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EVALUATION OF DIFFERENT TOOLS FOR AGRICULTURAL WATER ASSESSMENT AT DIFFERENT SPATIAL SCALES

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Abstract

Water saving is nowadays one of the most important focus of agricultural research, aiming at a more sustainable and targeted use. To achieve this purpose, several tools to support irrigation water management and assessment have been developed that can be adopted at different levels, from farmers to water authorities.

This study evaluates different regional tools, at different spatial scales, to assess their reliability and for identifying possible improvements for a concrete use to support farmers and land reclamation consortia.

In the first section, a comprehensive sensitivity analysis to quantify the robustness and possible improvements of two agro-hydrological models (CRITERIA-1D and Aquacrop) is conducted at field scale. Precipitation, leaf area index, soil texture and groundwater levels are implemented firstly basing on freely available datasets, and then improved basing on field observations. The analysis is performed on two model outputs: irrigation water requirement and water fluxes at 1 m soil depth. In the second section, a remote sensing crop classification by means of NDVI maps analysis is evaluated at district-scale. For the assessment, farmer-reported information are used as ground truth classification. In the third section, the two crops data are integrated in two modelling frameworks with different aims: CRITERIA-1D integrated with forecasting weather data and remote sensing classification; Irriframe model integrated with observed weather data and declared crop information. Measured irrigation withdrawals are then used to evaluate the two modelling tools.

Despite the data-rich environment at Emilia Romagna region, the sensitivity analysis shows the non-representativeness of regional datasets for the specific field application. On average, models prove to be mostly sensitive to the shallow groundwater level, suggesting a denser piezometers network to better estimate irrigation water needs. The remote sensing crop classification presents in general a good agreement with land use information, although the identification of several potential irrigated areas not declared by the farmers. Looking at the comparison between the estimated and measured seasonal volumes, there is a fair correspondence, with major differences attributable to the areas considered by the two modelling frameworks. On the contrary, looking at the volumes trends, no correspondence between estimations and measurements is found, mainly due to the non-consideration by the models of specific agronomical practices.

Overall, field-scale models application leads to very different results, mainly when the groundwater is shallow. For this reason, to provide support for the water management at this scale, the study suggests more specific model settings and calibration, with focus on the capillary rise process simulated by the two models. On the contrary, the seasonal estimated requirements by the modelling framework at district-scale performed better. For this reason, application at this distributed scale allows land reclamation consortia to meet legal requirements, even exploiting innovative technologies (i.e., remote sensing) to forecast water use. Some possible improvements are still identified also at this scale for the detected irrigated areas and the integration of additional irrigation practices into the models. More user-friendly modelling frameworks and greater collaboration between research and water actors should be also considered to make these tools more usable.

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1. INTRODUCTION AND MOTIVATION

In August 2021, the Intergovernmental Panel on Climate Change (IPCC) has defined climate change as widespread, rapid, and intensifying. In the agricultural context, increasing world temperature brings to the reduction of water availability and, with its influence to precipitations trends, to the alteration of the crop cycle (Masson-Delmotte et al., 2018; Shukla et al., 2019). Farmers has to adapt their practices to the new climate conditions, year-by-year, facing new difficulties, both managerial and economics (Huang et al., 2020; Masud et al., 2017). Drought together with crops water requirements will increase, bringing to lower yields and to the spread of new plant diseases.

Due to the growing human population, in recent decades the agricultural sector has been intensified and adapted to a globalised production system, to meet the world's growing food demand. Forests are constantly exterminated, aiming the agricultural expansion, and the use of fertilisers has increased to achieve better performances and yields. Nowadays agriculture represents the sector with the highest use of freshwater (i.e., the 70 % on average, https://www.fao.org/aquastat/en/overview/methodology/water-use) and a significant source of greenhouse gas emissions (Horton et al., 2021; Tang et al., 2021). Therefore, agriculture is a sector significantly affected by climate and environmental changes, but at the same time can be considered one of the major contributors (Foley et al., 2011).

Focusing on irrigation practice, climate change affects freshwater quality and quantity, from superficial to groundwater sources. Glaciers melting and consequent sea level rise will increasingly disclose the problem of water resources salinization, affecting water supply in coastal areas. It follows that the preservation of water in the agricultural sector is of fundamental relevance, to ensure as much as possible a lower agricultural water footprint and a sustainable use of the irrigation resource. From farmers to policymakers, resource management should increasingly be shaped on the new sustainable policies, from saving to choosing the most efficient irrigation method.

The overall mismanagement of irrigation water resources frequently results in considerable water withdrawals by far greater than the ones required for crops. Consequently, agricultural policies have acted on this. The European Water Framework Directive (WFD, 2000/60/CE) has the aim of preventing the qualitative and quantitative deterioration of water, improving its status and ensuring its sustainable use (Wriedt et al., 2009). In Italy, it has been incorporated through the Ministerial Decree dated 31st July 2015 (DM 31/07/2015, n.d.) set out by the Ministry of Agriculture, Food and Forestry Policies (MIPAAF). Guidelines to regulate irrigation volumes quantification method have been defined. More specifically, 100 [l s^{-1}] average represents the flow rate above which regions are obliged to impose the withdrawals measurements. Under 50 [l s^{-1}] average, obligation no longer exists. Between 50 and 100 [l s^{-1}], guidelines ask that land reclamation consortia *estimate* irrigation water withdrawals using instruments and/or suitable methods, in collaboration with regions and Public Administrations, who are allowed to change limits depending on specific territorial realities and needs.

Indeed, Article 3 established a permanent working table with the aim of monitoring and accompanying regional Guideline's implementations. Core of the Article 3, Annex 9 proposes to estimate agricultural water uses by equalizing them with irrigation water needs. In other words, the annex assumes that the exact amount of water that a specific crop need, corresponds to irrigation water withdrawals. The key methodology for the estimation of irrigation water requirements is codified by FAO (Food and Agricultural Organization) in the publication "Crop evapotranspiration - Guidelines for computing crop water requirements - Irrigation and drainage Paper 56", edited by Allen et al., 1998, based on the calculation of plant evapotranspiration. Irrigation advisory services and decision support systems are nowadays the most recommended operational tools to meet the requirements expected by the law. These tools support farmers and reclamation consortia in decision making, providing information regarding irrigation times and volumes. They are usually based on agro-hydrological balance models on a field scale which can be supported by innovative technologies to acquire information about input data (e.g., remote sensing, proximal sensing, weather forecast platforms).

In this context, the aim of the thesis is to assess available tools and modelling frameworks that have been developed to estimate agricultural water requirements and to support stakeholders and water players. More specifically, the research activities have been developed in the framework of two projects and one regional service which contribute to support land reclamation consortia and farmers in irrigation water management, raising awareness of the proper use of the water resource.

The first project is SWAMP European-Brazil cooperation project (Smart Water Management Platform, http://swamp-project.org/). This project had the aim to create an on-line platform based on the IoT (Internet of Things) concept for the development of a high-precision intelligent irrigation system, pursuing the optimisation of water use, distribution, and consumption. Specifically, the platform collects data from smart sensors (e.g., soil moisture sensors, piezometers) and weather stations, and integrates them into simulation models. Pilots were located in Italy, Spain and Brazil. The main idea was to enable the optimisation of irrigation, water distribution and consumption, based on a holistic analysis that collects information from all aspects of the system, including both the natural water cycle and the farmers behaviours. The result was to create a platform able to detects system leakages and losses, guaranteeing water availability in situation which limit its supply.

The second project is PRIN INCIPIT project (INtegrated Computer modelling and monitoring for

Irrigation Planning in Italy, https://www.principit2017.it/). This project aims to develop and test methodologies for agricultural water use, planning and control at different spatial scales and in different availability condition of hydrological and weather data, in response to the European and Italian laws on agricultural water accounting. Various hydrological models are applied in seven different study areas distributed across Italy, from the south to the north. These models include IDRAGRA, IRRIFRAME, IRRISAT, IRRISIAS and SIRR_MOD. The aim of the proposed working methods is both the estimation of crop water requirements, by means of remote sensing techniques, and at estimating irrigation water use, based on the use of agro-hydrological models combined with crop parameters and soil observations. The methods are tested at the different agro-environmental conditions of the Italian regions, trying to fill the gap between research and application and providing efficient methodologies to meet the Italian decree requirements.

Finally, the iCOLT system (irrigazione e Classificazione delle cOLture in atto tramite Telerilevamento – irrigation and classification of current crops by remote sensing, https://sites.google.com/drive.arpae.it/servizio-climatico-icolt) is a service provided by the regional environmental protection agencies ARPAe of the Emilia-Romagna region (Italy), which integrates the use of remote sensing data, seasonal weather forecasts and soil water balance predictions (Villani et al., 2014). The principal aim of this service is to estimate the expected water use before the following irrigation season of the Emilia Romagna region plain area. The procedure consists of two steps. The first step aimed to the spatial identification and quantification of the current agricultural crops. The second step aimed to integrate crops information and weather forecasts into the agro-hydrological model CRITERIA-1D. The final product is an estimation of the seasonal water needs, useful to support irrigation water management by the different water players, from farmers to reclamation consortia. The study area covers about 1,180,000 ha of regional plain, of which 800,000 ha are interested by agricultural activities.

Overall, despite the different methods, scales and time frame, whether it concerns methodologies to fulfil the law, devising platforms that optimize the irrigation process, or forecasting the use of the water resource, all the tools and services described above have the common goal of supporting regional authorities and land reclamation consortia in water resource management, collaborating with farmers to achieve a common sustainable goal. The study was carried out at two different spatial scales, field and irrigation district scale, in the Emilia Romagna region, integrating more conventional or innovative methods. As such, the intercomparison of different approaches at the same study areas provides a unique opportunity to highlight current challenges and opportunities for supporting a correct use of the water resource and to identify possible improvements.

More specifically, the thesis is structured as follow. A sensitivity analysis (MMEMO method) has been conducted to understand the robustness of agro-hydrological models for supporting water management and assessment at field scales (Chapter 2); a comparison between different crops classification has been performed at district scales to provide information regarding the routinely use of optical remote sensing for land use mapping (Chapter 3); an evaluation of different modelling frameworks based on measured irrigation water use has been conducted to answer how well integrated agro-hydrological models and remote sensing approaches performed for district-scale water assessment and forecasting (Chapter 4). The overall conclusions are reported in the final chapter (Chapter 5).

2. SENSITIVTY OF AGRO-HYDROLOGICAL MODELS TO INPUT AND PARAMETERS AT FIELD SCALE

2.1 INTRODUCTION

Agriculture is one of the first human activity that interferes with the water cycle, using water for supporting food production, implementing drainage systems to extend productive areas and, together with deforestation and wetland destruction, occupying approximately three-quarters of the Earth's ice-free land surface (Abbott et al., 2019). For this reason, a correct water management combined to an upgrade of the existing irrigation and conveyance systems has been recognized as a fundamental step towards a sustainable use of the water resource (Rosegrant et al., 2009).

In this context, the use of agro-hydrological models to estimate crop water requirements and to support irrigation water management has strongly progressed. Several modelling tools have been developed, differing depending on the required input, end users, degree of operational complexity and temporal perspective (Siad et al., 2019; Tolomio and Casa, 2020). It was also emphasized that the use of these models by a broader community could have been increased if models become more user- and data-friendly (Bastiaanssen et al., 2007). Motivated by these assessments, nowadays several agro-hydrological models of different complexity have been developed by research groups, environmental agencies and private companies (Kayatz et al., 2019; Xiong et al., 2021). These models can be relatively easily applied over large areas and their results can be visualized on on-line platforms (Kamienski et al., 2019), or even directly integrated into smartphone app for farmers (Migliaccio et al., 2016). For these reasons, these modelling tools have been integrated for impact assessment or in decision support systems at different levels, from field to regional scale (Mannini et al., 2013; Masia et al., 2021).

Despite that, several surveys have highlighted that end user's uptake (i.e., farmers and water user associations) of these support tools is still limited (Baroni et al., 2019a; Giannakis et al., 2016). Similarly, the uncertainty of these modelling tools for impact assessment has been often underlined (Wada et al., 2013). Among others, the reason has been recognized in the uncertainty and representativeness of model results. Therefore, it is still common for these end users to adopt alternative strategies based on direct measurements or personal experience (Annandale et al., 2011; Liang et al., 2016).

Specific model calibration based on, e.g., soil moisture observations, can minimize model uncertainty and it would provide a rigorous assessment of model performances (Cholpankulov et al., 2008; Rosa et al., 2012). Based on that, it is shown, for instance, that differences in model outputs due to different model structures are smaller than the effect of the uncertainty in input and parameters (Baroni et al., 2010; Campi et al., 2015; Rallo et al., 2012; Strati et al., 2018). However, calibration proceed needs additional field measurements (like soil moisture or evapotranspiration observations) that are generally performed and available only at few and specific experimental sites. In contrast, model calibration and assessment over large areas remains a key challenge in many scientific disciplines (Baroni et al., 2019b; Dembélé et al., 2020; Schilling et al., 2019; Széles et al., 2020). Therefore, models are used for impact assessment and water accounting (Masia et al., 2021; Supit et al., 2010) or they are integrated into decision support systems (Chitu et al., 2020), assuming the reliable representation of the system by the model (low uncertainty in model structure) and the representativeness of the input and parameters (low uncertainty in the input factors).

To test these hypotheses and to provide an assessment of the robustness of the modelling tools, several studies strive to quantify the uncertainty in model outputs and to identify the factors (e.g., input, parameters or model structure) that should be considered for further improvements, using scenario- or sensitivity-based frameworks (Pianosi et al., 2016; Razavi, 2021). In these frameworks, the models are usually not calibrated (to reproduce the reference model settings integrated in the decision support systems) and they are assessed comparing the model results based on different possible realizations of the targeted input factors. Considering agro-hydrological models, several studies focused for instance on the effect on the model output of more representative soil properties (Baroni et al., 2017; Borin et al., 2000; Constantin et al., 2020; Wesseling et al., 2020), crop parameters (Birhanu et al., 2019; Consoli and Vanella, 2014; Garrigues et al., 2015; Rahman et al., 2020), weather data for calculating evapotranspiration (Gharsallah et al., 2013; Ji et al., 2017) or precipitation datasets (Ramarohetra et al., 2013). In some cases, different model structures are also assessed (Rosenzweig et al., 2013; Ruane et al., 2016).

These analyses can be performed by assessing the effect of one single factor. For this reason they are referred in literature to one-at-the-time - OAT approach (Saltelli and Annoni, 2010). In this assessment, the importance of each dataset for a correct estimation of the targeted variable is quantified. However, the interplay over different factors is not explored limiting the understanding of its importance and the priority for further model improvements. To overcome this limitation, it is suggested to assess the model output by simultaneously combine all the possible factor realizations based on the so-called global sensitivity analysis - GSA (Pianosi et al., 2016; Razavi, 2021). Several methods have been developed (Baroni and Francke, 2020; Morris, 1991; Saltelli, 2008) that can be easily integrated for analyzing any type of factor (Baroni, 2014; Mai et al., 2020). These methods have also been used in the context of agro-hydrological models providing relevant results for the understanding of model behavior and improvements (Jabloun et al., 2018; Upreti et al., 2020). However, these methods require several simulations (e.g., > 1000), not always feasible due to computational burden. For this reason, intermediate strategies between simple OAT method and more comprehensive GSA have also been suggested and used. Specifically, a step-by-step approach has been proposed to quantify the relative importance of each input factor (Hulsman et al., 2020; Széles et al., 2020). A forward backward formulation has also been proposed to shed light on interaction effects between input factors (Francke et al., 2018). These intermediate methods are relatively easier to implement than other more computational demanding GSA, but they still provide a quantitative assessment of the model performance and the identification of possible model improvements by accounting for the interaction between factors.

In the present study we use the forward backward approach called multiple model enhancements and multiple objectives MMEMO method (Francke et al., 2018) to quantify the effect of more representative input factors on model simulations and to assess the robustness of agro-hydrological models for supporting agricultural water management. The following specific questions are formulated:

- Do freely available datasets allow the integration and use of agro-hydrological models for supporting agricultural water management?
- Are models results comparable or is a specific model calibration likely necessary?
- Are these freely available data-sets representative of agricultural field conditions?
- Which factors should be better monitored? Does this depend on the model, specific settings or hydrological conditions?
- Is a sensitivity analysis an effective tool for the assessment of the robustness of the model and to identify further improvements?

2.2 MATERIALS AND METHODS

2.2.1 Study area and experimental field site

The analysis is performed in Emilia-Romagna region (Italy), characterized by a humid temperate continental climate, with an average annual temperature of 12.8 °C and 924 mm of annual precipitation. Summers (June to September) are usually very warm, with moderately low precipitations that are not able to satisfy plant water requirements. For this reason, irrigations are usually carried out during this period. The region can be considered a relatively rich data environment where agro-hydrological modelling tools supporting agricultural water management can be easily implemented. Weather, soils or shallow groundwater table datasets are freely available online (web pages cited below in chapter 2.2.3.).

The analysis of the robustness of the modelling tools and the data representativeness is based on additional data collected at an irrigated pear orchard (*Pyrus communis L.*) in the adult stage of about 1.2 ha (Figure 1, WGS coordinates: 44.791091, 10.736216). The field is equipped with a drip irrigation system, with wings fixed at about 0.5 m high from the ground along the rows and drippers positioned every 0.5 m. The selected field is located within San Michele-Fosdondo irrigation district (Reggio Emilia province), managed by the local reclamation Consortium CBEC (Consorzio di Bonifica dell'Emilia Centrale), which oversees irrigation water management at district level. The site was selected due to the importance of this crop in the area.

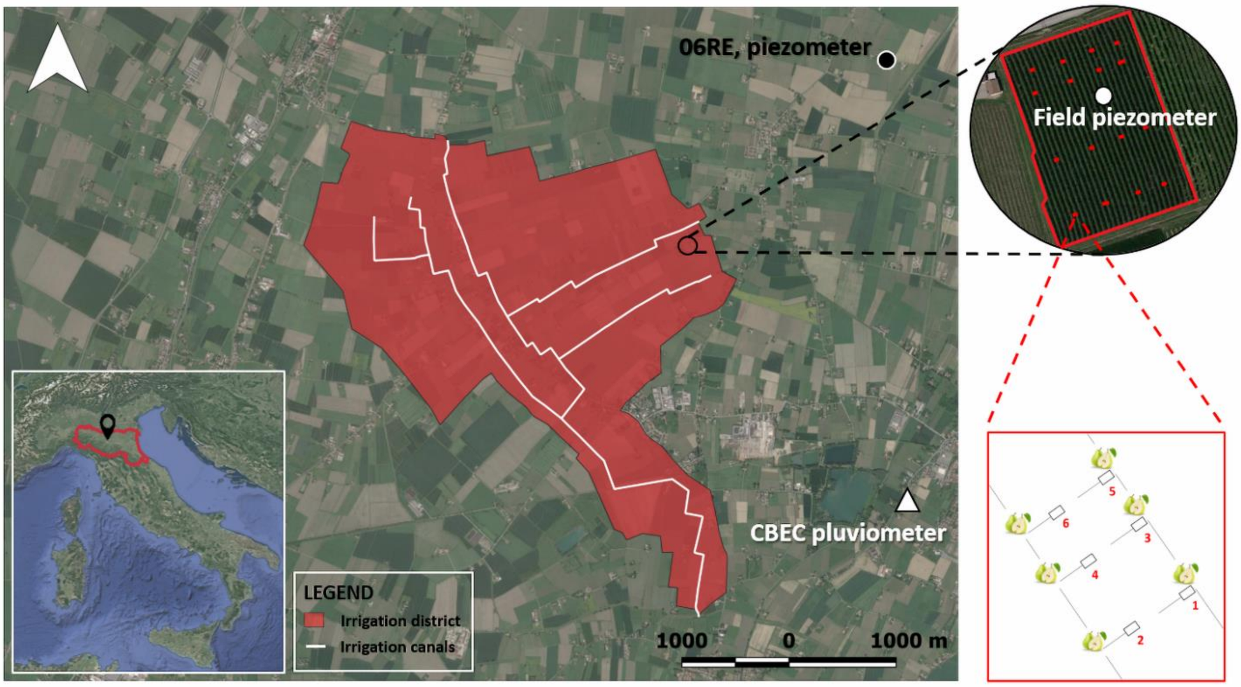

Figure 1 Location of the field case study within Italy, Emilia-Romagna region, and irrigation district. Location of the regional piezometer 06RE used in the base scenario (B), the CBEC pluviometer for the rainfall enhancement and the field piezometer for the groundwater enhancement are also depicted. Experimental design of Leaf Area Index measurements at the pear orchard are reported in the lower-right panel

2.2.2 CRITERIA-1D and AquaCrop models

Two agro-hydrological models have been used: CRITERIA-1D and AquaCrop. The former is an open-source agro-hydrological model developed by the environmental regional agency ARPAE. The code is written in C++ with Qt libraries available under the LGPL license and it can be compiled on several platforms (https://github.com/ARPA-SIMC/CRITERIA1D). The model has been used to simulate soil water fluxes in several studies (Campi et al., 2015; Strati et al., 2018), as well applied for irrigation scheduling (Consoli et al., 2016; Villani et al., 2018). AquaCrop is a dynamic crop-growth model developed by the Food and Agriculture Organization (FAO). The software is freely available (http://www.fao.org/aquacrop/software/software-download/en/?news_files=3), and it has a user-friendly interface. It requires a relatively limited number of input and parameters, representing a simple, accurate and robust model to predict crop transpiration, biomass and yield in response to environmental factors, but giving special attention to water (Raes et al., 2016; Steduto et al., 2009; Vanuytrecht et al., 2014).

Both models simulate crop development and vertical water fluxes over the soil-plant-atmosphere system. They compute at a daily time scale soil moisture dynamic, water stress, actual evaporation and transpiration, deep drainage, and surface and subsurface runoff. Irrigation can be triggered setting user-defined thresholds. We refer to the manual of each model for additional details (Antolini et al., 2016; Raes et al., 2016), while we provide below a short overview of the main differences in the simulation of the water fluxes in the soil-plant-atmosphere continuum that are relevant for the interpretation of the results of the present study.

Specifically, CRITERIA-1D can simulate infiltration and redistribution with two different approaches: a bucket semi-empirical conceptual approach or a numeric integration of the Richards equation. Here we selected the first approach, which discretizes the soil in several layers of 2 cm thickness. Soil texture characteristics (percentages of sand, silt and clay) are required. Soil hydraulic properties (parameters of Van Genuchten retention curve, saturated hydraulic conductivity, field capacity, and wilting point) can also be defined by the user, if available. When these are not available, the model considers the specific texture characteristics and assigns default values obtained through a reanalysis of various literature studies on different soil datasets (Carsel and Parrish, 1988; Schaap et al., 2001; Simota and Mayr, 1996; Wösten et al., 2001). Details of this implementation embedded in CRITERIA-1D can be found at https://github.com/ARPA-SIMC/CRITERIA1D. Water fluxes through the soil layers are calculated starting from the top of the profile: if the water content of the layer exceeds the field capacity it passes to the next one, and in case free water reaches the last layer, it leaves the system as deep drainage. Capillary rise is estimated using the steady state solution of Darcy's equation, as a function of depth to groundwater level, soil hydraulic conductivity and soil moisture (Antolini et al., 2016). The model implements parameters for both herbaceous crops and fruit trees and the plant development is represented by means of Leaf Area Index (LAI), which represents the total one-sided area of photosynthetic tissue per unit ground surface area (Schaaf, 2008). Plant water uptake is described by a sink term integrated over the root depth and accounting for the root density. Water stress occurs when soil moisture drops below a specific stress threshold. This threshold depends on soil properties (field capacity and wilting point) and on the plant stress tolerance, defined as the ratio between actual and potential transpiration: a value equal 1 means that no stress is tolerated. For the specific case study, the default stress tolerance of 0.95 suggested for the pear crop was used.

AquaCrop simulates the same water fluxes and crop developments described by CRITERIA-1D. For this reason, the comparison of the main components of the water balance simulated by the two models is straightforward. Considering the CRITERIA-1D version selected, the main differences lie on the soil discretization, the parameter used to describe plant development and the description of capillary rise. Specifically, AquaCrop divides the soil in 5 layers and hydraulic characteristics can be assigned at each of them. The same parameterization used in CRITERIA-1D is also used for AquaCrop.

The water balance calculation is then performed based on soil thicknesses of 10 cm thickness with soil characteristics of the soil layer to which they belong to. At each node, a water balance calculation is performed to derive water storage and percolation. Differently form CRITERIA-1D, AquaCrop was developed to simulate only herbaceous crops and the plant development is described by the Canopy Cover (CC). This parameter represents the proportion of the ground area covered by a vertical projection of the canopy (Jennings, 1999). To account for that, the values of LAI used in CRITERIA-1D have been transformed into canopy cover based on the relationship developed by Hsiao et al., 2009 and the developing stages have been defined to mimic the pear crop. The stress threshold is referred to the moment when the plant starts to close its stomata and it is described by a specified fraction of the total soil available water (field capacity – wilting point). Finally, AquaCrop simulates the capillary rise using an empirical function that considers the distance to groundwater level and some empirical parameters related to soil texture and soil hydraulic characteristics (Raes et al., 2016).

2.2.3 MMEMO method and scenarios

The Multiple Model Enhancements and Multiple Objectives method (MMEMO) (Francke et al., 2018) was applied to assess the effect of different factors enhancements to model results. The procedure is illustrated in Figure 2. This method considers a *base scenario* (B) in which mainly literature and available input and parameters are used. Therefore, this scenario represents the best model settings that are currently possible considering the application of the models over large area and for support agricultural water management. Additionally, other scenarios (B^+) are created in which enhancements are introduced by using values measured at the field or, in any case, closer to the real conditions. Starting from the base scenario plus the enhancements, the method also considers a *full scenario* (F), in which all the enhancements are together applied. Then, from the full scenario, other scenarios (F^-) are created, eliminating enhancements one at time. Using this forward and backward selection, the outputs of simulations run under different scenarios might differ. Nevertheless, their diversity depends just on one modified factor. The final aim is to understand which input has more influences on different model outputs.

As base scenario (B), both models have been implemented with data and parameter available from regional monitoring network and data bases. Specifically, meteorological data (i.e., precipitations, maximum and minimum air temperatures) were obtained by the ERG5 database from ARPAE, (https://dati.arpae.it/dataset/erg5-interpolazione-su-griglia-di-dati-meteo). This is a freely gap-filled and interpolated dataset on a grid of 5 km x 5 km provided by ARPAE. For the specific case study, the 01015 – S. Michele cell (WGS coordinates: 44.7675N, 10.7097775E) was used. Groundwater table data were provided by the monitoring network of the shallow water table of Emilia-Romagna region (http://faldanet.consorziocer.it/Faldanet/retefalda/index) (Figure 1, piezometer 06RE). Due to the lack of a continuous data collection, data were gap-filled by means of an empirical algorithm (Tomei et al., 2010), to obtain a continuous daily series (Villani et al., 2018). Soil textural characteristics refer to a silty loam soil with no gravel, typical of the regional plain area, provided by the Geological, seismic and soil survey of Emilia-Romagna regional database (https://geo.regione.emilia-romagna.it/cartpedo/). Specifically, the soil code used is SMB1 (Sant'Omobono 1). Soil hydraulic properties were derived based on the specific functions integrated in CRITERIA-1D, as previously described. The same parameters have also been assigned to AquaCrop (Table 1). For what concern reference crop parameters, CRITERIA-1D model uses the maximum Leaf Area Index parameter (LAI_{MAX}) and the growing degree day approach to describe the crop development. The first represents the maximum value for the selected crop; the second is the factor that determines the development of the crop as a function daily air temperature (Antolini et al., 2016). The base scenario uses literature leaf area index parameters referred to the type of selected crop and land cover. In this case, LAI_{MAX} is equal 3 [m^2 m^{-2}] for the pear orchard and a LAI equal 0.5 [m^2 m^{-2}] is also added to consider the soil covered by grass (LAI_{GRASS}). AquaCrop model uses the maximum Canopy Coverage (CC_{MAX}) as parameter to describe the crop foliage development. For this simulation case study the parameter has been defined for the base scenario equal to 81 %, following the relationship between leaf area index and canopy cover developed by Hsiao et al., 2009, as previously specified.

Starting from the base scenario (B), *modified scenarios* more representative of the study field are defined, based on four factor enhancements. Below each modified scenario is described.

a) *Modified scenario B^{+R} – Rainfall enhancement*: in place of the interpolated precipitations data available from the environmental regional agency, data from a rain gauge of the reclamation Consortium CBEC located in Correggio was used (Figure 1, CBEC pluviometer, WGS coordinates: 44.767763, 10.763850). This rain gauge is located at 6 km from the study site, and it is considered more representative of the field conditions.

b) *Modified scenario B^{+GW} – Groundwater enhancement*: in June 2019, a piezometer was installed in the pear orchard. The average difference between groundwater levels measured by the regional piezometer and the site-specific piezometer over the period June to November 2019 was calculated. This difference was assumed to be representative also for the previous years simulated by the models.

c) *Modified scenario B^{+S} – Soil enhancement*: for this scenario, soil samples have been collected at four depths down to 1 m at the experimental site. For each sample, the soil textures were analysed to have more precise and realistic model input data. As for the base scenario, soil hydraulic properties were derived based on the specific functions integrated in CRITERIA-1D. These parameters have also been used to set-up AquaCrop.

d) *Modified scenario B^{+C} – Crop enhancement*: as for the base scenario, the two models were modified in a different way. In CRITERIA-1D simulations an updated measured LAI_{MAX} value was used in place of the literature one. Measurements were carried out with the optical instrument AccuPAR LP80 ceptometer (https://www.metergroup.com/environment/products/accupar-lp-80-leaf-area-index/) during the summer 2019 through the conduction of four sampling campaign in the pear orchard. Spatial measurements were collected in 16 points on a regular grid and at each sampling point six measurements were taken around the plant. The ceptometer was placed at the ground level below the canopy but above the grass between two rows (Figure 1, lower-right panel). LAI measurements have been used to simulate the modified scenario also for the previous years. As for the base scenario, there is a LAI_{GRASS} equal 0.5 added to consider soil covered by grass. In Aquacrop, the crop enhancement has been introduced decreasing the canopy cover CC_{MAX} to 59%, always following the relationship between leaf area index and canopy cover developed by Hsiao et al., 2009.

Ten scenarios are then analysed for each model: the base scenario, the full scenario, and eight scenarios resulting from the enhancements i.e., 4 from the base plus enhancements (B^+), 4 from the full minus enhancements (F^-) (Figure 2). Simulations have been performed for five consecutive years, from 2015 to 2019. The first year was used as a warm-up year to have more precise initial conditions for the following years and results of this year were disregarded. Strong variability in meteorological conditions have been observed during these years, with main differences captured by precipitation. The year 2019 is characterized by high rainfall, with approximately 900 mm of precipitation. In contrast, 2017 is the driest year, with approximately 500 mm. 2016 and 2018 are characterized by similar rainfall amounts, 660 mm and 670 mm, respectively. For this reason, despite the relatively short simulation period (four years), results obtained and discussed in the present study represent a variety of hydrological conditions and water requirements (Ricchi et al., 2020). Models have been setup to mimic the drip irrigation of the study area by triggering 5 mm of irrigation when the soil water content falls below the stress thresholds. No further attempt to calibrate input data or parameters was carried out to test the default settings that the models would integrate in practical applications for impact assessment and in a decision support system at the regional scale (Borin et al., 2000; Drastig et al., 2016; Mannini et al., 2013; Masia et al., 2021; Mekonnen and Hoekstra, 2011; Riediger et al., 2016; Supit et al., 2010; Wriedt et al., 2009).

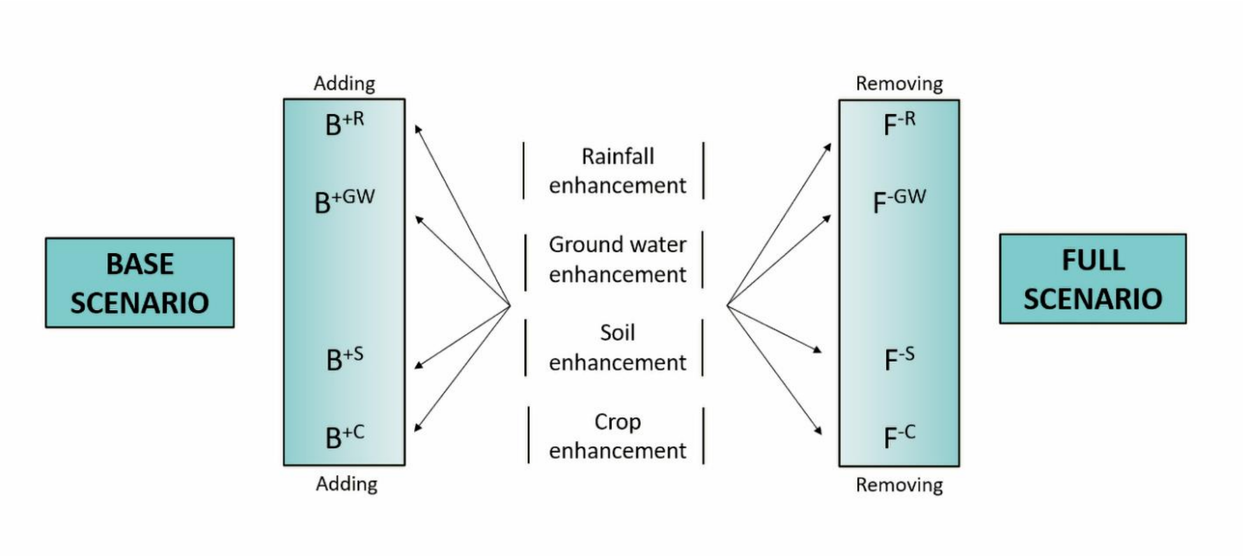

Figure 2 Forward and backward selection of model enhancements to the base (B) and from the full (F) scenarios (MMEMO method)

2.2.4 Data analysis and models comparison

The results of the simulations are first analysed comparing the different model outputs in the base scenario (B) and in the full scenario (F) to understand the models hydrological responses based on the different settings. The analysis is further extended to investigate the role of the different factors enhancements (i.e., rain, groundwater interaction, soil and crop properties) on the model results generally used for the assessment of the water management. Specifically, the output analysed is the cumulative irrigation water requirement (IWR) over the cropping season (20 March – 10 September). In addition, the cumulative bottom water fluxes (BF) at the lower boundary of the root zone (i.e., 1 m depth) were estimated. This output is calculated as a residual of the soil water balance considering water fluxes (i.e., net precipitation, evapotranspiration, runoff) and soil moisture changes over 1 m depth during the cropping season. Negative fluxes represent potential groundwater recharge, assuming no additional sink term but only a time delay to reach the groundwater body. In contrast positive fluxes represent the groundwater contribution (capillary rise), valuable for supporting crop water requirements.

The model results are then compared based on the following index:

$$S_i = \frac{|R^{M_i} - R|}{\max(R^{M_i}, R) - \min(R^{M_i}, R)} \qquad \text{Eq. (1)}$$

where R^{M_i} is the model output of the modified scenario based on the factor *i* that varies from 1 to the total number of factors (i.e., 4 for the specific application), and R represents the model output obtained from the reference scenario (base or full). This value is standardized based on the range (max – min) over all the scenarios, to allow easier comparison between the models. This index allows quantifying the importance of the factor in perturbing the model output, i.e., bigger value identifying more importance. A total sum of the indices over the different factors exceeding 1, indicates a non-additive model and interactions among the factors as captured by other sensitivity analyses indices (Razavi, 2021).

The index is calculated for each model (CRITERIA-1d and AquaCrop), for each reference scenario (base or full) and for each simulated year (four years). A total of 64 index values for each model output are then obtained (i.e., 16 index values for each factor). The results are then averaged over the two models, the reference scenarios and the years, to highlight the relevant features and to better summarize differences obtained in the different settings.

2.3 RESULTS AND DISCUSSION

2.3.1 Model results based on base scenario (B)

The cumulative irrigation water requirements (IWR) and the cumulative bottom fluxes out of 1 m soil depth (BF) are shown in Figure 3. Accumulated precipitation during the cropping season is also depicted for comparison. CRITERIA-1D estimates on average 131 mm of IWR (Figure 3a) with a strong variability over the years. For instance, IWR of 35 mm and 360 mm are simulated for the year 2016 and 2017, respectively. Noteworthy, these differences are obtained despite similar precipitation amount is registered during the cropping season (215 mm and 204 mm for 2016 and 2017, respectively). IWR estimated by AquaCrop (Figure 3a’) shows a similar variability but, on average, a significantly higher IWR (286 mm) than the one simulated by the CRITERIA-1D. This high difference between the IWR simulated by the models is less pronounced during 2017, with an IWR of 360 mm and 415 mm for CRITERIA-1D and AquaCrop, respectively.

By looking at the bottom fluxes (BF), CRITERIA-1D estimates, on average, approximately 179 mm of positive bottom fluxes, i.e., capillary rise (Figure 3b). As such, the groundwater contributes to increase soil moisture in the root zone and decreases the irrigation water requirements. This effect is stronger during 2016 and it can be explained considering that a relatively low precipitation occurs, but the groundwater level was shallow (on average 1.3 m below the soil surface). In contrast, during the year 2017, the same amount of precipitation occurs but a deeper groundwater level has been detected (on average 2 m below the surface), reducing the capability to increase soil moisture at 1 m depth. On the contrary, AquaCrop estimates on average 19 mm of negative bottom fluxes, i.e., potential groundwater recharge (Figure 3b’). The values are well correlated to the precipitation, i.e., increasing precipitation results in increasing potential groundwater recharge. This differences in the bottom fluxes simulated by the two models also explains the large difference between the IWR estimated (see Figure 4b).

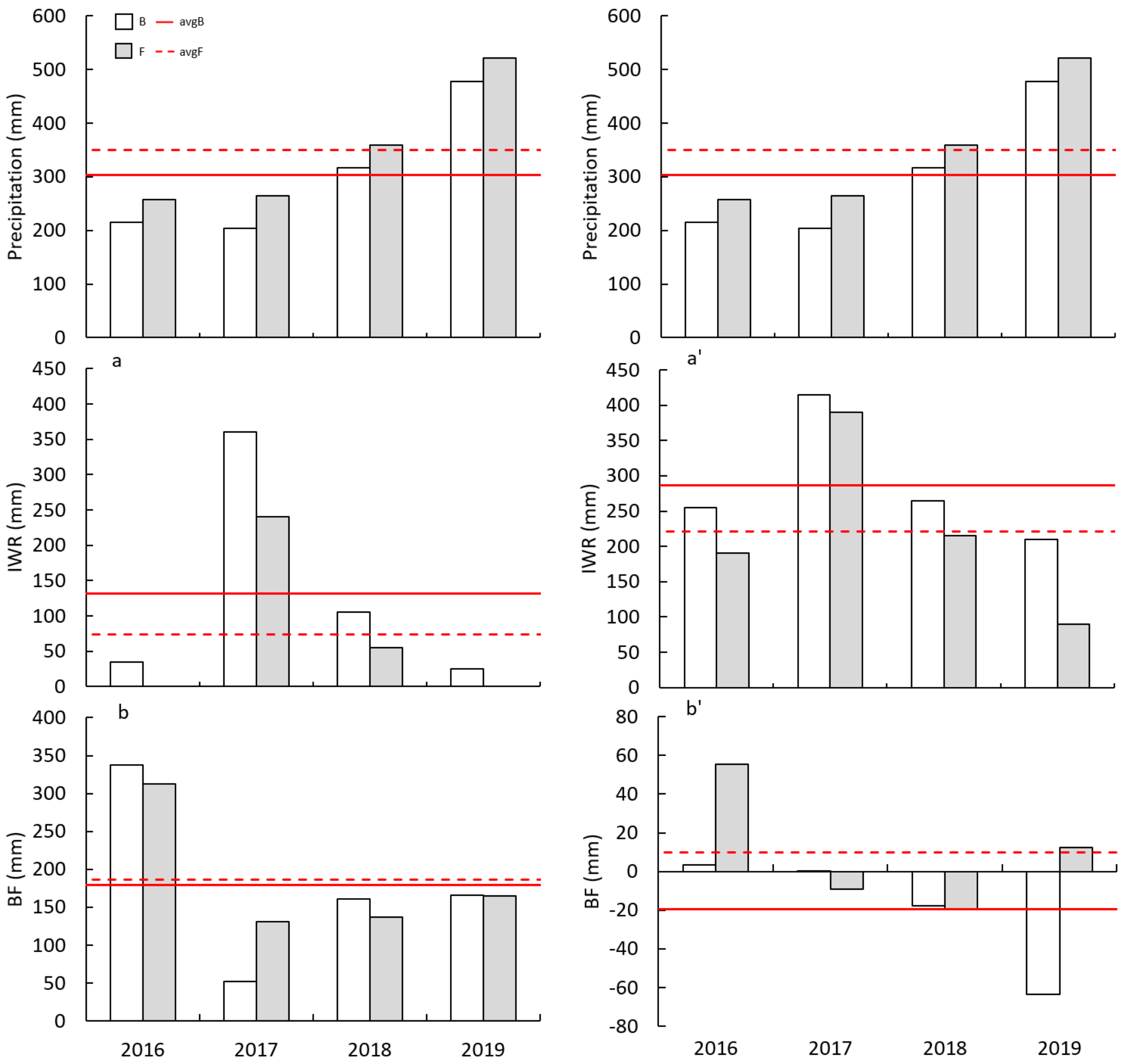

Figure 3 Accumulated precipitations, simulated irrigation water requirements (IWR) and fluxes at the lower soil boundary (BF) for the two models CRITERIA-1D (a, b) and AquaCrop (a', b'), for the two reference scenarios (B, F)

To better understand model's behaviour, results are analysed in more details by looking at the daily model outputs. Results of two years with different hydrological conditions are shown and discussed as example (Figure 4). The year 2017 (Figure 4, left panels) is characterized by a relatively low precipitation amount but also a relative deep groundwater level (WT, > 1.5 m from the surface). During this year, the soil water contents (WC) simulated by the models show a very similar dynamic. WC is relatively high at the beginning of the crop season until the end of May and it further decreases due to the increase of evapotranspiration not supported by the precipitation. WC drops below the stress threshold at the beginning of June for both models, triggering irrigation events constantly until the end of the irrigation season (September). Despite similar simulated WC dynamics, two important differences between the models are, however, identified. During the first months (March-April), simulated bottom fluxes (BF) by CRITERIA-1D are negligible, while a constant capillary rise is estimated by AquaCrop. As such, the difference between the fluxes simulated by the models is not detected by the soil moisture dynamic and highlights the need of looking at different model outputs for a proper assessment of the models. In the second period (May-September), the WC simulated by AquaCrop decreases much faster than the one simulated by CRITERIA-1D. This difference is explained by the higher capillary rise simulated by CRITERIA-1D. Despite this difference between the models, irrigations are triggered almost at the same days (beginning of June) because the stress threshold is higher in CRITERIA-1D than in AquaCrop.

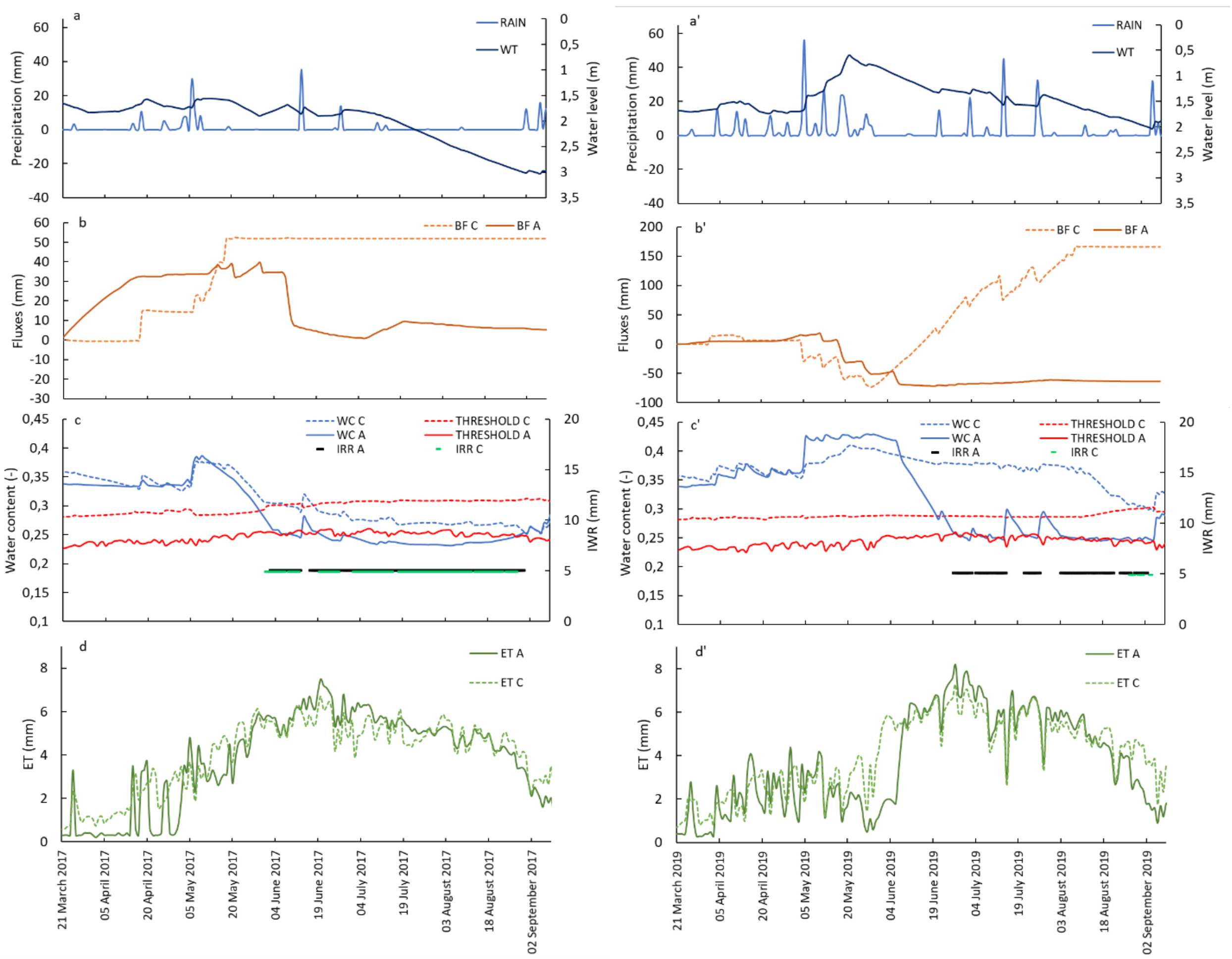

Figure 4 Input and main outputs of CRITERIA-1D (C) and Aquacrop (A) models for a dry year (2017, left panels) and for a wet year (2019, right panel), obtained running the base scenario: groundwater level (WT) and precipitations (RAIN) (a, a'), cumulated bottom water fluxes (BF) (b, b'), simulated water contents (WC), irrigation events (IRR) and water stress threshold (THRESHOLD) (c, c'), actual evapotranspiration (ET) (d, d')

The year 2019 is characterised by a higher amount of precipitation and shallower groundwater level than the year 2017 (Figure 4, right panels). During the first period (March-May), the states and fluxes simulated by the two models are very similar showing high water content (WC), negligible bottom fluxes (BF) and similar evapotranspiration dynamic. Later in the season (from May to September), strong differences are depicted. First, the high WC conditions in June produce a reduction of evapotranspiration simulated by AquaCrop. On the contrary, this wet crop stress is not simulated by

CRITERIA-1D (Figure 4d'). Moreover (Figure 4c'), irrigations in AquaCrop are triggered much earlier than in CRITERIA-1D (June and end of August, respectively). This remarkable difference is explained considering that CRITERIA-1D simulates a persistent capillary rise leading to an increase in WC and limiting plant water stress during this period. In contrast, negligible bottom fluxes (BF) are simulated by Aquacrop resulting in a persistent depletion of the soil WC by evapotranspiration and the need of earlier irrigations (Figure 4b'). Similar differences are found in the other simulation years (data not shown).

2.3.2 Factor enhancements

Differences between the implemented factor enhancements and the base dataset are presented in this section. Precipitation data collected with the rain gauge of the reclamation Consortium (CBEC) are higher than the one used for the base scenario (Figure 3). In addition, the rain intensity is higher for the local rain gauge and the number of events is smaller. On average during the plant developing periods, the rain gauge measured about 47 mm more precipitation than regional interpolated data. In 2017 was found the highest increase in precipitations of about 30 %, following 2016, with 20 %, 2018, with 13 % and 2019 with 9 %.

Groundwater level collected from June to November 2019 by the piezometer installed at the pear orchard field site is on average higher than the one provided by the regional agency, but with a very similar dynamic (data not shown). The average difference over the monitored period (13 cm) has been used to correct groundwater level for the modified scenarios (i.e., resulting in a shallower groundwater table).

Soil texture analysis on soil samples confirmed the same USDA classification (i.e., silty loam soil), with no gravel, but with a higher percentage of sand and organic matter (Table 1).

Table 1 Textural and hydraulic characteristics of the base (SMB1) and the enhanced (In situ) soil

		SMB1							In situ soil						
H	**Hd**	**sa**	**si**	**cl**	**OM**	**FC**	**WP**	**Ksat**	**sa**	**si**	**cl**	**OM**	**FC**	**WP**	**Ksat**
1	0-25	18.0	57.0	25.0	2.2	0.382	0.175	9.00	30.4	43.4	26.3	3.9	0.359	0.159	12.00
2	25-50	13.0	62.0	25.0	1.2	0.379	0.174	8.57	25.4	48.4	26.3	1.2	0.359	0.159	12.00
3	50-90	14.0	67.0	19.0	0.6	0.376	0.167	5.97	26.4	53.4	20.3	0.6	0.399	0.177	9.60
4	90-110	17.0	62.0	21.0	0.7	0.371	0.166	5.73	29.4	48.4	22.3	0.7	0.371	0.159	12.00
5	110-190	9.7	64.3	26.0	0.7	0.367	0.170	7.02	22.1	50.6	27.3	0.7	0.379	0.177	9.60
A	0-190	12.9	63.3	23.7	0.9	0.373	0.170	7.13	25.3	49.7	25.0	1.2	0.377	0.170	10.48

Note: H indicates the sequence of horizons; Hd the Horizon depth (cm); sa the percentage of sand (%); si the percentage of silt (%); cl the percentage of clay (%); OM the percentage of Organic Matter (%); FC the water content at Field Capacity (m^3 m^{-3}); WP the water content at Wilting Point (m^3 m^{-3}); K_{sat} the saturated hydraulic conductivity (cm d^{-1}); A the average value

Hydraulic parameters assigned by CRITERIA-1D for the soil enhancement result in a slightly higher conductivity but with very similar water retention capacity (field capacity – wilting point) to the one estimated for the base soil.

The value of leaf area index (LAI_{MAX}) measured at the field site by means of the ceptometer and used for the modified scenario is 1.7 [$m^2 m^{-2}$], a much lower value in comparison to the literature one used for the base scenario (i.e., 3 $m^2 m^{-2}$). Thus, a decreasing potential transpiration is expected.

2.3.3 Model results based on full scenario (F)

As expected by the results presented in the previous section, models running the full scenario F (i.e., implementing all the factor enhancements) estimate a lower irrigation water requirement (IWR) than models settled on base scenario B (Figure 3a and a'). This difference (B - F) is consistent over the simulated years and between the two models with, on average, 57 mm and 65 mm less IWR simulated by CRITERIA-1D and AquaCrop, respectively. Considering that the models provide 5 mm d^{-1} of irrigation depth to mimic the drip-irrigation method of the pear orchards, these differences translate to around 12 irrigation events less per season. These differences are relevant highlighting the need of improving the representativeness of model input and parameters to provide a reliable support for irrigation water scheduling.

A very different result is depicted by looking at the bottom fluxes (BF) (Figure 3b and b'). CRITERIA-1D estimates on average approximately 186 mm of capillary rise (Figure 3b), which is almost the same value obtained for the base scenario (179 mm). This result is remarkable considering that the factor enhancements do not change the model results. For this reason, in contrast to the analysis conducted for the IWR, input data used for the base scenario can be considered representative when looking at, e.g., long term potential groundwater recharge. Some variability is, however, depicted during different simulated years. The main difference is found during the dry year (2017) with a strong increase of the capillary rise (from 52 mm to 131 mm). On the contrary, AquaCrop based on the full scenario switches from simulating fluxes out of the soil (negative values) to reproduce capillary rise (positive values). However, a strong variability is identified over the years, highlighting the complex model response to the different model enhancements when different hydrological conditions are considered (Figure 3b').

Results from the two models based on the full scenario are analysed in more details by looking at the daily model outputs (Figure 5), as reported for the base scenario.

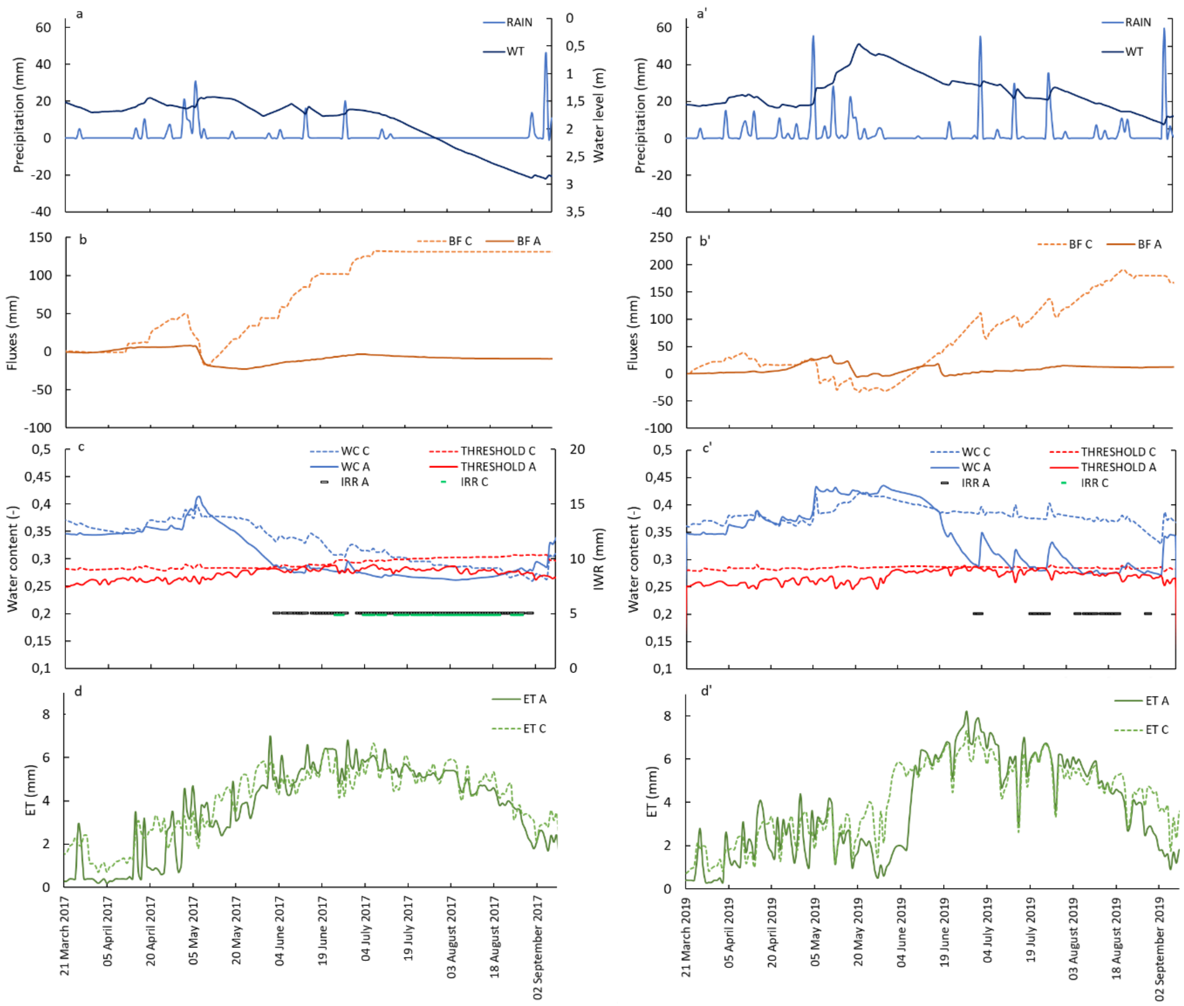

Figure 5 Input and main outputs of CRITERIA-1D (C) and Aquacrop (A) models for a dry year (2017, left panels) and for a wet year (2019, right panel), obtained running the full scenario: groundwater level (WT) and precipitations (RAIN) (a, a'), cumulated bottom water fluxes (BF) (b, b'), simulated water contents (WC), irrigation events (IRR) and water stress threshold (THRESHOLD) (c, c'), actual evapotranspiration (ET) (d, d')

As previously detected, the two models show a more similar behaviour during the dry year (2017, left panels) than during the wet year (2019, right panel). Differences between the models are mainly explained by the simulated bottom fluxes and by looking at the stress thresholds (Figure 5b, c). Specifically, CRITERIA-1D estimates a persistent capillary rise from May onwards, supporting a higher soil water content (WC) and delaying the triggering of irrigation. In contrast, AquaCrop produces higher negative bottom fluxes (potential groundwater recharge) and runoff (data not shown). Therefore, simulated soil WC is decreasing much faster. In addition, the stress thresholds of the two models based on the modified scenario becomes more similar than the one founded on the base scenario and they do not compensate anymore the difference in the simulated fluxes. Consequently, irrigations simulated by AquaCrop are triggered at the beginning of June as it was for the base scenario, while CRITERIA-1D starts irrigation in the third decade of June. During the wet year, the capillary rise simulated by CRITERIA-1D is even more pronounced and well supports the evapotranspiration during the entire season. Thus, no irrigations are triggered. In contrast, capillary rise simulated by AquaCrop is much smaller and several irrigations (90 mm) are still needed to support plant growth (Figure 5b', c', d').

2.3.4 Contribution of the different enhancements on model outputs

The analysis conducted to quantify the role of different factor enhancements is presented in Figure 6. The simulated irrigation water requirement (Figure 6, left panels) is on average more sensitive to the groundwater factor (GW) than to the other factors. The result is consistent independently from the model (figure 6a), the reference scenario, i.e., base or full (Figure 6b), and to a lesser extend from the simulated year (Figure 6c). For this reason, this clearly indicates the need of a representative monitoring of the shallow groundwater table to be integrated into the models for correctly support agricultural water management at the studied area.

In contrast, simulated IWR is less sensitive to the changes of other factors and it is not possible to clearly identify other priorities for model improvements. In addition, the sum of the factor indices exceeds 1. As such, results indicate the strong interaction between the factors and the non-cumulative effect on the model response. Noteworthy a strong interaction is depicted for the factor rain (R), i.e., the effect on the perturbation of the factor on model output strongly depends on the model, the reference scenario and on the year of simulations. This interaction is particularly strong, for instance, during the year 2018 where the factor rain (R) becomes even more important than the other factors. This is explained considering that during this year the increased amount of precipitation in the rainfall modified scenarios infiltrates into the soil. For this reason, it increases soil moisture and decreases the IWR. In contrast, during the other years a big fraction of the increased precipitation (on average 50%) contributes to runoff generation and it does not infiltrate into the soil (data not shown). Therefore, the IWR simulated by the models is less sensitive to the rainfall enhancement during these years.

For the case of the bottom fluxes (Figure 6, right panels), the model output is more sensitive to the changes of the GW factor. This agrees to the results obtained for IWR, emphasising the importance of GW improvements regardless the considered output. This sensitivity is also consistent independently from the model (Figure 6a'), the reference scenario, i.e., base or full (Figure 6b') and to the simulated year (Figure 6c'). Thus, the analysis supports the need to a representative monitoring of the shallow groundwater table also for correctly evaluate fluxes out of the root zone. However, the importance of the GW factor to explain model variability is less pronounced then for the IWR output and the factor relevance is overall more distributed over the factors. The sum of the factor indices exceeds 1 also by looking at this model output, indicating again the strong interaction between the factors and the non-cumulative effect on the model response. In addition to the factor rain (R), variability of the indices is depicted for the factor soil and crop when looking for instance at the different simulated years (Figure 6c'). Specifically, soil enhancement increases capillary rise, but only when groundwater level is close to the root zone. For this reason, this factor is less relevant during the year 2017 where groundwater level is relatively deeper (on average 2 m from soil surface). In contrast, crop enhancement (smaller LAI and crop fraction) leads to a reduction of the transpiration process. Consequently, a relevant reduction of the capillary rise is simulated, for instance, by CRITERIA-1D during all the years except for 2017. Therefore, this analysis shows the more complex behaviour of the different factors in explaining the variability of bottom fluxes and the difficulties to define a clear factor that is more relevant in all the conditions.

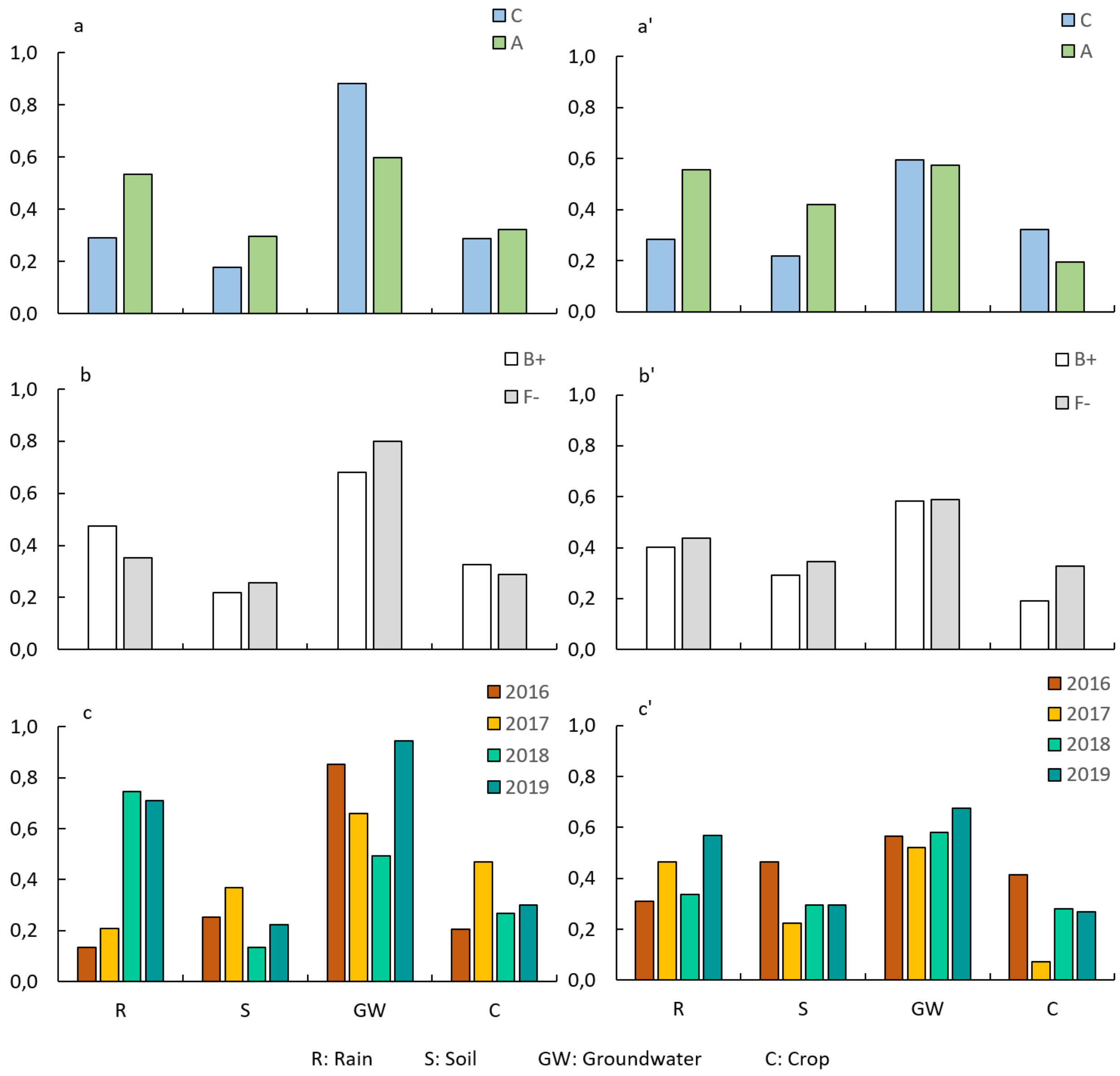

Figure 6 Factor importance index (eq. 1) on irrigation water requirement (IWR, left panels) and bottom fluxes (BF, right panels), averaged over the CRITERIA-1D (C) and AquaCrop (A) models (a, a'), reference scenario, i.e., base (B+) and full (F-) scenarios (b, b') and simulation years (c, c')

2.4 DISCUSSION

The results are further discussed in relation to the specific objectives and the research questions defined within the present study.

First, the results show that Emilia-Romagna region freely offers a rich agro-meteorological dataset that can be easily integrated for the application of agro-hydrological models. The data-sets ranges from checked and gap-filled weather data to groundwater levels. The resolution of all the input and parameters represents also an excellent test-bed for many modelling applications (Wood et al., 2011). As such, the model simulations can allow a seamless assessment of the main components of the soil water balance over large areas and can support the identification of possible critical locations and periods when environmental risk might occur (e.g., agricultural drought). The main data gap has been recognized on the availability of long-term ground-based soil moisture observations that can be used for further model assessment and comparison (Modanesi et al., 2021; Zhuo et al., 2020).

A significant difference between the results obtained with the two agro-hydrological models is found when looking specifically at the simulated irrigation water requirements IWR, i.e., CRITERIA-1D estimates a much smaller IWR than AquaCrop. These differences are explained considering that CRITERIA-1D simulates a strong capillary rise during all the years. These fluxes contribute to increase root soil moisture and to delay irrigations triggering. In contrast, AquaCrop switches between period when capillary rise is reproduced and period when fluxes out of the root systems are simulated (potential groundwater recharge). As such, soil moisture decreases much faster and irrigations are triggered earlier. In addition, a wet stress condition is also reproduced in AquaCrop, limiting transpiration when root soil moisture is relatively high. Noteworthy, these differences are less pronounced during the dry year when relatively less precipitation and a deeper groundwater system are present. In addition, they can be minimized based on tuning soil properties and plant stress, i.e., changing the default stress threshold to trigger the irrigation or calibrating the equations to better simulate the capillary rise and drainage processes. Thus, on the one hand the results well support the applicability of these models when groundwater level is relatively deep (e.g., 1 m below root depth). On the other hand, the results suggest the need to assess and improve the simulated bottom fluxes by the models based on dedicated studies at locations where groundwater is shallow and it can contribute to soil moisture redistributions and to support crop water requirements (Kroes et al., 2018). Specifically, concomitant monitoring of soil water content and potential at different depths above groundwater table would yield valuable information for comparing models' performance and improve model formulations. Noteworthy, however, this dedicated monitoring activities provide a relevant challenge considering the difficulties to collect representative root soil moisture measurements at agricultural field sites and over large areas (Domínguez-Niño et al., 2020;

Soulis et al., 2015). To overcome this limitation, the use of emerging non-invasive root zone soil moisture observations should be further explored (Li et al., 2018; Stevanato et al., 2019).

A significant difference between the results obtained with the base scenario and with the full scenario (i.e., integrating all factor enhancements) has also been found. Noteworthy, this difference is consistent between models. For this reason, despite the comprehensive regional freely available datasets, the analysis underlined a non-representativeness of the base dataset for the specific application and experimental site. Therefore, the results partially explain the general low adoption of these modelling tools for supporting agricultural water management by famers that has been identified in many areas (Baroni et al., 2019a; Giannakis et al., 2016) and the need of a more detailed monitoring of input data and parameters to better support agricultural water management.

Specifically, the analysis conducted based on the forward backward method MMEMO showed a significant importance of the groundwater level factor (GW) in explaining the difference between base and full scenario. This result is independent from the models, the setting (base or full scenario) and to some extent also from the hydrological conditions (year) and the considered output. Therefore, this study identified the need of improving the current regional monitoring of the shallow groundwater systems to provide a more representative groundwater level to be integrated into the two agro-hydrological models. Furthermore, the models showed to be sensitive to the factor rain (R) but only in some years and mainly for the model AquaCrop. Thus, this result underlines also the need of representative precipitation data to obtain consistent results but not for all the analysed conditions. In contrast, for the estimated bottom fluxes at 1 m depth, all the factors do not show a clear importance ranking. In addition, they show stronger interactions (e.g., they are more important during one year and less during another year). Thus, this result highlights how the improvement in the simulation of this hydrological process cannot be considered unique, but it depends on the specific agro-environmental conditions.

Finally, the study show that the sensitivity analysis successfully addressed all the objectives and research questions defined in the present study. As such, it shows to be a valuable tool for assessing the robustness of the modelling results and to identify further improvements. Noteworthy, these analyses can be performed without the need of observations to assess the model output (e.g., soil moisture or evapotranspiration measurements) but can be based directly on the variability of model output as demonstrated in the present study. Thus, on the one hand, the analyses can be implemented in a variety of conditions where dedicated monitoring activities are not taken place. On the other hand, the results can define prioritization of which observations should be better suited reducing the cost and effort of the field activities. These methods are receiving increasing attention in many scientific disciplines (Ferretti et al., 2016) even if perfunctory analyses are still quite common (Saltelli et al., 2019). In this context the specific applied method MMEMO (Francke et al., 2018) showed to be a simple but comprehensive method that can be easily integrated in any modelling framework by a broad scientific community as a relative low number of simulations are required. Still, additional more comprehensive global sensitivity analysis could be further implemented when much more factors are analysed and there are no computational limitations (Baroni and Francke, 2020; Pianosi et al., 2016).

2.5 CONCLUSIONS

This study implemented a comprehensive sensitivity analysis of two agro-hydrological models widely applied in different conditions for agricultural water accounting and management: CRITERIA-1D and AquaCrop. The analysis is performed based on a forward backward scenario method called MMEMO (Francke et al., 2018). This method adopts an intermediate strategy between the simple one-at-the-time approach and a more comprehensive global sensitivity analysis to assess the robustness of model results and to identify further model improvements. In the specific analysis, a total of 20 simulations (i.e., 10 per each model) based on available data and new more representative field measurements have been performed and analysed spanning four years with strong weather variability (dry and wet years).

Overall, the study shows that the results of the two agro-hydrological models are not robust considering the current state-of-the-art of model settings and available data for the specific application. Despite this analysis has been performed at one specific experimental site, the results can partially explain the general low adoption of these modelling tools for supporting agricultural water management by famers that has been identified in many areas (Baroni et al., 2019a; Giannakis et al., 2016). Similar concerns should be considered when these type of models are applied to impact assessments over large areas where no specific calibration can be performed (Masia et al., 2021; Supit et al., 2010). This analysis, however, also clearly identified two main aspects in explaining these uncertainties: the importance of the groundwater level and the simulated capillary rise. For this reason, on the one hand, this result supports the application of these models when groundwater level is relatively deeper (i.e., 1 m below root zone). In these conditions, in fact, small differences have been detected by the two models and the uncertainty in the groundwater level and in the simulated capillary rise does not propagate to the model results. On the other hand, this result highlights the need to design detailed monitoring activities at the deep root system to measure the capillary rise and to assess in specific the equations and the parameters integrated into the models to simulate this hydrological process. Concerning the Aquacrop model, a clarification has to be done. Being this model developed to simulate herbaceous crops, in this study some plant parameters adaptations have been done (e.g., representing the growing season). Despite water fluxes are well represented also referring to an orchard, further refinement could be considered in future studies.

In conclusion, the specific scenario-based method MMEMO showed to be a simple, flexible and effective method that can be easily applied to any models, locations and to any factor enhancements. Therefore, it can be considered a valuable strategy for the assessment of the robustness of modelling tools and for supporting their wider adaptation for agricultural water management by identifying their limitations and further improvements even before implementing any dedicated experimental sites.

3. ASSESSMENT OF A REMOTE SENSING APPROACH FOR LAND USE CLASSIFICATIONS AT IRRIGATION DISCRITCS SCALE

3.1 INTRODUCTION

Earth's surface observation and monitoring using remote sensing represents a non-invasive and low-cost methodology useful in many study areas (Agapiou et al., 2015; Lucchi et al., 2019; Usha and Singh, 2013). It allows to obtain information by surveying instruments that do not come into direct contact with the object of study, thus observing it from a pronounced distance. This distance depends on the platform used to support the instrument, e.g. aircraft, UAV (Unmanned Aerial Vehicle) or satellites. Exploiting the interaction phenomena between electromagnetic energy and natural surfaces, remote sensing allows to cover vast areas at a single glance and to represent them on a small scale through extremely detailed images and maps (Lanari et al., 2001).

Remote sensing instruments record the electromagnetic energy emitted, transmitted, or reflected by the objects from the earth's surface. It can acquire several images simultaneously, one for each spectral portion (i.e., spectral bands), and then interpret the same object in different wavelengths. This characteristic is called multispectral imaging, one of the peculiarities of remote sensing technique. Moreover, as a fundamental aspect in an environmental monitoring context, it allows to image the same scene at different and regular time intervals (i.e., multitemporal imaging).

The information is coded by digital images usually expressed in bitmap graphics. This type of graphic uses tiny, uniformly sized pixels, or picture elements, arranged in a two-dimensional grid made up of column and rows (i.e., matrix). Each pixel contains the information. Image's characteristics depends on sensors and platforms peculiarities, called resolutions. An image is characterized by four resolutions: spatial, radiometric, temporal, and spectral. The spatial resolution expresses the size of the smallest area that can be detected by the sensor. The radiometric resolution represents the number of different radiation intensities that the sensor can distinguish. The temporal resolution defines the time interval between two images of the same surface area. Finally, the spectral resolution translates the survey capacity of a sensor, i.e. the number of spectral bands of acquisition.

Remote sensing sensors can be divided into different groups of classification. Looking at the measuring principle, passive and active sensors stand out. Passive sensors collect the natural radiation emitted or reflected by the surface under investigation. Examples are spectroradiometer or radiometer. In active sensors, radiation is emitted directly from the sensor to measure the radiation reflected from the object. Some examples of active sensors for earth observation are radar and laser. These sensors are less weather dependent, e.g. they can work in absence of sunlight or in presence of clouds, and less affected by the atmosphere (Tempfli et al., 2009). Looking at their technology, sensors are divided according to the spectral portion in which they are concentrated: optical sensors, which work in the visible and in the near infrared portion, electro-optical sensors, which work in the visible and infrared portion, and microwaves sensors.

Any type of surface unit, objects or materials, is characterized by a spectral signature. This signature represents the variation of the unit spectral behaviour (i.e., the different reflection of electromagnetic waves) as a function of the wavelength. By knowing the spectral signature of an object or of a type of surface, it is possible to uniquely identify it, or to classify it depending on its physical conditions. Spectral signatures explain how remote sensing imaging functions. Looking at the three big groups of earth surface land cover, it is possible to identify bare soil, water and green vegetation. The principals' factors that influence the reflectance of bare soil are colour, water content, the presence of carbonates and iron oxide content. Indeed, bare soil spectral signature is different depending on these factors. Water has a low reflectance, around the 10% of the incident energy, mainly in the visible range and a little in Near-Infrared Radiation (NIR) rage. Vegetation has the highest capacity to reflect the incident light. Its spectral signature depends on leaves properties, including the orientation and the structure of the leaf canopy. In the visible range vegetation reflects more in the green band than in the blue and in the red ones. These portions of light are in fact absorbed by the chlorophyll. The highest reflectance is in the NIR range, and the amount depends on leaf development and cell structure. In the last part (SWIR, Short-Wave-Infrared Radiation range) the water content domains the reflection: more free water results in less reflectance (Tempfli et al., 2009). Therefore, the spectral portion on which a sensor is concentrated defines the possible sensor's types of applications.

Nowadays several families of artificial satellites orbiting the Earth exist. They are useful in different applications according to their characteristics. Sentinel is one of the newest programmes for Earth monitoring, still evolving. This programme was developed on behalf of the joint ESA (European Space Agency)/European Commission initiative Copernicus (https://www.copernicus.eu/en), and it consists in a series of next-generation Earth observation mission. Each mission is specific for a different aspect of Earth observation, mainly land, ocean and atmospheric monitoring. The aim was to ensure a continuity of data for ongoing research, replacing satellites near at their life end. Each Sentinel mission is composed by a constellation of two satellites (A and B) to fulfil revisit and coverage requirements. To name a few, Sentinel 1, launched between 2014 (A) and 2016 (B), is a day-and-night radar imaging mission for land and ocean services; Sentinel 2 (2015/2017) is a multispectral high-resolution imaging mission for land monitoring of any type, useful also for emergency services deliver information; the multi-instrument Sentinel 3 is specific for ocean forecasting system, environmental and climate monitoring; Sentinel 4 will be probably lunched in 2023 and it will be devoted to atmospheric monitoring.

Among others, the use of remote sensing in agriculture is nowadays very wide also thanks to the relative low-cost or freely-availability of remote sensing images form international initiatives (e.g., Copernicus). The use in agriculture includes many areas of application, like crop classification, yield forecasting, monitoring of crop nutritional status, water stress, weed infestation and crop health (Di and Üstündağ, 2021; Jung et al., 2021; Usha and Singh, 2013). In this context, Vegetation Index (VI) represents one of the most common approach to obtain information about plants from remote sensing observation. These mathematical combinations of reflectance are designed to enhance the sensitivity to the vegetation properties and minimize atmospheric or directional effect and soil background reflectance influence (Fang and Liang, 2014). Vegetation cover and growth status can be easily monitored by using these simples and effective parameters (Liang and Wang, 2020), becoming increasingly important in monitoring also the global agricultural yield (Yuan et al., 2016). To date, numerous vegetation indices have been developed, each suitable for obtaining information on one or more specific plant aspect, depending on the spectral bands that the index involves. Indices that use reflectance in the near infrared band can be used to obtain information about growth and vigour quantification of plants, related, for example, to water content; indices including thermal infrared spectral band in their mathematical formula allow the assessment of stomata dynamics that regulates transpiration rate of plants (Xue and Su, 2017). The Ratio Vegetation Index (RVI) is one of the first developed index, expressed like the ratio between the near infrared and the red bands. Jordan, 1969 develops this index starting from the principle that plant leaves absorb relatively more in the red light, so the more the canopy is voluminous, the greater will be the ratio index. The Difference Vegetation Index (DVI) can be expressed as the subtraction between the near infrared and the red band. This index is very sensitive to changes in soil background. One of the most used indices is the Normalized Difference Vegetation Index (NDVI). As it says, its formulation is the normalised ratio between the red and the near infrared spectral band. It is used mainly to characterize the growing phase of the plant, involving spectral bands absorbed mainly by leaves chlorophyll. Therefore, it is often compared to the Leaf Area Index parameter. Thus, depending on the case of study, one or more VIs can be calculated and used to understand the state of the crop.

Crops spatial distribution plays a key role in a time when resources are dwindling and population constantly increasing. Rice, wheat, corn and barley are staple crops in many parts of the world, therefore finding a way to monitor them at regional, national or global scale is fundamental (Orynbaikyzy et al., 2019). In this context, remote sensing assumes an important role in crop classification, giving information about large-scale agricultural monitoring (Sun et al., 2018). It has a geo-referenced statistical purpose, informing about the distribution of territorial crop macro classes. At the same time, it can support irrigation water management through the identification of the potentially irrigated areas (Nhamo et al., 2018) and integrate the information in agro-hydrological models to estimate in advance the irrigation needs of the identified agricultural crops, improving water use efficiency (de Albuquerque et al., 2021). Several studies have been conducted regarding crops classification from remote sensing e.g., through supervised and unsupervised classification models (H. Li et al., 2021; J. Li et al., 2021); combining different satellite sensors acquisitions (Chakhar et al., 2021; Fan et al., 2021); integrating remote sensing and geographical analysis systems (Jayanth et al., 2021).

With the aim of assessing the reliability of remote sensing products to support agriculture, this study focused on the assessment of a crop classification obtained through the analysis of NDVI images, performed within the iCOLT project by ARPAE (https://sites.google.com/drive.arpae.it/servizio-climatico-icolt). This existing classification has been compared in the present study to the declared land use of 2020 over some specific areas in Northern Italy obtained by the Bonifica Renana Consortium (https://www.bonificarenana.it/servizi/Menu/dinamica.aspx?idSezione=19034&idArea=19105&idCat=19131&ID=19131&TipoElemento=categoria). These data represent the territorial ground-truth based on farmer declarations in the framework of the consortium Acqua Virtuosa project. The aim is to understand if and how remote sensing can support water user associations and environmental agencies, providing valuable information for agricultural water management and planning over large areas.

The comparison between remote sensing classification and declared data provided by the Bonifica Renana Consortium has been carried out in a geographical information system environment (GIS) by means of vectors analysis of the areas assigned to the crop class identified. Percentages of accuracy in remote sensing classification have been then determined. All the analyses have been performed by QGIS 3.4, Madeira.

3.2 MATERIALS AND METHODS

3.2.1 Study areas and irrigation districts

The crop classification and comparison has been carried out at district scale in the framework of areas selected within the INCIPIT project (https://www.principit2017.it/). Specifically, nine districts located in the Emilia Romagna region plain area, under the management of the Bonifica Renana Consortium have been analysed (Figure 7). The area is located within the Reno River basin, north-east of the metropolitan city of Bologna, between Samoggia and Sillaro streams. Bonifica Renana Consortium manages about 341,953 ha extended in this area, of which 140,220 ha are interested by plain basins, taking care of the operation and maintenance of hydraulic network; 201,733 ha are interested by hill and mountain basins, in which the Consortium takes care of the regulation and the correct drainage, maintaining the hydrogeological supervision. Within the plain area, water comes mainly from surface water sources, such as the Po River, through the Canale Emiliano Romagnolo

(CER), the Reno River, wastewater treatment plant and consortium reservoir. 32 are the main plain basins, with a total of about 2076 km of canals and irrigation pipes. Irrigation is carried out mainly on demand and when necessary, using a rotation system. Figure 8 shows the Consortium plain area, water sources, canals, irrigation pipes, pump, and the location of the nine selected districts.

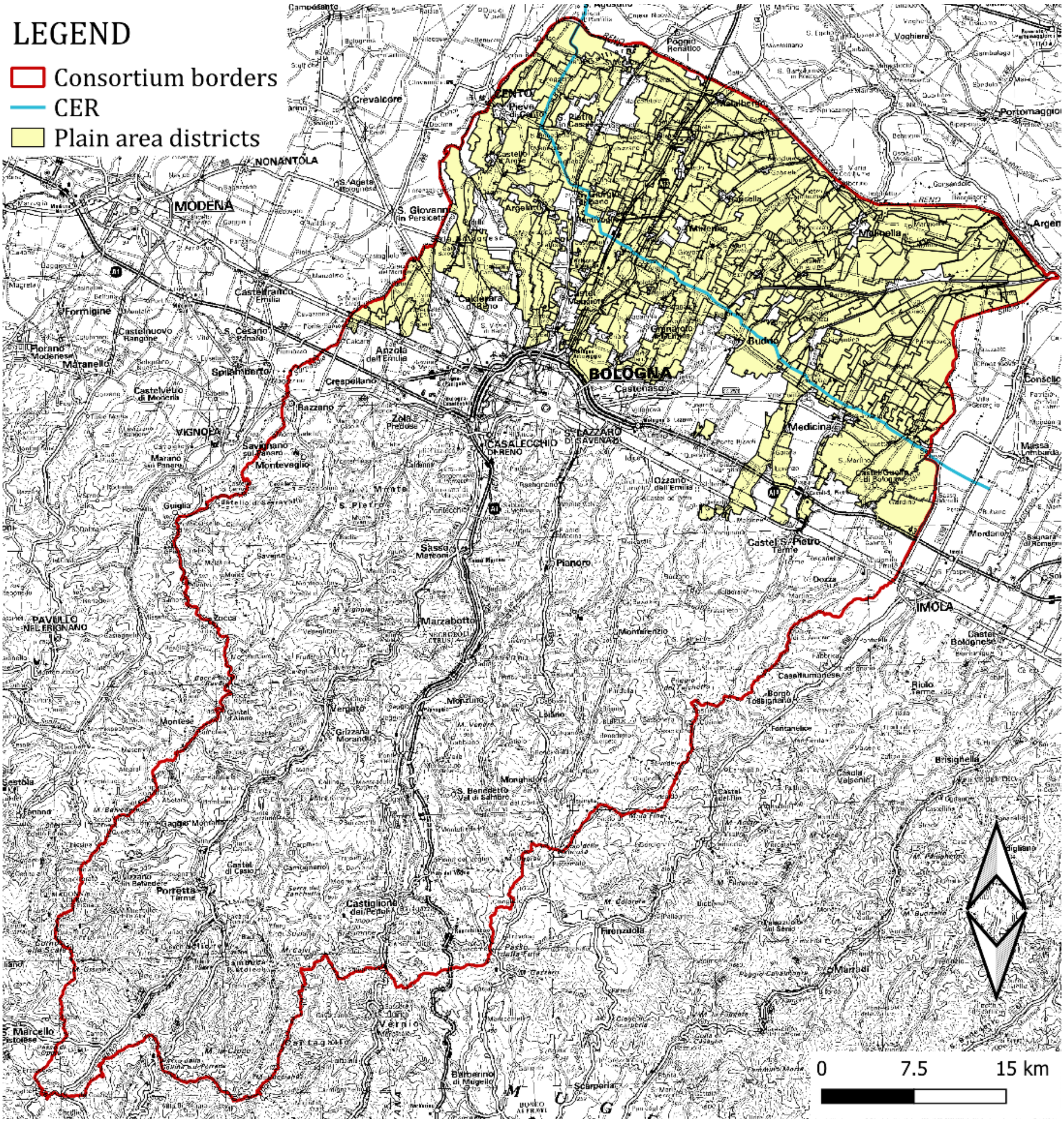

Figure 7 Bonifica Renana Consortium, source Report 2020, Bonifica Renana, 2020

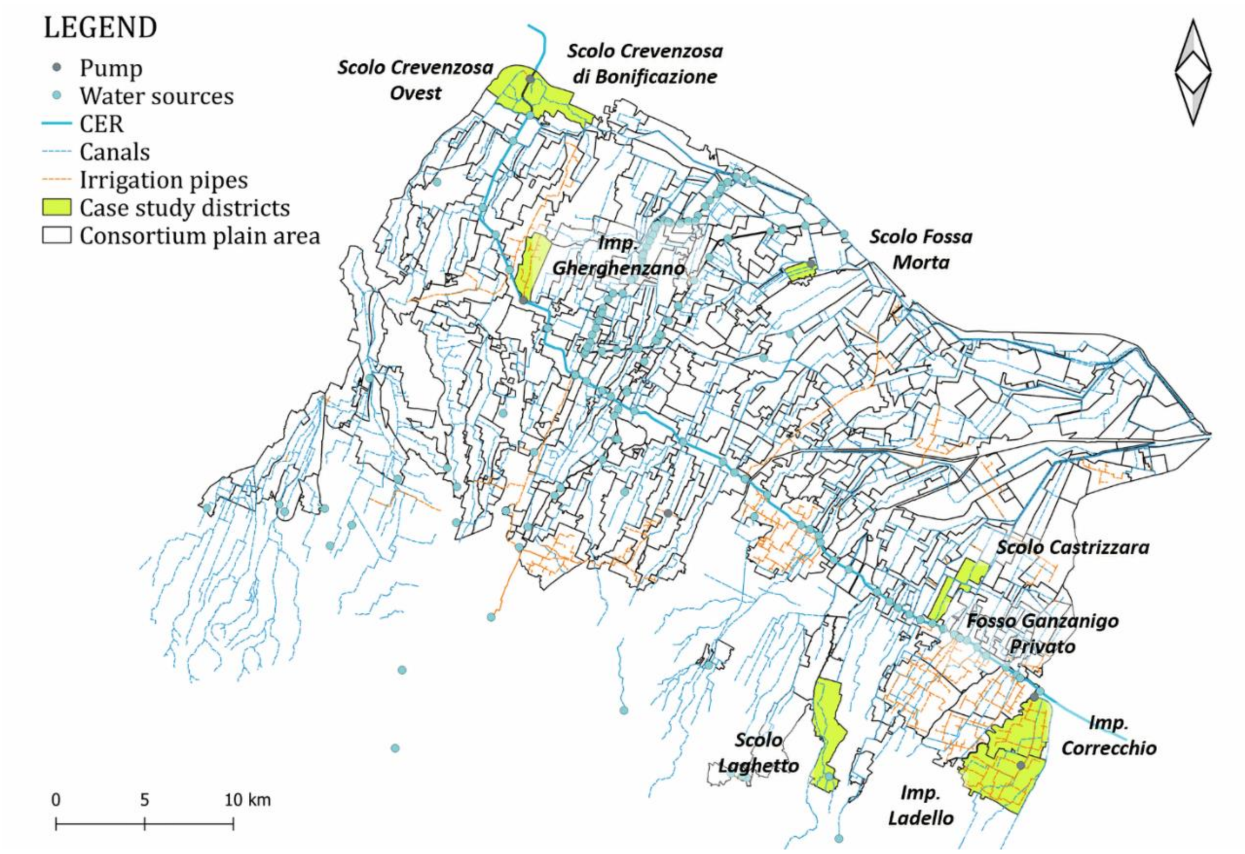

Figure 8 Bonifica Renana Consortium plain area and the selected nine districts

The nine selected districts can be distinguished into two main groups: three districts fed by pressurized pipe, six fed by open air canals. These districts are described in more details below.

Starting from the pressurized pipe group there is:

- *Impianto Ladello district*
  It is located in the east part of the Consortium, in the municipality of Imola. The west boundary corresponds to the Sillaro torrent, the east one to the Consortium border. It covers 1134 ha of territory; the district's water source is Canale Emiliano Romagnolo, through the "Correcchio invaso Ladello" pump.
- *Impianto Correcchio district*
  It is limited by the Ladello district to the south and it extends for 809 ha. The irrigation source is the CER through the "Correcchio distribution" pump.
- *Impianto Gherghenzano district*
  It is a smaller district (419 ha) deriving water from CER through the Gherghenzano pump.

In the open canals group, there is:

- *Fosso Ganzanigo Privato and Scolo Castrizzara districts*

These are two districts, the second downstream to the first, fed by the Ganzanigo Derivation (CER). Both are located under the municipality of Medicina (BO). For a better understanding of the data at the derivation, these two districts have been considered as one, for a total area of 377 ha.

- *Scolo Crevenzosa di Bonificazione and Scolo Crevenzosa Ovest districts*

These are two adjacent districts under the municipalities of Pieve di Cento and Galliera, fed by two separate pipelines by the Bisana Pump (CER). As in the case of the Gabzanigo Privato and Scolo Castrizzara districts, for a better understanding of the data at the derivation, they have been considered as a single district.

- *Scolo Fossa Morta district*

Fossa Morta is a small district located near San Gabriele di Baricella (BO). It is fed by the Marchette pump, which takes water from the Fiumicello delle Bruciate Inferiore (fed by CER) and, by means of an automatic system equipped with a float for measuring the water level in the canal, maintains a constant level by switching the pump on and off.

- *Scolo Laghetto distict*

This district is located in the municipality of Castel San Pietro Terme (BO). It is fed by the civil wastewater treatment plant and it covers 780 ha.

3.2.2 Crop classification using NDVI maps

To investigate on remote sensing use and reliability in agriculture, this chapter focused on the first part of the iCOLT system: identification and quantification of the current agricultural crops.

The aim of the iCOLT remote sensing analysis is to obtain the so-called *early crop map* by the end of April of every year (beginning of the irrigation season). This land use map is then integrated into the agro-hydrological model CRITERIA-1D to obtain forecast irrigation requirements by the end of June (Villani et al., 2021, 2014). Going into detail of this classification, land use is grouped in three macro-classes below reported:

- Spring-summer herbaceous crops – *SShc*
- Autumn-winter herbaceous crops – *AWhc*
- Poly-annual crops (i.e., alfalfa and meadow) – *PAhc*

The other classes, considered as permanent land cover, like fruit orchards and vineyards, have been derived through the integration of Agrea (Agenzia Regionale per le Erogazioni in Agricoltura) declaration of the previous year and the cadastre. Agrea is the regional paying agency that provides aid, award and contributions to all operators in the agricultural sector under community, national and regional producers (https://agrea.regione.emilia-romagna.it/agenzia). The agency collects information about crops distribution and makes them available every year at the end of August. This timing would not allow their use within the iCOLT service: therefore, the importance to have an alternative classification, at least for herbaceous crops, is fundamental in a forecasting support process of irrigation water management.

For 2020 year, the crops classification has been performed by analysing multi-temporal series of optical satellite images planned and acquired ad-hoc during the period between November 2019 and April 2020. Specifically, the classification is generally based on NDVI seasonal variation with respect to three acquisition windows (W) defined according to the phenological phases of the crop classes on a seasonal basis. Precisely:

- W1: 20/10 – 30/11
- W2: 25/01 – 28/02
- W3: 25/03 – 30/04

The reference equation for the calculation of this vegetational index is:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

In which *NIR* represents the Near Infrared Radiation, *RED* the Red one.

Sentinel 2 constellation (Table 2) has been chosen for 2020 classification, considering availability in the established temporal windows, the imaging in RED and NIR bands for the calculation of the NDVI index, the significant swath width of 290 km, and the obtainability of a spatial resolution of 22 m through down-sampling (Spisni, 2018).

Table 2 Sentinel 2 data characteristics

<table>
<tr><td>Data type</td><td></td><td>Sentinel 2, level 1C (Top of Atmosphere)</td></tr>
<tr><td>Spectral resolution</td><td></td><td>13 spectral bands</td></tr>
<tr><td>Temporal resolution</td><td></td><td>10 days, 5 days A and B combined</td></tr>
<tr><td rowspan="2">Spatial resolution</td><td>RED (B4)</td><td>10 m, resampled at 20 m through pixels average</td></tr>
<tr><td>NIR (B8a)</td><td>20 m</td></tr>
</table>

Classification procedure starts with satellite images pre-processing. It consists in read input parameters, import relevant bands (i.e., RED and NIR), reprojecting and resampling raster if required, clip data over the interested area, calibrate at top of atmosphere reflectance (TOA) and mask and correct in case of clouds or irrelevant features, like roads, railroads and anything is not considered as agricultural (Spisni, 2018).

Once the index has been calculated, the procedure applies a decision-making tree to assign the crop to its macro-class. To do that, three NDVI threshold, different for every acquisition window, have been defined, with the aim to identify the presence or the absence of vegetation (Figure 9). Reference thresholds have been derived from Sobrino et al., 2004, consequently adapted to the climate and the agriculture of Emilia Romagna region (Spisni, 2018). Following the decision-making tree logical reasoning, eight are the combinations that have been defined to classify the regional crops (Table 3).

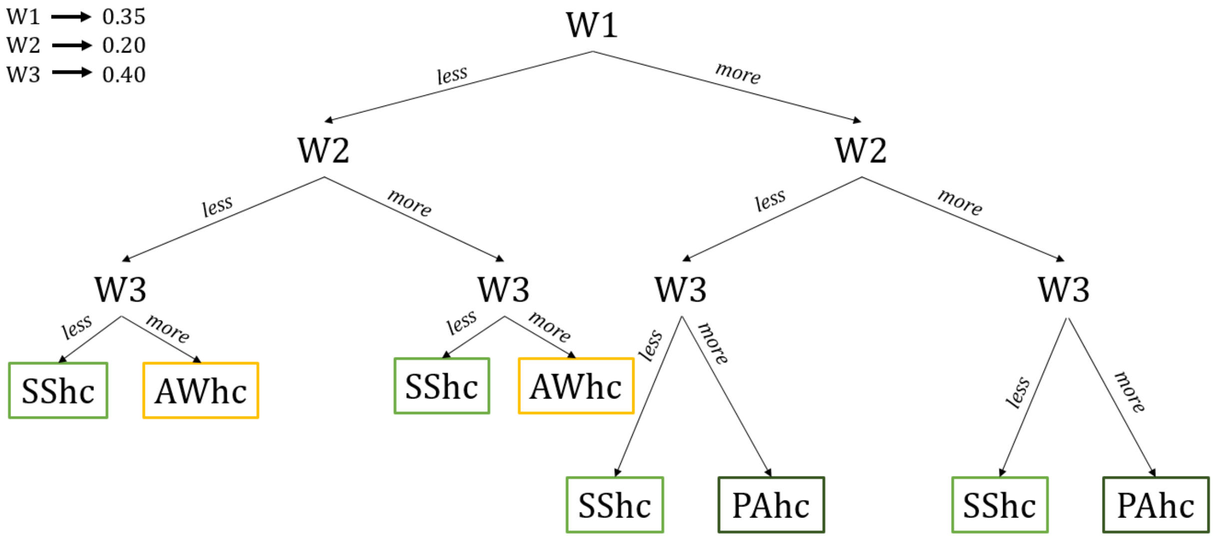

Figure 9 Decision-making tree and vegetation thresholds depending on acquisition windows

Table 3 Eight combinations defined following the decision-making tree logical reasoning

		W1	W2	W3	Info
1	SShc	no veg	no veg	no veg	Summer crops
2	AWhc	no veg	no veg	veg	Late wheat
3	SShc	no veg	veg	no veg	Weed with destination to summer crops
4	AWhc	no veg	veg	veg	Autumn-winter crops like wheat, barley, rape
5	SShc	veg	no veg	no veg	Horticultural crops like spinach, carrots, etc.
6	PAhc	veg	no veg	veg	Pure alfalfa
7	SShc	veg	veg	no veg	Alfalfa with destination to summer crop
8	PAhc	veg	veg	veg	Alfalfa and meadow

The post-classification phase starts with the class aggregation: even if the decision tree algorithm produces eight different final classes, they are incorporated into the three macro-classes with similar phenological stages (Villani et al., 2021). An exception in this procedure is made for those crops not agronomically defined as spring-summer herbaceous type, but which require irrigation; therefore, these crops are usually included in the spring-summer crops macro-class, considered as the only irrigated one in the second part of the iCOLT procedure.

Every year within the end of April, ARPAE produces the crop classification for the entire regional area.

In the framework of this iCOLT procedure first section, a classification accuracy is determined through field surveys leaded during the current irrigation season. Surveys should focus on fields with regular shape and their size should be at least greater than 1 ha in order to limit the impact of "mixed pixels". The amount of collected data must be representative of the defined aggregated classes for confusion matrix computation (Spisni, 2018). For 2020 season, due to the pandemic restrictions, the surveys corresponding to the third window (W3, April 2020) could not be carried out. A total of 338 fields with a surface area of 1065 ha have been detected, considering the entire regional plain area.

Focusing on the case study area, Figure 10 shows the iCOLT crop classification over the entire Bonifica Renana Consortium plain area for 2020 irrigation season. The class *Other* represent the collection of all permanent crops not identified by remote sensing (Figure 10, brown colour). By visual inspection it is possible to note the majority of spring-summer crops (irrigated, *SShc*), followed by rainfed winter crops (*AWhc*) and perennial crops (*PAhc*). The group *Other* has a relative limited extension, and it is mainly detected at the south-east boarder of the study area.

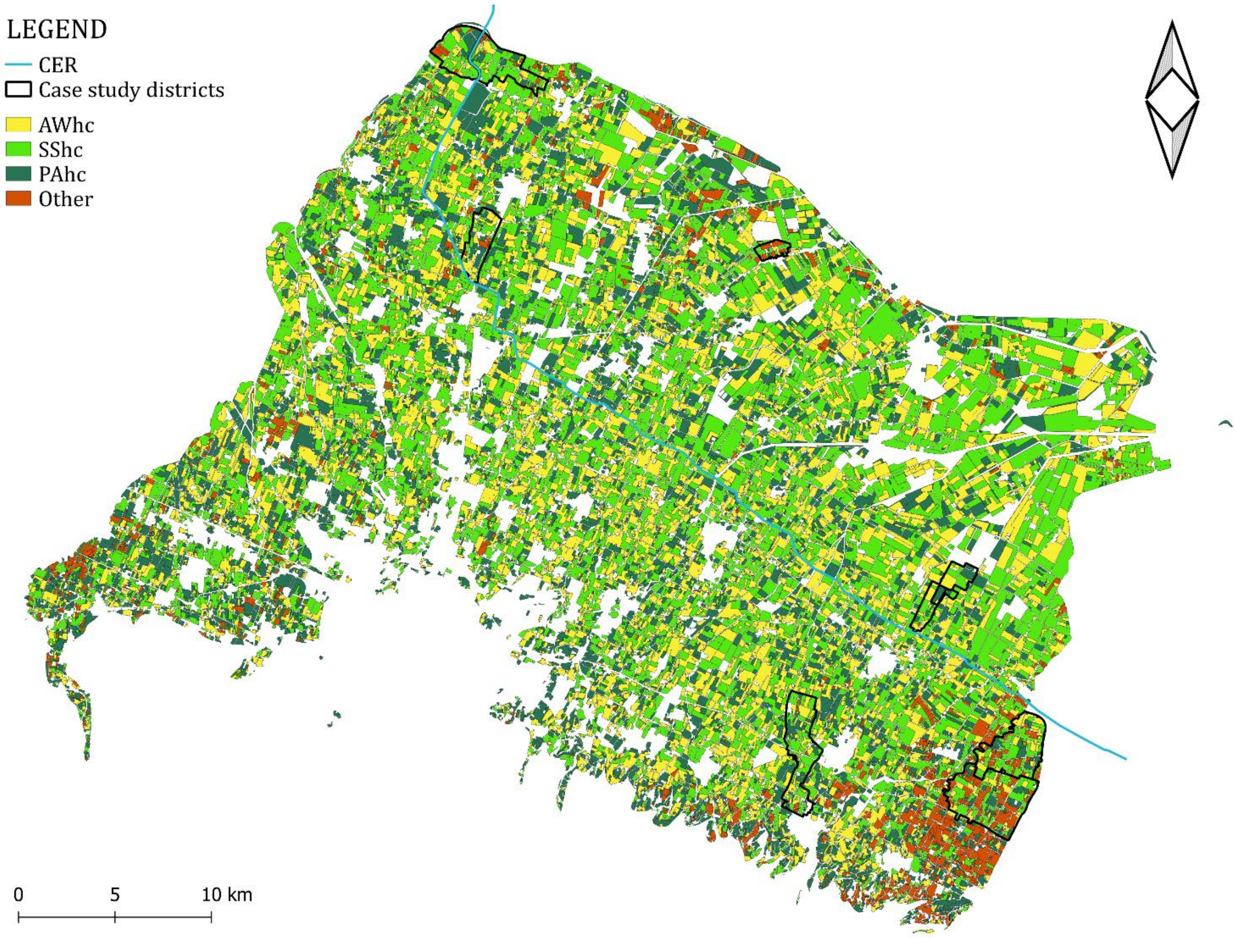

Figure 10 iCOLT crop classification over all the Bonifica Renana Consortium plain area for 2020 irrigation season; in yellow colour autumn-winter herbaceous crops, in green colour spring-summer herbaceous crops, in dark green colour poly-annual herbaceous crops, in brown colour permanent crops

3.2.3 Ground-truth based on farmer declaration: Acqua Virtuosa project

The Bonifica Renana Consortium conducts since 2014 the Acqua Virtuosa project (https://www.bonificarenana.it/servizi/Menu/dinamica.aspx?idSezione=19034&idArea=19105&idCat=19131&ID=19131&TipoElemento=categoria). Via short interviews, the Consortium collects in January, February and March all the information about fields that the farmers plan to irrigate during the following irrigation season. The main objective of this activity is to track irrigated areas for the coming season. These areas are subsequently digitalized within the TOLOMEO Web GIS platform, by which is possible to visualize the declared areas and allows spatial aggregation by districts. In general terms, by means of Acqua Virtuosa project (AV), the Consortium aims to (i) save the resource by optimising the use of irrigation water both at district and farm level; (ii) collect the essential data to quantify the irrigation contribution, according to the new Classification Plan; (iii) activate a direct communication with farmers (Report 2020, Bonifica Renana, 2020).

Figure 11 shows Acqua Virtuosa declared areas for 2020 irrigation season over the entire Consortium plain area.

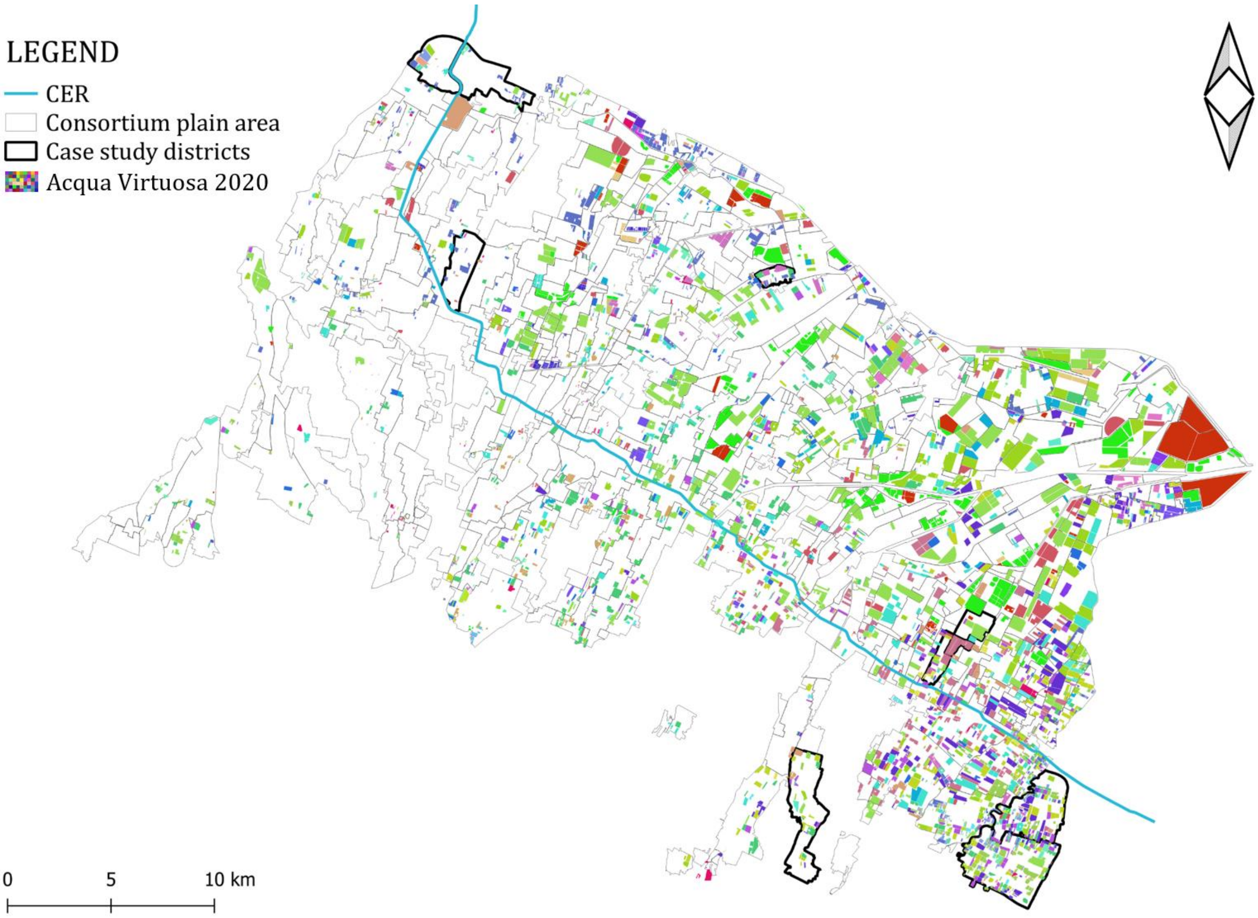

Figure 11 Acqua Virtuosa declared information for 2020 irrigation season

The information included into the geographical dataset are, for every declared field: crop type, irrigation method, hectares of extension, district of affiliation. For the season 2020, it is notable a relative low extension of declared areas, with majority of corn followed by seed crops and a considerable zone dedicated to wetlands (orange colour). Most of the declared areas are located in the Consortium southern area. Declared information regarding the nine selected districts have been used for the comparison with iCOLT remote sensing crop classification.

3.2.4 Comparisons between declared information and remote sensing

To obtain an effective and reasonable comparison, declared information regarding the crop type collected in the framework of the AV project have been aggregated into the iCOLT classification macro-classes (Table 4).

Table 4 Aggregation of Acqua Virtuosa declared information in the three iCOLT macro-classes (AWhc, SShc, PAhc) and in the new class Other

AWhc	***SShc***	***PAhc***	***Other***
Autumn-winter cereals	Asparagus, Asparagus (first year), Aubergine, Bean, Biomass sorghum, Biomass waxy corn, Cantaloupe, Carrot, Celery, Corn, Fruit vegetable crops, Garlic, Generic vegetable crops, Green bean, Leaf vegetable crops, Pee, Potato, Radish, Rice, Salad, Seed crop, Seed sugar beet, Soy, Spring onion, Squash, Strawberry, Sugar beet, Sunflower, Tomato, Watermelon, Zucchini <u>Autumn onion</u> <u>Cauliflower</u> <u>Alfalfa (first year)</u>	Alfalfa, Stable meadow, Wet meadow	Actinidia, Apple, Apricot, Bamboo, Cherry, Generic orchard, Peach, Pear, Plum, Vineyard Aromatic crops, Fish farming, Wetlands, Nursery, Other crops, Parks and gardens, Pulping mill

The aggregation has been made following a similarity criterion in the crop cycle. To accurately follow the iCOLT procedure, autumn-onion, cauliflower and alfalfa (first year) have been put in the spring-summer herbaceous class, due to their need of irrigation. Aromatic crops, fish farming, wetlands, nursery, other crops, parks and garden and pulping mill were not considered due to a difficulty in classified them and the small area that they cover in the interested districts (around the 2 % of the total classified area). For this reason, they were collected in the class *Other*, together with permanent crops.

As described in previous chapters and looking at Figure 10 and Figure 11, some specific characteristics of the two classifications should be highlighted for the further comparison. iCOLT is a pure crop classification tool over the all-regional extension, with the final aim to provide an irrigation prevision support; AV project obtains crop type information only regarding fields declared irrigated by the farmers for the coming irrigation season. Based on that, this study aims to underline the importance of this comparison in two aspects. On the one hand, the information declared through the AV project can be used to validate the classification by remote sensing; on the other hand, the iCOLT classification may be able to classify areas not declared irrigated by farmers, thus helping the Consortium to identify and locate undeclared situations.

Therefore, for the first purpose, to validate information obtained from remote sensing the classification has been clipped over the Acqua Virtuosa declared areas. As specified before, orchard and vineyards (i.e., *Other*) are usually considered as permanent land cover by the iCOLT project, collecting information from Agrea. Accordingly, only herbaceous crops have been considered for the comparison of macro-classes areas between the two classification tools. A percentage of accuracy for each macro-class's classification has been then determined, using the comparison tool of the QGIS software.

Differently, for the second purpose, to underlined potential irrigated areas not declared, firstly only areas classified as spring-summer herbaceous crops (*SShc*) has been selected, being the only macro-class considered as irrigated by the iCOLT. Consequently, among them, only areas not declared as irrigated in AV project have been selected, to obtain the so-called potential irrigated areas (*SShc_p*).

In the following chapter (3.3 Results) maps comparing the two datasets are shown, for each district, with relative descriptions (3.3.1 chapter); following, graphs and indices are provided to summarise the comparison (3.3.2. chapter).

3.3 RESULTS

3.3.1 Remote sensing and declared classification

In the following, a description of the remote sensing classification within the selected districts is firstly presented and discussed. The visualization of the correspondence between this classification and the declared land use, as specified in 3.2.4. Chapter, focuses only on herbaceous crops (i.e., *AWhc*, *SShc*, *PAhc*), using green colour for fields with correspondence, red colour for fields without correspondence, blue colour for potential irrigated areas not declared within the AV project (*SShc_p*).

<u>Impianto Ladello and Impianto Correcchio districts</u>

The two districts are presented together for similarity and convenience, due to their proximity.

In Ladello district, remote sensing classification allocates 985 ha to the agricultural usage, i.e. the 87 % of the total area (Figure 12a). The 34 % is identified as spring-summer herbaceous crops (335.5 ha). Approximately the same area is identified as other crops, with a strong presence of vineyards, covering 270 ha. Poly-annual crops and autumn-winter crops follow with respectively 176 ha and 137 ha.

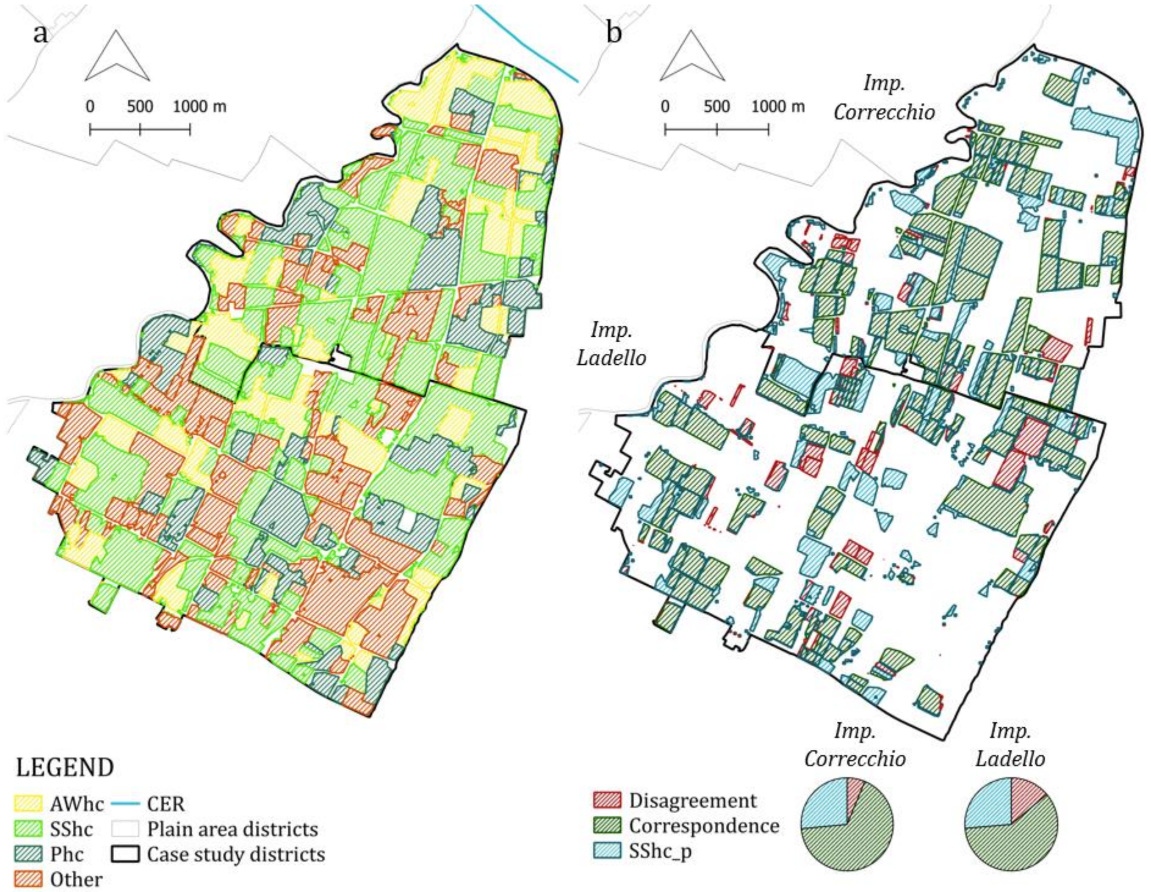

Figure 12 Impianto Correcchio and Ladello districts iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with potential irrigated areas (blue colour) (b)

Similarly to the Ladello district, the iCOLT classification shows for the Correcchio district a greater presence of spring-summer herbaceous crops (44.5 %), with 309.6 ha over the total cultivated area of 696 ha (Figure 12a). Autumn-winter herbaceous crops follow with 154.5 ha. A 17.6 % is dedicated to other crops, with a majority in vineyard (68.82 ha). A 16 % is dedicated to poly-annual crops.

Figure 12b shows a high-quality correspondence between declared and classified areas, for both districts. Noteworthy, some areas are still indicated as potential irrigated areas by the remote sensing classification while they are not declared within the AV project (*SShc_p)*.

<u>*Impianto Gherghenzano district*</u>

Looking at Figure 13a, the 34 % of the total cultivated area (327.7 ha) is assigned to autumn-winter crops, following with spring-summer herbaceous crops and poly-annual crops in a similar extension, respectively 98 ha and 94 ha. A small part (7 %) is dedicated to pear orchard. Considering the available ground truth, a very small percentage of the total Gherghenzano area has been declared by the farmers as spring-summer herbaceous crops, as it is shown in Figure 13b. In contrast, remote sensing classification identifies several areas as potential irrigated fields (*SShc_p)*.

Figure 13 Impianto Gherghenzano district iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with potential irrigated areas (blue colour) (b)

Fosso Ganzanigo Privato and Scolo Castrizzara district

At the Fosso Ganzanigo Privato and Scolo Castrizzara districts, remote sensing results show that spring-summer herbaceous crops are the main land use with an area of 144 ha, over the total cultivated area of 330 ha (Figure 14a). Following there are autumn-winter crops with an area of 115.3 ha and poly-annual crops with an area of 68.2 ha. Other crops are present in the form of vineyard in a small part (0.69 %). Figure 14b shows that most of the fields classified as spring-summer herbaceous crops were declared by farmers during AV interviews as correspondent to that class. Similarly, only few areas are identified as potential irrigated areas (*SShc_p)*.

Figure 14 Fosso Ganzanigo Privato and Scolo Castrizzara districts iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with undeclared potential irrigated areas (blue colour) (b)

<u>*Scolo Crevenzosa di Bonificazione and Scolo Crevenzosa Ovest district*</u>

At Crevenzosa di Bonificazione and Crevenzosa Ovest districts, remote sensing crop classification identifies a total of 856 ha of cultivated areas, over a total area of 996 ha (Figure 15a). The majority is assigned to spring-summer herbaceous crops, with 456.2 ha (53 %). Following poly-annual and autumn-winter crops equalized with approximately 157 ha each. Pear orchards totalize around 52 ha, as the most present crop under the *Other* classification. As for the Gherghenzano district, the available ground truth concerning herbaceous crops indicates a low number of fields; In contrast, the potential irrigated class *SShc_p* dominates the entire district area (Figure 15b).

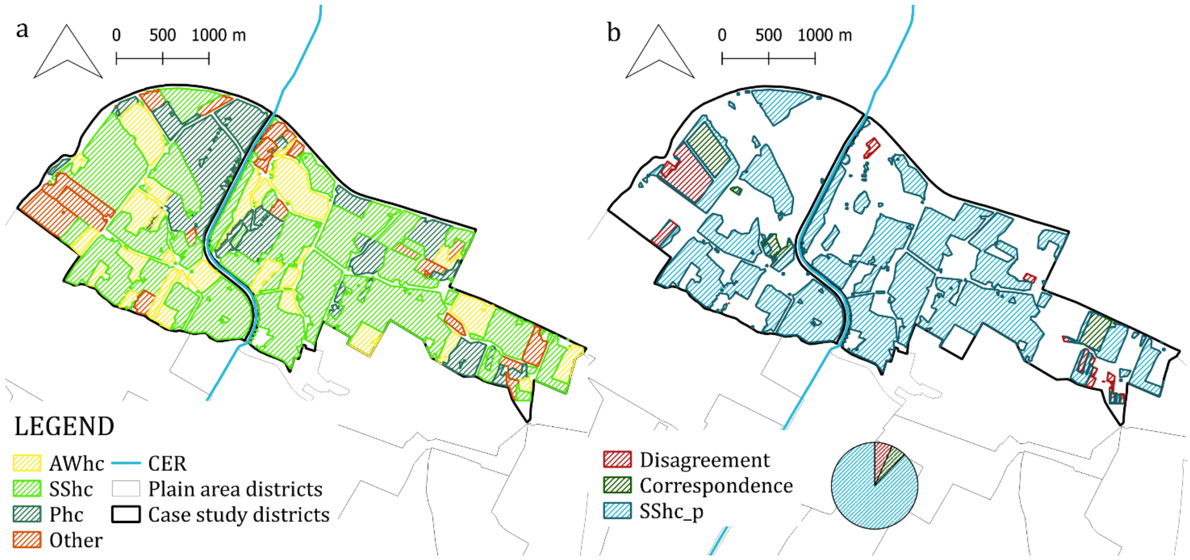

Figure 15 Scolo Crevenzosa di Bonificazione and Scolo Crevenzosa Ovest districts iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with potential irrigated areas (blue colour) (b)

<u>Scolo Fossa Morta district</u>

At Fossa Morta district, remote sensing crop classification identifies 106 ha of cultivated areas, over a total area of 129 ha (Figure 16a). The majority is interested by apple and pear orchards, with the 45 % of the total cultivated area. Spring-summer herbaceous crops follow with around 40 ha. Autumn-winter and poly-annual crops cover around 8 ha each one. Considering the available ground truth, the correspondence between the two datasets is very good (Figure 16b). However, several areas are classified as potential irrigation areas and not declared by AV project (*SShc_p)*.

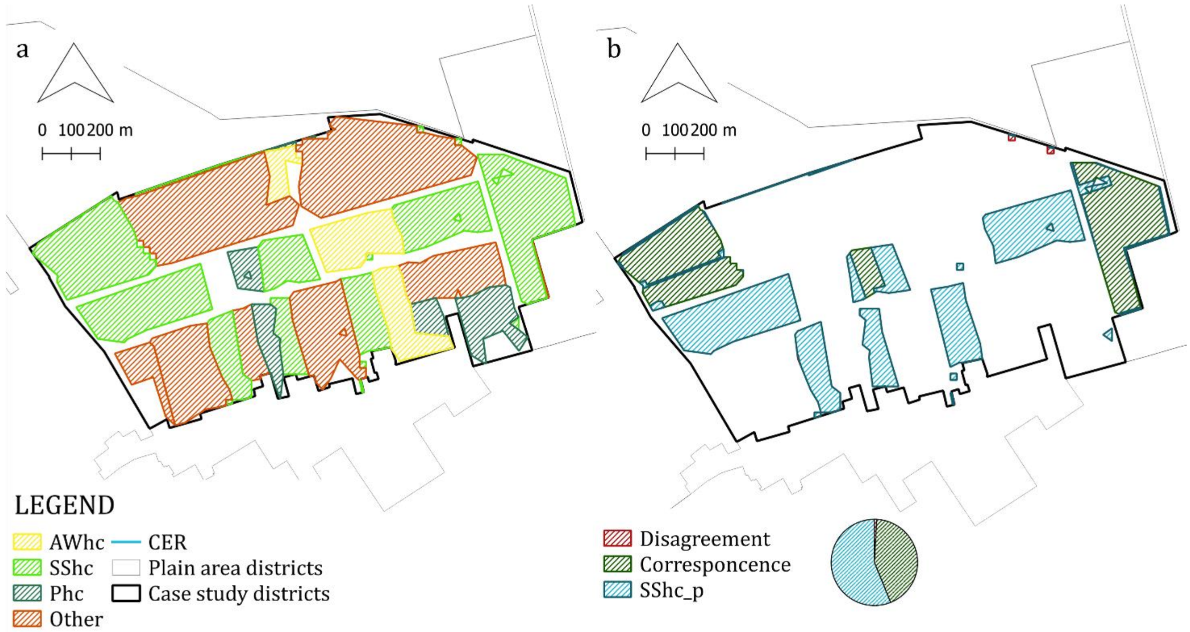

Figure 16 Scolo Fossa Morta district iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with potential irrigated areas (blue colour) (b)

Laghetto district

The Laghetto district area covers 780 ha, of which 620.2 ha are identified as cultivated areas by the remote sensing classification (Figure 17a). More than half of the cultivated area is classified as spring-summer herbaceous crops (317 ha). The 25 % of the remaining area is classified as autumn-winter herbaceous crops, and the 20 % as poly-annual crops. Only the 3 % is allocated to fruit orchard, mainly apricot and vineyard. Looking at Figure 17b, high correspondence between remote sensing classification and AV project can be detected. However, also in this case high percentage is dedicated to potential irrigated area (*SShc_p).*

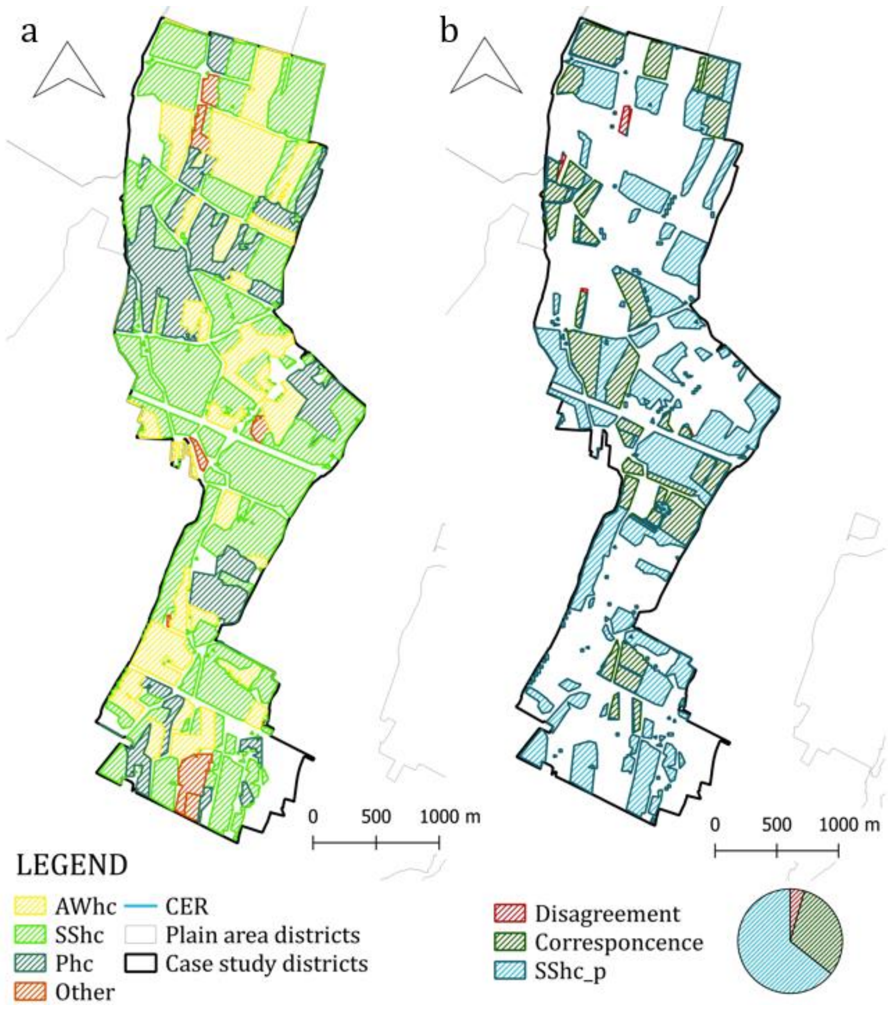

Figure 17 Scolo Laghetto district iCOLT crop classification (a); fields in disagreement (red colour) and in agreement (green colour) with the declared land use, together with potential irrigated areas (blue colour) (b)

3.3.2 Quantitative comparison of land use classification

In this section, some indices and plots are calculated and shown to effectively compare the remote sensing classification with the declared land use. As specified in chapter 3.2.4., to conduct this comparison iCOLT data have been clipped over the declared information obtained through the Acqua Virtuosa project.

Looking at the declared land use, it is interesting to note that only around 30 % of the total districts area has been declared as irrigated, i.e. 1290 ha over the total 4644 ha (Figure 11). After the aggregation of the specific crops of the AV dataset into macro-classes, it is found that more than half of the declared area is dedicated to spring-summer herbaceous crops (i.e., 751 ha), 37 % to *Other* class and only a small fraction is classified as autumn-winter and poly-annual crops (i.e., 1 % and 4 % respectively) (Figure 18). Overall, in terms of classified areas, the comparison between the two datasets is of high quality. In agreement with both the datasets, the class most cultivated in the selected nine districts is spring-summer herbaceous crops. Following there are the classes *Other*, *PAhc* and *AWhc*, always in agreement between the two information. Remote sensing classification slightly overestimates the presence of the three herbaceous macro-classes while, underestimates the presence of permanent crops (*Other*). Detailed results at each district are also reported in Table 5 but with no significant differences identified between the areas.

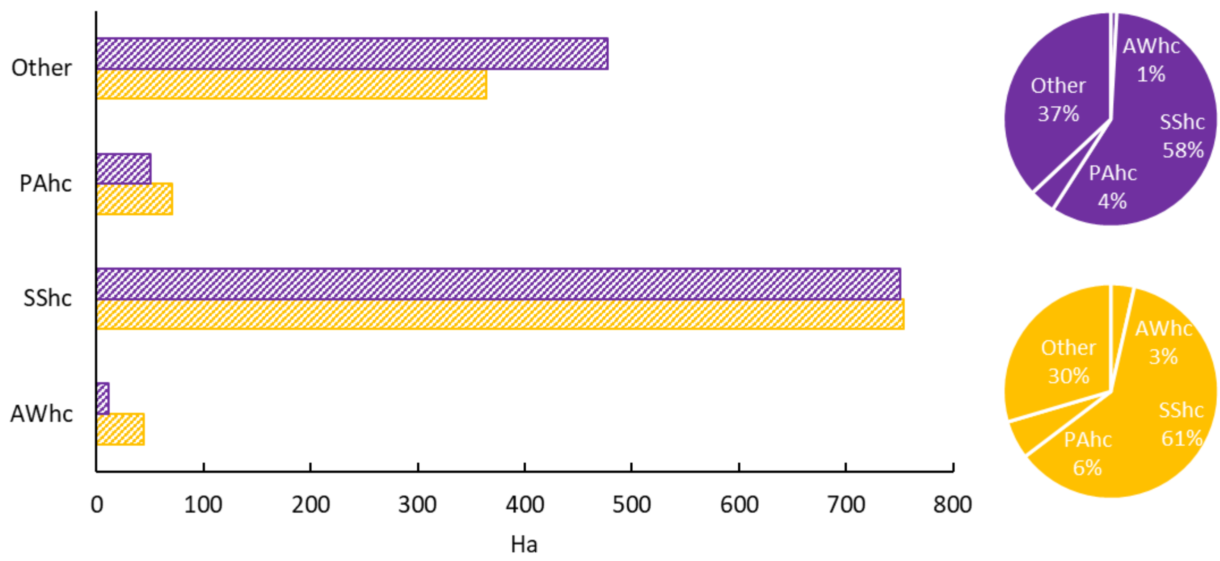

Figure 18 Bar diagram reporting the distribution of analysed hectares over all the selected nine districts following the Acqua Virtuosa declared land use (violet colour) and the iCOLT classification (yellow colour); on the right-side pie charts reporting the corresponding percentage of attendance

Table 5 Allocation in hectares of the three macro-classes following the iCOLT classification and the Acqua Virtuosa declared land use, for each selected district

	iCOLT			AV		
	AWhc	*SShc*	*PAhc*	*AWhc*	*SShc*	*PAhc*
I. Correcchio	9.83	220.98	16.15	7.48	244.81	5.02
I. Ladello	14.17	237.12	24.65		245.43	0.31
I. Gherghenzano	0.17	9.25	1.63		4.20	
F. Ganzanigo P. e S. Castrizzara	16.26	107.81	21.70	3.95	88.44	45.10
S. Crevenzosa di Bon. e Ovest	1.96	49.41	5.51	0.22	28.94	
S. Fossa Morta		17.48	0.06		18.81	
S. Laghetto	1.18	111.58	1.25		119.90	

In Figure 19 the percentage of correspondence and disagreement between the two datasets for each herbaceous macro-class is shown. Spring-summer crops is the better identified class from remote sensing; on the contrary, autumn-winter crops class is the worse classified. Poly-annual crops class stands in the middle with around a 35 % of correspondence and a 65 % of disagreement. For both the classes worse identified, most of the hectares in disagreement with the declared land use are interested by spring-summer herbaceous crops. Noteworthy, the presence of autumn-winter and poly-annual herbaceous crops is very low with respect to spring-summer herbaceous one (Figure 18). Therefore, the percentages of disagreement of these classes over the entire considered area are not such significance.

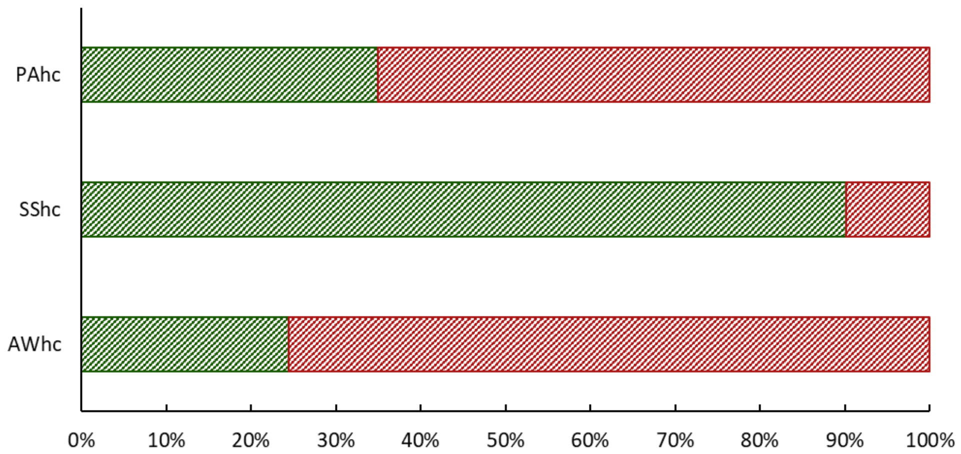

Figure 19 Percentage of the correspondence (green colour) and disagreement (red colour) between iCOLT classification and the Acqua Virtuosa declared land use for each herbaceous macro-class

Finally, the total area identified as irrigated by remote sensing but non declared in the framework of the AV project is shown for each district in Figure 20. On the right side a pie chart representing the

percentage over the entire district area is also depicted. Crevenzosa di Bonificazione and Crevenzosa Ovest are characterized by the highest potential irrigated areas over the entire district area (i.e., more than the 40 %). Correcchio, Ladello, and Gherghenzano districts are similar with around 100 ha of potentially irrigated areas. Noteworthy S. Fossa Morta district is characterized by the smallest number of *SShc_p* hectares (i.e., around 23 ha), which represent the 17 % of the total district area (Figure 20).
Noteworthy, despite only a more detailed survey based on direct field activities can shed lights on the reason of these potential irrigated areas, the value of remote sensing for prioritizing the targeted areas that needs further attention has been well capture also by this study.

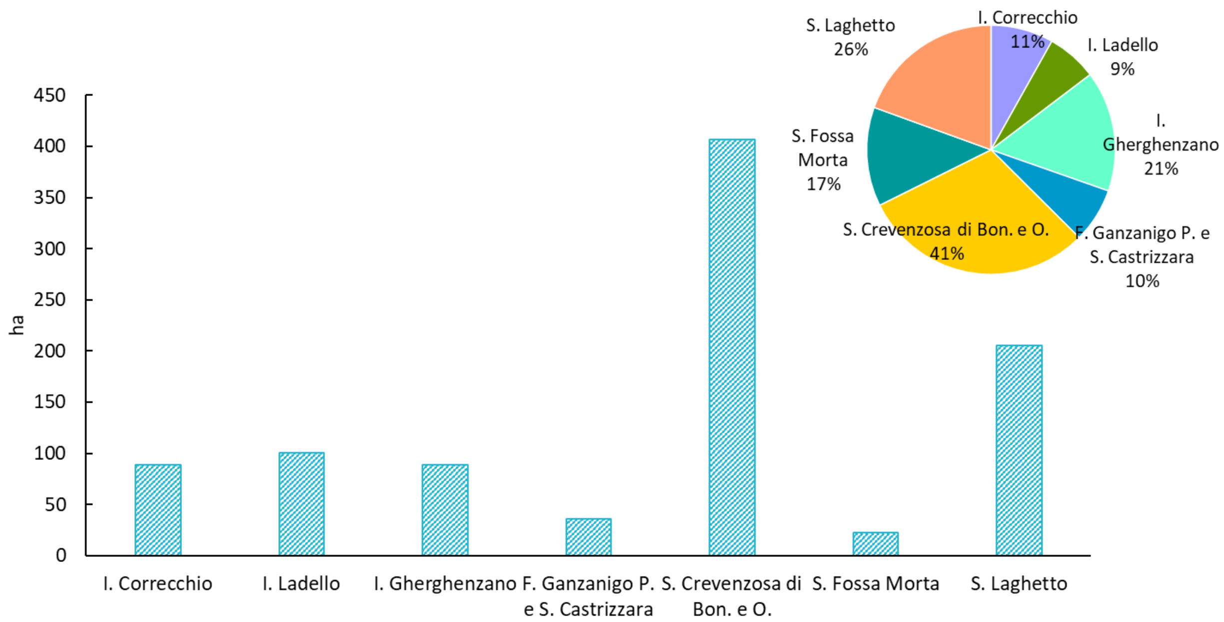

Figure 20 Bar diagram reporting the distribution of potential irrigated areas in each district; on the right-side a pie chart reporting the corresponding percentage of attendance over the entire district area

3.4 CONCLUSIONS

This study focused on the comparison between a remote sensing land use classification developed in the framework of the iCOLT project (https://sites.google.com/drive.arpae.it/servizio-climatico-icolt), and the declared land use by farmers collected by the Acqua Virtuosa project (https://www.bonificarenana.it/servizi/Menu/dinamica.aspx?idSezione=19034&idArea=19105&idCat=19131&ID=19131&TipoElemento=categoria). The analysis focused on nine districts managed by the Bonifica Renana Consortium selected within the INCIPIT project (https://www.principit2017.it/), with the aim to understand the irrigation water requirement over district areas and the capability of remote sensing and agro-hydrological modelling tools for supporting agricultural water management and assessment.

The objective of the analysis performed in this chapter was two-fold. On the one hand, the study analyses remote sensing application in crops classification to highlight how it can support land reclamation consortia in managing irrigation water request and use. Specifically, declared land use information has been considered as ground-truth to assess remote sensing crop classification; maps and indices of comparison have been performed. On the other hand, the comparison allowed to underlined areas where remote sensing classification identified potential irrigated areas not declared in the AV project.

Results show that iCOLT classification perform well, with the highest percentage of accuracy for the spring-summer herbaceous crops class (*SShc*). Autumn-winter crops and poly-annual crops are characterized by a lower accuracy, not so significance due to their scarce presence in the studied area. A significant discrepancy can be detected for the class *Other*, the one that is not classified by remote sensing. Considering the sources datasets, this difference is due to a disagreement between Agrea information and farmers declarations.

On the other hand, many areas detected by iCOLT identified as irrigable areas have been not included in the AV project declarations. Assuming remote sensing reliability in classify herbaceous crops, several reasons could be considered to account for that, e.g., a shallow groundwater system which support production without need of irrigation; irrigation coming from alternative sources than surface water managed by the Bonifica Renana Consortium, like private pumping wells; irrigation performed without declaration; inaccuracies during the digitalization of farmer's declared areas.

In conclusion, considering herbaceous crops classification through the calculation of the NDVI vegetation index, this study provides a proof that remote sensing could be a valuable instrument to macro-classify crops in a district scale. Further improvements of the remote sensing crop classification techniques should be considered in specific for the autumn-winter and poly-annual crops, e.g. increase the acquisition windows or accurately design the decision-making tree in order to obtain more combination to classify the regional crops. In this respect, the possibility of identifying autumn-winter crops that will later become summer crops could be investigated. Despite it is not possible to conclude about the potential irrigated areas identified by the remote sensing classification and not apparently declared by the farmers, further investigation could concern direct field inspection, in order to shed light on the real reasons about this considerable discrepancy. Consequently, available ground-truth could be upgraded with supplemental information, supporting consortia with a better control of declared data.

4. ASSESSMENT OF THE ESTIMATED IRRIGATION WATER REQUIREMENTS BY DIFFERENT MODELLING FRAMEWORKS AT IRRIGATION DISCTRICTS SCALE

4.1 INTRODUCTION

The application of agro-hydrological models in water resource management is nowadays widely used, both in research and as a component of decision support services (DSS). Land reclamation and irrigation consortia are increasingly moving towards the use of mathematical solutions to predict or control the use of the irrigation resource.

Differently from other modelling fields of application, agricultural systems are characterized by strong influence of human activities in space and time (e.g., land use, time of irrigation etc), which contribute to modify the natural hydrological cycle. For this reason, model's application become more arduous and requires the most precise consideration of human activities to better reproduce reality. Compared to field application (Chapter 2), the usage of distributed agro-hydrological models at irrigation district level involves additional issues. Challenges include collecting input data, conducting a parameter calibration, and determining results reliability, dealing with larger spatial variabilities, usually difficult to be reproduced by models.

The integration of declared information in agro-hydrological models could be very useful and functioning in supporting irrigation water management. However, this application implies the advance availability of information, in sufficient quantities for scenarios analysis, or the use of suitable models in which information are part of the simulation (e.g., agent-based models). In this context, remote sensing data integrated in agro-hydrological models is indeed a relevant contribution for supporting agricultural water management and assessment. All the different remote sensing products described also at Chapter 3 could be integrated. This integration could be performed from simple insertion, where new data are integrated when available, to more sophisticated data assimilation techniques.

In this chapter two distributed modelling frameworks are assessed, first analysing the irrigation water requirements estimated by the two approaches, second by comparing the estimation to water abstractions. The analyses are conducted at district levels over the nine districts previously described. The first modelling framework is based on the Irriframe model, declared irrigated area and historical meteorological datasets, in the context of Acqua Virtuosa (AV) project of the Bonifica Renana Consortium. The second modelling framework is based on CRITERIA-1D, on remote sensing classification and based on weather prediction over the irrigation season, in the context of iCOLT project. Noteworthy the two modelling frameworks have been developed for two different purposes.

While the model estimation in the context of AV project is conducted to assess the irrigation water requirements at the end of the irrigation season, the modelling framework in the context of iCOLT project is used for predictions before the irrigation season. Despite these two different purposes and input, the comparison can shed some lights on the value of the modelling frameworks and on the capability of different strategies to support agricultural water management and assessment.

4.2 MATERIALS AND METHODS

4.2.1 Integration of CRITERIA-1D model, weather forecasting and remote sensing

As specified in the introduction of the thesis, the iCOLT procedure consists of two consecutive steps. The first step, described in Chapter 3.2, aimed to classify crops in the entire regional area using remote sensing application. The second step integrates the obtained crop classification into a soil-water-balance model to estimate seasonal irrigation needs. The main objective is to support land reclamation consortia in water management before the irrigation season.

The model used for this application is CRITERIA-1D in its geographical version (https://github.com/ARPA-SIMC/CRITERIA1D). Details about model's theoretical basis can be find in Chapter 2. In the following the specific input and parameters integrated within this distributed application are described.

Meteorological data - From 2007, ARPAE produces probabilistic seasonal forecasts, obtained calibrating to local climate the operational multi-model seasonal predictions of the European System for Seasonal to Interannual prediction (EUROSIP) run at the European Centre for Medium Range Weather Forecasts. The Model Output Statistics (Pavan and Doblas-Reyes, 2013) scheme was used to calibrate the dataset at seasonal time scale. Six climate variables and indices are obtained: total precipitation, frequency of wet days, frequency of a wet day after a wet day, mean seasonal minimum and maximum temperature, and mean value of the difference of maximum temperature between dry and wet days. Observed data for calibration are interpolated dataset of daily precipitation and minimum and maximum temperature data at national level. The six seasonal climate indices are then used as input of a Weather Generator, together with local climate data. The final results are daily weather data of minimum and maximum temperature and precipitation, usable in CRITERIA-1D simulations (Tomei et al., 2010; Villani et al., 2021, 2014). In the framework of the iCOLT project, summer probabilistic forecasts referee to the months of June, July and August and are available from the middle of May.

Crop data - As crop input data, the early crop map produced in the first step of the iCOLT procedure has been used. Compared to the field case study (Chapter 2), basing on a crops macro-classes classification, in this context the crop parameterisation adopted is not specific. Each macro-class defined in Chapter 3 is represented by a typical crop belonging to that class, according to the features of the study area (Villani et al., 2021). For example, spring-summer herbaceous crop class is represented by *corn*. Between crop parameters, CRITERIA-1D gives the possibility to consider the irrigation method combined with a fixed irrigation volume. In the iCOLT procedure, irrigation method assigned is the typical one for each reference crop specifically for Emilia Romagna regional area. For instance, *corn* is combined to a sprinkler irrigation. As specified in chapter 3.2.2, the only macro-class considered as irrigated is spring-summer herbaceous crops, containing also crops not agriculturally defined as summer crops but with the need of irrigation (i.e., autumn onion, cauliflower, alfalfa first year).

Soil data - For soil input data, CRITERIA-1D has been implemented with the pedological map of 1:250.000 resolution of Emilia-Romagna region (https://ambiente.regione.emilia-romagna.it/it/geologia/cartografia/webgis-banchedati/webgis-suoli). Specific soil hydraulic parameters are derived by Look up table integrated in the model. For more details, please refer to Chapter 2.

Water table data – Water table depth over the region is monitored by Emilia-Romagna region (http://faldanet.consorziocer.it/Faldanet/retefalda/index) manually based on non-regular time intervals. The daily time series of water table data have been estimated by the model, starting from meteorological daily data and manually measured water table depth. The empirical equation has been developed by Arpa-Simc (Tomei et al., 2010) and calibrated on the Emilia Romagna piezometer network. The assumption is that in a plain area the outflows from the system are balanced by the inflows, so that the water table depth is related only to the sum of the climate water balance (CWB) on a recharge period (Villani et al., 2021), where CWB is defined as the difference between the daily precipitation and the potential evapotranspiration calculated using the Hargreaves and Samani equation. Following this approach is possible to obtain a continuous series of estimated and forecast water table depth only using predictions weather data.

Using the geographical version of CRITERIA-1D, a computational unit map where polygons are characterized by the same weather, soil and crop data is defined. The output of this procedure is a probabilistic irrigation seasonal prediction, provided by ARPAE every year in June. Specifically, for each climate variable, multiple seasonal anomaly forecasts are simulated.

For the conduction of this study, irrigation depths (mm) have been provided by ARPAE, expressed in a geographical shape file on a monthly time scale referred to every classified field within the Consortium plain area. Specifically, irrigation data have been made available as progressive accumulated data since the prevision date. Therefore, aggregating data by district, only volumes related to the nine case study districts were considered.

4.2.2 Integration of Irriframe model, declared land use and historical meteorological data

Irriframe (https://www.irriframe.it/Irriframe) is a decision support system (DSS) developed by ANBI (Associazione Nazionale Consorzi di gestione e tutela del territorio e acque irrigue, National Association Consortia of land and irrigation water management and protection), with the technical coordination of CER. It is about a real-time irrigation scheduling that freely provides the water amount for a specific crop day-by-day to the farmers, through a web interface or a phone text-message (Mannini et al., 2013).

The system is based on a soil water balance model for crop irrigation. Soil water dynamics embody the key process, represented by a tipping bucket conceptualization. Three layers are considered: a superficial reservoir, an upper root layer, and a deep layer. The soil capacity to retain rainwater is estimated for the first superficial layer considering its roughness and the succession of different surface treatments. For the other two layers the storage capacity is calculated using soil texture-related pedotransfer function. Infiltration, runoff and drainage, are obtained in excess of the amount of water available for crops beyond the field capacity. Crop growth is understood both as development stages and root system growth. Growing degree day is the lead factor in the process of changing stages. Evapotranspiration is estimated following the FAO 56 approach (Allen et al., 1998, p. 56). The model estimates the water table contribution in terms of percentage of crop evapotranspiration. The irrigation water volume is calculated as difference between an upper and a lower threshold defined for each crop, considering the growth stage and the irrigation system applied. Specifically, these values are defined for better crop growth and to have maximum yield. Comparing the soil water content with the lower threshold, when the minimum value is reached then the difference between the two threshold is made. No specific equations and parameters are available but for additional information we remind at the model manual https://www.irriframe.it/irriframe/Content/IF_Pub_3.htm.

As input data Irriframe requires crop data, field geographical location and irrigation system characteristics, information coming from Acqua Virtuosa project. Additionally, the model requires soil and meteorological data, integrated to the input dataset from external sources. Outputs are information regarding date and amount of water (in the form of height) to be distributed on the next day of irrigation.

For the conduction of this study, the Bonifica Renana Consortium has made available estimated irrigation depth (mm) every ten days per each cultivated field. Subsequently data have been aggregated on a monthly scale and for each district of study.

4.2.3 Measured irrigation withdrawals at district level

To evaluate model's performances, measured irrigation withdrawals have been provided by the Bonifica Renana Consortium. Table 6 shows for each district a monthly measured volume (m^3).

Table 6 Monthly measured volumes for each district of study

	I. Correcchio	I. Ladello	I. Gherghenzano	F. Ganzanigo P. S. Castrizzara	S. Crevenzosa di Bon. e Ovest	S. Fossa Morta
Gen	0	0	0	0	0	0
Feb	24428	3451	0	35516	0	0
Mar	18042	23057	5107	24705	93960	9072
Apr	84611	125504	21254	57545	102060	29160
May	216947	240224	28033	297913	127440	0
June	92916	130249	22544	136181	121500	117936
July	237537	514388	50740	232802	194400	75168
Aug	50900	104831	22986	53642	182520	23976
Sept	50548	110856	36134	50408	71820	47952
Oct	1868	6130	2317	0	540	9720
Nov	0	0	0	0	0	0
Dic	0	0	0	0	0	0
TOT	777797	1258690	189115	888712	894240	312984

A volumetric flow meter is installed in each district fed by pressurised pipe.

Irrigation withdrawals at the three districts fed by open air canals is calculated by multiplying the pump operational time, collected through an operational time counter, and the nominal flow rate.

Scolo Crevenzosa di Bonificazione and Scolo Crevenzosa Ovest, as already specified, are fed by the Bisana pump, characterized by a nominal flow rate of 150 $l\ s^{-1}$.

Scolo Fossa Morta is fed by the Marchette pump, which is represented by a nominal flow rate of 180 $l\ s^{-1}$. Differently from the Bisana pump, which takes water directly from CER, the Marchette pump takes water from Scolo Fiumicello Bruciate Inferiore, and it turns on and off automatically depending on the water canal level.

Fosso Ganzanigo Privato and Scolo Castrizzara are fed directly by the Ganzanigo derivation, through the opening and closure of a gate. The diverted discharges are calculated knowing the section of the canal, the measurements of the levels and basing on the opening time of the gate.

For what concern the Scolo Laghetto district, as specified in Chapter 3, it is fed by the civil wastewater treatment plant. Measured irrigation volumes are still not available for the conduction of the present study.

4.2.4 Models' comparison and assessment

First, a modelling frameworks comparison has been conducted. As known from Chapter 3, crop information from the two services covers different areas, interests a different number of fields, and is referred in one case to a macro-class reference crop (i.e., iCOLT) and in the other case to a specific crop (i.e., Irriframe). The two analysed models run on a daily scale and provide, when necessary, a plant irrigation requirement for each field considered. Consequently, to compare the two models, the focus has been put on average monthly estimated water requirement, and not on singular values, to exclude influences of the described differences. Specifically, regarding the iCOLT procedure, the average irrigation demand estimated for each macro-class during the irrigation season has been calculated. Concerning Irriframe model, a different procedure was adopted. Averages of the estimated needs per specific crop were calculated, and then averaged over the total number of crops belonging to the macro-class under consideration. In this way, a more reliable comparison between the two modelling frameworks has been made.

In the second part, the comparison of the two modelling frameworks (iCOLT vs. Irriframe) to the measured irrigation withdrawals has been performed. Estimated irrigation depths (mm) have been transformed into volumes (m^3), considering fields areas. Successively, coefficients have been applied to consider the specific characteristics of the distribution systems. Specifically, a 10 % of the total estimated volume has been considered as loss for each district fed by pressurized pipe, considering the recent construction. A 50 % has been considered for districts fed by open canals. These values represent a first attempt to reproduce the distribution systems efficiency, following Bonifica Renana Consortium advice. Coefficients related to irrigation method have been not applied, considering that depending on the model integrated method combined to the crop or macro-class, losses are already contemplated.

4.3 RESULTS

4.3.1 Comparison between the estimated irrigation water requirements by the modelling frameworks

In the following the estimated average water requirements trends simulated by the two models during the irrigation season are discussed for each district and focusing on the irrigated macro-classes (i.e., SShc and Other). For three districts the visualization of a third graph is referred to poly-annual crops trends estimated by the Irriframe model, not considered as irrigated by the iCOLT procedure.

<u>*Impianto Correcchio district*</u>

Concerning spring-summer herbaceous crops, at Correcchio district the iCOLT service estimates an irrigation season delayed in comparison to the one simulated by the Irriframe model, with lower accumulated seasonal water needs: 122 mm in comparison to 184 mm. Water requirements trends are similar, with a growing phase until the middle of the season (i.e., June for Irriframe model, July for iCOLT system) and a consequent decreasing phase until the end of the season. An average estimated water needs of around 7 mm in September is simulated by the Irriframe model, due to the presence in this class of the irrigated autumn onion (Figure 21 a and a').

Looking at the class Other, simulated irrigation seasons are more similar, but with different irrigation water requirements trends: Irriframe model simulates two pics of water request, in May and in July, instead of one simulated by the iCOLT service in July. Accumulated water requirements remain very dissimilar: 142 mm estimated by the iCOLT service in comparison to 281 mm estimated by Irriframe model (Figure 21 b and b').

At this district, Irriframe model estimates irrigation water requirements also for poly-annual herbaceous crops, i.e., alfalfa plots. The trend is very different in comparison with the one simulated for spring-summer crops and *Other* class: the model allocates irrigations mainly at the beginning and at the end of the irrigation season, with comparable accumulated values magnitude with the ones simulated for *SShc* (i.e., 165 mm) (Figure 21 c and c'). The iCOLT service does not estimate any water needs for poly-annual herbaceous crops because it considers alfalfa as non-irrigated crop.

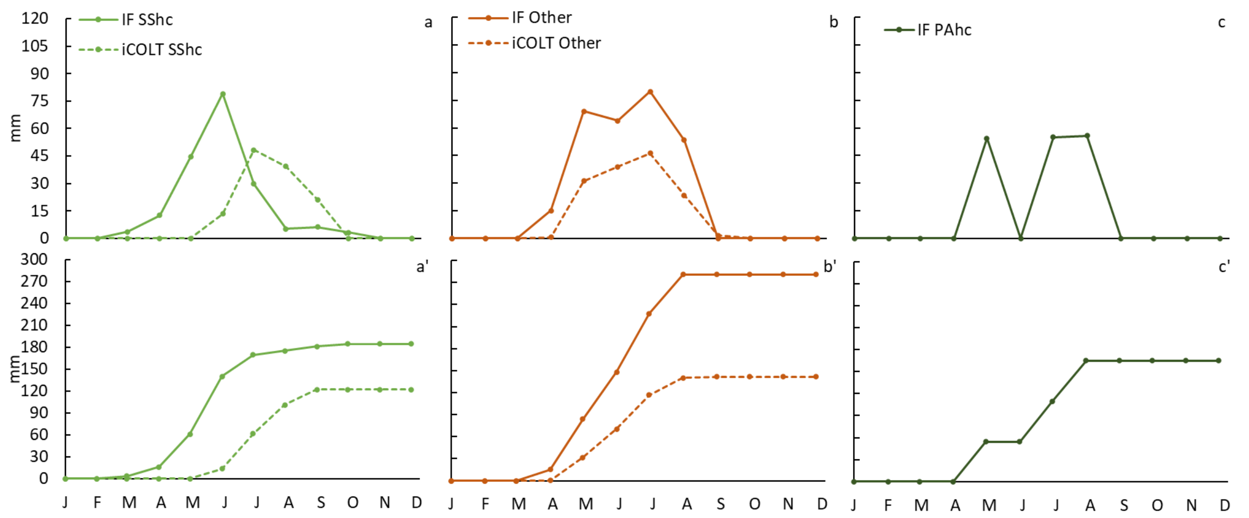

Figure 21 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at the Impianto Correcchio district: spring-summer herbaceous crops (*SShc*, green colour, a), *Other* class (brown colour, b), poly-annual herbaceous crops (*PAhc*, dark green colour, c). Below the correspondent cumulative values (a', b', c')

Impianto Ladello district

Looking at spring-summer herbaceous crops, also at Ladello district the iCOLT service simulates an irrigation season delayed in comparison to the one simulated by the Irriframe model, with lower accumulated seasonal water needs (i.e., 125 mm in comparison to 230 mm). Simulated trends are dissimilar: Irriframe model simulates at the beginning of the season a pic of water request, to then simulate a growing and a decreasing phase until October. The iCOLT service reproduce approximately the same trend seen in the Correcchio district for the *SShc* class (Figure 22 a and a').

Concerning the class Other, the situation reproduced for the Ladello district is almost equal to the one described above for the Correcchio district (Figure 22 b and b'), with similar trends between the simulated water requirements but higher total values for Irriframe than iCOLT.

Irrigation water needs estimated by the Irriframe model for the poly-annual class are located in the middle of the irrigation season (i.e., June and July), with an accumulated value of 191 mm, nearly comparable to the one simulated for the SShc class (Figure 22 c and c')

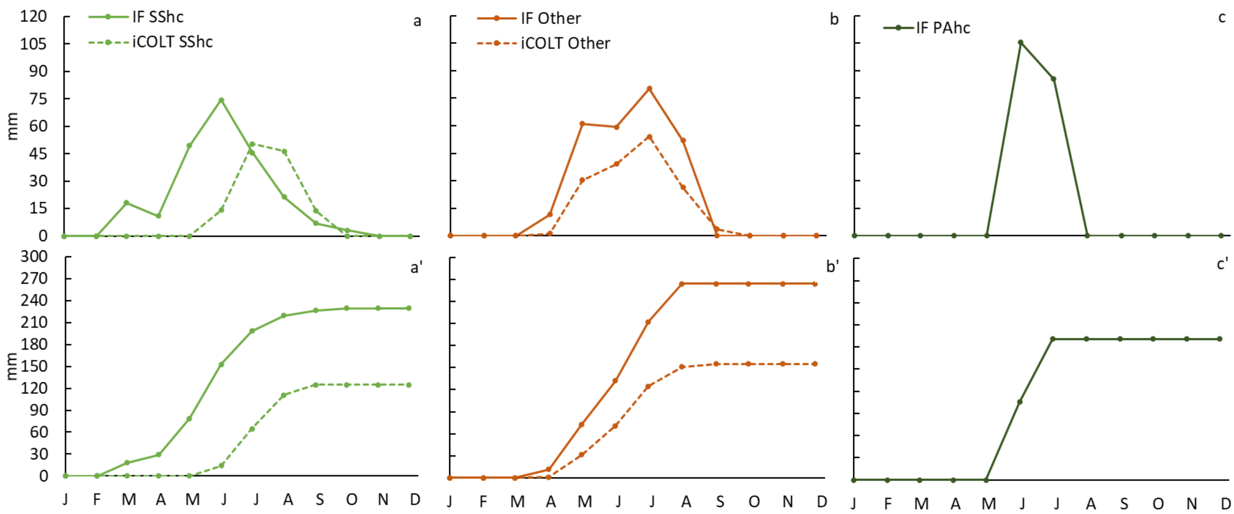

Figure 22 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at the Impianto Ladello district: spring-summer herbaceous crops (*SShc*, green colour, a), *Other* class (brown colour, b), poly-annual herbaceous crops (*PAhc*, dark green colour, c). Below the correspondent cumulative values (a', b', c')

Impianto Gherghenzano district

At Gherghenzano district, iCOLT spring-summer herbaceous crops irrigation season is shifted by one month in comparison with the situation described for the previous districts. Accumulated irrigation water needs remain very different: 138 mm simulated by the iCOLT system and 261 mm simulated by the Irriframe model (Figure 23 a and a').

Concerning the class Other, Figure 23 b shows a particular irrigation water requirements trend estimated by the iCOLT service, characterized by two pics of request in May and in July; on the contrary, Irriframe model simulates a growing and decreasing trend with a pic in July, lower than the one simulated by iCOLT. Accumulated values are quite similar, but in this district lower for the Irriframe estimations: 223 mm in comparison to 270 mm simulated by iCOLT service Figure 23 b').

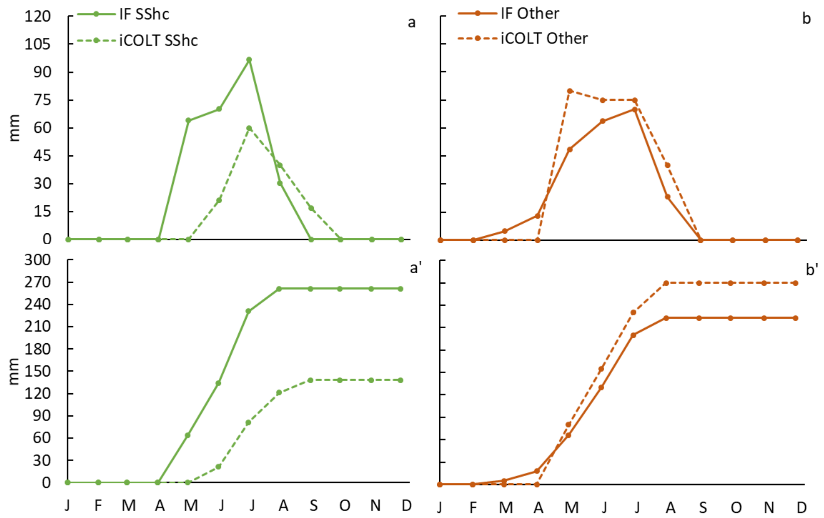

Figure 23 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at the Impianto Gherghenzano district: spring-summer herbaceous crops (*SShc*, green colour, a) and *Other* class (brown colour, b). Below the correspondent cumulative values (a', b')

Fosso Ganzanigo Privato and Scolo Castrizzara

Looking at spring-summer herbaceous crops, Figure 24 a shows very different trends of estimated water requirements by the two procedures. Indeed, at Ganzanigo and Castrizzara districts, the iCOLT system simulates a characteristic distribution of water, with a pic in August, before the end of the season. Irriframe model reproduce a growing and decreasing trend, with a clear average irrigation value estimated in the month of October, due to the presence of autumn onion. Irrigation seasons are always not correspondent. Accumulated water volumes are very similar: 135 mm for the iCOLT service and 193 mm for the Irriframe model (Figure 24 a').

Concerning the class *Other*, in these two districts occurs the greatest difference in accumulated values between the two procedures: iCOLT estimates around 60 mm over the entire season, Irriframe model estimates around 921 mm (Figure 24 b'). Trends are also very different, with a growing and decreasing phase for the iCOLT procedure and a more particular trend simulated by the Irriframe model. Significantly high values reported in June, July and August represent mainly the presence of wetlands, which need a lot of irrigation (Figure 24 b).

As for Correcchio district, Irriframe model estimates for poly-annual herbaceous crops consistent irrigation mainly at the beginning and at the end of the irrigation season, with accumulated values magnitude comparable with the one simulated for *SShc* class (Figure 24 c and c').

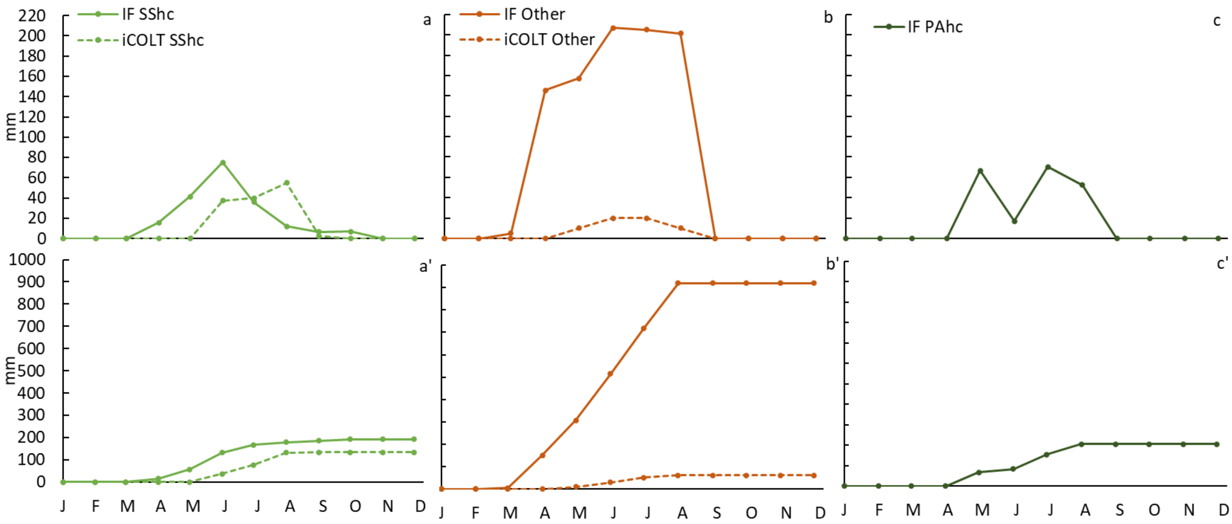

Figure 24 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at Fosso Ganzanigo Privato and Scolo Castrizzara districts: spring-summer herbaceous crops (*SShc*, green colour, a), *Other* class (brown colour, b), poly-annual herbaceous crops (*PAhc*, dark green colour, c). Below the correspondent cumulative values (a', b', c')

<u>*Scolo Crevenzosa di Bonificazione e Scolo Crevenzosa Ovest*</u>

Concerning spring-summer herbaceous crops, in these two districts irrigation water requirements trends are very different, with pics of water request in May for iCOLT service, in August for Irriframe simulation. Irrigation seasons are not correspondent (Figure 25 a). On the contrary, accumulated values are quite similar: 89 mm estimated by the iCOLT procedure and 112 mm estimated by the Irriframe model (Figure 25 a').

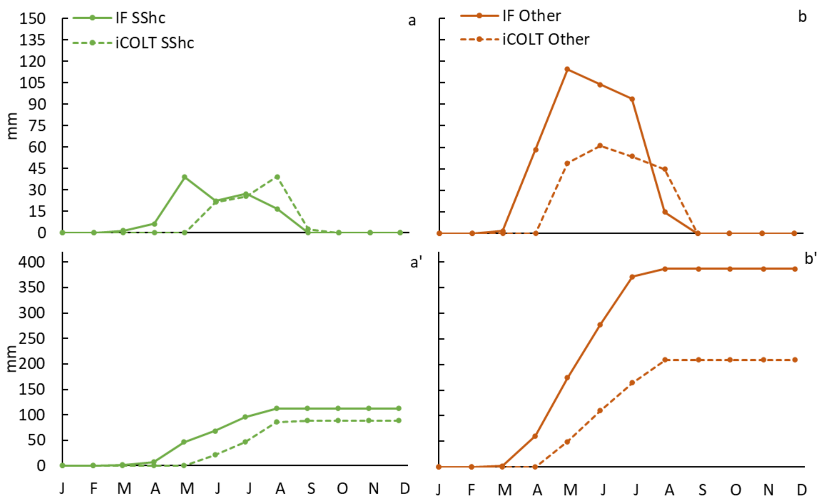

Figure 25 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at Scolo Crevenzosa di Bonificazione e Ovest districts: spring-summer herbaceous crops (*SShc*, green colour, a) and *Other* class (brown colour, b). Below the correspondent cumulative values (a', b')

Looking at *Other* class, also at these districts, accumulated irrigation water requirements are quite different: 208 mm represent the iCOLT estimated value, lower in comparison to the one simulated by the Irriframe model, i.e., 387 mm. This significant difference is mainly due to the presence in the AV database of a pulping mill plot, with the need of considerable water quantity for irrigation (Figure 25 b and b').

Scolo Fossa Morta district

At Fossa Morta district, looking at Figure 26 a, iCOLT and Irriframe procedures simulate considerable different irrigation water requirements trends for spring-summer herbaceous crops, with irrigation seasons corresponding only in the starting month and a lower accumulated value for the iCOLT procedure: 120 mm in comparison to 263 mm estimated by Irriframe model (Figure 26 a').

Concerning the class Other, Figure 26 b shows very similar trends simulated by the two procedures, with irrigation seasons starting with one month of difference and ending in the same month (i.e., September). Accumulated values come closer, with 245 mm estimated by iCOLT and 335 mm estimated by Irriframe (Figure 26 b').

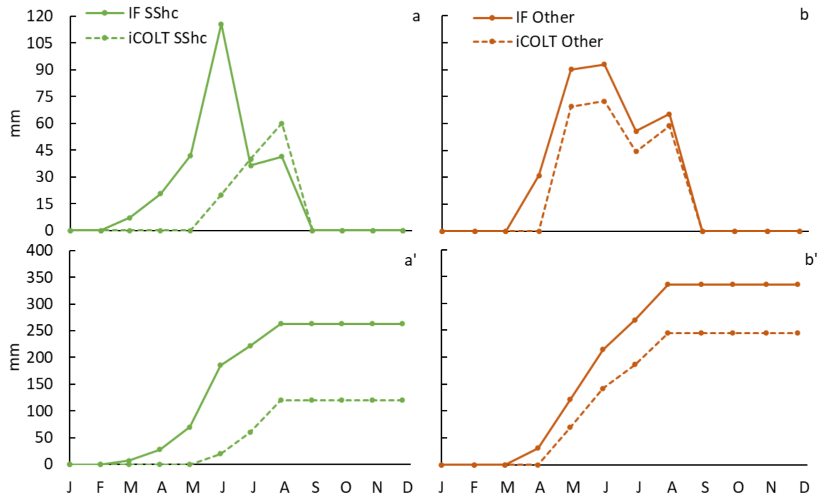

Figure 26 Estimated average water requirements trends simulated by iCOLT service (iCOLT) and Irriframe model (IF) for each macro-class identified at the Scolo Fossa Morta district: spring-summer herbaceous crops (*SShc*, green colour, a) and *Other* class (brown colour, b). Below the correspondent cumulative values (a', b')

Scolo Laghetto district

At Laghetto district, *SShc* class water requirement trends are more similar, with a growing and a decreasing phase, but distributed by the iCOLT service three months after than the Irriframe model (Figure 27 a). Accumulated values remain lower for the iCOLT procedure, with 130 mm in comparison to 232 mm estimated by Irriframe model (Figure 27 a').

Looking at class *Other*, differently from the other districts, iCOLT simulates an irrigation season starting before the one considered by the Irriframe model (i.e., May), ending together in September

(Figure 27 b). Trends are quite different but with similar accumulated irrigation water requirements values (i.e., 126 for iCOLT service, 149 mm for Irriframe model) (Figure 27 b').

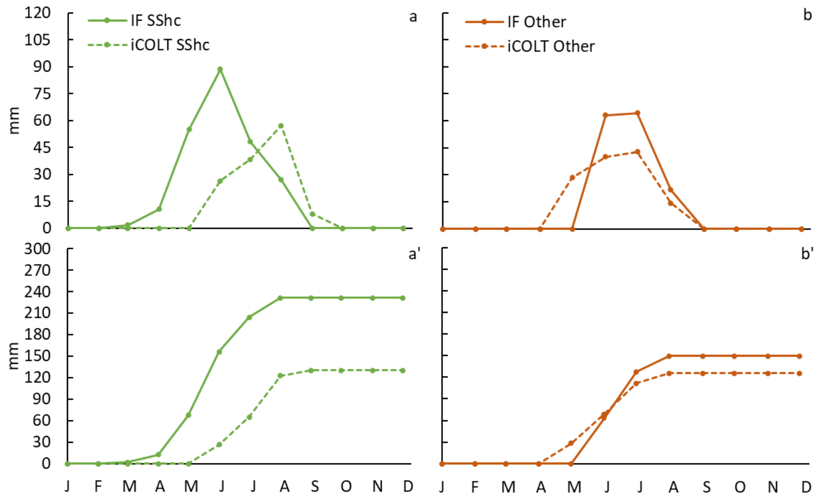

Figure 27 Estimated average water requirements trends simulated by iCOLT service and Irriframe model for each macro-class identified at the Scolo Laghetto district: spring-summer herbaceous crops (green colour, a) and *Other* class (brown colour, b). Below the correspondent cumulative values (a', b')

Taking a general look at the comparison between the average irrigation water requirement estimated by the two modelling frameworks for each crop macro-class, some considerations can be made. Trends in irrigation requirements simulated by the iCOLT procedure are more homogeneous than those simulated by the Irriframe model. This aspect, together with the delayed irrigation season, can be attributed to the consideration for each macro-class of reference crops by the iCOLT service, not always representing the specific crop characteristics. Furthermore, the estimated needs, which are mostly lower than those estimated by the Irriframe model, can be possibly traced back to a lower rainfall forecast in comparison to the observed ones. Results obtained in Chapter 2 can also help to motivate these discrepances: the strong capillary rise estimted by CRITERIA-1D model contributes to increase root soil moisture and consequently delaying irrigation triggering or reducing total water requirements. These aspects should be the topics of further investigations.

4.3.2 Assessment of the modelling frameworks

In this chapter, the comparison between irrigation water requirements volumes estimated by the iCOLT and the Irriframe procedures with the measured withdrawal water volumes (m^3) is depicted (Figure 28). For what concern the Scolo Laghetto district, as specified in 4.2.3 chapter, measured irrigation volumes are still not available for the conduction of the study. Therefore, it has been excluded from the analysis.

Noteworthy, despite the numerous differences which characterized these two modelling frameworks, i.e., model's structures, weather data, interested areas and crop classification, in most of the cases they simulate the order of magnitude of the irrigation water requirements correctly, and rank districts in the correct way, with higher water needs for the Ladello district and lower for the Gherghenzano district. The estimation is generally slightly underestimated in comparison to measured data with lower performances of iCOLT procedure suggesting an overuse of the water.

Some important differences are however also identified at some districts that can be attributed to the different irrigated areas and crop classifications used by the two modelling frameworks. Specifically, at Crevenzosa and Gherghenzano districts, a considerable percentage over the total district area has been identified as potential spring-summer irrigated herbaceous crop by the remote sensing method (i.e., 41 % for Crevenzosa district and 21 % for Gherghenzano district, Figure 20). In both cases, in comparison to the measured volumes, the iCOLT procedure overestimates irrigation water requirements; on the contrary Irriframe has an underestimation behaviour. Consequently, part of potentially irrigated areas in both districts could represents potential undeclared areas in the context of the Acqua Virtuosa project. At Ganzanigo and Castrizzara districts, the iCOLT procedure considerably underestimates the total irrigation volume in comparison to the measured one (Figure 28). The presence of a 12 % of poly-annual herbaceous crops following the AV declaration, considered as non-irrigated crops by the iCOLT modelling framework, may account for this underestimation.

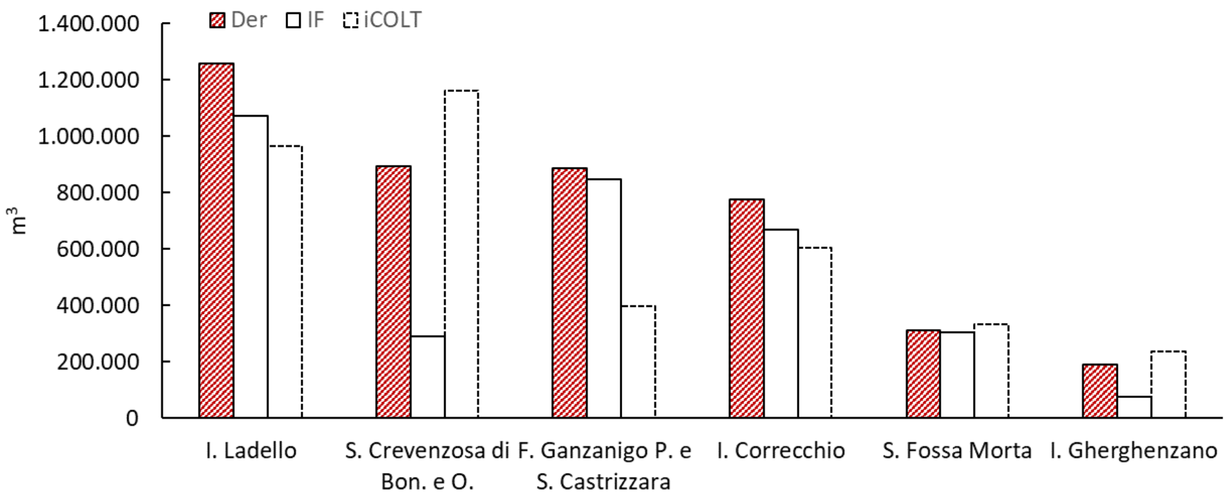

Figure 28 Comparison between irrigation water requirements (m^3) estimated by the iCOLT procedure (dashed line) and by the Irriframe model (solid line), and the measured data (red bars), for the entire irrigation season

Looking in more details at the seasonal water requirements (Figure 29), some additional differences between models and measurements are highlighted. The beginning of the irrigation season is in general better reproduced by the Irriframe model, starting in March; on the contrary, it ends mostly in October, as the iCOLT procedure simulates. Irrigation water request pics are depicted mainly in May and July, corresponding in broad terms to the ones simulated by the two modelling frameworks. The measured irrigation volumes trends represent characteristics hardly reproducible by the two modelling frameworks. These discrepancies suggest the presence of irrigations not always dependent from the estimated evapotranspiration process but related to other agronomic practices, e.g., soil preparation for sowing or harvesting, irrigation for late frosts. Furthermore, this fact could be explained in part by the different cultivated crop varieties, with different growth cycles and by different sowing and harvest dates, also function of farm organization needs, not always considered by the models. Also, distribution systems efficiencies used for the conduction of the study could represent a reason of discrepancies: coefficients could be different and variable during the agricultural season.

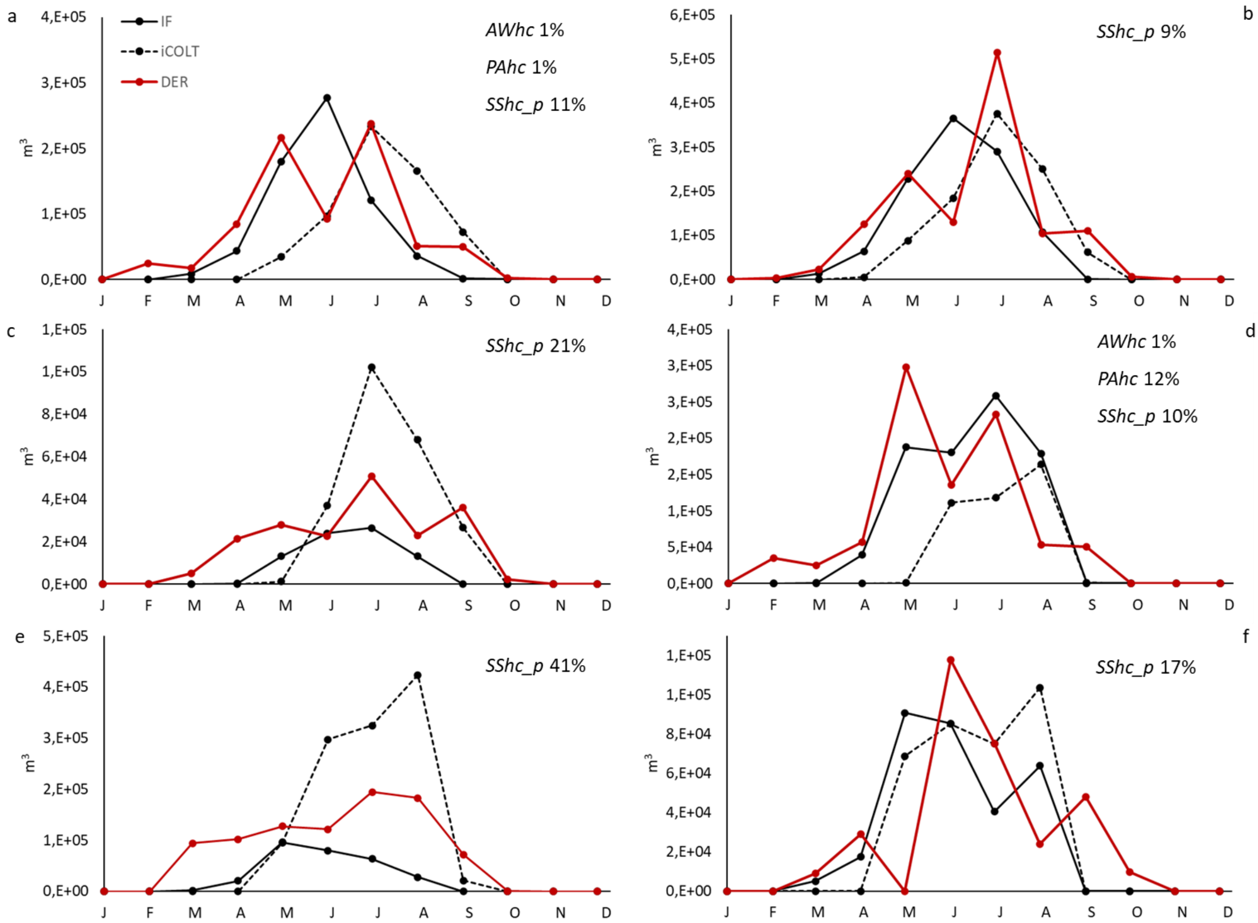

Figure 29 Irrigation water requirements trend estimated by the iCOLT procedure (dashed line) and by the Irriframe model (solid line), in comparison with the measured volumes (m^3, red line), for each studied district: Impianto Correcchio (a), Impianto Ladello (b), Impianto Gherghenzano (c), Fosso Ganzanigo Privato and Scolo Castrizzara (d), Scolo Crevenzosa di Bonificazione e Ovest e, Scolo Fossa Morta (f). For each graph the percentages of autumn-winter herbaceous crops (*AWhc*), poly-annual herbaceous crops (*PAhc*), and potentially spring-summer herbaceous crops (*SShc_p*)

4.4 CONCLUSIONS

This study focused on the comparison between estimated water requirements based on two modelling frameworks with measured irrigation volumes at district level. The first framework is included in the iCOLT procedure, it uses forecasting weather data and a remote sensing crop classification (https://sites.google.com/drive.arpae.it/servizio-climatico-icolt). The second framework uses the Irriframe model, implemented with observed weather data and declared land use, collected through the Acqua Virtuosa project (https://www.bonificarenana.it/servizi/Menu/dinamica.aspx?idSezione=19034&idArea=19105&idCat=19131&ID=19131&TipoElemento=categoria). The analysis focused on the nine districts managed by the Bonifica Renana Consortium also analysed in the Chapter 3, in the context of the INCIPIT project (https://www.principit2017.it/).

The objective of this study was to evaluate how these two modelling frameworks can support agricultural water management and assessment. Specifically, the study aimed to identify similarities between models' outputs which can give strength to the modelling practice applied in an agricultural district scale and to identify differences and further possible improvements.

Overall, this study has shown that the use of agro-hydrological models to support irrigation management is an effective and valuable tool at these specific conditions and scale. In a data-rich environment like Emilia Romagna region, modelling frameworks integrated with observed weather and declared land use data can provide a valid estimation of irrigation water needs at district and seasonal scale. The orders of magnitude of the total estimated irrigation volumes in the 2020 are indeed comparable with those measured. The introduction of these tools to land reclamation consortia could lead to a greater awareness of the irrigation water use and availability.

More specifically, by looking at the comparison between average irrigation water requirements estimated by the two approaches for each crop macro-class, results showed the lower variability of iCOLT estimated trends and differences probably related to the differences in the weather data. Despite that, looking at estimated irrigation volumes for each district, the two procedures simulate more similar trends between them than in comparison with measured data. Detected discrepancies can be mainly associated to the difference between the irrigated areas considered by the two approaches. For this reason, with the appropriate attention to the considered irrigated areas, even in forecasting scenarios and integrating models with remote sensing data, good results can be obtained.

Finally, estimated irrigation water use is also generally underestimated at the beginning of the irrigation season and at the end of the irrigation seasons. This result was detected for both modelling frameworks and it suggests the presence of irrigation practices not related to evapotranspiration but to other agronomic practices related to soil preparations for sowing and harvesting. For these reasons these practices, together with the main crop varieties characterized by unusual vegetation cycles worthy of consideration, should be better explored and integrated in the modelling frameworks in future studies. Finally, a more in-depth analysis of distribution efficiencies should be conducted.

5. SUMMARY AND CONCLUSIONS

Water is one of the fundamental resources for supporting life and society. Among others, this resource is strongly affected by an increasing land use and by current climate changes. Since agriculture is the most intensive user of freshwater, implementing correct management practices in this sector is considered one of the main levers to achieve a sustainable use of the water resources. In this context, the development of modelling tools to support agricultural water management and planning has been considered a relevant strategy, with applications ranging from farmers to water associations. In this context, this study wanted to assess different regional modelling frameworks, applied at different spatial scales and for different applications, trying to quantify their current realism and to identify possible improvements for a concrete use of models as a support for agriculture and water resources.

The thesis has been divided in three studies. In the first study (Chapter 2), a sensitivity analysis of two field-scale agro-hydrological models (i.e., CRITERIA-1D and Aquacrop) has been performed. The objective was to put the attention on uncertainty and representativeness of results at the farm scale. The forward backward MMEMO method was used, performing *base scenarios*, implemented with regional freely available datasets, together with *enhanced scenarios*, implemented with more representative field observations. Examined input factors were precipitations, leaf area index, soil textures and groundwater levels; analysed output were irrigation water requirements and water fluxes at 1 m soil depth. Results highlighted the flexibility of the method, as it could be applied to any modelling framework to identify results robustness and possible further improvements. Emilia-Romagna freely available datasets completely allowed the integration of agro-hydrological models, but with a low representativeness of the selected area. Specifically, a denser piezometers network would contribute to a better response of the two analysed models in estimating irrigation needs.

The work further proceeded with two analysis performed at the district scale. Specifically, in the second study (Chapter 3) a remote sensing crop classification through macro-classes was evaluated using as ground truth farmers' declared information collected in the context of the Acqua Virtuosa project. These crop classifications have been integrated into two distributed modelling frameworks for the estimation of the seasonal irrigation water requirements (Chapter 4). Specifically, in the context of the iCOLT service, the remote sensing classification was used to integrate an agro-hydrological model CRITERIA-1D for forecasting irrigation needs. This estimation has been compared with IrriFrame, an alternative integrated modelling framework based on observed weather data and declared crop information. The estimations have been compared to the measurements of irrigation volume withdrawals at district scales. The analysis led to the conclusion that, both in the context of crop classification and in the water needs estimation, potential irrigated areas, as a parameter for calculating irrigation volumes, are of primary significance. The use of a remote sensing crop classification gives good results, with the higher accuracy found for the spring-summer herbaceous crops class, also considering its higher presence in the selected area. However, it identifies several potential irrigated areas not declared by the farmers. These areas, in the application of the modelling frameworks for estimating irrigation needs, are responsible for the greatest discrepancies between the models. Consequently, in the case of the application of innovative technologies, the study suggests a more detailed investigation of those areas, to obtain the most truthful crop information. Overall, a similarity between the seasonal volume estimated by the two modelling frameworks and the measured one was detected in most of the cases, despite different trends in comparison with the actual ones. Some differences have been attributed to the presence of irrigation driven by agronomic practices not included in both modelling frameworks (e.g., soil preparation for sowing and harvesting), crop varieties not considered by the models, and finally distribution system efficiencies variable during the irrigation season.

Overall, the presented study shed light on several aspects regarding the use of regional available tools for estimating irrigation water requirements.

Agriculture and water management is indeed strongly influenced by human behaviours. Modelling tools face constant challenges, being always caught between the technological-scientific concepts and the complexity in adapting it to the real conditions that take place. Furthermore, the availability of representative datasets of the study area is crucial to obtain valid results. For these reasons, the analysis underlined that the use of these tools at farm scale, where detailed information is required, offers a weak support to irrigation water management. In contrast to the field scale, the study showed that the estimation of seasonal irrigation volumes using modelling frameworks also including innovative technologies (i.e., remote sensing), can be compared to the measured data to fulfil legal requirements. For this reason, land reclamation consortia could benefit from the routinely adaptation of these modelling tools. Nevertheless, fundamental aspects have to be considered, like further analysis on specific areas or insights into influential agronomic or farm practices specific to the regional or district context.

Based on the presented study and the gained experience, it can be concluded that the use of supporting tools in the agriculture field of application, needs a solid connection between what scientifically could provide support for a sustainable water management and use, and realities of the case. Improving research on the integrated use of innovative technologies and modelling frameworks, could replace the ground-data collection, providing a valid and more direct help in forecasting the use of the irrigation resource. In order to provide concrete support to land reclamation consortia, modelling tools should be practical and easy to use. Instead of increasing the model structures complexity, the specific regional environmental peculiarities should be included into the formulation, to obtain more suitable results to the investigated areas. To achieve a real and helpful solution, there should be a strong and stable collaboration between researchers and farmers or consortia, characterized by mutual learning and respect, aimed at a more integrated and sustainable vision. Research should try to increase farmers' awareness of a more sustainable use of water resource, rising their trust and stimulate a greater openness to the use of these tools, always considering the importance of their agricultural experience and learning from it.

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