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Research Paper

Estimating kiwifruit leaf stomatal conductance through artificial neural networks

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ABSTRACT

There is considerable literature attempting to model leaf stomatal conductance (g_s), both through mechanistic models and data-driven models. This study aimed at estimating g_s of kiwifruit vines through the comparison of artificial neural network models trained with different variables. To do so, in 2023, kiwifruit vines were submitted to four irrigation treatments, which were established as percentages of crop evapotranspiration (ETc), being 100, 68, 57 and 40% ETc. Nine days during the 2023 fruit growing season g_s measurements were performed throughout the day. Four vines per treatment were monitored with sap flow sensors. Additionally, to perform a further test of the performance of the models, in 2024 an experiment was conducted in a different orchard, on vines of a different variety which were monitored with sap flow sensors and daily measurements of g_s were performed. The data-driven models were obtained through artificial neural networks (ANN), which were trained considering different variables as input. The input variables were: vapor pressure deficit (D), photosynthetically active radiation (PAR), leaf and air temperature and sap flux density (J_s) and soil water content (SWC). The data-driven model with less input variables (D, PAR and J_s) presented low coefficient of determination ($R^2 \leq 0.26$). The highest correlation coefficient and R^2 were obtained by the ANN trained with D, PAR and leaf and air temperature ($r \geq 0.901$, $R^2 \geq 0.810$). When tested against the data obtained in 2024, the performance of these models was much lower, although obtaining correlation coefficients greater or equal to 0.693. These results demonstrate the potential use of data-driven models to estimate g_s.

1. Introduction

Kiwifruit vines (*Actinidia spp.*) are highly responsive to drought conditions, rapidly closing stomata to avoid reduction of leaf water potential (Gucci et al., 1997; Mills et al., 2009), and to high evaporative demand (Fernandes et al., 2025a), characteristic of the isohydric species. A correct irrigation management would benefit from the continuous monitoring of plant water status (Fernández, 2017). Stem water potential is one of the parameters that could be monitored, but for kiwifruit vines leaf stomatal conductance would be better, as it is more responsive to environmental changes (Fernandes et al., 2025a). However, there are no sensors able to monitor stomatal conductance continuously in field conditions. Therefore, modelling stomatal conductance (g_s) from variables monitored continuously, such as sap flux density, can improve the irrigation management of kiwifruit orchards, avoiding over irrigation and its negative effects. Some attempts have already been made to model and simulate leaf stomatal conductance by measuring sap flux density in other species such as olive (Hernandez-Santana et al., 2016,2018). However, kiwifruit vines are very different physiologically from olive trees, having large and sparse xylem vessels (Dichio et al., 2013).

Fernandes et al. (2025b) performed a preliminary analysis regarding the relation between sap flux density (J_s) and leaf stomatal conductance (g_s) of kiwifruit vines under full irrigation and three levels of deficit irrigation. These authors found that estimating g_s of kiwifruit vines cannot be done as it was done by Hernandez-Santana et al. (2018;2016) in olive trees. These authors simply obtained linear models between the ratio of sap flux density by vapor pressure deficit (D) and olive leaf stomatal conductance for each monitored tree. Fernandes et al. (2025b) obtained low coefficient of determination (R^2) values for linear models concerning the mean J_s/D and the mean g_s for each set of measurements by irrigation treatment, being 0.694 the highest R^2.

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Furthermore, the results obtained by Fernandes et al. (2025a) shed some light on the g_s limitation when vapor pressure deficit (D) overcome a certain threshold (ca. 1.8 kPa), regardless of the irrigation treatment. These authors also observed that, although g_s was limited when the maximum daily D was higher than this threshold, this was not the case for J_s, which continued high until sunset.

Sap flux density (J_s) is the velocity of sap in the xylem vessels, being represented in a unit of velocity, usually centimeters per hour (cm h^{-1}). There are several methodologies to monitor J_s, most of which involve the application of heat and the measurement of changes in temperature upstream and downstream (Vandegehuchte and Steppe, 2013). Sap flux density can be, in theory, scaled up from a single point to the whole sap wood area, getting an estimation of the whole tree transpiration. However, Fernández et al (2017) mentioned a recurring problem with sap flow up scaling, which is the high azimuthal sap flow variability. In other words, the choice of the installation spot can greatly influence the values obtained, as a more conductive tissue could be considered or not.

With the constantly growing pressure to reduce water consumption while maintaining productivity of fruit crops, models provide an alternative to improve the understanding of physiological responses of plants to environmental changes (Steppe et al., 2006; 2008). Mechanistic models are very useful in this sense, as they provide a comprehensible explanation for the physiological adaptations to abiotic stresses. Furthermore, the possibility of collecting continuous data in real time is higher than has ever been. With growing use of IoT (Internet of Things) and low-cost sensors, a greater effort to process and make sense out of the collected data is a growing need.

Mechanistic models such as those of Farquhar for net photosynthesis (Farquhar et al., 1980) and of Buckley-M-F for stomatal conductance (Buckley et al., 2003) help understanding the factors that affect the physiological processes. In contrast, with the growing use of machine learning techniques, the use of data-driven models is growing, mainly focused on the practical applications (e.g. Fernandes et al., 2017). These models are commonly called "black boxes" as there is little to no knowledge of the interactions between the influencing factors at the output variable.

The amount of data currently available through the use of sensors continuously monitoring fruit trees allows researchers to gather more information on the factors influencing the physiological responses of trees to environmental changes. However, environmental factors do not always influence physiological responses in a linear way, which could be easily detected by linear regression. In this sense, machine learning methods are becoming more and more useful, due to their ability to learn automatically from the data supplied. Machine learning models such as artificial neural networks (ANN) have already been widely applied in agriculture studies, such as fruit detection through images (Mengoli et al., 2023), vineyard water status prediction through multispectral images (Romero et al., 2018), among other uses. ANN are useful due to their ability to handle large and complex tasks and due to their ability to model both linear and nonlinear systems (Romero et al., 2018). Although not providing much knowledge on the relationships between the input and target variables, the use of machine learning techniques had already been proved worthy in agricultural applications, both for classification (Fernandes et al., 2017) and regression problems (Dawson and Wilby, 1998).

Considering the potential use of stomatal conductance (g_s) to improve irrigation management in kiwifruit orchards and considering the attempts in literature to model g_s in olive trees from sap flux density, this study aims at analyzing data driven models obtained with different input variables. These models were obtained using artificial neural networks from both meteorological and physiological variables, including sap flux density. The possibility to continuously monitor leaf stomatal conductance from meteorological and plant-based sensors could be an added value for decision support systems (DSS) along with the determination of threshold values of g_s for early detection of water deficit.

2. Materials and methods

2.1. Site experiment

The 2023 experiment was performed in a commercial orchard close to Imola, Italy (coordinates 44° 24′ 37.11" N, 11° 40' 42.45" E) on 8-years-old kiwifruit vines cultivar Jintao (*Actinidia chinensis*) with a planting distance of 4.5 m between rows of vines and 1.5 m between vines, in a silty clay loam soil (12 % sand, 34 % clay, and 54 % silt). The irrigation system consisted of two drip lines located approximately 0.20 m from the trees' trunk and about 0.40 m high. Additionally, there was a line of sprinklers at approximately 0.60 m from the soil. Four irrigation treatments were imposed during the whole fruit growing season as percentages of crop evapotranspiration (ETc) reposition through irrigation, being 100, 68, 57 and 40% of ETc (henceforth referred as T100, T68, T57, T40, respectively). The crop evapotranspiration was calculated from the reference evapotranspiration (ETo), which was estimated by the methodology proposed by Doorenbos and Pruitt (1977) on the FAO Irrigation and Drainage paper n° 24. The treatments were applied by using inline drippers of different outflow rates and distances between emitters (i.e., T100: 1.6 L h^{-1} drippers every 0.30 m; T68: 2.0 L h^{-1} drippers every 0.55 m; T57: 2.0 L h^{-1} drippers every 0.65 m; and T40: 1.1 L h^{-1} drippers every 0.50 m). The sprinkler system was used only a few days during the hottest days of summer (ca. mid-august). Vines were managed according to standard cultural practices for pruning, thinning, fertilization and defense. In 2023 the full bloom of this specific kiwifruit orchard happened on the 8^{th} of May. No ground cover was used between vines or between rows in the 2023 experiment. Further details on the irrigation treatments and on the level of drought stress to which the kiwifruit vines were subject can be found in the work by Fernandes et al. (2025a).

In 2024, an additional experiment was performed in a different orchard close to Faenza, Italy (coordinates 44° 19 52'.42" N, 12° 01' 29.86" E) with 7-year-old kiwifruit vines variety Jinyan (*A. eriantha* x *A. chinensis*) with a planting distance of 4.5 m between rows of vines and 2.1 m between vines, in a loam soil (34% sand, 22% clay and 44% silt). The irrigation system in this orchard consisted of one drip irrigation line with emitters of 2.1 L h^{-1} at every 0.5 m, and a sprinkler system with emitters of 51 L h^{-1} every 4.2 m. This irrigation system was considered as the full-irrigated treatment (T100), as the estimation of crop evapotranspiration (ETc) was performed by the decision support system Irriframe, provided by the agency that regulates the use of water in the Emilia Romagna region. The crop coefficients used by Irriframe do not consider shading nets and were equal to 0.85 from fruit set until final phase of fruit growth and equal to 0.75 at fruit ripening. In this orchard, three additional irrigation treatments were imposed. One of these was imposed with drippers of 2.3 L h^{-1} at every 0.60 m, and sprinklers of 39 L h^{-1} at every 4.2 m, which corresponded to a calculated 70% ETc. The additional irrigation treatments were similar to T100 and T70, until 74 DAFB (full bloom was on May 4^{th}), which corresponded to the first phase of fast fruit growth, after this day the sprinklers were closed, receiving water only through drip irrigation, a reduction of approximately 50% of the irrigation volume (T100.50 and T70.50). No ground cover was used between vines or between rows in the 2023 experiment. The irrigation volumes in each phase are reported in Table S3.

2.2. Meteorological conditions

Both kiwifruit orchards were monitored with an external meteorological station which recorded data of rainfall, solar radiation, air relative humidity and temperature during the season. Average values were registered every 15 minutes and transmitted to the cloud (WiNet s.r.l.). Additionally, air relative humidity and temperature were measured under the shading net (18% of shading) at 2.5 and 1.5 m from the ground. The measurements from the thermohygrometer at 1.5 m were used to calculate the atmospheric vapor pressure deficit (D, kPa) according to the methodology used to calculate evapotranspiration by FAO 56 (Allen et al., 1998).

Additionally, in 2023, soil water content (SWC) was measured at the treatments T100 and T68, at depths from 10 to 60 cm, every 10 cm, with the use of frequency domain reflectance (FDR) probes (Sentek Inc.) that were also connected to the data acquisition system by WiNet s.r.l. In 2024, SWC was monitored in each irrigation treatment, at 0.10, 0.20 and 0.30 m of depth, with the use of frequency domain reflectance (FDR) probes (Sentek Inc.).

The meteorological conditions during the 2023 season can be found in the study by Fernandes et al. (2025a), while the meteorological conditions (rainfall, irrigation volume and ETc) during the 2024 season are reported here in Figure S1. The meteorological conditions under the shading net were not used to refine the irrigation requirements. The data for the estimation of ETo was obtained from a standard meteorological station managed by the agency responsible for monitoring weather conditions in the Emilia-Romagna region (ARPAE Emilia-Romagna).

2.3. Leaf gas exchange and sap flow measurements

In 2023, four female plants in each irrigation treatment were chosen for the sap flow probes installation using the probes supplied by Tranzflo NZ Ltd. (Palmerston North, New Zealand). The T-max method (Cohen et al., 1981) was chosen to measure sap flux density (J_s, cm h^{-1}) in the kiwifruit vines, due to its higher accuracy for measuring high sap flow values. The sensing probes had two thermocouples, at 10 and 25 mm, and were positioned at 15 and 40 mm downstream from the heater. A datalogger CR1000 and a multiplexer AM16/32B (Campbell Scientific, UT, USA) were used to proceed with the heater activation and the difference in temperature between the sensing probes through single ended connections. The treatments were divided into two sets (each with 8 sap flow sensors), the heaters from the first set were activated at the minutes 00 and 30 of every hour, for 4 seconds, with data collection every second for 5 minutes. And the heaters from the second set were activated at the minutes 15 and 45 of every hour, also for 4 seconds with data collection every second for 5 minutes. Eight heat pulse controllers were used to power the heaters, and were controlled by the datalogger, being two heaters powered by each heat pulse controller. To obtain sap flux density (cm h^{-1}), the equations used were those used by Cohen et al. (1981), Green et al. (2003, 2009).

In 2024, the same methodology was used to monitor sap flux density in four female vines per irrigation treatment.

Periodically throughout the kiwifruit growing period, mainly during the period of greater water requirement, leaf gas exchange measurements were taken during the day, approximately at every hour. The measurements were taken using the LI-6800 Portable Photosynthesis System (LI-COR®) with the fluorometer chamber, using CO_2 concentration of 400 ppm and no humidity or temperature modifications. The measurements were taken concomitantly to those of sap flow on well-developed, not damaged leaves (one leaf per vine, 4 vines per irrigation treatment) fully exposed to the sun, using average environmental PAR (photosynthetically active radiation) as input. The average environmental PAR value used for every set of measurements (8 vines) was based on the values provided by the LI-6800 PAR sensor, measured under the shading net, shortly before the sap flow heater was turned on for all the trees in each sap flow set. This approach was used to avoid rapid changes of PAR during the same set of measurements due to cloudy conditions.

In 2023, the daily patterns of leaf gas exchange were monitored on nine days. In 2024, these measurements were also performed in nine days. The daily patterns were usually performed from approximately 08:30 until at least 16:45, the beginning of the measurements being delayed in case of moisture on the leaves due to condensation. However, only five of these days were considered for testing the data-driven models (i.e. 74, 88, 96, 109 and 130 DAFB), due to the amount of data obtained throughout the day and some limiting meteorological conditions (e.g. rainfall in the early afternoon). The seasonal behavior of daily maximum leaf stomatal conductance ($g_{s.max}$) in 2023 was reported by Fernandes (2025a), while the seasonal behavior in 2024 is reported here in Figure S2.

2.5. Data driven models

Four artificial neural network models were trained; the first model (ML1) had as input only vapor pressure deficit (D), photosynthetic active radiation (PAR) and sap flux density (J_s) measurements in both depths of the xylem as inputs. The second model (ML2) had as input only environmental variables (i.e. D, PAR), leaf temperature (T_{leaf}), air temperature (T_{air}) and soil water content (SWC), as the average SWC measured at 10, 20 and 30 cm. The third model (ML3) was obtained only with D, PAR, T_{air} and T_{leaf} as inputs. And the fourth model (ML4) was obtained considering the environmental variables (i.e., D, PAR, T_{air} and T_{leaf}) and the sap flux density (J_s) measurements in both depths of the xylem as inputs. The second model was obtained from data regarding treatments T100 and T68, where SWC sensors were installed. The first, third and fourth models were obtained with data from all irrigation treatments (T100, T68, T57 and T40). The information on the models is summarized in Table 1. All models were trained having the observed g_s as expected output. The Python library Keras, which is provided within TensorFlow, was used to train the models.

Both leaf and air temperature (T_{leaf} and T_{air}, respectively) were obtained from the LiCor 6800, being measured inside a chamber with a controlled atmosphere. It is noteworthy that these temperatures are probably influenced by the instrument itself, and that monitoring T_{leaf} through infrared sensors or thermocouples could have provided different values.

The data was randomly split into training and testing groups, being 80% of the data used for training and 20% for testing. Following, the data was normalized, aiming at having it all on the same scale, to avoid bias due to the bigger scale of certain variables, such as PAR.

The K-fold cross-validation technique was used within the training dataset used for each artificial neural network model. This methodology is used in the case of small datasets for training and testing, where the training dataset is further divided into K equal parts. Each of the parts is used for validation of the model, each time using K-1 parts for training. Therefore, K models were adjusted for each choice of input value, having their performance tested against the testing dataset. In this study, the training dataset was divided into 5 parts (K = 5), being trained with 4 parts and validated with 1 part. The performance of every K-fold was also evaluated with the testing dataset (i.e. 20% of the initial dataset).

The artificial neural network architecture that resulted in better performance constituted of three hidden layers, each one with 256 nodes, using the ReLU activation function (rectified linear unit). The optimizer chosen for this model was Adam – Adaptative Moment Estimation (Adam function from Keras). This optimizer was chosen as it combines the best features of other optimizers, avoiding local minima and stabilizing updates with adaptative learning rates for each parameter. These ANNs were trained for 100 epochs, with batch size of 32, in

Table 1
Machine learning models input variables, irrigation treatments included and size of training and testing datasets.

Machine learning model	Input variables	Treatments included	Training dataset	Testing dataset
ML1	D, PAR, J_s	T100, T68, T57, T40	823	206
ML2	D, PAR, T_{leaf}, T_{air}, SWC	T100, T68	408	102
ML3	D, PAR, T_{leaf}, T_{air}	T100, T68, T57, T40	823	206
ML4	D, PAR, T_{leaf}, T_{air}, J_s	T100, T68, T57, T40	823	206

other words, the model weights were updated every 32 samples (data points), within the same epoch. Mean squared error (MSE) was used aiming at minimizing the model loss in each epoch.

Mean absolute error (MAE), mean square error (MSE), coefficient of determination (R^2) and Pearson correlation coefficient (r) were used to analyze the performance of the data-driven models regarding the test dataset and the 2024 dataset, as follows:

$$MAE = \frac{\left(\sum_{i=1}^{n}|Y_i - \widehat{Y}_i|\right)}{n} \quad (1)$$

$$MSE = \frac{\left(\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2\right)}{n} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\widehat{Y}_i - Y_i)^2}{\sum_{i=1}^{n}(\overline{Y} - Yi)^2} \quad (3)$$

where n is the number of observations, $\widehat{Y}_i$ is the predicted ith value and Y_i is the actual ith $\overline{Y}$ value;s is the mean of the actual values (Chicco et al., 2021).

Before testing the models with the 2024 dataset, a selection of the data was performed, to ensure that every data point was within the range of values of the original dataset used to train the model, for every variable. The amount of data from 2024 that was used to test the models' performance is reported in Table S4.

3. Results

Modelling physiological variables can provide continuous estimation, which is useful when measurements are expensive and/or time consuming. Furthermore, data-driven models can improve the knowledge of the main factors influencing the response of plants to environmental changes.

The first model obtained in the present study had vapor pressure deficit (D), photosynthetic photon flux (PAR), and sap flux density (J_s) in both depths of the xylem as input variables. The values of mean absolute error and the mean square error obtained in each k-fold during training are reported in the supplementary material (Table S1). The performance of the model concerning the observed and estimated g_s regarding the test dataset (20% of the complete dataset, randomly chosen) in each k-fold is shown in Figure 1A-E, as well as the performance of the model in each k-fold concerning the 2024 dataset (Figure 1F-J).

Further indicators were calculated for each k-fold of the cross-validation process regarding the test dataset (Table S2), including coefficient of determination (R^2) and Pearson correlation coefficient (r). The mean absolute error ranged from 0.0623 to 0.0656 mol m^{-2} s^{-1} within the k-folds, while R^2 ranged from 0.1867 to 0.2635. Moreover, all k-folds resulted in correlation coefficient not greater than 0.5181, although being statistically significant (p-value < 0.001). Regarding the model's performance when tested with the 2024 dataset (Figure 1F-J and Table S5), it is evident that the model could not estimate g_s, as the correlation coefficients are low (r $\leq$ 0.316) and the coefficients of determination are negative.

The second model obtained in the present study had vapor pressure deficit (D), photosynthetic photon flux (PAR), leaf temperature (T_{leaf}), air temperature (T_{air}) and soil water content (average from 0.10 to 0.30 m, SWC) as input data. The values of mean absolute error and the mean square error obtained in each k-fold during training are reported in the supplementary material (Table S1). The performance of the model concerning the observed and estimated g_s regarding the test dataset (20% of the 2023 complete dataset, randomly chosen) and each k-fold is shown in Figure 2. The mean absolute error ranged from 0.0359 to 0.0468 mol m^{-2} s^{-1} within the k-folds, while R^2 ranged from 0.5972 to 0.7520. Furthermore, all k-folds resulted in highly significant correlation (p-value < 0.001) and correlation coefficient up to 0.87. As the soils were different from the trials in 2023 and 2024, too little SWC data from 2024 fit within the range of SWC from 2023. Therefore, it was not possible to assess the performance of this model concerning the data from 2024. Besides the difference in soil characteristics, assessing SWC is not an easy task, as the root distribution, distance from irrigation emitters and other factors might influence the measurements.

The third model was obtained from the data measured in all irrigation treatments (i.e., T100, T68, T57 and T40), including D, PAR, T_{leaf} and T_{air} as input variables. The distribution of observed and estimated g_s regarding the test dataset for each k-fold in the cross-validation process is shown in Figure 3. The values of mean absolute error and the mean square error obtained in each k-fold during training are reported in the supplementary material (Table S1).

When considering the model's performance regarding the test dataset from the 2023 season (Figure 3A-E, Table S2), the mean absolute

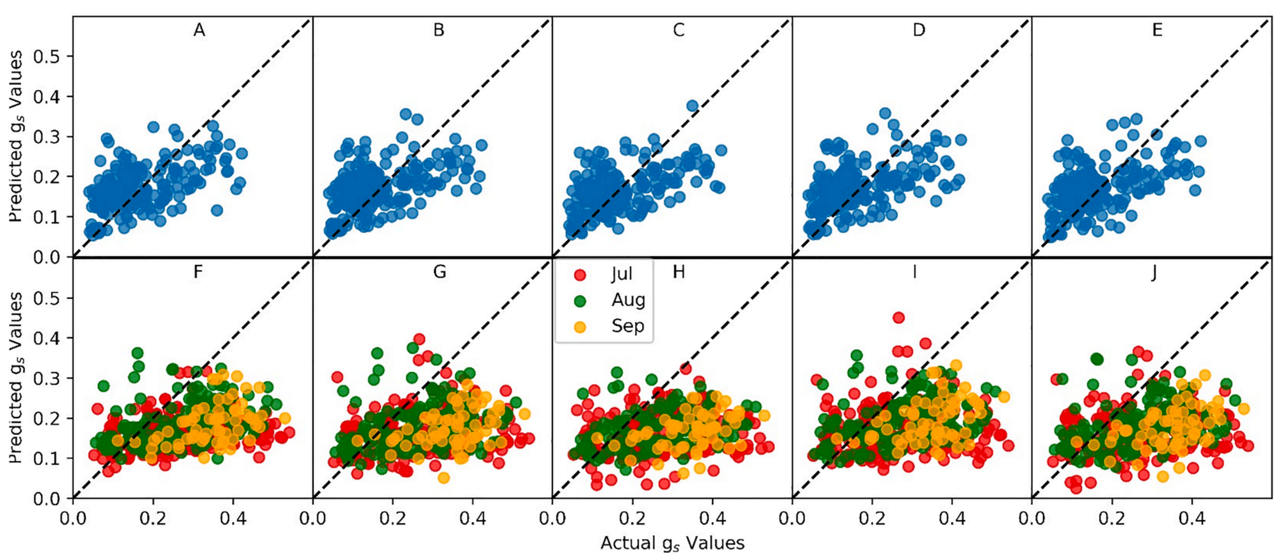

Figure 1. Actual vs. predicted leaf stomatal conductance (g_s, mol m^{-2} s^{-1}) from the k-fold cross validation used to train the ANN model (ML1) obtained from meteorological data (PAR and D) and sap flux density. Figures A-E show the performance of each k-fold regarding the dataset randomly chosen from the 2023 season, while Figures F-J show the performance of each k-fold regarding the dataset from 2024. The colors in the plots F-J represent the months in which the data was measured, as shown in the legend.

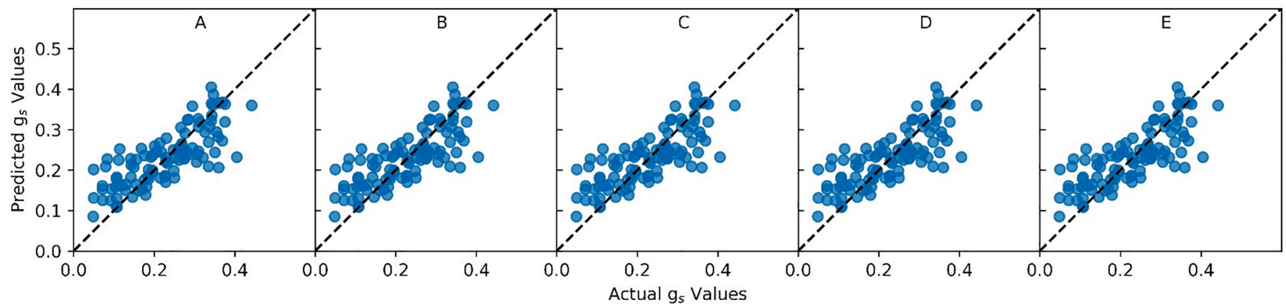

Figure 2. Actual vs. predicted leaf stomatal conductance (g_s, mol m^{-2} s^{-1}) from the k-fold cross validation used to train the ANN model obtained from meteorological data, leaf temperature, air temperature and soil water content. The data shown regards only the dataset randomly chosen for testing the model from T100 and T68.

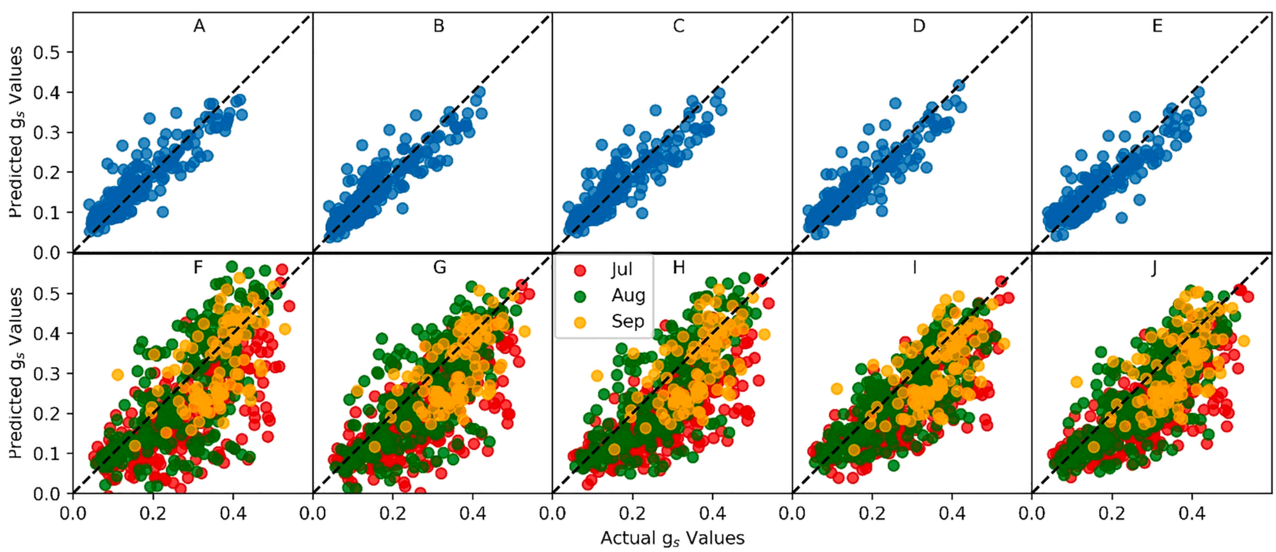

Figure 3. Actual vs. predicted leaf stomatal conductance obtained by each k-fold in the cross-validation process used to train the ANN model (ML3) obtained from meteorological data, leaf temperature and air temperature. Figures A-E show the performance of each k-fold regarding the dataset randomly chosen from the 2023 season, while Figures F-J show the performance of each k-fold regarding the dataset from 2024. The colors in the plots F-J represent the months in which the data was measured, as shown in the legend.

error ranged from 0.0291 to 0.0302 mol m^{-2} s^{-1} within the k-folds, while R^2 ranged from 0.8104 to 0.8201. Moreover, all k-folds resulted in highly significant correlation (p-value < 0.001) and correlation coefficients above 0.90. Meanwhile, when considering the performance of the model regarding the dataset from the 2024 season (Figure 3F-J, Table S5), the mean absolute error ranged from 0.0640 to 0.0799 within the k-folds, and correlation coefficients ranged from 0.693 to 0.785. However, the coefficients of determination were quite low, with the highest equal to 0.4351, corresponding to Figure 3I.

The fourth model was obtained from the data measured in all irrigation treatments (i.e., T100, T68, T57 and T40), including D, PAR, T_{leaf}, T_{air} and sap flux density (J_s). The distribution of predicted against actual g_s regarding the test dataset (2023 season) in all k-folds used for cross-validation is shown in Figure 4A-E. The values of mean absolute error and the mean square error obtained in each k-fold during training are reported in the supplementary material (Table S1).

The statistical coefficients on the model's performance regarding the test dataset are shown in Table S2, including coefficient of determination (R^2) and Pearson correlation coefficient (r). The mean absolute error ranged from 0.0294 to 0.0325 mol m^{-2} s^{-1} within the k-folds, while R^2 ranged from 0.7866 to 0.8194. Furthermore, all k-folds resulted in highly significant correlation (p-value < 0.001), and the lowest correlation index was 0.8880 (Fig. 4B).

Meanwhile, when testing the model's performance against the dataset from 2024 (Figure 4F-J, Table S5), the mean absolute error ranged from 0.0751 to 0.0878 mol m^{-2} s^{-1}, while the correlation coefficients were all above 0.6766. Nevertheless, the highest coefficient of determination was equal to 0.2779 (Figure 4J).

4. Discussion

Although some mechanistic models have already been able to estimate transpiration and photosynthesis of plants under water deficit (e.g. Liu et al., 2019), they require the continuous measurement of variables related to tree water status, such as stem water potential. Therefore, the use of these models depends on continuous monitoring of stem water potential to accurately estimate transpiration and photosynthesis.

Mechanistic models are useful and provide important insights on the main influencing variables on physiological responses of plants to changes in environmental conditions. However, it is not always easy to add new factors into these models. In this case, artificial neural networks and similar machine learning techniques turn out to be powerful tools to model physiological variables.

A consideration is needed at this point of the discussion regarding the source of leaf and air temperature for the models obtained in this study. As mentioned before, these temperatures were obtained inside a chamber with controlled atmosphere and were probably influenced by the instrument itself. Therefore, the application of these models in field

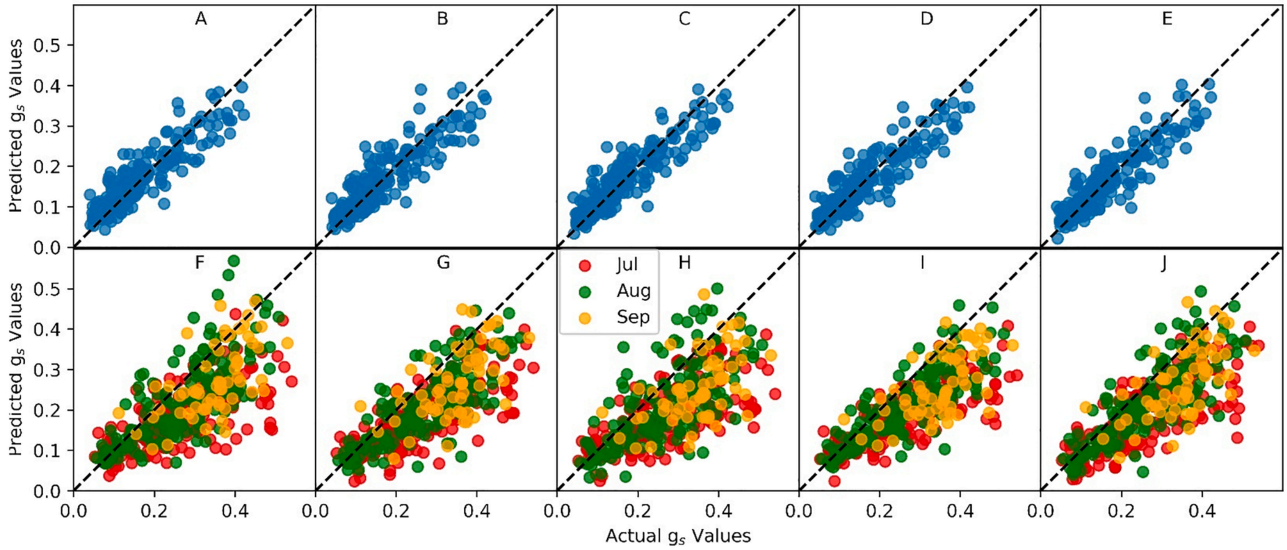

Figure 4. Actual vs. predicted leaf stomatal conductance (g_s, mol m^{-2} s^{-1}) by each k-fold used to train the ANN model (ML4) obtained from meteorological data, leaf temperature, air temperature and sap flux density. Figures A-E show the performance of each k-fold regarding the dataset randomly chosen from the 2023 season, while Figures F-J show the performance of each k-fold regarding the dataset from 2024. The colors in the plots F-J represent the months in which the data was measured, as shown in the legend.

conditions regarding temperature monitored by other means (e.g. infrared thermometry, thermal cameras, etc.) will probably influence the performance of the models.

The first data-driven model (ML1) was trained aiming at obtaining a continuous estimation of g_s throughout the growing season. This model would provide an estimation of g_s from sap flux density, as it was the plant-based sensor previously chosen to monitor the kiwifruit vines, based on what have been done in literature in other fruit crops (Hernandez-Santana et al., 2016,2018). Due to ML1 low performance (i.e. Pearson's r $\approx$ 0.50, Table S2), additional variables were included in the other models, such as T_{air} and T_{leaf}. Also, due to this low correlation between observed and predicted g_s, it was not possible to apply the model to the entire duration of the fruit growth season, as in the analysis performed by Hernandez-Santana et al. (2018) in olive trees. As could be expected, the model ML1 performed even worse when tested against the 2024 dataset (Figure 1F-J, Table S5), with even lower correlation coefficient (r > 0.32) and negative coefficients of determination (R^2). Negative coefficient of determination means that the model performed poorly, and it is only possible to obtain when testing a model with new data, as the dividend must be greater than the divisor of Eq. (3) (Chicco et al., 2021). According to these authors, when R^2 ranges between 0 and 1, it can be considered similar to percentage of correctness obtained by the model, in other words, how the model explains the distribution of the data.

Models ML2, ML3 and ML4 presented higher R^2 when tested against the test dataset from 2023 (Table S2) in comparison with ML1. Moreover, models ML3 and ML4, when tested with the dataset from 2024, presented positive R^2, although being quite low (Table S5). Even though they have low R^2, these models presented good correlation coefficients (r $\approx$ 0.7), meaning that there is a good correlation between the predicted and actual g_s values.

An important difference regarding the *Actinidia* clones of the orchards studied in 2023 and 2024 is the behavior of the kiwifruit vines regarding the drop in g_s when D increases. The response of kiwifruit vines to ranges of D from the 2023 experiment were reported by Fernandes et al. (2024), a similar plot regarding the 2024 experiment is presented in the supplemental material (Figure S3), alongside the plot presented by Fernandes et al. (2024). It is noteworthy that the *Actinidia spp.* clone from the orchard studied in 2024 is much more sensitive to a slight increased D (1-2 kPa), whereas the clone studied in 2023 presented a decrease in g_s in the range of D between 2 and 3 kPa.

The fact that the data-driven models that included leaf and air temperature (i.e. ML2, ML3 and ML4) performed better than ML1, can be explained by the chilling effect of higher stomatal conductance. In this case, the evaporation of water from the leaf reduces its temperature, causing a decrease in T_{leaf}. On the contrary, when stomata are closed, evaporation of water from the leaf surface is highly reduced, leading to higher T_{leaf}. This fact has recently been studied by Mira-García et al. (2023), by using infra-red thermometry to estimate leaf stomatal conductance in citrus trees. These authors also verified the important influence of atmospheric vapor pressure deficit (D) on leaf stomatal conductance (g_s).

Leaf or canopy temperature can be used directly to assess tree water status or can be integrated into water stress indicators such as the crop water stress index (CWSI, Idso et al., 1981). However, Mira-Garcia et al. (2023) reported low coefficients of determination (R^2) between g_s and canopy temperature (T_c), between g_s and T_c-T_{air} and between g_s and CWSI. These authors reported coefficients of determination ranging from 0.33 to 0.70, being the highest values obtained from the linear regression between g_s and T_c. In comparison to the results obtained by the data-driven models ML3 and ML4 of the present study, it is worth noting that the ability of the artificial neural networks to deal with multiple inputs improved their performance. Additionally, the comparison of the model in a new orchard, with a slightly different variety and conditions in the field from the 2023 dataset, shows that these models could be used in the future, and improved with more data for training.

Regarding the use of sap flux density, as mentioned before, the installation of these probes can have a great influence on the assessed tissue. Considering that kiwifruit vines are characterized by large and sparse xylem vessels in the trunk (Condon, 1992; Dichio et al., 2013), it increases the possibility of greater interconnections among vessels. Although sap flow methods had already been thoroughly calibrated, including in kiwifruit vines (Green et al., 2003 and 2009), the hydraulic connection between xylem vessels and leaves remains poorly understood. There are also studies in literature reporting the existence of plasticity of kiwifruit vine roots when submitted to partial rootzone drought (Green and Clothier, 1995) or root pruning (Black et al., 2011). It is possible to hypothesize that this kind of plasticity might also be seen in the kiwifruit vine trunk, due to the disturbance caused by the installation of sap flow probes. These facts regarding the physiological characteristics of kiwifruit vines might provide a possible explanation for the lower performance of the ANN model obtained only with sap flux density and environmental variables (i.e. ML1) and for the difference in performance between ML3 and ML4, as the first one did not include sap flux density as an input variable.

The approach by Hernandez-Santana et al. (2018;2016) in olives was also used by Doudou et al. (2022) in poplar trees (a clone of *Populus tomentosa*). As mentioned previously, these authors fitted linear regression models for each studied tree between g_s and J_s/D. Although this approach might be useful to study carbon allocation and water use, the models obtained are singular to the plants and to the installation of the sap flow probes. The preliminary analysis of the possibility of applying this approach to kiwifruit vines by Fernandes et al. (2025b) revealed that it would not be possible to fit good linear models between g_s and J_s/D. Therefore, the models obtained in the present study can be considered an advance on the path to achieve accurate models capable of estimating leaf stomatal conductance.

Possibly, the use of machine learning models to assess kiwifruit vines water status would benefit from the determination of leaf stomatal conductance threshold values. This would allow the use of classification machine learning techniques, similar to what has been done in olive concerning leaf turgor related measurements (Fernandes, et al. 2017), facilitating the interpretation by the farmers.

5. Conclusions

The artificial neural network model obtained with air and leaf temperature as an input, but without the sap flux density data (i.e. ML3), was the one that provided the best predictions (lowest MAE, highest R^2, highest Pearson's r). Although the models' performance when tested with the data collected in 2024 in another kiwifruit orchard resulted in lower R^2 and correlation coefficient, it still showed the great potential of this kind of approach to model and estimate leaf stomatal conductance and its potential future development in Decision Support Systems for irrigation scheduling.

Future research is needed to understand the partitioning of sap flow in kiwifruit vines, from stem to branches and shoots, which can provide useful knowledge on the plasticity of sap flow in plants.

Further research and data collection regarding kiwifruit leaf stomatal conductance under diverse environmental conditions (including water deficit) is necessary to improve the machine learning models trained in the present study. And to establish threshold values for the early detection of water deficit that could be used to manage irrigation through the integration of g_s monitoring in a DSS.

The development of sensors that allow continuous and precise measurement of leaf or canopy temperature could improve the precision irrigation management of kiwifruit orchards.

CRediT authorship contribution statement

Rafael Dreux Miranda Fernandes: Data curation, Funding acquisition, Methodology, Software, Writing – review & editing. **Andrea Giovannini:** Conceptualization, Investigation, Methodology, Writing – review & editing. **Melissa Venturi:** Investigation, Methodology, Writing – original draft. **Andrei Pasquali:** Investigation, Methodology. **Brunella Morandi:** Funding acquisition, Project administration, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Rafael Dreux Miranda Fernandes reports financial support was provided by Horizon Europe. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scienta.2026.115005.

Data availability

The data was already made available through the Zenodo repository at the following link: https://doi.org/10.5281/zenodo.15081713

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