**Title:**

LCIS DSS—AN IRRIGATION SUPPORTING SYSTEM FOR WATER USE EFFICIENCY IMPROVEMENT IN PRECISION AGRICULTURE: A MAIZE CASE STUDY

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**Abstract:**

The efficient use of water in agriculture is one of the most significant agricultural challenges that modern technologies are helping to cope with through Irrigation Advisory Services (IAS) and Decision Support Systems (DSS). These last are considered powerful management instruments able to help farmers achieve the best efficiency in irrigation water use and to increase their incomes through obtaining the highest possible crop yield. In this context, within the project "An advanced low cost system for farm irrigation support – LCIS" (a joint Italian-Israeli R&D project), a fully transferable DSS for irrigation support, based on three different methodologies representative of the state of the art in irrigation management tools (W-Tens, in situ soil sensor; IRRISAT®, remote sensing; W-Mod, simulation modelling of water balance in the soil-plant and atmosphere system), has been developed. These three LCIS-DSS tools have been evaluated, in terms of their ability to support the farmer in irrigation management, in a real applicative case study on maize grown on Andosols in a private farm in southern Italy in the 2018 season. The evaluation considered the predictive performance of the tools and also the pros and cons of their application, due their different spatial scale applicability, costs and complexity of use. The results have shown that all three approaches are able to realise the maximum obtainable maize production. However, the method based on in situ soil sensor (W-Tens) supplied 40% more water compared to the other two methods, whereas the IRRISAT® and W-Mod approaches represent the best solution in terms of irrigation water use efficiency (IWUE). Moreover, IRRISAT® has the advantage of being able to work without soil spatial information, although unlike W-Tens both the latter methods need a high level of user expertise and consequently support of external service providers. Integration between different tools represents an opportunity for improved water use efficiency in agriculture (e.g., field sensors and remote sensing).

**Keywords:** precision agriculture, DSS for irrigation, water use efficiency, maize

## 1. INTRODUCTION

United Nations and Food and Agriculture Organization of the United Nations (FAO), through the Sustainable Development Goal 2 (SDG2–Zero Hunger) and the Sustainable Crop Production Intensification (SCPI) Strategic Objective A of the FAO STRATEGIC FRAMEWORK 2010–2019 (FAO, 2009), have underlined the need for an increase in crop productivity and quality, based on scientific and sustainable practices able to improve resource use efficiency (water and nutrient), thereby also contributing to meeting the broader aims of food security, rural development and livelihood enhancement.

In this context, irrigated agriculture represents the bulk of the demand for water, being the first sector affected by water shortage, resulting in a decreased capacity to maintain per capita food production (Bonfante et. al., 2018). Therefore, the efficient use of water in agriculture is one of the most important agricultural challenges that modern technologies are helping to resolve (Navarro-Hellín et al., 2016).

To realise this purpose, we have also to consider the impact of climate change (CC) on the agricultural sector due to changing temperature and rainfall patterns. While temperature directly affects crop growth, influencing the duration of the growing season or establishment of the different phenological stages (e.g.. Cutforth et al., 2007; Hatfield et al., 2011; Southworth et al., 2000; Tingem et al., 2009), rainfall affects crop water availability and thereby crop yield production (Bonfante et al., 2015; Monaco et al., 2014).

Irrigation Advisory Services (IAS) as well as Decision Support Systems (DSS) designed for irrigation support are powerful management instruments to achieve the best efficiency in irrigation water use. The DSS for irrigation can help the farmer during the decision process, increasing incomes through optimisation of water use and guaranteeing the best expected crop production in a specific growing season. These systems often are conceptually oriented to simulate or predict the crop water demand, giving a set of options, rather than solutions for irrigation management (the decision is always in the farmer's hands). They are considered user friendly and able to function with minimum data input (lowering costs), and they minimise the need for professional consultancy.

Some irrigation DSS assist in the planning (Kuo et al., 2000) and operational phases (Nixon et al., 2001). Others are more general in application, as with SIMIS (Mateos et al., 2002), a DSS for irrigation scheme management adopted by the FAO.

Such systems, initially designed for desktop application, are now usually delivered via the web, as in the case of PlanteInfo (planteinfo.dk) launched in Denmark in 1996 (Jensen et al., 2000), WISE (Washington Irrigation Scheduling Expert) (Leib et al., 2001), IRRINET expert system developed by Rossi et al. (2004) and used in some regions of Italy (Mannini et al., 2013), IrriSAT (Australia), ISS-ITAP (Albacete, Spain), BEWARE (Crete, Greece), Anglia river Basin (UK), IRRISA (France), and IRRISAT® (Campania Region, Italy).

An important component for the successful application of a DSS is the graphical user interface, whose role is the communication between the system and the user (e.g., farmers), which is a key topic in the implementation of irrigation scheduling services.

The irrigation scheduling can be transferred to the user in various forms (e.g., irrigation turns or volumes) and with different delivery systems such as internet services or mobile phones (Belmonte et al., 1999; de Santa Olalla Sánchez, 1999).

DSS for irrigation management have been implemented combining various approaches in terms of spatial and temporal scale, data type and data collection techniques (in situ soil sensor or remote sensing) and level of modelling complexity.

Using variables related to climate is the most common approach to create crop water requirement models (Jensen et al., 1970; Smith and Raine, 2000; Zwart and Bastiaanssen, 2004). Root Zone Sensors (RZS) application is a widely used proximal sensing approach used to schedule irrigation (Pardossi et al., 2009; Zotarelli et al., 2009). Here, the farmer uses the data from the sensing point(s) in the root zone to determine the moment and duration of watering. Several devices (e.g., GP1, Delta-T Devices Ltd.) are commercially available to provide a 'start-and-stop' irrigation control based on two or more RZS buried in and underneath the root-zone. This set of sensors can monitor water movement into the deeper layers and minimise percolation losses.

Abrisqueta et al. (2015) and Valdés-Vela et al. (2015) incorporate the volumetric soil water content, manually collected with a neutron probe, along with agro-meteorological data. This information is then fed into a fuzzy logic system to estimate the stem water potential. Other approaches in the literature also make use of machine learning techniques—such as principal component analysis, unsupervised clustering, and artificial neural network—to estimate the irrigation requirements in crops (Navarro-Hellín et al., 2016).

Navarro et al. (2016) proposed an automated decision support system based on machine learning techniques to manage the irrigation on a certain crop field, taking into account both climatic and soil variables provided by weather stations and soil sensors. The authors emphasise the importance of soil sensor information, the use of which accomplished a 22% reduction in weekly error compared to using only weather information.

Remote sensing imagery from satellites, airplanes, UAVs or drones or similar systems has been recognized as an exceptional tool to produce spatial information for crop evapotranspiration (ET) assessment to be applied in standard procedures for estimating crop water requirements (e.g., the FAO-56 method, Allen et al., 1998). The ET estimation (e.g., big leaf area model and further development of the Penman-Monteith equation, Monteith and Unsworth, 1990; Shuttleworth, 1991) is used to calculate the net irrigation water requirements, which is the water that must be supplied by irrigation to satisfy evapotranspiration, leaching and miscellaneous water supply that is not provided by water stored in the soil and precipitation that enters the soil (Jensen et al., 1990).

The benefits of these methodologies with respect to most classical information sources (field measurements or general knowledge) are the possibility of covering large areas, enabling sampling at high spatial resolutions and zonation and/or integration over diverse areas (Calera et al., 2017).

Recently, Li et al. (2018) developed a web-based irrigation decision support system with limited inputs (WIDSSLI) based on the FAO-56 dual crop coefficient approach to simulate the soil water balance using an online weather forecast. The timing and quantity of irrigation was obtained by comparing the field water availability simulated by the system and the lower limit of the soil moisture for irrigation.

All the above approaches suffer from specific drawbacks. For example, irrigation models based only on climate parameters rely on an open loop structure. This means that the model is subject to stochastic events and it may not be able to correct the local perturbations that can occur when an unexpected weather phenomenon occurs (for instance irrigating the crop when it's already raining) (Dutta et al., 2014; Giusti and Marsili-Libelli, 2015). Machine learning techniques, unsupervised clustering and artificial neural networks do not specify the quantity of water needed (Dutta et al., 2014); they reduce the prediction to true or false, and/or they are based on open loop structures (Giusti and Marsili-Libelli, 2015; Jensen et al., 1970; Smith, 2000; Zwart and Bastiaanssen, 2004), only considering the weather information, and therefore are unable to correct deviations from their predictions.

To be really operable, the methods based on remote sensing approaches need high temporal and spatial resolution data capable of monitoring the crop biophysical parameters related to crop as well as field information for model calibration (e.g., Leaf Area Index – LAI, derived from satellite images). In recent decades, the increase in free and open access imagery (e.g., European Space Agency; 10-m imagery acquired by Sentinel-2), the number of commercial sensors at very high spatial resolution (e.g., of 1–5 m, WorldView2, PLEIADES, DMC, DEIMOS and Venµs) and the availability of low cost drones with multispectral cameras have contributed to making these approaches more widespread and operational.

The use of soil water status sensors is considered a key complement to modulating the water requirements of crops. Soil variables, such as soil water content or soil pressure head, are considered by many authors as a crucial part of scheduling tools for managing irrigation (Cardenas-Lailhacar and Dukes, 2010; Soulis et al., 2015). On the other hand, field sensors (soil and weather) need continuous and proper maintenance.

In this context, complex agro-hydrological simulation models of soil water balance could help to identify and schedule the best irrigation management for a specific crop (Coppola et al., 2019; Jiang et al., 2016; Marsal and Stöckle, 2012; Thorp et al., 2017), but to date their use is relegated to scientific applications rather than real and operational conditions. Indeed, while some meteorological variables are representative of a large area and can be easily measured by a single sensor for a vast land area, soil and plant variables are characterised by high spatial variability.

It follows that implementing appropriate management procedures is not always straightforward in practice, and each possible approach to irrigation support application presents pros and cons, due to different spatial scale applicability, costs and complexity of use.

Moreover, simulation models need high data input (e.g., soil spatial variability, soil morphology and hydraulic properties) as well as a high level of user expertise for proper application. They are seldom developed on a platform able to integrate automatic data acquisition with a user friendly graphical display (Wang et al., 2017).

It is clearly quite difficult to find a single approach able to cover all operational conditions (field dimension and soil spatial variability, farmer knowledge, farm infrastructure, etc.), and also the related costs for farmers, which might limit these systems' use.

The project “An advanced low cost system for farm irrigation support – LCIS” (a joint Italian-Israeli R&D project; “industrial track" funded by the Ministry of Foreign Affairs and International Cooperation General Directorate for Country Promotion - Italian Republic and Ministry of Science Technology and Space of the State of Israel), forms part of this scenario, with the development of a DSS for irrigation support based on the integration of the top tier knowledge of all scientific sectors related to agriculture systems' performance. The LCIS-DSS put together proximal, remote sensing and simulation modelling approaches in a unique and fully transferable system able to work at different spatial scales at specific spots on field, farm and district under different pedo-climatic conditions, and with different crop management under different water/nutrient resources availability.

The main idea is to use different approaches in order to create a flexible system dedicated to irrigation support, able to fit different field and operational conditions (soil spatial information, weather information, field data collection, etc.) and the farmer's willingness to invest in sustainable agricultural management (each approach is characterised by different operational cost). The system consists of three main tools for irrigation support, which are based on three different methodologies representative of the state of the art in irrigation management tools: W-Tens (in situ soil sensor), IRRISAT® (remote sensing) and W-Mod (simulation modelling).

Thus, the main objective of this paper is to report the results of the application of LCIS DSS tools in a real case study in maize and discuss their ability (pros and cons) to support the farmer in irrigation management.

# 2. MATERIALS AND METHODS

## 2.1. Methodology applied and DSS:

The LCIS web-DSS framework consists of three principal tools oriented to support decisions of end-users (farmer or stakeholder) in handling water and crop/soil stress (Fig. 1): W-Tens, IRRISAT® and W-Mod.

The system is implemented on a web-DSS platform designed to support users in irrigation management at field scale. The platform has a 3-tier structure, with the three components being: 1) the database, where the data from field sensors and remote sensing are stored and retrieved when required for data processing (e.g., daily climate data for the modelling application); 2) the server, that performs the data processing and controls the application functionalities; and 3) the graphical user interface, the component which displays the information coming from data processing and basically connects the users with the system.

The GUI architecture consists basically of three modules, each of which is designed to function as an interface with the three different LCIS irrigation tools, as reported below:

- ✓ **W-Tens:** the tool is based on a field tensiometer monitoring system consisting of a set of soil water status sensors (tensiometers are placed at different soil depths) communicating with a software/hardware system for data acquisition, recording and sending to LCIS DSS server. This system consists of an Arduino device (https://www.arduino.cc/), a power pack, a solar panel and a GSM module. The system collects the soil water pressure heads at different soil depths in the field, with a time-step of 10 minutes. This information is used by the DSS to advise the farmer when to start and stop each irrigation event during the cropping season. The irrigation is scheduled when the soil water pressure head, at a specific depth or at combinations of different soil depths, reaches a crop specific threshold (ht) (e.g., -600 cm for maize, absolute value), in accordance with *t* threshold values reported in Van Dam et al. (1997). A pre-alert threshold is fixed by the user based on the soil characteristics (e.g., at -150 cm less than the threshold (hp= -450 cm)). This rule was applied to allow time for the farmer to organise the water supply and to realise the irrigation event to avoid plant water stress (i.e., if the farmer was not able to realise the irrigation in one or two days after the system alert). During the irrigation event, the system shows the tensiometer behaviour in real time and advises the farmer when to stop the water supply. Normally, the irrigation is stopped when the field capacity is reached (- 330 cm), but the system allows for specific rules (e.g., consider two different tensiometer values at two different depths) and values of pressure head. Moreover, a pre-alert threshold can be applied to give time for the farmer to stop the irrigation and save water resources. Then the W-Tens tool determines the moment and duration of watering.
- ✓ **IRRISAT®:** It is a satellite-based irrigation advisory service developed in Italy and has been operational since 2007 in the Campania region (Southern Italy). Irrigation needs are estimated using high resolution data from Earth Observation satellites (EO) and an FAO methodology for the calculation of crop water requirements. Data are aggregated at various spatial scales

(from field or irrigation unit to district or river basin scale) and temporal scales (real time or historical series).

The methodology for the estimation of crop water requirements adopted in IRRISAT® is the so-called "one-step" approach of FAO-Paper 56 (Allen et al., 1998, D'Urso et al., 2013). The EO-direct approach for calculation of potential crop evapotranspiration ($ET_p$) is applied by using the crop albedo (α) and LAI derived from processing of Sentinel-2A/B data, assuming fixed values for the stomatal resistance (sr≈100 $sm^{-1}$) and crop height (hc=0.4 m), in the case of herbaceous crop. This approach exploits the consistent effort to estimate vegetation parameters (α, LAI) from EO in the VIS and NIR regions (Atzberger and Richter, 2012; Vuolo et al., 2015), allowing adaptation of the Penman–Monteith equation to be used directly with EO based LAI and α (D'Urso, 2010), which can be measured in the field, for providing an assessment of accuracy of the ET method and to derive the maximum irrigation water requirement (IWR) (Vanino et al., 2018). To do so the calculation of $ET_p$ requires standard meteorological data, LAI and surface α. The IWR is then calculated by considering the following simplified equation (Eq. 1):

$$IWR = ET_p - Pn \quad (1)$$

Runoff and percolation are negligible, considering the low amount of rainfall during the two growing seasons. Net precipitation (Pn) is calculated in the equation (Eq. 2) as a function of the actual rainfall (P), LAI and Fractional Cover (fc) by using the semi-empirical model of interception proposed by Braden (1985).

$$Pn=P-\alpha \cdot LAI(1-1/(1+(Fc \cdot P)/(\alpha \cdot LAI))) \quad (2)$$

where P is the actual rainfall in (mm $d^{-1}$), and α in (mm $d^{-1}$) is an empirical parameter representing the crop saturation per unit foliage area (~0.28 for most crops).

Maps of canopy development (LAI, α and fractional vegetation cover (Fc), used for the calculation of the Pn) have been derived from high-resolution multispectral satellite images, delivered in near real time (less than 12 hours) and processed by using in situ agro-meteorological variables (observed or modelled by Numerical Weather Prediction, i.e., COSMO-LEPS and BOLAM models).

- ✓ **W-Mod:** The W-Mod tool is based on the approaches reported in SWAP simulation model (Kroes et al., 2008) to solve the soil water balance. W-Mod is a physically based simulation model that assumes 1-D vertical flow processes and calculates the soil water flow through the Richards equation. It applied the soil water retention θ(h) and hydraulic conductivity K(θ) relationships proposed by Van Genuchten (1980). Unit gradient was set as the condition at the bottom boundary.

  The upper boundary conditions are described by the potential evapotranspiration $ET_p$, irrigation and daily precipitation. Then the potential evapotranspiration is partitioned into potential evaporation, $E_p$, and potential transpiration, $T_p$, according to the LAI evolution, following the approach of Ritchie (1972). W-Mod simulates water uptake and actual transpiration (Ta) according to the model proposed by Feddes et al. (1978). Crop growth was simulated by means of a simple crop model using, according to the development stage, the LAI and rooting depth measured in the experimental field and the water uptake parameters from the literature (Feddes et al., 1978). The LAI development was estimated with a minimal amount of input data by means of a simple thermal model, based on the underlying physiological and phenological processes that govern these properties in plants. The empirical model used for LAI development was the "Log Normal Model" (Su et al., 2015) based principally on GDD (Growing Degree Day), maximum LAI reached by the plant and the GDD corresponding to the maximum LAI. More details of the procedure are reported in Su et al. (2015). The data applied for the empirical model in the present case study were derived from experimental trials conducted on maize (same FAO class, same cycle length) in Campania region. During the cropping season the data collected in field on LAI and root development were used in a data assimilation procedure in order to improve the crop development description applied in the model and then the irrigation amount predictions.

The irrigation scheduling was realised using the ratio between actual and potential transpiration (Ta/Tp), which is fixed according to the type of crop and the farmer's requirement (e.g., the farmer can decide to irrigate in deficit). In the following case study on maize the value was fixed at 0.9.

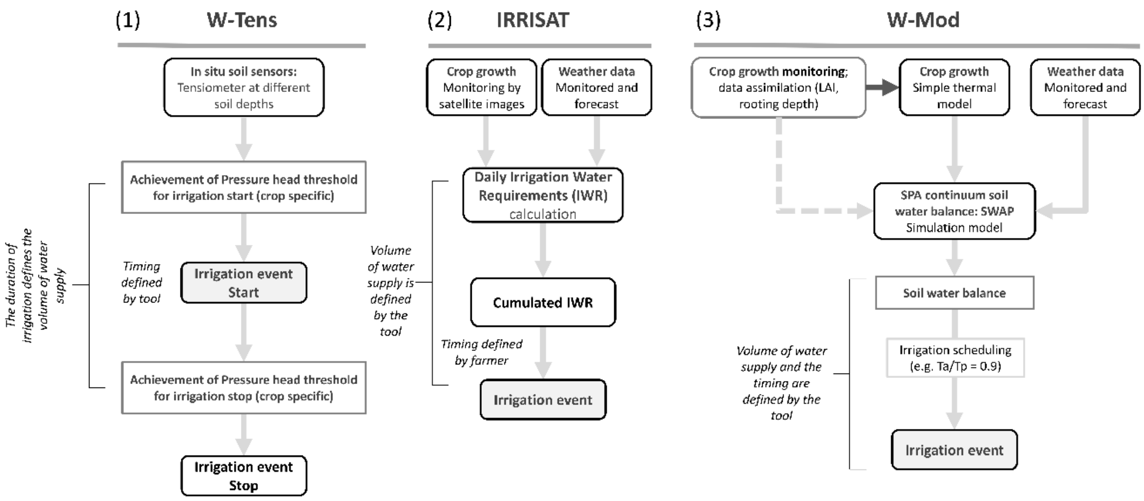


Fig. 1 LCIS DSS irrigation tools

## 2.2. Case study on Maize

The experimental site was located in southern Italy in the Campania Felix area at the "Arca 2010" experimental farm (Acerra – NA; 40°57.952' N, 14°25.808' E, 27 m a.s.l). The climate is typically Mediterranean (cold winters and hot summers), with an average monthly rainfall of 47.1 mm (±26), and mean air temperature of 19.7 °C (±4.3) during the maize growing season (from April to September, data from Servizio Metereologico Aereonatica Militare, period 1971-2000). The soils were developed on volcanic material, with a loam texture and high chemical and physical fertility.

**Field experiment:**

Silage maize (FAO class 700, P1921 Pioneer hybrid) was sown in mid-April of 2018 (0.75 m x 0.17 m) and harvested in early August under ordinary tillage practices (plough up to 0.4 m) and fertilisation (three treatments with urea 65 kg $ha^{-1}$ and two with ammonium sulphate 36 kg $ha^{-1}$).

The study was conducted in three plots: the first and second of about 1479 $m^2$ (≈22 m × 68 m) and the third of about 1224 $m^2$ (≈18 m × 68 m), in which the soil spatial variability was evaluated by a soil survey supported by a geophysical survey before the cropping season. A different irrigation management (timing and amount) was associated with each plot, based on the three different DSS tools: W-tens (P1), IRRISAT® (P2) and W-Mod (P3).

The irrigation was realised by means of surface drip irrigation, with emitters spaced 0.10 m apart on the drip lines and a nominal flow rate varying from 25-30 $m^3$ $h^{-1}$.

Each plot was equipped in accordance with the irrigation tool applied, in particular P1 (W-Tens) with tensiometers and P3 (W-Mod) with TDR probes (detailed information is reported in the following paragraphs).

During the experiments, the weather information was collected from the "Acerra" weather station of the Campania region meteorological network, located less than 100 m from the field experiment. Moreover, an additional weather station was placed in the experimental site (Watchdog 450 data logger, Spectrum technologies Inc., Plainfield, IL, U.S.A.). Daily reference evapotranspiration ($ET_0$) was estimated according to the equation of Hargreaves (Hargreaves and Samani, 1985). The daily weather information collected during 2018 was used as input in the W-Mod tool and IRRISAT®.

Moreover, for weather forecasting, data have been derived from the BOLAM model, produced at the CNR-ISAC Institute in Bologna. BOLAM is a limited-area hydrostatic model which integrates the primitive equations with a parameterisation of the atmospheric convection. At present, it is being run with a grid size of 0.075 degrees (8.3 km) in rotated geographical coordinates, with 60 atmospheric levels and 7 soil levels. BOLAM runs start at 00:00 UTC of each day with a 3-day forecast on the European-Mediterranean area.

**Crop and soil monitoring:**

Crop measurements were realised in all the plots during the cropping season on a weekly or biweekly basis.

The identification of crop sampling areas was realised with a new approach based on the analysis of unmanned aerial vehicle (UAV) multispectral images collected before the crop sampling. The procedure was based on normalised difference vegetation index (NDVI) spatial variability analysis inside each plot, and classification of the areas representative of crop behaviour over the whole plot. The crop samples were dissected (root, stem, leaves and ears) and fresh and dry weights were measured (fresh matter oven at 50 °C until constant weight was reached). At physiological maturity, maize biomass production was measured over the whole plot.

LAI was determined in field by means of LI-3100 AREA METER by LI-COR- INC., Lincoln, Nebraska (USA) and in lab on the plant sampled. Finally, the rooting depth was measured inside plot 3 where the W-Mod tool was applied.

Soil water status was monitored in two of the three plots (P1 and P3). In particular, in P1, where the W-Tens tool was applied, a tensiometers monitoring system was installed. The system consisted of four tensiometers (two tensiometers at -35 cm, one at -55 cm and one at -80 cm soil depth) connected to an Arduino system for real time monitoring. In P3 on the other hand, the soil water content (SWC) was measured by means of time domain reflectometry technique (TDR) (Tektronix, Model 1502 C, USA), applying TDR three-wire probes 15 cm long, placed at five different depths from 0 to -0.8 m soil depth (0-01 m - vertical; -0.30, -0.45, -0.65 and -0.8 m horizontal) with 2 replicates. The applied relationship between the water content and the dielectric constant was Topp’s formula (Topp et al., 1980).

**Soil pedological survey:**

A combined geophysical–pedological approach was used to study the soil spatial variability in the experimental field. This step is very relevant in order to avoid wrong conclusions being derived from comparison of the crop responses from different soil types (Bonfante et al., 2017). The soil survey (soil profiles, minipit and augering) was supported by non-invasive survey techniques such as geoelectrical soil mapping, which is considered a successful geophysical method that provides the spatial distribution of relevant agronomic information for precision farming (Lück et al., 2009). Methods based on electrical conductivity, which are strongly correlated to soil physical properties, which change in space, can represent spatial soil distribution. In this study the apparent soil electric conductivity (ECa) was obtained by electromagnetic induction (EMI) sensors, which are useful for identifying soil map units and soil properties related to clay content (Morari et al., 2009), soil depth (Saey et al., 2009), water content (Davies, 2004; Cousin et al., 2009; Lück et al., 2009; Tromp-van Meerveld and McDonnell, 2009)and water salinity (Doolittle et al., 2001).

The instrument used for surface mapping of the electrical conductivity was the EM38-DD (Geonics Ltd., Ontario, Canada) used in both vertical dipole mode (VDM) and horizontal dipole mode (HDM). The sensor was calibrated before the survey and maize cultivation in October 2017. The data were recorded on a GPS-equipped data logger with European geo-stationary Navigation Overlay Service and Wide Area Augmentation System correction (accuracy < 3 m), which made it possible to georeference and map the measured property.

Data post-processing was performed by means of ordinary kriging with 1m resolution. The final result of the EM38-DD survey was therefore a regular grid of data points, including ECa for two depths (1.6m for VDM and 0.76m for HDM). These horizontal (HDM) and vertical (VDM) ECa maps were used as baseline data for a pedological survey based on soil augering and soil profile descriptions.

Soil profiles were described according to IUSS (IUSS Working Group WRB, 2014). The soil texture was determined by a PARIO device (METER Group inc. USA) that automatically calculated the particle size distribution by Stokes' law. Undisturbed soil samples (volume 750 $cm^3$) were collected from each soil horizon and their hydraulic properties were determined in the laboratory to simulate the hydrological conditions of the soil by means of an agro-hydrological model. Soil samples were saturated from the bottom and the saturated hydraulic conductivity was measured by means of a permeameter (Reynolds et al., 2002; Wösten et al., 1999). After sealing the bottom surface to set a zero flux, measurements were taken during drying. At appropriate pre-set time intervals, the weight of the whole sample and the pressure head at three different depths were determined (the latter by means of tensiometers). An iterative procedure was applied for estimating the water retention curve from these measurements. The instantaneous profile method was used to determine the unsaturated hydraulic conductivity. Moreover, some points at a lower water content of the dry branch of the water retention curve were determined by a dew-point system (WP4 dew-point potentiometer, Decagon Devices Inc.). Details of the tests and overall calculation procedures have been described by Basile et al. (2012) and Bonfante et al. (2010).

**Data analysis and W-Mod model performance evaluation**

Statistical analyses of plot results were performed through the general linear model procedure of SAS/STAT. Duncan test at 0.05 probability level was used as mean separation test. All statistical analyses were carried out by using Graph Pad Prism v 6.01. Soil distribution map was drawn using Quantum GIS 2.18.15.

In the field experiment, the W-Mod model performance was evaluated by means of the agreement between measured and estimated values of soil water content (SWC), expressed by using the indexes proposed by Loague and Green (1991): the root mean squared error (RMSE, minimum and optimum=0), coefficient of residual mass (CRM, 0-1, optimum=0, if positive indicates model underestimation), modelling efficiency (EF, positive or negative values, 1 being the upper limit, while negative infinity is the theoretical lower bound; EF values lower than 0 result from a worse fit than the average of measurements) (Greenwood et al., 1985) and the parameters of the linear regression equation between observed and predicted values (Addiscott and Whitmore, 1987).

Finally, the irrigation DSS tool performance was evaluated by means of Irrigation Water Use Index (IWUI), which is the ratio between the yield and irrigation water supplied during the growing season. (Purcell, 1999; Skewes, 1997). It does not include rainfall, and therefore is only useful for comparing nearby fields or farms in the same season.

**Image processing**

In this study, n. 27 multispectral high-resolution images from Sentinel-2A and 2B were acquired. Sentinel is a mission of the European Space Agency, as part of the Copernicus program (http://www.copernicus.eu/ ) (Drusch et al., 2012). The multi spectral instrument on board Sentinel-2A/2B captures data at 10, 20 and 60 m of spatial resolution over 13 spectral bands (see supplemental material) with a very high temporal resolution of five days at the equator. Individual Sentinel-2 Level-1C granules (processed at Top-of-Atmosphere (ToA) reflectance) were acquired from Copernicus Open Access Hub (https://scihub.copernicus.eu/), ortho-rectified in UTM/WGS84 (image tiles of 100x100 $km^2$). The information recorded by the Sentinel-2 system (orbit, altitude, and viewing directions of all detectors) allows excellent accuracy for the geolocation of all Sentinel-2 pixels. The overall geolocation accuracy is around 11–12 meters, for about 97 % of the cases, which is about the size of one Sentinel-2 pixel. The standard need for multi-temporal registration errors is 0.3 pixels, and the current performance showed that in more than 50% of cases the performance does not meet that requirement.

By combining the Sentinel-2 satellite data with the weather data derived from the BOLAM model, maps of $ET_p$ and IWR forecasts were produced with a lead-time of up to 3 days.

# 3. RESULTS

## 3.1. Soil survey results and plot definition.

An EMI survey was conducted at the field experiment in order to support and guide the pedological survey (in terms of soil variability). The ECa maps (VDM and HDM configuration; Fig. 2) showed a low range of variation (from 13 to 21 mS $m^{-1}$). The presence of a hot spot in the lower part of the field was immediately recognised, in the maps. This outlier was due to the presence of a small, buried well. Therefore, by removing this outlier from the map, the field variability was reduced even more. Then, four soil profiles and 10 augers were localised to include points showing major variability (Fig. 2).

The homogeneity of the ECa map was confirmed by the pedological survey showing a homogeneous soil. One soil type, representative of the whole field, was identified as *Mollic Vitric Andosols* (IUSS Working Group WRB, 2014). This last classification was in agreement with that reported by Di Gennaro et al. (1999) for the representative soil of the Nola plain area in which the experimental field lies.

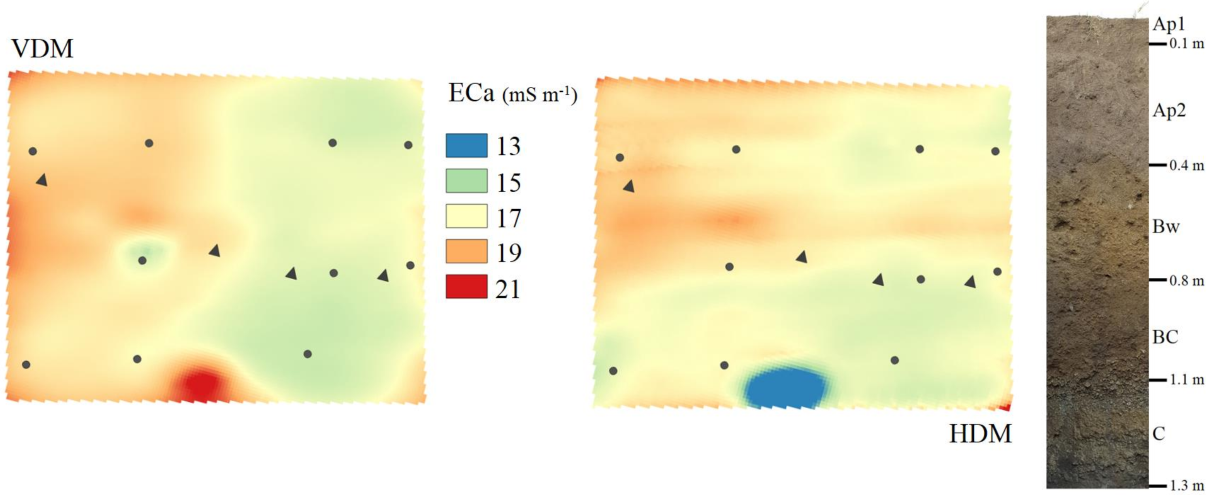


Fig. 2 Location of soil profiles (triangles) and augers (circles); ECa map of vertical dipole mode (VDM) and horizontal dipole mode (HDM). On the right is the representative soil of the field experiment.

The physical characteristics of soil profiles are reported in Table 1. The soil texture was sandy loam with an average value of clay content along the soil profile of 6.8% and an increase in sand content from the upper to lower soil horizon of about 70% (from 51 to 86%), concurrently with an increase in gravel from 7 to 42%. The saturated soil water content and “n” parameters were very close among the soil horizons, 0.43 (± 0.009) $cm^3\ cm^{-3}$ and 1.26 (± 0.02) respectively. Maximum saturated hydraulic conductivity was 200 cm $day^{-1}$ at the upper horizon (Ap1 soil horizon), and the minimum was 25 cm $day^{-1}$ between 0.4 and 0.8 m (Bw soil horizon).

Tab 1 Physical properties of representative soil of field experiment.

| Soil Horizon | Thickness (m) | Texture Clay | Silt | Sand | Gravel (0.2-2 cm) | Hydrological properties $\Theta_0$ ($m^3 m^{-3}$) | $K_0$ (cm $d^{-1}$) | α (1 $cm^{-1}$) | l | n |
|---|---|---|---|---|---|---|---|---|---|---|
| | | (g 100 $g^{-1}$) | | | | | | | | |
| Ap1 | 0-0.1 | 10.5 | 38.5 | 51.0 | 7.0 | 0.42 | 200 | 0.030 | -0.5 | 1.27 |
| Ap2 | 0.1-0.4 | 5.9 | 43.6 | 50.5 | 4.1 | 0.44 | 50 | 0.030 | -0.5 | 1.23 |
| Bw | 0.4-0.8 | 3.9 | 31.1 | 65.0 | 16.2 | 0.43 | 25 | 0.025 | -0.5 | 1.25 |
| BC | 0.8-1.1 | 11.6 | 15.4 | 73.0 | 10.9 | 0.44 | 50 | 0.034 | -0.5 | 1.27 |
| C | 1.1-1.3 | 4.6 | 9.4 | 86.0 | 41.6 | - | - | - | - | - |

The plowed soil layer (0-0.4 m) showed a pH of 7.2 with an organic matter content of 2.6 %, in agreement with the report for the same soil by Ottaiano et al. (2017).

Finally, from the obtained $EC_a$ maps, it was possible to identify the plots' surface omitting the hot spot present in the bottom part of field (Fig. 2).

### 3.2. **Maize case study results**

Figure 3 presents the trends of principal weather information collected during the maize cropping season (April-August) in the year 2018. The data show a mean air temperature of 22.3 (±3.4) °C (abs. max temp. 37.0 °C; abs. min temp. 7 °C), a cumulative rainfall of 134 mm (max event of 31 mm) and a cumulative $ET_0$ of 531 mm, with a hydrological deficit (Rainfall-$ET_0$) of 397 mm.

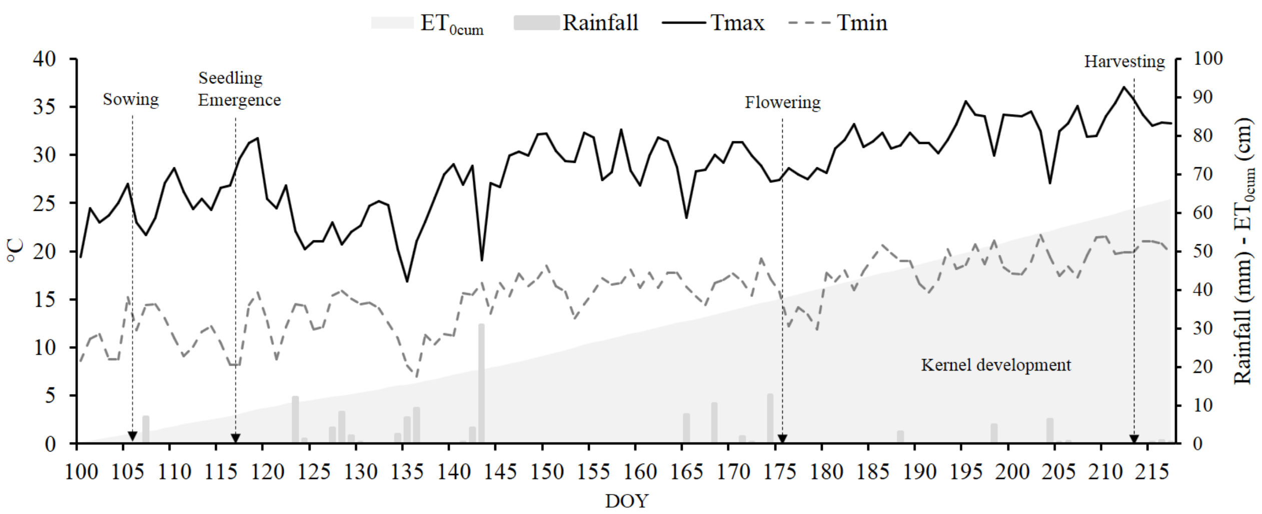


Fig. 3. Daily max and min air temperatures °C ($T_{max}$ and $T_{min}$), rainfall (mm) and cumulative reference evapotranspiration ($ET_{0cum}$; cm) during the maize growing season in the year 2018 at the "Acerra" experimental site.

To reduce the uncertainty as to the representativeness of the sampling area for crop growth analysis, UAV images collected during the growing season (until the achievement of the LAI peak) were analysed to identify areas inside each plot showing an average crop growth, where the samples of the vegetation were collected. Figure 4 shows two images defining the crop sampling areas (pixels in red colour) for two different times of the growing season: (a) early June during the crop development before the flowering and (b) after flowering in early July.

The main advantages in the implementation of this approach in a field experiment are to reduce the number of plants to collect, to have punctual crop samples representative of crop behaviour at plot scale and to avoid the collection of outlier samples, due for example to the effect of localised plant disease or from irrigation applied. An example of this last scenario is evident in Figure 4b, where the irrigation pipeline placed at the upper edge of the field produced an area not suitable for the crop sampling (the water pressure was probably higher in that section of the pipeline). Indeed, in the upper part, the NDVI was higher compared to the rest of field.

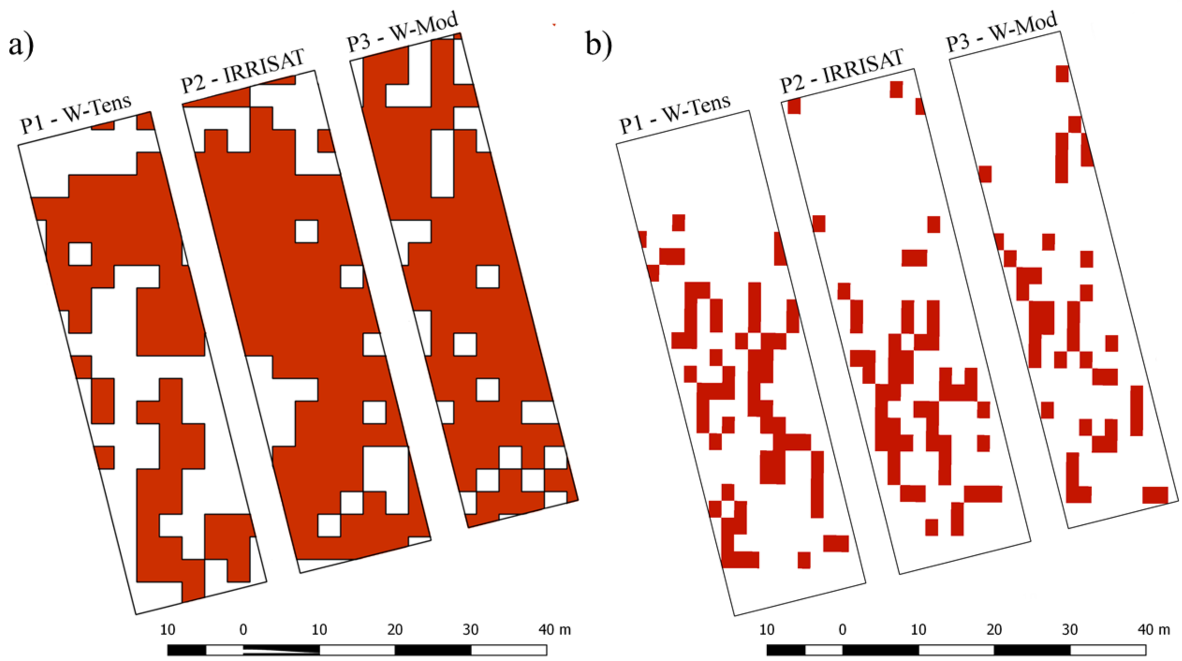


Fig. 4. The figure shows two examples of identification of crop sampling areas (red) according to the NDVI spatial information obtained by UAV multispectral images at 05/06/2018 (a) and 05/07/2018 (b) in each plot of field experiment (P1 - W-Tens; P2 - IRRISAT®; P3 – W-Mod).

About the crop growth, no significant differences in above ground biomass (AGB) were found among the three plots. The absence of differentiation between the plots is also clearly expressed by the LAI measurements realised in the three plots, as reported in Figure 5. The peak LAI was 4.6 $m^2 m^{-2}$ (±0.47) for P1, 5.0 $m^2 m^{-2}$ (±0.70) for P2 and 5.0 $m^2 m^{-2}$ (±0.50) for P3, with a maximum rooting depth of about 0.5 m (measured during the growing season in P3 for W-Mod application and verified at harvest in the other plots).

The similar crop behaviour between the plots is in agreement with the expectations of the irrigation tools (W-Tens, IRRISAT® and W-Mod), for which maximum production represents the main goal. In our specific case, a similar crop yield (fresh) was realised with the amount of water supplied ranging from 2819 to 4699 $m^3$ per hectare.

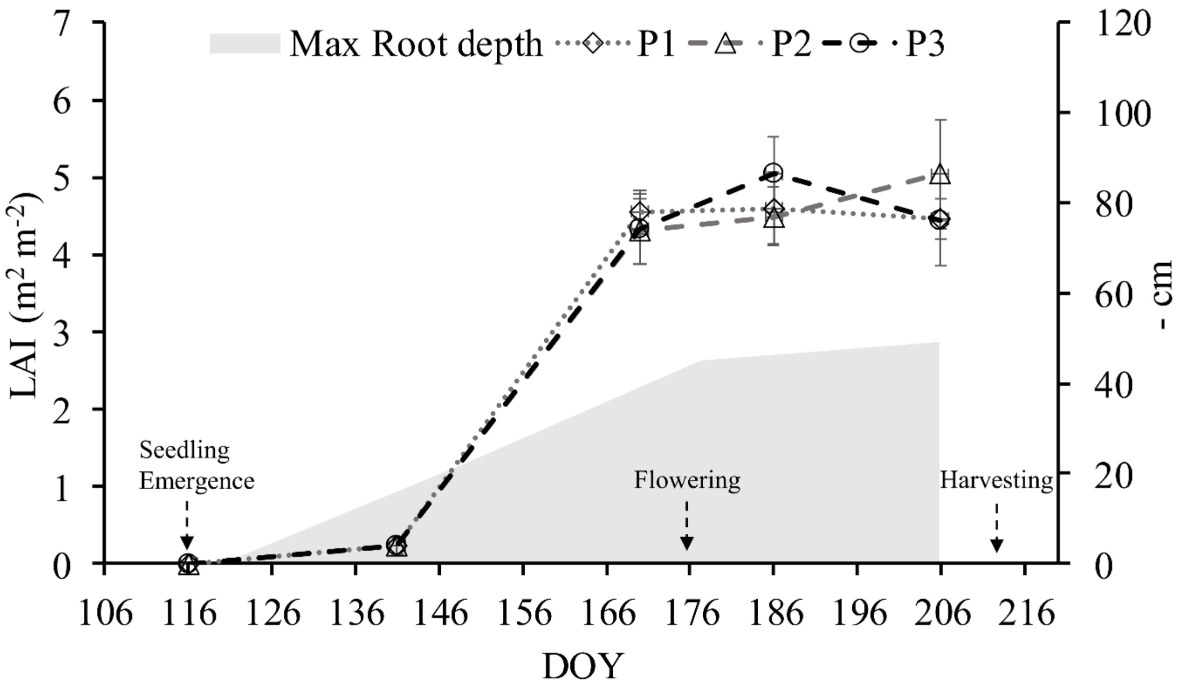


Fig. 5. The maize leaf area index (LAI, $m^2 m^{-2}$) trends of each experimental plot (P1, P2 and P3) and the maximum rooting depth (P3) measured during the 2018 growing season at the “Acerra” experimental site.

Tab. 2. Irrigation and maize yield results of LCIS DSS irrigation tools

| Irrigation information | LCIS DSS irrigation tool | | |
|---|---|---|---|
| | W-Tens | IRRISAT | W-Mod |
| Irrigation events (n°) | 9 | 8 | 6 |
| Total water volume ($m^3$) | 695 | 417 | 360 |
| Total water volume ($m^3 ha^{-1}$) | 4699 | 2819 | 2941 |
| Fresh yield at harvest (t $ha^{-1}$) | 57.3 | 58.6 | 60.2 |
| IWUI (t $m^{-3}$) | 0.012 | 0.021 | 0.021 |

The specific results for each tool are reported in the following paragraphs.

**W-tens:**

The irrigation timing and water volumes realised during the field experiment by applying the W-Tens tool are reported in Table 2. This irrigation tool defined nine irrigation events with an average water amount of 522 (±121) $m^3$/ha per event and crop yield of 57.3 t $ha^{-1}$.

In agreement with Van Dam et al. (1997), the irrigation events were performed applying the $h_{start}$ and $h_{stop}$ values for maize of -330 cm (field capacity) and -600 cm (start of crop water stress) respectively, with an $h_t$ of 150 cm.

Thus, the W-Tens tool warned the farmer each time the tensiometer value at -0.35 m reached the pressure head value of -450 cm. This rule was applied to give time for the farmer to organise the water supply and to realise the irrigation event.

In Figure 6, two irrigation events demonstrate the achievement of $h_{stop}$ (-600 cm) before the irrigation event on both dates at -0.35 m of soil depth.

From early June (DOY 155 to 162) to early July (DOY 185 to 189), the value of the pressure head at -0.55 m was, on average, lower after one month, reaching the peak of -600 cm. This behaviour was strictly dependent on the increase of temperature and the evapotranspiration demand, crop growth (the maximum LAI was reached at the end of June) and root depth which reached a length of -0.5 m (data collected in field).

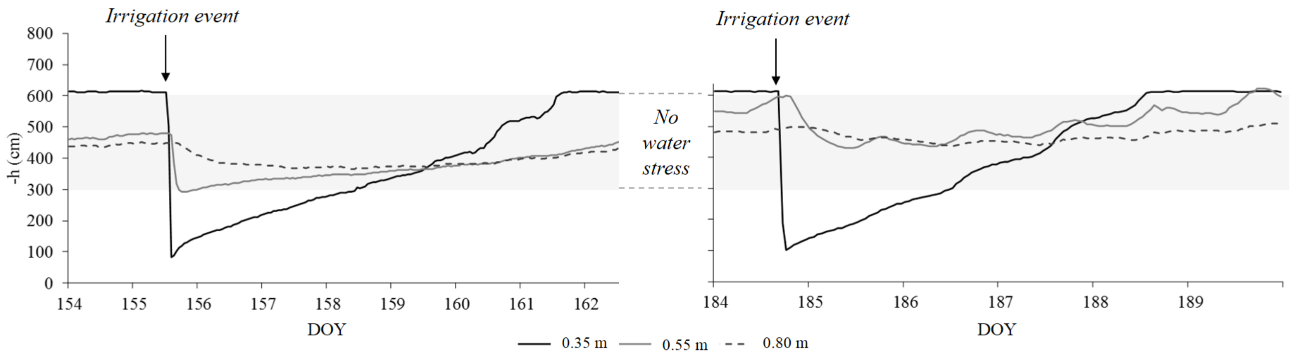


Fig. 6. Trend of soil water pressure head measured (-h, cm) by the tensiometers at three depths: -0.35, -0.55 and -0.80 m during two irrigation events (DOY 155 and 184).

**IRRISAT®:**

The irrigation timing and water volumes realised during the field experiment by applying the IRRISAT® tool are reported in Table 2. This irrigation tool defined eight irrigation events with an average water amount of 313 (±199) $m^3$/ha per event and a crop yield of 58.6 t $ha^{-1}$.

The application of the IRRISAT® procedure is reported in the supplemental material. Figure 7 reports the trends of daily and cumulated IWR estimated during the maize cropping season in plot 2 and applied to define the irrigation amount with IRRISAT® tool.

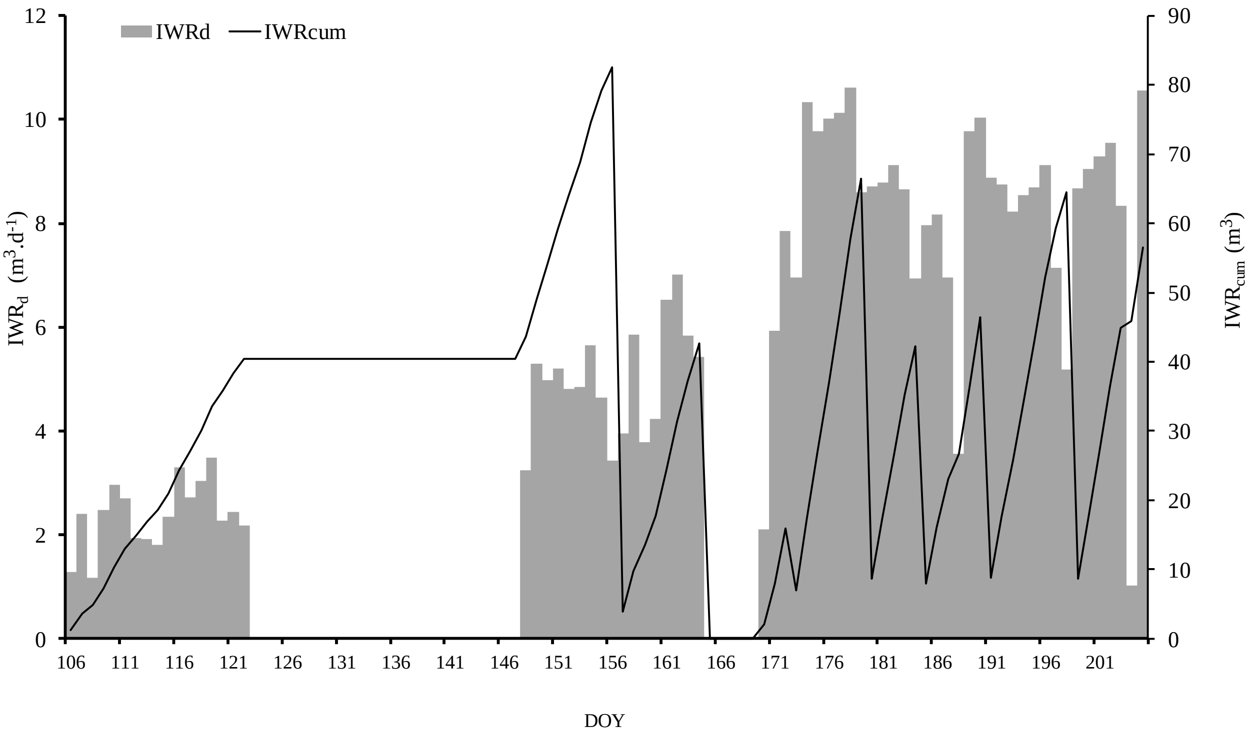


Fig. 7. Irrigation scheduling of Plot 2 (IRRISAT® tool): daily and cumulative values of IWR with irrigation scheduling.

The timing of irrigation was defined by the farmer in accordance with farm activities, corresponding in part to the date realised by W-Tens.

**W-Mod**:

The irrigation timing and water volumes realised during the field experiment by applying the W-Mod tool are reported in Table 2. This irrigation tool defined six irrigation events with an average water amount of 490 (±154) m$^3$ha$^{-1}$ per event and the highest crop yield at 60.2 t ha$^{-1}$.

For application of the tool, the soil physical properties (Tab. 1) were calibrated by modifying the soil water content at saturation through trial and error procedure realised on the first four TDR measurements (differences of $\Theta_0$ from lab to field of 10%). The accuracy of the simulation, applied to predict the irrigation scheduling, was evaluated by comparing the measured and estimated SWC values at five soil depths (0-0.1 m; -0.3 m; -0.45 m; -0.65 m; -0.80 m) (Fig. 8, Table 3). The statistical indexes applied have shown good agreement between measured and estimated SWC, with an average RMSE value of 0.02±0.005 $m^3\ m^{-3}$, EF of 0.76 ±0.28, CRM of -0.03±0.02 $m^3\ m^{-3}$ and r of 0.88±0.06. These results confirm the accuracy of the simulation and the irrigation amount defined, with an average RMSE of 0.012.

Tab.3. Evaluation of W-Mod performance

| Statistical Indexes | Year 2018 | | | | |
|---|---|---|---|---|---|
| | 0-0.1 m | -0.30 m | -0.45 m | -0.65 m | -0.80 m |
| RMSE ($cm^3\ cm^{-3}$) | 0.02 | 0.01 | 0.01 | 0.02 | 0.01 |
| EF | 0.95 | 0.98 | 0.97 | 0.41 | 0.48 |
| CRM | -0.06 | 0.00 | 0.00 | -0.07 | -0.03 |
| r | 0.91 | 0.94 | 0.82 | 0.92 | 0.79 |

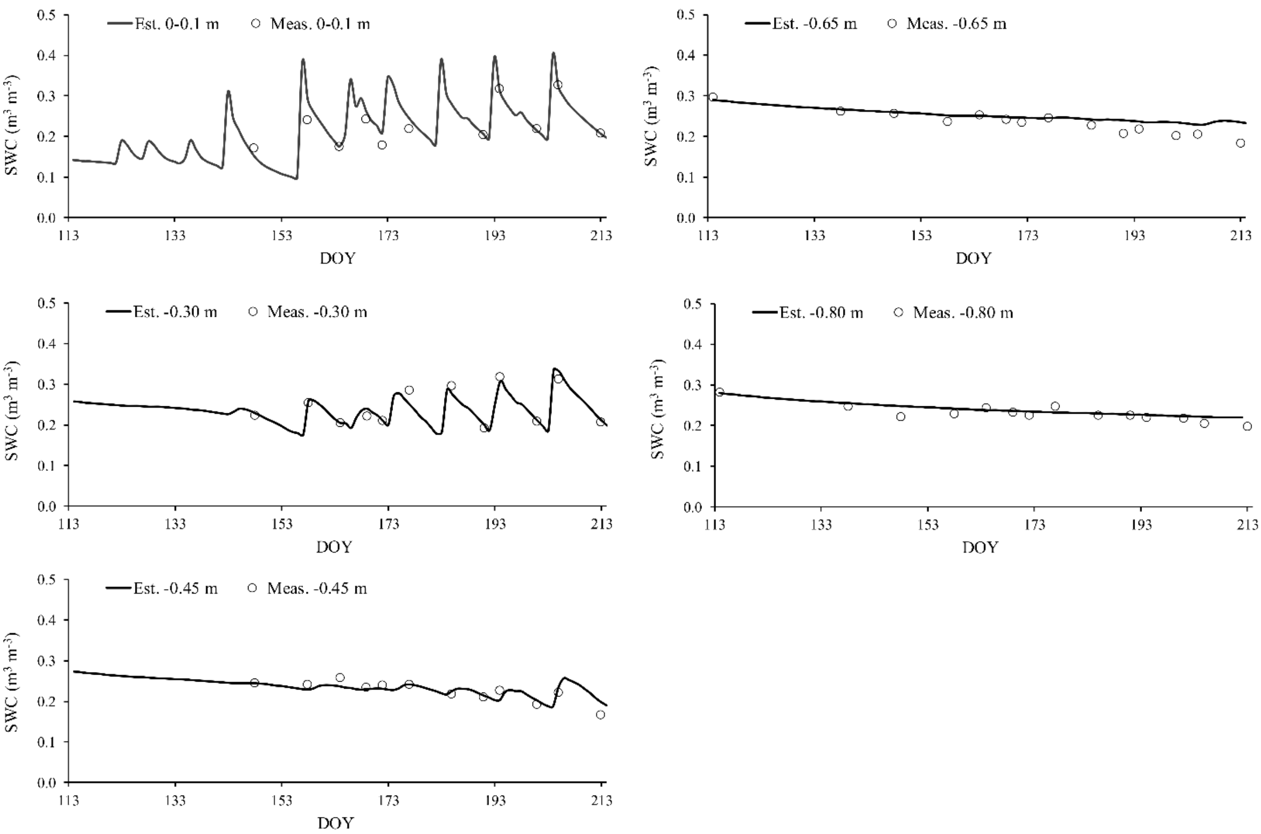


Fig. 8. Soil water content (SWC) measured (Meas.) and estimated (Est.) by the W-Mod model in the experimental site (Plot P3) at five different soil depths (0-0.1 m; -0.3 m; -0.45 m; -0.65 m; -0.80 m) during the 2018 maize cultivation.

## 4. DISCUSSION

Based on the results obtained in the case study of maize, a comparative analysis of each LCIS DSS tool for supporting irrigation has been carried out by taking into account i) limiting factors toward the operational support for improving irrigation efficiency, ii) implementation costs vs. production revenues and iii) current and future environmental issues (e.g., climate change, sustainable agriculture, SDG goals).

**W-Tens**:

The W-Tens tool has its strengths and weaknesses (Tab.4), the most important being as follows:

- **Duration of watering**: As evidenced by experimental field results, this system supplied 40% more water than the other methods, without any increase in crop production. The lack of efficiency in preserving water resources might be mainly attributable to the absence of the identification of soil specific pre-alert threshold for irrigation termination ($h_{stop}$ + $h_t$). In our case study, although we tried to take into account the wetting front velocity and the time needed by the farmer to switch off the irrigation system, the used $h_t$ proved to be not entirely efficient. This was because its nature is too dependent on the timing of field data acquisition and farmer reactivity to the system warning. The first factor was strictly influenced by the soil hydraulic characteristics, and in our case study the fixed value (10 min) was not able to optimise the irrigation management. Farmer reactivity can be overcome only through an automated irrigation system. The result of the combination of all factors is an excess of irrigation time and water applied. We have estimated about 20-30 min per irrigation event, with an excess amount of water of about 15 $m^3$, equal to 19% of the water supplied. The best way to optimise the water use with W-Tens is to use an automated irrigation system to switch on and off the pump directly through the system DSS.
- **Tensiometer management**: Tensiometers are quite fragile and must be operated carefully in order to avoid the formation of air bubbles in the shaft, which may result in temperature-dependent errors. Moreover, they must be protected from frost and need regular maintenance, for instance refilling the water in the tube and avoiding contamination by algae. They require more

maintenance, and in very dry soils they fail. Suitable hand-held vacuum pumps are generally supplied by tensiometer manufacturers to recharge tensiometers in situ.

- **W-Tens measurement accuracy and its dependence on other environmental variables**: This is a relevant strength of the W-Tens tool, because the accuracy of tensiometer measurements is not influenced by temperature or soil osmotic potential, because the salts move freely through the ceramic cup. Generally, tensiometers operate between 0 and 80°C. Below 0°C, it is necessary to take precautions due to ice formation, although some tensiometers can work even at −10 ° C. Application of W-Tens does not require environmental information such as weather information for its operability, and no medium-specific calibration is needed.
- **Spatial scale**: The efficiency of the W-Tens tool is strongly influenced by soil spatial heterogeneity, because it is based on punctual measurements that might be not be representative of all soil-plant patterns on the irrigated surface. To close this gap, the irrigated surface has to be divided into different sectors according to the soil spatial variability and managed separately, resulting in an increase in implementation costs for farmers (one point of irrigation control costs between 400 and 600€).

**W-Mod**:

The use of the W-Mod tool also has its strengths and weaknesses (Tab.4), and the most important among them are the following:

- **The estimation of soil water balance:** This aspect is the main strength of this tool. Indeed, compared to the other two methods, it was able to describe the soil water balance and identify the irrigation events (timing and amount) and also provide information on the accumulated or expected crop water stress. This aspect is powerful for the application of this tool in the agricultural sector, in which water stress management is important for the yield quality (e.g., viticulture) and for farmer incomes, as well as when a fixed seasonal amount of water must be managed for each specific crop (e.g., consortium constriction).

- **Spatial scale application:** The W-Mod tool does not have spatial scale restrictions. The limitations can be due to the quality of input information (weather and soil) which might not account for the spatial and temporal variability of the application area (different fields and irrigation sectors), creating spatial error in the model's application. In general, it is easier to apply the W-Mod tool in a small field, where the farmer can improve the model's performance using a low-cost weather station and add punctual crop information from field (e.g., crop growth). However, when the model is correctly spatially parameterised, then it is able to take into account the soil and weather spatial variability. Its application on a large scale can be done by integration with remote sensing (UAV for mid-scale and satellite for large-scale) information on spatial crop behaviour (e.g., LAI) to improve the ability to increase water use efficiency, thereby also conserving water resources.

  At the same time, it is important to emphasise that soil spatial information (detailed soil map) is an additional cost for the farmer. The measurements of soil physical properties for the simulation model parametrisation and application, as well as the know-how to apply it, represent a major cost for the farmer, which is necessary when they want to move towards precision farming. However, the soil physical parameters for simulations can be determined by lab measurements or estimated by means of PTF (pedotransfer functions); but in any case the applied soil physical parameters need to be calibrated by the user, representing a de facto requirement for the best W-Mod tool use and thus probably a cost for the user (e.g., external expertise). Once the soil physical properties have been calibrated, they can be used for irrigation management for subsequent cultivations with some precautions (change in soil tillage practices, as well as the organic carbon in soil, can strongly affect the soil hydraulic properties of first horizon "Ap", and a re-calibration of the simulation model might be needed).

- **Use of information from field:** Use of field information on crop (LAI) and root development during the cropping season is important to improve the model's performance. W-Mod has a thermal model for LAI crop development simulation (LAI-mod) as well as the simulation of potential root development. A difference in terms of water use has been evaluated by applying, in the simulation run, the crop growth data collected from the field (LAI and rooting depth data assimilation) and estimated by LAI-mod. The obtained results showed an average increase of water use of 252±112 $m^3$/ha, with the maximum increase being 340 $m^3$/ha, when LAI-mod and potential root development were used, compared to the application of data assimilated by field. The minimum difference was achieved when potential root development was associated with LAI development derived from field data (125 $m^3$/ha). Thus, the requirement of field data collection represents a cost for the farmer (Tab. 4). In this last scenario, some new smartphone App may help lower costs (e.g., LAI by smartphone, Confalonieri et al., 2013).

**IRRISAT®:**

The use of the IRRISAT® tool too has strengths and weaknesses (Tab.4), of which the most important are the following:

- **Estimation of IWR**: the main concept underlying IRRISAT® is that the irrigation water requirement is computed considering the actual crop development as described by the relevant parameters, i.e., surface albedo and LAI, which result from the actual soil conditions and local farming practices, including fertilisation. This method implicitly takes into account all the factors affecting crop growth, and it optimises the calculation of water needs. Uncertainty in LAI estimation can lead to slightly non-linear responses in $ET_p$ when the Penmann-Monteith method is applied. In general, a direct relation between LAI and $ET_p$ is reported in the literature. In particular, an LAI variation of ±30 % corresponds to an $ET_p$ variation of about ±13% (McKenney and Rosenberg, 1993). Moreover, for wheat crops Martin et al. (1989) reported that if LAI is increased by 15% with no other changes (e.g., climatic and plant parameters in the formula), the ET increases by 5% (for high or low flux days: 630 $Wm^{-2}$ and 342 $Wm^{-2}$), whereas if the climatic parameters involved in the Penman-Monteith equation also change, the $ET_p$ values can vary between -4% and +19%. The changes in LAI have a direct effect on $ET_p$ and as a consequence on estimated IWR. Obviously, the magnitude of the effect is strictly related to the specific climatic variables involved in the $ET_p$ calculation. Although the estimation of LAI from Earth Observation (EO) suffers from saturation effects for LAI>4, the value of the canopy resistance in the Penman-Monteith equation under standard conditions of water availability can also be considered as constant for LAI>4 (Allen et al., 1998; Gardiol et al., 2003; Kelliher et al., 1995; Shuttleworth and Wallace, 1985).

- **Spatial scale application**: The IRRISAT® tool does not have spatial scale restrictions in its use. Multiscalarity is a strength point of this tool. Indeed, it can cover different spatial scales corresponding to the details of the remote sensing spatial information. Currently, use of this tool at consortium scale represents the best solution available; however, for a small field, its proper use might require high resolution satellite images (not free) and a consequent increase in cost for its application.
- **Ease of use and application costs:** The development of the IRRISAT® tool and the elaboration of the information layers needed requires high expertise in remote sensing, which generally is not present on farm, so its application can be done only by means of an external service (www.ariespace.com). Use of the IRRISAT® approach is very easy for farmers. They do not need to buy or install any device, because the information is delivered through common communication channels (Internet, smartphones) by external service providers. The tool reports the irrigation volume to be applied, leaving to the farmer the decision about the exact schedule, according to their current practices. IRRISAT® does not only support irrigation management, but it also provides data and images about the crop growth uniformity, in line with the requirements of precision agriculture. Its usage is very intuitive and the user interface can be easily adapted to farmers' utilisation requirements. In particular, it can be used in a bi-directional way, i.e., the farmer can send information about the exact schedule adopted and pictures about peculiar issues observed in the field, such as weeds and diseases. However, IRRISAT® is not able to detect water stress conditions at the early stage, but only its effects

on crop growth, that is when the crop damage has already occurred. Otherwise, tensiometer readings are able to monitor directly the occurrence of water stress; soil water balance models can also identify this condition, provided that actual irrigation data are timely and included in the simulation runs. Finally, the costs of service can be supported by public bodies, as in the case of the Campania region, which gives free irrigation support to local farmers with the aim of conserving the limited water resources.

**General considerations, a final synthesis.**

Typically, the farmers decide when the irrigation event should be done, if they are supported in different ways by tools. The final choice is theirs, and it is not easy to convince them to operate in an alternative way. However, if farmers have full control of their fields, in terms of plant status and weather information, this rule may be considered useful because it represents real control on the field, the ability to make decisions on the basis of local evidence and personal knowledge oriented towards reducing the crop production risks. A proactive presence of the farmer in the operational decisions might help the DSS system performance.

For example, in our case study the farmer decided based on the farm's internal needs to anticipate a scheduled irrigation (defined by the model) of Sunday to Friday. This simple change led to an irrigation event one day before a rainfall event, with an apparently incorrect use of water for irrigation. However, when the rainfall event was introduced in the W-Mod, the simulation accounted for precipitation until the end of season, influencing the soil water balance and the dates of subsequent irrigations. Indeed, if a new simulation over the whole cropping season was performed, considering all rainfall events, the simulated plant transpiration was very close to that realised during the experimental case study (1 mm difference at harvest with field experiment result), but with an increase in irrigation amount and a shifting of irrigation dates.

Moreover, it is important to stress that some tools can be used in an integrated way. The point we are marking is not that in the case of the experimental field reported herein there have been advantages from the strengths of both models. The point is the integration of W-Ten with IRRISAT® which can work together, where the first is able to give in-field information on when irrigation is needed to avoid plant damage due to water stress, and the second can define the irrigation water needs. At the same time, integration between W-MOD and satellite image analysis can also be done, using this last method as model data input (data assimilation) to improve W-Mod results.

## 5. CONCLUSION

Implementing appropriate irrigation management procedures is not always straightforward in practice, and each possible approach presents pros and cons in its application, due to the nature of the methodology.

A DSS oriented towards realising a real and profitable irrigation support must integrate different methodologies to achieve the best solution for the farmer, which fits different application scenarios (environmental conditions, soil data availability, farmer know-how, farmer's spending capacity, farm dimension, etc.).

When three different approaches to support irrigation water supply (W-Tens, IRRISAT® and W-Mod) were applied in a real case study on maize cultivation, the following conclusions were reached:

- ✓ The compared approaches were able to realise the maximum maize production for that cropping season, but with different amounts of water applied.
- ✓ The method based on in situ soil sensor (W-Tens) supplied 40% more water compared to the other two methods. The excess of water applied can easily be reduced by means of automated irrigation events.
- ✓ The IRRISAT® approach represents, along with W-Mod, the best solution in terms of IWUE, with the advantage that it doesn't need information on soil spatial information for its application.
- ✓ W-Mod integrated with field data assimilation on crop development (LAI information temporally or spatially, e.g., by UAV images) can represent a great opportunity for irrigation

support at different scales. A current limit to an advantageous application of this method is the information required: detailed soil spatial information, daily weather data monitoring and forecasting and last but not least the necessity of irrigation field sectors being organised in accordance with soil spatial variability.

- Each method requires a different level of user expertise. The only approach really “user friendly” for the farmer is W-Tens, whereas both IRRISAT® and W-Mod require an external service.
- Finally, an integration between tools based on field sensors and remote sensing as well as the use of W-Mod with data assimilation from satellite or UAV image analysis might represent a significant future opportunity to improve water use efficiency in precision agriculture.

Tab. 4. Pros and cons of LCIS DSS system tools.

| DSS-Tool | Level knowledge required of user | Level of interaction of user with tool | Cost and Spatial scale | Limitation | Strengths | Soil spatial information | Weather information/ forecast | Farm type giving the best performance | Perspective |
|---|---|---|---|---|---|---|---|---|---|
| W-Tens | Low | Field (control and manage the tensiometer) | Increased spatial scale corresponds to an increased number of acquisiton systems and cost for info transfer from field to server | Presence of gravel in soil; the sensors and acquisition system cannot remain in field, they must be repositioned each cropping season after soil tillage | Low cost and know-how to use it. Useful to manage the crop under stress | Not strictly important** | Not strictly required | Small and mid farms, with drip irrigation system automized | Costs for field data acquisition can be easily reduced (e.g., Sigfox), besides possible improvement in data communication between several measurement points in the field |
| IRRISAT® | Low | Report the moment and amount of irrigation into the system | Increase of spatial detail corresponds to an increase in costs due to the highly detailed satellite image acquisition, field control and weather information | Not applicable in small scale farms, due to a low spatial imagery resolution. High resolution imagery data are costly | The farmer decides when to irrigate, according to farm needs(e.g. water availability by consortium); the soil characteristics are not a limitation in the tool application | Not required | Required with forecast | Mid and big farm, with no restriction for irrigation system applied. Useful in the management of rotation crops that require irrigation | Improvement of free satellite image resolution may allow the use of system in the small farm condition. The tool can be applied with UAV images |
| W-Mod | High | Report: (i) the timing and amount of irrigation into the system; (ii)LAI* measurements; (iii) root depth* measurements | Costs due to soil information needed for simulation modelling application increase with spatial scale, as do the costs for the crop data acquisition for modelling approach improvement and weather information | Soil complexity might be a limitation (e.g. extreme soil physical characteristics; presence of gravel in the soil horizons) | It takes into account the soil information and its spatial variability to realise the soil water balance and determine the irrigation event. Morever, it can give information on the crop water stress and manage the irrigation in stress | Required | Required with forecast | Small, mid and big farm where the detail of soil spatial information is high | Soil spatial information acquisition and provision is becoming increasingly important among farms that aim at environmental sustainability. The use of drones or a new app for user-friendly field data collection is also useful for the model's application |

** The system itself estimates the LAI development with a thermal model (LAI-Mod), but field measurements are able to improve the capability of tool to improve the water use efficiency.*

*** A preliminary soil survey to define the soil map of the farm allows identification of the different irrigation sectors where the tensiometer systems should be placed in field to improve the use of water*

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