Computers and Electronics in Agriculture 176 (2020) 105474

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

A survey on intelligent agents and multi-agents for irrigation scheduling

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ARTICLE INFO

Keywords:
Artificial intelligence
Intelligent agent
Irrigation scheduling
Precision irrigation
Multi-agent

ABSTRACT

Irrigation is very important for ensuring food security and reducing crop production vulnerability caused by the lack of rain. Sustainable irrigation is the rational practice of all the activities related to water application on the crops. In irrigation, the rationality of intelligent agents can be used to reach soil water content near the field capacity to increase yields and reduce waste of water. Rationality in artificial intelligence is the capability of the intelligent agents to decide their actions. This paper discusses how incorporating intelligent agents on irrigation systems allows significant advances in respect of current irrigation approaches. This paper review not only focuses on intelligent reactive systems as usual, but rather discloses developments in systems that incorporate other behaviors such as proactivity, planning, learning, social abilities, organization, coordination and negotiation. From the literature review, it is found that the use of soil, plant and environmental sensors, as well as reasoning, learning and communication capabilities, provides innovative technological support to improve sustainability in irrigated agriculture. The review also shows that intelligent agents can adequately consider the timing and the amount of water to apply according to the spatio-temporal variations of the soil–plant–atmosphere system. It is concluded that significant improvements in water savings and crop yield can be achieved incorporating artificial intelligence into precision irrigation. Further research is needed on irrigation scheduling based on multi-agent systems at different scales of agricultural production systems.

1. Introduction

Irrigation is the process to apply water to the soil in order to improve the crop growing, maintain landscapes and revegetate degraded soils in dry regions and periods of insufficient rainfall (Mrinmayi et al., 2016). Economical, water management and ecological criteria are used in the definition of decision-making on irrigation systems (Zhemukhov and Zhemukhova, 2016). Irrigation decisions in agriculture depend on how much water the crop of a particular species requires and how much water is available from local sources (Riediger et al., 2016). Soil moisture ensures the healthy growth of the roots and the overall development of the plant (Kumar et al., 2017). Its deficits can arise in times when evapotranspiration is higher than precipitation and soil water storage is not sufficient to maintain plants provision (Zhao et al., 2017). The lack of water in the soil impairs the correct plant development and its excess can reduce root respiration, affect the root growth and produce soil degradation problems such as surface runoff, soil erosion and nutrient leaching (Grashey-Jansen, 2014). Besides, inappropriate irrigation practices produce significant soil salinization and the climate change in many regions threatens to exacerbate this behavior (Tal, 2016).

Soil textures and their corresponding soil water retention functions should be considered in the irrigation strategies (Grashey-Jansen, 2014). The Total AvailableWater (TAW) is the volume of water that can be stored in the soil and used by plants (Barradas et al., 2012). It is characterized by the permanent wilting point (PWP) and the field capacity (FC). The PWP is the minimum soil moisture under which a plant cannot extract water from the soil. At this point, the vegetation cannot recover from the water loss, although water is applied again. On the other hand, FC is the amount of water that a soil can retain after saturation and free drainage, without losses by evaporation, until the soil moisture stabilizes, that is, between two and three days after raining or the irrigation application (Ghorbani et al., 2017). The water content available for a plant between (PWP) and (FC) is influenced by the soil composition and can be perceived as the most important component for high irrigation efficiency (Grashey-Jansen, 2014).

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https://doi.org/10.1016/j.compag.2020.105474
Received 19 December 2019; Received in revised form 11 March 2020; Accepted 30 April 2020
Available online 23 July 2020
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Water content in an effective root zone is estimated using the water balance approach (Eq. (1)). This equation is often used in irrigation modelling and simulation, with permanent re-calibration requirements (Andales et al., 2011).

$$WC_t = WC_{t-1} + IRR + R - ET_c - DP \quad (1)$$

where, $WC_t - WC_{t-1}(mm)$ is the change in the soil water content; is the irrigation amount; $R(mm)$ is the rain; $ET_c(mm)$ is the crop evapotranspiration and $DP(mm)$ is the deep percolation.

The effects of climate change on rain patterns and the amount of water available have decreased the accessibility to this important resource for agriculture. To face the challenges in production for food security and sustainable development, the need for generation of adaptive management strategies in agriculture is evident. Adaptation refers to include actions to adjust practices, processes, structures, and capital, in response to the field management and the reality or the threat of climate change (Howden et al., 2007). In crop irrigation, adaptive systems must be developed to manage water efficiently, maintaining the water content in the effective root zone near to the FC (Riediger et al., 2016). Additionally, irrigation systems must include soil-crop-environment responses to define the irrigation prescriptions and use these responses to improve the next irrigation activities (Smith et al., 2011). These considerations lead directly to the conceptualization of irrigation systems that determine the timing, magnitude and spatial pattern of irrigation applications.

To solve the problems caused by inadequate irrigation, intelligent irrigation systems have been proposed as an alternative to conventional timed controllers (Divya et al., 2014). Precision irrigation (PI) technologies are useful strategies in adaptive systems, allowing the precise evaluation of crop water needs and the variable or uniform application of water in the right place at the right time, using electronic systems and hydraulic elements with high volumetric efficiency (Morillo et al., 2015). Additionally, artificial intelligence is a promising strategy for information management and generation of models for precision agriculture applications.

Artificial intelligence studies how to make computers and robots to behave or think in the same way as humans. The fundamental concept of several AI systems is the rational behavior. This concept means that computers or robots can perform actions considered as the best possible option to achieve the objectives for which they were programmed. Systems, named intelligent agents, use rational behavior to determine actions in the surrounding environment (Jimenez et al., 2018).

An intelligent agent is an autonomous entity that uses sensors to obtain information from the environment, takes decisions using reasoning and learning strategies, and carries out actions to modify the environment using actuators (Russell and Norvig, 2016). A multi-agent system (MAS) consists in the interaction of several intelligent agents (Gonzalez, 2012). Agents in a multi-agent system can use sociable abilities to transmit and receive information from other agents. The behavior of agents together with other entities produces an intelligent group result (Hernández et al., 2018). This paper aims to provide a review of the considerations and technical analysis for the development of intelligent systems for precision irrigation. The motivation of this review is to collect relevant and promising information about the development trends in technologies used for the specification, design and implementation of the PEAS (performance measurement, environment, actuation and sensing) in an intelligent agent with applications in precision irrigation. This review explains the principal sensing technologies for estimating irrigation rates and times in agriculture and identifying control and actuation techniques used to regulate water flow in crops irrigation. Additionally, the methodologies and platforms are described for the implementation of Decision Support Systems (DSS), inference strategies and prediction mechanisms for irrigation management using artificial intelligence. With the use of these technologies, the early detection of plant water stress in crops is possible, before irreversible damage and yield losses are caused, as well as increase in water savings, optimally management of the water resource and enhancement of agricultural sustainability. This review highlights the interaction of multiple agents for the management of water resources in agriculture. The bibliographic review also aims to describe the technological advances in the specification of the AEIO (Agent, Environment, Interaction and Organisation) for the implementation of a Multi-Agent system for irrigation management in an irrigation district.

This review is organized into two sections: intelligent agents in crop irrigation and multi-agent systems applied to water resource management. The first section is split into the following subsections: conceptualization, sensors systems in irrigation intelligent agents, decision support systems for irrigation management and artificial intelligence applied to irrigation.

2. Methodology

In this review, the Search, ApprasiaL, Synthesis and Analysis method (SALSA) (Grant and Booth, 2009) was used to obtain a general and systematic overview of sensing and artificial intelligence systems in irrigation management. Additionally, the Facet, Derive and Combine (FDC) strategy was used to find the descriptors and search equation (Pawar and Lomte, 2017).

Table 1 shows the results obtained according to the Facet and Derive steps in the FDC strategy. The principal descriptors obtained in this stage were: multi-agent system, agent-based modeling, artificial intelligence, precision irrigation, intelligent irrigation, smart irrigation, decision support system, irrigation prescription and precision agriculture. Besides, more sources of information were obtained using the Combine step in the FDC strategy.

The search was conducted within the period from 2012 to 2019,

Table 1
FDC (Facet, Derive and Combine) Keywords.

Facet	Descriptors – Keywords
Study Object	Multi-Agent System, Intelligent Agent, Artificial Intelligence, Irrigation, Agent Based Modeling, Decision Support System, Onion, Lettuce, Horticultural, Distributed System, Distributed Control, Smart Irrigation, Smart Agriculture, Precision Agriculture, Precision Irrigation.
Action Type	Modelling, Evaluation, Analysis, Comparison, Design, Development, Implementation.
Theorical Concepts	Artificial Neural Networks, Deep Learning, Fuzzy Systems, Markov Chains, Bayesian Networks, Expert System, Machine Learning, Control, Automation, Holonic, Wireless Sensor Networks.
Data Acquisition	Soil Water Balance, Evapotranspiration, Crop Coefficient, Soil Moisture, Matric Tension, Dendrometer, Sap flow Sensor, Remote Sensing, Reflectance, Radar, Lidar, Thermal Images, Thermal Sensors, Bowen Station, Weather Station, Image Processing, Leaf Area Index, Vegetation Index, Fractional Vegetation Cover, Green Cover Percentage, Histogram, Lysimeter.
Methodological Strategies	Qualitative, Quantitative, Conceptual.
Place Names	Colombia, Boyacá, Europe, Spain, United States, Argentina, Israel, Egypt, Australia, Every Place.
Own names	Belaqziz Salwa, Germán Cely, Daniel Smith, David Isern, Farid Touati, E. Giusti, Harishankr, Pietervan Oel, Ahmad Esmaeili, Marsili-Libelli, Rodriguez Ortega, Antonio Canales, Brenda Ortíz, Gabriel Villarrubia, Yenifer de la Cruz, Andrés Pantoja, Andrés Jiménez.
Software and Tools	Samir, Matlab, Netlogo, Jade, Pangea, QGIS, ENVI, ERDAS, ARCGIS, Python, SAR, Wireless Sensors, Raspberry, Arduino, Tetracam, Sentinel, Landsat, UAV, MODIS, GPRS.

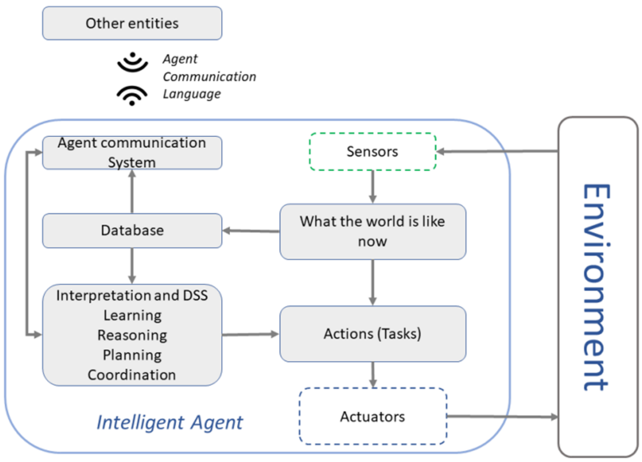

Fig. 1. General structure of an intelligent agent.

with references in English and Spanish, by title, abstract and keywords, using the scientific databases: SCOPUS, Web of Science, Science Direct, IEEE Explore, Springer Journal, Springer Books and Dialnet. The documents were ordered from the highest to the lowest according to the number of references found and classified in the following knowledge areas: water resources, agronomy, environmental sciences, computer science, electrical and electronic engineering, and social and economic sciences.

A total of 280 documents were selected, where 105 of these were published from the years 2014 to 2019, which evidences the relevance of the proposed research topic. Based on this analysis, a classification was established into the following thematic groups:

- *Sensors systems for irrigation management.* This thematic group contains the documents that reported developments and applications of climatic, soil or plant sensors for the definition of crop water requirements.
- *Support systems for decisions in irrigation management:* It includes some SSDs used for water resource management in land irrigation, irrigation districts and irrigation systems design.
- *Artificial intelligence systems applied to irrigation.* This contains works associated with the development of rational agents for irrigation management or systems that have some of the characteristics of an AI system.
- *Multi-agent systems applied to the management of the water resource.* In which the works associated with the use of multiagent systems for the irrigation management in a field, as in large-scale production systems are established.

Thanks to this review, the synthesis was carried out in the following sections, taking into account the concepts, advances, methodologies and procedures used in water resource management systems for irrigation, with thematic areas associated with engineering, especially where artificial intelligence techniques are applied.

3. Intelligent agents in crop irrigation

The words intelligent and smart are commonly used to represent similar things, but they are actually different. Smart refers to technological aspects and the ability to apply previously acquired knowledge in practical situations (Yurish, 2010). Intelligent refers to the functional behavior and the ability to acquire and apply new knowledge and skills (Augusto et al., 2010). The development of truly intelligent systems implies that they can learn habits, preferences and correctly diagnose situations; know where and when events of interest occur and provide a structured way of analyzing, deciding and reacting in their environments (Taymanov and Sapozhnikova, 2009).

Smart irrigation systems are technologies that estimate or measure the TAW depletion in order to control the irrigation for replenishing the water needs of the crop and minimizing the waste of resource (Nautiyal et al., 2010). Generally, these systems are programmed using initial site-specific set-up, executing schedule adjustments and including scheduling and required cycles, without human intervention (Rodriguez-Ortega et al., 2017). Intelligent irrigation systems use AI techniques to optimize water application on the crops, which make decisions using past experiences, analyzing real-time data and learning, according to the environment behavior (Shekhar et al., 2017).

Intelligent irrigation systems can be studied as intelligent agents, which are systems that possess intelligent properties similar to human ones. According to Fougères and Ostrosi (2018), an intelligent agent is a physical entity composed of hardware and software, or a virtual entity developed only by software, which seeks to fulfill assigned tasks. Intelligent agents are autonomous entities that demonstrate reactive, proactive and social skills, with the ability to infer, reason, learn and update (Esmaeili et al., 2017). An agent is rational if its actions executed on the environment in which it is located are appropriated according to the response caused, using a performance measurement (Russell and Norvig, 2016). According to Fig. 1, an intelligent agent is composed of sensors for acquiring information from the environment, actuators to influence on the environment and an interpretation and decision support system (with or without AI). Additionally, an agent could have communication components for exchanging information with other agents and attributes–functions capabilities such as learning, evolution, coordination and planning (Parker et al., 2002).

Fig. 2 shows the basic components of an intelligent agent for irrigation applications, where data about the hydric conditions of the crop is acquired using different kind of sensors. These sensors are installed and grouped into nodes or motes (Fig. 2a), which measure physical variables in plants, soil or the environment (e.g., relative humidity, temperature and radiation). Additionally, data can be acquired using non-invasive sensing technologies for obtaining images from the field using different electromagnetic wavelengths (thermal, multispectral, night vision or photometric cameras). The images can be captured by cameras installed in unmanned autonomous vehicles - UAV (Fig. 2b), terrestrial systems (ground robot or other ground vehicles), or from satellital systems (Fig. 2c) such as radars (e.g., Sentinel1 or RadarSat) or multispectral (e.g., Sentinel2, LandSat or MODIS) techologies.

The provided information by the sensor nodes or cameras must be georeferenced to establish with precision the geographical spatial location of the measurements. The data acquired can be obtained in real time or at previously established sampling times. The sensors data must be proportional to the measured physical variables and are delivered in a format of analog or digital electrical signals, which are sent to the data acquisition systems - DAQS (Fig. 2d). The DAQS receive, transform, scale and condition the electrical signals from the sensors to give digital data stored in a numerical format to be processed or integrated.

The digitized data that provide crop information are transmitted wirelessly through DTUs using wireless communication protocols (ZigBee, WiFi or Bluetooth). The DTUs are composed of modems and antennas (Fig. 2e), which conform a network of wireless sensor nodes that transfer remotely the crop data by a router linked to an information collection center or central master control system. The central master control system (Fig. 2f) is integrated by a high-performance computer or server with a specialized built-in software (Fig. 2g) that manipulates and processes the data and images collected from the crops using artificial intelligent processing techniques. The algorithms programmed in the central master control system allow displaying real-time information about the crop, interpreting and analyzing the data to give support and manage the irrigation applications, making decisions to generate control signals for the actuators that dose water in the field and predicting future behaviors of the crop.

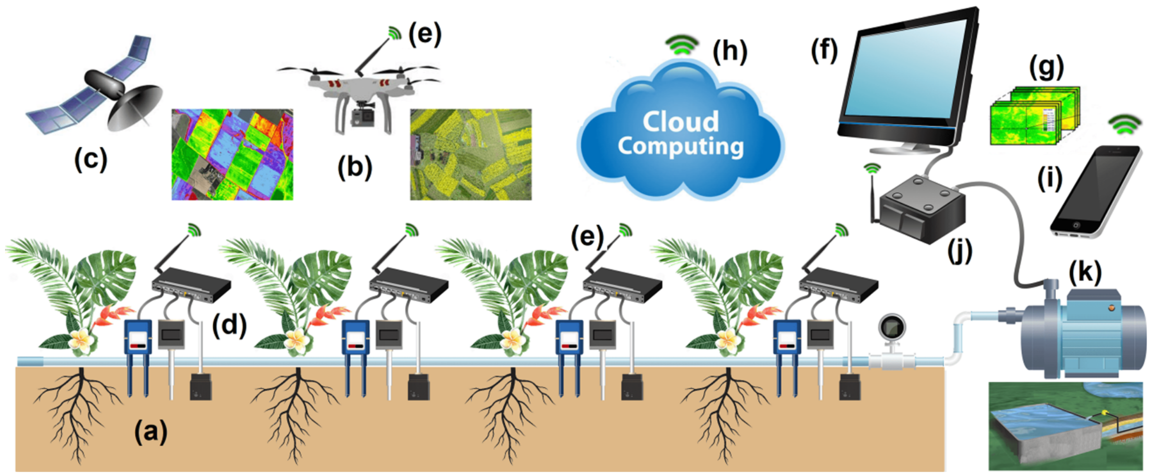

Fig. 2. Intelligent agent for irrigation applications. (a) nodes or motes, (b) cameras installed in unmanned autonomous vehicles - UAV, (c) images from satellital platforms, (d) data acquisition systems - DAQS, (e) data transmitter units - DTUs, (f) central master control system, (g) specialized software, (h) cloud computing, (i) internet of things, (j) master control center, (k) pumps, solenoid valves or other actuators for supplying the irrigation.

The crop information can be transferred and stored through internet (Cloud Computing) (Fig. 2h) or can be sent to mobile devices, laptops, tablets or other devices to track, manage or control remotely the irrigation applications (Internet of Things) (Fig. 2i). Additionally, irrigation control algorithms use several feedback control strategies to generate control actions that regulate the precise supply of water flow in each crop node. These control signals are transferred from the master control center and conditioned by an electronic system or driver (Fig. 2j) that automatically delivers the appropriate activation energy to the pumps, motor pumps or actuators for supply precision irrigation (Fig. 2k).

A review about intelligent agents and their components, applied to irrigation management, will be described in the next subsections.

3.1. Sensors in irrigation intelligent agents

Intelligent irrigation systems need to define the amount and time of water application by means of simulation, direct or indirect measurements or using historical data. Soil-crop responses to these applications are included, in order to improve the irrigation plans (Hashem et al., 2016). For the measurement of parameters associated with irrigation systems, a wide variety of technologies have been developed to program irrigation using data acquisition and instrumentation methods based on climatic data, soil or plant measurements.

3.1.1. Data acquisition methods for irrigation based on climate data

In recent years, the number of researches related to the development of electronic and software technologies has increased to determine the parameters useful for programming irrigation based on soil water balance and climatic data. This approximation uses the crop evapotranspiration (ET_c), calculated with the crop coefficient (k_c) and the reference evapotranspiration (ET_0), where $ETc = k_c * ET_0$ (Nautiyal et al., 2010). Researches in this topic are explained below from two perspectives: using field sensors and using remote sensors.

For calculating ET_0, the United Nations Food and Agriculture Organization (FAO) adopted the Penman-Monteith method, which uses meteorological stations as principal sources of data (Córdova et al., 2015). An Eddy Covariance system (CE) is used for the measurement of the turbulent flow calculation in an atmospheric layer. It generally consists of an omnidirectional sonic anemometer and gas analyzers (CO_2/H_2O), but can integrate other sensors such as radiometer, heat flow in the soil, soil temperature, soil moisture, precipitation or inclinometer. In Clulow et al. (2015), the use of CE in southern Africa is reported to determine evapotranspiration in a forest cover. The study highlights the difficulties of using this system in remote areas, due to the frequent need of equipment maintenance. Another system used to determine the value of evapotranspiration is the Bowen station, as in the research reported in Brazil by Bezerra et al. (2015). The equipment is based on the measurement of the energy balance according to Bowen's reason. In principle, it is a weather station with additional temperature and humidity sensors, which is much more economical than a CE.

A lysimeter is a measuring device used to measure the amount of actual evapotranspiration released by plants. In Jiménez-Carvajal et al. (2017), the results obtained in the implementation of a low-cost automated weighing lysimeter in potted plants are presented, to determine the water balance in irrigation periods, through the direct crop evapotranspiration determination, after calibration and validation of the equipment. According to their results, there is evidence of the need to study their response in several types of plants and the implementation of signal processing techniques to determine and filter atypical values. Another type of lysimeter is shown in Proulx-McInnis et al. (2012), which is considered as a volume lysimeter. The principle of this lysimeter is to isolate a volume of impermeable geotextile material, measuring the necessary inputs and outputs of water to maintain the system at the same level of water as the surrounding environment. This system is governed by a data logger, which sends signals to water suction pumps. The water levels in two containers of water inlet and outlet were measured by means of pressure sensors.

In Moorhead et al. (2017) they report a scintillometer (SLS) for the determination of evapotranspiration. This instrument is used in atmospheric studies, but its application in irrigation management is still under research, where there is no abundant scientific literature. The scintillometer measures contributions to flows in a fixed direction. Moorhead and his team used the SLS based on the energy balance equation (Zhemukhov and Zhemukhova, 2016).

$$LE = R_n - H - G \tag{2}$$

where Rn is the net radiation absorbed, LE is the latent heat flow (evaporated water), H is the sensible heat flow (air) and G is the heat flow in the soil (all measured in Wm^{-2}). An SLS consists of a transmitter and a receiver, separated by a distance ($100m - 4.5km$) and uses specific apertures (α) and wavelenght (λ). A wave with large aperture SLS ($\alpha = 10 - 30cm$, $\lambda = 880nm$) or microwave aperture SLS ($\alpha = 30cm$, $\lambda = 1 - 3mm$) is transmitted, so that the intensity of the beam fluctuates due to the phenomena of absorption and diffraction. These fluctuations are useful for determining the structural parameters of the medium, such as temperature, humidity and H. With error rates

Table 2
Summary of methods and sensors for irrigation scheduling using climate data.

Approaches to calculate	Identified Weather Variables	Sensors	Advantages	Disadvantages
Reference evapotranspiration*ETo*(Weather Station andBowen Station)	Solar Radiation. Air Temperature. Atmospheric humidity Wind speed.	Pyranometer, solarimeter or actinometer. Thermistor or Termocouple. Higrometer or humidity probe. Anemometer.	It includes smart operation and integrates tensiometer, soil moisture sensors, scales, data loggers with optional GPRS system and lightning protection. It supports solar panels to work. Not large dimensions.	It needs a wireless module for data transmission. Small sampling area. Divergence of water flow around the system, preventing quantitative estimation of flux concentrations.
Reference Evapotranspiration *ETo* (Eddy Covariance EC)	Carbon dioxide in the air CO_2. Water vapor flow in the air H_2O.	Anemometer. Infrared Sensor. Quality air sensor. Precision flowmeter or vapor flowmeter.	High precision and linearity. No moving parts. No calibration required. Easy installation. It includes datalogger.	It needs a wireless module for data transmission. Small sampling area. It requires power supply system. High cost.
Crop Evapotranspiration *Etc* (Lysimeter)	Weight Volume Evapotranspiration	Weight lysimeter. Volumetric Lysimeter	It controls the variations in weight and tension of the soil column to study. The lysimeter is the best method to define water requirements in irrigation systems. It includes smart operation and integrates tensiometer, soil moisture sensors, scales, data loggers with optional GPRS system and lightning protection. It supports solar panels to work. Not large dimensions.	Invasive Sensors. It needs a wireless module for data transmission. Small sampling area. Divergence of water flow around the system, preventing quantitative estimation of flux concentrations.
Percent Green Cover *PGC* Plant Effective Diameter *PED*	Cover classes. Percentage of crop covered in *PGC*. Basal crop area in *PGC*. Height and diameter of plants in PED. Vertical foliage projection in the crop.	RGB visible spectrum camera. Multiespectral Camera.	Useful to define root depth and crop coefficient. Estimation is close to reality. Non-invasive measurement method. It covers large dimensions of land with good precision. Algorithms calculate the parameters quickly (real-time), easily and efficiently. Acceptable adjustment or calibration.	Use platforms UAV and its control, GPS and remote communication systems. Specialized software for digital image processing. It requires prior tests so that the user becomes familiar with the software working environment. It requires adaptation to uneven terrain.
Enhanced Vegetation Index *EVI* Normalized Difference Vegetation Index *NDVI*	Plant biomass. Vegetable spectral radiation.	Near infrared camera. Multiespectral camera. Hiperspectral or thermal camera.	Useful to determine crop coefficients NVDI or EVI estimation is close to reality. Non-invasive measurement method. It covers large dimensions of land with good precision. Algorithms calculate the NVDI or EVI quickly (real-time), easily and efficiently. Friendly visualization of data and powerfull information analysis tools.	It requires the use of UAS-RPAS platforms, with their respective control, GPS and remote communication systems. Specialized Software for digital image processing. It requires prior tests so that the user becomes familiar with the software working environment. It requires adaptation to uneven terrain. It requires geometric, radiometric and atmospheric correction or adjustment. Saturation in digital levels for the NDVI.

as low as 14%, the SLS exhibits good results in irrigation systems, in the determination of crop coefficients or irrigation schedule (Moorhead et al., 2017).

There are also studies on the use of digital image processing to find the kc, determining the coverage that the plant has on the ground and other allometric measures, such as root depth and average plant height, where segmentation techniques play a fundamental role in the processing (Sabzi et al., 2017). Through these techniques, plants information is collected remotely and used for the crop evapotranspiration determination. In Carrasco-Benavides et al. (2016), a methodology is specified to determine the Leaf Area Index (LAI), which is a dimensionless variable defined as the leaf tissue area per soil area, related to the kc (Kirk et al., 2009; Cerekovic et al., 2010). The procedure consisted in comparing the LAI obtained from the processing of images acquired from a conventional camera (RGB, Red, Green and Blue) and the data obtained by defoliation in cherry trees. Their results show the robustness of the method to determine the LAI, indicating the calibration needs for each crop type.

Another parameter used is the percentage of plant cover (PGC, Percent Green Cover). Daniel Fernández et al. (2014) developed a method based on image treatment to estimate the crop coefficient using the *PGC* and the measurement of crop height. First, they used a weather station and a Bowen station to obtain the real k_c, then they estimated a function between *PGC* and h, and finally they found another function that relates $PGC/handK_c$. They also determined the relationship between root depth and k_c. Additionally, they obtained quadratic correlation coefficient values of 0.993 and 0.979 by estimating the height h from *PGC* and *Kc* from *PGC/h*, respectively, which demonstrated the validity of the method. The method needs calibration procedures according to the crop and soil types (Fernández-Pacheco et al., 2014).

In González-Esquiva et al. (2017), the development of a new model is explained for estimating the water balance of lettuce cultivation from the plant effective diameter (PED), which is calculated using the PGC value. It is based on the ratio of plant diameter (D) - biomass (B), using the allometric parameter $\alpha = 0.333$ that relates $dB/B = \alpha/D$. To determine the effective diameter, they used the calculation of the average square diameter, taking into account a reference frame in the soil and the number of plants that are within this frame, finding polynomial equations. They obtained economic and precise estimates, with errors of 2.1% with respect to the crop coefficient and less than 9% for root depth. The model needs to be calibrated with the crop and soil types and climatic conditions (González-Esquiva et al., 2017a). For image processing, they used a low-cost image acquisition device (González-Esquiva et al., 2017b) or a smartphone app (Hernández-Hernández et al., 2017), also allowing information processing through the Web (González-Esquiva et al., 2017c).

Remote sensing tools have also been used for irrigation scheduling with different spatial resolutions acquired from satellites, aircraft, unmanned aerial vehicles and ground equipment (Alvino and Marino, 2017). In their research Jarchow et al. (2017) used the Enhanced Vegetation Index (EVI), product MOD13Q1, of the Moderate Resolution Imaging Spectrometer (MODIS), highlighting the robustness of this index with respect to the Normalized Difference Vegetation Index (NDVI). They determined the crop coefficient as a function of the vegetation index (VI), so that $ET_c = f(VI)ET_0$, where ET_0 is determined using meteorological data and calibration using lysimeters or hydric balance studies. They obtained results that allow defining a directly proportional relationship between the LAI and the VI (Jarchow et al., 2017).

Additionally, in 2017, Li and colleagues, used the spatial–temporal fusion technique with MODIS and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) images, obtaining daily evapotranspiration with $90m$ of spatial resolution (Li et al., 2017). They installed a weather station, soil moisture and temperature sensors, with measurements of the LAI and the vegetation cover fraction at each site. It is worth mentioning that there were difficulties in obtaining evapotranspiration due to the temporary resolution of data acquired from the satellites. This can be solved using multiple sources of spectral information, especially data from Landsat-8 and Sentinel-2 satellites.

In Marshall et al. (2016), a study was reported with different narrow and wide band indices, with the purpose of dividing evapotranspiration between soil evaporation and crop transpiration. They found that to determine the crop transpiration, *NDVI* can be used to estimate the total *ET* in addition to the Photochemical Reflectance Index (PRI). To estimate soil evaporation, they proposed two derived indices from the infrared (743 and 953 nm), blue (428 nm) and short-wave infrared (1518 nm) bands. Finally, in Malamos et al. (2015) an application was developed in a GIS (Geographic Information System) with Python in ESRI's ArcMAp software, for the determination of monthly evapotranspiration, using the Penman-Monteith equation and data acquired from a weather station. The information was displayed on vector color maps, using crop coefficient data. Table 2 summarizes the main methods and variables measured to estimate or calculate parameters based on the weather conditions and useful for prescribing water amounts in irrigation systems.

3.1.2. Data acquisition methods for irrigation based on soil data

Soil moisture sensors (SMS) are used to determine the amount of water that is available for the plants and its temporal dynamics (Mrinmayi et al., 2016). Methods to measure the soil moisture content are direct and indirect (Li et al., 2012). Gravimetric and volumetric methods are directly obtained in the laboratory. The gravimetric method uses the mass as principal component, as shown in Eq. (3).

$$Gravimetric\ water\ content\ (GWC) = \frac{mass\ of\ soil\ sample - mass\ of\ dry\ soil}{mass\ of\ dry\ soil} \tag{3}$$

Volumetric water content (VWC) uses volumes as principal component, as in Eq. (4).

$$VWC = \frac{volume\ of\ water\ content}{voulme\ of\ sample\ soil} \tag{4}$$

Gravimetric and volumetric water contents are related using Eq. (5).

$$GWC = \frac{VMC * \rho_{water}}{\rho_b} \tag{5}$$

where ρ_{water} is the water density and ρ_b is the dry soil bulk density.

Indirect methods use physical variables that are related with the volumetric water content (VWC) or the soil moisture tension (SMT). Strategies using VWC are dielectric methods and the neutron moderation method. The soil dielectric constant constituents (water, air and solid particles), changes dramatically with the increment of water content. The dielectric constant of soil particles varies between two and seven, while those of air and water are of one and 80, respectively. The volumetric water content (VWC) can be associated with the soil dielectric permittivity in a frequency range between $50MHz$ and $17GHz$ (Sample et al., 2016).

Some examples of VWC methods are capacitance (Harris and Stonard, 2018), timed domain reflectometry (TDR) (Chandler et al., 2004), frequency domain reflectometry (Xu et al., 2012), amplitude domain reflectometry (Moroizumi and Sasaki, 2008), time domain transmission (Masbruch and Ferré, 2003), microwave methods (Liu et al., 2012), ground penetrating radar (Gerhards et al., 2008), X-ray tomography (Weller et al., 2018) and nuclear magnetic resonance (Pohlmeier et al., 2008). Examples of SMT techniques are the tensiometer (Bhatt et al., 2016), resistance block (Keyhani, 2001), granular matrix (Cardenas-Lailhacar and Dukes, 2010), heat dissipation (Flint et al., 2002) and the psychrometer (Mullins et al., 2000).

VWC methods are fast in response concerning SMT methods and its measurements are almost instantaneous. In mineral soils, the accuracy of the VWC, especially the TDR, is good and can be improved by the calibration of each soil. Calibration is essential for soils with a lot of organic content. In saline soils, significant energy losses limit the usefulness of the VWC methods. VWC methods use soil dielectric properties that are associated with the water available in the soil, however, SMT systems measure the tension related to the stress experienced by plant tissues (Shock and Wang, 2011). When there are water needs in the aboveground plant parts, a tension is transmitted to the roots for extracting more water from the soil. For this reason, irrigation scheduling based on SMT can be associated with the crop performance. A granular matrix sensor provides an indirect measurement of SMT, using the resistive value between two electrodes placed into a granular matrix container (Larson, 1985). Granular matrix sensors have advantages of low cost in comparison with the VWC sensors, no maintenance, and adaptability to widely variable wiring lengths. They can use manual or automatic systems to obtain the measurements, especially with the use of data loggers. Granular matrix sensors are useful on most of soil types and site-specific calibration is usually not required unlike the VWC that requires calibration according to the soil type. Sensor responsiveness is fairly rapid from 10 to 80 kPa, with a useful range extend to 200 kPa with appropriate calibration (Shock and Wang, 2011). These sensors are not repairable and temperature compensation is used in the calibration equations in meters and data loggers to improve the accuracy of SWT estimations (Shock et al., 2003).

According to Adeyemi et al. (2017), electrical conductivity, soil texture, bulk density and temperature influence the accuracy of the measurements. For this reason, it is important to consider the specific conditions of the site where the technology will be implemented, in order to perform the respective calibrations. In resistance blocks techniques, the ground temperature, the probes length, among other factors, affect the measurement. To correct the temperature problem, compensation strategies have been developed (Oates et al., 2015). The measurements of soil moisture in the field is quick and easy with sensors, but they are very sensitive to installation procedures, because the influence of the sourrounding material and air spaces between sensors and the soil can affect the measurement. Calibration must be carried out very carefully for each probe and each soil, in order to obtain accurate water content data.

Microwaves, in a wavelength range between 50 and 500 mm, are particularly effective for measuring the soil moisture of a surface. This occurs because they have minimal atmospheric attenuation and there is a large difference between the dielectric constants of water and dry soil, which results in a high sensitivity and accuracy in the lecture of the soil water content. In microwave methods, the principal parameter to estimate is the backscatter coefficient σ_0, which is the difference between the emitted and the reflected energy of the microwave radiation measured in dB, which depends on the dielectric constant of the soil. The spectral bands considered as the most sensitive to soil moisture are L $(0.5 - 1.5GHz)$, C $(4 - 8GHz)$ and X$(8 - 12GHz)$ (Karthikeyan et al., 2017). In the active microwave (radar) technique, an artificial radiation source or emitter is used, and the intensity of the radiation reflected by the ground is measured. Synthetic Aperture Radar (SAR) is a technology used to determine soil moisture using microwave wavelengths. Sensors of the projects RADARSAT, ENVISAT, TerraSAR-X and Sentinel-1 satellite systems can be used for soil moisture measurement.

The models to determine the soil moisture content using microwave data on satellite platforms can be theoretical, semiempirical and empirical. Theoretical models include the Kirchhoff approach, small disturbance model, small slope model, microwave dispersion in the canopy, integral equation method, and the advanced integral equation model. These models are useful only in certain conditions. Semi-empirical models can be applied at any location where the site conditions are within the prescribed limits of the models. The most important ones are the Oh and the Dubois models. In empirical models, field data is used to correlate with the data of σ_0, therefore, excellent quality is required in field measurements, with calibration for each site (Karthikeyan et al., 2017).

Water-Cloud is a semi-empirical model for determining soil moisture using microwave wavelengths on zones with vegetation. In this model, vegetation and soil contributions are taken into account in the backscatter coefficient according to the Eq. (6).

$$\sigma_0 = \sigma_{veg} + \sigma_{soil} \tag{6}$$

In addition to soil moisture measurements using microwaves, the soil roughness and the vegetation are two important factors that influence the emissivity and reflectivity of the soil. Although these factors can be taken into account in relatively simple linear regression models, which incorporate an empirical roughness parameter and the moisture content of the vegetation, they reduce the sensitivity of the method as they increase the emissivity related to background noise.

3.1.3. Data acquisition methods for irrigation based on the plant measurements

There are sensors that measure parameters associated with the definition of water requirements that are in direct contact with the plants. Examples of these technologies are the dendrometer (Van der Maaten et al., 2016), the xylem cavitation sensor (Nolf et al., 2015), the sap flow sensors (Poblete-Echeverría and Ortega-Farias, 2013), tissue condition sensors (Jones, 2004) and stomatal conductance sensors (Grashey-Jansen, 2014). Additionally, there are data acquisition systems that use remote sensors, specially crop canopy temperature systems (CCT). The use of indices and threshold calculations are the most used methods to define irrigation requirements using CCT.

The indices are operations between measurements of parameters in the environment and in the crop canopy temperature. The fundamental principle of these systems is based on the changes of the radiation emission in the spectral band of the long-wave infrared (LWIR), when the plants show wilting symptoms, which is manifested in the canopy temperature. For the use of these indices, it is important to take into account the variations in canopy temperature measurements due to fluctuations or changes in meteorological conditions at the moment of the acquisition. Due to this behavior, the indices cannot be considered as an absolute indicator of water stress.

Several researches have been developed to find operations or indexes that can describe the relationships of water stress and thermal behavior of plants (Alvino and Marino, 2017). One of the most studied indices is the Crop Water Stress Index (CWSI) (Jackson et al., 1981). According to the conditions of relative humidity and air temperature, this index uses the quantification of the crop behavior when it is and when it is not transpiring. There are several equations used in the literature to determine the CWSI index. In López-López et al. (2011), it is defined as the Eq. (7).

$$CWSI = 1 - ET_c/ET_0 \tag{7}$$

where ETc is the evapotranspiration of the real crop and ET_0 is the reference evapotranspiration. Alpaydin (2012) defines CWSI according to Eq. (8), where they use infrared thermometers or thermal images to determine the crop canopy temperature, using other environmental parameters, such as solar radiation, speed of wind, air humidity and air temperature. The canopy and air temperature difference $(Tc - Ta)$ is normalized to the lower and upper limits of the same difference; where m means measured data, $l$is a lower baseline (unstressed crop) and u indicates an upper limit (completely stressed crop).

$$CWSI = ((T_C - T_a)_M - (T_C - T_a)_l)/((T_C - T_a)_u - (T_c - T_a)_l) \tag{8}$$

In King and Shellie (2016), the CWSI index is defined as the Eq. (9).

$$CWSI = (T_{canopy} - T_{normal})/(T_{dry} - T_{normal}) \tag{9}$$

where T_{canopy}, T_{normal} and T_{dry}, are the current canopy temperature, when the crop is not stressed (well watered) and when the crop is severely stressed due to the low availability of water in the soil, respectively. To normalize CWSI values according to the effects of environmental conditions (radiation, air temperature, wind speed, relative humidity, etc.), the temperatures T_{normal} and Td_{dry} are used as the lower and upper baselines.

The CWSI index and its modifications have been used in grape crops (Agam et al., 2013), almond (Rojo et al., 2016), cotton (Colaizzi et al., 2003), watermelon (Orta et al., 2003), peach (Bellvert et al., 2016), pepper (Sezen et al., 2014), olive (Agam et al., 2013), apple (Osroosh et al., 2016) and corn (Mangus et al., 2016).

In investigations reported in Gonzalez-Dugo et al. (2013) and Gonzalez-Dugo et al. (2015), remotely piloted aircrafts were used to derive the CWSI, with high-resolution thermal images. Through this procedure they assessed the spatial variability of the crop water status, achieving the change of irrigation management from conventional to a variable rate application system. In these researches, the potentiality of this index for the irrigation management in agricultural crops is evidenced.

In Kullberg et al. (2017), a comparison and evaluation of water stress coefficients is made for the determination of crop evapotranspiration. They studied some indices that only use crop canopy temperature measurements, such as the Canopy temperature index (Tc), Degrees Above Non-Stressed index (DANS) and Degrees Above the Canopy Threshold index (DACT). These indices have the same potential to be used in irrigation scheduling, compared to those that use more information like the (CWSI).

The second method used estimates the temperature and time threshold (TTT) (Peters and Evett, 2007). It uses the so-called Biologically Identified Optimal Temperature Interactive Console (BIOTIC). The activation of an irrigation signal occurs when the accumulated time, in which the canopy temperature exceeds a specific temperature threshold, also exceeds a time threshold that has been calibrated locally. The temperature threshold for a crop is based on physiological parameters. The time threshold is defined using an energy balance model based on local climatic data (Wanjura et al., 2004).

In Evett et al. (2006), the application of the TTT method in agricultural irrigation is described, highlighting its potential as an automatic control response method that does not require additional temperature data for irrigation activation. In their study, they established the TTT method as a useful methodology to regulate the efficiency of water use. In O'Shaughnessy et al. (2006), they studied the use of soil moisture measurements, two thermal indexes and irrigation programming. The TTT algorithm obtained a reduction in the volumes of water applied, without affecting the crop yield negatively. In O'Shaughnessy et al. (2012) an integration is made between the CWSI index and the TTT procedure, with a threshold in CWSI and a threshold in time, called CWSI-TT. However, in this study they highlight the existence of possible false positives in some periods and results similar to irrigation programming using a neutron probe.

DeJonge et al. (2015) recommend the specification of the DACT parameter as an appropriate index to quantify water stress in corn, since it requires a single measurement of canopy temperature. Kullberg et al. (2017) compared four protocol methods in thermal remote sensing indices to estimate the evapotranspiration coefficients of the crops: CWSI, DANS, DACT and Tc ratio. They observed that the DANS and DACT thermal indices responded to the plant water stress, which is comparable to more data intensive methods such as CWSI. Table 3 summarizes the main methods and variables associated with the definition of water requirements that are in direct contact with the plants. Table 4 shows the remote sensing methods for defining irrigation scheduling using remote sensing technologies (Ihuoma and Madramootoo, 2017).

3.1.4. Integration of data acquisition systems for crop irrigation management

In general, plant, soil and atmosphere monitoring approaches for defining irrigation prescriptions have been studied in the bibliography. Usually, these methods are used independently, but an analysis of the data obtained with each technology could suggest the use of mixing sensing strategies. For example, plant monitoring strategies are very useful for defining when the plant is stressed, but useless to define the irrigation rate and times. For this reason, it is important the use of plant strategies with another method for determining irrigation prescriptions.

Weather measurements are useful to define the reference evapotranspiration, but if this value is not used in a soil water balance equation, there are troubles in the definition of the quantity of water to apply. Measuring automatically the amount of inputs and outputs of water in the crop using weather parameters has some challenges that are supplied with the use of soil moisture sensors for defining soil water depletion, rain gauges for defining water amounts that are supplied by precipitations, and other technologies for determining crop coefficients and the root depth in the plants. An important aspect of atmosphere monitoring approaches is that the heterogeneity in the irrigation system or the crop are not accounted (Jones, 2006).

Soil moisture sensors are useful to measure irrigation times and rates, obtaining the depletion percentage with respect to the total available water in the soil (FC-PWP), and when to stop the irrigation activity with the use of soil sensors at different depths. Soil sensors take no account of evaporative demand, so they cannot indicate plant stress. Additionally, soil sensors have the disadvantage that they are punctual measurements that in some cases are not representative for a full field.

Mixing irrigation sensing strategies could improve the automatic definition and control of irrigation scheduling in an intelligent agent. An intelligent agent could use the plant sensors for defining when the plants are stressed (start irrigation time), or atmosphere and soil monitoring approaches to define the amount of water to apply based on the water balance equation (rate and time), and the soil sensors could also be used to define the time to finish irrigation applications (stop irrigation time). In addition, the definition of several irrigation prescriptions using different sensor strategies could be used in the reasoning system for determining the prescription performance in the future for each strategy and evaluating the water use efficiency, using some crop model software. The agent could select the best option according to the future predictions and apply the irrigation amounts using this information.

In Osroosh et al., (2016), several irrigation scheduling algorithms were studied: TTT, CWSI, soil moisture sensors, evapotranspiration, soil water balance, a combination of soil sensors and water balance and conventional management, using a neutron probe as a reference point. This research highlights the successful functioning of climate and plant methods to supply enough water to plants and avoid water stress. The prescriptions using only soil moisture measurements failed in the water supply, presenting water stress and non-uniform plant growth. In addition, they explain that the feedback of measures in the plant presents excellent results in irrigation scheduling.

In Alexakis et al. (2017), a research reported the data fusion of passive sensors (Landsat 8, NDVI and Temperature), active sensors (Sentinel 1, Vertical (VV), C band) and field sensors, for the determination of the state of soil water. For the model determination, they used artificial neural networks, where the selected parameters were the backscatter coefficient $VV\sigma_0(dB)$, NDVI (vegetation and roughness), incidence angle θ (topography) and thermal infrared temperature (TIR) (water content). They found that the incidence angle is the least sensitive parameter, while the NDVI is the most sensitive to the precise estimation of soil moisture content.

Fig. 3 shows some sensors used to determine irrigation needs in agricultural crops. The classification of sensors for scheduling irrigation using parameters based on the environment, soil and plants is highlighted. It also highlights the use of remote sensors in the definition of irrigation and the use of the visible, infrared and microwave electromagnetic spectrum.

3.2. Decision support systems for irrigation management

The use of Information and Communication Technologies (ICTs) in agriculture requires the acquisition and analysis of data from sensors using specialized software. Additionally, this software has to make

Table 3
Summary of acquisition methods used in irrigation systems based on plant-based approaches.

Methods	Description	Advantages	Disadvantages
Stomatal conductance	Indirect indicator of plant water stress by measuring the stomata opening.	Good measure of plant water status. Used as benchmark for most research studies.	Intensive and unsuitable for automation and commercial application. Not very accurate for anisohydric crops.
Leaf water potential	Direct measurement of leaf water content.	Widely accepted reference technique.	Slow, destructive, and unsuitable for isohydric crops
Relative water content	Direct measurement of leaf water status.	Good indicator of the plant water status, requiring less sophisticated equipment.	Destructive and time consuming.
Sap flow measurement	It measures the rate of transpiration through heat pulse.	Sensitive to stomatal closure and water deficits. Adapted for automated recording and control of irrigation systems	It needs calibration for each tree and is difficult to replicate. It requires complex instrumentation and expertise
Stem and fruit diameter	It measures fluctuation in stem and fruit diameters in response to changes in water content.	Sensitive measure of plant water stress.	Not useful for the control of high frequency irrigation systems.

decisions and in some cases control input applications on the field. In water resource management, this means that the software has to decide when to irrigate and how much water to apply. These systems should consider the water quality, crop type, plants phenology, irrigation system, soil electrical conductivity (EC), drainage, nutrients required by the plants, solar radiation, vapor pressure deficit, rain, soil moisture, evapotranspiration, relative humidity and temperature, among others (Rodriguez-Ortega et al., 2017). A useful tool to obtain better performance in irrigation activities is a Decision Support System (DSS), that estimates if some process (irrigation) is required or not, and the water amount that is needed (Isern et al., 2012).

A DSS is a computer system that help decision makers choose between alternatives, through the application of knowledge about the decision domain (Kukar et al., 2019). It incorporates an explicit decision procedure based on a set of theoretical principles that represents its rationality (Aulinas et al., 2009). It can be used for structured and unstructured decisions and cannot replace the decision maker itself because DSSs do not possess the human decision-making abilities as imagination, creativity or intuition. The DSSs can be classified in data-centric (information) or model-centric (simulations and optimization modeling) (Kozisek and Hanzlík, 2014). Data-centric DSS or data-oriented DSS refer to an architecture where data is the primary and permanent asset, emphasizing on the access to and manipulation of current and historical data (time-series) to support decision tasks (Power, 2008). Centric or driven DSS emphasize on access to and manipulation of algebraic, decision analytic and financial, simulation and optimization models to provide decision support. Models in a model-driven DSS should provide a simplified representation of a situation that is understandable to a decision maker. Additionally, model-driven DSS uses data and parameters provided by users to support decision makers in analyzing a situation, but they are not necessarily data-intensive (Power and Sharda, 2007).

Environmental systems tend to comprise complex interactions among biological, ecological, climatic, social, physical and chemical processes. These systems may be difficult to represent, model and understand, causing considerable uncertainty (Heslinga et al., 2017). The effort to integrate new tools to deal with more complex systems has led to the development of the Environmental Decision Support Systems (EDSSs) (Papathanasiou and Kenward, 2014). Additionally, Intelligent Environmental Decision Support Systems (IEDSSs) are systems that use a combination of models, analytical techniques and information retrieval to help develop and evaluate alternatives, based on traditional AI approaches (Sànchez-Marrè, 2014).

The classification of some DSSs used in irrigation is presented in Table 5. The group in the first column uses plant, soil and climate data to determine water requirements. Some of them use crop models to estimate plant phenology, quantify Water Use Efficiency (WUE) and yield, evaluate and compare irrigation application models, compare simulated and real data and save time in determining plants responses without real crops in the field. In the second group are useful systems for water management in irrigation districts. Finally, the DSSs in the third group are used to decide how to install irrigation infrastructure on the field.

Regarding the use of AquaCrop, in Xiang et al. (2013) they

Table 4
Summary of acquisition methods used in irrigation systems based on plant-remote sensing approaches.

Methods	Description	Advantages	Disadvantages
Infrared Sensors			
Infrared thermometry	It measures canopy temperature, which increases as a result of water stress.	Reliable and non-destructive	It is based only on few point measurements.It does not take into account the heterogeneity of the soil and crops.
CWSI	It uses the difference between canopy and air temperatures to quantify crop water stress	Sensitive to stomatal closure and crop water deficit.	Influenced by cloud cover, it requires different baselines for different crops
DANS, DACT, and Tc ratio	It measures canopy temperature to quantify water stress	It requires less data than CWSI for detecting water stress. Tc ratio gives quantitative water stress coefficient (Ks) for calculating crop ET	Difficult scale up to large cropped fields.
Spectral Vegetation Indices			
Structural indices	It measures reflectance indices within the VIS and NIR spectral range (NDVI, RDVI, OSAVI, TCARI) to indicate canopy changes due to water stress.	Non-destructive with high temporal and spectral resolution.	Image analysis requirements are still a challenging task. It reduces precision from leaf scale to canopy scale.
Xanthophyll indices	It measures PRI and PRInorm, which are sensitive to the epoxidation state of the xanthophyll cycle pigments.	It accounts for physiological changes in photosynthetic pigment changes due to water stress	More work is needed to convert raw imagery to a user-friendly irrigation application.
Water indices	It measures the reflectance through the near-infrared region (WI, SRWI, and NDWI) used to represent canopy moisture content.	Rapid and non-destructive measure of leaf water content.	Problem of scaling up to canopy level.

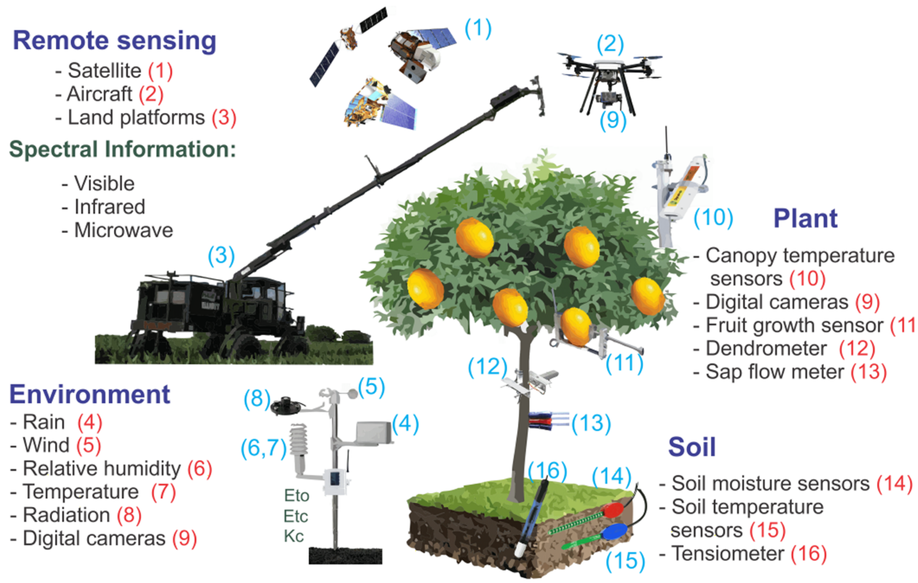

Fig. 3. Selection of some sensors used for irrigation programming.

simulated wheat yield under conditions of different irrigation scenarios, comparing the model with experimental data. The model in this study accurately estimated the soil water content of the radical zone, as well as biomass and wheat grain yields. In Xiang et al. (2013), they used AquaCrop to predict responses in cotton under drip irrigation. They determined the irrigation prescription taking into account parameters related with water in the soil and salinity. They compared data obtained in simulation of the canopy cover, root water storage and aerial biomass with field data, obtaining coefficients of determination $r^2 > 0.77$ and indices of agreement $d > 0.92$, with underestimation of yield. They concluded that AquaCrop can be used as a reliable tool to predict cotton growth response with respect to irrigation application.

The authors in Ran et al. (2018) perform the parameterization of AquaPro for the corn cultivation according to the conditions of the northwest region of China. The model variables used in parameterization were canopy coverage, aerial biomass, yield and water content in the soil. The default AquaCrop model, the new parameterized model and field data were compared, obtaining better results with the parameterized model. According to these results, the need to calibrate the model to conditions of the application site is established.

In Jiang et al. (2016), they used the Decision Support System for Agrotechnological Transfer (DSSAT) in an irrigation district located in northwestern China, to explore irrigation strategies that would reduce water consumption and maintain yields, under different climatic conditions. The model was first calibrated based on crop yield, phenological phases and soil water content data. Subsequently they used the calibrated model to simulate the effects of planting dates and different irrigation treatments on corn yield, calculating the amount of potentially reduced water. The work reported by Ovando et al. (2018) highlights the use of DSSAT to simulate the development and yield in soybean cultivation. They used the Clouds and the Earth's Radiant Energy System (CERES) and the Tropical Rainfall Measuring Mission (TRMM), providing spatial and temporal information on solar radiation and precipitation, respectively. This study evaluated and quantified the uncertainty in the estimation of soybean yield using a DSSAT model, when the recorded meteorological data is replaced by CERES and TRMM, finding that this satellite information can be used for the estimation of soybean yield.

Finally, in Winter et al. (2017) the development of a model based on the Water Evaluation and Planning System (WEAP) and the DSSAT, to link water supplies and Regional management with the demand for water at the field level and the growth of crops. WEAP-DSSAT was deployed and evaluated in Yolo County in California for corn, rice and wheat crops. WEAP-DSSAT was able to reproduce the results of DSSAT under conditions of good irrigation and reasonably simulate the average yields observed. The system is useful for determining future yields under limited water availability, irrigation optimization and strategies to increase drought resilience.

3.3. Artificial intelligence in agents: data interpretation and attributes–functions capabilities

The implementation of AI in DSSs is used in the study on rational use of water resources to interpret and analyze information acquired from sensors in field, and making water resources planning more scientific and accurate (Chen and Liu, 2010). AI was born in 1950s, which

Table 5
Decision Support Systems applied to irrigation.

Irrigation DSS	Irrigation DSS	Irrigation DSS
Several Scales	Irrigation Districts	Schematic Design
CropWat (Smith, 1992), MODERATE (Bergez et al., 2001), CropSyst (Stöckle et al., 2003), DSSAT (Jones et al., 2003), DSIRR (Bazzani, 2005), PlanteInfo (Thysen and Detlefsen, 2006), WaterSense (Inman-Bamber et al., 2007), HydroLOGIC (Richards et al., 2008), CropIrri (Zhang and Feng, 2009), HydroLOGIC (Richards et al., 2008), CropIrri (Zhang and Feng, 2009), AquaCrop (Steduto et al., 2009), IrriSatSMS (Car et al., 2012), APSIM (Holzworth et al., 2014)	SIMIS (Mateos et al., 2002), MODULUS (Oxley et al., 2004), GWRAPPS (Satti and Jacobs, 2004), MULINO (Mysiak et al., 2005), GISAREG (Fortes et al., 2005), IRRINET (Beutler et al., 2007), ADOR (Playán et al., 2007), TaiWAP (Acutis et al., 2010), AQUATER (Acutis et al., 2010), FIS-DSS (Yang et al., 2017), WIDSS (Wang et al., 2017)	DEMETER (Belmonte et al., 2005), MIRRIG (Pedras et al., 2009) AKLA (Khadra and Lamaddalena, 2010), WISCHE (Almiñana et al., 2010), DSS-FS (Barradas et al., 2012), SURCOS (Burguete et al., 2014).

aims were how to use a machine to simulate the intelligent behaviors of human beings (Chen and Liu, 2010). For a machine to exhibit intelligence, it has to interpret and analyze the input and result data in a problem, instead to simply following the instructions of a software algorithm.

Artificial intelligence according to Adeyemi et al. (2017), has the potential to solve complex and nonlinear problems, such as precision irrigation. These techniques applied in irrigation are based on the determination of parameters related with crop evapotranspiration, crop water stress or soil water content. The algorithms of AI, allow to emulate the human process of decision making for the management of different problems and has been used in the support of adaptive irrigation decisions. Some techniques and fields of AI used in irrigation are machine learning (Bustos and Ricardo, 2005; Kaur, 2016), knowledge engineering (Rafea et al., 2003), fuzzy logic (Gao et al., 2013; Zhang and Guo, 2018), artificial neural networks (Adamala, 2018; Shabani et al., 2017), case-based reasoning (Li and Yeh, 2004), expert systems (Fedra, 1994), bayesian networks or probabilistic networks (Castelletti and Soncini-Sessa, 2007), artificial life (Dessalegne and Nicklow, 2012), evolutionary computing (Ranjithan, 2005), genetic algorithms (Wardlaw and Bhaktikul, 2004), evolutionary strategies (Reddy and Kumar, 2008), evolutionary programming (Pant et al., 2010), artificial neurogenetic networks (Perea et al., 2015), support vector machines (Gill et al., 2006), data mining or Knowledge Discovery in Databases (KDD) (Li et al., 2012a; Khan et al., 2012), optimization algorithms (Alsukni et al., 2019; Nguyen et al., 2017) and Agent Based Modeling (ABM) - distributed artificial intelligence (Le Bars et al., 2002; Wanyama and Far, 2017).

Among all of these, the most widely used and constantly applied method for irrigation research purposes are the Artificial Neural Networks (ANN), based on the inter linked neural networks in the human brain and its electric signals. ANN can identify and learn about the relationships between data acquired by sensors and the corresponding outputs, useful in modeling when the underlying data relationship is not well defined. The models for irrigation scheduling are generally developed and trained using a large historical database that would influence the amount of water required by crops. Once built, the models are used on real time data, to define the irrigation prescription necessary to sustain the crop's healthy growth (Krupakar et al., 2016). The ANNs are useful in supporting decisions in irrigation management, due to the complexity of the water application to crops, their adaptive nature and learning capacity.

In Karasekreter et al. (2013), the development of an ANN for irrigation scheduling in a strawberry crop is presented using soil moisture and its physical properties. As shown in their results, water savings of 20.5% and energy savings of 23.9% were achieved. They emphasized that the ANNs require large amounts of data for training, whichmakes them limiting in their use for real-time decision support. In Feng et al. (2017), two models of ANN were developed for the ET_0 estimation with only temperature values, with results of relative average quadratic error lower than 0.198 and average absolute error lower than $0.267 mm/d$. The results show the excellent models capabilities to estimate ET_0. In Abdullah and Malek (2016), they analyzed the application of ANNs for the ET_0 determination using weather stations, showing its greater efficiency with respect to traditional methods that use the Penman-Monteith equation.

Common ANN models, do not have the ability to predict in time series forecasting (Jimenez et al., 2019). A Recurrent Neural Network (RNN) model is a deep learning technique useful in dynamic modelling tasks (Kumar, 2018). Long Short-Term Memory (LSTM) network is an extension of RNN with successful application in nonlinear dynamic systems (Gonzalez and Yu, 2018). The LSTM have been used in modelling sequential data of VWC using remote sensing (Lu et al., 2015), prediction of water table depth (Zhang et al., 2018) and VWC based on the past soil moisture, precipitation, and climate measurements (Adeyemi et al., 2018).

Fuzzy logic (FL) is an AI algorithm useful for modeling processes and supporting decisions, based in human experience. The FL uses membership sets and rules formulated by an expert (Mousa et al., 2014). This tool is used in the modeling of nonlinear systems and their fundamental axis is the common sense of language. In Patil and Desai, 2013, they used a FL system with moisture, weather and soil moisture data, as model inputs, to implement irrigation programming decisions. The system maintained soil moisture in the specified range of the algorithm. Additionally, in Mousa et al. (2014), they successfully applied a FL model in irrigation scheduling for sprinkler and drip systems, with crop phenology, soil moisture and evapotranspiration data. In Giusti and Marsili-Libelli (2015), the authors describe the development of an adaptive irrigation DSS, implemented with FL. The system used an inference system and a predictive model to keep soil moisture in an acceptable range. The system reacts to rain activity, achieving water savings of 13.55% in simulation.

Several AI strategies can be used together. For example, in Tsang and Jim (2016), they developed an artificial intelligence model for irrigation application based on ANN and FL. Their results showed that the model developed reduced water consumption in the crop by 20%. Wireless Sensor Networks (WSN) and FL have been used for irrigation management (Gao et al., 2013; Hamouda, 2017; Viani et al., 2017). They used input parameters as soil type, temperature, water depletion in the soil and crop growth. FL rules and linguistic values for inputs and outputs were selected with the help of agricultural experts, including farmers. These studies seek to reduce water waste and maximize crop yield according to the weather conditions and real water needs. In Viani et al. (2017), they obtained savings of up to 59.6% in simulation and 29.5% experimentally.

According to Table 6, there are artificial intelligence applications in irrigation scheduling that use algorithms based on data or models. Depending on the study, ANNs have to use a large amount of data or manage the number of categorical attributes to reduce time processing and avoiding overfitting or underfitting. Fuzzy Logic strategies use the experience of farmers, agronomists and scientists for defining the membership functions and intervals useful in the scheduling of irrigation prescriptions. Several researches were developed for simulating artificial intelligence strategies in water management. But at the implementation stage, there are failures related to the lack of parameters or aspects that could improve its performance. Examples of those parameters can be soil characteristics such as infiltration, percolation, soil moisture, hydraulic conductivity, water retention curves, soil water balance equation, FC or PWP; plant characteristics such as rooth depth, crop coefficient or crop water stress; and environmental characteristics such as rain, energy balance equations and evapotranspiration. The use of more information allows the definition of irrigation rates and times with agronomic criteria instead of the simple aperture and closure of valves. Finally, in the implementation of artificial intelligence systems for the irrigation prescription, one of the crucial issues is the sensors calibration and the model calibration according to site specific criteria.

3.4. Actuators and control in irrigation intelligent agents

An automatic irrigation system can refill the water used by the plants in a specific time interval with an open-loop controller (OLC). In this type of control, no field measurements are used to modify the application and the decisions are taken based on heuristics, expert knowledge or a system model (Romero et al., 2012). The OLC presents some limitations that can be overcome by the use of feedback or closed-loop controllers (CLC). The CLCs use mathematical models and additional information such as *ETc* (feed-forward control), changes in the *VWC* or plant-based measurements (feedback control) (Touati et al., 2012). The aim of irrigation controllers is to open and close the solenoid-valves (actuators) in order to apply water to every sector of the crop. Examples of irrigation controllers are explained in the following lines.

Table 6
Some artificial intelligence applications in irrigation scheduling.

Application Domain	Variables	Assumptions	Constraints	References
Irrigation ratios and time intervals. (ANN)	Soil moisture, soil type, product type and time interval	It performs irrigation at night, to reduce water losses from evaporation compared to daytime irrigation	Availability of water resources to apply irrigation at night	(Karasekreter et al., 2013)
ETo (ELM and GRNN)	Temperature	The models were trained/calibrated and tested using the local data of 6 weather stations. Penman Monteith as the benchmark	Eto determination only with temperature data. (Accuracy in the measurements)	(Feng et al., 2017)
ETo (ANN)	Air temperature, relative humidity, wind speed and solar radiation	Penman Monteith as the benchmark	Site specific applicability to all regions and for all weather conditions. Wide variety of weather parameters required for the prediction	(Abdullah and Malek,2016)
Time series- soil Moisture (RNN)	AMSR2 and SMOS, NDVI, LSTPRCand DEM data.	China regions were grouped into 4 main types: water, forest, short vegetation and barren. Only short vegetation was considered in this study.	Low spatial resolution for agriculture. Maps with spatial resolution of 0.25°	(Lu et al., 2015)
Predicting water table depth (LSTM)	Water diversion, precipitation, ETo, temperature, water table depth and time (monthly scale).	LSTM layer with a dropout method with another fully connected layer on top of it. Widely data variations with negative effect on the model's ability to learn -All variables were standardized to ensure the same scale.	It is used in places with complex hydrogeological characteristics and hydrogeological data are difficult to obtain	(Zhang et al., 2018)
Soil Moisture Content for Predictive Irrigation Scheduling (LSTM)	VWC based on past soil moisture, precipitation and climatic measurements.	The hourly data was resampled to daily (24 h) intervals as this is a time period applicable for field scale irrigation scheduling	It is demonstrated only in simulation using AQUACROP, one-day ahead prediction. The predictive system violates the lower bound threshold during the mid-growing season. It needs training for specific crops	(Adeyemi et al., 2018)
Fuzzy logic based intelligent irrigation control system and WSN	Soil moisture, leaf wetness, T and RH, plant root depth, soil type, plant water use.	To ensure proper design and operation of an irrigation system, only the variables studied in this study should be considered.	It is only used in simulation without real implementations.	(Patil and Desai, 2013)
ETo and irrigation amounts (Fuzzy Logic)	Temperature, Humidity, Wind, Radiation, soil moisture	Using the estimation of reference evapotranspiration and soil moisture monitoring calculates the irrigation time and irrigation schedule	It is only used in simulation in Matlab without real implementations. It allows no rain values as input in the system.	(Mousa et al. 2014)
Irrigation web service (Fuzzy DSS)	Crop phenophase, previous irrigations, growing degree days (GDD), ETc.	It improves an existing irrigation web service, based on the IRRINET (automated irrigation system). It combines a predictive model of soil moisture and an inference system.	It is calibrated only for corn, kiwi, and potato crops. It is demonstrated only in simulation.	(Giusti and Marsili-Libelli, 2015)
Irrigation water to green roofs (Neural-Fuzzy)	Soil Temperature and two soil moisture sensors (5 and 15 cm depth), rain sensor.	Green roof irrigation lacks cost-effective and reliable water conservation measures. A solution is the simulation of changes in soil moisture irrigation time and watering volume	Rain sensor used only to suspend irrigation application in the test experiments. No experimental design of replications.	(Tsang and Jim, 2016)
Intelligent irrigation system (WSN + FL)	Soil moisture, growth information, irrigation pipe, spray irrigation and irrigation control valve.	Real implementation in the field. The soil environment is a nonlinear and time delay system, so it is difficult to achieve precise control with traditional methods. Activation of irrigation using a threshold.	No sensors calibration according to soil type. It uses no reliable parameters associated with the crop.	(Gao et al., 2013)
Smart Irrigation DSS (WSN + FL)	Temperature and soil moisture.	The rate of soil moisture reduction is calculated from the current soil moisture reading and the previous one.	Only implemented in simulation No sensors calibration according to soil type. It uses no parameters associated with the crop.	(Hamouda, 2017)
Smart Irrigation DSS (WSN + FL)	Soil potential, drought stress, normalized rain, roostock resistance, irrigation need.	It is developed to estimate when, how much, and how irrigate the crop field according to the monitored data and the weather conditions. It works with a threshold of soil water content. Real implementation.	It mimics the human experience. No sensors calibration. It needs calibration for other crops.	(Viani et al., 2017)

Note: Extreme learning machine (ELM), generalized regression neural network (GRNN), advanced microwave scanning radiometer 2 (AMSR2), soil moisture and ocean salinity (SMOS), temperature (LST) and precipitation (PRC).

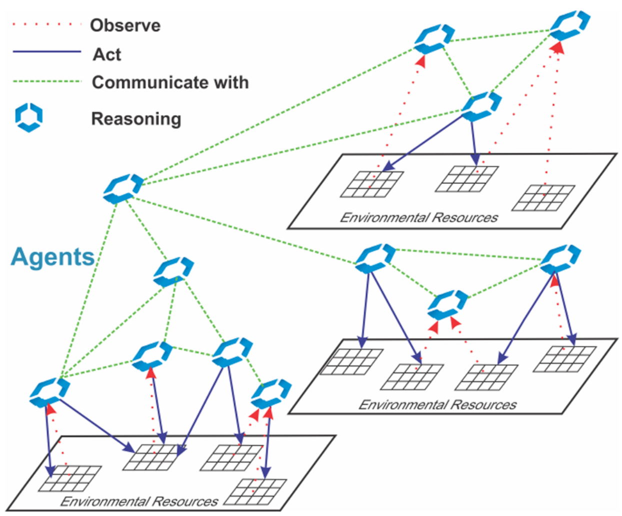

Fig. 4. General structure of a multiagent system for natural resources management.

- *On-Off control.* It consists on switching the controller output between a maximum and a minimum output according to a signal error. Applications of this controller in irrigation are using VWC (Boutraa et al., 2011), canopy temperature (O'Shaughnessy and Evett, 2010), soil matric potential (Romero et al., 2008) and sap flow sensor (Fernández et al., 2008).
- *Proportional-Integral-Derivative control (PID).* The control signal depends on the weighted sum of three terms: the error between the variable and the set-point, the integral of recent errors, and the rate by which the error has been changing. The PID control uses the measurements of a single variable (temperature, relative humidity, soil moisture or meteorological conditions) to compute the control action needed to be executed by an actuator. The output variable can be regulated at a desired set-point value. The application of a PID strategy has not yet been extensively considered in commercial irrigation controllers. An example using VWC is shown in (Romero, 2011).
- *Fuzzy logic control.* Fuzzy logic interprets real uncertainties and becomes ideal for nonlinear, time-varying and heuristic knowledge to control a system. Examples using soil water content, air temperature and light intensity can be found in (Xiang, 2010), or using soil measurements (moisture and temperature) and solar radiation in (Touati et al., 2013), and with multi-agent architecture in (Salazar et al., 2013).
- *MPC (Model predictive control).* There are few agricultural applications (mainly for regulating weather conditions in controlled environments, such as greenhouses) because it is difficult to obtain precise models that are appropriate for control purposes; however, it is a promising methodology for the design of irrigation controllers. An example using VWC is described in Romero (2011).
- *Non linear control.* Nonlinear control theory focuses on systems that do not obey the superposition principle (linearity). These systems are often governed by non-linear differential equations. An example is in control for irrigation canals (Benayache et al., 2008).
- *Artificial neural networks.* ANN are not really a class of controllers, but a modeling framework that can be used in advanced model-based controllers. Examples using soil water content are explained in (Capraro et al., 2008), Back-Propagation Neural Networks (BPNN) in (Hendrawan and Murase, 2011) and using ANN and FL in (Giusti and Marsili-Libelli, 2015).
- *Commercial automatic controllers.* These controllers apply irrigation when sensors detect that the measurements are below a certain predefined threshold until another predefined threshold is overcome (on–off control). Examples using soil water content are Acclima (Acclima, 2019), Watermark (Spectrum Technologies – Watermark, 2019), Rain bird (Rain Bird – ClimateMinder, 2019), Water Sense (Water Sense - Irrigation Controllers, 2019) and Irrinet (Irrinet Series Controllers, 2019).

In general, the actuators used to automatically dose irrigation in crops correspond to electromechanical systems (solenoid valves) that are controlled by electrical on–off signals or proportional continuous current signals. To ensure accuracy in the supply of water for irrigation, feedback control that provides proportional control signals is recommended. The control techniques reviewed can be used without complex problems in the implementation, since the response times of the crops are not critical. Additionally, the current digital systems such as microcontrollers or control cards support the peripherals and speed requirements that enables to implement any control action from on-off control, PID control and also more complex intelligent control algorithms such as diffuse or artifitial neural networks controllers. The simpler the controller, the better it is. In this sense, the PID or PI controller characteristics make it quite complete, such as simplicity, ease of implementation, excellent transient response in stable state, efficiency in performance, and finally the support, as it is the most popular controller used.

4. Multi-agent systems applied to water resource management

Multi-Agent Systems (MAS) are groups of agents that cooperate and solve problems, while exchanging information between them (Byrski et al., 2015). In MAS, the role is the combination of responsibilities, functions and behaviors in each agent. A group of agents has different nature, interfaces and behaviors defined with the roles (Ye-ping and Sheng-ping, 2011). In MAS, agents can act asynchronously and in parallel, resulting in an overall increase in speed-up, efficiency, robustness, reliability, flexibility and re-usability (Leppanen et al., 2013). In addition, as explained by Coelho et al. (2017), the MAS are useful to improve the systems reliability through procedures of fault tolerance, autonomy, responsiveness, scalability and profitability in the detection, communication and control processes. As shown in Fig. 4, in MAS, there is no centralized control of the whole system, but information is distributed. Each agent is independent, with different roles and capabilities and have no ability to solve the main problem alone (Shamshirband and Zafari, 2012). Additionally, MAS allow the coordination, cooperation and conflict resolution through negotiation, competition or consulting strategies (Jiang-Ping et al., 2013).

Researches on MAS, can be classified into Agent Based Modeling (ABM), Distributed Control (DC-MAS) and Intervention (I-MAS). In ABM, given the rules of the local agents, the aim is to find the collective behavior of the system, using analysis, modeling and simulation. In DC-MAS, given the desired collective behavior, the purpose is to design the rules of the agent that allow to find that desired behavior. In I-MAS, given the desired behavior, the aim is to control or intervene in the system without destroying the local system rules (Harmouch et al., 2016).

The ABM can model the explicit connection between the micro and the macro levels of a phenomenon or system (Grashey-Jansen, 2014), infer and make-decisions based on expert knowledge, perform statistical and predictive analysis, and make decisions through cooperation in agent networks (Ye-ping and Sheng-ping, 2011). In this approach, systems are represented as collections of autonomous decision-making entities or agents (Li et al., 2013). Emergence is the unexpected behavior of agents in the execution time, which were not observed in their requirement and design specification. The ABM captures emergent phenomena and provides a natural description of the system. The ability of ABM to deal with emergent phenomena is the main driving force behind its success as a modelling tool of complex adaptive systems. The ABM has introduced a group of technologies in the field of IEDSS, giving support to the management of environmental problems, mainly of those concerning the management of renewable resources (Jiang et al., 2013).

Multi-agent distributed control systems are spatially distributed systems consisting of a number of interacting agents. In DC-MAS, each agent can be considered as a control system and the control law of each agent can be designed using local information (Jiang et al., 2013). These networked MAS allow a high-level of abstraction of the system resources (Leppanen et al., 2013). Some applications of DC-MAS are dynamic tasks distribution between spacecrafts (Skobelev et al., 2016), adaptive planning of communication with nano-satellites (Belokonov et al., 2015), dynamic triage of victims in emergency scenarios (Mercadal et al., 2011) and unmanned aerial vehicles (UAVs) cooperative control (Han et al., 2013). Soft control is a novel method in I-MAS, whose central idea is to add one (or some) special agent(s) (called shill) into the original systems to guide it to the desired behavior, but without changing the local rules of the existing agents. The property of local interactions between agents makes that the influence of the shill spread out, thus adding shill agent(s) may control the behavior of the whole system (Harmouch et al., 2016).

4.1. MAS design methodologies and software

The Foundation for Intelligent Physical Agents (FIPA) is a standard organization of the Institute of Electrical and Electronics Engineers (IEEE) computer society that promotes agent-based technology and the interoperability of its standards with other technologies. According to FIPA, the agent platform is the environment where an agent can live and perform its tasks. Each platform has four default agents: Agent Management System (AMS), Agent Directory Facilitator (DF), Agent Communication Channel (ACC) and an Agent Resource Broker (ARB). The AMS contains the identifier and states of all the agents that exist in the platform. The DF is the agent that provides the default yellow page service in the platform and the ARB is used to interface with non-agent software (Fig. 5). The message transport system (MTS) controls message exchanges between different agents (Harmouch et al., 2016). Coordination, Organization, Institutions and Norms (COIN), is an internationally well-known community in multi-agent systems that focuses on the research about organizational structures in MAS and their coordination patterns (Esmaeili et al., 2017).

Agent-based computing introduces novel abstractions and programming structures, where, classical methodologies are non suited. Thus, from the point of view of software engineering, novel and specific agent-oriented approaches and agent platforms have been developed (Harmouch et al., 2016). Some examples of methodologies used in MAS are: CoMoMas (Glaser, 1996), Cassiopeia (Collinot et al., 1996), MASB (Moulin and Brassard, 1995), AOMEM (Kendall et al., 1995), CommonKADS (Iglesias et al., 1997), MaSE DeLoach (DeLoach, 1999), HIM (Elammari and Lalonde, 1999), AUML (Odell et al., 2000), DESIRE (Jonker et al., 2000), GAIA (Wooldridge et al., 2000), Adept (Jennings et al., 2000), MESSAGE/UML (Evans et al., 2001), Tropos (Castro et al., 2001), Prometeus (Padgham and Winikoff, 2002), PASSI (Harmouch et al., 2016) and ASPECS (Cossentino et al., 2010). Additionally, some examples of agent-oriented software are: AGENT ANALYST (Johnston, 2013), REPAST SIMPHONY (North et al., 2005), GAMA (Taillandier et al., 2010), SWARM (Minar et al., 1996), MASON (Luke et al., 2005), NETLOGO (Sklar, 2007), MESA (Masad and Kazil, 2015), AGENTBASE (Ono et al., 1999), JADE (Bellifemine et al., 2005), JASON (Bordini et al., 2007), ZEUS (Nwana et al., 1999), VOLTTRON (Haack et al., 2013), JANUS (Galland et al., 2010) and SPADE (Ballén et al., 2018).

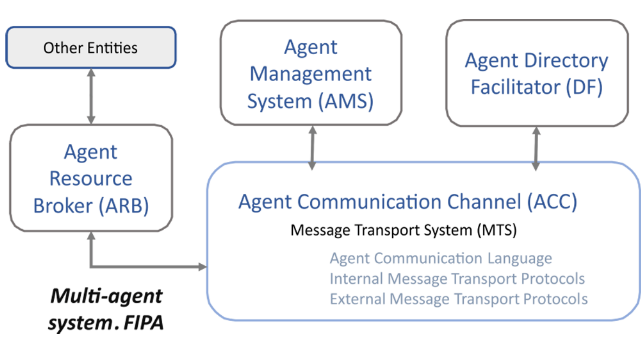

Fig. 5. FIPA agent platform reference model.

Agent Modeling Language (AML) is a semiformal visual modeling language for specifying, modeling and documenting systems that incorporate MAS. The AML language allows modeling roles and defining the behavioral aspect for the individual agents description and interactions between them (Belaqziz et al., 2011). AML incorporates and unifies the most significant concepts from the broadest set of existing multi-agent theories and abstract models such as Belief–Desire–Intentions (BDI) (Georgeff et al., 1998) and Distributed Artificial Intelligence (DAI) (Montes and Goertzel, 2019)). It also includes modeling and specification languages, such as Unified Modeling Language (UML), Agent UML (AUML), Taming Agents and Objects (TAO), Agent-Object-Relationship (AOR), Object Constraint Language (OCL), OntologyWeb Language (OWL) and UML-Based ontology modelling for software agents. Finally, it integrates some methodologies, agent platforms and multi-agent driven applications (Trencansky and Cervenka, 2005).

4.2. Multi-agent systems in irrigation and water management

In the MAS-based collaborative decision systems for crop production management, the external participants of the system include user, expert and administrator. Two major types of agents participate in agricultural systems. The first type are resource agents, including data management agents and knowledge management agents. The second type are the decision-making support agents, including knowledge model agents, agents of growth simulation models, management agents and control agents (Ye-ping and Sheng-ping, 2011). In (Farolfi et al., 2010), the authors describe some of the MAS applications in the field of intelligent DSSs for the management of environmental problems. The ABM has been used in the management of renewable resources, biodiversity, foresty, erosion and soil (Li et al., 2013). In agriculture and forestry, MAS have been applied to integrated pest management (Grovermann et al., 2017), agricultural robots simulation (Arguenon et al., 2006; Zhang and Noguchi, 2017), coordination and control system for harvesters (Ali et al., 2010), simulations to explore collaboration scenarios for plantations (Purnomo and Guizol, 2006), and research agricultural credit impacts on the farmer (Tolk et al., 2014) and sensor networks.

Likewise, MAS applications have been developed in crop irrigation management such as crop modeling irrigation management (Bonté et al., 2005; Matthews, 2006), water management policies in irrigation systems (Farolfi et al., 2010; Perugini et al., 2008; Rege et al., 2015), resource negotiation processes (Thoyer et al., 2001; Janssen and Baggio, 2016), groundwater use modeling (Barthel et al., 2005; Al-Amin et al., 2015), simulation of large-scale irrigation models, watersheds, distribution, primarily by flood irrigation (Grashey-Jansen, 2014; Belaqziz et al., 2011; Belaqziz et al., 2013; Guyennon et al., 2016), model of a garden-level sprinkler system (Isern et al., 2012), irrigation control simulation (Holloway-Phillips et al., 2008; Smith and Peng, 2009), emulation of irrigation water resource monitoring (Zhao et al., 2011) and MAS implementation for irrigation systems (Wanyama and Far, 2017; Salazar et al., 2013; De la Cruz et al., 2015; Villarrubia et al., 2017). Examples of developments in multi-agent systems applied to irrigation management are explained in the following lines.

- *Agent Based Modeling (ABM)*. It consists in a specialized software for deploying agents on a virtual environment. In some studies, agents are developed with roles, capabilities and proactive behaviour, while in others, agents are defined using some simple rules, with reactive behaviour, which can result in different sorts of complex and interesting group behavior when interacting with other agents.

Belaqziz et al. (2011) presents the development of an ABM for decision management in gravity irrigation systems. Humans were represented using reactive agents. Agents used in the simulation were center of manager, stakeholder, operators and farmers. With this ABM, the number of irrigation rotation and quantities assigned for the irrigation was established, considering particularities of each field, including crop, soil and water needs. As sensing variables, they used the SAtelliteMonitoring of IRrigation model (SAMIR), based on the FAO-56 method for obtaining crop evapotranspiration. For the SAMIR model, they used water balance, land use, phenology, pedology, water stress coefficients, reference evapotranspiration, rain and irrigation parameters. The data was collected on-field by weather stations and satellite images, especially NDVI images.

Later, Belaqziz, Khabba et al. (2013) explained the Irrigation Priority Index (IPR) model, calculated for each field studied and based on the water stress coefficient K_s (adjustment parameter of k_{cb}) and irrigation times. Then, Belaqziz, El Fazziki et al. (2013) integrated the IPR model with the ABM. Finally, Belaqziz et al. (2016) present the results of a simulation for water negotiation in irrigation with limited availability of water resources. In this ABM simulation, they employed reactive and cognitive agents for the definition of flood irrigation strategies. The resource negotiation process used the Contract-Net protocol, which employs the auction between manager and contractors in business. At the beginning of the agricultural season, the irrigation managers agents negotiate with the farmers the irrigation season planning.

In Holloway-Phillips et al. (2008) and Smith and Peng (2009), the development of a machine learning strategy for soil texture classification, based on the soil water retention curve is explained. The system was used in a MAS, where agents were systems that sense SMT at three depths, relative humidity and ambient temperature, in a network of seventy nodes. The system also measured data from a weather station, to collectively determine irrigation requirements. With the MAS implemented in Netlogo, each sector in the field was represented by three buckets or soil agents.

- *Distributed Control (DC-MAS) - Simulation*. The control signals in the simulations depend on the interaction of multiple agents. These systems use data of some variables (temperature, relative humidity, soil moisture or meteorological conditions) and decide the irrigation application on the field. For example, Isern et al., (2012) present results about the development of a MAS simulation for a sprinkler irrigation system in a garden using some real entities involved in the irrigation of a field. In this approach, a controller agent monitors the simulation and returns the result to the user. A zone agent represents a field region and its sprinklers, which are also represented as sprinkler agents. An irrigation controller (irrigation agent) acts as facilitator between the sprinklers and the fertilization agents. Finally, the current soil moisture, the initial humidity and the irrigation applied are defined as the plant agent. The system was useful for evaluating different irrigation applications, using plant type, plant humidity, soil moisture, fertilization and water pressure parameters. However, the simulation of this DC-MAS system, as in other studies for irrigation management, has some weakness due to the use of assumptions that need tuning with agronomic concepts.
- *Distributed Control (DC-MAS) - Implementation*. Implementing DC-MAS in irrigation applications has several challenges associated with the non-linearities and complexity of the variables associated with this application. Calibration of sensors and models with site-specific aspects have some difficulties that can be solved using protocols and methodologies identified in the research bibliography. For example, Salazar et al. (2013) describe the development of a MAS prototype consisting of a master agent, a control agent and a field agent for irrigation management. Field data was sent through an embedded system to a computer with serial communication. After receiving the data, it was processed by the intelligent agents installed in the MAS architecture implemented in JADE, based on FIPA standards. To determine the activation of solenoid valves, the MAS used reasoning mechanisms based on FL. In addition, the authors highlight the importance of using site-specific information, such as crop type and soil characteristics to determine irrigation requirements, but they specify neither calibration nor validation protocols.

Additionally, in De la Cruz et al., (2015a) and De la Cruz et al. (2015b), the authors present a drip irrigation system based on distributed control, developed to obtain water application accuracy and water savings. The technique used was based on the replicator dynamics for soil moisture control in multiple zones. They used precipitation, ambient temperature and soil moisture data, in addition to an actuator node and a controller, for four fields located consecutively. They got water savings of 51.70% compared to manual control and 32.20% versus ON-OFF control. In this research, they used calibration protocols for sensors and agronomic criteria for defining the amount and time of irrigation in the field.

- *Internet of Things and Multiagent Systems (IoT-MAS)*. Internet of things is a revolutionary area of research in the last years and it is included in MAS applications. Villarrubia et al. (2017) show the development of a system that combines MAS and WSN to monitor crop irrigation. They used the Platform for Automatic co-Construction of orGanizations of intElligent Agents (PANGEA) and fuzzy logic. The acquisition hardware consisted in the open hardware platform Open Garden (OG), for the collection of useful data for agricultural management. Their work highlights the use of agent models in devices with reduced computing capabilities and monitoring-controlling irrigation applications through a monitor or display. These developments are of critical importance, especially in the implementation of IoT-MAS applications in irrigation management, using the virtualization of farm entities. This application is specified for a single field and there are no calibration and validation procedures. The other constraint in this approach is that they use single entities as agents, such as light-agent, temp-agent, humidity-agent, electrovalves-agent, oxygen-agent, moisture-agent, water-agent and organization-agent. In that research, this system is considered as a MAS with the interaction of multiple agents, but in terms of the definition of an agent, there is only one agent that acquires information from the environment and acts using a solenoid valve as the actuator. For the scalability of this system for hundreds of fields, there would be a problem with the number of agents that will be incorporated in the MAS.

5. MAS in irrigation scheduling. Considerations and opportunities

The principal findings of this research are described in the following paragraphs:

- In precision irrigation, the accuracy in the measurement of soil, crop and environment parameters is very important to improve irrigation prescriptions on the field. A careful design of these sensing systems and their corresponding calibration are crucial for the sustainable management of water resources, which involves the application of water to the crop at the right time, with the right amount, on the right place and in the right manner, to meet specific plant water demands, while avoiding excessive or insufficient irrigation.
- The variability management is the principal justification for applying precision irrigation. For the management of that variability,

it is important to define irrigation management zones and place at least one soil moisture or plant sensor per zone, which could be limited by cost.

- The combination of multiple sensors deployed on the field that capture the spatial variability of the soil, weather and plant irrigation parameters is therefore likely to yield the most robust and accurate solution for precision irrigation (Adeyemi et al., 2017).
- Artificial intelligence, especially the intelligent agent concept, appears as a strategy to improve sustainability in precision irrigation. The conception of agents for irrigation tasks are useful to integrate input variables, decision support systems and actuation devices on the environment, that is, the agricultural field. Decision strategies could be implemented in the agent using reactive behaviors, models, goals, utilities or learning, as reasoning mechanisms.
- The variety of agents implemented in the researches studied in this review evidence the potentiality of the agents and the MAS in irrigation applications, with high abstraction level. According to the roles and characteristics of the agents in these studies, we propose the classification of functional agents, object agents, human agents and institutional agents. Functional agents are those that perform specific functions such as data-mining, database, constraint, predictor, heuristic, policy, monitoring, actuator, interface, treatment, planning, distribution, meteorologist, monitor, control, reasoning, information, communication or diagnostic. Object agents represent real entities such as pump station, water allocation, crop, plant disease, landscape, soil, plant, river, node, branch, robot, sensors, environment, sprinkler, species, field or dripping units. Human agents correspond to human representations like farmers, water managers, producers, water suppliers, consumers, policy makers, citizens, operators, advisors, supervisors, schedulers, coordinators or householders. Finally, some examples of agents that represent institutions are local government, geographical information service, associations of users from an irrigation district, companies, municipalities, water supply companies or villages.
- Agent-based modeling using the perception sequence from the agricultural field could be used for obtaining optimal water applications. The integration of multiples agents with different capabilities allows water resource management in regions such as irrigation districts.
- Researches in irrigation-MAS could be developed for the interoperability among the existent MAS platforms, methodologies and software, to obtain flexibility and fault tolerance (Daneshfar and Bevrani, 2009).
- The integration of irrigation systems, intelligent environmental decision support systems, multi-agents and geomatics technologies, such as remote sensing, global navigation satellite systems and geographical information systems, can improve the performance of irrigation scheduling for multiple users who share the same water source.

The research opportunities in multi-agent systems with applications in irrigation scheduling are described below:

- Scalability strategies, scheduling time for data transmission sessions (Skobelev et al., 2014), water distribution estimation, soft control, informed agent intervention, nonlinear interaction dynamics, constrained communication, optimal consensus control, competition, cooperation and negotiation are potential topics for scientific research (Jiang-Ping et al., 2013). Additionally, security is a key problem in the communication between agents in irrigation systems, because it is open to attacks or message modification, particularly in situations of water negotiation.
- In MAS, the emergence leads to the challenging issue of how to prevent undesired emergent behaviors from undermining the reliability of the system (Jiang-Ping et al., 2013). An emergent behavior at the component level (considering the behavior of agents individually) and the implied scenario at the system level (considering the multi-agent system behavior) may cause critical damage (Fard and Far, 2014).
- Holonic Multi-Agent Systems (HMAS). Holon is a word derived from the Greek holos, meaning whole, and the suffix on, meaning part. This word is associated to a biology and sociology concept introduced to describe the recursive and self-similar structures in biological and sociological entities (Koestler, 1968). Holonic organizations are among the successful organizational models that have been introduced in multi-agent systems recently. Its introduction resulted in the concept of HMAS, which is a multi-level structure composed of holons (Esmaeili et al., 2017). A holonic model brings several significant attributes to multi-agent systems, such as self-similarity, reliability, stability, and dynamism. In other words, there is no central unit for building and controlling the system, and the whole process is controlled by the agents, according to their local information and their neighbors in the MAS.
- Cooperative coevolution (CCEA) is a valuable approach for the evolution of heterogeneous MAS. The key advantage of CCEAs is that, as populations are isolated, it is possible for different populations to evolve, with genomes of different lengths or using evolutionary algorithms. A key element in the evolution of cooperative behaviors is synchronized learning, where agent populations should exhibit the development of mutual skills, in order to avoid the loss of fitness gradients and convergence to mediocre stable states (Gomes et al., 2015).
- Networked MAS (NMAS). The most important NMAS application is the Internet of Things (IoT), which is one of the most growing sectors in the global economy. One of the main contributions to NMAS is the development of distributed estimation techniques for sensor networks, where irrigation technologies have a high applicability. In NMAS, there are multiple controllers rather than a single controller and there also exist interactions among the agents that the individual agent controllers must consider. In NMAS, as the scale of the system increases, the captured real-time data and the required real-time computing will dramatically grow in size (Liu, 2017).

This review establishes the conception of an intelligent agent model for irrigation management. The intelligent agent uses soil, weather and plant sensing methods, historical and predictive information, artificial intelligence capabilities and social abilities, as illustrated in Fig. 6. This intelligent system is currently being developed by the authors.

Finally, with this research, the development of a MAS model for irrigation management was generated according to Fig. 7. The MAS system consists of multiple irrigation intelligent agents with some capabilities showed in Fig. 6. These agents obtain data from their fields and define irrigation prescriptions individually. In this model, there is an image processing agent in charge of estimating the irrigation prescriptions for several crop fields using remote sensing and weather data. The manager-agent is responsible for distributing the water to the fields, using pump station agents and water supply monitoring agents. There are two irrigation prescriptions, the global and field located. If one or several irrigation intelligent agents define a prescription with more amount of water than the defined using the global prescription for the corresponding field, negotiation protocols will begin for distributing the available resource efficiently. This model is being implemented in an irrigation district of Boyacá, Colombia.

6. Conclusions

The application of intelligent agents and multi-agent systems for irrigation scheduling, together with the advances in sensor and actuator technologies, has the capability of managing the non-deterministic nature of the agricultural fields, while considering the operational limitations of irrigation infrastructures.

Agent-based approaches and intelligent environmental decision

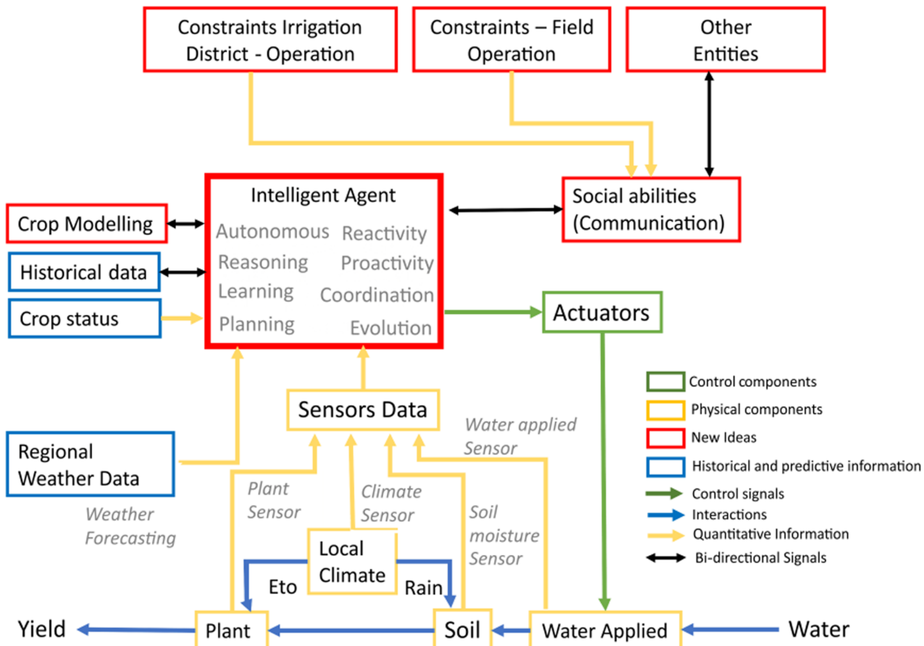

Fig. 6. Conceptual intelligent agent model for irrigation scheduling. New ideas from the authors with respect to the DSS model presented by Adeyemi et al. (2017).

support systems can extract the principal soil–plant-atmosphere relationships for determining the water depletion in the soil, the crop evapotranspiration and the crop stress, using artificial intelligence strategies. For this reason, the robustness and adaptability of the irrigation-MAS can be improved using the proper combination of soil, crop and environmental sensors.

In the irrigation-MAS, each agent has information about its environment (its field), but has incomplete information or capabilities for solving problems of negotiation, coordination and cooperation with other agents located in other fields. Thus, the importance of multi-agent systems is related to the behavior of multiple agents designed to solve a given problem together. In irrigation-MAS, data are decentralized, computation is asynchronous and there exists heterogeneity of agents.

The design and implementation of multi-agent systems with the objective of modeling the simulation and control of irrigation systems still require research to face many challenges. Some of the most important challenges are related to platforms and methodologies standardization; negotiation, coordination, planning, cooperation, co-evolution, security and communication among agents; and architectures, networks, integration with crop models and with other technologies, such as remote sensing, global navigation satellite systems and geographical information systems.

The development of user-friendly and cost-effective systems has the potentiality of enhancing the adoption of intelligent systems for irrigation management by farmers. These systems have to capture, storage, visualize, share, transfer, search and analyze data, with the coordination of multiple computing tasks in real time.

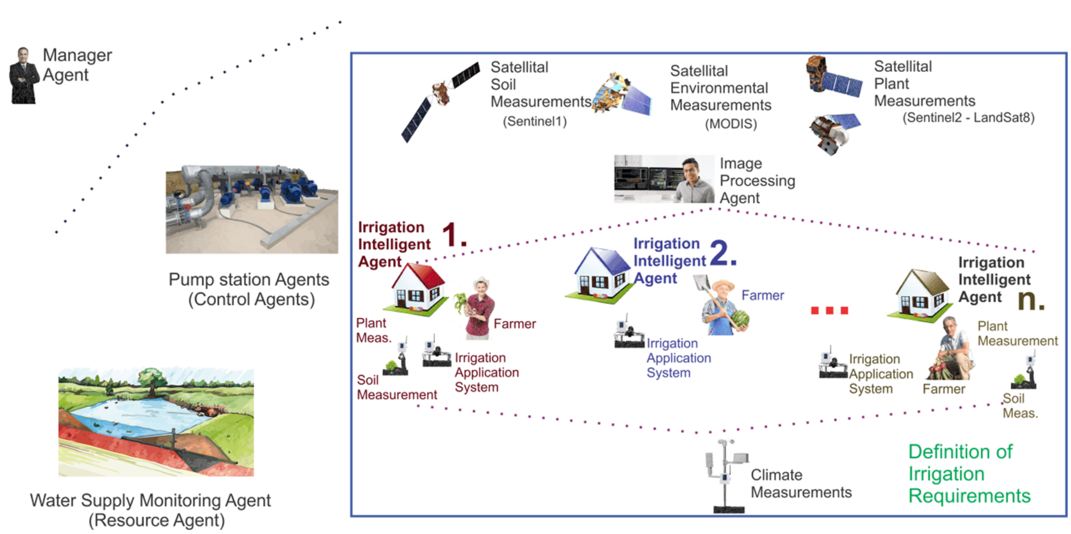

Fig. 7. Conceptual Multi-Agent System model for irrigation scheduling in an irrigation district.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

A.F. Jiménez expresses his gratitude to the Department of Boyacá and Minciencias – Colombia for the support through the scholarship program No. 733 - 2015 for the Ph.D. at the Universidad Nacional de Colombia and also to the Universidad de Los Llanos, Villavicencio, Colombia. Pedro Cardenas expesses his gratitude to MinCiencias - Colombia for the abroad doctorate study scholarship 2007.

Author contributions

Andres-F Jimenez, Pedro-F Cardenas, Fabian Jimenez and Alfonso Portacio conducted conceptualization, methodology and original draft preparation. Andres-F Jimenez, Fabian Jimenez and Antonio Canales conducted writing, review, editing and visualization.

Funding

This research was funded by Minciencias and the Department of Boyacá - Colombia with the PhD scholarship program No. 733 – 2015. Thesis name: Intelligent Agent-Based model to support irrigation management in agricultural crops – Cod: 46620 UNAL.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105474.

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