

# LARGE-SCALE GENOMIC PHENOTYPING OF RICE CROP HEALTH: INTEGRATING SENTINEL-2 NDVI COMPOSITES FOR CHARACTERIZED TRAIT SELECTION

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## ABSTRACT

Crop management practices that helps to detect the presence of stress or any abnormality at the right time are essential to ensure food security and maximum agricultural output. The crop stress leads to massive loss of crop yield since it affects the plant health. Stress in crops is caused by poor irrigation, deficiency or any infection by pests. Modern agricultural methods manual scouting to determine the health condition of the crop is not efficient and not viable to large scale farming or large-scale monitoring of the area by the government agencies. This paper offers a dependable and effective method of determining and mapping stresses area within the farmed area. An unsupervised clustering framework that is based on deep learning was chosen to segment stressed area that provides valuable benefit as it can detect clusters of pixels that share certain common features. Unsupervised learning method does not presuppose previous knowledge or marked training data. It thus becomes an effective and scalable technique to study the health of crops, and it is also possible to map the levels of different stresses in the field without any problem. To begin with, an Auto-Encoder was applied to produce a small lower dimensional representation of the multi-band images. The AE model uses the abundant spectral information of several bands of Sentinel-2 to extract salient features that describe the underlying biophysical attributes of the crops. Then the encoded features are further grouped with k-Means clustering algorithm to outline the healthy vegetation, moderately stressed and stressed vegetation areas. The efficacy of the proposed approach was checked with the help of multiple performance measures that illustrate the effectiveness of this approach to offer a scalable solution to crop remote monitoring. This solution helps farmers to implement specific interventions and improve the management of the farms.

**KEYWORDS:** deep learning, unsupervised clustering, AutoEncoder, k-Means clustering, sentinel-2, crop stress.

## 1. INTRODUCTION

Agriculture is currently facing an unprecedented challenge all over the world to guarantee food security to the expanding population in a sustainable manner overcoming numerous challenges such as the lack of agricultural resources, and even environmental shifts [1]. Enhancement of crop quality and yield is one of the main goals at this point. It will be necessary to detect and control crop stress at an early stage in a manner that will achieve the said goal. There are numerous factors (biotic and abiotic) which cause crop stress such as water scarcity, poor soil quality, pest infestation or any other abnormalities affect the plant physiology and ultimately affect the entire crop yield and hence causing a greater impact in economic loss [2].

The traditional techniques of monitoring and measuring the crop health are labor intensive and are primarily a reactionary process. The most prevalent one is manual scouting by farmers who inspect the farmland by looking at the crop to identify the level of crop health. This manual system cannot be scaled up, and cannot be embraced to monitor farmlands at the regional level with regards to time and logistics complexity. Furthermore, the cues or symptoms of the crop stress or any anomalies are manifested in later stages i.e. when considerable physiological damages to crop health have already been caused. The remedial action at this time might not be as effective and an invasion of disease or any pest may extend to other fields [3]. This makes it apparent that there is a necessity of an efficient, reliable and scalable way of monitoring crop health.

Remote sensing has become a potent solution that is able to get information about an object without getting a physical touch. Non-invasive and frequent monitoring of a large-scale farmland can be done using satellite. The development of remote sensing technology creates high-resolution images, and this has opened up the benefits of remote sensing. Sentinel-2 mission of the European Space Agency (ESA) is one of the milestones of this revolution. The Sentinel2 is a constellation of two satellites (Sentinel-2A and 2B) and it image provides multispectral images up to resolutions of 10 meters and a revisit period of 2-5 days [4].

The availability of spectral bands in various spatial resolutions made sentinel 2 data useful to most literatures in crop health monitoring and decision making in other agricultural activities. It has high reflective Near-Infrared (NIR) bands and critical Red-Edge bands [5]. Red-Edge is a small spectral band that includes absorption of chlorophyll conversion to NIR scattering. The red-edge band or information based on the red-edge band can be used to detect the vegetative stress in crops at an early stage that are not noticeable to the human eye [6].

Sentinel 2 can be used in crop health monitoring and other agricultural activities, and this relies primarily on the abundance of spectral bands on the satellite. Sentinel2 has a high reflection Nearest Infrared (NIR) bands and the most important Red-Edge bands [5]. The Red-Edge is a thin band spectrum, over which the chlorophyll absorption passes through to the scattering of NIR. To identify stress at an early stage that can not be observed by the human eye [6]. It is possible to affect the variations in the Red-Edge spectral band by changes in the chlorophyll of plants that are highly sensitive to the changes in the plant health that even could not be perceived [6]. Different vegetation indices (VI's) of the different satellite bands can be used to identify crop health information which is not clearly observable using traditional multi-color images. The raster images of these VI can be worked to appropriately identify and map stressed areas in the field.

Normalized Difference Vegetation Index (NDVI) is among the most popular indices and it is developed on the basis of the fact that healthy plants reflect a lot of NIR light and absorb a lot of red light. On the other hand, stressed plants respond weaker and is reflected in lower value of NDVI [7]. Therefore, the analysis of the NDVI map of cultivated field is the effective evaluation of crop health with lesser values pointing to the potential stress. The multi-spectral images have high spatial information and are susceptible to exploitation with a comprehensive approach to explore all the spectral without being limited to a single spectral. The unsupervised clustering has a major merit in classifying the similar data or pixels into clusters using their spectral properties [8]. Precisely speaking, the NDVI is an effective and stable source of data in terms of detecting crop stress in the mid-crop growth period since it is simple and quantitative data of canopy density and photosynthetic activity of a crop. When a healthy crop is at the mid-growth stage of the crop cycle, it would have a well-developed leaf canopy and very high level of chlorophyll captures red-light spectrum and would give a high reflection of the NIR spectrum. When a crop is in stress caused by inadequate irrigation, lack of nutrients in the soil and disease, photosynthetic efficiency of the crop reduces and cell structure starts to degenerate. This results in a large alteration in spectral signature whereby there is decreased absorption of red light as well as reduced reflection of NIR spectrum. This difference in Red/NIR ratio leads to the decrease in the value of NDVI as an early warning of stress which can be perceived before the naked eye can observe any actual signs of the stress. So, NDVI is regarded as a good non-invasive method of crop health observation at the time when it is crucial.

There is another significant index of assessing crop health, which is the Normalized Difference Moisture Index (NDMI) and it helps in determining water stress in the crop. This index is used to compare the NIR reflectance and the Short-wave Infrared (SWIR) reflectance. The percentage of moisture contained in the grown crop absorbs the SWIR spectrum and decrease in water content of crop will enhance SWIR reflectance and, consequently, decrease the NDMI value. The NDMI is a dependable index to observe the state of hydration of crop and the index is also a useful measure of accurate management of irrigation. The Red-Edge Chlorophyll Index (CI<sub>re</sub>) can be used to identify early stress.

The Red-Edge bands (Bands 5, 6 and 7) of Sentinel-2 are linked to the spectral band in which the reflectance of a healthy crop grows at a high rate. Stress leads to reduced chlorophyll content on a crop and alteration in the reflectance of the red edge spectrum. The CI<sub>re</sub> is very sensitive to this variation, and it allows to detect the stress early (before the biological process gets affected by the infection). The Modified Soil Adjusted Vegetation Index (MSAVI) may be regarded as the superior substitution of NDVI in case of a low vegetation cover area under survey. MSAVI also reduces the influence of any underlying reflectance of the soil that can bias the findings and creates a false measurement of the health of crops. The vegetation status can be better measured by use of MSAVI that distinguishes between the bare or sparsely vegetated soil and the stressed crop. The respective index that understands the effect of the soil on the spectral signal was estimated by a complex mathematical expression.

Based on the spectral data of Sentinel-2 imagery, this paper suggested a valid procedure of determining and mapping strained crop areas by utilizing the tools of deep learning approaches to produce greater representation of the features that exist in VI rasters. Auto-Encoder was used to find a low-dimensional representation of the multispectral data. It is a model of deep learning that can detect the complicated and non-linear associations in the data. The Auto-Encoder is able to extract the most noticeable characteristics that characterize the underlying biophysical characteristics of the crops [9] and cluster them to distinguish between the healthy vegetation region and the stressed/ unhealthy region. Thematic map to identify the boundary of healthy and stressed area is produced in form of output to guide the management of precision agriculture.

## 2. LITERATURE REVIEW

The need to have sustainable and accurate agricultural practices has been heightened by other government and non-government agencies to establish global food security. The latest development in remote sensing and AI technologies has made it possible to detect crop stress early and accurately [10]. This is a preventive measure that can be used to intervene on time, and prevent losses in yield due to biotic and abiotic conditions [11]. Multispectral imagery is used to produce a time series giving a complete overview of crop health [12]. This multi-spectral data was subjected to sophisticated analysis programs to identify very fine physiological variations in crop even before they are perceived with naked eye. According to the recent research, the integration of spectral data of various sources of satellites has been associated with a goal to enhance the quality of the detection regardless of the change in the environmental conditions (cloud cover, cloud shade, and tree shadows) [13].

Processing of this enormous amount of data has been made easier by the application of deep learning techniques. The traditional approaches are based on creating the manual inferences among the different estimated vegetation indices. However, non-linear and complex patterns in the stack of vegetation indices can be detected by using high-level deep learning algorithms. One of the most recent studies [14] revealed the rising position of ML models to the correct classification of crop stress. Equally, a recent research demonstrated the usefulness of the Convolutional Neural Networks (CNNs) to analyze the multi-spectral images in order to measure the spatial temporal variations of the health of crops that is significant in identifying the disease and pest infestations which change over time [15].

The direction that the field of precision agriculture is taking is that of more integrated and efficient systems. Sensors with multispectral and thermal images on the UAVs [16] are used to record data on the farm level in high-resolution and this data is compared to the ground-data to obtain a model to show the amount of the soil moisture and nutrients present in the field. The creation of cloud platforms and AI predictive systems offer their farmers live dashboard with information regarding irrigation, fertilization and pest infestation to enable the farmers to engage in proactive management of their farms [17]. The massive expansion in the use of remote sensing is impacting the holistic, scalable multi sensor systems that will give detailed application of crops, a more sustainable and resilient future of agriculture. A framework based on the detection of drought stress in maize fields using Sentinel-2 multispectral data and a hybrid CNN-LSTM model [18] has been created. The spatial features of the raster images and temporal variation in vegetation indices across the cultivation the cultivation period have been extracted by the convolution layers and LSTM layers of the CNN model respectively. The hybrid model was found to be more accurate in the identification of the development and intensity of water stress than the performance of the independent models when performing the task of identifying water stress. Sentinel-2 images were used to identify nitrogen deficiency in wheat [19]. Several Red-Edge-based vegetation indices were calculated and then Gradient Boosting Machine (GBM) was used to categorize various levels of nitrogen stress. These findings suggested that the models with Red-Edge indices were much more precise in the ability to differentiate between healthy and stressed crops in comparison with the use of the traditional NDVI, indicating the relevance of specific indices to be used to identify a particular nutrient deficiency.

The article presented in [20] created a deep learning architecture to early identify late blight in potato yields. Time series of Sentinel-2 were used to extract spatial and temporal features in a 3D-CNN which used the combination of these features. Although it appears that training a 3D model is extremely complicated in time and space, this method revealed infected area correctly, which proves the possibilities of deep learning to fight crop diseases by means of offering early warning signs. A different work made use of a multi-scale CNN to discriminate between weeds and crops, a type of biotic stress [21]. This model was trained on high-resolution images that were taken by a drone and the processing of the data at various spatial resolutions. This procedure could determine single weeds as well as bigger patches of weeds. The solution suggested by this study assists in facilitating the specific application of herbicides thereby decreasing the prices and the impact on the environment.

A study to be conducted in [22] to identify the presence of downy mildew disease in vineyards with the help of Sentinel-2 images: A system [22]. An unsupervised clustering method was used to cluster pixels together based on spectral signature. Through monitoring the evolution of these clusters over a time the authors were in a position to identify and trace the disease evolution in the vineyard thereby offering an economical solution compared to the expensive manual field inspection. In study presented in [23] a combination of multi-spectral and thermal images was applied to identify water and heat stress in the farm field. The spectral information of the crop health and temperature information of the variation in temperatures that the researchers have used has enabled them to come up with a model which has better forecasted the levels of stress. The model which was constructed using hybrid yielded more beneficial results compared to the models constructed using one of the data sources. This underscores the influence of trusted crop monitoring systems that are created based on hybrid models that are created through different data streams. A new approach of stress detection using a combination of hyperspectral measurements of a field spectrometer with Sentinel-2 is established in [24]. The hyperspectral data (high-fidelity) was first trained on a deep learning model and then applied to the Sentinel-2 satellite imagery. This combined method showed the possibility of using the detailed ground-based data in enhancing the precision of the large scale remote sensing based stress mapping the cultivated fields.

The problem of high-dimensional satellite data was solved with the help of an automated feature selection technique. The method of feature selection was created in [25] with the help of ensemble of machine learning models which helped include the most crucial and significant S2 bands and vegetation indices in the classification of the types of stress. The data processing pipeline was also optimized in order to enhance the computational efficiency of the models that were used to detect the stress. In [26], a real-time system of crop health monitoring based on cloud computing was suggested. Sentinel-2 data is automatically downloaded and processed by the system, which calculates several vegetation indices and makes instant alerts and visual maps of the areas in problem with farmers through a web application. This study is a significant move towards ensuring that advanced remote sensing technologies are made available and viable in making decisions in farms. An example of time-series sentinel-2 data was used to model crop phenology or the stages of crop growth [27]. An average phenological curve of a healthy crop was made and it is regarded as a baseline. The model would be able to detect the deviations of this baseline which are usually the first indicators of stress. This forecasting method allows the farmers to make plans and take preventive or corrective actions ahead of time before the stress seriously affects the crop.

As a result of the literature review, it is quite evident that the progress of developing data-driven approaches to crop stress detection is evident. The recent research has heavily depended on the supervised machine and deep learning models that cannot be attained without large and labeled datasets as well as multi-sensor data fusion. The suggested methodology adopts an unsupervised clustering model, which is a trusted alternative that does not demand the data intensive demands of the supervised approaches. This method involves the use of a blend of vegetation indices such as Red-Edge Chlorophyll Index (CI<sub>re</sub>), NDVI and NDMI. CI<sub>re</sub> assists in determining the initial stress, NDVI the vigor of the crop in the middle of the growing, and the NDMI that was employed in identifying the stress caused by water. S2 satellite source was used to extract the vegetation indices to create a scalable and accessible solution to farms that did not have historical ground-truth data.

### 3. Overview of Study area and Sentinel-2 data

The research was carried out at a village called Rama Reddy Palem, which is located in ChillakurMandal, Nellore District, Andhra Pradesh, India. The area is located between 14.05° -14.08° N and 80.05° -80.09° E and has an area of about 320 ha of paddy (*Oryza sativa*) under cultivation (satellite map of the target area is provided in Fig. 1). The significant crop in the Kharif season is Paddy, and the fields are described as standing water, different density of canopy, and high spectral variation among phenological stages. These properties render the area highly appropriate in analyzing the functionality of the MAX-RNB compositing, interpolation as well as clustering algorithms toward identifying regions of stress. The products of Sentinel-2 Level-2A surface reflectance were utilized to identify the stressed areas in the study area. The period to be covered by images of the study region was between January 2025 and April 2025 as this is the period of active growth and maturation of paddy. This was chosen to include vegetation dynamics at different field conditions. The spectrums have significant spectral bands including Blue (B2), Green (B3), Red (B4), Near-Infrared (B8), and Shortwave Infrared (B11, B12), and the spatial resolution is 10-20 m. These are significant computing vegetation indices. The polygon of Fig. 1 represents the boundary of the paddy cultivation fields that were used to identify the presence of stress with the help of the Sentinel-2 imagery.



Fig. 1. Spatial extent of the study area

### 4. METHODOLOGY

The proposed approach to identifying stressed areas on crops was premised on unsupervised clustering framework on Sentinel- 2 satellite images as shown in Fig. 2. It was broken down into three major steps, namely data pre-processing, vegetation index calculation, and unsupervised clustering. Sentinel-2 Scene Classification Layer (SCL) was used to apply cloud and shadow masking and thereafter to compose. To reduce the residual cloud contamination the MAX-RNB compositing method was applied after which the spatial (mean based) and temporal (maximum and median based) interpolation processes were used to fill in the remaining gaps. The clustering analysis was done using the final composite datasets to define healthy and stressed crop areas.

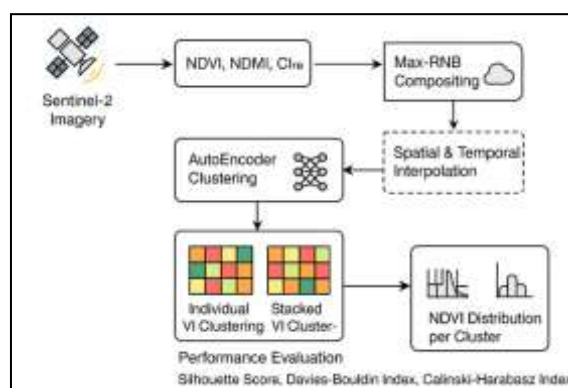


Fig. 2. Schematic view of proposed methodology

#### 4.1 Pre-processing

Sentinel-2 rasters in their raw form were then processed following a set of appropriate pre-processing tasks that converted the data to an effectively clean and spatially aligned data that was useful in further processing.

i. **Data Acquisition:** This is the process that is triggered by the acquisition of the Bottom of the atmosphere (BOA) reflectance data of Sentinel-2. Atmospherically incorrect products Level-2A products had atmospheric errors removed to remove atmospheric effects like scattering and absorption. It gives a better depiction of the land surface. In order to estimate vegetation indices, the spectral bands required in this research were Bands 2 (Green), 4 (Red), 8 (Near-Infrared) and 11 (Short-Wave Infrared).

ii. **Matching and Resampling of the Resolutions:** Sentinel-2 bands are in different spatial resolutions. To analyze the bands pixel-by-pixel the different bands need to be resampled to the same spatial resolution. Core bands used in this study (B2, B4 and B8) were at 10 meters with B5, B7, and B11 at 20 meters. Bilinear interpolation was used to sample the 20-meter bands at a 10-meter resolution in order to have the pixel aligned across all the rasters,

iii. **Clipping and Masking:** The samples are once more clipped to the exact farm field boundary. Following the clipping, a preliminary mask was used to isolate a non vegetated pixel, such as roads, buildings, and water bodies, so that the analysis was done on the crop alone. A basic vegetation index was used to carry out this masking. The Sentinel-2 images were obscured with NDVI to remove the non-vegetated areas. Near-Infrared (Band 8) and Red (Band 4) bands of the image were used to calculate an NDVI raster. NDVI raster was then subjected to a threshold value of 0.2. Any pixel of NDVI of less than this value was considered non- vegetated/ sparse vegetation and it was masked. It leaves only the vegetated parts of an image to be analyzed further.

iv. **Cloud and Shadow Filtering:** Clouds and their shadows influence the overall efficiency of the remote sensing based analysis. Scene Classification Layer (SCL) band is an output of the Sen2cor algorithm of Sentinel 2 Level 2A images. It is a popular mechanism of finding and sifting clouds and cloud shadows and other atmospheric and land-cover structures in raster data. It gives each pixel a definite integer value of its most probable class (cloud, cloud shadow, cirrus and so on).

## 4.2 Vegetation Index Calculation

The computation of the vegetation indices that were necessary to be analyzed was done using the stacked multi-band raster after the pre-processing steps. CIre was utilized to detect stress in the early stages of growth since it is highly sensitive to chlorophyll content variations, NDVI was utilized to measure stress in the middle of the growth period by effectively tracking canopy cover and photosynthesis, and NDMI was utilized as a direct stress indicator of the amount of water held by the plant.

### 4.2.1 Max-RNB Composite

The computed index rasters (of various parameters of crop health) were then the input to the clustering algorithm. This phase of the methodology aimed at producing one and only one high quality raster per month of the growing season. This has been done through the processing of all available Sentinel-2 images of a particular month. Given a series of images  $I_1, I_2, \dots, I_n$  captured in a month, a monthly composite image  $C$  month was made. The essence of this compositing scheme was the Max-RNB [28] scheme. Unlike averaging pixel values, the method picks the pixel value with maximum RNB in all the images available at a single location. This is founded on the fact that the RNB value at a particular point in time, over a certain time, reflects the best health of the vegetation. The low values are usually created by atmospheric interference such as clouds or aerosol.

The RNB index is calculated using the reflectance value of blue and near-infrared (NIR) bands of the surface. In any given place, the more the RNB value, the more the observation is clear. This is due to the fact that clouds, haze, or snow/ice have a tendency of increasing the reflectance of both the blue and NIR bands such that the ratio between the two approaches that of one. However, when there are no clouds in the sky, the RNB value generally increases far beyond one particularly when the atmosphere has been taken into account. The effect of cloud shadows is the reverse, which is to lower the values of RNB as cloud shadows become a significant decreaser of NIR reflectance with minimal impact on the blue band. The blue band continues to get a lot of light in dark places because the Rayleigh scattering is more intense that gives diffuse light in various directions (Luo et al., 2008). Though, the effect of Rayleigh scattering in the atmosphere can be corrected through atmospheric correction, it leaves shadowed areas comparatively bright in the blue band than in the NIR band due to this effect of diffuse light on shorter wavelengths. Residual clouds, haze, snow/ice and cloud shadows can be practically eliminated by choosing pixels with the highest possible RNB values to compose, in order to obtain a photographic image. The MAX-RNB algorithm uses surface reflectance, instead of top-of-atmosphere (ToA), reflectance, because it does not require any further data preparation steps, yet provides similar results.

#### Algorithm: max-rnb composite method

Notation:

Pixel Domain:  $x \in \Omega \subset Z^2$

Date indices in the month:  $\tau = \{1, \dots, T\}$

Blue, Red and NIR reflectances at pixel  $x$  on date  $t$ :  $B_t(x), R_t(x), N_t(x) \in [0, 1]$ .

Optional other bands  $b$ :  $B_t^{(b)}(x)$

Validity mask (cloud/shadow/water/invalid):  $M_t(x) \in \{0, 1\}$  ( $1 = valid$ ).

Optional per-pixel quality score (higher = better):  $Q_t(x) \in \mathbb{R}$

Small constant to avoid division by zero:  $\varepsilon > 0$ .

Temporal midpoint index (for tie-break):  $t_{mid} = \frac{1+T}{2}$

Step 1: For each satellite date compute NDVI

$$NDVI_t(x) = \frac{N_t(x) - R_t(x)}{N_t(x) + R_t(x) + \varepsilon}$$

Step 2: Estimate ratio of NIR to blue score which increases with high NIR and low Red.

$$RNB_t(x) = \frac{N_t(x)}{B_t(x)}$$

Step 3: Mask invalid pixel values: Use the validity mask  $M_t(x)$  to mask off the invalid pixels along with  $-\infty$  for penalization.

$$\widetilde{RNB}_t(x) = M_t(x)RNB_t(x) + (1 - M_t(x))(-\infty)$$

Also restrict maximization to the valid set:

$$\tau_{valid}(x) = \{t \in \tau : M_t(x) = 1\}$$

Step 4: Select pixel value from best date per pixel: argmax

$$t^*(x) = \arg \max_{t \in \tau_{valid}(x)} RNB_t(x)$$

Step 5: if multiple  $t$  maximize RNB then use combine quality and temporal-centrality score to resolve.

Let  $A(x) = \arg \max_{t \in \tau_{valid}(x)} RNB_t(x)$ . Then choose

$$t^*(x) = \arg \max_{t \in A(x)} [\lambda \tilde{Q}_t(x) - \mu |t - t_{mid}|]$$

where  $\tilde{Q}_t(x)$  is a normalized quality metric in  $[0, 1]$  derived from  $Q_t(x)$  (or 0 if unavailable),  $\lambda \geq 0$  and  $\mu \geq 0$  weight quality vs. temporal centrality.

Step 6. Compute NDVI at the selected date for each pixel, or compute NDVI from selected bands;

$$C(x) = NDVI_{t^*(x)}(x)$$

Step 7. After composing  $C(x)$  a bilateral filter was applied to reduce pixel-level temporal speckle noise.

#### 4.2.2 Interpolation

The procedures used to fill gaps of the MAX-RNB composite stack before the clustering process are outlined in this subsection. Small local gaps were filled by a spatial interpolation and temporal max / temporal median operators filled temporal gaps with the information of adjacent composite dates. Spatial interpolation is used to fill single pixel or small clusters of empty spatial gaps at a particular date  $t$  with a neighbor pixel (valid pixel of the same date. To define the set of valid spatial neighbors at time  $t$ . For a missing pixel  $(x, t)$  (i.e.,  $M(x, t) = 0$ ), define the set of valid spatial neighbors at time  $t$

$$S_r(x, t) = \{y \in N_r(x) : M(y, t) = 1\}.$$

If  $S_r(x, t) \neq \emptyset$ , then weighted spatial mean estimator is defined as follows;

$$\hat{C}_{spatial}^{(w)}(x, t) = \frac{\sum_{y \in S_r(x, t)} w_{xy} C(y, t)}{\sum_{y \in S_r(x, t)} w_{xy}}$$

The value of  $r$  was decided to be 3 pixels such that field boundaries are not too softened by spatial averaging.

Temporal interpolation is the process that fills the temporal gaps in a process that involves the observation of the pixel at other dates that are adjacent. Temporal max was either preferred to give preference to the clearest or strongest vegetation signal (consistent with MAX-RNB value) or temporal median to have a strong central estimate.

For a target missing entry  $(x, t)$  where  $M(x, t) = 0$ ; the set of valid times within a temporal window was defined:

$$\tau_h^{valid}(x, t) = \{s \in W_h(t) : M(x, s) = 1\}$$

The temporal max estimator can be defined mathematically as follows if  $\tau_h^{valid}(x, t) \neq \emptyset$ ;

$$\hat{C}_{tmax}(x, t) = \max_{s \in \tau_h^{valid}(x, t)} C(x, s)$$

Temporal max selects the largest observed value in the window, which tends to pick the clearest / least-attenuated observation. The temporal median estimator can be defined mathematically as follows if  $\tau_h^{valid}(x, t) \neq \emptyset$ ;

$$\hat{C}_{tmed}(x, t) = \text{median}\{C(x, s) : s \in \tau_h^{valid}(x, t)\}$$

Temporal median provides a robust central tendency and reduces influence of outliers (e.g., remaining cloud contamination, extreme noise).

Algorithm:

Step 1: For all  $(x, t)$  with  $M(x, t) = 1$ , set  $\hat{C}(x, t) = C(x, t)$ .

Step 2: For each  $(x, t)$  with  $M(x, t) = 0$ , compute  $\hat{C}_{spatial}^{(w)}(x, t)$  using  $S_r(x, t)$ ; then set  $\hat{C}(x, t) \leftarrow \hat{C}_{spatial}^{(w)}(x, t)$  and mark as filled.

Step 3: For remaining  $(x, t)$  compute  $\hat{C}_{tmax}(x, t)$  or  $\hat{C}_{tmed}(x, t)$  using  $\tau_h^{valid}(x, t)$ ; then set  $\hat{C}(x, t) \leftarrow \hat{C}_{tmax}(x, t)$  or  $\hat{C}_{tmed}(x, t)$ .

Step 4: For any time/ pixel still missing after applying steps 2 and 3, use one of the following strategies

- i. Enlarge spatial radius  $r$  or temporal window  $h$  and repeat, or
- ii. Apply separable spatio-temporal average:

$$\hat{C}_{sep}(x, t) = \frac{\sum_{y \in N_r(x)} \sum_{s \in W_h(t)} M(y, s) C(y, s)}{\sum_{y \in N_r(x)} \sum_{s \in W_h(t)} M(y, s)}$$

Step 5: Finally clip all the vegetation indices to their respective min-max range;

$$\hat{C}(x, t) \leftarrow \min(1, \max(-1, \hat{C}(x, t)))$$

#### 4.3 Unsupervised Clustering and Performance Analysis

This step was the heart of the stress identification, in which the vegetation index rasters were grouped together to identify the area of stress.

i. **Feature Vector Creation:** The vegetation index raster data were merged into a multi-dimensional feature-vector of each pixel and, therefore, each pixel in a single observation date would be represented by a set of values ([CIre, NDVI, and NDMI]). The combination of these indices gives a far more detailed account of crop condition than any of them individually, since it gives the unsupervised clustering algorithm more opportunity to pick up the finer details of relationships between chlorophyll status, canopy vigor, and moisture stress hidden by any single index. With time-series data, this feature vector can be further expanded to feature indices values corresponding to several dates so that the model could learn spatial and time-dependent patterns of crop health.

ii. **Clustering Algorithm:** The multi-modal data of vegetation indices (CIre, NDVI, NDMI, and their multi-temporal forms) were initially changed with the help of the AutoEncoder network. The auto encoder was trained to learn a nonlinear compressed latent representation of the multi-index feature space, it eliminates redundancy and noise to retain the most informative spectral and physiological variations. These latent features represented a more discriminative and lower dimensional embedding of every pixel, which can be used to express more complex relationships between canopy vigor, chlorophyll content, and moisture status, which are hard to separate in the original index space.

Latent feature vectors are then clustered using K-Means. The parameter that is critical is the number of clusters,  $K$ , that regulates the granularity of the segmentation. The learned latent vectors of each pixel were clustered into one of  $K$  clusters by minimizing the intra-cluster variance in the latent space. It enabled groups of pixels classified based on their underlying crop conditions to be grouped with a high level of reliability even in cases where their underlying raw index values had an overlapping or nonlinear pattern. The convergent cluster labels are then mapped back after convergence to produce a segmented farmland map using spatial locations which emphasized areas with similar vegetation health and water status. Clusters that had low latent responses with lower CIre, NDVI, and NDMI were considered to be stressed areas, which had high levels of low chlorophyll concentration, ineffective canopy structure or a lack of moisture, where on the other hand, high latent activations were considered as healthy and optimal areas of crop production.

iii. **Performance and Validation Analysis:** Conventional performance metrics used for supervised learning methods are not applicable to evaluate the performance of the methods used in this study as unsupervised clustering approach was employed. The performance of the clustering algorithm was evaluated using silhouette score and davies-bouldin index. A high silhouette score represent that the clusters are well separated and the pixels within a cluster are tightly grouped.

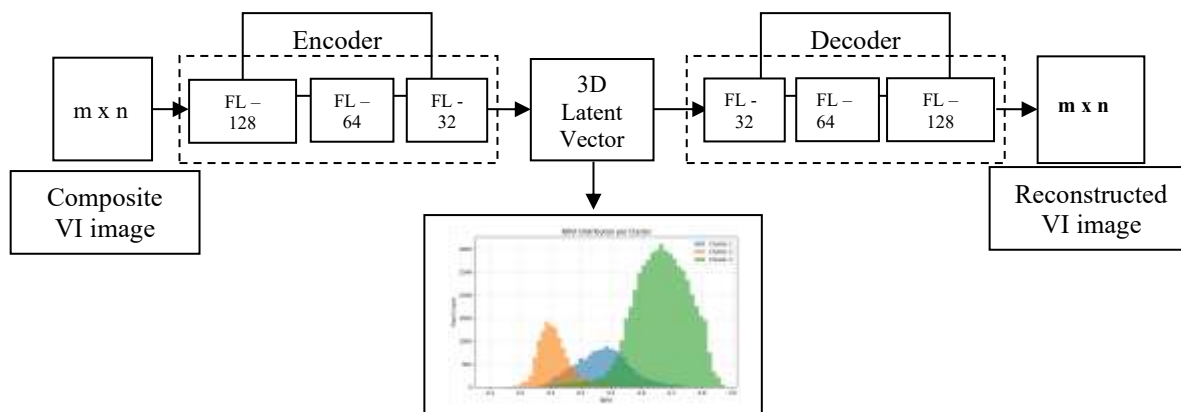
## 5. EXPERIMENTAL SETUP

Sentinel-2 Level-2A images were collected on different dates throughout the crop growth period of the research region. Vegetation Index (VIs) such as Normalized Difference Vegetation Index (NDVI), Normalized Difference moisture Index (NDMI) and Red-Edge Chlorophyll Index (CIre) were calculated on each date of acquisition to depict the state of vegetation vigor, moisture condition and the concentration of chlorophyll respectively. atmospheric variability and cloud cover, Max-RNB compositing was used To reduce the effect of . The date of the maximum NDVI value was determined in each pixel, and reflectance values on the date of the maximum NDVI value were used to create a monthly composite image. This made sure that the composited imagery had the most desirable vegetation signal. The missing values that occurred due to the cloud and shadow masking were filled with spatial and temporal interpolation as the spatial interpolation technique applied the mean filtering with an adaptive kernel size to determine the missing pixel values and preserve temporal continuity. Table 1 summarizes the list of parameters and the values of the parameters.

The VI composites were then preprocessed and then unsupervised clustering was performed to detect stressed regions. The process of clustering was carried out in two modes, (i) individual VI, where the individual VI, NDMI and CIre were clustered, (ii) stacked VI, where the three VI were put together in a multi-channel data set and then clustered. An AutoEncoder (AE)-based deep clustering architecture was used because of its capability to discover non-linear and compact feature representations, which boost the separability of vegetation stress levels in the latent space. The AE defined an encoder, a latent representation layer and a decoder and was trained with a mixture of Deep Clustering Embedding (DCE) loss and categorical entropy to prevent reconstruction error and cluster consistency together. The latent properties were then grouped in a K-Means into three vegetation categories such as healthy, moderately stressed, and stressed areas.

**Table 1.** Summary of hyperparameters (AutoEncoder)

Parameter	Value
Number of clusters (k)	3
Background threshold	0.0
Latent dimension	3
Training epochs	50
Learning rate (lr)	$1 \times 10^{-3}$
Loss function	DCE + Categorical Entropy
Optimizer	Adam



**Fig 3.** Architecture of AutoEncoder used for clustering

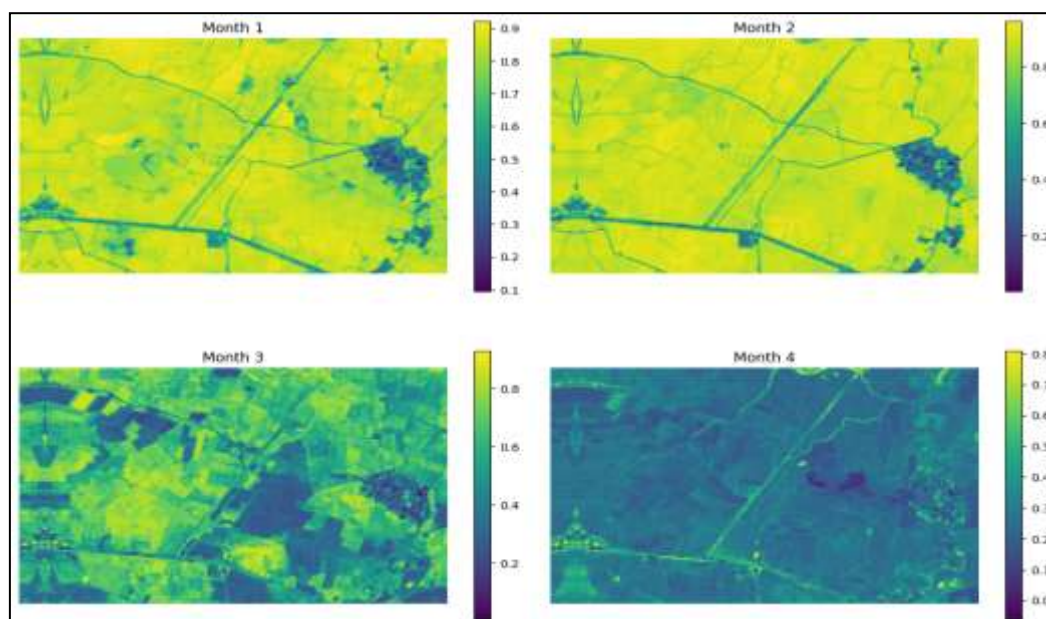
### 5.1 Auto Encoder Training

The Autoencoder (AE) used in the study was constructed with the purpose of pricing important latent features out of the vegetation indices derived by Sentinel-2 (NDVI, NDMI, and CIre), and allowing the strong distinction of the agricultural fields conditions. NDVI of every month during the cultivation period is estimated and represented in Fig. 4 and average NDVI of all months represented in Fig. 5. The architecture is symmetrical and has three key components, namely, an encoder, a latent space and a decoder designed to optimize both reconstruction and discriminative clustering. The encoder encodes the input features (high-dimensional) by sequentially contracting the encoder with three fully connected 128, 64, and 32 neuron layers, respectively.

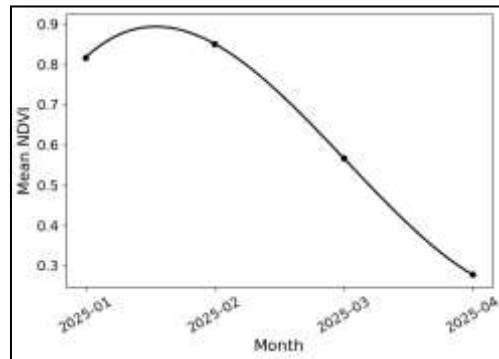
The layers use non-linear activation to learn intricate spatial -spectral associations and reduce redundancy in the information. The resulting compressed image is projected to a latent space of three dimensions (latent dim = 3) which is directly proportional to the number of clusters ( $k = 3$ ), which then enables features pertaining to healthy, moderately stressed, and stressed vegetation states to be naturally separated.

The decoder resembles the encoder but has 32, 64 and 128-neuron layers, and is used to decode the latent representation in the same dimensions as the original input. This rebuilding process guarantees that little information is lost which is stored by the learned features. It has been trained over 50 epochs with a learning rate (lr) of 0.001 using Adam optimizer which is chosen due to its adaptive adjustment of learning rates per parameter and converges faster than traditional stochastic gradient descent (SGD). It uses the loss function consisting of Deep Clustering Embedding (DCE) loss that encourages tight and separated clusters in the latent space and Categorical Cross-Entropy loss that imposes discriminative boundaries on cluster assignments. This bi-objective optimization guarantees both good reconstructions of data as well as good separability of clusters.

The design of the AE offers a number of benefits such as Dimensionality reduction without a handcrafted feature engineer, Cluster-aware learning which aligns latent dimension with the number of clusters and efficient optimization by Adam that supports sparse gradients and does not experience vanishing or exploding gradient problems. This architecture also provides a powerful model to classify the vegetation conditions unsupervised which is more effective than the conventional clustering algorithms by exploiting deep feature representation and regularization through reconstructions.



**Fig. 4** Estimated NDVI raster during cultivation period

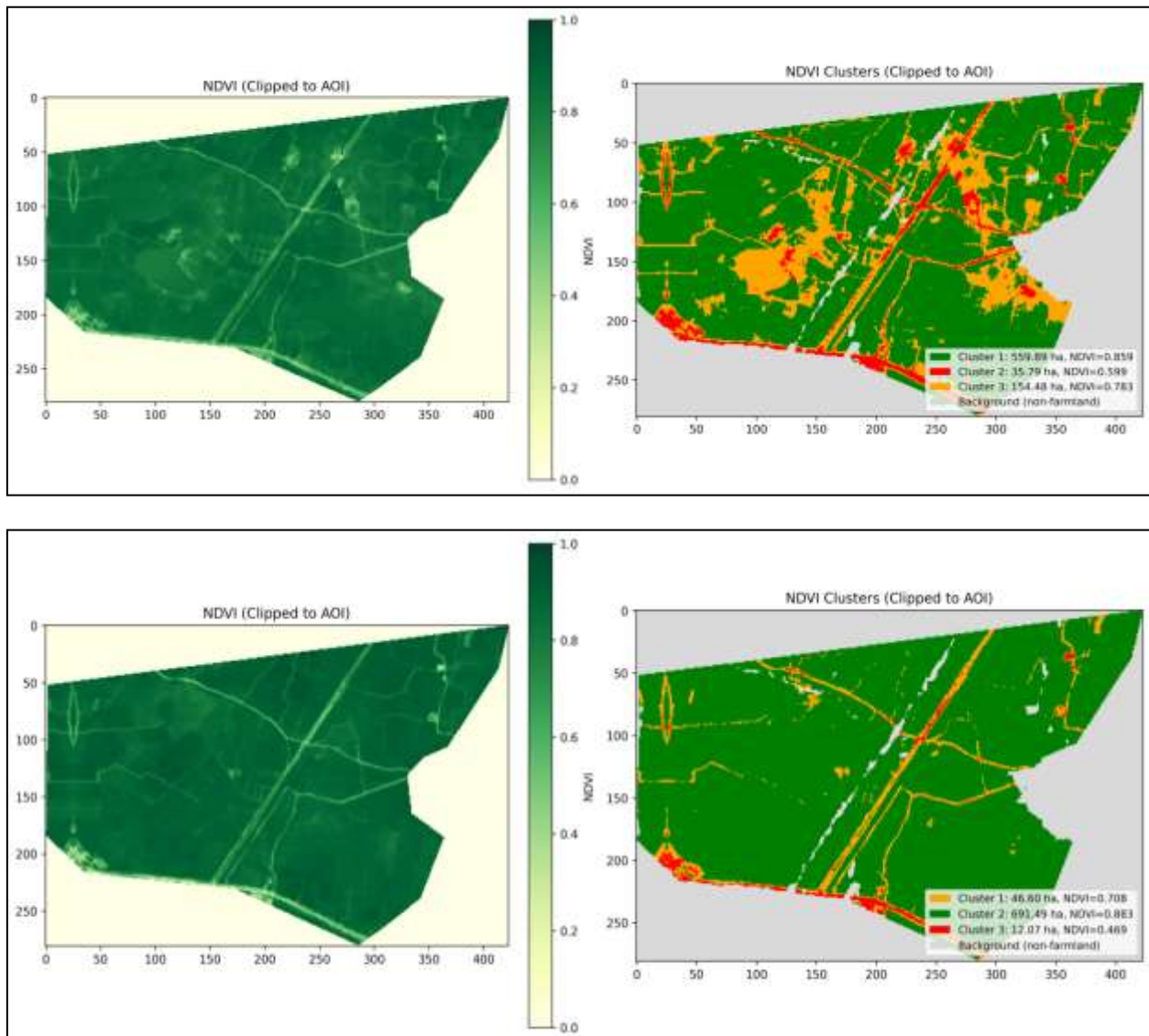


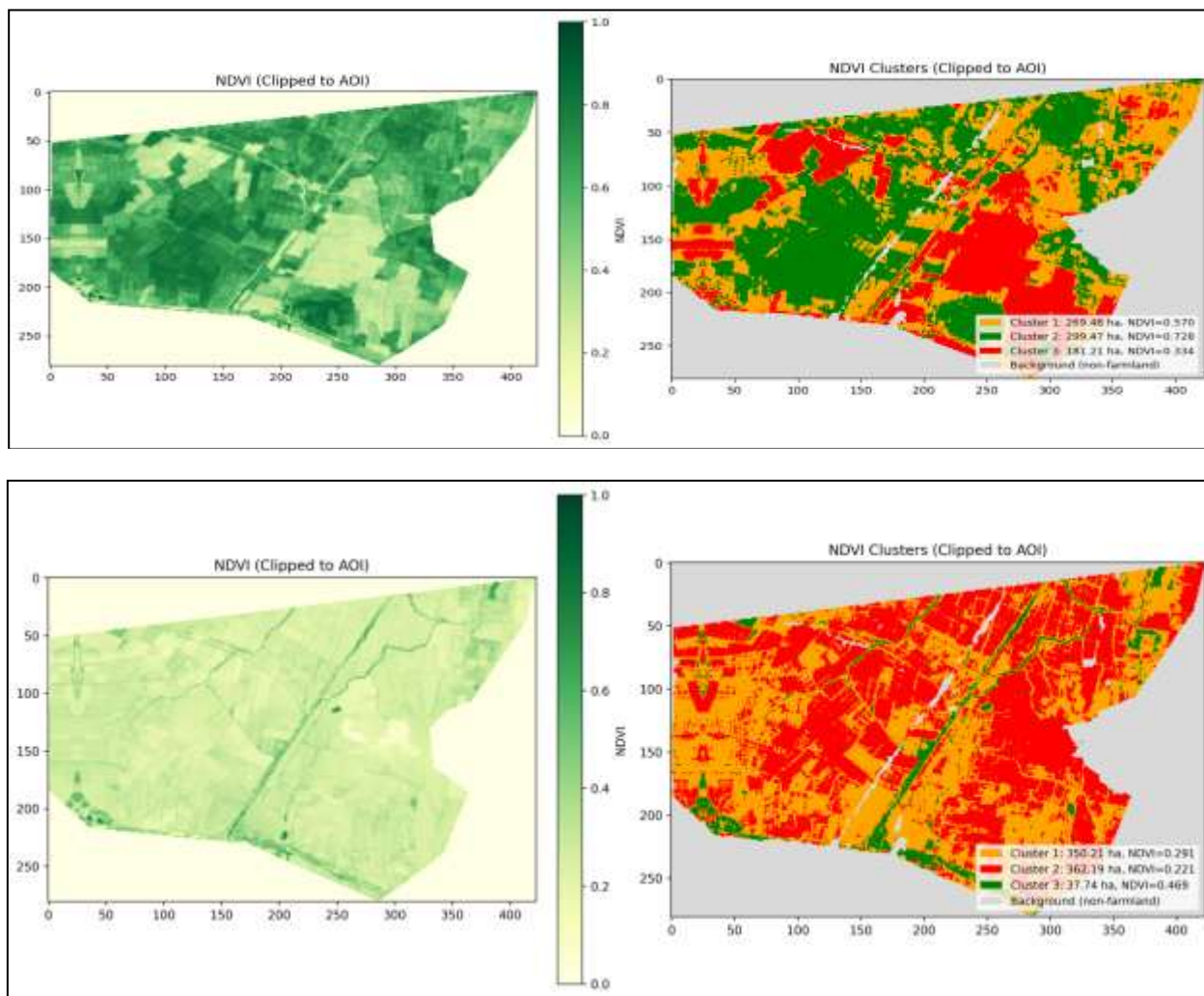
**Fig. 5** Plot of mean NDVI of cultivation period

The temporal trend of the mean NDVI values throughout the four months period of cultivation of the paddy crop illustrated a clear trend that represents the stages of crop growth. In January (0.81) and February (0.84), the NDVI values were the maximum, which means that the vegetative activity and the overall condition of crops were active and in favor of good growth in the early and medium stages of growth. The further fall in March to 0.57 is related to the beginning of the reproductive and the grain-filling phase, whereby the chlorophyll content normally declines as the crop grows. A devastating decline to 0.28 in April is a sign of the senescence period, in which vegetation cover reduces, and the crop is nearly in harvest maturity. Such a gradual decrease in the NDVI at the later stages can be attributed to the physiological processes in the crop, as well as a decrease in photosynthetic activity.

### 5.2 Performance Evaluation of NDVI (single band) Clustering

Fig. 6 shows the clustered NDVI raster of every month of the cultivation period. These results validate the claim that NDVI could be useful in identifying the phenological changes of paddy and can be used as a credible measure of crop condition throughout the cultivation period.





**Fig. 6** Clustered NDVI for each month of cultivation period

**Table 2.** Summary of NDVI statistics per cluster for each month

Month	Healthy region		Moderately stressed		Stressed region	
	Avg. NDVI	AREA	Avg. NDVI	AREA	Avg. NDVI	AREA
1	0.859	559.89	0.783	154.48	0.599	35.79
2	0.883	691.49	0.708	46.60	0.469	12.07
3	0.728	299.47	0.570	269.43	0.334	181.21
4	0.469	37.74	0.291	350.21	0.221	362.19

The cluster-based NDVI statistics of Table 2 demonstrate that the algorithm can preserve a clear ranking of the vegetation health in every month. The value of mean NDVI in the non-stressed group is the highest (with the range of 0.728 to 0.883), and the values of the most severely stressed group are the lowest (with the range of 0.221 to 0.599). This overall continuous decline in mean NDVI proves that NDVI-based clustering represents aggregate greenness gradients and gives a crude distinction between stressed and unstressed regions.

The spatial distribution of areas of clusters, however, indicates significant constraints. The severely stressed class occupies a quite small area (e.g. 35.79 ha in Month 1 and 12.07 ha in Month 2) in early months, which indicates that the clustering of NDVI alone underestimates the degree of stress when the stress is intense (e.g. in the early months) and/or medium (e.g. in Month 2). During later months, specifically Month 4, the stressed and moderately stressed ones prevail in the cultivated area (350.21 ha and 362.19 ha, respectively), which implies that NDVI-based clustering is more sensitive to the advanced stress or senescence conditions.

**Table 3.** Summary of performance metrics (clustering NDVI raster)

Month	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Index
1	-0.03753934	19.11558209	150.4477
2	0.003171486	4.412007588	3139.091
3	0.37507537	0.8145864354	81913.516
4	-0.029365344	14.47783116	199.98682

Table 3 that indicates the internal clustering performance measures also point to the shortcomings of NDVI-only clustering. Months 1, 2, 4 (-0.038, 0.003, and -0.029 respectively) are negative or close to zero, which means that there

is no strong separation of stressed and non-stressed clusters in NDVI feature space. Both the DaviesBouldin Index is similarly also large during these months (19.12 in Month 1 and 14.48 in Month 4), which indicates that there is a lot of overlap in cluster NDVI distribution. In Month 3, only NDVI-based clustering shows better results with positive Silhouette Score (0.375) and lower DaviesBouldin Index (0.815) indicating that NDVI is more discriminative in such times when vegetation contrast is strong.

The Calinski-Harabasz Index reveals the high variability in the months, with the highest value of 150.45 recorded in Month 1, and 81,913.52 recorded in Month 3, which means that the compactness of the clusters and the variance between clusters are greatly influenced by the seasonal conditions. The temporal variability of NDVI-only clustering performance and dependence on phenological stage instead of inherent stress properties are highlighted by this variability. On the whole, although NDVI raster-based clustering can effectively differentiate broad classes of vegetation vigor and reflect the patterns of stress at the end of stress stages, it shows a variable performance by month and a weak performance to separate out clusters in early and intermediate stress environments. Such results imply that NDVI does not give a complete picture of crop physiological health and the combination of other vegetation indices is encouraged to obtain more strong and temporally stable stressed regions representations.

### 5.3 Performance Evaluation of Multi-band Clustering

The multi-band clustering method combines NDVI, C<sub>ire</sub>, and NDMI to manage vegetation greenness, chlorophyll content and canopy water status at the same time. The multi-dimensional representation allows more accurately describing the physiological state of crops as opposed to NDVI. Through out all the four months, the clustering algorithm was able to distinguish cultivated areas into three significant vegetation health categories, which were high, moderate and low NDVI. The mean NDVI values of the clusters have a pronounced and monotonic order (shown in Table 4) that demonstrates that the clustering is not solely based on the NDVI.

**Table 4.** Summary of NDVI statistics per cluster for each month (clustering multi-band raster)

Month	Healthy region		Moderately stressed		Stressed region	
	Avg. NDVI	AREA	Avg. NDVI	AREA	Avg. NDVI	AREA
1	0.8605	454.71	0.825	36.01	0.7807	260.36
2	0.9025	334.82	0.8665	342.34	0.6939	73.92
3	0.7632	157.04	0.6362	330.77	0.3884	263.27
4	0.3898	83.31	0.2527	16.04	0.2508	651.73

Month 1 The high-NDVI cluster covers the largest area of cultivated land, and the moderate and low NDVI clusters cover smaller yet non-insignificant areas. During Months 2 and 3, the moderate NDVI cluster is greatly extended, which indicates the growing spatial heterogeneity of crop condition probably due to the difference in the growth stage or the early stress development. In Month 4, the sharp change has already taken place as NDVI low cluster occupies the most significant area, which is an indicator of crop stress or senescence to the later period of the season.

**Table 5.** Summary of performance metrics (clustering multi-band raster)

Month	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Index
1	0.063779	1.994978	15053.71
2	0.295275	0.857397	52009.25
3	0.358196	0.716353	105131.5
4	0.141888	111.1042	19447.12

The quality measurements of clustering as shown in Table 5 also add up to the effectiveness of multi-band approach. All silhouette scores are positive in all months, and this is a plus of better cluster compactness as well as separation. The value of Davies-Bouldin Index is significantly lower during Months 1-3 indicating that there was less overlap between clusters. Also, the values of Calinski-Harabasz Index are high especially in the Months 2 and 3 as they show strong between-cluster variance compared to within-cluster variance. On the whole, these measures prove that the multi-band feature space allows more coherent and well-separated clusters.

### 5.4 NDVI-only and Multi-band Clustering Comparisons.

The comparison of NDVI-only clustering and multi-band clustering shows that there are obvious benefits of the multi-band method. In the experiments that involve NDVI alone, the quality of the cluster is substantially different within the months. The low score of -0.3, -0.2, and -0.4 on silhouette in Months 1, 2, and 4 indicate that the clusters are weakly separated, and the high values of DaviesBouldin Index indicate that there is a lot of overlap in the distribution of NDVI. Even though the performance of Month 3 is better, the clustering of NDVI alone is still not constant throughout the temporal field. In addition, NDVI-only clustering only displays greenness gradients and fails to effectively discriminate stress regimes caused by other factors (e.g., low chlorophyll concentration or lack of moisture in the canopy).

However, the multi-band clustering has better and more stable silhouette scores that are consistently positive over the entire study period, which shows strong cluster separability. The fact that the values of the DaviesBouldin Index are lower

in the majority of the months supports the idea that the intra-cluster dispersion is lower and the separation between the vegetation health classes is better. Notably, the distributions of the cluster areas of the multi-band results provide more realistic spatial distributions, where moderate and low NDVI cluster areas are covering more areas and more continuously when crop stress is increasing.

Physiologically speaking, the clustering algorithm can be used to detect stressful areas, which might have moderate NDVI values but with lower chlorophyll content or water availability because of their inclusion of CIre and NDMI. Consequently, the multi-band method has earlier and more predictive stress identification than NDVI-only clustering, which is more likely to underestimate the extent of stress and gives unreliable cluster boundaries. The general analysis of the experimental findings reveals that the multi-band raster based clustering is far better than the NDVI based clustering both quantitatively and qualitatively. Combination of NDVI, CIre and NDMI results in better cluster separability, higher temporal consistency and more significant spatial demarcation of stressed and non-stressed cultivated fields. The presented results indicate that multi-index feature spaces are significant in crop stress analysis and validate the appropriateness of the AutoEncoder and K-Means model to physiologically targeted classifications of vegetation.

## 6. CONCLUSION

The paper investigates how well unsupervised clustering can be used to provide information on stressed and non-stressed cultivated farmlands using satellite derived vegetation indices. A multi-band raster with NDVI, CIre and NDMI was also used and an Auto-Encoder-K-Means framework applied to NDVI-only raster data. Cluster-wise NDVI statistics and traditional internal cluster performance measures were used to systematically assess the result. The experimental findings indicate that NDVI-only clustering can distinguish broad vegetation vigor classes especially at times of extreme crop stress. Nevertheless, it does not perform consistently over the months with negative/near-zero Silhouette Scores, high values of Davies-Bouldin Index and significant temporal fluctuations in the Calinski-Harabasz Index. These occurrences suggest poor cluster separation and high overlap between stressed and non-stressed classes when NDVI is utilized as the single feature particularly in early stages and moderate stress situations. Conversely, multi-band-raster based clustering method has always been superior to the NDVI-only clustering technique. The combination of NDVI, CIre, and NDMI results in a better compactness of clusters, a better definition of stressed and non-stressed areas, as well as the temporal stability. The multi-band method has greater Silhouette Scores, smaller values of Davies-Bouldin Index, and much larger values of Calinski-Harabasz Index in most months. Spatially determines bigger and coherent stressed regions earlier in the growing season, sensitivity to Chlorophyll degradation and canopy water stress, which cannot be adequately understood by NDVI alone. Comprehensively, the findings verify the hypothesis that multi-band vegetation index fusion in an AutoEncoderKMeans framework offers a better and more robust, physiologically significant method of identifying crop stress. This process can help to detect stressed areas better and provide meaningful information in terms of agricultural monitoring and decision support systems. Although the presented multi-band clustering framework gains high results in the context of crop stress identification, there are a number of areas that the future research and development can focus on. The present research is based on monthly composites that can reduce short-term stress signals. The analysis of higher temporal resolution which could be based on a biweekly or weekly composite, as a method to capture fast onset and recovery processes, could be examined in future work. Adding time continuity constraints can also enhance the consistency of time-temporal classification of stress.

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