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Benchmarking the Reliability of Sentinel-2 Satellite Data for Estimating Vineyard NDVI and LAI Parameters through UAV LiDAR and Multispectral Imagery

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Abstract: The use of satellite data in precision agriculture, especially for woody crops, has gained prominence. Such data aids in forecasting yield, predicting crop quality, and irrigation management by providing insights into crop conditions. However, the accuracy of parameters such as Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI) derived from satellites is questioned. This research compares Sentinel-2 satellite imagery with LiDAR data and multispectral imagery gathered over a vineyard in northern Spain using Unmanned Aerial Vehicles (UAVs) in July, August, and September 2022, focusing on veraison, a key stage in precision viticulture. The findings reveal a moderate correlation between satellite and UAV NDVI values (up to $R^2 = 0.6$) but a discrepancy in leaf area estimations from satellite imagery, suggesting its limited use for such applications in hedgerow systems in agriculture. Nonetheless, satellite data's ability to detect crop spatial variability remains useful for field management. The study emphasizes the potential benefits and drawbacks of diversifying remote sensing techniques for effective agricultural management.

Keywords: Sentinel 2; remote sensing; precision agriculture; precision viticulture; LAI; leaf area; NDVI; vineyard management; hedgerow systems

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1. Introduction

Recent advancements in remote sensing technology have greatly impacted the agricultural sector, especially in viticulture and woody crops, driving transformations, and positive changes and encouraging sustainable farming methods [1]. One such transformation is the employment of remote sensing data in several applications, an expanding domain that holds significant potential for precision agriculture, particularly in woody crops. Leveraging the capabilities of remote sensing platforms, researchers have harnessed spectral information to monitor and assess health [2], quality [3] vegetative development [4,5] and yield of woody crops, offering insights that are difficult to obtain by ground-level assessments.

Among available remote sensing platforms, the use of satellite-based products offers an unprecedented opportunity to accumulate detailed information on crop conditions, facilitating multifaceted insights ranging from yield forecasting and crop quality prediction to proper irrigation management [6]. This approach not only provides a macroscopic view of vast agricultural landscapes but also provides granular knowledge essential for effective farm management.

Nevertheless, despite the potential benefits of these satellite-based remote sensing tools, challenges arise when dealing with low-resolution imagery, especially with Vegetation Indices (VIs). For instance, although the Normalized Difference Vegetation Index

(NDVI) values within a pixel are correlated with the leaf area in the vineyards [7], it is affected by the mixed pixels effect, that encompass vegetation, soil, and shadows. Moreover, these values can vary over the season, influenced by a variety of factors, including the loss of grapevines due to diseases or abiotic stress.

On the other hand, in recent years, Unmanned Aerial Vehicles (UAVs) equipped with multispectral cameras, have been instrumental in creating detailed high-resolution images, offering a more granular look at crop conditions [8–10]. Specifically, in the domain of disease management, UAVs have proven indispensable. For instance, in the detection and spatial visualization of risks associated with the Botrytis bunch rot (BBR) disease in grapevine, widespread concern affects yield and wine quality [2]. UAV-based imagery, particularly when combined with methodologies such as deep or machine learning, has been shown to provide accurate assessments of disease likelihood, underscoring the importance of spatial variability [11].

Despite this, satellite platforms, especially Sentinel-2 with its distinct spectral and temporal resolution, offer advantages over UAVs. Techniques like time series analysis, which are challenging to implement using UAV data, become feasible with satellite information [12,13]. This enables the extraction of detailed spatial information about vineyards and their correlation with essential agronomic parameters. Nevertheless, before applying these complex techniques, it is essential to understand the relationship between the satellite imagery and the actual crop data.

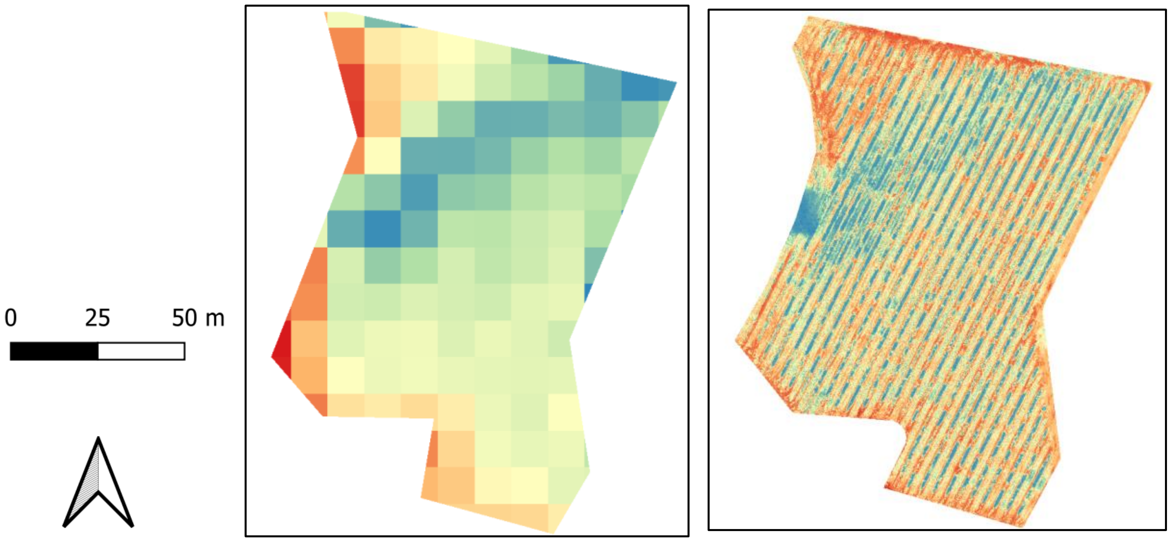
To this end, this study examines the constraints of using satellite-based Sentinel-2 imagery for monitoring vineyards in precision agriculture. Specifically, it investigates how accurately Sentinel-2 can estimate important vineyard metrics like Normalized Difference Vegetation Index (NDVI) and leaf area. The accuracy of Sentinel-2 data is contrasted with measurements from LiDAR, and multispectral imagery taken by UAVs as ground truth.

2. Materials and Methods

The study was undertaken in a commercial vineyard of the variety *Vitis vinifera* cv. Loureiro, owned by Terras Gauda. It is located in northern Spain, in ‘Tomiño, Pontevedra’, Galicia. Coordinates X: 516989.02, Y: 4644806.53 (ETRS89/UTM zone 29 N).

Vineyard data was gathered using a UAV DJI M300 multi-rotor platform (DJI Sciences and Technologies Ltd., Shenzhen, Guangdong, China), outfitted with two payloads: a Micasense Altum camera (AgEagle Sensor Systems Inc., Wichita, KS, USA) and a DJI Zenmuse L1 LiDAR sensor, allowing the capture of both detailed topographical data and multispectral imagery. The UAV flights were planned and executed over the vineyard in July, August and September 2022, timed around the veraison period, given its relevance as a crucial phenological stage in precision viticulture, and coordinated with the satellite’s orbit.

Satellite data was sourced from Sentinel-2, an Earth observation mission from the Copernicus Programme that systematically acquires optical imagery. This data can be accessed freely through the Copernicus ESA Copernicus Open Access Hub [https://scihub.copernicus.eu/]. The satellite images were processed to generate NDVI and LAI data using the SNAP software, which includes the biophysical processor. Then, the satellite-derived products were compared with the corresponding UAV-derived products (Figure 1). This comparison was made using QGIS (version 3.22. X, QGIS developer team 2022), and R software (version 4.2. X, R Foundation for Statistical Computing, R Core Team 2019, Vienna, Austria), allowing the performance assessment of satellite measurements against the UAV datasets.



(**a**) (**b**)

Figure 1. NDVI data derived from (**a**) Sentinel-2 satellite imagery, (**b**) UAV imagery.

Satellite LAI was compared to the planimetric canopy area [14], or planar area, calculated from the Canopy Height Model (CHM). To extract the CHM from LiDAR data, the open-source CloudCompare software (v.2.12.4, GPL software) was employed, for its efficiency and comprehensive set of specialized tools. A crucial part of this process was distinguishing between ground and vegetation data points. To achieve this, the Cloth Simulation Filter plugin [15] was used. After clearly separating the 'ground' from 'vegetation' points, the next step involved rasterizing the vegetation data, enabling its conversion into the Digital Surface Model (DSM). Simultaneously, the Digital Terrain Model (DTM), which represents the ground surface, was generated by rasterizing the data points belonging to the 'ground' class. Finally, the CHM was computed by subtracting the DTM from the DSM.

3. Results and Discussion

NDVI exhibited a moderate to strong relationship (up to $R^2 = 0.6$) in terms of the R-squared value throughout the three experimental phases. However, this correlation decreased as the campaign progressed, dropping from 0.6 in July to 0.36 in September (Figure 2). Conversely, when comparing the LAI obtained from Sentinel-2's biophysical processor with the planar area derived from the point cloud, there was no evident correlation between the two variables (Figure 3).

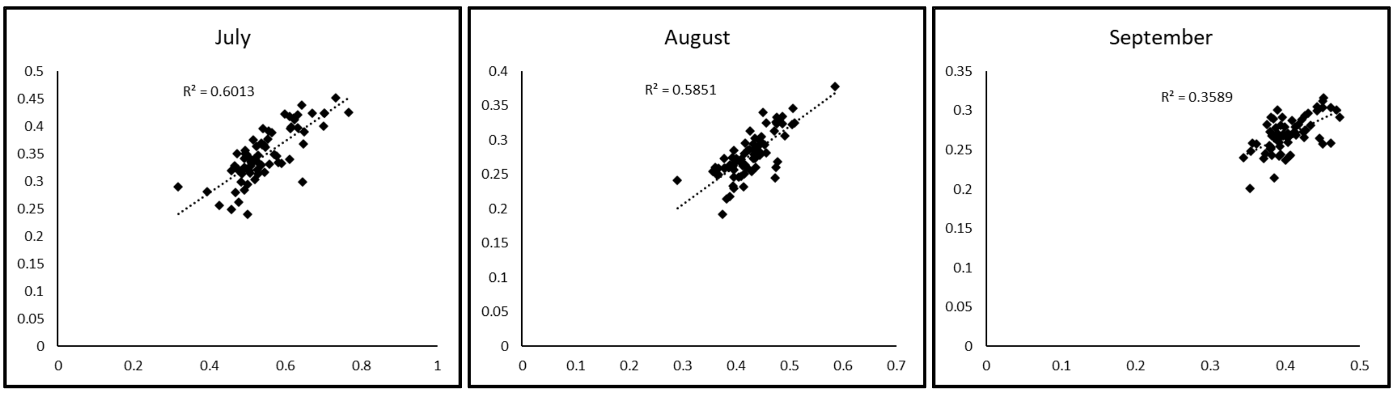


Figure 2. NDVI values. Y-axis: Sentinel-2 satellite values. X-axis: UAV values.

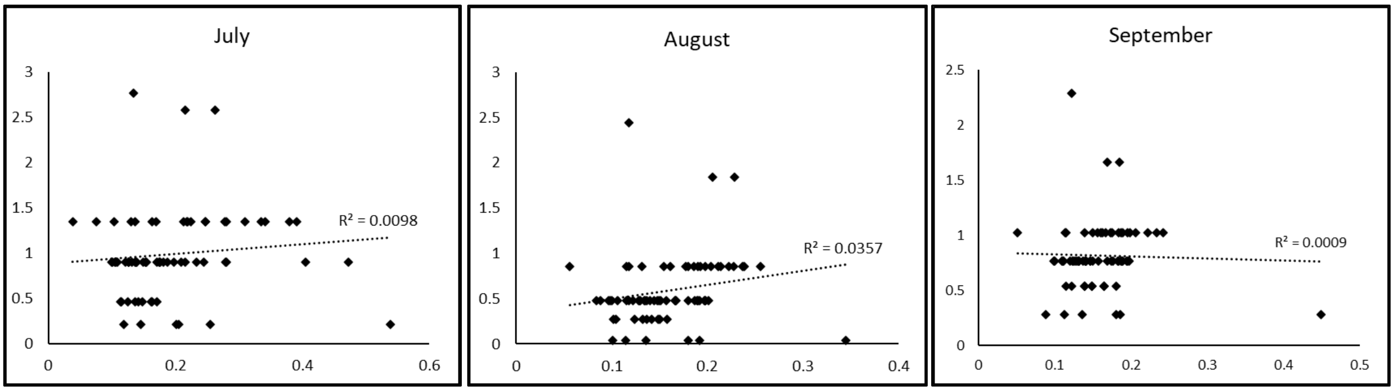


Figure 3. LAI vs. planar area values. Y-axis: Sentinel-2 satellite LAI values. X-axis: UAV planar area values.

While this work is focused on vineyards, it is worth noting that in the context of broadacre crops, many studies have been conducted to assess the potential of Sentinel-2 satellite imagery for various applications. For instance, Zhang et al. [16] utilized Sentinel-2A/B satellites for urban land cover classification and found that the optimized Random Forest classifier outperformed conventional classifiers in terms of accuracy, precision, and recall when discriminating between land cover classes such as buildings, trees, roads, water, and crop fields. Furthermore, Felegari et al. [17] integrated Sentinel-1 and Sentinel-2 satellite images for crop mapping in the Tarom region of Iran. Their study reported a maximum accuracy of 85%, emphasizing the benefits of combining radar and optical data for enhanced classification accuracy. Skakun et al. [18] assessed the efficiency of multiple satellite sensors, including Sentinel-2, to estimate corn and soybean yields at sub-field scales. Their findings highlighted the importance of the spatial resolution of the images and the significance of specific spectral bands in explaining yield variability.

However, when it comes to woody crops planted in hedgerow systems, the literature indicates some challenges. Although advances have been made [3,19,20], concerns about the accuracy of Sentinel-2 data in these systems persist. A study by Sozzi et al. [21] found a strong correlation between Sentinel-2 and UAV data at both field and sub-field scales. As in the present study, they observed similar variability in both datasets, and indicated that eliminating border pixels enhanced the relationship between Sentinel-2 and UAV vegetation indices. As can be observed, spatial patterns can also be easily discerned in this work (Figure 1).

Finally, while Sentinel-2 satellite information has shown potential in various applications, its reliability varies depending on the type of crops, their management, and the specific parameters being estimated. Further research is needed to optimize its use, especially in woody crops planted in hedgerow systems.

4. Conclusions

The study underlines the potential advantages and disadvantages of integrating various remote sensing methods for enhanced agricultural management. Satellite data has shown its potential in precision agriculture, particularly for woody crops, by offering valuable insights into crop conditions, yield forecasts, and irrigation strategies. While this study identified a reasonable correlation between Sentinel-2 satellite and UAV NDVI measurements, there were notable differences (no correlation found) in leaf area (LAI) estimations using satellite imagery.

These findings emphasize that, when using spaceborne sensors to monitor vegetation in hedgerow systems, VIs are more effective than derived products like LAI in assessing the present condition of crops. The values show a strong correlation with UAV data, underscoring the significance of combining various remote sensing techniques to improve the precision and efficiency of agricultural management practices.

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Conflicts of Interest: The authors declare no conflict of interest.

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