PROXIMAL AND SUBORBITAL VEGETATION INDICES IN YIELD PREDICTION OF ‘SYRAH’ GRAPEVINES

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Abstract:

Various vegetations indices (VI) derived from different wavelengths necessitate identifying the most suitable spectral combinations to represent agronomic variables in precision viticulture. This study evaluated the ability of proximal and suborbital VIs to explain the spatial variability of yield in ‘Syrah’ grapevines. The experiment was conducted in a vineyard in Souhtheast Brazil in 2023 crop cycle. Suborbital data were acquired with a MicaSense RedEdge-M multispectral camera mounted on a UAV, and proximal data were collected with a Crop Circle ACS-430 sensor. Nine VIs, computed from the red, red-edge, and near-infrared bands, were compared to yield per plant. Data were tested for normality and homoscedasticity of residuals ($\alpha = 0.05$), and Pearson correlations between each VI and yield were calculated. Correlations above the moderate threshold ($0.40 < r < 0.69$) were retained for modeling. Spatial autoregressive models (SARs) were then fitted to account for spatial autocorrelation and improve predictive performance. Model quality was assessed using the pseudo-coefficient of determination (pseudo-R^2), root mean squared error (RMSE),and mean absolute error (MAE). Indices based on the red band (NDVI, RDVI, MSR, NIRv) showed limited performance, exhibiting weak correlations and low spatial predictive capacity for yield. Indices incorporating the red-edge band performed better at explaining yield spatial variability; the red-edge chlorophyll index (CI RedEdge) and NDRE produced the highest correlations and best SAR fits, particularly for UAV data ($r = 0.57$; pseudo-$R^2 = 0.40$; $p < 0.001$; RMSE = 0.69 kg plant^{-1}; MAE = 0.57 kg plant^{-1}). Overall, the red-edge band proved more sensitive to canopy physiological variations related to productivity and improved spatial yield prediction across platforms. High-resolution multispectral VIs from UAV imagery outperformed proximal sensor indices and more effectively captured spatial yield patterns with lower error metrics.

Keywords: *Remote sensing, precision viticulture, spatial autoregressive modeling.*

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Introduction

Yield predicition in vineyards is highly complex due to the spatial variability observed among plants (Acevedo-Opazo et al., 2026). Conventional methods typically rely on point samplings conducted before harvest and on historical production records (Araya-Alman et al., 2019). Although widely used, these procedures require substantial operational effort and may not adequately represent the heterogeneity present in the vineyard. Consequently, errors associated with yield estimates can range from 10 to 40% (Carrillo et al., 2016), which justifies the search for alternative methods capable of representing the spatial variability of production.

Grapevine yield exhibits considerable spatial variability within vineyards, with areas that maintain consistent patterns of high and low yield over the years (Bramley & Hamilton, 2004). Knowledge of this variability is a core principle of precision viticulture, as it allows identification of management zones and the adoption of targeted strategies for different vineyard áreas.

Spectral attributes obtained by remote sensing have been widely investigated as indirect indicators of yield (Ferrer et al., 2020; Ferro et al., 2023; Dorin et al., 2024). Canopy reflectance varies according to the structural and physiological characteristics of the vegetation and thus enables the derivation of indices capable of representing spatial differences in plant development. Vegetation indices (VI) are one of the main tools used for this purpose, as they synthesize spectral information through mathematical combinations of different bands of the electromagnetic spectrum.

The normalized difference vegetation index (NDVI) and the normalized difference red edge index (NDRE) (Vera-Esmeraldas et al., 2025) are used to estimate attributes related to vegetative development and yield in vineyards (Ferrer et al., 2020; Giovos et al., 2021). They are also used to characterize spatial variability and to define management strategies in precision viticulture (Bassoi et., 2024; Pereira et al., 2025; Acevedo-Opazo et al., 2026).

The high spatial variability of yield poses an additional challenge for its modeling. Taylor et al. (2005) reported coefficients of variation near 50% and strong spatial autocorrelation of production. They also showed that plants located in nearby areas tend to exhibit similar responses due to the influence of environmental factors and management practices. This spatial dependence can violate the independence assumption required by conventional statistical methods, resulting in less accurate estimates. In this context, spatial autoregressive (SAR) models are an alternative to incorporate spatial autocorrelation into models and improve explanatory capability.

Thus, the objective of this work was to evaluate the performance of VIs obtained by proximal and suborbital sensing in estimating the yield of a vineyard, and identifying the indices with the greatest potential to represent its spatial variability.

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).

The spectral information originated from two distinct platforms. The proximal data were obtained with the Crop Circle ACS-430 active optical sensor (Holland Scientific Inc., USA), which operates in the red (670 nm), red edge (730 nm), and near-infrared (780 nm) bands. Measurements were georeferenced by a GNSS receiver and recorded in a GeoSCOUT GLS-

400 datalogger. The sensor was positioned approximately 0.30 m above the canopy and operated at a 10 Hz acquisition frequency while moving along the vineyard rows.

The suborbital data were obtained using a DJI Matrice 300 RTK UAV equipped with a RedEdge-M multispectral camera (MicaSense Inc., Seattle, USA), which captures bands in the blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near-infrared (842 nm). Flights were conducted at 40 m altitude, 3.0 m s^{-1} speed, with 85% front and side overlap, resulting in images with an approximate spatial resolution of 2.7 cm.

Radiometric calibration used a reflectance panel and a downwelling light sensor (DLS). Georeferencing was refined with eight ground control points obtained with high-precision GNSS receivers. Image processing was performed in Agisoft Metashape® (Agisoft LLC, Russia) and included image alignment, radiometric calibration, dense point cloud generation, digital elevation model creation, and construction of the multispectral orthomosaic.

Using the reflectance values, the following VI were calculated: a) red edge chlorophyll index (CI RedEdge); b) infrared percentage vegetation index (IPVI); c) modified simple ratio (MSR); d) normalized difference red edge (NDRE); e) normalized difference vegetation index (NDVI); f) near-infrared reflectance of vegetation (NIRv); g) renormalized difference vegetation index (RDVI); and h) simple ratio (SR).

Yield was determined at 42 sampling points (Fig. 1). During harvest, grape clusters were collected individually by plant and weighed on an electronic scale (KL-20001, Bel Engineering, Italy) to obtain yield per plant.

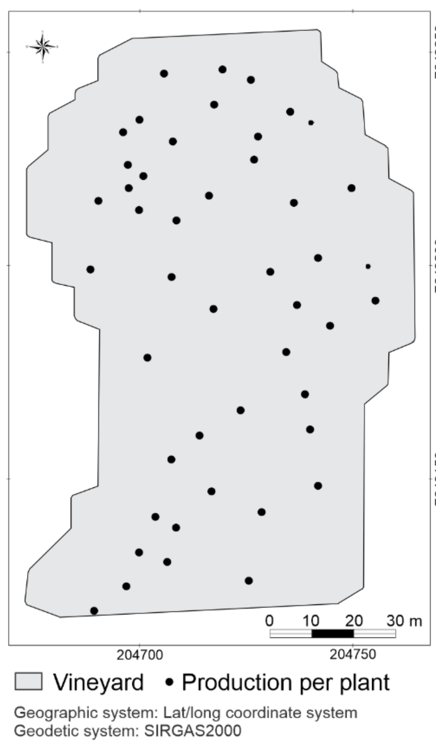

Fig. 1. Spatial distribution of harvest sampling in the vineyard for yield recording.

Statistical analyses were performed in the R environment (R Core Team, Vienna, Austria). Initially, the data were tested for normality and homogeneity of residuals. Then, the Pearson correlation coefficient (r) between each vegetation index and yield was calculated.

The interpretation of the correlation coefficients followed the classification proposed by Schober et al. (2018): very weak ($0 < r < 0.19$), weak ($0.20 \le r < 0.39$), moderate ($0.40 \le r < 0.69$), strong ($0.70 \le r < 0.89$), and very strong ($0.90 \le r \le 1.00$). Only indices that showed a moderate or higher correlation were selected for the spatial modeling stage. For this purpose, spatial autoregressive models of the Spatial Autoregressive Model (SAR) type were fitted. Model performance was evaluated using the pseudo-coefficient of determination (pseudo-R^2), root mean square error (RMSE), and mean absolute error (MAE).

Results and discussion

VI derived from proximal sensing showed low predictive ability for yield per plant. Although CI RedEdge and NDRE produced the best results (Table 1), both reached only moderate correlations ($0.40 \le r < 0.69$) and a maximum pseudo-R^2 of 0.25, indicating that about 75% of yield variability was not explained by the models. The RMSE (0.70 kg per plant) and MAE (0.57 kg per plant) values reinforce this limitation. The remaining indices performed worse, with weak correlations for MSR, NDVI, RDVI, and SR, while IPVI had no significant relationship with the response variable (Table 1).

The low predicitive predictive ability observed for some of the proximal VI is supported in the literature. Dorin et al. (2024) reported weak correlations between proximal spectral indices and grapevine yield across different seasons and growing conditions. Similar results were also observed by Yu et al. (2021), who did not find a significant correlation between NDVI obtained with the Crop Circle ACS-430 sensor and grapevine yield ($r = 0.03$).

Table 1 – Pearson correlation coefficient (r), pseudo coefficient of determination (pseudo-R^2), root mean square error (RMSE), mean absolute error (MAE) for proximal and suborbital vegetation indices and yield per grapevine in the 2023 crop cycle.

Vegetation indice	Yield (kg plant^{-1})							
	Proximal				Suborbital			
	r	Pseudo-R^2	RMSE	MAE	r	Pseudo-R^2	RMSE	MAE
CI RedEdge	0.48***	0.25	0.70	0.57	0.57***	0.40	0.69	0.58
IPVI	0.29^{ns}	-	-	-	0.34*	-	-	-
MSR	0.31*	-	-	-	0.37*	-	-	-
NDRE	0.48***	0.25	0.70	0.57	0.57***	0.39	0.69	0.57
NDVI	0.31*	-	-	-	0.38*	-	-	-
NIRv	0.38*	-	-	-	0.36*	-	-	-
RDVI	0.37*	-	-	-	0.37*	-	-	-
SR	0.31*	-	-	-	0.34*	-	-	-

***, **, *: significant at levels of 0.1 %, 1%, and 5% ($\alpha = 0.05$), respectively; ns: not significant.

In contrast to the proximal indices, VI derived from suborbital sensing showed a stronger association with yield, especially those calculated using spectral response from the red-edge region. CI RedEdge and NDRE had the highest correlation coefficients, classified as moderate ($0.40 \le r < 0.69$), both with $r = 0.57$ ($p < 0.001$) (Table 1). These indices also produced the best model fits and the lowest error metrics, with RMSE of 0.69 kg per plant and MAE of 0.58 kg per plant for CI RedEdge, and RMSE of 0.57 kg per plant for NDRE. Despite their superior performance relative to the other indices evaluated, these coefficients indicate moderate predictive ability and suggest that a significant portion of yield variability remains associated with other factors not captured by the models. Conversely, IPVI, MSR, NDVI, NIRv, and SR showed weak correlations with yield (0.20 ≤ r < 0.39) and demonstrated lower sensitivity for representing the spatial variability of grapevine yield.

Ferro et al. (2023) reported correlation coefficients of 0.75 for NDRE and NDVI obtained from aerial imaging. In this study, the observed values were 0.57 and 0.38, respectively. Although both studies indicate a positive association between vegetation indices and yield, the results here showed a lower magnitude of correlation.

NDVI, MSR, RDVI, NIRv and SR showed lower correlations with yield (Table 1). NDVI is the most widely used index in agriculture, and this behavior suggests lower sensitivity to physiological variations related to crop yield. In vineyards with high vegetative growth, indices dependent on the red band may exhibit spectral saturation and reduce the ability to discriminate vigor differences among plants (Delegido et al., 2011; Gitelson et al., 2002; Qiao et al., 2024).

The superior performance of CI RedEdge and NDRE is associated with the greater sensitivity of the red-edge spectral region to changes in chlorophyll content and canopy structure (Li et al., 2014; Qiao et al., 2024).

VI derived from the multispectral camera showed higher correlation coefficients and better fits of the spatial models compared to indices obtained from the proximal sensor. These results indicate that the continuous spatial coverage provided by aerial imagery more effectively represents the spatial patterns of vineyard yield.

Conclusion

CI, RedEdge and NDRE showed the best performance in estimating yield of ‘Syrah’ grapevines for both proximal and suborbital data. Indices derived from suborbital sensing had stronger associations with yield and better model fits compared to proximal indices. Despite the superiority of red-edge–based indices, the moderate correlation coefficients and low pseudo-R^2 values indicated limited predictive ability. The results demonstrated the potential of CI RedEdge and NDRE for precision viticulture applications but highlighted the need to incorporate complementary variables to improve yield.

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References

Acevedo-Opazo, C., Cañete-Salinas, P., Araya-Alman, M., Ackerknecht-Espinosa, C., Vásquez, L., Moreno-Simunovic, Y. (2026). Mid-season yield estimation in high-productivity vineyards: a preliminary modeling framework for free-canopy systems. *Agronomy*, 16(11), 1106. https://doi.org/10.3390/agronomy16111106.

Araya-Alman, M., Leroux, C., Acevedo-Opazo, C., Guillaume, S., Valdés-Gómez, H., Verdugo-Vásquez, N., Pañitrur-De la Fuente, C., Tisseyre, B. (2019). A new localized sampling method to improve grape yield estimation of the current season using yield historical data. *Precision Agriculture,* 20, 445-459. https://doi.org/10.1007/s11119-018-9615-y.

Bassoi, L. H., Oldoni, H., Costa, B. R. S., Silva, T. M. M., Farinassi, L. G., Pereira, A. J., et al. (2024). Viticultura de precisão na produção de vinhos de colheita de inverno. In L. H. Bassoi, A. C. C. Bernardi, C. M. P. Vaz, J. L. F. Pires, L. Gebler, L. A. C. Jorge, & R. Y. Inamasu (Eds.), *Agricultura de precisão: um novo olhar na era digital* (pp. 543–553). São Carlos, Brasil: Editora

Cubo.

Bramley, R. G., Hamilton, R. P. (2004). Understanding variability in winegrape production systems 1. Within-vineyard variation in yield over several vintages. *Australian Journal of Grape and Wine Research*, 10(1), 32-45. https://doi.org/10.1111/j.1755-0238.2004.tb00006.x.

Carrillo, E., Matese, A., Rousseau, J., Tisseyre, B. (2016). Use of multi-spectral airborne imagery to improve yield sampling in viticulture. *Precision Agriculture*, 17(1), 74-92. https://doi.org/10.1007/s11119-015-9407-8.

Delegido, J., Verrelst, J., Alonso, L., Moreno, J. (2011). Evaluation of Sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors*, 11(7), 7063-7081. https://doi.org/10.3390/s110707063.

Dorin, B., Reynolds, A. G., Lee, H. S., Carrey, M., Shemrock, A., Shabaniam, M. (2024). Detecting cool-climate Riesling vineyard variation using unmanned aerial vehicles and proximal sensors. *Drone Systems and Applications*, *12*, 1-18. https://doi.org/10.1139/dsa-2023-0024

Ferrer, M., Echeverría, G., Pereyra, G., Gonzalez-Neves, G., Pan, D., Manuel Mirás-Avalos, J. (2020). Mapping vineyard vigor using airborne remote sensing: Relations with yield, berry composition and sanitary status under humid climate conditions. *Precision Agriculture*, 21(1), 178-197. https://doi.org/10.1007/s11119-019-09665-9

Ferro, M. V., Catania, P., Miccichè, D., Pisciotta, A., Vallone, M., Orlando, S. (2023). Assessment of vineyard vigour and yield spatio-temporal variability based on UAV high resolution multispectral images. *Biosystems Engineering*, 231, 36-56. https://doi.org/10.1016/j.biosystemseng.2023.06.001.

Giovos, R., Tassopoulos, D., Kalivas, D., Lougkos, N. PRIOVOLOU, A. Remote sensing vegetation indices in viticulture: a critical review. *Agriculture*, 11(5), 457, 2021. DOI: 10.3390/agriculture11050457.

Gitelson, A. A., Kaufman, Y. J., Stark, R., Rundquist, D. (2002). Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment*, 80(1), 76-87. https://doi.org/10.1016/S0034-4257(01)00289-9.

Li, F., Miao, Y., Feng, G., Yuan, F., Yue, S., Gao, X., Liu, Y., Liu, B., Ustin, S. L., Chen, X. (2014). Improving estimation of summer maize nitrogen status with red edge-based spectral vegetation indices. *Field Crops Research*, 157, 111-123. https://doi.org/10.1016/j.fcr.2013.12.018.

Pereira, A. J., Farinassi, L. G., Costa, B. R. S., Oliveira Junior, I., Santos, R. A., Jorge, L. A. C., et al. (2025) Assessing grapevine water status and rootstock effects using vegetation indices from UAV and proximal sensors. *Remote Sensing Applications: Society and Environment*, 39, e101708, doi:10.1016/j.rsase.2025.101708

Qiao, K., Zhu, W., Xie, Z., Wu, S., Li, S. (2024). New three red-edge vegetation index (VI3RE) for crop seasonal LAI prediction using Sentinel-2 data. *International Journal of Applied Earth Observation and Geoinformation*, 130, e103894. https://doi.org/10.1016/j.jag.2024.103894.

Schober, P., Boer, C., Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & Analgesia*, 126(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864.

Taylor, J., Tisseyre, B., Bramley, R., Reid, A. (2005). A comparison of the spatial variability of vineyard yield in European and Australian production systems. In: Stafford, J. V. (Ed.), *Precision Agriculture ‘05, Proceedings of the 5th European Conference on Precision Agriculture* (pp. 907-914). Wageningen: Wageningen Academic Publishers.

Vera-Esmeraldas, A., Pizarro-Oteíza, S., Labbé, M., Rojo, F., & Salazar, F. (2025) UAV-Based spectral and thermal indices in precision viticulture: a review of NDVI, NDRE, SAVI, GNDVI, and

CWSI. *Agronomy*, 15(11), 2569, https://doi.org/10.3390/agronomy15112569.

Yu, R., Brillante, L., Torres, N., Kurtural, S. K. (2021). Proximal sensing of vineyard soil and canopy vegetation for determining vineyard spatial variability in plant physiology and berry chemistry. *OENO One*, 55(2), 315–333. https://doi.org/10.20870/oeno-one.2021.55.2.4598.