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UAV-Based Multispectral Data Collection for Monitoring Early Sunflower Growth

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Abstract. Monitoring sunflower crops in the early stages of germination is essential for profitable crop management. Traditional manual, ground-based methods are laborious, subjective, and error-prone. This study explores the applicability of different multispectral data sources to tasks related to sunflower monitoring. A collection of multispectral and RGB images was captured using a UAV and processed. The data collection establishes a foundational framework, enabling additional analyses to be conducted based on applied mathematical models and machine learning algorithms to provide field coverage research in supporting advanced agronomic decision-making.

Keywords: Multispectral imaging, Precision agriculture, UAV, Satellite, Earth observation, Sunflower

1.1 INTRODUCTION

Sunflowers are among the most important crops grown in the world. In sunflower cultivation, the density of the sprouted plants is an important factor for future yield. Therefore, monitoring the emergence of sunflowers during the early growth stages is essential for making objective agronomic decisions. Manual counting or sampling, as traditional ground-based methods for assessing plant density, are laborious, inaccurate, time-consuming, and generally impractical for large fields. In recent years, a number of remote sensing technologies, such as those based on unmanned aerial vehicles (UAVs) and satellite platforms, have offered efficient alternatives for agricultural monitoring. The use of UAVs equipped with high-resolution multispectral sensors is a promising solution for crop analysis. Unlike satellite imagery, UAVs support higher spatial resolution and greater temporal control, but cover smaller areas and have higher operational costs. However, current UAV technology can already cover medium-sized fields (up to hundreds of ha) efficiently in a single day, with the prospect of extending its application to large fields as UAV technology progresses and flight times increase.

This study presents the use of UAV-acquired multispectral imaging to monitor sunflower emergence and estimate plant density in the early stages of growth in a sunflower field. Twelve series of high-resolution UAV imagery acquisitions were conducted over three months in five spectral bands: B (Blue), G (Green), R (Red), RE (Red Edge), and NIR (Near Infrared). The resulting data were cleaned and consolidated into a dataset suitable for post-processing and annotation to aid in the development of plant counting and segmentation algorithms.

1.2 UAVs AND SATELLITES FOR CROP MONITORING

Satellites and UAVs are now often used for crop monitoring, with each method offering strengths and weaknesses. Satellites offer broad coverage, while UAVs provide detailed images, enabling informed decisions for resource management, optimizing inputs, and improving yields.

Satellite monitoring provides extensive coverage for observing long-term crop changes. However, its lower spatial resolution and susceptibility to atmospheric conditions, such as cloud cover, often limit its ability to detect details at the plant level. Conversely, UAV monitoring offers high-resolution imagery for pinpointing localized issues but faces constraints due to limited flight time and coverage.

A comparison on several criteria gives a more accurate view of their advantages and flaws.

Spectral accuracy: Capturing accurate reflectance spectrum is challenging for both UAVs and satellites, due to atmospheric effects (absorption, scattering). For satellites, these negative effects are more pronounced because spectral distortions occur on both the illuminating and the reflected sunlight. Satellite operators usually apply an atmospheric correction algorithm (Sen2Cor in Sentinel-2) to the received data in an attempt to compensate for these effects [1], [2]. In contrast, UAVs being closer to the scene are only affected by the distortions in the illuminating sunlight spectrum. There are two major approaches for compensation: the use of a radiometric correction target (plate) and the use of a spectrometer (on the ground or UAV mounted). Both work well in clear skies. The former degrades quickly when there are temporal variations in the spectrum (e.g., due to cloud dynamics and sun angle) and the latter may fail when the scene and the UAV-mounted spectrometer are illuminated by light with different spectra (UAV is shaded by a cloud, but the scene is not).

Spatial resolution: In terms of spatial image resolution, UAVs have a clear advantage over satellites. While satellites work at a fixed altitude and coarse spatial resolution (e.g., up to 10m/px for Sentinel-s), UAVs can be flown at different altitudes (up to 120 m without special permission in the European Union (EU), except in restricted zones, such as airports, military facilities etc.) and very high spatial resolutions that capture fine plant detail [3].

Revisit time and cloud cover: Satellites have a fixed revisit time (approx. 5 days for Sentinel-2) and imaging in the visible and near infrared (VNIR) bands is impossible through cloud cover. In contrast, UAVs can be operated at a desired date and are still usable under cloud cover (considering the challenges with spectral dynamics mentioned above). It has to be mentioned, though, that UAVs cannot be operated safely in strong winds and rain and in situations where the observation site is inaccessible (muddy roads), which sometimes puts them at a disadvantage compared to satellites. Additionally, there are special zones around airports and military facilities that sometimes overlap with the studied fields. In these zones, UAV operation is either not allowed or there are more strict flight altitude limitations (down to 50 m in the EU) [3].

Cost to operate: Satellite operators offer both free and paid data access. Identifying and processing relevant data to derive insights about a field requires expertise. UAVs may require capital investment and a licensed operator, and while data is usually easy to consume, deriving insights is not trivial. Therefore, historically, UAV-acquired data has been more expensive than satellite data, even though there is a recent downward trend in the price of UAVs.

Interoperability: Apart from spectral inaccuracies, another issue that makes combining data from different multispectral sources non-trivial is the lack of an agreed-upon standard for central wavelengths and bandwidths of the named spectral bands, such as NIR, R etc. Consequently, the bands used for calculating popular vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) are also not standardized [4], [5].

Both technologies can be used to help farmers make informed decisions.

Satellite monitoring offers lower resolution imagery, which is better for large-scale crop monitoring. For small to medium-sized farms, the use of UAVs for crop monitoring is more versatile and adaptable. UAVs can be chosen because of their capacity to deliver frequent, localized, high-resolution data that aids in precision farming methods. Additionally, UAVs provide faster reactions to changes.

1.3 UAV DATA COLLECTION AND PROCESSING

Following the guidelines from the above-presented analysis, a specialized, multispectral UAV platform - Da-Jiang Innovations (DJI) P4 Multispectral high precision drone [6], was used to collect data from a small 2.5 ha experimental field. Data was taken on twelve dates over a three-month period (15.04.2024 to 24.07.2024), approximately 10 days apart. The data acquisition period spans the initial and active development phases, with plant height starting at 3 cm and settling to a stable 172 cm on the last two acquisition dates.

Two major types of missions were carried out, aerial and low-altitude. Aerial images were taken from an altitude of 120m, while the low-altitude images were taken at different altitudes (2, 5, 10, 20, and 40 m), because the optimal altitude was not known a priori. The primary goal of the collected data was to enable the exploration of different approaches for plant density estimation, such as spectral characterization (from aerial images) and plant counting with object detection, instance or panoptic segmentation (from low-altitude images). All data obtained was cleaned, processed, validated and consolidated into the “sunflower-density-estimation-2024” dataset, published on the “Hugging Face” platform [7].

UAV platform specifications and imaging capabilities

DJI P4 Multispectral is equipped with a top-mounted spectrometer (Integrated Spectral Sunlight Sensor), a regular RGB camera and a 5-sensor multispectral camera, with bands suitable for agriculture monitoring and vegetation index (VI) calculation. Both cameras have a pixel resolution of 1600x1300 px. The RGB camera produces JPEG images, while the multispectral camera produces TIFF images. All images are geotagged with the UAV coordinates at the moment of image capture. Flight autonomy is specified as 27 min (approx. 20 min observed in practice).

The UAV was operated in an autonomous flight mode, controlled by the DJI GS Pro software [8].

Data Description

All data was collected with a vertical camera orientation in “Hover&Capture at point” mode. Each capture point yields one RGB image file in JPEG format and 5 single band image files in TIFF format in the following bands B: 450 nm ± 16 nm; G: 560 nm ± 16 nm; R: 650 nm ± 16 nm; RE: 730 nm ± 16 nm; NIR: 840 nm ± 26 nm (Fig.1).

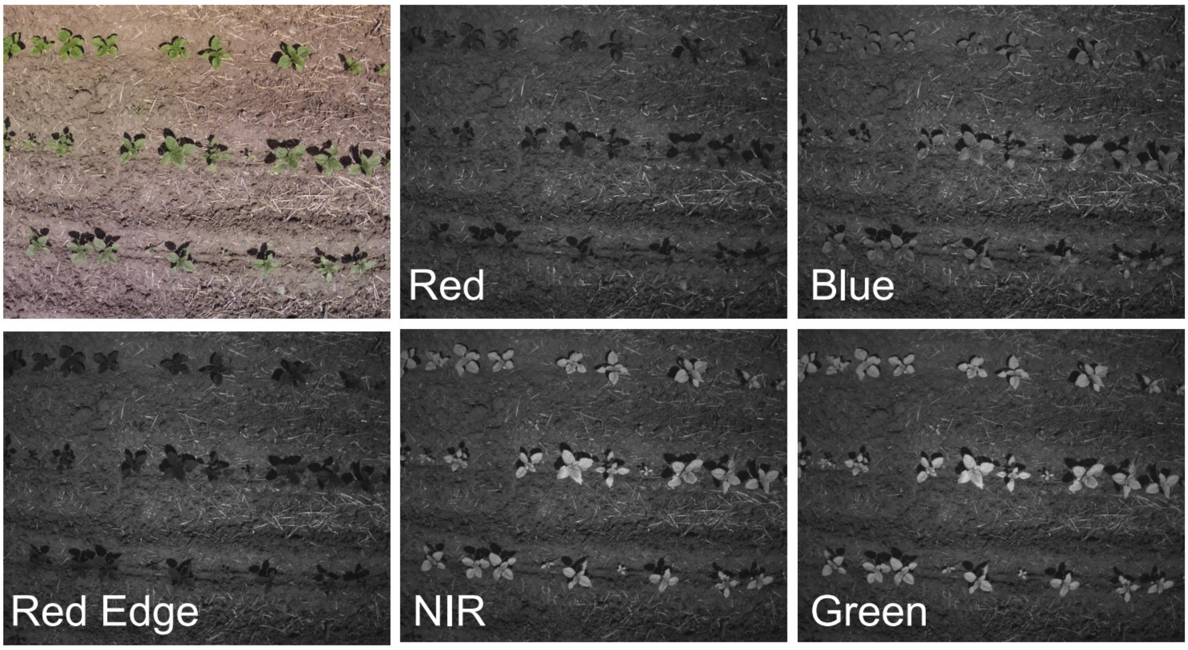

Figure 1. RGB and five spectral images in the corresponding bands.

Each image is georeferenced with its center point coordinates and the UAV’s altitude at the moment of acquisition. This information is recorded in the image’s

EXIF (Exchangeable Image File format) metadata, along with camera and light sensor calibration data. The pixel values of the single-band TIFF images contain the raw, unitless, 16-bit integers, also known as digital numbers (DN). They correspond to the light intensity received at the camera's sensor matrix. This value can be converted to reflectance with a radiometric calibration method or can be used directly in the vegetation index formulae.

Aerial images (120 m) were taken on all of the 12 studied dates with 75% front and 60% side overlap. They were later post-processed with DJI Terra [9] for panoramic reconstruction and orthorectification and resulted in one orthophoto per date, for each band. The ground sampling distance (GSD) at the given altitude of 120m is 6.35cm/px.

Low-altitude photos were initially acquired from an altitude of 2 m on the first four dates. As plants grew, the altitude was increased to 5 m and additional altitudes of 10 m, 20 m, and 40 m were introduced in the later observations. Each low-altitude mission covers 32 waypoints, resulting in 32 RGB images and 160 spectral images, a total of 192 images per single altitude.

Orthophotos and low-altitude images were organized into directories with a total size of 30 GB and published in the dataset mentioned above.

1.4 Applications for Sunflower Monitoring

The collected data is not limited to acquiring UAV multispectral imagery. Incorporating novel numerical and machine learning methods and applied mathematical modeling techniques that elevate the work beyond a descriptive remote-sensing study, it can be used for many purposes in the context of sunflower crop management.

One possible use is to compare the applicability of various vegetation index formulae to the different plant development stages. Many vegetation indices can be calculated from the bands available in the dataset, but their performance will vary depending on the plant development stage.

The vegetation-index computation integrates nonlinear algebraic formulations**.** For example, the Modified Soil Adjusted Vegetation Index (MSAVI) [10], Eq. (1), is a type of vegetation index that uses the R and NIR bands, and is usually preferred when vegetation cover is sparse. This index is a mathematically derived transformation designed to stabilize spectral responses under variable illumination and background conditions.

$$\mathrm{MSAVI} = \frac{2\mathrm{NIR} + 1 - \sqrt{(2\mathrm{NIR} + 1)^2 - 8(\mathrm{NIR} - \mathrm{RED})}}{2} \quad (1)$$

The NDVI, Eq. (2), another widely used vegetation index, employing the same bands to measure vegetation density, works better when the field has a sufficient vegetation cover [11].

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (2)$$

Both indices are then used as predictors in regression or machine-learning models for early-stage plant density estimation.

Spectral characterization

Plant density can be estimated directly from the spectral reflectance using regression models such as support vector regression, random forest, gradient boosted regression trees, etc. [12]. The machine learning model f(·) parameterized by weights Θ maps an input crop image $X_i \in \mathbb{R}$^{H × W × C} to a predicted continuous spatial density map $\{Y\}_i \in \mathbb{R}$^{H × W}, Eq. (3):

$$\{Y\}_i = f(X_i; \Theta) \quad (3)$$

Object detection and segmentation

Yet another use of the dataset is to train object detection or segmentation models on the multispectral low-altitude images, for the purposes of plant counting and phenotyping.

Due to the large data volumes, authors suggest the use of real-time object detectors, such as the YOLO family of models [13] or the more contemporary, transformer-based D-FINE [14] detection model, but with an adaptation to multispectral data. This research direction is important, since most of the leading pretrained object detection and segmentation models are restricted to RGB data and don't operate on multispectral images without adaptation.

1.5 Conclusions

This paper explored an approach for multispectral UAV data collection for early-stage monitoring of sunflower crops. Multispectral images were acquired in both low-altitude, high-resolution and aerial, low-resolution settings. Twelve observation sessions were conducted over a 3-month period.

The collected data underwent pre-processing, orthorectification, and consolidation. The integration of mathematical methods and machine learning algorithms extends beyond data collection and serves as a basis for further research in precision agriculture. Published as an open dataset, this data can also be used by other researchers in the field.

1.6 Acknowledgments

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