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Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management

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ABSTRACT

Remote sensing can provide a fast and reliable alternative for traditional in situ water status measurement in vineyards. Several vegetation indices (VIs) derived from aerial multispectral imagery were tested to estimate midday stem water potential (Ψ_{stem}) of grapevines. The experimental trial was carried out in a vineyard in the Shangri-La region, located in Yunnan province in China. Statistical methods and machine learning algorithms were used to evaluate the correlations between Ψ_{stem} and VIs. Results by simple regression between VIs individually and Ψ_{stem} showed no significant relationships, with coefficient of determination (R^2) for linear fitting smaller than 0.3 for almost all the indices studied, except for the Optimal Soil Adjusted Vegetation Index (OSAVI); $R^2 = 0.42$ with statistical significance ($p \le 0.001$). However, results from a model obtained by fitting using Artificial Neural Network (ANN), using all VIs calculated as inputs and real Ψ_{stem} from plants within the study site (n = 90) as targets (Model 1), showed high correlation between the estimated water potential through ANN ($\Psi_{stem\ ANN}$) and the actual measured Ψ_{stem}. Training, validation and testing data sets presented individual correlations of R = 0.8, 0.72 and 0.62 respectively. The models obtained from the study site were then applied to a wider area from the vineyard studied and compared to further Ψ_{stem} measured obtained from different sites (n = 23) showing high correlation values between $\Psi_{stem\ ANN}$ and real Ψ_{stem} ($R^2 = 0.83$; slope = 1; $p \le 0.001$). Finally, a pattern recognition ANN model (Model 2) was developed for irrigation scheduling purposes using the same Ψ_{stem} measured in the study site as inputs and with the following thresholds as outputs: Ψ_{stem} below −1.2 MPa considered as severe water stress (SS), Ψ_{stem} between −0.8 to −1.2 MPa as moderate stress (MS) and Ψ_{stem} over −0.8 MPa with no water stress (NS). This model can be applied to analyze on a plant by plant basis to identify sectors of stress within the vineyard for optimal irrigation management and to identify spatial variability within the vineyards.

1. Introduction

Water is the key factor affecting quality and quantity of wine grapes. Excessive water applications may result in increases of the vegetative growth and yield, but other parameters associated to quality traits, such as sugar content, acidity and pigment synthesis may be adversely affected. In contrast, severe water stress will drive to partial or complete stomatal closure, causing a reduction on the photosynthetic activity (Van Leeuwen et al., 2009).

In regions where precipitations are scarce and concentrated in brief periods along the year, irrigation plays a significant role to achieve desired yield and quality. To manage irrigation scheduling there are three questions to answer: (i) when to irrigate, (ii) how much to irrigate and (iii) where to apply water. The latter question can be only answered with a spatial assessment of plant water status. Water potential (Ψ) is one of the in situ methods, that has been traditionally effective to assess crop water status in agriculture (Smith and Mullins, 2000; Choné, 2001; Van Leeuwen et al., 2006; Jones, 2007). However, the most accurate measurements of Ψ can be achieved by using a pressure chamber (Scholander et al., 1964), which applied to a large scale can be both labor intensive and time consuming. Hence, adequate sampling and repeatability are usually limited to a few sentinel plants and assumed to

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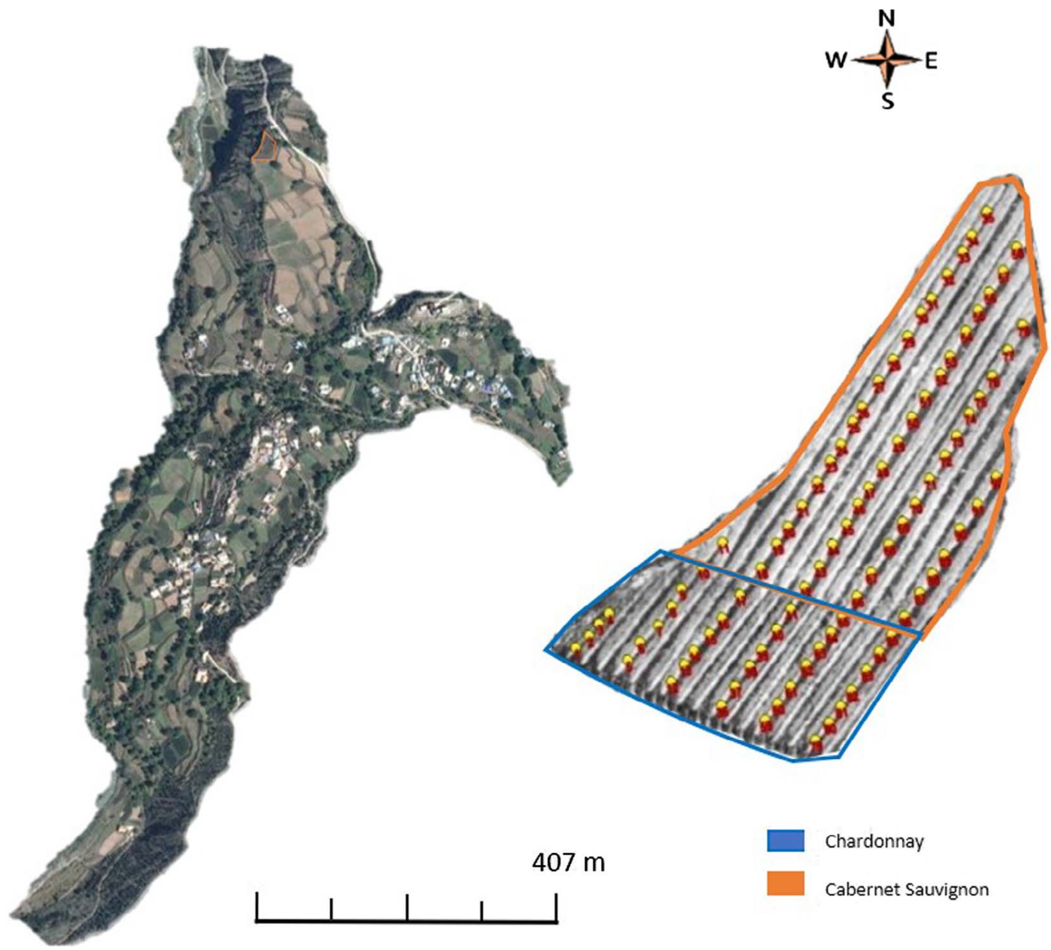

Fig. 1. Location of the study in the Southern of China and reference plot used for this study. Yellow dots denote the locations where plant measurements were performed in a grid for each cultivar: Chardonnay (n = 35) in the bottom section and Cabernet sauvignon (n = 55) at the top section. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

be representative of the whole field. These assumptionscomplicate the implementation of efficient irrigation scheduling practices and any other management practices focused to control or uniform yield or quality within vineyards. The latter, mainly due to the heterogeneity of soils and microclimate found in most of vineyards around the world. Therefore, more efficient monitoring systems that have both, high temporal and spatial resolutions are required.

Technological advances in remote sensing have provided non-invasive, time and cost-effective techniques that can detect the spatial variability of plant water status at a wider range of temporal scales compared to any manual method (Acevedo-Opazo et al., 2008; Dorigo et al., 2007). Over the last 30 years, spectral reflectance data have been used more and more in the studies of vegetation, due to the connection between the spectral proprieties and their biochemical and biophysical attributes, e.g., biomass, leaf pigment contents, canopy water content, crop coefficient and crop evapotranspiration (Penuelas et al., 1997; Zarco-Tejada et al., 2005; Rodríguez-Pérez et al., 2007;Baluja et al., 2012; Ferreira et al., 2012; Hunt et al., 2012; Pôças et al., 2015; Costa et al., 2016). Spectral data are commonly used as mathematical combinations of two or more spectral bands, which are named as spectral indices. The rising availability of sensors with the ability to provide reflectance information over a spectral range, has contributed to increase the interest in using vegetation indices (VI) based on the visible, red-edge and near infrared (NIR) regions of the electromagnetic light spectrum. The VIs based on the visible and red-edge regions have been reported to be able to detect crop water status at the canopy level (Rossini et al., 2013). This is based on the knowledge of the effect of water deficit in the photosynthesis process, specially, the epoxidation states of xanthophyll cycle pigments and the chlorophyll fluorescence emission (Moya et al., 2004). Even though there is not water absorption in the visible spectra domain, several VIs based on this region have shown high correlation levels with plant water status and are commonly used as its proxy to improve vineyard management (Govaerts and Verhulst, 2010; Pôças et al., 2015; Rodríguez-Pérez et al., 2007).

The large amount of data collected through remote sensing allows to describe almost the whole plant physiology and even changes within plants depending on the resolution of sensors. Nevertheless, the response of the plant to different environmental changes not always corresponds to linear relationships, for this reason sometimes traditional statistical approach are not powerful enough to obtain accurate plant water status estimations. In this case, the use of Artificial Neural Network (ANN) to deal with large and complex task become a good alternative due to its ability to model both linear and nonlinear systems. The learning performed by a network runs automatically and it is based on the selection of appropriate value of weight (Riad et al., 2004; Samborska et al., 2014). The ANN models have shown to be powerful prediction tools for support decision making in the area of agriculture, several examples could be mentioned such as: rainfall-runoff process (Hsu et al., 1995), prediction of evaporation (Sudheer et al., 2002), soil erosion and its relationship with leaking of nutrients in plants (Kim and Gilley, 2008), estimation of plant water uptake (Qiao et al., 2010), plant classification using leaf recognition (Wu et al., 2007), crop yield prediction (Khairunniza-Bejo et al., 2014) and vegetation mapping (Carpenter et al., 1999). Nevertheless, in terms of modelling plant water