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A decision support system for managing irrigation in agriculture

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ABSTRACT

In this paper, an automatic Smart Irrigation Decision Support System, SIDSS, is proposed to manage irrigation in agriculture. Our system estimates the weekly irrigations needs of a plantation, on the basis of both soil measurements and climatic variables gathered by several autonomous nodes deployed in field. This enables a closed loop control scheme to adapt the decision support system to local perturbations and estimation errors. Two machine learning techniques, PLSR and ANFIS, are proposed as reasoning engine of our SIDSS. Our approach is validated on three commercial plantations of citrus trees located in the South-East of Spain. Performance is tested against decisions taken by a human expert.

1. Introduction

The efficient use of water in agriculture is one of the most important agricultural challenges that modern technologies are helping to achieve. In arid and semiarid regions, the differences between precipitation and irrigation water requirements are so big that irrigation management is a priority for sustainable and economically profitable crops (IDAE, 2005).

To accomplish this efficient use, expert agronomists rely on information from several sources (soil, plant and atmosphere) to properly manage the irrigation requirements of the crops (Puerto et al., 2013). This information is defined by a set of variables, which can be measured using sensors, that are able to characterise the water status of the plants and the soil in order to obtain their water requirements. While meteorological variables are representative of a large area and can be easily measured by a single sensor for a vast land extension, soil and plant variables have a large spatial variability. Therefore, in order to use these parameters to effectively schedule the irrigation of the plants, multiple sensors are needed (Naor et al., 2001).

Weather is one of the key factors being used to estimate the water requirements of the crops (Allen et al., 1998). Moreover, it is very frequent that public agronomic management organisms have weather stations spread around the different regions. These weather stations usually provide information of key variables for the agriculture like reference evapotranspiration (ET_0) or the Vapour Pressure Deficit (VPD) that are of great importance to calculate the water requirements of the crops. Using variables related to the climate is the most common approach to create crop water requirement models (Jensen et al., 1970; Smith, 2000; Zwart and Bastiaanssen, 2004). Using these models, based on solely meteorological variables, a decision-making system can determine how a given crop will behave (Guariso et al., 1985).

However, not all the regions have access to an extensive network of weather stations or they may not be nearby a given crop, thus the local micro-climates are not taken into account if only these parameters are used. Besides, irrigation models based only on climate parameters rely on an open loop structure. This means that the model is subject to stochastic events and it may not be able to correct the local perturbations that can occur when a unexpected weather phenomenon occurs (for instance irrigate the crop when it's already raining) (Dutta et al., 2014; Giusti and Marsili-Libelli, 2015). Finally, monitoring other variables, such as hydrodynamic soil factors or water drainage, might increase the chances that the irrigation predicted by the models is properly used by the plants (Kramer and Boyer, 1995). Therefore, the usage of sensors that measures the soil water status is a key complement to modulate the water requirements of the crops. Soil variables, such as soil moisture content or soil matric potential, are considered by many authors as crucial part of scheduling tools for managing irrigation (Cardenas-Lailhacar and Dukes, 2010; Soulis et al., 2015).

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The information from soil sensors can be used to create better decision models with closed loop structures that adapt to weather and soil perturbations (Cardenas-Lailhacar and Dukes, 2010; Soulis et al., 2015). This practice, however, has not been widely adopted due to the technological limitations of available soil sensors, which required measured information to be registered and stored, traditionally using wired dataloggers, and limiting the installation flexibility and the real time interaction. This has changed recently with new generation sensors and sensor networks that are more versatile and suited to the agricultural environment (Navarro-Hellín et al., 2015).

Combining climate and soil variables has therefore potential to properly manage irrigation in a more efficient way than other traditional approaches. However, it also entails a series of challenges related with the increased amount of data flow, its analysis and its use to create effective models, in particular when data provided by different sources may seem contradictory and/or redundant. Traditionally, this analysis and modelling is performed by a human expert who interprets the different variables. The need of a human agronomist expert is required due to the complexity introduced by the soil spatial variability, crop species variability and their irrigation requirements over the growth cycle (Maton et al., 2005), which require comparing crops models and local context variables to determine the specific water requirements to achieve a certain goal at a particular location.

The complexity of this problem and the different sources of variability makes than even the best model may deviate from the prediction, which favours the use of close loop control systems combining soil and climate sensors over open loop systems as a way to compensate possible deviations in future predictions.

Human expertise has been proved effective to assist irrigation management but it is not scalable and available to every field, farm and crop and it is slow in the analysis of the data and real time processing. Instead, applying machine learning techniques to replace the manual models and to assist expert agronomists allows the viability of creating automatic Irrigation Decision Support System. Machine learning techniques have been used previously to estimate relevant parameters of the crop (Sreekanth et al., 2015). Giusti and Marsili-Libelli(2015) present a fuzzy decision systems to predict the volumetric water content of the soil based on local climate data. Adeloye et al. (2012), proposed the use of unsupervised artificial neural networks (ANN) to estimate the evapotranspiration also based on weather information solely. King and Shellie (2016) used NN modelling to estimate the lower threshold temperature (Tnws) needed to calculate the crop water stress index for wine grapes. In Campos et al. (2016) the authors presented a new algorithm designed to estimate the total available water in the soil root zone of a vineyard crop, using only SWC sensors, which are very dependent of the location. Taking advantage of the soil information, Valdés-Vela et al. (2015) and Abrisqueta et al. (2015) incorporates the volumetric soil water content, manually collected with a neutron probe, to agro-meteorological data. This information is then fed into a fuzzy logic system to estimate the stem water potential. Other approaches in the literature also make use of machine learning techniques – such as principal component analysis, unsupervised clustering, and ANN – to estimate the irrigation requirements in crops. However they do not specify the quantity of water needed (Dutta et al., 2014), they reduce the prediction to true or false, and/or they are based on open loop structures (Giusti and Marsili-Libelli, 2015; Jensen et al., 1970; Smith, 2000; Zwart and Bastiaanssen, 2004), only considering the weather information and, therefore, unable to correct deviations from their predictions.

This paper proposes an automated decision support system to manage the irrigation on a certain crop field, based on both climatic and soil variables provided by weather stations and soil sensors. As discussed, we postulate that the usage of machine learning techniques with the weather and soil variables is of great importance and can help to achieve a fully automated close loop system able to precisely predict the irrigation needs of a crop. Our presented system is evaluated by comparing it against the irrigations reports provided by an agronomist specialist during a complete season in different fields.

2. System structure

An irrigation advice system is based on the concept of predicting the waters needs of the crops in order to irrigate them properly. Traditionally this decision has been taken by an experienced farmer or an expert agricultural technician. Fig. 1 shows the flow diagram of which the proposed system is based.

In this schema, an expert agronomist is in charge of analysing the information from different sources: Weather stations located near the crops that collect meteorological data, Crop and Soil characteristics (type, age, size, cycle, etc.) and Soil sensors installed in the crop fields. The expert analyses the information to provide an irrigation report, which indicates the amount of water needed to irrigate properly the crops in the upcoming week. To make this decision making process manageable, the information needed to create the irrigation report on the next week is only the information of the current week.

Based on this concept, our Smart Irrigation Decision Support System (SIDSS) is proposed. In order to evaluate the performance and validity of our approach, the decision system will use the same information used by the expert agronomist and will output the water requirements for the upcoming week. This will ensure a fair comparison between the decisions taken by a human expert and the SIDSS. To accomplish this, the machine learning system must be trained with historical data and irrigations reports of the agronomist, using the irrigation decisions taken in these reports as the groundtruth of the system. The aim of the system is to be as accurate as possible to this groundtruth. Several machine learning techniques were applied and evaluated to achieve the best performance. Fig. 2 shows a diagram of the SIDSS.

The Irrigation Decision System is composed of three main components: a collection device that gathers information from the soil sensors, weather stations that provide agrometeorological information and the SIDSS that, when trained correctly, is able to predict the irrigation requirements of the crops for the incoming week. Table 1 shows the set of possible input variables of the system.

2.1. Collection device and soil sensors

The information from the soil sensors is gathered using our own developed device that has been proved to be completely functional for irrigation management in different crops and conditions (Navarro-Hellín et al., 2015). This device is wireless, equipped with a GSM/GPRS modem, and is completely autonomous, so that the installation procedures are accessible to any farmer.

Fig. 3 shows the collection device installed in a lemon crop field located in the South-East of Spain.

The device allows to fully configure the recording rates of all the embedded sensors. In our experiments, a sampling rate of 15 min was set, since this gives a good balance between providing enough information to support a correct agronomic decision and maintaining the autonomy of the device with the equipped solar panel and battery (López Riquelme et al., 2009; Navarro-Hellín et al., 2015). The information is received, processed and stored in a relational database.