Sustainable Water Management in an Evolving Tomato Cultivation Testbed

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***Abstract*—Nowadays traditional agricultural irrigation practices present significant challenges for both sustainability and productivity, resulting in excessive water consumption—70% of the world's water consumption is dedicated to agricultural irrigation—and inefficient resource management. The adoption of innovative solutions and technologies to support smart agriculture applications allows to overcome these problems and improve the productivity in terms of crop yield, fruits quality, efficiency, resource management, and waste reduction. Guided by these goals, this work examines the activities carried out within the NextGenerationEU-funded AGRITECH project in an evolving tomato cultivation testbed. The evaluation has been conducted for two consecutive years, namely, 2023 and 2024, with the deployment of Internet of Things devices and the support of the *Agriware* cloud platform. In particular, the automated irrigation system deployed during the second year of experimentation allowed for more precise and efficient irrigation scheduling with respect to that of the first year (manually managed). In fact, 0.13 m^3 of water per square mater have been saved, while the water use efficiency improved by 22.2%, considering the global yield, thanks to the revised automated system. The experimental results demonstrate the feasibility of *on-field* automated irrigation processes, allowing to reduce the water consumption, increasing the accuracy, and improving the efficiency, if compared to manually managed irrigations. Overall, the experimental findings clearly highlight that a fully automated decision support system could enhance agricultural practices by enabling more precise resource management and by reducing water waste and farmers' workload.**

***Index Terms*—Automated irrigation technologies, data-driven Internet of Things (IoT), precision agriculture, sustainable smart agriculture (SA), water saving.**

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I. Introduction

NOWADAYS, smart agriculture (SA) is gaining increasing interest as it allows to optimize traditional agricultural activities, enhancing both productivity and sustainability. This can be achieved through the deployment and implementation of Internet of Things (IoT)-like technologies, enabling real-time monitoring, automation, and data-driven decision-making.

Several efforts have been dedicated in the last years, on this topic, at both national and international levels. In this perspective, a relevant example is represented by DEMETER [1], a large-scale international research initiative active in the period 2019–2023 and mainly focused on smart farming and agricultural digitization. DEMETER includes 60 European partners and implements more than 20 pilot projects across 18 countries, covering different agricultural sectors (e.g., arable farming, horticulture, and livestock farming). DEMETER mainly focuses on 1) increasing efficiency and profitability of agricultural operation, 2) improving food security through precision farming, and 3) developing a standardized agriculture data-sharing ecosystem in Europe. In the four-year TITAN project [2], DNA-based methods, blockchain, artificial intelligence (AI), and IoT technologies are integrated in order to improve sustainability and transparency of the agri-food supply chain, particularly focusing on small- and medium-sized enterprises. Similar objectives are addressed by SMALLDERS [3], a PRIMA-funded project leveraging smart models and digital technologies to enhance resilience and sustainability of local agri-food values chains. Considering national initiatives (and, in particular, Italian projects), the National Research Centre for Agricultural Technologies (AGRITECH) [4] is pivotal, being an initiative under Italy's National Recovery and Resilience Plan aiming at addressing the challenge of sustainably producing safe and sufficient food amid climate instability and resource competition. Hence, by leveraging multidisciplinary expertise, infrastructure sharing, and key enabling technologies, AGRITECH seeks to enhance productivity, sustainability, and digital transition in agriculture. The project fosters the collaboration with companies and farmers to develop new research models, train future experts, and support policy-making to strengthen agri-food supply chains and ensure long-term resilience.

These issues are also addressed by the industrial world, where different platforms have been developed for dealing with specific agricultural tasks and help farmers' work. Relevant examples are represented by *Plantix* [5], an application designed to diagnose plant diseases, pests and nutrient deficiencies through image recognition, and *Agrivi*, an end-to-end platform for farm management with AI-powered decision-making [6]. Moreover, the Irriframe platform [7], [8] is an Italian cloud service, developed by the Water Boards Italian Association [9], which provides irrigation-specific recommendations (in terms of amount of water and irrigation time) taking into account the cultivation type, the irrigation system, the crop location, and the continuum water balance between soil, plant, and environment.

In the context of water use optimization in SA applications, this work describes the activities carried out in the context of the AGRITECH project, in a testbed related to tomato (*Solanum lycopersicum* L.) cultivations active during two consecutive seasons, namely, 2023 and 2024 spring-summer periods. The testbed was set up at the "Azienda Agricola Sperimentale Stuard" [10] located in Parma, Emilia Romagna region, Italy.

More in detail, the *main scope* of this work is to investigate the effects of water stress in a tomato cultivation. In particular, tomato has been chosen since its cultivation is widely adopted in most climatic regions of the world, and has a historical importance for Italian culinary tradition [11]. Unfortunately, at the same time, tomato is highly sensitive to water stress conditions, which might significantly decrease crop yields [12]. In fact, tomato cultivation is associated with one of the most intensive uses of agricultural land (in terms of water usage and chemical input), especially in the Mediterranean area [13]. Instead, the *main motivation* driving the proposed study is to reduce water consumption in agricultural practices by providing farmers with decision support systems (DSSs)—as highlighted by the Food and Agriculture Organization of the United Nations [14], 70% of the global water is dedicated to agricultural irrigation. Moreover, it was also estimated that, in Mediterranean countries, the agricultural area would increase by 15% within a few years [15].

In order to efficiently collect the information generated by IoT devices in the testbed and correlate it with other relevant data, a modular cloud-oriented integration platform, denoted as *Agriware* and directly derived from the platform city2i described in [16], has been developed. The tomato testbed comprises different types of IoT sensors and actuators. Specifically, during the first year, irrigation was manually managed by the farmer with the support of IoT sensors to monitor the development and yield of tomato plants. Then, during the second year, the IoT network was extended to include IoT actuators, enabling a fully automated IoT irrigation system.

The *main contributions* of the proposed experimental activity to the agricultural sector consists in: 1) validating IoT-based applications in a real-world system; 2) providing effective insights to optimize the water consumption; 3) monitoring the evolution of the same testbed across different years; and 4) providing farmers with new tools implementing a DSS, thus supporting them in traditional farming activities.

The rest of this article is organized as follows. Section II presents the relevant related works and studies. Section III provides a description of the materials and methods applied to the evolving tomato testbed, including a description of the deployed IoT networks, the automated irrigation system management, and the different watering regimes taken as references. A discussion of the experimental results, with a particular focus on water savings, is reported in Section IV. Finally, Section V concludes this article and presents possible future developments.

II. Related Works

In a SA scenario, various kinds of IoT devices can be used to support traditional farming practices. For example, IoT sensors can be applied to measure water use and crop-related parameters, such as soil moisture, water volume, soil water potential, and environmental parameters, allowing continuous monitoring of the overall crop status. In addition, IoT actuators can be deployed to perform actions on crops, such as, for example: to enable automatic irrigation or fertilisation; to help in the harvesting or other plant-care operations, creating a real smart environment [17]. New solutions and models, mainly based on IoT technologies, have been introduced in the agriculture sector aiming at improving productivity, efficiency, and at supporting research, experimentation, and practical applications [18]. In [19], the use of Unmanned Aerial Vehicles (UAVs) allowed a quantitative and qualitative analysis of the spatial distribution of diseases in grapevines plants. In [20], an automated clip-type IoT camera-based system was proposed for a tomato crop to assist farmers with growth monitoring and harvest date prediction.

In the wide range of SA applications implemented in recent years around the world, one of the main topics is related to irrigation management and water consumption monitoring. In last years, several studies focused on water-related topics, such as: 1) identification of optimal irrigation volumes for production, water use efficiency (WUE), and economic returns [21]; and 2) water savings through the deployment of autonomous irrigation systems [22], [23]. In fact, improving water consumption and efficiency is crucial for addressing food scarcity, ensuring future growth, and sustaining rural communities, thus improving socio-economic conditions in these areas [24]. In addition, an increasing number of DSS are appearing in SA applications, combining information from IoT devices. The main objective of DSSs is to simplify decision making processes by suggesting optimal irrigation timing, along with fertilizer use and crop rotation, in a crop related data-driven model [25]. Smart irrigation DSSs can effectively manage water resources and significantly impact global food security by improving crop yields and water efficiency, enabling remote access and control, facilitating climate change adaptation, and promoting sustainability [26], [27]. To enable data collection, different communication protocols are used at network and application layers. As explained in [28], in the network layer physical environment data are sent wirelessly to the gateway, using various protocols, such as Long Range Wide Area Network (LoRaWAN) [29] and IEEE 802.11 Wi-Fi [30]. At the application layer, protocols, such as Message Queuing Telemetry Transport (MQTT) [31] and Hypertext Transfer Protocol (HTTP) [32], can be used to enable database interaction. Finally, as detailed in [33], integrated frameworks combining multiple technologies can provide cohesive and interconnected solutions for sustainable, efficient, and technologically advanced farming practices, offering economic and environmental benefits.

In this context, the proposed work provides relevant contributions mainly on irrigation management and water consumption

TABLE I
COMPARISON OF CONTRIBUTIONS AND LIMITATIONS OF SOME RELEVANT RELATED WORKS WITH THE PROPOSED APPROACH

Ref.	Relevant Contributions	Limitations	Our Contribution
[21]	Simulation of different environmental conditions, with a focus on balancing productivity, profitability, WUE, and sustainability.	Lack of validation under climate changing scenarios and absence of a specific algorithm for the DSS.	Two-year evolving testbed with the implementation of two Watering DSSs.
[22]	Two-years evolving testbed (2021—2023) with up to 50% reduction in water consumption.	Average irrigation session duration estimated based on the local farmers' empirical knowledge.	The Irriframe platform provides support for both manual and automated irrigation systems.
[23]	Automated irrigation monitoring system providing real-time data and alerts, enabling effective water utilization.	No comparison between different irrigation regimes or algorithms due to a single testbed managed under a uniform regime.	Two-year evolving testbed with a crop division into five lines managed under five distinct watering regimes.

monitoring. As detailed in Table I, the main innovative aspects of the proposed approach regard 1) the management of a two-year consecutive testbed, with the reference of the Irriframe platform, and 2) the decisions made by the two different Watering DSSs implemented considering different watering regimes and allowing a consistent comparison of observations.

III. MATERIALS AND METHODS

A. Tomato Crops Testbed

The research activities featured the deployment of heterogeneous IoT devices into two experimental crops, both located at the "Azienda Agricola Sperimentale Stuard" near the city of Parma, Italy (60 m a.s.l., 44° 48' 29.888" N, 10° 16' 29.074" E), covering two consecutive years of tomato cultivation (namely, 2023 and 2024). For clarity and conciseness, in the rest of this article the experimental crop related to the year 2023 will be identified as $\mathcal{C}_{\mathrm{Y}1}$, while that related to 2024 will be identified as $\mathcal{C}_{\mathrm{Y}2}$.

More in detail, both $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$ involved the adoption of a common approach, namely, considering the watering recommendation of the Italian Irriframe platform as a relevant reference for the tomato irrigation management. Then, $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$ have been divided into different experimental tomatoes lines aiming at verifying and validating different irrigation regimes, which, in turn, allowed to evaluate the tomato plants behaviour and the potential of water savings, even with water percentages lower than the Irriframe recommendations. For the sake of clarity, in the experimental testbed, each tomato line in both $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$ is considered as a plot, and is monitored through sensors. Considering the evolution aspects between $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$, it should be highlighted that the irrigation policies in $\mathcal{C}_{\mathrm{Y}1}$ were managed directly by the farmer, autonomously checking the irrigation recommendations from the Irriframe platform and manually controlling the irrigation system accordingly. Instead, in $\mathcal{C}_{\mathrm{Y}2}$, the usage of the proposed IoT network has been enhanced, thus allowing a fully automated irrigation management through the considered platform (as further discussed in Section III-C). In general, in both $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$, a single irrigation regime has been assigned and applied to a single tomato line, as described below.

On the practical side, the deployment of $\mathcal{C}_{\mathrm{Y}1}$—which an exhaustive description of, in terms of setup and general results, can be found in [34]—was carried out between 29 June 2023 and 13 September 2023, with three different tomato plants lines, each 90 m long, being monitored through an IoT network and treated according to the following three different irrigation regimes, all derived from the Irriframe recommendations:

1) a tomato plant line denoted as $\mathcal{I}_{100}$ and manually irrigated using 100% of the water amount recommended by the Irriframe platform;
2) a tomato plant line denoted as $\mathcal{I}_{60}$ and manually irrigated by the farmer with a water quantity equal to 60% of the Irriframe platform recommendation;
3) a tomato plant line denoted as $\mathcal{I}_{30}$ and manually irrigated with a water quantity equal to 30% of the Irriframe platform recommendation.

Moreover, the crop area was organized with experimental lines separated by "boundary" unmonitored lines—this was required in order to allow the passage of the tractors and separate the experimental lines, thus preventing undesirable cross-interference between the different irrigation regimes.

The second phase of the testbed, associated with $\mathcal{C}_{\mathrm{Y}2}$, was deployed in the time period between 12 June 2024 and 7 September 2024. The goal was to leverage IoT-enabled monitoring and irrigation control mechanisms to evaluate the water savings by reducing the tomato plants standard irrigation amount. In this context, five different tomato lines (67 m long and separated by "boundary" lines) were monitored and irrigated using a network composed of 38 IoT devices, as further described in Subsection III-B. Then, similarly to the first phase, each $\mathcal{C}_{\mathrm{Y}2}$ experimental line was associated with a specific irrigation regime. In particular, *four* out of the five $\mathcal{C}_{\mathrm{Y}2}$ lines were watered according to 100%, 80%, 60%, and 30% of the Irriframe water recommendations, while the the *last* experimental line, as described in Section III-E, was automatically irrigated on the basis of the output decision of a custom algorithm based on the soil humidity levels recorded in real-time by the IoT sensors deployed along this line. To this end, the notation adopted to indicate the water regimes applied to the experimental lines in $\mathcal{C}_{\mathrm{Y}2}$ is the following.

1) A tomato line denoted as $\hat{\mathcal{I}}_{100}$ is automatically irrigated using 100% of the water quantity recommended by the Irriframe platform.
2) A tomato line denoted as $\hat{\mathcal{I}}_{80}$ is automatically irrigated using 80% of the water quantity suggested by the Irriframe platform recommendation.
3) A tomato line denoted as $\hat{\mathcal{I}}_{60}$ is automatically irrigated using a water quantity corresponding to 60% of the Irriframe platform recommendation.

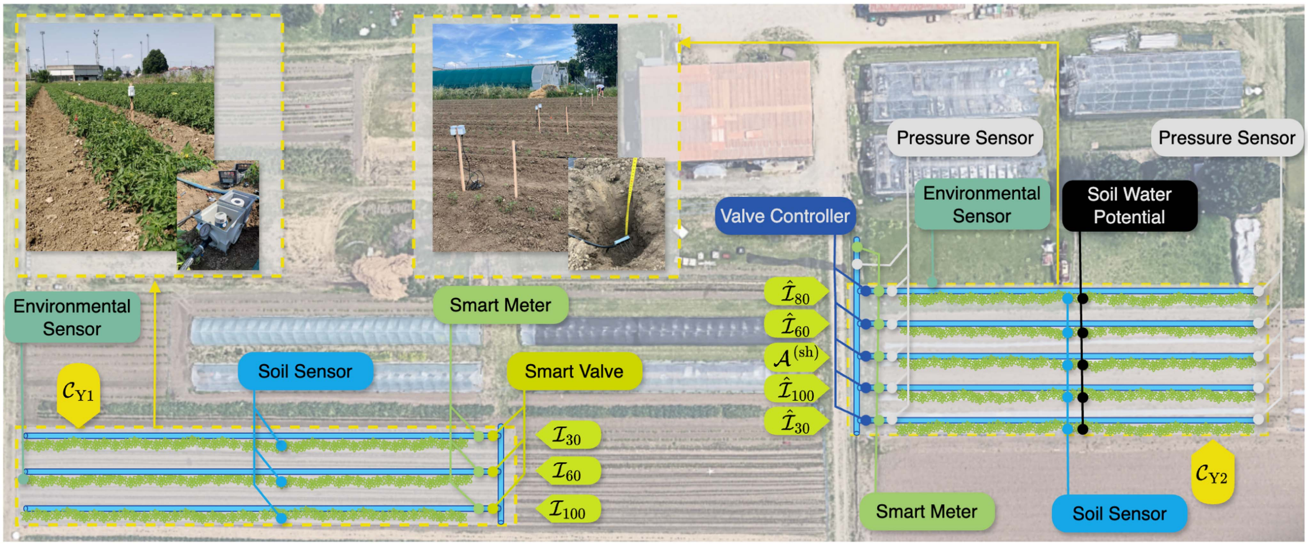

Fig. 1. Experimental setup of the proposed testbed, together with the experimental rows location for both $\mathcal{C}_{Y1}$ and $\mathcal{C}_{Y2}$ crops.

TABLE II
YEAR-TO-YEAR AGRONOMIC MANAGEMENT

	2023	2024
Transplant	01 June	01 June
Harvesting date	13 September	04 September
Fertilization	Distribution of N, P, K	Distribution of N, P, K
Line distance	1.5m	1.5m
Plant distance	0.3m	0.23m
Plant population	$\approx$ 300 each line	$\approx$ 300 each line
Line length	88m	70m

4) A tomato line denoted as $\hat{\mathcal{I}}_{30}$ is automatically irrigated using a water quantity corresponding to 30% of the Irriframe platform recommendation.
5) A tomato line denoted as $\mathcal{A}^{(sh)}$ is automatically irrigated according to the frequency and water quantity recommended by the custom algorithm (described in Section III-E), which calculates the water needs on the basis of the soil humidity level.

For the sake of clarity and completeness, in Fig. 1 the complete testbed setup, together with the experimental rows location for both $\mathcal{C}_{Y1}$ and $\mathcal{C}_{Y2}$, is shown. Moreover, organic farming protocols were applied to both $\mathcal{C}_{Y1}$ and $\mathcal{C}_{Y2}$, characterized by silty loam soil. Fertilisation was managed in the same way: during the first three weeks after transplanting, 118.8, 90, and 180 units $\cdot$ ha^{-1} of N, P, K, respectively, were distributed and, then, during the crop season, additional amounts of N, P, K were added for a final amount of 180, 90 and 200 $\cdot$ ha^{-1}, respectively. Harvesting took place when 95% of fruits were considered ripe. Further details regarding the agronomic management can be found in Table II.

In order to contextualize year-to-year differences, Table III provides seasonal information on total rainfall and average air temperature for both tomato seasons (namely, 29 June 2023–13 September 2023 and 12 June–7 September 2024) as well as across each year.

TABLE III
SEASONAL YEAR-TO-YEAR DIFFERENCES

	Total rainfall [mm]	Air temperature [°C]
2023 tomato season	69.3	25.5
2024 tomato season	178.8	25.47
2023 year	582.4	16.33
2024 year	1082.9	15.49

B. *Monitoring Level: IoT Sensors Network*

The testbed deployed at the "Azienda Agricola Sperimentale Stuard" was managed and continuously monitored during the two considered seasons thanks to the support of an IoT-based sensor network mainly composed by commercial off-the-shelf devices. In particular, different types of IoT sensors and actuators were deployed in the experimental lines of $\mathcal{C}_{Y1}$ and $\mathcal{C}_{Y2}$, all equipped with LoRaWAN connectivity. This allowed them to communicate and synchronize together with the open-source The Things Network (TTN) LoRaWAN platform [35], especially thanks to the presence of a LoRaWAN gateway deployed in the neighborhood. More in detail, the devices composing the considered IoT network can be summarized as follows.

1) Milesight UG67: Outdoor LoRaWAN gateway deployed in the farm's main building to support the connectivity across the whole testbed area [36].

2) Milesight EM500-CO2: Environmental sensor allowing to measure crop environmental parameters (e.g., air humidity; air temperature; barometric pressure; carbon dioxide, CO_2, and concentrations) in harsh environments [37].

3) Milesight EM500-SMTC: Soil sensor specifically designed to be planted in the ground in order to measure soil-related parameters (e.g., soil moisture, soil temperature, and soil electrical conductivity) [38]. In the considered experimental testbed, various nodes of this type have been installed in each experimental line in both $\mathcal{C}_{Y1}$ and $\mathcal{C}_{Y2}$, in order to measure the

TABLE IV
DETAILS ON THE IOT DEVICES EMPLOYED IN THE EXPERIMENTAL TESTBED AT THE "AZIENDA AGRICOLA SPERIMENTALE STUARD" AND THEIR CORRESPONDING MONITORED PARAMETERS

IoT Device	**Devices in $\mathcal{C}_{\mathrm{Y1}}$ [num.]**	**Devices in $\mathcal{C}_{\mathrm{Y2}}$ [num.]**	**Sampled Parameters**	**Dimension**
Milesight UG67 Gateway	1	1	—	—
Milesight EM500 CO_2	1	1	Air moisture Air temperature CO_2 level Barometric pressure	%RH °C ppm hPa
Milesight EM500 SMTC	3	10	Soil moisture Soil temperature Electrical conductivity	%RH °C μS/cm
Milesight EM500 PP	—	11	Water pressure	kPa
Talkpool OY1310	3	5	Water usage	m^3
Decentlab DL-TRS21	—	11	Water potential	kPa
MClimate T-valve	3	—	Water temperature Valve state	°C [0, 1]
Milesight UC512	—	5	Valve state	
Rainbird LFV-075 DN20	—	5	Valve state	[0, 1]

soil parameters at different depths: 15 cm in $\mathcal{C}_{\mathrm{Y1}}$; 15 cm and 30 cm in $\mathcal{C}_{\mathrm{Y2}}$.

4) Milesight EM500-PP: Pipe pressure sensor designed to monitor the water pressure inside pipelines [39]. In the considered experimental testbed, it has been deployed only in $\mathcal{C}_{\mathrm{Y2}}$, in particular with two pressure sensors being installed at the *beginning* and the *end* of each experimental tomato line. Then, to monitor the overall pressure available in $\mathcal{C}_{\mathrm{Y2}}$, an additional pressure sensor has been installed at the beginning of the irrigation network (in the "master" line).

5) Talkpool OY1310: Smart water meter enabling to continuously monitor the water usage in the irrigation network [40]. With regard to the experimental testbed, one water meter has been installed in each experimental tomato line in both $\mathcal{C}_{\mathrm{Y1}}$ and $\mathcal{C}_{\mathrm{Y2}}$. Then, in the case of $\mathcal{C}_{\mathrm{Y2}}$, an additional Talkpool OY1310 m has been installed at the beginning of the irrigation network (in the "master" line) to register its overall water usage.

6) Decentlab DL-TRS21: Water potential sensor designed to monitor the water potential levels in the soil [41]. Referring to the considered testbed (and similarly to the soil sensors detailed in Section III-B3), this device has been deployed only in $\mathcal{C}_{\mathrm{Y2}}$, namely, with two water potential sensors in each experimental line and located at different soil depths: 15 cm in $\mathcal{C}_{\mathrm{Y1}}$; 15 cm and 30 cm in $\mathcal{C}_{\mathrm{Y2}}$.

7) MClimate T-Valve: Smart valve enabling to control the status (*open/close*) of the valves installed on the pipes in the crop irrigation system [42]. In the considered experimental testbed, this device has been deployed only in $\mathcal{C}_{\mathrm{Y1}}$: being provided with an *open/close* external button, it leaves the possibility to the farmer to manually turn ONand OFFthe irrigation along the tomato lines.

8) Milesight UC512: Solenoid valve controller acting as an IoT actuator [43] and allowing to remotely control the solenoid valves deployed in each production line in $\mathcal{C}_{\mathrm{Y2}}$. This controller is then connected with the Rainbird LFV-075 DN20 [44] solenoid valve still present in each line.

For completeness, additional details about 1) the amount of IoT devices deployed in each crop and 2) the monitored environmental and plants parameters are presented in Table IV.

C. Information Level: Data Management System

The data streams generated by the different IoT devices deployed in the considered testbed are integrated into a general data acquisition platform, denoted as *Agriware*. In detail, this software platform, following the architecture of city2i [16], is specifically designed to uniformly manage and analyze heterogeneous—in terms of communication protocols, vendors or manufacturers—sources of information within SA applications, thus acting as a *middleware*, as described in [34].

On the operational side, Agriware features the following main functionalities: 1) integration of IoT-generated data and other cultivation-related measurements; 2) possibility to define custom software modules for data streams processing (e.g., compute indicators of interest, derive insights, apply AI models on the collected information); 3) monitoring of parameters related to specific crops and cultivations (i.e., water consumption for irrigation optimization); and 4) sharing data streams with other applications. For the sake of clarity and completeness, the different building blocks of Agriware, together with their interactions, are shown in Fig. 2.

In fact, Agriware has been designed to enable seamless ingestion of different information streams from heterogeneous sources, regardless of the specific communication protocol used for transmitting them (e.g., LoRaWAN, IEEE 802.11 Wi-Fi, cellular 4G/5G) as well as of the data format adopted for information representation (e.g., JSON, CSV, and XML). Thus, a *first* category of data sources of interest consists of IoT devices, while all the data generated by other software platforms can also serve as potential sources for Agriware. Hence, in general, all these data sources can be considered as input streams for the overall platform.

The *Connectors* correspond to software modules enabling the integration of the aforementioned data streams from various sources. Their main goals are to allow the integration of relevant input data into the Agriware ecosystem and to facilitate the interaction with other software modules within the architecture through a *data normalization* stage. Thus, any class of data sources integrated into Agriware has a corresponding connector, typically implemented as a Python script, and with connectors

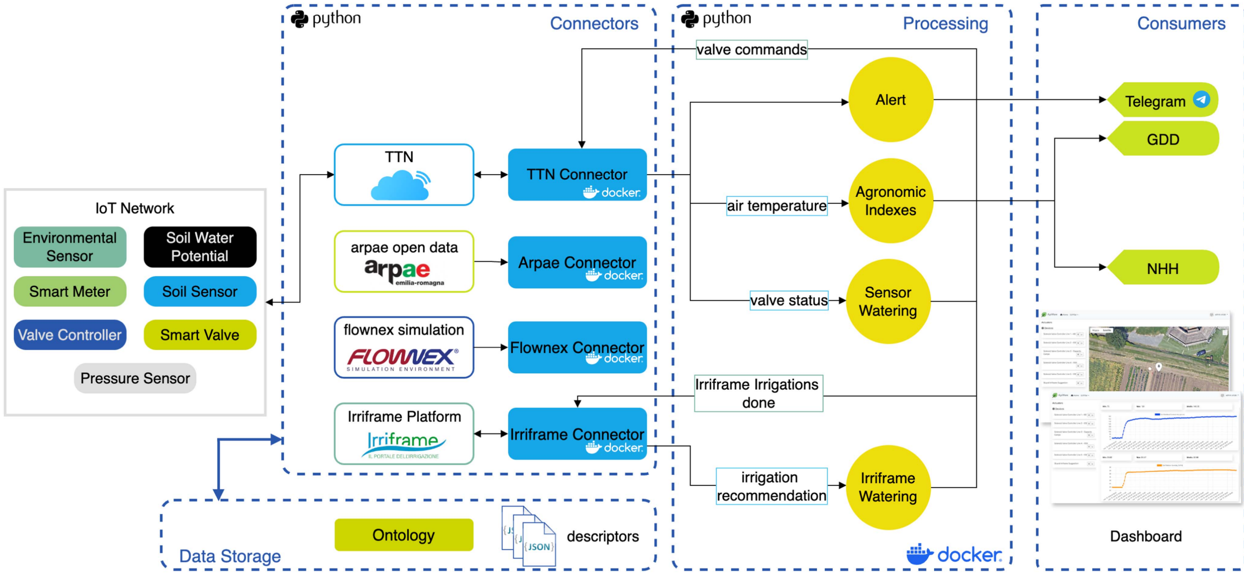

Fig. 2. Agriware architecture main building blocks, with reference to the testbed implementation.

being organized as Docker containers activated depending on the specific needs of the Agriware platform.

Finally, the output streams generated by the connectors correspond to generic geo- and time-referenced datasource streams. Then, in order to simplify the representation of the obtained information, unnecessary details (e.g., communication protocol- or technology-specific) are pruned, while details of interest are mapped to the internal *ontology* of Agriware. This opens to a unified and coherent data representation across the entire Agriware ecosystem.

For the sake of completeness, in the following each connector developed as part of the Agriware platform is detailed.

1) TTN Connector: Since all the IoT devices involved in the experimental testbed have LoRaWAN connectivity, they have all been registered as *end devices* and associated with specific applications inside the TTN platform. Then, an HTTP *WebHook integration* has been configured for each TTN application targeting, as destination endpoint, the Agriware TTN connector module. In this way, each time new data are generated by the IoT devices registered in the TTN platform (through LoRaWAN uplinks), these new data will be pushed to the specified WebHook endpoint. Basically, the Agriware TTN connector corresponds to an HTTP server 1) receiving uplinks, 2) interpreting the payload format defined in TTN, and 3) converting new data to the Agriware datasources format, coherently with the internally-defined ontology. To this regard, a JSON descriptor file has been associated with each IoT device's model that should be integrated. In the descriptor, each measure sampled by the specific device is mapped to an Agriware datasource property, in turn associated with an ontology item.

Finally, the TTN connector is also in charge of converting events for the actuators (e.g., valves controller) from the formats used in Agriware to vendor-specific downlink commands. Once this conversion is done, the generated downlink payload is sent to TTN through its HTTP REST APIs, in order to let the actuating command reach the target IoT device.

2) Irriframe Connector: As mentioned in Section III-A, in $\mathcal{C}_{\text{Y1}}$ the input parameters required by the Irriframe platform have been managed directly by the farmer who, during the whole agricultural season, has checked daily the Web interface of Irriframe and has manually irrigated in accordance to the irrigation advice. Instead, in $\mathcal{C}_{\text{Y2}}$ a Python-based Irriframe connector has been defined and activated. In detail, it has been configured to periodically interact with the Irriframe Web page (exploiting the Azienda Stuard's Irriframe credentials) through HTTP requests to obtain the current suggestion, and to convert this information to an Agriware-like datasource comprising 1) irrigation volume, 2) irrigation duration, and 3) irrigation date. Then, in the case no irrigation is recommended, no data are generated for the corresponding datasource. Finally, the Irriframe module is also responsible to save on the Irriframe Web platform 1) the irrigation duration and 2) the date then the irrigation was done. This information is relevant for—and required by—the Irriframe's algorithm in order to correctly produce and provide future irrigation suggestions. In the Agriware platform, this is managed in the same way of the IoT commands, namely through downlink commands.

3) Flownex Connector: With regard to the benefits provided by the integration of data related to the irrigation system's digital model, a Flownex connector—corresponding to a 1-D lumped-parameter simulation software widely used to create fluid dynamic simulation models—has been defined. Thus, a digital models of the irrigation systems of both $\mathcal{C}_{\text{Y1}}$ and $\mathcal{C}_{\text{Y2}}$ have been developed according to the framework proposed in [45]. On the technical side, this connector integrates simulation data in the Agriware platform through a Python script periodically polling new data being then generated in the digital model. This enables the implementation of advanced control loops or the development of virtual sensors. The goal is to increase the lifetime of the deployed LoRaWAN devices.

4) ARPAE Connector: Finally, since the availability of weather data are always relevant in SA scenarios, a specific connector devoted to this kind of information has been defined and deployed in the Agriware platform. In detail, the connector interacts with the HTTP REST APIs freely provided by the regional agency "Agenzia Prevenzione Ambiente Energia Emilia-Romagna" (ARPAE) [46] to retrieve open data related to weather parameters registered by several stations installed in the Emilia–Romagna region. Then, data are filtered, selecting only the information sampled by the regional weather station located in San Pancrazio, Parma, Italy (latitude: 44.8080648744358, longitude: 10.272446082304139), near the Azienda Stuard. This data stream is integrated in the Agritech platform as an additional information to be correlated with all other datasources.

D. Data Processing

Once the data streams have been correctly integrated and normalized, they can be used in the *Processing* module, a component serving as *core* of Agriware and enabling flexible and configurable processing of datasources integrated by the different *Connectors*. On the operational side, this module is designed with a layered architecture, whose fundamental building blocks are referred to as *Processing Units* and correspond to custom software modules facilitating management and transformation of the collected data. Then, they can be uploaded to the Agriware platform to perform specific processing tasks on the basis of one or more input datasources, while the generated outputs are then considered in Agriware as new data streams (also denoted as *layers*) serving as inputs for other processing units, thereby creating a fully configurable, layered architecture for the Processing module.

Similarly to other modules in the Agriware platform, the current implementation of the processing units is based on the use of Python scripts, whereas the information routing between them exploits the MQTT protocol. Then, the Mosquitto MQTT broker is used to support routing and to assign each data stream a unique MQTT topic. Therefore, the processing units (that can work as both MQTT publishers and subscribers) interested in the output of one or more datasources should subscribe to the corresponding topics, and publish their results on the topic(s) assigned to its output. With regard to the described testbed, various specific processing units have been activated to perform different tasks: 1) calculate agronomic indicators, such as growing degree days, heat units, and normal heat hours curve [47], [48], [49]; 2) manage the automatic irrigation, according to the different irrigation regimes, or specific algorithms; 3) perform validation on the status of the irrigation system, issuing alerts and warning in the case of problems.

Hence, all the information managed by Agriware can be finally accessed by the Azienda Stuard farmers and researchers through a Web-based dashboard.

E. Decision Support and Modeling Level: Water Management Automation

As described in Section III-A, the main evolution in the considered experimental testbed across the two years regards the fact that, in $\mathcal{C}_{\mathrm{Y2}}$, the irrigation is automatically controlled by IoT actuators, unlike in $\mathcal{C}_{\mathrm{Y1}}$, where the irrigation is manually controlled by the farmer. Considering the modeling and decision support level aspects, the experimental setup for $\mathcal{C}_{\mathrm{Y2}}$ was designed to emphasize and enhance the irrigation automation, with the setup described in Sections III-B and III-C enabling precise, customizable, and automatically managed irrigation, primarily targeting water waste reduction.

In fact, Milesight UC512 IoT actuators were used in $\mathcal{C}_{\mathrm{Y2}}$ by the Agriware platform that autonomously "decides" the time instant to remotely open and close valves (through LoRaWAN downlink commands) according to the watering regimes planned in the testbed. Hence, the watering decision (WD) process based on the Irriframe recommendations and the one based on soil sensors samplings, are detailed, together with the developed irrigation alert system, are detailed in Sections III-E1, –III-E3, respectively.

1) Irriframe-Based WD: As anticipated in Section III-C2, Agriware considers as input datasource the Irriframe's recommendations data, then generating a (daily updated) information stream representing the input of a processing unit that, in turn, subscribes on the corresponding MQTT topic. Then, every day this unit decides *if* the irrigation has to be activated on the basis of the following steps.

1) Check the current recommendation proposed by Irriframe.
2) *If* Irriframe does not recommend an irrigation, the process ends, until the next day.
3) *Otherwise*, the recommended irrigation period (dimension: [min]), denoted as $\mathcal{T}_i$, is retrieved and assigned to the line $\hat{\mathcal{I}}_{100}$, while the corresponding proportional values for lines $\hat{\mathcal{I}}_{30}$, $\hat{\mathcal{I}}_{60}$, and $\hat{\mathcal{I}}_{80}$ are calculated as the corresponding fraction of $\mathcal{T}_i$.
4) The calculated values are published as outputs and converted (by the TTN Connector module) into LoRaWAN downlink commands, to be then sent to the Milesight UC512 devices controlling the tomato lines.
5) The "irrigation performed" event is sent to the Irriframe platform (by the Irriframe Connector module), since it represents an input required by Irriframe to correctly estimate future irrigation recommendations.

For the sake of clarity and reproducibility, the pseudocode representation of the Irriframe-based WD process is detailed in Listing 1.

2) Sensor-Based WD: With regard to the WD process based on sensor readings, a threshold-based processing unit has been implemented to carry out a "sip irrigation" model on the automated line $\mathcal{A}^{(\mathrm{sh})}$ in $\mathcal{C}_{\mathrm{Y2}}$, aiming at maintaining the soil moisture within an ideal range for tomato cultivations. Hence, the main objective of the sensor-based WD task is to gradually apply small quantities of water (namely, 30-min irrigations) to avoid the phenomenon of water percolation and soil overwatering. Then, lower and upper levels of the developed irrigation range are evaluated according to the framework provided by [50], with the irrigation decision module subscribing to 1) the datasources associated with the deepest soil sensor and 2) the controller valve located in the line $\mathcal{A}^{(\mathrm{sh})}$.

Then, for each new soil moisture measurement, the DSS decides according to the following steps:

1) *if* the soil moisture is less than a lower threshold (denoted as `SMlow` and equal to 24%), watering is triggered *on* a

```
irriframe_advice = get_Irriframe_advice()

if irriframe_advice.irrigation_date != today:
    wait_until_next_day()
else:
    Ti = irriframe_advice.irrigation_time
    T100 = Ti
    T80 = 0.8 * Ti
    T60 = 0.6 * Ti
    T30 = 0.3 * Ti
    output = [T100, T80, T60, T30]

    TTNConnector.publish(output)
    downlink = TTNConnector.convert(output)
    TTNConnector.send(downlink)

    IrriframeConnector
        .send_event("irrigation performed")
```

Listing 1. Pseudocode representation of the Irriframe-based WD process.

```
soil_moisture = get_soil_moisture()

if soil_moisture <= SMlow:
    activate_watering(SI)

else if (SMlow < soil_moisture < SMup) and
        (valve_open == True):
    activate_watering(SI)

else if (soil_moisture >= SMup) and
        (valve_open == True):
    send_command("valve_close")
```

Listing 2. Pseudocode representation of the sensor-based WD process.

time interval equal to a “sip irrigation” (denoted as `SI` and equal to 30 min);

2) *if* soil moisture values are higher than the upper threshold (denoted as `SMup` and equal to 27%), a “valve close” command—equal to a watering *off*—will be issued in order to terminate the irrigation;
3) *if* the soil moisture is between `SMlow` and `SMup` *and* the solenoid valve was open during the last check, watering is triggered *on* for a supplementary `SI`.

For the sake of clarity and completeness, the pseudocode of the process carried out by the sensor-based WD process is detailed in Listing 2.

3) Irrigation Alert System: Finally, regarding the need to notify the farmer about the irrigation status, a processing unit, interacting with a Telegram bot, has been developed for sending alerts when a *strange* situation happens, e.g., something seems to be not working in the irrigation automation operations or in the DSS. To this end, critical features to be monitored include 1) the water pressure in the pipes and 2) the continuous communication between physical devices and processing units during irrigations (e.g., a valve is not closing). In fact, *if* probes at the beginning of each irrigation line measure a pressure below a threshold denoted as `Pstart` (namely, 75 kPa) *and* a pressure at the end of the line below a threshold denoted as `Pend` (namely, 10 kPa),

```
while True:
    for i in range(num_lines):
        pressure_start = get_pressure_start(i)
        pressure_end = get_pressure_end(i)
        communication = check_communication(i)
        changed = valve_state_changed(i)

        if (pressure_start < Pstart) and
           (pressure_end < Pend):
            TelegramBot.send("low pressure!")

        if not communication:
            TelegramBot.send("error")

        if changed:
            state = get_valve_state()
            TelegramBot.send(state)

if is_morning():
    irriframe_advice = get_Irriframe_advice()
    TelegramBot.send(irriframe_advice)

else if is_evening():
    activities = get_activities_summary()
    TelegramBot.send(activities)
```

Listing 3. Pseudocode representation of the Irrigation Alert System process.

the current flow rate will fall below the reference model used by Irriframe for its recommendations, thus leading to a different irrigation condition.

Moreover, every morning the developed processing unit interacts with the Telegram bot in order to notify the interested users with the daily recommendation provided by Irriframe, while every evening a summary of the network activities is provided as well. Then, the irrigation alert system also sends a notification when a solenoid valve changes its state from *open* to *closed* or vice versa—this is useful for maintenance and to make the farmer aware of the events happening in the monitored crops.

For the sake of clarity and completeness, a pseudocode representation of the Irrigation Alert System process is detailed in Listing 3.

IV. Results

A. Irrigation Duration and Volume

As mentioned in Section III-E, the irrigation recommendation provided by Irriframe is applied considering both the irrigation duration and the irrigation volume. *First*, in order to assess the system precision, the deviation (dimension: [s]) between the recommended watering and the current time valves were opened was measured. For completeness, Table V details the average precision error related to the irrigation period duration for each irrigation regime in $\mathcal{C}_{Y2}$—namely, $\hat{\mathcal{I}}_{100}$, $\hat{\mathcal{I}}_{80}$, $\hat{\mathcal{I}}_{60}$, and $\hat{\mathcal{I}}_{30}$.

The results detailed in Table V indicate that the proposed monitoring system enables precise irrigation on the basis of the Irriframe recommendations, with an average precision error, across all tomato lines, on the order of 3.6 s. Thus, the automated irrigation system can irrigate crops more precisely and in a timely way, unlike a farmer who may irrigate less accurately.

TABLE V
AVERAGE PRECISION ERRORS FOR THE WATER REGIMES CONSIDERED IN THE $\mathcal{C}_{\mathrm{Y}2}$ CROP

Water Regime	Precision Error [s]
$\hat{\mathcal{I}}_{100}$	0.15
$\hat{\mathcal{I}}_{80}$	7.30
$\hat{\mathcal{I}}_{60}$	6.95
$\hat{\mathcal{I}}_{30}$	0.09
Average	3.6

TABLE VI
WATER VOLUME LEVELS FOR $\mathcal{C}_{\mathrm{Y}1}$ AND $\mathcal{C}_{\mathrm{Y}2}$

Water Regime	Irrigation Volume [m^3]
$\mathcal{I}_{100}$	0.43
$\mathcal{I}_{60}$	0.28
$\mathcal{I}_{30}$	0.17
$\hat{\mathcal{I}}_{100}$	0.34
$\hat{\mathcal{I}}_{80}$	0.24
$\hat{\mathcal{I}}_{60}$	0.19
$\hat{\mathcal{I}}_{30}$	0.11
$\mathcal{A}^{(\mathrm{sh})}$	0.24

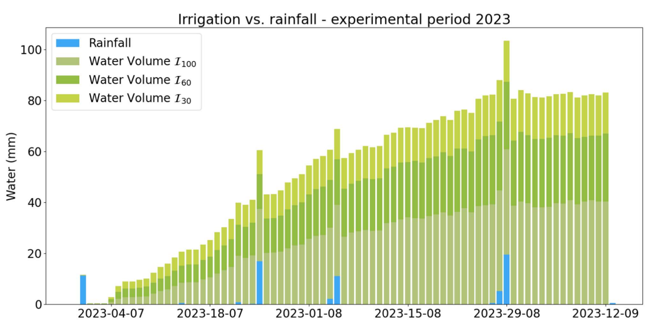

Fig. 3. Comparison between total rainfall and the 90 m experimental tomato lines in $\mathcal{C}_{\mathrm{Y}1}$ for the 2023 tomato season.

Then, also the precision—in terms of irrigation volume—has been evaluated, in detail calculating the difference between the water volume (dimension: [m^3]) recommended by the Irriframe platform and the effective water volume (dimension: [m^3]) released to the crop. As a result, in $\mathcal{C}_{\mathrm{Y}2}$ the difference is equal to 4.25 m^3 for the line $\mathcal{I}_{100}$, i.e., equal to 0.06 m^3, per meter of each tomato plants line. At the opposite, a similar precision level cannot be assessed for $\mathcal{C}_{\mathrm{Y}1}$ because of the farmer who did not track the Irriframe advices, unlike the automatic system in $\mathcal{C}_{\mathrm{Y}2}$. This result highlights the fact that an automated irrigation system also simplifies the traceability of the operations, with recommendations being followed more effectively.

B. Water Saving

As detailed in Section III-B, water meters have been employed in the evolving tomato cultivation testbed to keep track of the water consumption (dimension: [m^3]) for each experimental tomato line in both $\mathcal{C}_{\mathrm{Y}1}$ and $\mathcal{C}_{\mathrm{Y}2}$. To this end, Table VI reports the measured water consumption levels per square meter for each tomato line, while the observed water consumption for the three experimental lines deployed in $\mathcal{C}_{\mathrm{Y}1}$ are shown in Fig. 3.

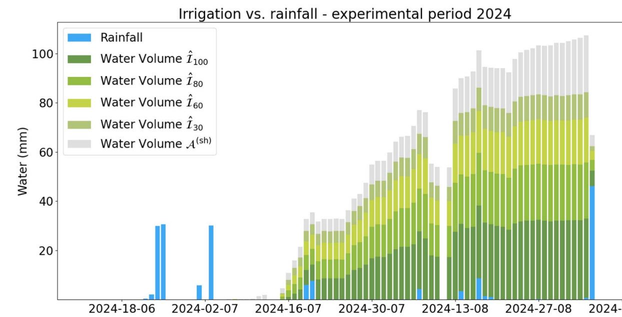

Fig. 4. Comparison between total rainfall and the 67 m experimental tomato lines in $\mathcal{C}_{\mathrm{Y}2}$ for the 2024 tomato season.

Furthermore, Fig. 3 shows a timeline comparing the irrigation regimes and rainfall during the experimental period in 2023. On the other hand, Fig. 4 shows the total amount of water irrigated in $\mathcal{C}_{\mathrm{Y}2}$, as detected by the water meters deployed in each tomato line, alongside rainfall recorded during the 2024 experimental period. Overall, it is evident that the automated irrigation deployment in $\mathcal{C}_{\mathrm{Y}2}$ allows a reduction in terms of water consumption, if compared to the situation manually managed in $\mathcal{C}_{\mathrm{Y}1}$.

More in detail, a comparison of the total water volume used for the evolving tomato testbed for the line $\mathcal{I}_{100}$ along the two consecutive years (2023–2024) was performed. On one side, in $\mathcal{C}_{\mathrm{Y}1}$ the line $\mathcal{I}_{100}$ was irrigated totally using 0.48 m^3 of water for each square meter of crop surface for the entire season. On the other side, in $\mathcal{C}_{\mathrm{Y}2}$ the line $\hat{\mathcal{I}}_{100}$ was irrigated using 0.35 m^3 of water per square meter of crop surface for the entire season. Therefore, a 0.13 m^3 water saving per square meter can be observed, corresponding to 8.71 m^3 of water saving for an entire tomato plant line.

The analysis was carried out also considering the precipitations. In this case, in $\mathcal{C}_{\mathrm{Y}1}$ the ARPAE weather station recorded a total volume of rain over the crop surface equal to 18.9 m^3. By including this additional data of interest to the irrigation volume, the total water received per square meter amounts to 0.69 m^3. Instead, in $\mathcal{C}_{\mathrm{Y}2}$ the weather station recorded 21.78 m^3 of rain volume. Therefore, considering both precipitations and irrigation water, in $\mathcal{C}_{\mathrm{Y}2}$ the tomato crop received 0.64 m^3 per square meter. Although the second year of the experiment was more rainy, the automatic irrigation system allowed to save water.

For completeness, a comparison between the most performing irrigation regime for the 2023 season (namely, line $\mathcal{I}_{60}$) and the automated tomato line $\mathcal{A}^{(\mathrm{sh})}$ was carried out. In fact, in $\mathcal{C}_{\mathrm{Y}1}$ the $\mathcal{I}_{60}$ tomato line was irrigated using 0.35 m^3 of water per square meter over the entire season. On the other end, in $\mathcal{C}_{\mathrm{Y}2}$ the tomato line $\mathcal{A}^{(\mathrm{sh})}$ was automatically irrigated using 0.25 m^3 of water per square meter over the entire season. It can be observed a 0.10 m^3 water saving per square meter of tomato crop surface, corresponds to 6.7 m^3 for an entire tomato plants line. Moreover, by including the total rain for the 2023 season, one obtains a total amount of water per square meter equal to 0.56 m^3. In contrast, in the 2024 season the total amount of water (due to irrigations and rain) is equal to 0.55 m^3 per square meter.

As a result, the automated irrigation system allows more precise and efficient scheduling of the irrigation processes. In particular, the IoT-based automation system allows the irrigation to be scheduled during the night or early in the morning, thus ensuring a strict adherence to the Irriframe recommendations while irrigating at times when the sun is not directly impacting the plants. This is particularly important because the irrigation timing has a significant effect on the plants growth: a reduced plant growth seems to be linked to increased daily water stress during the growing season, as the direct sunlight on the plants enhances water evaporation, leading to water waste [51].

A probabilistic approach, based on a Monte Carlo simulation [50], was used to assess the potential water savings over 1.000 growing seasons by deploying the control framework implemented for the line $\mathcal{A}^{(\mathrm{sh})}$. Each growing season lasted 70 days, resulting in 10.080 samples when considering the LoRaWAN network transmission rate of one samples every 10 min. From an operational standpoint, a normal distribution—characterized by a given mean value μ and standard deviation σ—was derived from the data collected during $\mathcal{C}_{\mathrm{Y2}}$. Based on this statistical assumption, a new normal distribution—then used as input for the Monte Carlo method—has been defined to represent the irrigation behavior performed for the automated line, with μ_{new} equal to the soil capacity level and $\sigma_{\mathrm{new}} = \frac{\mu-\sigma}{2}$. As a result, the Monte Carlo simulation estimates water savings ranging from 15% to 30%, by considering the simulated activation inputs in conjunction with the nominal flow rate of the irrigation network.

C. Water Use Efficiency (WUE)

Typically, in conjunction with the evaluation metrics detailed in Sections IV-A and IV-B, the plants drought stress can be assessed using another metric of interest, denoted as WUE index (dimension: [kg/m^3)]) [52] and useful for agricultural purposes, being inversely proportional to the water consumption. In fact, as shown in (1), the WUE index is expressed as the ratio between the final yield (dimension: [kg/ha]) and the total amount (including irrigation water and rainfall) of applied water (dimension: [m^3/ha]) as

$$\mathrm{WUE} = \frac{\text{yield}}{\text{irrigation water + rainfall}}. \tag{1}$$

For each water regime in $\mathcal{C}_{\mathrm{Y1}}$ and $\mathcal{C}_{\mathrm{Y2}}$, two different WUE index values have been considered, on the basis of two final yields types: the global yield (dimension: [kg/ha]) and the marketable yield (dimension: [kg/ha]) [53]. As a consequence, typically a high WUE stands for a crop producing a higher yield per unit of water consumed, thus leading to plants being more efficient in their water usage. On the operational side, WUE values have been utilized to perform a comparison between the crops across the two consecutive years.

In particular, considering the global yield, $\hat{\mathcal{I}}_{60}$ in $\mathcal{C}_{\mathrm{Y2}}$ achieved the highest WUE (equal to 28.5 kg/m^3). This value is relevant because it represents a 22.2% increase over the WUE value of $\mathcal{I}_{60}$ in $\mathcal{C}_{\mathrm{Y1}}$ (equal to 22 kg/m^3), which was the best-performing water regime for the 2023 season. In other words, the obtained results suggest that, for tomato crops, providing less water to the plants leads to a better water management by the plants themselves, allowing also to save around 40% of water for an entire tomato line. Moreover, $\mathcal{A}^{(\mathrm{sh})}$ achieves an attractive performance, as its global WUE value is equal to 28.5 kg/m^3, thus comparable to $\hat{\mathcal{I}}_{60}$. This result highlights that the sensor-based WD approach proposed in Section III-E2 allows for a good yield, making the $\mathcal{A}^{(\mathrm{sh})}$ tomato line more efficient than a standard water use, characterized by a 100% of the Irriframe recommendations water usage.

Finally, considering the marketable yield, the higher value of WUE, equal to 22.3 kg/m^3, was obtained by $\hat{\mathcal{I}}_{60}$, followed by $\hat{\mathcal{I}}_{80}$, which return a WUE equal to 21.3 kg/m^3. This result shows that saving water not only leads to more sustainable agriculture with less waste, but also increases the amount of marketable tomatoes. In fact, the tomato lines using a limited quantity of water (namely, 60% and 80% of the Irriframe advice) had an higher efficiency index, compared to the 100% water regime, resulting in a marketable WUE of 14.9 kg/m^3.

V. Conclusion and Future Works

This work presents the activities carried out in a two-year SA testbed, with the aim of optimizing the watering process through the integration of IoT technologies and the use of a cloud data management platform denoted as Agriware. The proposed approach allows to obtain a water usage optimization through a continuous monitoring of an evolving tomato cultivation located at the "Azienda Agricola Sperimentale Stuard," Parma, Italy. The testbed was applied, *first*, in $\mathcal{C}_{\mathrm{Y1}}$ (2023) with the integration of IoT devices and a manual irrigation, and, *then*, in $\mathcal{C}_{\mathrm{Y2}}$ (2024), with a fully automated irrigation system. IoT data have been collected and processed through the Agriware integration platform.

Overall, the proposed approach not only minimizes water consumption, but also promotes a sustainable agriculture. In fact, the obtained results shows that automating the irrigation process allows an efficient water distribution. In fact, $\mathcal{C}_{\mathrm{Y2}}$ achieves more accurate control on the irrigation, lower water consumption, and higher WUE values, if compared to the manually managed $\mathcal{C}_{\mathrm{Y1}}$. In addition, the benefits brought by the use of the proposed framework have been statistically quantified by simulating 1.000 growing seasons and obtaining a water saving ranging from 15% to 30%. Furthermore, an economic evaluation of the proposed solution, performed in [54], highlights how the total investments can return in 1.9 years.

Taking into account the positive results obtained in the two considered experimental tomato seasons, the experimental evaluation is still ongoing, with an operational plan to extend the tomato monitoring to 2025 spring-summer period. In particular, the integration of new IoT devices, such as fruit and stem dendrometers, has been planned to monitor tomato plants growth. This will allow an even finer control of the growth process, expedient to further optimize production.

References

[1] DEMETER, "DEMETER - empowering farmers," Accessed: Jul. 01, 2025. [Online]. Available: https://h2020-demeter.eu/

[2] TITAN, "TITAN project - providing digital technologies that increase transparency." Accessed: Mar. 20, 2025. [Online]. Available: https://titanproject.eu/

[3] SMALLDERS, "SMALLDERS project - empowering the smallholders." Accessed: Jul. 01, 2025. [Online]. Available: https://smallders.com/

[4] AGRITECH, "Agritech center - ricerca e innovazione per l'agricoltura sostenibile." Accessed: Jul. 01, 2025. [Online]. Available: https://agritechcenter.it/

[5] I. Samal, T. K. Bhoi, A. K. Pradhan, and D. K. Mahanta, "Plantix app: A success story of artificial intelligence in plant protection," *Van Sangyan*, vol. 10, pp. 24–44, 2023.

[6] Agrivi, "AGRIVI: Il software di gestione agricola leader per l'agricoltura digitale." Accessed: Jul. 01, 2025. [Online]. Available: https://www.agrivi.com/it/

[7] Irriframe, "Home page." Accessed: Jul. 01, 2025. [Online]. Available: https://www.irriframe.it/Irriframe

[8] F. Vurro et al., "In vivo sensing to monitor tomato plants in field conditions and optimize crop water management," *Precis. Agriculture*, vol. 24, no. 6, pp. 2479–2499, 2023.

[9] ANBI, "Home page," Accessed: Jul. 01, 2025. [Online]. Available: https://www.anbi.it/?lang=en

[10] A. Agraria and S. Stuard, "Home page," Accessed: Jul. 01, 2025. [Online]. Available: https://www.stuard.it/

[11] D. Gentilcore, "Pomodoro! a history of the tomato in italy," in *Arts and Traditions of the Table: Perspectives on Culinary History*. Columbia University Press, 2010, doi: 10.7312/gent15206.

[12] A. Gerszberg and K. Hnatuszko-Konka, "Tomato tolerance to abiotic stress: A review of most often engineered target sequences," *Plant Growth Regulation*, vol. 83, pp. 175–198, 2017.

[13] M. Rinaldi and R. Ubaldo, "Spatial simulation of water use efficiency in a mediterranean environment," in *Proc. Int. Conf. Water Saving Mediterranean Agriculture Future Res. Needs*, Valenzano, Italy, Feb. 2007, pp. 121–141.

[14] Food and Agriculture Organization of the United Nations (FAO), "Water for sustainable food and agriculture," Accessed: Jul. 01, 2025. [Online]. Available: https://openknowledge.fao.org/server/api/core/bitstreams/b48cb758-48bc-4dc5-a508-e5a0d61fb365/content

[15] T. Crovella, A. Paiano, and G. Lagioia, "A meso-level water use assessment in the mediterranean agriculture. Multiple applications of water footprint for some traditional crops," *J. Cleaner Prod.*, vol. 330, 2022, Art. no. 129886, doi: 10.1016/j.jclepro.2021.129886.

[16] L. Davoli et al., *Data Integration in a Smart City: A Real Case*, Cham, Switzerland: Springer, 2024, doi: 10.1007/978-3-031-39446-1_2.

[17] S. I. Hassan, M. M. Alam, U. Illahi, M. A. Al Ghamdi, S. H. Almotiri, and M. M. Su'ud, "A systematic review on monitoring and advanced control strategies in smart agriculture," *IEEE Access*, vol. 9, pp. 32517–32548, 2021, doi: 10.1109/ACCESS.2021.3057865.

[18] V. K. Quy et al., "IoT-Enabled smart agriculture: Architecture, applications, and challenges," *Appl. Sci.*, vol. 12, no. 7, 2022, Art. no. 3396, doi: 10.3390/app12073396.

[19] S. F. Di Gennaro et al., "Unmanned aerial vehicle (UAV)-based remote sensing to monitor grapevine leaf stripe disease within a vineyard affected by ESCA complex," *Phytopathologia Mediterranea*, vol. 55, no. 2, pp. 262–275, 2016, doi: 10.14601/Phytopathol_Mediterr-18312.

[20] U. Lee et al., "An automated, clip-type, small Internet of Things camera-based tomato flower and fruit monitoring and harvest prediction system," *Sensors*, vol. 22, no. 7, 2022, Art. no. 2456, doi: 10.3390/s22072456.

[21] P. Garofalo et al., "AquaCrop model to optimize water supply for a sustainable processing tomato cultivation in the mediterranean area: A multi-objective approach," *Agricultural Syst.*, vol. 223, 2025, Art. no. 104198, doi: 10.1016/j.agsy.2024.104198.

[22] S. F. Di Gennaro et al., "Development of a low-cost smart irrigation system for sustainable water management in the mediterranean region," *Smart Agricultural Technol.*, vol. 9, 2024, Art. no. 100629, doi: 10.1016/j.atech.2024.100629.

[23] N. K. Nawandar and V. R. Satpute, "IoT based low cost and intelligent module for smart irrigation system," *Comput. Electron. Agriculture*, vol. 162, pp. 979–990, 2019, doi: 10.1016/j.compag.2019.05.027.

[24] M. Yadav et al., "Improving water efficiencies in rural agriculture for sustainability of water resources: A review," *Water Resour. Manage.*, vol. 38, no. 10, pp. 3505–3526, 2024, doi: 10.1007/s11269-024-03836-6.

[25] V. Kumar, K. V. Sharma, N. Kedam, A. Patel, T. R. Kate, and U. Rathnayake, "A comprehensive review on smart and sustainable agriculture using IoT technologies," *Smart Agricultural Technol.*, vol. 8, 2024, Art. no. 100487, doi: 10.1016/j.atech.2024.100487.

[26] A. Morchid, I. G. M. Alblushi, H. M. Khalid, R. El Alami, S. R. Sitaramanan, and S. Muyeen, "High-technology agriculture system to enhance food security: A concept of smart irrigation system using Internet of Things and cloud computing," *J. Saudi Soc. Agricultural Sci.*, 2024, doi: 10.1016/j.jssas.2024.02.001.

[27] A. Morchid, R. Jebabra, H. M. Khalid, R. El Alami, H. Qjidaa, and M. O. Jamil, "IoT-based smart irrigation management system to enhance agricultural water security using embedded systems, telemetry data, and cloud computing," *Results Eng.*, vol. 23, 2024, Art. no. 102829, doi: 10.1016/j.rineng.2024.102829.

[28] E. Avşar and M. N. Mowla, "Wireless communication protocols in smart agriculture: A review on applications, challenges and future trends," *Ad Hoc Netw.*, vol. 136, 2022, Art. no. 102982, doi: 10.1016/j.adhoc.2022.102982.

[29] J. de Carvalho et al., "LoRaWAN—A Low Power WAN Protocol for Internet of Things: A Review and Opportunities," in *Proc. 2017 2nd Int. Multidisciplinary Conf. Comput. Energy Sci. (SpliTech)*, Split, Croatia, 2017, pp. 1–6.

[30] C. Deng et al., "IEEE 802.11be Wi-Fi 7: New challenges and opportunities," *IEEE Commun. Surv. Tut.*, vol. 22, no. 4, pp. 2136–2166, Fourthquarter 2020, doi: 10.1109/COMST.2020.3012715.

[31] MQTT, "MQTT protocol: The standard for IoT messaging." Accessed: Jul. 01, 2025. [Online]. Available: https://mqtt.org

[32] H. Nielsen, R. T. Fielding, and T. Berners-Lee, "Hypertext Transfer Protocol–HTTP/1.0," RFC 1945, Internet Engineering Task Force, May 1996, doi: 10.17487/RFC1945.

[33] A. U. Rehman, Y. Alamoudi, H. M. Khalid, A. Morchid, S. Muyeen, and A. Y. Abdelaziz, "Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics," *Cleaner Energy Syst.*, vol. 9, 2024, Art. no. 100132, doi: 10.1016/j.cles.2024.100132.

[34] M. Galaverni et al., "An IoT-based data analysis system: A case study on tomato cultivation under different irrigation regimes," *Comput. Electron. Agriculture*, vol. 229, 2025, Art. no. 109660, doi: 10.1016/j.compag.2024.109660.

[35] The Things Industries, "The things network (TTN) platform." Accessed: Mar. 20, 2025. [Online]. Available: https://www.thethingsnetwork.org

[36] Milesight, "UG67 outdoor LoRaWAN gateway." Accessed: Jul. 01, 2025. [Online]. Available: https://www.milesight.com/iot/product/lorawan-gateway/ug67

[37] Milesight, "Milesight EM500-SMTC environmental sensor." Accessed: Jul. 01, 2025. [Online]. Available: https://www.milesight.com/iot/product/lorawan-sensor/em500-co2

[38] Milesight, "Milesight EM500-SMTC soil sensor." Accessed: Jul. 01, 2025. [Online]. Available: https://www.milesight.com/iot/product/lorawan-sensor/em500-smtc

[39] Milesight, "Milesight EM500-PP pipe pressure sensor." Accessed: Jul. 01, 2025. [Online]. Available: https://www.milesight.com/iot/product/lorawan-sensor/em500-co2

[40] Sensational Systems Limited, "Talkpool OY1310 single-jet LoRaWAN smart water meter." Accessed: Jul. 01, 2025. [Online]. Available: https://connectedthings.store/gb/industrial-devices/water-valves-meters/talkpool-oy1310-single-jet-lorawan-smart-water-meter.html

[41] D. GmbH, "Decentlab DL-TRS21 soil water potential and temperature sensor." Accessed: Jul. 01, 2025. [Online]. Available: https://www.decentlab.com/products/soil-water-potential-and-temperature-sensor-for-lorawan

[42] MClimate, "MClimate LoRaWAN t-valve." Accessed: Jul. 01, 2025. [Online]. Available: https://mclimate.eu/products/mclimate-t-valve

[43] Milesight, "Milesight UC512 solenoid valve ControllER," Accessed: Jul. 01, 2025. [Online]. Available: https://www.milesight.com/iot/product/iot-controller/uc51x

[44] Rain Bird Corporation, "Rainbird LFV-075 DN20," Accessed: Jul. 01, 2025. [Online]. Available: https://www.rainbird.com/it/products/valvola-bassa-portata-serie-lfv

[45] L. Preite, F. Solari, and G. Vignali, "Water management optimization in agriculture: A digital model development," *Water Resour. Manage.*, vol. 39, pp. 1261–1279, Feb. 2025, doi: 10.1007/s11269-024-04030-4.

[46] Agenzia Prevenzione Ambientale Energia Emilia Romagna (ARPAE), "Home page," Accessed: Jul. 01, 2025. [Online]. Available: https://www.arpae.it/it

[47] S. Saadi et al., "Climate change and Mediterranean agriculture: Impacts on winter wheat and tomato crop evapotranspiration, irrigation requirements and yield," *Agricultural Water Manage.*, vol. 147, pp. 103–115, 2015, doi: 10.1016/j.agwat.2014.05.008.

[48] R. Machado et al., "Prediction of optimal harvest date for processing tomato based on the accumulation of daily heat units over the fruit ripening period," *J. Horticultural Sci. Biotechnol.*, vol. 79, no. 3, pp. 452–457, 2004, doi: 10.1080/14620316.2004.11511789.

[49] A. Ferrante and L. Mariani, "Agronomic management for enhancing plant tolerance to abiotic stresses: High and low values of temperature, light intensity, and relative humidity," *Horticulturae*, vol. 4, no. 3, 2018, Art. no. 21, doi: 10.3390/horticulturae4030021.

[50] L. Preite and G. Vignali, "Artificial intelligence to optimize water consumption in agriculture: A predictive algorithm-based irrigation management system," *Comput. Electron. Agriculture*, vol. 223, 2024, Art. no. 109126, doi: 10.1016/j.compag.2024.109126.

[51] S. L. Warren and T. E. Bilderback, "Irrigation timing: Effect on plant growth, photosynthesis, water-use efficiency and substrate temperature," *Acta Horticulturae*, pp. 29–37, Feb. 2004, doi: 10.17660/actahortic.2004.644.1.

[52] N. Katerji, M. Mastrorilli, and G. Rana, "Water use efficiency of crops cultivated in the mediterranean region: Review and analysis," *Eur. J. Agronomy*, vol. 28, no. 4, pp. 493–507, 2008, doi: 10.1016/j.eja.2007.12.003.

[53] A. Zairi et al., "Irrigation scheduling strategies for horticultural field crops under limited water availability," *Acta Horticulturae*, vol. 537, pp. 503–510, Oct. 2000, doi: 10.17660/actahortic.2000.537.59.

[54] R. Stefanini, E. Bottani, L. Belli, L. Davoli, G. Ferrari, and G. Vignali, "Selection of 4.0 sensors for small holders: The compromise between the advantages and the costs of the implementation," in *Proc. Proc. 9th Int. Food Operations Process. Simul. Workshop (FoodOPS 2023)*, 2023, Art. no. 007.

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