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Efficient Assessment of Crop Spatial Variability Using UAV Imagery: A Geostatistical Approach †

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Abstract: Precision agriculture has seen significant advancements with the integration of remote sensing technologies. However, challenges such as real-time data availability, and computing limitations persist. This study aimed to develop a standardized method for generating spatial variability maps for vineyard management using UAV (Unmanned Aerial Vehicle) imagery. Using IDW (Inverse Distance Weight), nadir images with geotagged locations were processed to extract spectral information. The results were analyzed using NGRDI (Normalized Green-Red Difference Index) and demonstrated that geo-interpolation methods are effective compared to traditional photogrammetry-based methods, but 90% faster, highlighting their potential in real-time applications and edge computing. In addition, IDW correlation with Sentinel 2 imagery reached values as high as r = 0.8. This method offers a faster, less resource-intensive alternative to existing techniques for crop mapping, addressing the current challenges in precision agriculture.

Keywords: Sentinel 2; remote sensing; precision agriculture; precision viticulture; woody crops; vegetation index; NGRDI; vineyard management; drone

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1. Introduction

Precision agriculture (PA) leverages technology and data to enhance crop production while minimizing environmental impact. By collecting and analyzing data from satellites, Unmanned Aerial Vehicles (UAVs), field sensors, and soil samples, PA identifies field variability for site-specific management [1]. This allows for efficient input application, improving yields and reducing waste [2]. On the other hand, Site-Specific Crop Management (SSM) focuses on understanding how spatial variability impacts crop development [3], and remote sensing, especially with the innovation in agriculture, aids in tasks related to SSM, like disease detection [4] and crop variability management [5].

Conversely, satellites, paired with GIS, have been used for remote sensing since the 70s [6], with Vegetation Indices (VIs) being a key tool to analyze spatial variability in agriculture [7–11]. In this aspect, affordable UAVs have become pivotal, providing high-resolution imagery for several key applications [12,13]. Yet, often, moderate-resolution images suffice for mapping crop variability [14,15], as variability is frequently closely related to large-scale factors [16]. Therefore, the choice of the data source depends on the study's requirements.

Low-resolution images might not reveal intra-field variability in homogeneous vegetation, but different resolutions can yield similar results in heterogeneous fields. In this way, several studies have found correlations between satellite and UAV images, suggesting both can assess field conditions effectively [17–19]. In addition, in agriculture, timely information is crucial for optimal decision-making. While photogrammetric techniques offer detailed insights, they can be costly and time-consuming. Moreover, rural environments often face challenges like limited computing capacity and connectivity [20].

Hence, in agricultural settings, the challenge lies in acquiring fast, costly effective and reliable remote-sensing products, often in limited environments. On the other hand, spatial interpolation methods have been recognized as fast and effective tools for analyzing spatial variability in natural settings. Among such techniques, IDW (Inverse Distance Weight) holds a distinct position, being one of the most prevalent methods in geostatistics and spatial interpolation for natural landscapes [21–24]. While there have been instances of combining UAVs with geostatistical techniques such as IDW, their primary application was for validation, not for the generation of spatial variability maps [25]. In light of the above, there is a gap in the literature of methods, that can provide rapid, cost-effective, and reliable remote-sensing products, especially in constrained environments, such as the countryside.

This study seeks to introduce a novel approach to UAV precision agriculture to generate spatial variability maps using Vegetation Indices and IDW interpolation, focusing on crafting standardized workflows to facilitate swift evaluations of crop differences. Specifically, this work addresses challenges related to (i) rapid processing of UAV data for real-time insights, and (ii) the exploration of alternative techniques to conventional photogrammetric methods and those relying on pre-trained models.

2. Materials and Methods

In 2022, the experiments were conducted in a vineyard located in "Tomiño, Pontevedra", Galicia, Spain. This vineyard, *Vitis vinifera* cv. Loureiro, is owned by 'Bodegas Terras Gauda, S.A.' and spans 1.06ha within the "Rias Baixas DO" (Designation of Origin). The grapevines, planted in 1990, have a NE-SW orientation with 2.5 meters between plants and 3 meters between rows. They were trained using vertical shoot positioning (VSP) and grafted onto 196.17C rootstock, suitable for humid soils. The vineyard adheres to the DO protocol and legislation. For aerial imagery, a DJI Phantom 4 RTK drone was used, capturing high-resolution nadir images for mapping and surveying. The flight over the vineyard was conducted on 12 July 2022, at 30 m height, resulting in 282 RGB images. The drone's camera, equipped with a mechanical shutter, captures 20-megapixel images in JPEG format, with a 4:3 or 3:2 aspect ratio.

The main innovative approach of this methodology is the paralell processing of UAV images and metadata, extracting both spectral and spatial data, to create a spatial variability map based on Vegetation Indices using geostatistics. To this end (Figure 1), a Region of Interest (ROI) is cropped from the center of each image, from which the Normalized Green Red Difference Index (NGRDI) is calculated. NGRDI serves as an exemplary VI in this case, but other indices could also be computed, provided the necessary bands are accessible. The spatial information is obtained from the image metadata, and a discretization process combines this with the spectral data. The Inverse Distance Weighted (IDW) interpolation method is then applied to create the spatial variability map. This method assumes that closer points are more similar, and it uses the values of nearby measured locations to estimate values at specific locations.

To validate the generated maps, high-quality orthomosaics are produced using a standard photogrammetric workflow in Agisoft Metashape Professional software. These orthomosaics are then compared to the maps generated by the proposed method. For a detailed comparison, three grid layers with varying tile sizes (1m, 3m, and 10m) are employed, representing sub-plant, plant, and plant-group levels respectively. The aim is to analyze differences in spatial variability between the products at different scales. Additionally, the products were compared with freely available satellite images (Sentinel 2) from the same or closely matched dates. The processing is conducted on a high-performance Linux system, and Spearman correlation analysis is used to assess the correlations between the datasets.

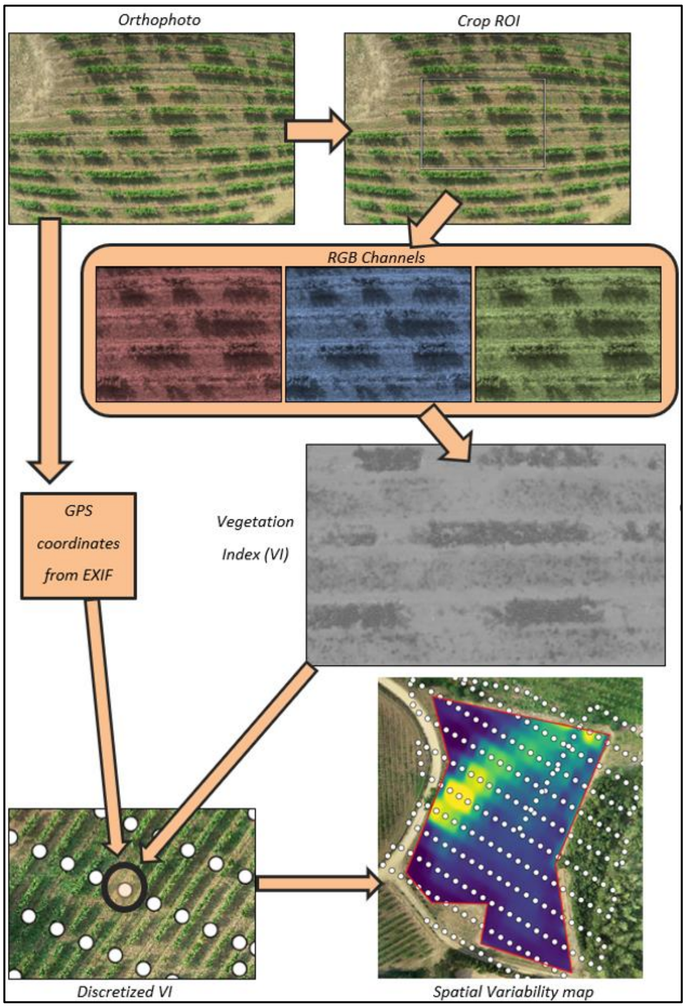

Figure 1. Workflow showcasing the product generation. Starting with nadir images from the UAV flight, the Vegetation Index is determined and discretized based on coordinates from the metadata of each image. This results in a spatial interpolation to produce the spatial variability map.

3. Results and Discussion

The maps generated using the IDW interpolation method showed patterns consistent with those of orthomosaic-based maps. In the IDW map, an area in the west displayed higher VI values, possibly influenced by shade from a tree. Another notable feature was a strip running from west to northeast, which was also faintly visible in the NGRDI derived from the orthomosaic.

The results of the Spearman correlation analysis indicated strong correlations between the datasets, achieving a correlation up to r = 0.93 for the 10m tile size (Table 1). The study found that, as expected, as the grid size used for analyzing spatial variability increased, the correlation between the generated variability maps and the vegetation maps produced by the orthomosaic also increased.

Table 1. Spearman correlation for 1m, 3m and 10m tile size between the NGRDI (Normalized Green Red Difference Index) values of the orthomosaic and the values of IDW (Inverse Distance Weight). All values had a p-value < 0.001.

Tile Size		
1m	**3m**	**10m**
0.52	0.71	0.93

Furthermore, the results were compared with Sentinel-2 satellite images, finding that the correlation between the satellite images, the products generated by the proposed method and the products generated by photogrammetric techniques was very similar (r up to 0.66).

The main advantage of the method proposed in this study is the speed, since it was notably faster than traditional photogrammetry-based methods (Figure 2). In this way, it consumed 90% less time, offering significant advantages in the agricultural sector. On the other hand, UAVs have become an essential tool for generating VIs in agriculture, like the NGRDI. This index has shown its utility in various agricultural contexts, such as evaluating nitrogen balance. Therefore, the proposed method, combined with other VIs, could potentially be useful for assessing other parameters and key variables. Additionally, the flexibility of the methodology, requiring only geotagged images, theoretically allows it to be integrated into more complex processes, potentially enhancing real-time agricultural operations and edge computing.

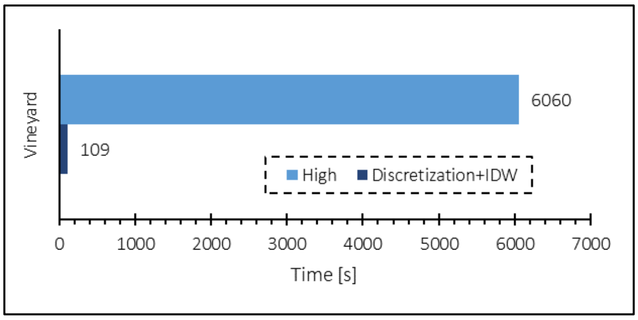

Figure 2. Duration for each procedure (measured in seconds). The figure outlines the time needed for photogrammetry; and the proposed method, composed of discretization (converting images to points) and IDW (Inverse Distance Weight) interpolation.

The generated spatial variability maps can be helpful for quick agricultural assessments. For instance, in the vineyard, the IDW maps highlighted a belt, a known phenomenon in agriculture, which can be influenced by factors like terrain topography and ephemeral streams. Such maps can provide insights into spatial variability, even with a lower spatial resolution than the original images. Conversely, the northern part of the vineyard, being at a lower elevation, can influence sediment transport, affecting soil texture and composition, which in turn can impact plant development and vegetation amount.

The study utilized a specific sensor type, yet the methodology could be adaptable to any geotagged image. This adaptability should not be a concern, given that the common sensors used in agriculture routinely produce geotagged images [26,27]. The flexibility of the methodology, combined with its speed and efficiency, makes it a promising tool for real-time agricultural assessments, potentially aiding in tasks such as irrigation leak detection, soil parameter estimation, and vegetation monitoring.

4. Conclusions

The study introduced a method using geostatistical interpolation, specifically IDW, to create spatial variability maps from nadir images with geotagged locations. This approach, applied in images from vineyards, offers a faster and more energy-efficient alternative to traditional photogrammetry techniques, achieving high correlations (up to r = 0.93) for spatial variability assessment. The versatility of the methodology allows for the use of any nadir image, ensuring accurate spatial information, crucial for Site-Specific Crop Management (SSM). Its efficiency, consuming more than 90% less time and power, makes it suitable for real-time evaluations, edge computing, and integration with satellite images, even in low-bandwidth scenarios. Future research could further refine this workflow, integrating variabilities such as other locations, other UAVs, and other sensors.

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