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Funded by the European Union (Grant n. 101086216). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or REA. Neither the European Union nor the granting authority can be held responsible for them.

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Operational Group (OG)

GO SURF

OG funding

OG SURF is a project funded by PRS Feasr 2014 – 2022 of Regione Toscana, sub-provision 16.2

“Support for pilot and cooperation projects”

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Index

Index of figures

Index of tables

Drones and multispectral cameras in forest health monitoring (FHM)

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Abstract

Forest Health Monitoring (FHM) is essential for assessing and maintaining the health of forest ecosystems, especially in the context of climate change. While traditional in situ surveys are limited by subjectivity, logistical complexity, and high costs, remote sensing (RS) offers a more efficient alternative. Among RS technologies, Unmanned Aerial Vehicles (UAVs) equipped with multispectral cameras have proven particularly effective. These drones provide high-resolution, cost-effective, and flexible monitoring solutions, capturing detailed data across various wavelengths. This enables precise identification of vegetation stress and damage, facilitating timely and targeted interventions. As demonstrated by the GO-SURF project, UAVs with multispectral sensors are becoming indispensable tools for sustainable forest management.

1. Introduction

Forest Health Monitoring (FHM) is a process aimed at assessing the health status of forest ecosystems (Trumbore et al. 2015). This monitoring involves observing and recording various indicators, such as the degree of defoliation, the presence of diseases or pests, and other signs of stress. The main goal of FHM is to promptly detect any changes in forest health in order to take measures to mitigate damage and preserve the health of forest ecosystems (Ecke et al. 2022).

Establishing FHM systems is particularly relevant in the context of climate change, where vegetation increasingly experiences stress effects with a loss of photosynthetic activity (Puletti et al. 2019), and where extreme events such as fires and insect infestations (Kautz et al. 2024) and other pathogens are becoming more impactful. Therefore, it has become increasingly important and essential for every forest manager, both public and private, to establish FHM monitoring systems to mitigate potential problems in the forest stands and to intervene promptly.

In the Italian and European context, in situ forest health monitoring has been carried out for several decades at local, regional, and global levels, using standard indicators based on field surveys conducted by trained personnel who, for example, identify the degree of crown defoliation (Canullo et al. 2012). These monitoring networks provide a standardized framework for assessing forest health, though at a limited number of points, allowing for national-scale monitoring, but not aligning with the needs of forest managers. Public and private forest managers increasingly face the impact of forest disturbances on their stands and, as previously mentioned, it is crucial to implement FHM monitoring systems that promptly identify potential problems, enabling timely mitigation interventions.

However, classic in situ surveys conducted by operators present a high degree of uncertainty because the quality depends on the experience and subjective perception of the observers. Therefore, specific training courses are necessary to carry out surveys in a standardized and optimal manner. Moreover, in situ surveys are logistically complex and costly in terms of time and labor, making them feasible only at the plot or single parcel scale. For this reason, remote sensing (RS) has established itself as part of FHM, allowing the acquisition of forest health indicators in an objective, quantitative, and repetitive manner at various spatial scales (Lambert et al. 2013; Ecke et al. 2024).

In this context, satellite-based remote sensing still dominates research and applicability in the FHM sector. Indeed, publicly accessible multispectral image data such as Landsat, MODIS, and Sentinel-2, allow for monitoring systems over large areas, thanks to the temporal and spatial resolution that is often sufficient to identify disturbances (Francini and Chirici 2022). However, as highlighted by some research, satellites can present difficulties in monitoring, for example due to cloud cover (Giannetti et al. 2021) that can obscure portions of the forest, making it challenging in some contexts, such as the mountainous areas of the Alps and the Apennines, to establish early warning systems. These issues, for instance, are incompatible when biotic or abiotic factors cause rapid changes in forests. To overcome these problems, manned aircraft can meet these requirements because they can fly below the cloud cover (Ecke et al. 2024). However, in practice, due to high costs and logistical limitations, they are used only annually or biennially over large areas. This makes them, in fact, not suitable for early identification of stress (Ecke et al. 2024).

It is in this context that UAVs have found increasing use, not as competitors but as a complementary technology to traditional Earth observation platforms (Ecke et al. 2024). In the context of the Go-SURF Operational Group, drones equipped with multispectral cameras have been used to map stress in forest stands. UAVs, compared to satellites and aircraft, cover smaller areas but are unbeatable in spatial resolution, which can reach a Ground Sampling Distance on the order of centimeters. They are also very efficient in terms of costs, flexibility, and especially revisit times, which can be frequent as they depend only on the operator.

The area that can be covered with these UAV ranges from one hectare to several square kilometers in a single flight. The coverage is mainly influenced by the type of UAV, propulsion technology, camera type, terrain type, and area accessibility. Also, UAV operation regulations must be considered as a limiting factor for coverage. However, the new European regulation allows flying at an altitude of 120 meters above ground level with a buffer distance of 500 meters, which allows even the most performant drones to comfortably cover 10-20 hectares in a single flight.

However, besides the drone, what makes the difference in establishing an FHM system is the sensor the drone can carry onboard. Recently, numerous new multispectral cameras have become available on the market. These cameras, thanks to their ability to capture different wavelengths of the electromagnetic spectrum, can be used to map various types of forest stress (Barzagli et al. 2018; Zhang et al. 2019; Ecke et al. 2022).

Nevertheless, the variety of cameras available on the market and the various vegetation indices that can be derived from them make it difficult to navigate a constantly evolving research and technical advancement landscape. For this reason, this article aims to provide an overview of vegetation indices useful for mapping forest stress, an overview of some of the cameras available on the market, and the most straightforward or promising processing techniques, based on the results of the EIP-AGRI GO-SURF and also considering international literature, to offer useful information to technicians involved in forest monitoring.

2. Multispectral Cameras and Vegetation Indices

Multispectral cameras are advanced imaging devices that capture visual information across different bands of the electromagnetic spectrum. These bands can include the visible spectrum (red, green, blue) and the near-infrared (NIR), and in some cases, the red-edge near-infrared. By using these various wavelengths, multispectral cameras provide detailed data that can be used to analyze various aspects of vegetation, soil, and forests. Specifically, thanks to the ability to acquire information in the infrared spectrum, it is possible to investigate the photosynthetic activity of plants, assess tree health, and highlight the presence of diseases or other types of stress. Like RGB cameras, they can be used for photogrammetric acquisitions that allow the derivation of not only 2D data (multispectral orthomosaic) but also 3D data such as point clouds and digital surface models (DSM) useful for analyzing forest structure (Barzagli et al. 2018; Giannetti et al. 2020).

However, their main advantage, as previously mentioned, is their ability to capture images in different wavelengths of the electromagnetic spectrum, allowing operators to distinguish variations in chlorophyll content in vegetation that can promptly indicate the presence of stress, diseases, or pathogens. Indeed, thanks to the ability to acquire information at different wavelengths, they can be easily used to derive various vegetation indices through simple mathematical operations between the images of different bands, also using common GIS applications like QField through the raster calculator functions.

Among the vegetation indices that can be calculated, we report those in Table 1, which are the most promising for monitoring stress in forest environments and can be calculated with currently available multispectral cameras.

Table 1. Vegetation Indices Useful for Forest Monitoring That Can Be Calculated with Multispectral Cameras

Vegetation Index	**Formula**
NDVI (Normalized Difference Vegetation Index)	$NDVI = \frac{NIR-Red}{NIR+Red}$
NDRE (Normalized Difference Red Edge)	$NDRE = \frac{NIR-RedEdge}{NIR+RedEdge}$
GNDVI (Green Normalized Difference Vegetation Index)	$GNDVI = \frac{NIR-Green}{NIR+Green}$
LCI (Leaf Chlorophyll Index)	$LCI = \frac{RedEdge-Red}{RedEdge+Red}$

SAVI (Soil-Adjusted Vegetation Index)	$SAVI = \frac{(1+L)(NIR-Red)}{NIR+Red+L}$ where L is a constant depending from the soil conditions (tipically L= 0.5)
OSAVI (Optimized Soil-Adjusted Vegetation Index)	$OSAVI = \frac{(NIR-Red)}{NIR+Red+0.16}$
MCARI (Modified Chlorophyll Absorption Ratio Index)	$MCARI = \frac{(RedEdge-Red)-0.2x(RedEdge-Green)}{RedEdge+Red}$
CIRE (Chlorophyll Index Red Edge) EVI (Enhanced Vegetation Index)	$CIRE = \frac{NIR}{RedEdge} - 1$
EVI (Enhanced Vegetation Index)	$EVI = 2.5\ x \frac{NIR-Red}{NIR+6xRed-7.5xBlu+1}$
VARI (Visible Atmospherically Resistant Index)	$VARI = \frac{Green-Red}{Green+\ Red-Blue}$

The NDVI (Normalized Difference Vegetation Index) is perhaps the most widely used index for monitoring plant health. However, its tendency to saturate can sometimes hinder the early detection of stress in forests. The index is based on the fact that chlorophyll in living plants strongly reflects near-infrared (NIR) light and absorbs red light. High NDVI values, close to 1, indicate dense and healthy vegetation, while lower values below 0.7 suggest stress, and values below 0.6 indicate plant death. However, according to the experience of the GO-SURF project and the literature review in the context of poplar cultivation (Chianucci et al. 2021), NDVI may be the least accurate index for detecting stress.

For instance, the GNDVI (Green Normalized Difference Vegetation Index) is more sensitive for early warning of stress. This index is similar to NDVI but uses the green band instead of the red band for normalization with the NIR band. This makes it useful for monitoring plants with high leaf density or identifying water stress, allowing for early warnings (Raddi et al. 2021). For assessing chlorophyll content, the LCI (Leaf Chlorophyll Index) is very sensitive to the chlorophyll present in leaves (Gallardo-Salazar et al. 2023). Chlorophyll absorbs red light and reflects red-edge light, making this index useful for directly estimating chlorophyll content, which is an indicator of the plant's photosynthetic capacity. Similarly, the CIRE (Chlorophyll Index Red Edge) is even more correlated with the nutritional status of plants (Kleinsmann et al. 2023).

The NDRE (Normalized Difference Red Edge) is particularly useful for identifying plant stress in canopy sections. The Red Edge is very sensitive to changes in leaf structure and chlorophyll content, allowing for the detection of small variations (Minařík and Langhammer 2016). It is useful for identifying plants that may be affected by diseases or nutritional deficiencies before these issues are visible to the naked eye. The MCARI (Modified Chlorophyll Absorption Ratio Index) is designed to be less sensitive to soil variations, enhancing the ability to detect plant stress in heterogeneous environments with exposed soil (Zou et al. 2019). For evaluating photosynthetic activity and vegetative vigor, the EVI (Enhanced Vegetation Index) improves sensitivity in high-density vegetation areas and reduces atmospheric and soil interferences compared to NDVI. The VARI (Visible Atmospherically Resistant Index) can be used to monitor vegetation using only the visible bands, making it useful in conditions where NIR bands are unavailable, such as with RGB cameras.

3. Drones and Multispectral Cameras on the Market

Among drones with an integrated multispectral sensor, the DJI Mavic 3M combines a 20 MP RGB camera and four 5 MP multispectral cameras that capture in the green (560nm±16nm), red (650nm±16nm), red-edge (730±16nm), and NIR (860nm±26nm) bands, along with an integrated light sensor. This setup captures solar irradiance, allowing for post-processing compensation for any light fluctuations in the images. The manufacturer claims a flight autonomy of 43 minutes with a coverage per flight of 2 km^2. The drone is also available with an RTK module, providing precise georeferencing of the survey with high accuracy.

Another DJI drone with an integrated sensor is the P4 Multispectral, equipped with six different cameras of 2.08 MP—one RGB camera and five multispectral cameras capturing in the blue (450±16nm), green (560±16nm), red (650±16nm), red-edge (730±16nm), and near-infrared (840±26nm) bands. This drone also features a light sensor and RTK module for light correction in the image and precise georeferencing of the survey. The manufacturer claims a flight autonomy of 27 minutes and a maximum operational area per flight of 0.63 km². In a recent study in Germany (Ecke et al. 2024), this drone was used to acquire high-resolution multispectral images of 235 different large-scale forest monitoring areas (ICP Level-I plots) distributed in Bavaria over a three-year monitoring period (2020-2022). Despite the heterogeneous dataset acquired over time under various weather and lighting conditions, in forests with diverse compositions spread over a large study area, the article demonstrates how it was possible to classify five tree species, at the genus level, dead trees, and the health status of the main tree species into 14 different classes using the EfficientNet CNN architecture. The article highlights that this monitoring methodology can significantly reduce field acquisition costs and times, allowing for data standardization.

Among the cameras that can be mounted on various types of drones, such as the DJI Matrice 300, Wingtra One Gen II, and senseFly eBeeX, the MicaSense RedEdge-MX stands out as one of the most efficient but also one of the most expensive. This camera captures images in the blue (475nm±20nm), green (560nm±20nm), red (668nm±10nm), red-edge (717nm±10nm), and near-infrared (840nm±40nm) bands, offering high spectral precision and consistency, making it ideal for analyzing forest vegetation. The camera is equipped with a light sensor and a reflectance panel for calibration, which must be captured at the drone's takeoff and landing.

This camera was also tested in the GO-SURF project, where it was used to acquire images of various areas in the Tuscany region using the Wingtra One Gen II drone. Image processing through segmentation techniques based on the "Simple Linear Iterative Clustering (SLIC)" method (Achanta et al. 2012) allowed the identification of dead and declining plants by identifying stress thresholds. SLIC is an algorithm used for image segmentation, particularly for creating superpixels—groups of contiguous pixels with similar characteristics, which simplify image analysis by reducing the number of elements to consider while maintaining most of the relevant information. Specifically, in the GO-SURF project, multispectral images were processed using photogrammetric software Metashape Agisoft to generate an orthomosaic in different bands (blue, green, red, red-edge, near-infrared). The images were imported into R-Cran software, using various processing packages to initialize the algorithm. During initialization, the algorithm uniformly distributes superpixel centers across the image. These centers are chosen to cover the entire image uniformly. Each pixel in the image is then assigned to the nearest superpixel center based on combined distance (space and color). The combined distance considers both spatial coordinates and color values (CIELAB space). The algorithm iterates until it segments the individual canopies. This algorithm can also be used through desktop software like SAGA GIS. Tests conducted in the GO-SURF project showed that forest environment segmentation works very well even using only the red-edge band, not multiple bands. This band seems most sensitive to identifying individual canopies or canopy portions with similar photosynthetic activity. The segmentation method reduces time compared to complex methods and accurately detects individual canopies or canopy portions with different photosynthetic activities, such as dead or declining canopy portions. However, to classify different decay classes (dead canopy portion, declining canopy portion, live canopy portion), vegetation indices need to be extracted from the polygons generated by SLIC, calibrating thresholds to identify dead plants. Thus, for each superpixel, thresholds are applied to vegetation indices to classify superpixels as representing healthy, stressed, or dead plants. The advantage of this method is that superpixel segmentation reduces the number of units to analyze, making the analysis faster and more efficient. Additionally, superpixels tend to follow the natural contours of plants, improving classification accuracy compared to single-pixel methods.

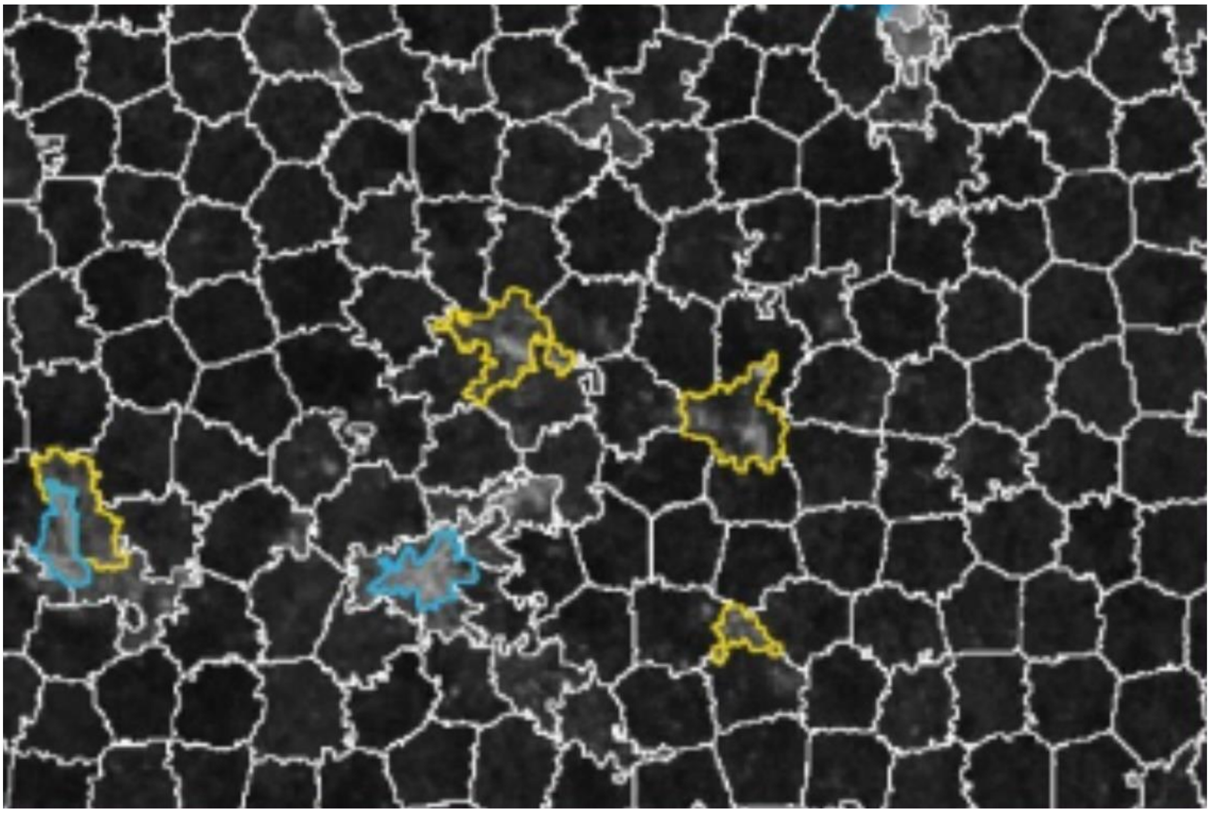

Figure 1. Identification of Superpixels with White Contours, Detection of Declining Canopy in Yellow, and Dead Canopy Portions in Blue

The use of SLIC Superpixels in drone imagery represents an advanced technique for identifying and monitoring dead plants. By segmenting images into homogeneous regions and applying thresholds on vegetation indices, it is possible to obtain an accurate map of problematic areas, allowing for timely and targeted interventions in crop management.

Among other multispectral cameras on the market at a lower cost compared to those previously mentioned are the Parrot Sequoia, the Sentera Double 4K, the Mapir Survey3, and the Mapir Survey2. All these cameras, like the others, acquire multispectral information in the red, blue, green, and near-infrared bands, but not in the Red-Edge near-infrared. This makes them less effective in calculating some of the indices previously mentioned.

4. Conclusions

It is impossible to have a complete overview of all the cameras available on the market at this time. However, based on our experience, it is essential to focus on those cameras that allow for the calculation of different vegetation indices, which can contribute to accurately mapping potential damage. This is because it is increasingly important to be able to intervene promptly. Despite some limitations, drones equipped with multispectral cameras represent a powerful and versatile tool for forest monitoring, as demonstrated by the GO-SURF project already implemented at the Italian level. It is anticipated that further technological developments and increasing accessibility to drones will make these tools increasingly fundamental in sustainable forest management.

5. Acknowledgments

This contribution has been made within the framework of the FOREST4EU project, funded by the European Union's Horizon Europe Research and Innovation Programme under Grant Agreement N° 101086216.

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