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COMPARAÇÃO DO NDVI OBTIDO POR MEIO DE DRONE E SATÉLITE NAS FASES FENOLÓGICAS DA VIDEIRA

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1 RESUMO

As diversas interações do meio biofísico, sejam por fatores bióticos ou abióticos, dificultam os estudos do comportamento das áreas cultivadas através de métodos padrões. A utilização de plataformas com sensores de alta resolução espacial possibilita detectar a heterogeneidade de culturas como a videira, por meio do NDVI. O objetivo do trabalho foi avaliar o NDVI obtido por imagens do VANT *AggieAir Minion* e do Landsat 8, em diferentes fases fenológicas da videira *Pinot Noir.* As imagens foram coletadas no Condado de Sacramento, Califórnia USA. O processamento das imagens foi realizado por meio do *Quantum GIS* (QGIS). Constatou-se uma subestimação do NDVI calculado por meio das imagens do Landsat 8, na fase de crescimento de baga, apresentando valores menores (0,68) do que os encontrados pelo VANT (0,87). Nessa fase os valores de NDVI devem ser mais próximos de 1,0, pois a planta encontra-se em pleno desenvolvimento vegetativo. O detalhamento das imagens depende da resolução espacial do sensor que a plataforma carrega, sendo assim considerando que a distância entre as linhas da videira era de 3,35 m, e devido ao tamanho do pixel do Landsat 8, foi detectado uma maior área de solo exposto devido à influência da máxima semelhança de veracidade que é utilizada pela linguagem do algoritmo utilizado no *software* de programação. Portanto, pode-se concluir que a resolução espacial influência em valores de índice vegetativo em fases fenológicas da videira e, consequentemente, nos parâmetros biofísicos estimados por ele, mostrando assim que as imagens capturadas por VANT expressam valores mais próximos do real para a avaliação do NDVI em videiras.

Palavras-chave: VANT *AggieAir*, Landsat 8, *Pinot Noir*.

COMPARISON OF NDVI OBTAINED BY DRONE AND SATELLITE IN THE PHENOLOGICAL PHASES OF GRAPEVINE

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2 ABSTRACT

Several interactions of the biophysical environment, whether by biotic or abiotic factors, hinder the study of crops' behavior using standard methods. The use of platforms with high spatial resolution sensors enables detecting heterogeneity of crops such as grapevine through NDVI. This study aimed to evaluate the NDVI obtained using images from the *AggieAir Minion* UAV and Landsat 8 in different phenological phases of the *Pinot Noir* grapevine. The images were collected in Sacramento County, California, USA. Image processing was performed using *Quantum* GIS (QGIS). We observed an underestimation of the NDVI calculated using Landsat 8 images in the berry growth phase, presenting lower values (0.68) than those obtained by the VANT (0.87). The NDVI values should be closer to 1.0 in this phase because the plant is in full vegetative development. The details of the images depends on the spatial resolution of the sensor that the platform carries. Thus, considering that the distance between the lines of the vine was 3.35 m, and due to the pixel size of the Landsat 8, a larger soil-exposed area was detected as a consequence of the maximum similarity of veracity used by the algorithm language employed in the programming software. The resolution influences the vegetative index values in phenological phases of grapevine and, consequently, the biophysical parameters estimated by them, showing that the UAV images convey values more similar to reality for NDVI evaluation in grapevines.

Keywords: UAV *AggieAir*, Landsat 8, *Pinot Noir*.

3 INTRODUCTION

Water and biogeochemical cycles are increasingly influenced by climate change, which is causing extreme weather conditions due to a variety of factors, such as land-use changes and forest fires. In this sense, remote sensing is a technology capable of providing information with relevant spatial resolutions of the Earth's surface, exploiting geophysical data and providing information on soil characteristics and vegetation biomass (HUBBARD *et al*., 2021).

There is a growing demand for the use of remote sensing through vegetation indices for the evaluation of agricultural crops because this tool enables real-time data collection, shorter periodic analysis, and a reduction in manual labor compared with traditional field evaluation methods (COSTA; NUNES; AMPATZIDIS, 2020).

Vegetation indices can be used to analyze the spectral properties of vegetation, whether in an ecosystem or an agricultural area, through arithmetic operations between the spectral bands of the images collected by the sensors due to the reflectance behavior of the analyzed surfaces (FRANCISCO *et al*., 2020). Although several vegetation indices exist, the normalized difference vegetation index (NDVI) has proven to be quite efficient in the analysis and interpretation of Earth's surface data (ALVES; LOVERDE-OLIVEIRA, 2020).

Several studies that use remote sensing techniques in the monitoring of agricultural crops are contributing to the growing use of the NDVI in the estimation of evapotranspiration, discrimination of agricultural areas, and pest and disease attacks, among other applications (JUNGES *et al*., 2017; MAHMOUD; GAN, 2019). Castro *et al*. (2018) reported the feasibility of using the NDVI to monitor the phenological phases of several crops (rice, corn, sunflower, walnut and grape), optimizing the management of cultivated areas.

Despite the increasing use of remote sensing through imagery, there are several limitations, such as the frequency and resolution of the sensors onboard the platforms. When satellite imagery is compared with unmanned aerial vehicle (UAV) imagery, the resolution can influence the analysis of the results obtained since higher resolutions can extract more detailed information about the Earth's surface (GOMES, 2019).

The demand for highly detailed spatial information on agricultural areas and ecosystems is growing daily. Through the information collected via high-resolution remote sensing techniques, it is possible to manage reliable agricultural information, thus enabling producers to make faster decisions regarding their crops. This can even assist managers in strengthening rural development policies, food security, and the competitiveness of the agricultural sector (UNITED NATIONS ORGANIZATION FOR FOOD AND AGRICULTURE, 2013; MINISTRY OF AGRICULTURE AND RURAL DEVELOPMENT, 2018).

According to Dash, Pearse and Wantt (2018), the emergence of new sensors and platforms makes it possible to increase the reach of remote sensing techniques, providing detailed information on vegetation, with UAVs being platforms that allow the use of high-resolution sensors, with characteristics that are more sensitive to changes in vegetation, and can detect physiological stress even in individual trees.

Although UAVs are an alternative for capturing high-resolution images at lower frequencies than satellites do, some studies suggest the integrated use of both platforms. Despite the lower resolution of satellite images, they are essential for assessing large areas. Therefore, some studies report that integrating UAVs ~~and~~ satellites within the same coverage area produces more accurate maps without losing spatial heterogeneity, allowing for better classification of agricultural land cover or ecosystems (PLA *et al*., 2019; ZHAO *et al*., 2019).

Vegetation monitoring with UAVs can provide relevant data, such as the NDVI, for the evaluation of agricultural crops due to the resolution of the onboard sensors, since when combined with procedures to link the mapped variables, the UAV can be a useful tool for optimizing the proper management of agricultural systems (BLEKOS *et al*., 2021).

The NDVI is an excellent index for indicating vegetative vigor, especially when considering crops with low growth (cereals or vegetables).—This study provides information on the photosynthetic vegetative activity and biomass growth density of plant species. For discontinuous tree crops, such as grapevines, the spectral response of the canopy top describes only a portion of plant vigor, since the total vegetative growth of the plant is not adequately assessed when this analysis is performed via low spatial resolution sensors (MATESE; DI GENNARO, 2021).

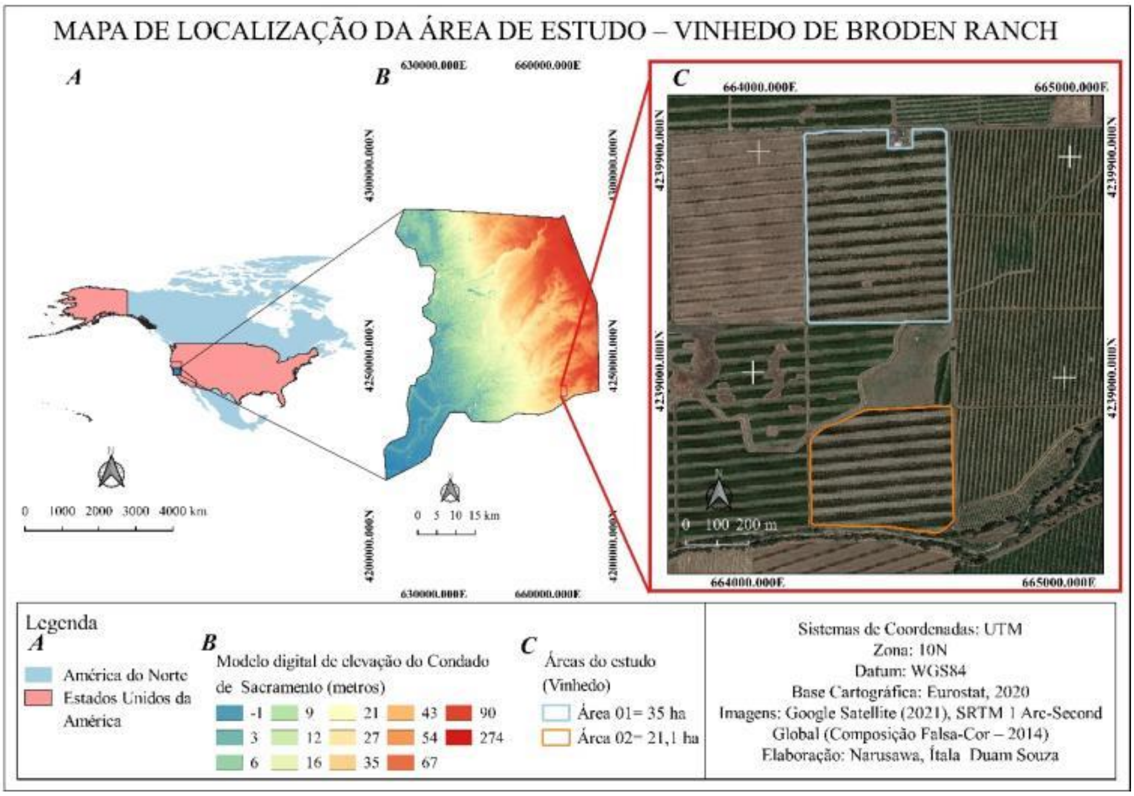
Analyzing the literature on this subject, it is clear that the use of platforms with high spatial resolution sensors is more suitable for evaluating grapevine vigor, as the high heterogeneity of vineyards can have different physiological responses, with direct consequences for the quality and yield of production, making studies that prioritize these aspects of vigor of utmost importance.

Given the above, the development of technologies to assist in vineyard management is of fundamental importance for winegrowers. Although remote sensing is a widely used tool, this research aims to evaluate the NDVI calculated by the *AggieAir UAV. Minion* and the Landast satellite 8 in different phenological phases of the *Pinot vine Noir*.

4 MATERIALS AND METHODS

The study area is located in Sacramento County, California, USA, on a *Broden vineyard Ranch* with *Pinot Noir*, at geographic coordinates of 38°17'35.21" and 38°16'41.58" North latitude, 121°7'23.12" and 121°7'2.94" West longitude (Figure 1), and an altitude of 37 m. The *datum* used was WGS 84/UTM ZONE 10 N.

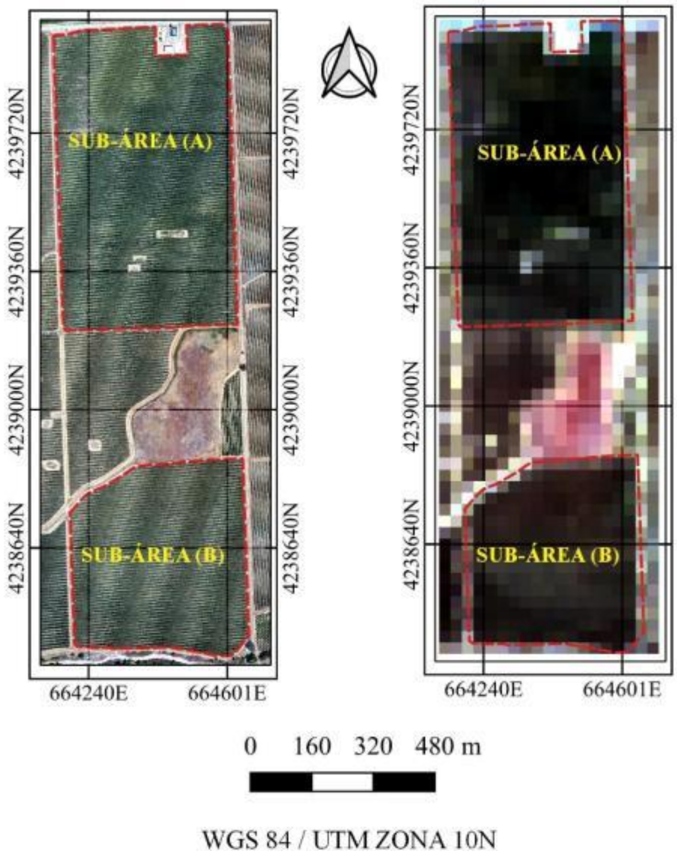
Figure 1. Locations of the study vineyards in the USA (A), the state of California (B) and Borden Ranch (C) in Sacramento County



The images used for this research were funded by the GRAPEX Project (*Grape Remote Sensing Atmospheric Profile and Evapotranspiration eXperiment*) from the United States Department of Agriculture (*United States Department of Agriculture - USDA*) and were collected by the research group at the Water Research Laboratory at the University of Utah (Utah State University - USU).

The images were captured by the *AggieAir UAV Minion* and the Landsat-8 satellite. The study area covers 55.4 ha and is divided into two subareas: Subarea A, which refers to northern China, and subarea B, which refers to southern China, with 34.4 and 21 ha, respectively (Figure 2).

Figure 2. Aerial images of the study area captured by the AggieAir UAV (left) and by the Landsat-8 satellite (right) at the same location, both of which were obtained on July 11, 2015.



Source: Prepared by the authors

According to the Koppen climate classification, the region's climate is of the Csa type, characterized as a hot-summer Mediterranean climate, with average annual temperatures of 15°C and the driest month of summer receiving less than 30 mm of rain.

The area has vines irrigated by a drip system in clay soil, with two emitters per plant located 30 cm above the ground, with an average measured flow rate of 4 L h $^{-1}$. The vine trellises are spaced 3.35 m apart, with two cordons, the first located 1.45 m above the ground and the second located 1.9 m above the ground. Typically, most of the *Pinot vine biomass Noir* is concentrated in the upper half of the canopy height, and this species generally grows 2.0--2.5 m above the ground (KUSTAS *et al*., 2018).

The cameras used on the AggieAir UAV ranged from commercial-grade Canon S95 cameras to industrial-grade Lumenera monochrome cameras. The Canon S95 camera had 8-bit radiometric resolution and 15 cm optical/digital surface model resolution, whereas the Lumenera monochrome camera had 14-bit radiometric resolution and 10 cm optical/digital surface model resolution. Both were equipped with RGB (*red*, *blue*, and *green*) and NIR (*near-infrared*) spectral band filters equivalent to the specifications of the sensors used on Landsat 8.

Images were collected during the flowering phase (02/05/2016), 1st berry growth phase (02/06/2015), 2nd berry growth phase (11/07/2015) and fruit ripening (09/08/2014). The average temperature and relative humidity on the days the images were collected were 21°C and 48%, 19°C and 57%, 21°C and 59% and 19°C and 57%, respectively.

Unlike satellite imagery, the UAV imagery was calibrated via a *calibration ground target* to calibrate the camera sensors, allowing for reflectance corrections on each flight day. All four flights were conducted with the UAV elevated at 450 m above the ground.

Landsat 8 satellite imagery was acquired via the *EarthExplore* user interface (*UNITED STATES GEOLOGICAL SURVEY*, 2019), a tool developed by *the United States Geological Survey* (USGS). To estimate the NDVI via satellite images, it was necessary to perform radiometric conversion of bands 4 and 5 of the Landsat-8 satellite, which refers to the conversion of digital numbers (DN) into physical values, and atmospheric correction, which was performed via the DOS (*dark object subtraction*), presented by Chavez (1988).

In radiometric conversion, DNs are transformed into spectral radiance values (Equation (1)) according to the methodology proposed by Allen *et al* . (2002) .

$$L_{\lambda} = M_L\ Q_{cal} + A_L \qquad (01)$$

where Lλ = spectral radiance at the top of the atmosphere, $Wm^{-2}\ sr^{-1}.\mu m^{-1}$; ML = band-specific multiplicative rescaling factor from the metadata file; AL = band-specific additive rescaling factor from the metadata (offset); and Qcal = pixel values of the spectral band (DN).

Then, the reflectance of each band was calculated (Equation 2) by the ratio between the radiation flux reflected by the surface and the incident global solar radiation flux, according to Allen *et al.* (2002).

$$\rho_{\lambda} = \frac{\pi \times L_{\lambda} \times d^2}{ESUN_{\lambda} \times \cos Z} \qquad (02)$$

where ρλ = reflectance at the top of the atmosphere, dimensionless; Lλi is the spectral radiance of each band; and ESUNλ = mean solar irradiance at the top of the atmosphere for each band, $Wm^{-2}.\ \mu m^{-1}$; Z = solar zenith angle (radians); ed = Earth–Sun distance in astronomical units.

All correction and processing processes of satellite images, as well as UAV images, were carried out via the *Quantum GIS* (QGIS) computational resource, version 2.14.9.

The NDVI was calculated via the near-infrared and red bands of images obtained by the AggieAir UAV and the Landsat 8 satellite (Equation 3) by the ratio between the difference in reflectances of the near-infrared and red bands ~~and~~ the sum of these same reflectivities (ROUSE *et al*., 1973). This index is a sensitive indicator of the quantity and condition of vegetation, whose values vary in the range of -1--1.

$$NDVI = \frac{\rho 4 - \rho 3}{\rho 4 + \rho 3} \qquad (03)$$

where ρ4 and ρ3 are the reflectance values of the near-infrared and red bands, respectively.

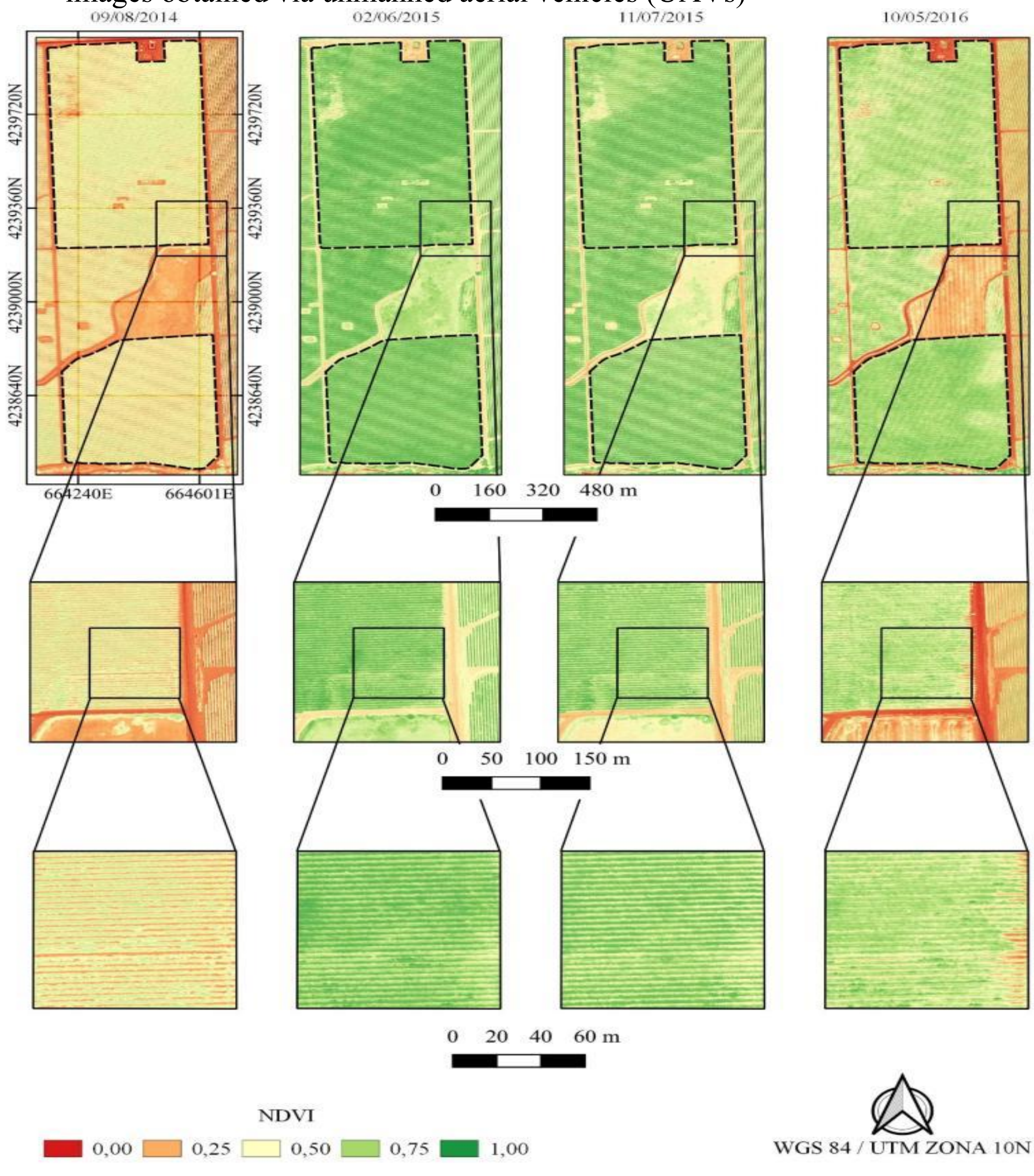
5 RESULTS AND DISCUSSION

The spectral behavior of vegetation and soil, obtained through images using specific sensors on a platform, such as a UAV or an orbital platform, can be evaluated through vegetation indices of surface targets and portray the behavior of temporal and spatial changes on the Earth's surface.

The NDVIs obtained through UAV images (Figure 3) and the Landsat 8 satellite data (Figure 4), with the dates sequenced in these figures representing the final ripening phases, 1st and 2nd berry development phases and flowering, are presented below.

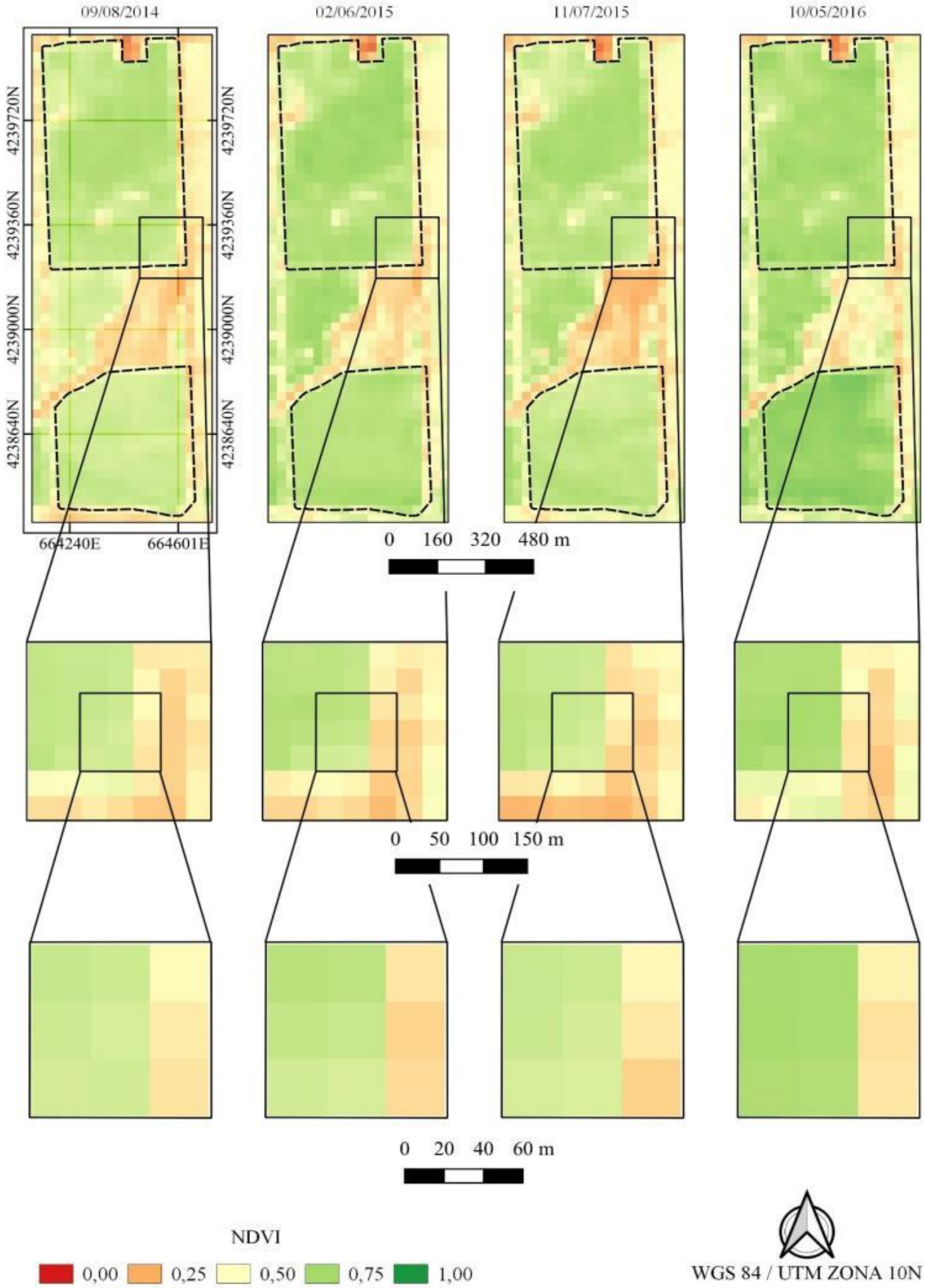
The details of the images depend on the spatial resolution of the sensor that the platform carries.

Figure 3. Normalized difference vegetation index (NDVI) for grapevine crops determined via images obtained via unmanned aerial vehicles (UAVs)



Source: Prepared by the authors

Figure 4. Normalized difference vegetation index (NDVI) for grapevine crops determined via Landsat 8 satellite imagery



Source: Prepared by the authors

The sensors used in the AggieAir UAV to capture images and obtain the NDVI have a spatial resolution of 0.15 mx 0.15 m in the image from August 9, 2014, and 0.10 mx 0.10 m in the other images. These spatial resolutions result in 44 pixels/m² and 100 pixels/m², respectively. The sensors (*OLIs—operational land images) used in the* Landsat 8 platform have a spatial resolution of 30 m × 30 m, which means that the area of each pixel in the image is 900 m².

Sun *et al*. (2017) used images collected by Landsat 7 and Landsat 8 to obtain the NDVI in grapevines in the same study area as those used in this research and reported differences in the values obtained by these platforms, indicating that one of the reasons is the difference in the sensors regarding the reflectance of the bands used to calculate the NDVI, as they have different radiometric resolutions, equal to 8 and 12 bits, respectively. Radiometric resolution is the sensitivity of the sensor in detecting small variations; therefore, the OLI sensor (Landsat 8) has greater sensitivity and a higher gray level than the ETM+ sensor (Landsat 7), consequently representing a greater intensity of electromagnetic energy.

Considering that the area of a pixel in Landsat 8 images is 900 m², Figure 4 shows the low spatial resolution of these images compared with the images from the AggieAir UAV (Figure 3). Therefore, the image detail is influenced by the pixel size. Sampaio *et al*. (2020), analyzing the NDVI obtained with images from sensors onboard UAVs and Landsat 8, revealed that spatial resolution interferes with the quality of the images and, consequently, with the resulting vegetation index, corroborating the results of this research.

Observing the area highlighted in the UAV and satellite images, it is clear that the NDVI calculated via the Landsat 8 images may not represent the actual behavior of the field data, since, owing to the pixel size, a larger area of exposed soil was detected because the distance between vine rows was 3.35 m. This occurs as a consequence of the influence of the maximum similarity of truthfulness used by the language of the geoprocessing *software algorithm*, which makes it difficult to assess crop variability through the spectral mixture of soil, plants and shade.

In this context, it can be stated that UAV images obtain greater detail of the area and, consequently, express better results of the indices calculated by them. Khaliq *et al*. calculated the NDVI in vineyards *via satellite and UAV images*. (2019) reported that spatial resolution can alter the results, as the smaller the image pixel is, the better the representation of crop vigor and canopy, resulting in high spatial resolution maps when UAV images are used compared with maps acquired via satellite images.

The NDVI is used to detect various vitality characteristics of agricultural crops. However, for this characterization to represent conditions as closely as possible, it is essential to have a high-resolution image. This allows for the characterization of the biomass, photosynthetic rate, and water demand of the crop, which requires greater detail of the area.

According to Khaliq *et al. (2019), the* radiometric information acquired by orbital platforms does not have sufficient spatial resolution to adequately assess vine canopy vigor and crop variability, corroborating the results of this research.

To map grapevine phenology on a detailed scale through NDVI analysis to understand its phenological phases and biophysical processes, images captured by UAVs present advantages, as they have greater potential in analyzing critical periods of production than do the phenological dynamics recorded by satellite images, as a spatial resolution of 30 mx 30 m can compromise the results (BERRA, GAULTON, BARR, 2019; LIU *et al*., 2017).

NDVI values can vary between -1 and 1, with surfaces containing water or clouds represented by values less than zero, areas containing exposed soil with values close to or equal to zero, and areas with vegetation presenting values greater than zero and close to 1 (PEREIRA; SILVA; PAMBOUKIAN, 2016). In this research, the

NDVI values calculated via UAV and satellite images in each area and crop phase are shown in Table 1.

Table 1. Normalized difference vegetation index (NDVI) values for the North and South subareas calculated via images from the *AggieAirMinion Unmanned Aerial Vehicle (UAV)* and the Landsat 8 satellite

Phenological stage	LANDSAT 8 SUBAREA A (NORTH)	LANDSAT 8 SUBAREA B (SOUTH)	UAV SUBAREA A (NORTH)	UAV SUBAREA B (SOUTH)
Flowering	0.72 (0.039) [x]	0.66 (0.027) [x]	0.75 (0.050) [x]	0.75 (0.029) [x]
1st stage of berry growth	0.67 (0.040) [x]	0.77 (0.042) [x]	0.87 (0.038) [x]	0.88 (0.016) [x]
2nd stage of berry growth	0.68 (0.050) [x]	0.69 (0.029) [x]	0.84 (0.050) [x]	0.85 (0.023) [x]
Fruit ripening	0.71 (0.040) [x]	0.62 (0.029) [x]	0.59 (0.026) [x]	0.58 (0.024) [x]

[x] represents the standard deviation (σ) of the values for each phenological stage studied and for each method used.
Source: Prepared by the authors

The NDVI behavior is expected to increase in the budding phase until the beginning of maturation, as ~~it corresponds~~ to the vegetative growth phase and, subsequently, to the filling of the fruits; it is constant in the phase close to harvest until the harvest itself, ~~since~~ at this phase, the entire leaf area is already developed and the supply of "drains" (fruits) is occurring; and it decreases after the harvest phase, considering that after this phase, pruning is carried out so that the leaves can be renewed with a new flowering.

At the beginning of the flowering process, the NDVI should be greater than that during the fruit ripening phase and lower than that during the berry growth phase. The NDVI values expressed by the captured images are similar on both platforms. However, when comparing them with previous phases within the same platform, we notice that the values expressed by Landsat 8 images (Table 1) do not behave appropriately, as the variation between phases does not consistently follow the increasing, constant, and decreasing values in the studied phases.

During the berry growth phase, the NDVI values should be greater than those during the fruit ripening phase, as the plant is in full development during these phases. These values are more coherent in the UAV images (Table 1), with an increase compared with the previous phase (fruit ripening) of 50% in the first berry growth phase and 44.8% in the second berry growth phase in subarea A and increases of 50% and 46.5% in subarea B, respectively. The NDVI values expressed by the LANDSAT 8 images decreased by 5.6% and 4.2% in subarea A and increased by 13% and 23% in subarea B, respectively.

The NDVI values during grapevine fruit ripening, expressed in the images captured by Landsat 8 (0.71 and 0.68), are greater than those expressed in the UAV images (0.58). At this stage, the image was captured in late summer and close to autumn. During this period, the grapevine leaves begin to turn red and yellow, resulting in a reduction in chlorophyll, and consequently, the NDVI values are lower.

Therefore, it can be inferred that the NDVI values should be lower or closer to zero, representing an area with exposed soil and little vegetation. In the images captured by the UAV, this lower value can be seen in both areas, possibly because the image presents better spatial resolution, so the algorithm calculates the expected index more accurately.

Studies analyzing the canopy ~~of~~ grapevines carried out in California indicate that 30 m × 30 m resolution images from Landsat 8 are useful for assessing the variation in crop development conditions. However, high-spatiotemporal-resolution images allow for more detailed information on the plants and between rows, thus facilitating the acquisition of results expressed by vegetative indices, including those during the critical phenological stages of the crop (SUN *et al*., 2017).

Junges *et al*. (2017), studying grapevines in the Serra Gaúcha region, reported that the temporal normalized difference vegetation index (NDVI) profiles obtained through remote sensing via images from terrestrial platforms reflect the accumulation of biomass throughout the cycle, enabling the monitoring of plant growth and development during phenological stages and canopy changes. The same authors state that the NDVI, obtained through sensors on terrestrial platforms, can be used to characterize the vigor of the vegetative canopy in vineyards, in contrast ~~to~~ the use of meteorological data and real-time management practices, which are difficult to quantify via other traditional methods already used. Compared with orbital platforms, a terrestrial platform for remote data collection is indicated as a fast and accurate option.

A case study for vineyards in Washington state, USA, carried out to estimate crop growth through the NDVI via satellite images revealed an overestimation of the NDVI values in the analyzed phases (BADR *et al* ., 2015) , corroborating the results of this research, since the NDVI values found through the Landsat 8 orbital platform in the fruit ripening phase are greater than those found via the UAV terrestrial platform (Table 1), which is an overestimation because this is a phase in which the crop has a smaller leaf area and the leaves have lower chlorophyll levels, which should result in a lower NDVI value.

Junges *et al*. (2017), using sensors on terrestrial platforms, reported NDVI values for the vine between 0.80 and 0.86 in the fruiting phase, confirming the results of this research, in which NDVI values ranging from 0.84 to 0.88 were found via UAV in the same phase mentioned above (Table 1).

6 CONCLUSION

radiometric resolutions influence the NDVI values of grapevines at each phenological stage and, consequently, the biophysical parameters that can be estimated via this index. The images captured by UAVs expressed values closer to reality and on a more satisfactory time scale for use in grapevine irrigation management than images captured by the Landsat 8 satellite did.

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