Portfolio of methods developed in OPERA to improve irrigation

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OPERA

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OPERA consortium members

	OPERA Consortium partners	**Short name**
1	Wageningen Environmental Research (Alterra), The Netherlands	WEnR
2	Stellenbosch University (SU), South Africa	SU
3	Evenor Tech (Evenor), Spain	Evenor
4	Instituto de Recursos Naturales y Agrobiologia de Sevilla (IRNAS – CSIC), Spain	IRNAS
5	French National Institute for Agricultural Research (INRA – EMMAH), France	INRA
6	University of Florence (UNIFI – DISPAA), Italy	UNIFI
7	Council for Agricultural Research and Economics (CREA) – Research Centre for Policies and Bioeconomy (CREA-PB), Italy	CREA
8	Institute of Technology and Life Sciences (ITP), Poland	ITP

Table Content

Summary

One of the challenges encountered in irrigated fields and irrigated territories (irrigated sector, catchment area) is to improve the efficiency of water use in irrigation to cope with growing needs and a declining or more variable water resource. In OPERA we aimed at developing improved approaches based on different levels of innovation such as using simulation models to better assess soil water content, remote sensing to characterize the vegetation status and take profit of the new capabilities of the recent satellite missions and, ensemble weather forecast to account for uncertainties of meteorological forecast. Six methods are developed in OPERA:

1- Agroclimatic and remote sensing-based Indices developed by EVENOR Spain and implemented Olive trees. The aim is to improve their characterisation and propose combinations of indices to improve irrigation recommendations.
2- Plant-based irrigation method developed by IRNAS-CSIC Spain implemented on Olive trees. The irrigation needs are assessed using stomata conductance modelling and thus better considers the plant control of the transpiration.
3- The APSoMoCo method based on soil-crop modelling developed by WENR – the Netherlands implemented on field crop (potatoes). It is based on the use of a soil-crop model and ensemble weather forecast to provide soil moisture forecast and associated uncertainties.
4- The CROPIRR method based on soil-crop modelling developed by ITP — Poland implemented on field crop (leaf parsley, celery and sugar beet). It is based on the use of a soil water balance model and meteorological forecast to provide soil moisture. The method aims on estimation of short term forecast of irrigation water needs.
5- The IRRICROP method based on remote sensing and the crop model developed by UNIFI and CREA on field crop (tomato, corn). The method intends to improve the IRRISAT tool, already operated for commercial application, by adding an assessment of the soil moisture using the Aquacrop Model and meteorological forecast to address uncertainties on the forecasts.
6- Irrigation requirements at the territory level method based on crop model and remote sensing developed by INRA on a large variety of irrigated crops (grass, orchard, gardening, field crop, vineyard, olive trees). The method aims at mapping actual irrigation water needs at the level of an irrigated sector.

These methods are mostly designed for farmers, but they can be up-scaled and thus can be made of interest to a wider range of users as administration and water association.

The objective of this deliverable is to present the main innovation underlying the tools that were implemented to improve the irrigation efficiency and tested in pilot sites as reported in D3.3. In this deliverable we remind the objective and the rationale of every method, which were presented more extensively in D2.1. In this report, we give details on the development required to implement the methods and provide an assessment of the results that will be further used to improve irrigation decision and manage water shortage. Therefore, the analysis of the full implementation of the method to manage irrigation, as well as their test on pilots were made in WP3 and reported in D3.3.

1 Introduction

One of the challenges is to improve the efficiency of water use in irrigation to cope with growing needs for water and a declining or more variable water resource. Such a situation is accentuated in the context of global changes with stronger demographic pressure and climate change. Improving irrigation can be done either by working on the water application techniques or by optimizing its use and reducing losses. In OPERA it is essentially on this second axis of improvement that we have focused.

Methods for scheduling irrigation have been the subject of much research and innovation in the past. Beyond the farmer's expertise, we can consider that the current standard is to control irrigation based on an estimate of the climatic demand (ET0) and the development of the vegetation cover. Many service companies have invested in this field. Some estimation methods rely on sensors that characterize the water status of the soil (tensiometer, watermark probe, capacitive probes, TDR) or vegetation (diameter of fruits). Despite the fact that the ideas of using such sensors are old, their implementations in an agricultural context, the analysis of the signals and the formalization of the decisions remain a difficulty not always mastered, which would explain the absence of generalization of their use.

In OPERA, we aimed at developing improved approaches based on the following levels of innovation:

- Integration of different sources of information and models. Methods will integrate different sources of information and models (T2.2).
- Coupling RS (remote sensing) data and models. Use of high-resolution satellite images (Sentinel and Landsat 8) with a crop or soil-crop model (data assimilation, model input, model calibration) to provide spatial soil water content, plant requirements and assess the quality of irrigation implementation (T2.3).
- Use of in situ sensors to monitor vegetation status and development of upscaling strategies to account for heterogeneities at the field and the farm-scale using models and remote sensing (T2.4).
- Implementation of ensemble weather forecast in crop or soil-crop models and uncertainty assessments (T2.5).

The definition of irrigation scheduling methods is very dependent on the context of the application, which takes the cropping systems into account, the organization of the sectors and the management of the water resources and the tensions on the uses of water. In OPERA, the methods that have been developed are based on concrete cases at the pilot sites (see WP3) and the skills of the teams in charge of the developments. Note that the methods developed are not intended solely for irrigation management by the farmers at the plot / field scale, but also targets other levels of decision-making, such as water resources administrations and managers.

Six methods have been developed or applied in OPERA:

1- *M1 Agroclimatic and remote sensing-based Indices* developed by EVENOR (Spain) and implemented olive trees. The aim is to improve their characterisation to improve irrigation recommendations.
2- *M2 Plant-based irrigation method* developed by IRNAS-CSIC (Spain) implemented on olive trees. The irrigation needs are assessed using stomata conductance modelling, which takes the plant control of the transpiration into account.
3- *M3 The APSoMoCo method* based on soil-crop modelling developed by WENR (the Netherlands) implemented on a field crop (potatoes). It is based on the use of a soil-crop model and ensemble weather forecast to provide soil moisture forecast and associated uncertainties.
4- *M4 The CROPIRR method* based on crop modelling developed by ITP (Poland) as implemented on field crops. It is based on the use of a soil-crop model and meteorological forecast to provide soil moisture.
5- *M5 The IRRICROP method* based on remote sensing and the crop model developed by UNIFI (Italy) on field crop (tomato, corn). The method intended to improve the IRRISAT tool, already operated

for commercial application, by adding an assessment of the soil moisture using the Aquacrop model.

6- *M6. Irrigation requirements at the territory level* method based on crop model and remote sensing developed by INRA (France) on a large variety of irrigated crops (grass, orchard, gardening, field crop, vineyard, olive trees). The method aims at mapping actual irrigation water needs at the level of an irrigated sector.

Table 1. *Methods characteristics*

Method ID	Users	Model	RS*	Field Sensors **	MF***	Crops in OPERA and limitation
M1	Farmers, public administration		X			Olive should be calibrated for other crops
M2	Farmers, public administration	X	X	X		Olive should be calibrated for other tree production
M3	Farmers, water distributor	X		(x)	X	Potatoes all crops being modelled by SWAP-WOFOST
M4	Farmers, advisory services	X		X	X	Sugar beet, Parsley, Celery Can be applied to any crops
M5	Farmers, farmer's association, public administration	X	X		X	Tomato and Corn Limited to crop modelled by the Aquacrop model
M6	Irrigation association, public administration	X	X			Orchard, Grass land, gardening, Olive, Vineyard, field crop can be applied to any crop simulated by STICS or Aquacrop models

* Remote sensing
** Field sensors to assess soil and/or crop water stress status involved in the method implementation
*** Meteorological Forecasts (in green the method used ensemble forecast)

The goal of this deliverable is to report on the developments made on the six methods and evaluate their potential of improvement. The report associated with activities made in WP2 is centred on OPERA innovations. We recall their rationale and their expected field of application already presented in D.2.1 and we present the development leading to implementable processes and make and assessment of the expected performance. The work made in WP2 is complementary to that made in WP3, where pilots based on the innovation were tested in real conditions to demonstrate the benefit of the developed innovations in improving irrigation efficiencies (see D3.3).

2 Innovation developments

2.1 *Agroclimatic indicators* developed by Evenor (Spain)

2.1.1 Rationale and aims

The developed method aims at providing irrigation requirement at the field scale to provide an objective assessment of the actual water need for olive orchards. The method is based on the estimation of water requirement at plot level using meteorological station and satellite image through agroclimatic indices.

The NDVI-Csw method is another method addressed in this study. It is useful for managing the water resources of Mediterranean olive groves. The NDVI is used characterize the canopy development and thus infer the crop coefficient while CSW is a short-term water stress factor (Maselli et al. 2009, 2013) able to represent the ET under stressed conditions. The two-layer nature of the olive groves requires a separate estimate of NDVI for trees and for the underlying grass cover, which can be obtained by applying appropriate statistical operations to satellite images with different space-time properties. The crop coefficients (Kc) can be obtained from data obtained by remote sensing and combined with daily potential evapotranspiration estimates for the operational prediction of real evapotranspiration (ETA).

The **inputs data** required are summarized in the following table:

Table 2. *Input data of the NDVI-CSW method*

Input Type	Variable identification and metric	Temporal and spatial scale	Data source
Climate	Precipitation (mm), Air temperature min and max (°C), Wind speed (m/s), Vapour pressure (mbar), Solar radiation (MJ/m²) PET Potential evapotranspiration (mm)	Hour and Daily – spatial unit	Regional Agricultural Government and National Environmental Government
Soil	% Clay % Sand Field capacity (mm) Dry Bulk density Permanent wilting point	Spatial unit	Soil map of Andalusia 1:400.000 and soil samples
Vegetation	NDVI, NDWI	Spatial unit	Sentinel 2A and 2B
Agricultural practices	Crop type and variety Irrigation (rules or calendar)	l/h	Local expertise

Innovations in OPERA were focused on Climate change impact analysis on olive crops using agroclimatic indices and the use of Sentinel 2 to upgrade the spatio-temporal resolution in NDVI in order to implement the NDVI-CW method.

2.1.2 Development and results

All Developments were supported by 8 test sites for a total of 28 plots (each site having at least 3 plots) located in Andalusia. These sites are described in detail in D3.3.

The NDVI-Csw method implementation was done according to the diagram given in Figure 1. The workflow can be summarized as follow. AW, which refers to the water available in l/m2, which corresponds to the ratio between the sum of the water supply (precipitation, irrigation) and the daily reference Evapotranspiration (ET0) of the last 20 days.

Secondly (2) CWS was calculated, which refers to the Water Stress Quotient. Subsequently (3) the fraction of vegetation cover (FVC) was derived from the NDVI values that were obtained in QGis and applying the NDVImax and NDVImin values referring to the study plot

Subsequently (4), Actual transpiration (TR_a), the current transpiration in l/m^2, was calculated, where the values of ET0 were substituted by the value of the study day in l/m2; KcVeg, the crop coefficient (determined by the ratio between evapotranspiration of the cultivated olive trees versus some of the reference ones, fixed at 0.7 (Battista et al. 2016); together with the FVC and CWS values that were obtained previously.

The calculation of the actual soil evaporation EV_a (5), which refers to the current evapotranspiration in l/m^2, was done. For this, the values previously obtained for AW, ET0 and FVC were used, and the KcSoil for bare soil was fixed to 0.2 (battista et al. 2016).

Next, $ET_{A,t}$ (6), the current evapotranspiration in l / m2 was calculated, adding the values obtained from EVa and TRa. The calculations were continued by determining the parameter Wt (7), which refers to the total water in the system, adding Pt and IRt, which refer to precipitation and irrigation respectively, both in l/m^2.

Finally, the study variable Vt will be calculated from the previous date (Vt-1), which refers to the volumetric content of water in the soil in l / m2, with all the parameters calculated, the parameters DPt (drainage), $ET_{A,t}$ and Wt were replaced. Vt initialized to the field capacity in l / m2 as obtained after heavy rainfall.

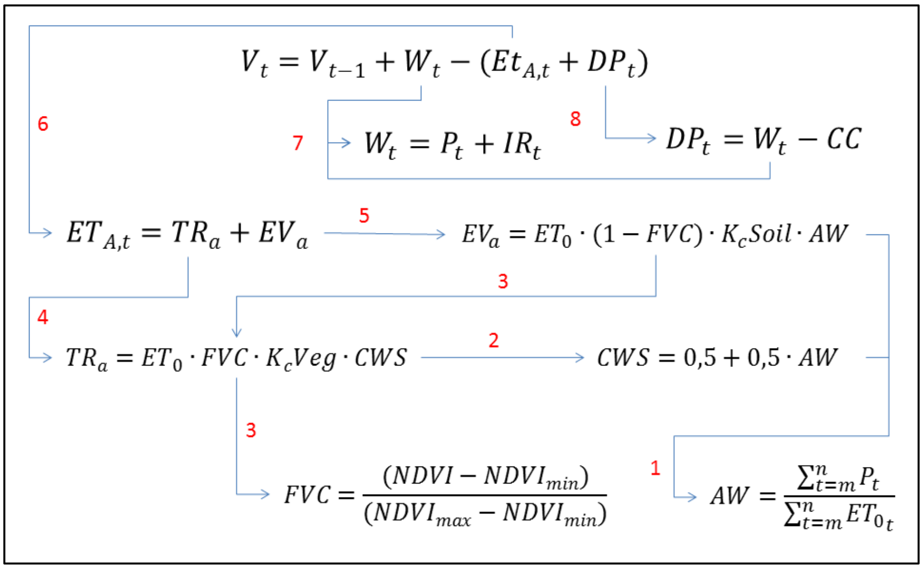


Figure 1. *Conceptual implementation of the NDVI-CWS method*

In our study the aim was to test the interest of the high space-time resolution offered by Sentinel and thus having a better monitoring of the vegetation cover (FVC) (Figure 2 and 3) The figures have shown a clear improvement in characterizing temporal patterns in NDVI.

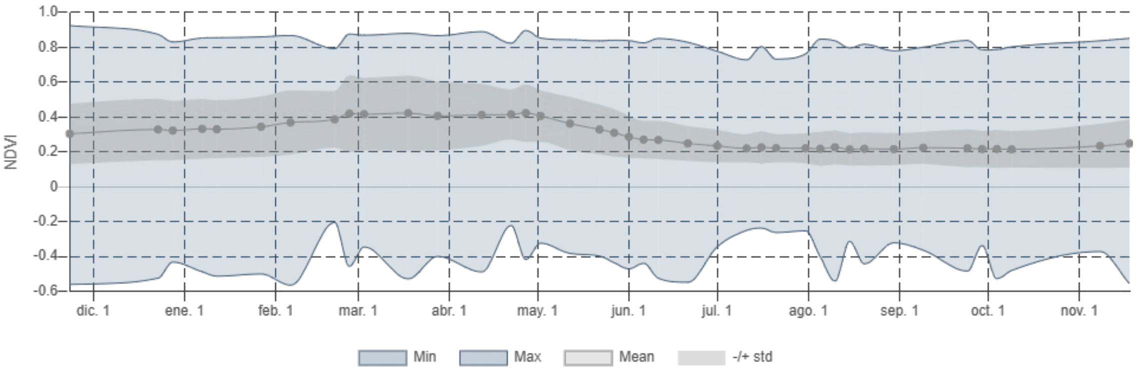


Figure 2. *NDVI values from Sentinel 2 (29-Sept-2017 to 29-Sept-2018)*

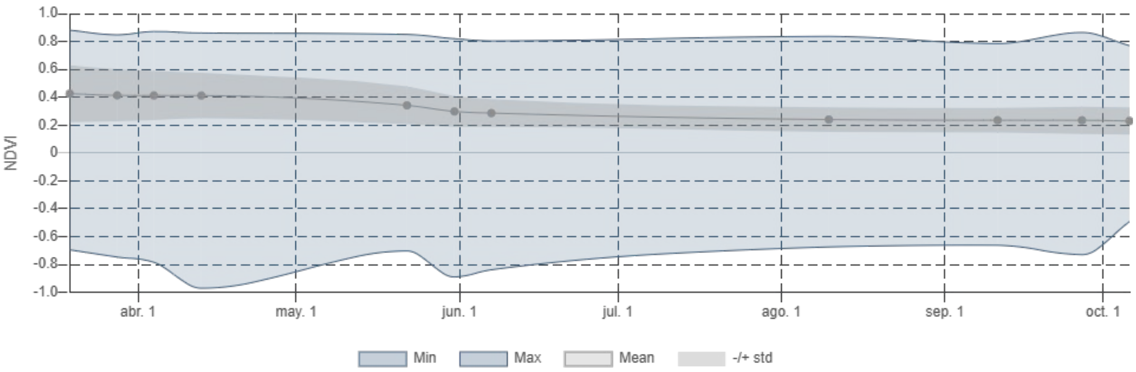


Figure 3. *NDVI values from Landsat 8 (29-Sept-2017 to 29-Sept-2018)*

NDVI relevance was assessed on Olive tree fields over different sites in Spain. Results have shown good correlation between NDVI and actual evapotranspiration as shown in Table 3

Table 3. *Correlation between actual ET and NDVI on different sites in Spain*

Study site	Correlation coefficient
Campaniche	0.54
El Águila	0.72
El cañuelo	0.67
El Rancho	0.69
La Baldía	0.86
Mirágenil	0.42
Quijano	0.43

2.2 Plant-based irrigation method developed by IRNAS-CSIC (Spain)

2.2.1 Rationale and aims

The goal of the method to be implemented in OPERA is to provide a calculation of tree water use for applying precision irrigation in crops to optimize water management based on physiological knowledge. Irrigation is applied by drippers and we will use a regulated deficit irrigation strategy. The method is based on the estimation of stomatal conductance which is in the crossroad of CO_2 and H_2O fluxes. It allows us to estimate the accumulated photosynthesis in each individual tree which has been proven to be closely related to fruit growth and oil synthesis. A microclimatic weather forecast for our site is provided and used for programming irrigation 3 days in advance. Remote sensing data will help us to understand the spatial heterogeneity and the temporal heterogeneity of some key parameters like LAI and photosynthetic capacity. The final outcome is a protocol of irrigation for farmers and managers at the farm level and a tool which can be used by both farmers and public administration in relation to the regional water management.

The method is summarized in Figure 4, where the two main outputs are the net photosynthesis rate and the transpiration making the link between production and water needs possible.

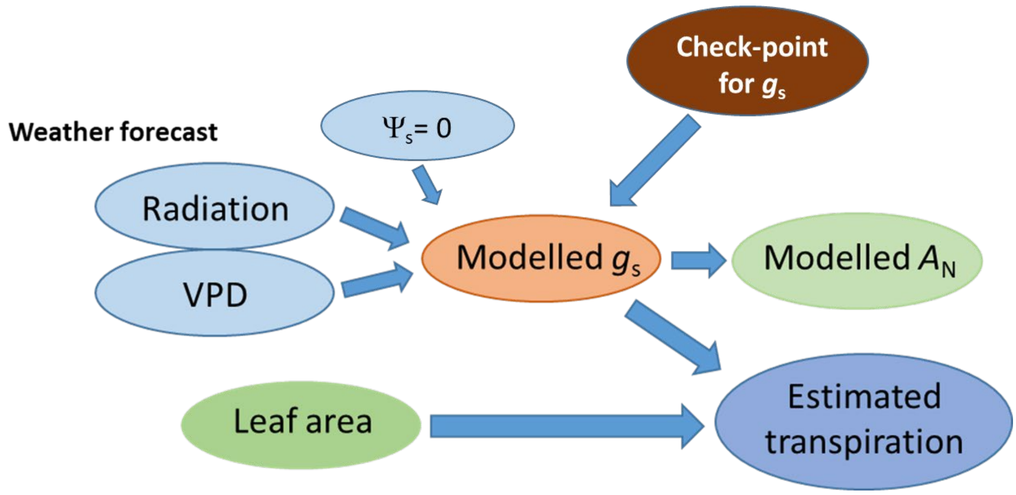


Figure 4. *Scheme of how transpiration is estimated representing the water needs required by the plants. Symbols represent Ys= soil water potential; g_s= stomatal conductance; A_N= net photosynthesis.*

For implementing the method, the following information is necessary:

The input data required to use the models and apply the methodology are:

- Leaf area
- The model of stomatal conductance requires: soil water potential, air temperature, and humidity and photosynthetically active radiation PAR. Environmental variables should come ideally from weather forecasts. We use a micro-weather forecast provided by a specialized company. In the case of estimation of full water requirements of the plant, soil water potential (ψ_s) can be assumed to 0 Mpa. The check-point for gs refers to the use of a plant sensor which can be used to check that we are achieving the desired level of stress.

The leaf area and stomatal conductance are the two main unknowns of the Penman-Monteith equation that describes the plant transpiration. In the OPERA project, the IRNAS-CSIC team has focused on these two variables. Remote sensing with drones at the whole orchard level has been used to estimate the tree crown volumes and from that the leaf area. On the other hand, plant-based sensors were used to estimate stomatal conductance in a continuous and automatic way using a very novel approach.

2.2.2 Development and results

Photosynthesis is a good proxy to assess olive fruit production

The rationale of the developed approach is based on the analogy between the relationship of yield versus transpiration or water use and the relationship of photosynthesis versus stomatal conductance. Figure 5 represents this analogy with actual data from an olive orchard, which has been studied by CSIC research team for 9 years.

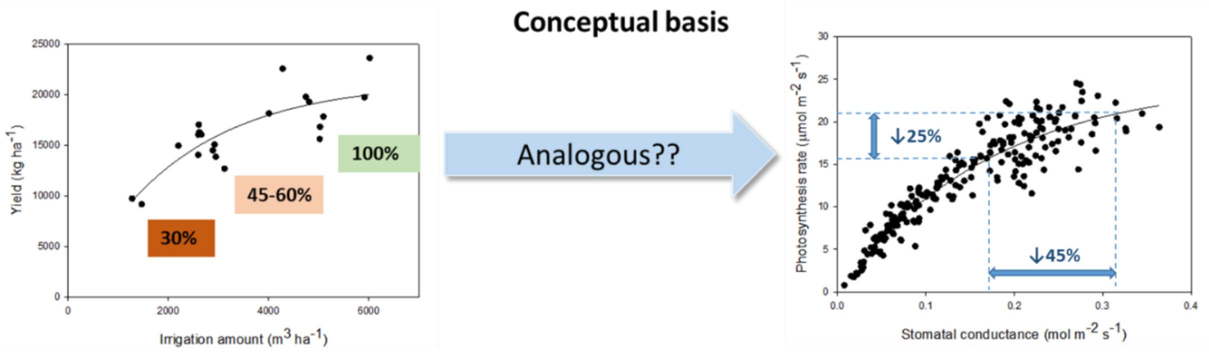


Figure 5. *Left panel: the relationship between the yield of olive fruits and irrigation applied. In our environment, during the growing season there is no rain and all water applied is lost by the plantation by evapotranspiration. Right panel: the relationship between photosynthesis and stomatal conductance for the trees in the same orchard.*

This principle was investigated in the case of olive trees under different irrigation strategies. It has been demonstrated (Hernández-Santana et al., 2018) that photosynthesis is the main determinant for fruit growth as shown in Figure 6 where the relationships between An and fruit growth was investigated in full watered orchard (100c treatments) and orchard conducted by deficit irrigation (45RDI treatments)

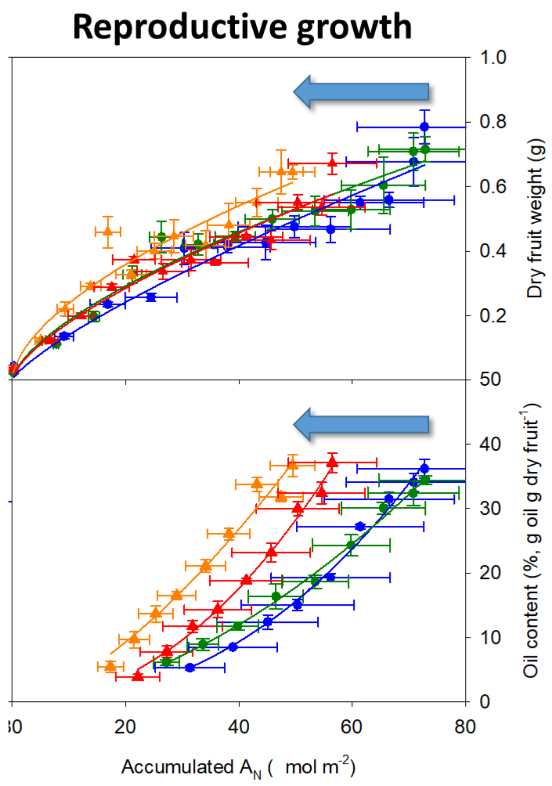


Figure 6. *Two variables related to reproductive growth have been correlated to accumulated photosynthesis (AN). The green and blue points correspond to a full covered of irrigation need (100c treatments) and the red and orange points correspond to deficit irrigation strategy (45RDI treatments)*

Figure 6 shows clearly how it is not necessary to accumulate more than 47 molCO_2 m^{-2} to get the maximum olive oil content in fruits. This is an example of how we can use the new approach based on stomatal conductance to set thresholds for irrigation. The most innovative aspect of the method is that this threshold is physiologically based, i.e. stomatal conductance, and can be interpreted unambiguously.

Stomatal conductance modelling to infer transpiration and photosynthesis rate.

As shown in Figure 4 the determination of gs is central in the approach. A novel aspect of the developed method is the use of a mechanistic model of stomatal conductance (BMF model, Buckley et al, 2003). This model has the advantage that its parameters have full physiological meaning. A simplified version was obtained some years ago by our research group and it has been applied with success several times and with several species for agronomical interest (Diaz-Espejo et al., 2012; Rodriguez-Dominguez et al., 2016).

Input variables
Soil water potential ($\approx \Psi_{pd}$)
VPD
PPFD
$[CO_2]$
Temperature

$$g_s = \frac{\chi\beta\tau\,(\Psi_s + \pi_e)}{1 + \chi\beta\tau\; R\, VPD}$$

Parameters
Plant hydraulic resistance (R)
Guard cells sensitivity to turgor ($\chi\beta\tau$)
Osmotic pressure (π_e)

This equation represents the response of stomatal to environmental conditions according to the hydromechanical model of Buckley et al. (2003). Input variables are regular meteorological variables: air vapour pressure deficit (VPD, Pa), photosynthetic photon flux density (PPFD, μmolm^{-2}s^{-1}), CO2 concentration (CO2, set to 400 ppm) and air temperature (ºC). Also soil water potential (Ψ_s, MPa) is included and it can be estimated from soil water content and soil hydraulic properties, or in the case of full irrigation, it can be used the predawn water potential as a surrogate of soil water potential. The parameters obtained have full physiological meaning, which is a strong aspect of the use of this model, and represent: plant hydraulic resistance (R, MPa mmol^{-1} m^2 s) from soil to leaf, the sensitivity of guard cells to turgor ($\chi\beta\tau$, mol m^{-2} s^{-1} MPa^{-1}) where the role of ABA is included and finally, the osmotic pressure (π, MPa).

The model was applied assuming a soil without any water deficit (Ψ_s=0). Results of the developed method were evaluated against the widely used method based on the crop coefficient considered here as a benchmark. Figure 7 shows the comparison of both methodologies in a hedgerow olive orchard intensively studied for the last 9 years, in which the crop coefficient method is finely tuned. One can. see how the differences between both methods are minimal, and even our method allowed for the saving of 18% of the water.

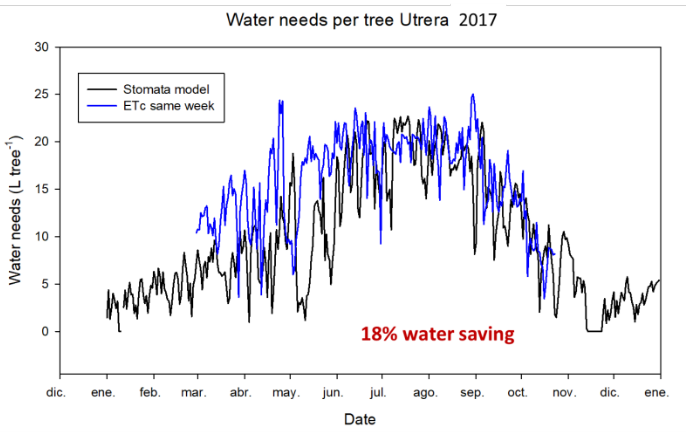


Figure 7. *Comparison of the stomatal conductance method with the crop coefficient method (benchmark) for a hedgerow olive orchard.*

Leaf area estimation

We developed a method based on drone information from multispectral, hyperspectral and infrared cameras allowed to discriminate perfectly each treatment an even individual trees (each pixel is 8 cm). The most valuable results were: in the case of the multispectral cameras we were able to separate the effect of the NDVI values from soil and weeds from the canopy. Reconstruct the canopies in 3-D using a visible 4K camera was a very promising result. We have been able to use this information to estimate the heterogeneity of plant sizes in the experimental site (Figure 8).

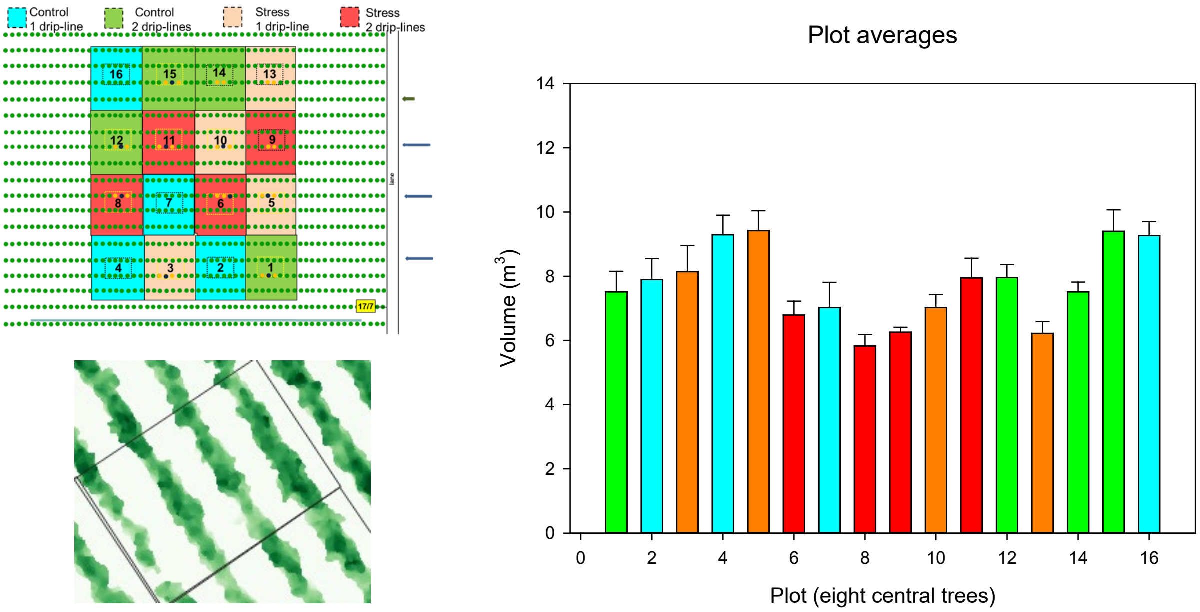


Figure 8. *Estimation of plant sizes (represented by plant volume) in the experimental farm. Each colour represents a water treatment and each bar the average of eight trees.*

Further use of tree sensors

Here the implementation of the stomatal conductance was made under the assumption that the soil was well watered. The determination of Ψ_s in soils with water deficit is a key issue to fully take the benefit of the proposed approach. The use of tree sensors can be a way to estimate soil water potential status. But this requires further investigations to better handle the relationship between the dynamic delivered by trees sensors (as fruit or stem diameter) and the soil water content.

2.3 APSoMoCo method based on crop modelling developed by WENR (The Netherlands

2.3.1 Rationale and aims

Accurate prediction of the amount of water in the root zone for the coming several days as a result of weather predictions can provide insight to farmers and water distributors if irrigation is needed the coming days. This is typically of interest to farmers that do not have to irrigate on a regular basis and who have to make decisions on when and where (which field) to use a moving irrigation system. In the current method the soil moisture content is predicted by using a soil water balance simulation model including a crop model. Major inputs for this model are the weather input variables which determine the input (rainfall) and output (evapotranspiration). Currently weather forecasts for several days ahead are available, but these are by definition uncertain. By using ensemble weather forecast (multiple realizations of weather forecasts) will result in multiple estimates of the pattern of simulated soil moisture content for the coming days. Based on the average together with the uncertainty band width of such a predicted soil moisture depletion can help the farmer to plan his decisions on irrigation.

A common practice is to consider the current status of the soil (feel by hand, depth of groundwater level, expert knowledge, or in some cases actual measured soil water content) to determine if and how much irrigation is needed. In some cases, farmers may use the average weather forecast provided by the news.

The innovation of the new method is that the actual status of the water available in the root zone is monitored (by a simulation model) and that ensemble weather forecast are used to predict how this amount of water changes in the coming 1 to 15 days. By using the individual forecast that makes up the ensemble (51 in total) it is also possible to show the range of predictions or uncertainty. In OPERA the development work consisted of implementing in farm context the whole modelling chain with ensemble meteorological forecast, assess the accuracy of the simulation and the range results generated by the variability of the ensemble forecast.

2.3.2 Development and results

Modelling framework

The total water content in the root zone was modelled by a one-dimensional model (SWAP-WOFOST; Kroes et al., 2017, Boogaard et al., 2011; http://swap.wur.nl/). Each day i) the climate inputs (rainfall, air temperature, air humidity, radiation, wind speed) as used in the model were updated by using the climatic data for the previous day of a nearby weather station (for instance in the network of the Royal Dutch Meteorological Institute (KNMI); http://www.knmi.nl/home), and ii) ensemble weather forecasts (for instance the 51 ensemble weather forecasts from ECMWF[1]) were obtained for the grid cell in which the site is located. The model simulations resulted in a predicted time course of the total water content in the root zone for the coming 15 days, which were visualized as the median of the 51 predictions surrounded by a grey area representing the e.g. 20-80% uncertainty range (see examples provided later). This approach was automated, and each day graphical output was sent by E-mail.

In the Netherlands, there is land-covered information on soil types (soil profiles), soil physical properties, and groundwater levels (all at scale: 1:50 000). For all possible combinations of these aspects model input files have been generated in the scope of the Watervision Agriculture ("Waterwijzer Landbouw") project[2]. For the test location (see below) the best corresponding data files were selected. It was decided to make use of locally determined soil profiles and groundwater levels and the subsequently derived soil physical soil layers in order to mimic better the local situation. An example of the application of the method can be found in deliverable D3.3.

Model evaluation

The model was tested on a potato field of a commercial farmer in the south of the Netherlands. To implement the model the farmer's agricultural practices (basically crop type and growing season) and general soil physical properties (from the Dutch national soil physics database; not locally measured). Figure 9 shows the correspondence between measured and simulated water contents. Since on the one hand the sensors were not calibrated for the local soil (the manufacture calibration line was used) and on the other hand the model used general soil physical properties, one cannot expect exact correspondence. One could choose for future applications to calibrate the soil physical properties op the top soil layer such that measured and simulated water contents match as good as possible. However, the current application still is satisfactory. For example, the changes (increases) in water content due to the seven irrigation events resulted in similar estimates of the volume of water applied (Figure 9). One can note that a calibration can be done such that the absolute water contents match, or such that the change in water content for a certain period of time matches. For the latter case the absolute values may be different, but the increases and decreases in water content are still similar.

[1] The ECMWF weather forecasts are obtained via KNMI based on a paid-for license for the duration of the OPERA project (Sept 2017-Sept 2019). The data can only be used for research purposes without commercial intention.

[2] http://waterwijzer.stowa.nl/

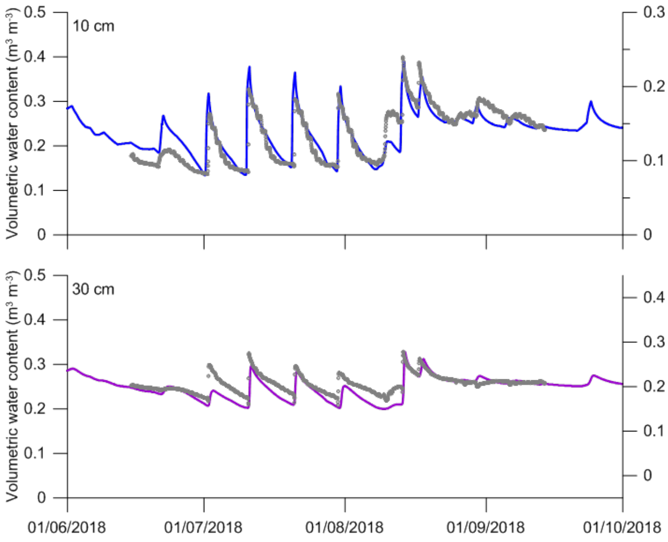


Figure 9. *Simulated (lines) and measured (symbols, averaged for the replicates; right y-axis) time courses of volumetric water content at depths 10 cm (top) and 30 cm (bottom).*

Impact of the weather forecast

The impact of the weather forecasts is displayed in Figure 10 which shows the variability of the simulated soil water content in the top 0-30 cm for a lead 1, 7 and 15 days ahead and comparison of the median forecast with that obtained using the actual climate (hindcasting analysis). In the beginning of the growing season (May-June) the predictions were somewhat uncertain due to high variability in ensemble rain forecasts, and during the dry summer of 2018 the predicted water contents in the root zone were well in accordance with actual water contents, where main variations are mainly driven by irrigation events that were prescribed at the actual dates. The quality of the prediction is therefore much better during the dry period, when decision on irrigation has to be taken. This is a very promising result for the implementation of the method in an operational context.

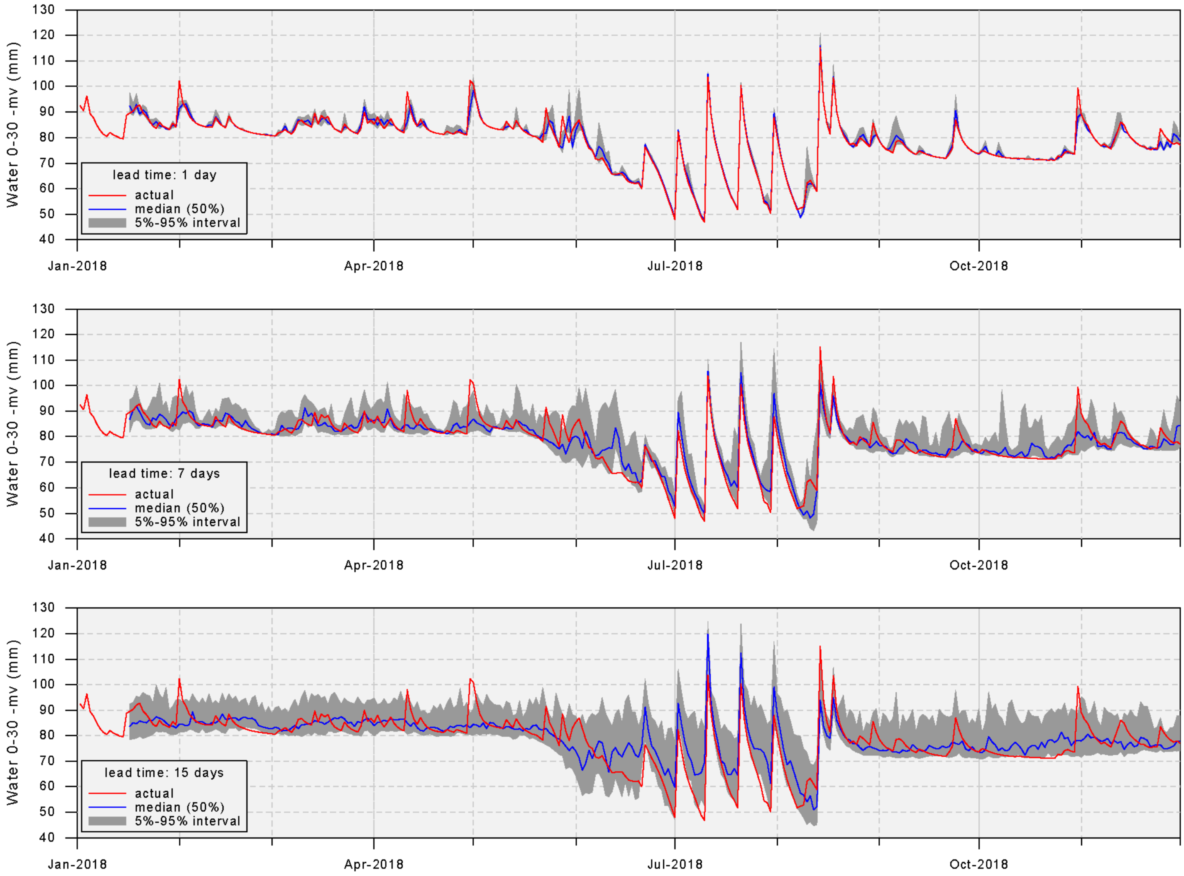


Figure 10. *Predicted water contents in the 0-30 cm layer for lead times 1 day ahead (top), 7 days ahead (middle) and 15 days ahead (bottom) (blue lines with grey confidence interval) compared to the true or actual situation (red line) simulated using actual weather data.*

It has been shown that the method works well and can be easily automated. The method provides the farmer with information on predicted behaviour of the water content in the root zone for the coming 1 to 15 days to be used by farmers in scheduling irrigation. The uncertainty increases with lead time, and it is estimated that workable lead times could be up to say 1 week.

Conclusions

Applicability. It has been shown that the method works well and can be easily automated. It depends on the model input data. For Dutch conditions soil and groundwater level related information is available at the complete National scale; however, it is advised to determine local field data regarding soil profile and corresponding soil physical building blocks and groundwater level characteristics, which is relatively easy to do. The method provides the farmer with information on predicted behaviour of the water content in the root zone for the coming 1 to 15 days. He or she can use this information in scheduling irrigation. Currently the system does not give an advice on when and how much to irrigate. This could be simply added; however, it was not decided to do so in the beginning to avoid overwhelming farmers with a system that tells them what to do. The primary idea is that farmers should first adopt the idea of using forecast information.

Robustness. The automated system is rather robust. Of course, the system is depended on data made available by others. In a very few occasions these data were either unavailable or some data were lacking, which resulted in no output. This required some manual intervention after which the system worked fine again.

Strength and weakness. The strength of the system is that it provides an estimate of the total water content in the root zone for the coming up to 15 days, including an estimate about the uncertainty. The current weakness is that it has yet not been tested thoroughly for other soil-crop combinations, no experience is available how the system performs for locations (countries) where much less detailed information on soil profiles, soil physical properties and/or groundwater level information is available.

Another weakness is that it makes use of ECMWF data that need to be paid for, especially when the aim is to operationalize/commercialize the product. The discrepancy between model predictions of soil water content and actual measured water contents can be seen as another weakness; however, the system could gain robustness in case the measured water contents are used to calibrate (say on a weekly basis) some model parameters so that the predicted and measured water contents are and remain consistent. Because of time and budget limitations this automatic calibration was not performed in the OPERA project.

2.4 The CROPIRR method developed by ITP (Poland)

2.4.1 Rationale and aims

The method is intended to aid the operation of irrigation systems using real time information on meteorological conditions and forecast. The CROPIRR model, coupled with the data collection, transmission and processing techniques, is used to predict on real time crop water demand and schedule irrigation. The CROPIRR method is based on soil-crop water balance modelling. It is developed by ITP on the basis of the FAO guidelines to estimate crop water requirements (Allen et al., 1998) and implemented on field crops. The method aims at providing a useful and accurate forecast of the soil water balance components at short term for operational planning irrigation. It could prevent water shortage as well as water excess and ensure more effective water use. The method will be used at both field regional (county) scales by modelling irrigation water demand and scheduling irrigation for different types of soils and crops on the basis of soil maps.

Innovation relies on modelling of the crop-soil-atmosphere continuum coupled with measured actual weather conditions, short-term weather forecast to make predictions of soil water content up to 5 days ahead. It will enable the best fitting of irrigation water supply to the actual crop water demand in a more flexible way.

2.4.2 Development and results

Model development

The CROPIRR model, coupled with the data collection, transmission and processing techniques, is used to predict real time crop water demand and schedule irrigation. The developed system (Figure 11) consists of:

- a telemetric system including automatic meteorological measurements of precipitation, air temperature and humidity, wind velocity and solar radiation (for model simulation) with data collection and transmission by GPRS;
- a system of short-term (for each day of the 5-day period ahead) meteorological forecast including daily precipitation, air temperature and humidity, wind velocity and solar radiation for evapotranspiration estimation, predicting crop water deficit and required water application in irrigation;
- a model representing water transfer in a soil-plant-atmosphere system crop evapotranspiration, crop water demand, soil water balance and irrigation water requirement calculation;
- information tools to disseminate recommendations to farmers supporting their decision on irrigation performance: the method is foreseen to be used directly by farmers after training or by regional agricultural advisory service (Regional Advisory Centre, water user associations, producers groups), disseminating recommendations by local media, internet, sms.

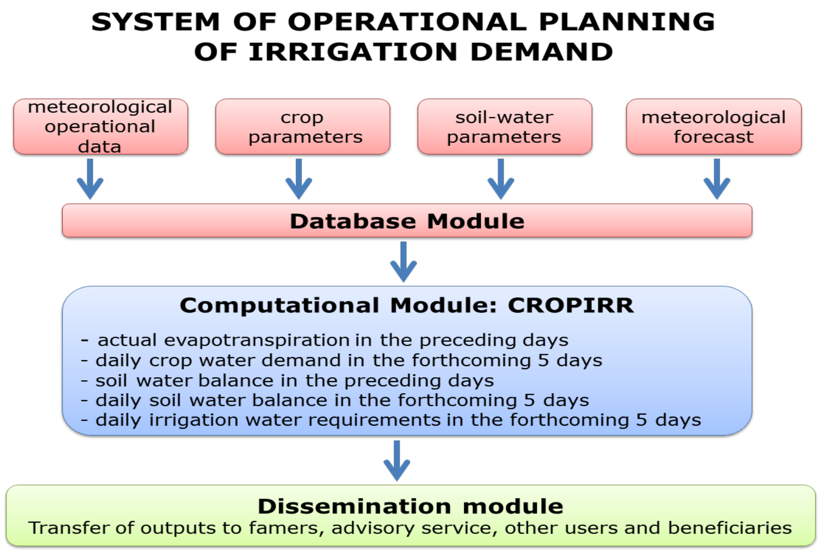


Figure 11. *The scheme of the System for operational planning of irrigation demand in Poland.*

The FAO approach based on a simple soil water balance model CROPWAT is used (Smith, 1992a, 1992b; Allen et al. 1998). The standard modelling approach is based on the FAO guidelines to estimate crop water requirement. The model simulates soil water content changes using the water balance equation. The methods and equations used are presented by Łabędzki and Kanecka-Geszke (2009), Ostrowski, Łabędzki and Kanecka-Geszke (2015) and Łabędzki and Ostrowski (2018). Actual crop evapotranspiration and crop water demand are assessed using the Penman-Monteith reference evapotranspiration and crop coefficients Kc. Kc coefficients for highly yielding crops are determined in lysimeter investigations carried out in Poland as well as from literature (Allen et al. 1998). They are tabulated for crop development stages and for 10-day periods of a growing season for a given plant. When soil water reserves are below readily available soil water, soil-water stress coefficient is used to reduce evapotranspiration, according to the method shown by Allen et al. (1998). The model also predicts potential crop yield reduction due to the lack of irrigation or insufficient irrigation using yield response factor Ky (Doorenbos and Pruitt 1997; Allen et al. 1998).

In the CROPIRR model, evapotranspiration and soil water content changes in the preceding period are calculated using measured values of meteorological variables as well as soil and plant parameters. For the five forthcoming days, crop water demand, soil water content changes and required water application are predicted daily. Therefore, irrigation doses are proposed according to the crop, and the soil assuming that the potential of soil water has to stay within a range of −10 kPa and −100 kPa. Irrigation scheduling is generated daily (recommended not less frequently than every 5 days) for the forthcoming 5 days.

The calculations are performed in Excel Worksheets. The user can run the model every day for precise irrigation at farm scale or every five days for regional scale.

To implement the described method, the following information is necessary:

- Meteorological data: measured and forecast daily values of solar radiation, air temperature and humidity, wind speed and rainfall.
- Soil profile description: number and depths of horizons, soil water content at WP and FC or available soil water content (measured in the field, derived from texture using PTF, derived from soil map, derived from pF curve).
- Crop data: area of irrigated units (fields); standard rooting depth on the base of observations and literature; crop coefficient Kc, for highly yielding crops, determined in lysimeter investigations carried out in Poland or literature (e.g. Allen et al. 1998); yield response factor Ky as a function of the development stage, determined from literature (e.g. Doorenbos and Pruitt 1997; Allen et al. 1998).

Kc estimation using NDVI

One of the issues of the CROPIRR implementation is the estimation of the Kc crop coefficients. If they can be tabulated (Allen et al 1998) to have on overall overview of the Kc under an average climate, it cannot be used in operational concept where the actual Kc dynamic is dependent on soil properties, climatic history and farm management practices. Therefore, a method to estimate Kc from NDVI Hornbuckle et al., 2016 after Trout and Johnson, 2007) was tested. Figure 12 depicts the decadal (10-day) values of Kc in 2019. The graph presents the Kc values compared to the estimated on the basis of NDVI from the satellite images of the examined parsley field. Because of the cloud cover, only a few values of satellite-based images were available (*see D3.3*). Except early growth in April and May, the values of Kc were comparable. Parsley is a crop with long emergence period (3-4 weeks) when the soil is not covered by plants. This time NDVI values are close to zero whereas physiological processes in plants take place.

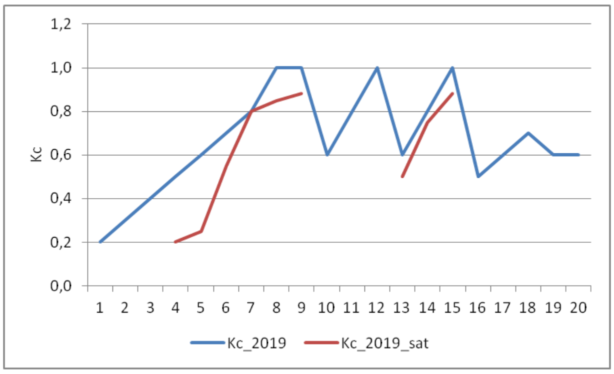


Figure 12. *Decadal crop coefficients (Kc) courses for flat leaf parsley in 2019 actual values (blue line) and estimated remotely (satellite images from IrriSAT, red line). On X axis 1= 1st decade of April.*

Model evaluation

We compared the daily measured values of soil water content in the root zone and two data sets of modelled values. The first one was the output of the modelling on the basis of irrigation time and doses used by farmer. The second one was the output of the model on the basis of irrigation time and doses estimated according to the 5-day weather forecast and depletion of available water content below a certain point. For evaluation purpose the following statistics were used: the root mean square error (RMSE), the mean absolute error (MAE), the r Pearson coefficient and per cent bias (PBIAS) (Table 4).

These evaluation statistics are commonly used in environmental sciences to assess the agreement between simulated and observed data. RMSE and MAE are expressed in the units of the variable of interest (e.g., mm), while *r* Pearson is a dimensionless statistic and PBIAS is expressed as a percentage. According to Willmott (1982) the *r* Pearson is insufficient to well-define model performance and the author recommends RMSE and MAE as the best overall measures. The smaller are RMSE and MAE, the better is the fit between the values that are compared. MAE is less sensitive to extreme values than RMSE, but more appealing, because it avoids exponentiation. PBIAS is the percentage deviation of the evaluated data. It measures if the average tendency of the simulated data is larger or smaller than their observed counterparts. The low-magnitude values indicate accurate model simulation.

Results are displayed in Table 4 and Figure 13. The values of *r* Pearson are high, showing consistent variation in both simulated and observed soil moisture. The PBIAS indicates high difference between measured with sensors and modelling results, its negative values indicate model underestimation comparing to the sensor measured values. During the 35 first day, the soil root depth is small and the agreement between simulated and observed soil moisture is very good. The bias appears when the root depth is maximum (after day 35) and might be explained by errors in soil hydraulic properties and/or soil moisture calibration in the deeper layers. However, it is interesting to note that there is a good correlation between simulated and observed values demonstrating that the relative variations of soil moisture can be interpreted and used for irrigation recommendation even if soil hydraulic properties cannot be established accurately.

Table 4. *Soil water content assessment in the leaf parsley root zone.*

Year	Error estimator	Evaluation terms		
		sensor / model, farmer irrigation	sensor / model, w. f. irrigation	farmer irrigation / w. f. irrigation
2019	r Pearson	0.928	0.935	0.945
	MAE	22.57	17.85	4.95
	RMSE	25.84	21.28	8.46
	Pbias Moriasi	-0.25	-0.26	0.07

Explanations: w.f. – weather forecast

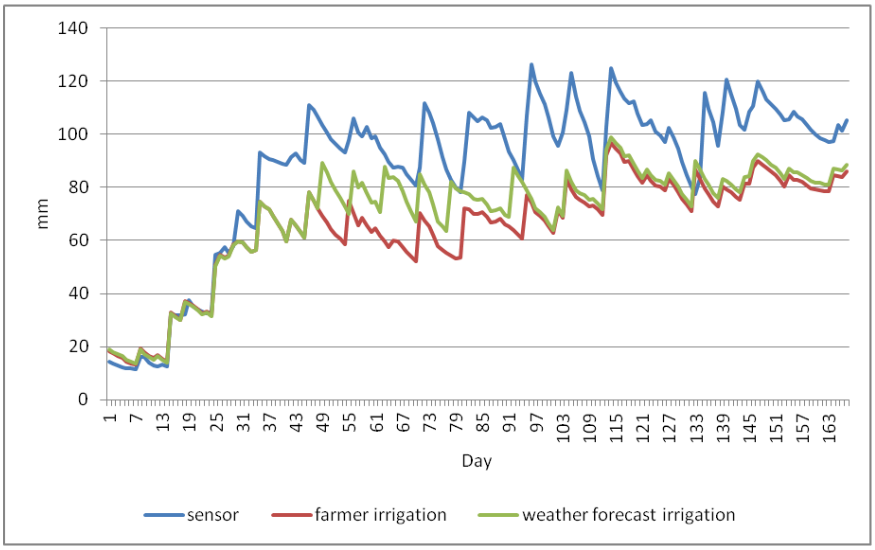


Figure 13. *Time courses of soil water content in the leaf parsley root zone (from 10 cm to 50 cm depth) measured by profile sensor (blue line) and modelled on the basis of actual farmer irrigation (red line) and weather forecast irrigation (green line); 1 - day 17 April 2019.*

Weather forecast accuracy

The weather forecasts were verified (Tables 5 and 6). The temperature forecasts are close to the actual meteorological conditions, while precipitations remain more uncertain with a weak correlation but with rather low errors (<2 mm/d) due to the fact that days without rains are well forecasted.

Table 5. *Precipitation forecast assessment.*

Year	Error estimator	Forecast terms				
		1 day	2 days	3 days	4 days	5 days
2018	r Pearson	0.16	0.20	0.12	0.06	0.03
	MAE	2.41	2.46	2.35	2.59	2.90
	RMSE	5.48	5.47	5.56	5.83	6.16
	Pbias Moriasi	-0.25	-0.17	-0.34	-0.26	-0.13
2019	r Pearson	0.31	0.39	0.41	0.22	0.13
	MAE	1.25	1.21	1.28	1.56	1.89
	RMSE	3.63	3.34	3.36	3.80	4.58
	Pbias Moriasi	0.07	0.17	0.19	0.33	0.38

Table 6. *Temperature forecast assessment.*

Year	Error estimator	Forecast terms				
		1 day	2 days	3 days	4 days	5 days
2018	r Pearson	0.67	0.67	0.67	0.68	0.65
	MAE	2.63	2.68	2.71	2.72	2.90
	RMSE	3.69	3.70	3.69	3.64	3.76
	Pbias Moriasi	0.03	0.03	0.03	0.03	0.03
2019	r Pearson	0.98	0.98	0.97	0.96	0.95
	MAE	1.10	1.21	1.32	1.45	1.59
	RMSE	1.32	1.47	1.62	1.81	2.05
	Pbias Moriasi	-0.04	-0.04	-0.05	-0.05	-0.05

Conclusions

Applicability. The method works well and can be used to determine the time and doses for irrigation. To be applied at the farm scale, the user (farmer) needs to know the soil characteristics (at least texture). To predict water demand the used model (method) needs good quality rainfall forecast or to build his own scenario of the forecast for operational planning of water needs (time and dozes) for irrigation.

Robustness. The proposed and tested model requires standard input data (meteorological, soil type and soil hydraulic properties, crop species). The model uses plant parameters summarized in decadal crop coefficients (e.g. crop parameter) and root depth. It provides average estimates for a wide range of soil/environmental conditions. The model can be used for operational (current and short-term forecast) determining the water needs of various crops and grasslands. However, to have suitable results at field scale, a calibration soil and crop parameters is recommended to account for specific field conditions.

The **weakness** of the method is that root depth is not always well established. In case of parsley, we have not carried out investigations confirming the real depth of leaf parsley. It was assumed on the basis on literature, discussion with farmers and rare sampling plants in the field. On the other hand, parsley as all other irrigated crops has a shallower root system than not irrigated crops.

Once correctly determined, root depth is an important parameter in our method to increase irrigation water use efficiency. The **strength** of the method is also possibility for the users to enter the custom value of efficiency of the used irrigation system according to their experience. Estimation of Kc on the basis of actual development stage with support of actual remote sensing data is the improvement comparing to the existing decadal values of the coefficient. Better (close to real growth stage conditions) estimation of Kc had a positive impact for modelling results.

2.5 The IRRICROP method developed by UNIFI and CREA(Italy)

2.5.1 Rationale and aims

IRRICROP provides optimal approaches for dynamic assessment of crop water demand based on sequential assimilation of remote sensing (RS; Sentinel-2A) observations in a crop growth model. The aim was to develop rules for optimum water management under climate variability and uncertainties in the Mediterranean, especially in Italy. IRRICROP allows farmer's associations, regional government, land and water reclamation authorities to schedule irrigation in a more rational way. In OPERA the selected irrigated crop was processing tomato irrigated using drip systems. The optimization is foreseen at water management level, through the availability of dynamic information about the crop evapotranspiration and its trend based on pedo-climatic conditions.

In IRRICROP, the fractional cover (fc) estimated by Sentinel-2 is sequentially assimilated into the AquaCrop model, by direct insertion, in place of the simulated canopy cover (CC). The sequential direct insertion is applied under the assumption that a continuous update of one crop model state based on remote observations can reduce the biases induced by the model simplifications of the processes and environmental conditions influencing the crop growth dynamics. Compared to the already adopted methodologies based on remote sensing as delivered by the irriSAT service delivered by ARIESPACE, the use of the model introduces the estimation of the soil water balance which, in turn, affects the crop transpiration. In this way, the dynamics of water losses are better reproduced allowing a more precise determination of the actual water requirements. In this sense, the innovation will be the availability of information to farmers about the real water requirements of their crops and the availability of the same information together with real data about water use to land reclamation consortia. The IRRICROP method is expected to lead to a more efficient water crop water use in the field, a more efficient water management at catchment level and a more correct distribution of water among different users (and consequently the pricing policy).

For implementing the described method, the following information is necessary:

- Crop: sowing/transplant date, plant density, plant phenology, canopy cover, rooting depth, biomass production, yield, irrigation supplied
- Soil: soil characteristic (texture, bulk density, organic matter, composition, moisture and hydraulic properties)
- Climate: weather variables for calculating ET0 and model run (rainfall, air temperature, relative humidity, solar radiation, wind speed)
- Satellite: Sentinel-2A imagery for crop state assessment of study areas.

2.5.2 Development and results

Biophysical variables estimated from Sentinel 2

The Multi Spectral Instrument (MSI) on board of Sentinel-2A/2B captures data at 10, 20 and 60 meter of spatial resolution over 13 spectral bands with a very high temporal resolution of five days at the equator. Individual Sentinel-2 granules Level-1C (processed at top-of-atmosphere reflectance), were acquired from Copernicus Open Access Hub (https://scihub.copernicus.eu/), already ortho-rectified in UTM/WGS84 (image tiles of 100x100 km2). The information gathered by Sentinel-2 system (orbit, altitude, date accuracy, and viewing directions of all detectors) is exploited for geolocating all Sentinel-2 pixels with an accuracy of about 11 m 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 performances show that for more than 50% of the cases, the performance does not meet that requirement. The resolution is estimated to be 3 times the registration error, thus the resolution Sentinel-2 time series is around 30 m.

Level-1C products were processed into Level-2A - Bottom-of-Atmosphere (BoA) reflectance - data using the ESA's Sen2Cor v2.5.5 tool. Sen2Cor tool performs the atmospheric, terrain and cirrus correction of Top-Of-Atmosphere Level 1C input data, and creates Bottom-Of-Atmosphere, optionally terrain and cirrus corrected reflectance images; additional, Aerosol Optical Thickness, Water Vapor, Scene Classification Maps and Quality Indicators for cloud and snow probabilities.

In order to obtain homogeneous and comparable products as time series, all value-added products (LAI, α and fc) are calculated based on atmospherically corrected Level-2A data. In order to obtain homogeneous and comparable products as time series, all value-added products (such as LAI, α and the fractional vegetation cover fc) are calculated from Level-2A images, which include the atmospheric correction obtained by means of Sen2Cor v2.5.5 algorithm published by ESA.

LAI and fc are calculated by S2ToolBox, LAI and fc being obtained by an Artificial Neural Network (ANN) algorithm, trained by using radiative transfer simulations from PROSPECT and SAIL models, and tailored for Sentinel-2 data. A detailed description of the algorithm can be found in Weiss. The algorithm requires eight Sentinel-2 spectral bands (B3-B7, B8a, B11 and B12) at 10 and 20 meters (pixel size), which are all resampled to 10 m to derive LAI and fc. Experimental studies have shown the accuracy of this approach for LAI estimation in different environments and crops. In this study, average and variance of LAI and fc at parcel scale were assessed by taking a minimum of 50 pixels falling within each parcel, after excluding pixels affected by boundary effects or cloudiness, according to the quality indicator provided by S2ToolBox.

Implementation of the aquacrop model

AquaCrop is a crop water productivity model developed by the Land and Water Division of FAO in 2009. It simulates yield response to water of crops and it is mainly used to increase water efficiency practices in agricultural production.

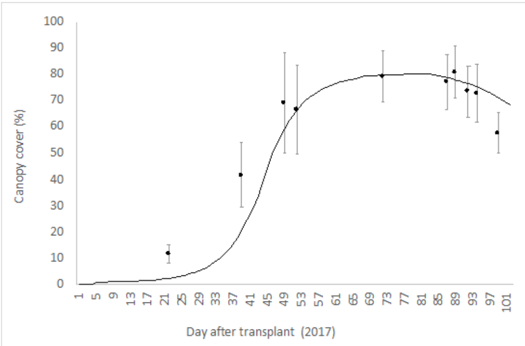
AquaCrop simulates crop yield in four steps: crop development, crop transpiration, biomass production and yield formation. It calculates the daily soil water balance and divides evapotranspiration into soil evaporation and crop transpiration. AquaCrop describes the foliage development of the crop by implements the canopy cover (CC), which is that is formally equivalent to the fractional cover (fc) estimated by Sentinel-2 imagery, i.e. it is the fraction of soil surface covered by the green canopy, to describe the foliage development of the crop, differently from majority of crop models which use LAI. Hereinafter, we use the two terms canopy cover (CC) and fractional cover (fc) just to distinguish the two variables, respectively derived with AquaCrop and Sentinel-2 imagery.

Transpiration is a function of CC, while evaporation is proportional to the area of soil not covered by vegetation. The CC is multiplied by reference evapotranspiration (ETo), determined by the FAO Penman-Monteith equation, and the crop coefficient (Kc) to calculate potential crop transpiration. Actual transpiration (Ta) is calculated starting from the potential one by accounting for water stress. Then, Ta is used for the calculation of crop biomass though its multiplication with water productivity normalized for the climate. By using a harvest index (HI), crop yield is obtained by the biomass. To describe the effect of water stress, the model considers different thresholds of water available to the root zone.

In this study, a limited number of AquaCrop parameters were partly calibrated with field observations, including management information: transplant dates and densities, flowering date and duration, starting of senescence, maturity, and final yield were used for local calibration of the model. For simulating irrigation, the model was set in net irrigation requirement mode, which estimates the crop water requirement based on a selected threshold of allowed root zone (water) depletion (RZD). In order to reproduce the irrigation method adopted by the farmer, drip irrigation was simulated to ensure that RZD was always above 50% of the readily available water (RAW).

The proposed method for assessing crop water requirements was to integrate Sentinel-2 crop derived biophysical parameter in AquaCrop. In particular, the fractional cover (fc) estimated by Sentinel-2 has been sequentially assimilated into AquaCrop, by direct insertion, in place of the canopy cover (CC) simulated by the model. The sequential direct insertion is applied under the assumption that a continuous update of one crop model state based on remote observations can reduce the biases induced by the model simplifications of the processes and environmental conditions influencing the crop growth dynamics.

Crop CC simulated by AquaCrop along the growing season and the fc values measured by satellite were compared in Figure 14.



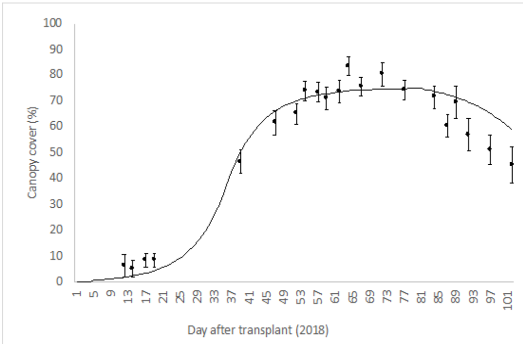


Figure 14. *Canopy cover of tomato simulated by AquaCrop, after calibration with field data (line) and corresponding fractional cover values (dots) retrieved by Sentinel-2 imagery during 2017 (left) and 2018 (right) growing seasons, with corresponding standard deviations.*

The growth of the green canopy simulated by the model was compared with the fc values observed by IRRISAT. In both seasons (2017-2018) the simulated growing curve fitted well with the satellite observations, although an underestimation for the initial canopy cover (late April-early May) and an overestimation during the last part of the growing season (July) was observed (Figure 14).

The differences between observed (Sentinel2) and simulated results (Aquacrop) were statistically analysed by means of Pearson Correlation Coefficient (r), Root mean square error (RMSE%), Coefficient of variation of (normalized) root mean square error CV(RMSE%), Nash-Sutcliffe model efficiency coefficient (EF), and Willmott index of agreement (d) (Table 7)

Integrating Sentinel-2 imagery with crop growth model such as AquaCrop, can be an effective strategy for assessing crop water requirement in the initial and development stages of the crop, as well as for identifying the senescence stage. Further, since the satellite imagery contains spatial information, the integration into a crop model can help in assessing crop water requirements at the field or higher scales, i.e. at territorial level.

Table 7. *Evaluation of canopy cover simulation results: number of observations/simulations (n), Pearson Correlation Coefficient (r), Root mean square error (RMSE%), Nash-Sutcliffe model efficiency coefficient (EF), Willmott index of agreement (d).*

	n	r	RMSE	EF	d
2017	10	0.95	9.10	0.8	0.96
2018	22	0.97	8.10	0.91	0.98

The impact of assimilating yield and evapotranspiration is given in Table 8. AquaCrop parameters were calibrated to obtain the best fit between field observations and simulations, both in 2017 and 2018. AquaCrop simulated yields were 7.23 and 7.60 t/ha (dry weight) in 2017 and 2018, with an error of 0.42% and 3.40%, respectively. The use of assimilated data provides comparable results than with the calibrated simulation with an overestimation of the yield in 2017 and a good match in 2018. The overestimation in 2017 is due to the beginning to the higher FC at the beginning of the cycle. A calibration of FC forced model might improve the simulations.

Table 9. *Crop and water balance variables (Tr: crop transpiration, E: soil evaporation, ETp: potential evapotranspiration).*

		Yield (t/ha)	Tr (mm)	E (mm)	ETp (mm)
2017	Observed	7.20			
	IRRISAT				450
	AquaCrop	7.23	345	192	537
	Assimilation	8.23	372	165	537
2018	Observed	7.35			
	IRRISAT				349
	AquaCrop	7.60	291	137	428
	Assimilation	7.34	273	139	412

Conclusions

The method can be considered **robust** as it is based on the integration of two validated tools already adopted for irrigation management, remote sensing and crop modelling. Nevertheless, the method should be validated for a longer period of time (at least three years) and on more irrigated crops in order to make it more robust. The applicability depends on different factors, but probably the most important is the availability and the quality of data for running the simulation model. In fact, besides the agrometeorological information, which can be derived from existing or ad-hoc weather stations or provided by databases as for IRRISAT, the model also requires a local calibration and a validation based on specific crop parameters and soil characteristics. Therefore, a period of time is necessary for calibrating and testing the system before its operational application.

The **strength** is mainly related to the fact that, compared to the already adopted methodologies only based on remote sensing, the use of the model introduces the estimation of the soil water balance which in turn affects the crop transpiration. In this way, the dynamics of water losses are better reproduced allowing a more precise determination of the actual water requirements. On the other hand, the use of satellite information, which has a considerable spatial coverage, allows the upscaling (up to territorial) of the application. In this way, the method can be used from farm to territorial level, thus responding both to farmers needs of optimizing irrigation and crop productivity, and to water managers to optimize water allocation and manage water shortages.

Concerning **weaknesses** of the developed method, a simple direct insertion has been applied in this study for assimilating satellite canopy cover into AquaCrop, which does not guarantee an optimal model-data integration. Based on that, more advanced data assimilation techniques should be tested, accounting for the structure of the model state and observation errors.

2.6 Irrigation requirements at the territory level developed by INRA (France)

2.6.1 Rationale and aims

The goal of the methods is to provide irrigation need maps at the field level and different temporal terms (meteorological forecast for the coming weeks, over the irrigation period using climatology (past and future), seasonal forecast). The main expected users are the water managers that have to implement decisions in the water allocation to the farmers (amount of water, distribution calendar). But a fair evaluation of the water needs will be also appreciated by the individual farmer by providing an objective basis to decide restrictions that usually arise tensions.

The proposed method is a suite of models that lead to estimate on every field of the area the required irrigation water amount. This led to the following steps:

- **Step 1:** detect irrigated crop using the temporal series of satellite images. We will start with existing land use product as a benchmark and then improve irrigated crop detection using the characteristics of the Sentinel satellites: 1) frequent observations provide time series able to capture dynamic patterns of the vegetation development, 2) spatial resolution able to address small fields, which are frequent in irrigated area, and 3) rich spectral content useful to characterize plant traits (LAI, faPAR, vegetation water content, soil moisture …). The challenge is then to identify patterns in the temporal evolution of satellite vegetation indices that improves the identification of irrigated crop and if possible, the cropping system variants that lead to different requirements type of trees, grassy inter-rows, tree arrangement in the fields).
- **Step 2:** set up the water estimation modelling framework. The simulator is based on two components: a simulation case generator to address the spatial variability of soil, climate and agricultural practices, and a crop simulator to represent the crop behaviour and the assessment of the water budget.
    - **The simulation case generator**: it is a pre-processing module that will prepare the different crop simulations cases. For every simulation unit (here a field) it is necessary to determine crop type, crop characteristics (variety...) and agricultural practices (irrigation, fertilization...), soil characteristics, and climatic data able to compute the potential evapotranspiration ET0 as determined by the FAO method (Allen et al., 1998);
    - **The crop simulators differed from one crop to another.** The STICS crop model (Brisson et al., 1998, Brisson et al., 2008) will be privileged when possible for instance irrigated grass, sunflower and wheat are simulated using STICS in the current simulator). For the other crops (orchard, vegetable, garden market, olive tree, vine) we currently use a simplified approach based on the determination of a crop coefficient varying for each crop along the cultural season (Kc ET0, FAO56 method) and the potential evapotranspiration (ET0).

The simulator was already developed in previous projects over the Crau Area. The main innovations developed in the project are related to step 1 mentioned before:

- Developing methods to map irrigated fields using the Sentinel 2 data over the two studied sites.
- Characterization of the vegetation development of the main crops through the annual cycle thanks to the satellite short revisit time (<5d), from the analysis of the temporal profiles of biophysical variables such as LAI, or spectral vegetation indices derived from Sentinel 2.
- Develop a method to identify flooding irrigation spatial patterns to assess the required amount of water to perform the irrigation.

Inputs of the simulator have already been presented in D.2.1. These covered four domains that are the climate, the soil hydraulic properties, the land use and the agricultural practices. Concerning the new development, the inputs are series of Sentinel 2 images (atmospherically corrected and georeferenced, with a cloud mask downloaded from the THEIA platform https://theia.cnes.fr/atdistrib/rocket/#/home), and shapefile with field boundaries, an urban and forest masks, learning and validation observation points (where the vegetation cover is known).

2.6.2 Development and results

Mapping irrigated orchards and vineyards

Various crop classification methods exist based on the use of different spectral bands reviewed by (Cheng et al., 2017; Orynbaikyzy et al., 2019) but very few have concerned orchards and vineyards both because of the complexity of these heterogeneous crops and associated agricultural practices and the spatial resolution of most of the considered satellites not fine enough (Kozhoridze et al., 2018). Since the arrival of the new Sentinel 2 data, numerous papers have explored the potential of the combination of spectral bands acquired at high frequency to map cultivated crops (Caiserman et al., 2019; Ferrant et al., 2017). During the OPERA project, as a lot of ground observations have been collected in 2018 (90 points) and 2019 (more 200 points), to which are added the surveys at field scale obtained beside 7 farmers, including more 150 fields described for the main agricultural practices, different strategies of supervised classifications were evaluated by varying the learning and validation dataset, the number of considered dates, spectral bands and the classification methods (support vector machine, maximum likelihood and random forest). Figure 15 summarizes the main steps of the processing chain.

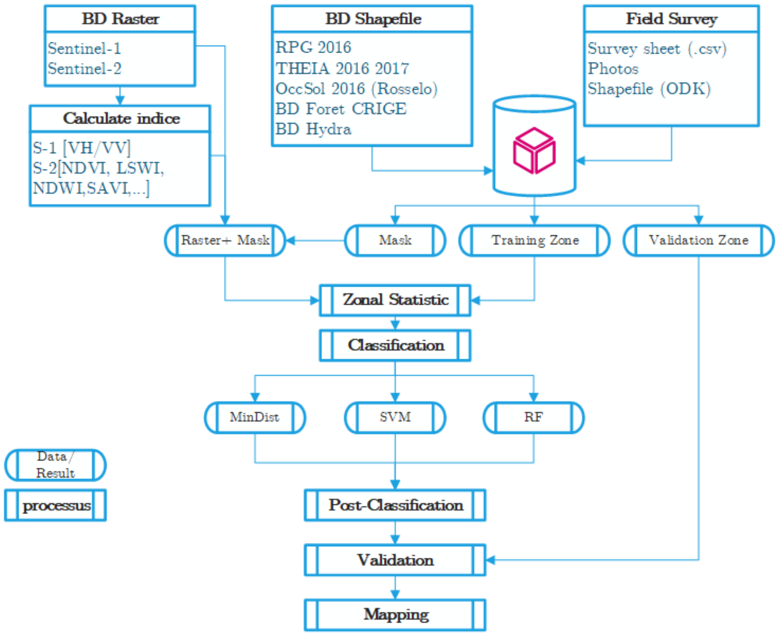


Figure 15. *Main steps for land use classification based on ground observation and Sentinel images.*

The choice of the relevant dates and spectral bands (or spectral indices) useful for classification resulted from a previous analysis of the temporal profiles of the spectral signatures of the main land-use classes. As shown in Figures 16 and Fig 17, the spectral responses of orchards and vineyards were close, whatever the year. Orchard NDVI appeared slightly higher than for the vineyards, mainly because, the vegetation development is more important for orchard than for vineyard and more orchards are also irrigated compared to vineyards (more wine than wine table). On these profiles, the cultural practices of the leaf thinning for vineyards and the cut of some orchard branches can be clearly detected in July. Different combinations of spectral bands have been explored particularly using SWIR and NIR bands, in order to better differentiate these crops and irrigation practices, but the signatures were not significantly different. For orchards, distinction between irrigated fields and non-irrigated field is clear while with vineyards little differences were observed, with higher NDVI in the non-irrigated case. This unexpected pattern can be explained by the fact that vineyards irrigation was done on fields dedicated to table grape which a very different structure than un-irrigated fields dedicated for wine production.

Based on selection of the acquisition time, an implementation of the classification led to the map given in Figure 18 with scores reported in Table 10.

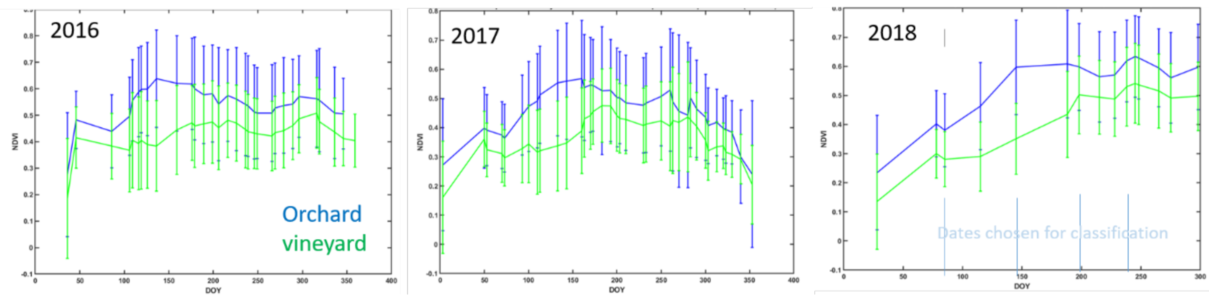


Figure 16. *NDVI over time (DOY) on two type of field (orchard in blue, and vineyard in green) for three different years.*

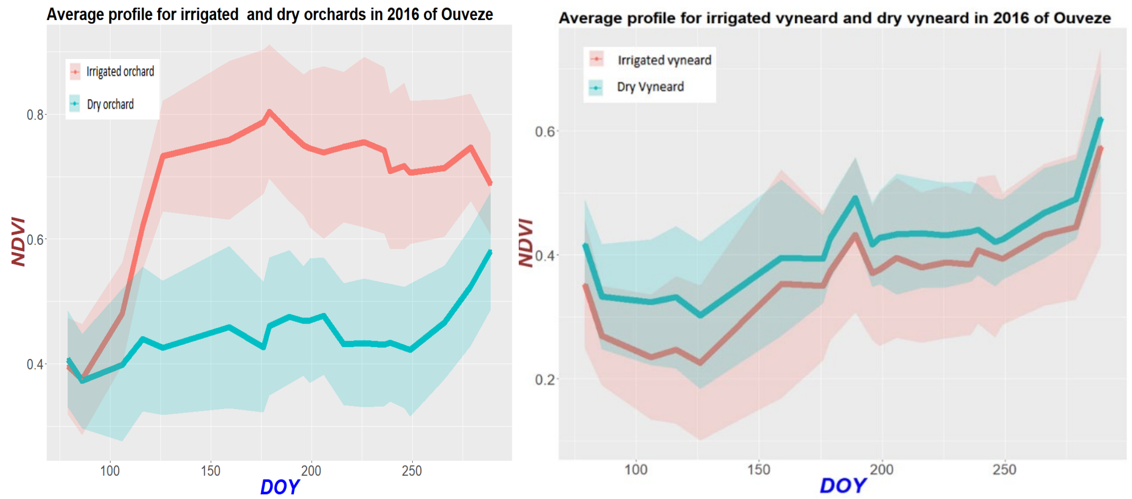


Figure 17. *NDVI over time (DOY) on two types of agricultural fields (irrigated field in red, and non-irrigated field in blue) for three different years.*

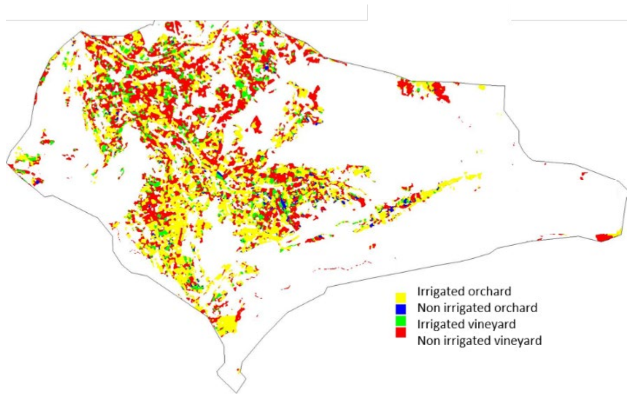


Figure 18. *Supervised classification by likelihood method obtained in 2018 on the Entrechaux site using the following Sentinel spectral bands: B2-3-4-8-11 acquired at 4 dates: 26/03/2018, 25/05/2018, 17/07/2018, 26/08/2019.*

Table 10. *Accuracy of the classification*

Total accuracy	Irrigated orchard	Non-irrigated orchard	Non-irrigated vineyard	Irrigated vineyard
62%	80%	13%	50%	24%

For the Crau case study, the best results in terms of LU classification were obtained with the SVM method (K-index 0.78). Figure 19 shows the resulting land use classification.

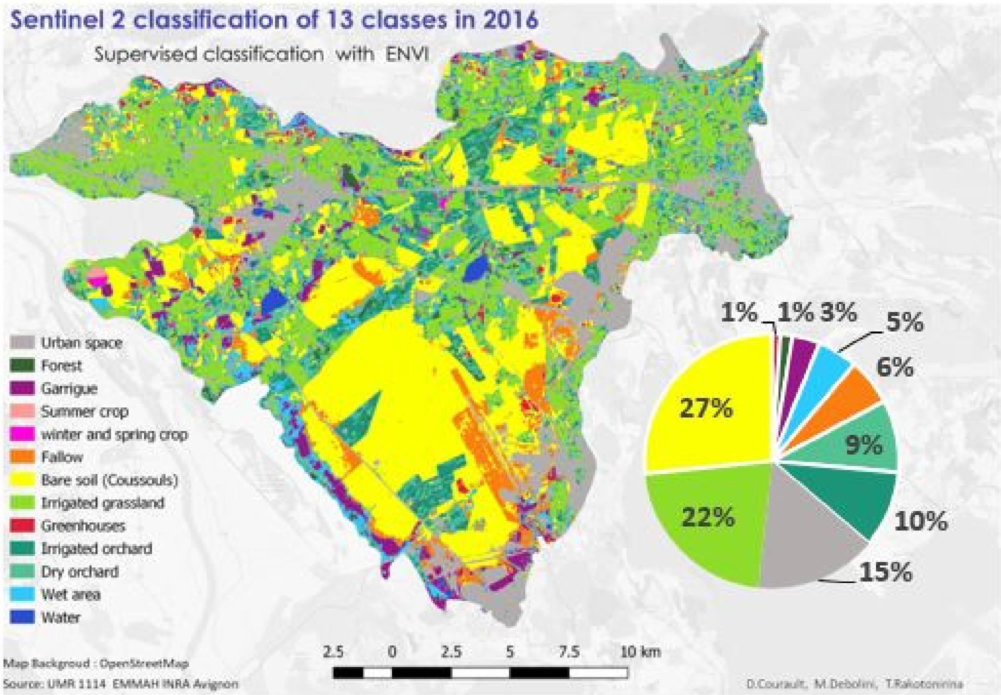


Figure 19. *Classification results made on the CRAU area*.

The evaluation of the classification was displayed in Table 11 which displayed good accuracy. Classification made using band are slightly better than that using spectral indices. Better results are obtained in 2017 thanks to the possibility of having more dates after the launch of Sentinel 2b.

Table 11. *Evaluation of the accuracy of land use classification using the SVM method.*

Type of classification	Overall accuracy %	Kappa index
SVM 2016 (band)	75	0.8
SVM 2017 (band)	84	0.71
SVM 2016 (indice)	76	0.72
SVM 2017 (indice)	80	0.75

Determining flooding patterns in the Crau site

The amount of water required per unit area depends on the distance to be covered by the flooding front to cross the field (hereafter to as the length of the irrigation unit) and thus allow the field being fully irrigated. Optimally, the shortest this distance is, the lowest amount of water is required. However, to save working time, farmers prefer to irrigate their field along the largest distance in order to have longer irrigation sequences. To determine the amount of water used to irrigate it is therefore important to characterize the length of an irrigated unit. The way to characterize such a length is to capture an irrigation event during which the field is partially flooded. The comparison of the shape of the flooding area and the geometry of the field give us an indication of the flooding direction (see Figure 20). The goal in OPERA was then to develop a method able to distinguish within a field flooded area from the non-irrigated area.

Figure 20. *Schematic scheme to determine flooded irrigation patterns.*

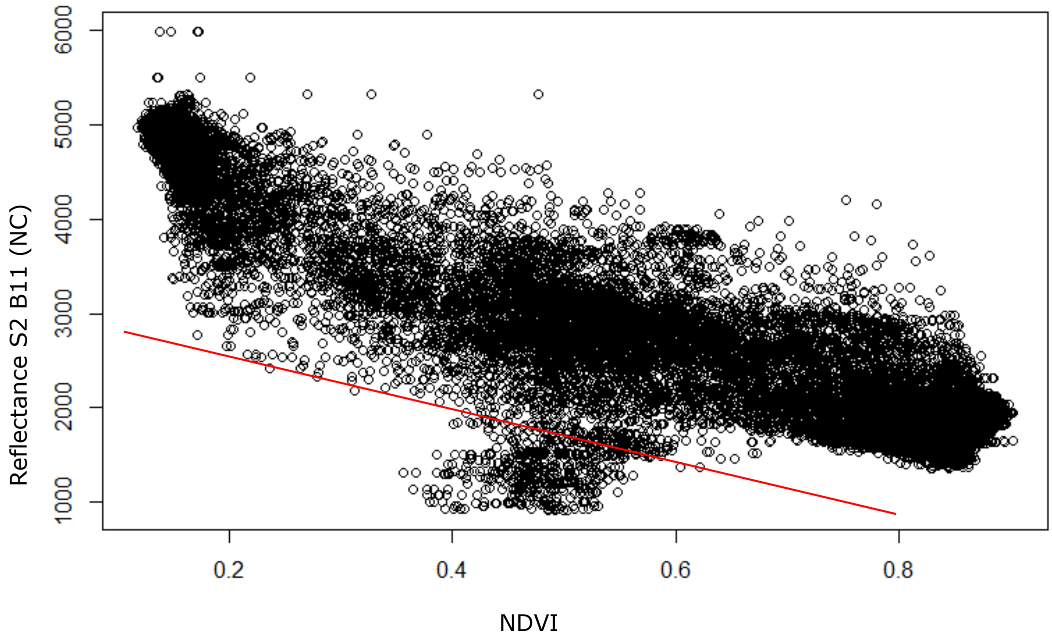


Figure 21. *Scatterplot between rsbu1= NDVI (NDVI is the Normalised Difference Vegetation Index) and Sentinel 2 Band 11 reflectance centred at 1613 nm. Each point corresponds to pixels classified in irrigated grassland for different dates though the growing season. The redline corresponds to a threshold below which the surface is assumed to be flooded.*

A few studies deal with spectral signature of flooded vegetation on grass. With rice, it has been shown that the LSWI (Land surface water Indicator) indicator involving the mid-infrared spectrum is suitable to detected flooded rice field while radar measurement made by Sentinel 1 can be a suitable approach thanks to strong specular reflexion on the free water plan. Many tests were done with radar measurement without leading to conclusive results. As the matter of facts speckle effects might be too strong with respect to signal induced by the free water plan (the specular reflexion being partly hidden by the scattering on the vegetation above this plan. The use of the mid-infrared was much more promising with a clear drop of the reflectance when the surface is flooded (Figure 21)

The results displayed in Figure have shown there is a threshold in B11 reflectance, below which the surface can be considered as flooded. This threshold depends on the plant development (NDVI in the Figure) but appears less clearly with well-developed vegetation covers (NDVI > 0.7). The drop in B11 reflectance can be explained by the contrast in soil moisture and its impact on the mid-infrared reflectance, flooded soil being saturated in contrast with the unflooded part of the field which is drier. Note that the presence of free water has little effect on the soil reflectance since water is almost transparent in that wave length band.

The equation to obtain this threshold line is the following:

TRB11S2=3617-3083·NVDI

where TRB11S2 is the threshold given in numerical count (NC). Applying such a threshold led to determine a flooded/not flooded status as displayed in Figure 22. After comparing the reflectance to the threshold in a given field, is declared as being irrigated if a minimum of 10 pixels is found as flooded, if the spatial localisation of the flooded pixels belongs to patches and if no rainfall larger than 20 mm were encountered during the last 3 data. Such filtering is required to avoid artefacts has the border effect or remaining saturated area.

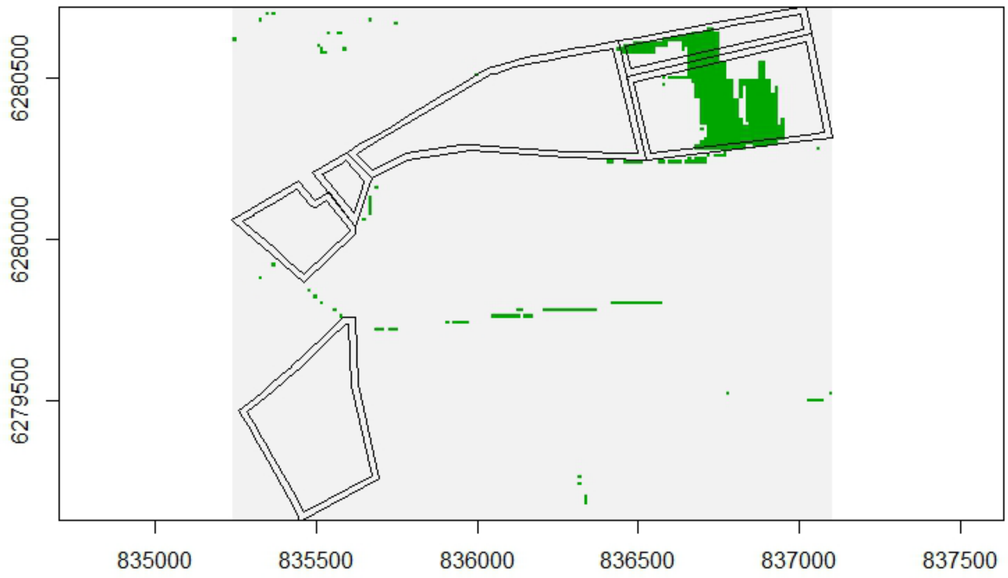


Figure 22. *Detected flooded pixel (in green) using the TR_{B11S2} threshold to flag the pixels. The fields are represented by the polygons. In each polygon a buffer of 20m was set to remove border effects.*

We can see in Figure 22 the flooded pattern with a clear vertical structure (South to North) with a strip that was fully irrigated and an adjacent strip in progress. The images show clearly a transversal irrigation with several sectors. Moreover, we can see that the two fields were merged and irrigated together. Note that an assessment of a method based on LSWI was done. The sensitivity of the indicator was less sensitive to flooding than using the B11 directly likely due to the combination with the near-infrared band and the normalised difference. However, the method based on the B11 was more sensitive to cloud effects that are partly mitigated in normalised indices. This feature will be further discussed.

The evaluation was done on three farms where irrigations were registered over 2016 (The first year with sentinel 2 acquisition) and 2017 (2018 irrigation calendars were not ready during the study). Results are displayed in Table 3.

Table 12. *Detection of irrigation events (Positive means that a field was identifiers has been irrigated).*

Farm	Number of field	year	True positive	False positive	Rate of good determination
Boisvert	55	2016	7	0	100%
		2017	11	2	85%
		2018	17	1	95%
Suffren	47	2016	4	0	100%
		2017	15	2	88%
		2018	18	2	90%
Aqueduc	23	2016	7	0	100%
		2017	16	1	94%
		2018	19	3	86%
Merle	9	2016	10	1	91%
		2017	19	1	95%
		2018	31	4	87%

Results displayed in Table 12 have shown a good skill in detecting irrigation events when observed. However, the number of irrigated fields during a year remains small in comparison to the total number of fields (between 17 and 34% in 2017 when both Sentinel 2a and 2b were operating). Capitalization of the results over several years will likely lead to better spatial coverage. Moreover, A method to analyse the shape of the flooded patch in order to determine the direction of the flooding front still has to be developed. At the end of this process, we expect having only a partial characterization of the area only. Therefore, to upscale the results to all irrigated grass fields a stochastic model will be still necessary. But the information given by our method will provide much more reliable statistics thanks to a large number of fields documented by our method

As mentioned in the previous section, the method is sensitive to atmospheric conditions. It was found that the cloud mask is not enough to flag pixel affected by the atmosphere. We found with some types of clouds that the pixels located at the border of the clouds are affected by the atmosphere. When processing a large series of images, filtering pixels is then an important issue. In our case we have expanded the cloud mask over a 1 km distance.

Conclusions

Orchard and vineyard detection. The discrimination between the orchards and vineyards on the Entrechaux site has shown worse results than in the Crau region for the different land use map tests. The best score was around 68% of accuracy. The main reasons were the complexity of the crops (small fields on a topography more pronounced, row plants with or without grass in inter rank, various tree ages more and less vigorous, and drip irrigation not easy to detect). Nevertheless, thanks to the large dataset collected during this project, we have improved the existing maps on this area. The distinction of the irrigation varied a lot according to the number of the learning points and the land use classes analysed. The best performances were obtained for the irrigated orchards globally better estimated (up to 80%) than the irrigated vineyards (max 50%). More investigations are needed to improve these first results. The analysis of Sentinel 1 VV and VH polarisations and other finer resolution images (Pleiades or drone images?) are planned in the next months to go further.

Flooded irrigation pattern detection. The developed method is tailored to answer a very specific question e.g. the detection of the flooded pattern associated with flooded irrigation techniques. There is still a need to develop a shape pattern analysis to determine the direction of irrigation. Once this will be achieved we expected to have a much larger data base to develop stochastic models to distribute length of the irrigation unit in every field. Detection of the flooded area can be further useful to detect rice flooding or flooded soils in winter

3 Conclusions

The innovations introduced in the OPERA project mainly concern the estimation of crop water needs for optimal irrigation and a good distribution of water resources at the scale of a territory (irrigated sector, catchment area) in shortage conditions. The assessment of water quantities is generally made to cover crop water needs in optimal conditions. The issue of deficit irrigation is only addressed in the method 2 developed by IRNAS-CSIC on olive orchard irrigation. Methods to address deficit irrigation must then be based on an assessment of the consequences of water shortage on production which remains challenging. In the case of the IRNAS-CSIC method, this was done by an ecophysiological approach that takes the coupling between photosynthesis and transpiration into account.

Among the innovation levels considered at the time of the project's submission (remote sensing, crop modelling, using meteorological forecast data and in situ sensors), sensor-based irrigation management was the least developed. This approach has been widely used in the past and has not been the subject of recent technological breakthroughs. Existing methods still face the problem of the spatial representativeness of sensors (spatial variation; calibration) and the constraints of sensor implementation. The reduction in sensor costs and the progress made in connecting these sensors to other information (e.g., models) could support new innovations in the future.

On the other hand, OPERA has been able to benefit from a technological breakthrough offered by the SENTINEL satellite earth observation mission, which makes it possible to develop new applications based in particular on the high temporal frequency (potentially every 5 days). In addition, the exhaustive spatial coverage and free access to images offer guarantees for the development of operational services. Most of the methods are based on the dynamics of leaf cover allowing:

- to directly characterize the water requirements by linking the cultural coefficient kc to the vegetation index (method 1 - NDVI-CW; Evenor, Spain);
- assimilate the LAI in the AQUACROP model to better understand the development of the cover simulated by the model (method 5 – IRRICROP; UNIFI, Italy);
- improve the classification of irrigated cropping systems by analysing foliar development over the entire cropping cycle (Method 6 - INRA, France). In this method, an original development was made to determine some characteristics of water supply in the case of gravity irrigation.

The use of soil-crop modelling is the second innovation level. Modelling makes it possible to synthesize climate, agricultural practices and soil and thus to take the role of soil into account, which plays a buffer role against climate variability through its water storage capacity. In addition, because crop models are climate-driven, the soil-crop are well suited to integrate weather forecasts. The main difficulty of these models remains the determination of the input parameters, which are numerous and can have a strong impact on the results. However, the development of spatial product soil, cropping systems, and climate, all being reinforced by the widespread use of remote sensing, can make it possible to implement them within an operational framework that requires parameters to be determined everywhere. In the OPERA project, methods 3 (WENR, the Netherlands), 4 (ITP, Poland), 5 (UNIFI, Italy) and 6 (INRA, France) are all based on soil-crop models. Their implementation in the project shows on some verification points that the models satisfactorily simulate the dynamics of water in the soil. The challenge now is to verify in a much more exhaustive way the robustness of such models implemented with easily accessible spatial information layers. Such verification is necessary to give credibility to the results and thus convince farmers to use such approaches. We can note the intermediate approach developed in method 2, where water needs and the consequence of hydric stresses are represented by a mechanistic model of stomatal conductance while soil control is indirectly derived from observations given stress sensors such as the measurement of the turgidity pressure of certain plant organs (stem, trunk, fruit).

Finally, we can highlight the use of weather forecasts that are now easily accessible at spatial scales of interest. While potentially all the methods developed in OPERA are likely to use them, the quality of these forecasts and the uncertainties apprehended by ensemble approaches have only been analysed within the framework of methods 3 (WENR) and 4 (ITP). These temperate climate assessments highlight uncertainties about poorly predicted precipitation over a few days. The representation of the uncertainties generated using ensemble forecast illustrates the uncertainties and their degradation when considering longer time windows. However, the median seems to be a reasonable estimator.

Perspectives: the work carried out in WP2 was focused on method development and a proof-of-concept. It is now necessary to build systematic evaluation strategies to demonstrate their robustness and improve their credibility with potential users. One of the main areas of progress lies in the combination of model/remote sensing/sensors.

4 References

Allen R.G., Pereira L.S., Raes D., and Smith M., 1998. Crop evapotranspiration. Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper No. 56, Rome, Italy.

Battista, P., Chiesi, M., Rapi, B., Romani, M., Cantini, C., Giovannelli, A., et al., 2016. Integration of Ground and Multi-Resolution Satellite Data for Predicting the Water Balance of a Mediterranean Two-Layer Agro-Ecosystem. Remote Sensing, Vol. 8, 731.

Boogaard, H.L., A.J.W. de Wit, J.A. te Roller and van Diepen. C.A.; 2011. User's guide for the WOFOST Control Center 1.8 and WOFOST 7.1.3 crop growth simulation model. Wageningen.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M. H., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., Richard, G., Beaudoin, N., Recous, S., Tayot, X., Plenet, D., Cellier, P., Machet, J. M., Meynard, J. M., and Delecolle, R., 1998. STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. Agronomie 18, 311-346.

Brisson, N., Launay M., Mary, B and Baudoin N., 2008. Conceptual basis, formalizations and parameterization of the STICS crop Model, Editions Quae, Paris, France ISBN 978-2-7592-0169-3

Buckley, T.N., Mott, K.A. and Farquhar, G.D., 2003. A hydromechanical and biochemical model of stomatal conductance. Plant Cell Environ. 26, 1767–1785.

Caiserman, A., Dumas, D., Bennafla, K., Faour, G., and Amiraslani, F., 2019. Application of Remotely Sensed Imagery and Socioeconomic Surveys to Map Crop Choices in the Bekaa Valley (Lebanon). Agriculture-Basel 9.

Cheng, G., Han, J. W., and Lu, X. Q., 2017. Remote Sensing Image Scene Classification: Benchmark and State of the Art. Proceedings of the IEEE 105, 1865-1883.

Diaz-Espejo, A., Buckley, T.N., Sperry, J.S., Cuevas, M.V., de Cires, A., Elsayed-Farag, S., Martin-Palomo, M.J., Muriel, J.L., Perez-Martin, A., Rodriguez-Dominguez, C.M., Rubio-Casal, A.E., Torres-Ruiz, J.M., Fernández, J.E., 2012. Steps toward an improvement in process-based models of water use by fruit trees: a case study in olive. Agric. Water Manag. 114, 37–49.

Doorenbos J. and Pruitt W.O., 1977. Guidelines for predicting crop water requirements. FAO Irrigation Drainage Paper No. 52, Rome, Italy.

Ferrant, S., Selles, A., Le Page, M., Herrault, P. A., Pelletier, C., Al-Bitar, A., Mermoz, S., Gascoin, S., Bouvet, A., Saqalli, M., Dewandel, B., Caballero, Y., Ahmed, S., Marechal, J. C., and Kerr, Y. (2017). Detection of Irrigated Crops from Sentinel-1 and Sentinel-2 Data to Estimate Seasonal Groundwater Use in South India. Remote Sensing 9.

Hernandez-Santana, V., Fernandes, R.D.M., Perez-Arcoiza, A., Fernández, J.E., Garcia, J.M. and Diaz-Espejo, A., 2018. Relationships between fruit growth and oil accumulation with simulated seasonal dynamics of leaf gas exchange in the olive tree. Agric. For. Meteorol 256–257, 458–469.

Hornbuckle, J., Vleeshouwer, J., Ballester, C., Montgomery, J., Hoogers R. and Bridgart, R., 2016. IrriSAT technical reference.

Kozhoridze, G., Orlovsky, N., Orlovsky, L., Blumberg, D. G., and Golan-Goldhirsh, A., 2018. Classification-based mapping of trees in commercial orchards and natural forests. International Journal of Remote Sensing 39, 8784-8797.

Kroes, J.G., J.C. van Dam, R.P. Bartholomeus, P. Groenendijk, M. Heinen, R.F.A. Hendriks, H.M. Mulder, I. Supit, and van Walsum, P.E.V., 2017. SWAP version 4. Theory description and user manual. Report 2780, Wageningen Environmental Research, Wageningen, the Netherlands.

Łabędzki L. and Kanecka-Geszke, E., 2009. Standardized evapotranspiration as an agricultural drought index. Irrigation and Drainage. Vol. 58, Issue 5, pp. 607-616, DOI: 10.1002/ird.421.

Łabędzki L. and Ostrowski, J., 2018. Precipitation preventing deficit of readily available soil water in arable soils in Poland. Atmosphere 9(4), 121; doi:10.3390/atmos9040121.

Maselli, F., Papale, D., Chiesi, M., Matteucci, G., Angeli, L., Raschi, A., Seufert, G., 2014. Operational monitoring of daily evapotranspiration by the combination of MODIS NDVI and ground meteorological data: Application and evaluation in Central Italy. Remote Sens. Environ., 152, 279–290.

Maselli, F., Papale, D., Puletti, N., Chirici, G., and Corona, P., 2009. Combining remote sensing and ancillary data to monitor the gross productivity of water-limited forest ecosystems. Remote Sensing of Environment, 113, 657–667.

Orynbaikyzy, A., Gessner, U., and Conrad, C., 2019. Crop type classification using a combination of optical and radar remote sensing data: a review. International Journal of Remote Sensing 40, 6553-6595.

Ostrowski, J., Łabędzki, L. and Kanecka-Geszke, E., 2015. Parameterization and cartographic presentation of water deficits of cultivated plants. International Agrophysics. Vol. 29. No. 3, 341-351. Doi: 10.1515/intag-2015-0041.

Rodriguez-Dominguez, C.M., Buckley, T.N., Egea, G., de Cires, A., Hernandez-Santana, V., Martorell, S. and Diaz-Espejo, A., 2016. Most stomatal closure in woody species under moderate drought can be explained by stomatal responses to leaf turgor. Plant Cell & Environ. 39, 2014–2026.

Smith, M., 1992a. CROPWAT: A computer program for irrigation planning and management. FAO Irrigation and Drainage Paper No. 46, Rome, Italy.

Smith, M., 1992b. Report on the expert consultation on revision of FAO methodologies for crop water requirements. Land Water Devel. Div., FAO, Rome, Italy.

Trout, T.J., Johnson, L.F. 2007. Estimating Crop Water use From Remotely Sensed NDVI, Crop Models and Reference ET. 2007 USCID Fourth International Conference on Irrigation and Drainage. Sacramento, California October 3-6, 2007; pp275-285