

A Novel Multi-Index Approach For Crop Health Analysis Using PCA-Derived Spectral Weights

Shivani S. Bhosle¹, Dr. Prapti D. Deshmukh²

¹Research Fellow, Dr.G.Y.Pathrikar College of Computer Science and Information Technology, MGM University, Chhatrapati Sambhajinagr, Maharashtra,

Email: shivanibhosle21@gmail.com, ORCID: 0009-0003-4050-7420

²Principial, Dr.G.Y.Pathrikar College of Computer Science and Information Technology, MGM University, Chhatrapati Sambhajinagr, Maharashtra

Email: prapti.research1@gmail.com, ORCID: 000-0002-3065-6057

Abstract:

For precision agriculture, resource optimization, and sustainable farm management, prompt and correct crop health assessment is vital. Conventional vegetation indexes like NDVI and EVI offer insightful observations, yet they usually fall short of portraying the whole spectrum of physiological and structural conditions seen in several crops and habitats. By means of Principal Component Analysis (PCA), this study introduces a novel Multi-Vegetation Health Index (MVHI) integrating five complementary spectral indices—NDVI, EVI, SAVI, GNDVI, and NDRE—to derive objective statistical weights. Thirteen scenes from June–December 2024 from Sentinel-2A surface reflectance imagery were preprocessed using cloud filtering, spatial point extraction, and temporal index computation at field sites in Mahalaxmikheda village, Maharashtra. MVHI was built from the first principal component, which accounted for 82.30% of total spectral variation, hence confirming great information compression and index strength. Accuracy assessment using one-way ANOVA shown significant discriminatory ability across independently defined crop health groupings ($F = 211.50$, $p < 0.001$), with a large effect size ($\eta^2 = 0.522$). Comparative ANOVA results demonstrated that MVHI offers a balanced alternative to highly sensitive individual indices such NDRE and GNDVI. Spatial mapping of MVHI revealed clear gradients of crop vigor and stress, hence supporting its applicability for field-scale monitoring and agronomic decision-making. MVHI turns out to be a trustworthy, data-driven and whole crop health indicator fit for operational remote sensing and scientific study purposes.

Keywords: Crop Health Analysis, PCA, NDVI, Sentinel-2A

1. Introduction

Crop health monitoring is an important resource in sustainable agricultural management which can give timely actions to minimize loss of yields and maximize resource use. These traditional field-based assessment methods are accurate, but time-consuming, labor-intensive and often impossible for large-scale agriculture landscapes [1]. As satellite remote sensing increasingly uses multispectral imagery, vegetation indicators of crop vigor, chlorophyll concentration, canopy structure and stress are now capable of providing useful models of crop survival, sunlight concentration, and stress distribution [2]. Among these are commonly used indices such as the normalized difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), Green Normalized Difference Vegetation Index (GNDVI), and Normalized Difference Red Edge Index (NDRE), which further evaluate plant physiological status [3].

Yet single indexes are limited enough to use. NDVI saturates under dense canopy conditions, EVI requires high atmospheric calibration, SAVI is sensitive to soil reflectance, and red-edge-based indices such as NDRE capture stress signals, but do not accurately represent overall canopy greenness [4]. There are none of the vegetation indexes which does not consistently show the fusion of complex biophysical characteristics of crops that vary in scale and location. As a result, there is a growing demand for integrative

approaches that combine the strengths of dozens of indexes into a single and robust crop health indicator [5].

To address the gap, the present study proposes an integrated multiple index approach that blends five commonly used vegetation indices—NDVI, EVI, SAVI, GNDVI, and NDRE into a single composite metric using Principal Component Analysis. By extracting statistically optimized spectral weights from the first principal component, we develop a Multi-Vegetation Health Index (MVHI) that captures spectral variance, which does not appear to be sensitive or stable; but, sensitivity and stability are much more significant than sensitivity and stability. The PCA-derived weighting technique can be used to approximate the objectivity of the method, reduce redundancy of correlated factors, and enhances interpretation of crop health differences.

The MVHI framework provides several benefits such as greater accuracy to detect early stress, robustness across soil and canopy densities, able to integrate structural, biochemical and physiological vegetation signals, and suited to precision agriculture applications where spatial variability is needed. Through an implementation of the MVHI as geospatial point data from agricultural fields, this study shows how spatial stress hotspots can be identified, categorized into the categories of crop health, and that a computerized method of finding the effects of the PCA-derived composite index can serve as a way to make an actionable decision for farmers and farmers. This multi-index methodology helps to develop the remote sensing systems of crop detection and provides a scientific basis for large-scale operational monitoring applications. Following section consist of related work followed with study area description. Later section explained detailed methodology and followed with result discussion and conclusion.

2. Related Work

Remote sensing-based crop monitoring has been extensively studied, with numerous investigations exploring the use of vegetation indices and statistical methods to assess plant health, detect stress, and quantify biophysical characteristics across diverse agricultural systems. Employing UAVs, segmentation, and vegetation indexes, one of the studies monitored cassava health and revealed notable growth variances as well as a strong connection between important indicators like NDVI and GNDVI, therefore informing more effective agricultural management. With R^2 values ranging from 0.95 to 0.98, the Normalized Difference Vegetation Index (NDVI) and Green Normalized Difference Vegetation Index (GNDVI) showed a solid link. This strong link suggests that both indexes are successful in forecasting plant health through UAV-based monitoring [6]. Another study developed and validated a novel Sentinel-2 based Vegetation Health Index (SVHI) using spectroscopy and global sensitivity analysis. This new index demonstrated superior capability in detecting multiple vegetation stressors and effectively monitoring crop phenology compared to traditional indices like NDVI and NDMI [7].

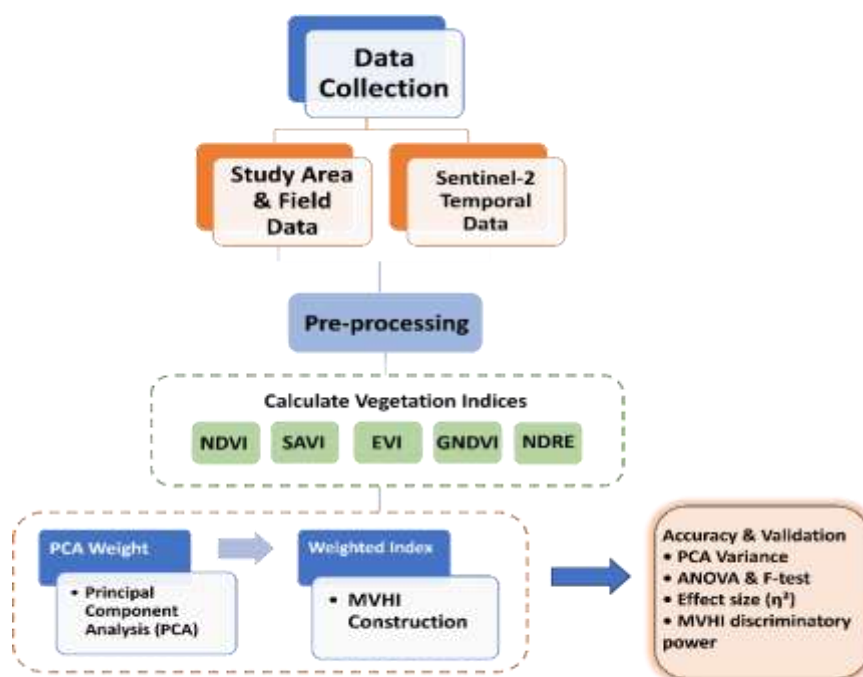
Another study utilized Principal Component Analysis (PCA) to identify key wavelengths for vegetation indices (VIs) like CARI, DD, REIP, and Clred-edge, which effectively monitored sweet maize's yield and physiological responses under varying water and nitrogen conditions, but did not employ ANOVA. The result shows red-edge group indices (CARI, DD, REIP, Clred-edge) were good predictors of yield and physiological parameters in sweet maize. DD, REIP, and Clred-edge VIs were able to discriminate different stress conditions [8].

One of the author used PCA for analyzing vegetation indices derived from remote sensing data, enhancing interpretability and detecting changes. PCA provides an effective dimensionality-reduction technique that preserves the majority of variance while transforming correlated variables into new uncorrelated components. It enhances data interpretability, enables detection of subtle temporal or spectral changes, and remains highly adaptable across diverse datasets. In most remote sensing applications, the first few principal components capture the dominant proportion of variance, making PCA both efficient and robust for vegetation analysis [9].

3. Methodology

The research methodology as shown in figure 2, combined with satellite-based multispectral data assesses crop health over the investigated region. Sentinel-2A images were processed to extract useful vegetation signaling and the PCA process was used to generate a single multi-Vegetation Health Index (MVHI). As a result, this systematic process from data acquisition and preprocessing to spectral index generation, MVHI construction, and spatial analysis ensures an objective, repeatable assessment of field-level crop conditions.

Figure 2: Proposed Methodology



3.1. Data Collection

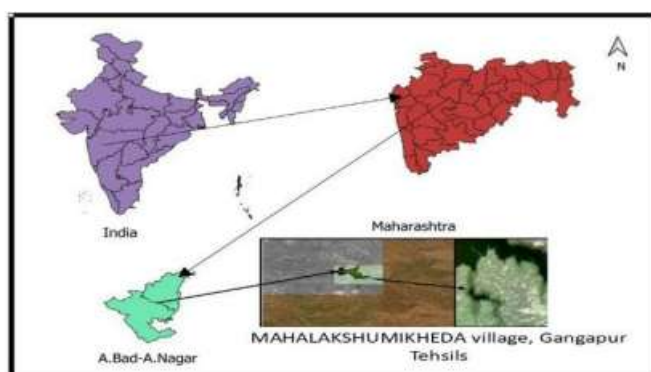
Data Collection is done for selected study area of Chhatrapati Sambhajnagar district, Maharashtra. For the same region sentinel-2A multispectral images were collected.

3.1.1. Study Area

The selected study area for research is Mahalaxmikheda village (19.82°N, 75.03°E) of Gangapur Tehsil, Chhatrapati Sambhajnagar district, Maharashtra as depicted in figure 1. The climate of the region is subtropical with hot summers, monsoon peaks from June to September, and mild winters. Agricultural life is an important business dominated by

agriculture, and fresh waters and irrigation from the Upper Jayakwadi Dam provide fertile soil and irrigation. The landscape is mostly small to medium sized lands filled with large crops such as cotton, sweet lime, sugarcane, corn and wheat. The diversity of agriculture and crops, soil types, and agriculture practices makes it suitable for remote sensing and assessment of crop health by means of satellite-based vegetation indices and crop health measures.

Figure 1: Study Area



3.1.2. Sentinel-2A Temporal Images

Sentinel-2A is part of the European Space Agency's Copernicus Earth observation program and has high-resolution multispectral imagery for farm monitoring. The instrument, MSI has 13 spectral bands that cover all the spectral bands including the visible and shortwave infrared bands. These bands span the blue (490 nm), green (560 nm), red (665 nm), near-infrared (842 nm), narrow vegetation red-edge bands (705, 740, 783 nm) and SWIR bands (1.61 m and 2.19 m) that allow for precise assessment of vegetation vigor, biochemistry, and canopy structure. Sentinel-2A can be read at a spatial resolution of 10 m, 20 m and 60 m depending on band, while the relevant vegetation-relevant bands (Red, Green, Blue, NIR) are available at 10-meter resolution. The satellite, which also includes Sentinel-2B as well as has a equator revisit time of 5 days, is especially good at recording temporal crop dynamics [10]. This study used 13 cloud-free Sentinel-2A scenes between June 2024 and December 2024 in our collection. This photographic data were processed at SR level, which is correct for atmospheric effects and offers reflectance values that are useful for quantitative vegetation analysis.

3.2. Pre-processing

This study utilizes preprocessed surface reflectance imagery in Google Earth Engine to provide radiometrically consistent and ideally prepared datasets for radiometrically consistent coverage. The preprocessing process started by selecting the GPS points for field GPS and space filtering the satellite scenes to include only imagery near study location. During the active crop growth period between June and December 2024, Temporal Filtering was used to select data from the June-December 2024 dates. The data was then also screened using a cloud-coverage threshold of 20% CLOUDY_PIXEL_PERCENTAGE and retained only high quality images [11]. The filtered dataset presented reflects geometrically corrected, atmospherically adjusted Sentinel-2 surface reflectance values. These images are clean, reliable data to aid future vegetation analysis and MVHI construction to ensure the assessment of crop health is not influenced by cloud contamination, poor quality acquisitions or timing across study area.

3.3. Calculate Vegetation Indices

Spectral transformations obtained from multispectral satellite images that measure crop vigour, canopy density, chlorophyll content, and biochemical stress responses are vegetation indexes. Strongly sensitive to vegetation structure and physiological state, they depend mostly on reflectance in the visible, near-infrared, and red-edge bands. Five often used indexes, : NDVI, SAVI, EVI, GNDVI, and NDRE as shown in table 1, were calculated in this study to represent various aspects of crop health. Whereas SAVI adjusts for background noise in scarce vegetative conditions [12], NDVI offers a starting measure of greenness and biomass. Reducing atmospheric and canopy-shadow effects helps to improve sensitivity in high-biomass regions [13]. GNDVI emphasizes green reflectance and is strongly related to nitrogen content and chlorophyll activity [14]. A red-edge-based index, NDRE gives more knowledge into early stress conditions that might not be seen via conventional greenness measurements. These indicators combine to offer a strong multi-dimensional picture of crop physiological performance [15].

Table 1: Vegetation Indices

Index Name	Formula	Purpose in Crop Analysis
NDVI (Normalized Difference Vegetation Index)	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	Measures general greenness, canopy vigor, and biomass; detects stressed vs. healthy vegetation.
SAVI (Soil-Adjusted Vegetation Index)	$1.5 \times (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + 0.5)$	Corrects soil brightness influence; useful in areas with sparse vegetation or exposed soil.
EVI (Enhanced Vegetation Index)	$2.5 \times (\text{NIR} - \text{Red}) / (\text{NIR} + 6 \times \text{Red} - 7.5 \times \text{Blue} + 1)$	Improves sensitivity in dense vegetation; reduces atmospheric and background noise; ideal for high-biomass crops.
GNDVI (Green NDVI)	$(\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$	Sensitive to chlorophyll content and nitrogen status; useful for nutrient stress detection.
NDRE (Normalized Difference Red-Edge Index)	$(\text{NIR} - \text{RedEdge}) / (\text{NIR} + \text{RedEdge})$	Detects early stress, nutrient deficiencies, and photosynthetic variation; performs well even in dense canopies.

3.4. Principal Component Analysis (PCA)

To lower the five vegetation indices' (NDVI, EVI, SAVI, GNDVI, and NDRE) dimensionality and to pinpoint the main spectral variance driving crop health, Principal Component Analysis (PCA) was applied. All indicators were standardized with z-score normalization prior to PCA to guarantee equal numerical effect among variables [16]. As depicted in equation 1, StandardScaler was used to normalize all index values, ensuring equal contribution to the PCA model.

$$X_{std} = \frac{X - \mu}{\sigma} \quad (1)$$

PCA broke down the index data set into orthogonal components graded based on their explained variance. PC1 accounted for 82.30% of the total spectral variance in this study, which suggested that the first component captures most of the physiologically relevant information across the indexes. The significant contribution of PC1 validates PCA as an appropriate technique to get integrated spectral weights and confirms strong multicollinearity among vegetation indices. The loading coefficients of PC1 were utilized as the statistical weights for generating the Multi-Vegetation Health Index (MVHI), hence

guaranteeing a fair, data-driven integration of spectral data as opposed to arbitrarily selected weights.

3.5. MVHI Construction

Built as a single measure of crop vitality and stress, the Multi-Vegetation Health Index (MVHI) combines the five vegetation indices utilizing PCA-derived spectral weights. Every vegetation index was multiplied by its normalized PC1 loading value, and the weighted numbers were added to create the weighted values. This guarantees that indicators with more explanatory power (e.g., NDRE, GNDVI, NDVI) significantly influence the ultimate health measure whereas indices with less impact have less effect. MVHI simultaneously records several physiological dimensions including early stress response (NDRE), soil-adjusted reflectance (SAVI), chlorophyll-nitrogen status (GNDVI), and canopy density (NDVI, EVI). MVHI therefore offers a more delicate and complete measurement of crop condition than do single-index methods. Higher MVHI levels point to more robust vegetation; lower values imply different degrees of physiological stress, hence supporting efficient spatial analysis, stress discrimination, and field-level monitoring.

PCA transforms the standardized indices into components that maximize statistical variance. The first principal component (PC1) typically captured >70% of variance and was used to derive MVHI as shown in equation 2.

$$MVHI = (NDVI \times w_1) + (EVI \times w_2) + (GNDVI \times w_3) + (SAVI \times w_4) + (NDRE \times w_5)$$

(2)

where w_n represents PCA-derived loading weights normalized to unity. MVHI values therefore reflect a weighted biological signal, emphasizing indices contributing the most to crop vigor and minimizing noise from soil and illumination effects.

3.6. Accuracy Assessment

Accuracy validation of the MVHI framework was conducted using two complementary statistical measures: PCA variance analysis and ANOVA-based discriminatory power assessment. PCA variance analysis quantified how effectively the first principal component captured the shared spectral variability among the vegetation indices, thereby confirming the robustness of the PCA-derived weights used in MVHI construction. Complementarily, one-way ANOVA evaluated the ability of MVHI and individual indices to discriminate between different crop-health groups [17]. The high F-values and significant p-values obtained from ANOVA demonstrated strong discriminatory capability, confirming that MVHI provides a statistically reliable and sensitive indicator of crop health variation across the study area.

4. Result and Discussion

Instead of a classification or predictive model, the suggested Multi-Vegetation Health Index (MVHI) is a composite spectral index based on several vegetation parameters. Therefore, conventional accuracy indices like total accuracy, confusion matrix, or RMSE are not immediately relevant. Following established guidelines in the literature of vegetation index and remote sensing, MVHI accuracy was assessed using statistical robustness and discriminatory power instead. Two complementary validation approaches were employed:

- 1) PCA-based variance explanation, to assess the statistical reliability of MVHI construction.
- 2) ANOVA-based discriminatory validation, to examine the capability of MVHI to distinguish crop health conditions.

4.1. PCA Results

Principal Component Analysis (PCA) was used to quantify how much of the total information contained in the original vegetation indices is captured by MVHI. Since MVHI is derived from the first principal component (PC1), the variance explained by PC1 directly reflects the statistical completeness and robustness of the index. PCA was performed on standardized NDVI, EVI, SAVI, GNDVI and NDRE values. The eigenvalue-based variance contribution of each principal component is presented in Table 2.

Table 2: PCA Variance Explained by Principal Components

Principal Component	Variance Explained (%)
PC1	82.3
PC2	15.73
PC3	1.22
PC4	0.75
PC5	0

The PC1 alone accounted for 82.30% of the total spectral variance, indicating very strong coherence among the five vegetation indices. This result confirms that:

- The majority of crop health information is concentrated in a single dominant component.
- Redundancy among individual indices is minimized.
- MVHI provides a compact yet comprehensive representation of crop health.

In agricultural remote sensing studies, PC1 variance values exceeding 70% are considered robust; therefore, the obtained value of 82.30% represents excellent statistical validation of the MVHI framework.

4.2. ANOVA-Based Discriminatory Validation

This validation is done for NDRE based health analysis and for MHVI based analysis. Also we have done comparative discriminatory analysis with individual indices.

4.2.1. Health Group Definition

To evaluate discriminatory power, crop health groups were defined independently using NDRE-based stress thresholds, ensuring that the validation was not circular. The dataset was categorized into:

- Stressed ($\text{NDRE} < 0.15$)
- Moderate ($0.15 \leq \text{NDRE} < 0.25$)
- Healthy ($\text{NDRE} \geq 0.25$)

The distribution of samples across groups was specified in table 3:

Table 3: Health groups based on NDRE

Health Group	Number of Samples
Healthy	282
Stressed	57
Moderate	51

This distribution provided sufficient representation for one-way ANOVA.

4.2.2. ANOVA Results for MVHI

A one-way ANOVA was conducted to assess whether MVHI values differ significantly across health groups. Results are presented in Table 4.

Table 4: ANOVA Results for MVHI

Metric	Value
F-value	211.5
p-value	< 0.001
Effect Size (η^2)	0.522

The ANOVA results indicate:

- A highly significant difference in MVHI values between health groups ($p < 0.001$).
- A large effect size ($\eta^2 = 0.522$), meaning that 52.2% of MVHI variability is explained by crop health condition.

According to standard effect size classifications ($\eta^2 \geq 0.14 = \text{large effect}$), MVHI demonstrates very strong discriminatory capability between stressed, moderate, and healthy crop conditions.

4.2.3. Comparative Discriminatory Analysis with Individual Indices

To further contextualize MVHI performance, the ANOVA results of MVHI were compared against individual vegetation indices. Results are summarized in Table 5.

Table 5: Comparative ANOVA Results of Vegetation Indices

Index	F-value	Effect Size (η^2)
NDVI	510.61	0.725
EVI	33.09	0.146
GNDVI	625.42	0.764
SAVI	510.62	0.725
NDRE	680.84	0.779
MVHI	211.5	0.522

Stress-sensitive indices such as NDRE and GNDVI exhibit higher F-values because they directly reflect chlorophyll and nitrogen variability and were used for defining stress thresholds. However, MVHI maintained a large and statistically significant effect size while integrating multiple physiological signals. This confirms that MVHI is not designed to maximize stress sensitivity but to provide a balanced and holistic assessment of overall crop health, incorporating canopy vigor, structural response, soil background adjustment and biochemical stress indicators.

Figure 3 illustrates the interrelationships among the five vegetation indices and the MVHI using a correlation heatmap. The strong positive correlations highlight the coherence of spectral indicators and support the PCA-based construction of the composite health index. Figure 4 presents the spatial variability of crop health across the study area using MVHI values mapped over geographic coordinates. The gradient visualization effectively identifies healthy zones and stress hotspots, enabling field-level interpretation for precision agriculture. Figure 5 shows the statistical distribution patterns of individual

vegetation indices along with the MVHI histogram. These distributions provide insights into overall spectral behavior and reveal how MVHI consolidates multi-index information into a single interpretable measure.

Figure 3: Correlation Matrix of Vegetation Indices and MVHI

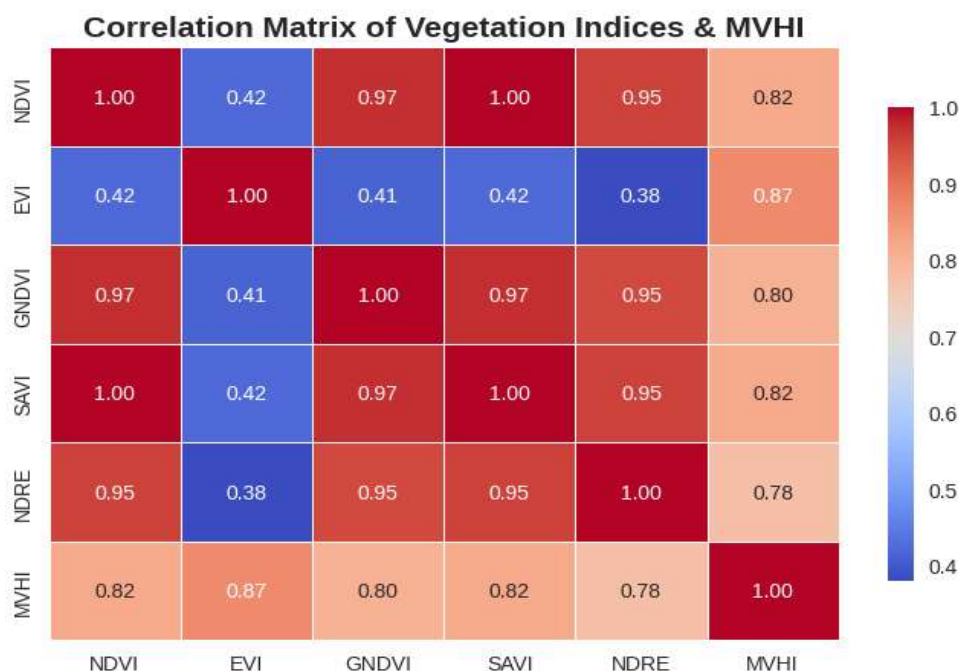


Figure 4: Spatial Distribution of Crop Health (MVHI)

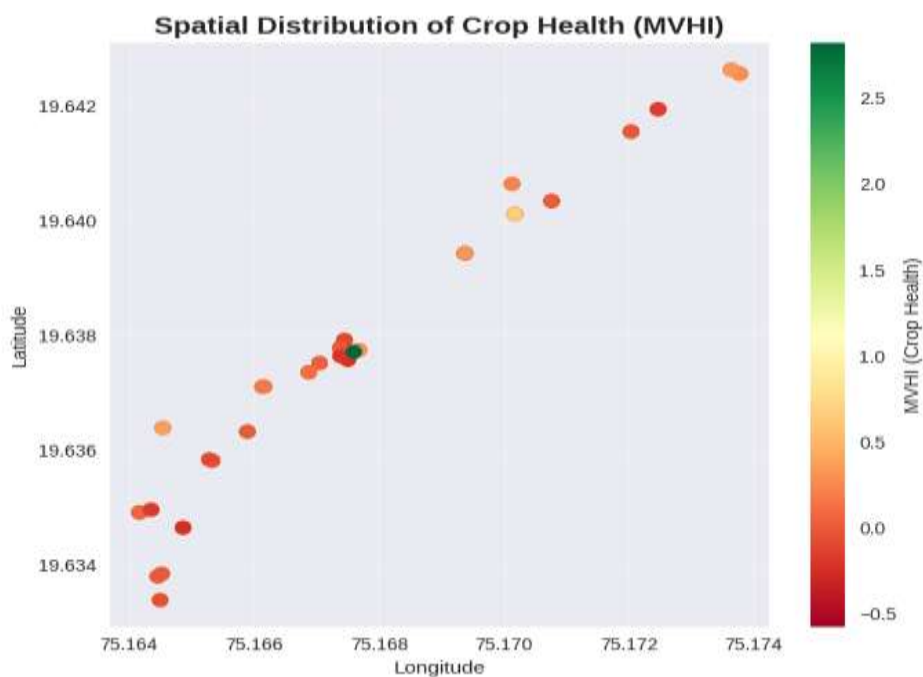
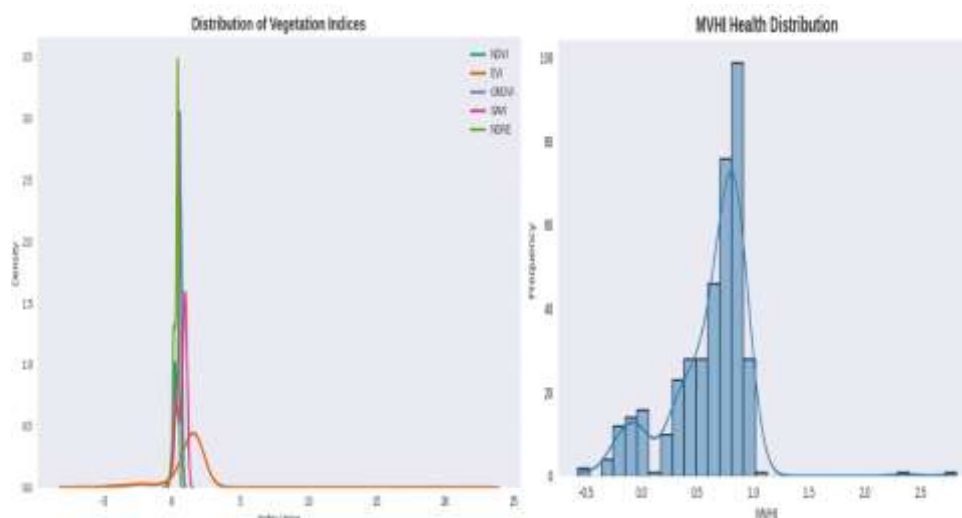


Figure 5: Distribution of Vegetation Indices and MVHI Health Distribution

4.3. Summary of Accuracy Assessment

The validation framework confirms that MVHI is both statistically robust and discriminatively powerful:

Table 6: Summary of Accuracy Assessment

Validation Method	Evidence	Strength
PCA Variance Explained	PC1 = 82.30%	Excellent
ANOVA (MVHI)	$F = 211.50$, $\eta^2 = 0.522$	Very Strong
Comparative Analysis	MVHI competitive with single indices	Balanced

The combined results of PCA and ANOVA show that the MVHI structure has statistical integrity and is agronomically significant. PCA confirms that while ANOVA clearly demonstrates its great discriminatory ability in distinguishing crop health conditions over the study region, MVHI captures most of the spectral variance connected to vegetation health. MVHI helps to get over the drawbacks of simple index strategies like NDVI or EVI alone by combining several vegetation indices into a balanced, data-driven composite measure. Together, this multi-tiered validation makes MVHI a trustworthy and scientifically sound marker appropriate for advanced academic research as well as operational crop health monitoring.

5. Conclusion

For thorough assessment of crop health, this study created a novel Multi-Vegetation Health Index (MVHI) integrating the complementary strengths of NDVI, EVI, SAVI, GNDVI, and NDRE utilizing PCA-derived spectral weights. Sentinel-2A multispectral images and field-based sampling stations from Mahalaxmikheda (Maharashtra, India) were used to

build a multivariate crop-health framework supported by strong preprocessing, vegetation index computation, and pixel-level spectral information extraction. PCA analysis confirmed that MVHI contains the bulk of significant plant information by showing that the first principal component accounted for 82.30% of total spectral variation. ANOVA-based discriminatory validation further verified that MVHI dramatically distinguishes between stressed, moderate and healthy crop conditions, with a high effect size ($\eta^2 = 0.522$).

MVHI turned out to be a statistically robust, balanced, and operationally realistic index for field-scale crop monitoring overall, allowing for better interpretability than single-index approaches. The study emphasizes the possibilities of multivariate, data-driven spectral integration for scalable agricultural health evaluation and establishes a basis for future research in yield forecast, stress diagnosis and precision agriculture applications.

Acknowledgements

The Authors would like to acknowledge the SARTHI Fellowship; CSMNRF 2022/2022-23/2341 for financial assistance and Dr. G. Y. Pathrikar college of Computer Science and Information Technology, MGM University, Chhatrapati Sambhajinagar for providing resources for the study

6. References

1. Omia, E., Bae, H., Park, E., Kim, M. S., Baek, I., Kabenge, I., & Cho, B. K. (2023). Remote sensing in field crop monitoring: A comprehensive review of sensor systems, data analyses and recent advances. *Remote Sensing*, 15(2), 354.
2. Brewer, K., Clulow, A., Sibanda, M., Gokool, S., Naiken, V., & Mabhaudhi, T. (2022). Predicting the chlorophyll content of maize over phenotyping as a proxy for crop health in smallholder farming systems. *Remote Sensing*, 14(3), 518.
3. Yu, H., Kong, B., Hou, Y., Xu, X., Chen, T., & Liu, X. (2022). A critical review on applications of hyperspectral remote sensing in crop monitoring. *Experimental Agriculture*, 58, e26.
4. Vidican, R., Mălinaş, A., Ranta, O., Moldovan, C., Marian, O., Gheţe, A., ... & Cătunescu, G. M. (2023). Using remote sensing vegetation indices for the discrimination and monitoring of agricultural crops: A critical review. *Agronomy*, 13(12), 3040.
5. Wu, B., Zhang, M., Zeng, H., Tian, F., Potgieter, A. B., Qin, X., ... & Loupian, E. (2023). Challenges and opportunities in remote sensing-based crop monitoring: A review. *National Science Review*, 10(4), nwac290.
6. Maryana, S., Herdiyeni, Y., Wahjuni, S., & Santosa, E. (2025). UAV-Based Segmentation and Correlation Analysis of Vegetation Indices for Cassava Crop Health Assessment. *JOIV: International Journal on Informatics Visualization*, 9(4), 1381. <https://doi.org/10.62527/joiv.9.4.3078>
7. Kumar, S., Ghosh, S. S., Mandal, D., Bhattacharya, A., Porwal, A., & Karthikeyan, L. (2025). Enhancing Vegetation Monitoring: A Proposal for a Sentinel-2 Based Vegetation Health Index. <https://doi.org/10.20944/preprints202501.1235.v1>
8. Sellami, M., Albrizio, R., Colovic, M., Hamze, M., Cantore, V., Todorovic, M., Piscitelli, L., & Stellacci, A. M. (2022). Selection of Hyperspectral Vegetation Indices for Monitoring Yield and Physiological Response in Sweet Maize under Different Water and Nitrogen Availability. *Agronomy*, 12(2), 489. <https://doi.org/10.3390/agronomy12020489>
9. Sharma, A., & Guest. (n.d.). Principal component analysis (pca) in the evaluation of vegetation indices derived from time-series remote sensing data: a review.

10. Li, J., Wu, Z., Hu, Z., Li, Z., Wang, Y., & Molinier, M. (2021). Deep learning based thin cloud removal fusing vegetation red edge and short wave infrared spectral information for Sentinel-2A imagery. *Remote Sensing*, 13(1), 157.
11. Nagy, D., Warshavsky, Z., & Hughes, L. H. (2021, July). Improved Image Aggregation for Large-Scale Cloud-Free Image Creation. In 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS (pp. 3889-3892). IEEE.
12. Vera-Esmeraldas, A., Pizarro-Oteíza, S., Labbé, M., Rojo, F., & Salazar, F. (2025). UAV-Based Spectral and Thermal Indices in Precision Viticulture: A Review of NDVI, NDRE, SAVI, GNDVI, and CWSI. *Agronomy*, 15(11), 2569.
13. de Oliveira, J. F., de Alcântara, J. F., Santana, D. C., Teodoro, L. P. R., Baio, F. H. R., Coradi, P. C., ... & Teodoro, P. E. (2023). Spectral variables as criteria for selection of soybean genotypes at different vegetative stages. *Remote Sensing Applications: Society and Environment*, 32, 101026.
14. Khunrattanasiri, W. (2023). Application of remote sensing vegetation indices for forest cover assessments. In *Concepts and Applications of Remote Sensing in Forestry* (pp. 153-166). Singapore: Springer Nature Singapore.
15. Melnyk, O., & Brunn, A. (2025). Analysis of Spectral Index Interrelationships for Vegetation Condition Assessment on the Example of Wetlands in Volyn Polissya, Ukraine. *earth*, 6(2), 28.
16. Uddin, M. P., Mamun, M. A., & Hossain, M. A. (2021). PCA-based feature reduction for hyperspectral remote sensing image classification. *IETE Technical Review*, 38(4), 377-396.
17. Flynn, K. C., Lee, T., Endale, D., Franzluebbers, A., Ma, S., & Zhou, Y. (2021). Assessing remote sensing vegetation index sensitivities for tall fescue (*Schedonorus arundinaceus*) plant health with varying endophyte and fertilizer types: A case for improving poultry manure sheds. *Remote Sensing*, 13(3), 521.