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Multispectral Reconnaissance of Operational Areas²

Abstract

Multispectral and hyperspectral imaging offer complementary capabilities for remote reconnaissance by sampling reflected energy in several optical wavelength bands. This study evaluates their suitability for operational area monitoring, with an emphasis on light-weight, drone-borne sensors. A theoretical overview explains how spectral signatures arise from electronic transitions and molecular vibrations, leading to characteristic vegetation and soil reflectance patterns. Common vegetation and moisture indices are introduced, noting their sensitivity to chlorophyll content, water absorption and the limitations of MSI sensors lacking short-wave infrared bands. Remote-sensing platforms including handheld spectrometres, satellites and unmanned aerial vehicles are compared. UAVs equipped with multispectral cameras offer a favourable balance of spatial resolution, cost and ease of deployment. The DJI Mavic 3 Multispectral is selected for field experimentation due to its integrated four-band sensor (green, red, red-edge, near-infrared), sunlight sensor and RTK positioning. Other MSI cameras (MicaSense RedEdge-MX, Parrot Sequoia+) and representative hyperspectral cameras are briefly reviewed, highlighting tradeoffs in weight, spectral resolution and cost. A case study over a military training ground uses the M3M to acquire two flights – before and after a rain event – and processes the images using WebODM, QGIS and MATLAB. Vegetation indices map plant vigour and relative soil moisture, and change detection highlights vehicle tracks and wet areas. Results demonstrate that NDRE remains linear at high biomass and that simple red-edge metrics sensitively capture moisture changes despite the absence of SWIR. While the Mavic 3M lacks a blue band and SWIR band limits the calculation of some water related indices, its portability and affordability make it a valuable tool for rapid reconnaissance. The paper concludes by discussing future directions, including the integration of machine learning and additional sensors to enhance material identification and real-time processing. The index-based analysis is explicitly interpreted

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as relative operational change detection rather than absolute biomass, reflectance or soil-moisture retrieval, because independent ground-reference measurements were not available during the field campaign.

Keywords: IMINT, CUAV, multispectral, hyperspectral imaging systems, image processing

Introduction

Remote sensing platforms have become indispensable for military and civil reconnaissance because they can monitor large areas without exposing human observers to danger. Multispectral (MSI) and hyperspectral (HSI) imaging systems capture reflected electromagnetic energy in a few or many optical wavelength bands, permitting analysts to infer material composition, vegetation health or land-use changes. In an operational context, the ability to detect footprints, vehicle tracks or the emergence of new objects relative to baseline imagery can provide early warning of adversary activities.³ In defence applications both the visible and thermal bands are widely used, but the application of narrow-band spectral processing in operational contexts remains an active area of research. The paper therefore moves in a deliberate sequence: it first reviews the physical background of spectral imaging, then compares the main sensing platforms and sensor categories, finally presents a drone-based case study to show how these principles translate into operational area monitoring in practice.

Physical background of spectral reconnaissance

Spectral imaging involves measuring the distribution of reflected or emitted electromagnetic energy as a function of wavelength. Multispectral imaging captures radiation in a limited number (e.g. 4–20) of broadbands using filters tailored to particular phenomena such as vegetation or water absorption. Hyperspectral imaging acquires hundreds of contiguous narrow bands ($\Delta\lambda \approx 1\text{--}10\text{ nm}$), effectively recording a full reflectance spectrum at each pixel. The key difference is therefore spectral resolution: HSI provides a quasi-continuous spectrum enabling subtle material identification, whereas MSI offers selected bands and is often sufficient when speed, cost and ease-of-use are paramount.⁴

The advantage of HSI is its ability to detect narrow absorption features associated with electronic transitions (e.g. chlorophyll absorption in the red) or molecular vibrations (e.g. water and hydroxyl bands in the short-wave infrared). However, hyperspectral instruments are heavier, more expensive and yield very large data volumes, which limits their use on small drones. Multispectral sensors, by contrast, use a handful of filters corresponding to specific phenomena (green, red, red-edge,

³ RAM et al. 2024.

⁴ RAM et al. 2024.

near-infrared), enabling lightweight and relatively inexpensive cameras that can be flown on compact drones such as the DJI Mavic 3 Multispectral (M3M). Their lower spectral resolution reduces the ability to unambiguously identify minerals or distinguish among similar vegetation types, but their simplicity and high spatial resolution make them attractive for operational reconnaissance tasks where rapid coverage is critical.⁵

Spectral signatures and material identification

Materials possess characteristic spectral signatures that arise from fundamental physical processes. In the visible and near-infrared (VNIR) region ($\approx 400\text{--}1,000\text{ nm}$) absorption is dominated by electronic transitions in pigments and minerals. For vegetation, the chlorophyll-a and chlorophyll-b molecules embedded in the thylakoid membranes of chloroplasts have strong absorption around $400\text{--}500\text{ nm}$ and $650\text{--}680\text{ nm}$ because of their molecular structure. The strong absorption in the red ($\approx 680\text{ nm}$) explains the low red reflectance of green leaves, while the decrease in absorption beyond 700 nm and the high internal scattering in leaf mesophyll cause a sharp rise in reflectance known as the red edge.⁶ Rocks and dry soils have weak absorption patterns because of metal ions and vibrations in their crystal structure, while water and hydroxyl groups absorb much more strongly in the short-wave infrared part of the spectrum at wavelengths longer than $1,000\text{ nm}$.⁷

Vegetation and soil spectral behaviour

The spectral behaviour of vegetation and soil can be explained by combining molecular absorption and canopy structure. Healthy leaves have low reflectance in the blue and red due to chlorophyll absorption, a steep red edge between $680\text{--}750\text{ nm}$ and high reflectance in the near-infrared due to multiple scattering within the spongy mesophyll. The position and slope of the red edge are sensitive to chlorophyll content, leaf structure and stress, which is why many sensors include a red-edge band.⁸ Dry soil exhibits relatively high reflectance across the visible and near-infrared, with gentle slopes and minimal absorption features; moisture darkens the soil and introduces absorption features around $1,450\text{ nm}$ and $1,950\text{ nm}$ (SWIR – Short Wave Infrared), so indices combining near-infrared and SWIR bands are often used to estimate soil water content.⁹

⁵ RAM et al. 2024.

⁶ GITELSON–MERZLYAK 1998.

⁷ TEIXEIRA et al. 2025.

⁸ DU et al. 2025.

⁹ TEIXEIRA et al. 2025.

Vegetation and moisture indices

Because multispectral sensors sample only a few bands, analysts often derive indices to enhance contrast between features of interest. The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), defined as

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$$

where ρ denotes reflectance, NIR is Near Infrared and R stands for Red. NDVI exploits the contrast between low red reflectance and high near-infrared reflectance. It correlates with vegetation vigour and is widely used for yield prediction, crop classification and irrigation management. The simplicity and general applicability of NDVI make it popular, but it saturates in dense vegetation and is sensitive to soil background and atmospheric effects. Other formulations, including soil-adjusted and red-edge-based indices, are often used to mitigate these limitations while preserving simple physical interpretation.¹⁰

For clarity, the notation used in the index equations refers to band-specific reflectance values rather than to wavelengths alone: ρ_{NIR} , ρ_R , ρ_{RE} , ρ_G and ρ_{SWIR} denote the measured reflectance in the near-infrared, red, red-edge, green and short-wave infrared bands, respectively. This distinction is important because the indices are calculated from reflectance values acquired in the corresponding spectral bands, not from the nominal band-centre wavelengths.

In unambiguous reflectance notation, the formulas can be written as: $NDVI = (\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R)$, $NDMI = (\rho_{NIR} - \rho_{SWIR})/(\rho_{NIR} + \rho_{SWIR})$, and $NDRE = (\rho_{NIR} - \rho_{RE})/(\rho_{NIR} + \rho_{RE})$.

Moisture indices combine bands sensitive to water absorption. The Normalized Difference Moisture Index (NDMI) uses near-infrared and SWIR reflectances

$$NDMI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$$

to estimate vegetation or soil water content. The NDMI requires a SWIR band, so cameras lacking SWIR (e.g. M3M) cannot compute it directly. The Normalized Difference Water Index (NDWI) has multiple definitions; one common formulation uses green and NIR bands and is used to highlight open water.¹¹ Other indices, such as the Perpendicular Drought Index (PDI), calculate distances in the red-NIR reflectance space relative to a soil line to quantify soil moisture. Red-edge (RE) based indices like the Normalized Difference Red-Edge Index (NDRE)

$$NDRE = \frac{\rho_{NIR} - \rho_{RE}}{\rho_{NIR} + \rho_{RE}}$$

¹⁰ ROUSE et al. 1974.

¹¹ GAO 1996.

are sensitive to chlorophyll content and may complement NDVI when red-edge data are available.¹²

In this study, the NDWI calculation was used in a relative operational sense rather than as an absolute soil moisture retrieval method. Since the DJI Mavic 3 Multispectral does not include a SWIR band, SWIR-based moisture indices cannot be computed directly. Therefore, the green–NIR formulation of NDWI was applied

$$NDWI = \frac{\rho G - \rho NIR}{\rho G + \rho NIR}$$

where ρG and ρNIR denote the reflectance values measured in the green and near-infrared bands, respectively. This formulation is commonly used to enhance water-related spectral contrast, but in the present case it is interpreted as a relative indicator of surface wetness and post-rainfall changes. Without independent ground reference measurements, reflectance panel calibration or SWIR data, the resulting NDWI values should not be interpreted as absolute soil water content. Instead, they support the identification of spatial anomalies, wet areas and temporal changes when compared with a baseline acquisition. In operational reconnaissance, this relative interpretation is often sufficient, because the main objective is the rapid detection of disturbed surfaces, vehicle tracks and moisture-related changes rather than the quantitative retrieval of biophysical parameters.

Remote-sensing platforms and sensor selection

Ground truth measurements are essential for calibrating and validating airborne data. Handheld spectrometres measure reflectance spectra with fine spectral resolution and are often used to build spectral libraries or calibrate drone imagery. Their advantages include high spectral accuracy and flexible deployment, but they sample only a few points, so they cannot map large areas quickly. In operational reconnaissance, handheld spectrometres may be used to characterise materials in the field (e.g. soils, vegetation, camouflage fabrics) and to train classifiers that will later be applied to airborne imagery.¹³

Satellite remote sensing

Satellites provide consistent, large-scale coverage and free imagery. The Sentinel-2 mission of the European Space Agency (ESA) offers multispectral data at 10–60 m ground resolution with bands in the visible, red-edge and SWIR regions (Figure 1).¹⁴ Their long revisit history supports temporal monitoring, but spatial resolution generally remains

¹² GITELSON–MERZLYAK 1998.

¹³ RAM et al. 2024.

¹⁴ DRUSCH et al. 2012.

too coarse for routine detection of very small disturbances such as individual vehicle tracks when compared with centimetre-level UAV imagery.¹⁵



Figure 1: Sentinel-2 SWIR image of research operational area

Source: picture made by the author

UAVs and drone-based remote sensing

UAVs bridge the gap between ground measurements and satellites by providing high-resolution imagery (centimetre-level ground sampling distance) over user-defined areas. Drones can be flown below clouds and scheduled on demand, making them ideal for reconnaissance tasks. The choice of sensor depends on the mission: multispectral cameras like the DJI M3M, MicaSense RedEdge-MX or Parrot Sequoia capture a few targeted bands, while hyperspectral scanners such as the Headwall Micro-Hyperspec or Cubert ULTRIS provide dozens to hundreds of bands but are heavier and more expensive. In practice, MS cameras mounted on small quadcopters provide a good tradeoff between resolution, weight and cost.¹⁶

Representative multispectral cameras

- MicaSense RedEdge-MX: A widely used UAV multispectral sensor family in environmental and agricultural remote sensing. Published studies show that

¹⁵ DRUSCH et al. 2012.

¹⁶ SOUSA et al. 2022.

RedEdge systems can generate research-grade reflectance products, but they also emphasise that radiometric calibration remains a critical step for reliable quantitative analysis.¹⁷

- Parrot Sequoia (Figure 2): A lightweight four-band multispectral camera with a sunshine sensor, widely used in precision-agriculture and UAS radiometry studies. Published evaluations report useful geometric and radiometric consistency, while also noting that calibration and processing strategy strongly affect the final reflectance products.¹⁸
- DJI Mavic 3 Multispectral (Figure 2): The M3M integrates an RGB camera and a four-band multispectral module (560 ± 16 nm – green, 650 ± 16 nm – red, 730 ± 16 nm – red edge, 860 ± 26 nm – NIR) along with a sunlight sensor and RTK GNSS.¹⁹ A recent field study by Rand and Khan evaluated the M3M for cryospheric research and found that it successfully mapped the spatial distribution of red-snow algae using spectral indices and random-forest classification, assessed snowmelt timing and identified glacial surface features with 68% classification accuracy.²⁰ The authors emphasised the drone's low weight, low cost and ease of use, noting that the principal limitation is the absence of a blue band. The M3M therefore offers an attractive platform for operational reconnaissance and was selected for the case study in this paper.



Figure 2: DJI M3M and Parrot Sequoia multispectral cameras

Source: picture made by the author

¹⁷ DANIELS et al. 2023.

¹⁸ FRANZINI et al. 2019.

¹⁹ DE SOUZA SILVA et al. 2025.

²⁰ RAND-KHAN 2024.

Representative hyperspectral cameras

- Headwall Micro-Hyperspec: a representative push-broom UAV hyperspectral sensor. Such systems provide high spectral fidelity for material mapping, but payload, data rate and scanning requirements make deployment more demanding than with compact multispectral cameras.²¹
- Cubert ULTRIS: a representative snapshot hyperspectral camera. Snapshot systems capture all bands in a single exposure, which simplifies acquisition relative to line scanners, but they typically offer lower spatial sampling and remain costly for routine field deployment.²²
- Specim FX: a representative line-scan VNIR hyperspectral camera widely used in research and industrial settings. Its acquisition requires stable motion and synchronisation, making it better suited to larger airborne platforms than small quadcopters.²³

Platform tradeoffs in operational use

The choice between UAVs, handheld instruments and satellites involves tradeoffs among spatial resolution, spectral resolution, cost and coverage. UAV-mounted multispectral cameras achieve centimetre-level spatial resolution, enabling detection of small objects or footprints, but they measure only a few spectral bands. Hyperspectral sensors provide rich spectral information but are heavier and slower. Satellites cover large areas and include SWIR bands but have coarser spatial resolution and are subject to cloud cover. Handheld spectrometers provide high spectral resolution at point locations. Operational reconnaissance missions often employ UAV-borne multispectral sensors to obtain timely, high-resolution data and combine them with satellite data for broader situational awareness.²⁴

Radiometric and geometric considerations

All remote-sensing systems measure radiance, which must be corrected to reflectance to derive physical indices. Radiometric calibration typically uses a reflectance panel of known albedo and corrects for illumination variability. Geometric correction ensures that the multispectral images align across bands and between acquisition dates. Mismatches can introduce artefacts into indices. In this study, images were orthorectified and mosaicked using software such as WebODM, and the multispectral bands were registered in MATLAB to create a data cube on a smaller scale.²⁵

²¹ SOUSA et al. 2022.

²² SOUSA et al. 2022.

²³ SOUSA et al. 2022.

²⁴ DRUSCH et al. 2012.

²⁵ OLSSON et al. 2021.

Relative index-based assessment without absolute ground reference

The purpose of the index-based analysis in this study is not to derive absolute biophysical parameters, calibrated soil-moisture values or laboratory-grade reflectance spectra. No independent reflectance-panel observations, handheld spectrometre measurements or in-situ soil-moisture measurements were available during the field campaign. Therefore, the analysis is deliberately restricted to normalised spectral indices and relative temporal differences within the same sensor, flight area and processing workflow.

This limitation also reflects a common operational reconnaissance scenario: reference measurements are often unavailable, while rapid information about spatial anomalies, vehicle tracks, wet areas or vegetation disturbance is still required. Under these conditions, normalised indices such as NDVI, NDRE and NDWI are useful because they reduce the influence of absolute brightness differences and allow changes to be interpreted relative to a baseline acquisition. The resulting products should therefore be interpreted as operational change indicators, not as absolute environmental measurements.

Case study and processing workflow

The operational area selected for this case study was a closed military training ground in a temperate environment. Two flights were performed on the same day (10:00 and 13:00 local time) with a rain shower occurring between the flights, providing an opportunity to monitor changes in soil moisture and detect disturbances. A flight plan was created using a georeferenced KMZ file to ensure consistent coverage and overlap. The M3M's RTK module enabled centimetre-level positioning accuracy, reducing the need for ground control points.²⁶

The two acquisitions were consequently treated as a short-term baseline-and-follow-up pair. The morning flight served as the reference state, while the afternoon flight represented the post-rainfall state. Because the objective was rapid reconnaissance rather than absolute calibration, the evaluation focused on whether index differences could reveal spatially coherent changes that are consistent with observable surface disturbance and post-rainfall wetness patterns.

Flight execution and data processing

During each flight, the M3M captured multispectral (green, red, red edge, NIR) and RGB images at approximately 5 cm GSD (Ground Sampling Distance).²⁷ The integrated sunshine sensor recorded ambient irradiance for later radiometric correction.²⁸ After

²⁶ DE SOUZA SILVA et al. 2025.

²⁷ DE SOUZA SILVA et al. 2025.

²⁸ DE SOUZA SILVA et al. 2025.

data was downloaded, each band was separated into different directories. These separated images were imported into WebODM to generate an orthomosaic for each band and RGB, which was further processed with QGIS (Figure 3).²⁹



Figure 3: NIR orthofoto of operational area merged with satellite image

Source: compiled by the author

The multispectral bands were co-registered in MATLAB using cross-correlation and manual tie points to produce a four-band data cube. Vegetation indices and moisture proxies were computed on a per-pixel basis. Because the M3M lacks a SWIR band, the classical NDMI could not be calculated; instead, relative moisture was assessed via changes in red, red-edge and NIR reflectances.³⁰ The difference between the morning and afternoon mosaics provided a proxy for changes induced by rainfall, but meaningful comparison still depended on careful radiometric correction (Figure 4).³¹

Relative change detection workflow

The practical workflow consisted of the following steps:

1. Orthomosaics were generated separately for each spectral band.
2. Multispectral layers were brought onto a common spatial grid.
3. Relative radiometric normalisation was performed on post-rain data.
4. Normalised indices were calculated for each acquisition.
5. Pixel-by-pixel difference maps were produced between the morning and afternoon flights.
6. Spatial patterns in the difference maps were compared with visually identifiable surface features such as tracks, vegetation patches, bare soil and low-lying wet areas.

²⁹ GAAVWASE GBAGIR et al. 2023.

³⁰ TEIXEIRA et al. 2025.

³¹ OLSSON et al. 2021.

This procedure increases the scientific interpretability of the demonstration without claiming absolute validation. The comparison is internally consistent because it uses the same sensor, the same area and a short temporal separation. At the same time, the absence of independent reference measurements means that the output should be reported as relative change evidence. Where numerical reporting is required, the difference maps can be summarised over manually selected image-based regions of interest, for example by reporting mean, median and standard deviation values for disturbed ground, undisturbed vegetation and wet low-lying areas.

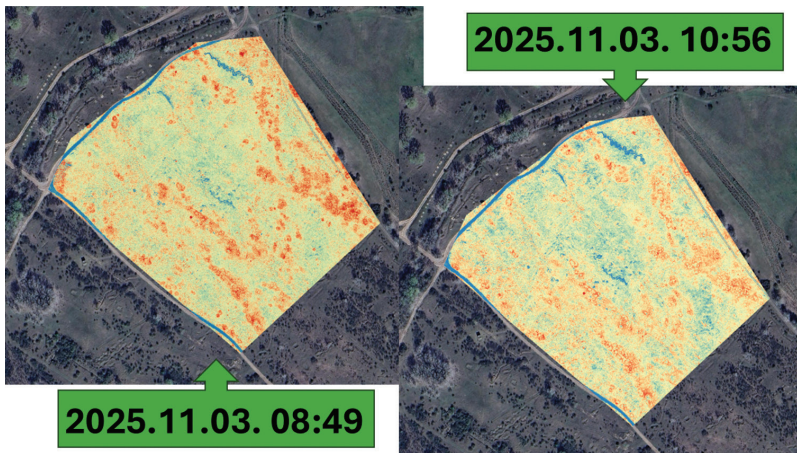


Figure 4: NDWI index of operational area calculated with QGIS before and after rain

Source: compiled by the author

Results and discussion

On the orthomosaic maps, several indices were calculated, analysed and compared between the two measurement sessions. To identify disturbances between flights, pixel-by-pixel subtraction was performed for all the NDVI, NDRE and NDWI maps created during the pre- and post-raining event. Areas where vehicles traversed the ground showed a decrease in NDVI, reflecting crushed vegetation and exposed soil. Conversely, some lower ground areas displayed increased NDWI due to soil darkening and slight increases in red-edge reflectance after the rain. The lack of SWIR limited the ability to quantify absolute soil moisture, but relative changes were evident. These results indicate that multispectral drones can support rapid change detection in operational areas, especially when baseline images are available for comparison.³²

Accordingly, the results are interpreted in comparative terms. A decrease in NDVI over track-like features is considered evidence of relative vegetation disturbance or exposed soil only when the change forms a coherent spatial pattern and differs

³² TEIXEIRA et al. 2025.

from nearby undisturbed vegetation. Similarly, increased NDWI-like response after rainfall is interpreted as a relative wetness-related signal rather than as an absolute soil-moisture estimate. This conservative interpretation directly follows from the lack of independent ground reference data.

To strengthen the quantitative part of the evaluation, the same difference maps can be evaluated with image-based reference regions. Reporting the distribution of ΔNDVI , ΔNDRE and ΔNDWI values for disturbed, undisturbed and wet areas would allow the reader to judge class separability even without external ground-truth measurements. Such statistics are suitable for supporting the operational conclusion because they test whether the observed changes are systematic rather than purely visual.

Spectral data cube analysis

Visualising the four-band data cube in MATLAB's Hyperspectral Viewer allowed exploration of spectral signatures at each pixel (Figure 5). Leafy vegetation showed the expected red absorption and high NIR reflectance.³³ Wet soil in the afternoon flight exhibited lower reflectance across all bands and a reduced red-edge slope.³⁴ Although only four bands were available, principal component analysis separated vegetation, dry soil and wet soil classes, illustrating that even limited spectral data can aid classification (Figure 6). The case study therefore demonstrates the practical value of the M3M for operational reconnaissance tasks.

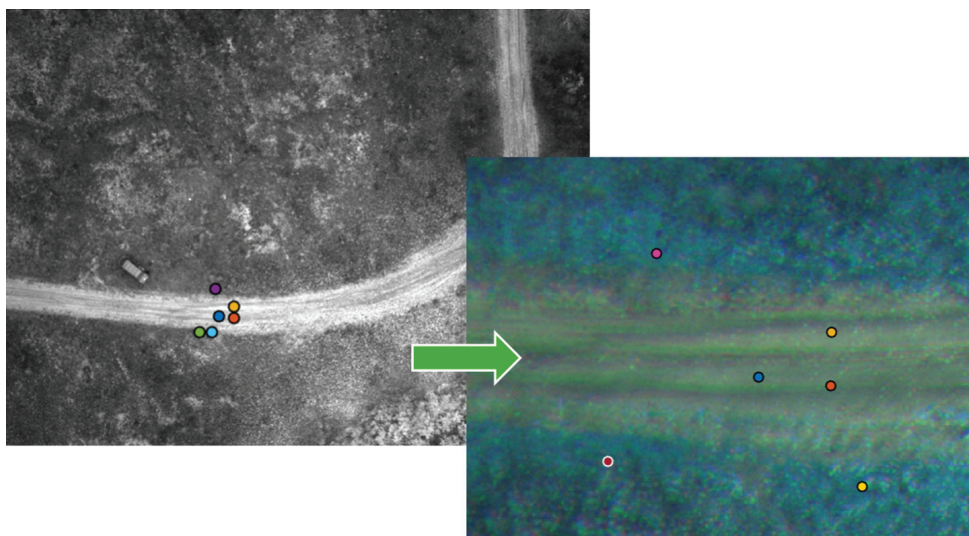


Figure 5: Sample points of spectral measurement on dirt road and vegetation at different points

Source: compiled by the author

³³ GITELSON–MERZLYAK 1998.

³⁴ TEIXEIRA et al. 2025.

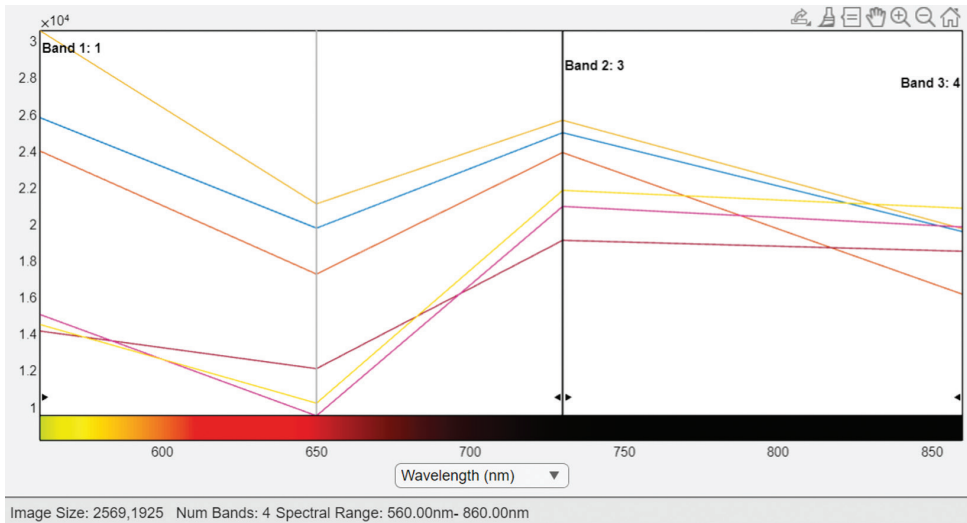


Figure 6: Spectrum of sample points, colour matched

Note: upper three curves connected to dirt road, bottom three curves for vegetation at different areas

Source: compiled by the author

Operational advantages and limitations of the M3M

The DJI Mavic 3 Multispectral provided several advantages for the mission: it is lightweight and easily transported to remote areas, integrates an RTK module for accurate geolocation, and captures both RGB and multispectral data.³⁵ Its bands coincide with those used in common vegetation indices, allowing the derivation of NDVI and NDRE. Its relatively low cost compared with professional systems (e.g. MicaSense RedEdge-MX) makes it accessible to a wider range of users. Nevertheless, there are certain limitations: the absence of a blue band precludes the calculation of some indices like EVI and ARVI. Without SWIR, moisture indices such as NDMI cannot be computed directly; this study used relative red-edge metrics instead. Radiometric calibration is essential to ensure comparability between flights, and changes in illumination (e.g. due to cloud cover) can introduce errors.³⁶ In addition, the limited number of spectral bands and the need for multiple flight lines over larger areas reduce flexibility compared with higher-end modular systems.³⁷

A further limitation of the present case study is the lack of independent absolute reference data. For this reason, statements about moisture and vegetation condition are formulated as relative indicators. The method is therefore most appropriate for rapid change detection, anomaly highlighting and prioritisation of field inspection,

³⁵ RAND-KHAN 2024.

³⁶ DANIELS et al. 2023.

³⁷ RAND-KHAN 2024.

while absolute soil-moisture retrieval or material identification would require reflectance-panel calibration, ground spectrometry or direct field measurements.

Future directions: From indices to artificial intelligence

While indices provide simple, interpretable metrics, emerging applications demand more sophisticated analysis. The next step is to apply convolutional neural networks (CNNs) or other machine learning algorithms to multispectral data to automatically detect changes and classify materials. Deep learning methods can exploit spatial and spectral patterns beyond simple band ratios.³⁸ EdgeAI hardware accelerators could enable on-board processing, reducing data transmission and enabling real-time alerts. However, the limited number of bands in multispectral cameras may restrict performance. Combining multispectral imagery with RGB, thermal or LiDAR data could improve accuracy.³⁹ Additionally, integrating SWIR or hyperspectral sensors would enable absolute soil moisture estimation and more robust material identification.⁴⁰ The inclusion of contextual information such as elevation, slope and historical imagery could further enhance change detection algorithms.

Conclusion

This paper presented a comprehensive overview of multispectral and hyperspectral reconnaissance of operational areas, focusing on drone-based imaging and the DJI Mavic 3 Multispectral. This paper summarises the physics of spectral signatures, reviewed vegetation and moisture indices and explained the tradeoffs among hand-held, drone and satellite platforms. Comparison was performed on commonly used multispectral and hyperspectral cameras and justified the choice of the M3M. A case study showed that the M3M can deliver high-resolution data suitable for vegetation monitoring and change detection, although the absence of SWIR limits absolute moisture estimation. Indices such as NDVI, NDRE and relative red-edge metrics provided useful proxies for vegetation health and soil moisture, and different maps revealed disturbances between flights. Future work should leverage machine learning to extract richer information from multispectral data and explore the integration of additional spectral bands or sensors. The main methodological contribution of the case study is therefore the demonstration of a practical relative index-based workflow for operational change detection under limited-reference field conditions. The results should not be interpreted as absolute soil-moisture or biomass estimates; rather, they show that coherent relative index differences can reveal surface disturbance and post-rainfall wetness patterns when a baseline acquisition is available.

³⁸ RAM et al. 2024.

³⁹ SOUSA et al. 2022.

⁴⁰ TEIXEIRA et al. 2025.

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