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WITHIN-VINEYARD VARIABILITY IN GRAPE COMPOSITION AT THE ESTATE SCALE CAN BE ASSESSED THROUGH MACHINE-LEARNING MODELING OF PLANT WATER STATUS IN SPACE AND TIME

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Abstract

Aim: Through machine-learning modelling of plant water status from environmental characteristics, this work aims to develop a model able to predict grape phenolic composition in space and time to guide selective harvest decisions at the estate scale.

Methods and Results: Work was conducted during two consecutive seasons in a ~40ha (100ac) premium wine estate located in the Adelaida District AVA of Paso Robles, CA, USA. The vineyard topography was very diverse, with a large variation in slope grade (0-30%) and exposure (0-359). One hundred experimental units were identified by a maximum dissimilarity sampling algorithm based on environmental attributes derived from a digital elevation model and a soil map. Reflecting the estate varietal distribution, ~70% were Cabernet-Sauvignon units, 20% Cabernet-Franc, and 10% Petit-Verdot units grafted on 1103P or 420A (~50-50%). Grapevine water status was monitored by weekly measurements of stem water potentials, Ψstem, and analysis of carbon isotope discrimination of grape musts, δ13C, at harvest. The grape composition during ripening was assessed by measuring total soluble solids, titratable acidity, and pH of musts and by a comprehensive assessment of skin phenolic composition with HPLC-DAD. Additional field measurements included shoot-count and yield assessment. Vegetation indexes were derived from canopy reflectance obtained from ~3m resolution CubeSat satellites. Irrigation amounts were provided by the grower, and weather data were obtained from three on-site stations.

Grapevine Ψstem was modelled from weather data (temperature, relative humidity, rainfall), irrigation amounts, vegetation indexes, topographic attributes, soil type using a gradient-boosting-machine algorithm. The model was able to predict plant water status with <0.1 MPa of error (estimated as root mean squared error in a cross-validation procedure). Significant differences in water status were observed between rootstocks and main environmental drivers were slope grade and aspect (i.e. exposure). External validation of the model was carried out by correlating predictions with δ13C. The model allowed obtaining high-resolution daily mapping of Ψstem at the estate scale. Time-series of grapevine Ψstem were significantly correlated with the content of total soluble solids of musts, grape anthocyanin amounts, and the ratio of tri-hydroxylated to di-hydroxylated compounds at harvest and mapped. Spatial-clustering of grape anthocyanin composition was obtained from Ψstem model-estimates and used to guide harvest selectively.

Conclusion: Grapevine water status confirmed to be an important driver in the variability of grape composition, even though the vineyard was irrigated. Variability in water status was related to environmental attributes (slope, aspect, incoming radiation) and the machine-learning approach proved to be useful to predict and understand plant-environment interactions and effects on grape composition in a varied and large dataset.

Significance and Impact of the Study: Vineyards are often located on slopes and accurate modelling of grapevine water status in hillslope conditions is a challenging task. This research demonstrates for the first time that it is possible to obtain daily estimates of grapevine water status at the estate scale by re-elaborating routine measurements with machine-learning technologies. This information can be used to drive selective harvest decisions and clustering within-vineyard variability at the estate scale to easily implement selective harvest decisions.

Keywords: Grapevine water status, machine learning, phenolic composition