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Prescriptive watering: Data-driven optimization of water consumption in kiwifruit orchards

Alex Baiardi [a], Matteo Francia [a],*, Matteo Golfarelli [a], Alessandro Vittorio Papadopoulos [b],*, Manuele Pasini [a]

[a] DISI – University of Bologna, Cesena, Italy
[b] Mälardalen University, Västerås, Sweden

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ABSTRACT

Climate change and increasing water scarcity demand innovative irrigation strategies, especially for high-value crops like kiwifruit that require precise water management. Traditional irrigation systems often fail to address the spatial and temporal variability of soil moisture in orchards, where factors like canopy coverage and localized watering patterns complicate remote monitoring. This paper introduces SMARTER, a soil-agnostic, prescriptive irrigation system designed specifically for kiwifruit orchards. It uses a two-dimensional grid of sensors to construct detailed, real-time soil moisture profiles, which are then processed to recommend irrigation volumes. SMARTER operates in two phases: an offline phase, where agronomists define optimal soil moisture targets, and an online phase, where data-driven monitoring and Proportional–Integral control algorithms guide irrigation decisions. Field evaluations during the 2023 and 2024 irrigation seasons in two commercial kiwifruit orchards in Italy demonstrated water savings of up to 40% compared to traditional irrigation practices, without compromising fruit quality and with a break-even point of two years. Unlike traditional simulators or data-hungry machine learning models, SMARTER does not require complex parameter calibration, soil-specific tuning, or historical data, making it deployable and actionable as soon as sensors are deployed. Furthermore, SMARTER effectively adapts to events like rainfall and irrigation deviations.

1. Introduction

Agriculture constitutes one of the foundational pillars of human society. Throughout its evolution, closely intertwined with humankind's anthropological and economic development, agriculture has periodically faced challenges that undermine its efficiency and create imperative demands for innovative solutions. Climate change, along with the steady increase in the world's population and water scarcity, now represents the most compelling factor driving the need for innovation in the agricultural industry (Calzadilla et al., 2013). Numerous research papers have studied how the increase in temperatures, frequency of drought periods (Leng et al., 2015), and severity of atmospheric events (Cogato et al., 2019) will impact agriculture (Calzadilla et al., 2013), particularly in developing countries whose economy heavily relies on the primary sector (Maja and Ayano, 2021). According to estimates presented in 2020 (D'Odorico et al., 2020), agriculture consumes up to 70% of the available freshwater, underscoring the need for optimized usage.

For instance, kiwifruit (*actinidia chinensis*) is a woody vine native to southern China, where in most production zones the annual precipitation is sufficient to provide the ideal environment for kiwifruit plants to thrive, even considering their high water requirements (He et al., 2023) which must be meticulously managed to achieve optimal fruit yield and quality. Over the past decade, kiwifruit production in Italy has increased significantly, making it the world's third-largest exporter. Despite the warm and moderate climate, the annual precipitation in Italy is insufficient to meet the water needs of kiwifruit, making irrigation crucial for this crop; additionally, predictions of a 10% increase in irrigation requirements due to the increasing frequency of drought periods (Villani et al., 2011) make the optimization of irrigation practices vital for the sustainability and productivity of the agricultural sector.

To optimize water use, we present SMARTER, a SMART watERing system that utilizes near real-time data to manage orchards' irrigation efficiently. We focus on orchards (and not open fields) as (i) they cannot

* Corresponding author.
E-mail addresses: alex.baiardi@unibo.it (A. Baiardi), m.francia@unibo.it (M. Francia), matteo.golfarelli@unibo.it (M. Golfarelli), alessandro.papadopoulos@mdu.se (A.V. Papadopoulos), manuele.pasini@unibo.it (M. Pasini).

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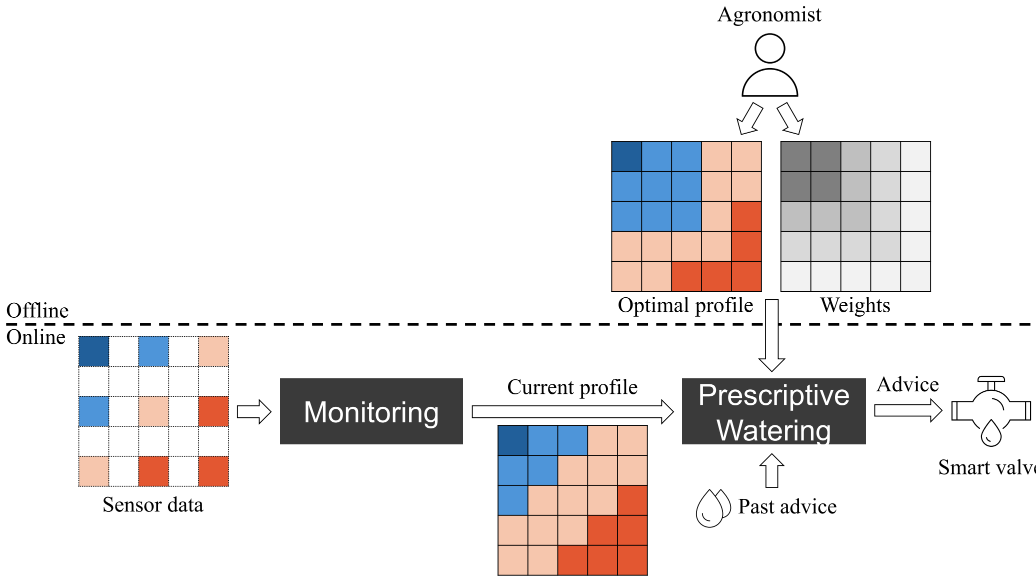


Fig. 1. Overview of SMARTER. In the offline phase, agronomists set the desired moisture state of the field. In the online phase, SMARTER monitors and transforms sensor data into a detailed profile that, coupled with past irrigation and the optimal state set by agronomists, is used to calculate watering advice.

be effectively monitored using remote sensors (e.g., satellites) since canopies or nets hinder precise measurements, and (ii) irrigation is usually organized in pipelines of drippers that cause heterogeneous soil moisture (which is higher close to plants and gradually lower between rows of plants).

The overall flow of the system is illustrated in Fig. 1. SMARTER involves two main phases. In the *offline* phase (e.g., monthly or for each fruit growth stage), agronomists define an optimal soil-moisture state depending on the characteristics of fruits, plants, and soil. In the *online* phase, SMARTER samples the current state of soil moisture through in-field sensors, models, and builds soil moisture profiles using artificial intelligence (Monitoring), and calculates how much water is necessary to keep the soil moisture as close as possible to the optimal state (Prescriptive Watering). We conducted an empirical evaluation during the 2023 and 2024 irrigation seasons (from June to October) in two kiwifruit orchards, achieving water savings of up to 40% and comparable fruit quality to that of traditional irrigation practices. SMARTER adapts to different fields, is deployable without prior historical data, and its adoption is calibration-free. In other words, SMARTER can be adopted immediately (from day 0, once sensors are installed), as it is independent of soil properties (e.g., soil texture is not an input) and requires no prior training or calibration.

The paper is organized as follows. Section 2 provides a literature overview on smart irrigation systems, while Section 3 describes the materials and methods leveraged in this approach. Finally, the evaluation (including two case studies in real fields) is presented in Section 4, and conclusions are drawn in Section 5.

2. Related work

The approaches to monitor and estimate the irrigation requirements of fruit orchards can be classified based on the strategies they adopt for: (i) modeling the physiological and environmental conditions of the orchards, and (ii) determining the optimal irrigation volumes. We recall that we focus on orchards rather than open-field crops, as irrigation management strategies differ significantly between these two contexts.

2.1. Physically-based simulators

A common approach for modeling plant–soil–water dynamics involves the application of physical models and numerical simulators, such as HYDRUS (Simunek et al., 2009) and CRITERIA (Bittelli et al., 2015). These tools simulate water flow and solute transport in variably saturated porous media across one-, two-, and three-dimensional spatial domains and have been extensively applied to estimate soil–plant–water dynamics (Barezzi et al., 2024; Delgoda et al., 2016) and irrigation requirements (Bittelli et al., 2025; Barezzi et al., 2024) under various scenarios. IRRINET and IRRIFRAME (Mannini et al., 2013) are decision support systems developed by the Consorzio Canale Emiliano Romagnolo (Italy) for irrigation management. These tools leverage meteorological data and detailed soil maps to provide irrigation recommendations based on user-inputted information concerning crop type and growing conditions. However, they require users to supply a substantial amount (around 30 parameters) of detailed and dynamic information (e.g., phenological stage, canopy coverage periods). Their estimations of water requirements are based on large-scale water balance models, which, despite being informative, may not always yield optimal irrigation outcomes, particularly in complex systems such as orchards, where spatial and temporal heterogeneity play a significant role.

Overall, the adoption of simulators has the following issues.

- They require an intensive parameter calibration phase, which can involve iterative simulations on data collected from in-situ sensors to optimize the set of soil/crop parameters that best describe the observed soil–plant interactions (Bittelli et al., 2025). Moreover, certain parameters required for tuning these simulation models are derived from detailed laboratory analyses, which can be both resource and time-intensive.
- Although a tuned simulator may perform well within the specific conditions for which it was tuned, its ability to generalize to unseen scenarios is frequently limited, posing significant challenges to scalability and broader adoption in diverse agricultural contexts.
- Water demand is heavily dependent on several exogenous factors affecting the decision-making process (e.g., weather conditions,

ridge tillages, and soil cracking), but integrating them into simulators amplifies the complexity of the problem we want to solve.

2.2. Sensor-based approaches

An alternative to crop simulation models for monitoring plant–soil–water dynamics is the direct monitoring through sensing technologies. Within this approach, two primary categories can be distinguished: *remote* and *in-situ* sensing.

2.2.1. Remote sensing

Satellite imagery (e.g., Sentinel and Landsat) offers a cost-effective and widely accessible solution for monitoring agricultural landscapes (Huang et al., 2024; Velazquez-Chavez et al., 2024). Studies in the literature evaluate the effectiveness of these data sources. Meier et al. (2020) underscore the challenges posed by the spatial resolution of satellite imagery, specifically for orchard monitoring. Their findings indicate that to capture meaningful spatial variability and derive useful insights, a bare minimum resolution of 10 m is required, with an optimal resolution of 5 m suggested for future advancements in remote sensing technologies. The analysis further demonstrates that, within the studied agricultural landscapes, nearly 20% of orchard fields are entirely unrepresented (with one pixel at most covering them) when using imagery with a spatial resolution of 20 m, while approximately 80% of orchards are covered by less than 50 pixels at the same resolution. This sparse pixel representation significantly constrains the precision and reliability of satellite-derived data, highlighting the need for higher resolution remote sensing tools to improve orchard water management strategies. Furthermore, the presence of protective nets commonly employed in orchards to shield crops from adverse weather conditions, such as hailstorms or excessive sunlight, further complicates satellite-based monitoring by altering surface reflectance properties and possibly obscuring key spectral signatures, reducing the accuracy of remote sensing data used to assess crop health and soil moisture status. Deng et al. (2023) highlight additional limitations of satellite-based monitoring, noting that adverse weather conditions compromise the reliability of images, especially for small-scale farms. To address these challenges, the authors suggest that unmanned aerial vehicles (UAVs) offer a promising alternative, providing higher spatial resolution and greater flexibility than satellite platforms (Deng et al., 2023; Peeters et al., 2024; Zhang et al., 2023).

Wang et al. (2025) leverage UAV-based multispectral data combined with machine learning to estimate soil moisture in kiwi orchards. Although their results show promising accuracy for moisture prediction at 20 cm depth under ideal conditions, this depth may be insufficient for precise irrigation guidance, given that the main root system of kiwifruit extends deeper in the soil. Moreover, the responsiveness of their approach is inherently constrained by the UAV flight schedule. Furthermore, the widespread adoption of UAVs remains limited by their elevated costs, operational complexity, and required expertise, making them less accessible to smallholder farmers. These constraints continue to hinder their scalability and wider use in precision agriculture, particularly in orchards and resource-limited contexts.

2.2.2. In-situ sensing

In-situ sensors represent a promising alternative for orchard monitoring. Such sensors come in various types, mostly soil moisture sensors, weather monitoring devices, and phytosensors designed to assess plant physiological conditions. Phytosensors remain prohibitively expensive at present, whereas weather and soil moisture sensors have proven to be accessible and cost-effective tools for irrigation management.

In the following, we focus on real applications to orchards (rather than solutions applied in more experimental settings, such as Cáceres et al. (2007) and Miranda et al. (2005)) and we distinguish such applications based on the family of techniques used to compute the watering advice given sensor data.

Rule based. Osroosh et al. (2015) propose a rule-based irrigation framework for apple orchards that uses data from a sensor network that monitors weather conditions and soil moisture levels. Implementing this system requires numerous parameters, both field-specific and research-derived, necessitating extensive site-specific calibration and posing challenges to scalability across diverse orchards and climates. Hamouda et al. (2024) introduce an irrigation management system for pear orchards based on soil water content (SWC) thresholds. SWC sensors require detailed calibration tailored to the specific soil properties of the monitored site. The calibration process typically involves laboratory analysis of the hydraulic characteristics of the soil, which limits the widespread and efficient adoption of such a system. Barezzi et al. (2024) adopt a soil matric potential-based approach to estimate irrigation requirements in apple and kiwifruit orchards. In their methodology, matric potential thresholds are determined using HYDRUS-1D simulations, and matric potential data is collected by one sensor placed at a 20 cm depth for kiwifruit orchards and two sensors positioned at 20 cm and 40 cm depths for apple orchards. An irrigation control algorithm then applies predefined rules to maintain the monitored matric potential values within the computed thresholds. While this approach benefits from the lack of scenario-specific calibration requirements, the reliance on a single sensor in kiwifruit orchards assumes a uniform soil moisture distribution, which may not adequately capture spatial variability within the root zone. Zheng et al. (2025) propose a multi-objective optimization framework balancing yield, fruit quality, and water productivity through the different fruit's growth stages. However, the approach depends on long-term forecasts, expert-driven parameter calibration, and process-based simulators, limiting its practical applicability and interpretability. Moreover, the evaluation primarily relies on simulated rather than field data.

Machine-learning based. Numerous studies in the literature have explored the application of artificial intelligence techniques to determine irrigation requirements in orchards. Goldstein et al. (2017) and Navarro-Hellín et al. (2016) analyze and compare various machine learning models for orchard irrigation, utilizing both weather forecasts and an extensive set of measured variables. Artificial Neural Networks (ANNs) have been studied for irrigation management. Kang et al. (2023) present two ANN models: the first predicts soil moisture levels for the upcoming week based on current moisture level, weather data, and crop coefficients, while the second leverages the output of the first model to estimate the optimal irrigation volumes. Likewise, Ding and Du (2022) propose a reinforcement learning approach for irrigation management. Their method combines in-situ measurements with weather forecasts and soil water content data to train an agent that mimics agronomic expertise, aiming to maintain soil water content within the range defined by permanent wilting point and field capacity.

The main challenges associated with machine learning, and even more so with ANNs, include the requirement for large amounts of high-quality data to train the models, along with the risk of overfitting to specific scenarios influenced by environmental variables that significantly affect sensor measurements, such as soil texture and ridge tillage (Umutoni and Samadi, 2024; Sharma et al., 2025). While this issue can be alleviated by training models on data from heterogeneous scenarios, it further underscores the generalization challenge faced by learning models, as it demands an even broader range of high-quality data. This indicates that a model performing well on a particular crop at a specific growth stage, cultivated on a field with distinct pedological characteristics, might perform poorly when applied in a different scenario (Umutoni and Samadi, 2024). This also entails a *cold start* problem: due to their limited generalization capabilities, learning models must first be trained on data specific to a scenario before they can effectively be deployed in it. Umutoni and Samadi (2024) highlight the limitations of black-box machine learning solutions that operate without human oversight in the decision-making process. Although these techniques show potential in supporting irrigation management, further research is required to establish them as transparent decision support tools for domain experts rather than fully autonomous and opaque systems.

Control-theory based. A controller processes the measured system output and computes corrective actions to minimize deviations from a desired set point. Some approaches are documented in literature, ranging from proportional derivative controllers (Goodchild et al., 2015) to more advanced model predictive controllers (Lozoya et al., 2016; Garcia et al., 2025). Goodchild et al. (2015) carried out their evaluation within a controlled polytunnel environment, whereas Lozoya et al. (2016) implemented their approach in an open-field pepper crop. However, the latter approach is built upon oversimplified assumptions that are often invalid in real-world orchards' conditions, such as plain land, absence of surface runoff, no rainfall, and no capillary rise. In contrast, Garcia et al. (2025) conducted their MPC-based approach evaluation in a pecan orchard. Nevertheless, as acknowledged by the authors, a key limitation of their model-based strategy is the need to experimentally determine system parameters for each specific crop, soil type, and irrigation system.

2.3. Distinguishing features

With respect to the cited works, SMARTER:

- is designed to control irrigation of orchards through a controller that solely relies on soil water potential measurements and recent irrigation data as inputs. Using a small number of input variables enhances the explainability of SMARTER's decisions, distinguishing it from black-box models such as ANNs. Also, since we operate in orchards where frequent monitoring and irrigation are usually possible, there is no need to build complex forecast models with many exogenous variables.
- employs a 2D grid of gypsum block sensors, which enables a precise monitoring of the spatial dynamics of water movement within the soil. We choose to employ soil water potential sensors, which, unlike soil water content sensors, do not require labor-intensive calibration tailored to the specific soil properties of the deployment site.

3. Materials and methods

SMARTER (Fig. 1) is an automatic system for the irrigation of orchards that optimizes water consumption while achieving high fruit quality. The *offline* phase includes the deployment of sensors (see Section 3.2) and the definition of the optimal soil-moisture state by *agronomists* depending on the characteristics of fruits, plants, and soils; the optimal state can be changed during the watering season. During the *online* phase, sensor data are continuously collected. Moisture variability is due to both the irrigation system (e.g., single or double lines of drippers) and plant transpiration; SMARTER uses a 2D grid of sensors to get a better understanding of the water dynamics. Sensor data fuels the Monitoring module (Section 3.3), which models the current state of soil moisture in the field through artificial intelligence. Then, the Prescriptive Watering module (Section 3.4) recommends a water advice given the current state of soil moisture and the past advice. The water advice represents how much water is necessary to keep the soil moisture as close as possible to an *optimal state*.

3.1. Assumptions

SMARTER takes decisions based on "certain" data: 2D grids of soil moisture sensors (e.g., gypsum block sensors[1]) and past irrigation. The underlying assumption is that *past* sensor-based measurements provide a good combination of simplicity, robustness, and precision. This statement is supported by the following considerations.

Soil moisture changes gradually, so it is usually sufficient to make irrigation adjustments afterward to keep it within the optimal range.

External events affecting soil moisture (e.g., heavy rains) can be detected through frequent, precise sensor measurements. Other "certain" events (e.g., fertigation) can be manually accounted for in advance, keeping SMARTER both simple and adaptable.

Forecasting typically requires training and tuning in the specific field, thus increasing complexity and preventing fast adoption. Although future weather forecasts (e.g., precipitation and temperature) can provide useful insights, their inherent uncertainty often limits their practical value. On the one hand, if an orchard can be frequently irrigated (e.g., every 1–2 days), there is no point in integrating predictions on uncertain events since field conditions do not change abruptly from one day to the next. On the other hand, field conditions are more dynamic for low-frequency irrigation (e.g., every 5–7 days). However, the longer the time interval, the lower the trustworthiness of future forecasts. For instance, a forecast predicting heavy rainfall in the next 7 days might induce a predictive system to reduce irrigation. If the rainfall does not occur, plants would face water stress for longer irrigation intervals, and failed predictions would require even more drastic corrective actions.

Following these considerations, we assume that it is simpler and more interpretable to make decisions based on actual data than to integrate predictive strategies that accumulate errors from uncertain events.

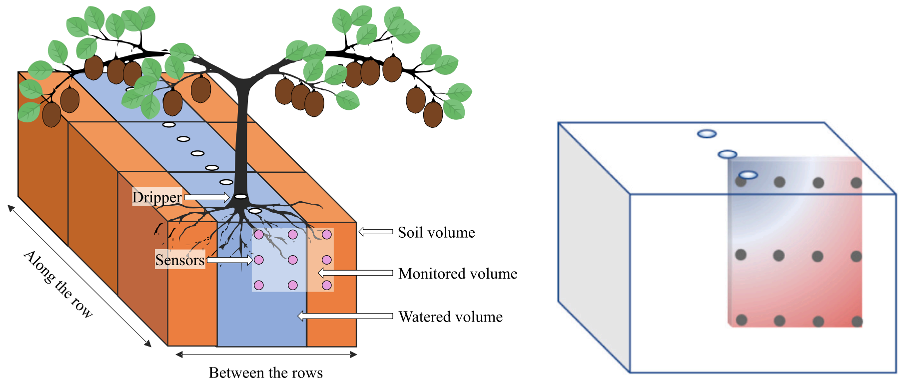
3.2. Setup of sensors

Fruit orchards are usually organized in sectors: areas irrigated with the same irrigation system. Each sector is further decomposed into rows of fruit plants. A grid of sensors is deployed for each sector and is assumed to be representative of the whole sector. In case of intra-sector heterogeneity (Hamouda et al., 2024), it is possible to install multiple grids to represent different homogeneous sub-areas and to compose their prescriptions (e.g., by averaging the amount of water necessary in each sub-area).

The setup of the sensors follows these steps.

1. Determine the *soil volume*: the portion of the soil occupied by most of a plant's roots (Fig. 2(a)).
2. Determine the *watered volume*. Different irrigation systems can be adopted, such as drippers or sprinklers located along the tree lines. The choice of the irrigation method determines the *watered volume*: the portion of the soil that the irrigation system can effectively moisten (Fig. 2(a)). While sprinklers cover a wide area and produce uniform irrigation, drippers cover narrower areas where moisture is not uniform and decreases with the distance from the dripper.
3. Determine the *monitored volume*. The sensor grid should be arranged to capture moisture variability caused by both the irrigation system and plant transpiration. Consequently, it must cover *at least* the watered volume and, ideally, the entire soil volume. In practice, however, covering the entire soil volume is rarely feasible, both for logistical reasons (e.g., avoiding damage from vehicle passage) and for economic reasons (i.e., the substantial amount of sensors required). Moreover, since prescriptive irrigation can only influence the watered volume, monitoring the entire soil volume would provide only limited additional value. The most effective setup is to place one column of sensors as close as possible to a plant and another column just beyond the boundary separating watered and unwatered zones; this boundary can be identified empirically through simple field observations. The remaining sensor columns can then be distributed at equal intervals. In sprinkler irrigation, where no clear

[1] Gypsum-block sensors use two electrodes placed into a small block of gypsum to measure soil water tension. Wires connected to the electrodes are connected to either a portable hand-held reader or a data logger. The amount of water in the soil is determined by the electrical resistance between the two electrodes within the gypsum block. The presence of more water in the soil will reduce resistance, while less water will increase it.



(a) Relevant elements in an orchard. (b) Monitored soil volume.

Fig. 2. Simplified representations of a kiwifruit orchard and the deployed sensors. Sensors (circles) are deployed orthogonally to the dripper/tree line to capture the spatial variability of soil moisture that is typical of fruit orchards.

(a) (b)

Fig. 3. A sensor grid (left) monitoring soil moisture close to a kiwi tree in a commercial orchard located in Faenza, Italy (right). The watering system is composed of single-pipeline drippers.

boundary exists between watered and unwatered zones, the grid can instead be positioned to encompass the primary root mass.

The grid size is a trade-off between robustness and cost. On the one hand, the more sensors, the better the accuracy of representing soil moisture dynamics and the greater the robustness of SMARTER to hardware faults. On the other hand, too many sensors are not deployable due to economic and (spatial) field constraints. In Francia et al. (2022), we studied the trade-off between accuracy for grids including from 4 (i.e., 2 columns with 2 sensors at different depths; the minimum number of sensors for a regular grid) to 12 sensors (i.e., $4 \cdot 3$; the grids we leverage for research purposes), and we demonstrated that grids of 9 (i.e., $3 \cdot 3$) or 6 (i.e., $3 \cdot 2$) sensors provide an accurate representation of soil moisture dynamics.

Example 1. In an orchard in a flat region, single pipelines of drippers moisten "circles" with a radius of around 50 cm. To control the monitored volume, we use four columns of three sensors at different distances (e.g., 0 cm, 25 cm, 50 cm, and 75 cm) and depths (e.g., −20 cm, −40 cm, and −60 cm for kiwifruit); see Fig. 3. The maximum distance from the tree (75 cm) is determined by the area moistened by drippers (75 cm > 50 cm), while depths are determined by the shape of the roots of the kiwifruit plant.

3.3. The Monitoring module

The goal of this module is to approximate the actual soil moisture (Fig. 4(a)) with a soil moisture profile (Fig. 4(c)) using a grid of sensors (Fig. 4(b)).

Definition 1 (*Sensor Grid*)**.** A *sensor grid* $S = \{s^1, \dots, s^{|S|}\}$ is a 2-dimensional layout of $|S|$ sensors installed in a soil volume. Each *sensor* s^i is defined by a 2-dimensional displacement $(s^i.x_1, s^i.x_2)$ with respect to the plant, and by a soil moisture value $s^i.v$.

After sampling the data, we interpolate a soil moisture profile (Fig. 4(c)).

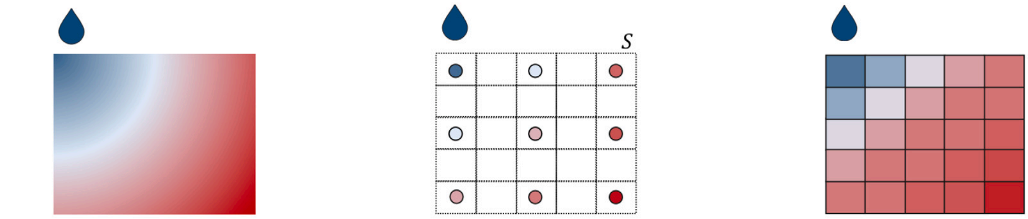
Definition 2 (*Moisture Profile*)**.** Given a 2-dimensional sensor grid S, the *moisture profile* is a 2-dimensional grid $P = \{p^1, \dots, p^{|P|}\}$ that approximates, in each p^i, the soil moisture measured by S. P is *fine-grained* with respect to S since $|P| > |S|$.

The approximation $p^i.v$ is assumed to be constant in the region surrounding p^i, whose granularity (i.e., the covered area of the order of cm^2) depends on $|P|$.

Soil moisture profiles can be obtained using statistical techniques such as bilinear interpolation or machine learning (Francia et al., 2022). In this work, SMARTER uses bilinear interpolation to create soil moisture profiles based on sensor data.

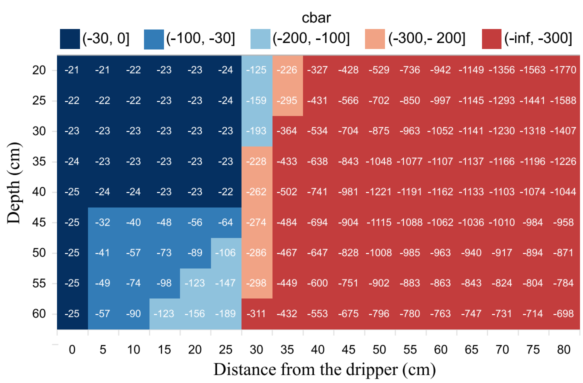
3.4. The Prescriptive Watering module

For each monitored field, *agronomists* specify the optimal soil moisture profile (i.e., the optimal soil moisture distribution for a given plant in a given field) and the preferred irrigation time t; the optimal profile can be manually defined or selected from those collected by the Monitoring module. Choosing the optimal moisture level in orchards is a common task even in traditional farming: agronomists control irrigation by looking at the state of the orchard and other relevant factors,

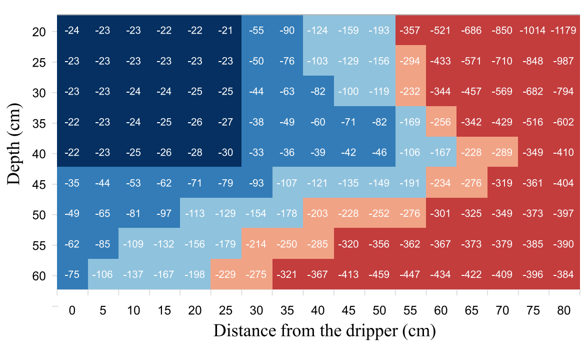


(a) Actual soil moisture. (b) Raw sensor grid (c) Soil profile

Fig. 4. Computing a fine-grained soil moisture profile from a grid of sensors. Starting from a continuum of soil moisture (a), the sensor grid samples soil moisture (b) out of which SMARTER builds a detailed soil moisture profile (c).



(a) Current soil moisture profile.



(b) Optimal soil moisture profile.

Fig. 5. Examples of soil moisture profiles from the Ancarani orchard. The goal of Prescriptive Watering is to bring the current soil moisture (a) as close as possible to the optimal profile (b) by providing the minimal amount of necessary water.

and they even do that "blindly" without quantitative information from the field since this decision is often left to their expertise alone. The added value of SMARTER is leveraging sensors to understand the soil-moisture dynamics and reach an optimal level specific to that orchard (and phenological state, etc.) through data-driven decisions.

For the sake of clarity, with *agronomist* we refer to people with a "scholar" background as well as a good understanding of the orchard and its dynamics, and with *farmer* we refer to people using traditional irrigation techniques. Nonetheless, in real orchards, SMARTER has been used by both agronomists and farmers with agronomic knowledge about the crop, the capability to map a qualitative optimal moisture profile to a quantitative measure of soil moisture potential, and minimum digital skills. Noticeably, none of the farmers had problems in defining the conversion from qualitative profile to quantitative soil moisture potential.

Definition 3 (*Optimal Moisture Profile*)**.** The *optimal moisture profile* $\hat{P}$ is a target moisture profile that indicates the soil moisture distribution (of the monitored volume) that should be achieved and maintained through irrigations to optimize orchard production.

Prescriptive Watering brings the current soil moisture profile (Fig. 5(a)) as close as possible to the optimal soil moisture profile (Fig. 5(b)). Converging towards the optimal profile ensures that soil moisture is kept in equilibrium during the irrigation season.

Example 2 (*Prescriptive Watering*)**.** Fig. 6 shows the behavior of SMARTER on a real kiwifruit orchard. The average soil moisture of the sensed profile (blue line) is kept close to the optimal state (green line) by controlling daily irrigations (purple bars). Divergence is due to weather and soil dynamics, and is automatically corrected by the prescriptive algorithm. The significant divergence since September 7th is due to heavy precipitation (red bars). SMARTER becomes aware of these events from the sensors and stops the irrigation.

3.4.1. The prescriptive watering algorithm

At the designated irrigation time t (e.g., every day at 9:00), the system computes the distance between the sensed and the optimal soil moisture profiles. Such distance and the past irrigation are the inputs necessary to compute the new irrigation. The distance between the current (Fig. 5(a)) and optimal (Fig. 5(b)) profiles at time t is computed cell-wise.

$$e^t = \frac{\sum_{i=1}^{|P|} (\ln(|P_i^t|) - \ln(|\hat{P}_i|)) \cdot W_i}{\sum_{i=1}^{|P|} W_i} \tag{1}$$

We weight the distance calculation with a matrix W of $|P|$ weights, where each cell is a weight $W_i \in [0, 1]$. Weights can be tuned by agronomists (if unspecified, weights are set to 1 by default) and determine the degree to which each cell contributes to the distance from the optimal soil moisture profile. If the given irrigation system cannot directly water a portion of the soil volume, such a portion should be assigned lower weights compared to cells within the watered volume (Fig. 7(a)). This prevents inefficiencies in water management: without a weight matrix, if the chosen optimal profile suggests high moisture levels in areas that the irrigation system cannot reach, the system may waste water to erroneously attempt to achieve unattainable moisture levels in those areas. Since gypsum block moisture sensors measure soil water potential (which ranges from values ranging in the orders of -10^3 to -10^1), a logarithm is applied to the absolute value of each moisture value. The cell-wise distances are depicted in Fig. 7(b), and they are finally averaged into e^t.

The computed distance e^t is fed to a Proportional–Integrative (PI) controller that determines the recommended irrigation amount to bring the distance from the optimal state as close to zero as possible. A PI controller is a widely utilized feedback control mechanism, particularly in managing dynamic systems where achieving precision and stability is essential. The controller regulates and maintains a process variable as close as possible to a desired output by combining two different

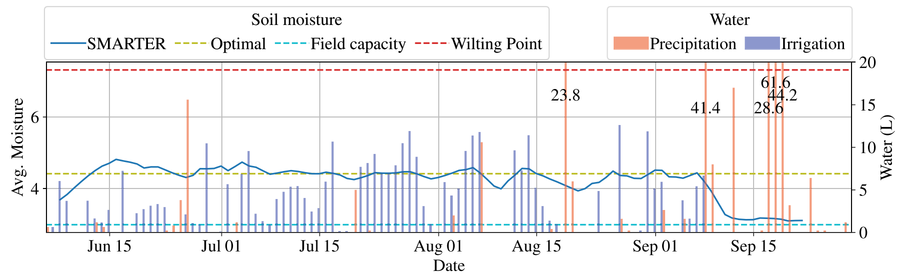
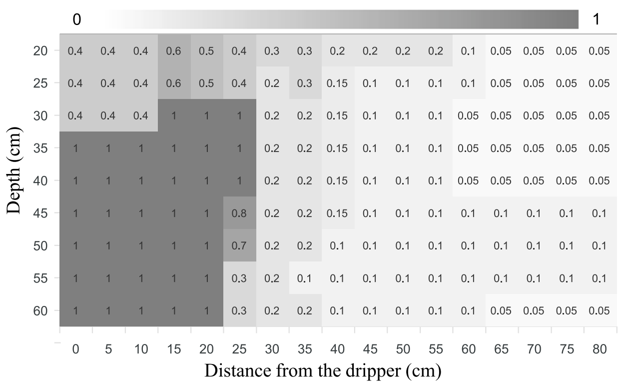
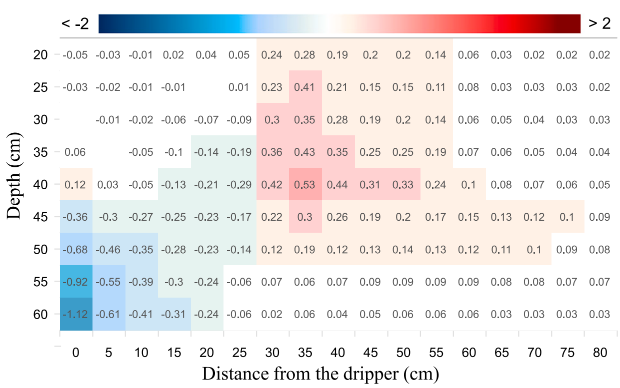


Fig. 6. Comparison of SMARTER (blue line) and optimal (dotted green line) average soil moisture levels on a logarithmic scale (where higher/lower values indicate drier/wetter conditions) in the Ancarani orchard (Faenza, Italy) during 2024. Bars represent the recommended irrigation (in blue, liters per dripper) and the precipitation events (in red, liters per m^2).



(a) Weights set by agronomists.



(b) Cell-wise distances.

Fig. 7. Examples of cell-wise (a) weights (b) and distances from the Ancarani orchard. Cell-wise distances are computed between Figs. 5(a) and 5(b).

control actions: a proportional control, which produces an output that is directly proportional to the current error, and an integral control, which allows the controller to account for the cumulative error over time. Combining these two effects allows a PI controller to respond to both current deviation and accumulated errors.

$$\Delta u^t = K_P \cdot \left(e^t - e^{t-\Delta t}\right) + K_I \cdot e^t \tag{2}$$

$$u^t = advice^{t-\Delta t} + \Delta u^t \tag{3}$$

$$advice^t = \min\left\{\max\left(u^t, 0\right), advice_{\max}\right\} \tag{4}$$

where Δu^t is the proportional–integrative correction, $e^{t-\Delta t}$ is the previous error (e.g., 24 h before), K_P and K_I are hyperparameters that are automatically set in Section 3.4.4.

Algorithm 1 SMARTER

Require: S: sensor grid, $\hat{P}$: optimal soil moisture, W: weight grid, $advice^0$: baseline irrigation (liters), $advice_{\max}$: maximum irrigation (liters), *first*: first irrigation, Δt: time period, K_P: proportional constant, K_I: integrative constant

Monitoring module

1: $S^t \leftarrow sample(S)$ ▷ Read the sensor data
2: $P^t \leftarrow profile(S^t)$ ▷ Compute the current soil moisture profile

Prescriptive Watering module

3: **if** *first* **then** ▷ If it is the first advice
4: $\quad advice^t \leftarrow advice^0$ ▷ Recommend the baseline irrigation
5: **else** ▷ If it is not the first advice
6: $\quad e^t = \frac{\sum_{i=1}^{|P|}(\ln(|P_i^t|)-\ln(|\hat{P}_i|))\cdot W_i}{\sum_{i=1}^{|P|} W_i}$ ▷ Distance between current & optimal profiles
7: $\quad u^t = advice^{t-\Delta t} + \Delta u^t$ ▷ Compute the irrigation amount
8: $\quad advice^t = \min\left\{\max\left(u^t, 0\right), advice_{\max}\right\}$ ▷ ... and bound it

---

K_P and K_I represent proportional and integral gains, respectively, and $advice^{t-\Delta t}$ is the previous recommendation. While the K_P component defines how heavily the controller should react to changes in error, K_I defines how heavily the controller should adjust the output based on the history of the error, addressing any steady-state error. When $e^t - e^{t-\Delta t}$ tends to 0, the error is stable and the contribution of the proportional component is almost null.

Finally, u^t is capped between 0 (no irrigation should be provided) and $advice_{\max}$ (the maximum allowed irrigation) to get the final $advice^t$. Planned events (e.g., fertigations manually scheduled by farmers) can be directly subtracted from u^t; if the difference is zero or negative, no irrigation is recommended.

Example 3 (*Calculating e^t and $advice^t$*)**.** With reference to Figs. 5(a) and 5(b), the value of e^t is 0.06. Given $e^{t-\Delta t} = 0.44$ and $advice^{t-\Delta t} = 9.58$, and assuming $K_P = 1$ and $K_I = 0.25$, it follows that $advice^t = 9.22$.

SMARTER is summarized in Algorithm 1. The algorithm runs at the scheduled irrigation time t, samples the sensor grid (Line 1), and computes the soil moisture profile out of the sensor data (Line 2). For the first irrigation (Line 3) it recommends the baseline as the irrigation amount (Line 4). Otherwise, it computes the distance e^t (Line 6), applies the PI controller (Line 7), and computes the watering amount $advice^t$ (Line 8).

We emphasize that SMARTER is independent of specific soil characteristics, as it makes decisions based on (i) current and past soil moisture states, (ii) previous recommendations, and (iii) the desired optimal state. To simplify decision-making, our system does not use weather forecasts as inputs because soil moisture reflects them: past rainfall affects the current moisture measured by sensors, while the impact of future (uncertain) rain will be captured at the next irrigation. For example, if rain and irrigation occur on the same day, the soil will be wetter, making SMARTER less likely to irrigate the following day.

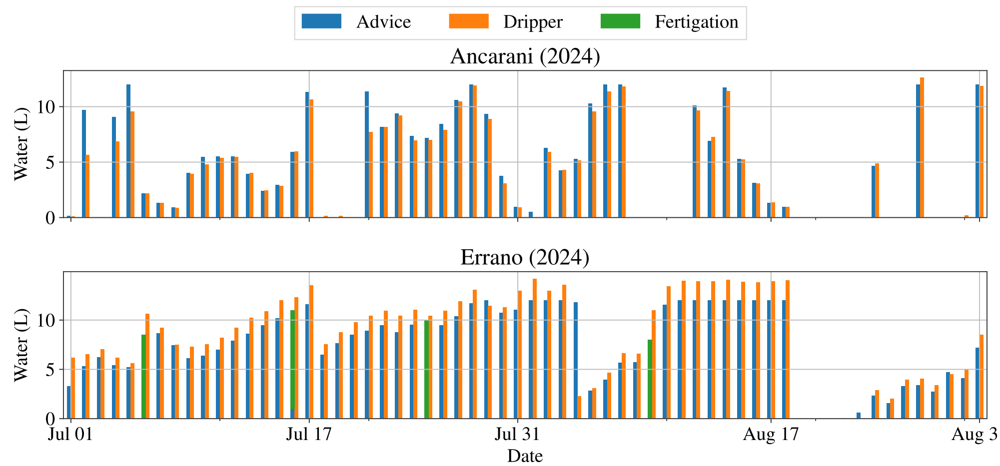


Fig. 8. Comparing recommended (blue bars) and actual irrigation (orange bars) volumes (liters per dripper) in two commercial orchards (Ancarani and Errano). In green, the fertigations that farmers manually schedule.

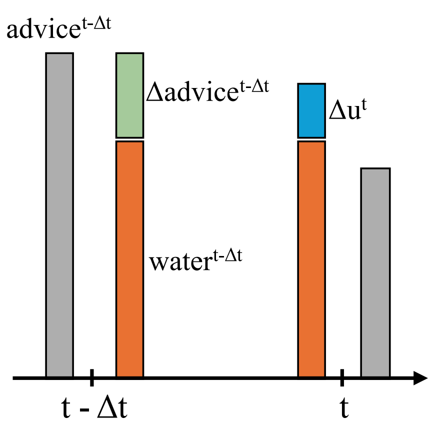


Fig. 9. Feed-forward correction: at time t, the recommended water is the sum of the previous irrigation ($water^{t-\Delta t}$) and the proportional–integrative correction (Δu^t).

3.4.2. Robust handling of irrigation deviations

The amount of water recommended by SMARTER may not precisely match the quantity actually delivered by the irrigation system (which could be measured by a flow sensor, see Fig. 8). For example, some water pumps operate based on activation time rather than water volume. Therefore, a conversion factor is needed to translate the recommended volume (in liters) into the corresponding pump activation time (in hours). Since this is an estimation, the conversion may not be perfectly accurate. Furthermore, pump pressure can vary over time and typically requires some time to stabilize at the desired level.

To address deviations between the recommended and delivered water volumes ($advice^t$ and $water^t$, respectively), if a sensor is available to measure the delivered quantity $water^t$, when calculating u^t, we can apply the following feed-forward correction

$$\Delta advice^{t-\Delta t} = water^{t-\Delta t} - advice^{t-\Delta t} \tag{5}$$

so that Eq. (3) changes to

$$u^t = \underbrace{water^{t-\Delta t}}_{\text{measured actuation at } t-\Delta t} + \Delta u^t \tag{6}$$

For details, see Appendix.

Example 4. Let us consider two irrigation schedules t and t', with $t = t' - \Delta t$ (Fig. 9). As of t, the recommended water was 10 l ($advice^t = 10$), but the actual water delivered to the field was only 8 l ($water^t = 8$). As of t', when computing the $advice^{t'}$, we consider $water^t = 8$ rather than $advice^t = 10$. This ensures that SMARTER is aware of the actual water delivered to the field.

If a sensor measuring $water^t$ is available, we consider Eq. (6) rather than Eq. (4) in Algorithm 1 Line 7.

Henceforth, the recommended irrigation volume is represented *per single dripper*.

3.4.3. Alerting

The optimal soil moisture profile may not always be physically achievable. For example, suppose a uniform moisture level is set as the target for a soil volume irrigated with drippers. In that case, SMARTER will attempt to reach a moisture distribution that is inherently unattainable due to system constraints. Indeed, drippers produce localized, narrow wetting patterns. As a result, the system may overestimate the required irrigation, leading to inefficient water use and unnecessary waste in pursuit of an unrealistic goal.

This issue is mitigated by continuously monitoring the soil moisture profile and refining the target moisture distribution based on historical soil moisture dynamics. Additionally, suppose irrigation requirements change due to evolving plant growth stages. In that case, a new suitable optimal soil moisture profile can be selected to reflect those changes, allowing for more precise and adaptive water management.

To help agronomists, we automatically alert them when SMARTER recognizes plateaus. Given the history of the last h errors $H = [e^{t-h}, \dots, e^t]$, if past errors are all above the threshold ϵ (formally, $|\{e^i : e^i \in H, |e^i| > \epsilon\}| = h$; i.e., we are far from the optimum state) and the derivative is close to 0 (formally, $\frac{e^t - e^{t-h}}{h} < 0.1$), then we alert farmers and agronomists since the system is stuck away from the optimal state (Fig. 10). For instance, the alert is raised when the optimal state is too wet and unachievable due to high evapotranspiration or to exogenous factors that affect the irrigation system.

In our implementation, we consider $h = 5$ days and ϵ as the 10% of the average humidity of the optimal soil moisture profile (dotted line in Fig. 10).

3.4.4. Reference values for K_P and K_I

The parameters necessary to run SMARTER are K_P and K_I (i.e., how fast the system should respond to current and past errors).[2] To adopt SMARTER in a real orchard, we provide the initial setup of K_P and K_I. Then, agronomists observe how the system operates and

[2] The optimal soil moisture profile, weight grids, and maximum irrigation are parameters set based on the experience of the agronomist.

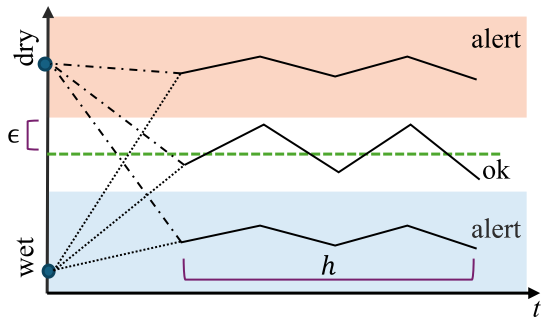


Fig. 10. Examples of soil moisture plateaus causing alerts in SMARTER. For instance, the alert is raised when soil moisture is stable and stuck in the "dry region" (in red) for several consecutive days; this condition could be caused by limited water delivery due to faults in the irrigation system.

Algorithm 2 Tuning K_P and K_I

Require: Soil textures $\boldsymbol{X}$, weather scenarios $\boldsymbol{W}$, range $\boldsymbol{K_P}$, range $\boldsymbol{K_I}$, budget b

1: $(K_P, K_I)^* \leftarrow \emptyset$ ▷ Initialize the best configuration
2: $error^* \leftarrow +\infty$ ▷ Initialize the best error
3: $i \leftarrow 0$ ▷ Initialize the current iteration
4: **while** $i < b$ **do** ▷ While the budget is not expired
5: $error \leftarrow 0$ ▷ Initialize the total error
6: $(K_P, K_I) \leftarrow$ AutoML$(\boldsymbol{K_P}, \boldsymbol{K_I})$ ▷ Choose the next configuration
7: **for each** soil texture $X \in \boldsymbol{X}$ **do** ▷ For each soil texture
8: **for each** weather condition $W \in \boldsymbol{W}$ **do** ▷ For each weather condition
▷ Simulate & get the error
9: $RMSE \leftarrow$ Orchard3D-Lab$(X, W,$ SMARTER$(K_P, K_I))$
10: $error \leftarrow error + RMSE$ ▷ Accumulate the error
11: **if** $error < error^*$ **then** ▷ If the simulation improves the error
12: $(K_P, K_I)^* \leftarrow (K_P, K_I)$ ▷ Set the best configuration
13: $error^* \leftarrow error$ ▷ Set the new error
14: $i \leftarrow i + 1$ ▷ Increase the iterations
15: **return** $(K_P, K_I)^*$ ▷ Return the best configuration

can manually fine-tune it (this may be necessary since fields can have different behaviors).

To define the initial setup, we carried out an extensive set of simulations in a range of feasible values for K_P and K_I, i.e., $\boldsymbol{K_P} = [0, 30]$ and $\boldsymbol{K_I} = [0, 30]$ (we denote with bold symbols domains or set of values); 0 represents no reactivity to errors, while the upper bound represents the highest reactivity. We leverage Orchard3D-Lab (Bittelli et al., 2025), a field simulator based on physical equations that computes soil moisture dynamics. Orchard3D-Lab is a three-dimensional, process-based simulator that computes the soil water balance in orchards, with a focus on fruit trees. It integrates detailed representations of evapotranspiration, root system architecture, and soil–water dynamics under drip irrigation and sloped land conditions. Each simulation of Orchard3D-Lab over a period T requires a time series of weather conditions (including precipitation, solar radiation, wind speed, air temperature, etc.), a soil texture, and the irrigation strategy (i.e., both the irrigation interval and the algorithm determining the irrigation recommendation) — in our implementation Eq. (4). Out of a simulation, we compute the Root Mean Squared Error (RMSE), i.e., how far SMARTER is from the optimal state indicated by the agronomist over the period T.

$$RMSE = \sqrt{\frac{\sum_{t \in T} (e^t)^2}{|T|}} \tag{7}$$

We recall that e^t (Eq. (1)) already represents the distance between the optimal and current state.

Algorithm 2 outlines how the reference values of K_P and K_I are computed, representing the best configuration for different soil textures

Table 1
Reference values of K_P and K_I for different soil textures.

Name	Sand (%)	Silt (%)	Clay (%)	K_P	K_I
Clay Loam	30	30	40	12	3
Sandy Loam	60	30	10	7	3
Silt Loam	30	60	10	10	3

and weather conditions simulated with Orchard3D-Lab. Given a configuration K_P and K_I (Line 6), to assess its stability, for each texture X (Line 7) and for each weather condition W (Line 8) we run a simulation with Orchard3D-Lab and get the RMSE (Line 9). The performance of each configuration is obtained by summing the RMSE (Line 10) for the different soil textures and weather conditions.

If the configuration is better than the previous ones (Line 11), we store it (Line 12) along with its error (Line 13). Our tuning approach selects the next promising configuration (Line 6) of K_P and K_I to explore using AutoML (He et al., 2021) until a budget of iterations is reached (Line 4); the first configuration is extracted at random. Finally, the best configuration of K_P and K_I is returned (Line 15).

We choose a simulation period of one month, a limited number of iterations $b = 100$ (i.e., a constrained budget), four weather conditions from a weather station in Emilia-Romagna (Italy) between 2021 and 2024, and as soil textures we consider $\boldsymbol{X} = \{Clay\ Loam, Sandy\ Loam, Silt\ Loam\}$ (Table 1). Overall, the reference parameters for SMARTER are $K_P = 12$ and $K_I = 3$.

Example 5. Given a Clay Loam soil, Fig. 11 depicts four simulations with different weather conditions and how SMARTER converges to the optimal state with optimal values $K_P = 12$ and $K_I = 3$. Precipitations are represented in red; the complete weather conditions (including temperature, humidity, etc.) can be found in our repository (see Section "Software and data availability").

Example 6. Given the 2021 scenario from Fig. 11, Fig. 12 shows the effects of different values for K_P and K_I by comparing the best ($K_P = 12$ and $K_I = 3$) and worst ($K_P = 22$ and $K_I = 29$) configurations explored by Algorithm 2. Noticeably, higher values of K_P and K_I cause abrupt changes in the irrigation (blue bars), keeping SMARTER farther from the optimal state.

We also tested how K_P and K_I can be fine-tuned with respect to each single soil type ($Clay\ Loam, Sandy\ Loam, Silt\ Loam$). In other words, we consider the reference values for specific soil textures. To do so, we run Algorithm 2 by considering one texture at a time. Table 1 reports the texture-specific reference values of K_P and K_I. On the one hand, the value of K_P ranges from 7 for Sandy Loam to 12 for Clay Loam. Because Sandy Loam soils respond more quickly to variations in soil moisture, the proportional correction is smaller compared to soils like Clay Loam, where moisture levels change more gradually. On the other hand, $K_I = 3$ in all soil textures, meaning that past discrepancies from the optimal state do not depend on the soil texture. Overall, SMARTER provides stable results even across different textures, meaning that soil moisture converges to the optimal state by adapting and reacting to the heterogeneous soil characteristics.

4. Evaluation

We start by evaluating SMARTER based on field experiments in two commercial orchards. Then, we provide the economic evaluation of its adoption in these fields. Finally, we test its robustness for different soil textures and irrigation intervals in a simulated environment, also with respect to existing approaches for automatic irrigation control.

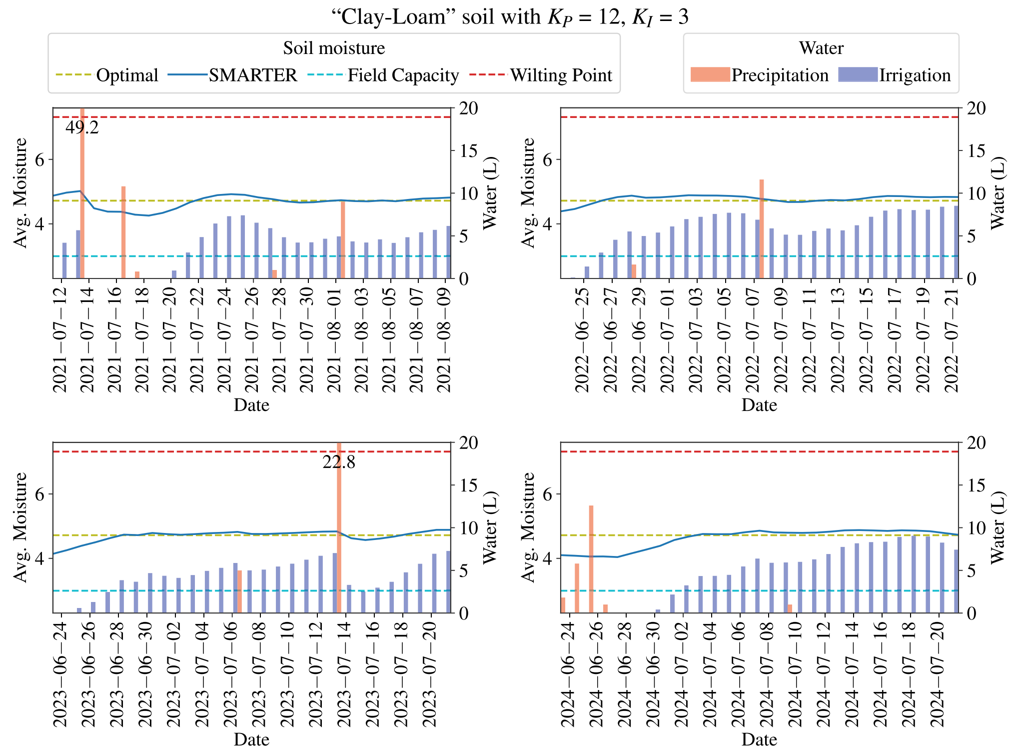


Fig. 11. Behavior of SMARTER (with reference values $K_P = 12$ and $K_I = 3$) along four irrigation seasons with different precipitation events and weather conditions.

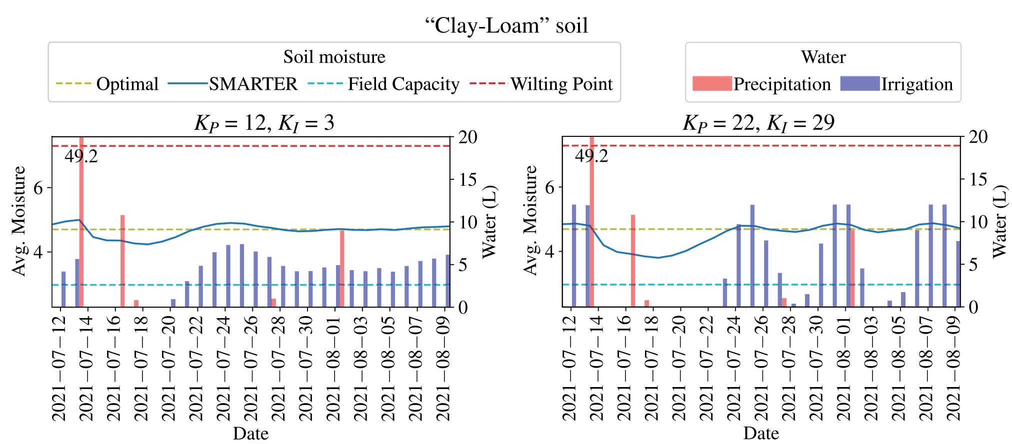


Fig. 12. Comparing the best (left) and worst (right) configuration values of K_P and K_I. Higher values of K_P and K_I cause stronger watering corrections and, consequently, higher soil moisture variations.

4.1. Field experiments

SMARTER is implemented as a cloud-based application that collects sensor data from different orchards to make data-driven decisions on their irrigation. We tested SMARTER from June to October in two commercial kiwifruit orchards in Italy: Errano (located in Ravenna; Fig. 13(a)) since 2023 and Ancarani (located in Faenza; Fig. 13(b)) since 2024. The two orchards have different soil textures, dripper densities, flow rates, plant densities, and sensor layouts. Their distinguishing characteristics are summarized in Table 2.

Irrigation can be scheduled every day at noon (formally, t represents the timestamp for irrigation—such as t = ‘2025-05-15 12:00:00’–and $\Delta t = 24$ h).

Soil moisture is monitored using 2D grids of gypsum block sensors (Fig. 14) that cover portions of the soil volume. We employ gypsum block sensors because they measure water potential rather than water content. Water potential measures how freely water can move from areas of high water potential to low water potential (i.e., how difficult it is for a plant to extract water) and allows agronomists to define reference scales for different stress levels. In contrast, water content is strongly dependent on the specific characteristics of the soil. A soil with relatively low volumetric water content may still provide abundant plant-available water, while a soil with high water content may offer almost none.

Two grids were deployed in each orchard to monitor and compare irrigation sectors managed by SMARTER and the farmer. Every 15 min, irrigation quantities are sampled via a drip flow meter, and weather data is collected via on-site weather stations. Data is sent to the cloud through the SIGFOX protocol. Farmers attended dissemination events where agronomists showed and explained to them the optimal moisture target for kiwifruit; then farmers controlled irrigation with their traditional approaches to reach the target.

(a) Errano. (b) Ancarani.

Fig. 13. Settings of the field experiments in two commercial orchards. Two-dimensional grids of gypsum block sensors are deployed to measure soil moisture, and drippers are automatically controlled by SMARTER: (a) a grid of 4 columns of 3 sensors has been installed, and (b) a grid of 3 columns of 3 sensors has been installed.

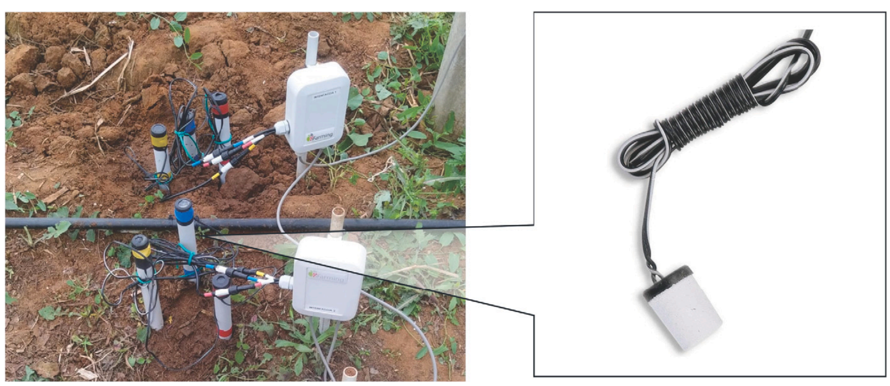


Fig. 14. Gypsum block sensors installed in a grid.

Table 2
Characteristics of the two commercial orchards used for the field evaluation.

Field	Errano	Ancarani
Test seasons	2023/24	2024
Area	10 ha	15 ha
Plant distance	2 m	2.5 m
Row distance	4.5 m	4.5 m
Irrigation	Single wing	Single wing
Dripper flow rate	$4\ \frac{l}{h}$	$2\ \frac{l}{h}$
Dripper distance	0.66 m	0.5 m
#Drippers per ha	3367	4444
Soil texture	Clay Loam	Clay Loam
Sand (%)	30	20
Silt (%)	30	47
Clay (%)	40	33
#Sensors	12	9
Grid layout (columns × rows)	4 × 3	3 × 3
Grid coverage (width × depth)	0.8 m × 0.6 m	0.6 m × 0.6 m

Farmers provided us remote control of their (electric) water pumps, allowing SMARTER to control irrigation automatically. To do so, knowing the capacity of each dripper (watering sectors have homogeneous irrigation systems), we can simply turn on water pumps for an amount of time equal to the ratio of water advice and dripper capacity. We also asked farmers the maximum time span for irrigation ($advice_{\max}$ in Algorithm 1) to ensure that our water management is compliant with their energy and irrigation policies.

Fig. 15 compares the performance of farmers' and SMARTER's managements of two commercial orchards. Tables 3 and 4 summarize statistics on irrigation and fruit quality, respectively. We recall that, at time t, $advice^t$ is the water recommended by SMARTER, $water^t$ is the water actually delivered to the field, and $\Delta advice^t$ is the discrepancy between them. Given a temporal span T, with $advice$ we refer to $\sum_{t \in T} advice^t$, the same goes for $water$ and $\Delta advice$.

The main insights are discussed below.

Convergence to the optimal state. SMARTER keeps soil moisture closer to the optimal state set by agronomists than expert farmers (the blue line is closer to the optimal green line than the purple one in Fig. 15) while also saving water. Noticeably, (i) the RMSE error (see Eq. (7))

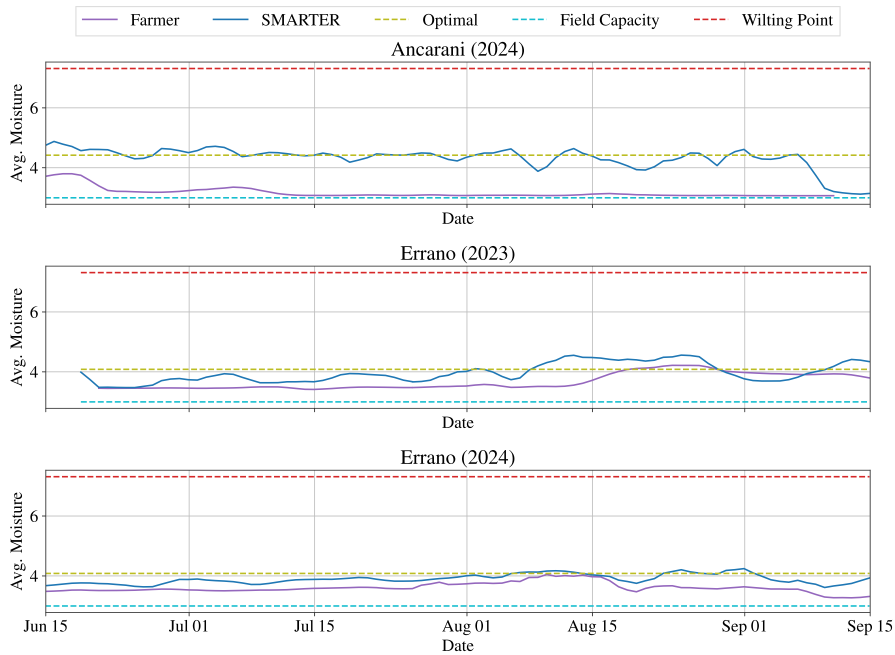


Fig. 15. SMARTER vs. farmer: comparing watering performance from Jun 15th to Sep 15th in two commercial orchards (Ancarani and Errano). Average soil moisture is represented on a logarithmic scale. SMARTER proves to be closer to the optimal state.

Table 3
Summary of *water* consumption (liters per dripper) and RMSE with respect to the optimal soil moisture state for the farmers' and SMARTER's management strategies.

Field	Year	*water* ↓			RMSE ↓	
		Farmer	SMARTER	Saving	Farmer	SMARTER
Ancarani	2024	410	**339**	−17.32%	1.24	**0.22**
Errano	2023	883	**522**	−40.88%	0.43	**0.31**
	2024	787	**670**	−14.87%	0.47	**0.21**

over 92 days (from Jun 15th to Sep 15th) is higher for the farmer's management (Table 3), and (ii) SMARTER is in the optimal range (i.e., within a distance of $\pm 10\%$ of the optimal state) in 80% of the days of the irrigation season, while for the farmer's management it is only 50%. Divergence from the optimal state is due to environment and weather conditions (e.g., significant precipitation), but the system reacts to and eventually recovers from them.

In SMARTER, the amount of applied water is adjusted automatically using a PI control system. The proportional part of the controller reacts to the difference between the desired soil moisture and the actual moisture. The integral part looks at how long this difference has existed, and reacts to the cumulative difference that adds over time. Together, they correct both immediate and long-term changes in soil moisture.

During an extreme drought, the proportional part reacts strongly because the difference is large, and the integral part increasingly reacts because the soil has been dry for a prolonged period of time. As a result, both parts push the system to apply a large amount of water. The delay between the irrigation event and the change in soil moisture is responsible for a response lag that could lead to an overshoot: the soil becomes too wet and, as soon as this change is detected by sensors, SMARTER decreases the amount of irrigation once again.

During heavy rainfall, the following considerations are necessary. First, the correction applied by SMARTER is asymmetric (we can wet dry soils, but we cannot dry wet soils). Second, the correction depends on the soil conditions over time. If the soil has already been saturated (e.g., due to prolonged rainfall), the proportional and integral terms provide no contributions (the soil has been wetter than the optimal state for some time). If rainfall occurs when the soil is drier than the optimal, the proportional term provides no water, but the integral term may still be adding water because it has not yet adjusted from earlier dry conditions. This could cause the system to keep irrigating longer than needed, showing a form of response lag as the integral part incrementally corrects itself.

Overall, our tests over four years with different weather conditions in two different locations showed that when outside the optimal range, SMARTER recovers in 1.5 days in dry conditions and 3 days in wet conditions. In case of extreme/outlier events, the farmer can compensate with manual corrections to SMARTER. This would act as a feed-forward signal to the decision provided by the PI controller, including additional information on weather or environmental conditions.

Water saving. An excerpt comparing the daily irrigation provided by SMARTER and farmers is shown in Fig. 16. For example, in Ancarani, farmers maintain a constant level of irrigation, even when it is unnecessary, whereas SMARTER continuously adapts irrigation to the monitored soil moisture profile.

Table 3 presents the total volume of *water* supplied by SMARTER and the farmers, the overall water savings achieved, and the deviation of both SMARTER's and the farmers' management from the optimal soil moisture profile, measured by RMSE. SMARTER achieves savings of up to 40% (where $Water\ Saving = \frac{water_{\mathrm{SMARTER}} - water_{Farmer}}{water_{\mathrm{SMARTER}}}$), with the greatest reductions occurring in June and September. During these months, farmers often struggle to assess soil moisture levels accurately and tend to over-irrigate. On the other hand, July and August are hotter months and higher water volumes are genuinely needed, leading to a smaller gap between the irrigation patterns of farmers and SMARTER. The lower water savings observed in 2024 compared to 2023 can be primarily attributed to differences in precipitation during June, July, and September (Fig. 6). In 2024, increased rainfall reduced irrigation needs during the months when SMARTER typically yields the highest savings.

Fruit quality. Table 4 presents a comparison of kiwifruit production and quality. Overall, enhancements in fruit quality are evident, reflected by a lower proportion of overripe fruits, higher sugar content (RSR), and increased dry matter percentage, all contributing to a longer

Table 4
Summary of kiwifruit quality analysis: overripe fruits were assessed after two months of cold storage, while all other samples were evaluated at harvest.

Field	Year	Management	Size (g/fruit) ↑	Firmness (Kg) ↑	RSR (°Brix) ↑	Dry mass (%) ↑	Color (°Hue) ↓	Overripe (%) ↓
Errano	23	Farmer	**143**	**5.50**	10.10	17.40	104.60	8.0
		SMARTER	**143**	5.20	**11.60**	**18.20**	**102.90**	**2.0**
	24	Farmer	142	**6.00**	8.88	18.10	**104.80**	1.4
		SMARTER	**150**	5.90	**9.50**	**18.40**	104.90	**0.0**
Ancarani	24	Farmer	**149**	**4.94**	10.50	17.60	102.40	**0.0**
		SMARTER	140	4.86	**12.30**	**18.60**	**100.80**	**0.0**

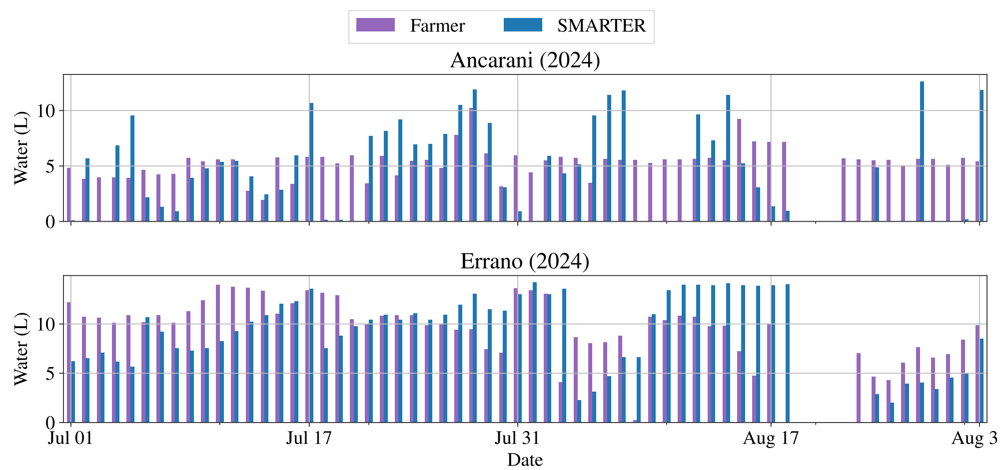


Fig. 16. SMARTER vs. farmer: comparison of daily irrigation per dripper in liters. Farmers tend to have constant watering amounts, providing water even when it is not necessary.

Table 5
Relative difference between the *water* delivered to the field and the *advice* by SMARTER. *water* and *advice* represent liters per dripper.

Field	Year	*water*	*advice*	$\Delta advice$
Ancarani	2024	339	370	−8.38%
Errano	2023	522	477	9.43%
	2024	670	557	20.29%

shelf life. A more detailed analysis of kiwifruit quality is provided in Baldi et al. (2023).

Deviations in the watering system. Table 5 summarizes the deviations between the amount of water recommended by SMARTER ($advice^t$ in Eq. (4)) and the amount actually delivered to the field ($water^t$) over the entire irrigation season T. Deviations may be positive or negative and vary in magnitude, underscoring the need for SMARTER to account for them; see Eq. (6).

4.2. Economical impact

We provide a cost analysis for our pilot studies, where we compare the energy and water costs by operating manual irrigation and SMARTER (note that this is not a generic, all-encompassing cost–benefit analysis for commercial applications). SMARTER is based on commercial hardware provided, installed, and maintained by an Italian IoT service provider.

Table 6 details the capital and operational costs. Electricity and water costs are averaged to 0.5 $\frac{€}{\text{kWh}}$ and 0.4 $\frac{€}{\text{m}^3}$. Both orchards rely on water pumps that can supply water to the entire field simultaneously with a power consumption of 10 kW. Based on the orchards' characteristics and the water consumption reported in Tables 2 and 3, Table 7 summarizes the yearly costs and savings per hectare. Assuming a three-year depreciation period for the system, the annual cost amounts to 1150 $\frac{€}{\text{year}}$. Under this assumption, the break-even point for SMARTER (considering a single sensor grid) exceeds one year only for orchards smaller than 5 ha. For larger orchards, the break-even point is reached within one year, even when accounting solely for water and electricity savings.

Table 6
Capital and operational costs details. Capital costs refer to a complete grid installation, whereas operational costs refer to maintenance and electricity and water costs (averaged over two years and across the two orchards).

Capital costs		Operational costs			
HW	Installation	SW licenses	HW maintenance[a]	Water	Electricity
1600 €	500 €	250 $\frac{€}{\text{year}}$	200 $\frac{€}{\text{year}}$	0.4 $\frac{€}{\text{m}^3}$	0.5 $\frac{€}{\text{kWh}}$

[a] It includes periodic system checks and replacements in case of breakage; the most vulnerable component is the gypsum block sensor, which costs 50 €.

Table 7
Comparison between the farmer and SMARTER management: yearly costs and savings for the two orchards.

Field	Size (ha)	Management	Consumption Water (m^3)	Consumption Electr. (kW)	Cost Water ($\frac{€}{\text{year}}$)	Cost Electr. ($\frac{€}{\text{year}}$)	Saving per ha ($\frac{€}{\text{year ha}}$)	Saving Total ($\frac{€}{\text{year}}$)
Errano	10	Farmer	27 831	2088	11 132	1044	–	–
		SMARTER	**19 865**	**1490**	**7946**	**745**	349	3485
Ancarani	15	Farmer	27 330	2050	10 930	1025	–	–
		SMARTER	**22 600**	**1698**	**9080**	**848**	138	2071
						Average	243	2778

Table 8
Comparison of RMSE and irrigation amounts (liters per dripper) across soil textures, irrigation intervals, and strategies. SMARTER consistently provides the best performance with respect to its competitors.

Soil texture	Irrigation interval	RMSE ↓			*water* ↓		
		ET0	GBRT	SMARTER	ET0	GBRT	SMARTER
Clay Loam	1	67.17	46.43	**17.16**	776	725	**528**
	2	63.18	66.41	**18.99**	769	878	**523**
	3	58.57	71.54	**21.40**	741	901	**490**
	5	81.21	68.99	**26.26**	655	864	**453**
	7	42.22	79.47	**32.01**	769	955	**586**
Sandy Loam	1	65.47	38.87	**23.17**	777	658	**501**
	2	61.40	58.73	**26.36**	769	787	**481**
	3	58.90	55.65	**28.21**	741	737	**440**
	5	76.47	67.19	**35.42**	655	662	**396**
	7	56.30	78.35	**42.53**	769	1009	**481**
Silt Loam	1	93.71	35.90	**18.75**	777	730	**610**
	2	42.43	60.68	**22.96**	769	928	**599**
	3	38.04	61.03	**25.98**	741	891	**550**
	5	58.94	61.65	**31.65**	655	849	**521**
	7	41.57	74.74	**39.68**	769	1084	**637**

4.3. Robustness of SMARTER and comparison with existing approaches

To assess the robustness of SMARTER, we simulate three distinct orchards with different soil textures (loamy, sandy, and silty soils), irrigated at different intervals (from 1 to 7 days), and with four different weather conditions between 2021 and 2024. In this setup, we compare SMARTER against an evapotranspiration-based baseline (ET0), which follows the method proposed by Zheng et al. (2025), and against Gradient Boosted Regression Trees (GBRT), a machine learning model employed by Goldstein et al. (2017) for predicting irrigation requirements. The complete experimental setup and implementation are publicly available for reproducibility at https://github.com/big-unibo/smarter.

Table 8 summarizes the results: each cell represents the cumulative RMSE error across four periods of simulation in different years and under different weather conditions. We recall that the RMSE is computed for each scenario as the daily deviation from the optimal state at the decision-making time and then accumulated across each scenario.

Inputs. The evaluated irrigation strategies differ in the input data they require to make their recommendations.

- ET0 is computed using the Penman–Monteith equation that approximates net evapotranspiration (ET) from meteorological data, as a replacement for direct measurement of evapotranspiration. ET0 serves as a baseline for estimating the water needs of other crops. To find the water needs for kiwifruit, we multiply ET0 by an average crop coefficient (Kc) equal to 1[3]; i.e., $ETc = ET0 * 1$.
- GBRT (Goldstein et al., 2017) is built on 16 features (including current/past soil moisture at different depths and past/future weather conditions) and learns to relate them to the irrigation manually applied by the farmer. In other words, it emulates what a farmer would do in different scenarios.
- SMARTER is based on the sensor grid and determines the irrigation amount based on the distance between the current and optimal states.

Training and tuning. The approaches also differ in how they need to be adapted to different scenarios.

- ET0 does not require adjustments through different soil textures (Penman–Monteith is computed from meteorological data) nor for different irrigation intervals (evapotranspiration is aggregated over time).
- GBRT (Goldstein et al., 2017) must be retrained for different soil textures and different irrigation intervals since farmers' decisions change in different conditions. Before being applied, GBRT requires collecting manual irrigation data under many different weather and soil conditions, and a full retraining for each irrigation interval and soil texture.
- SMARTER can be applied to different soil textures by using its reference parameters $K_P^{ref} = 12$ and $K_I^{ref} = 3$ (see Section 3.4.4). Using SMARTER with different irrigation intervals benefits from tuning the values of K_P and K_I: longer intervals require bigger corrections proportionally to the days elapsing between irrigations: $K_* = K_*^{\text{ref}} \cdot \left(1 + \frac{\text{days}-1}{2}\right)$. For instance, given $K_P^{ref} = 12$ and $K_I^{ref} = 3$ and an irrigation interval of 2 days, it is $K_P = 12 \cdot 1.5 = 18$ and $K_I = 3 \cdot 1.5 = 4.5$.

Results. SMARTER consistently maintains soil moisture closer to the optimal state across all soil textures and irrigation intervals, while simultaneously reducing the total water applied to the field. This improvement can be attributed to SMARTER's capacity to limit over-irrigation, which typically occurs during early and late irrigation seasons, after heavy rainfall events, and in the case of low-frequency irrigation (ET0 and GBRT tend to result in frequent over-irrigation). While ET0 is a baseline solution that requires no maintenance and no cold start, its applicability to decision-making is too simplistic to represent the ongoing dynamics of a real orchard. Conversely, the primary limitation of machine learning solutions is the substantial amount of real-world quality and heterogeneous data required for training. Data can only be collected during irrigation seasons, which usually span from June to October in Italy, complicating the development and validation of robust models.

Finally, a proportional relationship can be observed between RMSE and irrigation interval, highlighting the importance of the trade-off between longer irrigation intervals and the regulation of hydric stress.

5. Conclusions

This paper introduces SMARTER, a control theory-based smart irrigation system that relies on a fine-grained soil moisture profile to determine the irrigation needs of kiwifruit orchards. Given data from in-situ sensors, SMARTER models the current state of soil moisture and computes the amount of water necessary to reach an optimal state set by agronomists. The main advantages of the proposed approach are its simplicity and transparency in the decision-making process (e.g., no weather forecasting models or training data are necessary) and robustness to its adoption in different weather, soil, and irrigation conditions. SMARTER smoothens the problems related to point measurements by applying a grid of soil moisture sensors; in the case of heterogeneous orchards, multiple grids could be installed, and their recommendations aggregated to derive an averaged irrigation recommendation.

Empirical results in two commercial kiwifruit orchards over two years show that SMARTER saved up to 40% of water while maintaining comparable (or better) fruit quality with respect to farmers' irrigation practices. With respect to farmers' water management, the break-even point is one year for orchards bigger than 5 ha, even by considering only water and electricity savings. During the two years of experimentation and in the dissemination events where we demonstrated SMARTER, no agronomist reported problems in interpreting the data and data-driven decisions.

Future works include (i) applying this approach to different crops such as grapes and pears to further evaluate its robustness across crop varieties, (ii) incorporating annual water budget constraints (e.g., limiting irrigation to a maximum of 2000 liters per hectare per watering season), and (iii) the integration of remote-sensing data for a better management of orchard heterogeneity (e.g., satellite images could provide aggregated – but less accurate – information that is complementary to spot measurements).

[3] https://www.fao.org/4/x0490e/x0490e0b.htm.

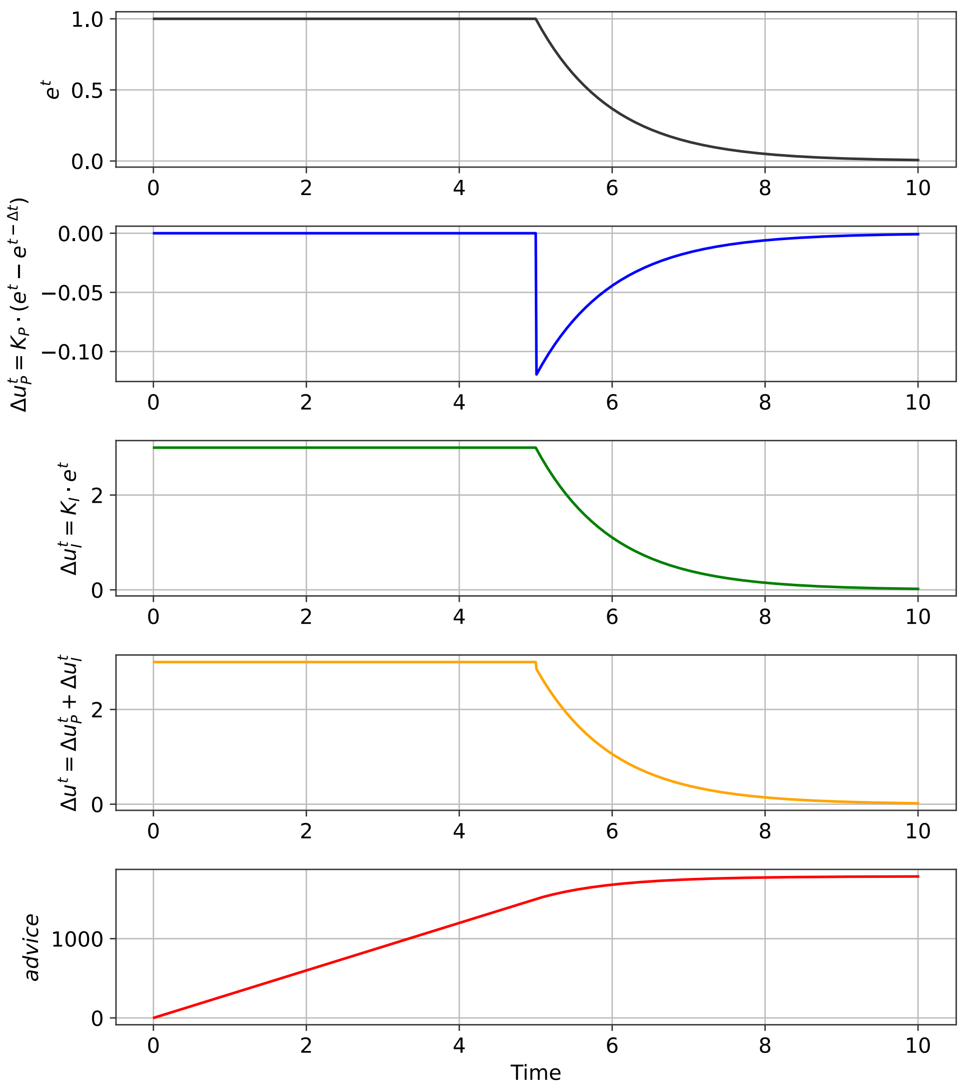


Fig. 17. Behavior of a PI controller, where e is the error function, and Δu_P and Δu_I are the contributions of the proportional and integral components. $advice$ incrementally increases until the error stabilizes to 0.

CRediT authorship contribution statement

Alex Baiardi: Visualization, Validation, Software, Formal analysis, Data curation, Conceptualization. **Matteo Francia:** Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matteo Golfarelli:** Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Conceptualization. **Alessandro Vittorio Papadopoulos:** Writing – original draft, Validation, Formal analysis, Conceptualization. **Manuele Pasini:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Software and data availability

The experimental settings and data are available in the GitHub repository at https://github.com/big-unibo/smarter. A demo of SMARTER is available at https://big.csr.unibo.it/projects/smarter/.

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.

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Appendix. PI controller implementation with actuator compensation

This appendix summarizes the discrete-time PI control laws discussed above, including:

1. The standard velocity-form PI.
2. Replacing the internal "old advice" term with the measured actuator output (water) to achieve built-in anti-windup.

A.1. Velocity-form PI (Baseline)

A textbook discrete-time PI controller in *velocity form* is written as

$$\Delta u^t = K_P \cdot \left(e^t - e^{t-\Delta t}\right) + K_I \cdot e^t, \tag{A.1}$$

$$u^t = advice^{t-\Delta t} + \Delta u^t, \tag{A.2}$$

$$advice^t = \min\left\{\max\left(u^t, 0\right), advice_{\max}\right\}, \tag{A.3}$$

where:

- e^t is the control error at time t.
- u^t is the (unsaturated) PI output at time t.
- $advice^t$ is the saturation of u^t between 0 and $advice_{\max}$.
- K_P and K_I are the proportional and integral gains, respectively.

Eq. (A.1) computes the incremental change in the controller output, and (A.2) accumulates that change. When $advice^t$ saturates, the integrator in effect winds up if nothing corrects it. Fig. 17 shows how the proportional and integral components of a PI system behave given $K_P = 12$, $K_I = 3$, and the error function e^t.

A.2. Using measured actuator output ($water$) to replace old advice

To prevent windup when $advice^{t-\Delta t}$ differs from what the actuator actually delivered (denoted $water^{t-\Delta t}$), one replaces the "old" term $u^{t-\Delta t}$ in (A.2) with $water^{t-\Delta t}$. Define

$$\Delta advice^{t-\Delta t} = (water^{t-\Delta t} - advice^{t-\Delta t}), \tag{A.4}$$

Then, the modified equations become:

$$\Delta u^t = K_P \cdot \left(e^t - e^{t-\Delta t}\right) + K_I \cdot e^t, \tag{A.5}$$

$$u^t = advice^{t-\Delta t} + \Delta u^t + \Delta advice^{t-\Delta t} \tag{A.6}$$

$$= advice^{t-\Delta t} + \Delta u^t + water^{t-\Delta t} - advice^{t-\Delta t} \tag{A.7}$$

$$= \underbrace{water^{t-\Delta t}}_{\text{measured actuation at } t-\Delta t} + \Delta u^t, \tag{A.8}$$

$$advice^t = \min\left\{\max\left(u^t, 0\right), advice_{\max}\right\}. \tag{A.9}$$

By feeding in $water^{t-\Delta t}$ instead of $advice^{t-\Delta t}$, any mismatch due to saturation or nonideal actuator behavior is immediately "seen" by the integrator. In effect, this yields built-in anti-windup.

Data availability

Data will be made available on request.

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