

SOIL PROXIMAL SENSING PROVIDES DIRECTION IN DELINEATING PLANT WATER STATUS OF 'CRIMSON SEEDLESS' (*VITIS VINIFERA* L.) VINEYARDS

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Abstract:

Context and Purpose of the Study – 'Crimson Seedless' (*Vitis vinifera* L.) is a late-ripening, red seedless table grape cultivar with inadequate anthocyanin accumulation and less than ideal berry size issues. It was necessary to understand the natural variations in the vineyard as well as the application of proximal sensing to monitor, and estimate these variations to get desirable attributes in this cultivar. The objective of this study was to use of proximal and remote sensing tools, specifically soil electrical conductivity (EC), canopy normalized difference vegetation index (NDVI), and carbon isotope discrimination in a precision agriculture context, to assess the water status variability, and determine the effect of inferred variability on skin anthocyanin and flavonol concentration at harvest.

Material and Methods – A 'Crimson Seedless' (*V. vinifera* L.) grafted on to 'Freedom' (27% *vinifera* hybrid) rootstock vineyard was studied for two years with contrasting precipitation amounts. Soil electrical conductivity (EC) was proximally sensed with electromagnetic induction and canopy reflectance was sensed remotely to calculate normalized difference vegetation index (NDVI). Random and equi-distant (30 m × 30 m) sampling grids were utilized in 2016 and 2017 to ground truth proximally sensed data. Grape primary metabolites, including total soluble solids, total acidity, isotopic discrimination of berry sugars ($\delta^{13}\text{C}$) and pH were measured, and secondary metabolites were characterized with a C18 reversed-phase HPLC.

Results – Soil EC was related to the variation of season-long plant water status in 2016 (Deep EC: $r = -0.71$; Surface EC: $r = -0.53$). There was not a significant relationship between NDVI and plant water status in either year. The vineyard was separated and delineated into two water status zones based on stem water potential (Ψ_{stem}) in each year, and the water status between two zones were significantly and consistently different. The juice pH showed significant differences between two zones. The $\delta^{13}\text{C}$ was directly and significantly related to Ψ_{stem} integrals and the differences between the two water status zones were confirmed by either method in 2016. There were no differences in total anthocyanins in 2016. However, anthocyanin derivatives were greater in the low water status zone in the following year. Flavonol amounts were not consistently different between the two zones in either year. Our results indicated deep soil EC, season-long water status or $\delta^{13}\text{C}$ can be used interchangeably to spatialize and cluster management zones in commercial table grape vineyards.

Key Words: Crimson Seedless, table grapes, anthocyanins, flavonoids, water status, electrical conductivity, normalized difference vegetation index (NDVI), spatial variability, viticulture.

1. Introduction.



Proximal Soil Sensing for Vineyard Management in 'Crimson Seedless' Table Grape

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Abstract

A 'Crimson Seedless' vineyard was modeled to examine the acceptability variation and plant water status influence on productivity and berry chemistry for two years. Electrical conductivity (EC) of the soil was proximal sensed with electromagnetic induction. A stratified random sampling method and an equal distance 30 m x 10 m grid sampling were utilized in 2016 and 2017 to generate proximal sensed EC maps. EC was related to variation of plant water status in 2016 (R² = 0.62, p < 0.001; R² = 0.44, p < 0.001). The proximal sensed EC maps were related to grape vine water status, and the two years were significantly related to mean water stress, primary metabolite concentration for total soluble solids, total acidity, pH and berry weight. Only pH showed significant differences based on different degrees of water stress in both years. Secondary metabolites were characterized with a 0.8 reversed-phase HPLC. The results indicated that proximal sensed EC maps demonstrated a strong correlation with soil water stress. This study provides evidence for optimizing the application of proximal sensing to monitor, estimate, and manage the specific microclimate of plant water status and berry chemistry in a large-scale vineyard.

Introduction

'Crimson Seedless' is a high-yielding, red seedless table grape cultivar released by the U.S. Dept. of Agriculture (Department of Agriculture, University of California, Davis, CA, USA). This cultivar was developed during the 1980s and is still the most widely planted and profitable table grape variety in the world. It is a high-yielding, red seedless table grape cultivar that is well adapted to the warm climate of California's Central Valley. The region is classified as Region IV with high evapotranspiration demand (Blaug and Wadell, 1994) and all table grape producers use supplemental irrigation.

Vineyards need to have minimal variation in soil electrical conductivity and topography over the entire growing site (Kilgus, Odom et al., 2011). These proximal sensed EC maps determine soil water availability by the proximal sensed EC maps (Kilgus, Odom et al., 2011).

Previous studies have been investigating precision agriculture as a tool to manage and estimate the spatial variation (Pill, Leach et al., 2012; Bragg, Proffitt et al., 2016). This approach allowed more focused and targeted fertilization because the existing modern technologies, such as global positioning systems (GPS), remote sensing, and geographical information systems (GIS) uncovered the ability to precisely measure site conditions based on the whole vineyard system. By using geospatial, traditional on-site measurements can be linked to proximal sensed EC maps, and the data can be processed with a computer-based GIS to make appropriate management decisions by lighting and fertilizing multiple maps (Pill, Leach et al., 2012). Previous research has been conducted on the relationship between soil water (Lynch, Medina et al., 2014; Kilgus, Odom et al., 2011) and proximal sensed EC (Kilgus, Odom et al., 2011) with theoretical evidence by predicting vineyard growth.

The purpose of this study was to investigate the application of proximal sensed EC maps to assess the variability in soil water status in 'Crimson Seedless' vineyard on monitoring soil EC, and how it can be linked to plant water status. Furthermore, to study on how plant water status can influence grape berry growth and associated metabolites in large commercial vineyards.

Materials and Methods

Vineyard Site and Plant Materials: This study was conducted in a commercial 1000-hectare 'Crimson Seedless' vineyard planted into Fresno (Row 16.57 x Ridge 5.376) V-shaped layout. High vines, semi-dwarf (about 0.80 m) and dwarf (about 0.40 m) vines were planted at 2.3 x 3.33 m (dwarf + row). The grapevines were trained to a quadrilateral system with training zone spaced 90 cm apart and head 1.2 m above ground. The vines were canopy trained, leaving 8 canes per vine and 4, two-dimensional open-rod system.

Soil Measurements: The instrument used for surface mapping of the electrical conductivity was the EM38-PK (Geonics Ltd., Ontario, Canada) used in both normal (dipole mode (DM)) and normal dipole mode (NDM). The instrument was placed on a PVC sled and pulled by a tractor along the rows at a distance of about 5 m to avoid interference processes.

Leaf Measurements and Berry Chemistry Analysis: Plant water status was measured at other parts as stem water potential (SWP) and berry measurements (Bragg, 2016; Bragg, 2017) were utilized to establish plant water status. Berry primary metabolites were measured, including total soluble solids (TSS), total acidity (TA), pH and berry weight. Six thousand berries were analyzed by SP-110C (Dickay & Warrington, 1995) for berry chemistry in 10 vineyard rows using random grid (Kilgus, Odom et al., 2012).

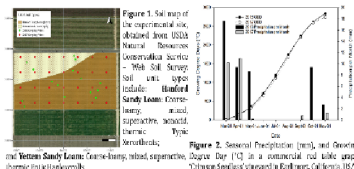


Figure 1. Soil map of the experimental site, showing EC maps for 2016 and 2017. The map displays the spatial distribution of electrical conductivity across the vineyard rows and columns.

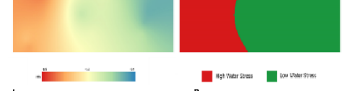


Figure 2. Seasonal precipitation (mm) and Growing Degree Day (°C) in a commercial red table grape 'Crimson Seedless' vineyard in California, USA.

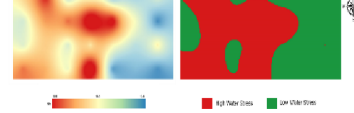


Figure 3. Interpretation map of soil water potential (PS) and its cross clustering in 2016. (A) Proximal sensed EC map, and (B) cross clustering of soil water potential for larger area in the vineyard.

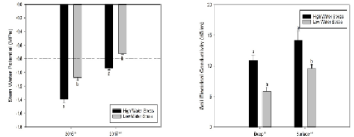


Figure 4. Interpretation map of soil water potential (PS) and its cross clustering in 2017. (A) Proximal sensed EC map, and (B) cross clustering of soil water potential for larger area in the vineyard.



Figure 5. Stem water potential (SWP) comparison between the two years in 2016 and 2017. The bar chart shows SWP values for different rows in 2016 and 2017, with error bars representing standard deviation.

Table 1. Berry Composition between Two Clusters Based on Stem Water Potential in Red Table Grape 'Crimson Seedless' in 2016 and 2017.

	2016		p-value	2017		p-value
	High Water Stress	Low Water Stress		High Water Stress	Low Water Stress	
Brix (°Brix)	20.58 ± 0.29	20.85 ± 0.27	0.541	19.58 ± 0.51	19.60 ± 0.17	0.935
TA (g/100g)	0.18 ± 0.01	0.19 ± 0.01	0.381	0.19 ± 0.01	0.19 ± 0.01	0.989
pH	4.02 ± 0.01	4.04 ± 0.01	0.329	3.97 ± 0.01	3.97 ± 0.01	0.918
Berry Weight (g)	5.15 ± 0.05	5.75 ± 0.10	0.110	5.00 ± 0.11	5.10 ± 0.06	0.980
TS (mg/kg DM)	1658.81 ± 65.05	1807.10 ± 272.76	0.076	1713.21 ± 277.94	1702.41 ± 128.72	0.110
TA (mg/kg DM)	180.90 ± 5.90	207.91 ± 22.26	0.079	179.10 ± 13.59	203.20 ± 23.52	0.217
SWP (kPa)	-175.84 ± 1.81	-11.28 ± 0.26	0.025	-77.10 ± 0.84	-63.91 ± 0.81	0.086
SWP (kPa)	-125 ± 4.57	-7.20 ± 0.27	0.001	-5.8 ± 0.58	-4.61 ± 0.51	0.285

SWP is compared to the mean (±SD) of the two clusters. The values are the mean and standard deviation of the two clusters. The values are the mean and standard deviation of the two clusters.

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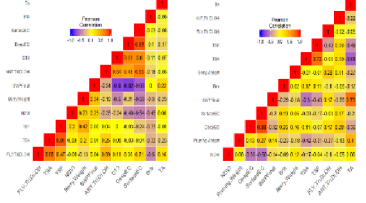


Figure 6. Correlation matrix values were expressed in Pearson Correlation (R) in 2016 and 2017. The figure shows two heatmaps for 2016 and 2017, showing the correlation between different variables.

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