CONSISTENCY OF THREE VEGETATION INDICES FROM SUBORBITAL AND PROXIMAL SENSING IN PRECISION VITICULTURE

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Abstract.
The integration of proximal and suborbital sensing platforms can expand the practice of precision viticulture. However, the consistency of vegetation indices (VIs) derived from different sensors remains a critical issue. This study quantified the agreement between VIs obtained by proximal and suborbital sensing using complementary metrics of association, error, and agreement. The research was conducted in a vineyard in Southeast Brazil during the 2023 growing season. Proximal measurements were performed with a Crop Circle ACS-430 active optical sensor, and suborbital data were acquired with a MicaSense RedEdge-M multispectral camera mounted on an unmanned aerial vehicle. Three VIs were evaluated: chlorophyll content index (CCCI), normalized difference red edge index (NDRE), and normalized difference vegetation index (NDVI). Association was assessed using Pearson's correlation coefficient (r). Error magnitude was quantified by root mean squared error (RMSE) and mean absolute error (MAE). Agreement was assessed using Lin's concordance correlation coefficient (CCC), Bland–Altman analysis (bias and limits of agreement), and Cohen's kappa coefficient for categorical data (two classes). All indices showed a statistically significant linear association between platforms ($p < 0.001$). CCCI had the highest correlation, followed by NDRE, and both were classified as very strong. NDVI showed a strong correlation. The smallest errors occurred for CCCI and NDRE, while NDVI showed the largest discrepancies. Concordance analysis confirmed this pattern: CCCI showed the highest agreement, followed by NDRE (both indicating substantial agreement), whereas NDVI showed low agreement despite its high correlation, indicating systematic disagreement. Cohen's kappa values were 0.71 for CCCI, 0.65 for NDRE, and 0.44 for NDVI. Bland–Altman analysis revealed a negative bias for all indices, indicating systematic underestimation by suborbital measurements. The limits of agreement were narrower for CCCI and NDRE and wider for NDVI, which showed lower absolute agreement. Overall, CCCI demonstrated the most robust performance, followed by NDRE. These results

indicate that indices based on the red-edge band provide greater agreement between proximal and suborbital sensors and have greater potential for multi-platform applications in precision viticulture.

Keywords.
Vitis vinifera L., Lin's concordance correlation, Bland-Altman analysis, Cohen's kappa coefficient.

Introduction

Precision viticulture has increasingly integrated advanced remote sensing technology to characterize spatial variability and subsidize site-specific management practices (Ferro; Catania, 2023; Bassoi et al., 2024; Loggenberg et al., 2024). Proximal sensors and systems mounted on unmanned aerial vehicles (UAVs) are particularly prominent, enabling acquisition of information across multiple spatial and temporal scales (Matese et al., 2018a; Singh et al., 2022).

Vegetation indices (VI) have been used for indirect assessment of vegetative vigor, plant physiological status, and growth estimation (Xue and Su 2017; Givos et al., 2021). The Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge Index (NDRE), and the Canopy Chlorophyll Content Index (CCCI) have been widely used to estimate attributes related to biomass, chlorophyll content, and vineyard yield potential (Matese et al., 2018b; Costa et al., 2023; Dorin et al., 2024, Vera-Esmeraldas et al., 2025).

Despite the increasing adoption of multiple sensing platforms, the comparability of indices obtained from different sensors remains a challenge (Vidican et al., 2023; Samadzadegan et al., 2024). Differences in spatial resolution, acquisition geometry, sensor spectral response, and processing techniques can lead to discrepancies among measurements, thereby hindering integration of data from different plataforms.

The majority of studies comparing proximal and suborbital sensors rely primarily on correlation analyses (Darra et al., 2021). However, high correlation coefficients do not necessarily indicate equivalence of values obtained from different sensors. Therefore, complementary error and agreement metrics are essential to evaluate the consistency of vegetation indices and to assess the feasibility of integrated use of these technologies (Wu et al., 2023).

Moreover, studies have demonstrated that vegetation indices incorporating the red-edge spectral region (e.g., NDRE and CCCI) exhibit greater sensitivity to variations in chlorophyll content and reduced susceptibility to spectral saturation compared with NDVI, particularly in crops exhibiting high vegetative vigor (Pereira et al., 2025; Costa et al., 2023; Ju et al., 2010).

In this context, the objective of the study is to evaluate the cross-platform consistency of CCCI, NDRE, and NDVI indices obtained via proximal and suborbital remote sensing in a commercial vineyard. Complementary metrics of association, error, and agreement were employed.

Materials and methods

The study was conducted in a vineyard located in Ribeirão Preto, state of São Paulo, Brazil (21°17′20.74″ S, 47°50′45.11″ W), planted with cv. Syrah grafted onto rootstock Paulsen 1103. The experimental area comprised 1.1 ha, with row and vine spacings of 2.8 m and 1.0 m, respectively. Grapevines were drip irrigated and trained on an espalier trellis and managed as a unilateral Royat cordon. Data were collected at the berry maturation phenological stage (100 days after pruning) during 2023 crop cycle, from January to July (grape harvesting in winter season due to double pruning practice).

Suborbital data were acquired using a RedEdge-M multispectral camera (MicaSense, Inc., Seattle, USA) mounted on a DJI Inspire 2 multirotor UAV. The sensor records spectral information in the blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (842 nm) bands. Flights were conducted at 30 m altitude to acquire imagery with an approximate spatial resolution of 0.02 m. To ensure adequate coverage of the experimental area, 75% forward and lateral overlap was applied.

Image processing was performed using Agisoft Metashape® version 1.5.3 (Agisoft LLC, St. Petersburg, Russia). Raw digital numbers were first converted to reflectance values using the MicaSense radiometric calibration panel. Multispectral orthomosaics were then generated and subjected to canopy segmentation to remove nonvegetation elements. Image classification was conducted using the Maximum Likelihood (ML) algorithm implemented in the Semi-Automatic Classification Plugin (SCP) for QGIS version 3.16.14.

Proximal measurements were obtained with an active optical sensor Crop Circle ACS-430 (Holland Scientific, Inc., Lincoln, Nebraska, USA) coupled to a Global Navigation Satellite System (GNSS) receiver. The instrument operates in the red (670 nm), red-edge (730 nm), and near-infrared (780 nm) spectral bands to acquire canopy reflectance measurements independent of ambient illumination conditions.

During data acquisition, the sensor was maintained at approximately 0.30 m above the canopy top and oriented vertically relative to the canopy. Measurements were collected manually along all vineyard rows, maintaining a constant walking speed to ensure sampling uniformity. Geographic coordinates recorded by the GNSS receiver enabled spatial integration of the proximal data with products derived from the UAV-acquired imagery.

Using the spectral information collected from both platforms, the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red-Edge Index (NDRE), and the Canopy Chlorophyll Content Index (CCI) were calculated.

Consistency between indices obtained via proximal and suborbital sensing was assessed using multiple statistical metrics in RStudio version 3.6.3 (R Core Team, Vienna, Austria). The following packages were used: *stats* for correlation analyses (Pearson's correlation coefficient, r); *Metrics* for error metrics (root mean square error, RMSE, and mean absolute error, MAE); *DescTools* to estimate Lin's concordance correlation coefficient (CCC) which ranges from −1 to 1, with values closer to 1 indicating greater agreement between methods; *BlandAltmanLeh* for Bland–Altman analysis to estimate mean bias and limits of agreement (LOA); *irr* for Cohen's kappa coefficient to evaluate agreement in management zone classification considering two classes; and *ggplot2* and *patchwork* for figure generation. A significance level of 5% ($p < 0.05$) was adopted for all analyses.

The magnitude of correlation coefficients was interpreted according to the criteria of Schober et al. (2018), classified as very weak ($0 < r < 0.19$), weak ($0.20 \leq r < 0.39$), moderate ($0.40 \leq r < 0.69$), strong ($0.70 \leq r < 0.89$), and very strong ($0{,}90 \leq r \leq 1{,}00$).

Results and discussion

All Vis showed statistically significant correlations between sensing platforms ($p < 0.001$) (Table 1). CCCI exhibited the highest correlation ($r = 0.926$), followed by NDRE ($r = 0.900$), both classified as very strong. NDVI showed a strong correlation ($r = 0.808$) but was lower than the other indices. Pereira et al. (2025) observed a strong association between proximal and suborbital platforms, reporting correlation coefficients of 0.72 for NDVI and 0.70 for NDRE. Unlike the present study, NDVI displayed the highest correlation among the evaluated platforms in their work.

Error analyses revealed the lowest RMSE and MAE values for CCCI and NDRE. In contrast, NDVI exhibited the largest errors between platforms, indicating lower measurement consistency (Table 1).

Table 1. Association, error, and agreement metrics between vegetation indices obtained by proximal and suborbital sensing.

Vegetation indice	Pearson (r)	RMSE	MAE	Lin's CCC	Mean Bias	Upper Limit of Agreement	Lower Limit of Agreement	Cohen's Kappa
CCCI	0.926***	0.045	0.038	0.688	-0.033	0.028	-0.094	0.710
NDRE	0.900***	0.048	0.044	0.622	-0.043	0.002	-0.087	0.650
NDVI	0.808***	0.082	0.078	0.230	-0.078	-0.031	-0.125	0.440

***: significant at 0.1% level.

Agreement analysis corroborated these findings. CCCI exhibited the highest Lin's concordance correlation coefficient (CCC = 0.688), followed by NDRE (CCC = 0.622), both indicating moderate agreement. In contrast, NDVI showed a CCC of only 0.230, reflecting poor agreement between platforms. These results demonstrate that strong correlation does not necessarily imply high agreement. Correlation assesses the strength of the linear association between two variables, whereas concordance quantifies the degree of equivalence between observed values. This pattern was evident for NDVI, which displayed a strong correlation (r = 0.808) but low concordance between platforms. Conversely, CCCI and NDRE combined high correlation coefficients with higher concordance values, indicating greater consistency between acquisition methods.

Kappa results also corroborated this interpretation. CCCI achieved the highest categorical agreement (Kappa = 0.71), followed by NDRE (Kappa = 0.65). NDVI exhibited only moderate agreement (Kappa = 0.44) (Table 1).

The Bland–Altman analysis revealed a negative bias for all indices, indicating a systematic underestimation of measurements obtained by suborbital sensing compared with proximal sensing (Table 1). The smallest bias was observed for CCCI (-0.033), followed by NDRE (-0.043). NDVI showed the largest mean bias (-0.078) and exhibited greater discrepancy between the platforms. The limits of agreement were also narrower for CCCI (-0.094 to 0.028) and for NDRE (-0.087 to 0.002), while NDVI showed the widest limits (-0.125 to -0.031) and had greater variability between the methods.

In the Bland–Altman analysis (Figure 1), the solid line represents the mean bias between the methods, while the dashed lines correspond to the upper and lower limits of agreement (LOA). CCCI showed a more homogeneous distribution (Figure 1A) of residuals around the mean bias, followed by NDRE (Figure 1B). In contrast, NDVI exhibited greater dispersion of residuals and evidence of systematic disagreement across the range of observed values (Figure 1C).

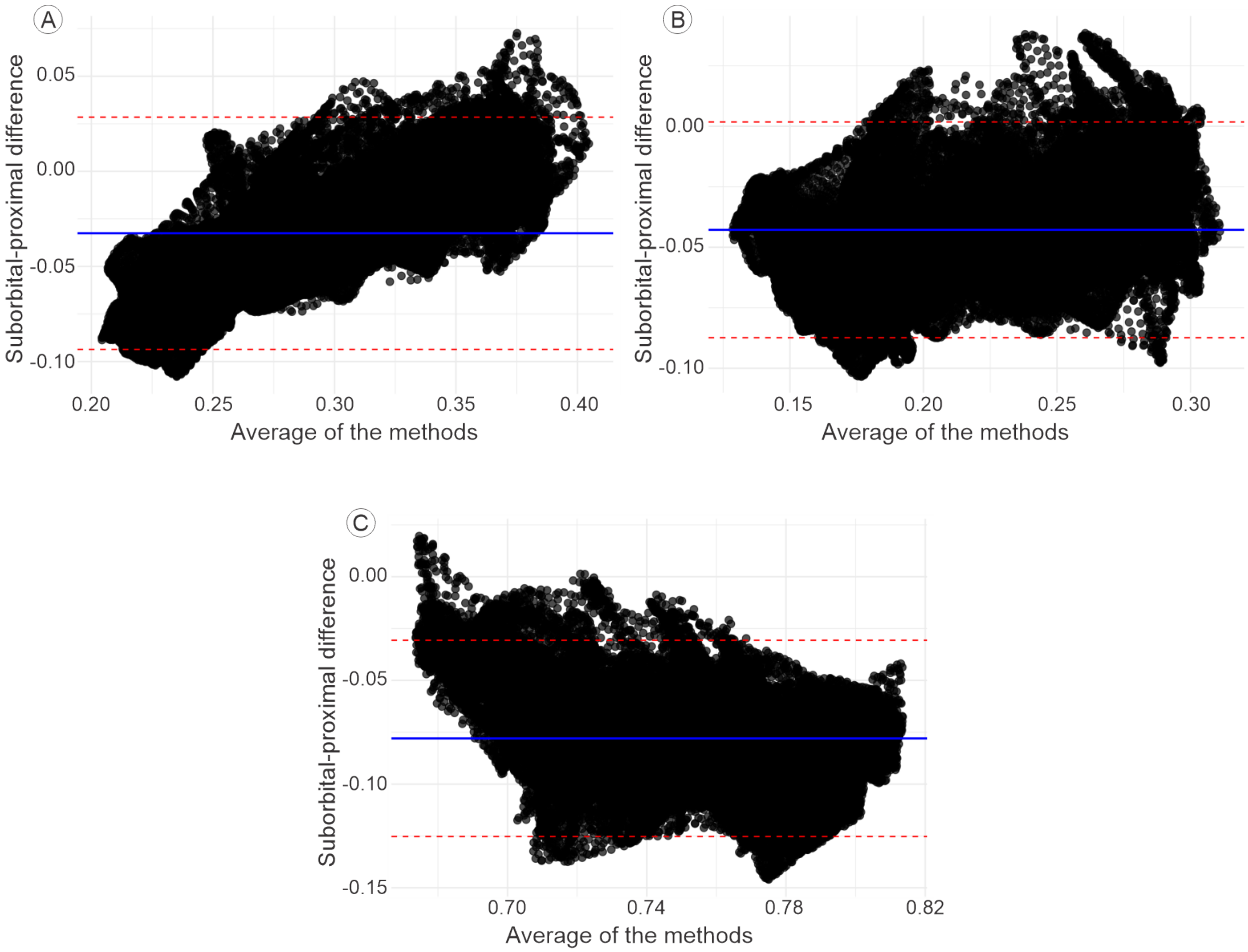

Fig 1. Bland–Altman analysis for comparison of CCI (A), NDRE (B), and NDVI (C) obtained by proximal and suborbital sensing.

The superior performance of CCI and NDRE is likely associated with the use of the red-edge spectral region, known for its high sensitivity to chlorophyll content and lower susceptibility to spectral saturation under conditions of high vegetative development. Conversely, NDVI tends to saturate in dense canopies, a characteristic often observed in the evaluated vineyards, which can increase discrepancies between sensors operating at different spatial (Huang et al., 2021).

Conclusion

Vegetation índices of vineyard differed in consistency between proximal and suborbital sensing methods. CCCI showed the greatest consistency between platforms, followed by NDRE, as evidenced by higher correlation and concordance coefficients, as well as lower error magnitudes. In contrast, NDVI showed lower equivalence between methods, with larger errors and lower agreement. Overall, the results indicate that indices based on the red-edge region are better suited for multi-platform applications in precision viticulture and have greater potential for integrating data obtained from proximal and suborbital.

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