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An econometric model for crop water footprint assessment

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Abstract
The Italian wine industry, while economically significant, is also associated with environmental impacts, including the over-exploitation of water resources and the deterioration of water quality. As a result, water management has become an increasingly important objective for enhancing the sustainability of agricultural systems. Among the various available methods, the Water Footprint Network approach is a powerful tool for assessing both the direct and indirect water usage in agricultural production. This study primarily aims to assess the water footprint of a large-scale winemaking facility in Italy, which serves as a national reference. Among the different water fractions that constitute the water footprint, green water is especially relevant in agriculture, as it is the water directly available to plants and can be estimated through evapotranspiration, the volume of water lost to the atmosphere from land and plant biomass. Accurately estimating evapotranspiration is complex and costly, yet it is essential for determining crop water needs. In this study, an econometric modeling approach based on primary collected data was employed to incorporate plant stomatal conductance (the rate at which gas diffuses through plant stomata) into the widely used Penman–Monteith equation for evapotranspiration calculation. This research moves beyond the limitations of using a constant parameter for stomatal conductance in evapotranspiration models by providing a novel approach that endogenizes values from collected data into the model. This method resulted in a water footprint of 375.83 L of water per 0.75 L bottle of wine, from cradle to gate. Compared to existing literature, this water footprint is smaller, potentially due to the overestimation of evapotranspiration in other commonly used methods or due to the specific case study's use of a water recycling system, which reduces overall water consumption.

Keywords Water footprint, Wine, Evapotranspiration, Green water footprint, Stomatal conductance model

1 Introduction

The wine industry is a relevant sector of the Italian economy, representing a substantial share of the country's exports. In 2021 Italy contributed to the global wine market with around 55.2 million hectoliters of product, making the country the largest wine exporter in the world [16]. However, along with its economic importance, the wine industry is associated with relevant environmental impacts threatening the integrity and functioning of ecosystems and the future availability of natural resources [18, 23, 60].

Most notably, these impacts include the emission of greenhouse gases (i.e., carbon dioxide, methane, etc.), nutrients over-enrichment of land and aquatic ecosystems and overexploitation of freshwater resources. Globally, agriculture is the largest water use sector, responsible for around 70% of global freshwater withdrawals and up to 80% in southern European countries [4, 29, 93]. Freshwater resources make up just 2.5% of the global water supply, with an even smaller portion accessible for environmental and human use. Over the past century, population and economic growth have led to a tenfold increase in freshwater use, significantly disrupting natural cycles and availability [43]. As a result, water scarcity is a globally relevant phenomenon. It is estimated that around 4 billion people already live in areas that experience water scarcity at least one month per year and it is associated with detrimental effects on the health of ecosystems as well [54].

Several methods and indicators have been developed to evaluate environmental degradation. Among these, the footprint family indicators are commonly used to measure the appropriation of natural resources or the emission of pollutants [32, 63, 90]. The footprint family indicators include various tools that assess different aspects of environmental impact, such as the carbon footprint, ecological footprint [10, 62, 68], and nitrogen footprint [26, 45, 59]. To assess the exploitation of water resources the most used tool, within the footprint family, is the water footprint developed by Hoekstra and by the Water Footprint Network (WFN) [33]. The WFN methodology allows to evaluate the human appropriation of freshwater resources and to relate water use to phenomena of water depletion and scarcity. The water footprint is thus expressed in terms of volumes of water appropriated (m^3). The WFN approach also allows water resources to be classified according to their hydrological origin: *blue water* (freshwater resources from surface water bodies or groundwater aquifers), *green water* (the non-run-off fraction of rainwater) and *grey water* (the volume of water required to dilute pollutants). The sum of all the different water footprints makes up the total water footprint, which is a volumetric estimation of the water appropriated for a production activity.

In addition to the WFN framework for water footprint assessment, several other methodologies have been developed. Most notably, the ISO 14046:2014 [35] which assesses water use within a life cycle assessment (LCA), a methodology that analyzes all material and energy flows in the production of goods or services [34, 36]. Unlike the WFN volumetric approach, LCA uses conversion factors to translate water inventory data (e.g., Waterstat, World Bank, USGS) into environmental impact measures like water scarcity or availability, as seen in the WULCA-developed AWARE methodology [13]. LCA applications of the water footprint are widely used and recommended in Europe, notably in the Product Environmental Footprint (PEF) and Organization Environmental Footprint (EF) methods to harmonize environmental performance assessments across Member States [17]. For clarity, this paper uses the terms blue and green water footprints solely in reference to the WFN's volumetric approach [32].

Water footprint assessment in agriculture is crucial due to the strong link between water and food security [77]. Food security is a central focus of the United Nations Sustainable Development Goal 2 (SDG2): "Zero Hunger," which addresses issues like climate change, food waste, and unequal distribution. Sustainable agriculture and support for small-scale farmers are key to achieving SDG2 and ensuring global food security [50, 88].

Rainfed farming constitutes 80% of the world's cropland and produces more than 60% of the world's cereal grains [56]. This fraction of rainwater is not incorporated into surface runoff, but it is stored in the soil as moisture, directly available for plant growth and, subsequently, as crop production. However, providing reliable estimates for this specific fraction of water (green water sensu [33]) proves to be difficult. Most of the uncertainty in green water estimates can be explained by the difficulty in effectively quantifying evapotranspiration (ET), i.e. the volume of water lost to the atmosphere from land and plant biomass. ET is a crucial component of eco-hydrological processes, and it is influenced by climatic conditions (i.e., temperature, wind, air humidity etc.), as well as the physiological and ecological characteristics of vegetation, alongside underlying surface conditions [40, 71, 100]. Accurate characterization of the ET is of utmost significance for understanding carbon, water, and energy cycles, especially in the context of climate and environmental changes. Models have become a prevalent tool for characterizing ET due to their cost-effectiveness [7, 42, 101] and since ET measurement is limited by temporal and spatial factors. Several models, equations and software are available to evaluate evapotranspiration for water footprint purposes, most notably the Penman–Monteith equation [57, 65], the FAO-developed AQUACROP model [24] and the CROPWAT model [81]. These models describe the path of water vapor from the soil and leaf surface to the atmosphere above the canopy through a series of conductances (Rochett et al. 1991). However, flaws and limitations are present in these methodologies.

Among several parameters that contribute to ET, stomatal conductance (SC), which regulates both photosynthesis and transpiration, holds significance in accurately estimating ET, emphasizing the importance of its representation in models [52, 80, 96]. However, because of the difficulty of obtaining direct measurements, stomatal conductance is mostly estimated through modeling or by keeping it constant (e.g., FAO CROPWAT model). There have been some attempts to characterize SC parameter using meteorological and vegetation elements to improve the accuracy of the models. The ST model by Stannard (ST) [83] expresses stomatal conductance using meteorological variables and the leaf area index (LAI). Another model, the Jarvis-Stewart (JS) model, estimates stomatal conductance by limiting the maximum stomatal conductance considering meteorological factors [38] and [84]. The Ball-Berry (BB) model [6] couples plant photosynthesis, relative humidity, and CO_2 concentration with stomatal conductance. The ST, JS, and BB models have been applied and verified for farmland, grassland, and shrub ecosystems in arid and semi-arid regions [46, 95, 97]. However, these generalizations may not capture the reality of the ET phenomenon [64] and thus lead to uncertainty in the evaluation of water footprint.

While a vast amount of content can be found exploring the relationship between ET and stomatal conductance [3, 8, 76], crop ET evaluation and wine production [19, 72, 82] ET and water footprint [49, 74, 98] very little can be found regarding the application of stomatal conductance-based methodologies for evapotranspiration and water footprint assessment for the wine sector [41]. This work aims to contribute to filling this knowledge gap by focusing on the development of an innovative methodology in the context of a relevant productive sector.

Correct estimations of ET are crucial to ensure reliable evaluations of the water footprints of agricultural products and activities. This study aims to contribute to water footprint accounting by introducing a new approach to evaluating ET through the modeling of stomatal conductance dynamics of grapevine leaves using an econometric model. This method allows for the identification of relationships between stomatal conductance and their key environmental determinants. Subsequently, the stomatal conductance predictions generated by the econometric model, based on a new set of primary environmental data, are used in the formula for calculating evapotranspiration. This approach allows stomatal conductance to be treated as an endogenous variable in the evapotranspiration formula, thus avoiding the use of standardized parameters provided by the FAO, which are typically considered as given in this type of calculation. Unlike other methodologies, this approach specifically tailors the complex phenomenon of ET to on-site, local biophysical conditions resulting in a more specific evaluation.

This study aims to address the inherent limitations of utilizing a constant parameter for stomatal conductance to describe evapotranspiration by implementing a novel approach. This results in more accurate and site-specific measurements of grapevine water footprint, based on a volumetric approach. Utilizing an econometric model allows to endogenize and predict stomatal conductance, calibrated on primary chemical and physical data along with plant physiology. Such methodology may provide a useful tool for efficiently allocating water resources by tailoring the assessment to local and site specific conditions. This novel methodology was applied to a pilot case study.

2 Material and methods

2.1 Case study

As a case study, it was selected a conventional large-scale wine operation located in central Italy, in the hilly region of south of the Tuscany region. Because of the techniques of production and characteristics of the site, the selected case study can be as a proxy for Italian wine production.

The area dedicated to the cultivation and harvesting of wine grapes covers an expansive 1007 hectares. The grape varieties utilized include *Sangiovese*, *Moscadello*, and *Trebbiano Toscano*, and are cultivated employing traditional vine training systems such as *spurred cordon*, *guyot*, and *goblet*, with plant density ranging from 4000 to 5000 plants per hectare. A drip micro-irrigation system is employed, selected for its water efficiency. Pruning is carried out through a combination of manual and mechanical methods, while grape harvesting predominantly involves mechanical means, including both self-propelled and towed grape harvesters. The growing season begins approximately in April and grapes are harvested toward the end of August. The vinification phase occurs in the cellar and involves pressing the grapes using compressed air pumps to initiate the fermentation process, the duration of which varies significantly depending on the type of wine being produced. The final stage of winemaking is bottling and packaging, both these processes occurring in the cellar. Along with a substantial production, exceeding 10 million wine bottles between 2020 and 2023, the company is dedicated to sustainability by setting up measures to reduce environmental impacts. Such measures include, among others, a water recycling system. The functional unit was defined as one 0.75-L wine bottle, and the water footprint was evaluated in terms of liters of water used per functional unit (L/FU) following the WFN volumetric approach.

2.2 Water footprint accounting

Water footprint accounting for grapevine crop was carried out utilizing concepts and procedures from the guidelines of the Water Footprint Network [33]. The overall production flow was categorized into two distinct stages: vineyard and cellar. In turn, the vineyard phase consists in growth and harvest of crops, and the cellar phase of winemaking and packaging, see (Fig. 1).

The study covered a timeframe of 7 months, from April to October 2023, i.e. the growing period of the crop. According to the scope of this study, namely assessing water consumption based on ET evaluations, only the green and blue water footprint fractions were considered for the agricultural and the cellar and packaging phases. For the agricultural phase, the green and blue water footprints were calculated directly from ET values applying a partitioning factors of 70% and 30% respectively [75], due to the lack of primary data on irrigation over the timescale of the study. For the cellar phase and packaging, primary company data on blue water consumption were used and added to agricultural water use (green + blue). The grey water footprint was excluded from the analysis, this was motivated by the lack of primary data on pollutants and nutrient inputs for both the agricultural and cellar phases. However, as it is reported in the literature [53] the contribution of the grey water footprint to the overall is relatively smaller when compared to the green and blue water fractions. It was thus decided to focus on primary green and blue water data to capture the site-specific characteristics and features of the case study. Furthermore, the grey water footprint is more connected to qualitative aspect of water use. This study was concerned exclusively with the quantitative, volumetric aspect of water consumption of wine making (green + blue water footprint). As such the grey water footprint evaluation was deemed out the scope of this research. As for the functional unit (FU), a 0.75 wine bottle was set as FU. The workflow that was adopted for this study, starting with data collection from the field and ending with the measurement of the actual water footprint of one FU of product, is shown in Fig. 2

Water use in the vineyard phase was assessed using a combination of primary data and econometric and hydrological modeling. Primary data was collected using the LI-600

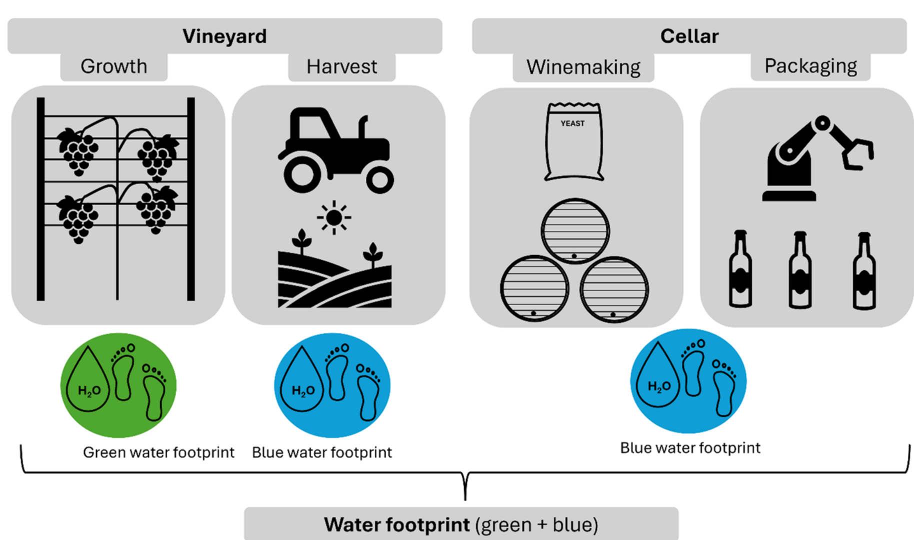


Fig. 1 Representation of the life cycle of one 0.75 L wine bottle at the case study operation. The growth and harvest periods spanned from August to October 2023

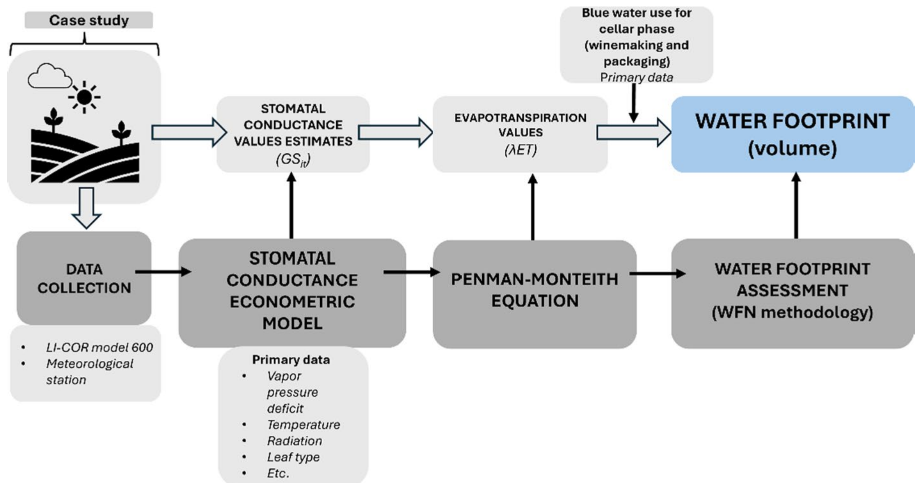


Fig. 2 Workflow of water footprint accounting as carried out in this study. The study covers a timeframe that spans from April to October 2023. Note: * following the WFN method a partitioning factors of 70% green water and 30% blue water was used to allocate the total amount of evapotranspiration

porometer (LI-COR model 600, LI-COR Biosciences, Lincoln, NE) on leaves. The LI-600 measures stomatal conductance (mol H_2O m^{-2} s^{-1}) from the water vapor differential across the leaf cuvette and the molar flow rate of air through the cuvette. During the collection of stomatal conductance measurements, the following parameters were also recorded by the porometer:

- Photosynthetically active radiation (PAR, µmol photons m^{-2} s^{-1}), measured with a photodiode;
- Vapor pressure deficit (VPD, kPa), calculated as the difference between the saturation vapor pressure in the leaf and the vapor pressure in the cuvette;
- Leaf temperature (°C), measured in the cuvette with a non-contact infrared thermometer.

The measurements were carried out at three sampling stations at the case study site, selected to be representative of the entire vineyard area due to their different pedoclimatic characteristics (such as altitude, soil organic matter content, soil composition, sunlight and wind exposure) and vine training system: *spurred cordon*, *guyot*, *young goblet* (less than 5 years of age*)*, *goblet* (between 5 and 15 years*)*, and *old goblet*(older than 25 years*)*. For each sampling station, measurements were taken at three different levels of canopy height: low canopy (approximately 30 cm above the ground), medium canopy (approximately 1 m above the ground) and high canopy (approximately 1.70 m above the ground) and repeated every two hours from 7:00 am to 1:00 pm monthly from April to October 2023. The resulting dataset (approximately 2700 units) was used for model specification. Prior to fitting the regression models, we applied an interquartile-range (IQR) filter to detect and remove outliers from the dataset. Water consumption data for the cellar and packaging phases were provided by the company as an aggregated value and measured over the total wine production.

2.3 Stomatal conductance model

To estimate stomatal conductance of grapevine plants at the case study site, a fixed effects panel regression was used, deeming it the most suitable for the collected data type. The model is formalized as follows:

$$GS_{it} = \beta_{VPD}VPD_{it} + \beta_{VPD^2}VPD_{it}^2 + \beta_{VPD^3}VPD_{it}^3 + \beta_{TEMP}TEMP_{it} + \beta_{TEMP^2}TEMP_{it}^2 + \beta_{RAD}RAD_{it} + \beta_{LEAF}LEAF_i + \mu_i + \lambda_t + f(w_{it}) + \epsilon_{it} \quad (1)$$

The dependent variable, GS_{it}, represents the measurement of stomatal conductance for the vine unit leaf *i* at time *t*. Different specifications were tested by combining various predictors associated with linear and nonlinear forms. The specification used was chosen based on results of some tests such as Akaike's and Bayesian information criterion and theoretical considerations. The specification described by Eq. (1) includes environmental determinants of stomatal conductance such as vapor pressure deficit (*VPD*), its square (VPD^2) and cubic (VPD^3), the temperature (*TEMP*), its square ($TEMP^2$), radiation (*RAD*), and leaf type (*LEAF*) which describes the leaf height. Low canopy was taken as the reference level, therefore, the estimated coefficients of the other levels, mid canopy and high canopy, should be interpreted relative to the reference low canopy category. μ_i is a vector of fixed effects for entities, λ_t is a vector of fixed effects for time and $f(w_{it})$ indicates the cubic natural spline function. The vector of fixed effects for entities consists of two elements: the type of grapevine tree cultivation and the code assigned to each of the land areas of measurement. The betas are the coefficients associated with the regressors to be estimated. The vector of fixed effects for time comprises two elements, namely, the day and month. By including these fixed effects, this model controls for unobserved entity and time-specific variability, helping mitigate potential sources of endogeneity and ensuring consistent estimates [92]. The function of natural cubic splines is defined as follows [30, 37]:

$$f(w_{it}) = \beta_1 w_{it} + \sum_{s=1}^{3} \theta_s h_s(w_{it}) \quad (2)$$

where w_{it} is the variable describing the time distance between the moment of measurement and 7 o'clock in the morning, and $h_s(w_{it})$ represents three bases functions (3 knots). The coefficients thetas are parameters to be estimated by the model that quantify the contribution of each basis function in the relationship between w_{it} and the dependent variable. In this case, splines are used to capture nonlinear relationships of unobserved time-variant factors whose intraday variability is a function of time and that may affect the stomatal conductance of the grapevine plant, allowing more accurate control for unobserved temporal variations that may influence stomatal conductance. Finally, ϵ_{it} is the error term.

Since the Breusch–Pagan [14] test rejects the null of homoscedasticity, we allow for heteroscedastic variances and compute heteroscedasticity-robust standard errors for all coefficient estimates. We also performed the Durbin–Watson test [21] to assess serial correlation in the residuals (Durbin–Watson statistic (DW) = 1.3192 (*p* value = 0.9021)), which indicates that we cannot reject the null hypothesis of no first-order autocorrelation.

The model was used to estimate stomatal conductance depending on environmental factors such as solar radiation, temperature, vapor pressure deficit, leaf type and all those unobserved variables captured by the fixed effects and splines that affect the dynamics of stomatal conductance. These variables reflect the different climatic and productive conditions that characterize the site, over the study period between April and October 2023. Predictions for stomatal conductance were carried out employing a new set of primary data from a meteorological station located within the company boundaries. This station provided live feeds on meteorological data including temperature, wind speed, precipitation, vapor pressure deficit and solar radiation. The productive conditions were implemented in the model by predicting multiple runs under different wine training systems. Five wine training systems are used at the site, as described above. To capture the different meteorological conditions, each run was carried out predicting at four times of day: 10:00 am, 1:00 pm, 3:00 pm, and 7:00 pm. As such, multiple sets of stomatal conductance values, each belonging to one wine training system at a specific time of the day, were obtained. The overall dataset accounted for 4,200 single stomatal conductance values. Each wine training system comprises 840 values organized into 4 times of day (210 values each).

2.4 Penman–Monteith

Each predicted stomatal conductance value was then implemented in the Penman–Monteith Equation to evaluate reference evapotranspiration [57, 65] according to the values of the other variables measured by the station, which, in turn, enter the evapotranspiration formula (Eq. 3). The Penman–Monteith Equation is widely used for estimating crop evapotranspiration based on a combination of an energy balance, an aerodynamic formula and bulk surface resistance [1, 57, 65, 102].

$$\lambda ET = \frac{\Delta \left(R_n - G\right) + \rho_a C_P \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma \left(1 + \frac{r_s}{r_a}\right)} \tag{3}$$

where:

- λET is the latent heat flux, representing the evapotranspiration rate (in MJ/m^2/day).
- R_n is the net radiation, indicating the difference between incoming and outgoing radiation at the Earth's surface (in MJ/m^2/day).
- G is the soil heat flux, reflecting the conductive heat transfer within the soil (in MJ/m.^{2}/day)
- (e_s-e_a) is the vapor pressure deficit, representing the difference between the saturation vapor pressure (e_s) and the actual vapor pressure (e_a) of the air (in kPa).
- ρ_a is the mean air density at constant pressure (in kg/m^3).
- C_P is the specific heat of the air (in MJ/kg/°C).
- Δ is the slope of the saturation vapor pressure–temperature relationship (in kPa/°C).
- γ is the psychrometric constant, representing the ratio of the specific heat of moist air at constant pressure to the latent heat of vaporization of water (in kPa/°C).
- r_s and r_a are the surface and aerodynamic resistances, respectively, related to the roughness of the surface and the aerodynamic properties of the atmosphere (in s/m).

As a result, 210 ET values for each of the four times of day (10, 13, 15, 19) for every wine training system were evaluated. Total evapotranspiration was calculated by summation of each individual ET value, for each time of day and wine training system.

2.5 Water footprint

The water footprint (WF_{proc}) was calculated based on these ET values. The water footprint of the process of growing crops or trees is the sum of the green ($WF_{proc.green}$), and blue ($WF_{proc.blue}$) components. As mentioned above, the grey component was not evaluated in this study due to the complexity of calculations and lack of site specific data on water pollution (Eq. 4):

$$WF_{proc} = WF_{proc.green} + WF_{proc.blue}\left[{}^{volume}/_{mass}\right] \tag{4}$$

The green and blue components (CWU_{green} and CWU_{blue}) in water use were calculated, over the length of the growing period (*lgp*) by applying a factor of 10 on the ET values thus converting them from mm to m^3/ha [33] (Eqs. 5 and 6).

$$CWU_{green} = 10 \times \sum_{d=1}^{lgp} ET_{green}\,[volume/mass] \tag{5}$$

$$CWU_{blue} = 10 \times \sum_{d=1}^{lgp} ET_{blue}\,[volume/mass] \tag{6}$$

Partitioning factors of 70% and 30% were used to allocate the total amount of evapotranspiration water requirements [75] into the green use ($WF_{proc,\ green}$, m^3/ton) and blue water use ($WF_{proc,\ green}$, m^3/ton) components, see Sect. 2.2. The green and blue water footprints were then calculated by dividing CWU by crop yield.

$$WF_{proc.green} = \left(\frac{CWU_{green}}{Y}\right)\left[{}^{volume}/_{mass}\right] \tag{7}$$

$$WF_{proc.blue} = \left(\frac{CWU_{blue}}{Y}\right)\left[{}^{volume}/_{mass}\right] \tag{8}$$

Each water footprint component was then related to the functional unit by multiplying by the quantity of grapes necessary to obtain one FU of 0.75 L of wine. The water footprint was obtained by summation of the individual green and blue components for each hour considered (10 am, 1 pm, 3 pm, 7 pm) (see table in results). For each wine training system, the water footprint (green + blue) was calculated as the mean of the daily values. The water footprint for the cellar and packaging phases was calculated by dividing water use, provided by the company, by product yield, in terms of bottles of wine. The overall water footprint for the entire production was calculated by summation of the individual water footprints for the different productive phases [33].

3 Results and discussion

Table 1 presents the estimates from three model specifications. Specification 1 (column 1) is the most parsimonious and includes only the environmental covariates and a leaf-height indicator for each measurement. Specification 2 (column 2) retains the same covariates as Specification 1 and adds spline terms. Specification 3 (column 3)—the full model defined by Eq. (1)—further incorporates entity and time fixed effects in addition to the spline terms. In the discussion that follows, we focus on the results from Specification 3. All the regressors of interest, namely vapor, vapor squared, vapor cubed,

Table 1 Results of the regression model

Estimations			
Predictors	**(1)**	**(2)**	**(3)**
Intercept	1.626 (0.222)***	1.581 (0.221)***	0.572 (0.231)*
VPD	0.037 (0.099)	− 0.087 (0.102)	− 0.377 (0.097)***
TEMP	− 0.166 (0.021)***	− 0.151 (0.021)***	− 0.077 (0.021)***
$TEMP^2$	0.005 (0)***	0.004 (0)***	0.003 (0)***
VPD^2	− 0.179 (0.035)***	− 0.143 (0.035)***	− 0.076 (0.03)*
VPD^3	0.017 (0.004)***	0.014 (0.004)***	0.009 (0.003)**
RAD	0 (0)***	0 (0)***	0.00003 (0)***
LEAF: high	− 0.005 (0.006)	0.009 (0.005)	0.013 (0.005)**
LEAF: medium	− 0.013 (0.006)*	− 0.004 (0.005)	0 (0.005)
Entity fixed-effect	Not applied	Not applied	Applied
Time fixed-effect	Not applied	Not applied	Applied
Natural cubic splines	Not applied	Applied	Applied
R^2	0.52	0.60	0.67
Adj. R^2	0.52	0.59	0.66

$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

temperature, temperature squared, and radiation, are highly statistically significant (p value < 0.001), except for the variable "leaf", where the "medium" category is not significant while the "high" category is significant at a 99% confidence level (p value = 0.01). The effect of VPD on stomatal conductance is nonlinear. Specifically, it has a cubic nonlinear effect. The coefficients of the VPD and VPD squared variables are negative ($\widehat{\beta_{VPD}} < 0$) and $\widehat{\beta_{VPD^2}} < 0$), while that of vapor cubed is positive ($\widehat{\beta_{VPD^3}} > 0$). The effect of temperature on stomatal conductance is nonlinear, which can be described by a U-shaped curve ($\widehat{\beta_{TEMP}} < 0$ and $\widehat{\beta_{TEMP^2}} > 0$). Radiation is positively correlated with stomatal conductance ($\widehat{\beta_{RAD}} > 0$): a unit increase in solar radiation results in an increase in conductance of 0.00003 mol m^{-2} s^{-1}. Regarding the leaf variable, a leaf placed at a high height causes an increase in stomatal conductance compared to a leaf placed at a low height (by 0.013 mol m^{-2} s^{-1}). The full results are given in Table 2 in the Appendix.

Figure 3 shows the marginal effect of temperature, vapor, humidity, and solar radiation on stomatal conductance[1] respectively. As for natural cubic splines, it is observed that the coefficients are statistically significant. The adjusted R-squared is equal to 0.66, indicating that more than 66% of the variability in stomatal conductance is explained by the linear model under consideration. This is indeed good value, considering that the specification with the same regressors but without fixed effects has an adjusted R-squared of 0.52, while that with the addition of splines is 0.59.

To assess the model's out-of-sample performance, we implemented a leave-one-group-out (LOGO) cross-validation using two grouping factors—plant type and zone (Table 3 in the Appendix). When each plant type was held out in turn, the model achieved an average RMSE of 0.0999, MAE of 0.0797, and R^2 of 0.5204, indicating that roughly 52% of the variability in stomatal conductance is explained even for unseen plant types. Using zone as the grouping factor yielded improved accuracy (RMSE = 0.0849, MAE = 0.0650, R^2 = 0.5604), suggesting stronger generalization across spatial contexts. Unlike time-series forecasting—where past values predict the future via autoregressive

[1] In each graph, average values of continuous variables were used. For categorical variables, the following levels were considered: "small tree", "zone 106", "day 25", "August month", "leaf medium height". Due to space constraints, we reported a single case which exemplifies the relationships between stomatal conductance and environmental factor.

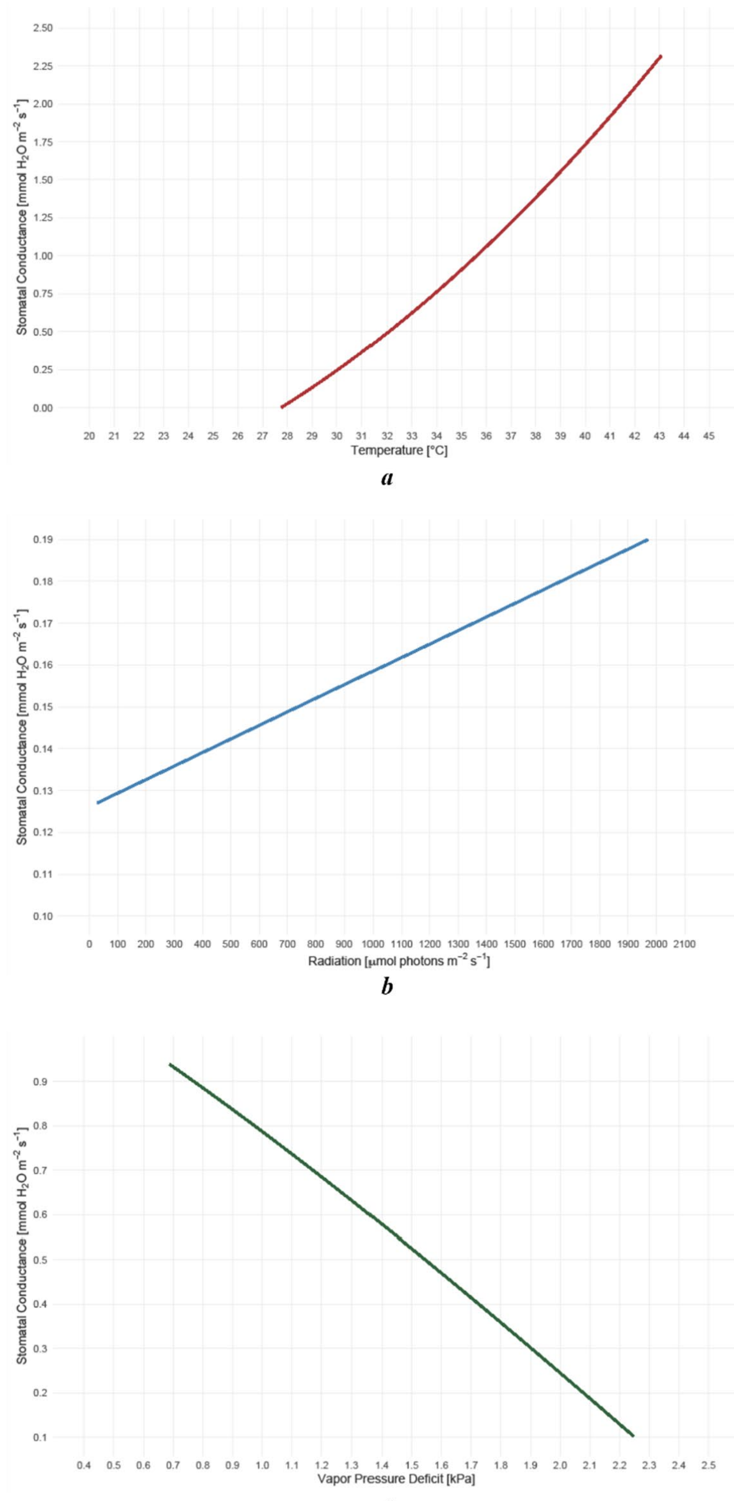
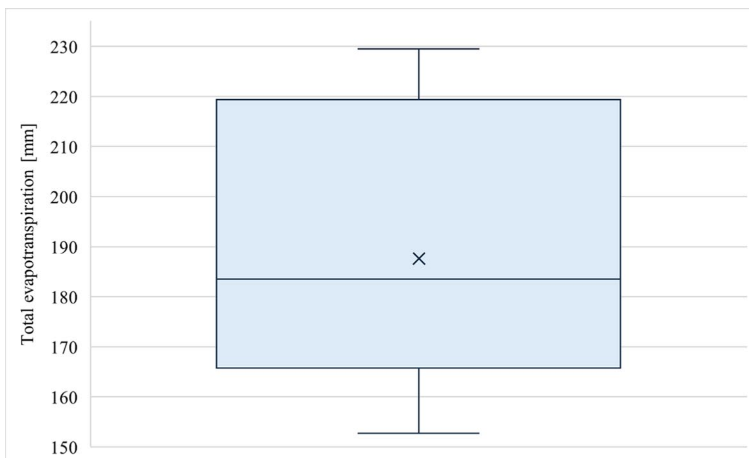


Fig. 3 Relationship found between stomatal conductance (mmol H_2O $m^{-2}s^{-1}$) and temperature (°C). The figure depicts the marginal effect of temperature on stomatal conductance. **b** Relationship between stomatal conductance and radiation (micro mol photons $m^{-2}s^{-1}$). The figure depicts the marginal effect of solar radiation on stomatal conductance. **c** Relationship between stomatal conductance and vapor pressure deficit (kPa). The figure depicts the marginal effect of vapor pressure deficit on stomatal conductance

dynamics—our model treats time as an explicit covariate and is not intended for temporal extrapolation. Consequently, look-ahead bias is avoided and there is no need for rolling- or expanding-window cross validation. LOGO cross-validation is instead appropriate for our panel dataset, as it directly evaluates the model's ability to predict stomatal conductance under new combinations of environmental and structural conditions.

The Evapotranspiration values under all wine training systems and time of day showed an average of 187.61 mm, a median of 183.54 mm, a range of 76.73 mm and a standard deviation of 26.45 mm (see Fig. 4a). Evapotranspiration values are expressed in mm as the direct output of the model. ET is then converted to m^3/ha following the WFN guidelines (see Materials and Methods, Sect. 2.5). All the training systems analyzed increased



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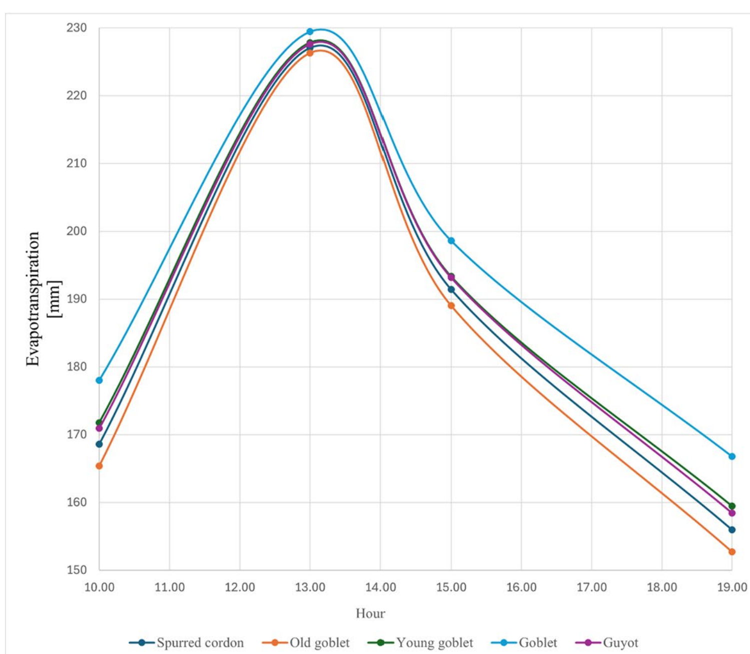

b

Fig. 4 **a** distribution of ET data for all five training systems analyzed in this study (average:187.61 mm, median of 183.54 mm, range of 76.73 mm, standard deviation of 26.45 mm). **b** Temporal distribution of ET values for each individual training system at four times of day (10:00 am, 13:00 pm, 15:00 pm, and 19:00 pm)

ET in the morning, reaching its maximum value at 13:00. It then decreased in the afternoon (see Fig. 4b).

Regarding the vineyard phase, the individual water footprint results for each training system were calculated as the mean between the different daily values. The overall water footprint for the vineyard phase was calculated as the mean between all of the total WF values from each training system (see Table 4 in Appendix) and amounted to 374.51 L/FU, 70% green WF (262.16 L/FU) and 30% blue WF (112.35 L/FU).

The total water use of the cellar phase amounted to 7696 m^3 extracted from groundwater sources. This value was divided by the total wine production of the company (primary data provided) of 4,370,000 L and then related to the functional unit of one 0.75 L bottle, resulting in 1.32 L of water per bottle used for the cellar and packaging phases. As a result, by adding all the phases together, the WF for a 0.75 L bottle of wine at the case study amounts to 375.83 L.

Evapotranspiration represents the sum of water lost from the surface through direct soil evaporation and plant transpiration. In most studies, stomatal conductance is considered a parameter within models incorporating plant transpiration. The innovative contribution of this research lies in the approach to "endogenize" the "stomatal conductance" variable within the Penman–Monteith equation. While an exogenous variable is typically independent of other variables in the model, stomatal conductance, in our context, should not be considered exogenous. Instead, it is influenced by the other components of the equations, e.g., temperature, humidity, radiation etc., and should be treated as an endogenous variable. Stomatal conductance can be modeled through three approaches: empirical (data-based), mechanistic (process-based) and economic (optimization-based). The empirical and mechanistic approaches are used together since the data-based one makes assumptions about factors to which stomata respond, becoming partly mechanistic [15]. In this case, it is assumed that, based on the literature, stomatal conductance is a function of certain environmental and biological factors, resulting in $GS = G(X)$, where X is a vector of factors, such as temperature, radiation, etc. The way these factors affect stomatal conductance is data-driven, in the sense that several specifications are tested, and the one selected, (i.e. the most suitable specification), is used to estimate the model. The selected specification is considered the most appropriate to represent the relationships between conductance and its environmental determinants and it is used to estimate the model, reflecting the mechanisms and relationships exactly as they occur in nature, without imposing assumptions on specific behaviors. Regarding the considered factors, a positive correlation was found between radiation and stomatal conductance, which was also found by several authors using different approaches such as partial least square and general regression models [5, 48, 91]. This result is easily explained since light is a stomatal opening signal, due to the receptors of blue light on the guard cells [94]. Moreover, this response to light could also be the reason behind the positive correlation found between the higher position of the leaf and the stomatal conductance. In contrast, leaves in shade are known to have lower levels of stomatal conductance [27]. Temperature was also considered to affect stomatal conductance [38], and it was found that up to a certain point, GS responds negatively to an increase in temperature, but beyond this point, the increase in temperature begins to have a positive effect on the dependent variable, producing a U-shaped curve. In fact, at higher temperatures, plants can benefit from cooling due to increased transpiration [89].

Regarding the effect of VPD on stomatal conductance, it has been found quite common that above a certain VPD value (which depends on the plant species), stomatal conductance decreases [47, 67, 79], probably due to an interaction with the transport or the signaling of the abscisic hormone (ABA hormone) [85], Tardieu and Davies, 1992). The advantage of using regression models lies in the fact that, once the coefficients associated with the regressors of interest are estimated, it is possible to make predictions on conductance values according to the estimated model by arbitrarily varying the values of all independent variables, see Table 1. The regression results outline the estimated coefficients of predictors, along with their corresponding standard errors in parentheses, and p-values, across three specifications. The first one involves an Ordinary Least Squares (OLS) model, the second entails an OLS model with the time variable modeled using natural splines, and the third specification pertains to a fixed-effects OLS model with natural splines, which includes both entity and time-fixed effects, alongside splines (Eq. 1 in methodology paragraph).

Once we obtained estimates from the model described by Eq. (1), we used a new set of primary data from the case study company stations to predict stomatal conductance values in several scenarios under 5 training systems (s*purred cordon*, *guyot*, *young goblet, goblet, old goblet)* at 4 times of day (10 am, 1 pm, 3 pm, 7 pm). Then we incorporated the predicted stomatal conductance values into the evapotranspiration formula, which is now treated as an endogenous variable, as it is predicted by the econometric model based on the specific values of other variables, also collected through the monitoring station, that are incorporated into the ET formula. This allows us to let stomatal conductance change according to the values of other input variables, such as temperature, humidity, etc. The ET trends resulting from each agricultural training system show a peak in the parameter at 13:00, as also observed by other authors [2, 39, 99].

It should be noted that the panel is not fully balanced, as on some (very few) observation dates, not all types of vine cultivation were observed. Additionally, the measurements are confined exclusively to the summer period. This situation could limit the external validity of the model. The model will be specific to the summer season, with potential difficulties in generalizing the results to other seasons. Seasonal dynamics can vary significantly, and such variability could affect the validity of forecasts in different periods of the year. The fixed effects incorporated in the model will primarily reflect the variations that occurred during the summer season. Consequently, the assumptions and conclusions drawn from the model may be limited to this period, and careful explanation is required before extending the conclusions of the model to other sites or months other than the April to October period. However, the highest and most variable evapotranspiration values were found in the months considered, when the leaf area index is the highest [58, 61].

The methodology proposed in this article resulted in a WF accounting that is in line with the available literature. WF results were compared with 11 articles that involved water footprint assessment of various wine companies (see Fig. 5a). Said articles were selected based on the evapotranspiration and water footprint methodologies used. Said methodologies were the same used in this study. Specifically, the Penman–Monteith equation/CROPWAT model and the WFN volumetric approach. As for the functional unit, one 0.75 L bottle was selected.

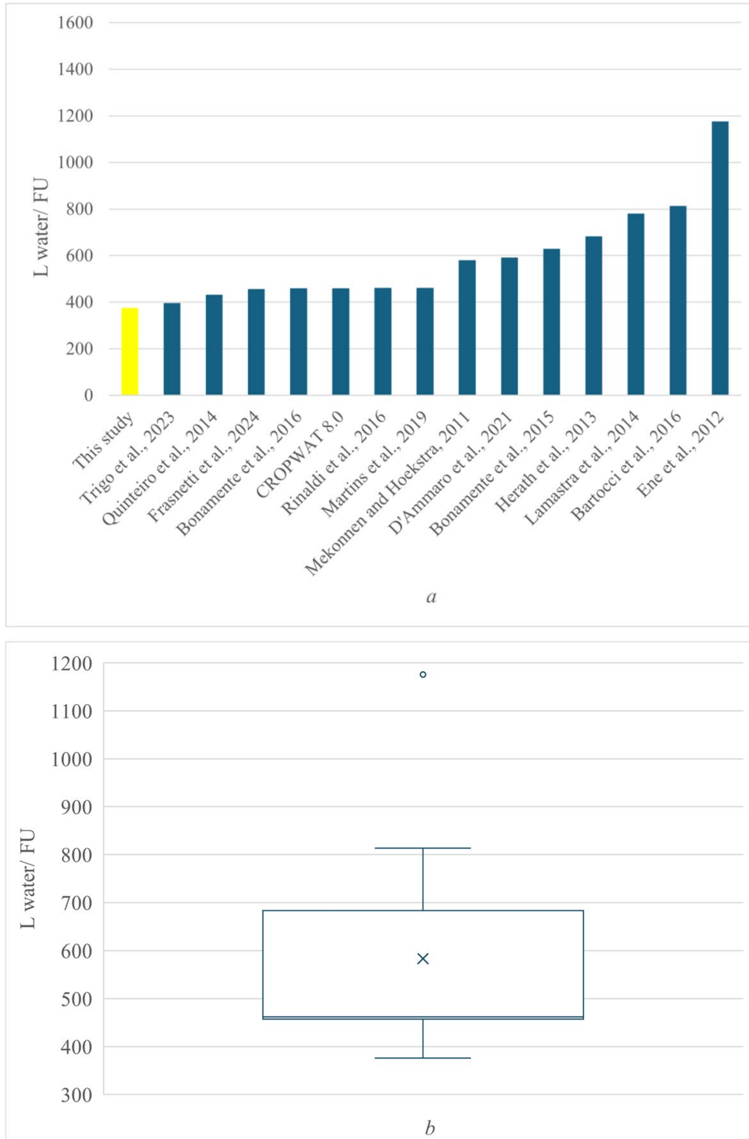

Fig. 5 **a** Comparison between relevant literature WF values and the value obtained by applying this study methodology (highlighted in yellow). **b** data distribution of the WF values from the selected articles. The values from the literature were adjusted by subtracting grey water footprint values to keep consistency with this study

It must be noted that the assessment of grey water fraction was not included in this study. The exclusion of the grey fraction from the water footprint measurement was due to the complexity of its calculations, data availability and thus uncertainty regarding the approach to apply to the case study. As such, it was necessary to adjust the values from literature by subtracting the grey water footprint values to allow a meaningful comparison with our case study. When explicitly stated, the specific grey water fractions were subtracted from the total water footprint (e.g., [12, 31, 70]). Otherwise, a value of 17% for the grey water footprint was taken, following Mekonen and Hoekstra [53].

The exclusion of the grey water fraction has important implications for the comparability of results. Mainly, it required to readapt literature data to accommodate the lack of the grey fraction. This may result in increasing uncertainty because the exact volume of the grey fraction may not be directly stated from the literature source and thus has to be estimated (e.g., [53]). This inherent limitation of the research is acknowledged.

The selected dataset has an overall range of 799.72 L water/FU, with a median of 462.14 L water/FU and an interquartile range of 226.30 L water/FU, showing a certain level of variability between the different WF values. With a value of 375.83 L/FU, the WF of the case study positions itself as the smallest value of the dataset (see Fig. 5b).

Two main factors may contribute to such a low ranking of the case study WF value: the crop coefficient specification and the specificity of the case study. The crop coefficient K_c incorporates crop characteristics and averaged effects of evaporation from soil [33] and it is calculated for individual crops based on Allen et al. [1], and Hoekstra et al. [33]. However, despite being widely used, the application of these coefficients is connected to some level of uncertainty.. Crop coefficients are calculated under ideal conditions, without limitations from water or salinity stress, poor soil fertility, pests, diseases, weeds, or suboptimal crop density. However, such optimal conditions are rarely encountered in the field. One or a combination of different stressors usually act on plants resulting in a modulation of ET rates. When plants are stressed (due to a lack of water or nutrients, or an excess of salts), transpiration slows down so that actual ET is less than potential ET [1]. As such, some estimates of crop water consumption may be excessive [66]. For comparison, CROPWAT software was used to calculate an ET value for the case study vineyard utilizing the same primary data used for model training and by keeping stomatal conductance constant (0.01 mol m^{-2} s^{-1}). As a result, an ET value of 230.04 mm was calculated which gave a total WF value of 459.22 L/FU (70% green water and 30% blue water). When compared to the WF value obtained utilizing the econometric model of 375.83 L/FU, the total WF value from CROPWAT ET estimates is around 22% higher, representing a potential overestimation of the total WF value. Other methodologies are used to adjust ET values for non-optimal conditions. Most notably, a crop stress coefficient used to scale the depression of transpiration due to water deficit [87] or the crop water stress index (CWSI), determined by empirical methods based on relating the leaf-air temperature difference to the air vapor pressure deficit of a non-water-stressed baseline [73]. This study follows the lines of such methodologies, trying to endogenize and tailor ET estimates to a specific crop, productive characteristics and pedoclimatic conditions. By doing so it could be possible to achieve a larger level of detail, moving away from simplified models and constant values. It must be noted that, in this study, partitioning factors were used to allocate water resources between blue and green water based on ET. This was determined by the lack of consistent primary irrigation data over the entire timeframe of the study. Given the relationship between ET rates and water availability, which in turn is affected by irrigation activities, the availability of primary data on irrigation is critical to increase the accuracy of ET estimates. This may allow to capture how plants modulate their physiological activity in response to external conditions, including water deficit.

A growing consensus about significant climate change in the near future highlights the importance of adaptation for the winemaking sector [55]. The ability to estimate ET values for crops considering the specific local conditions may prove extremely useful for decision making and to efficiently and sustainably allocate water resources.

Furthermore, this methodology may allow to include in ET measurements how individual plant species modulates their transpiration levels, and thus their water requirements and balance, adding another level of detail. However, the methodology proposed in this study comes with a few drawbacks and potential limitations. Namely these include the matter of time and data intensity, applicability concerns and validation. Data for this study was collected daily on the field over a period of 7 months through a meticulous process, which required the use of instruments to measure climatic and physiological parameters, such as vapor pressure, leaf type, temperature etc. This data is necessary to calibrate the model on, and thus endogenizing and tailoring it to the conditions recorded at the case study. The case study is a large-scale wine making operation with ample ability to provide and handle large amount of data. On the other hand, obtaining sufficient detailed data for model training can be challenging, especially for smaller farms or companies. Furthermore, external applicability of the results is also a concern. Results from this study refer to the specific case study and it could be argued that, because of the very structure and functioning of the model, applicability and comparison with other cases may be limited. However, it must be noted that the results are in line with other wine WF studies (see Fig. 5a). One way to address this limitation could be to extend the application of the methodology to multiple years to capture climactic and meteorological variability. This study was carried out over 7 months, successive rounds of measurements and application of the methodology could improve validation.

The second factor that may contribute to the low total WF of wine production can be attributed to the specific case study. The case study company implements a custom-designed water recycling system that significantly reduces the company's internal water use. The recycling of water does not include irrigation but includes all the different water uses for the company facilities and, most importantly, the cellar and packaging phases. The water is abstracted from the company wells, and diverted to the facilities where it undergoes multiple cycles of use and treatment before being returned to the environment, specifically to the nearby river. As such, the water use for the cellar and packaging phases is substantially small (i.e., 1.32 L/FU) when compared to the agricultural phase (374.51 L/FU).

Future developments could adapt the econometric model to other Mediterranean crops like olives, orchards, annual crops and vegetables by integrating crop-specific parameters. Additionally, incorporating machine learning models could enhance the accuracy of evapotranspiration predictions, supporting more efficient water management amid climate challenges [28].

Data measured directly in the field, such as those collected from plant leaves surface (e.g., PAR, VPD, leaf temperature), are essential for monitoring crop health. To extend these data to larger areas, they can be combined with information from advanced technologies like IoT sensors, drones, and satellite imagery, which provide a broader view of environmental conditions. This way, local phenomena can be scaled to similar contexts, improving crop management and enabling the application of more efficient farming practices, even for small farms [78].

4 Conclusions

This study proposes the application of an ad hoc developed econometric model that, trained on primary data, estimates stomatal conductance values. Based on the results from the model, evapotranspiration and water footprint were calculated for an important wine-making company in central Italy. The application of this novel methodology results in a water footprint (green + blue), for the winemaking process from cradle to gate, of 375.83 L for a 0.75 L wine bottle. Specifically, the green water footprint of the vineyard phase accounted to 262.16 L, and the blue water footprint for 112.35 L, while the cellar and packaging phases contributed with a blue water footprint of 1.32 L per wine bottle. When compared to other similar case studies from the literature, this study ranks the lowest.

Conventional methodologies for evapotranspiration and water footprint estimations are based on the modeling of crops under optimal conditions (i.e., without water limitations). Results from this work may suggest that a more case study-specific approach could result in better capturing the physiological response of plants (i.e., stomatal conductance) to local climatic conditions, and hence more realistic evaluation of the water use of crops. This may help water managers to allocate resources more efficiently and sustainably. On the other hand, specific water management practices set in place in the case study (i.e., water recycling system) may contribute to lowering substantially the overall water footprint, especially for the cellar and packaging phases. The site-specific methodology is more time and data-intensive than standard approaches, requiring data collection on climatic and physiological parameters. This includes daily measurements over a long period to calibrate the model for local conditions. However, the investment in data and effort is offset by the method's capacity to deliver actionable insights for better-informed and more efficient water management strategies.

As previously discussed, the external validity of this methodology is constrained by its reliance on observational data from the analyzed agricultural enterprise, gathered over the April–October period, a limitation imposed by the pilot nature of the project and the available dataset. Scaling up to a nationwide analysis with stratified sampling representative of Italy's vine crops would entail considerable logistical complexity and cost. Therefore, future work should extend data collection including diverse pedoclimatic regions—incorporating different grape varieties and geographic zones—and span additional seasons and years to capture interannual and seasonal variability, thereby bolstering the robustness of our findings.

Concurrently, enhancing the model's transferability to other crops and climatic zones will require the development of dedicated calibration and parameter-scaling protocols. First, the model should be fitted to multi-site datasets—including vineyards and herbaceous crops in Mediterranean, continental, and maritime settings—to derive scalers for key parameters such as vapor pressure deficit sensitivity and radiation response curves. These scalers can then be adapted to new crops via recalibration of standard agronomic indices. In situations where in-situ measurements are scarce, remote-sensing products will provide homogeneous, comparable inputs across sites. Finally, adopting a hierarchical or Bayesian framework will facilitate knowledge transfer by sharing a priori distributions of stomatal response parameters while allowing for local adaptation. Together, these steps will establish a true parametric scalability protocol, extending the model's validity to a broad spectrum of agronomic environments.

Furthermore, to increase accuracy of the WF calculations, partitioning of the ET values into blue and green water fractions should be based on primary irrigation data. This may better capture the response of the crop to the water status of the soil, which is influenced by irrigation. Finally, the grey water footprint fraction should be included to ensure full compliance with the Water Footprint Network methodology and comparability of results.

Nonetheless, this work provides the basis to develop even further the potentiality of data-driven models to estimate the water needs of crops, trying to provide an alternative use alongside well-established evapotranspiration and water footprint evaluation methodologies.

Appendix

See Tables 2, 3 and 4.

Table 2 Results of the regression models

Estimation			
Covariates	**(1)**	**(2)**	**(3)**
Intercept	1.626 (0.222)***	1.581 (0.221)***	0.572 (0.231)*
VPD	0.037 (0.099)	−0.087 (0.102)	−0.378 (0.097)***
TEMP	−0.166 (0.021)***	−0.151 (0.021)***	−0.077 (0.021)***
$TEMP^2$	0.005 (0)***	0.004 (0)***	0.003 (0)***
VPD^2	−0.179 (0.035)***	−0.143 (0.035)***	−0.076 (0.03)*
VPD^3	0.017 (0.004)***	0.014 (0.004)***	0.009 (0.003)**
RAD	0 (0)***	0 (0)***	0 (0)***
LEAF: high	−0.005 (0.006)	0.009 (0.005)	0.013 (0.005)**
LEAF: medium	−0.013 (0.006)*	−0.004 (0.005)	0 (0.005)
Splines (Time, df = 4)1		0.107 (0.012)***	0.066 (0.018)***
Splines (Time, df = 4)2		0.1 (0.013)***	0.079 (0.018)***
Splines (Time, df = 4)3		0.135 (0.017)***	0.105 (0.03)***
Splines (Time, df = 4)4		0.197 (0.016)***	0.178 (0.027)***
Young goblet			0.039 (0.013)**
Old goblet			0.044 (0.028)
Spurred cordon			0.052 (0.006)***
Guyot			0.037 (0.012)**
Area108			0.057 (0.008)***
Area820			−0.02 (0.026)
Area2107			0.002 (0.009)
Day18			0.013 (0.008)
Day25			−0.016 (0.006)**
Day28			0.086 (0.01)***
R^2	0.52	0.60	0.67
Adj. R^2	0.52	0.59	0.66

The table reports estimates from three different specifications examining the relationship between stomatal conductance and environmental factors. The first specification includes only environmental covariates and leaf height. The second specification extends this by adding natural cubic splines to account for unobserved intra-day variations affecting all observations similarly. The third specification corresponds to the full model described in Eq. (1) (Sect. 2.3). Standard errors are robust to heteroscedasticity

$p < 0.1$; *$p < 0.05$; **$p < 0.01$;***$p < 0.001$

Table 3 Cross validation

Type	Resample	RMSE	MAE	R^2
Type of cultivation	Fold Goblet	0.0561	0.0435	0.333
Type of cultivation	Fold *Young goblet*	0.1260	0.1000	0.455
Type of cultivation	Fold Old *goblet*	0.1300	0.1170	0.558
Type of cultivation	Fold Purred cordon	0.0966	0.0741	0.617
Type of cultivation	Fold Guyot	0.0909	0.0640	0.638
Area	Fold_Area_106	0.0632	0.0443	0.650
Area	Fold_Area_108	0.0781	0.0610	0.603
Area	Fold_Area_2107	0.0836	0.0684	0.560
Area	Fold_Area_2110	0.0909	0.0640	0.638
Area	Fold_Area_820	0.0934	0.0777	0.663
Area	Fold_Area_824	0.1000	0.0745	0.245
		Average RMSE	Average MAE	Average R^2
Type of cultivation		0.0999	0.0797	0.520
Area		0.0849	0.0650	0.560

It reports the model's out-of-sample performance for each fold of the leave-one-group-out cross-validation. The "type" column denotes whether the held-out group was defined by cultivation type or by geographic zone, and "Resample" identifies the specific fold. Presenting results at the fold level highlights how the model generalizes when each cultivation type or zone is excluded in turn

Table 4 Evapotranspiration and water footprint values for each individual training system

Training system		Evapotranspiration (mm)	WF_{blue} (L)	WF_{green} (L)	WF_{total} (L)
Spurred cordon	Mean	185.78	259.60	111.26	370.86
	Median	180.03	251.57	107.82	359.39
	SD	31.19	43.58	18.68	62.25
	Min	155.99	217.98	93.42	311.41
	Max	227.05	317.28	135.98	459.22
Old goblet	Mean	183.37	256.24	109.82	366.05
	Median	177.22	247.64	106.13	353.78
	SD	32.34	45.19	19.37	64.56
	Min	152.73	213.42	91.47	304.88
	Max	226.31	316.24	135.53	451.77
Young goblet	Mean	188.10	262.85	112.65	375.50
	Median	182.56	255.10	109.33	364.44
	SD	29.96	41.87	17.94	59.81
	Min	159.46	222.83	95.50	318.32
	Max	227.83	318.37	136.44	454.82
Goblet	Mean	193.23	270.02	115.72	385.74
	Median	188.33	263.18	112.79	375.97
	SD	27.51	38.44	16.48	54.92
	Min	166.81	233.09	99.90	332.99
	Max	229.45	320.64	137.42	458.05
Guyot	Mean	187.55	262.09	112.32	374.41
	Median	182.06	254.41	109.03	363.45
	SD	30.33	42.38	18.16	60.55
	Min	158.47	221.44	94.90	316.34
	Max	227.62	318.07	136.32	454.39

Abbreviations

ABA	Abscisic acid hormone
AWARE	Available water remaining model
BB	Ball-Berry model
Com	European commission
CWSI	Crop water stress index
CWU	Crop water use
CWU_{blue}	Crop water use blue
CWU_{green}	Crop water use green
EF	Environmental footprint
ET	Evapotranspiration
FAO	Food and agriculture organization of the United Nations
FU	Functional unit
ISO	International organization for standardization
JS	Jarvis-Stewart model
LAI	Leaf area index
LCA	Life cycle assessment
OLS	Ordinary least squares
PAR	Photosynthetically active radiation
PEF	Product environmental footprint
RAD	Radiation
SC	Stomatal conductance
SD	Standard deviation
ST	Stannard model
TEMP	Temperature
USGS	United States geological survey
VPD	Vapor pressure deficit
WFN	Water footprint network
WF_{proc}	Process water footprint
$WF_{proc\ blue}$	Process water footprint blue
$WF_{proc\ green}$	Process water footprint green
WULCA	Water use in LCA
Y	Yield

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Author contributions

Conceptualization, V.N., C.M., M.M.K., G.C., M.M., S.P., A.D.N., E.A.; Methodology, V.N., C.M., M.M., S.P., A.D.N., E.A.; Validation, V.N., G.C.; Investigation, M.M.K., M.M., S.P., A.D.N.; Data curation, M.M.K., M.M., S.P., E.A.; Visualization, C.M., E.A.; Writing—original draft preparation, V.N., C.M, S.P., A.D.N., E.A.; Writing—review and editing, V.N., C.M., G.C., M.M., S.P., A.D.N., E.A.; All authors have read and agreed to the published version of the manuscript.

Availability of data and materials

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

All authors have agreed to participate and collaborate in elaborating the manuscript

Consent for publication

All authors have agreed to the final version of the manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Grammarly in order to provide assistance on the readability of the language. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Competing interests

The authors declare no competing interests.

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