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A novel Observer-based Architecture for Water Management in Large-Scale (Hazelnut) Orchards

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Abstract: Water management is an important aspect in modern agriculture. Irrigation systems are becoming more and more complex, trying to minimize the water consumption while ensuring the necessities of the plants. A fundamental requirement to define efficient irrigation policies is to be able to estimate the water status of the plants and of the soil. In this context, precision agriculture addresses this problem by using the latest technological advancements. In particular, most of the works in the literature aim to develop highly accurate estimations under the assumption of the availability of a dense network of sensors. Although this assumption may be adequate for intensive farming (e.g. greenhouses), it becomes quite unrealistic in the context of large-scale scenarios. In this work, we propose a novel observer-based architecture for the water management of large-scale (hazelnut) orchards which relies on a network of sparsely deployed soil moisture sensors along with a weather station and on remote sensing measurements carried out by drones with a pre-defined periodicity. The contribution is twofold: i) First a novel model of the water dynamics in an hazelnut orchard is proposed, which includes the water dynamics in the soil and in the plants, and ii) then, on the basis of this model and of the available measurements, the use of a Kalman filter with intermittent observations is proposed, taking also into account the availability of the weather station measurements. The effectiveness of the proposed solution is validated through simulation.

Keywords: Kalman Filter, Observers, Estimatos, Agriculture, System models.

1. INTRODUCTION

Precision agriculture is a farming management paradigm which is based on the idea of observing, measuring and responding to inter and intra-field variability in crops. As a matter of fact, irrigation systems represent one of the critical aspects of orchards management. Over the last decades, the importance of efficient irrigation policies to minimize water consumption has pushed agronomists to improve and refine these systems. To do so, a fundamental requirement is to be able to get a good estimation of the current water status of the plants and the soil (Özmen, 2016; Gerhards et al., 2016; Buitrago et al., 2016). In this context, precision agriculture has grown as an important farming management concept of how to control the activities of an orchard (Wachowiak et al., 2017; Srbinovska et al., 2015).

A large-scale plantation typically consists of thousands of plants spread over several hectares. In such a setting, a recurrent problem for irrigation systems is the choice of the sensors to be installed and of the variables to be estimated in order to monitor and control the current orchard status. Several approaches have been proposed in the literature focusing on soil, plants, or climate conditions as status indicators (Xiang, 2011; Osroosh et al., 2015; Veysi et al., 2017).

A very common approach to control irrigation systems is to focus on the levels of soil humidity. Briefly, the main idea is to estimate the soil water needs through the use of soil moisture probes. This information is typically used within dynamic models (e.g. the one proposed in Allen et al. (1998)) to predict the soil moisture dynamics. Following this approach, several control strategies have been presented in the literature including: ON/OFF controllers based on humidity thresholds (Cáceres et al., 2007; Boutraa et al., 2011) and PID controllers able to ensure a certain soil moisture reference value (Goodchild et al., 2015). Model Predictive Control (MPC) techniques have also been explored, as in Saleem et al. (2013); Lozoya et al. (2014), which make use of a soil storage model. It is important to remark that soil-based approaches should take into account the possible soil spatial variability of the plantation (Gemtos et al., 2013). However, this aspect is disregarded in most of the existing control approaches. Recent agronomic literature has pointed out that the use of soil humidity-based techniques induces some limitations in terms of accuracy of the treatment. In fact, as shown in Jones (2004), the water plant response to the same conditions of soil humidity can be quite different for different evaporation demands and plant water status.

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In order to improve the estimation of the water needs of plantations, several approaches to monitor the water plant status have been developed in the context of intensive farming (e.g greenhouses). The use of direct plant measurements provides, with a high level of accuracy, the water needs of the plant at every moment. Following this idea, in Steppe et al. (2008) a flow and storage model of the plant is developed, where the stem diameter variation is used to control the water status of the plant and to manage the irrigation system. In Verbeeck et al. (2007) a similar model is applied using sap flow measurements. However, even if these techniques provide very good results in terms of water needs estimation, they result unsuitable for large-scale orchards where a single sensor per plant cannot be economically deployed and maintained. Therefore, these approaches cannot be considered in our case study due to the impossibility of applying them to large-scale scenarios.

Recently, remote sensing (i.e. based on the use of sensors mounted on UAVs that fly over the farm) has been proposed to compute water stress indicators in large plantations. Using remote sensing as the main source of information, Osroosh et al. (2015) introduces an automatic irrigation scheduling based on CWSI (crop water stress index) provided by the use of thermal cameras. In Quebrajo et al. (2018), remote sensing is used to cover areas with high spatial variability in terms of soil characteristics. In Toureiro et al. (2017), remote sensing is used to measure the soil moisture. Note that, while the remote sensing can provide information on all the plants of a plantation, this information is available only during the operation of the UAV. In most realistic settings, it is not possible to ensure that a same portion of the plantation is visited more often than a few times per week.

In this paper we propose a novel scheme to estimate the water content of the plants and of the soil for a large-scale plantation making use of soil moisture sensors (sparsely distributed within the orchard), remote sensing data (which is provided with a low sampling frequency), and meteorological information. This work is motivated by a real-world case study (Azienda Agricola Vignola, Province of Viterbo) considered in the EU project PANTHEON "Precision farming of hazelnut orchards" (Grant Agreement number 774571). We believe this case study to be representative for the majority of professionally farmed large-scale orchards.

To summarize, the contribution of this paper is twofold. The first contribution of this paper is to propose a novel storage-model able to describe the soil, the plant dynamics, and their interactions. To the best of our knowledge, this is the first storage-model (i.e. based on mass conservation) able to describe the interactions between plant and soil. The second contribution is the design of an observer to estimate the variables of this model which takes into account the intermittent arrival of measurements from the remote sensing. Our solution is based on the idea of Kalman filtering with intermittent observations, as developed in Sinopoli et al. (2004); Garone et al. (2012), which allows to take advantage of the partial measurement of the environmental disturbances (rain and evapotranspiration).

The rest of the paper is organized as follows. In Section 2, a description of the model is presented. In Section 3, the sensing architecture for the monitoring of the orchard is described and the related mathematical model derived. In Section 4, we present the proposed observer and in Section 5, some numerical simulations are performed. Finally, in Section 6 conclusions are drawn and some directions for future works are given.

2. MODEL DESCRIPTION

In this section we propose a dynamic model which describes the water dynamics in an orchard. An orchard can be seen as a dynamical system consisting of a collection of trees and of soil plots (or parcels) that interact with each other exchanging water. The proposed model describes: i) the soil water absorption/storage; ii) the plant water dynamics; iii) the effects of the external disturbances (solar radiation, air temperature and humidity, and rain) and of the controlled inputs (irrigation).

It should be noticed that although there exist several models for the water dynamics in the soil (Allen et al., 1998; Abramopoulos et al., 1988; Han and Zhou, 2013) and a few models describing the water dynamics in a fruit tree (Gemtos et al., 2013; Verbeeck et al., 2007) and in its leaves (Özmen, 2016), to the best of the author's knowledge, this work provides the first mass balance model linking explicitly these two phenomena presented in the literature. The coherence of the proposed model has been assessed qualitatively by comparing its predictions with empirical evidence found within the agronomic literature (Özmen, 2016; Bregaglio et al., 2016; Bittelli, 2011). Future works within the context of the PANTHEON project will be focused on the experimental validation of the proposed model.

2.1 Geometric characterization of the orchard

In line of principle, the water dynamics in the soil should be modelled as a Partial Differential Equations (PDEs) model, so as to capture the various water transportation phenomena. In order to define a tractable model where soil spatial variability is still contemplated, in this paper we consider a Finite Element Method (FEM)-like approximation of the orchard soil.

In particular, based on the soil storage model introduced in Allen et al. (1998), the orchard is divided into rectangular plots where a water balance is applied. In this paper, these soil plots are referred as parcels. For every parcel, we consider the evolution of the soil moisture as a variable representing the quantity of stored water. What we obtain is thus a representation of the field as a collection of nodes, where each parcel is identified by its centroid (uniquely described by its geographical coordinates). Figure 1 provides a graphical depiction of this representation.

Note that, according to the description given above, neighbouring parcels interact with each other. In particular, it is reasonable to assume that each parcel interacts directly only with its neighbours, i.e., parcels which are adjacent to it, (in Figure 1 a dark blue parcel is depicted together with its neighbouring parcels coloured in light blue).

2.2 Model of the ground

The dynamics of each soil parcel can be derived by resorting to a hydrological balance model. A common approach, originally introduced in Allen et al. (1998), is to consider the soil water storage variation as the result of the soil water inflows (irrigation, rainfall, capillary rise and horizontal ground inflow) minus the soil water outflows (evapotranspiration, deep percolation, and horizontal water outflow). Notably, this model has been effectively used in several irrigation control strategies as

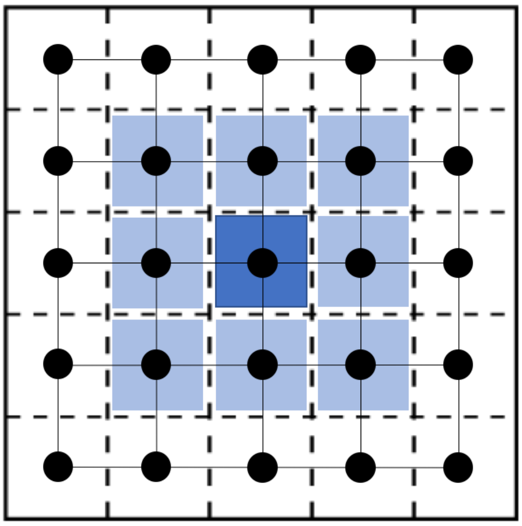

Fig. 1. Division of the field into squares.

(Saleem et al., 2013; Toureiro et al., 2017; Steppe et al., 2008; Tous et al., 1994).

Some of the phenomena considered in the modelization strongly depend on the morphology (e.g. inclination of the soil), the climatic zone, and on the irrigation system of the orchard. According to the irrigation characteristics of the pilot orchard considered in this study, i.e. a hazelnut orchard in the Viterbo area, Italy, located on hills with moderate slope and equipped with underground drip irrigation, the water surface runoff can be neglected. This assumption is realistic for most hazelnut orchards equipped with dripping irrigation systems (Saleem et al., 2013; Lozoya et al., 2014).

Accordingly, to describe the variation of the soil water storage for the i-th parcel we can propose the following model

$$\dot{\theta}_i = -Et_i + I_i + R_i - P_i \pm UG_i, \tag{1}$$

where the variation of soil moisture $\dot{\theta}_i$ depends on the evapotranspiration Et_i (combination of evaporation and transpiration), the irrigation I_i, the rainfall R_i, the deep percolation P_i, and the underground water flow UG_i. Considering the nature of these various phenomena, equation (1) can be rewritten only in terms of soil moisture content θ_i, irrigation input I_i, and meteorological disturbances (reference evapotranspiration Et_o and total rainfall R_{tot}) as

$$\begin{aligned}\dot{\theta}_i(t) = &-c_{1,i}\,\theta_i(t) + \sum_{k\in N_i} c_{2,k,i}(\theta_k(t) - \theta_i(t)) - c_{3,i}\,Et_o(t)\\ &+ I_i(t) + c_{4,i}\,R_{tot}(t) \qquad i = 1,\ldots,N,\end{aligned} \tag{2}$$

where $c_{1,i},\ldots,c_{4,i}$ are constant parameters that can be estimated on the basis of the composition of the soil and of the morphology of each parcel i of the orchard (Sarmadian and Taghizadeh-Mehrjardi, 2014; Bethune et al., 2008). Thus leading to a natural modeling of the soil spatial variability, which is extremely important in the case of large-scale orchards where the assumption of soil homogeneity becomes generally inadequate due to the extension of the land.

For the sake of simplicity, in equation (2) deep percolation is modelled as a linear function of the soil moisture content ($P_i = c_{1,i}\theta_i$), and the underground water flow between parcels UG_i depends on the difference of soil moisture, being N_i the set of neighbours of the parcel i. This assumption is coherent with existing literature Lozoya et al. (2014) and our preliminary observations.

2.3 Model of the plant

For what regards the plants, using the mass model defined in Steppe et al. (2008); Verbeeck et al. (2007), the dynamic of the j-th plant can be described as

$$\dot{W}_j = \sum_{i\in F_j} c_{5,j,i}\theta_i(t) - c_{6,j}W_j(t) + c_{7,j}Et_o(t) \qquad j = 1,\ldots,n, \tag{3}$$

where the state variable W_j represents the water stored in the j-th plant, F_j is the set of soil parcels touched by the roots of the j-th plant, and $c_{5,j,i},\ldots,c_{7,j}$ are constant parameters. It can be noticed that the variation of water stored in the plant $\dot{W}_j$ depends on the soil moisture content θ_{F_j}, on the water stored in the plant W_j, and on the reference evapotranspiration Et_o.

As it will become clear in Section 3, it is also of interest to model the quantity of water present in the leaves. This will be done by introducing a further state variable. Based on preliminary field observations, it seems reasonable to consider the dynamics between the overall water content of the leaves and the water status of the plant as a delay. As such, we can assume that the overall water content on the leaves of the j-th plant at time t is given by $W_{rem,j}$ as

$$W_{rem,j}(t) = W_j(t - t_{delay}). \tag{4}$$

From a preliminary analysis of data collected from our case study which will be detailed later in Section 5, we consider a fixed delay t_{delay} for all plants. This delay is approximated using a Padé approximation, which in state space results in the following model

$$\dot{W}_{rem,j}(t) = -\frac{2}{t_{delay}}W_{rem,j}(t) + \frac{2}{t_{delay}}W_j(t) - \dot{W}_j(t). \tag{5}$$

2.4 Overall model

The overall model of the orchard is obtained by combining the soil water storage model, the plant water storage model and the water dynamics of the overall content of the leaves. Where, globally, the whole orchard can be seen as a set of N plots and n plants, described by the following dynamical system:

$$\begin{aligned}\dot{\theta}_i(t) &= -c_{1,i}\theta_i(t) + \sum_{k\in N_i} c_{2,i}\left(\theta_k(t) - \theta_i(t)\right) - c_{3,i}Et_o(t)\\ &\qquad + c_4R(t) + I_i(t), \quad i = 1,\ldots,N\\ \dot{W}_j(t) &= \sum_{i\in F_j} c_{5,j,i}\theta_{F_j}(t) - c_{6,j}W_j(t) + c_{7,j}Et_o(t), \quad j = 1,\ldots,n\\ \dot{W}_{rem,j}(t) &= -\frac{2}{t_{delay}}W_{rem,j}(t) + \left(\frac{2}{t_{delay}} + c_{6,j}\right)W_i(t)\\ &\qquad - c_{6,j}\theta_{F_j}(t) - c_{7,j}Et_o(t), \quad j = 1,\ldots,n\end{aligned} \tag{6}$$

For the sake of readability, we will compactly denote the dynamical system as

$$\dot{x}(t) = A_c\,x(t) + B_c\,u(t) + B_{d,c}\,d(t) \tag{7}$$

where

$$A_c = \begin{bmatrix} A_{11} & 0 & 0\\ A_{21} & A_{22} & 0\\ -A_{21} & \dfrac{2}{T_{delay}}I_{n\times n} - A_{22} & -\dfrac{2}{T_{delay}}I_{n\times n}\end{bmatrix}, \tag{8}$$

$$B_c = \begin{bmatrix} B_1 \\ 0_{n\times m} \\ 0_{n\times m} \end{bmatrix}, B_{d,c} = \begin{bmatrix} B_{d1} & \varphi \\ B_{d2} & 0_n \\ -B_{d2} & 0_n \end{bmatrix}; \tag{9}$$

$x = [x_1^T \quad x_2^T \quad x_3^T]^T \in \mathbb{R}^{N+2n}$ where $x_1 = [\theta_1, \ldots, \theta_N]^T$, $x_2 = [W_1, \ldots, W_n]^T$, $x_3 = [W_{rem,1}, \ldots, W_{rem,n}]^T$. And where u represents the irrigation inputs and d the meteorological disturbances. Since the sensing is carried out through digital devices, in the remainder of the paper we will sample the system (7) with the zero-order hold method, obtaining the following equivalent discrete time system

$$x_{k+1} = Ax_k + Bu_k + B_d d_k, \tag{10}$$

where $x_k = [x_{1,k}^T \quad x_{2,k}^T \quad x_{3,k}^T]^T$, with $x_{1,k}^T = x_1(kT_s), x_{2,k}^T = x_2(kT_s)$, $x_{3,k}^T = x_3(kT_s)$, $u_k = u(kT_s)$, and $d_k = d(kT_s)$ where T_s is the sampling time of the sensors.

3. SENSORS AND REMOTE SENSING

In this work, inspired by the real-world case study of the PANTHEON project, i.e., a portion of an orchard of the Azienda Agricola Vignola, in the Province of Viterbo, Italy, we consider a similar set of available measurements available in the field, as detailed in the following:

i) Soil moisture measurements obtained from an agrometeorological monitoring network deployed in the field;
ii) Remote sensing, e.g., obtained with UAVs flying over the field, for estimating the water content of the leaves;
iii) Weather measurements obtained from a weather station deployed in the field.

3.1 Soil moisture probes

Soil moisture measurements are obtained through an IoT agrometeorological monitoring network which has been developed within the PANTHEON project. More specifically, this IoT monitoring network is composed of nodes which are equipped with sensors capable of measuring the water content of the soil and the temperature of the soil. These sensors are typically placed underground at a depth which depends on the plants' root structure to better capture the "useful" moisture of a parcel. In the case of hazelnuts, for each node of the network two sensors are deployed at a depth of approximately 15 *cm* and 40 *cm*, respectively. Accordingly, we can assume that a soil moisture sensor placed on the i-th parcel is able to measure θ_i. The measurements are available at each sampling time T_s.

As a matter of fact, it should be noticed that in a large-scale orchard it is unrealistic to place sensors in all the parcels. On the contrary, soil moisture sensors are more realistically sparsely distributed. By following this observation, we will assume that the orchard has $p < N$ soil moisture sensors, and without loss of generality (it is always possible to do a relabelling of the variables) we assume that the sensors are placed on the first p parcels. Accordingly, the vector $y_k^{moist} \in \mathbb{R}^p$ of the moisture measurements at time k is

$$y_k^{moist} = \Phi x_{1,k}, \tag{11}$$

where $\Phi \in \mathbb{R}^{p\times N}$ is

$$\Phi = \begin{bmatrix} I_{p\times p} & 0_{p\times(N-p)} \end{bmatrix}. \tag{12}$$

3.2 Remote sensing

Remote sensing is typically performed through UAVs equipped with various sensors (commonly thermal and multi-spectral cameras) which allow to estimate the overall water content of the leaves of a plant (Gerhards et al., 2016; Santesteban et al., 2017; Egea et al., 2017).

In a realistic setting, these measurements are available only at some specific time, i.e. when a UAV is sensing a specific area of the orchard, which typically happens not more than a few times per week (in a normal orchard, typically once per week during the vegetative season). We denote the availability of measurements on the leaves of the i-th plant with the binary variable $\gamma_{i,k}$, i.e. $\gamma_{i,k} = 1$ if the remote sensing measurements on the i-th plant is available at time k, and $\gamma_{i,k} = 0$ otherwise. Where $m_k \leq n$ represents the number of plants with remote sensing data available at time k. Accordingly, the vector $y_k^{remote} \in \mathbb{R}^{m_k}$ representing the remote sensing measurements available from the orchard at time k is

$$y_k^{rem} = \Lambda_k x_{3,k} \tag{13}$$

where $\Lambda_k \in \mathbb{R}^{m_k\times n}$, is the selection matrix selecting the remote measurements obtained at each time k, i.e.

$$\Lambda_k = [e_i^T]_{i|\gamma_{i,k}=1}, \tag{14}$$

where e_i is the i-th vector of the canonical basis.

3.3 Meteorological measurements

Meteorological measurements are obtained through a weather station which is part of the IoT-based agro-meteorological monitoring network that has been developed within the PANTHEON project. As a matter of fact, meteorological conditions have a big impact on the plants and soil behaviour (Xiloyannis et al., 2012; Baldwin et al., 2001). Indeed, these disturbances are part of the irrigation model (10) and denoted as

$$d_k = \begin{bmatrix} Et_{o,k} \\ R_k \end{bmatrix} \tag{15}$$

where $Et_{o,k}$ is the evapotranspiration at time k and R_k is the rainfall.

Notably, rainfall and evapotranspiration are two climatic aspects that can be measured through the deployed weather station. These measurements are available at each sampling time T_s. It is important to remark that these measurements (especially the evapotranspiration ones) are subject to a non-negligible uncertainty.

4. OBSERVER ESTIMATION

Accordingly to the previous sections, the available measurements for the whole orchard, $y_k \in \mathbb{R}^{p+m_k}$, at time instant k can be defined as

$$y_k = \Gamma_k C x_k \tag{16}$$

where $\Gamma_k \in \mathbb{R}^{(p+m_k)\times(p+n)}$ is

$$\Gamma_k = \begin{bmatrix} I_{p\times p} & 0_{p\times n} \\ 0_{m_k\times p} & \Lambda_k \end{bmatrix}, \tag{17}$$

and $C \in \mathbb{R}^{(p+n)\times(N+2n)}$ is

$$C = \begin{bmatrix} \Phi & 0_{p\times 2n} \\ 0_{n\times(N+n)} & I_{n\times n} \end{bmatrix}. \tag{18}$$

The orchard system can thus be described as

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + B_d d_k \\ y_k = \Gamma_k C x_k. \end{cases} \tag{19}$$

In order to estimate the state of the orchard using the available measurements, we make use of a suitably adapted version of the Kalman filter with intermittent measurements, developed in Sinopoli et al. (2004); Garone et al. (2012), able to take into account the availability of the soil and weather measurements. Specifically, the introduced matrix Φ considers the use of additional sparse fixed sensors where the interaction between parcels is used to improve the estimation between neighbouring elements.

Furthermore, as already remarked, the values measured by the meteorological station are subject to non-negligible measurement noise. In first approximation, the measurement noise can be considered stochastic white noise (realistic under the assumption that the meteorological station is calibrated sufficiently often). As such we can rewrite the disturbance d_k as the measurable signal $\hat{d}_k$ plus a stochastic term $w_{1,k}$

$$d_k = \hat{d}_k + w_{1,k}$$

with $w_1 \backsim N(0,Q_1)$ a Gaussian distribution with mean 0 where $Q_1 \in \mathbb{R}^{2\times 2}$ is a covariance matrix. We also assume that each variable of the model is subject to a process disturbance $w_2 \backsim N(0,Q_2)$. The matrix Q_2 is typically non-diagonal and has nonzero terms for the variables describing adjacent parcels and trees. Taking into account these considerations, and making use of the measured vector $\hat{d}_k$ we can rewrite the system as

$$\begin{cases} x_{k+1} &= Ax_k + Bu_k + B_d\hat{d}_k + w_k \\ y_k &= \Gamma_k\left(Cx_k + \nu_k\right) \end{cases} \tag{20}$$

where $\nu_k \in \mathbb{R}^{p+n}$ represents stochastic sensor noise which is assumed $\nu \backsim N(0,R)$ with R the noise covariance matrix and $w_k = B_d w_{1,k} + w_{2,k}$. Note that since

$$E[\bar{w}] = E[B_d w_1 + w_2] = E[B_w w_1] + E[w_2] = 0 \tag{21}$$

and

$$Cov(\bar{w}) = Cov(B_d w_1 + w_2) = B_d Q_1 B_d^T + Q_2 = \bar{Q}. \tag{22}$$

then $w \backsim N(0,\bar{Q})$.

The main novelty in this approach lies in the resulting non-diagonal matrix $\bar{Q}$, which considers the relation between adjacent elements (Q_2) and between all elements affected by the meteorological conditions ($B_d Q_1 B_d^T$). That allows the observer, as these relations are part of the estimator, to spread the information between the states when just a few of them are measured and thus improve the estimation.

At this point the state of the orchard can be estimated using an intermittent Kalman filter (see Sinopoli et al. (2004); Garone et al. (2012)) where the prediction step is:

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k + B_d\hat{d}_k \tag{23}$$

$$P_{k+1|k} = AP_{k|k}A^T + \bar{Q}, \tag{24}$$

and the correction step is

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(y_{k+1} - \Gamma_{k+1}C\hat{x}_{k+1|k}) \tag{25}$$

$$K_{k+1} = P_{k+1|k}C^T\Gamma_{k+1}^T(\Gamma_{k+1}(CP_{k+1|k}C^T + R)\Gamma_{k+1}^T)^{-1} \tag{26}$$

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1}\Gamma_{k+1}CP_{k+1|k}. \tag{27}$$

where $\hat{x}_{k|k}$ is the estimated value of the state at time k given the information available at time k and $P_{k|k}$ is the error covariance matrix of the estimation at time k.

Note that, for the dynamical system under analysis which describes a large-scale hazelnut orchard, the eigenvalues of the A matrix are strictly in the unitary disc. Accordingly, it is not necessary to define a minimal measurement arrival ratio (see Sinopoli et al. (2004); Garone et al. (2012)) to ensure the convergence of the estimator.

5. SIMULATION RESULTS

In this section, we provide simulation results to numerically demonstrate the effectiveness of the proposed architecture. In particular, first we describe the real case study from which simulations are based on, then we numerically demonstrate the effectiveness of the proposed observer-based architecture by emphasizing the benefits coming from introducing in the estimation the measurements coming from the weather station.

5.1 Case Study

The numerical setting used for the numerical validation mimics the experimental setting proposed in the PANTHEON project which comprises a portion of an orchard within the “Azienda Agricola Vignola”, a farm located in the municipality of Caprarola, in the province of Viterbo. Figure 2 shows the IoT agrometeorological monitoring network installed on the field which comprises 9 soil moisture nodes, denoted with a circle, and a weather station, denoted with a triangle, installed on the field.

Fig. 2. PANTHEON experimental setting: IoT agrometeorological monitoring network layout.

Figure 3 depicts the portion of the orchard which has been chosen for the numerical simulations along with the related discrete representation based on parcels. We point out that although the proposed architecture targets large-scale orchards, for the numerical simulation only a small portion of the orchard has been considered for the sake of simplicity and with no lack of generality. Indeed, results can be easily scaled up to larger areas by proportionally scaling up also the distribution of the IoT agrometeorological network. In particular, the selected area shown in Figure 3 covers a part of the section of adult hazelnut plants which includes 4 soil sensors. This permits to evaluate the difference of estimation between parcels with and without soil measurements. It is also assumed that the remote sensing is carried out every 48 hours. Regarding the weather and soil conditions, real meteorological data collected from the IoT agro-meteorological network deployed in the pilot orchard is used for the simulations. Random initial conditions for the soil parcels and plants water content are considered.

5.2 Architecture Evaluation

In order to evaluate the effectiveness of the proposed observer, the dynamical model given in eq. (20) was simulated for 359

Fig. 3. PANTHEON experimental setting: simulated area.

hours (approximately 15 days). In particular, the proposed intermittent observer is compared with a classic intermittent Kalman filter which does not take into account the correlation in the measurements coming from the weather station. The aim is to demonstrate the improvement in the large scale scenario, when not all plants are measured, of this approach when using the same amount of available measurements. As indicator of the difference in performance between these two scenarios, we compute the absolute error estimation at each time instant for every state

$$e_k = \left| x_k - \hat{x}_{k|k} \right|. \tag{28}$$

Figure 4 depicts the absolute error estimation over time of the plant water status. In this plot, the values are obtained from a parcel where there is a sensor probe measuring the soil humidity status a every time instant k. As it is evident from the figure, the difference of water content between the two estimations is negligible.

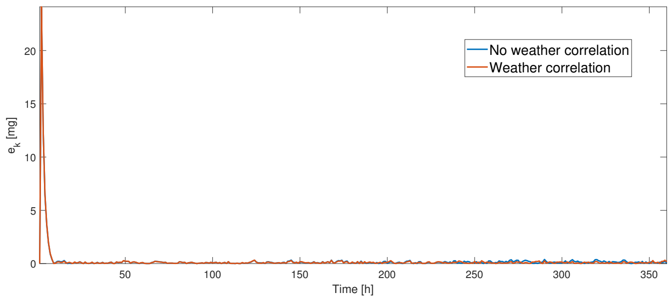

Fig. 4. Evolution of the state estimation absolute error of the plant water content in a measured parcel

In Figure 5, the evolution over time of the estimation error is depicted for a plant belonging to a parcel with no soil moisture measurements. In this case, the only direct measurement of the plant comes from the intermittent remote sensing. As we can see, the estimation error in this case is clearly larger than in the previous estimation. This result shows the big difference when not using the assumption of meteorological data correlation as part of the estimator.

Notably, these numerical results corroborate the fact that in the context of large-scale orchards, where it is not realistic to assume that a soil moisture probe is available for each parcel, the use of the relation between common measurements coming from a weather station can be significant in order to ensure a good estimation of the plant status. Also, they support the fact that classical approaches are not suited for the large-scale scenario.

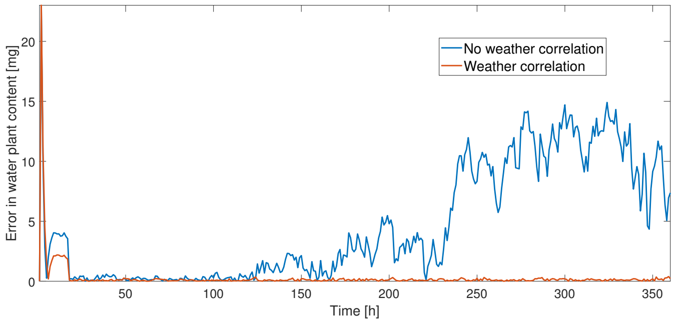

Fig. 5. Evolution of the state estimation absolute error of the plant water content in an unmeasured parcel

Finally, we would like to reiterate that in our study we focused on the study of water status estimation in the case of large-scale orchards and how this estimation can be improved by resorting to common weather measurements. Since no previous model at the state of the art considers similar sensing restrictions, we believe that a comparison with other models would not be informative (and fair) enough for the large-scale setting under analysis.

6. CONCLUSIONS

In this paper, we have presented an observer-based architecture purposely designed for water management in large-scale orchards. Briefly, this architecture is based on a novel model for the description of the water dynamics in an orchard and on the design of an observer based on the idea of Kalman filtering with intermittent observations. The aim is to estimate the water status of the orchard in order to improve the water irrigation system. To deal with the spatial sparsity of soil measurements, we have numerically demonstrated that the consideration of correlated error in climate disturbances improves the performance of the estimator. This work has been developed within the context of the H2020 PANTHEON project which is focused on the precision farming of hazelnut orchards. Future works will focus on the experimental validation of the proposed dynamical model along with an experimental validation of the proposed architecture for water management.

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