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NITROGEN ESTIMATION IN SUGARCANE FIELDS FROM AERIAL DIGITAL IMAGES USING ARTIFICIAL NEURAL NETWORK

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Abstract

Knowing the nitrogen status of crop is essential for agricultural operations management, nevertheless conventional methods are time consuming and expensive. In this research, possibility of using digital aerial images as a remote sensing method to determine the nitrogen content of sugarcane plant was studied. Arial images were captured from 3 sugarcane fields using a 12.9-megapixel digital camera mounted on a Phantom 3 quad-copter from 5 and 10 m heights. At the same time, four healthy top branches of sugarcane plants were cut from imaging points as plant samples. The nitrogen value of the samples was measured using Kjeldahl test at laboratory. Multilayer perceptron (MLP) artificial neural network (ANN) algorithm was used to estimate nitrogen status in the crop from the aerial digital images. Color indices of images were extracted using image processing in MATLAB software and their correlation with the nitrogen value were determined. The indices that had correlation with nitrogen were selected as inputs of the ANNs and the nitrogen value was the output. There was no significant difference between the nitrogen values predicted by ANNs and its actual values. The average errors of the ANNs training were 0.145 and 0.022 and the correlation coefficients of the predicted and actual values of nitrogen were 0.89 and 0.94, for 5 m and 10 m heights respectively. Also, the RMSE values of nitrogen estimation was 0.181 and 0.174, at 5 m and 10 m heights respectively. So, nitrogen estimation of sugarcane fields is possible by aerial digital imaging.

Key words: artificial neural network, digital aerial image, image processing, nitrogen content, sugarcane field

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1. Introduction

Sugarcane is very important plant for sugar production in the World. Sugarcane's need of water and nutrients (including nitrogen, calcium oxide, phosphorous oxide, potassium oxide) is high. The amount of these elements in the soil affects the growth of the plant, as well as the quantity and quality of the sugarcane plant (Taghizad Fanid et al., 2012). In conventional agriculture, all types of farm soils are assumed to be homogeneous in terms of fertility; so fertilization is carried out uniformly. But agricultural lands have variable fertility and require different amounts of fertilizer applied in different parts of the farm (Bagheri et al., 2011). The optimum application of nitrogen provides economic benefits and environmental protection. Considering the fact that conventional fertilization has undesirable consequences, it is necessary to look for appropriate methods that are based on the correct use of fertilizer and the increase in yields. Variable nitrogen fertilization is one of the methods that can be used to reduce environmental effects. An effective application of nitrogen variable fertilization at the farm surface depends on the ability to detect the nitrogen content of the plant during fertilization. Therefore, non-

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destructive methods for determination of plant nitrogen status are extremely important in fertilization management. Among the non-destructive methods is the use of remote sensing. Researchers have investigated various methods for determining nitrogen amount and have finally introduced the remote sensing method as an indirect and suitable method for determining the nitrogen content (Lemaire et al., 2008). Remote sensing could improve fertilisation by monitoring crop nitrogen (N) status using non-invasive methods (Gabriel et al., 2017).

The images used for remote sensing studies and preparation of different maps for the farms are of three types: the ground surface imagery, the aerial imagery and the satellite imagery (Heege, 2013). The satellite images has facilitated the protection and monitoring of ecological environment. But, has limitations that make it difficult for it to be used in agricultural researches. some of these limitations are the timing of images production and their high prices, the limited number of images taken by some satellites during the plant's growing season, the need for atmospheric correction, the problem of coincidence between image capture and ground sampling, and in general, their low power of distinguishing in spectral, temporal and spatial aspects (Al-Wassai and Kalyankar, 2013). Although satellites can cover large areas, but their resolutions are still not enough for a fine-grained crop analysis (Barbedo, 2019). In the ground surface imagery, the camera is installed on the vehicle while working in farm and takes pictures of the product surface. Then, by processing these images immediately, the amount of nitrogen in the product is determined and appropriate amount of inputs (nitrogen fertilizer or solution) are injected according to the needs of each point of the field. This method takes time, damages the crop and is expensive for large fields (Hosseini, 2017). Aerial imagery, which uses unmanned airplanes and helicopters, requires high cost and flight band that limit their use, but using unmanned aerial vehicles (UAV) as a new, simple and inexpensive technology has removed the limitations (Bagheri, 2016; Beloev, 2016; Hogan et al., 2017; Zhang and Kovacs, 2012).

Some studies have estimated various crop parameters using spectral imagery technology. The best colour region that has the highest correlation with the nitrogen percentage in corn leaves is 530 to 780 nm (Alchanatis et al., 2005). The possibility of using remote sensing technology to predict the protein content of the seeds was confirmed. The spectral characteristics is significantly correlated with leaf nitrogen, seed protein and vegetation index (VI green) (Zhao et al., 2005). Feng et al. (2008) determined the nitrogen concentration of wheat leaves using the multi-spectral reflection of vegetation. The results showed that nitrogen-sensitive spectrum bands often occur in the visible and infrared light limits. They concluded that investigation of the plants remote sensing reflection was more suitable for the identification of plant characteristics in comparison with the sampling method. Also, the determination of spectral properties of plants is a fast, safe and non-destructive method for finding their physiological characteristics. Ahmadi Moghaddam et al. (2009) used color images processing to determine the nitrogen status of sugar beet leaves. Experiments were carried out in phytotron with the sugar beet grown in pots at six different levels of fertilization (0, 100, 200, 300, 400 and 500 kg/ha) in five repetitions. Grayscale model had a good relationship with leaf chlorophyll content (R2 = 0.79) and needed less time for image processing (approximately the half time of image processing in colour space). However, in colour space, the R-2B model showed the highest correlation (R2=0.93) to estimate the leaf chlorophyll content. Bagheri et al. (2011) used ASTRR satellite images with three bands in the visible and infrared (520-860 nm), six bands in the middle infrared (1600-2430 nm) and five bands in the thermal infrared (1095-8475 nm) spectral ranges. Radmoghaddam (2011) evaluated the nitrogen status of spinach plant using the chlorophyll-meter index and image processing based on artificial neural network (ANN). The results of this study showed that the use of image processing and neural network has a good relationship with spinach plant chlorophyll estimation (R2 = 0.92) and the highest correlation was obtained for estimating leaf chlorophyll (R2 = 0.97). There was a good relation between colour components and the leaf nitrate level (R2 = 0.84). Using colour image processing was able to obtain a good correlation between the amount of nitrogen in rice leaf and colour indices with determination coefficient equal to 0.488 (Tewari et al., 2013). Jia et al. (2014) conducted a study to develop a non-destructive method to monitor the growth of cotton and its nitrogen status using a digital camera. The obtained coefficient of determination for estimation of nitrogen status was equal to 0.978.

Barbedo (2019) reported that multispectral, hyper-spectral, CIR, RGB, thermal sensors are common for the aerial monitoring of nutrient status in crops. Li et al. (2015) showed that aerial photography by UAV at an altitude of 50 m had the ability to assess paddy rice (Oryza sativa L.) nitrogen status in the field in large-scale crop plantations. Gabriel et al. (2017) investigated the ability of proximal (SPAD® and Dualex®) and airborne sensors (a multispectral camera and a hyper-spectral sensor at 80 and 330 m above ground level, respectively) to identify the nutritional N status of maize field (with five fertiliser rates ranging from 0 to 220 kg/ha). Higher accuracy was obtained with indices combining chlorophyll estimation with canopy structure or with polyphenol indices. Zheng et al. (2018) evaluated three sensors (RGB, color-infrared and multispectral cameras) onboard UAV for the estimation of N status at individual stages and their combination with the field data collected from a two-year rice experiment. Compared with the counterpart indices from the RGB and color-infrared images, the indices from the multispectral images performed better in most cases. RGB sensors with regression modelling have been used for aerial nitrogen estimation of corn (Hunt et al., 2005; Zermas et al., 2015), Macadamia (Felderhof and

Gillieson, 2011), rice (Zhu et al., 2009), wheat (Golmohammadzadeh et al., 2015; Lukina et al., 1999; Schirrmann et al., 2016; Yakushev and Kanash, 2016) and maize (Corti et al., 2019), but using ANN modelling can improve the modelling accuracy (Ahmadi Moghaddam et al., 2011).

In the previous studies that used image processing technique to estimate the amount of plant nitrogen requirement in the field, either ground digital images have been taken with cameras in close proximity to the plant or aerial imagery provided by different sensors has been used. Using ground images makes it impossible to monitor the farm quickly and extensively. Also, due to the high cost of multi-spectral cameras, their use increases the price of aerial crop monitoring systems. Therefore, the use of ordinary digital cameras that provide images in visible band and are cheaper and available everywhere, can greatly reduce the cost of aerial images of the fields. The purpose of this research was to study the usability of aerial images taken at the visible spectrum (which are taken using a conventional digital camera mounted on a quad-copter) to estimate the amount of crop nitrogen in sugarcane fields; this is an area that has hitherto received low attention. To achieve better results, the ANN methodology was used.

2. Materials and methods

2.1. Field experiments

This research was carried out in three sugarcane fields with 100 × 120 m2 area, located in Debal Khozaie sugarcane agro-industry company, Khuzestan, Iran, in which cps9-1062 sugarcane cultivar has been planted on three different dates (125, 100, 80 days ago). At first, in each field four rows were identified in the longitudinal direction of the field at 20 m distance from each other. Then on each row, five points were determined at 20 m distance from each other.

Therefore, as shown in Fig. 1, in each farm, 20 points were selected and marked for imaging and sampling with 20 m distance from the sides.

Field imaging was carried out using a vertical flight vehicle (quad-copter), a Phantom 3 Professional model produced by DJI, China. This quad-copter is an UAV with 4 wings and 1216 g weight. It has a 12.9 megapixel, 4K camera, 3-axis gimbal system and Live HD View produced by DJI Company. The DJI Phantom 3 Professional allows for easily taken crisp aerial videos and images from the sky. It has the ability to send images wirelessly as well as storing them on internal memory and then transferring them to a computer with a USB port. It also has various sensors such as compass, altimeter, accelerometer, gyroscope and ultrasonic (Anonymous, 2017).

Imaging height has direct impact on the quality of captured images and the imaging time. By decreasing the flight altitude, the quality of crop images and the imaging time increase and vice versa. But due to natural and artificial obstacles such as trees, buildings and utility poles, it is not possible to reduce the imaging height from a certain amount. By examining the obstacles in the selected fields, two heights of 5 m and 10 m were selected for imaging (Fig. 2a).

(a) (b)

Fig. 1. (a) The sugarcane field view and (b) The map of points for sampling and imaging of sugarcane fields

(a) (b)

Fig. 2. (a) Filed imaging by quad-copter and (b) Sugarcane leaf samples

The quad-copter was fixed on top of each point for taking the image and the image of each point was taken from two heights and recorded in the memory of the camera. After the fields aerial imaging, the photos were transferred to a laptop for image processing. Since the angle of view affects the quality of the image, the taken images were perpendicular to the surface of the ground. At the same time as the aerial imaging, sampling was done at the specified points. From each point, four healthy heads of sugarcane braches with their green leaves - placed in 45 cm from each other - were cut and put in plastic bags.

2.2. Laboratory experiments

Samples were transferred to the laboratory to measure the nitrogen value of the leaves on the same day. In the laboratory, the third, fourth, fifth and sixth leaves were selected and their veins were separated (Fig. 2b). After being weighed, they were placed inside the electric oven for drying. After drying of the samples, the nitrogen values of the samples were measured using the standard Kjeldahl method (Anonymous, 2016; Sharifi and Haj Abbasi, 2005). Kjeldahl test is a common method for the quantitative determination of nitrogen contained in organic substances (Muñoz-Huerta et al., 2013).

2.3. Image processing algorithm

As shown in Fig. 3, the designed image processing algorithm to extract color indices from sugarcane fields' images consists of the following steps (Golzarian et al., 2014; Gonzalez et al., 2009).

2.3.1. Preprocessing

To extract the required color indices, the fields' images were analyzed using the image processing toolbox of MATLAB software in two stages: (1) preprocessing (including reducing image size, producing binary image, image uniformity, noise reduction and noise removing to enhance the quality and quantity of the image), and (2) final processing, during which in order to improve the algorithm's efficiency and increase the accuracy of the leaf nitrogen estimation based on its surface reflection, first the color image of the crop was called, and then the image histogram was expanded to remove the noise and increase the clarity.

2.3.2. Uniform illumination

The adaptive histogram equalization (AHE) was used to smooth the image and eliminate light conditions. At this step, first, to obtain the binary image of the original image, the plant area should be white and the background should be black. Then the binary image is multiplied in the original image. And finally, the light uniformity code is applied to the resulting image.

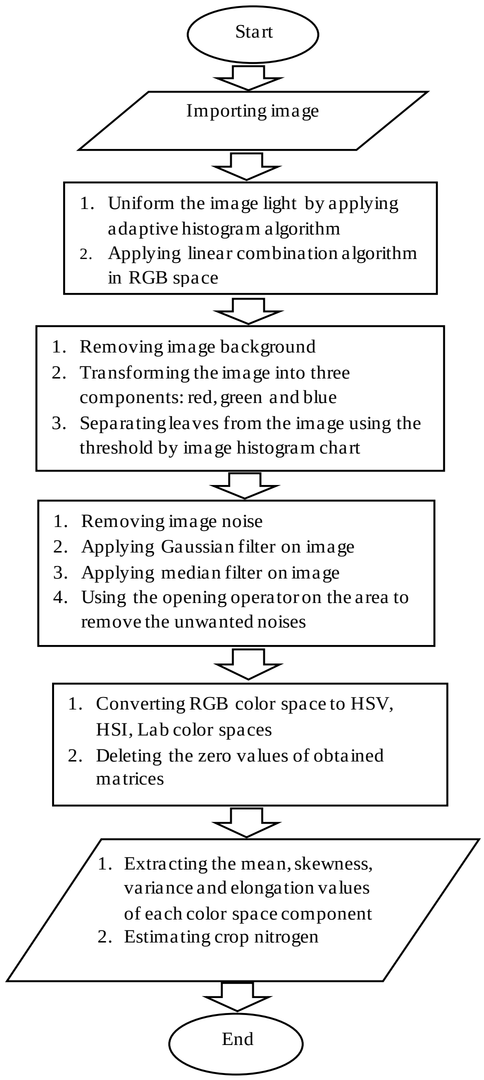


Fig. 3. The image processing algorithm flowchart for color indices extracting from sugarcane crop images

2.3.3. Removing noise and image background

There are several algorithms for image background removal. After testing the existing algorithms, the linear combination algorithm of the RGB space was more appropriate than the rest of the algorithms. Therefore, this algorithm was used to delete the image background. The linear combination algorithm of the RGB space was implemented in three steps:

- Dividing the original image into its three components (red, green and blue)
- Separating the leaf from the image field
- Removing the image noises

First, the original image was divided into red, green and blue monochrome images (Fig. 4a). Then, using thresholds and histogram intensity graph, the threshold values were determined to remove the field pixels (soil) from the image. Finally, the separation accrued using the threshold function in Eq. (1) (Ahmadi Moghaddam et al., 2011).

$$g_i(x,y) = f(x) = \begin{cases} 0 & f_i(x,y) \le T_i \\ f_i(x,y) & f_i(x,y) \ge T_i \end{cases} \quad (1)$$

In this Equation $g_i(x,y)$ is the gray level value of each pixel in the separated image, $f_i(x,y)$ is the gray level value of each pixel in the original image, T_i is the threshold value and i represents the component of the image in the red, green and blue channels. According to the Eq. (1), the intensity of the sugarcane leaf pixels did not change and only the amount of the image background pixels became zero (Fig. 4b).

Gaussian and median filters were used to remove the noise. After removing the image background, the 'openin' operator was used on the area for noise removing from the image and rebuild the deleted points of the crop. Since the image had been taken in uncontrolled conditions and had a series of unwanted noise, they were deleted using this operator.

2.3.4. Extracting and selecting image features

After performing the initial preprocessing and removing the image background, color indices were extracted in the next step. The image was turned from the RGB color space to the desired color spaces (HSV, HSI, and Lab), as shown in Fig. 4. After zero removal, the mean, variance, skewness and elongation values of each color space components were determined from Eqs. (2-5) (Kumar and Gupta, 2012).

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{N} \quad (2)$$

$$s^2 = \frac{\sum_{i=1}^{n} (X_i - \overline{X})^2}{N} \quad (3)$$

$$sk \approx \frac{\sum_{i=1}^{n} (X_i - \overline{X})^3}{s^3} \quad (4)$$

$$ku = \frac{1}{N} \frac{\sum_{i=1}^{n} (X_i - \overline{X})^4}{s^4} - 3 \quad (5)$$

where, N is the number of variables, X_i is the i variable, $\overline{X}$ is the total average of the color indices, s^2 is the total variance of the color indices, s is the standard deviation of color indices, sk is the total skewness of the color indices and ku is the total elongation of the color indices.

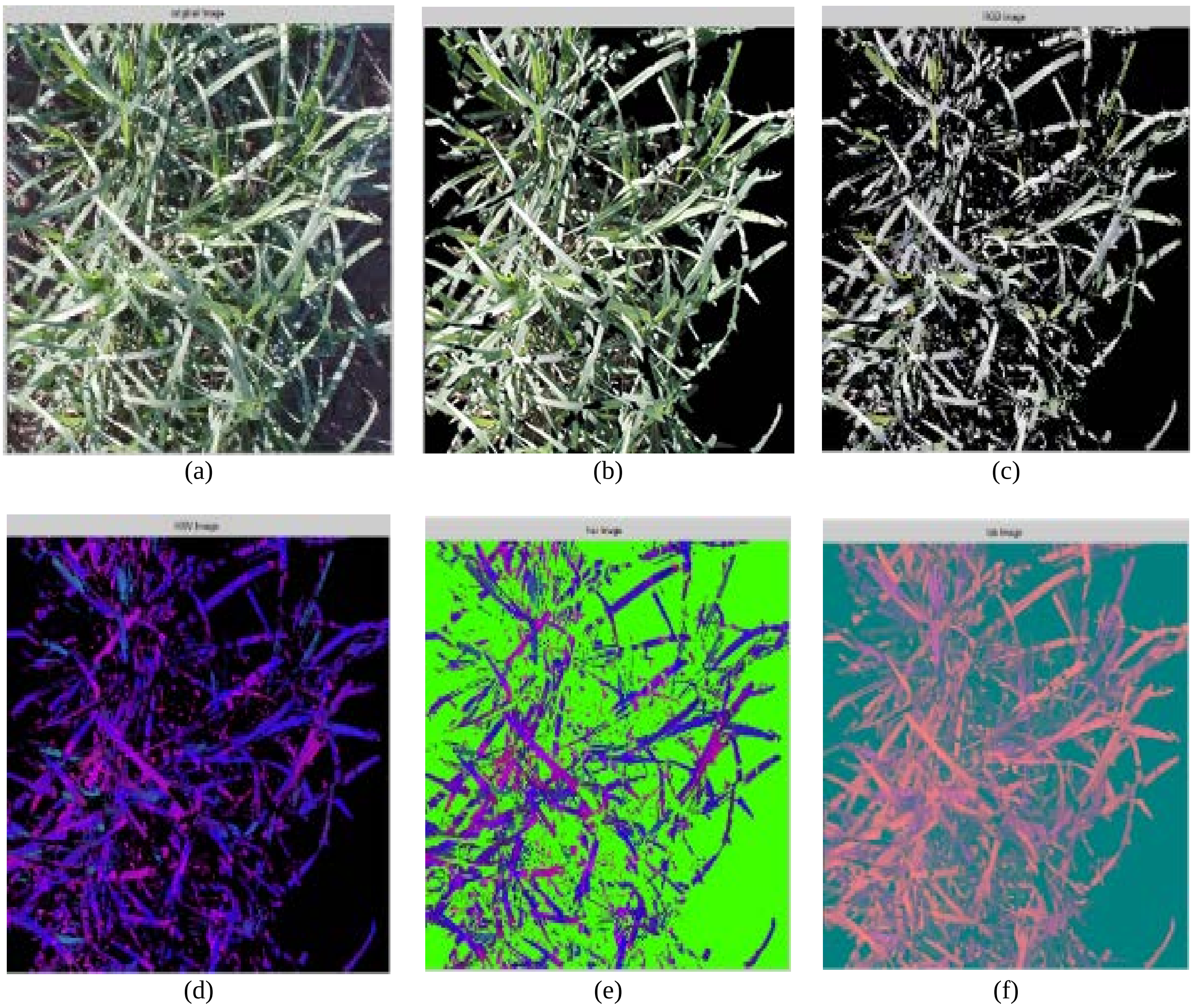


Fig. 4. Sugarcane images in different color spaces: (a) Original image, (b) Background and nose removing, (c) RGB space, (d) HSV space, (e) HSI space and (f) Lab space

2.4. Artificial Neural Networks modeling

Multilayer perceptron artificial neural network (MLP-ANN) was used to determine the relationship between the amount of nitrogen in sugarcane crop and its color indices. According to the general approximation theorem, only one hidden layer was considered for the designed ANN. As shown in Fig. 5, the three common color spaces components (including red, green, blue, hue, saturation, value/brightness, hue, saturation, intensity/luminance, respectively named as R, G, B, H, S, V, H, S, I) were used as the ANN inputs and the nitrogen content of the crop as the ANN output. Five different functions were selected as activation functions of each neuron to determine the best activation functions. In order to obtain different data and gain better training results for the ANN, aerial imagery was conducted at three different growth stages of sugarcane in the fields.

Initially, for convergence and improvement of the ANN learning performance, color space components and nitrogen values were normalized by linear normalization method in the range of [0.1, 0.9]. 70% of the data were randomly assigned to train and obtain optimal values of the ANN parameters and 30% of the remaining data were used to evaluate the ANN generalization capability. Back-propagation with declining learning-rate factor (BDLRF) algorithm was used for training the ANN. The BDLRF training algorithm begins with fixed and relatively big values for the learning rate (η) and the momentum factor (α). Also, before the network becomes unstable or its convergence slows down, in each T repetition ($3 \leq T \leq 5$), the η and α values uniformly decrease through the account progression until these values reach x% (5%) of their initial values. Network learning occurs in two phases of pre-propagation and past-propagation. The weights of each layer of the ANN are calculated through Eqs. (6-7) (Masoudi and Rohani, 2016).

$$u_{jk}(n+1) = u_{jk}(n) - \eta \frac{\partial E}{\partial u_{jk}} + \alpha(u_{jk}(n) - u_{jk}(n-1)) \tag{6}$$

$$w_{jk}(n+1) = w_{jk}(n) - \eta \frac{\partial E}{\partial w_{ij}} + \alpha(w_{jk}(n) - w_{ij}(n-1)) \tag{7}$$

where w_{ij} is the weight gain between i, j nodes and u_{jk} is the weight gain between j and k nodes.

The initial values of these weights were randomly selected from -0.25 to 0.25 range. *η* and *α* are learning rate and momentum factor, the values of which are in the interval from 0 to 1 and n is the counter of the algorithm repetition (n = 1, ..., N). Twelve and l3 are number of neurons in hidden and output layers, respectively. The computer program for the image processing and its graphical user interface (GUI) (as shown in Fig. 6) and the MLP-ANN algorithm were developed using MATLAB 2014a software (Golzarian et al., 2014; Gonzalez et al., 2009).

2.5. Statistical analysis of results

Preparation of the data was done in Excel 2013 software and statistical analysis of the results carried out by SPSS version 21 software. To compare the performance of the MLP-ANN models in predicting nitrogen content of sugarcane, student t-test was used. Also root mean square error (RMSE) (Eq. 8) and mean absolute percentage error (MAPE) (Eq. 9) of statistical indices were used to evaluate the performance of the MLP-ANN models (Masoudi and Rohani, 2016).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(dv - pv)^2}{n}} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{dv - pv}{dv}\right| \tag{9}$$

where *n* is number of samples and *dv* and *pv* are the actual and the predicted values of nitrogen in the sugarcane, respectively.

3. Results and discussion

Pearson correlation analysis was used to examine the relationship between two variables with distance scale. As shown in Tables 1, 2, based on the Pearson correlation analysis – among 48 color features extracted by image processing including mean, variance, skewness and peak level of the color indices of each image in RGB, HSV, I, Lab color spaces – 24 features including "$\bar{R}$, $\bar{G}$, $\bar{B}$, $\bar{H}$, $\bar{S}$, $\bar{V}$, $\bar{H}_I$, $\bar{I}_I$, $\bar{a}$, B_K, S_{I_K}, L_K, a_K, H_g, V_g, S_{I_g}, L_S, a_S, H_v, S_v, V_v, S_{I_v}, a_v, L_v" had suitable correlation with the amount of nitrogen in leaves; so they were selected for determination of regression equations. Therefore, neurons number in the input layer of the MLP-ANN decreased from 48 neurons to 24 neurons with respect to the selection of effective indices.

Two neural networks were trained using the try and error method by the Levenberg-Marquardt training algorithm with 10 and 4 neurons in the hidden layer for images from 5 m and 10 m heights, while "tansig" and "purelin" transfer functions were used in the hidden and output layers, respectively. The results of the MLP-ANN training to predict the amount of nitrogen with the color indices obtained from 5 and 10 m heights images are shown in Fig. 7.

The mean squared error (MSE) values in validation phase of the MLP-ANN training for the height of 5 m and 10 m are 0.41 and 0.022, respectively. Also, correlation coefficients between predicted values and actual values of nitrogen were equal to 0.89 and 0.94 for 5 m and 10 m heights, respectively. Li et al. (2015) showed that dark green color index (DGCI) values predicted the nitrogen concentrations and nitrogen balance index (NBI) of paddy rice with R^2 equal to 0.672 and 0.711, respectively.

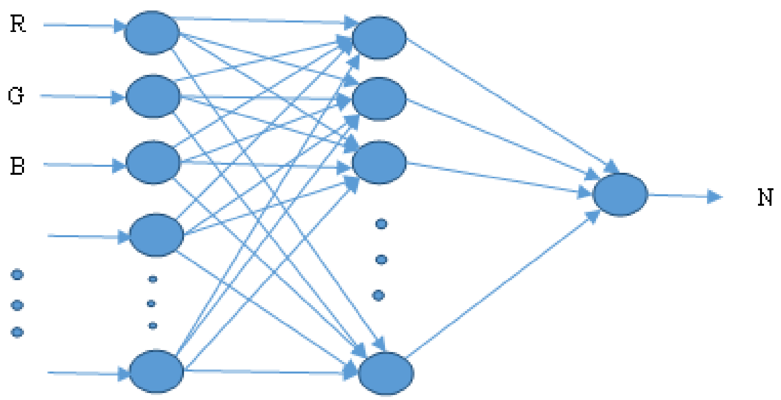
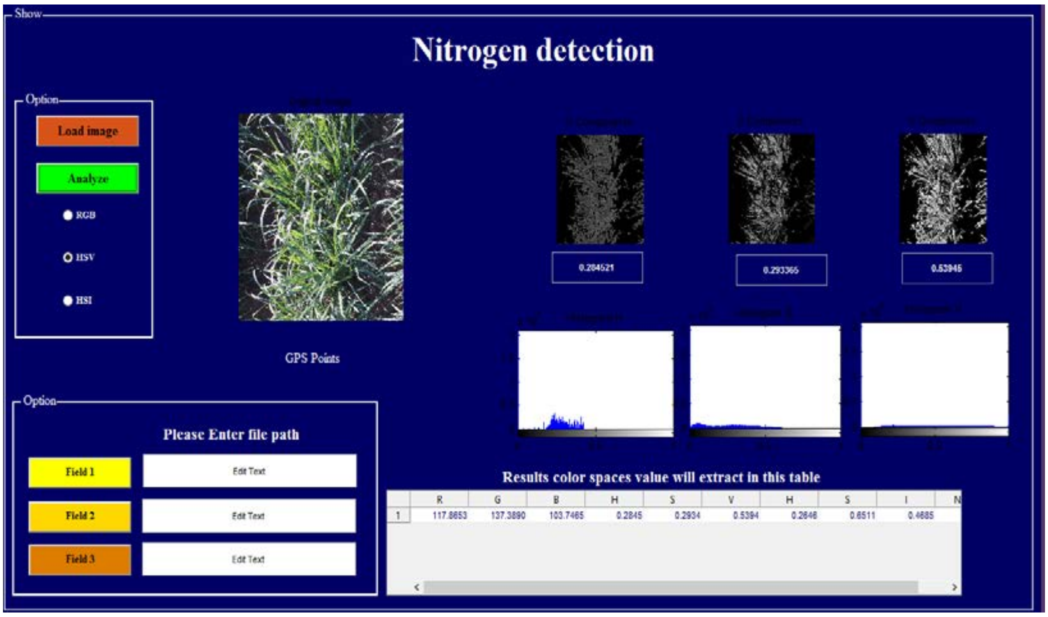
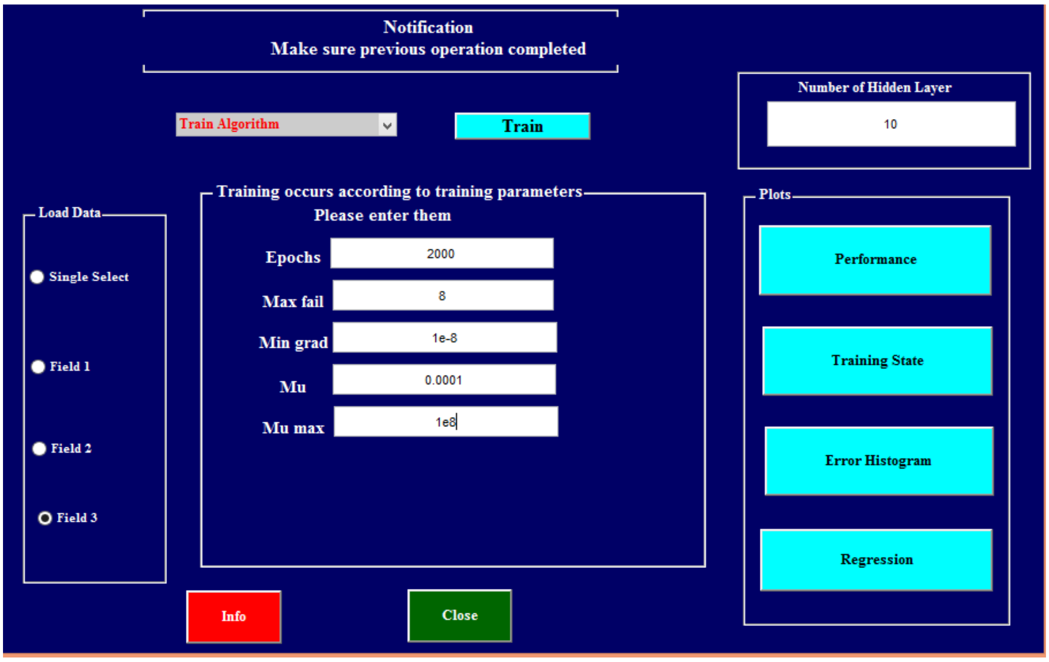


Fig. 5. The ANN used for sugarcane nitrogen value estimation from color indices



(a)



(b)

Fig. 6. Designed graphical user interface (GUI): (a) Image processing window and (b) ANN modeling window

These show that there is a good relationship between input and output variables, and the ANNs can be used for predicting the nitrogen content of sugarcane fields from aerial digital images with better performance. The amount of MSE in training the MLP-ANN and the proximity of the predicted values to the actual values of leaves nitrogen in the images provided from 10 m height is more appropriate, so the height of 10 m is better than the height of 5 m for monitoring the sugarcane nitrogen content. These results could be due to the presence of more sugarcane plants in 10 m height images.

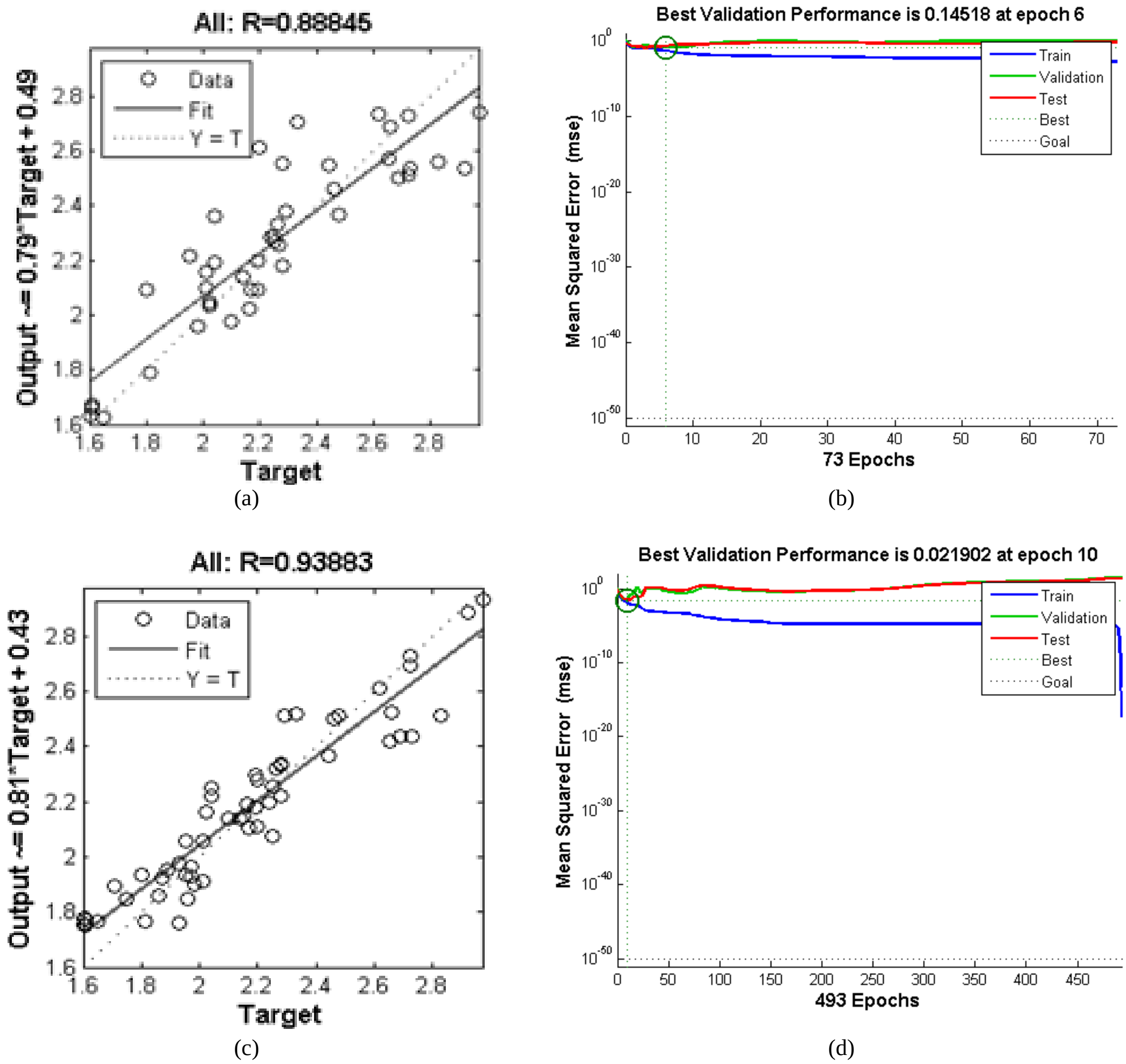


Fig. 7. The MLP-ANN performance: (a) Nitrogen target and output values relation from 5m hieght, (b) Mean error of ANN for 5m hieght, (c) Nitrogen target and output values relation from 10m hieght and (d) Mean error of ANN for 10m hieght

Table 1. Pearson correlation between nitrogen content and color indices from 5 m height

Height	*Average*	*r*	*Variance*	*r*	*Skewness*	*r*	*Kurtosis*	*r*
5 m	R_{avg}	0.611 **	R_{var}	-0.108 ^{ns}	R_{skw}	0.081 ^{ns}	R_{krt}	-0.055 ^{ns}
	G_{avg}	0.673 **	G_{var}	-0.158 ^{ns}	G_{skw}	0.018 ^{ns}	G_{krt}	0.039 ^{ns}
	B_{avg}	0.525 **	B_{var}	0.164 ^{ns}	B_{skw}	0.251 *	B_{krt}	-0.277 *
	H_{avg}	0.594 **	H_{var}	0.477 **	H_{skw}	-0.265 *	H_{krt}	-0.174 ^{ns}
	S_{avg}	0.459 **	S_{var}	0.682 **	S_{skw}	-0.315 *	S_{krt}	-0.166 ^{ns}
	V_{avg}	0.653 **	V_{var}	-0.281 *	V_{skw}	0.165 ^{ns}	V_{krt}	0.183 ^{ns}
	H_{avg}	0.396 **	H_{var}	0.254 *	H_{skw}	-0.246 *	H_{krt}	-0.173 ^{ns}
	S_{avg}	0.126 ^{ns}	S_{var}	0.398 **	S_{skw}	0.357 **	S_{krt}	-0.311 **
	I_{avg}	0.612 **	I_{var}	-0.116 ^{ns}	I_{skw}	0.135 ^{ns}	I_{krt}	-0.115 ^{ns}
	L_{avg}	0.217 *	L_{var}	0.326 **	L_{skw}	0.455 **	L_{krt}	-0.277 *
	a_{avg}	0.842 **	a_{var}	0.549 **	a_{skw}	0.578 **	a_{krt}	-0.301 *
	b_{avg}	0.050 ^{ns}	b_{var}	-	b_{skw}	-	b_{krt}	-

Table 2. Pearson correlation between nitrogen content and color indices from 10 m height

Height	***Average***	***r***	***Variance***	***r***	***Skewness***	***r***	***Kurtosis***	***r***
10 m	R_{avg}	0.520 **	R_{var}	-0.278 *	R_{skw}	-0.028 ^{ns}	R_{krt}	-0.019 ^{ns}
	G_{avg}	0.629 **	G_{var}	-0.372 **	G_{skw}	-0.050 ^{ns}	G_{krt}	0.033 ^{ns}
	B_{avg}	0.535 **	B_{var}	-0.194 ^{ns}	B_{skw}	0.000 ^{ns}	B_{krt}	-0.078 ^{ns}
	H_{avg}	0.692 **	H_{var}	0.329 **	H_{skw}	-0.315 **	H_{krt}	-0.185 ^{ns}
	S_{avg}	0.137 ^{ns}	S_{var}	0.502 **	S_{skw}	-0.506 **	S_{krt}	-0.322 *
	V_{avg}	0.586 **	V_{var}	-0.421 **	V_{skw}	-0.068 ^{ns}	V_{krt}	-0.017 ^{ns}
	H_{avg}	0.350 **	H_{var}	0.035 ^{ns}	H_{skw}	-0.136 ^{ns}	H_{krt}	-0.118 ^{ns}
	S_{avg}	0.205 ^{ns}	S_{var}	0.085 ^{ns}	S_{skw}	0.049 ^{ns}	S_{krt}	-0.129 ^{ns}
	I_{avg}	0.569 **	I_{var}	-0.325 **	I_{skw}	-0.058 ^{ns}	I_{krt}	0.011 ^{ns}
	L_{avg}	-0.117 ^{ns}	L_{var}	0.473 **	L_{skw}	0.430 **	L_{krt}	-0.453 **
	a_{avg}	-0.808 **	a_{var}	0.584 **	a_{skw}	0.691 **	a_{krt}	-0.322 **
	b_{avg}	-0.385 **	b_{var}	-	b_{skw}	-	b_{krt}	-

Comparison of the predicted nitrogen values by the MLP-ANN from the color indices values of the images taken from 5 m (NANN_5m) and 10 m (NANN_10m) heights, with the actual nitrogen values (NR) obtained from the Kjeldahl test using the student t-test is presented in Table 3. The predicted nitrogen values from 5 m and 10 m heights are not significantly different from each other and from actual nitrogen values. Ahmadi Moghaddam et al. (2011) showed that the neural network model is capable of estimating the sugar beet leaf chlorophyll from digital images with a reasonable accuracy, where the R^2 and MSE between the ANN estimated and the measured SPAD values appeared to be 0.94 and 0.006, respectively. Also, Gabriel et al. (2017) reported that proximal and airborne sensors provided useful information of maize N nutritional status. Therefore, the nitrogen values determined from the aerial digital images of sugarcane fields can provide a reasonable estimate of the actual nitrogen of the field and can be used for decisions about the fertilizer application in the farm.

Table 3. Comparing of determined nitrogen values with the student's t-test

Treatments	***Mean difference***	***t value***
$\mathbf{N_R}$**-**$\mathbf{N_{ANN\_5m}}$	-0.0406	-0.106 ^{ns}
$\mathbf{N_R}$**-**$\mathbf{N_{ANN\_10m}}$	0.00439	0.167 ^{ns}
$\mathbf{N_{ANN\_5m}}$**-**$\mathbf{N_{ANN\_10m}}$	-0.005	-1.415 ^{ns}

ns = No significant difference

The RMSE and MAPE values, which indicate the error value in predicting the amount of nitrogen with ANNs, are listed in Table 4. The least error in predicting the amount of nitrogen has occurred for 10 m height. Therefore, between two heights of imaging, the height of 10 m is more suitable than the height of 5 m, and is therefore recommended for aerial monitoring of the nitrogen content of the sugarcane fields.

Table 4. The error values of nitrogen estimation in sugarcane crop using MLP-ANN

Imaging height	***RMSE***	***MAPE***
5 m	0.181	0.061
10 m	0.174	0.056

The least error in the estimation of sugarcane crop nitrogen content was at 10 m height which was better than the 5 m height, so taking images from heights more than 10 m by non-stopped UAV is necessary in next researches to develop the practical type of proposed system. Also, determination of other features for sugarcane crop and filed (such as water content, maturity, nutrient elements value, diseases, etc.) can be done, and the effect of other variables (such as angle of insolation, maturity of the plants, soil color, day light etc.) on the results should be investigated in the next researches. Finally, it is proposed this research be carried out using data fusion of different sensors (RGB, infrared, multispectral, etc.) that will increase performance of the proposed system (Gabriel et al., 2017; Zheng et al., 2018)

5. Conclusions

In this research, possibility of using digital aerial images as a remote sensing method for nitrogen content determination of sugarcane plant was studied. To have high quality images the flight heights were low (5 and 10 m) and the UAV was stopped whenever a new picture was taken, so the area that can be potentially covered before batteries run out of power is not very large.

Among the color indices extracted from field images at RGB, HSV, HSI, Lab color spaces, 24 features had suitable correlation with the amount of nitrogen in leaves, and were used as the most effective features in the ANN training process. The MLP-ANN was successfully used to predict the amount of nitrogen in sugarcane leaves from aerial digital images. The predicted nitrogen content using the MLP-ANN was not significantly different from the actual nitrogen content of the sugarcane crop.

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References

Ahmadi Moghaddam P., Haddad Darafshi M.A., Shayesteh M., (2009), Laboratory estimation of sugar beet leaf nitrogen status by color image processing, *Journal of Agricultural Science and Sustainable Production* (in Persian with Abstract in English),**19**, 189-199.

Ahmadi Moghaddam P., Haddad Derafshi M., Shirzad V., (2011), Estimation of single leaf chlorophyll content in sugar beet using machine vision, *Turkish Journal of Agriculture and Forestry*, **35**, 563-568.

Alchanatis V., Schmilovitch Z., Meron M., (2005), In field assessment of single leaf nitrogen status by spectral reflectance measurements, *Precision Agriculture*, **6**, 25-39.

Al-Wassai F.A., Kalyankar N.V., (2013), Major limitations of satellite images, *Journal of Global Research in Computer Science*, **4**, 51-59.

Anonymous, (2016), A guide to Kjeldahl nitrogen determination methods and apparatus, LABCONCO, On line at: http://www.ExpotechUSA.com.

Anonymous, (2017), Phantom 3 Professional, China DJI, On line at: https://www.dji.com/phantom-3-pro.

Bagheri N., (2016), Development of a spectrograph unmanned aerial vehicle for aerial imaging of agricultural farms, *Physical Geography Research*, **47**, 533-546.

Bagheri N., Ahmadi H., Omid M., AlaviPanah S.K., (2011), Preparation of a nitrogen variability map for corn crop, as based on satellite imagery, *Iranian Journal of Biosystem Engineering* (in Persian with Abstract in English), **42**, 103-111.

Barbedo J.G.A., (2019), A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses, *Drones*, **3**, 40, https://doi.org/10.3390/drones3020040.

Beloev I.H., (2016), A review on current and emerging application possibilities for unmanned aerial vehicles, *Acta Technolgica Agriculturae*, **19**, 70-76.

Corti M., Cavalli D., Cabassi G., Vigoni A., Degano L., Gallina P.M., (2019), Application of a low-cost camera on a UAV to estimate maize nitrogen-related variables, *Precision Agriculture*, **20**, 675-696.

Felderhof L., Gillieson D., (2011), Near-infrared imagery from unmanned aerial systems and satellites can be used to specify fertilizer application rates in tree crops, *Canadian Journal of Remote Sensing*, **37**, 376-386.

Feng W., Yao X., Zhu Y., Tian Y.C., Cao W.X., (2008), Monitoring leaf nitrogen status with hyper spectral reflectance in wheat, *European Journal of Agronomy*, **28**, 394-404.

Gabriel J.L., Zarco-Tejada P.J., López-Herrera P.J., Pérez-Martín E., Alonso-Ayuso M., Quemada M., (2017), Airborne and ground level sensors for monitoring nitrogen status in a maize crop, *Biosystems Engineering*, **160**, 124-133.

Golmohammadzadeh F., Golmohammadi A., Rasouli Sharabyani V., Kisalaei A., (2015), Estimation of nitrogen status of wheat leaf using image processing, in Proceedings of the 1st national congress of strategies for achieving sustainable development in science and technology sectors, Policies Toward Sustainable Development Center (in Persian), Tehran, Iran.

Golzarian M.R., Kazemi F., Hajiabolhasani Z., (2014), *Digital Image Processing using MATLAB: from Principles to Applications* (in Persian), Ferdowsi University of Mashhad Publication, Mashhad, Iran.

Gonzalez R.C., Woods R.E., Eddins S.L., (2009), *Digital Image Processing using MATLAB*, 2nd Edition, Gatesmark Publishing, USA.

Heege H.J., (2013), *Precision in Crop Farming, Site Specific Concepts and Sensing Methods: Applications and Results*, Springer Science Publishing, New York, USA.

Hogan S.D., Kelly M., Stark B., Chen Y., (2017), Unmanned aerial systems for agriculture and natural resources, *California Agriculture*, **71**, 5-14.

Hosseini S.A., (2017), *Estimation of nitrogen status of crop in sugarcane fields using aerial digital images and artificial neural networks* (in Persian with Abstract in English), MSc Thesis, Shahid Chamran University of Ahvaz, Ahvaz, Iran.

Hunt E.R.Jr., Cavigelli M., Daughtry C.S.T., Mcmurtrey J.E., Walthall C.L., (2005), Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status, *Precision Agriculture*, **6**, 359-378.

Jia B., He H., Ma F., Diao M., Jiang G., Zheng Z., Cui J., Fan H., (2014), Use of a digital camera to monitor the growth and nitrogen status of cotton, *The Scientific World Journal*, **2014**, https://doi.org/10.1155/2014/602647.

Kumar V., Gupta P., (2012), Importance of statistical measures in digital image processing, *International Journal of Emerging Technology and Advanced Engineering*, **2**, 56-62.

Lemaire G., Jeuffroy M.H., Gastal F., (2008), Diagnosis tool for plant and crop N status in vegetative stage theory and practices for crop N management, *European Journal of Agronomy*, **28**, 614-624.

Li J., Zhang F., Qian X., Zhu Y., Shen G., (2015), Quantification of rice canopy nitrogen balance index with digital imagery from unmanned aerial vehicle, *Remote Sensing Letters*, **6**, 183-189.

Lukina E., Stone M., Raun W., (1999), Estimating vegetation coverage in wheat using digital images, *Journal of Plant Nutrition*, **22**, 341-350.

Masoudi H., Rohani A., (2016), Mass and volume prediction of orange fruit (Dezful local variety) using MLP neural networks, *Journal of Agricultural Engineering*, **39**, 133-142.

Muñoz-Huerta R.F., Guevara-Gonzalez R.G., Contreras-Medina L.M., Torres-Pacheco I., Prado-Olivarez J., Ocampo-Velazquez R.V., (2013), A review of methods for sensing the nitrogen status in plants: advantages, disadvantages and recent advances, *Sensors*, **13**, 10823-10843.

Radmoghaddam M., (2011), *Evaluation of the nitrogen state of spinach plant using chlorophyll index and image processing based on artificial neural network* (in Persian with Abstract in English), MSc Thesis, University of Tabriz, Iran.

Schirrmann M., Giebel A., Gleiniger F., Pflanz M., Lentschke J., Dammer K.H., (2016), Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, *Remote Sensing*, **8**, 706, https://doi.org/10.3390/rs8090706.

Sharifi M., Haj Abbasi M.A., (2005), *Investigating the Possibility of Using Direct Distillation Method to Measure Total Nitrogen of Soil* (in Persian), Proc. of the 9th Iranian soil science congress, Tehran, Iran.

Taghizad Fanid A., Haghipour S., Andalib A., (2012), Man-made object detection based on fractal features and morphological operations in aerial images (in Persian with Abstract in English), *Tabriz Journal of Electrical Engineering (TJEE)*, **42**, 13-24.

Tewari V.K., Arudra A.K., Kumar S.P., Pandey V., Chandel N.S., (2013), Estimation of plant nitrogen content using digital image processing, *Agricultural Engineering International: CIGR Journal*, **15**, 78-86.

Yakushev V.P., Kanash E.V., (2016), Evaluation of wheat nitrogen status by colorimetric characteristics of crop canopy presented in digital images, *Journal of Agricultural Informatics*, **7**, 65-74.

Zermas D., Teng D., Stanitsas P., Bazakos M., Kaiser D., Morellas V., Mulla D., Papanikolopoulos N., (2015), *Automation Solutions for the Evaluation of Plant Health in Corn Fields*, Proc. of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 28 September-2 October 2015; 6521-6527.

Zhang C., Kovacs J.M., (2012), The application of small unmanned aerial systems for precision agriculture: a review, *Precision Agriculture*, **13**, 693-712.

Zhao C.L., Liu J., Wang W., Huang X., Song C.L., (2005), Predicting grain protein content of winter wheat using remote sensing data based on nitrogen status and water stress, *International Journal of Applied Earth Observation and Geo-information*, **7**, 1-9.

Zheng H., Cheng T., Li D., Zhou X., Yao X., Tian Y., Cao W., Zhu Y., (2018), Evaluation of RGB, color-infrared and multispectral images acquired from unmanned aerial systems for the estimation of nitrogen accumulation in rice, *Remote Sensing*, **10**, 824, https://doi.org/10.3390/rs10060824.

Zhu J., Wang K., Deng J., Harmon T., (2009), *Quantifying Nitrogen Status of Rice Using Low Altitude UAV-Mounted System and Object-Oriented Segmentation Methodology*, Proc. of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, San Diego, CA, USA, 30 August-2 September 2009, 1-7.