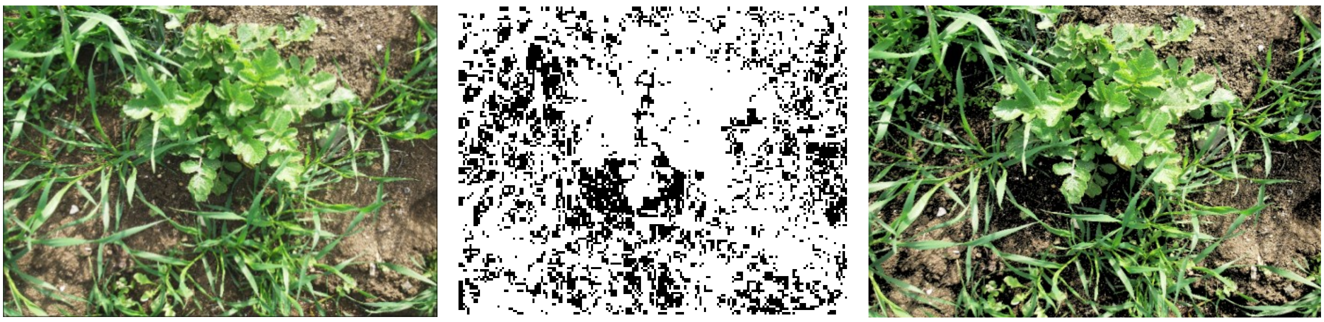

Figure 1. Masking application

2.2.2.2. Acquisition of a gray-level image

As known, plants have green leaves at different tones. But variations in the factors such as water, fertilizer and season may influence the color of leaves; and using color images may cause various problems about the formation of plant patterns (Husin et al., 2012). Masked images were transformed into gray-level images at this phase in order to troubleshoot and have faster results with small size images (Figure 2).

Figure 2. Obtaining gray-level images

2.2.2.3. Acquisition of black and white images

In the gray-level image, the suitable threshold value was determined, transforming the areas corresponding to the same gray tone as green portions into black, and the left areas into white. The threshold value varies between 0 and 1. The suitable threshold value was detected by starting the concerning value on Matlab commands where the application had been carried out, from 1 and scaling it down by degrees at the steps of 0.01 until the whole areas belonging to green portions had become completely black. It was ensured that the black areas represented the green portions and the white ones represented those other than the green portions (Figure 3).

Figure 3. Obtaining black-white image from gray image

2.2.2.4. Removal of wheat from the image

Wheat plant is narrow-leaved while target weeds are broadleaved. This leads to a significant difference in terms of image in order to distinguish between wheat and weeds. However, it does not apply to narrow-leaved weeds like wheat. In any case, either pesticides are not applied to narrow-leaved weeds or applied only at a very low rate using costly selective pesticides. This uneconomic application is not widespread at present. Therefore, only broad leaved weeds were evaluated in the study.

Wheat leaf widths of randomly selected 50 images were measured. The mean leaf width was found as 50 pixels and this figure was considered as radius value. Circular erasers were formed depending on this radius value. The black areas corresponding to green portions (wheat and weeds) in the black and white images were perceived with MATLAB. These areas were caught and automatically erased with the circular erasers setup. Thanks to this, wheat plant was removed from the image (Figure 4).

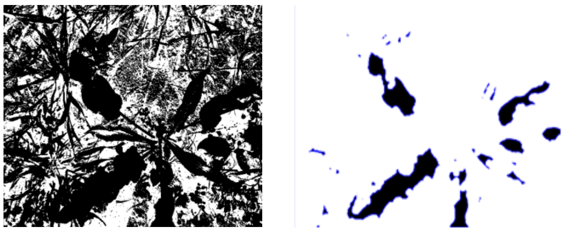

Figure 4. Removal of wheat from the image

2.2.2.5. Determination of real area from images

Area losses occur especially during the separation of wheat from the image with image processing instructions applied on the original photo in previous steps. These losses actually take place during the automatic erase process by the circular erasers. Even though the determined radius value erases the wheat in the images, the images of weeds equal to or less than this value are also erased as if they were wheat, consequently the weeds meeting these conditions are also separated from the image as are wheat. As a result, losses occur also in the areas belonging to weeds (Figure 5).

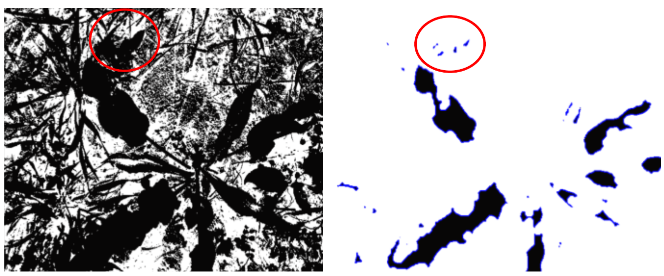

Figure 5. Losses in weed covered areas

Adobe Photoshop program was used to determine the actual areas by minimizing the losses. All the broadleaved weeds existing within the image were cut with a tolerance value of 30%. Afterwards, the weeds were transferred to a white background of the same size as the original image by leaving behind the wheat and other materials. And then, the actual weed covered areas (AWCA) in these images were detected (Figure 6).

Figure 6. Measuring AWCA

2.2.3. Artificial neural networks

In the study, ANN techniques were used to estimate the Actual Weed Covered Area (AWCA). In the ANN model, Weed Covered Areas Acquired by Image Processing Techniques (WCAAIPT) was used as input parameter; and Actual Weed Covered Areas (AWCA) as output parameter. In the study, a total of 262 data consisting of 244 data for training and 18 data for test were used. The input and output data used were normalized between 0 and 1 (Purushothaman and Srinivasa, 1994).

For normalization, the following formula was used:

$$y_{nor} = \frac{y - y_{min}}{y_{max} - y_{min}} \tag{1}$$

To obtain real values from the normalized values, “y” value was calculated using the same formula.

In the ANN model, Feed Forward Back Propagation (BP), Multilayer Perceptron (MP) network structure were used. The BP algorithm in this network is the most popular and commonly used algorithm. It minimizes the total error by varying the weights in order to enhance the network performance (Jacobs, 1988; Minai and Williams, 1990). The Levenberg-Marquart (LM) algorithm was used as training algorithm. The LM training algorithm, being a quite successful optimization method, is one of the different learning techniques (Levenberg 1944, Marquardt 1963). Training of the network was continued until the test error reaches the determined tolerance value. After training of the network ended successfully, the network was tested by test data (Kalogirou, 2001).

A regression estimation equation was obtained, by conducting a regression analysis on the data of the Weed Covered Areas Acquired by Image Processing Techniques (WCAAIPT) beside the ANN.

2.2.4. Determining the performances of the results

In order to determine the performances of the results, RMSE and R^2 values that are considered to be principal accuracy measures and that are based on the concept of mean error and commonly used were calculated using the following formulas (Bechtler and et al., 2001).

$$RMSE = \left(\frac{1}{m} \sum_{i=1}^{m} (x_{1i} x_i)^2 \right)^{1/2} \tag{2}$$

$$R^2 = 1 - \left(\sum_{i=1}^{m}(x_{1i} - x_i)^2\right) \Big/ \left(\sum_{i=1}^{m}(x_{1i})^2\right) \quad (3)$$

Here, $RMSE$, Root Mean Square Error, R^2, coefficient of determination, m, number of data, x, real value and, x_1, estimated value.

It is possible to state that the closer the goodness of fit is to zero, the closer agreement exists between the models. The goodness of fit (U^2) between the measured values and the values obtained by calculation methods was calculated using the following equation (Bağırkan 1993):

$$U^2 = \left(\sum_{i=1}^{m}(x_{1i} - x_i)^2\right) \Big/ \left(\sum_{i=1}^{m}(x_{1i})^2\right) \quad (4)$$

3. Results and Discussion

3.1. Image processing

During the image processing stage, the masking process was implemented to make the green parts apparent. Filtering process was applied in masking. The appropriate ranges of color filtering determined for filtering process applied in the study are given in Table 1. The areas on which masking will not be applied in the study are the green color areas with the color density of at least 73 units; and these areas represent the areas where the green parts are present.

Table 1. Color filtering ranges used in masking

Red	Green	Blue
0	73	0
255	255	255

The reason why the upper threshold value for all colors stays at the value of 255 (white) being the maximum density is that weeds with white spotted leaves are commonly observed on the area surface in images and that these areas are wanted to appear without leaving them out of application. Therefore, notably the white stones on the area surface and the areas with similar characteristics were also excluded from masking. During the image processing stage, it was also determined that the proper threshold value used for transforming the gray level image to white image was 0.1.

In removing the wheat from the image, it was determined that the appropriate radius value for circular erasers used in the imdilate command and erasing process was 50 pixels. The appropriate radius value in forming the circular erasers was found based on the mean leaf width of wheat. By these erasers, the wheat crop and the black regions that are smaller than the wheat crop were removed from the medium.

There are materials such as soil, stone and stubbles in the images and these materials may have the same gray color value with green parts according to their positions. Since they have smaller values than the mean wheat leaf width because of the fact that the widths of these materials that are generally perceived as green parts are non-homogeneous structures, they are automatically removed from the image during the image processing application.

It will increase the success of the study to conduct imaging in the field at the hours when there are no clouds or very little clouds. Imaging should be carried out definitely before plants cover the soil surface during the herbicide application generally in the tillering period. Xavier et al. (2011) reported that they had achieved more successful results in determining maize and weed in the fields where proper tillage techniques were applied, intra-rows were linear and weed development was apparent (inter-rows were not covered and soil was seen). Otherwise, it becomes difficult and even impossible to distinguish between wheats and weeds. That there are materials such as stubbles, stones and clods in the images negatively affects the success.

3.2. Regression model

The regression model was obtained by conducting regression analysis on the data from the Weed Covered Areas Acquired by Image Processing Techniques (WCAAIPT) and the Actual Weed Covered Areas (AWCA). R^2 value of the model was found to be 85%. The regression model obtained is given below:

$$y=-5272\times x^2+1.4567x+0.0799 \quad (5)$$

3.3. Artificial neural networks model

In the ANN model, 1 input parameter was used as the Weed Covered Areas Acquired by Image Processing Techniques (WCAAIPT) and 1 output parameter as the Actual Weed Covered Areas (AWCA) (Figure 7). The data for WCAAIPT used in the study varied between 9743 and 6245366; and the data for AWCA varied between 0 and 11888027.

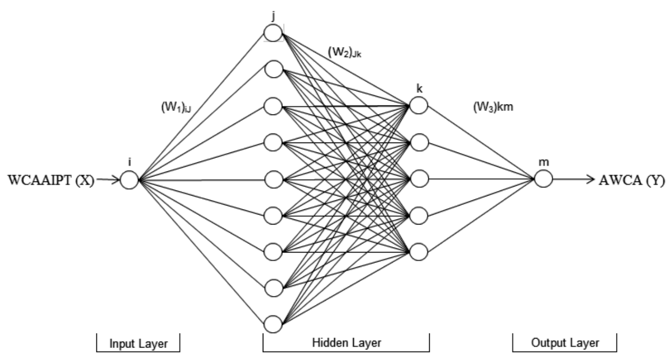

Figure 7. The network structure of the ANN model

In the ANN model, the structure of the network was designed in the form of 1-(9-5)-1, consisting of 1 input layer, 2 hidden layers and 1 output layer; and the number of neurons in the hidden layer were obtained to be 9-5. In the structure of the network developed, tansig was used in the first hidden layer, logsig in the second hidden layer; and purelin transfer functions were used in the output layer. The lowest training error value for the network was obtained at the epoch number of 82.

The mathematical formula of the ANN model is given in Eq. 6.

$$y = \sum_{k=1}^{k} (\mathrm{W}_3)_{\mathrm{k,m}} {*}\mathrm{F_k} + b_k \quad (6)$$

The LOGSIG transfer function for the second hidden layer (Fk),

$$F_k = \frac{2}{(1+e^{(-NET_k)})} \quad (7)$$

$$NET_k = \sum_{j=1}^{j} (\mathrm{W}_2)_{\mathrm{j,k}} {*}\mathrm{F_j} + b_j \quad (8)$$

The TANSIG transfer function for the first hidden layer (Fj),

$$F_j = \frac{2}{(1+e^{(-2\times NET_j)})} - 1 \quad (9)$$

$$NET_j = \sum_{i=1}^{i} (\mathrm{W}_1)_{\mathrm{i,j}} {*}x_1 + b_i \quad (10)$$

were calculated by the equations shown above.

In these equations; i, number of inputs, j, number of neurons in the first hidden layer, k, number of neurons in the second hidden layer, m, number of outputs, $\mathrm{W}_1, \mathrm{W}_2, \mathrm{W}_3$, connection weights, x, input parameter, y, output parameter and b, bias. The weights are given in Tables 2-4 and bias values in Table 5.

Table 2. Weight values in the first hidden layer (W_1)

Number of neurons in the first hidden layer (J)	$(W_1)_I$
1	24.2581
2	-25.7301
3	25.3669
4	-25.6961
5	28.0206
6	27.0447
7	-26.0234
8	-25.589
9	24.3651

The variation of the performance values (RMSE and R^2) of the ANN model with respect to the number of neurons in the hidden layer is given in Table 6. It was determined that the ANN model in which the number of neurons was 9 in the first hidden layer and the number of neurons was 5 in the second hidden layer yielded the best results. In the ANN model, for test, R^2 value was found to be 0.9921 and RMSE value to be 0.0201 being the lowest; for training, R^2 value was found to be 0.9760 and RMSE value to be 0.0393.

Table 4. Connection weight values (W3) for Eq. (6)

Number of outputs (m)	$(W_3)_{k1}$	$(W_3)_{k2}$	$(W_3)_{k3}$	$(W_3)_{k4}$	$(W_3)_{k5}$
1	3.7326	-2.4223	-0.9753	-3.0893	1.2204

Table 5. Bias values

Number of neurons	b_k	b_j	bi
1	-1.0121	3.7496	-26.1374
2		-0.2228	21.3964
3		-0.9842	-18.6569
4		1.2359	14.9784
5		3.1419	-10.8891
6			-8.2434
7			4.8921
8			3.8762
9			-0.5875

Table 6. Performance values for training and test in the ANN model

Number of neurons in the hidden layers	Training		Test	
	RMSE	R^2	RMSE	R^2
3 5	0.0460	0.9669	0.0181	0.9936
4 5	0.0454	0.9679	0.1729	0.9941
5 5	0.0450	0.9685	0.0202	0.9921
6 5	0.0431	0.9711	0.0221	0.9907
7 5	0.0480	0.9644	0.0119	0.9969
8 5	0.0411	0.9739	0.0206	0.9918
9 5	**0.0393**	**0.9760**	**0.0201**	**0.9921**
10 5	0.0423	0.9723	0.0219	0.9909

The data from the Actual Weed Covered Areas (AWCA) and the test results obtained from the ANN and regression models are compared in Figures. 8-9. It is seen that AWCA data are in good agreement with the test data obtained from the ANN model.

Table 3. Weight values in the second hidden layer (W2)

Number of neurons in the second hidden layer (k)	$(W_2)_{j1}$	$(W_2)_{j2}$	$(W_2)_{j3}$	$(W_2)_{j4}$	$(W_2)_{j5}$	$(W_2)_{j6}$	$(W_2)_{j7}$	$(W_2)_{j8}$	$(W_2)_{j9}$
1	-0.5607	-0.6589	0.4872	-0.4652	-3.2518	2.1607	1.6699	0.9962	-0.5362
2	-1.0071	1.0871	-3.1351	0.2721	-6.5355	-1.5291	2.176	-1.5403	0.3328
3	1.9584	0.3441	0.731	-2.5982	1.3314	0.9787	-0.6598	1.7885	-0.3351
4	2.1416	0.7456	2.3663	-0.5605	-2.2054	1.3984	2.7535	-3.2553	-0.9253
5	1.1681	-0.6352	-1.706	-1.1982	1.8564	0.6953	-1.8618	-3.1867	2.6483

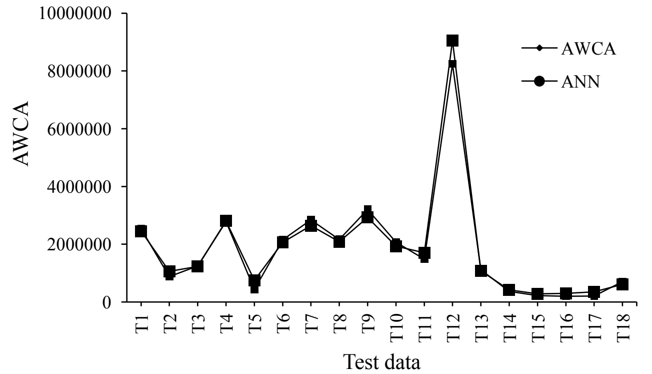

Figure 8. Data obtained from the ANN model and data from AWCA

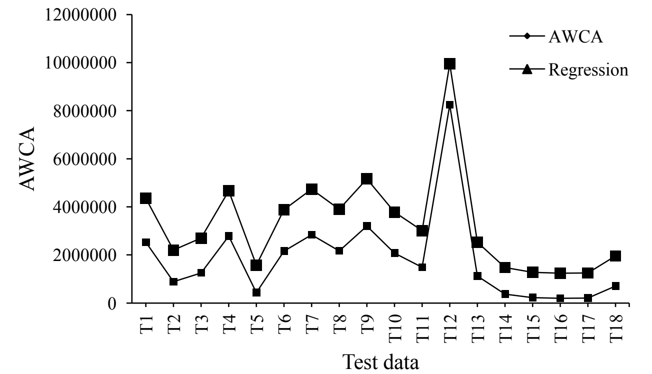

Figure 9. Data obtained from the regression model and data from AWCA

The determination coefficients (R^2) of the correlation between the AWCA data and the values calculated from the ANN and Regression models were found to be 98.83% (Figure 10) for the ANN model and 98.67% (Figure 11) for the Regression model.

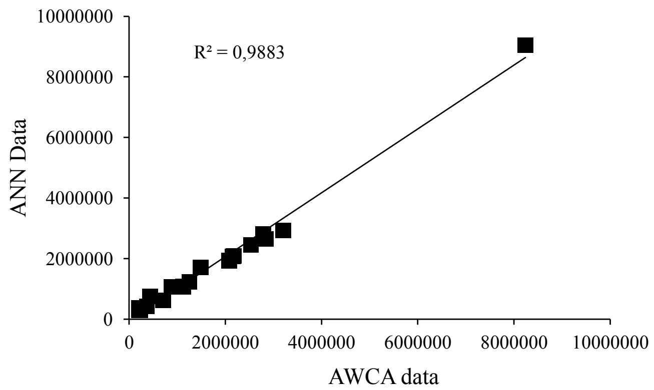

Figure 10. Correlation between the AWCA data and the data from the ANN models

The goodness of fit values (U^2) between the the AWCA values and the values belonging to the ANN and Regression models were calculated to be 0.000436 for the ANN model and 0.008431 for the regression model. It was determined that the results obtained from the ANN model, compared to the regression model, were in better agreement with the AWCA values and that they were closer to the zero value being the desired agreement degree.

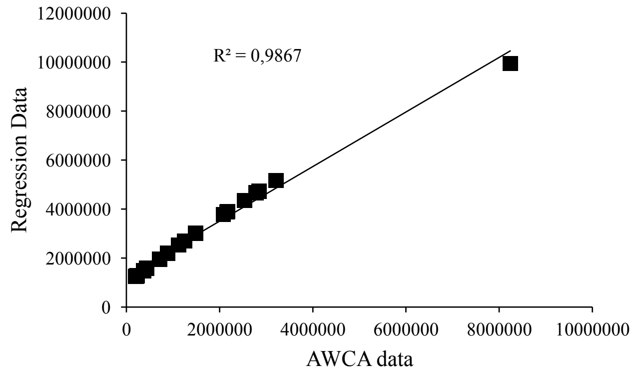

Figure 11. Correlation between the AWCA data and the data from the Regression models

4. Conclusions

In this study, an ANN model was constructed, that will contribute to determine the density of broad leaf weeds and reduce herbicide use in wheat grown fields. For this purpose, Image Processing Techniques were used in this study; and Artificial Neural Networks (ANN) and regression models were developed for determination of weeds. For this purpose, Image Processing and Artificial Neural Network techniques were used. The images taken from the field were processed by the Image Processing Techniques, and evaluated using the Artificial Neural Network architectures. At the end of the evaluations, a success at acceptable level was achieved for determination of the weed covered area from the images.

Masking was applied in order to make the green parts apparent during image processing. Filtering was applied in masking. The proper minimum and maximum filtering values for green color were determined to be 73 and 255 units, respectively. The most appropriate threshold value was found to be 0.1 for transforming the gray level image to black and white image. In the process of removing the wheat from the image, the most proper radius value for the circular erasers used was determined to be 50 pixels.

The structure of the network in the ANN model was designed to be 1 input layer, 2 hidden layers and 1 output layer; and the number of neurons in the hidden layers were obtained as 9-5. Using the tansig transfer function in the first hidden layer; the logsig transfer function in the second hidden layer; and the purelin transfer function in the output layer produced the most appropriate result.

In the study, two models were developed, the ANN and regression models. R^2 values of the ANN and regression models were found to be 99% and 85%, respectively. Results from the ANN and regression models were compared with those from AWCA. The goodness of fit values (U^2) between the AWCA values and the values belonging to the ANN and Regression models were calculated to be 0.000436 for the ANN model and 0.008431 for the regression model. It was seen that the results obtained from the ANN model were in agreement with the AWCA results.

It was concluded that the ANN model would be used successfully in agricultural machinery industry to determine the broad leaf weed density and reduce the herbicide use in wheat grown areas. Application of this model to chemical sprayers by the industry and their use by farmers will help to reduce chemical usage and contribute to conservation of the human health and environment as well as save on energy and costs of production. This system could be also used in crops such as other grains (barley, triticale, oat, rye), paddy and maize beside wheat.

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