Proximal sensing and vegetation indices for site-specific evaluation on an irrigated crop tomato

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Abstract
The present paper deals with proximal sensing technique applied to a drip irrigated tomato field. The aim of this “on farm” research was the evaluation of three Vegetation indices, WI (Water index) WI/NDVI and TSAVI (Transformed Soil Adjusted Vegetation Index), to analyze the correlation among VIs and tomato yield, to assess the spatial variability of a tomato crop, and finally to identify homogeneous crop area.

Until 90 days after transplanting, tomato field was almost uniform, either at a visual assessment or according to spectroradiometric readings. At the end of the vegetative growth stage (from 90 days after transplanting), a spot crop area showed increasing soil moisture conditions due to soil topography. In this spot area, plants first yellowed and after started dying. Among indices, TSAVI appeared the most effective to detect excess soil water conditions, infect at 105 DAT TSAVI index was highly significant correlated to tomato yield, demonstrating to be a good index for early detecting excess crop water status. This study reinforce the possibility of detecting plant water stress by spectroradiometric measurements at field scale (ground-based measurements) and at territorial level.

Keywords: Tomato yield, vegetation indices, irrigation management, spatial variability.

Introduction
Precision agriculture is aimed to optimize the farm inputs such as fertilisers, herbicides, seed, and irrigation by doing the right thing, at the right place at the right time. Precision agriculture, using site-specific knowledge, can assist farmers and stakeholders in better management of their limited resources through new technologies [Bongiovanni and Lowenberg-Deboer, 2004].

Under conventional management fields receive uniform applications of fertilizers, irrigation, seed, etc., whereas a precision agriculture approach adopts a variable rate applications of inputs based on spatial variability (e.g. soil types, field slope and exposure, presence of water table) [Mulla, 2013]. Precision agriculture also increases crop productivity and farm profitability through improved management of farm inputs, leading to better environmental
quality [Larson and Robert, 1991; Mulla, et al., 1996; Mulla et al., 2002; Tian, 2002; Zhang et al., 2002; Mukherjee et al., 2010]. Among all the inputs, water (management, frequency, amount, spatial distribution) plays the most critical role in most crops, as in the case of tomato that needs irrigation throughout the growing season, since water stress may lead to significant reduction in crop yield [Obreza et al., 1996; Pulupol et al., 1996; May and Gonzalerz, 1999; Köksal, 2008; Patanè et al. 2011]. For this reason, quantitative and rapid methods for evaluating leaf water status are required for plant water stress management in tomato. Remote and proximal sensing techniques, in particular multispectral reflectance, can provide an instantaneous, non-destructive, and quantitative information about the agricultural crop conditions and crop spatial variability [Haboudane et al., 2004; Marino et al., 2013]. Proximal sensing and proximal remote sensing techniques (sensors mounted on tractors, spreaders, sprayers or irrigation booms) allow real time site specific management of fertilizers, pesticides or irrigation and provides ground-truth data to map cropped areas for Precision Agriculture [Mulla, 2013].

Numerous spectral vegetation indices (VIs) have been developed to characterize vegetation canopies using crop reflectance at different wavelengths from remote and proximal sensing data [Zhao et al., 2005; Clay et al. 2006; Li et al., 2007; Basso et al., 2011]. Vegetation indices are more sensitive than individual bands to vegetation parameters [Qi et al., 1994; Haboudane et al., 2004]. Changes in canopy water content also affect the canopy spectral response [Peñuelas et al., 1993]. Several indices using the near-infrared region have been proposed as water stress indices with varying results depending on the species [Carter, 1991; Peñuelas et al., 1996].

The changes in a reflectance trough at 950-970 nm corresponding to weak water absorption band are effective at plant and canopy levels. Peñuelas et al. [1993, 1996, 1997] showed that the ratio between the reflectance at a reference wavelength, 900 nm, and the reflectance at 970 nm (WI, water index) closely tracked changes in plant and canopy relative water content in several species.

WI/NDVI was also calculated in order to correct the WI for the effect of NDVI (due to usual relation between greenness and moisture of vegetation, NDVI and WI are usually related). Among VIs, TSAVI (Transformed Soil Vegetation Index) is an index widely used for the ability to minimize the contribution of soil reflectance to the canopy reflectance [Baret and Guyot, 1991] and is therefore used to predict sowing, emergence parameters, crop growth and yield variables and to compare the results for the whole range of crop situations [Guérif and Duke, 2000]. As reported by Qi [1994], Rondeaux et al. [1996], Huete [1988] the TSAVI in most cases performed better than the other soil-adjusted indices and hence is the only soil-adjusted index reported.

There are few works on the study of the effectiveness of vegetation indices on tomato crop [Gianquinto et al., 2011], and there is not studies on the effectiveness of VIs on over-irrigated in tomato field crop.

The present study aimed at filling the lack of information on tomato spectroradiometry. The experiment was carried out in 2011 to assess the spatial variability of a drip irrigated tomato crop using hyperspectral radiometric measurements, to analyze the correlation among VIs and tomato yield and to identify homogeneous areas for the tomato field management.

The other objective of this research performed ‘on farm’ is the evaluation of the capacities
and limits of three different VIs to early detect over-irrigation in a spot area due to soil topography as recorded in the previous year on the same field on an onion crop [Marino et al., 2013].

Material and methods

Study area

The experiment was carried out during the crop-growing season 2011 in Southern Italy on a plain dedicated to horticultural crops. The field had a rectangular shape with a total surface of 1.5 ha. The cultivar Perfectpeel (“Monsanto Agricoltura Italiana S.p.A.” trademark Seminis) of processing tomato was transplanted on the 16th of May in a twin row spacing of 180 cm, with a final plant density of 30,000 plants ha\(^{-1}\); 40 cm between rows and 30 cm plants on the row. Harvest was performed on the 12th September (120 day after transplanting, 120 DAT). The texture of the soil was clay, with medium organic matter and total N content, and C/N, and high CaCO\(_3\) %; soil was moderately alkaline. Soil physical and chemical properties are summarised in Table 1. All agronomic practices were based on locally managed schemes. Fertilization was performed using inorganic fertilizers: diammonium phosphate (18%, 300 kg ha\(^{-1}\)) on the 4th of April, Urea (46%, 100 kg ha\(^{-1}\)) on the 15th of June, Magnisal (with 11% of Nitrate and 9.6% of Mg, 50 kg ha\(^{-1}\)) on the 5th of July. The crop was fertirrigated four times with Bitter-Mag (Mg sulphate, 200 kg ha\(^{-1}\)), added with phosphate, sulphate, ammonium and calcium nitrate. Average decadal maximum and minimum temperatures, total rainfall and daily average standard crop evapotranspiration (ET\(_c\)) are reported in Table 2. agro-meteorological data were recorded through a standard agro-meteorological station by the Extension Service of the Molise Region (ARSIAM), in close proximity of the farm.

Table 1 - Selected physical and chemical soil properties (layer 0-50 cm) of the experimental site (mean of 24 samples). *Particle size distribution determined using pipette method [Indorante et al., 1990], *Organic matter using the Walkley and Black [1934] method, *Soil pH was determined in a 1:5 soil/water extract (mixture) [Sorensen, 1909], *Gasometric method [Dreleimanis, 1962] *Total nitrogen (N) was determined by the Kjeldahl method [Hesse, 1971].

| Properties          | Value |
|---------------------|-------|
| Sand\(^a\) (%)      | 30    |
| Silt\(^a\) (%)      | 24    |
| Clay\(^a\) (%)      | 46    |
| Organic matter\(^b\) (%) | 1.83 |
| pH\(^c\)            | 7.61  |
| CaCO\(_3\)\(^d\) (%) | 21   |
| C/N                 | 9.14  |
| Total N\(^e\) (g kg\(^{-1}\)) | 1.16 |
In the tomato crop season (May - September), the mean maximum day temperature was recorded in the first decade of July (40.5 °C) and the mean minimum night temperatures in the second decade of May (5.4 °C). Rainfall over the same period averaged about 203 mm, with high rain value in the third decade of July (94 mm). The ETc was calculated with Penman-Monteith equation [Allen et al., 1998]. The total seasonal ETc reached 590 mm, with two peak values in the second decade of July and the first decade in August. In between, a reduction of the crop ET was evident, due to abundant rainfall. The crop coefficients utilized were those obtained in a similar environment [Tarantino and Onofri, 1991], with values of 0.35 from transplant to establishment, and 0.55 in the early stages of blooming, 0.90 in blooming-setting, 1.1 in the phase of berry growth—veraison, and 0.95 from the beginning of ripening till the end of the cycle. A drip irrigation system was used for irrigation. The crop was watered using Aqua-TraXX PC emitters (0.64 l min⁻¹, TORO Ag), pressure compensating, (ISO 9260-9261) flow exponent X = 0.2, coefficient of variation ≤ 0.3% for all emitters, suitable for irrigation crops in difficult topographical conditions. Irrigation was applied following the evapotranspiration (ETc) method according to soil water balance (ETc=ET₀×Kc). The seasonal water volume was 2250 m³ha⁻¹.

**Measurements**

Georeferenced measurements were performed on a surface of 1.5 ha, according to a grid of 12 x 15 m. The total and marketable productions were recorded on 75 georeferenced data, and the dry mass of aboveground plant components (stems, leaves and fruits) was determined. Spectroradiometric readings and agronomic measurements were carried out at 45 DAT, 60 DAT and 105 DAT. A FieldSpec® Hand-Held Pro portable spectroradiometer (Analytical Spectral Device, Boudler, CO, USA) was used to measure the reflected light from the canopy. The spectral range of the radiometer ranged from 350 to 1100 nm, the sensor FOV was 25 ° and measurements were taken inside each plot, with a spectral sampling distance of < 1.5 nm. Spectral reflectance was measured at nadir in cloud-free days and converted to reflectance by referencing a 99% Spectralon (Labsphere Inc., North Sutton, NH, USA) panel at various times during each sample date.

To improve the quality of canopy spectra, a 10-point Savitzky-Golay filter was applied to the original spectra. The Savitzky-Golay [1964] filter is based on least squares polynomial fitting across a moving window within the data. After filtering, the VIs were calculated using the equation:

| Meteorological variable | May | Jun | Jul | Aug | Sept |
|-------------------------|-----|-----|-----|-----|------|
| Rainfall (mm)           | 47.2| 1.2 | 94.6| 1.4 | 58.2 |
| Maximum air temperature (°C) | 28.4| 40  | 40.5| 39  | 39   |
| Minimum air temperature (°C) | 5.4 | 11  | 13.5| 14.4| 5    |
| ETc (mm d⁻¹)            | 1.6 | 5.4 | 6.3 | 5.6 | 4.0  |

Table 2 - Average month rainfall (mm), maximum and minimum temperatures (°C), and daily average ETc (mm d⁻¹) on tomato field crop during crop season.
Because greenness and moisture of vegetation are usually related, NDVI and WI were negatively correlated. In order to remove from WI the effect of NDVI on the relationship between moisture content and WI, WI/NDVI (a composite index) was calculated.

WI/NDVI [Peñuelas et al., 1997]:

$$\text{WI} = \frac{R_{950}}{R_{900}}$$  \[1\]

TSAVI [Baret et al., 1989]:

$$\text{TSAVI} = A\left((\text{NIR} - AxR_{660} - B) / R_{660} + Ax(\text{NIR} - B) + 0.08x(1 + A^2)\right)$$  \[3\]

where A and B are the coefficients of the soil line (A=1.086588029, B=4.037537356), the subscripts ‘NIR’ and ‘R’ represent, respectively, the spectral reflectance in the near-infrared and the red bands.

**Geostatistical analysis**

Ordinary kriging (OK) is a commonly used linear method of spatial prediction to provide estimates of variables at unvisited sites. The procedure uses information from neighboring points to predict at a target point [4]; weights are assigned to these points based on their distance from the target. The equation for ordinary punctual kriging is:

$$Z^*_0(x_0) = \sum_{i=1}^{n} w_i z(x_i)$$  \[4\]

where $Z^*_0(x_0)$ is the OK estimate at an unsampled location ($x_0$), n is the number of samples in the search neighbourhood, $w_i$ are the weights assigned to the $i$th observation $z(x_i)$. Weights are assigned to each sample such that the estimation or kriging variance, $E = \left[\{Z^*_0(x_0) - Z(x_0)\}^2\right]$, is minimized and the estimates are unbiased [Webster and Oliver, 2007]. The weights depend on the relative positions of the samples in the neighbouring both to one another and to the target point, and on the variogram. The latter describes the spatial correlation and covariance structure between data points for each variable [5]. The variogram can be computed by Matheron’s [1965] usual method of moments as follows:

$$\hat{\gamma} = \sum_{i=1}^{m(h)} \left[\left(z_i(x) + h\right) - z(x_i)\right]^2$$  \[5\]
where $y$ is the semivariance between two observation points, $z(x_i)$ and $z(x_i + h)$, separated by a distance $h$, and $m(h)$ is the number of pairs at $h$.

The best variogram model for each parameter was selected based on cross validation. Cross validation was performed using mean error (ME), root mean square error (RMSE) and standardized mean square error (SMSE) [Delhomme, 1978; Merino et al., 2001] (Tab. 3).

The semivariogram was computed using GS+ version 8, while kriging was done using surfer version 9 (Golden software, Golden, Colorado, USA) according to Selvaraja et al. [2012], with $x$; $y$ representing the UTM coordinates (expressed in meters), and $z$ the parameter values.

| Model       | Nugged | Sill  | Range | residual |
|-------------|--------|-------|-------|----------|
|             | ME     | RMSE  | SMSE  |
| Yield       | spherical | 0.44 | 3.68  | 60   | 0.530586 | 0.000246 | 1.002559 |
| TSAVI (45 DAT) | Exponential | 0.001099 | 0.002737 | 28.79 | 0.00228 | 0.04778 | 1.070177 |
| TSAVI (60 DAT) | Spherical | 0.000168 | 0.000361 | 30   | 0.002314 | 0.015676 | 1.043742 |
| TSAVI (105 DAT) | Spherical | 0.00647 | 0.01744 | 33.2 | 0.014702 | 0.12125 | 1.014964 |

### Regression analysis
Regression analysis, coefficients of determination, significance levels and RMSE, were computed, on the 75 georeferenced data, using the statistical package Origin PRO 8 (Origin Lab Corporation, Northampton MA 01060 USA).

### Results and discussion
The study was a real representation of a tomato field, it was conducted on a drip irrigated tomato crop with a spot area exposed to over-irrigation and waterlogging problem starting from 90 DAT caused by a soil depression (maximum of about 20 cm depth), inducing an evident waterlogging starting from 100 DAT. Soon after leaves become yellowing and started dying, the result was a complete lack of marketable fruit harvested (120 DAT). The plants surrounding the spot area did not die even though they were stressed and they showed a reduction in biomass and yield. Nevertheless, the average yield of tomato field (9.45 kg m$^{-2}$) was comparable to the results of other experiments and the maximum yield value was higher than many works on the same tomato hybrid [Giorio et al., 2007; Riahi et al., 2009; ARSIA, 2010].

The figure 1 shows the field map of tomato yield; the highest productive areas were characterized by red and orange colours on the right side of the field, with a fruit yield of more than 10 kg m$^{-2}$; at the top centre and on the north left side of the field, yield value average was of about 8 kg m$^{-2}$. In a left area starting from about 50 m to 100 m (violet area) is visible the spot area with null yield and a surrounding area with yield from 4 kg m$^{-2}$ to 8 kg m$^{-2}$. The surrounding area showed a yield reduction confirming what was found by Sairam et al. [2008], and Karlen et al. [2008] on tomatoes subject to excess soil-water.
In order to find significant correlations between VIs and tomato yield, georeferred data of WI, WI/NDVI and TSAVI collected at different stages of plant growth (45, 60 and 105 DAT), were related to the same georeferred crop yield data (Fig. 2). The use of VIs based upon plant greenness for the evaluation of tomato crop yield and crop nutritional status has already been considered by Koller and Upadhyaya [2005] and successfully used by Gianquinto et al. [2011] for nitrogen plant status, no data were found on tomato water stress and in detail on over irrigation except for the work carried out by Mastrorilli et al. [2010] who identified NDVI as a new possibilities in planning irrigation scheduling on a territorial level. No relationships between tomato yield and WI, WI/NDVI, TSAVI were found in the first two sampling dates. At 45 DAT WI showed mean value of 1.06, with a small difference between minimum and maximum values (1 to 1.1), at 60 DAT WI ranging from 1.05 to 1.18 with a mean value of 1.12. WI/NDVI showed at 45 DAT a mean value of 1.36, ranging
from 1.24 to 1.61 at 60 DAT a mean value of 1.26 ranging from 1.21 to 1.33. TSAVI index showed at 45 DAT a mean value of 0.76 (from 0.62 to 0.87) and at 60 DAT a mean value of 0.89 (from 0.82 to 0.91).

At 45 and 60 DAT, the ground cover was 40% and 50% respectively, since the field was uniform, in this field it was no over irrigation. The sampling data at 105 DAT, fifteen days before the beginning of the increase in soil moisture and 5 days after the onset of the first symptoms on leaves, showed a significant correlation between yield and TSAVI, it was linear and highly significant ($R^2 = 0.74$). On the other hand, WI and WI/NDVI showed no significant relationship with tomato yield, with $R^2$ of 0.16 for WI and $R^2$ of 0.31 for WI/NDVI. The TSAVI value ranged from 0.35 to 0.84 (mean 0.72), the WI value from 0.99 to 1.25 (mean 1.13) and the WI/NDVI value from 1.28 to 1.96 (mean 1.51).

It is known that the sensitivity of VIs to biophysical parameters may change substantially with vegetation density, resulting in function of the biophysical parameters [Ji and Peters, 2007], therefore monitor crop status during the crop cycle was important to detect either healthy plants or stressed plants. In this study WI do not have a significant correlation with plant yield probably because is too small the reflectance differences among minimum and maximum value in all sampling dates according to different studies such as Riggs and Running [1991] and Römer et al. [2012] which confirmed the possibility to have values...
very close to each other. The water index divided by normalized difference vegetation index also showed no relationship with tomato yield, the $R^2$ was higher in WI/NDVI than WI because the NDVI is affected by structural and color changes (loss of pigments) in the overirrigated plants, and therefore it is indirectly related to the water concentration of living plants. WI normalized with NDVI were not significant indicators of plant water status in different studies, such as found by Mastrorilli et al. [2010] on three different species. On the contrary, TSAVI showed a significant relationship with yield; however, the TSAVI index reflected differences in phenological development, in growth (biomass) and in the soil. The amount of green biomass certainly determined the spectral response of the tomato surfaces in the red and near-IR wavelengths and, therefore the TSAVI values observed on tomato growing under different plant water content were different. The significant regression between the TSAVI and yield gave no information about the spatial yield variability and the ability of the TSAVI to identify areas with tomato yield loss.

The spatial assessment of TSAVI confirmed that was found by regression, the maps at 45 DAT and 60 DAT (Fig. 3a, b) were homogenous and do not highlight different management zones. The map of the TSAVI at 105 DAT (Fig. 3c) highlighted an area with lower values, namely the above said spot area characterized by excess soil moisture conditions that led plants to die starting from 105 DAT on. Furthermore, the spot area subjected to water stress was detected in the maps. The spatial assessment provided three different management zones with different plant status and tomato yield.

Figure 3 - TSAVI measured at 45 (a), 60 (b) e 105 (c) DAT, processed using geostatistical techniques (ordinary kriging).
Conclusions
The experiment was performed on one of the most cultivated tomato hybrid (Perfetpeel) all over the world to test the spectroradiometric measurements as an early warning tool to detect crop water stress caused by over irrigation. The yield results was comparable to standard of Perfectpeel hybrid in other favourable agronomic conditions. The field appeared uniform until thirty days before harvest, either with a visual assessment or spectroradiometric readings (WI, WI/NDVI, TSAVI).
At 105 DAT a significant high correlation between TSAVI and fruit yield was found, while no correlations among yield and other VIs were significant.
The TSAVI map at 105 DAT detected three different zones, a large well watered field area with the highest tomato yield values, a spot area subjected to soil saturated conditions (no yield at harvest) and a surrounding area with intermediate yield values from stressed plants.
Among three different vegetation indices, TSAVI was an accurate tool to estimate the tomato yield losses at field scale; furthermore it appears to be an effective tool to manage excess soil moisture conditions, when applicable (e.g. malfunctioning of irrigation system), and/or to identify different agronomic zones. Further studies will be necessary to confirm the ability of TSAVI to detect over irrigation at territorial scale and when plant stress occurring at vegetative crop stages.

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