Creation of a digital twin based on microtensiometer indices (Florapulse), climatic variables and crop data for sustainable production in Stone Fruit Crops.

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***Abstract*— Efficient water management in agriculture is critical for sustainability, especially in water-limited regions. The use of advanced technologies, such as microtensiometers like the FloraPulse, allows accurate monitoring of plant water status, providing essential data to optimize irrigation. This article focuses on identifying the most relevant data provided by FloraPulse for assessing water stress and developing a digital twin with machine learning models that can monitor and accurately predict FloraPulse values using climatic variables and crop indices with the goal of determining when and how much to irrigate.**

***Keywords*— digital twin, microtensiometer, water stress, stem water potential.**

I. INTRODUCTION

Precision agriculture has made significant progress in recent years, providing tools that allow for improved irrigation management and efficient water use. However, water availability is a key factor determining maximum productivity potential and represents one of the main economic concerns for farmers worldwide [9]. Outdoor crops face various environmental stresses throughout their growth cycle, with drought being the most severe, with negative impacts on plant productivity [15]. This challenge is even greater in arid and semi-arid areas, such as the Mediterranean region, where water scarcity and increasing food demand, driven by population growth, exacerbate the situation [12][26].

Sensors based on the physiological status of plants, such as the FloraPulse, play a crucial role in this field by continuously integrating soil water availability and atmospheric water demand throughout all phenological stages of crops [10][11][14][19]. Among the various methods available to assess tree water status, stem water potential (Ψ stem) has stood out for its sensitivity and accuracy [17][18][25]. However, traditional measurement of Ψ stem is laborious and requires specialized equipment, which limits its use in immediate irrigation adjustments [2][5][8].

The Ψ stem directly measures water tension within the trunk by quantifying the pressure required to push sap through the petiole of a leaf whose transpiration has been stopped. Traditionally, this measurement is made with a pressure chamber, which involves a destructive and temporally discrete process [23]. The need for automated and non-destructive methods has driven the development of continuous plant-based sensors, capable of providing real-time data on the water status of trees and of being integrated into autonomous irrigation systems [24].

Among these advances, microtensiometers have emerged as a viable option for continuous measurement of trunk water potential (Ψ trunk). These devices use microelectromechanical pressure sensors embedded in the tree trunk, providing continuous and accurate measurements of water potential [21]. Compared to traditional methods, microtensiometers allow real-time monitoring and have been shown to positively correlate with values measured by pressure chambers [4][7]. However, research on their use under different environmental conditions and over entire seasons remains limited [16][13].

The PEACH project focuses on the transition towards sustainable management of stone fruit trees through cooperation between companies, research centres and farmers. Its objectives include the development of precision

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fertigation techniques in an organic farming context and the evaluation of the influence of plant covers on biological pest control and pollination. Within this study, it is hypothesized that the minimum data of trunk water potential provided by FloraPulse are more indicative of immediate water stress than the maximum values recorded, due to their sensitivity to daily weather conditions.

On the other hand, artificial intelligence (AI) and Machine Learning (ML) has recently been widely applied in agriculture. AI-powered solutions will help farmers produce more with fewer resources, improve the quality of their crops, and reduce the time it takes for their products to reach the market [27].

The goal of this work is to develop a digital twin that monitors the water stress status of stone fruit crops and integrates ML models that can accurately predict their FloraPulse values using climate variables and crop indices, allowing us to help farmers adjust their irrigation systems more precisely, thus optimizing irrigation management and reducing water stress in stone fruit crops.

II. METHODOLOGY

A. *Field conditions*

The experiment was carried out from March to October 2023, in a peach plot, variety Grocivac 2 (IVIA), in Alquería, Jumilla, Murcia (Spain, 38°29'35.5" N, 1°21'52.7" W). Organically managed cultivation, with a planting frame of 5.5x3.0 m, sandy loam texture soil, where a precision fertigation system has been implemented that includes subsurface drip irrigation (depth of 35 cm, 10 drippers per plant with a flow rate of 2.3 L/h each), control of the soil water status (humidity probes) and control of the water status of the trees (florapulse). The plot has been divided into 4 treatments with 2 repetitions each.

B. *Agrometeorological status*

During the experimental period, the agrometeorological data (air temperature, T; relative humidity, RH; precipitation, P; radiation, RS; wind speed, W; vapor pressure deficit, VPD; daily evapotranspiration, ETo_{daily}) were taken from the meteorological station (code: JU62) belonging to the Agrometeorological Information System of the Region of Murcia (SIAM) because it is located in an area close to the experiment. The reference hourly evapotranspiration of the crop (ETo, mm) was calculated following the Penman -Monteith equation [1].

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\left(\frac{900}{T+273}\right)u_2(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34u_2)} \qquad (1)$$

where Rn refers to the net radiation at the crop surface (MJ m-2 day-1), G is the soil heat flux (MJ m-2 day-1), T refers to the mean air temperature at 2 m height (C), u2 wind speed at 2 m height (ms-1), es saturation vapor pressure (kPa), ea actual vapor pressure (kPa), es - ea designates the vapor pressure deficit (kPa), Δ refers to the slope of the vapor pressure curve (kPa C-1), and γ is the psychrometric constant (kPa C-1).

C. *Soil water status*

Soil water status was continuously monitored by soil water content (SWC, %) measurements, starting with the installation of multi-depth capacitive Drill & Drop probes (Sentek Sensor Technologies, Sydney, Australia), eight PVC access tubes were installed 10 cm from the emitter located close (0.75 m) to the tree trunk in eight representative trees (one in each replicate). Each capacitance probe had sensors at 0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75 and 0.85 m depth, and was connected to a data transmission unit. The values were read every 5 min, and the average was recorded every 15 min. At this point it was considered that, although the peach tree root system is very branched, the absorption roots do not go deeper than 45 cm in drip irrigation [22].

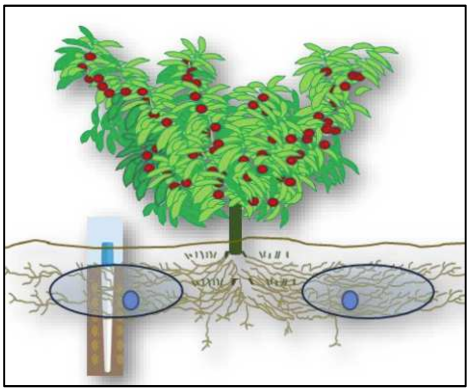

Fig. 1. Underground irrigation on each side, with Drill & Drop capacitive probe (Sentek Sensor Technologies, Sydney, Australia).

D. *Water potential of the trunk and stem*

Ψ trunk was recorded every 15 min in eight trees, one for each replicate, using microtensiometers connected to a solar-powered data logger (FloraPulse, Davis, CA, USA). Microtensiometers were embedded in the trunk of the selected trees away from direct sunlight. Microtensiometers were reinstalled on the tree during the same campaign in case of anomalies. The daily range of Ψ trunk was calculated as the daily difference of Ψ trunk between the maximum and minimum value recorded by the microtensiometers.

Fig. 2. Position of the FloraPulse on each tree. Source: Irrigation Department, CEBAS-CSIC, Murcia.

Stem Ψ was measured manually with the Scholander pressure chamber (Model 615D, PMS Instrument Company, Albany, OR, USA) at solar noon on two occasions during the campaign on each tree on healthy, mature, shaded leaves located close to the trunk per treatment. Leaves were covered with aluminium foil for at least 2 hours prior to measurements [17]. This was done to evidence the correlation between Ψ trunk reported by microtensiometers and Ψ stem measured using a pressure chamber (Figure 2), allowing the use of microtensiometers to continuously monitor tree water status [3].

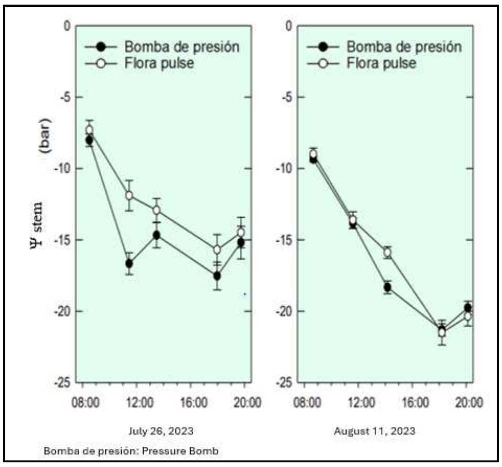

Fig. 3. Correlation between the measurement of stem potential with the Scholander Chamber vs Florapulse , on different days and times. Source: Irrigation Department, CEBAS-CSIC, Murcia.

E. Machine Learning algorithms

In this work, Support Vector Regression (SVR), Random Forest (RF) and K-Nearest Neighbours (KNN) are selected as ML algorithms to create different ML models.

SVR is a type of regression analysis that uses the principles of Support Vector Machines (SVM). It aims to find a function that deviates from the actual observed targets (data points) by a value no greater than a specified threshold, called epsilon (ε). The goal is to identify a hyperplane in a high-dimensional space that best fits the data while allowing for some margin of error. Unlike traditional linear regression, SVR is more robust to outliers and can effectively model complex relationships by using kernel functions, which transform the input space into a higher-dimensional space. This allows SVR to capture non-linear patterns in the data.

On the other hand, Random Forest is an ensemble learning method primarily used for classification and regression. It builds multiple decision trees during training and merges their outputs to improve accuracy and control overfitting. Each tree in a random forest is constructed using a random subset of the training data and a random subset of features, promoting diversity among the trees. When making predictions, RF aggregates the predictions of all individual trees, usually by majority voting for classification or averaging for regression. This approach generally results in high accuracy and robustness against overfitting, making it a popular choice in various applications.

Finally, KNN is a simple, instance-based learning algorithm used for both classification and regression. The core idea is to predict the output of a new data point based on the outputs of its 'k' nearest neighbors in the feature space. The distance metric (e.g., Euclidean distance) determines how the neighbors are identified. For classification, KNN assigns the class that is most common among the k nearest neighbors, while for regression, it typically averages the values of those neighbors. KNN is intuitive and easy to implement, but it can be computationally expensive, especially with large datasets, as it requires calculating distances to all training samples.

III. RESULTS AND DISCUSSION

Preliminary results show an improvement in water use efficiency and better control of soil moisture, contributing to more sustainable production. By analysing the data provided by the microtensiometers and the recorded climatic variables, the aim is to create a predictive model that accurately predicts the FloraPulse value under different environmental conditions (input data), thereby identifying the optimal times for irrigation and the amount of water needed to maintain an adequate water status in the plants. This integrative approach will allow for more precise and efficient irrigation management, adapted to the specific conditions of the environment and the physiological needs of the trees.

A. Identification of Relevant FloraPulse Data (Maximum and Minimum of Trunk Water Potential)

The FloraPulse provides continuous data on the stem Ψ, including maximum and minimum values. To identify water stress, it is essential to determine which of these data provides the most relevant information.

a) Trunk Water Potential Maximums (Ψmax):

- Indicative of the plant's nocturnal recovery
- Useful for evaluating the plant's ability to recover its water status during the night, which is crucial for its long-term health.

b) Trunk Water Potential Minimums (Ψmin):

- They reflect the maximum level of water stress during the day.
- More sensitive to immediate environmental conditions and evaporative demand.
- Critical for making daily decisions about irrigation, especially in conditions of high evaporative demand.

B. Analysis and Selection

Minimum Ψ trunk data are generally more indicative of immediate water stress than maximum values, due to their sensitivity to daily weather conditions. Therefore, the use of minimum Ψ trunk values is prioritized for water stress prediction and irrigation management. The daily minimum Ψ trunk was often reached during the afternoon, when atmospheric demand was highest [3].

With this information, the different Ψ trunk limits or critics for the good development of the fruit, described in Table I, were considered, which will condition the results of the mathematical model.

TABLE I. CRITICAL VALUES OR LIMITS OF THE Ψ TRUNK FOR OPTIMAL FRUIT DEVELOPMENT. SOURCE: IRRIGATION DEPARTMENT, CEBAS-CSIC, MURCIA, MURCIA.

Fruit development stage	**Limit Ψ trunk (MPa)**
Cell division	-0.9
Hardening of the stone	-1.8
cell expansion	-1.0
Postharvest	-1.8

C. *Development of a Mathematical Model for Irrigation Prediction*

To create an efficient predictive model, the following variables are integrated:

a) Climate:

At this point, the different climatic variables were evaluated to identify the correlation with the variations of the FloraPulse indices. In a study carried out by Blanco and Kalcsits (2021), it was determined that the microtensiometer showed the minimum daily values in the afternoon, when the VPD reached the highest daily values, which showed the correlation between them. Below are the climatic variables that were used in the mathematical model:

- Air temperature (T)
- Precipitation (P)
- Relative humidity (RH)
- Solar radiation (Rs)
- Wind speed (U)
- Vapor pressure deficit (VPD)
- Evapotranspiration (ETo)

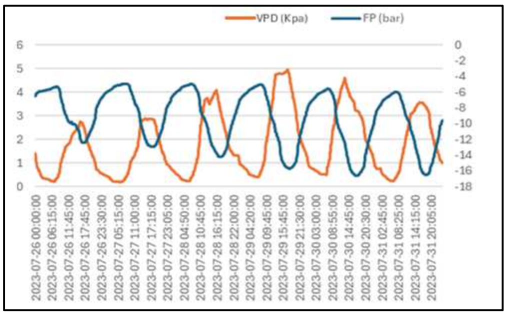

Fig. 4. Example of correlation between climatic variables (VPD) vs FloraPulse.

b) FloraPulse:

- Minimum water potential of the trunk (Ψmin)

c) Soil:

- Moisture content, with SWC measurement at the different depths described.
- Applied irrigation (IR) throughout the campaign. The mathematical model may include a delay factor that considers the response time between the application of irrigation and the observable variation in the water potential of the trunk, determined mainly by the type of soil and its infiltration capacity [6].

d) Plant:

- The model is adjusted by integrating a crop coefficient (Kc) to consider the different phenological phases of the crop, which determine how water demand changes throughout the plant's life cycle. The Kc varies according to the phase in which the crop is found (growth, flowering, fruiting, ripening, etc.), and its inclusion in the model helps to adjust irrigation needs for each development phase.

D. *Model Structure*

The model is based on a multivariate regression that relates climatic variables, soil, plant and FloraPulse data to irrigation needs. The model equation has the form:

$$R = Kc * (\gamma + \delta_1 \Psi_{min} + \delta_2 T + \delta_3 RH + \delta_4 Rs + \delta_5 U + \delta_6 P + \delta_7 VPD + \delta_8 ETo + \delta_9 IR + \delta_{10} SWC + \xi) \qquad \square 2 \square$$

where:

- R is the amount of irrigation needed (mm)
- Kc is the crop coefficient that adjusts the amount of irrigation according to the crop phase
- γ is the model constant
- Ψmin is the minimum stem water potential (MPa) measured in real time with FloraPulse
- T = Air temperature (°C)
- RH = Relative humidity (%)
- Rs = Solar radiation (Wm^{-2})
- U = Wind speed (ms^{-1})
- P= Precipitation (mm)
- VPD= Vapor pressure deficit (KPa)
- ETo = Evapotranspiration (mm)
- IR= Applied irrigation (L/tree)
- SWC = Soil water content (%)
- $\delta_1, \delta_2 \ldots \delta_{10}$ are the adjustment coefficients of the variables
- ξ is the error term

E. *Model Flow*

- Continuous monitoring with FloraPulse: The FloraPulse sensor measures the water potential of the trunk (Ψmin) continuously. This data is the main indicator of the need for irrigation.
- Threshold Determination: If the value of Ψmin falls below Ψcritical, the system must activate irrigation.
- Calculating How Much to Water: When irrigation is necessary, the model uses the equation to calculate the amount of water to apply (R) based on weather and soil conditions.

F. *Implementation and Validation*

- Data Collection: Soil, plant and FloraPulse data are measured and collected over multiple growing seasons using physical devices. A Python script is programmed to collect sub-hourly climate variables.
- Model Training: To train the models, all input data were divided into training (70%) and test (30%)

sets. The input variables are climatic variables (T, P, RH, Rs, U, VPD and ETo), crop coefficient (Kc), soil water status (SWC), applied irrigation (IR), also the previous FloraPulse values. Each climatic variable was set to one hour earlier (lagged). The FloraPulse values were lagged by two hours. Finally, IR and precipitation were set to six hours prior to allow time for their effects to take place. The hyperparameter tuning process using Random Search with 5-Cross Validation (CV5) is applied to find the optimal configuration of each ML.

- Validation: The ML models are validated with an independent test set to evaluate their accuracy and also tested for their generalization ability with other peach plots. Field tests will be carried out using the model to define optimal irrigation.

G. Model Results

Since the peach plot is divided into several zones and rows, the subplot named T3.2 has the most complete data and is used to train and validate the ML models. Table II shows the statistical metrics of each phase. In the training phase, Mean Absolute Erro (MAE) is used as an evaluation metric to rank the hyperparameter configurations. In validation phase, R-squared (R2), MAE and Mean Absolute Percentage Error are used to evaluate the performance of the models.

TABLE II. TRAINING AND VALIDATION RESULTS OF ML MODELS

Model	Training (CV-5) MAE	Test R2	Test MAE	Test MAPE
SVR	0.049	0.989	0.249	4.320
RF	0.059	0.985	0.302	4.595
KNN	0.044	0.993	0.189	2.445

All models achieved excellent results, with R2 above 0.98, MAE ranging from 0.189 bar to 0.249 bar and MAPE ranging from 2.445% to 4.595%, with KNN showing the best performance in all three metrics.

To test the generalization ability of the models, data from subplots T1.1, T2.1, and T4.2 are used. The results are show in Table III.

TABLE III. MODEL TEST RESULTS IN OTHER PEACH PLOTS

Model	**T1.1**		
	R2	**MAE**	**MAPE**
SVR	0.751	1.813	17.762
RF	0.899	1.170	12.628
KNN	0.769	1.784	18.532
Model	**T2.1**		
	R2	**MAE**	**MAPE**
SVR	0.804	2.340	19.053
RF	0.966	1.158	8.793
KNN	0.907	1.781	15.096
Model	**T4.2**		
	R2	**MAE**	**MAPE**
SVR	0.749	1.89	41.63
RF	0.944	1.019	29.620
KNN	0.753	1.906	48.14

It can be seen that in other subplots, all models have worse performance and KNN has a brutal decay, which means that it had an overfitting problem. However, RF showed better generalization ability with R2 ranging from 0.899 to 0.966, MAE around 1.1 bar in all three subplots, and MAPE ranging from 8.793% to 29.62%. Therefore, RF will be used as the model to predict FloraPulse values in the future process.

Currently, information on the use of trunk water potential (Ψ trunk) for irrigation management is limited, and existing studies focus mainly on irrigation scheduling based on farmers' experience [20] or on crop evapotranspiration requirements (ETc) [4].

Data analysis indicates that trunk water potential minima Ψmin are highly predictive of daily water stress in stone fruit crops. The developed model shows a strong correlation between climatic variables, FloraPulse data and irrigation needs, allowing accurate predictions and optimizations in irrigation management.

IV. CONCLUSION

The use of sensors such as FloraPulse, in combination with mathematical models that incorporate climatic variables and physiological data from plants, represents a significant advance in precision agriculture. These systems not only facilitate the continuous monitoring of the water status of trees, but also optimize irrigation management, contributing to sustainability and efficiency in agricultural production, with special attention to areas where water resources are scarce.

Experiments have shown that trunk water potential can be more sensitive than other traditional indicators such as stem or leaf water potential, especially under conditions of severe water stress. Furthermore, the ability to continuously monitor this indicator reduces the need for destructive and laborious measurements, providing a more sustainable, automatic and efficient method for managing irrigation in stone fruit trees.

This mathematical model takes the minimum water potential of the trunk (Ψmin) as the main indicator to define when to irrigate and complements it with climatic variables to determine how much water to apply. The critical value of Ψmin acts as the threshold that triggers irrigation, while the amount of water applied (R) is dynamically adjusted according to environmental conditions.

Considering that real-time Ψ trunk data and the obtained mathematical model enable irrigation automation, further research is needed to establish accurate Ψ trunk threshold values that ensure an efficient irrigation decision support system. Furthermore, it is essential to evaluate the long-term stability and performance of the trunk microtensiometers. The results of this study highlight the potential of these microtensiometers as advanced biosensors to accurately and in real-time monitor plant water status, allowing their interaction with climatic, soil and plant variables to give a more efficient irrigation scheduling. In future studies, it will be essential to integrate additional variables that consider both harvest quantity and quality to further optimize irrigation decisions.

With the implementation of the ML models, future FloraPulse values can be accurately predicted. Therefore, the next step is to use different optimization algorithms to find the minimum amount of water needed at each irrigation interval and the change in FloraPulse values (predicted by the model) is within a configured range. In this way, the goal of determining when and how much to water can be achieved.

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