

Operational Precise Irrigation for Cotton Cultivation through the Coupling of Meteorological and Crop Growth Models

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Abstract In this paper, we tested the operational capacity of an interoperable model coupling system for the irrigation scheduling (IMCIS) at an experimental cotton (*Gossypium hirsutum L*.) field in Northern Greece. IMCIS comprises a meteorological model (TAPM), downscaled at field level, and a water-driven cultivation tool (AquaCrop), to optimize irrigation and enhance crop growth and yield. Both models were evaluated through on-site observations of meteorological variables, soil moisture levels and canopy cover progress. Based on irrigation management (deficit, precise and farmer's practice) and method (drip and sprinkler), the field was divided into six sub-plots. Prognostic meteorological model results exhibited satisfactory agreement in most parameters affecting ET_o , simulating adequately the soil water balance. Precipitation events were fairly predicted, although rainfall depths needed further adjustment. Soil water content levels computed by the crop growth model followed the trend of soil humidity measurements, while the canopy cover patterns and the seed cotton yield were well predicted, especially at the drip irrigated plots. Overall, the system exhibited robustness and

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good predicting ability for crop water needs, based on local evapotranspiration forecasts and crop phenological stages. The comparison of yield and irrigation levels at all sub-plots revealed that drip irrigation under IMCIS guidance could achieve the same yield levels as traditional farmer's practice, utilizing approximately 32% less water, thus raising water productivity up to 0.96 kg/m³.

Keywords Irrigation scheduling \cdot Precise irrigation \cdot Meteorological model \cdot Crop growth model \cdot TAPM \cdot AquaCrop

1 Introduction

Globally, the agricultural sector is considered as the dominant water user, accounting for approximately 70% of blue water withdrawals, and signifying the strong dependence of agricultural production on water availability. Climate change is expected to exert significant pressure on agricultural water resources availability, while irrigation water requirements will be globally increased by 70–90% until 2050 (Garrote et al. 2015; Kreins et al. 2015; Molle 2008). Precision Irrigation (PI) is part of the Precision Agriculture concept introduced in the '90s (McBratney et al. 2005), having the potential to lead towards the sustainable water use in farming, both under current and future climate conditions. PI has been defined as "the accurate and precise application of water to meet the specific requirements of individual plants or management units and minimize adverse environmental impact" (Raine et al. 2007). PI focuses on the application of precise amounts of water at the right place in the right time, applied uniformly across the field (Camp et al. 2006), or as recently stated "PI should consider spatial inhomogeneity and variability" (Sadler et al. 2005). Thereby, PI can increase the crop productivity, enhance the water use efficiency, reducing in parallel the irrigation energy costs (Shah and Das 2012).

The implementation of PI requires the combined use of existing tools (models, on-site monitoring systems, remote sensing, etc.), leading ultimately to the development of Irrigation Scheduling (IS), i.e., a time plan of future irrigation actions, based on forecasted meteorologic conditions and current soil and plant water needs. Drip irrigation, is at the moment, the most commercially used PI system, but more accurate and complex systems, emphasizing on the spatial inhomogeneous water distribution have been developed (Buchleiter et al. 2000; Duke et al. 1992; Evans et al. 2000). On the other hand, IS is mainly based on methods related to "soil water content" or to "plant based methods" (Jones 2004). Regarding the first category, scheduling of irrigation events is based on the soil moisture status. When the latter reaches a certain minimum threshold value, an irrigation event is triggered. On the contrary, plant parameters based methods are inspired by the fact that many plant physiological characteristics (stomatal conductance, sap flow, plant water status) are highly depending on fluctuations of "the water status in the plant tissues rather than bulk soil water content" (Jones 2004).

A more recent approach in IS is the application of Crop Growth Models (CGMs). These models, such as ISAREG (Teixeira and Pereira 1992), AquaCrop (Raes et al. 2009; Steduto et al. 2009), Mohid_Land (Simionesei et al. 2016), Daisy (Hansen et al. 1991) and SIMETAW# (Mancosu et al. 2015) are integrating aspects such as the soil water and soil nutrient balance to specific crop characteristics. CGMs provide to their users the option to perform different irrigation scenarios, evaluate existing irrigation schedules and search for optimal irrigation under certain constraints. The complexity as well as the robustness and precision of these models vary moderately.

Nevertheless, most of these IS tools have been used to a limited extent by the majority of the farmers. This situation can be attributed to one or more of the following reasons: some tools are too complicated for end users; and others are still under development, not commercialized, too expensive, inaccurate in their predictions or not widely known. These considerations have led the EU to fund the FIGARO Project, as part of an FP7 Program, with the overarching goal to develop an innovative, robust and user-friendly web-PI platform, contributing to the significant increase of water productivity. As an initial step in this project, we developed a system, known as 'Interoperable Models Coupling for Irrigation Scheduling' (IMCIS), to combine meteorological downscaled forecasts, produce predicted precipitation and evapotranspiration levels and initiate a crop growth model for soil water balance estimation and irrigation scheduling. Based on literature search, other integrated, operational systems combining meteorological, crop growth models together with field and remote sensing data are not available. Therefore, the novelty of IMCIS lies in the automatized integration of all of the above components into a system for water saving at farm level.

This paper presents in detail the methodological and functional framework of the system, as well as the results obtained when IMCIS was used in a precise irrigation experiment carried out for cotton in Northern Greece during the 2013 cultivation period. In this area, it is considered that from the irrigation water applied in a typical field, approximately 55% is used by the crop, 12% is lost through its transfer, 8% is lost through its application and 25% is considered as excess water, lost through evapotranspiration and surface runoff (Papazafiriou 1996). IMCIS capacity on improving water productivity was tested under the most commonly applied irrigation techniques in Greece, namely sprinkler and drip. Traditional farmer's irrigation strategy and irrigation scheduling based on IMCIS were further compared in terms of the water irrigated and the final seed cotton yield. The necessity of transition from traditional farming to the "new information era" of farming in Greece is highlighted.

2 Materials and Methods

2.1 IMCIS Application Site Description

The experimental site is located at Xanthi coastal plain in Northern Greece (41.046°N; 24.892°E; 13 m altitude), having a trapezoidal plan view, covering an area of 1.97 ha. The experimental field was cultivated with cotton and divided into 6 sub-plots, in which different irrigation treatments were applied during the cultivation period (May–October 2013). Each sub-plot contained 17–18 sowing lines. The irrigation treatments were defined based on the applied: a) irrigation system; and b) irrigation scheduling method. Therefore, three sub-plots were irrigated using sprinkler system, while the other three sub-plots were irrigated using drip irrigation. Irrigation scheduling in one drip and one sprinkler sub-plots was based on IMCIS results, while two other sub-plots were irrigated with 25% less water (defined as deficit irrigation) than that estimated by IS. Aiming to underline the value of PI, irrigation scheduling for the last two sub-plots was scheduled by the farmer. The irrigation method and practice for each sub-plot of the experiment are illustrated in Fig. 1.

Fertilization was uniform throughout all sub-plots to eliminate the impact of fertigation on plants growth. Before the start of the cultivation period, soil samples were collected from the field and Saturation Point (SP), Field Capacity (FC) and Permanent Wilting Point (PWP) were determined with pressure plate extractors, while the saturated hydraulic conductivity (Ksat)



Fig. 1 Irrigation management subplots at the experimental site (northern Greece)

was measured with the falling head method. Soil profiles for the crop growth model were created based on the soil analysis results presented in Table 1.

The instrumentation installed in the experimental site for in-situ monitoring included:

a) a meteorological station equipped with a telemetric unit, recording total solar radiation, barometric pressure, air temperature, humidity, precipitation, wind speed and direction.

Subplots	Layers	Saturation, SAT (%)	Field Capacity, FC (%)	Wilting Point, WP (%)	Saturated Hydraulic Conductivity, Ksat (mm/d)
1	0–35	38	28.1	13.99	196.9
	35-75	42.3	35.1	21.11	52.6
	75-175	44	34.8	25.7	82.7
2	0-35	38	28.1	13.99	196.9
	35–75	42.3	35.1	21.11	52.6
	75-175	44	34.8	25.7	82.7
3	0-35	43.0	33.5	20.9	169.9
	35-75	48	41.2	28.5	82
	75–175	48	41	33.6	55.6
4	0-35	37.3	24.5	10.4	169.9
	35-75	41.5	33.5	23.9	82
	75–175	43	33.11	23.6	55.6
5&6	0-35	39.9	27.8	16.6	612.5
	35-75	51	36	26.2	81.8
	75–175	51	36	26.1	57.3

Table 1 Soil input parameters for Aquacrop implementation

Data were automatically transferred to a server with a 15-min time-step and daily and monthly data reports were produced.

 a Sentek's Diviner 2000 capacitance probe to determine soil water content profiles up to 100 cm depth, for 9 points within the experimental field. Soil water measurements were conducted approximately once per week.

As a plant growth indicator, the green Canopy Cover (CC) was used. CC was determined throughout the whole experiment through cell-phone photos, obtained from the same height above ground, thus covering the same area in each sub-plot. Photographs were transferred to a PC and processed with the GIMP image editor to calculate the respective CC values.

2.2 Interoperable Models' Coupling

The methodological framework followed to develop the interoperable models' coupling system for irrigation scheduling (IMCIS) is presented in Fig. 2. Two numerical models lie in the core of this system, namely TAPM and Aquacrop. TAPM model serves as a weather



Fig. 2 Data flow and model sequence constituting the interoperable models' coupling system for precise irrigation (IMCIS)

prognostic model driven by the Global Forecasting System (GFS) to produce a five-day weather prediction. Initial GFS low-resolution $(0.5^{\circ} \times 0.5^{\circ})$ data were further downscaled using the TAPM model and weather predictions were corrected every second day, based on data recorded by the meteorological station installed in the study field. The high-resolution meteorological forecasts, produced by TAPM, were further used to calculate reference evapotranspiration (ETo), on a daily basis, by applying the FAO-56 Penman-Monteith method (Allen et al. 1998). The whole process was automatized through a Python script to compose the climate file imported in AquaCrop model. The AquaCrop plug-in (v.4.0) simulates crop growth and water balance for a specific soil profile and a specific crop. The IMCIS process, initiates daily at 06:00 AM, prepares and stores all files at the appropriate format and server location for the examined crop field. The process ends within an hour and the user assesses all historic and prognostic information regarding the current soil water content (SWC) levels, the plants growth stage and the upcoming precipitation events. Based on the above-mentioned data, the user is able to determine an irrigation schedule. Moreover, the consistency of crop growth and water balance simulations are checked by SWC and CC measurements, respectively, conducted on the field, and the appropriate adjustments are made in AquaCrop parameters to improve the performance of the model.

2.3 The Weather Prognostic Model

The Air Pollution Model (TAPM) is an operational prognostic meteorological and pollutant dispersion model (Hurley and Luhar 2009; Hurley et al. 2005). This model is used for the first time as a tool providing localized, short-term forecasts for precision agricultural management. It solves the momentum equations for horizontal wind components; the incompressible continuity equation for the vertical velocity in a terrain-following coordinate system; and the scalar equations for potential virtual temperature, specific humidity of water vapor, cloud water/ice, rain water and snow.

Aiming to derive the predicted weather conditions for the next five days at the PI experimental site, TAPM was configured on a five-nested grids mode, with constant horizontal spacing at each grid, reaching the level of the experimental field size $(300 \times 300 \text{ m})$. TAPM at first solves the governing equations for the outer grid and progressively the inner grids are solved. In the present case, the outer grid was supplied by synoptic forecasted data with $0.5^{\circ} \times 0.5^{\circ}$ spatial resolution (NOAA/GFS), covering the area 8-28° E and 34-45° N. GFS outputs were then interpolated vertically from the Eta model levels to the pressure levels and horizontally from the Arakawa E-grid to a regular un-staggered A-grid, to agree well with the grid spacing of the coarse synoptic grid. The model provides hourly values for wind speed and direction, air temperature, relative humidity, net radiation, extraterrestrial radiation, sensible and evaporative heat fluxes, and rainfall rates. Forecasted results at the farm level grid were compared to the on-site meteorological station for model calibration and validation. Further, model forecasted parameters were utilized to estimate the hourly ET_o-values, integrated on a daily basis and serving as inputs to the crop growth model.

2.4 The Crop Growth Model

AquaCrop (v.4.0) model is a water-driven model simulating the growing cycle of grains, vegetables and root-tuber crops. It requires as inputs only explicit and intuitive parameters and variables, and produces as output a considerable balance between accuracy, simplicity and

robustness (Battilani et al. 2014; Farahani et al. 2009; García-Vila et al. 2009; Hussein et al. 2011). The model calculates the daily transpiration T_r according to an empirical parameterization, as:

$$T_r = K_S \times CC^* \times K_C T_{rx} \times ET_0 \tag{1}$$

where: ET_o is the reference evapotranspiration; $K_cT_{r,x}$ the mid-season crop coefficient, adjusted for crop ageing and possible adverse early senescence effects (Allen et al. 1998); K_s the soil water crop coefficient integrating water logging, stomatal closure and early senescence effects; and CC^* the adjusted to micro-advective effects green canopy cover, given by:

$$CC^* = 1.72CC - CC^2 + 0.30CC^3 \tag{2}$$

The cumulative aboveground dry biomass (B) is estimated utilizing the daily ratios of T_r over ET_o , and the water productivity (WP), a parameter expressing the biomass increase per mm of water transpired by the plants, as:

$$B = WP \times \sum \frac{Tr}{ET_0} \tag{3}$$

The final seed cotton yield (Y) is derived as the product of B on the harvesting day, and the harvest index HI, i.e., the percentage ratio of seed cotton yield to aboveground dry biomass, as:

$$Y = B \times HI \tag{4}$$

The model solves the soil water balance equation (Allen et al. 1998) to estimate the deficit of water in the root zone (D_r). Three SWC threshold limits define the plant water stress status: the first threshold refers to the optimum canopy cover expansion (W_{exp}); the second indicates the stomatal closure effect (W_{sto}) and the third the triggering of the early canopy senescence (W_{sen}). These threshold levels differ among cultivars. Based on the above, three different types of data were imported into AquaCrop model through IMCIS, corresponding to meteorological, cultivar and soil profile data.

2.5 Irrigation Scheduling Algorithm

The decision of when and how much to irrigate depends on the root-zone depletion level, the plant development stage and the levels of soil moisture threshold limits. During the initial rapid plant-growing phase, for approximately 70 days after sowing (DAS), the actual soil water content (Wr) in the root zone should remain close to the optimum canopy cover expansion threshold. After this period, "regulated deficit irrigation" regimes could be implemented, to control the excessive vegetative growth, as well as to improve the HI, and consequently, the final yield (Chalmers et al. 1981). Considering the above, the IS algorithm applied in the current IMCIS is presented in Table 2, exhibiting details on the irrigation scheme followed during the different stages of cotton growth. When an irrigation criterion is met, but the meteorological model predicts a precipitation event within the next 3 days with a depth \geq 7 mm, then irrigation is postponed. After the event, even if it happens or not, IMCIS recalculates the soil water balance and a new IS is created. The threshold of 7 mm was arbitrarily set, based on the mean daily cotton evapotranspiration (~ 5 mm). Additionally, the temporal 'window' of 3 days as a forecast limit was based on the uncertainty of the weather prediction and the fact that postponing irrigation for 3 days will not severely harm cotton plants.

Table 2 Irrigation a	dgorithm for different cottor	n development stages		
Days after sowing	Stage	Plant Development Stage	Irrigation objective target	Irrigation Criterion (IC) - Irrigation Amount (IA)
1–14	Emergence	Almost 90% of the cotton seeds are emerged.	Soil water content on the upper soil layer should be retained close to FC levels.	IC: $W_r \le W_{FC}$ -15 IA = W_{FC} - W_r
15-70	Rapid Growing Stage	Plants keep growing producing new stems and increasing rapidly their green canopy cover.	Soil water content at the root zone must be retained to the required levels for maximum canopy growth.	IC: $W_r \le W_{exp}$ IA = $W_{FC} - W_r$
71–113	Lag Growing Stage	Flowering is triggered; plant's green canopy cover increases, until its maximum; color in blossomed petals changes from creamy white to yellow and then into pink; Petals are withered and bolls are created.	Soil water content at the root zone should be retained at levels slightly lower than those needed for maximum canopy growth	IC: $W_r \le W_{exp} - 10 \text{ IA}$ = $W_{FC} - W_{exp}$
114-169	Senescence - Maturity	Plants reach maximum height; moist fibers are created and grow inside the bolls; finally, bolls are opened and the fluffy cotton bursts forth; approximately on day 123 cotton senescence is triggered, resulting into the slight decline in green canopy cover.	Water levels should fluctuate above stomatal closure and below maximum canopy growth levels.	$ W_r \leq W_{sto} + 10 $ IA = 6–18 mm
W _{FC} SWC in FC (ir	1 mm), W _r actual SWC (in 1	mm), W _{exp} SWC for optimum canopy expansion (in n	nm), W _{sto} SWC triggers stomatal closure (in mm)	

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2.6 System Performance Evaluation

The standard Taylor diagram (Taylor 2001) was used to evaluate the fidelity and robustness of TAPM and AquaCrop models. On this diagram three statistical parameters are displayed; the correlation coefficient (r), as:

$$r = \frac{\frac{1}{N} \sum_{n=1}^{N} (O_n - O)(S_n - S)}{\sigma_O \sigma_S}$$
(5)

the centered Root Mean Square Difference (cRMSD), as:

cRMSD =
$$\sqrt{\frac{1}{N} \sum_{n=1}^{N} \left[(O_n - O)(S_n - S) \right]^2}$$
 (6)

and the ratio of the standard deviations of the observed and simulated data (σ_o , σ_s), where O_n and S_n represent the observed and the simulated values, respectively; and *S* the corresponding observed and simulated mean values; and N the number of measurements.

For IMCIS evaluation in terms of yield production, the Relative Yield (RY) indicator (t/t), defined as the measured yield normalized by the local potential yield, was used. In Northern Greece, a potential seed cotton yield is roughly 4.5 tons (seed cotton yield)/ha.

$$RY = \frac{\text{Actual Yield}}{\text{Potential Yield}}$$
(7)

The contribution of IMCIS on improving the efficiency of the distributed water (irrigation + effective precipitation) was evaluated through the Water Productivity WP (kg/m³) determined as:

$$WP = \frac{Y_{act}}{AW} \tag{8}$$

where: Y_{act} is the actual marketable dry crop yield (kg/ha); and AW the available water in terms of irrigation and effective rainfall (m³/ha).

3 Results

3.1 TAPM – AquaCrop Performance Evaluation

The results obtained from the prognostic meteorological model TAPM (300×300 m grid) during the cultivation period were compared to the corresponding data from the meteorological station. The trends between predicted and measured data were found to be tuned fairly adequate (Fig. 3, 4a). Atmospheric temperature and ET_o appeared satisfactorily simulated (Fig. 4b), exhibiting a slight overestimation in the case of air temperature (cRMSD =0.4; r = 0.95; $\sigma_s = 1.02$) and a minor underestimation in the ET_o prediction (cRMSD =0.4; r = 0.94; $\sigma_s = 0.89$). However, TAPM did not perform with the same robustness regarding the prediction of wind speed, relative humidity and precipitation depth. Wind speed depicted overall significant underestimation ($\sigma_s \sim 0.25$) with a relatively low correlation ($r \sim 0.7$) and a



Fig. 3 Temporal variation of daily-mean meteorological parameters at the experimental site during the cotton cultivation period: **a** air temperature, **b** solar radiation, **c** wind speed, **d** relative humidity. Red lines represent recorded data, blue lines represent the TAPM forecasts

cRMSD approximately of 0.8. This could be attributed to the fact that TAPM predicted the wind speed at the height of 10 m above ground, while the field weather sensor was at the height of 2 m above ground. Similarly to the wind speed, precipitation depth was systematically underestimated by the model (cRMSD =0.9; r = 0.41; $\sigma_s = 0.45$). It is noteworthy that



Fig. 4 a Temporal variability of the recorded (*red bar*) and forecasted (*blue bar*) daily precipitation and evolution of daily ET_o based on measurements (*red line*) and model forecasts (*blue line*), during the cotton cultivation period at the experimental site; **b** Taylor diagram for the assessment of TAPM model operational forecasts

despite these discrepancies in the precipitation depth prediction, especially in the cases of heavy rainfall, precipitation events were accurately predicted by the model (Fig. 4a). These errors may be attributed to the unstable atmospheric conditions prevailing in the area during spring, and the problematic NOAA/GFS forecasts imposed as boundary conditions at the outer grid. Relative humidity simulation presented the worst results in both terms of accuracy (cRMSD =0.95) and precision (r = 0.55).

AquaCrop model overall performance was quite satisfactory. Figure 5 illustrates the predicted and measured CC-values at each sub-plot during the cultivation period. Model's ability to simulate the CC evolution was assessed through a Taylor diagram (Fig. 6a). Sub-plot 1 exhibits the best fit, with cRMSE and σ_0 equal to 0.32 and 1.03, respectively, while r reached 0.95. AquaCrop overestimates observed conditions in sub-plots 4 and 6, while it underestimates sub-plot 2. On the contrary, sub-plots 1, 2 and 6 were correctly phased, with r > 0.9, whilst sub-plots 3, 4, 5 and 6 depicted cRMSE-values above 0.5. Regarding seed cotton yield, the model performed better for drip irrigation experiments (Fig. 6b), with σ_S and cRMSD equal to 0.99 and 0.51, respectively, while the correlation coefficient approximated 0.9. In the case of sprinkler irrigated sub-plots, the model seems to overestimate significantly the seed cotton yield ($\sigma_S = 2.7$; cRMSD =2.16). Finally, considering all experimental sub-plots, it appears that the model simulated the seed cotton yield reasonably well ($\sigma_S = 1.39$; cRMSE =0.97) with a substantial correlation to observed data (r = 0.72).

Figure 7 illustrates the SWC variability as simulated by AquaCrop model and measured by Diviner 2000, in sub-plot 1, during the cultivation period. Even though the trend between the measured and observed soil water moisture followed the same pattern, in some cases the



Fig. 5 Canopy cover change as simulated by AquaCrop (solid line) and measured on-site (points) at all subplots during the cotton cultivation period



Fig. 6 Taylor diagram assessing AquaCrop's simulation efficiency **a** for canopy cover estimation at all subplots; **b** for seed cotton yield estimation, as harvested at the drip, sprinkler and all subplots

measured SWC depicted substantial higher or slightly lower values than those simulated. This can be attributed to the fact that the Diviner measurements were performed utilizing the manufacture's calibration curve, while previous studies indicated that a site specific calibration is needed for more accurate measurements (Al-Ain et al. 2009; Evett et al. 2006; Geesing et al. 2004; Paraskevas et al. 2012). Additionally, the SWC showed a significant deviation among the different measuring points within the sub-plot, underlining the spatial inhomogeneity of the soil physical properties, as well as the uneven distribution of water during the irrigation events due to imperfections of the irrigation system.

3.2 IMCIS Performance Evaluation

The actual seed cotton production, the estimated through IMCIS seed cotton production and the amounts of water irrigated in each sub-plot are summarized in Table 3. Total precipitation



5	7	5

Plot	Irrigation practice	Irrigation Method	Irrigated Water (mm)	ICMIS Simulated Yield (ton/ha)	Harvested Yield (ton/ha)
1	Drip	Deficit	227	3.284	3.393
2	Drip	Precise	271	3.720	4.303
3	Drip	Farmer	368	4.425	4.484
4	Sprinkler	Deficit	351	3.426	3.939
5	Sprinkler	Precise	351	3.040	3.454
6	Sprinkler	Farmer	400	4.510	3.939

Table 3 Irrigation method and amounts, actual and simulated seed cotton production at each sub-plot

depth during the cultivation period was 178 mm. Sub-plot 1 (deficit drip irrigation) received the minimum amount of water (227 mm), while sub-plot 6 (farmer's irrigation with sprinkler) the maximum (\sim 400 mm). Due to restrictions related with gun irrigation radius, the implementation of initial planning was hampered, and therefore, sub-plots 4 and 5 were irrigated with the same amounts of water (determined by the IMCIS).

Using IMCIS on a daily basis as an irrigation scheduling tool for the precise management of cotton irrigation in sub-plots 2 and 5, the root zone depletion during the plant rapid growing phases was constantly kept above the optimal canopy cover threshold level (Fig. 8). During the remaining cultivation period, SWC was maintained through irrigation above the early canopy senescence threshold level. In sub-plot 1 (deficit drip), irrigated water was 25% less than that irrigated in sub-plot 2 (drip IMCIS).

Regarding the harvested seed cotton production, the maximum yield was produced at the drip-irrigated sub-plots 2 and 3, whilst the lower at the drip deficit-irrigated sub-plot 1. When the final seed cotton yield was normalized, based on the local potential yield of 4.5 tn/ha, IMCIS drip and farmer drip sub-plots, as well as sub-plots 4 and 6 achieved relative yield values ~ 0.9 t/t (Fig. 9a). The worst performance was depicted in the deficit drip sub-plot, with a relative yield equal to 0.75 t/t.

Additionally, when the rational management of the available distributed water was evaluated (Fig. 9c) the sub-plots 2 and 1 showed the best performance with a WP equal to 0.96 kg/







Fig. 9 Precise irrigation assessment parameters for the different subplots, regarding **a** the relative yield (t/t), **b** water savings (%), and **c** water productivity (kg/m³)

m³ and 0.84 kg/m³, respectively. Sub-plots 3 and 4 had a moderate performance (WP = 0.7–0.8 kg/m³), whilst the IMCIS sprinkler and farmer's sprinkler irrigated treatments exhibited the lowest water productivity (WP ~ 0.67 kg/m³). Using as basis the most irrigated treatment (farmer's sprinkler), the deficit drip and IMCIS drip sub-plots consumed 43% and 32% less irrigated water, respectively (Fig. 9b). The farmer applied 8% less water at drip cotton treatment compared to the sprinkler treatment.

4 Discussion

In this study a novel system (IMCIS) was devised and tested in a typical cotton field of northern Greece, irrigated with various irrigations techniques and strategies. IMCIS consists an agro-engineering approach for IS management at field-scale, by involving: a) explicit soil textural and hydraulic characteristics; b) short-term meteorological predictions and relevant soil-water balances; c) in situ monitoring of soil available moisture and crop-growth development stages; and d) tools for optimal crop-growth and total yield forecasts, based on external dominant factors and irrigation strategies followed. By the end of FIGARO project it is expected that the finalized IMCIS system will be commercialized providing a reliable, low cost, user-friendly tool for the public services and individual IS consultants. On the other hand, the system will offer to the farmers the simple information they need and understand "when and how much to irrigate", allowing them to save water and reduce energy costs.

Until now, few works in the literature propose a validated and operational PI system leading to decisions on irrigation scheduling, and even less studies have integrated the above-described individual components. Al-Kufaishi et al. (2006) followed a similar approach using the AMBAV agro-meteorological toolbox to assess the irrigation needs for sugar beet in Germany. Casadesús et al. (2012) developed an algorithm for irrigation scheduling using daily evapotranspiration estimates (not forecasts), on-line soil and crop monitoring, and tuning and re-adaptation procedures to control the agro-system. Yunping et al. (2009) developed an intelligent system for precision agriculture, based on web-GIS services, able to incorporate geo-referenced soil properties, integrate existing web-based weather predictions, and utilize soil databases to assist PI decision-making. Based on historical climate data analysis, Geerts et al. (2010) used AquaCrop model to create three different irrigation scenarios for dry, normal and wet years for quinoa cultivar in Central Bolivian Altiplano. Utilizing the advances in artificial computation intelligence, Perea et al. (2015) developed an Artificial Neuro-Genetic Network for a short-term determination of water demands.

In the present study, the prognostic meteorological model TAPM was utilized for the first time as a tool providing localized, short-term forecasts for precision agricultural management. These forecasts were linked to an ET_o -Python script to solve the water balance for the next five days, and force a crop growth model (FAO AquaCrop) to assess existing soil water content and irrigation needs to reach the optimal crop growth conditions. The above model 'chain' was run automatically on a daily basis through the use of the IMCIS and results were consistently evaluated by on-line sensors and manual systems, throughout the various cotton growth stages.

When assessing meteorological forecasts during this downscaling, it was obvious that relative humidity and precipitation depths were connected and depended on model's microphysics; therefore, it was not surprising that when one of these two parameters was not well predicted, this also affected the other. Generally, it is difficult to predict rainfall levels with a high degree of accuracy for short term forecasting. Several techniques have been proposed in the literature to predict daily precipitation depths utilizing regional circulation model results through the application of linear and non-linear multi-regressions, fuzzy models and neural networks (Wetterhall et al. 2008). Our rainfall predictions could be improved by examining the patterns hidden in historic synoptic datasets (as provided by NOAA/GDAS), regional and local precipitation forecasts (provided by TAPM) and local weather stations. Even if wind speed and relative humidity correlation coefficients were relatively low, ET_o correlation was rather higher. This was attributed to the relatively high degree of accuracy in the air temperature and the fact that the weight of the latter in the FAO-56 Penman-Monteith equation is significant.

AquaCrop model simulated quite satisfactorily the CC growth pattern and the seed cotton final yield, especially at the drip irrigated plots. On the contrary, model's performance at sprinkler irrigated plots appeared rather poor. This could be attributed to the substantial water losses experiencing sprinkler systems due to evaporation and drift during irrigation events, as well as to the uneven water distribution along these sub-plots, affecting the input irrigation file. Li et al. (2015) developed a model to simulate the sprinkler water distribution, while Tarjuelo et al. (2000) proposed a model to estimate the losses of the irrigated water, but such models were not considered in the present study. Their impact on AquaCrop performance could be the subject of future research. Nevertheless, considering the fact that IS during this experimental period was based on a crop file created by a previous study and the uncertainties in the sprinkler irrigated amounts, AquaCrop's overall performance appears rather satisfactory.

Overall, the drip irrigated treatments achieved a more rational use of the available water resources (WP > 0.8 kg/m³), indicating the need of precise irrigation systems if IS based on PI is to be applied. The IMCIS drip sub-plot scored the maximum WP, while at the same time resulted in RY > 0.9 t/t, highlighting the potential role it could play in the reduction of fresh water consumption from the agricultural sector in Greece. Farmer's empirical IS achieved a marginally higher RY, but a substantial lower WP. It is noteworthy that by just utilizing the drip system, even the farmer irrigated 8% less water than the amount applied using the hose-traveling sprinkler system. The combined use of drip irrigation and PI through IMCIS reduced water use by 33% compared to farmer's sprinkler practice.

Based on the irrigated amounts of the current experiment and the fact that on the plains of northern Greece roughly 32,000 ha of cotton are cultivated annually, a single transition from sprinkler to drip systems could save approximately 10.2 million m³ of fresh water per year, while the utilization of IMCIS could lead to water savings of 41.2 million m³ per year. The potential water savings through the combined use of drip and precise irrigation is well-known concept. Nevertheless, quantified data regarding the potential water savings for cotton cultivation in northern Greece are reported herein for the first time.

5 Conclusions

In this paper the structure and implementation of an interoperable coupled models system (IMCIS), combining a meteorological model, an ET_o calculation script and a crop growth model, and integrating on-line sensors and manually collected datasets is presented. The system was tested at an experimental field for cotton cultivation in Northern Greece, divided into sub-plots of different irrigation treatment. The experiment proved that it is feasible to manage irrigation – in terms of timing and quantities – based on the short-term meteorological predictions, downscaled at farm-level, the soil moisture content and the estimated crop water demand according to its growing stage. Results showed that if precision irrigation is to be implemented in Greece, a transition from the sprinkler to drip irrigation systems is required, as the latter can significantly raise the water productivity, while its combination with precision irrigation could further enhance system's efficiency and productivity. The IMCIS could be further improved through the development of a precipitation statistical downscaling module, a local calibrated crop file, accurate SWC measurements and the introduction of an expert decision support system, optimizing irrigation and yield.

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