DELIMITATION OF MANAGEMENT ZONES IN VINEYARD USING ORBITAL AND SUBORBITAL SENSING

L. R. S. Correa[1], H. Oldoni[1], T. M. M. Silva[1], E. A. Speranza[2], L. H. Bassoi[3]

[1]Programa de Pós-Graduação em Engenharia Agrícola, Depto de Engenharia Rural e Socioeconomia, FCA Unesp Av. Universitária, 3780 CEP 18610-034, Botucatu - SP, leoruanagro@gmail.com, henriqueoldoni@gmail.com, thassio_monteiro@hotmail.com
[2]Embrapa Agricultura Digital, Av José Tosello, 209 CEP 13083-886, Campinas - SP, eduardo.speranza@embrapa.br
[3]Embrapa Instrumentação, Rua XV de Novembro 1452 CEP 13561-206 São Carlos, P, Brasil, luis.bassoi@embrapa.br

Abstract: This paper presents the validation of a methodology that uses the K-means data clustering algorithm and vegetation indices (NDVI, RVI, EVI_2, and SAVI) at both the proximal and orbital scales to delineate potential management zones in a vineyard. The comparison between the two sensing methods revealed distinct findings regarding the number of management zones. A more robust division favors two zones, while the inclusion of an intermediate zone with moderate acceptance corresponds to three zones. In contrast, four zones resulted in excessive fragmentation.

Keywords: *Vitis vinífera* L., clusterng, vegetation indices

DELIMITAÇÃO DE ZONAS DE MANEJO EM VINHEDO UTILIZANDO SENSORIAMENTO PROXIMAL E ORBITAL

Resumo: Este trabalho apresenta a validação de uma metodologia que utiliza o algoritmo de agrupamento de dados K-means e os índices de vegetação NDVI, RVI, EVI_2 e SAVI, nas escalas proximal e orbital, para a delimitação de potenciais zonas de manejo em um vinhedo. A comparação entre as duas formas de sensoriamento mostraram constatações distintas considerando a quantidade de zonas de manejo: uma divisão mais robusta considerando duas zonas; a inclusão de uma zona intermediária com aceitação moderada para três zonas; e uma fragmentação excessiva e de difícil interpretação para quatro zonas.

Palavras-chave: *Vitis vinífera* L., clusterização, índices de vegetação.

1. Introduction

Precision agriculture has established itself as a strategy for optimizing inputs and maximizing productivity by addressing intra-field variability and dividing crop areas into management zones (Filintas et al., 2023). Clustering methods such as K-means and Fuzzy C-Means are widely used for this segmentation, as they enable unsupervised grouping of spectral and soil data, which allows for the adjustment of water, fertilizers, and pesticides to the specific needs of each zone (Janrao, Mishra, & Bharadi, 2019). These techniques have proven effective in capturing patterns of variability across small and large farms, thereby reducing waste and environmental impacts. The objective of this work is to validate a methodology that utilizes the K-means data clustering algorithm and vegetation indices at both proximal and orbital scales to delineate potential management zones in a vineyard.

2. Materials and Methods

2.1 Study area

The study was conducted in a commercial vineyard of the 'Chardonnay' cultivar, located in soil with a sandy loam texture. The vines were spaced 3 x 1 meters (2,500 plants per hectare), trained in espalier, with a drip irrigation system, in Espírito Santo do Pinhal, state of São Paulo, Brazil (22° 10′ 49.1″ S; 46° 44′ 28.4″ W; approximately 875 m altitude ± 10 m). The vineyard, covering 1.1 hectares, was divided into two adjacent plots, referred to as area 1 (0.6 ha) and area 2 (0.5 ha), separated by approximately 15 meters.

2.2 Acquisition of proximal and orbital sensing data

The assessments were conducted during the grape ripening stage, a phase when chlorophyll degradation and the accumulation of phenolic compounds cause significant changes in the spectral signature of leaves and fruit (Lima Filho et al., 2009). Canopy reflectance was measured using the CropCircle ACS-430 active sensor (Holland Scientific, USA), which operates in four discrete visible and near-infrared bands (460, 520, 670, and 730 nm) and provides the active NDVI (Normalized Difference Vegetation Index). Measurements were taken by walking through areas 1 and 2, maintaining the sensor approximately 0.30 m above the canopy, parallel to the vine rows, ensuring continuous sampling at approximately 10 readings per second. Each transect was around 200 meters long, resulting in an average of 15,000 readings per area. It is important to note that the spectral data series used in this study were extracted from previous works: data from the 2017 and 2018 growing seasons were obtained by Oldoni (2019), while data from the 2019 growing season were provided by Silva (2020) (Figure 1). All measurements followed the same field protocol and used the sensor's internal radiometric calibration, ensuring temporal comparability and methodological consistency across the different harvests.

Images PlanetScope (Planet Labs Inc., USA) from the DoveClassic nanosatellite constellation, with 3 m spatial resolution and global daily revisits, provided by RedeMAIS/MJSP, were used for regional-scale analysis. Scenes were selected on dates with less than 5% cloud cover (April 5, 2021, April 13, 2018, and April 21, 2019), corresponding to field collections conducted on April 6, 2017, and April 15, 2018 by Oldoni (2019), and on April 22, 2019, by Silva (2020).

The raw images underwent rigorous preprocessing on the Planet Analytics platform, which included radiometric calibration, orthorectification, and atmospheric correction, ensuring consistent and comparable data for spectral analysis.

2.3 Process for Defining and Evaluating Management Zones

2.3.1 Geostatistical resampling of Crop Circle data for the 3m grid of PlanetScope

The resampling of the near-sensing data involved converting an original irregular centimeter-resolution grid to a regular 3-meter grid using local ordinary kriging available in Vesper 1.62 software (Nasny, McBratney & Whelan, 2005). Instead of simply aggregating 3m values to a finer resolution, a geostatistical resampling from high to low spatial density was applied. This approach, which differs from the inverse spatial refinement method (from 3m to centimeter resolution), preserves the variability structures observed in situ and allows for direct comparison with orbital imagery of the same spatial resolution.

2.3.2 Criteria for Vegetation Indices Selection

Indices based solely on ρNIR (780 nm) and ρRed (670 nm), common to both CropCircle ACS-430 and PlanetScope satellites, were selected to ensure direct comparability. The following indices were calculated: NDVI, related to vegetative vigor (biomass); RVI, characterized as a simple and robust ratio; EVI2, which reduces saturation at high vegetation coverage; and SAVI, which corrects for soil influences, capturing variations in phytosanitary status, stress, and vegetation cover. This concise combination facilitates monitoring grape ripening and detecting biochemical changes accurately at both scales.

2.3.3 Vegetation Indices Calculation in QGIS Software

Vegetation indices were generated in QGIS (version 3.34.9) using the "Raster Calculator" tool, applying standardized expressions to the NIR and red bands of both PlanetScope imagery and CropCircle's proximal rasters. Each calculation was performed in batch mode, producing raster files referenced to a standard coordinate reference system (UTM zone 23S). This process ensured uniformity in spatial data and facilitated rapid integration of the two data sources.

2.3.4 Application of the K-means Algorithm for Delimiting Management Zones

The K-means clustering algorithm (MacQueen, 1967) was chosen for its efficiency in partitioning large volumes of standardized data into K groups that minimize intra-cluster variance. Data processing was carried out in RStudio using the kmeans() function from the base stats package (R Core Team, 2024). The indices were normalized using Z-scores before clustering, and the optimal K was determined based on the elbow (WSS) and silhouette methods. The analyses for proximal and orbital sensors were performed separately, ensuring the robustness and comparability of the resulting management zones.

2.3.5 Assessment of Agreement between Proximal and Orbital Sensors via F_1-Score

The F_1-Score (Van Rijsbergen, 1979) was used to compare the management zones generated for each sensor independently. The F_1-Score was calculated between the cluster labels of each sensor (with the proximal sensor as the reference and the orbital sensor as prediction, and vice versa), providing a synthetic measure of spatial agreement and the sensitivity of the methods in detecting vigor and maturity patterns.

3. Results and Discussion

The determination of the optimal K was based on the elbow method (WSS) applied to data from 2017, 2018, and 2019 (Figure 1) for areas 1 and 2. It was observed that K = 2 resulted in a significant reduction in the intra-cluster sum of squares, preventing excessive fragmentation of the zones. For exploratory purposes, K = 3 and K = 4 were also evaluated. Although these options showed only marginal gains in explaining variability, evidenced by smaller decreases in WSS, they can reveal finer spatial subdivisions, providing support for subsequent refinement of the management zones.

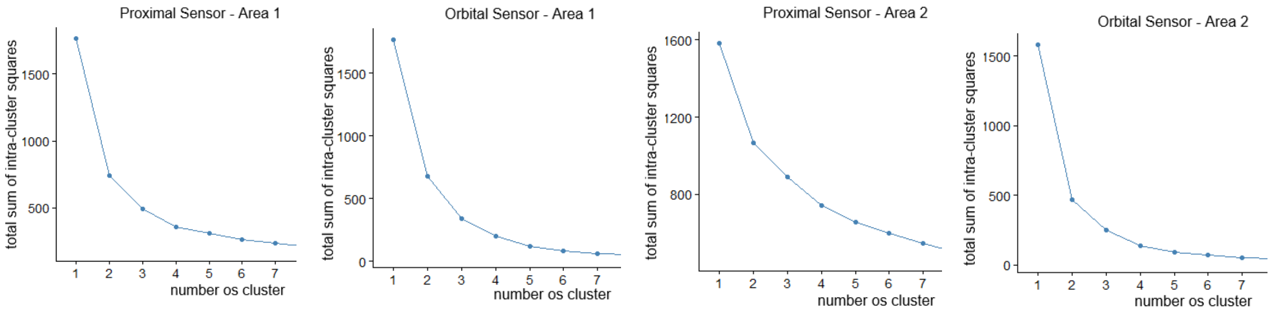

Figure 1. Average silhouette vs number of cluster in area 1 and 2

Between 2017 and 2019, the maps generated for each sensor reveal consistent patterns:

for K = 2, a zone of low vigor (cluster 1) and a zone of high vigor (cluster 2) are clearly distinguished (Figure 2). In orbital sensing (PlanetScope), both zones appear as continuous patches, facilitating the definition of general strategies. In proximal sensing (Crop Circle), pockets of high vigor are visible dispersed within the low vigor zone, indicating local heterogeneities useful for targeted interventions. At K = 3, an intermediate cluster emerges, marking vigor transitions and suggesting a balance between operability and phenological detail, with more concentrated in continuous bands in orbital sensing and more dispersed in proximal sensing. For K = 4, increased spatial fragmentation, especially in proximal sensing, results in fine mosaics that, while informative for detailed investigations, can make field management difficult.

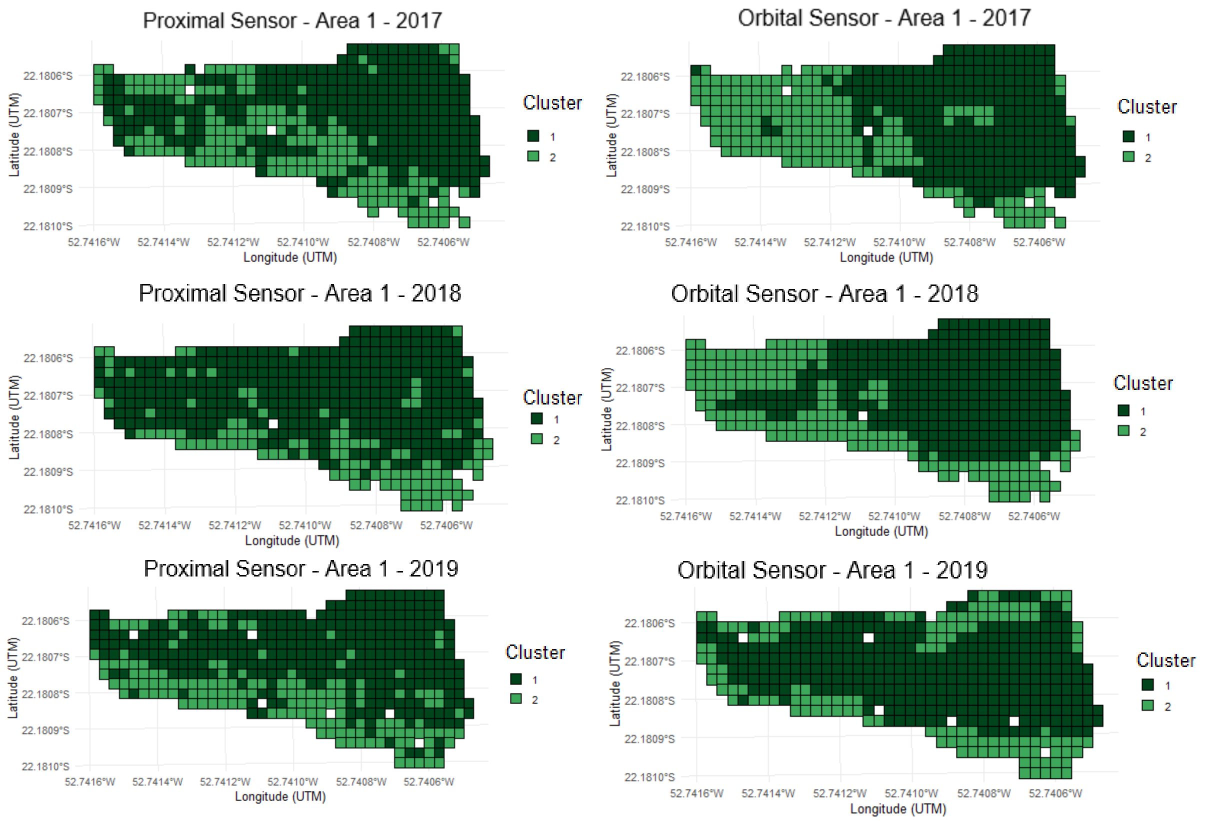

Figure 2. Maps of management zones in area 1 for the three growing seasons and K=2.

Macro F_1-scores consistently decline as K increases from 2 to 4. For K = 2, the highest scores were observed in both areas (0.679, 0.504, and 0.413 in 2017, 2018, and 2019 for area 1; 0.554, 0.357, and 0.259 for the same years in area 2), reflecting high agreement in the binary vigor distinction. At K = 3, there was a moderate reduction, indicating that the introduction of an intermediate cluster complicates the correspondence between sensors but still captures relevant gradients. For K = 4, F_1-scores fell below 0.30, demonstrating substantial discordance between the proximal and orbital sensors.

4. Conclusions

Orbital and proximal sensing, combined with the standardization (Z-score) of NDVI, EVI_2, RVI, and SAVI, and the application of K-means, enable the vineyard to be divided into two vigor zones (K = 2), with the option of a third level (K = 3). This approach balances operational simplicity with phenological detail.

For delimiting homogeneous areas, the orbital sensor excels at generating continuous, less fragmented patches, whereas proximal sensing, due to its higher level of detail, tends to produce more heterogeneous and fragmented maps.
Validation using the F_1-Score confirmed the consistency of clustering between the two sensors, demonstrating robustness even at different spatial resolutions.

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