CAN WITHIN-SEASON GRAPEVINE PREDAWN LEAF WATER POTENTIALS BE PREDICTED FROM METEOROLOGICAL DATA IN NON-IRRIGATED MEDITERRANEAN VINEYARDS?

James A. TAYLOR[1,6*], Cesar ACEVEDO-OPAZO[2], Anne PELLEGRINO[3], Hernan OJEDA[4] and Bruno TISSEYRE[5]

1: INRA, UMR LISAH, Bât. 24, 2 Pl. Pierre Viala, 34060 Montpellier, France
2: University of Talca, Facultad de Ciencias Agrarias, CITRA, Casilla 747, Talca, Chile
3: SupAgro-M, UMR LEPSE, Bât. 7, 2 Pl. Pierre Viala, 34060, Montpellier, France
4: INRA, UE999 Pech Rouge, 11000 Gruissan, France
5:SupAgro-M, UMR ITAP/Irstea, Bât. 21, 2 Pl. Pierre Viala, 34060 Montpellier, France
6:Present address: Cornell Lake Erie Research and Extension Laboratory, Department of Horticulture, CALS, Cornell University, 6592 West Main Rd, Portland, NY, USA, 14769

Abstract

Aims: Climate-based indices exist for viticulture, particularly for modelling phenological events, but not for vine water status. In this work, climatic variables are linked to the temporal evolution of the water status of the vine

Methods and Results: Within-season time-series of predawn leaf water potential from previous studies across 8 seasons in the south of France were collated. Meteorological data were also collected at each site. A stepwise linear regression model was developed to predict the mean predawn leaf water potential of a vineyard block at a given date from climatic variables and time. Variables selected were growing degree days, short-term humidity and temperature effects. Application of the stepwise model to an independent data set, collected at the other two research sites, produced a linear response but required a local calibration at each site.

Conclusion: The analysis demonstrated that climatic variables can be used for predicting the temporal evolution of vine water stress in non-irrigated vineyards.

Significance and impact of study: The modelling can assist with within-season crop management and future vineyard planning/development in non-irrigated regions. In irrigated vineyards the application is more restricted but it may be used to identify when to start irrigation.

Keywords: vine water status; time-series; evapotranspiration; growing degree days

Résumé

Objectifs: En viticulture, des indices climatiques existent pour estimer les dates des stades phénologiques. En revanche, il n'existe pas d'indice climatique pour prédire l'état hydrique de la vigne. Ce travail a pour objectif de proposer une relation, définie localement, entre variables climatiques et état hydrique de la vigne.

Méthodes et résultats: Huit séries temporelles localisées dans le sud de la France ont été utilisées. Chaque série temporelle correspond au suivi du potentiel hydrique de base sur l'ensemble du cycle végétatif de la vigne. Pour chaque série, les données climatiques ont également été collectées. Une régression linéaire pas à pas a été utilisée pour prédire le potentiel hydrique de base moyen d'une parcelle à une date donnée à partir du temps et de plusieurs variables climatiques. Les variables sélectionnées à l'issue de cet apprentissage sont le temps thermique, l'humidité relative et la température intégrées sur trois jours. Le modèle obtenu a été appliqué à des données mesurées n'ayant pas servi pour son étalonnage et situées sur des sites différents dans la même région. Les résultats montrent que la réponse du modèle reste linéaire mais nécessite un facteur de correction propre au site considéré.

Conclusion: L'analyse a démontré que les variables climatiques peuvent être utilisées pour prédire l'évolution temporelle de la contrainte hydrique de la vigne dans les vignobles non irrigués.

Importance et impact de l'étude: En condition non irriguée, le modèle proposé présente un intérêt pour caractériser le millésime en cours. En conditions irriguées, l'intérêt d'un tel modèle est plus limité, il peut toutefois être utilisé pour identifier la date à laquelle l'irrigation doit débuter.

Keywords: état hydrique de la vigne; séries temporelles, évapo-transpiration; degrés-jours de croissance

manuscript received 1st June 2011 - revised manuscript received the 18th May 2012

J. Int. Sci. Vigne Vin, 2012, **46**, n°3, 221-232

*Corresponding author:james.taylor@cornell.edu

INTRODUCTION

Climatic data are widely used in viticulture, particularly for generating indices relating to vineyard site suitability. The majority of these indices are based on temperature effects and may be either calculated over the entire growing season or directed at particular periods of production. Examples of seasonal indices include the growing degree approach introduced by Amerine and Winkler (1944) and refined by Galdstones (1992), the simple homoclime rationale (Smart, 1977), the latitude-temperature Index of Jackson and Cherry (1988) and the Heliothermal Indices of Branas *et al.* (1946) and Huglin (1978). Examples of time-specific indices include the Harvest Maximum Temperature Index (Happ, 1999), and the Spring Frost Index (Gladstones, 2000). All these indices identify climates with favourable heat and sunshine conditions for grape maturity. The assumption with these indices is that water supply to the vine, either via natural precipitation or irrigation, is not detrimental to production.

While temperature-based indices are dominant, other authors have also proposed indices that incorporate a water supply threshold, for example, the bioclimatic index of Constantinescu (1967), which was adapted for Mediterranean (Spanish) conditions by Hidalgo (1980), or indices that include a measure of aridness or dryness such as those proposed by Dry and Smart (1988) and Tonietto and Carbonneau (2004). However, like the temperature-based indices, these indices generate a single value that characterises the entire production season. Thus they can be related to a seasonal effect on vine water stress but not to a weekly or daily effect.

While indices are common, there have also been attempts to use climatic variables in more specific models. For example, researchers (Due *et al.*, 1993; Beselat *et al.*, 1995; Bindi *et al.*, 1997; de Cortázar-Atauri *et al.*, 2009; Nendel, 2010) have modelled phenological stages, particularly budburst and floraison, from temperature variables but again have not directly considered the water status of the plant.

Understanding the daily or weekly evolution of vine water restriction is a key issue for growers. Grape production, particularly grape quality, is strongly influenced by the level of water stress that the vine undergoes during production. Optimum quality is usually achieved through imparting some minor to moderate water stress during the reproductive phase (Dry and Loveys, 1998; Acevedo-Opazo *et al.*, 2010b). Water stress early in the season during the vegetative stage or too much water stress during the reproductive stage can be detrimental to production (Wilkinson and Davies, 2002). Consequently, growers are keen to have information on the within-season temporal change in plant water status (Ψ) in their vineyards. However, this information is difficult to obtain due to the cumbersome and expensive nature of directly measuring Ψ (Jones, 2007). For real-time information on vine water stress and to drive irrigation decisions, most producers opt to measure soil moisture potential as a surrogate for plant water potential (Stevens and Harvey, 1996; McCarthy, 1997; Ortega-Farías *et al.*, 2004). The fraction of transpirable soil water (FTSW) has been shown to be a relevant variable in predicting grapevine assimilate source and sink activities and leaf water status (Pellegrino *et al.*, 2004, Pellegrino *et al.*, 2005; Pellegrino *et al.*, 2006; Lebon *et al.*, 2006). In addition, FTSW can be accurately predicted using a simple water balance model, as described by Lebon *et al.* (2003).

However, soil moisture monitoring or modelling as a surrogate for vine water status has limitations. Soil moisture sensors require correct installation with good soil contact to ensure accurate operation, particularly in the case of capacitance sensors. This is often difficult in stony/rocky soils that are characteristic of the Languedocien viticulture region. It is also often difficult to take into account rooting depth and differences in the texture and depth of horizons when calibrating soil moisture sensor systems. This is particular problematic for sensors, such as the Neutron Probe, that require a complete water balance to be established for correct operation. Correct installation and calibration are paramount to obtain precise readings from soil moisture sensors, and without this the sensor output can only be used subjectively as an indication of the trend in soil moisture change (Lieb *et al.*, 2003). The range of soil moisture potential over which a sensor operates may also be a limitation in dry environments, with some sensor types, e.g. tensiometers, ineffective at very low soil moisture potentials (< -0.2 MPa). Difficulties in estimating the total transpirable soil water (TTSW) and the available soil water (ASW) at budburst make it difficult to rely on the water balance model to accurately predict changes in FTSW and Ψ_{PD} over the cropping season (Lebon *et al.*, 2003; Pellegrino *et al.*, 2006).

Therefore, a climatic model to directly predict Ψ, and in particular identify when a vine is being placed under water stress, would be a very useful inclusion in any decision-support tool for managing crop production. Theoretically, the amount of water restriction that a plant undergoes is related to the flux of water in the system (e.g. precipitation, irrigation, transpiration, evaporation, drainage). Since many climatic variables are routinely measured or calculated by meteorological stations, the intention of this paper is to investigate if it is possible to predict Ψ from climatic variables (such as temperature, growing degree days, crop evapotranspiration, precipitation etc.) at an accuracy that is sufficient to assist in decision-making. The model will also be compared to a simple model based on the day of the year to verify that the evolution of vine water stress is not simply time dependent.

The context for the model is a non-irrigated vineyard in a Mediterranean climate. The scale of the proposed prediction model is at the block level. To achieve this, two key assumptions are made. The first is that climatic data is homogeneous across the block, while the second is an assumption of homogeneous soil type and depth in the block, or more specifically homogenous soil moisture storage and drainage. Thus water stored, supplied and lost is assumed constant across the domain. In reality these assumptions, particularly the second, are known to be flawed with blocks within a single soil unit shown to exhibited a considerable level of spatial variation in vine water stress (Acevedo-Opazo *et al.*, 2010a). However, current management decisions are generally made at the block level, therefore this is considered an appropriate level for prediction. Furthermore, prediction at a block level does not preclude a subsequent spatial extrapolation of the mean response to generate site-specific (sub-block) responses as suggested by Acevedo *et al.* (2009 and 2010b) and Taylor *et al.* (2010).

MATERIAL AND METHODS

1. Site locations

Model development, calibration and an initial cross validation were performed with data from the experimental vineyard of INRA Pech Rouge, Gruissan, Aude, France (43°08' N, 3°08' E). The vineyard consists of 45 blocks, with an average block area of ~1 ha. The blocks are not contiguous and are spread over an area of ~170 ha, which encompasses three broad pedological units. These are the local Littoral, La Clape and Colombier soil units, which are derived from sand, limestone and marlstone parent material respectively. They are classified (respectively) as Endosalic Arenosols, Calcisols (skeletic) and Calcisols/Regosols (clayic) (IUSS Working Group WRB, 2006).

A second validation of the model was also performed on an independent data set collected at several sites within the Languedocien viticulture plain (~60-100 kilometres NW of Gruissan). The validation vineyards were located near Roujan (43°29' N, 3°19' E) and Sauteyrargues (43°50' N, 3°55' E), which, while geographically displaced from each other and Gruissan, are still subject to a Mediterranean climate. The soils have been previously described as a Calcaric cambisol and Ferialsol luvique (FAO-UNESCO, 1981) for Roujan and Sauteyrargues respectively (Pellegrino *et al.*, 2006).

2. Predawn leaf water potential (ψ_{PD}) data collection

The Ψ data used in this paper are legacy data from previously published studies. Full details can be found in the relevant publications but are briefly introduced here.

The Ψ was measured as predawn vine water status (ψ_{PD}). In all cases, ψ_{PD} was measured on a mature, non-senescing leaf located on the middle third of a shoot using the pressure chamber method of Scholander *et al.* (1965). There are several possible methods of measuring plant water status (Jones 2007). A predawn measurement was preferred as it is generally considered to represent soil water status in non-irrigated systems (Carbonneau *et al.*, 2004 ; Sibille *et al.*, 2007; Beis and Patakas, 2010; Yamane *et al.*, 2009). Alternative measurements, such as solar noon leaf water potential measurements, are subject to short-term climatic effects that may not truly represent the underlying conditions. The pressure chamber technique is also considered to be the most accurate, though more laborious, of the measurement techniques available for monitoring plant water stress (Acevedo-Opazo *et al.*, 2008).

a. Gruissan data set

The Gruissan data were derived from two previous studies on the Pech Rouge vineyard. The first data set (Acevedo-Opazo *et al.*, 2009) contained ψ_{PD} data measured at 49 sites within two individual blocks. Measurements were taken from a block of Shiraz on 7 dates during the 2003 growing season and 6 dates in 2004. In 2005 the same sampling scheme was applied to a block of Mourvedre at 6 dates. Both fields were located on the Clape (Limestone) soil unit. For each date across the three years, the results from the 49 individual sites were averaged to produce a mean block ψ_{PD} value. The second data set (Taylor *et al.*, 2010) consisted of ψ_{PD} measured on 6 blocks within the vineyard on 2 dates in 2006 and 4 dates in 2007. There were 3 blocks assigned to each of two dominant soil units, the Clape and Colombier units, which are limestone and marlstone derived soils respectively. Within each block either 27 (2006) or 15 (2007) measurements were taken per date and averaged to generate a block mean.

The merging of these two data sets is dependent on two assumptions, an absence of a soil effect and cultivar effect on the ψ_{PD} data. A previous analysis of the vineyard scale data (Taylor *et al.*, 2010) established that cultivar has little influence on ψ_{PD} once the vines begin to undergo water stress (ψ_{PD} < -0.4 MPa) (Ojeda *et al.*, 2005). It also demonstrated that in general there was no significant difference between the ψ_{PD} values on the Clape and Colombier units at a given date. The vineyard does contain a third soil unit, a sandy unit, which was analysed by Taylor *et al.* (2010). This sandy soil unit exhibit a different ψ_{PD} response over the season due to the presence of a shallow water table. The data from the sandy soil unit has been omitted here to preserve the assumption of no cultivar and soil effect on the ψ_{PD} data. The model calibration (and validation – see below) has been deliberately restricted to vineyards that exhibit a low TTSW, i.e., vineyards where vines are prone to moderate to severe late season water stress. This has some obvious inferences on the future application of the model which will be discussed later.

Across the 5 years (2003-2007), dates of measurement ranged from mid-June to late August and mean field ψ_{PD} ranged from –0.12 to –1.13 MPa. In total there were 76 individual field means derived from 25 different dates.

b. Languedocien data set

The second data set is derived from an investigation of vine water stress under different water regimes (Pellegrino *et al.,* 2006). While Pellegrino *et al.* (2006) used multiple field sites in their experimental design, only sites that were non-irrigated and exhibited at least a moderate water stress (ψ_{PD} < -0.5 MPa) at the end of the season were selected for this analysis. In their study, Pellegrino *et al.* (2006) had some non-irrigated sites that did not exhibit moisture stress, even in July and August. These sites were assumed to be located in areas where the roots have access to groundwater although this was not verified by soil coring. The depth to groundwater is known to be highly variable in this region and has a considerable effect on ψ_{PD} (Guix-Hébrard *et al.*, 2007). Measurements were taken at 9 dates in 1998 on a Grenache block at Sauteyrargues and on 7 and 9 dates in 2000 and 2001 respectively on a Shiraz block at Roujan. There was one date in 1998 (6th August) which was omitted as the measured ψ_{PD} (-0.21 MPa) indicated no water stress. There had been a rainfall event (15 mm) within the previous 72 hours which appears to have influenced this measurement. The data from these two sites are collectively referred to as the Languedocien data.

In addition to the measured data, a ψ_{PD} value of –0.1 MPa was assumed for April 1st in each year for all sites. At the start of April budburst has already occurred in this region and the vine is undergoing rapid growth and stem elongation. Soil moisture stored over winter and spring is non-limiting to production thus the vine is under no water stress. Under these conditions a ψ_{PD} range of –0.05 to -0.2 MPa is common in these areas and supported by the early season (May) measurements of Pellegrino *et al.* (2006).

3. Meteorological data

At Gruissan, the daily climatic data for the period June 2002 to October 2008 was obtained from a meteorological station located on the vineyard, which forms part of INRA's 'Climatik' network. The Languedocien data vineyards had weather stations either installed within the vineyard or on a neighbouring vineyard during the relevant growing seasons. At all metrological stations the minimum, mean and maximum temperature (T_{min}, T_{mean} and T_{max}), the minimum, mean and maximum daily relative humidity (H_{min}, H_{mean} and H_{max}), the mean daily windspeed (W), the mean daily solar radiation incidence (R) and the daily precipitation (P) were recorded and daily evapo-transpiration (ET) was modelled using the Penman-Monteith equation (Allen *et al.*, 1989; Pereira *et al.*, 1999).

As well as the basic meteorological data there were several other secondary climatic variables derived at daily timesteps. The mean maximum and minimum temperature for the previous 3 and 7 days (T_{3max} and T_{7max} and T_{3min} and T_{7min}) were calculated. Previous research (Due *et al.*, 1993) has shown that mean temperatures prior to a phenological stage, such as bud burst or floraison, are significantly associated with the timing of the phenological stage. These variables were derived to capture and project forward information relating to extreme changes in temperature (both hot and cold).

The growing degree day (GDD) value was calculated for each day as:

$$GDD = [(T_{max} + T_{min})/2] - T_{base} \quad (1)$$

where T_{max} and T_{min} are the maximum and minimum daily temperature and T_{base} is a threshold temperature below which plants are considered inactive. For vines this is considered to be 10 °C (Gladstones, 1992).

The cumulative GDDs (GDD_C) were derived at daily time steps for the growing season (April 1st (t = 91) to September 30th (t = 274)) as:

$$\mathrm{GDD}_{C(t)} = \sum_{t=91}^{t} \mathrm{GDD}_{(t)} \tag{2}$$

t = the day of year (January 1st = 1)

Similarly cumulative reference ET (ET_C) and cumulative seasonal precipitation (P_C) were determined at daily time steps for the same period by replacing GDD with ET and P respectively in Eq. (2).

$$\mathrm{ET}_{C(t)} = \sum_{t=91}^{t} \mathrm{ET}_{(t)} \ ; \ \mathrm{P}_{C(t)} = \sum_{t=91}^{t} \mathrm{P}_{(t)} \tag{3}$$

The cumulative climatic water balance (WS_C) for a given day (t) during the growing season (April 1st – September 30th) was calculated as:

$$WS_{C(t)} = P_{C(t)} - ET_{C(t)} \tag{4}$$

Finally a weighted daily precipitation statistic ($P_{W(t)}$) was calculated using a recursive filter:

$$P_{W(t)} = \alpha(P_{(t)}) + (1-\alpha)(P_{W(t-1)}) \tag{5}$$

where $P_{(t)}$ is the measured daily precipitation at day (time) t, $P_{W(t-1)}$ is the weighted precipitation value for the previous day, α is a weighting factor and a value of 0.3 is used here.

A recursive daily index of precipitation was preferred to the raw daily values as a precipitation event is known to influence plant water restriction measurements in the days following the rainfall event. For this reason, no ψ_{PD} field measurements were taken for 48 hours after rainfall. However, within season precipitation may have a diminishing residual effect over the subsequent days post-precipitation. For this reason, it was considered preferable to include P_{Wt} and allow the model to determine if it was necessary or not. The value of α selected (0.3) results in a precipitation event having an influence for ~ 1 week after the event.

The climatic variables for each sampling date were extracted along with the time covariate (*t*, where January 1st = 1) and joined to the mean ψ_{PD} values for the date. The 2004 data was adjusted where necessary to account for the leap year.

4. Temporal Model Development and Calibration

In total there were 18 climatic variables plus *t* available. To generate a parsimonious model, a stepwise linear regression (SLR) was used to select the optimum covariates and co-efficients for the model. The SLR was run using the 'step' procedure (stats package) in R (R Development Core Team 2008) starting with the intercept model. The stepwise direction was 'both' (omnidirectional) allowing for variables to be added or removed at any step. All climatic variables and *t* (see Model 1 for list) were available for addition to the model. Variables were added until the stopping criterion (minimisation of the Akaike Information Criterion (Akaike, 1973)) was reached. This model then became the basis for the validation procedures.

$$\psi_{PD} \sim f(GDD + GDD_C + ET + ET_C + WS_C + T_{min} + T_{mean}, + T_{max} + H_{min} + H_{mean} + H_{max} + W + T_{3min} + T_{3max} + T_{7min} + T_{7max} + P_C + PW_t + t) \qquad \text{Model 1}$$

In addition to the model selected by SLR, two further 'expert-defined' models were chosen. These were a model based only on time (*t*) and another model based on GDD_C and WS_C. These were respectively labelled Model 2 and Model 3. Model 2 tests the assumption that the evolution of water stress is related only to time and not to climatic variation during the season. Model 3 is a simplified model using the most widely accepted climatic covariate in viticulture (GDD) and WS_C, which incorporates information on both ET and P.

$$\psi_{PD} \sim t \qquad \text{Model 2}$$

$$\psi_{PD} \sim GDD_C + WS_C \qquad \text{Model 3}$$

5. Model validation

a. Cross-validation with Gruissan data

The three different models (Models 1, 2 and 3) were validated using a leave-one-year-out cross validation (LOYOCV) procedure with the Gruissan data. Data from a particular year was omitted, the model calibrated with data from the remaining years and then validated against the omitted data. Model performance was assessed by calculating the root mean square error (RMSE) and the square of Lin's concordance correlation (ρ^2) statistic (Lin, 1989), which is the fit of a 1:1 line between the actual and predicted data sets, from data across all years. The RMSE and ρ^2 were calculated across the whole seasonal data and also for a seasonal subset where $\psi_{PD} < -0.4$ MPa. While it is important to know when there is no vine water stress (> -0.4 MPa), the precision of this estimation is not critical to a management decision. As vine water stress increases, growers will require more accurate and precise information to ensure that any management intervention is timely. The determination of RMSE and ρ^2 in situations where $\psi_{PD} < -0.4$ MPa tests the quality of the model when intervention to account for the seasonal evolution in vine water stress is possible.

b. Recalibration and validation with the independent Languedocien data

J. Int. Sci. Vigne Vin, 2012, **46**, n°3, 221-232

The stepwise model derived with the Gruissan data was applied to the climatic data at Sauteyrargues and Roujan to predict ψ_{PD} and the output was compared to the measured mean ψ_{PD} block response at Sauteyrargues and Roujan respectively. The expectation was for a linear response between the observed and predicted values but not necessarily a 1:1 response. The differences in the local climate, soil/landscape attributes, measurement equipment (weather stations and ψ_{PD} equipment) and measurement protocol were expected to have some effect on both measured and predicted ψ_{PD} values. A linear response would allow the model to be easily re-calibrated with a local correction co-efficient to account for these differences, which are assumed to be constant at a site, if it deviated from the 1:1 line. A non-linear response would indicate that the model cannot be extrapolated to other regions.

The local model recalibration was performed by determining the mean difference between the measured and predicted response and using it to correct the model output. The calculation of the mean difference was performed on per year basis using a) all the available data and b) all data available between mid-June and mid-July (2-3 points per year). This second period was selected as a period where water restriction is usually increasing but is often non-limiting. Thus the data from this period could be used to recalibrated the model in a new year or at a new location as the vine begins to undergo some water stress but before water restriction becomes potentially critical (< -0.4 MPa) (Ojeda *et al.*, 2005). In this way the model could be calibrated within-season and used immediately to drive decision-making, thereby avoiding a year delay between model calibration and application. Although the local climates differed between the Gruissan and Languedocien data, it is important to note that all sites were located within a Mediterranean climate, characterised by hot, dry summers.

RESULTS AND DISCUSSION

The stepwise regression procedure yielded the following equation:

$$\psi_{PD\,(t)} = -0.4161555 - 0.0005316GDD_C + 0.0019155H_{mean(t)} + 0.0328048T_{7max(t)} - 0.0216608T_{max(t)} \quad (6)$$

The variables in Eqn 6 are presented in the order selected in the stepwise procedure. There was one variable, *t*, which was selected and then later removed. *t* was initially selected at the second step, after GDDc. The selection of GDD_C and *t* early in the stepwise procedure provides some validation for the selection of the expert-defined models (Models 2 and 3). The selection of GDDc also re-enforces the utility of this climatic index for both a whole season and within-season understanding of vine development. The general downward trend of ψ_{PD} over the season is driven by the GDDc response. GDDc has a negative coefficient and, by definition, GDDc must accumulate as the season progresses. Therefore the influence of the GDDc variable on the predicted ψ_{PD} increases as the season progresses. The range of values for the other variables (H_{mean}, T_{7max} and T_{max}) remains relatively stable over the course of the season compared to the increase in GDDc. The humidity and temperature variables are therefore more important at the start of the season and for short-term (1 day to 1 week) fluctuations. In Figure 2 there is a periodicity evident in the fitted splines (see for example the 2004 response), that is likely linked to the periodicity in weather patterns and the selection of a weekly variable (T_{7max}). The third variable selected, H_{mean}, has a positive coefficient indicating that for a given day the vines are under less water stress (higher ψ_{PD}) if humidity is higher. This agrees with the general understanding of plant physiology whereby drier atmospheres tend to drive higher transpiration rates and exert higher water stresses on plants (Schulze, 1986). There were two temperature variables selected

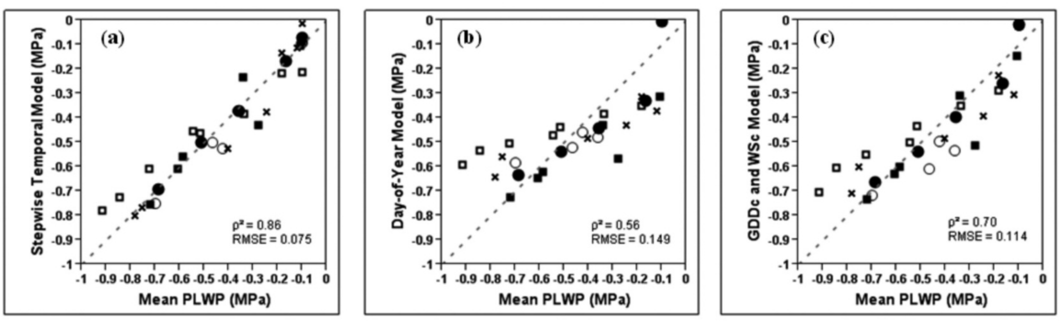

Figure 1 - Fits of (a) Model 1 (Stepwise LR), (b) Model 2 (t) and (c) Model 3 (WSc and GDDc) from the leave-one-year-out cross-validation. Points are labelled according to year – 2003 (□) 2004 (■), 2005(x), 2006 (○) and 2007 (●). The root mean square error (RMSE) for the fit to the region where values ψ_{PD} < -0.4 and the ρ^2 for all values of ψ_{PD} are shown on the plots.

(T_{7max} and T_{mean}) with differing coefficient signs. T_{7max} is positive and T_{mean} negative. There appears to be an interaction between these terms to adjust the GDDc response which is also temperature-derived (Eqns 1 and 2).

Plots of the measured vs. predicted from the LOYOCV of the Gruissan data are presented in Figure 1 for the stepwise model (Eq. (6)), Model 2 and Model 3. The RMSE and Lin's ρ^2 are recorded on the plots.

The LOYOCV results confirmed that the stepwise model was the best predictive model. The RMSE of prediction is 0.075 MPa, which is well within the threshold of 0.2 MPa used by most growers when making irrigation decisions (Ojeda *et al.*, 2005). The model did not show inter-annual effects despite climatic differences between years. Relying on only *t* for prediction caused problems, especially at higher water restrictions. In Figure 1b it can be seen that the response for each year is strongly linear but there is either a bias (for example the 2004 data) or gradient change (for example the 2003 and 2005 data) in prediction, which resulted in a lower ρ^2 value and larger RMSE. The bias and gradient shift are less noticeable in the expert-defined water supply model (Figure 1c) but there is more scatter, as evidenced by the higher RMSE, around the 1:1 line when compared to the stepwise model (Figure 1a).

The robustness and goodness of fit prediction between years, lead to a daily prediction of ψ_{PD} for each growing season from 2003 to 2007 (Figure 2). The ψ_{PD} data is fitted with a spline (λ = 100) to show the annual trends, which were not identical for each year. Information pertaining to the annual date of veraison, a key phenological stage of development, for a Shiraz block on the Clape soil unit is also indicated in Figure 2. Since veraison does not occur uniformly within a block, the date used was the median date of veraison recorded from a survey of vines in the block (data courtesy of Unité Experimental Pech-Rouge of INRA). By chance the median date of veraison across the 5 years fell within +/- 1 day of two particular dates (*t* = 201 and 209), which are indicated in Figure 2. It can be clearly seen that the water restriction at veraison differs between years and is often associated with a period of rapid decline in ψ_{PD}. In some years (e.g. 2003 and 2005) vines are already in a period of moderate water stress (<-0.4 MPa) before veraison.

Prior to veraison, strong vegetative growth is required to promote light interception and carbon acquisition within the plant for effective reproductive (yield) development. Severe water stress prior to veraison is undesirable and may lead to poor fruit set or alternatively an inability of the vine to mature the grapes properly (Hardie and Considine, 1976; Ojeda *et al.,* 2002). Strong vegetative growth post-veraison is usually counter-productive to quality grape (harvest) production (Ojeda *et al.,* 2002; Deloire *et al.,* 2004). The vine water status during this post-veraison period largely determines the type of wine produced. A total absence of water stress (ψ_{PD} > -0.3 MPa) produces diluted, "herbaceous", and acids wines. In the case of very severe water stress (ψ_{PD} < -0.8 MPa) red wines are too tannic, hard, astringent and alcoholic, whereas white wines have lost much of their flavour. If water stress is intermediate (between -0.3 < ψ_{PD} < -0.7 MPa), the wines are balanced and give the best aromatic expression (Deloire *et al.,* 2005; Ojeda, 2007).

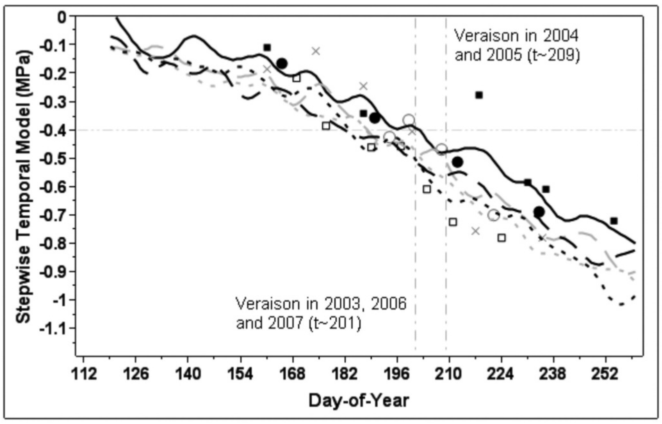

Figure 2 - Fitted spline (λ = 100) of the daily ψ_{PD} predictions with the manual measurements and the median *t* of veraison for Shiraz for each year overlaid. Legend for measurements and lines is 2003 ---/□; 2004 —/■; 2005 — —/x; 2006 ---/○; 2007 — —/●. Greyed vertical lines indicate the medium date of veraison while the greyed horizontal line indicates the threshold below which vines are considered to be undergoing a moderate water stress.

1. Independent validation

Application of the Gruissan calibrated model to the climate data at Sauteyrargues and Roujan produced ψ_{PD} predictions approximately twice that of the input data (Predicted values of -0.24 - -1.01 c.f. measured values of -0.06 - -0.60). Even though the predictions were higher, a fit of a linear model between the measured and predicted values exhibited a strong linear relationship (r^2 0.54-0.88 (Table 1)). The 1:1 fit (ρ^2) was not as strong (Table 1). The gradients of the relationship between the measured and predicted values for each year did not divert significantly from 1 (Table 1). Therefore, the suggested local calibration based on the mean difference between the measured and predicted responses should be effective. As outlined in the Methods, the adjustment can be made by considering only early season values or the entire seasonal data. Both results are presented in Table 1. There was no advantage in any year to the use of the whole data set c.f. only using early season data. The RMSE presented is from the adjustment using all the data.

The individual year and combined RMSE from the independent validation (Table 1) were all lower than the general error accepted by growers (Odeja *et al.*, 2005). The Sauteyrargues 1998 and Roujan 2000 showed very good fits and low RMSE (< 0.1 MPa). The Roujan 2001 predictions had the worst fits (r^2, ρ^2 and RMSE). The predictions are visualised in Figure 3, which displays the predicted versus measured data from all three years and the ψ_{PD} response over time to illustrate the difference in response between years. The reason for the poorer fit for the Roujan 2001 data is unknown and may be due to a different physiological response, an altered management practice or measurement error. The measured ψ_{PD} are higher (less water stress) in 2001 compared with 2000 at Roujan even though the 2001 season was warmer (mean seasonal (t = 91-243) temperatures of 24.7 °C and 25.6 °C for 2000 and 2001 respectively), there was considerably less cumulative within-season rainfall in 2001 (170 mm c.f. 279 mm in 2000) and the soil profile was not fully saturated at the start of the 2001 season due to poor winter/spring rainfall (see Pellegrino *et al.*, 2004). Under these conditions higher water stresses were expected but not observed (Figure 3). The vineyard meteorological station was also dismantled and reinstalled between 2000 and 2001, which could cause error if the instruments were not properly calibrated for one or both years.

The local calibration corrections were -0.129, -0.289 and -0.394 for Sauteyrargues (1998), Roujan (2000) and Roujan (2001), respectively. The results from the LOYOCV at Gruissan indicate that the response at a site was temporally stable. Therefore a similar coefficient was expected at Roujan for the two years. This was not observed. If the annual calibration factors were swapped between years at Roujan the error of prediction was increased by 25% (data not shown). As discussed in the previous paragraph, the response in 2001 at Roujan did not follow an expected pattern even though the 2001 predictions were within a currently accepted error. At this point it appears reasonable to conclude that a simple local calibration can be used to successfully re-calibrate the model. However it is uncertain if the local calibration is stable over time or requires an annual determination. It is likely that any adjustment or disturbance to the method of measuring climatic variables will require a recalibration of the model. However, the results of recalibrating the model on the independent data using only early season data indicate that there is no loss in model performance. Therefore the model can be calibrated using local measurements during a period when information on ψ_{PD} is not critical.

Table 1 - The results from a linear model between the measured and predicted values from the independent Languedocien data. The fit (r^2), slope (m) and concordance coefficient (ρ^2) are shown for results before calibration and ρ^2 and RMSE shown for results after applying the local calibration to the model predictions.

	Uncalibrated Predictions			Calibrated Predicitons		
	r^2	m	ρ^2	ρ^2 (early data)	ρ^2 (all data)	RMSE (all data)
Sauteyrargues 1998	0.89	0.79	0.48	0.85	0.86	0.06
Roujan 2000	0.84	1.11	0.14	0.81	0.81	0.09
Roujan 2001	0.58	1.28	0.04	0.45	0.45	0.15
All 3 years				0.67	0.67	0.11

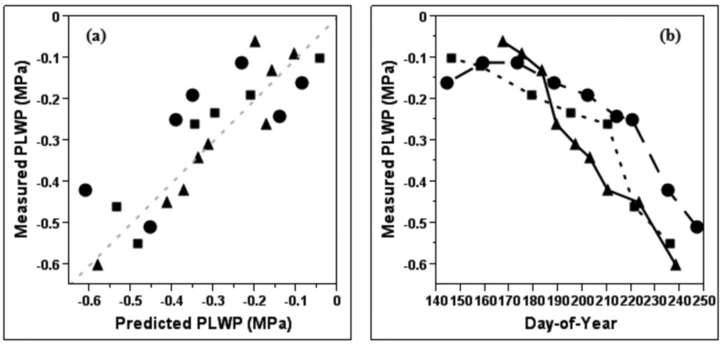

Figure 3 - (a) Fit of the Languedocien validation data to the model after a local calibration using data from the entire season and (b) Temporal evolution of measured ψ_{PD} at each site
Legend for both plots: ▲ = Sauteyrargues 1998 ■ = 2000 Roujan and ● = 2001 Roujan. Line in (a) is the 1:1 fit.

2. Considerations on incorporating the model into decision support systems.

The model framework adopted for this analysis is a simple linear model. Given the nature of the variable to be predicted (ψ_{PD}) and its known response to short-term climatic effects, such as precipitation and extreme heat or wind, an auto-regressive (AR) model may be a preferable alternative. This was considered; however there was insufficient temporal resolution in the ψ_{PD} data to properly calibrate an AR model. It is therefore important to realise that the model may not respond appropriately to precipitation or extreme climatic events and expert knowledge may be required when making decisions during or immediately after such events.

The model has also only been calibrated from April to September, i.e. only for the growing season up until harvest. Historically, there has been no ψ_{PD} data collected post-harvest as ψ_{PD} is considered important for within-season management. The absence of post-harvest data meant that the model could not be calibrated and therefore cannot be applied to this period. In Mediterranean climates the harvest is generally early (August-September), allowing an extended vegetated state post-harvest for the vine to store assimilates, increase the absorption of minerals and start the production of new roots (Freeman and Smart, 1976; Van Zyl, 1984; Conradie, 2005). This period is therefore critical for setting the vine up for the subsequent season(s). This period is also often characterised by rainfall events in late Summer/Autumn to which the model is unable to respond.

The results of the model validation and calibration on the Gruissan data indicate that there is a temporal stability to the model response at a particular location. Thus, when the model is re-calibrated at a new location, legacy data could be used from previous seasons to determine the correction co-efficient. If the method of climatic data collection changes, for example a change in sensor type or location or reinstallation, then it is likely that the local calibration will require adjustment. The results from the independent validation with the Languedocien data did not indicate the same level of temporal stability but the Languedocien data set for validation is limited (2 years at Roujan) and the assumption of a permanent fixed meteorological station was not met.

Although not investigated here, the calibration is also likely to be related to the soil water availability (e.g. soil texture, soil depth and the degree of saturation of the profile at bud-break). Soil moisture is generally measured using FTSW in these systems (Pellegrino *et al.*, 2004). The relationship between FTSW and ψ_{PD} has been used, concomitantly with a water balance model, to calibrate the total transpirable soil water (TTSW) (Pellegrino *et al.*, 2006). Unfortunately no direct measurements of TTSW were available for either the Gruissan or Languedocien sites to determine if a relationship exists between the calibration needed and TTSW. Within a domain, differences in ψ_{PD} (and therefore calibration) between production systems (fields or vineyards) are likely to be driven primarily by soil differences, particularly late in the season (Taylor *et al.*, 2010). If a domain is characterised by several disparate soil types, then a separate recalibration may be needed for each soil type.

Since the calibration is the difference between the actual and predicted values, the co-efficient could be estimated from a single measurement. However, this is not recommended as individual measurements may contain significant stochastic error leading to poor calibration. The approach adopted here of using 2 – 3 early/mid-season (mid-June to mid-July) ψ_{PD} measurements worked well and there was no advantage to including data from the entire season in the calibration (Table 1).

The absence of a 'water supply' variable in the model would appear to pose an interesting question for application when irrigation is available. The cumulative index WS_C was used to identify if the cumulative precipitation within the season had a 'dampening' effect on the seasonal evolution of ψ_{PD}. However, this was not observed, probably because the effect of summer ET is so dominant in this climate. As a result, the use of the model in an irrigated system in this region will only be applicable at the start of the season to identify the first relevant stages for intervention with irrigation. The absence of a precipitation-based variable in the model means that supplementary irrigation cannot be accounted for. The model continues to predict changes in ψ_{PD} based only on temperature and humidity derived values. It is possible that large natural rainfall events in mid-summer (e.g. >50 mm) may affect predictions in non-irrigated systems. Only one significant rainfall event (>20 mm) (15/08/2006, 43 mm) occurred from mid-June to mid-September between 2003 and 2007 at Gruissan (the model development site). The occurrence of this singular rainfall event late in the growing season, and at the height of ET demand (mid-August), did not adversely affect the model prediction a week later (22/08/2007). However, as noted in the Methods, one point in the validation was deliberately omitted (06/08/1998) as a dramatic increase in ψ_{PD} was observed between measurements taken before and then 72 hours after a rainfall event (15 mm). This demonstrates that precipitation does have an immediate short-term impact on ψ_{PD}. The non-selection of $P_{W(t)}$ probably due to the lack of available data in the period within which this variable is expected to have an effect. With higher temporal resolution data, and a better understanding of how vines in this climate respond to precipitation events, then the $P_{W(t)}$ may be pertinent in modelling ψ_{PD}, especially, as discussed previously, within an AR model framework. However, the inclusion of this variable is likely to only correct for short-term variation, rather than the general seasonal trend in ψ_{PD}.

In non-irrigated viticulture systems, the model cannot be used for instigating irrigation but it will provide regular information on ψ_{PD} (and crop) development, which may be used, for example, to adjust the optimal crop load, to predict phenological development and to optimise the timeliness of within-season management.

CONCLUSIONS

This analysis has shown that ψ_{PD} can be modelled with climatic data at an accuracy that is suitable for management. The climatic parameters identified in the model are likely to be relevant for any domain within a Mediterranean type environment as long as a local calibration is performed. It is possible to recalibrate the model using early to mid-season measurements, such that the model can be used within-season to predict response. The calibration also indicated that it may be possible to use legacy data to generate the local calibration, provided the legacy data do account for the spatial variation in ψ_{PD} and represent a true estimation of the mean ψ_{PD} over the domain. However, model performance in other climates is unknown and the optimal climatic parameters for prediction are likely to vary. For example, it would be expected that a precipitation-based variable may be more relevant in climates with significant mid-summer precipitation.

Acknowledgements : James Taylor's position at INRA is funded by the Agropolis Foundation. The authors would like to acknowledge Jean-Noël Lacapere (INRA – UE Pech Rouge) for technical assistance and help in the grapevine water potential measurements.

REFERENCES

Acevedo-Opazo C., Tisseyre B., Guillaume S., Ortega-Farías S. and Ojeda H., 2008. Is it possible to assess the spatial variability of vine water status? *J. Int. Sci. Vigne Vin*, **42**(4), 203-219.

Acevedo-Opazo C., Tisseyre B., Ojeda H. and Guillaume S., 2009. Spatial extrapolation of the vine (*Vitis vinifera* L.) water status: A first step towards a spatial prediction model. *Irrigation Sci.*, **28**(2), 143-155.

Acevedo-Opazo C., Ortega-Farias S. and Fuentes S., 2010a. Effects of grapevine (*Vitis vinifera* L.) water status on water consumption, vegetative growth and grape quality: An irrigation scheduling application to achieve regulated deficit irrigation. *Agric. Water Manage.*, **97**(7), 956-964.

Acevedo-Opazo C., Tisseyre B., Taylor J.A., Ojeda H. and Guillaume S., 2010b. A model for the spatial prediction of water status in vines (*Vitis vinifera* L.) using high resolution ancillary information. *Prec. Agric.,* **11**(4), 358-378.

Akaike H., 1973. Information Theory and an Extension of the Maximum Likelihood Principle. *In: Petrov B.N. and Csaki, F. (Eds), Second International Symposium on Information Theory*. Akademiai Kiado, Budapest, Hungary. p. 267-281.

Allen R.G., Jensen M.E., Wright J.L. and Burman R.D., 1989. Operational Estimates of Reference Evapotranspiration. *Agronomy J.,* **81**, 650-662.

Amerine M.A. and Winkler A.J., 1944. Composition and quality of musts and wines of Californian grapes. *Hilgardia*, **15**, 493-675.

Beis A. and Patakas A., 2010. Differences in stomatal responses and root to shoot signalling between two grapevine varieties subjected to drought. *Funct. Plant Biol.*, **37**(2), 139-146.

Bindi M., Miglietta F., Gozzini B., Orlandini S. and Seghi L., 1997. A simple model for simulation of growth and development in grapevine (*Vitis vinifera* L.). I. Model description. *Vitis*, **36**(2), 67-71.

Branas J., Bernon G. and Levadoux L., 1946. *Éléments de viticulture générale*. Dehan, Montpellier, France

Carbonneau A., Deloire A. and Costanza P., 2004. Le potentiel hydrique foliaire : sens des différentes modalités de mesure. *J. Int. Sci. Vigne Vin*, **38**(1), 15-19.

Conradie W.J., 2005. Partitioning of mineral nutrients and timing of fertilizer applications for optimum efficiency. *In: Christensen, P. and Smart, D.R. (Eds.), Proceed. of the Soil Environment and Vine Mineral Nutrition Symposium*. American Society for Enology and Viticulture, Davis, CA. p. 69-81.

Constantinescu G., 1967. Méthodes et principes de détermination des aptitudes viticoles d'une région et du choix des cépages. *Bull. OIV,* **441**, 1179-1205.

de Cortázar-Atauri I.G., Brisson N. and Gaudillère J.P., 2009. Performance of several models for predicting budburst date of grapevine (*Vitis vinifera* L.). *Int. J. Biometeorol.,* **53**(4), 317-326.

Deloire A., Carbonneau A., Wang Z. and Ojeda H., 2004. Vine and Water, a short review. *J. Int. Sci. Vigne Vin*, **38**(1) 1-13.

Deloire A., Ojeda H., Zebic O., Bernard N., Hunter J-J. and Carbonneau A., 2005. Influence de l'état hydrique de la vigne sur le style de vin. *Progrès Agric. Vitic.,* **122**(21), 455-462.

Dry P.R. and Loveys B.R., 1998. Factors influencing grapevine vigour and the potential for control with partial rootzone drying. *Aust. J. Grape Wine Res.,* **4**, 140-148.

Dry P.R. and Smart R.E., 1988. Vineyard site selection - Chapter 10. *In: Coombe B.G. and Dry, P.R. (Eds.), Viticulture, vol. I: Resources in Australia*. Australian Industrial Publishers, Adelaide, p. 190-204

Due G., Morris M., Pattison S. and Coombe B.G., 1993. Modelling grapevine phenology against weather: considerations based on a large data set. *Agric. Forest Meteorol.,* **56**, 91-106

FAO-UNESCO, 1981. Soil map of the world, vol. 5 Europe, 1:5 000 000, FAO, Rome, Italy

Freeman B.M. and Smart R.E., 1976. A root observation laboratory for studies with grapevines. *Am. J. Enol. Vitic.*, **27**(1), 36-39.

Gladstones J., 1992. *Viticulture and Environment*. WineTitles, Adelaide. ISBN 1875130128

Gladstones J., 2000. Past and future climatic indices for viticulture. *In: Proceed. of the 5th International Symposium for Cool Climate Viticulture and Oenology*, Melbourne, Australia 10p

Guix-Hébrard N., Voltz M., Trambouze W., Garnier F., Gaudillère J.P. and Lagacherie P., 2007. Influence of watertable depths on the variation of grapevine water status at the landscape scale**.** *Eur. J. Agron.,* **27**(2-4), 187-196.

Happ E., 1999. Indices for exploring the relationship between temperature and grape and wine flavour. *Australian and New Zealand Wine Industry J.,* **14**(4), 1-6.

Hardie W.J. and Considine J.A., 1976. Response of grapes to water-deficit stress in particular stages of development. *Am. J. Enol. Vitic.,* **27**, 55-61.

Hidalgo L., 1980. Caracterización macrofísica del ecosistema medioplanta en los viñedos españols. *Comunicaciones INIA Series Producción Vegetal,* **29**, Instituto Nacional de Investigaciones Agrarias, Madrid.

Huglin P., 1978. Nouveau mode d'évaluation des possibilités héliothermiques d'un milieu viticole. *C.-R. Académie Agric.*, p. 1117-1126.

IUSS Working Group WRB, 2006. World reference base for soil resources. *World Soil Resources Reports,* **103** (2nd ed.), FAO, Rome.

Jackson D.I. and Cherry N.J., 1988. Prediction of a district's grape-ripening capacity using a latitude temperature index (LTI). *Am. J. Enol. Vitic.,* **39**, 19-28.

Jones H.G., 2007. Monitoring plant and soil water status: established and novel methods revisited and their relevance to studies of drought tolerance. *J. Exp. Botany,* **58**(2), 119–130.

Lebon E., Dumas V., Pieri P. and Schultz H.R., 2003. Modelling the seasonal dynamics of the soil water balance of vineyards. *Func. Plant Biol.,* **30**, 699-710.

Lebon E., Pellegrino A., Louarn G. and Lecœur J., 2006. Branch development controls leaf area dynamics in grapevine (*Vitis vinifera* L.) growing in drying soil. *Annals of Botany,* **98**(1), 175-185.

Leib B.G., Jabro J.D. and Matthews G.R., 2003. Field evaluation and performance comparison of soil moisture Sensors. *Soil Science,* **168**(6), 396-408.

Lin L.I-K., 1989. A concordance correlation coefficient to evaluate reproducibility. *Biometrics,* **45**, 255-268.

McCarthy M.G., 1997. The effect of transient water deficit on berry development of cv. Shiraz. *Aust. J. Grape Wine Res.,* **3**, 102-108.

Nendel C., 2010. Grapevine bud break prediction for cool winter climates. *Int. J. Biometeorol.,* **54**(3), 231-241.

Ojeda H., Andary C., Kraeva E., Carbonneau A. and Deloire A., 2002. Influence of pre and post-veraison water deficit on synthesis and concentration of skin phenolic compounds during berry growth of *Vitis vinifera* L., cv Shiraz. *Am. J. Enol. Vitic.,* **53**(4), 261-267.

Ojeda H., Carrillo N., Deis L., Tisseyre B., Heywang M. and Carbonneau A., 2005. Precision viticulture and water status II: Quantitative and qualitative performance of different within field zones, defined from water potential mapping. *In : Shultz, H.R. (Ed.), Proceed. of the 14th GESCO Congress*. Geisenheim, Germany, p. 741-748.

Ojeda H., 2007. Irrigation qualitative de précision de la vigne. *Progrès Agric. Vitic.,* **124**(7), 133-141.

Ortega-Farías S., Acevedo C., Acevedo A. and Leyton B., 2004. Talca irrigation management system (TIMAS) for grapevine. *Acta Hortic.,* **664**, 499-504.

Pellegrino A., Lebon E., Voltz M. and Wery J., 2004. Relationships between plant and soil water status in vine (*Vitis vinifera* L.). *Plant Soil*, **266,** 129–142.

Pellegrino A., Lebon E., Simonneau T. and Wery J., 2005. Towards a simple indicator of water stress in grapevine (*Vitis vinifera* L.) based on the differential sensitivities of vegetative growth components. *Aust. J. Grape Wine Res.,* **11**(3), 306-315.

Pellegrino A., Gozé E., Lebon E. and Wery J., 2006. A model-based diagnosis tool to evaluate the water stress experienced by grapevine in field sites. *Eur. J. Agron.* **25**, 49-59.

Pereira L.S., Perrier A., Allen R.G. and Alves I., 1999. Evapotranspiration : review of concepts and future trends. *J. Irr. Drain. E-ASCE,* **125**, 45-51.

R Development Core Team (2008). *R : A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/

Scholander P. F., Hammel H. T., Brandstreet E. T. and Hemmingsen E. A., 1965. Sap pressure in vascular plants. *Science,* **148**, 339-346.

Schulze, E.D. (1986) Carbon dioxide and water vapour exchange in response to drought in the atmosphere and soil. *A. Rev. Plant Physiol.*, **37,** 247-274

Sibille I., Ojeda H., Prieto J., Maldonado S., Lacapere J N. and Carbonneau A., 2007. Relation between the values of three pressure chamber modalities (midday leaf, midday stem and predawn water potential) of 4 grapevine cultivars in drought situation of the southern of France. Applications for the irrigation control. *In : Sladonja, B. (Ed), Proceed. of the 15th Int. Symp. of GESCO*, The Institute of Agriculture and. Tourism, Porec, Croatia, p.685-695

Smart R.E., 1977. Climate and grapegrowing in Australia. *In : Proceed. of the Third Australian Wine Industry Technical Conference*, Australian Wine Research Institute, Urrbrae, SA, Australia, p. 12-18.

Stevens R. and Harvey G., 1996. Soil water depletion rates under large grapevine. *Aust. J. Grape Wine Res.,* **2**(3), 155-162.

Taylor J.A., Acevedo-Opazo C., Ojeda H. and Tisseyre B., 2010. Identification and significance of sources of spatial variation in grapevine water status. *Aust. J. Grape Wine Res.,* **16**(1), 218-226.

Tonietto J. and Carbonneau A., 2004. A multicriteria climatic classification system for grape-growing regions worldwide. *Agric. Forest Meteorol.*, **124**, 81-97.

Van Zyl J. K., 1984. Response of colombar grapevines to irrigation as regards quality aspects and growth. *S. Afr. J. Enol. Vitic.*, **5**(1), 19-28.

Wilkinson S., and Davies W.J., 2002. ABA-based chemical signalling : the co-ordination of responses to stress in plants. *Plant Cell Environ.,* **25**, 195-210.

Yamane T., Shibayama K., Hamana Y. and Yakushiji H., 2009. Response of Container-Grown Girdled Grapevines to Short-Term Water-Deficit Stress. *Am. J. Enol. Vitic.,* **60**(1), 50-56.