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DEVELOPMENT OF A SPATIO-TEMPORAL CHANGE DETECTION APPROACH FOR CROP AND DROUGHT STRESS MONITORING USING SENTINEL-2 IMAGES

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ABSTRACT

The change detection technique is suitable for the assessment of crop and drought stress using multi-temporal satellite images to identify the temporal changes in vegetation and moisture conditions. It offers information about how agricultural conditions have changed over time, making it possible to identify areas under stress, patterns of recovery, and persistent stress areas associated with prolonged drought. By linking stress patterns to their length and intensity, change detection enhances the accuracy of agricultural stress mapping and drought monitoring when paired with vegetation indices and machine learning categorization. The primary aim of this research is to find an appropriate technique for change detection in crop stress and drought stress monitoring. The study is conducted on Haldharmau village in the Gonda District of Uttar Pradesh, where multi-temporal Sentinel-2 satellite images with a spatial resolution of 10 meters are used. For change detection, three techniques are employed: post classification comparison (PCC), change vector analysis (CVA), and Image Differentiation on NDVI and NDWI images for the years of 2023, 2024, and 2025, from January to June, which is the Rabi crop season when wheat is cultivated. Change detection was analyzed for the 2024–2023, 2025–2024, and 2025–2023 pairs of years, where the first two pairs are single-year change detection, and the last is persistent stress change detection. The study's conclusions improve precision agriculture and food security planning in the region by offering a method that can be used in other semi-arid and drought-prone regions with similar crop phenology and farming methods. Precision agricultural decision-making, impact assessment, and early warning systems all depend on this technique.

KEYWORDS: Change Detection, Change Vector Analysis, Post Classification Comparison, Sentinel-2 Image, Phenology, Crop Stress and Drought Stress.

1. INTRODUCTION

Change detection techniques, which are an essential part of remote sensing analysis, are crucial to comprehending the temporal development of land surface conditions in response to environmental, climatic, and anthropogenic influences. A few often used methods for assessing crop stress, drought dynamics, land use changes, and ecological disturbances are CVA, PCC, and image differentiation [1-3]. Each of the previously stated methods accomplishes certain monitoring goals and offers unique analytical benefits. Image Differencing is the simplest and most computationally efficient change detection method. It involves subtracting, pixel by pixel, two co-registered multi-temporal pictures obtained at different times. The resulting difference image highlights areas of change over time. Positive and negative values represent increases or decreases in plant vigor or surface moisture conditions. Image Differencing is of particular use in biophysical monitoring to the use of vegetation and moisture indices, such as the normalized difference vegetation index (NDVI) and the normalized difference water index (NDWI) as it is able to preserve continuous spectrum data. [4,5]. However, choosing the right threshold values is crucial to this method's dependability since incorrect thresholds might cause misunderstanding between real environmental change and background noise. "Change detection," which is the process of extracting, assessing, and describing changes from remotely sensed pictures, often entails comparing two registered images that were taken at different times. Spectral change vector analysis (CVA) and spectral feature-based analysis are the two main types of remote sensing change detection methods now in use [6–9]. Image that are simultaneously acquired are employed primarily in spectrum analysis that incorporates direct comparison, post-classification comparison, and multi-spectral transformation methods to compute alterations in type of features and information distribution. Are CVA, however, a better improvement over conventional differencing approaches: It considers the difference at a large number of spectral dimensions rather than a single band or spectral index [10,11]. Using this method, it is possible to represent change as a vector of multidimensional space, the magnitude of which is the extent of change, and the direction of which is the nature of transitions, i.e. drought conditions or vegetation stress. Since CVA integrates various indices, primarily, NDVI and NDWI, to provide a more detailed description of environmental variability and fewer misclassifications related to single-index variability, it can be of great benefit to the detailed analyses of vegetation indices and drought development [12-15].

In place of the direct use of raw reflectance data, a distinctive approach, post-classification comparison (PCC) compares independently classified thematic maps across different periods of time in order to examine changes in land cover or conditions. Such a pixel-wise cross-tabulation method is very effective in drought modeling and agricultural surveillance since such cross-tabulation mapping is easier to understand by policy-makers and it is less susceptible to atmospheric effects [16,17]. The method offers quantitative estimates of class change besides providing insight, relating to the formation of stress, maintenance of stress and dissolution of stress. PCC offers an overall approach to detecting environmental change when combined with such methods as image differencing and CVA. This is especially the case on a situation where vegetation indices that enable moderately fair evaluation of agricultural stress and drought across different durations and locations are denoted including NDVI and NDWI [18]. Even with its advantages, PCC is susceptible to the issue of classification errors. This is solved in multidate classification where labeled pixels are required but each transition is considered as a different class. Alternatively, compound classification takes the benefit of the temporal coincidences and 2 methods: a mutual approach to extensive information exchange of all the photographs, and cascade technique that classifies using previous photographs, which further makes use of the temporal information [19-21].

Given the increasing quantity of satellite photos, it is both advantageous and necessary to use their various advantages simultaneously. Change detection, for example, is the process of using satellite imagery to measure changes and qualitatively analyze the temporal consequences of various events. This paper is organized as follows. The following sections comprise the structure of the paper: The research area is contained in Section II, while Section III provides a description of the recommended methodology. Section IV provides a detailed presentation of the proposed method; Section IV displays the change detection findings for real data sets; and Section V provides a conclusion.

2. STUDY AREA AND SATELLITE IMAGES USED

2.1. Study Area

The research area is Haldharmau village in the

Gonda district of Colonelganj tehsil in Uttar Pradesh, India. It is around 20 km from the district capital and 31 km from the Ghaghra River, located at 27°08′43″ N latitude and 81°47′41″ E longitude. The town is located at 180.7 meters above mean sea level and spans 190.81 hectares, mostly used for agriculture. The area has a subtropical climate, with temperatures ranging from 1.0°C in the winter to 49°C in the summer, with an annual mean precipitation of around 1552 mm, mostly during the monsoon season. Different agricultural methods are supported by the region's alluvial soils, which are made up of sandy loam, loam, and clay loam. With a cultivation intensity of 157%, around 60% of the arable land is irrigated. Paddy, wheat, mustard, corn, and sugarcane are important crops that depend on the availability of water from irrigation and rainfall. The Ghaghra River and its tributaries have a major impact on the hydrological dynamics, which include soil moisture, sediment transport, and the distribution of water resources. Furthermore, different land-use mosaics that impact crop stress and land-use change are shown by satellite photography. A microcosm for evaluating agricultural health and hydrological connections is Haldharmau village.

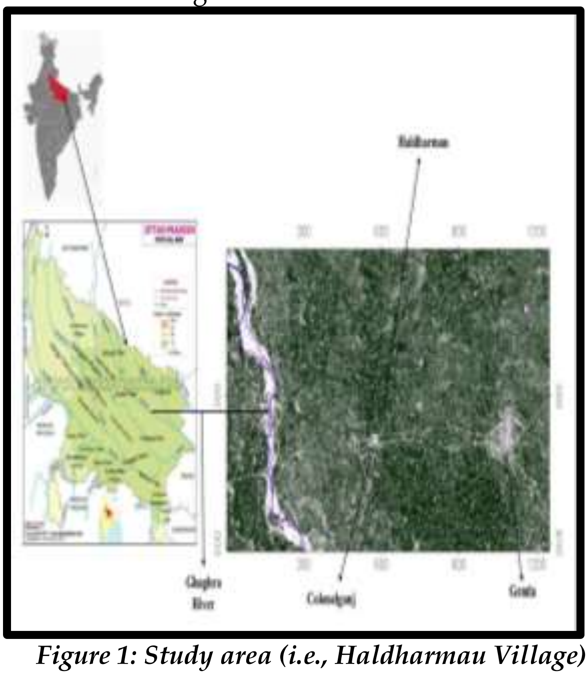


Figure 1: Study area (i.e., Haldharmau Village) shown in India and Uttar Pradesh maps.

2.2. Satellite Images Used

The planting and reaping of wheat crops in the research region are monitored in this study by using the Sentinel-2A satellite images. Red, near-infrared, and short-wave infrared bands are among the bands whose reflectance is measured at a resolution of 10 m in these images, and these bands have been utilized for crop stress and drought stress monitoring. The rabi season, for which sowing is usually done in October/November and is harvested in March/April, was covered by six Sentinel-2A images (i.e. Januarty to June) downloaded from the Copernicus Portal and analyzed for three consecutive years: 2023, 2024, and 2025 to observe the spatio-temporal changes in crop and drought stress monitoring. The details, such as the acquisition Id and dates of Sentinel-2 images, are given in Table 1.

Table 1: Details of Sentinel-2 images of 2023, 2024, 2025 used for change detection analysis.

Acquisition Date	Acquisition id
23/01/2023	S2A_MSIL2A_20230123T051111_N0510_R019_T44RNR_20240810T040852
02/02/2023	S2A_MSIL2A_20230222T050821_N0510_R019_T44RNR_20240821T150015
04/03/2023	S2A_MSIL2A_20230304T050711_N0509_R019_T44RNR_20230304T085603
23/04/2023	S2A_MSIL2A_20230423T050651_N0509_R019_T44RNR_20230423T092849
23/05/2023	S2A_MSIL2A_20230523T050651_N0509_R019_T44RNR_20230523T090404
02/06/2023	S2A_MSIL2A_20230602T050701_N0509_R019_T44RNR_20230602T090153
23/01/2024	S2B_MSIL2A_20240123T051119_N0510_R019_T44RNR_20240123T064628
07/02/2024	S2A_MSIL2A_20240207T051001_N0510_R019_T44RNR_20240207T085751
28/02/2024	S2A_MSIL2A_20240328T050651_N0510_R019_T44RNR_20240328T085651
22/04/2024	S2B_MSIL2A_20240422T050649_N0510_R019_T44RNR_20240422T081329
05/02/2024	S2B_MSIL2A_20240502T050649_N0510_R019_T44RNR_20240502T074253
11/06/2024	S2B_MSIL2A_20240611T050659_N0510_R019_T44RNR_20240611T073619
17/01/2025	S2B_MSIL2A_20250117T051039_N0511_R019_T44RNR_20250117T093134
21/02/2025	S2C_MSIL2A_20250221T050851_N0511_R019_T44RNR_20250221T111652
28/03/2025	S2B_MSIL2A_20250328T050659_N0511_R019_T44RNR_20250328T072008
22/04/2025	S2C_MSIL2A_20250422T050711_N0511_R019_T44RNR_20250422T102513
07/05/2025	S2B_MSIL2A_20250507T050659_N0511_R019_T44RNR_20250507T074549
06/06/2025	S2B_MSIL2A_20250606T050649_N0511_R019_T44RNR_20250606T074213

3. METHODOLOGY

Crop and drought stress change detection is evaluated through the CVA technique by using the

NDVI and NDWI index images, respectively. Vegetation change (ΔNDVI) for crop stress is computed using NDVI measurements from both the current and historical periods [22-24], where pixels are categorized into stress levels based on a predetermined NDVI threshold, and non-agricultural areas were hidden. Water availability variations were indicated by NDWI changes (ΔNDWI) in drought assessment, with thresholds indicating new, persistent, or recovered moisture conditions [25]. The post-classification comparison (PCC), which is another change detection approach, classifies vegetation stages and evaluates transitions like stable, new stress, and recovery to improve CVA by comparing land surface characteristics over time [2,14,26]. Compared to raw index data, PCC tracked changes in land condition more precisely. Hence, in this paper, for the effective monitoring of the effects of climate change on agriculture from January to June in 2023, 2024, and 2025, CVA has been combined with PCC to measure the intensity of changes in vegetation and moisture dynamics. To execute the methodologies, time series data is organized in three combinations of 2023-2024 (Comb-I), 2024-2025 (Comb-II), and 2023-2025 (Comb-III), where the first two pairs provide the change over one year, while the last pair will be used to monitor the changes between two years period.

3.1. Change-Vector Analysis (CVA)

CVA is a multivariate change analysing technique examining the scale and direction of spectral variability of agricultural landscapes over time [28]. NDVI and NDWI index pictures have been analyzed using CVA in order to examine vegetation and moisture dynamics. CVA provides a multidimensional view of agricultural health compared to the conventional binary methods of change detection because it characterizes vegetation health variations and access to moisture, thereby improving the understanding of crop stress and drought cases [29].

3.1.1. CVA using NDVI

For analyzing crop stress change detection, the following CVA formulae based on NDVI and crop mask are employed:

ΔNDVI= 〖NDVI〗_t- 〖NDVI〗_(t-1) (i)

Where t is the current year and t-1 is the previous year.

Condition	Interpretation
ΔNDVI < 0 and both years stressed	Persistent Stress
ΔNDVI < 0 and previously healthy	New Stress
ΔNDVI > 0 and previously stressed	Recovered
ΔNDVI > 0 and stable, healthy	Stable Healthy
Crop Mask = = 0	Non-crop area

3.1.2. CVA using NDWI

Similarly, for drought stress, NDWI and crop mask are utilized with the given formulae:

ΔNDWI= 〖NDWI〗_t- 〖NDWI〗_(t-1) (ii)

Where t is the current year and t-1 is the previous year.

Condition	Interpretation
$\Delta NDWI$ < 0 and $\Delta NDWI$ < 0	Persistent Drought
$\Delta NDWI$ < 0 and previously wet	New Drought
$\Delta NDWI$ > 0 and previously dry	Recovered Humidity
$\Delta NDWI$ > 0 and stable	Stable Healthy
Crop Mask = = 0	Non-crop area

3.2. Post Classification Comparison (PCC)

Using classified thematic maps instead of raw pixel values, the PCC technique provides a dependable way to detect changes for environmental monitoring [18,30]. PCC has been applied to examine drought dynamics using NDWI and crop stress dynamics using NDVI throughout three time periods (2023–2024, 2024–2025, and 2023–2025) from January to June. PCC's primary benefit is that it minimizes sensitivity to atmospheric fluctuation and sensor variances by concentrating on land condition categories [31-33].

3.2.1. PCC using NDVI

NDVI values for crop health are divided into two vegetative states: stressed (1) and healthy (0). This resulted in a transition matrix that measures responses to climatic circumstances. Agricultural stress may be tracked thanks to the classification, which makes it possible to differentiate between stable, new, recovery, and persistent stress.

3.2.2. Crop Stress State Transition

Let St, St-1 be class labels derived from NDVI:

Healthy Crop = 0

Stresses Crop = 1

The following conditions have been applied to observe the changes, which are as follows:

CropPCC(x,y)={0, Non-Crop Mask 1, S_(t-1)=0 ∧ S_t=0 (Stable healthy) 2, 〖〖S〗_(t-1)=0 ∧ S〗_t=1 (New Stress) 3, 〖〖S〗_(t-1)=1 ∧ S〗_t=0 (Recovered) 4, 〖S_(t-1)=0 ∧ S〗_t=1 (Persistent Stress) } (iii)

3.2.3. PCC using NDWI

To improve knowledge of drought emergence and recovery, NDWI maps are transformed into binary classes of normal moisture (0) and drought (1). Planning for agriculture and managing water resources are aided by this strategy. High interpretability, pixel-level transition monitoring, noise reduction, and quantitative statistical analysis are some of PCC's advantages [34,35].

3.2.4. Drought Transition

Let Dt, Dt-1 be drought class labels derived from NDWI:

No Drought= 0
Drought Stress=1

The following conditions have been applied to observe the changes, which are as follows:

DroughtPCC(x,y)={0, Non-Crop Area 1, 〖 D〗 _(t-1)=1 ∧ D_t=1 (Persistent Drought) 2, 〖〖 D〗 _(t-1)=0 ∧ D〗 _t=1 (New Drought) 3, 〖〖 D〗 _(t-1)=1 ∧ D〗 _t=0 (Recovered humidity) } (iv)

PCC is employed to compare the temporal behavior of the crop condition derived as NDVI and the drought condition derived as NDWI maps of 2023, 2024 and 2025 to study the dynamics of crop stress. It then identifies conditions of crops as being Healthy (0) or Stressed (1) after the application of a non-crop mask. The PCC outputs give pixel-by-pixel difference in the conditions of crop stress, which describe the pattern of emergence, persistence, and recovery. There are six spatiotemporal classes of crop health they are Class 0 non-crop; Class 1 stable and healthy; Class 2 new stress; Class 3 recovered, improved crops; and Class 4 persistent stress.

3.3. Image Differencing

Another pixel-based change detection method that is commonly used and popular is referred to as the image differencing; this method involves subtraction of two images captured on different dates to identify changes in the vegetation and moisture dynamics [36-38]. It quantifies changes using sensitive approach dynamic indices like NDVI and NDWI. Positive numbers are indicative of improvement where negative numbers are indicative of a decrease in vegetation and potential drought stress. To ensure that it is easier to locate the areas of crop stress spatially, the data are categorized in four classes regardless of severe decrease, moderate decline, no change and improvement [39-43]. This technique enables a quantitative investigation of time-dependent vegetation transformations with the help of multi-temporal Sentinel-2 images and gives a detailed insight into the change patterns specific to each crop throughout the period of rabi [44-50]. The mathematical formulation of image differencing on vegetation indices is discussed in discussion below:

3.3.1. NDVI-Based Greenness Change Detection

D= 〖NDVI〗 _T2- 〖NDVI〗 _T1
(v)

Where T1 and T2 are selected years for image differencing.

3.3.2. Elucidation.

NDVI Difference Range	Outcome
D < -0.3	Severe Crop Stress
-0.3 ≤ D < -0.1	Moderate Stress
-0.1 ≤ D ≤ 0.1	Stable/ Healthy Crops
D > 0.1	Recovered

The generated change map will have four change classes: severe crop stress, moderate crop stress, stable or healthy crops, and crops recovered from crop stress.

3.3.2. NDWI-Based Moisture Change Detection

D= 〖NDWI〗 _T2- 〖NDWI〗 _T1
(vi)

Where T1 and T2 are selected years for image differentiation

3.3.3. Elucidation.

NDWI Difference Range	Outcome
D<-0.30	Severe Drought Stress
-0.30≤ D <-0.1	Moderate Drought Stress
-0.10 ≤ D ≤ 0.10	Stable Soil Moisture
D >0.10	Recovered

The generated change map will have four change classes: severe drought stress, moderate drought stress, stable soil moisture, and crops recovered from drought stress.

3.4. Development of Spatiotemporal Crop and Drought Stress Analysis Approach

To extract crop pixels and describe vegetation and moisture stress conditions, a categorized crop map produced by a CNN–ViT hybrid model is first merged with Sentinel-2 images-derived vegetation and moisture indices, namely NDVI and NDWI. Crop and non-crop areas are separated using the softmax probability layer, producing multi-temporal crop stress maps and masked index layers for 2023, 2024, and 2025. Three change detection methods are then used to analyze these stress maps: change vector analysis (CVA), image differencing of NDVI/NDWI, and post-classification comparison (PCC). While image differencing uses thresholded difference maps to show the amount and direction of stress change, PCC is used to identify stress transition types such as stable, newly stressed, recovered, and chronic stress areas. By examining the direction and magnitude of spectral index vectors, CVA is able to further capture multidimensional change patterns. The workflow diagram of the spatiotemporal crop and drought stress analysis approach is shown in Figure 2.

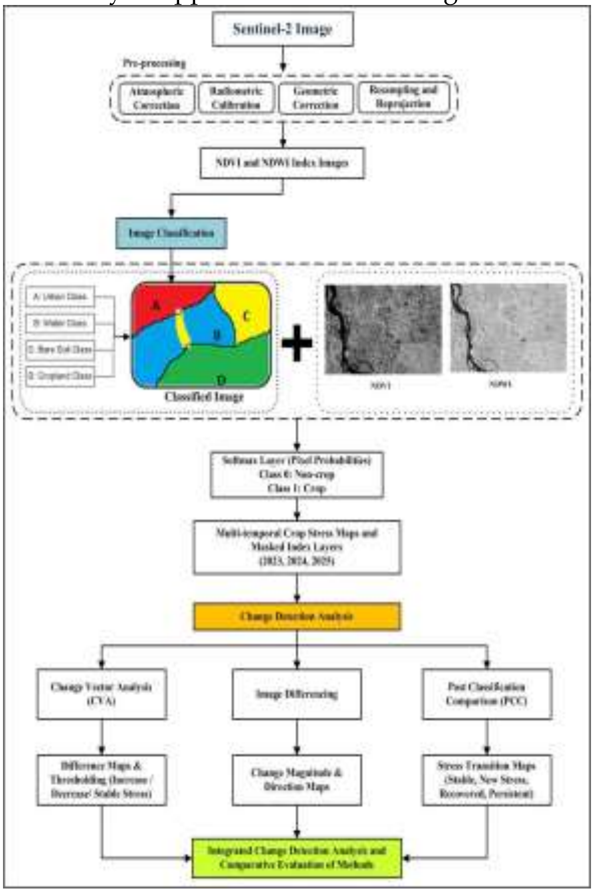


Figure 2: Workflow diagram of spatiotemporal crop and drought stress analysis approach.

(a) Comb-I_CVA (Crop Stress) (b) Comb-II_CVA (Crop Stress)

(c) Comb-III_CVA (Crop Stress)

To analyze spatiotemporal change based crop stress and drought the workflow diagram proposed in Figure 2 involves the integration of multi-method change detection and advanced machine learning-based crop mapping to analyze spatiotemporal change. The final outcome of all three change detection strategies is that quantitative and comparative analysis of the dynamics of crop stress and drought is obtained, thus being able to make spatiotemporal monitoring reliably and precision agricultural decision support. The main contribution in this workflow is that it is able to combine multiple change detection algorithms with deep learning-based crop classification to comprehensively observe crop stress and drought. The approach enables quantifying the direction of multidimensional change, spectral extent of change, and categorical transitions in stresses in a single framework with the combination of PCC, image differencing, and CVA. Such a combined solution enhances the decision support of precision agriculture and the long-term drought monitoring through the enhancement of the stress detection reliability, reduction in the method-specific uncertainty and provides reliable comparative analysis of the drought-induced crop stress.

4. RESULTS AND DISCUSSION

4.1. CVA-based Change Detection

4.1.1. Change Detection in Crop Stress

Comb-I (i.e., 2024- 2023), Comb-II (i.e., 2025- 2024) as well as Comb- III (i.e., 2025- 2023) have been combined with NDVI images of 2023, 2024, and 2025 and studied to address the most essential dynamics of crop health using the CVA approach. Figures 3(a), 3(b) and 3(c) illustrate change detection maps detected using CVA. Visual coherency Ensuring visual coherence through the application of a layer of a single color legend consists of giving all the change detection methods a single color legend where green represents stable or unchanging vegetation or representative of healthy vegetation. Non crop areas are represented by black. The recovered regions of the stress, which had previously been stressed and presently recovered areas are shown in yellow and any new stress that is discovered is shown in orange. On the other hand, Red is applied when there is a significant or a continuous stress and that was the case in the two years used in the determination of changes.

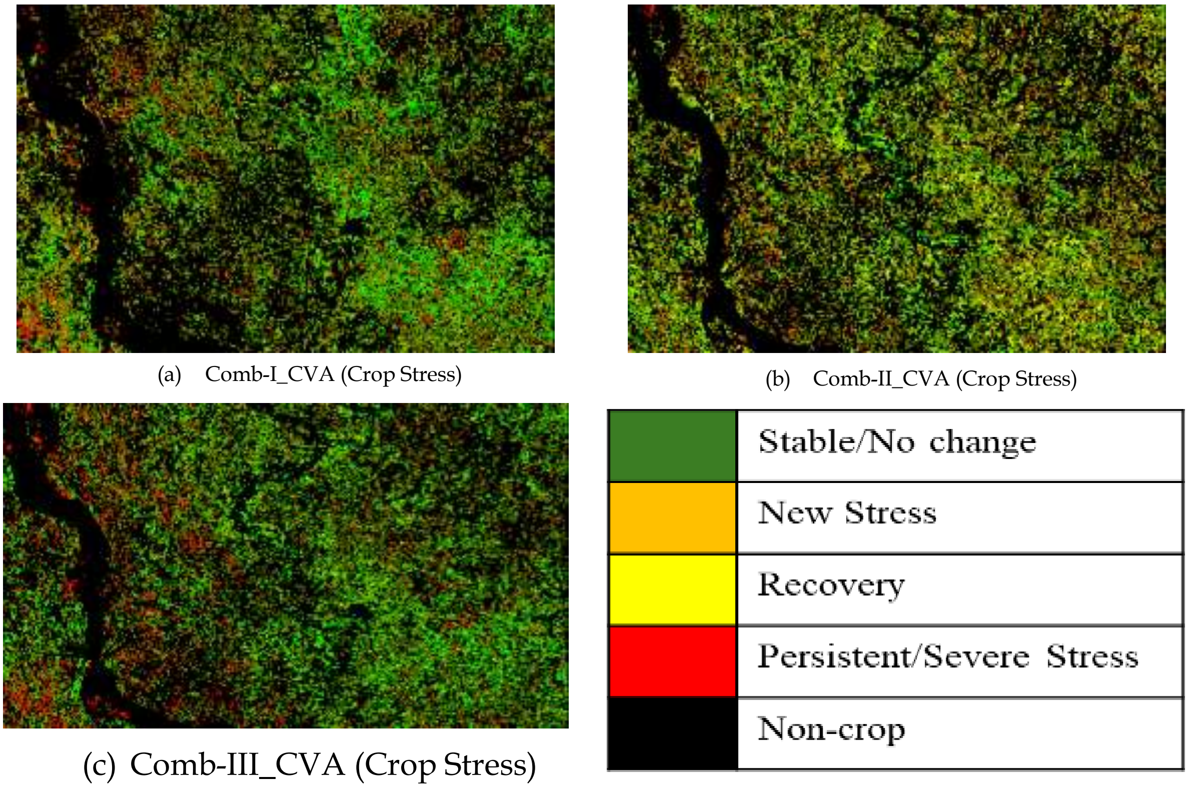


Figure 3: Change maps for multi-temporal crop stress monitoring using CVA.

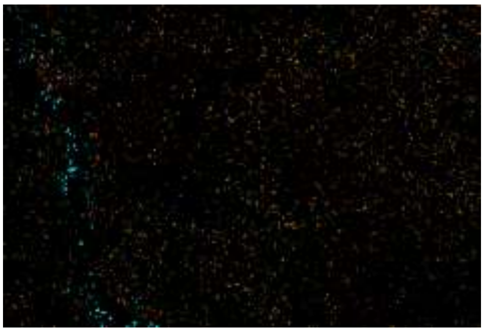
In Figure 3(a) CVA map, there is a significant pixel-level variation of NDVI changes in the locations of the onset of climatic aberration and moisture deficit, particularly in the locations where vegetation vigour has declined over the past year. Conversely, regions which maintained consistency of conditions would have probed to have benefited through specific rainfalls or by utilizing effective irrigation methods. A disturbing rise in stressed regions can be observed in Figure 3(b), which is associated with the poor trends in NDVI that are influenced by the cumulative effects of droughts and permanent water resource shortages. However a few pixels possess signs of recovery that are attributed to the improved agricultural practices or rain infrequently. The patterns of the change of the NDVI over the long-term are also presented by the change map in Figure 3(c) that emphasizes that the environmental challenges affect most of the agricultural areas over time but emphasize other regions of recovery and consistent performance illustrating the way in which different crops may be more resilient. The CVA relies on the NDVI based methodology, which is required to keep a record of increases and decreases in the crop conditions. It is able to retain continuous spectrum data unlike regular single-date evaluations and this enables a deeper comprehension of the vegetation dynamics. Crop mask usage enhances the procedure and thus is feasible to realize long-term degradation, track rehabilitation after positive conditions, recognize stress, and direct agricultural decisions and drought assessments. Altogether, NDVI-based CVA can be a potent approach toward multi-temporal monitoring of crop stress to enhance the analysis of agricultural vulnerability to shifting climatic conditions and supplement traditional techniques.

4.1.2. Change Detection in Drought Stress

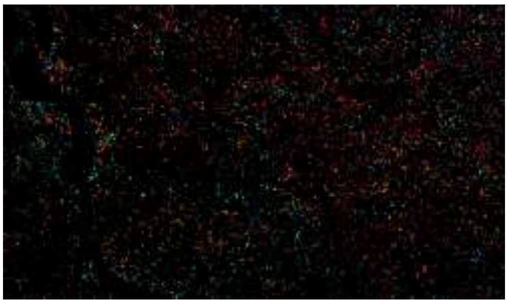
The CVA technique has been applied to the NDWI images of Comb-I, Comb-II, and Comb-III to observe the drought stress. Figure 4 presents CVA drought-related stress dynamics, which are based on NDWI images, where Figure 4(a) and 4(b) show yearly change and Figure 4(c) shows long-term change. Each pixel reflects a change in NDWI magnitude, but as compared to crop stress change detection maps, drought stress change detection maps are not clearly visible, where Black color represents all the non-crop area; red depicts intensified drought stress, which is persistent.

Orange shows early or moderate stress, while cyan presents the recovered area, and green, which is minutely present in Figure 4(a), 4(b), and 4(c), stands for healthy crop areas.

(a) Comb-I_CVA (Drought Stress)



(b) Comb-II_CVA (Drought Stress)



(c) Comb-III_CVA (Drought Stress)

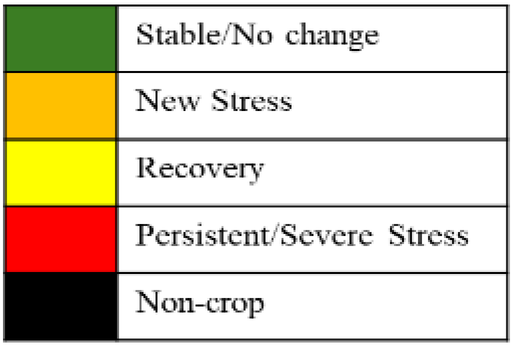


Figure 4: CVA-based change maps for drought stress analysis.

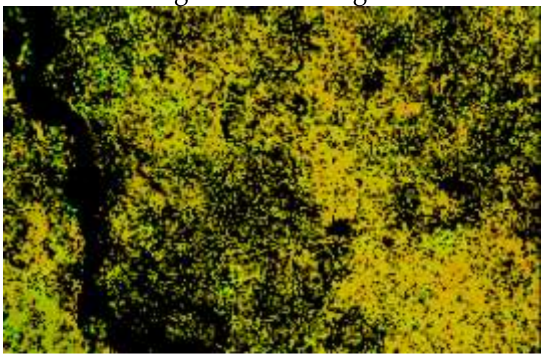
Crop stress intensity varies both spatially and temporally over the course of the study, as shown by the NDWI-based CVA maps. While the change map in Figure 4(b) shows stress continuation and extension, in Figure 4(a), CVA emphasizes early stress signals with localized healing. The long-term CVA comparison shown in Figure 4(c) makes it evident which agricultural zones are persistently impacted by drought, as indicated by the cumulative reduction in NDWI. The diverse pixel-level patterns show how CVA can effectively capture continuous vegetation dynamics beyond categorical change detection, reflecting field-scale heterogeneity in crop conditions and water availability. It has been observed that CVA is not suitable for change detection analysis as drought stress maps are not clear to show the areas that are stressed, recovered, or healthy within a couple of years.

4.2. Image Differencing-based Change Detection

4.2.1. Change Detection in Crop Stress

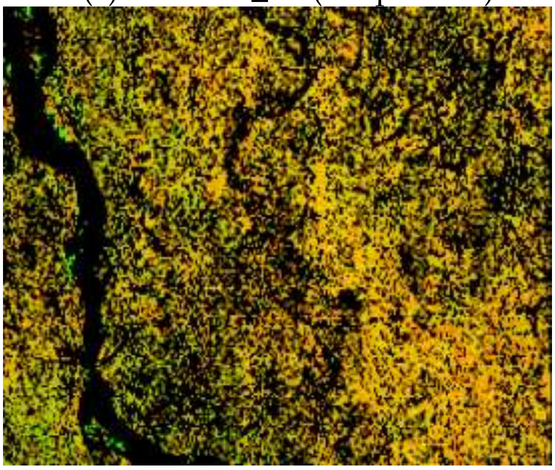
Image differencing (ID) method has been applied on the NDVI images of the Comb-I, Comb-II and Comp-III because it has been identified that the NDVI differencing is particularly useful in monitoring the crop degradation, crop recovery, as well as crop stability and it calculates the differences in pixel NDVI values to determine vegetation vigour and health. A positive number indicates improved vegetations, whereas a negative one indicates poor metabolism and even, stress. Figure 5(a) reveals the localized negative changes of NDVI in 20242023 that can be a result of crop getting stressed because of irrigation issues or the lack of moisture. Most of the alterations at this period are low magnitude showing stable vegetation although there are places of recovery. There are increasing negative values of NDVIs in Figure 5(b), which depict massive loss of crop vigor due to drought conditions or shortage of moisture with intervals of recovery. Large regions with large negative NDWI changes can be identified in Figure 5(c), which is the evidence of the further agricultural degradation; the lack of the positive changes indicates the lack of the recovery. By and large, the NDVI differencing maps can be of critical information regarding the inter-annual variation on the health of vegetation which is vital in the understanding of future stresses and recovery of crops in the respective timeline under monitoring.

They also reveal the effectiveness of NDVI image distinction in observing the subtle vegetation strain with a period of time.



(a) Comb-I_ID (Crop Stress)

(b) Comb-II_ID (Crop Stress)



(c) Comb-III_ID (Crop Stress)

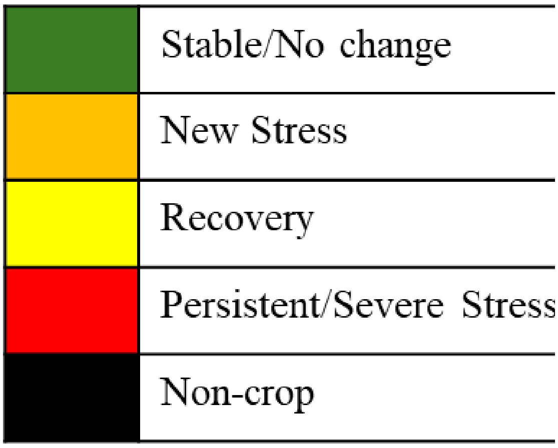


Figure 5: Change maps depicting inter-annual vegetation change based on Image differencing.

4.2.2. Change Detection in Drought Stress

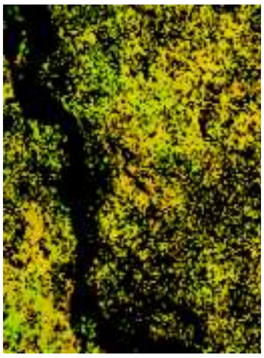
The inter-annual crop moisture fluctuations have been observed by comparing the pixel by pixel NDWI values of the three consecutive years and using the image differentiation maps of the NDWI processed by Comb-I, combine-II, and combine-III as shown in Figure 6(a), 6(b), and 6(c). The NDWI index is also dependent on soil moisture and water content in vegetation with a varying seen in moisture availability with positive outcomes

(a) Comb-I_ID (Drought Stress) (b) Comb-II_ID (Drought Stress)

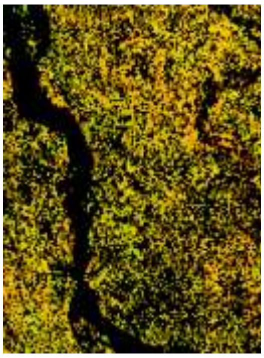
(c) 2025-2023_ID (Drought Stress)

indicating improving situations, whereas negative variations of the index imply stress in conditions with drought. Moving averages and local drying are observed in Figure 6(a), which means that drought starts in a number of production zones. The latter change map (figure 6b) however demonstrates a more dispersed negative NDWI variation, which was driven by the aggravation of drought conditions across the area, which is, presumably, caused by the higher evapotranspiration or rain shortage. These differences in moisture are presented in a graphical way on the maps through a color-coded technique. Orange to red spots will have a declining vegetative water content and drought stress whereas yellow regions will have a constant moisture level. Extensive yellow signifies stability of the moisture in Figure 6(a), whereas limited areas of orange-red color signifies local stress. The presence of the few green areas shows a marginal recovery. Comparatively, Figure 6(b) demonstrates less yellow zones and more orange-red meaning that there was a significant decrease in the moisture conditions and no restoration.

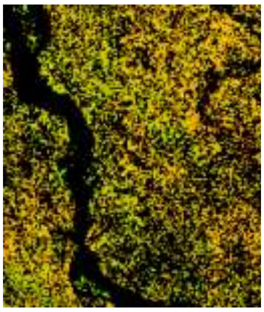
Figure 6: Image differencing-based change maps illustrating inter-annual moisture change.



(a) Comb-I_ID (Drought Stress)



(b) Comb-II_ID (Drought Stress)



(c) 2025-2023_ID (Drought Stress)

Furthermore, the shift from yellow to orange-red indicates that the drought situation is getting worse. By accurately capturing the amount and direction of moisture changes, the NDWI image differencing approach aids in the identification of drought-vulnerable agricultural regions and promotes preventive drought management strategies. Figure 6(c) highlights changes in crop moisture conditions. While yellow tones indicate consistent moisture levels, orange to dark orange regions demonstrate significant decreases in plant and soil moisture due to rising drought stress. Although the intermittent green patches exhibit little increases in moisture, their scarcity relative to the larger orange sections indicates that recovery has not been enough.

The NDWI-based image differencing map (2025–2023) qualitatively captures the effects of drought, but how they are interpreted relies on thresholds. Compared to CVA, which still records spectral variability while taking change direction and magnitude into consideration, this is an improvement. Conversely, PCC could offer a more precise assessment of agricultural drought. While PCC aligns well with NDWI and CVA, it offers better interpretability for long-term agricultural drought monitoring by distinguishing between stable, recently stressed, recovered, and consistently drought-affected regions.

(a) Comb-I_PCC (Crop Stress) (b) Comb-II_PCC (Crop Stress)

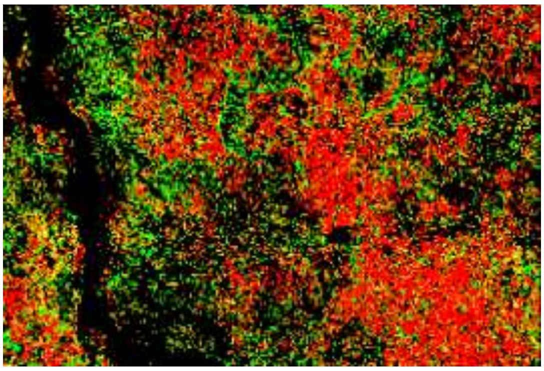
(c) Comb-III_PCC (Crop Stress)

4.3. PCC-based Change Detection

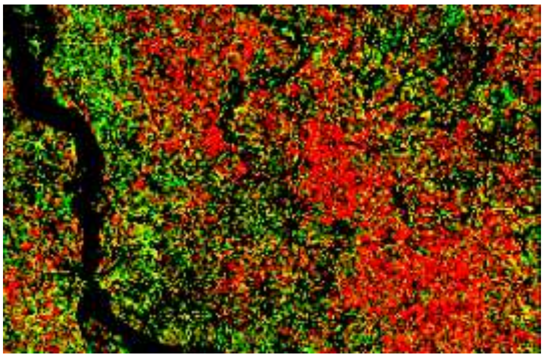
4.3.1. Change Detection in Crop Stress

PCC assisted the development of monthly and seasonal shift maps which demonstrate the changes in stress and drought. These maps show the stable, new, recovered and permanent states coded in colors. The automatically generated information provided useful data on the seasonal and time-based analysis of the stress reactions. The study demonstrated the efficacy of PCC in monitoring the well being of agricultural ecosystems by identifying patterns of stress progression, recovery patterns, and seasonal variation caused by climate factors; all of them are essential in the precision agriculture and decision-making procedure of sustainable irrigation management. The PCC technique results can create change maps, such as the one that was shown in Figure 7(a), 7(b), and 7(c) to clearly show the complex view of the crop stresses and recovery.

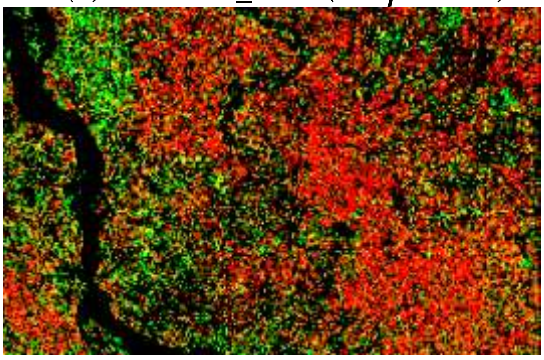
Figure7: Change maps for crop stress analysis based on PCC.

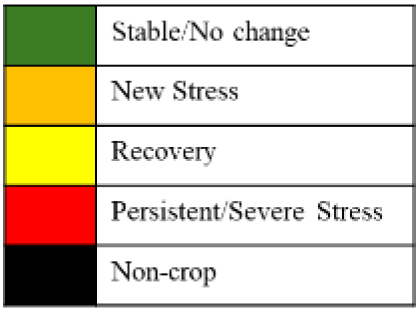


(a) Comb-I_PCC (Crop Stress)



(b) Comb-II_PCC (Crop Stress)





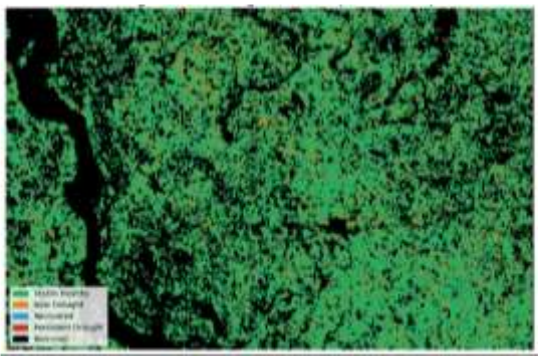
Additional stress points across 20242023 reflect the emergence of the undesirable environment, despite the continuation of the current stress patch territory being subject to constant susceptibility to climate change. It can be seen in Figure 7(a) 20242023 PCC maps that crop conditions changed, and New Stress (Class 2) pixels show the first signs of drought or negative environmental impact. Regions that were Stable Healthy (Class 1) had not lost the proper crop vigor and those that were Persistently Stress (Class 4) areas still persisted with poor soil or water supply. Both the Class 3, which shows an increase in rainfall or water management, and a maintenance of Persistent Stress (Class 4), which shows a long-term drought are recorded on the change map as Figure 7(b) presents. Although the areas of maximum growth maintain an expanding region, the comparison of 2024–2025 also shows localized recovery in response to factors such as rain and irrigation reactions by the crops, as reflected by the regional variations. The figure 7(c) shows the changes of stress over the long-term periods, with the areas that are classified as Persistent Stress as high-risk, and Recovery and Stable Healthy areas as robust. Patterns of recovery and persistence Reduced New Stress shows major recoveries and perspectives through the landscape, with the majority of stress being earlier on in life...

The PCC-based crop stress state transition study provides a rational perspective in the understanding of agricultural stress on the pixel level and differentiating a variety of stress differentiating between different types of stress such as new, persistent, and recovering areas among others. It simplifies the agricultural planning process and improves the crop status mapping produced by the NDVI to the accurate drought effect estimates. Recognizing the dynamics of crop stresses, the approach contributes to the monitoring of droughts in the long run and the way of addressing them. Altogether, PCC can be regarded as a powerful decision-support tool that provides valuable information regarding the time and place changes of crop stress due to climate change.

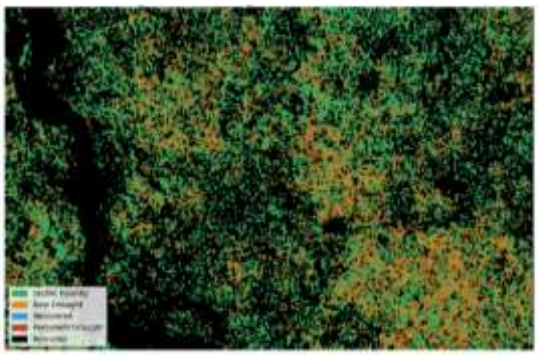
4.3.2. Change Detection in Drought Stress

The PCC change detection approach has been applied to the NDWI images of Comb-I, Comb-II, and Comb-III to observe the drought stress as shown in Figure 8(a), 8(b), and 8(c) where change maps are divided into four drought states: New Drought (Orange), Recovered (Cyan), Persistent Drought (Red), and Stable Healthy (Green) because it precisely records categorical drought state changes, unlike continuous change detection approaches. The PCC-based change maps' spatial patterns show that drought stress gradually increased from 2023 to 2025, with a discernible rise in pixels moving from healthy to stressed circumstances, especially in Comb-II and Comb-III. Long-term moisture deficits are indicated by persistent drought patches, and the farming system's resilience is suggested by limited recovery zones.

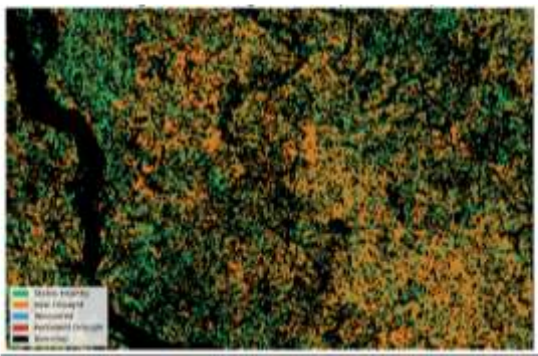
In Comb-I, shown in Figure 8(a), about 10,334 ha were under fresh drought stress, whereas about 65,991 ha were steady and healthy. About 3,944 hectares were impacted by the ongoing drought, while about 2,455 ha recovered, showing general improvement but indications of drought growth. Whereas in Comb-II, shown in Figure 8(b), healthy crops significantly decreased to around 35,058 ha, new drought stress grew to about 19,832 ha, and chronic drought increased to about 7,877 ha, with only about 898 ha recovering, which indicated a spike in drought-affected areas.



(a) Comb-I_PCC (Drought Stress)



(b) Comb-II_PCC (Drought Stress)



(c) Comb-III_PCC (Drought Stress)

	Stable/No change
	New Stress
	Recovery
	Persistent/Severe Stress
	Non-crop

Figure 8: PCC-based change maps for inter-annual change detection in Drought Stress.

According to Comb-III, shown in Figure 8(c), long-term statistics, new drought areas increased to about 32,553 ha, stable areas decreased to about 23,112 ha, and there was a chronic drought at about 4,999 ha with a marginal recovery of about 870 ha. The maps in Figure 6(a), 6(b), and 6(c) show that the drought has intensified, going from green to red, and that there has been little recovery, which is consistent with NDWI behavior. The NDWI's importance in policy planning and drought monitoring is strengthened by its continual moisture sensitivity. According to the analysis, drought stress gradually increased between 2023 and 2025, with decreasing consistent moisture conditions and little crop recovery. Using a crop mask guarantees that the analysis is limited to agricultural land, improving interpretability for managing and monitoring drought. By highlighting specific stress state changes across time, the PCC drought maps successfully proved to be superior to CVA and image differencing-based evaluations, offering an intuitive and decision-oriented depiction of drought evolution.

5. CONCLUSION

The analysis in this paper shows that a combined strategy of monitoring the dynamism of crop stress and drought was applied when the data was collected using multi-temporal Sentinel-2 satellite images based on CVA, image differencing, and PCC change detection strategies. Those methodologies are based on NDVI and NDWI that provides quick assessment of vegetative vigor, but in transitional periods, they are ambiguous. Whereas CVA enhances the analysis by quantifying the changes in the stress, PCC is an efficient method of identifying drought transitions across various categories. The PCC approach is helpful in the assessment of crop and drought, as maps are useful because of low susceptibility to environmental changes that indicate varieties of transitions of drought, which cover healthy crops and permanent dry zones. Findings indicate a positive effect of drought stress on the period 2023- 2025, which was not reversible, and the healthy crops decreased. The integrated approach provides a scalable framework of sustained monitoring drought observation, citing the mutuality of different methods in analyzing crop stress, and is an essential aspect of accuracy agriculture and weather-resilient planning. This innovative multi-temporal Sentinel-2 satellite imagery with improved methods to identify the background improves precision agriculture and drought risk management. Future research may improve crop stress and drought applications through the use of multi-source climatic variables to better relate remotely sensed indicators with the hydro-meteorological factors. The early warning of drought can be enhanced to include advanced deep learning networks such as CNN–LSTM or Transformer networks which are designed to be similar to the time variation of drought. Also, a greater number of Sentinel-1 radar characteristics and spectral indices can make the detection more resilient in bad weather. The strategies such as XAI which consider explainability and quantification of uncertainty will be more likely to be accepted by policymakers. Finally, near real-time data and scaling strategic measures to monitor operational drought and plan agriculture in less drought-resilient areas and larger multi-crop classes will be provided.

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