Water Management Optimization in Agriculture: a Digital Model Development

Water Management Optimization in Agriculture: A Digital Model Development

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Abstract: Water scarcity is one of 21st century's most pressing global issues. The anthropogenic pressure and climate change will be the main drivers of freshwater depletion in the coming decades. According to the FAO, the amount of water needed to support all human activities will be 20-30% higher by 2050. A closer look reveals how agriculture is a major contributor to water scarcity, with irrigation accounting for 70% of global water use. In this framework, the development of effective water management approaches is a key solution to turn the tide and change current patterns. Despite that, there still exists a gap in the scientific literature in the development and validation of innovative water management strategies using advanced technologies.

This study aims to address this gap by developing a digital model of a real irrigation network able to accurately predict the water distribution across the network at different operating conditions. A living lab was used for the experimental activities, where a low-power wide-area network was used to acquire data from the system. For modeling purposes, the integration of the 1-D and 3-D simulation was leveraged to fluid-dynamically characterize all the components involved. The numerical model resulted to be accurate in predicting both pressure and velocity patterns (determination coefficient higher than 93%). The proposed model could be considered a starting point for the implementation of a digital twin to support agricultural water management in both the design and management of an irrigation network by defining the correct network configuration and detect anomalous conditions.

Keywords: Water Management, Agriculture 4.0, Digital Twin, Fluid Dynamic Simulation.

1 Introduction

Humanity is dealing with several challenges in the 21st century. Just some of the pressing issues are climate change, resource depletion, environmental degradation, poverty, and inequality (Nguyen et al., 2023). As a result, all major global questions have incorporated the three pillars of sustainable development – social, environment and economy (Moldan et al., 2012). As shown in the literature, the human footprint and climate change are major drivers of water scarcity and soil degradation (Pierrat et al., 2023). Hence, these problems have been increasing in a worrying manner over the years and require appropriate strategies to be handled (IPCC, 2023). When delving into the issue of water scarcity, agriculture is a major player, using nearly 4750 million hectares of land worldwide (Food and Agriculture Organization of the United Nations, 2023). By way of illustration, irrigation represents almost 70% of total global water withdrawals. In addition, the increasing trend towards extreme events is negatively affecting crop productivity by causing irreversible damage (Furtak & Wolińska, 2023). Against this backdrop, sustainable strategies to efficiently manage water use and enhance food security are needed to turn the tide and mitigate negative impacts (Elnashar & Elyamany, 2023).

There were several efforts in the scientific literature to improve smart agricultural practices for reducing water consumption (Karunathilake et al., 2023). In this regard, both external and internal parameters of the crops can be monitored

(Simbeye et al., 2023). Indeed, to indirectly monitor the impact of drought on the crop, a typical approach was to assess environmental and soil characteristics (Ayoub Shaikh et al., 2022). As an alternative, the stress can be identified by directly evaluating certain intrinsic parameters, such as sap ion concentration (Vurro et al., 2023). (Han et al., 2023) implemented a new model for modeling drip irrigation at both field and basin scale, by considering the water balance in terms of precipitation, evaporation, transpiration, percolation. (Abioye et al., 2023) used a data-driven prediction model based on soil, weather and crop features to strike a balance between water savings and crop yield and quality. The behavior of water in the subsurface soil layers is an issue to consider when working on an irrigation system. (Bohaienko et al., 2024), developed a simulation-based approach to optimize subsurface drip irrigation systems, balancing water loss due to evaporation and deep infiltration while maintaining water availability for crops. (Vishwakarma et al., 2023) analyzed soil moisture movement and wetting patterns under point-source trickle irrigation in an apple orchard, with the goal of providing accurate information on moistening patterns to aid in the design and selection of optimum emitters.

Industry 4.0 technologies therefore represent a possible solution to reduce the environmental impact of agriculture and to make it more sustainable (Petit et al., 2022). Some of them are already widely applied, while others are still cutting-edge technologies (Lysova et al., 2022; Solari et al., 2023). The authors of (Purcell & Neubauer, 2023) outlined the gap in applying digital twin for agricultural operations. Furthermore, there were several limitations to the diffusion of digital twin in farming (Shang et al., 2021). These included low potential for investments by farmers, widespread misinformation, and complex interactions between objects, entities, plants and human (Purcell et al., 2023). In (Pylianidis et al., 2021), the authors have provided insights into some applications developed with FIWARE, which is an open-source solution for managing digital models in different sectors.

Among Industry 4.0 technologies, simulation allows to know the behavior of the system at every single point, which is impossible to achieve using only sensors. Extended period simulations based on the gradient method to provide a numerical solution are typically used to determine water losses in water distribution networks. These models do not focus on the system inertia as it can be neglected when considering an extended period. In (Coronado-Hernández et al., 2024), the effect of system inertia on the total amount of leakage is evaluated by implementing the rigid water column model. Thus, an overestimation and an underestimation of 37.1 % and 55.2% respectively can occur if the inertia is not taken into account.

In recent years, simulation models have also been widely adopted in the development of digital twin for the design, control, maintenance of industrial and, more in general, real systems. A digital twin is an accurate replica of a real process able to bidirectionally communicate with the physical layer (Singh et al., 2021). Reliably predicting and thus optimizing the performance of the physical counterpart is the main purpose of this technology, bringing multiple benefits (i.e., reducing total costs, monitoring a wide range of parameters, testing various configurations, improving safety and energy efficiency and many others) to many fields such as aerospace, automotive, smart cities, and many others (Attaran & Celik, 2023). According to (Bergs et al., 2021), the link between the physical entity and the digital representation followed three different data integration layers: i) digital model (DM), ii) digital shadow (DS), and iii) digital twin (DT). For water management purposes, the authors of (Zhou et al., 2024) developed a digital twin of a pump station to address several issues, such as high energy demand, adaptability to different undesired operating conditions, and efficiency. In this framework, high responsiveness and efficiency were reached with an energy-saving of 9.78%.

In agriculture, according to the authors of (Preite et al., 2023), only a few studies have focused on quantifying the positive impact of the strategies involved to manage and optimize irrigation networks. They provided insights into the effectiveness of the systems reported in the literature and highlighted how a deeper pool of data can help scientists to monitor a wide range of valuable parameters. In this way, machine learning or control algorithms can be trained to reliably predict the correct amount of the water to deliver to crops under different operating conditions (Preite & Vignali, 2024). Problems exist not only in the management of an irrigation system, but also in the design step, as it is a complex and expensive operation that involves different methods to determine the optimal configuration to meet all the requirements and minimize the total cost. In (Samarinas et al., 2024), a robust solution, compatible with the most widely used optimization models, has been implemented to determine the network configuration, which minimizes the total cost.

The emerging gaps underscore how this technology has been widely used in several disciplines but there still exists a lack of both digital twin and digital model applications for the accurate monitoring and management of water distribution systems in agriculture. Therefore, this study aims to address this gap by developing a digital model of an irrigation network to assess how it could help in improving the efficiency, ensuring the right amount of water and nutrients for crops, and determining the optimal network design. To this end, a living lab was developed in collaboration with a local farmer in Northern Italy, where tomatoes were irrigated with a drip system. A living lab is a cutting-edge research method that allows to address concrete problems by focusing on the collaboration of different stakeholders in a real experimental environment (Hossain et al., 2019).

The digital model, obtained by integrating the use of both three dimensional and mono dimensional fluid dynamics simulation, was finally validated with a proper experimental session carried out in the previously described living lab.

The developed digital model proved to reliably predict the water distribution along the irrigation network under different operating conditions and to detect possible failures that could be caused by breakages or other internal or external causes. The proposed application is a preliminary step for the development of a digital twin of the irrigation network that can help to mitigate the negative effects of water scarcity by applying the associated benefits to agricultural operations.

The next section describes the methodology used to drive the present work. All the results achieved are presented in section 3 and subsequently discussed in section 4. Finally, the last section draws the conclusions and illustrates future developments.

2 Materials and Methods

2.1 Living Lab Description

The activities were focused on an organic tomato crop (Solanum Lycoperium L.cv. HEINZ 1301). Figure 1 shows an overall view of the experimental field, highlighting the part considered for the present study, consisting of three rows (length = 90 meters, distance between rows = 1.5 m) each equipped with a flow control system. As can be noted, blue highlighted section has not been included in the digital model.

The layout of the experimental field, as well as the definition of irrigation regimes, were defined based on agronomic criteria that are not the subject of the present study. Specifically, the watering recommendation provided by the national platform IRRIFRAME was taken as 100% of the total volume to be delivered to the first row (Row 1) of the experimental line. For Row 2 and Row 3, 60% and 30% respectively were used.

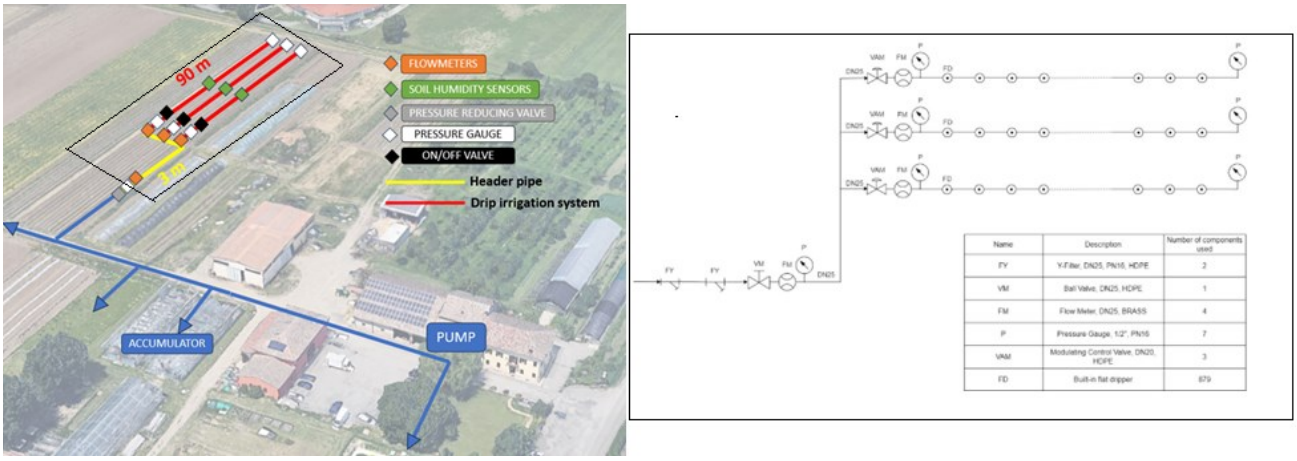

Fig 1 Overall representation of the experimental field (left) with the detail and the piping & instrumentation diagram of the part included within the digital model (right)

The drip irrigation system consisted of a of low-density polyethylene drip line with built-in flat drippers with a labyrinth configuration to prevent debris from clogging the outlet section (Figure 2). The drippers, having a nominal flow rate of 1 liter/hour, are located every 30 centimeters, resulting in 293 drippers per row.

A low-power wide-area network (LoRaWAN) were employed to manage water use and to collect all the data recorded during experimental campaign.

2.2 Drip System Modeling

To characterize the behavior of the drip system under different operating conditions and to derive its characteristic curve, which will be used to reproduce as closely as possible the behavior of the dripping wing within the 1D lumped-parameter model described later, a fluid dynamic model was defined using Ansys Fluent 2022 R2. Ansys Fluent is a finite volume-based software widely used for solving fluid dynamics and Multiphysics problems within three-dimensional domains. The geometry of the dripper was accurately measured, and a three-dimensional replica was obtained (Figure 2). A volume of water upstream and downstream of the geometry was added to move the boundary conditions away from the volume of interest to minimize negative influences on the results achieved. The upstream volume is a prismatic volume having dimensions (h x l x d). A sensitivity analysis was conducted to obtain the optimal dimensions of the prism, by comparing the results obtained, in terms of pressure drops across the dripper, for a given operating condition, with three different configurations (Table 1). As regards the downstream volume it is a cylindrical volume having a length equal to 7 times the outlet diameter.

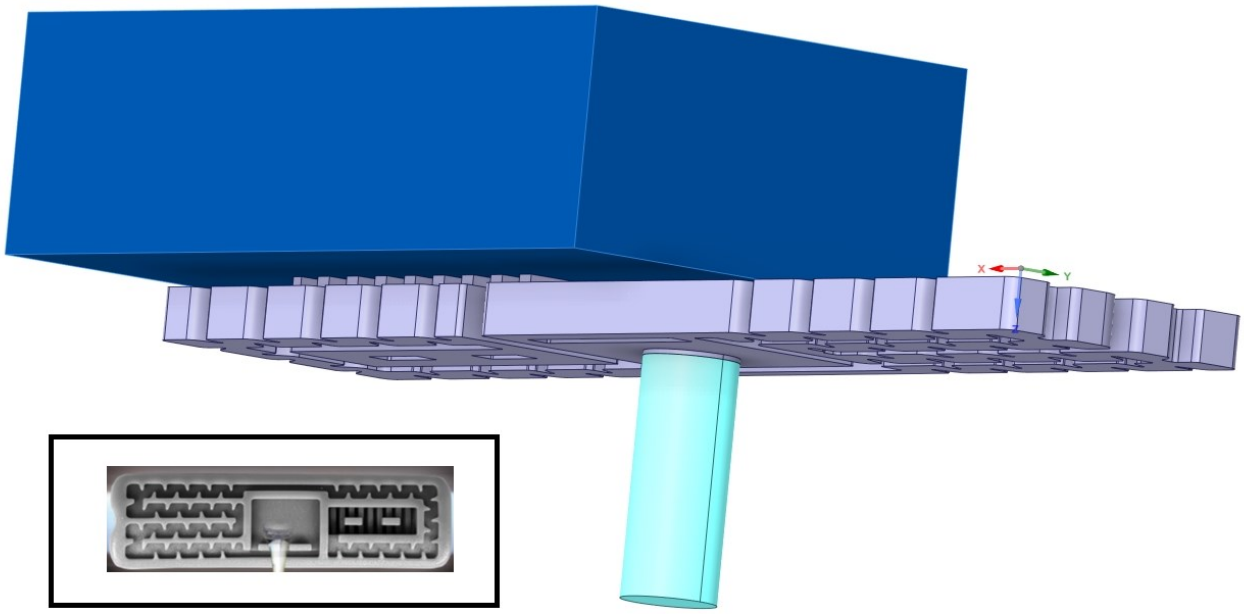

Fig 2 Real dripper geometry compared with the 3D reproduction consisting of: dripper geometry (grey) reproduction with the additional upstream (dark blue) and downstream (light blue) water volume

Table 1 Results obtained with three different dimensions of the upstream region

h [mm]	l [mm]	d [mm]	Pressure drop [Pa]
5	18	10	3163
8	21	13	3151
10	23	15	3140

It can be observed that by increasing the size of the region, the pressure drop variation does not exceed 1%. The region with the lower volume was therefore selected.

The geometry was first discretized with a tetrahedral mesh, which was then converted to a polyhedral mesh to improve the quality of the computational grid and reduce the number of elements. Each polyhedron is in fact obtained by the union of several tetrahedra (usually 4 or 5); it therefore follows that the most distorted elements, which could negatively affect the outcomes of the calculation, are joined to other elements (3 or 4) having better shape factors, thus resulting in a polyhedron with a higher shape factor.

A sensitivity analysis was performed to identify the mesh parameters: four different computational grids, characterized by different sizing parameters, were compared for a fixed operating condition, as reported in Table 2.

Table 2 results of the mesh sensitivity analysis

	minimum number of elements across cross-section	Maximum element size within the dripper [mm]	Number of polyhedral cells	Pressure drop [Pa]
Mesh 1	7	0.7	1036899	3136

Mesh 2	10	0.5	1397517	3163
Mesh 3	15	0.3	2546515	3212
Mesh 4	17	0.15	3244440	3201

It can be observed that the calculated pressure drops are independent of the mesh characteristics, having fluctuations in the values within a range of 2.5%. Mesh 2 was chosen as the one with the best trade-off between result resolution and computational time. The resulting mesh, having a minimum orthogonal quality of 0.202, is represented in Figure 7.

Simulations were then conducted by imposing a velocity on the inlet sections and a reference pressure on the outlet section. The characterization was performed at five different flow rates (0. l/h, 0.75 l/h, 0.98 l/h, 1.1 l/h, 1.2 l/h) and, for each flow rate value, the pressure drop was evaluated at the ends of the drip system.

2.3 Digital Model Development

A 1-D lumped-parameter simulation software, Flownex® 2022 Update 1, was used to design and develop the digital model of the irrigation network. Flownex® is an extensively validated and verified simulation software engineered under a quality system accredited to ISO 9001 and ASME NQA1.

Thermo-fluid dynamic processes were numerically modeled by setting valuable boundary conditions and solving the fundamental differential equations (Zubair et al., 2021). These were the conservation equations for mass, momentum, and energy, respectively. In addition, Flownex® can be equipped with an Application Programming Interface (API) that allows the software to interface with other applications.

The identification of the network section to be modeled, and thus the definition of the computational domain, was done considering the following criteria: (i) the boundary conditions (i.e., inlet and outlet condition) must be known and/or measurable; (ii) all network components should be modeled in terms of characteristic curve. In this study, the flow rate was set at the inlet section of the header pipe, where it is monitored by a dedicated sensor, and the atmospheric pressure was set at the outlet section of each dripper. All the pipes were modeled by specifying length, diameter, and material. Specifically, once the element material has been defined, a proper Flownex® library provided the corresponding roughness value, which was used to evaluate the associated primary losses. Secondary losses were assumed to be insignificant along the pipes.

The modulating control valves were simulated by defining the corresponding diameter, the connected pipe diameter, and the valve flow behavior. This latter parameter was set as a linear function with a valve flow coefficient at maximum opening of 0.75 m3/[sqrt(bar)*h)]. T-junctions and bends were also modeled based on the Flownex libraries, which are regulated by the ASME 16.9 standard, by specifying geometric dimensions and the material composition. Finally, 879 drippers of the system (293 per each experimental row) were replicated as a customized pressure drop using the resulting characteristic curve (pressure drop vs. flow rate) evaluated according to the method described in 2.2.

Three trigger buttons, four pressure gauges, and three progress bars were added to the digital model to immediately visualize the performance of the system. The buttons were required to simulate the on/off action of the IoT valves, the pressure gauges were related to a specific node and showed the corresponding pressure, and the progress bar visualized the flow rate delivered to each row. The obtained model is represented in Figure 3.

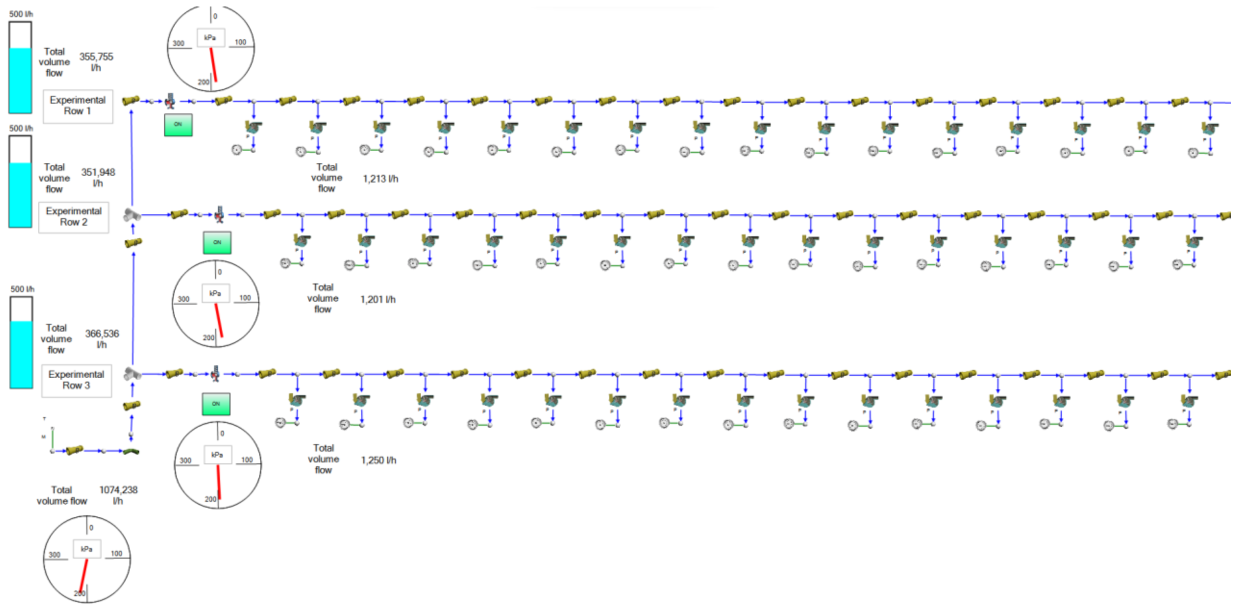

Fig 3 Digital Model of the experimental irrigation network developed with Flownex

2.4 Data Acquisition

All the data were monitored and collected, every 10 minutes, over a *Long-Range Wide Area Network* (LoRaWAN), which is typically configured with *end nodes* (EN), *gateways* (GW), and a *network server* (NS) (Hirsch et al., 2023). As shown in figure 4, the data were transmitted over two different layers: the end nodes communicated with the gateway via LoRa communication protocol, meanwhile the gateway used an IP-based protocol to interface with the network server. From the network server the data were gathered exploiting the *Message Queue Telemetry Transport* protocol (MQTT).

The ENs installed in the field were:

- Flowmeters to monitor the cumulative amount of water delivered to each experimental row.
- Pipe pressure sensors to constantly monitor pipe pressure.
- Modulating control valves to apply the different water regimes.

The gateway (Milesight, 2023), which can serve an area with a radius of hundreds of meters, has been installed in the farm's warehouse, as it needed a suitable power supply and internet connection to communicate with the NS.

As mentioned above, the end nodes provided an action layer characterized by both sensors and actuators. This means that the action layer allows data to be gathered and corrective actions to be taken, which in perspective, could become the core part of the digital twin.

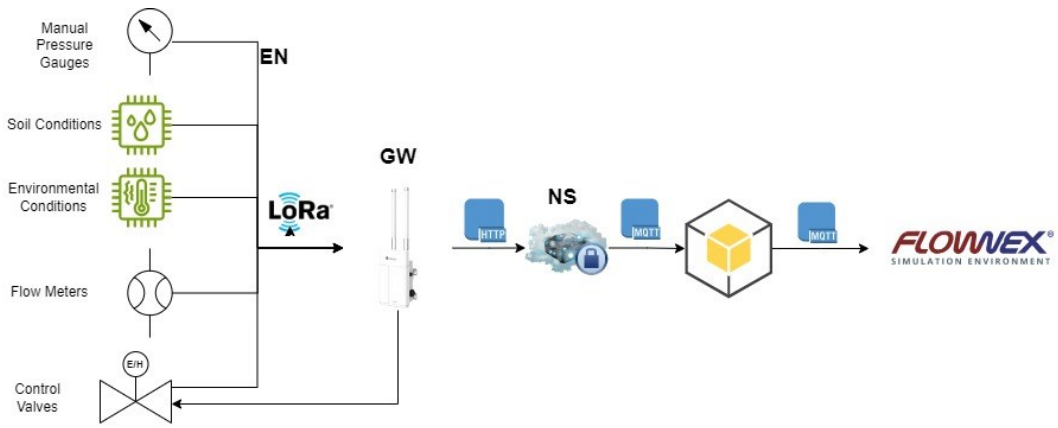

Fig 4 LoRaWAN-based data acquisition system that collects data from environmental and soil sensors, pressure gauges, flow meters, and control valves.

2.5 Testing and Validating Phase

The data collected were used to test and validate the digital model. Three different watering combinations were considered during seven irrigation tests carried out along the 2023 crop season, resulting in 21 steady-state operating conditions. In the first combination all three rows were activated, in the second one only Row 1 and Row 2 were activated and, finally, in the third combination only Row 1 was activated.

For each of the tests, a comparison was made between the simulated and the measured data. The flow rate entering in each row, the pressure drops along the network and the flow rate exiting from each dripper were used to calculate the performance accuracy. All data were gathered from the described acquisition layer, except for the drippers flow rate, which is evaluated by considering a reference value calculated according to equation (1). Specifically, this was calculated by dividing the flow rate measured along the entire drip line by the total number of drippers. For the other parameters, the steady-state value was considered for each irrigation event. In this perspective, an amount of 21 samples for each parameter was used to calculate the coefficient of determination (R^2) and the mean-square error (MSE), given by equation (2-3), respectively.

$$Dripper\ Flow\ Rate\ Reference\ Value\ = \frac{Distribution\ Drip\ Lines\ Flow\ Rate\ (measured)}{Number\ of\ drippers} \quad \textbf{(1)}$$

$$R^2\ = 1 - \frac{\sum_{i=1}^{21}(Measured\ Value - Simulated\ Value)^2}{\sum_{i=1}^{21}(Measured\ Value - Average\ Of\ Collected\ Value)^2} \quad \textbf{(2)}$$

$$MSE\ = \frac{\sum_{i=1}^{21}(Measured\ Value - Simulated\ Value)^2}{21} \quad \textbf{(3)}$$

3. Results

3.1 Drip System Modeling

The fluid dynamic results were evaluated in terms of both velocity and pressure distribution along the dripper. Figure 5 shows velocity vectors over a longitudinal section and the pressure streamlines colored according to pressure values. The vector field shows how the geometry of the dripper forces several sudden changes in flow direction that cause a drastic drop in pressure along each streamline This behavior prevents the flow from flowing freely out of the outlet hole, thus achieving the desired drip-drip effect.

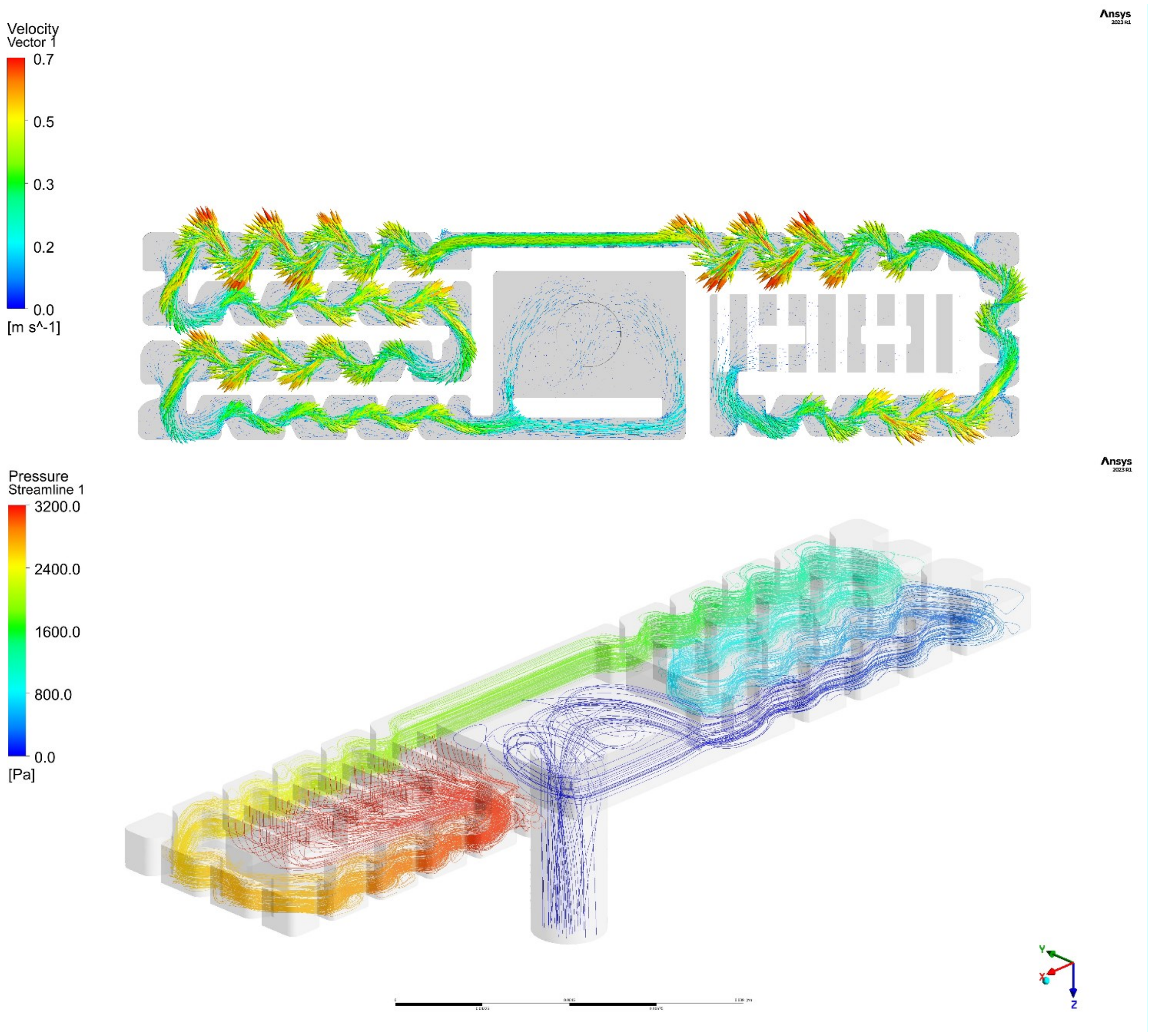

Fig 5 Velocity vectors over a longitudinal section of the dripper and pressure distribution along different streamlines

The characteristic curve of the drip system was finally derived, as shown in Figure 8. Specifically, the resulting curve reports the pressure drop versus the water flow rate.

3.2 Digital Model Development

As shown in Figure 6, the fluid velocity and pressure distributions along the network were calculated for all the 21 configurations analyzed by solving the system of mathematical equations in steady-state conditions.

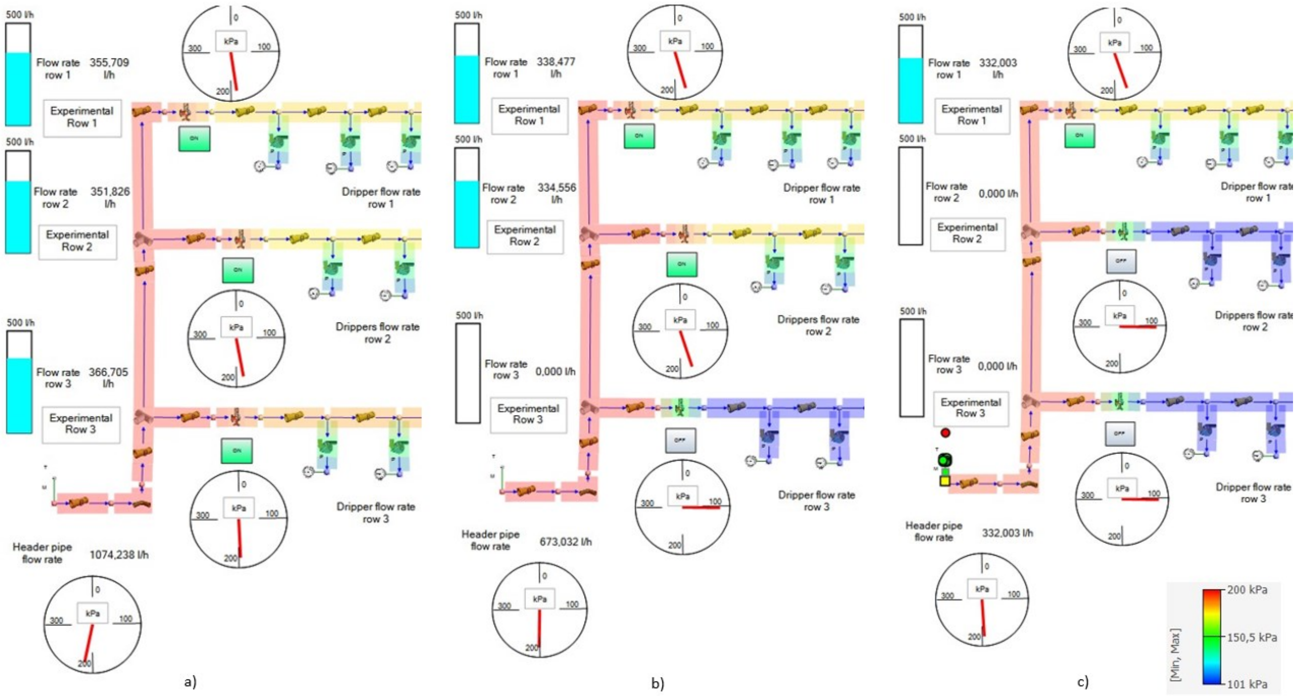

Fig 6 Steady-state pressure patterns along the experimental irrigation network in three different configurations of the 21 modeled; a) three experimental rows activated, b) two rows activated, and c) only one row activated.

3.3 Testing and Validating Phase

As it shown in Table 3, R^2 and MSE values showed that water distribution along the network, both in terms of pressure and flow rate distribution, was assessed with a high degree of accuracy. Concretely, the pressure field was reproduced with a R^2 ranging from 91% to 97%, while the R^2 achieved for the velocity field ranged between 93% and 99%. The resulting MSE for the pressure along the network ranges from 0.0009 to 0.005 bar, with a weight of 0.10 % to 0.80 % on the corresponding mean. The drip line flow rate was predicted with an MSE that falls in the range of 5.25 to 7.33 liters per hour, and finally, the amount of water discharged from the drippers was characterized by an MSE varying from 0.005 to 0.002 liters per hour.

Table 3 Coefficient of determination and mean square error for simulating pressure and velocity patterns

Quantity	Location	R^2	MSE	MSE/Mean value of the measured variable
Pressure	Header Pipe	0.91	0.0023	0.26 %
	Row 1 (100%)	0.97	0.0009	0.11 %
	Row 2 (60%)	0.97	0.005	0.80 %
	Row 3 (30%)	0.97	0.005	0.80 %
Flow rate	Row 1 (100%)	0.93	7.33	2.39 %
	Row 2 (60%)	0.99	6.7	3.32 %
	Row 3 (30%)	0.99	5.25	4.87 %
Flow rate drippers	Row 1 (100%)	0.95	0.005	0.05 %
	Row 2 (60%)	0.99	0.003	0.10 %
	Row 2 (30%)	0.99	0.02	0.05 %

A detailed comparison between measured and simulated results are reported in appendix.

4 Discussion

Digging deeper into the results, the developed model allows for a detailed and precise assessment of water distribution along a water distribution network, thus giving important information both during the designing phase and the operating phase. In the first case, the simulation allows for a quick, inexpensive, and effective evaluation of how the selected components (types of valves, drippers, pumps, etc.), or the variation of any parameters (pipe diameter, number of rows, number of drippers per row, operating pressure) affect the performance of the system. In the latter case, the model could predict in real time how any regulations would affect the system's behavior, thus identifying the values would allow it to work under the desired conditions. Furthermore, the data from the digital model can be easily transferred to a web application or dashboard for real-time monitoring, as well as to any other application, through an integrated *Application Programming Interface* (API), thus allowing the development of a digital twin of the system. Controller add-ins can be added to the model for directly acting on the IoT valves to trigger the irrigation delivery.

Finally, if properly trained, the model could enable the detection of abnormal operating conditions by continuously assessing the deviations between the simulated solution (representing the ideal operating condition) and the measured condition (monitored by the field sensors). This requires a detailed study of the possible failure modes of the system (Failure Mode & Effects Analysis) and the identification of how each failure and/or anomaly affects the operating conditions. Furthermore, the proposed model could be integrated with models that assess the moisture movement and wetting patterns, such as the one described by (Vishwakarma et al., 2023), to adjust the water distribution according to the specific soil conditions in the different areas of the field. These are some of the most interesting issues to be investigated in future research.

A detailed cost analysis of the implemented acquisition layer has been performed by (Stefanini et al., 2023), which shows how the investment could be recouped in 1.9 years. However, there are some limitations such as the cost of purchasing and maintaining the software, which is significant and can be a limiting factor for the farmer.

Finally, the proposed framework can be easily adapted to any type of crop and to any space scale (i.e., regional, and national level), as long as accurate boundary conditions could be derived. In any case the focus should be on the prediction of the water distribution along a specific network through the fluid dynamic representation of the interaction components. For instance, at the farm level the focus may be on the evaluation of the water provided to the crops, while at the regional scale, the distribution of water from the basin to different field slices may be the question to be investigated.

5 Conclusion

The future of the earth is being severely threatened by various issues. As it highlighted in the scientific literature, almost 70% of the global water demand was used to lead agricultural operations. In this context, the development of advanced solutions for improving the sustainability of water management in agriculture has become a crucial feature.

From the state-of-the-art analysis, as mentioned in the introduction section, emerged that there still is a gap in the scientific literature on the development of digital model of irrigation network in agricultural applications aiming in optimizing water distribution. The main reason can be related to the fact that the optimization of water management can be also performed by using IoT technologies, that can achieve good performance, without the aid of simulation models. Moreover, IoT based solution are generally more cost-effective than real-time control solutions based on simulation models. These applications have been widely described in the scientific literature and are mainly related to the automation of irrigation operations. To fill the gap mentioned above, the effectiveness of a digital replica of an irrigation network was investigated in the proposed work.

Specifically, the irrigation network was modeled using a lumped parameters computational fluid dynamics simulation model (Flownex), where the drippers characteristic curve was obtained through 3D fluid dynamics simulation (Ansys Fluent). The model was then validated under seven irrigation conditions, consisting in 21 steady-state operating situations. In this regard, different metrics, such as coefficient of determination, R^2, and the mean square error, MSE, were calculated to assess results accuracy.

As a result, over 93% accuracy was achieved in simulating the pressure and velocity distributions, and the MSE was less than 5% of the corresponding mean value in all the cases modeled.

In summary, compared to other studies in the scientific literature, the proposed framework leverages the power of fluid dynamic simulation to support irrigation strategies in designing the proper network, ensuring a precise and efficient distribution of water at every point of the crop, and highlight any deviations from ideal operating conditions. For instance, at the farm level, the added value is the possibility of knowing the actual operating conditions at each point of the network. Indeed, whereas the flowmeters measure the water flow rate in each drip lines, they do not assess the actual water distribution through all the drippers in the lines, thus failing in predicting the actual amount of water supplied to each plant.

Moreover, the proposed digital model can also be used to develop advanced control systems for distribution networks.

In future research activities, the proposed framework could be scaled up to a wider spatial scale, as long as reliable boundary conditions can be derived. In addition, future research should be focused on refining simulation models and on developing simulation-based real-time control systems able to optimize water distribution during the whole cropping season, and to develop predictive maintenance models as well as fault prevention and/or identification. Moreover, the impact of the digital twin on farmers and society could also be assessed to provide valuable insight into the acceptance of the technology by the stakeholders.

Appendix

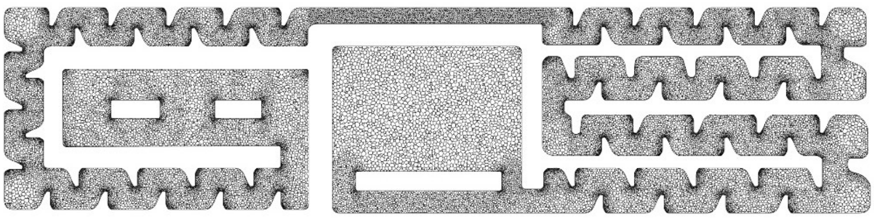

Fig. 7: The resulting mesh characterized by 1397517polyedra with a minimum orthogonal quality of 0.202

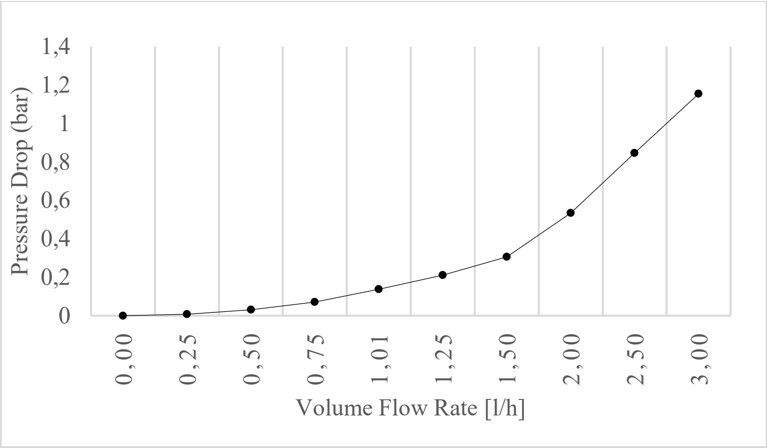

Fig 8: Characteristic curve of the dripper reporting the pressure drop versus the water flow rate

Specifically, Table 4 analyzes the pressure patterns at the header pipe and the at the different experimental rows. Table 5 shows the values of measured flow rate, the simulated flow rate, and the difference between them for each experimental line. The former has been evaluated by dividing the cumulative volume of water by the irrigation cycle. Finally, the same features are described in Table 6 for the flow rate delivered by the drippers of each row.

Table 4: Absolute pressure - comparison between real data and simulated data

Pressure Header Pipe [bar]			Pressure Row 1 [bar]			Pressure Row 2 [bar]			Pressure Row 3 [bar]		
Real Data	Simu-lated data	Dif-ference	Real Data	Simu-lated data	Dif-ference	Real Data	Simu-lated data	Dif-ference	Real Data	Simu-lated data	Dif-ference
0.9	0.88	0.02	0.6	0.57	0.03	0.6	0.5	0.1	0.6	0.5	0.1
0.9	0.85	0.05	0.6	0.59	0.01	0.6	0.5	0.1	0.6	0.5	0.1
0.9	0.85	0.05	0.6	0.65	0.05	0	0	0	0	0	0
1.1	1.05	0.05	0.95	0.9	0.05	0.95	0.9	0.05	0.95	0.9	0.05
1.1	1.04	0.06	0.95	0.92	0.03	0.95	0.9	0.05	0.95	0.9	0.05
0.9	0.9	0	0.7	0.7	0	0	0	0	0	0	0
1.1	1.1	0	0.95	0.96	0.01	0.93	0.8	0.13	0.93	0.8	0.13
1.1	1	0.1	0.95	0.9	0.05	0.93	0.9	0.03	0.93	0.9	0.03
1.1	1.1	0	0.95	0.91	0.04	0	0	0	0	0	0
0.7	0.67	0.03	0.55	0.57	0.02	0.55	0.53	0.02	0.55	0.53	0.02
0.7	0.7	0	0.55	0.55	0	0.55	0.55	0	0.55	0.55	0
0.7	0.67	0.03	0.55	0.57	0.02	0	0	0	0	0	0
0.7	0.7	0	0.55	0.53	0.02	0.55	0.6	0.05	0.55	0.6	0.05
0.7	0.67	0.03	0.55	0.54	0.01	0.55	0.54	0.01	0.55	0.54	0.01
0.7	0.67	0.03	0.55	0.54	0.01	0	0	0	0	0	0
1	1.05	0.05	0.9	0.95	0.05	0.9	0.93	0.03	0.9	0.93	0.03
0.9	0.95	0.05	0.8	0.8	0	0.75	0.6	0.15	0.75	0.6	0.15
0.9	0.9	0	0.87	0.87	0	0	0	0	0	0	0
1.1	1.1	0	0.97	0.99	0.02	0.93	0.85	0.08	0.93	0.85	0.08
1.1	1	0.1	0.9	0.92	0.02	0.9	0.8	0.1	0.9	0.8	0.1
1.1	1	0.1	1	0.95	0.05	0	0	0	0	0	0

Table 5: Flow rate flowing in each row - comparison between real data and simulated data

Flow Rate Row 1 [liters/hour]			Flow Rate Row 2 [liters/hour]			Flow Rate Row 3 [liters/hour]		
Real Data	Simulated data	Differ-ence	Real Data	Simulated data	Differ-ence	Real Data	Simulated data	Differ-ence
309.45	312	2.55	301.82	305	3.18	329.45	324	5.45
314.44	315	0.56	310.22	311	0.78	0.00	0	0.00
309.27	309	0.27	0.00	0	0.00	0.00	0	0.00
334.80	336	1.20	318.40	320	1.60	360.00	355	5.00
324.80	325	0.20	320.00	321	1.00	0.00	0	0.00
310.67	311	0.33	0.00	0	0.00	0.00	0	0.00
290.00	288	2.00	277.00	280	3.00	301.00	297	4.00
292.00	292	0.00	288.00	288	0.00	0.00	0	0.00
302.00	302	0.00	0.00	0	0.00	0.00	0	0.00
344.00	339	5.00	320.00	325	5.00	361.00	356	5.00
336.00	337	1.00	335.00	334	1.00	0.00	0	0.00
310.00	310	0.00	0.00	0	0.00	0.00	0	0.00
364.75	366	1.25	346.00	352	6.00	363.50	360	3.50
332.00	331	1.00	333.78	335	1.22	0.00	0	0.00
355.09	355	0.09	0.00	0	0.00	0.00	0	0.00
253.59	257	3.41	267.66	265	2.66	256.88	258	1.12
255.00	260	5.00	315.54	310	5.54	0.00	0	0.00
267.95	270	2.05	0.00	0	0.00	0.00	0	0.00
280.97	279	1.97	274.76	276	1.24	287.17	288	0.83
276.32	272	4.32	263.05	267	3.95	0.00	0	0.00
267.95	275	7.05	0.00	0	0.00	0.00	0	0.00

Table 6: Average flow rate exiting from the drippers in each row - comparison between real data and simulated data

Flow Rate Drippers Row 1 [liters/hour]			Flow Rate Drippers Row 2 [liters/hour]			Flow Rate Drippers Row 3 [liters/hour]		
Real Data	Simulated data	Differ-ence	Real Data	Simulated data	Differ-ence	Real Data	Simulated data	Differ-ence
1.05	1.06	0.01	1.03	1.04	0.01	1.12	1.1	0.02
1.07	1.07	0.00	1.06	1.07	0.01	0.00	0	0.00
1.05	1.05	0.00	0.00	0	0.00	0.00	0	0.00
1.14	1.14	0.00	1.09	1.13	0.04	1.23	1.2	0.03
1.11	1.11	0.00	1.09	1.09	0.00	0.00	0	0.00
1.06	1.06	0.00	0.00	0	0.00	0.00	0	0.00
0.99	0.98	0.01	0.94	0.96	0.02	1.03	1.01	0.02
0.99	0.99	0.00	0.98	0.98	0.00	0.00	0	0.00
1.03	1.03	0.00	0.00	0	0.00	0.00	0	0.00
1.17	1.16	0.01	1.09	1.13	0.04	1.23	1.2	0.03
1.15	1.15	0.00	1.14	1.14	0.00	0.00	0	0.00
1.06	1.06	0.00	0.00	0	0.00	0.00	0	0.00
1.24	1.23	0.01	1.18	1.2	0.02	1.24	1.22	0.02

1.13	1.14	0.01	1.14	1.13	0.01	0.00	0	0.00
1.21	1.21	0.00	0.00	0	0.00	0.00	0	0.00
0.86	0.88	0.02	0.91	0.87	0.04	0.88	0.9	0.02
0.87	0.97	0.10	1.08	0.99	0.09	0.00	0	0.00
0.91	0.91	0.00	0.00	0	0.00	0.00	0	0.00
0.96	0.95	0.01	0.94	0.94	0.00	0.98	0.98	0.00
0.94	0.93	0.01	0.90	0.91	0.01	0.00	0	0.00
0.91	0.91	0.00	0.00	0	0.00	0.00	0	0.00

Statements & Declarations

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Ethical Approval

Not applicable

Consent to Partecipate

All authors have approved the manuscript and agree to partecipate for publication

Consent to Publish

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Competing interests

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.

Author Contributions

Conceptualization: Luca Preite, Federico Solari, Giuseppe Vignali; Methodology: Luca Preite, Federico Solari, Giuseppe Vignali; Software: Luca Preite, Federico Solari; Validation: Luca Preite, Federico Solari, Giuseppe Vignali; Formal analysis and investigation: Luca Preite, Federico Solari; Writing - original draft preparation: Luca Preite, Federico Solari; Writing - review and editing: Luca Preite, Federico Solari, Giuseppe Vignali; Visualization: Luca Preite, Federico Solari; Funding acquisition: Federico Solari, Giuseppe Vignali; Resources: Luca Preite, Federico Solari, Giuseppe Vignali; Supervision: Federico Solari, Giuseppe Vignali.

Availability of data and materials

Data sets generated during the current study are available from the corresponding author on reasonable request.

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