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Analyses of Vegetation Spectral Characteristics for Accurate Identification

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ABSTRACT

This study focuses on analyzing the spectral characteristics of vegetation, investigating the spectral signatures of different vegetation types, and identifying the most informative spectral bands for vegetation identification. The interaction between vegetation and electromagnetic radiation creates unique spectral signatures that serve as a fingerprint for classification. The study highlights the significance of various spectral bands, including the Visible Spectrum (Blue, Green, Red), Near-Infrared (NIR), Short-Wave Infrared (SWIR), and Thermal Infrared (TIR), in providing insights into vegetation properties. Vegetation indices, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI), are quantitative metrics used to assess vegetation density, health, and vitality. The findings of this study demonstrate the importance of understanding the spectral characteristics of vegetation and the limitations of vegetation indices. The effectiveness of vegetation indices is influenced by environmental factors, and their application demands careful consideration of the local environmental context. This study contributes to the development of more accurate and robust methods for vegetation identification and classification, using optical satellite images, and has implications for remote sensing applications in environmental monitoring and management.

Keywords: Vegetation spectral signatures, Remote sensing, Vegetation indices, Spectral bands Environmental monitoring

INTRODUCTION

The fundamental basis for identifying vegetation from optical satellite imagery, lies in comprehending how different vegetation types interact with electromagnetic radiation across various spectral bands (Chuvieco, 2020). This interaction creates unique spectral signatures that serve as a fingerprint for classification.

Different surface materials exhibit distinct responses to electromagnetic radiation, reflecting or absorbing energy in specific parts of the spectrum, which makes them detectable by remote sensing instruments (Elachi & Van Zyl, 2021). For vegetation, this spectral signature is a complex interplay resulting from the interaction between incoming light (modified by the atmosphere) and the intricate phylogenetic, biophysical, biochemical, morphological, physiological, and phenotypic traits of the plant (Moor et al., 2017; Paul & Frey, 2023).

A key characteristic of healthy green vegetation is its strong absorption of red wavelengths due to chlorophyll, coupled with a robust reflection in the Near-Infrared (NIR) wavelengths (Hernández-Clemente et al., 2019). The overall spectral signature of a crop canopy, for instance, is not monolithic but rather a mixture of the reflectance from the crop itself, any exposed soil background, and other canopy components

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like stems and weeds (Kuester & Spengler, 2018). The subtle uniqueness in the spectral behavior of different vegetation species, particularly in the precise positions and magnitudes of maxima and minima within their reflectance curves, forms the bedrock for accurate species detection and differentiation (Chen et al., 2023).

MATERIALS AND METHODS

The study is a review work on the existing literature that were conducted on satellite image interpretation and information extraction, specifically, spectral characteristics of vegetation. The study focuses on analyzing the spectral characteristics of vegetation, investigating the spectral signatures of different vegetation types and identifying the most informative spectral bands for vegetation identification. Remote sensing techniques, such as spectral signature analysis and vegetation index calculation, were reviewed to extract information on the application of satellite imagery for vegetation mapping. A comprehensive literature review was conducted to identify the most informative spectral bands and vegetation indices for vegetation identification. The materials that were used, were obtained from google scholar search engine. Initially, the search engine was customized to obtain publications made within the last eight years. However, few studies that were conducted earlier than that, were also used where necessary.

Key Spectral Bands and Their Significance

Optical satellite sensors capture data across various spectral regions, each offering unique insights into vegetation properties.

- **Visible Spectrum (Blue, Green, Red)**: These bands collectively form the Red, Green, and Blue (RGB) composite, which provides a colorful representation of the Earth's surface, akin to what the human eye perceives (Chen et al., 2023).
  - **Blue Band**: This band is particularly valuable for specialized applications such as flower counting and bloom density analysis due to its heightened sensitivity to the presence of flowers (Angel et al., 2025). It enables the clear distinction of flowers from surrounding leaves, where red or green bands might fail to differentiate them. Beyond bloom detection, the blue band is essential for generating true color (RGB) composites, which are fundamental for visual interpretation and context. It also plays a crucial role in the formulation of several vegetation indices, including the Enhanced Vegetation Index (EVI), Green Leaf Index (GLI), and Visible Atmospherically Resistant Index (VARI), and contributes to correcting for atmospheric interference and soil background noise (van der Kooi et al., 2016; Yamaguchi et al., 2008).
  - **Green Band**: Healthy vegetation typically exhibits a local maximum reflectance in the green spectral region, as some green light is reflected rather than absorbed by chlorophyll (Buschmann et al., 2012).
  - **Red Band**: In contrast, vegetation shows a local minimum reflectance in the red spectral region, a direct consequence of strong absorption by chlorophyll for photosynthesis (Ustin & Jacquemoud, 2020).
- **Near-Infrared (NIR)**: The NIR band is profoundly informative, revealing crucial details about vegetation health and vigor that are imperceptible to the human eye (Sarvakar & Thakkar, 2024). Vegetation strongly reflects in the NIR region due to its cellular structure, making it a powerful indicator of photosynthetic activity and overall plant health (Glenn et al., 2008). Studies have shown that the near-infrared band can explain a significant portion (41%) of the variance in species richness, while visible wavelengths contribute far less predictive power (Rocchini et al., 2007). This observation has led to the conceptualization of a "near infrared way" for assessing species richness directly from remotely sensed data. A common practice involves combining Near-Infrared, Red, and Green bands to create false-color composites that effectively highlight vegetation in red, making it

stand out distinctly (Hayem-Ghez et al., 2015).

- **Short-Wave Infrared (SWIR)**: The SWIR spectrum, typically defined between 1 µm and 3 µm, is a reflected light region that is invisible to human perception (Wilson et al., 2015). It possesses unique properties, including the ability to penetrate haze and smoke, and a high sensitivity to moisture content. SWIR bands are particularly recognized for their strong absorption by water, as well as distinct absorption bands related to water vapor and CO_2 (Hansen & Malchow, 2008). This sensitivity to moisture allows SWIR data to be correlated with critical metrics such as leaf water content, overall plant water stress, and even the severity of forest fire burns. Common SWIR bands utilized in satellite imagery fall between 1.55 µm and 1.75 µm, with some sensors also incorporating bands around 1.25 µm and 2.1-2.4 µm (Fagbohun, 2015). Notably, Landsat 8 OLI introduced a new SWIR band (1.36-1.38 µm) positioned within a region where water vapor typically absorbs radiation, offering further diagnostic capabilities (Rogalski & Chrzanowski, 2017).
- **Thermal Infrared (TIR)**: TIR data, typically spanning the 3-14 µm range, provides unique and invaluable information, especially for detecting vegetation water stress and retrieving biophysical parameters (Gerhards et al., 2019). Canopy temperature, derived from TIR measurements, serves as a key indicator of water stress, canopy conductance, and transpiration, making it an effective tool for optimizing irrigation schedules (Nanda et al., 2018). Crucially, TIR can detect pre-symptomatic water stress, meaning stress conditions can be identified before any visual symptoms become apparent. Beyond stress detection, TIR data is also instrumental in retrieving biophysical parameters such as Leaf Area Index (LAI), demonstrating fewer saturation issues at high LAI values compared to visible/NIR/SWIR data (Berger et al., 2022).

The increasing spectral resolution of optical sensors, transitioning from multispectral to hyperspectral capabilities, enables a finer discrimination of vegetation properties and stress levels. However, this advancement comes with increased costs and data complexity (Upadhyay & Kumar, 2018). While broad bands like NIR are highly useful for general vegetation health assessment and specific bands like Blue prove effective for detecting phenomena such as flower presence, the discussion of hyperspectral sensors as "powerful tools for determination and precise detection of vegetation dominant species" due to their "almost continuous spectra and narrow bands" signifies a move towards more detailed and specific analysis (Thenkabail et al., 2018). The ability to identify precise absorption bands for water vapor and CO_2 in the SWIR spectrum, and the capacity of TIR to detect pre-symptomatic stress, further underscores this enhanced diagnostic power (Gerhards et al., 2019). This progression, however, involves a clear trade-off: hyperspectral data, while providing richer information, incurs higher economic costs and may offer relatively lower spatial resolution compared to RGB data. This implies that while greater spectral information offers superior diagnostic capabilities, it also introduces challenges related to data acquisition cost, processing complexity, and potentially a reduction in spatial detail. Consequently, the selection of sensor type and spectral resolution becomes a strategic decision, contingent upon the specific needs and budgetary constraints of the application.

Vegetation Indices and their Applications

Vegetation indices (VIs) are quantitative metrics specifically designed to assess vegetation density, health, and vitality from remote sensing data. They are indispensable tools in precision agriculture and broader environmental monitoring efforts (Giovos et al., 2021). The process of normalization and ratioing inherent in VI calculations helps to minimize the influence of external factors, such as illumination changes, and establishes robust correlations with ground-based measurements, thereby enabling the estimation of vegetation conditions across large areas (Meng et al., 2024).

- **Normalized Difference Vegetation Index (NDVI)**:
  - Formula: NDVI = (NIR – Red) / (NIR + Red).

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- Applications: Widely used for crop health monitoring, biomass estimation, drought assessment, land cover mapping, and long-term vegetation studies.
- Typical Values: Values range from -1 to +1. Healthy vegetation typically falls between 0.2 and 0.8, with dense, healthy vegetation exhibiting values from 0.6 to 0.9. Bare soil usually registers around 0 to 0.1, and water bodies around -0.25 to 0.
- Significance: Higher NDVI values are indicative of healthier and denser vegetation, making this index highly effective for tracking vegetation changes over time and comparing plant health across different regions (Ozyavuz et al., 2015).

- **Enhanced Vegetation Index (EVI)**:
  - Formula: EVI = 2.5 * ((NIR – Red) / (NIR + 6 * Red – 7.5 * Blue + 1)) (Ozyavuz et al., 2015).
  - Applications: Primarily used for vegetation health monitoring, biomass estimation, land surface phenology, rainforest monitoring, and detailed canopy structure studies.
  - Significance: EVI is designed to mitigate the saturation issues often encountered with NDVI in areas of dense canopy, thus providing a more accurate representation of vegetation health in such environments. The inclusion of the blue band in its formula helps to correct for atmospheric interference and soil background noise, enhancing its robustness.
- **Soil-Adjusted Vegetation Index (SAVI)**:
  - Formula: SAVI = ((NIR – Red) / (NIR + Red + L)) * (1 + L), where L is a soil brightness correction factor, typically set to 0.5 (Ozyavuz et al., 2015).
  - Applications: Particularly useful for vegetation health monitoring in areas with varying soil cover, monitoring arid regions, and assessing vegetation during early crop growth stages where soil is often exposed.
  - Significance: SAVI's key advantage lies in its ability to minimize the influence of soil brightness on the vegetation signal, making it especially valuable in regions with sparse vegetation where soil background effects can significantly distort other vegetation indices.
- **Normalized Difference Water Index (NDWI)**:
  - Formula: NDWI = (Green – NIR) / (Green + NIR) (Ozyavuz et al., 2015).
  - Applications: This index is designed to indicate vegetation water content and water stress levels. It is applied for drought monitoring, irrigation planning, assessing fire risk, and mapping wetlands.
  - Significance: Positive NDWI values generally signify healthy, well-watered vegetation, while negative values suggest water stress. Water bodies typically exhibit high positive values (>0.3).
- **Other specialized indices**:
  - **Green Normalized Difference Vegetation Index (GNDVI)**: (NIR – Green) / (NIR + Green) – Used for assessing overall vegetation health, quantifying green vegetation cover, and general crop monitoring.
  - **Difference Vegetation Index (DVI)**: NIR – Red – Applied for vegetation vigor assessment, drought monitoring, and crop yield estimation.
  - **Normalized Green–Red Difference Index (NGRDI)**: (G−R)/(G+R) – Utilized for crop monitoring, vegetation health assessment, and land cover mapping.
  - **Chlorophyll Index (CI)**: (R750 – R705) / (R750 + R705) – Directly related to the chlorophyll content within vegetation.
  - **Leaf Area Index (LAI)**: (K * CT) / (1 – CT) – Important for crop growth monitoring, forest structure analysis, and ecosystem modeling.
  - **Normalized Difference Infrared Index (NDII)**: Employs the SWIR spectrum (specifically 1.55 µm – 1.75 µm) to identify historic fire scar damage and assess canopy water stress.
  - **Visible Vegetation Index (VVI)**: Derived from RGB channels, with low values indicating bare ground and high values corresponding to vegetation.

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- ○ **Excessive Greenness (ExG)**: A continuous index also derived from RGB, where low values indicate bare ground and high values imply vegetation.

Table 1: Common Vegetation Indices for Optical Remote Sensing

Index Name	**Formula**	**Key Spectral Bands Used**	**Primary Applications**	**Typical Value Range**	**Significance/Advantages**
NDVI	(NIR – Red) / (NIR + Red)	Red, NIR	Crop health, biomass, drought, land cover mapping, long-term studies	-1 to +1 (Healthy: 0.2-0.8)	Widely used, higher values = healthier/denser vegetation
EVI	2.5 * ((NIR – Red) / (NIR + 6 * Red – 7.5 * Blue + 1))	Blue, Red, NIR	Dense canopy health, biomass, phenology, rainforest monitoring	-1 to +1 (Healthy: 0.2-0.8)	Less sensitive to saturation in dense canopies, corrects for atmospheric/soil noise
SAVI	((NIR – Red) / (NIR + Red + L)) * (1 + L)	Red, NIR (L=soil factor)	Vegetation health in varying soil cover, arid regions, early crop growth	-1 to +1 (Healthy: 0.2-0.8)	Minimizes soil brightness influence, useful in sparse vegetation
NDWI	(Green – NIR) / (Green + NIR)	Green, NIR	Vegetation water content/stress, drought, irrigation, fire risk, wetland mapping	-1 to +1 (Positive: healthy/wet)	Indicates water content, useful for stress detection
GNDVI	(NIR – Green) / (NIR + Green)	Green, NIR	Vegetation health, green cover quantification, crop monitoring	–	Similar to NDVI but uses green band, sensitive to chlorophyll content
DVI	NIR – Red	Red, NIR	Vegetation vigor, drought monitoring, crop yield estimation	–	Simple difference, direct measure of vigor
NGRDI	(G-R)/(G+R)	Green, Red	Crop monitoring, vegetation health, land cover mapping	–	Uses visible bands, sensitive to greenness
CI	(R750 – R705) / (R750 + R705)	Red Edge, NIR (specific wavelengths)	Chlorophyll content	–	Directly related to plant pigment concentration
LAI	(K * CT) / (1 – CT)	– (derived from spectral)	Crop growth, forest structure, ecosystem modeling	–	Quantifies leaf area per unit ground area

NDII	(NIR – SWIR)/ (NIR +SWIR) (Conceptual)	NIR, SWIR (1.55-1.75µm)	Fire scar damage, canopy waterstress	–	Sensitive to water content in vegetation, penetrates haze
VVI	Based on RGB channels with reference green	RGB	Vegetation filtering, bare ground distinction	0 to 1 (Low: bare ground, High: vegetation)	Cost-effective, uses standard RGB data
ExG	2g-r-b (normalized RGB)	RGB	Vegetation filtering, greenness quantification	Continuous (Low: bare ground, High: vegetation)	Effective for distinguishing green vegetation from background

CONCLUSION

Vegetation indices are not universally robust; their effectiveness is influenced by environmental factors, necessitating context-specific application and potential adaptation. While VIs like NDVI are widely adopted, research highlights their limitations. For example, EVI was developed to address NDVI's saturation issues in dense canopies and includes corrections for atmospheric interference and soil background noise. Similarly, SAVI is specifically formulated to mitigate the influence of soil brightness.

More critically, studies explicitly demonstrate that the "influence of soil type on soil-adjusted vegetation index (SAVI) and enhanced vegetation index (EVI2) was approximately equal and varied from 60% (shooting phase) to 80% (tillering phase)". This research further contends that the simplification of soil background influence to merely brightness variations leads to an underestimation of soil's true impact on crop canopy reflectance and vegetation indices. This suggests that a "universal vegetation index is unlikely" and that indices should ideally be "adapted to local soil conditions".

This observation implies that while VIs are powerful tools, their application demands careful consideration of the local environmental context. Future research efforts should therefore focus on developing more robust, context-aware indices or sophisticated models that explicitly account for these intricate environmental influences.

REFERENCES

1. Angel, Y., Raiho, A., Kathuria, D., Chadwick, K. D., Brodrick, P. G., Lang, E., Ochoa, F., & Shiklomanov, A. N. (2025). Deciphering the spectra of flowers to map landscape-scale blooming dynamics. *Ecosphere, 16*(2), e70127.
2. Berger, K., Machwitz, M., Kycko, M., Kefauver, S. C., Van Wittenberghe, S., Gerhards, M., Verrelst, J., Atzberger, C., van der Tol, C., Damm, A., Rascher, U., Herrmann, I., Paz, V. S., Fahrner, S., Pieruschka, R., Prikaziuk, E., Buchaillot, M. L., Halabuk, A., Celesti, M., . . . Schlerf, M. (2022). Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review. *Remote Sensing of Environment, 280,* 113198. https://doi.org/https://doi.org/10.1016/j.rse.2022.113198
3. Buschmann, C., Lenk, S., & Lichtenthaler, H. K. (2012). Reflectance spectra and images of green leaves with different tissue structure and chlorophyll content. *Israel Journal of Plant Sciences, 60*(1-2), 49-64.
4. Chen, Y., Wang, Y., Zhang, F., Dong, Y., Song, Z., & Liu, G. (2023). Remote sensing for lithology mapping in vegetation-covered regions: methods, challenges, and opportunities. *Minerals, 13*(9), 1153.
5. Chuvieco, E. (2020). *Fundamentals of satellite remote sensing: An environmental approach*. CRC press.

6. Elachi, C., & Van Zyl, J. J. (2021). *Introduction to the physics and techniques of remote sensing*. John Wiley & Sons.
7. Fagbohun, B. J. (2015). *Combining dominant spectral features in airborne SWIR and TIR imagery for mineralogical mapping* University of Twente].
8. Gerhards, M., Schlerf, M., Mallick, K., & Udelhoven, T. (2019). Challenges and future perspectives of multi-/Hyperspectral thermal infrared remote sensing for crop water-stress detection: A review. *Remote Sensing*, *11*(10), 1240.
9. Giovos, R., Tassopoulos, D., Kalivas, D., Lougkos, N., & Priovolou, A. (2021). Remote sensing vegetation indices in viticulture: A critical review. *Agriculture*, *11*(5), 457.
10. Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors*, *8*(4), 2136-2160.
11. Hansen, M. P., & Malchow, D. S. (2008). Overview of SWIR detectors, cameras, and applications. Thermosense Xxx,
12. Hayem-Ghez, A., Ravaud, E., Boust, C., Bastian, G., Menu, M., & Brodie-Linder, N. (2015). Characterizing pigments with hyperspectral imaging variable false-color composites. *Applied Physics A*, *121*, 939-947.
13. Hernández-Clemente, R., Hornero, A., Mottus, M., Peñuelas, J., González-Dugo, V., Jiménez, J. C., Suárez, L., Alonso, L., & Zarco-Tejada, P. J. (2019). Early diagnosis of vegetation health from high-resolution hyperspectral and thermal imagery: Lessons learned from empirical relationships and radiative transfer modelling. *Current forestry reports*, *5*, 169-183.
14. Kuester, T., & Spengler, D. (2018). Structural and spectral analysis of cereal canopy reflectance and reflectance anisotropy. *Remote Sensing*, *10*(11), 1767.
15. Meng, X., Peng, J., Hu, J., Li, J., Leng, G., Ferhatoglu, C., Li, X., García-García, A., & Yang, Y. (2024). Validation and expansion of the soil moisture index for assessing soil moisture dynamics from AMSR2 brightness temperature. *Remote Sensing of Environment*, *303*, 114018. https://doi.org/https://doi.org/10.1016/j.rse.2024.114018
16. Moor, H., Rydin, H., Hylander, K., Nilsson, M. B., Lindborg, R., & Norberg, J. (2017). Towards a trait-based ecology of wetland vegetation. *Journal of Ecology*, *105*(6), 1623-1635.
17. Nanda, M. K., Giri, U., & Bera, N. (2018). Canopy temperature-based water stress indices: potential and limitations. *Advances in crop environment interaction*, 365-385.
18. Ozyavuz, M., Bilgili, B., & Salici, A. (2015). Determination of vegetation changes with NDVI method. *Journal of environmental protection and ecology*, *16*(1), 264-273.
19. Paul, E., & Frey, S. (2023). *Soil microbiology, ecology and biochemistry*. Elsevier.
20. Rocchini, D., Ricotta, C., & Chiarucci, A. (2007). Using satellite imagery to assess plant species richness: The role of multispectral systems. *Applied Vegetation Science*, *10*(3), 325-331.
21. Rogalski, A., & Chrzanowski, K. (2017). Infrared devices and techniques. In *Handbook of optoelectronics* (pp. 633-686). CRC Press.
22. Sarvakar, K., & Thakkar, M. (2024). Different Vegetation Indices Measurement Using Computer Vision. In *Applications of Computer Vision and Drone Technology in Agriculture 4.0* (pp. 133-163). Springer.
23. Thenkabail, P. S., Lyon, J. G., & Huete, A. (2018). Advances in hyperspectral remote sensing of vegetation and agricultural crops. In *Fundamentals, sensor systems, spectral libraries, and data mining for vegetation* (pp. 3-37). CRC press.
24. Upadhyay, V., & Kumar, A. (2018). Hyperspectral remote sensing of forests: technological advancements, opportunities and challenges. *Earth Science Informatics*, *11*(4), 487-524.
25. Ustin, S. L., & Jacquemoud, S. (2020). How the optical properties of leaves modify the absorption and scattering of energy and enhance leaf functionality. *Remote sensing of plant biodiversity*, 349-384.
26. van der Kooi, C. J., Elzenga, J. T. M., Staal, M., & Stavenga, D. G. (2016). How to colour a flower: on the optical principles of flower coloration. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1830), 20160429.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

27. Wilson, R. H., Nadeau, K. P., Jaworski, F. B., Tromberg, B. J., & Durkin, A. J. (2015). Review of short-wave infrared spectroscopy and imaging methods for biological tissue characterization. *Journal of biomedical optics*, *20*(3), 030901-030901.
28. Yamaguchi, M., Haneishi, H., & Ohyama, N. (2008). Beyond red–green–blue (RGB): spectrum-based color imaging technology. *Journal of Imaging Science and Technology*, *52*(1), 10201-10201-10201-10215.