Designated value for a field polygon based on imagery data: A case study of crop vigor in agricultural application for irrigation

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Abstract. *Any irrigation action for a field management zone, which is based on images, requires a transformation into single value. Since data distribution is ab-normal in an image, using a mean value to estimate the crop coefficient (Kc), an overlaid polygon may not represent properly its water demand. Therefore, this project's aim was to examine to which extent different statistics of potential designated values will affect an estimated Kc, and consequently affect irrigation practices.*

Satellite imageries of Landsat8 and Sentinel2a were used to produce images of vegetation indices (VIs), for cotton, almond, tomato and vineyard at six sites. Four statistical measures that can be used as a potential designated value for a field polygon, were calculated: median, mode, mean ± threshold and mean within full width half maximum of histogram peak (FWHM). Their calculated VIs values were compared, and differences were transformed into Kc values based on known models. A threshold value of less than 0.1 in Kc was determined empirically as none substantial difference.

Analysis results highlighted the preferable statistical approach to produce a single designated value, which reflects more adequately a specific field attribute, independent of sensor or crop phenological stages. Using the VI of EVI indicated no sustainable difference in all tested cases, comparing the mean ± standard deviations and FWHM.

Keywords. *Zonal statistics, image processing, Crop coefficient, GIS*

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Introduction

There are two types of quantified spatial information sources, which are commonly used in agricultural decision support systems (DSS): raster and vector. Since irrigation infrastructure is a vector type, with a specific control unit of water supply capacity, any irrigation action generates based on imagery the raster data, needs to be transformed into a single value. This can be done by a vast model, which transforms spectral information, extracted from hyper-multi spectral images into vegetation status, that is mainly related to vigor and coverage such as the normalized difference vegetation index (NDVI, Rouse et al., 1974) and the enhance vegetation index (EVI, Huete et al., 1997). This remote sensed information can be used as an alternative way to estimate the crop coefficient, which is a basic component in an irrigation protocol (Allen et al., 1998). However, no matter that spectral index (VI) is produced, when it is related to a specific zone, the spatial continues data is transformed into one single corresponding attribute value.

The platform of spatial analysis and associated modeling techniques, such as spatial DSS and the geographical information system (GIS) software packages, supplies common statistical measures, which were calculated for a unit area. Yet image data is distributed ab-normal which means that using the mean value as is, for a designated value of a polygon, could not properly represent the status of that field area section. This might lead to biased information, which was later on integrated in agronomical decisions and even resulted in crop damage. Therefore additional measures should be applied while considering agronomical knowledge.

One of the common techniques in image and signal processing is the usage of a histogram for detecting data features (Maravall & Patricio, 2003). It enables to detect the abundance of particular values within an image. Meaning, it captures field features such as high or low crop vigor as it is recorded by VIs image. In this study, image histograms of field plots were investigated along the season and their statistical measure of FWHM was used for comparison with the common statistical measures.

Materials and methods

Study area

Six sites of commercial crops in arid and semi-arid zones were used as a case study. It included cotton, processing tomato and almonds in Israel as well as cotton and vineyard in Australia (Table 1). All plots were irrigated in addition to precipitation (200-600 mm year total).

Table 1. Study areas and imageries

			# Imageries	
Site	**Location**	**Crop**	**Landsat8**	**Sentinel2**
Alonim	Israel, N	Cotton	4	5
Debroi	Australia, NW New South Wales	Cotton	2	2
Deganim	Israel, SW	Almond	2	4
Megido	Israel, N	Tomato	2	5
PNV	Australia, NW New South Wales	Vineyard	-	2
Yagur	Israel, N	Cotton	-	3

Data

Imageries of surface reflectance, which had been taken under clear sky conditions on various dates along the season, were chosen (10 of Landsat8 and 21 Sentinel2) and transformed into VIs images of indices EVI and NDVI (Eq. 1 and 2, respectively). Each field plot of the above-mentioned sites was clipped out from imagery, using an inner buffer of 15 m, to eliminate outlier values due to typical crop damage along the plot boundaries. Then histograms were produced and the statistical measures were calculated for both NDVI and EVI images of each field plot along the season.

Models of VIs

$$EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + 6 \times \rho_{Red} - 7.5 \times \rho_{Blue} + 1} \quad (1)$$

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (2)$$

Where ρ is the reflectance at each band of *NIR, Red*, and *Blue*.

Statistical measures

FWHM is a common technique, which expresses the extent of change in energy flow through a system adopted from signal processing. Figure 1 illustrates a histogram shape that may represent data distribution within an image of field plot including FWHM along with the other common statistical measures that were used in this study.

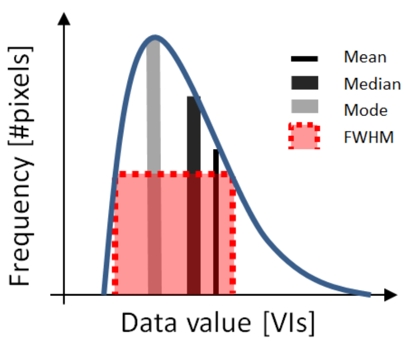

Figure 1. Histogram characteristics: unimodal frequency distribution with skewness to the left, and corresponding mean, median, mode and span of values indicated by FWHM (dashed line and shaded)

When the shape of the histogram is a-symmetric, then there is a typical relation between the values of statistical measures. For left skewness *Mode* < *Median* < *Mean* whereas for right skewness *Mode* > *Median* > *Mean*. An additional measure, based on mean ± standard deviation (std), was calculated using a span of values, that were determined by mean - 1std up to mean +2std (not shown in Fig. 1). A mean value of the FWHM depends on the skewness of the shape of the histogram and will usually fall between the mode and median values. Being so, FWHM of the histogram peaks captured field features as it is recorded by VIs image, and all other measures were compared with it.

Evaluation of differences between the measures

The evaluation of the calculated differences between the statistical measures of the remote sensing information is meaningful, when it is related to a plant measure. In this study, important information will be the substantial difference in terms of Kc values since it affects the crop water demand. Empirically it was determined as 0.1 Kc and the equivalent threshold values for NDVI and EVI were calculated by using equations 3, 4 following Tasumi et al. (2006) and Nagler et al. (2013) respectively.

$$Kc = (1.1875 \times NDVI + 0.05) \tag{3}$$

Where *Kc* is estimated crop coefficient and *NDVI* is vegetation index.

$$Kc = 1.65 \times \left(1 - e^{(-2.25 \times EVI)}\right) - 0.169 \tag{4}$$

Where *Kc* is estimated crop coefficient and *EVI* is vegetation index.

Results

Histograms characteristics as indicator of phenology

Plotted histograms of all dates in all field crop sites, for both EVI and NDVI values, indicated the phenological stages as expected. In most of the tested cases, histogram shapes were transformed from left skewness through more symmetric into right skewness. In almond and vineyard this phenomena was generally similar. In these cases, the orchard sites, the histogram phenology also described late season, contrary to field crops were it usually ends just before harvest time. Figure 2 is an example of this typical change of shape of the phenological histograms.

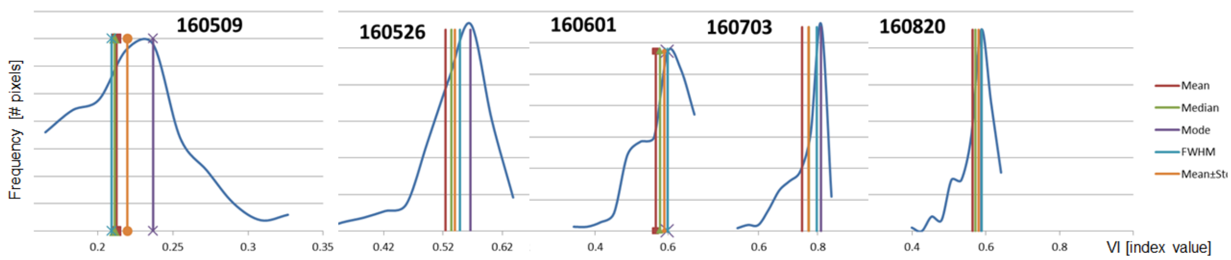

Figure 2. Phenological histograms - Time line of data distribution of EVI images, Alonim, Israel, 2016 in 5 dates [yymmdd]

Additionally to the change in the histogram shape, was a change in their location along the x-axis. Meaning, the VIs values were increasing through development up to maturity and reflecting higher values of Kc towards the season end (data is not shown). The decrease in VIs at the last stage (20-August-2016) occurred after the irrigation ended. This is a routine act as a part of preparation for the harvest.

Table 2 is an example of the statistical measures as overlaid figure 2 (vertical lines over the histograms). A comparison of these measures along the season resulted with a cluster of values around the FWHM towards the end of the middle stage and the beginning of canopy decline (Fig. 2, dates 160601, 160820). At this stage histogram shapes were tend to be more symmetric, leading to minimum differences between the measures by considering each date by itself.

Table 2. Value of the four statistical measures at the *end-middle* stage and their differences using FWHM as base for comparison. I. – Israel, A. – Australia

Crop, Site	Date	Source	Mean (std)	Median	Mode	Mean±std (std)	FWHM (std)	Differences 1	2	3	**4**
EVI											
Tomato, I.	160509	L8	0.275 (0.021)	0.278	0.293	0.281 (0.012)	0.284 (0.007)	0.009	0.006	0.009	0.003
Tomato, I.	160526	S2	0.519 (0.053)	0.525	0.529	0.537 (0.035)	0.543 (0.025)	0.024	0.018	0.014	0.006
Almond, I.	160625	S2	0.322 (0.024)	0.324	0.331	0.329 (0.016)	0.33 (0.014)	0.008	0.006	0.001	0.001
Almond, I.	160712	L8	0.361 (0.025)	0.364	0.377	0.37 (0.018)	0.374 (0.01)	0.013	0.010	0.003	0.004
Cotton, A.	170122	L8	0.59 (0.079)	0.593	0.617	0.607 (0.055)	0.609 (0.041)	0.019	0.016	0.008	0.002
Cotton, A.	170210	S2	0.726 (0.069)	0.737	0.75	0.745 (0.049)	0.759 (0.038)	0.033	0.022	0.009	0.014
NDVI											
Tomato, I.	160509	L8	0.344 (0.042)	0.346	0.362	0.353 (0.03)	0.342 (0.026)	0.002	0.004	0.020	0.011
Tomato, I.	160526	S2	0.758 (0.054)	0.772	0.797	0.778 (0.031)	0.799 (0.016)	0.041	0.027	0.002	0.021
Almond, I.	160625	S2	0.274 (0.075)	0.255	0.227	0.273 (0.056)	0.278 (0.035)	0.004	0.023	0.051	0.005
Almond, I.	160712	L8	0.294 (0.021)	0.295	0.304	0.299 (0.015)	0.301 (0.013)	0.007	0.006	0.003	0.002
Vineyard, A.	161020	S2	0.294 (0.021)	0.295	0.304	0.299 (0.015)	0.301 (0.013)	0.007	0.006	0.003	0.002
Cotton, A.	170122	L8	0.781 (0.073)	0.79	0.812	0.801 (0.043)	0.808 (0.033)	0.027	0.018	0.004	0.007
Cotton, A.	170210	S2	0.893 (0.095)	0.918	0.879	0.921 (0.050)	0.967 (0.017)	0.074	0.049	0.088	0.046

Evaluation of the measures

Table 3 summarizes the differences between the four statistical measures, mean, median, mode, mean±std, and the FWHM, for the NDVI and EVI images of all sites and crops. Results of comparison showed that generally, difference of mean > median > mode > mean±std comparing to FWHM (average values of 0.031, 0.019, 0.017 and 0.015 respectively, including both VIs and all dates). Differences of median, mode, and mean±std from FWHM, for NDVI and EVI, were respectively smaller than 0.04 and 0.08 (the equivalent threshold values of 0.1 Kc). In some cases, differences between mean and FWHM for NDVI images were ≥ 0.04. However, the smallest differences were found between the two measurers of mode, mean±std and FWHM for both VIs with clear advantage for mean±std.

Table 3. Average* difference between the common measures and FWHM. I. – Israel, A. - Australia

Name, Site	Crop	Source	Mean	Median	Mode	Mean±std
EVI						
Alonim, I.	Cotton	L8	0.028	0.016	0.014	0.013
Debroi, A.	Cotton	L8	0.026	0.019	0.009	0.008
Deganim, I.	Almond	S2	0.050	0.027	0.020	0.037
Megido, I.	Tomato	S2	0.041	0.021	0.010	0.020
Yagur, I.	Cotton	S2	0.040	0.024	0.018	0.018
NDVI						
Alonim, I.	Cotton	L8	0.029	0.013	0.015	0.013
Debroi, A.	Cotton	L8	0.051	0.036	0.033	0.027
Deganim, I.	Almond	S2	0.006	0.004	0.009	0.002
Megido, I.	Tomato	S2	0.028	0.011	0.020	0.016
PNV, A.	Vineyard	Sn	0.005	0.015	0.026	0.003
Yagur, I.	Cotton	S2	0.031	0.017	0.008	0.012

* Average was calculated for all stages excluding low values of early stage when no irrigation is applied

Discussion and conclusion

The analysis results indicated that the images of the histogram are ab-normal as expected. For both, NDVI and EVI data extracted from 10 m^2 and 30 m^2 resolutions of Sentinel and Landsat imageries, no substantial difference was found comparing the potential designated values, which were calculated using the mean±std and FWHM. Based on these findings, both calculated statistical measures incorporating selective span of values, can be used as a designated polygon value to relate a crop coefficient of a cultivated field. Considering an online application for mobile devices, employing mean±std is simpler.

The base for comparison was the measure of FWHM adopted from signal processing since it enables to detect the abundance of particular values within a signal, the VI image. The measure of skewness can be calculated and may be used as an indicator of phenological stages when histograms are unimodal. In this study, we used the inner buffer of 15 m for a polygon of an irrigation zone, resulted with a unimodal histogram in most of the cases. A bimodal histogram suggests two entities within the irrigation zone. When occurred at the beginning of the season they are negligible – then, VIs values lower than the threshold indicating substantial Kc values of the required irrigation. Yet when bimodal histogram occurs in later stages, its lower values peak may be used as indicator for a spot that needs to be taken special care of.

As the analysis result indicated, the statistical measures tend to be clustered around the FWHM of the polygon histogram when its shape is more of a symmetric nature. Therefore, using statistical measure based on threshold value of means±2std, will lead for overestimation in cases where data distribution is the type of a left skew histogram. Most of these cases occurred at the beginning of the season when VI values were much lower than the required irrigation indicating a substantial Kc value. Contrary to that is the case of data with a right skew histogram shape towards the end of the middle stage. Then using a statistical measure based on threshold value of means±2std will just overcome inherent errors within models, such as estimating Kc values using VIs from imagery. However, these results highlight the preferable statistical approach to produce a single designated value which reflects more adequately a specific field attribute, independent of sensors or crop phenological stages.

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