Detecting variability in plant water potential with multi-spectral satellite imagery

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Abstract. *Irrigation Intelligence is a practice of precise irrigation, with the goal of providing crops with the right amount of water, at the right time, for optimized yield. One of the ways to achieve that, on a global scale, is to utilize Landsat-8 and Sentinel-2 images, providing together frequent revisit cycles of less than a week, and an adequate resolution for detection of 1 ha plots. Yet, in order to benefit from these advantages, it is necessary to examine the information that can be extracted from both sensors to detect crop water potential. Our hypothesis is that these indices can be used successfully to depict significant changes in water quantity in commercial plots during the growth stage of the season, which may assist in monitoring crop water stress. Two data sets were used: published multi-spectral of full-stressed and non-stressed leaves, and satellite imagery with their corresponding leaf or stem water potential (LWP or SWP, respectively) of crop fields and orchards. Whenever possible, the leaf area index (LAI) as well as vegetation fractions were taken. Image processing includes the calibration to surface reflectance and calculation of known and new spectral vegetation indices (VIs). The ability of the tested VIs to capture water potential variability was developed in three steps: Firstly, the published dataset was used to present the sensitivity of each index to depict the differences between stress and non-stress at the leaf and canopy levels. These results not only show the magnitude of the relationships but also their direction (positive or negative). Secondly, we used our satellite imagery and field measurements datasets to report the statistical relationships among these spectral indices and the physical LWP or SWP over the growing season. The best index, which consistently depicts the differences, was employed in the third step, to map crop water potential in commercial plots. We tested these maps by measuring LWP or SWP in the extreme points (driest and wettest) and found significant differences among the points, although their canopy fraction or LAI were similar.*

Keywords. *Irrigation Intelligence, crop water potential, Landsat, Sentinel*

Introduction

Droughts, global warming and the increasing development of precision agriculture requires smart irrigation and to increase the ratio of yield to water. Huge research work was conducted to understand how to increase this ratio, the water use efficiency (WUE), and when is the best period during the growing season to apply water stress for higher yield quality and quantity. This method is generally called precision irrigation or irrigation intelligence and the common controllers are measurements of leaf water potential (LWP) or stem water potential (SWP). Examples for utilize these measurements to determine HOW MANY and WHEN can be found for cotton (Crimes et al., 1987), alfalfa (Sharratt et al., 1983), Citrus (Lurbe 2013) grapevines (Netzer et al., 2009), almonds (Goldhamer et al., 2006; Prunus and Eichi 2013), apples (Naor et al. 1995) and so on (McCutchan and Shackel 1992; Shackel et al. 1997). Furthermore, these measurements are highly correlated to the evapotranspiration (ET) and the vapor-pressure-deficit (VPD, Kopyt and Tsadok, 2015), which are important to determine the quantity (HOW MANY) and the timing (WHEN) of the irrigation.

To answer the WHERE question, remote sensing is utilized to map the plant water requirements via an application of Vis-NIR and thermal regions (Moran et al. 1994). This method, also known as the crop water stress index (CWSI, Jackson et al., 1981), can be used for a specific field or farm with a plant sensor (Kullberg et al., 2017), unmanned aerial systems or airplanes (Cohen et al. 2017). However, only Landsat can be used for a global coverage scale, with a repetition of 16 days and 100-m pixels. These Landsat characters do not allow decision making on a weekly basis or for small plots, and require new methods that can be used for multi-spectral imagery. Further, to broaden the use of more than one satellite, and thus to eliminate the dependency in one system, the spectral indices should be validated with other sensors. Until now, several publications already presented the sensitivity of spectral indices to water stress as the normalized difference water index (NDWI, Hardisky et al., 1983), the normalized multi-band drought index (NMDI, Wang and Qu 2007), the ratio of the short-wave-infra-red (SWIR) to the blue band and the Tasseled-cap-Wetness (Phillips et al., 2006). Yet their sensitivity to the LWP or SWP should be explored.

In order to explore and define the utilities of satellite imagery for mapping LWP/SWP, we outlined three objectives: (1) to test the effect of water stress on published and new-introduced Vis-NIR spectral indices; (2) to correlate these indices from different satellite sensors to field crop LWP and orchards SWP; and (3) to assess the accuracy of the best index by crop measurements solely based on this index.

Methods

We conducted the research in commercial plots of alfalfa, cotton, vineyards, almonds and citrus (Table 1). The research sites were in Israel and in New South Wales, Australia. We located each site in the center of Landsat-8 pixel and at least 60 meters from the border of the plot, to insure to eliminate border effects. We conducted the crop measurements at the same day, or one day after the satellite overpassed. At each time, we confirmed that the irrigation was not operated a couple of hours before the measurements took place as well as between the times of the measurement and the overpassing of the satellite.

We performed the crop water potential measurements around the time of solar zenith. In orchards the leaves were warped during the morning and were picked at least two hours after the time of solar zenith, while in field crop leaves were warped prior to clipping. After clipping the leaves, both, in orchards and field crops, we stored the leaves in dark cooling boxes and conducted the measurements within no more than 15 minutes. We utilized the pressure chamber model 655 (PMS Instrument Company, Albany, OR, USA) for the LWP and SWP measurements. In addition, we calculated vegetation fraction by a mobile application- Canopy Cover Free (https://apkpure.com/canopy-cover-free/com.heaslon.canopycover) and leaf-area-index (LAI) by SunScan model SS1 (Delta-T Devices, Cambridge England).

Table 1. Data collection sites, dates and sensors

Crop	Central point coordinates (Lat/Long)	Measurements date	Sites	Sensor
Almonds	32.8 / 35.5	7-Apr-2016	3	LS8
	32.8 / 35.5	16-Apr-2016	3	SN2
	32.8 / 35.5	16-May-2016	3	SN2
	32.8 / 35.5	26-May -2016	3	SN2
	31.6 / 34.6	26-June-2016	3	LS8
	31.6 / 34.6	26-June-2016	3	SN2
	32.8 / 35.5	25-Augr-2016	3	SN2
	31.6 / 34.6	14-Sep-2016	6	LS8
	-34.2 / 145.9	18-Oct-2016	9	LS8
	-34.2 / 145.9	2-Nov-2016	9	LS8
	32.8 / 35.5	10-Oct-2017	6	SN2
Citrus	32.5 / 34.9	9-March-2017	5	LS8
	32.5 / 34.9	12-April-2017	5	LS8
	32.4 / 34.9	9-May-2017	5	SN2
	31.4 / 34.6	21-May-2017	3	SN2
	32.4 / 34.9	4-June-2017	3	LS8
	31.4 / 34.6	20-July-2017	3	SN2
Vineyards	31.9 / 34.9	3-June-2016	3	SN2
	31.9 / 34.9	25-June-2016	3	SN2
	31.9 / 34.9	26-June-2016	3	LS8
	31.9 / 34.9	12-July-2016	3	LS8
	-34.1 / 146.1	18-Oct-2016	8	LS8
	-34.1 / 146.1	2-Nov-2016	8	LS8
	-34.1 / 146.1	21-Dec-2016	8	LS8
	-34.1 / 146.1	17-Feb-2017	8	SN2
Cotton	32.6 / 35.2	5-June-2016	4	SN2
	32.6 / 35.2	26-June-2016	3	LS8
	32.6 / 35.2	4-July-2016	5	LS7
	33.0 / 35.6	12-July-2016	3	LS8
	31.8 / 34.8	20-July-2016	5	LS8
	32.6 / 35.2	25-July-2016	4	SN2
	33.0 / 35.6	28-July-2016	3	LS8
	32.7 / 35.1	13-Aug-2016	4	LS8
	32.7 / 35.1	13-Aug-2016	4	SN2

	31.8 / 34.8	28-Aug -2016	4	LS7
	-34.3 / 145.8	10-Feb-2017	8	SN2
	32.6 / 35.3	30-July-2017	6	SN2
Alfalfa	32.5 / 34.9	11-May-2017	4	SN2
	32.5 / 35.5	20-June-2017	5	SN2
	32.5 / 35.6	13-July-2017	3	LS8
	32.5 / 35.5	1-Aug-2017	3	LS8
	32.5 / 35.6	10-Aug-2017	3	SN2
	32.5 / 34.9	16-Aug-2017	4	LS8
	32.5 / 34.9	7-Sep-2017	4	SN2
	32.5 / 35.5	22-Mar-2018	6	LS7

We downloaded the Landsat imagery Level 1 from the US geological Survey website (https://earthexplorer.usgs.gov/) and processed the images to top-of-atmosphere (TOA) reflectance and brightness temperature values for each pixel (https://landsat.usgs.gov/sites/default/files/documents/Landsat8DataUsersHandbook.pdf). The Sentinel-2 imagery were downloaded from the European Space Agency (https://scihub.copernicus.eu/dhus/#/home) with TOA reflectance values. We converted the TOA values to surface reflectance with an Empirical Line model, utilizing 12-15 sites with different land-covers. We collected the surface reflectance values for this model from the Landsat Collection Level -2 products. We calculated different vegetation indices (Table 2) and extracted these values from the pixels of the sites. In addition to the water stress and spectral indices described above, we also tested several indices that are known to be sensitive to crop vigor and mass, as the normalized differences vegetation index (NDVI, Rouseet al., 1974)), the enhanced vegetation index (EVI, Huete et al. 2002) the red-blue normalized index and the green-red normalized index (RBNI and GRNI respectively, Beeri et al., 2017). We introduced new indices (equations 9-12, Table 2) based on evaluation of spectra from well-watered and water-stressed plants, as will be described later.

The spectral data was paired to the corresponding crop measurements, and we calculated the correlation for each date and each image. We also performed an ANOVA test with post-hoc Tukey-HSD to check if sites in the same field differ significantly from each other.

Table 2. Spectral vegetation indices

Equation number	Index Name	Equation	Known sensitivity
1	NDVI	(B4 – B3)/(B4 + B3)	Vigor
2	EVI	2.5*(B4 – B3)/(B4 + 6*B3 – 7.5*B1 + 1)	Vigor
3	Tasseled Cap Wetness	(B1*0.14+B2*0.18+B3*0.33+B4*0.34-B5*0.62-B7*0.42)	Moisture
4	B7/B1	B7/B1	Moisture
5	NDWI	(B4 – B5) / (B4 + B5)	Moisture
6	NMDI	(B4 – (B5 - B6)) / (B4 + (B5 - B6))	Moisture
7	RBNI	(B3 – B1) / (B3 + B1)	Vigor
8	GRNI	(B2 – B3) / (B2 + B3)	Vigor
9	GBNI	(B2 – B1) / (B2 + B1)	
10	WSI1	(B5 + B6)/ B4	
11	WSI2	(B5 – B1) / B4	
12	WSI3	(B4 – (B5 + B6)) / (B4 + (B5 + B6))	

Bands central wavelength (nm): B1-495; B2-560; B3-665; B4-835; B5-1615; B6-2200

Results

The effect of leave and plant water stress as expressed in the sensor bands and the vegetation indices

To examine the effect of water stress on leave and plant spectra, we utilized dataset published by Hunt et al (Hunt et al., 1987), including Landsat bands spectra of 4 groups: full watered (non-stress) and very dry (water-stressed), both on leaf and plant levels. We calculated the above spectral indices based on this dataset and further calculated the relative difference between the non-stress and the water-stressed indices values as follows:

Relatively difference = (non-stress – water-stressed) / (non-stress)

These results show that vigor indices, as the NDVI, EVI and GRI had low sensitivity to the water stress, while the SWIR bands and their related indices had higher sensitivities with consistent results for both leaf and plant levels. Further, the new-introduced indices, WSI1-WSI3, reach the highest sensitivity values. These results confirmed our knowledge that vigor indices are not suitable to detect water stress while moisture indices have better sensitivity to this parameter.

Table 3. Spectra of leaves and plants, with and without water stress of *Agave deserti*. The values for the first rows, B1 to B6 are from Table 1 in Hunt et al, 1987. A relatively difference is calculated according to the equation 13 above

		Spectra				Relatively difference	
Index sensitivity	Index/band name	Non-stress leaf	Water-stressed leaf	Non-stress plant	Water-stressed plant	Water stress of leaf	Water stress of plant
	B1	0.343	0.356	0.045	0.068	-4%	-51%
	B2	0.493	0.483	0.069	0.083	2%	-20%
	B3	0.383	0.373	0.040	0.050	3%	-25%
	B4	0.859	0.850	0.388	0.372	1%	4%
	B5	0.262	0.371	0.042	0.085	-42%	-102%
	B6	0.116	0.167	0.018	0.037	-44%	-106%
Vigor	NDVI	0.383	0.390	0.813	0.763	-2%	6%
Vigor	EVI	0.751	0.841	0.674	0.693	-12%	-3%
Moisture	Wetness	0.344	0.249	0.130	0.099	28%	24%
Moisture	B7/B1	0.338	0.469	0.400	0.544	-39%	-36%
Moisture	NDWI	0.533	0.392	0.805	0.628	26%	22%
Moisture	NMDI	0.709	0.613	0.883	0.771	14%	13%
Vigor	RBI	0.055	0.023	-0.059	-0.153	58%	-159%
Vigor	GRI	0.126	0.129	0.266	0.248	-2%	7%
	GBI	0.179	0.151	0.211	0.099	16%	53%
	WSI1	0.440	0.633	0.155	0.328	-44%	-112%
	WSI2	-0.094	0.018	-0.008	0.046	119%	691%
	WSI3	0.389	0.225	0.732	0.506	42%	31%

Correlation analysis between the spectral indices and the field crop LWP and orchards SWP

We calculated the above indices from the satellite imagery and conducted correlation analyses on the crop water potential. The differences inside the crop plots are directly related to the successfulness of the imagery detection (Figure 1). When the water potential values in different sites are not differing from each other, the ability of the imagery to detect any spatial variability is very low. However, when there are differences in the crop LWP, the correlations to the imagery are higher. Another issue is that when clouds were observed near the crop measurement locations, the correlations were also low. This may be related to the effect of clouds on the imagery calibration accuracy, and these clouds may present low VPD, which also relates to low LWP or SWP. Both issues decrease the ability of imagery to detect spatial variability in the crop water potential.

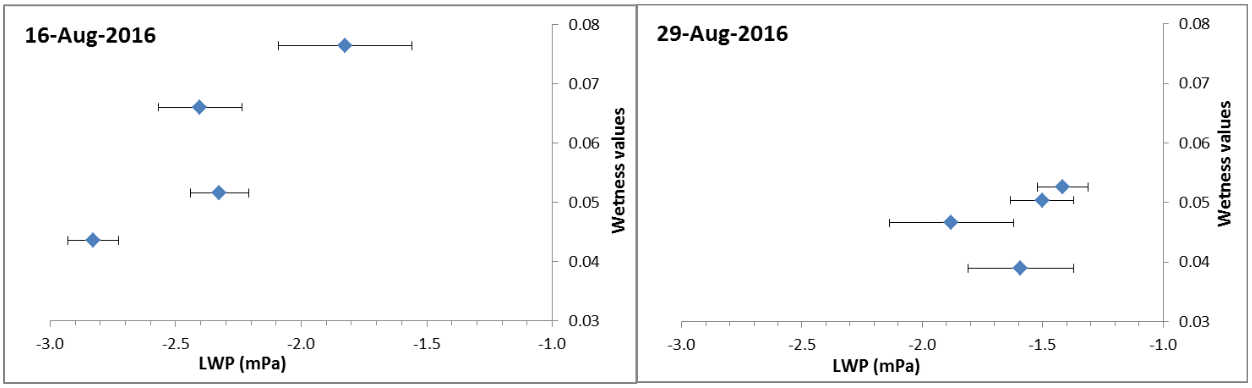

Figure 1. LWP average values (+STD) plotted against Wetness values in cotton fields

The correlation analyses (Table 4) show very low values in the vineyards, suggesting that more work needs to be done (for example pan-sharpening to eliminate the soil or cover crop signals), prior to utilize satellite imagery for this propose. The correlations for the other crops present the effectiveness of the Wetness, which detects the spatial variability in the crop water potential, together with the NDWI, WSI1 and WSI3. It is worth to notice that the highest value in cotton is a vigor index, which represents a strong control on the crop growth via the weekly irrigation amounts in micro irrigation applications.

Table 4. Correlation values between satellite imagery indices and LWP for alfalfa and cotton and SWP for vineyards, almonds and citrus. The bold numbers represent the highest value for each crop

	Alfalfa	Cotton	Vineyard	Almonds	Citrus
NDVI	0.66	0.69	-0.19	0.81	0.72
EVI	0.66	**0.77**	-0.14	0.47	0.62
Wetness	0.66	0.72	-0.27	**0.88**	**0.93**
B7/B1	-0.43	-0.13	0.19	-0.71	-0.76
NDWI	0.66	0.71	-0.34	0.84	0.88
NMDI	0.25	0.53	-0.21	0.25	-0.23
BRNI	0.59	0.52	-0.20	0.66	0.86
GRNI	0.67	0.51	**0.34**	0.22	0.36
GBNI	**0.69**	0.71	-0.12	0.82	0.81
WSI1	-0.68	-0.72	0.33	-0.86	-0.88
WSI2	-0.67	-0.59	0.29	-0.86	**-0.93**
WSI3	0.67	0.71	-0.33	0.86	0.88

<u>Accuracy assessment of the water stress indices</u>

These findings lead us to utilize the Wetness index as a proxy, and assess its accuracy by measure the crop water potential in the extreme points. We conducted this assessment in alfalfa, cotton and almonds.

The alfalfa assessment includes two plots, scanned by Landsat-7 at 21-March-2018. The

Wetness map (Figure 2) presents higher values in the western plot, therefore we placed 3 sites in each plot. The first site in each plot was in the driest place (41, 44), the second was in the most moisture pixel (42, 45) and the third was in a pixel with mid-range values. Another consideration to select the specific pixel in each place was the proximity of the NDVI values, to eliminate the effect of crop vigor and mass.

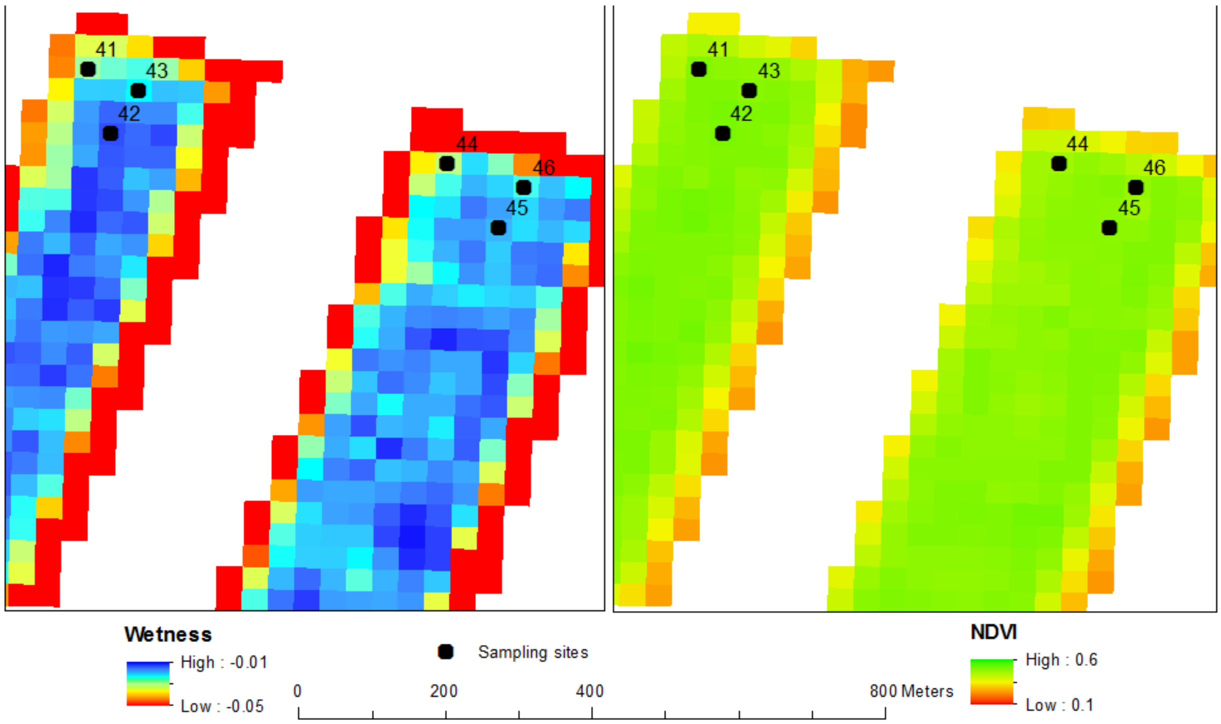

Figure 2. Landsat-7 Wetness and NDVI maps, 21-March-2018

The alfalfa measurements revealed significant differences in the LWP (*P* <0.05), but no differences in the vegetation fraction parameter. Further, as expected from Figure 2, the western alfalfa plot (sites 41-43) is wetter than the eastern plot (sites 44-46) while sites 42 and 45 are wetter than 41 and 44 respectively.

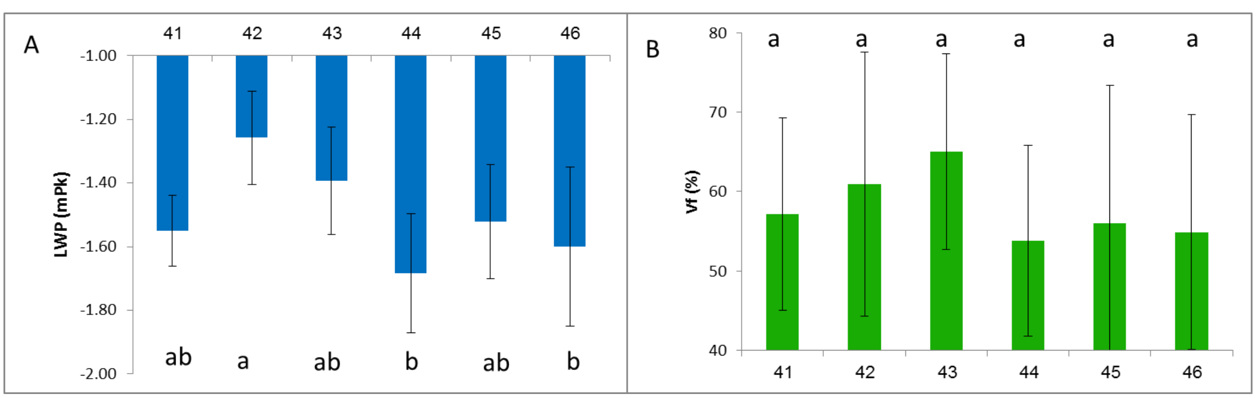

Figure 3. Alfalfa LWP and vegetation fraction average (+STD), 23-March-2018

The cotton assessment was based on a Sentinel-2 image (Figure 4). We selected two sites in a dry area (201,203), two in a wet (202,204) and two in a mid-range (205-206).

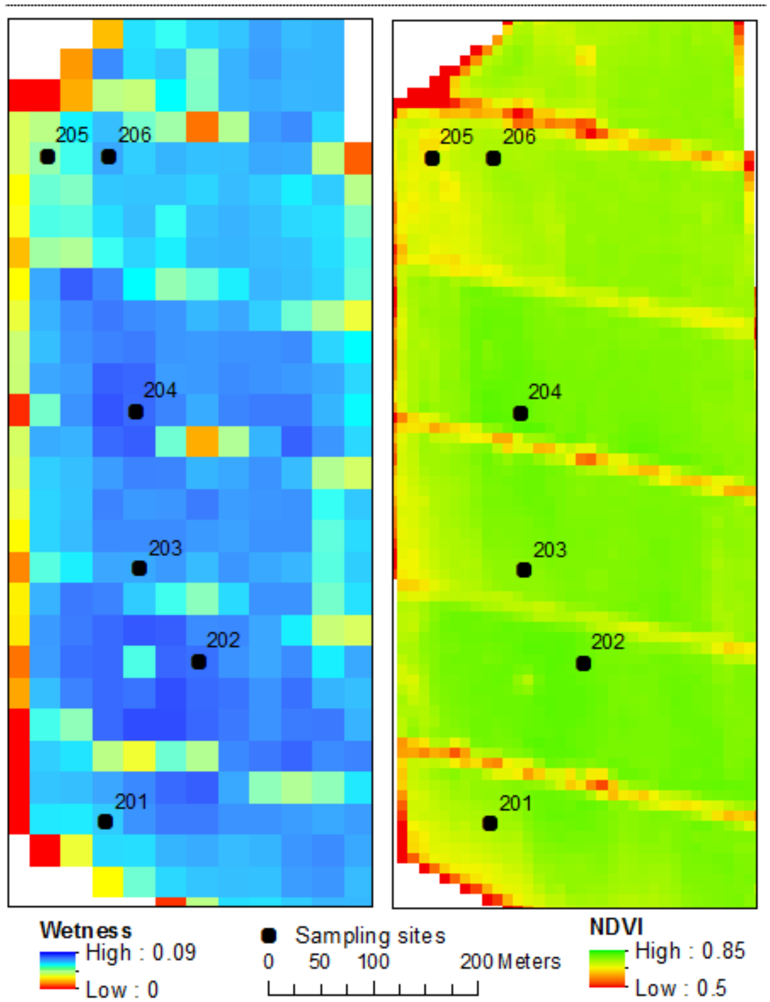

Figure 4. Sentinel-2 wetness and NDVI maps, 30-July-2017

The results confirmed this assumption (Figure 5), with significant differences in the LWP between the dry and the wet pixels (P <0.05). Furthermore, the LAI measurements, as proxy to vigor and mass, exhibit different patterns, especially in sites 203,205,206, with no difference in the LAI parameter, but with a significant difference between 203 to 205-206 in the LWP.

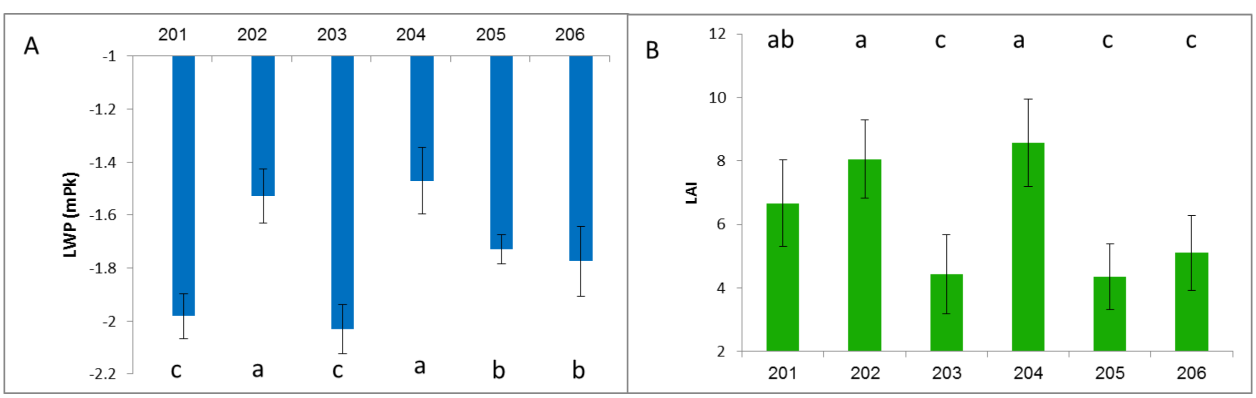

Figure 5. Cotton LWP and LAI measurements average (+STD), 31-July-2017. The small letters

represent a significant difference between the sites

The almonds assessment was based on a Sentinel-2 image and the resulted Wetness and NDVI maps (Figure 6). We choose 6 sites, 171-173 on the dry plots and 174-176 on the wet plots.

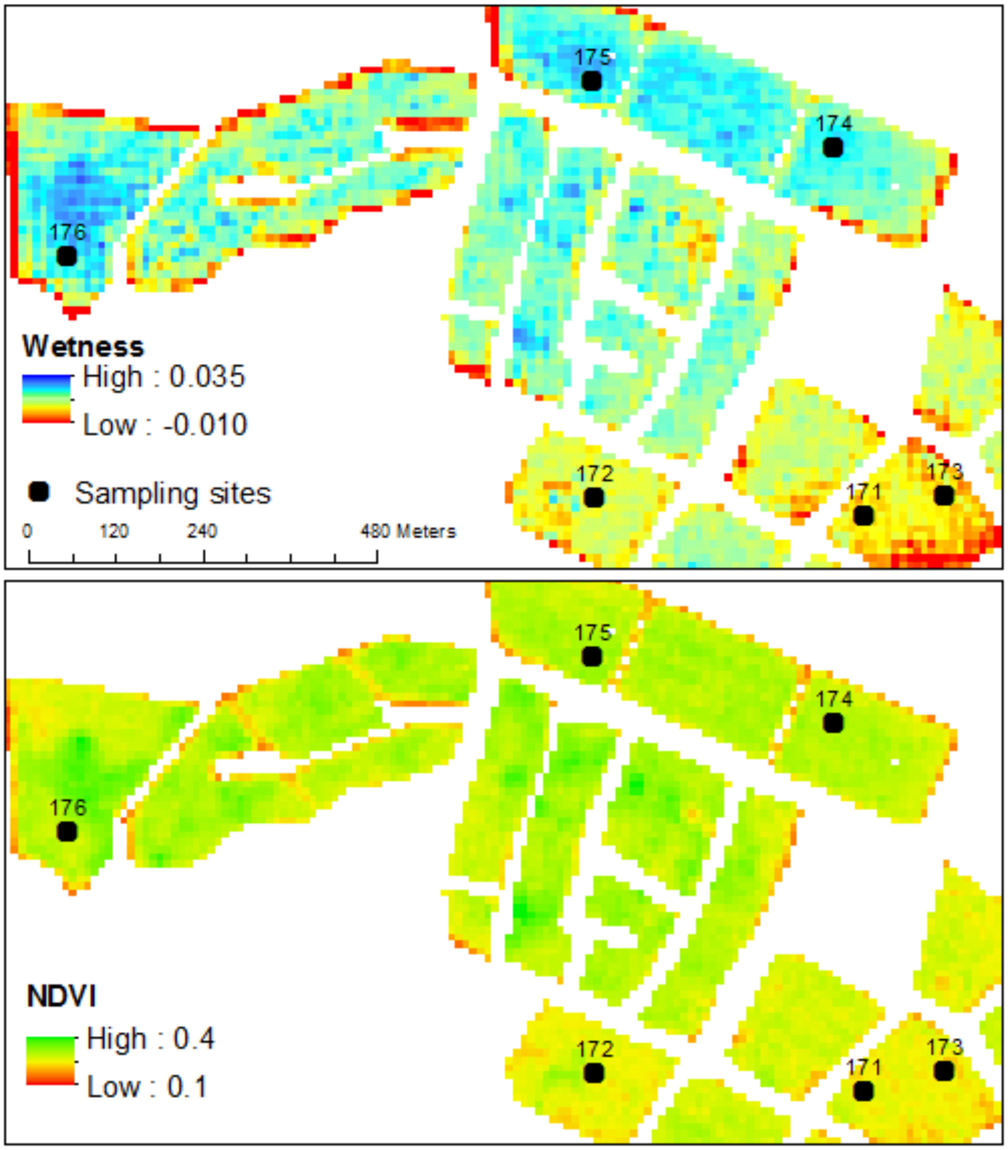

Figure 6. Sentinel-2 Wetness and NDVI maps, 10-Oct-2017

The LWP measurements confirmed our assumptions about huge differences among the wet and the dry plots (P <0.05). Yet, as the NDVI map is highly correlated to the Wetness map, the LAI measurements, with no significant differences between the plots, may also confirm the effect of the SWP on the NDVI values.

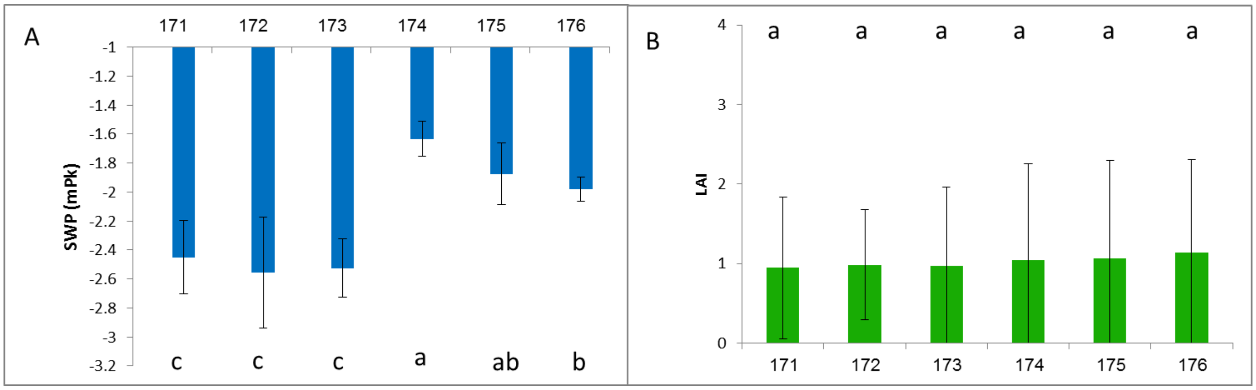

Figure 7. Almonds SWP and LAI average (+STD), 11-Oct-2017. The small letters represent a significant difference between the sites

Conclusions

Our results confirm the sensitivity of the Wetness and the water-stress-indices (based on the SWIR bands) to the spatial variability of LWP or SWP. More tests should be conducted on different crops and management protocols, but it can be concluded that Landsat-8 and Sentinel-2 can be used together or separately to map relative plant water quantity in commercial plots and help growers to optimize their irrigation water usage.

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