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AN INTELLIGENT APPROACH OF DETERMINING RELATIONSHIP BETWEEN TOMATO LEAVES COLOR AND SOIL MOISTURE AND TEMPERATURE

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Abstract

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In this article is presented a model of the relationship between the soil moisture and its temperature and the color of the leaves of greenhouse tomato plants. This dependency is modelled using nonlinear regression statistical Quasi-Newton method. Piecewise linear regression with breakpoint models are received. The impacts of the factors non-included in the model are taken into account, as they are equated to the random error. A methodology for collection, characterization and processing of information from the experiments is proposed. During the experiment wireless sensors for soil moisture and temperature, handheld portable colorimeter and combined device for measuring environmental parameters are used. In statistical processing of the information the software platform Statsoft STATISTICA is used. The obtained models predict soil moisture based on the measured RGB values and the soil temperature, with an error ranging between -4.85% to +14.98%. The resulting dependency allows creation of an intelligent system for optimal managing the process of irrigation of greenhouse plants.

Key words: soil moisture, color of tomato leaves, nonlinear estimation
Abbreviations and Acronyms: µm – micrometer; kLx – kilolux; θ (theta) – soil moisture, m^3/m^3; T – soil temperature, °C; R, G and B – color components of the color model RGB; R_{avg}, G_{avg}, B_{avg} – average values of the color components; A and C – qualitative factors group: A1 – before irrigation, A2 – after irrigation, C1 – young leaves, C2 – older leaves, FC – field capacity

Introduction

There are various sensors for measuring soil moisture (wireless or not), but they are relatively expensive especially when they are wireless, or if they are wired that hampers the infrastructure in a greenhouse. On the other hand, during the process of irrigation, most of the water is drained into the soil, and only a small part of it is absorbed by the plant. Water should be saved because it is a priceless natural resource that is scarce in many regions of our planet.

All this requires looking for a smarter approach for determining the relationship between irrigation and the amount of absorbed water. A method that provides information that the plant is well watered and which eliminates the disadvantages of wireless and wired soil moisture sensors. This method needs to be sufficiently objective to ensure optimum irrigation and water saving.

The studies in this matter are too scarce and the analysis of the literature so far concerns the following information, engaged partly with the problem:

The temperature of the leaves is used for measuring the water status of the plant, which determines index of water stress, which in turn can be used for the creation of schedule for irrigation (Gallardo, 2004; Ton et al., 2001; Ton and Kyput, 2003). This method has the problem that it is late indicator of water stress because the temperature rise is starting

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when there is partial stomatal closing, leading behind to reduction of other more sensitive processes as growth through leaves expansion (Gallardo, 2004).

In another study the water stress index of a kind of grass (Lolium perenne) is determined using infrared thermometry (Stanghellini and De Lorenzi, 1994 and Nemali and Iersel, 2008).

The thickness of the leaves is also used to determine the schedule for irrigation (Sharon and Bravdo, 2001). The sensor continuously measures the leaf thickness with an accuracy of ± 1 μm. The method is based on the fact that the thickness of the leaf is related to the potential of the hardness of the leaves and the fact that if the plant is subject to water stress there is reducing in its hardness. It was tested on fruits be turned on irrigation system in response to changes in the thickness of the leaf, leading to watering with high frequency and low water volume, resulting in water savings of 30% in tests of citrus crops for six years, avocado for three years and cotton during the season (Sharon and Bravdo, 2001).

According to preliminary supposition, based on observations of the plants on the crop level before the actuall study experiments, young leaves (at the top of the plant) should be carriers of information about the need for watering and thats why twice as many RGB color samples are taken from them. Based on the same observations, during a period of drought the color of the both the young and older leaves darken.

The main goal of this paper is to establish a relationship between the soil parameters **θ** and T on one side and the color of the leaf mass of greenhouse tomato plants on another (represented in RGB color space) and to obtain a mathematical model describing this relationship. This modelling can be an intelligent approach for determining the need for irrigation with practical advantage optimizing the process of watering.

Materials and Methods

Study area

The studies were performed in certified tomato greenhouse located in the city of Plovdiv (Bulgaria), where all environmental parameters and the health of plants are kept in optimal range. The dimensions of the greenhouse are approximately 50 m to 35 m (in length of 15 columns by 3 m, each row is approximately 2 m wide). Tomatoes are grown here year-round within two harvests (from January to July and from August to December).

The studied tomatoes are from one sort – Panekra and they were planted on 31.07.2015. Experiments were conducted on the 18th and the 28th of September 2015, the first one 24 hours after irrigation, the second one 24 hours before irrigation, as follows:

- ■ First experiment in clear and sunny weather, humidity in the greenhouse 73% (W_1), temperature of the air in the greenhouse 25.7°C (W_2), humidity outside the greenhouse 65.8% (W_3), temperature of the air outside the greenhouse 25.5°C (W_4) and luminance in the greenhouse 39-47 kLx (W_5);
- ■ Second experiment in cloudy and rainy weather, humidity in the greenhouse 84% (W_1), temperature of the air in the greenhouse 19.8°C (W_2), humidity outside the greenhouse 85.8% (W_3), temperature of the air outside the greenhouse 16.8°C (W_4) and luminance in the greenhouse 5.2-6.2 kLx (W_5).

The studies were conducted at the end of a row, separated specifically for this purpose. The test section has a length of 15.53 m with controlled irrigation through two taps. Before the first tap, as for the whole greenhouse, the irrigation norm is 30 m^3 decare^{-1}. Between the first and second tap is 20 m^3 decare^{-1} and after the second tap to the end of the row it is 10 m^3 decare^{-1}. Fertilization is carried out by dissolving 20 kg of fertilizer and the solution is put on drip irrigation with the water – 20 m^3 decare^{-1}.

In measurements of the all environment parameters following tools were used:

- ■ Wireless sensor for measurement of θ (Model Onset W-SMC);
- ■ Wireless sensor for measurement of T (Model Onset W-TMB);
- ■ Handheld portable colorimeter for measuring the color of the foliage PCE-RGB2;
- ■ Device for measuring humidity and temperature of air and the luminance PCE-EM 883.

In statistical data processing software platform Statsoft STATISTICA 10.01.11 were used. The statistical data processing was conducted in University of Ruse.

Soil data

The soil in the greenhouse is alluvial meadow. Its main water-physical properties for the layer 0–40 cm are characterized by the following indicators: bulk density is 1.33 t m^{-3}, moisture on FC is 30.9% volumetric water content and the maximum water supply is 164.4 mm. The irrigation norm is calculated for moistening of layer 0–0.40 m, while still maintaining moisture before irrigation over 80% from FC (Ovcharova and Harizanova-Petrova, 2012).

The alluvial meadow soil has a low usable water reserve (TAW = 116 mm m^{-1}). It consists mainly of sand – between 68% of the surface and 53% and the lower-lying horizons. The content of physical clay is between 9% and 22%. The hydraulic conductivity at saturation fluctuates from 62–82 cm day^{-1} to 10 cm day^{-1} in the clay soil layer 60–100 cm (Popova and Ivanova, 2012).

Calibration of the sensor for the particular soil type

The calibration of the sensor for this particular soil is described in details by Atanasov (2015). The calibration follows the standard procedure for capacitive sensors calibration described by Starr and Palineanu (2002).

Methodology applied in soil moisture and color of the leaves data collection

The colorimeter measures the color of the leaves in 10-bit RGB color model. Studied are nine randomly selected plants – six measurements were performed on young leaves for each plant (from the top of the plant), three measurements of older leaves for each plan (from the lowest part of the plant) or altogether as follows – for young leaves after irrigation (C1 A2) – 54 measurements, for older leaves after irrigation (C2 A2) – 27 measurements, for young leaves before irrigation (C1 A1) – 54 measurements and for older leaves before irrigation (C2 A1) – 27 measurements.

In the first experiment, the plants were with a height of about 1.50 m and in the second about 1.90 m. Readings for each plant are averaged and in the further work are used four basic tables with average values of RGB (Table 1, 2, 3, 4).

Table 1
Aggregated measurements data of plants, young leaves after irrigation (C1 A2)

	R_{avg}	G_{avg}	B_{avg}	θ, m³/ m³	T, °C
Plant 1	119.33	141.00	90.00	27.28	20.89
Plant 2	116.33	137.67	83.33	24.31	20.94
Plant 3	120.50	141.50	90.33	27.83	20.94
Plant 4	118.67	140.50	86.33	25.52	20.72
Plant 5	126.67	149.00	87.67	24.53	21.10
Plant 6	123.17	144.17	89.33	28.16	21.65
Plant 7	97.17	115.83	71.67	26.62	21.27
Plant 8	126.67	147.67	91.17	23.87	21.37
Plant 9	123.67	143.50	92.00	31.02	21.80

Table 2
Aggregated measurements data of plants, older leaves after irrigation (C2 A2)

	R_{avg}	G_{avg}	B_{avg}	θ, m³/ m³	T, °C
Plant 1	149.00	168.67	121.33	27.28	20.89
Plant 2	129.00	150.00	102.00	24.31	20.94
Plant 3	126.33	149.33	100.00	27.83	20.94
Plant 4	141.00	164.00	105.33	25.52	20.72
Plant 5	146.67	168.67	112.00	24.53	21.10
Plant 6	140.00	161.33	99.67	28.16	21.65
Plant 7	148.00	168.00	117.67	26.62	21.27
Plant 8	154.00	175.33	119.33	23.87	21.37
Plant 9	146.33	165.33	111.33	31.02	21.80

Table 3
Aggregated measurements data of plants, young leaves before irrigation (C1 A1)

	R_{avg}	G_{avg}	B_{avg}	θ, m³/ m³	T, °C
Plant 1	100.83	123.83	74.83	24.75	19.18
Plant 2	115.50	141.83	79.33	22.55	19.44
Plant 3	95.50	116.67	71.50	24.64	18.51
Plant 4	108.50	133.17	76.17	20.02	19.03
Plant 5	104.33	127.83	74.83	24.31	19.13
Plant 6	129.33	166.50	82.33	26.73	18.70
Plant 7	107.33	130.50	79.67	21.67	19.22
Plant 8	117.00	142.83	82.33	24.20	19.03
Plant 9	100.33	121.83	75.17	25.74	20.72

Table 4
Aggregated measurements data of plants, older leaves before irrigation (C2 A1)

	R_{avg}	G_{avg}	B_{avg}	θ, m³/ m³	T, °C
Plant 1	147.67	167.67	122.67	24.75	19.18
Plant 2	138.67	157.00	114.33	22.55	19.44
Plant 3	133.67	156.67	106.67	24.64	18.51
Plant 4	131.67	149.67	106.67	20.02	19.03
Plant 5	146.67	168.00	116.67	24.31	19.13
Plant 6	138.00	159.33	111.67	26.73	18.70
Plant 7	141.33	160.67	108.00	21.67	19.22
Plant 8	139.67	157.67	118.33	24.20	19.03
Plant 9	135.00	153.33	106.33	25.74	20.72

θ and T were measured once, near the plant and in the root zone, in the soil layer 10–20 cm. In the second experiment (before irrigation) three additional plants were examined, which were later used as control values to verify the developed model.

Multifactorial approach for representation of the object of study and methodology

The object of the study is multifactorial at the input of which acts the controllable factor **θ** and the uncontrollable, but measurable factor T. The influence of all other disturbing (W_1–W_5) and unaccounted factors is equivalently replaced by the random error ε (Figure 1).

The scheme in Figure 1 corresponds to the so-called active-passive experiment and is characteristic of the real objects (Mitkov and Minkov, 1985). In terms of the mathematical treatment of the results from multivariable experimental studies it is not necessary the input factors to be divided into two groups – controllable and measurable (Mitkov and

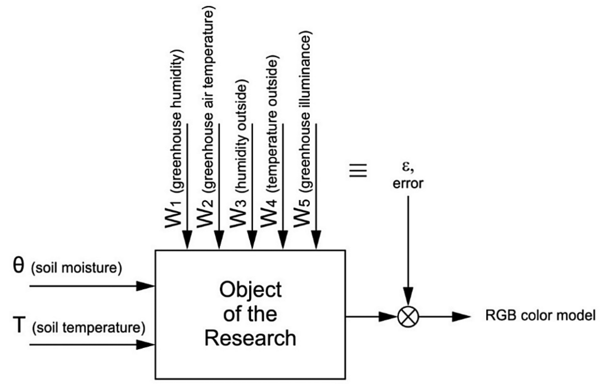


Fig. 1. The object of the study with one controllable and one uncontrollable factor

Minkov, 1985). Therefore, hereinafter factors θ and T are considered as independent variables and color components as dependent variables, depending on θ and T.

The task is to find a mathematical model describing the relationship between the average value of the parameters of the color components from one side and the factors θ and T, on the other.

Because factors θ and T are measurable, the connection between them and the average value of each component of the color model has been investigated using the methods of the multi-factor regression analysis.

Because the factors „before/after irrigation" and „young/older leaf" are qualitative, their impact has been investigated using the statistical multi-factor analysis of variance.

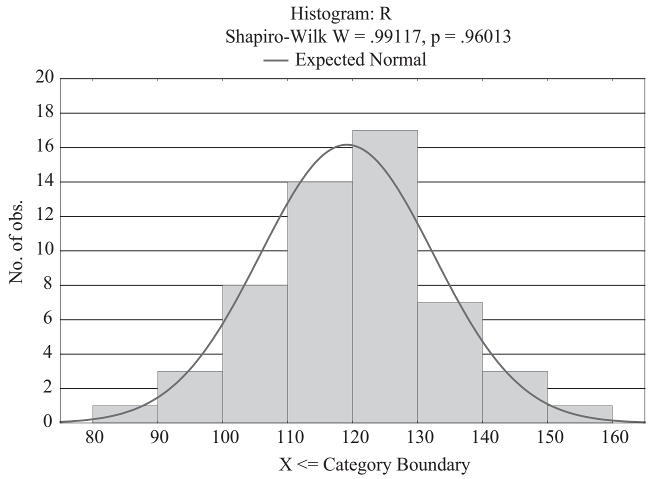
During the studying of the normal distribution of the values the full set of the samples was used, and for the variance and the regression analysis – the averages R_{avg}, G_{avg} and B_{avg} were used.

Results

Study of the distribution of the random variables

Firstly, it was examined the distribution of the obtained experimental data for the color components of each plant (random variables). There were used 54 measurements of young leaves before and after watering and 27 measurements of older leaves before and after irrigation. Determined were standard deviation and coefficient of variation (variance) for each of the measured color components. It was chosen Shapiro-Wilk test for normality, because in smaller samples and medium sized samples its power is significantly better than other known tests. It is assumed that big is the sample for which the number of observations is equal to or larger than 30, i. e. $n \geq 30$.

Figure 2 provides an illustration of the normal distribution of R (red color component) in young leaves after irrigation, using Shapiro-Wilk test W = 0.99 and its level of significance p = 0.96. Because p >> 0.05, this indicates that the data is normally distributed (in other words, the null hypothesis is true). The result shows that the component R in young leaves after irrigation has Gaussian (Normal) distribution.



	Descriptive Statistics (Young leaves after irrigation - 54 measurements.sta)					
Variable	Valid N	Mean	Std.Dev.	Coef.Var.	Skewness	Kurtosis
R	54	119.1296	13.32616	11.18627	-0.061494	-0.217699

Fig. 2. Study of the distribution of the obtained values for R in C1 A2

At the bottom of Figure 2 are shown: "ValidN" – number of measurements (54); „Mean" – arithmetical mean (119.1296); „Std.Dev." – standard deviation (13.33); „Coef.Var." – coefficient of variation (11.18627), representing the standard deviation divided by the arithmetic mean (in percentage) – in this case 11% means that the data is very tightly around average and have a very good homogeneity; standard error (1.81) and the last two parameters (skewness and kurtosis) show how distorted distribution is: asymmetry (-0.06) and excess (-0.22).

An analogous manner is used to analyze all the parameters of the distribution of all color components. In Table 5 are shown summarized results (where "Var." is variable, "F1" and "F2" are Factor 1 and Factor 2, "C1" means young leaves, "C2" means older leaver, "A1" means before irrigation, "A2" – after irrigation, "ND" – availability of normal distribution (Yes/No)).

From the summarized results in Table 5 it can be concluded that most components have Gaussian distribution, only components B in C1 A2 and C2 A2 and G in C1 A1 don't possess Gaussian distribution.

Table 5
Aggregated parameters of the distribution of values

Var.	F1	F2	W	p	Std. Dev.	Coef.Var.	Skewness	Kurtosis	ND
R	C1	A2	0.99	0.96	13.33	11.19	-0.06	-0.22	Y
G	C1	A2	0.99	0.90	15.05	10.74	-0.05	-0.34	Y
B	C1	A2	0.95	0.02	9.66	11.14	-0.64	0.002	N
R	C2	A2	0.96	0.42	11.55	8.12	0.19	-0.80	Y
G	C2	A2	0.95	0.18	11.58	7.09	0.22	-0.83	Y
B	C2	A2	0.91	0.02	11.04	10.05	0.52	-1.04	N
R	C1	A1	0.98	0.33	14.97	13.77	-0.11	-0.77	Y
G	C1	A1	0.95	0.03	20.92	15.63	0.73	1.88	N
B	C1	A1	0.99	0.74	9.31	12.04	0.03	-0.14	Y
R	C2	A1	0.97	0.71	13.03	9.37	0.08	-0.75	Y
G	C2	A1	0.98	0.91	14.57	9.17	0.08	-0.49	Y
B	C2	A1	0.98	0.78	11.77	10.47	-0.37	-0.09	Y

Analysis of variance (ANOVA)

Main effects ANOVA (Figure 3) is used for each color component, based on the data from Tables 1-4 plus added qualitative factors A (before/after irrigation) and C (young/older leaves). Each color component is dependable variable, A and C are categorical predictors (factors).

Effect	Univariate Tests of Significance for R (Spreadsheet1) Sigma-restricted parameterization Effective hypothesis decomposition SS	Degr. of Freedom	MS	F	p
Intercept	583571.2	1	583571.2	7529.697	0.000000
A	410.1	1	410.1	5.292	0.027885
C	6449.4	1	6449.4	83.216	0.000000
Error	2557.6	33	77.5		

Fig. 3. Results from YES-influence of factors A and C on R_{avg}

Figure 3, taken from the program, shows that the both factors A and C have significant impact on R_{avg}, since the probability p for both factors is less than 0.05. Stronger influence has factor C (as can be seen from Figure 4, 5). The component R_{avg} has the largest values in older leaves after irrigation.

Following the same procedure, for the remaining G_{avg} and B_{avg} color components were obtained the following conclusions: Only factor C has proven influence on G_{avg} and B_{avg}. G_{avg} and B_{avg} have the largest values in older leaves after watering.

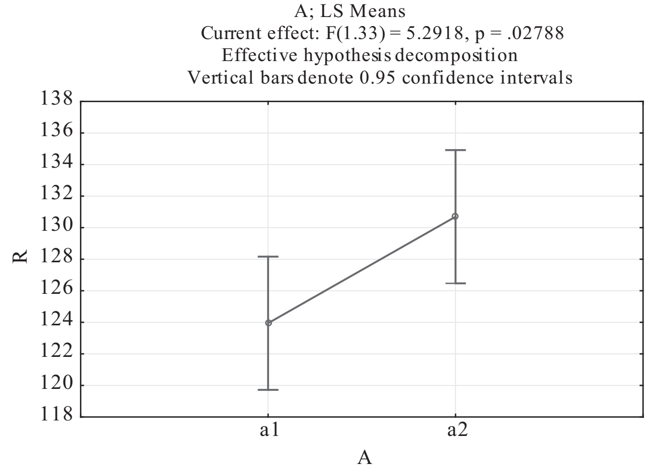


Fig. 4. Influence of factor A on R_{avg}

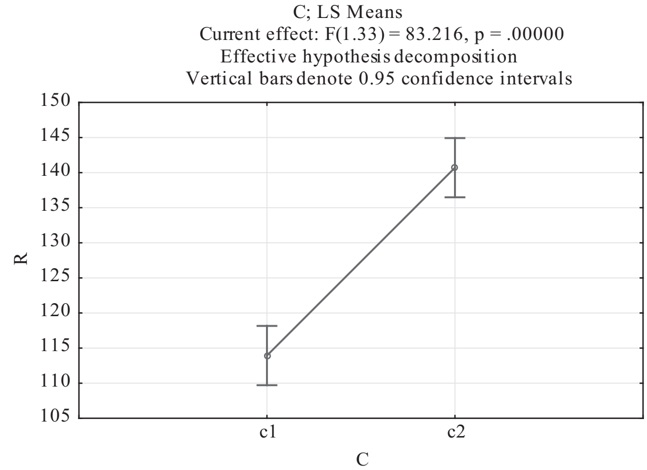


Fig. 5. Influence of factor C on R_{avg}

Regression analysis

The principle of progressive complication of the model was used, i.e. transition from simpler to more complex models, until reaching an adequate object model (Mitkov and Minkov, 1985). Unsuitability of the multiple linear regressions and the polynomial regression of the second degree has been established on the base of previous studies, during the modelling of the relationship between the studied parameters.

Modelling with Piecewise linear regression with breakpoint

The data were modelled using nonlinear estimation – partially-linear regression with breakpoint, also known as stepwise regression.

From the above- mentioned studies, conducted so far (multiple linear regression and the polynomial regression), it became apparent, that the environmental factors, which are the object of this study, have inherent nonlinear behavior according the color of the leaves. During the data modelling with Piecewise linear regression with breakpoint it was once again assumed that the color of the leaves is a dependent variable, which varies against the independent variables θ and T (as predictors). The variation of the data for θ and T does not follow a distinct linear relationship in terms of the color of the leaves. It is difficult such a dynamic relationship to be modelled using conventional linear methods such as multiple linear regression. Therefore, it was used the approach of non-linear estimation to calculate the relationship between the set of independent variables and the dependent variable. The model is divided into two parts and the estimates of the model are obtained using the nonlinear Quasi-Newton method, representing non-linear, multivariate, iterative, repetitive optimization method, which significantly minimizes inconsistencies and the errors in the process of predicting of color. In Quasi-Newton method, in order develop a model for predicting the color of the leaves, the derivative of the first order of the function is calculated at a given point in order to find its slope at this point. The subsequent derivative of second order shows how quickly the slope of the point and its direction is changing (Prasad et al., 2006).

The following coefficients of the empirical equation were obtained using this method.

The general model, computed by the least squares method, looks like:

$$y = (b_{01} + b_{11}x_1 + ... + b_{m1}x_m)(y \le b_n) + \\ + (b_{02} + b_{12}x_1 + ... + b_{m2}x_m)(y > b_n) \quad (1)$$

Using parameters R_{avg}, G_{avg}, B_{avg}, θ and T the model can be rewritten as:

$$\{R_{avg}.G_{avg}.B_{avg}\} = \\ (b_{01} + b_{11}\theta + b_{21}T)(\text{for } \{R_{avg}.G_{avg}.B_{avg}\}) \le \text{breakpoint } b_0) \\ \text{or } (b_{02} + b_{12}\theta + b_{22}T)(\text{for } \{R_{avg}.G_{avg}.B_{avg}\}) > \text{breakpoint } b_0) \quad (2)$$

Thus, STATISTICA calculates two separate linear regression equations (one for the y values, which are smaller or equal to the breakpoint (b_0) and one for the y values bigger than the breaking point) and the exact value of the breakpoint. Later in studies it was found that breakpoint is equal of the mean value of the specific color component.

For R_{avg} from Table 1 according the model (2) was obtained the showed in Figure 6.

The coefficient of determination is 98.669%. It shows that 98.669% of the variance of R_{avg} is due to changes in the percentage of θ and T. The rest 1.331% is due to factors not included in the model. These conclusions are valid for the other color components – G_{avg} and B_{avg}. Table 6 summarizes all the model coefficients for all the color components from Table 1.

This iterative method is suitable for several independent variables and one dependent variable (RGB color compo-

Table 6
Model coefficients and breakpoint for R_{avg}, G_{avg} and B_{avg} (at C1 A2)

Variable from the model	Coefficients	R_{avg}	G_{avg}	B_{avg}
Constant	b_{01}	868.17	2.35	611.21
θ	b_{11}	–3.80	–12.44	–1.73
T	b_{21}	–31.49	20.90	–23.19
Constant	b_{02}	10.35	28.84	63.16
θ	b_{12}	–1.06	–1.24	0.22
T	b_{22}	6.66	6.99	0.99
	Breakpoint	119.13	140.09	86.87
R		0.99	0.99	0.99
Variance explained (%; R^2)		98,67%	98.03%	97.46%

	Model is: Piecewise linear regression with breakpoint (Young leaves after irrigation.sta) Dependent variable: R Loss: Least squares Final loss: 8.555109364 R= .99332 Variance explained: 98.669%						
N=9	Const.B0	θ	T	Const.B0	θ	T	Breakpt.
Estimate	868.1665	-3.79798	-31.4949	10.34683	-1.06165	6.658626	119.1296

Fig. 6. Piecewise linear regression modelling of R_{avg} from Table 1 (C1 A2)

	Model is: (Young leaves after irrigation.sta) Dep. Var. : R		
	Observed	Predicted	Residuals
1	119.3333	120.4836	-1.15028
2	116.3333	116.3333	-0.00000
3	120.5000	120.2326	0.26737
4	118.6667	118.6667	-0.00000
5	126.6667	124.8015	1.86519
6	123.1667	124.6099	-1.44325
7	97.1667	97.1667	0.00000
8	126.6667	127.3000	-0.63333
9	123.6667	122.5724	1.09429

Fig. 7. Observed, predicted values and residuals for R_{avg} at C1 A2

nent) for values above and below the breakpoint. With this non-linear optimization approach are achieved acceptable small values of residuals, with predicted values very close to the observed values, as shown in Figure 7.

Figure 8 shows that all experimental data are inside or are very close to confidence area (at confidence level $\gamma = 0.95$) and the regression line passes close to the experimental points.

Figure 9 shows that, the values of residuals are within acceptable limits with even distribution. The high value of $R^2 = 0.99$ for R_{avg} from Table 6, shows that the color component significantly depends on the variables included in the model. The points are located close to the straight line, i.e. it can be assumed that the residuals have a normal distribution.

Similar reasoning can be applied to all other examined color components shown in Table 6 through Table 9. The

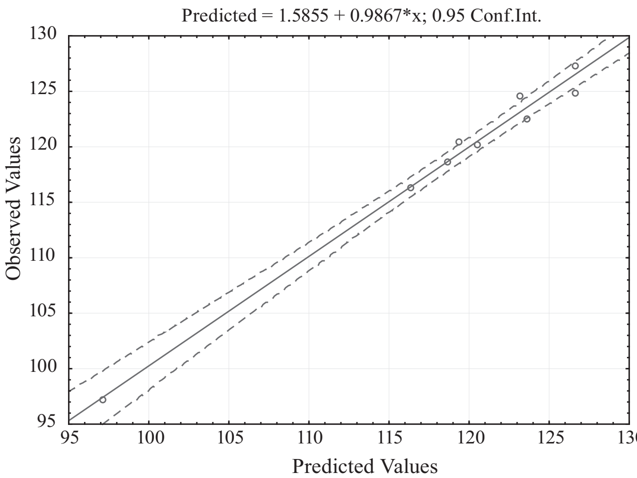


Fig. 8. Scatter diagram – predicted against measured values of R_{avg}, C1 A2, model (2)

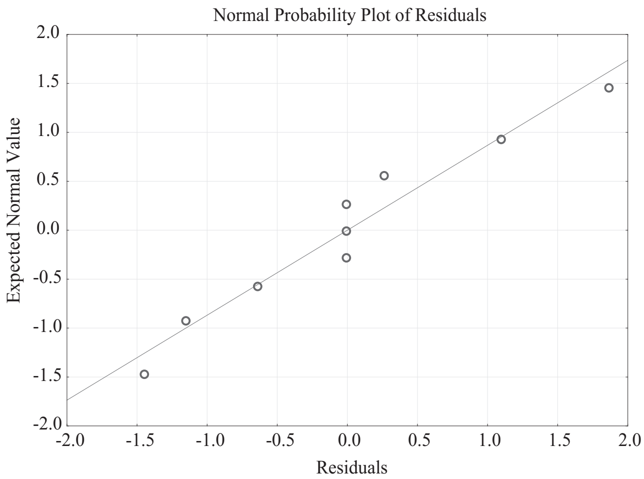


Fig. 9. Normal probability graph of the residuals of the model (2)

Table 7
Coefficients and breakpoint for R_{avg}, G_{avg} and B_{avg} models (at C2 A2)

Variable from the model	Coeffi-cients	R_{avg}	G_{avg}	B_{avg}
Constant	b_{01}	-1.61	-201.15	180.44
θ	b_{11}	-0.62	-0.19	-0.54
T	b_{21}	7.22	16.99	-3.06
Constant	b_{02}	110.74	55.37	272.8
θ	b_{12}	-0.84	-1.45	-0.07
T	b_{22}	2.84	7.14	-7.26
	Breakpoint	142.26	163.41	109.85
R		0.86	0.98	0.95
Variance explained (%; R^2):		74,68%	95.52%	89.37%

model coefficients of the color components, according Table 2, Table 3 and Table 4 are summarized in Table 7, 8 9.

Verification of the developed model (2)

After that, using the model (2), a verification of reverse dependence, researching θ as dependent variable and the color component and temperature as independent, was made.

For this purpose, during the experiment, are taken RGB values for three control plants before irrigation (Plants 10–12). With them the model (2) adequacy was approbated.

Analytically model (2) is rewritten in accordance with θ as follows:

Table 8
Coefficients and breakpoint for R_{avg}, G_{avg} and B_{avg} models (at C1 A1)

Variable from the model	Coefficients	R_{avg}	G_{avg}	B_{avg}
Constant	b_{01}	104.72	137.12	57.18
θ	b_{11}	-2.12	-2.59	-0.59
T	b_{21}	2.48	2.57	1.63
Constant	b_{02}	-746.30	-1727.72	131.70
θ	b_{12}	9.26	19.02	0.25
T	b_{22}	33.59	74.11	-2.98
	Breakpoint	108.74	133.89	77.35
R		0.98	0.99	0.98
Variance explained (%; R^2)		96,98%	97.51%	95.14%

Table 9
Coefficients and breakpoint for R_{avg}, G_{avg} and B_{avg} models (at C2 A1)

Variable from the model	Coefficients	R_{avg}	G_{avg}	B_{avg}
Constant	b_{01}	122.18	169.45	122.02
θ	b_{11}	0.53	1.16	0.42
T	b_{21}	0.02	-2.16	-1.25
Constant	b_{02}	-785.96	-512.82	-222.52
θ	b_{12}	2.89	2.96	4.80
T	b_{22}	44.99	31.73	11.75
	Breakpoint	139.15	158.89	112.37
R		0.93	0.95	0.97
Variance explained (%; R^2):		87.42%	91.13%	93.54%

Table 10
Approbation of the model (3) in C1 A1

	R_{avg}	G_{avg}	B_{avg}	$\boldsymbol{\theta}_{measured}$	T
Plant 10	108.83	131.67	81.50	22.00	19.03
$\boldsymbol{\theta}_{model\ calculated}$	23.32	20.93	25.30		
Model error	+5.99%	-4.85%	+14.98%		
Plant 11	118.67	146.33	81.67	23.21	18.96
$\boldsymbol{\theta}_{model\ calculated}$	24.63	24.66	25.13		
Model error	+6.14%	+6.23%	+8.28%		
Plant 12	110.50	133.50	80.67	21.45	18.89
$\boldsymbol{\theta}_{model\ calculated}$	24.01	20.09	20.37		
Model error	+11.92%	-6.36%	-5.05%		

Table 11
Approbation of the model (3) in C2 A1

	R_{avg}	G_{avg}	B_{avg}	$\boldsymbol{\theta}_{measured}$	T
Plant 10	131.67	152.67	101.33	22.00	19.03
$\boldsymbol{\theta}_{model\ calculated}$	16.96	20.94	7.48		
Model error	**-22.93%**	+4.81%	**-66%**		
Plant 11	153.67	174.33	128.00	23.21	18.96
$\boldsymbol{\theta}_{model\ calculated}$	29.93	28.93	26.61		
Model error	+28.94%	+24.65%	+14.65%		
Plant 12	154.00	175.33	117.33	21.45	18.89
$\boldsymbol{\theta}_{model\ calculated}$	31.13	30.02	24.56		
Model error	+45.13%	+39.95%	+14.50%		

$$\theta = \frac{(\{R_{avg}.G_{avg}.B_{avg}\} - b_{01} - b_{21}T)}{b_{11}(\text{at } \{R_{avg}.G_{avg}.B_{avg}\})} \leq \text{breakpoint } b_0$$
or
$$\frac{(\{R_{avg}.G_{avg}.B_{avg}\} - b_{02} - b_{22}T)}{b_{12}(\text{at } \{R_{avg}.G_{avg}.B_{avg}\})} > \text{breakpoint } b_0 \qquad (3)$$

In this way the model (3) is obtained.

The results are provided in Table 10 and Table 11. "Model error" is the difference between θ calculated (predicted) with the model (3) and θ measured, in %.

The results from Table 10 and 11 clearly show, that the older leaves are not suitable for determination of irrigation needs, because the predicting error in too large. The young leaves before the irrigation are most informative, because the error is acceptably small.

Conclusions

During the studing of the normal distribution was found that almost all investigated values to RGB components have a Gaussian distribution, except the B component in young and older leaves after irrigation and the G component in young leaves before irrigation.

The Analysis of variance shows that both the factors A and C have significant impact on the R_{avg} color component. Stronger influence has factor C. On G_{avg} and B_{avg} color components proven influence has only factor C. Components R_{avg}, G_{avg} and B_{avg} have greatest values in older leaves after irrigation, which proves the second part of the preliminary suppositions, based on observations of the plants on the crop level before the actuall study experiments, that during a period of drought the color of both the young and older leaves darken.

In the regression analysis is proven the availability of a non-linear relationship between the examined one dependent (color component) and two independent variables (θ и T). Because of the resultant high coefficient of determination R^2, the model (2) and the method piecewise linear regression with breakpoint can be used to predict with high precision the values of the color components, based on the moisture and temperature of the soil. During the data processing it was found that the breaking point is coinciding with the mean value of the each examined color component.

In the younger leaves, the model (3) and the method piecewise linear regression with breakpoint can be used to predict with high precision the values of the soil moisture (and hence the need of watering), based of the color of the leaves and soil temperature, because of the low levels of error in predicting (Table 10). That confirmes the first part of preliminary supposition, based on observations of the plants on the crop level before the actuall experiments, that the younger leaves (at the top of the plant) are the carriers of information about the need for watering. That in turn justifies the methodology and why twice as many RGB color samples are taken from them during the experiments.

The color components of older leaves before irrigation are not suitable for establishing the need for irrigation, because of the obtained high levels of errors (Table 11).

This models (2) and (3) can be used as base of creation of farmer's information and/or monitoring systems, used to determine the need of irrigation.

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