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# Estimation of corn coefficients with vegetation indices using multispectral camera and drone

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**Abstract:** Optimum irrigation scheduling and new technologies are the key to the successful practice of modern agriculture and natural resources, such as water management. A three-year research project was conducted at Velestino, Magnesia, Greece. The aim was to study whether vegetation indices can be used to estimate the crop coefficients of corn in order to apply an intelligent method of irrigation using drones in the future. The normalised difference vegetation index (NDVI), the soil-adjusted vegetation index (SAVI), the renormalised difference vegetation index (RDVI) and a new index [difference infrared – green vegetation index (DIGVI)] were calculated using multispectral photos from a camera adapted to a drone. Three different methods were applied to calculate the crop coefficients: (*i*) the water balance and the FAO Penman-Monteith reference evapotranspiration, (*ii*) the climatic data, (*iii*) the vegetation indices. The irrigation dose covered 100% of the crop water needs according to the soil moisture measurements and the single crop coefficient values. The statistical analysis and the simple linear regression method showed that the corn crop coefficients can be estimated when these indices are used as independent variables.

**Keywords:** crop monitoring; modern irrigation; reference evapotranspiration; remote sensing; spectral indices

Daily agricultural practices help to keep the timeless problem of rational irrigation scheduling in the limelight. It is well known that the need to produce agricultural products intended for human consumption is constantly increasing as a result of the increase in the earth's burgeoning population (Gu et al. 2020). On the other hand, it is also known that water is the most indispensable natural resource for the agricultural sector and it must be maintained in both quantity and quality, at least, in its current state, so as to remain in sufficient supply for future generations.

Further developments in technologies have led to a new era in irrigation scheduling. Satellite images have been used to calculate vegetation indices and through them to also estimate different characteristics of cultivated plants. The success of these methods is based on the quality of the photos which are often negatively affected by the altitude of the captured image (Radhadevi et al. 2016). In addition, irrigation scheduling requires field data to be taken on a weekly basis. In the case of satellite photos, the time it takes for the satellite to pass repeatedly over a field and to capture an image of the same field may exceed a period of one week and if someone takes the time that is needed to buy, process and use the satellite photos in irrigation scheduling into consideration, this time is even longer. Nowadays, in agricultural production, new techniques in the calculation of vegetation in-

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dices based on multispectral photos taken by drones are being applied (Sylvester 2018). Vegetation indices are used to assess the health of cultivated plants in open field conditions (Papanikolaou and Sakellariou-Makrantonaki 2020a). However, they are also used in the estimation of various crop characteristics, such as the leaf area index (Potgieter et al. 2017), the estimation of the soil cover by the foliage of cultivated plants (Toureiro et al. 2017; Papanikolaou and Sakellariou-Makrantonaki 2020b), and the estimation of biomass production (Latifi et al. 2015; Papanikolaou and Sakellariou-Makrantonaki 2020a).

Different vegetation indices have been devised by numerous researchers. The best known one is the normalised difference vegetation index (NDVI), which has been used in the estimation of the plant leaf area index (Toureiro et al. 2017) and crop evapotranspiration (Droogers et al. 2010). NDVI is used in empirical equations to estimate the single and double crop coefficient (Zhang et al. 2019). Zhang and Zhou (2019) maintain that the water status of plants can be estimated both by vegetation indices sensitive to plant moisture variation and by indices used to estimate plant growth. Such indices are the soil-adjusted vegetation index (SAVI) and the renormalised difference vegetation index (RDVI).

Irrigation scheduling by means of the reference evapotranspiration method continues to be a reliable method for calculating crop water needs. Specifically, the calculation of the crop evapotranspiration ($ET_c$) through the multiplication between the crop coefficient ($K_c$) and the reference evapotranspiration ($ET_o$) is widely used (Allan et al. 1998). In Greece, Papazafeiriou (1999) studied the crop evapotranspiration and estimated crop coefficients for many different crops, including corn. In those studies, the $ET_o$ was calculated through the Modified Penman method as described in FAO 24 manual, and the FAO Penman-Monteith as described in FAO 56 manual. New technologies in the agricultural sector are leading to the ongoing race for even greater modernisation in irrigation scheduling. Therefore, the challenge is to combine the application of new and existing techniques in order to improve the water use efficiency and, if possible, to minimise wasting irrigation water.

In the present research corn was chosen because it is one of the most important cultivated plants for the agricultural economy of Greece as it has great nutritional value (Papanikolaou and Sakellariou-Makrantonaki 2020b). Secondly, the Greek farmers are already experienced in corn cultivation techniques and they have already made large investments in agricultural equipment used in corn cultivation. Thirdly, it is a plant that can be affected by different irrigation doses (Toureiro et al. 2017). Finally, corn is a plant with a high biomass production and it can be used as an energy plant for the production of solid fuels (pellets) or liquid ones (bioethanol) (Ambrosio et al. 2017).

Taking all the above into account, a three-year research project was conducted. The aim was to study whether vegetation indices can be used to estimate the crop coefficients of corn in order to apply an intelligent method of irrigation using drones in the future. This research is the first step in using a multispectral camera adapted to a cheap drone to achieve this aim. It is an innovative research project because, for the first time, vegetation indices are applied in the estimation of the crop coefficients of corn for the climatic conditions of Central Greece. A major advantage of this technique over satellite photos is that it is less affected by clouds, has a lower cost and photos can be taken at regular intervals over a period of less than a week and according to the irrigation schedule that is set by the farmer. In particular, the objectives of this research were: (*i*) the estimation of the crop coefficients per stage of crop development using vegetation indices and multispectral photos from a drone and (*ii*) the evaluation of the results using the vegetation indices with the corresponding results from the application of two alternative crop coefficient calculation methods.

## MATERIAL AND METHODS

A three-year study (2018–2020) was conducted at the Laboratory of Agricultural Hydraulics, Department of Agriculture, Crop Production and Rural Environment, University of Thessaly. Specifically, the open field experiment was conducted at the Experimental Farm of the University of Thessaly, in Velestino, Magnesia, Greece (latitude: 39°02'N, longitude: 22°45'E) (Figure 1). The altitude is about 70 m a.s.l. The soil texture is 38% clay, 32% silt, and 30% sand and classified as clay to clay loam (USDA classification). Undisturbed soil samples were taken and the field capacity and the permanent wilting point were measured at the laboratory using a pressure plate device. The soil samples were taken from two different depths, 0–30 and 30–60 cm. The average field capacity at the depth

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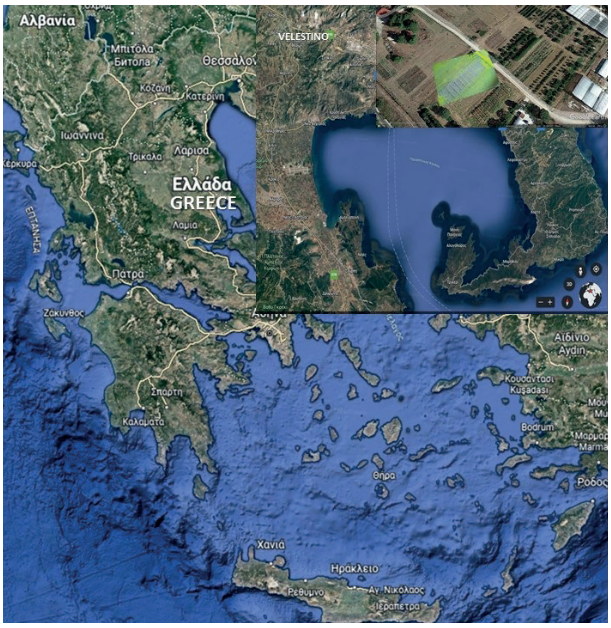


Figure 1. The study area

of 0–60 cm was 0.387 $cm^3 \cdot cm^{-3}$ and the permanent wilting point was 0.218 $cm^3 \cdot cm^{-3}$. Both the field capacity and the permanent wilting point were used to calculate the total available soil water (TAW) and the readily available soil water (RAW) (FAO 1998). Afterward, the RAW value was used to calculate the Practical applied irrigation dose for a 0.50 m effective root depth. As a depletion fraction, a value of 0.50 was used according to Allan et al. (1998). The practical applied irrigation dose was found to be equal to 51 mm which was used to calculate the maximum irrigation interval for the most crucial month of the irrigation period (Papanikolaou and Sakellariou-Makrantonaki 2020b). Following this procedure, the maximum irrigation interval was calculated as the quotient of the division between the practical applied irrigation dose and the average $ET_o$ of the crucial month for the Central Greek conditions (July, $ET_o \approx 6.3$ mm·day$^{-1}$), based on recorded data, and was found to be 8 days.

The research included different treatments, each in three replications, while the experimental design was used randomised complete blocks (Montgomery and Runger 2003; Sakellariou-Makrantonaki and Papanikolaou 2008a, 2008b; Makrantonaki et al. 2009; Papanikolaou and Sakellariou-Makrantonaki 2012; Papanikolaou et al. 2018; Papanikolaou and Sakellariou-Makrantonaki 2019). The full research contained three treatments where a different amount of irrigation water was applied. In the first treatment (full irrigation), the crop water needs covered 100% (E100), while, in the E75 treatment, the irrigation dose was 25% less than the full one and, in the E50 the irrigation treatment, the dose was 50% less than the full irrigation.

The meteorological data and the $ET_o$ were recorded every day by an agrometeorological station which is located 50 m away from the plots (average distance). The area is characterised by a typical Mediterranean climate. Figures 2A, B show the mean daily air temperature and the total rainfall (10-day average values) in the study area, during the 2018 and 2019 cultivating period, in comparison

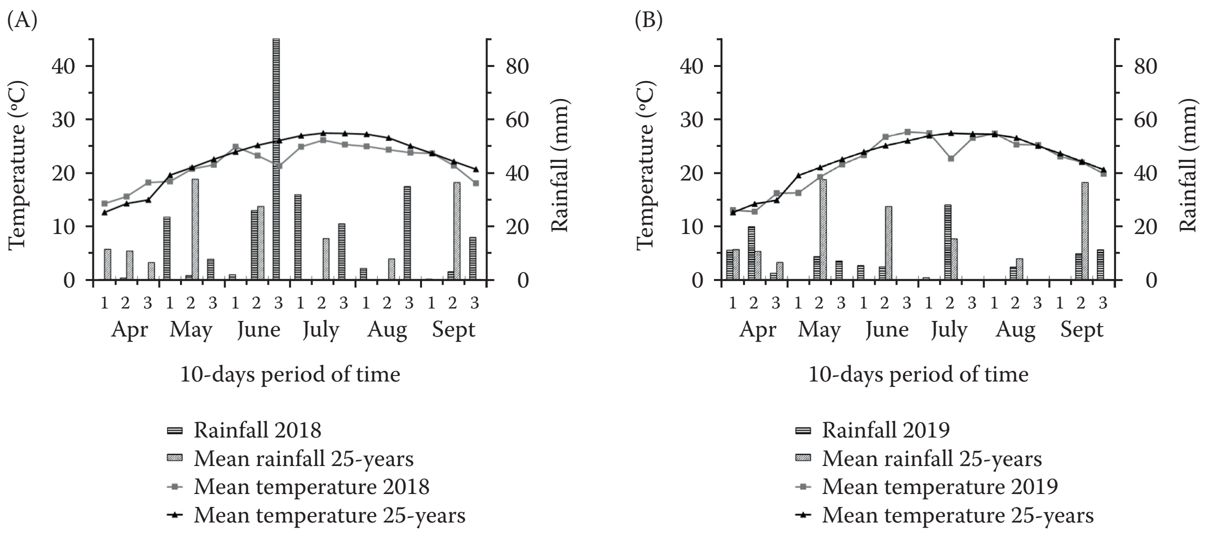


Figure 2. Average daily temperature and total precipitation of the years (A) 2018 and (B) 2019 in comparison with the average values of the last 20 years

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with the corresponding average values of the last 25 years. In general, during the years (2018–2020), the mean air temperature followed the pattern of the average year. An exception was observed during the period from May to August 2018. During the 2019 period, the air temperature followed a pattern even closer to the temperature of the average year. The third year of the research (2020) was close to the second year (2019).

During the cultivating period of 2018, the rainfall was high. The total actual rainfall from the sowing date to the end of August was 242.0 mm and half of this rainfall (118.0 mm) fell from June 10 to July 10. During those thirty days, the corn water needs were covered by the rainfall exclusively and there was no need for further irrigation even though the growth rate of the crop was high. On the other hand, in 2019, the total actual rainfall between the sowing date and the end of August was just 41.0 mm. Only 23 mm of rain fell during the irrigation period and the crop water needs were mainly covered by the irrigation treatments. The third year of the research (2020) was close to the second year (2019).

The maize was sown on Apr 17, 2018; Apr 22, 2019 and Apr 15, 2020 with a four-row seeder. The distance between the plants was 13 cm while the distance between the rows was 80 cm. The total surface of each plot was 40 $m^2$. The maize was harvested from Sept 10 to Sept 20 (728 growing degree days) each year. The nitrogen fertilisation covered the crop needs fully as described in the National Optimized Fertilization Code, i.e. 180 units of nitrogen per hectare. Two chemical applications, one before planting and the other after the emergence of the corn plants, were applied and weeding by hand weeding occurred when the maize was 40 cm high, just before the installation of the drip irrigation laterals, to control the weeds each year (Papanikolaou and Sakellariou-Makrantonaki 2019, 2020b).

The surface drip irrigation system was used to apply the irrigation dose. The distance between the emitters was 0.5 m and the distance between the irrigation lines was 1.60 m. The dripper flow rate was 4.0 $L \cdot h^{-1}$. The irrigation programme started on May 16, 2018; May 31, 2019 and May 15, 2020. Before the drip irrigation programme, two sprinkler irrigations were applied in 2018 and three sprinkler irrigations were applied in 2019 and 2020 in order to achieve the optimal germination rate. The irrigation intervals were set at 6 days, 2 days earlier compared to the maximum irrigation interval that was mentioned above in order that the irrigation dose did not to exceed the practical irrigation dose (Papanikolaou and Sakellariou-Makrantonaki 2019).

The irrigation dose was calculated following the available soil moisture method. This particular method calculates the amount of the irrigation dose so that the soil moisture will rise from its current level to the field capacity each time as proposed by Papanikolaou and Sakellariou-Makrantonaki (2012). According to this methodology, the irrigation dose had to be applied every time the soil moisture sensors recorded the soil moisture close to 30% *v*/*v*. The irrigation dose was calculated based on Equation (1):

$$IR = \frac{FC - SM_i}{100} \times RD \tag{1}$$

where: $IR$ – net irrigation dose (mm); $FC$ – field capacity (% *v*/*v*); $SM_i$ – soil moisture measured by the soil moisture sensor (% *v*/*v*) early in the morning of every sixth day after the former irrigation; $RD$ – effective root zone (sample measures showed that the mean value was near to 500 mm in depth).

Before each irrigation, the soil moisture values were recorded and the irrigation dose was calculated through Equation (1). The applied irrigation dose completely covered the total irrigation needs.

In this study, the simple $K_c$ was used, as the findings are going to be used in the daily irrigation practice to support farmers in their optimal irrigation scheduling.

Three different methods of calculating the plant growth rates of corn were applied. The growth stages of corn are listed in Table 1.

The first applied method to calculate the crop coefficients at the stage of the maximum and final growth was the water balance method and FAO Penman-Monteith reference evapotranspiration using the following Equation (2):

$$ET_c = P_e + IR + CR - DP - RO \pm SMD \tag{2}$$

where: $ET_c$ – daily crop evapotranspiration (mm); $P_e$ – effective precipitation (mm); $IR$ – irrigation depth that infiltrates the soil (mm); $CR$ – capillary rise from the deep water table (ignored); $DP$ – deep percolation (assumed to be 0); $RO$ – surface run off (assumed to be 0); $SMD$ – soil moisture difference between two consecutive days (mm).

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Table 1. Corn growing stages

| Years | Growth stages duration | | | |
|---|---|---|---|---|
| | initial | development | mid-season | end-season |
| 2018 | 17/4–9/5 | 10/5–24/6 | 25/6–8/8 | 9/8–23/8 |
| 2019 | 22/4–10/5 | 11/5–22/6 | 23/6–3/8 | 4/8–21/8 |
| 2020 | 14/4–4/5 | 5/5–17/6 | 18/6–30/7 | 31/7–17/8 |

It must be noted that the capillary rise drops to zero when the deep water table is at least 1 m below the bottom of the root zone and there is no contribution through the capillary rise from the groundwater into the root zone (Allan et al. 1998). Furthermore, under surface drip irrigation and the exact calculation of the crop water needs, the *RO* drops to zero and the *DP* also drops to zero as the soil moisture sensor showed (at a depth of 70 cm). The soil moisture content (volumetric) was measured in real time every hour from the beginning of the drip irrigation to its completion, with three capacitance soil moisture sensors at depths of 30, 50 and 70 cm. Daily precipitation values lower than 0.2 of the $ET_o$ were assumed to be zero as they evaporated directly from the soil (Allan et al. 1998). The crop coefficient per growth stage is calculated through Equation (3):

$$ET_c = K_c + ET_o \tag{3}$$

where: $ET_c$ – the crop evapotranspiration (mm·day$^{-1}$); $K_c$ – the crop coefficient per growth stage; $ET_o$ – the reference evapotranspiration (mm·day$^{-1}$). $ET_o$ was recorded from an agrometeorological station following the FAO Penman-Monteith Equation.

According to the second method, the crop coefficients in the maximum and final growth were calculated with the mathematical equations based on climatic data as described by Allan et al. (1998):

$$K_{c\,mid} = K_{c\,mid(Tab)} + \left[0.04 \times \left(u_2 - 2\right) - 0.004 \times \times \left(RH_{min} - 45\right)\right] \times \left(\frac{h}{3}\right)^{0.3} \tag{4}$$

$$K_{c\,end} = K_{c\,end(Tab)} + \left[0.04 \times \left(u_2 - 2\right) - 0.004 \times \times \left(RH_{min} - 45\right)\right] \times \left(\frac{h}{3}\right)^{0.3} \tag{5}$$

where: $K_{c\,mid(Tab)}$ – value for $K_{c\,mid}$ taken from the bibliography (Allan et al. 1998); $K_{c\,end(Tab)}$ – value for $K_{c\,end}$ taken from the bibliography (Allan et al. 1998); $u_2$ – mean value for the daily wind speed at 2 m height over the grass during the mid-season growth stage (m·s$^{-1}$), for 1 m·s$^{-1}$ ≤ $u_2$ ≤ 6 m·s$^{-1}$; $RH_{min}$ – mean value for the daily minimum relative humidity during the mid-season growth stage (%), for 20% ≤ $RH_{min}$ ≤ 80%; $h$ – mean plant height during the mid-season stage (m) for 0.1 m ≤ $h$ ≤ 10 m.

The initial $K_c$ was calculated through the graphical method (Allan et al. 1998). This method takes the average amount of rainfall or irrigation applied at this stage and the average value of the reference evapotranspiration for the same period into account. In the year 2018, in a period of 30 days, from sowing until 10% of the soil being covered by the leaf area of the plants, two irrigations of 20 mm each were applied with the total amount of water, while the total rainfall for this period was 19 mm and the average $ET_o$ was 3.3 mm·day$^{-1}$. For the same period in 2019, three irrigations were applied with a total rainfall of 20 mm each, while the total rainfall was only 9 mm and the average $ET_o$ was 2.8 mm·day$^{-1}$. In the year 2020, three irrigations were applied with the same amount of water as in the previous years, while the total rainfall was only 2 mm and the average $ET_o$ was 3.7 mm·day$^{-1}$.

According to the third method, the crop coefficients in the maximum and final growth were estimated with regression Equations where vegetation indices were used as independent variables.

In the present research the *NDVI*, *SAVI*, *RDVI* and a new index [difference infrared – green vegetation index (*DIGVI*)] were used.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad \text{(Tucker 1979)} \tag{6}$$

$$SAVI = \frac{\left(1 + 0.5\right) \times \left(NIR - RED\right)}{NIR + RED + 0.5} \quad \text{(Huete 1988)} \tag{7}$$

$$RDVI = \frac{NIR - RED}{\left(NIR + RED\right)^{0.5}} \quad \text{(Roujean and Breon 1995)} \tag{8}$$

The new vegetation index calculated through the following Equation (9):

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$$DIGVI = \frac{NIR - GRE}{NIR + GRE + RED} \tag{9}$$

where: $DIGVI$ – difference infrared vegetation index ($NIR$) – green vegetation index ($GRE$) has values between –1 to +1 and positive values for the crop in normal development; $RED$ – red vegetation index.

A Survey 3W compact single-sensor multispectral camera (RGN) (Mapir, USA) was used. This camera uses the near-infrared channel centred at 850 nm with an interval –20 to +20 nm, the red channel is centred at 660 nm with an interval –10 to +10 nm and the green channel is centred at 550 nm with an interval –10 to +10 nm (Mapir 2022). This camera was used with a cheap Hubsan H501S X4 drone (Hubsan, China) (Hubsan 2022).

According to the Index Database of vegetation indices, Equation (10) is not mentioned. Only the Norm $F$ equation is listed (Index DataBase 2021) as follows:

$$\text{Norm}(F) = \frac{(F)}{NIR + GRE + RED} \tag{10}$$

where: $F$ – $NIR$ or green or red band each time.

The statistical package of the Minitab (version 16 for Windows) was used in the analysis of the data. Specifically, a one-way ANOVA was used with a significance level $P$ < 0.05. The simple linear regression method was used to estimate the crop coefficients (Montgomery and Runger 2003). The dependent variable was the crop coefficient of the corn per the growth stage and the independent variables were the vegetation indices. The root mean square deviation (RMSD) and relative mean deviation (RMD) were used to evaluate the results as they are described in the following equations:

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - Y_i\right)^2}{n}} \tag{11}$$

$$\text{RMD} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|X_i - Y_i\right|}{\bar{X}}\,100 \tag{12}$$

where: $X_i$ – values of the $K_c$ that are found in the bibliography (Allan et al. 1998); $\bar{X}$ – mean value of all the $X_i$ values ($i$ = 1……$n$); $Y_i$ – values of the $K_c$ as was estimated by the vegetation indices ($VI$s).

For the evaluation of the estimation equations of the crop coefficients, the method of 'Leave-One-Out' cross validation was used (Cunha et al. 2010; Lindberg et al. 2013). This method is used to evaluate estimation equations when a subset of the data is used to generate these equations while the rest of the data are used as evaluation values. The evaluation is completed by applying Equations (11) and (12).

## RESULTS AND DISCUSSION

The first method applied in the calculation of the crop coefficient in corn was the soil water balance. Figure 3 shows the variation in the soil moisture

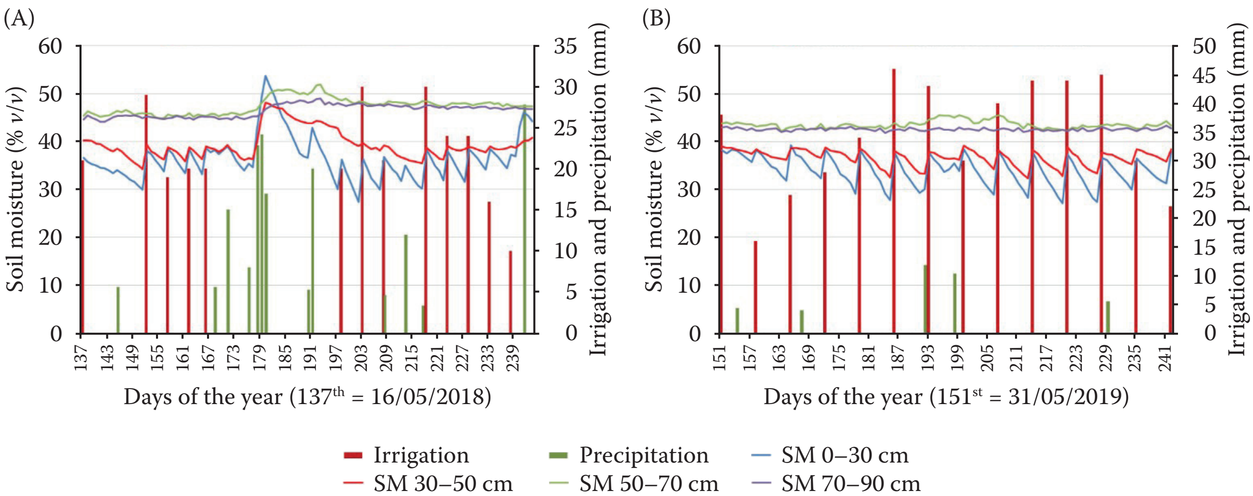


Figure 3. Soil moisture changes in volumetric percent (lines) in four different soil depths and the irrigation (brown bar) and precipitation events (green bars) during (A) 2018 and (B) 2019

SM – soil moisture

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at four different soil depths, 30, 50, 70 and 90 cm for two of the three years of the research (2018, 2019). The graph shows that there is no water loss due to the deep percolation since the soil moisture at a depth of 70 and 90 cm remains almost constant. The same figure shows the applied irrigation doses for the years 2018 and 2019 (2020 was close to the year 2019). The statistical analysis showed that the value of the initial $K_c$ = 0.35 differed significantly from the value of 0.30 proposed by Allan et al. (1998) for cereals. Regarding the crop coefficient at the maximum growth stage of the crop, the average value of $K_{c\,mid}$ = 1.174 was not statistically different compared to the value of $K_{c\,mid}$ = 1.150 proposed by the same researchers. Finally, the crop coefficient at the end of the growing season ($K_{c\,end}$ = 0.390) did not differ compared to the value 0.35 proposed by the above researchers.

The second method to calculate the crop coefficients was based on climatic data and the equations proposed by Allan et al. (1998). The crop coefficient values for the years 2018, 2019 and 2020 per growth stage of the corn were calculated by Equations (4) and (5). The statistical analysis showed that the three-year mean value of the maximum crop coefficient ($K_{c\,mid}$ = 1.157) was closer to the value proposed by Allan et al. (1998) ($K_{c\,mid}$ = 1.150) compared to the corresponding value ($K_{c\,mid}$ = 1.174) that was calculated through the soil water balance method. The crop coefficient values at the end of the growing period of the corn ($K_{c\,end}$ = 0.362) did not differ significantly from the value ($K_{c\,end}$ = 0.350) proposed by Allan et al. (1998), but the difference was significant compared to the corresponding value of the crop coefficient as calculated through the soil water balance method ($K_{c\,end}$ = 0.390).

The third method applied to calculate the crop coefficients of corn was based on the estimation regression equations where the vegetation indices were used as independent variables. The simple linear regression method was used, where the independent variables were four different vegetation indices and the crop coefficient was the dependent variable. The estimation equations of the crop coefficient for the whole vegetation period were calculated with the application of simple linear regression for each of the vegetation indices *NDVI*, *SAVI*, *RDVI* and *DIGVI*, which are given by Equations below:

$$K_c = 0.188 + 1.320 \times NDVI, \quad R^2 = 85.2 \tag{13}$$

$$K_c = -0.045 + 1.280 \times SAVI, \quad R^2 = 90.6 \tag{14}$$

$$K_c = -0.019 + 0.496 \times RDVI, \quad R^2 = 87.5 \tag{15}$$

$$K_c = 0.281 + 1.070 \times DIGVI, \quad R^2 = 88.9 \tag{16}$$

Table 2 presents the average values of the crop coefficient for the years 2018, 2019 and 2020 per growth stage of the corn as calculated by the Equations (13–16).

Table 2. Corn coefficients ($K_c$) values per growth stage during the three-year research study using vegetation indices

| Growth stage | $K_c$ values per year and *VI* | | | | $K_c$ values from the tables* |
|---|---|---|---|---|---|
| | *NDVI* | *SAVI* | *RDVI* | *DIGVI* | |
| **2018** | | | | | |
| Initial | 0.313 | 0.329 | 0.385 | 0.359 | 0.300 |
| Mid-season | 1.120 | 1.108 | 1.081 | 1.119 | 1.150 |
| End-season | 0.651 | 0.617 | 0.609 | 0.989 | 0.350 |
| **2019** | | | | | |
| Initial | 0.359 | 0.366 | 0.398 | 0.374 | 0.300 |
| Mid-season | 1.166 | 1.115 | 1.090 | 1.142 | 1.150 |
| End-season | 0.676 | 0.592 | 0.594 | 0.978 | 0.350 |
| **2020** | | | | | |
| Initial | 0.384 | 0.399 | 0.398 | 0.378 | 0.300 |
| Mid-season | 1.151 | 1.137 | 1.103 | 1.159 | 1.150 |
| End-season | 0.668 | 0.592 | 0.627 | 1.008 | 0.350 |

*according to Allan et al. (1998); *VI* – vegetation index; *NDVI* – normalised difference vegetation index; *SAVI* – soil-adjusted vegetation index; *RDVI* – renormalised difference vegetation index; *DIGVI* – difference infrared – green vegetation index

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The statistical analysis of the data showed that the value of the initial $K_c$ differed significantly from the value of 0.30 proposed by Allan et al. (1998) for cereals. The mean value of the maximum crop coefficient ($K_{c\,mid}$ = 1.087) had a statistically significant difference compared to the value ($K_{c\,mid}$ = 1.150) proposed by Allan et al. (1998) and compared with the corresponding value calculated with the application of the other two methods. The crop coefficient at the end of the growing ($K_{c\,end}$ = 0.631) differed significantly from the value ($K_{c\,end}$ = 0.350) proposed by Allan et al. (1998) and in comparison with the corresponding value calculated with the application of the other two methods.

Generally, there were differences between the methods in regards to the crop coefficients. At the initial stage, the crop coefficient was calculated following the graphical method proposed by Allan et al. (1998) and the vegetation index one. The $K_c$ at the initial stage (beginning of the growing) of the crop ($K_{c\,ini}$) values obtained from the *RDVI* and *DIGVI* vegetation indices were higher than those of the $K_{c\,ini}$ based on the other methods and the difference was statistically significant. The lower $K_{c\,ini}$ value that was proposed by Allan et al. (1998) in the tables of the FAO 56 manual was significantly different when compared with the $K_{c\,ini}$ calculated using the graphical method.

At the stage of full crop growth, the statistical analysis showed that there were differences between the three methods of the crop coefficient calculation. In particular, the crop coefficients calculated from the soil water balance gave significantly higher values when compared with the other methods. By contrast, the $K_{c\,mid}$ values estimated with the *RDVI* were the lowest with a statistically significant difference from the other methods. Table 3 shows the average values of the $K_c$ for the three years of the research (2018–2020).

At the end of the growth period of the corn, the statistical analysis showed that the crop coefficient values were different between the three methods of calculation. In particular, the $K_{c\,end}$ values according to the soil water balance method, mathematical Equation (1) and those proposed by Allan et al. (1998) show in the tables of the FAO 56 manual are almost the same without any statistical difference between them. According to these methods, the $K_{c\,end}$ values were statistically lower than the $K_{c\,end}$ values estimated from the vegetation indices. The $K_{c\,end}$ values estimated from the *NDVI*, *SAVI* and *RDVI* did not differ from each other, too, but differed statistically significantly from the $K_{c\,end}$ value estimated from the *DIGVI*, which gave the maximum $K_{c\,end}$ value of all the vegetation indices.

Table 4 shows the different statistical indices that were used to evaluate the estimation equations for the crop coefficients when the vegetation indices *NDVI*, *SAVI*, *RDVI* and *DIGVI* were used as the independent variables. In the case of *NDVI*, the table shows that the RMSD for the estimation of $K_c$ has a value of 0.115 which is the highest among the vegetation indices while the regression coefficient ($b$ = 1.320) is the highest among the coefficients of the other vegetation indices. The values of RMSD and $b$ indicate that when *NDVI* is used as independent variable, it estimates the $K_c$ value with high accuracy. It is noteworthy that the statistical evaluation shows that of the four vegetation indices, *DIGVI* seems to be the best predictor variable in the $K_c$ estimation for corn throughout the whole germination period.

To further discuss the above results, the average initial crop coefficient value of the corn for the three years of the research was $K_{c\,ini}$ = 0.350. This value was close to the value proposed by Allan et al. (1998), but the difference was statistically significant. Piccinni et al. (2009) found similar $K_{c\,ini}$ values for corn. In Greek climatic conditions, Papazafeiriou (1999) calculated similar crop coefficient values ($K_{c\,ini}$ = 0.40) for the Modified Penman method of reference evapotranspiration calculation,

Table 3. Corn coefficients ($K_c$) mean values per growth stage and method of calculation during the 3-year research study

| Growth stage | Mean $K_c$ values per method | | | | | | $K_c$ values from the tables* |
|---|---|---|---|---|---|---|---|
| | water balance | FAO Eq. | *NDVI* | *DIGVI* | *SAVI* | *RDVI* | |
| Initial | $0.353^{ab}$ | $0.353^{ab}$ | $0.313^{ab}$ | $0.359^{a}$ | $0.329^{ab}$ | $0.385^{a}$ | $0.300^{b}$ |
| Mid-season | $1.174^{a}$ | $1.157^{ab}$ | $1.120^{ab}$ | $1.119^{ab}$ | $1.108^{bc}$ | $1.081^{c}$ | $1.150^{ab}$ |
| End-season | $0.390^{a}$ | $0.362^{a}$ | $0.651^{b}$ | $0.989^{c}$ | $0.617^{b}$ | $0.609^{b}$ | $0.350^{a}$ |

$^{a,b,c,d}$ means followed by the letter are significantly different at $P < 0.05$; *according to Allan et al. (1998); *NDVI* – normalised difference vegetation index; *SAVI* – soil-adjusted vegetation index; *RDVI* – renormalised difference vegetation index; *DIGVI* – difference infrared – green vegetation index

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Table 4. Statistical indicators of the four equations that estimate the corn coefficients ($K_c$) values per growth stage ($n$ = 16)

| Vegetation indices | $b$ | $R^2$ | Estimation | | Cross validation | |
|---|---|---|---|---|---|---|
| | | | RMSD | RMD (%) | RMSD | RMD (%) |
| *NDVI* | 1.320 | 0.852 | 0.115 | 8.079 | 0.109 | 7.732 |
| *SAVI* | 1.280 | 0.906 | 0.092 | 8.432 | 0.022 | 7.788 |
| *RDVI* | 0.496 | 0.875 | 0.106 | 10.034 | 0.101 | 9.388 |
| *DIGVI* | 1.070 | 0.889 | 0.099 | 6.783 | 0.095 | 6.283 |

*NDVI* – normalised difference vegetation index; *SAVI* – soil-adjusted vegetation index; *RDVI* – renormalised difference vegetation index; *DIGVI* – difference infrared – green vegetation index; $b$ – regression coeficient; $R^2$ – coefficient of determination; RMSD – root mean square deviation; RMD – relative mean deviation

while he proposed $K_{c\,ini}$ = 0.50 for the FAO Penman-Monteith one. During the full growth stage, the $K_{c\,mid}$ ranged between 1.000 and 1.220 and the average $K_c$ value for the three years of research reached 1.174. This value did not statistically differ from the value proposed by Allan et al. (1998) which was also observed by other researchers (Piccinni et al. 2009; Trout et al. 2018). However, Papazafeiriou (1999) proposed $K_{c\,mid}$ = 0.80 for the Penman method for the reference evapotranspiration calculation and $K_{c\,mid}$ = 1.05 for the FAO Penman-Monteith one. The $K_{c\,end}$ value ranged between 0.350 and 1.000. Piccinni et al. (2009) reported crop coefficient values in the final growth stage of corn growth close to 0.90. The high $K_{c\,end}$ value could be related to the number of irrigations required at this growth stage due to the climatic conditions of the study area (Central Greece). Papazafeiriou (1999) proposed $K_{c\,end}$ = 0.45 for the modified Penman method and $K_{c\,end}$ = 0.60 for the FAO Penman-Monteith, which is very close to the values of $K_{c\,end}$ taking *NDVI*, *SAVI* and *RDVI* into consideration having lower values only from the $K_{c\,end}$ of *DIGVI* ($K_{c\,end}$ = 0.989).

The mathematical calculation of the crop coefficients for the corn equations as proposed by Allan et al. (1998) were also used. The $K_{c\,ini}$ values were similar to those of the previous method. At the maximum growth stage, the average crop coefficient was calculated at 1.157 and the difference was neither significant in comparison with the $K_{c\,mid}$ value according to the soil water balance nor in comparison with the values proposed by Allan et al. (1998) in the FAO 56 tables. The maximum value of the crop coefficient at this stage was calculated at 1.222, which was very close to the value measured by Hou et al. (2014). The mean value for the fourth stage ($K_c$ = 0.362) was almost the same as proposed by other researchers (Liu and Pereira 2000; Allan et al. 1998).

Based on the correlation coefficient ($R^2$), the estimation equation for the $K_c$ values according to the simple linear regression estimated the $K_c$ values with high accuracy when vegetation indices were used as predictors. In particular, when *NDVI* is used, it is estimated that the regression coefficient has a value of $b$ = 1.320 (Table 4) and the difference from the corresponding value proposed by Toureiro et al. (2017) to estimate the simple crop coefficient is significant in their research, while it is quite close to the estimated value of the double crop coefficient. According to the analysis of Pôças et al. (2015), the value of the regression coefficient $b$ shows that Equation (13) overestimates the value of the crop coefficient. In the present study, it is also noted that when *NDVI* is used as predictor, then the correlation coefficient has a lower value than the $R^2$ value when *SAVI* is used as predictor of the crop coefficient, which agrees with the results mentioned by Pôças et al. (2015). Table 4 also shows that *SAVI* gives a fairly good estimate of the $K_c$ values for the growth period of corn, a result also reported by Pôças et al. (2015) and Zhang et al. (2019). This observation is also confirmed by the lower RMSD and RMD values when *NDVI* is used as an independent variable compared to the same values when *SAVI* is used.

Table 4 shows that *RDVI* also gives acceptable results in estimating the crop coefficient. However, despite the high correlation coefficient ($R^2$ = 0.875), the regression coefficient ($b$ = 0.469) shows that it underestimates the crop coefficient, in addition to which the value of RMSD (10.034) shows that, when this vegetation index is used, the estimation of the crop coefficient lags behind the equations where *NDVI* and *SAVI* indices are used. The case of *DIGVI* is interesting. According to Table 4, the regression coefficient b has a value of 1.070, the closest value to the unit, which shows that if full irrigation

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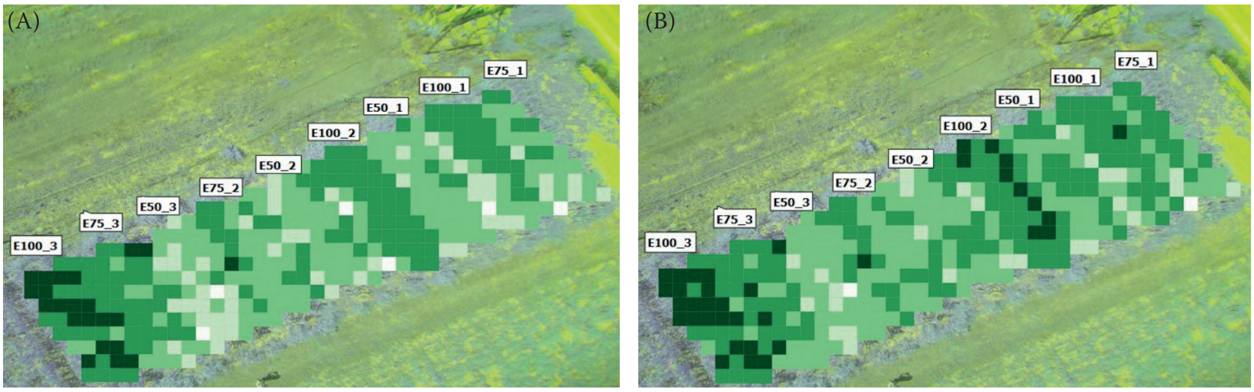


Figure 4. Differences in the vegetation growth of each plot and treatment (A) using the vegetation indices *NDVI*, *SAVI* and *RDVI* and (B) using the new vegetation index *DIGVI*

*NDVI* – normalised difference vegetation index; *SAVI* – soil-adjusted vegetation index; *RDVI* – renormalised difference vegetation index; *DIGVI* – difference infrared – green vegetation index

is used with the corn in the region of Central Greece, it gives a very good estimation of the $K_c$ values for the whole growth period. The correlation coefficient $R^2$ had the second highest value (0.889) among the $R$ values for the four used indices. RMSD also had the second lowest value (0.099) and RMD had the lowest value (6.783) among the used indices as well. These results are relevant to the results of the cross validation and, finally, *DIGVI* was the most crucial and accurate predictor for the corn crop coefficient among the other predictors.

The above analysis confirms that the vegetation indices can be used as independent variables to estimate the crop coefficients of corn during the whole growing period in the case of Central Greece. This is in agreement with the results of other studies (Pôças et al. 2015; Toureiro et al. 2017; Zhang et al. 2019). Figure 4 shows the differences in the corn growth as a result of the different irrigation dose according to the calculation of the different vegetation indices and the data from the multispectral photos and the drone. The left photo shows the differences when the indices, *NDVI*, *SAVI* and *RDVI*, were used while the right one shows the differences when *DIGVI* was used.

## CONCLUSION

Four vegetation indices, *NDVI*, *SAVI*, *RDVI* and *DIGVI*, were used as independent variables and the crop coefficient for each growth stage of corn as the dependent one in a regression analysis. All the equations gave estimations of the crop coefficient with high accuracy as the statistical criteria confirm. Of the four indices, the newly-proposed one (*DIGVI*) seems to be very promising as confirmed by the evaluation procedure, since the regression coefficient was closer to the value of one, compared to the regression coefficient of the other three indices. At the initial stage and at the stage of full development, the values of the crop coefficient that were estimated using the *DIGVI* method were very close to the corresponding values proposed by different researchers as well as those calculated using the other methods. An overestimation of the crop coefficient was calculated during the final stage of development and remains to be further investigated, but the average value of the crop coefficients for the whole growing season of corn, per vegetation index, seems to be close to the values proposed by other researchers in Greek climatic conditions. In the case of the $K_{c\,end}$ value, based on *DIGVI*, a weighting value equal to 0.65 is proposed to be used so that the final values can be close to those from the other vegetation indices. In conclusion, the multispectral index *DIGVI* is very promising for future use in agriculture as it seems to be more sensitive to different irrigation doses than the other three indices which were used in the present research.

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