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A Comparative Analysis between Heuristic and Data-Driven Water Management Control for Precision Agriculture Irrigation

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Abstract: Modeling and control theory applied to precision agriculture irrigation systems have been essential to reduce water consumption while growing healthy crops. Specifically, implementing closed-loop control irrigation based on soil moisture measurements is an effective approach for obtaining water savings in this resource-intensive activity. To enhance this strategy, the work presented in this paper proposed a new set of water management strategies for the case in which multiple irrigation areas share a single water supply source and compared them with heuristic approaches commonly used by farmers in practice. The proposed water allocation algorithms are based on techniques used in real-time computing, such as dynamic priority and feedback scheduling. Therefore, the multi-area irrigation system is presented as a resource allocation problem with availability constraints, where water consumption represents the main optimization parameter. The obtained results show that the data-driven water allocation strategies preserve the water savings for closed-loop control systems and avoid crop water stress due to the limited access to irrigation water.

Keywords: real-time computing; precision agriculture; closed-loop irrigation; water efficiency; feedback scheduling

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1. Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations, it is estimated that around 70% of all water withdrawal worldwide is due to agricultural applications [1], contrasting the industrial sector at 20% with municipalities' local infrastructure for services and domestic water use taking the remaining 10%. This seems a logical percentage distribution given that around 2000 to 3000 L of water are required to grow food per person daily [2]. Nonetheless, what is more concerning regarding this volume of water is that 93% never returns to its original source, signifying an apparent complete loss of the resource.

Irrigation efficiency refers to the ratio of water the crop uses to the total amount of water extracted from the source [3]. Different factors affect irrigation efficiency, like water run-off, evaporation, and deep percolation. Water efficiency mostly depends on the hydraulic infrastructure and irrigation method, while surface irrigation has a water efficiency from 50% to 65%, sprinklers range from 60% to 85%, and drip irrigation from 80% to 90% [4]. Surface irrigation implies surface evaporation, which contributes to water loss. Sprinkler technology reduces water loss but, still, the applied water evaporates off the leaves of the crop canopy. In contrast, drip irrigation delivers water directly to the plant's root zone, reducing losses due to run-off and evaporation [5]. In any case, water efficiency can be considerably improved when a sensor-based smart irrigation system is installed over the hydraulic infrastructure [6].

Notwithstanding, food production is stated to rise in the following ten years and for many decades to come. In [7], the author states that the demand for food and agricultural products is projected to further increase by up to 70% by 2050 in order to satisfy the requirements for an estimated 10 billion person population by then. That, in addition to the growing effect of climate change on water shortage worldwide, can have terrible consequences in the near future regarding resource allocation and availability for agricultural purposes. Vulnerable communities in arid regions would potentially suffer the consequences of water scarcity and global warming more [8]. Moreover, severe social conflicts have already occurred in rural communities due to the unfair assignation of water resources for agricultural activities [9]. Therefore, technology and data-driven solutions for water management are required to improve resource efficiency, reduce water waste, and contribute to sustainable agriculture practices [10].

The waste and overuse of water resources for crop irrigation is a relevant topic that has been addressed by precision agriculture from different perspectives [11]. In this sense, automatic irrigation systems aim to optimize water utilization while helping farmers to improve crop yields by providing the right amount of water, at the right time, in the right place in the field [12]. To control the amount of water used during irrigation, typically these systems conduct measurements of soil moisture levels (volumetric water content), environmental parameters (solar radiation, wind speed, air temperature, air humidity), and crop conditions (canopy temperature, chlorophyll content, trunk diameter) [6].

Efficient water management is typically achieved by implementing closed-loop irrigation, where real-time soil moisture measurements gathered from large crop areas determine when to activate irrigation. Wireless sensor networks provide the communication infrastructure for the devices to transmit and receive data. A control device receives soil moisture data from sensors, executes a control algorithm, and activates or deactivates the irrigation valves to determine how much water to apply to the crops. In addition, the control unit may receive complementary information, such as environmental parameters and crop conditions, to improve algorithm accuracy using model-based estimations. The strategies to implement the algorithms are mostly based on classical and modern control theories like on-off control [13], PID (proportional-integral-derivative) control [14], and MPC (model predictive control) [15,16]; however, recently artificial intelligent approaches such as fuzzy logic [17–19], machine learning [20,21], and multi-agent systems [22,23] have gained the attention of the research community due to the initial promising results in the area of data-driven agriculture. However, most works on closed-loop irrigation consider one crop and a single irrigation area without water constraints. Therefore, they usually assume full water availability, which in practice is not always true, especially in arid regions where water management is a priority for sustainable and economically profitable crops.

Real-time systems refer to computing devices that react within precise time constraints to events in the environment [24]. Around this concept, different algorithms have been developed mainly within the scope of operating systems theory, where multiple control tasks are simultaneously executed, sharing common resources [25]. In these systems, the allocation of resources is commonly formulated as a constrained optimization problem, where the aim is to maximize the benefits of control performance subject to efficient use of the available resources. Real-time computing for control systems has been deployed over various fields of industry and services like automotive systems, mobile robotics, smart grids, gas and water distribution, and food and petrochemical industries, among others [26].

The work presented in this paper integrated modeling and control theory with real-time computing to develop dynamic water allocation algorithms for precision agriculture, considering different irrigation areas with different characteristics, such as crop types, soil conditions, and water needs. Under this scenario, water availability is constrained and can only be supplied to one irrigation area at a time. Experimental data show that dynamic resource allocation in multiple irrigation areas avoids stressed crops and improves water utilization compared to the empirical approaches commonly used by farmers.

2. Materials and Methods

2.1. Irrigation Dynamics

An irrigation area can be modeled as a finite two-dimensional space where vegetation is to be raised, with water being the primary input resource for the system. Other relevant physical variables that can be considered in the analysis of the crop's growth include, but are not limited to, soil physical characteristics (texture, structure, drainage), environmental parameters (temperature, air humidity, solar radiation, wind speed), and crop attributes (type of crop, development stage, plants health).

A single variable that can show the irrigation's overall performance concerning water usage is the soil moisture level $\theta(t)$. As evidenced by its name, it measures the water in the soil. Soil moisture data are obtained by sensors that measure the volumetric water content VWC, which is defined as the ratio of water volume $V_W(t)$ to the unit volume of soil $V_s(t)$. Therefore, soil moisture can be defined as

$$\theta(t) = \frac{V_w(t)}{V_s(t)}. \tag{1}$$

Even though irrigation dynamics present non-linear behavior, it is common to approximate the system as a linear model divided into three main operating zones according to normalized soil moisture levels [15]. As illustrated in Figure 1, these three areas are denoted as

1. Gravitational (water saturation zone);
2. Available (water available in the root crop zone);
3. Unavailable (hydric stress region).

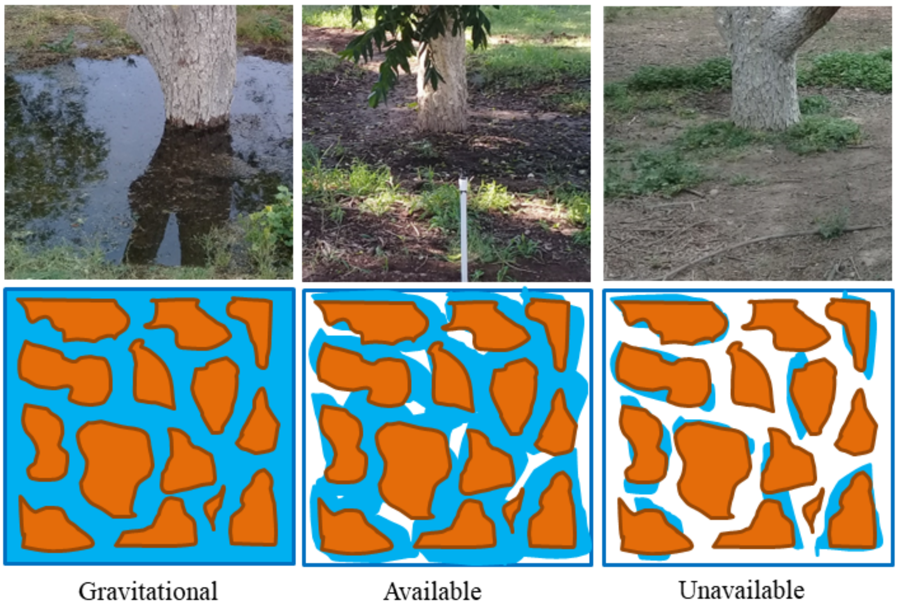

Figure 1. Water content zones according to the soil moisture level, figure adapted from [27].

In the first workspace region, soil cannot retain water which is allowed to drain freely, provoking a significant amount of water waste. The second operating region consists of a state where the soil retains water and it is available for the crops. In the third area, there is not enough water available; at this point, visible damage can become apparent to the vegetation and, if not treated, can lead to crop loss. These three zones are exemplified in Figure 2, where it can be noticed that soil moisture dynamics are different for each region, and the two irrigation events rapidly raise the volumetric water content.

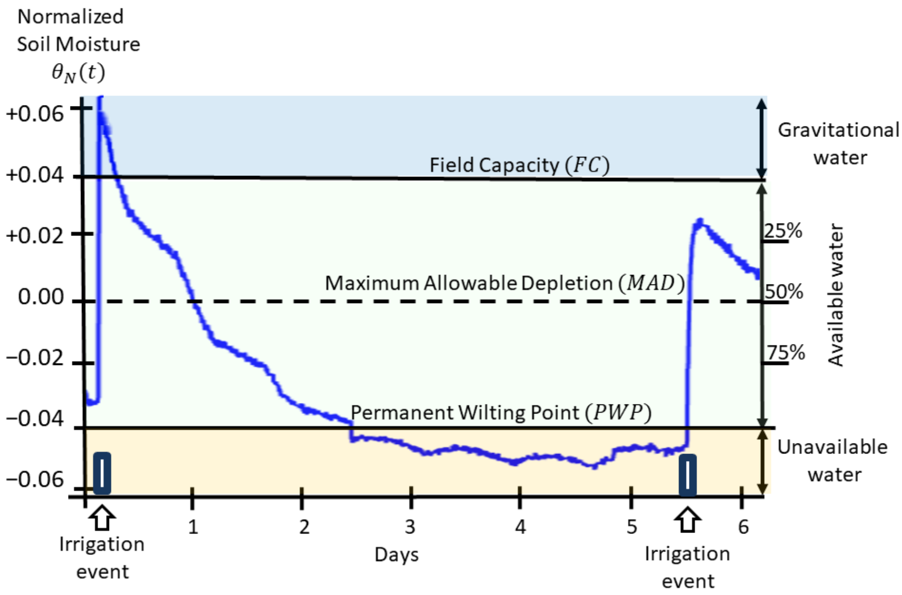

Figure 2. Soil moisture dynamics for an irrigation system, figure adapted from [15].

Normalized soil moisture uses the maximum allowable depletion (MAD) as a reference level and is defined as

$$\theta_N(t) = \theta(t) - MAD, \tag{2}$$

where MAD specifies the maximum soil water deficit that the crop may support without experiencing any water stress. Typically, the MAD level is located at 50% of the total available water capacity in the rooting zone [28]. Table 1 illustrates typical MAD values and maximum root zone depths for selected crops. As for the field capacity (FC), their volumetric water content percentage depends on the soil texture with values form 30% to 40% for silt loam, clay loam, and silty clay loam types of soil [27].

Table 1. Percentage values for maximum allowable depletion (MAD) and ranges of root depth for common crops. Data obtained from Allen et al. (1998) [29].

Crop	MAD (%)	Root Depth (m)
Alfalfa	55	1.0–2.0 m
Apple	50	1.0–2.0 m
Cotton	65	1.0–1.7 m
Maize	50	0.8–1.2 m
Pecan	50	1.7–2.4 m
Green pepper	45	0.5–1.0 m
Potato	35	0.4–0.6 m
Tomato	40	0.7–1.5 m
Turf grass	50	0.5–1.0 m
Wheat	55	1.0–1.5 m

Closed loop irrigation aims to keep soil moisture above MAD and below FC level; this is an optimal spot for the stability of the crop's growth since it avoids crop hydric stress and water waste.

2.2. Irrigation Model

Based on the previous observations, a linearized model at the operating points is proposed; it is important to base the irrigation dynamics on experimentally-confirmed differential equations that allow for a proper realization of the input–output relationship for the system. A model solely based on irrigation as input is too ideal to execute according to the expected outcomes. Therefore, another humidity-related environmental factor must be added to the equation. This second time-dependent variable will be reference evapotranspiration $eto(t)$. It can be inferred as the amalgamation of the evaporation and transpiration processes that the vegetation may suffer and it can be obtained using weather variables (solar radiation, wind speed, air temperature, and relative air humidity) according to the FAO Penman-Monteith method [29]. Thus, it accounts for the vaporization of the moisture from the soil surface through heat transfer mechanisms such as convection and radiation from the immediate environment and it also takes into consideration the loss of water from the plant tissues through the stomata. The model can be enhanced by recognizing the variations of soil moisture with respect to time. This new variable, $\dot{\theta}(t)$, should be equivalent to the difference of humidity inlets minus the outputs of liquid matter, according to the law of conservation of matter.

Although a realistic model could employ dozens of variables, the simplest of them all are sufficient in many cases, including the scenario in which the climate is dry with minimum rainfall (which is the circumstance in which the $eto(t)$ data were collected), a straightforward equation can take the following form via the work of [30]:

$$\dot{\theta}(t) = c_1 ir(t) + c_2 rf(t) - K_c eto(t) - dp(t), \tag{3}$$

where $ir(t)$ and $rf(t)$ represent water inflow from irrigation and rainfall since, in arid regions, rainfall does not have a significative impact, then coefficient c_2 is zero, while c_1 represents the irrigation efficiency which depends on the hydraulic infrastructure with values that range from 0.3 to 0.9 and may vary considerably from one irrigation area to another. Crop coefficient K_c in conjunction with the $eto(t)$ integrates the actual crop evapotranspiration, K_c depends on the crop type and crop growth stage, and the reference value of 1.0 corresponds to plain grass crop. Finally, $dp(t)$ stands for the effects of deep percolation, which is the gradual descent of surface water to underground levels.

It is important to remark that the effect of irrigation is not immediate and thus a time delay τ can be considered in the expression. This time delay depends on the depth location of the sensors but also soil compactness level. As for the deep percolation, as it can be inferred from the soil moisture levels in the ground, it can be defined as being proportional to $\theta(t)$. Consequently, the soil water balance model can be re-written as

$$\dot{\theta}(t) = c_1 ir(t-\tau) - K_c eto(t) - c_3\theta(t), \tag{4}$$

where c_3 denotes the proportionality of the soil moisture to the deep percolation effect.

Now, (4) can be represented as a second-order state space model in the form of

$$\dot{x}(t) = \boldsymbol{A}x(t) + \boldsymbol{B}u(t), \tag{5}$$

where $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{2\times 2}$ are the state and input matrices, which incorporate coefficients c_1, c_3, and K_c, and they can be experimentally obtained from measurements per crop area. The state vector $x(t)$ and the input vector $u(t)$ are respectively defined as

$$x(t) = \begin{bmatrix} \theta(t) \\ \delta(t) \end{bmatrix} \tag{6}$$

and

$$u(t) = \begin{bmatrix} ir(t-\tau) \\ eto(t) \end{bmatrix}, \tag{7}$$

where $\delta(t) = \dot{\theta}(t)$ and denotes the dynamic of the soil moisture variations.

2.3. Model Validation

Over 45 days, data were collected from four different irrigation areas with different crop types, irrigation systems, and soil characteristics, as denoted in Table 2.

Table 2. Irrigation areas characteristics used for data collection.

Crop Type	Crop Area Size	Irrigation System	Soil Texture
Green pepper	21 m × 8 m	Drip irrigation	Silt loam
Wheat	21 m × 8 m	Drip irrigation	Silt loam
Pecan	45 m × 12 m	Sprinkle irrigation	Clay loam
Maize	18 m × 8 m	Drip irrigation	Silty clay loam

As depicted in Figure 3, the irrigation areas were monitored with a solar cell-powered data acquisition system that sensed the crop soil moisture level every minute from three volumetric water content sensors (10HS Sensor from Meter Group), solar radiation (PYR Sensor from Meter Group), wind speed (Davis Cup from Meter Group), air temperature and relative humidity (VP-4 Sensor from Meter Group), and water consumption (Flow-Sync from Hunter Industries) through a wireless sensor network as described in [31].

Figure 3. Evaluated irrigation areas.

Coefficients values for matrices **A** and **B** from Equation (5) were experimentally obtained to model the soil moisture dynamics for each evaluated area properly. The estimation algorithm proposed by [15] was used to create a linear dynamic state space model for each operating zone (gravitational, available, and unavailable). Figure 4 shows the correlation between the estimated normalized soil moisture values calculated from the model $\hat{\theta}_N(t)$ and the normalized measured soil moisture values obtained from the sensor readings $\theta_N(t)$ for a specific crop. Irrigation flow $ir(t)$ is expressed in m^3/mm and reference evapotranspiration $eto(t)$ in mm/day. Correlation results showed that the identified model adequately captured the irrigation dynamics for the crop.

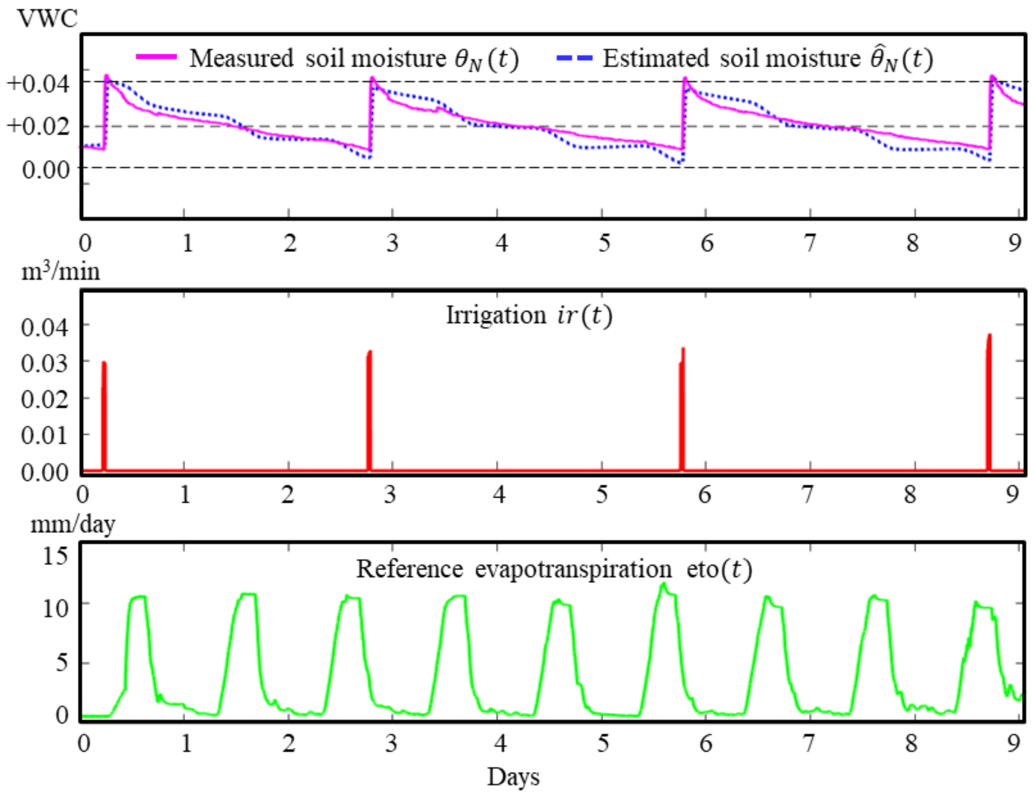

Figure 4. Validation results for the system identification.

Once the proposed irrigation model was experimentally validated with four different crops, an optimization problem was formulated to evaluate the various water management strategies for a case where multiple irrigation areas share a water supply source.

2.4. Optimization Problem

For real-time systems, control performance optimization and efficient use of the available resources are two key elements in the design of resource-constrained control applications [24]. This paper analyzed the scenario in which four irrigation areas with different crops compete for water supply. The proposed algorithms try to solve a water management optimization problem in order to minimize water consumption and crop hydric stress subject to the constraint of water availability, which can be defined as

$$\text{minimize} \quad J = \frac{1}{n}\sum_{i=1}^{n}(J_{c_i} + J_{s_i}) \tag{8}$$

$$\text{subject to} \quad \sum_{i=1}^{n}\frac{c_i}{h_i} \leq U_{ref}, \tag{9}$$

where n is the number of irrigation areas, J is the cost function which integrates water consumption J_c and crop hydric stress J_s for the i area. Also, c_i is the irrigation time required to move soil moisture from the low threshold to the high threshold for each specific area and h_i is the task period which represents the deadline before soil moisture reached stress levels. Finally, U_{ref} is the required water utilization level for the entire group of n irrigation areas.

Cost functions for water consumption and hydric stress are respectively defined as

$$J_c = \frac{1}{t_{days}} \sum_{k=1}^{t_{eval}} ir_k \quad (10)$$

$$J_s = \frac{100}{t_{eval}} \sum_{k=1}^{t_{eval}} s_k, \quad (11)$$

where t_{eval} is the total number of minutes for the 45 days evaluation period. J_c is the daily water consumption in m^3/day, while J_s is the percentage of time that the crop suffers from hydric stress; hence, s corresponds to the total time the crop soil moisture level is under the maximum allowable depletion level, i.e., $\theta_N < MAD$.

Figure 5 shows the evaluated scenario, where a single water source supplies irrigation to only one area at a time by activating the electro-valves (actuators) while the sensors conduct periodic soil moisture and environmental measurements. The water management algorithm runs in the controller to schedule the irrigation events for the areas.

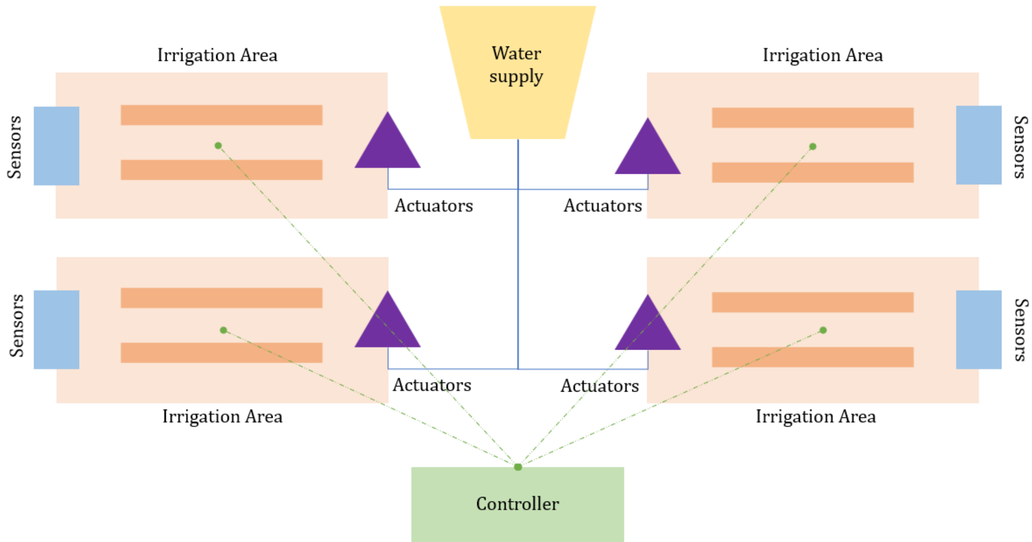

Figure 5. Irrigation system for four areas.

2.5. Evaluated Algorithms

A total of six algorithms were evaluated for a simulation time of 45 days. The evaluation was conducted through a simulation implemented in the Python programming language. The first algorithm considers the ideal case where no water constraint is considered; each irrigation area receives water immediately when needed. Then, two heuristic irrigation algorithms based on time-partitioning schemes and three data-driven techniques based on real-time control were considered in the analysis.

1. Full-Satisfaction Irrigation (FSI): This ideal case was used as a reference, where no water constraint was applied. If the moisture level is found below some established level MAD, it is time for irrigation. The input signal stops when the soil moisture reaches a certain ceiling FC. $IrrValue$ represents the flow in m^3/min provided by the hydraulic system when the electro-valve is activated. Therefore, $ir(t)$ has only two possible values: $\{0, IrrValue\}$. The control law can be summarized as an on–off hysteresis controller with full water availability:

$$ir(t) = \begin{cases} IrrValue, & \theta_N(t) < MAD \\ 0, & \theta_N(t) > FC. \end{cases} \quad (12)$$

2. Time Partitioning Irrigation (TPI): In this heuristic algorithm, a time slot is assigned to each area; during this time period, the area is irrigated until field capacity is reached. Let T_i be the period of time placed in the i-th order where area i can be irrigated. The irrigation cycle is formed by $T = (T_0, \ldots, T_i, \ldots, T_k)$. Once T_k is over, the circle repeats itself. Irrigation on area i cannot occur if, at time t, $t \notin T_i$. Therefore,

$$ir(t) = \begin{cases} IrrValue, & (t \in T_i) \wedge (\theta_N(t) < MAD) \\ 0, & (t \notin T_i) \vee (\theta_N(t) > FC). \end{cases} \tag{13}$$

3. Greedy Time Slotting (GTS): Like TPI, irrigation is divided into fixed time slots in a predetermined order. The main difference is that to recompense the expected stress during the periods of no irrigation, watering will be forced as long as $t \in T_i$. Therefore, the proposed control law is

$$ir(t) = \begin{cases} IrrValue, & t \in T_i \\ 0, & t \notin T_i. \end{cases} \tag{14}$$

4. Mutual Exclusion Resource Locking (MERL): In this data-driven algorithm analog to a first-come, first-serve scheme, the first land lot under the MAD level will gain access to water for irrigation. While it is being watered, no other crop can be irrigated. It deals with the scenarios of access collision like in the dining philosophers' problem proposed by [32]. Different processes (irrigation areas) may require access to a shared resource (water supply) in this strategy. Then, to control concurrency and avoid deadlock, a mechanism (algorithm) allows access only if the resource is available; if not, the process will wait a random period of time to check if the resource is now available. It is not a perfect solution but, given a good random seed, the probability that different processes keep colliding becomes null in practice. The proposed control law is defined as

$$ir(t) = \begin{cases} IrrValue, & (\theta_N(t) < MAD) \wedge (water = available) \\ 0, & (\theta_N(t) > FC) \vee (water \neq available). \end{cases} \tag{15}$$

5. Earliest Estimated Deadline First (EEDF): Given that an available mathematical model is obtained through system identification techniques [33], an approximate behavior of the real plant can be estimated. To determine which irrigation area to give the most priority, one can compute which one has the sooner *deadline* and define a priority ranking among the competing areas. The deadline is calculated by estimating the time for the area to reach the MAD threshold since, below this level, the crop will suffer from hydric stress. In this dynamic scheduling algorithm, the highest priority is assigned to the task with the earliest deadline to avoid water stress. Once the area has access to the water supply, no preemption is allowed until the irrigation area reaches the field capacity level. The proposed control law is defined as

$$ir(t) = \begin{cases} IrrValue, & (h \in min\{h_i\}) \wedge (water = available) \\ 0, & (h \notin min\{h_i\}) \vee (water \neq available). \end{cases} \tag{16}$$

6. Dynamic Feedback Priority (DFP): This resource-aware algorithm is based on the feedback scheduling concept, where the resource manager continuously monitors the soil moisture level for all the areas. Similarly to the EEDF strategy, the water resource is assigned to the irrigation area based on how close the moisture level is with respect to the MAD threshold to avoid water stress. Here, the difference is that the resource manager may preemptively interrupt the current irrigation area anytime if it is determined that another area is in a more critical stage, i.e., closer to the water stress limit. Unlike the previous scheduling technique, where the priority will be

calculated after finishing the irrigation, in this new dynamic feedback algorithm, the priority is continuously estimated for each sample period,

$$ir(t) = \begin{cases} IrrValue, & h \in min\{h_i\} \\ 0, & h \notin min\{h_i\}. \end{cases} \quad (17)$$

3. Results and Discussion

The evaluation results in terms of water stress percentage J_s and water consumed daily J_c are displayed in Figure 6, with a legend to signal the four individual areas and their performances. The left side belongs to an ideal case and the empirical methods, while the right side stands for the proposed data-driven techniques.

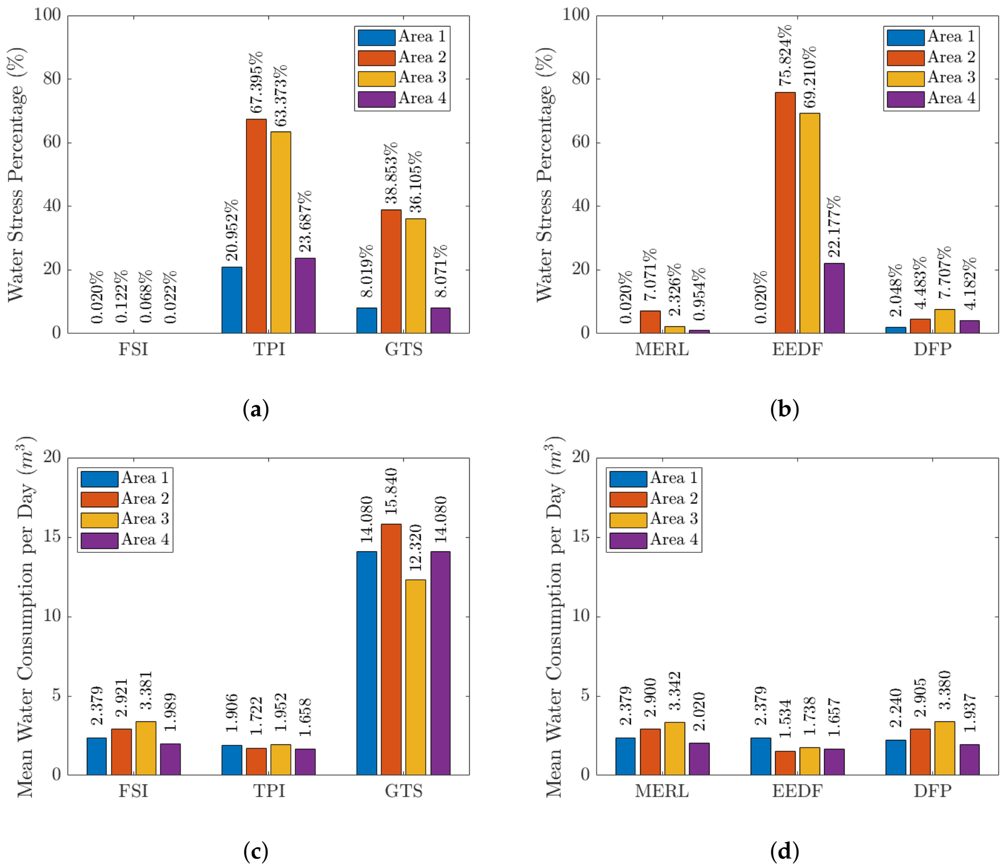

Figure 6. Numerical results of the 45-day simulation period for each irrigation area following the scheduling policies and the constraints imposed into the system. (**a**) Water stress on each area for the ideal case and the heuristic algorithms. (**b**) Water stress on each area for the data-driven algorithms. (**c**) Irrigation water consumed daily in m^3 by area for the ideal case and the heuristic algorithms. (**d**) Irrigation water consumed daily in m^3 by area for the data-driven algorithms.

The ideal scenario of unlimited water is present in the FSI algorithm. Under there, every time the sensed moisture goes below the permitted threshold, irrigation is activated regardless of the state of the other lots. When it surpasses the upper threshold, irrigation stops. Therefore, as expected, the crops spend practically no time under stress even though it may consume a surplus of water.

Otherwise, TPI irrigates only when necessary during the selected time slots permitted periodically. One can infer that, although it will save a good amount of resources, the plant will be placed under constant stress for most of the study horizon. If one agrees to irrigate heedless of the state variables during the allowed period, the expected result is a reduced level of water stress due to the incoming stagnant water to alleviate the climate in the subsequent periods at the expense of an augmented degree of resource usage. GTS is a technique commonly used by farmers to reduce crop water stress, since they use the soil to store water for the future; however, soil capacity to store water is very limited and this considerably increases the water waste.

MERL enables the capacity to emulate the limitless resource case's response while setting boundaries on how much water can be used in practice. Hence, the overall performance under this algorithm is similar to FSI. Earliest deadline scheduling functions similarly to the time-division multiplexed algorithms, with a considerable upgrade. EEDF, by always following the then-closest area to moisture fulfillment, ensures that the periods between irrigation will always be the shortest ones possible. However, three crops suffered from water stress under this algorithm and only one avoided the hydric stress; this can be explained by the no preemption mechanism imposed by the algorithm.

Finally, the DFP algorithm obtained similar results to the MERL approach. This is because it is essentially a straight line along the lower threshold of the moisture level percentage. Nonetheless, it is excellent yet surprising news. The only mode in which one can achieve this kind of constant response is by periodically placing marginal magnitudes of the input at a fast and constant rate. This sort of reaction is the same as in drip irrigation, where the water is placed drop by drop into the root area. This method minimizes the erosion and evaporation of water commonly found in sprinkler irrigation while saving up to 60% of the water used and increasing crop yield by over 50% (see [34]). At first sight, the data-driven approaches seem to improve the extent of hydric stress in submerged areas. Also, they present a more organized and fair way to distribute the resources with the correct constraints in a real land lot.

For a deeper evaluation, Table 3 presents the obtained cost function results as defined by Equations (10) and (11).

Table 3. Cost function results of the evaluated algorithms.

Algorithm	J_c	J_s
FSI	2.668	0.058
TPI	1.809	43.852
GTS	14.080	22.762
MERL	2.660	2.593
EEDF	1.827	41.808
DFP	2.616	4.605

It can be observed that, even though the heuristic approaches tend to the highest and lowest values in both categories, the ability of the data-driven methods is more balanced and they produce an overall better performance. It is clear that, with the exception of EEDF, the plant suffers from much less hydric stress than with the heuristic methods. Additionally, at most, MERL and DFP allowed just under 5% water stress, while TPI and GTS put the crop under stress for more than 20% the duration of its intended growth.

Additionally, water consumption stays below the ideal scenario of FSI, whose only true competitor is time partitioning schemes that increment the water stress exponentially, making them unsuitable for actual applications even if they are already used in practice by most farmers due to their experience and background. Of all the above, the best irrigation strategies that one can and should implement are the mutual exclusion resource locking (MERL) and the dynamic feedback priority (DFP), since they provided a balance of avoiding water stress while reducing water consumption in comparison with the heuristic TPI and GTS approaches. The first one shows how arbitrarily blocking the access of some agents to the main hydration supply can diminish the expenses and protect the vital resources in play while at the same time keeping the areas in good condition. The latter has more rewards that safeguard water utilization in this sector and consider the conservation of the immediate environment.

The obtained results have demonstrated that data-driven water management strategies reduce irrigation water consumption while avoiding water stress on crops in conditions where multiple crop areas share a water supply. However, the drawbacks of implementing these automated solutions reside in the installation and maintenance cost, which most farmers are unwilling to accept if the return on investment is not clearly defined. To illustrate this, just the acquisition cost and the proper installation and maintenance of soil moisture sensors have a high level of complexity [31]: sensors require individual off-line calibration for the specific soil texture to reach a reliable accuracy, then installation must be carefully conducted to avoid soil air gaps to obtain representative readings; also, at least three sensors are required for an irrigation area and it is a good practice to unearth sensors each year for re-calibration. Since soil moisture sensor is, so far, the element on which closed-loop irrigation is based, lowering costs and efforts must be a priority to make sensor-based automated irrigation a feasible option for farmers.

4. Conclusions

A set of dynamic water allocation algorithms was proposed to optimize water consumption and avoid hydric stress for an agricultural irrigation system composed of multiple areas and a single water source. The dynamics of each area were modeled to represent different crops with different soil properties. The water management algorithms were integrated with closed-loop controllers based on soil moisture measurements for each irrigation area. Simulation results based on experimental data showed that the proposed strategies obtained a similar performance regarding water savings and avoiding water-stressed crops to when total water is available. They provided superior results compared with the heuristic strategies commonly used by farmers in practice. The proposed data-driven algorithms were formulated as a real-time computing optimization problem with resource constraints. The results encourage looking for other data-driven techniques to be applied in irrigation management. Water management for agricultural activities may have different perspectives: environmental, social, and economic, and the use of data-driven solutions may positively impact sustainable agriculture practices. Therefore, future works consider implementation in vulnerable communities where farmers share common water resources.

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Abbreviations

The following abbreviations are used in this manuscript:

DFP	Dynamic Feedback Priority
EEDF	Earliest Estimated Deadline First
FC	Field Capacity
FSI	Full-Satisfaction Irrigation
GTS	Greedy Time Slotting
TPI	Time Partitioning Irrigation
MAD	Maximum Allowable Depletion
MERL	Mutual Exclusion Resource Locking
PWP	Permanent Wilting Point
VWC	Volumetric Water Content

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