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Advancing Precision Agriculture: Integrating Satellite Remote Sensing For Crop Health Monitoring And Assessment

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Abstract

This study presents an integrated remote sensing approach for monitoring and assessing the health and development of wheat crops in Allahabad district, Uttar Pradesh, an important wheat-producing region in India. Satellite images from Landsat 7 and Landsat 8, acquired on five key dates during the 2015–2016 growing season (December 24, 2015; January 24, 2016; February 10, 2016; March 21, 2016; and April 14, 2016), were utilized to derive the Normalized Difference Vegetation Index (NDVI) across 110 contiguous wheat fields spanning the all eight tehsils of the district. The temporal NDVI analysis revealed a clear phenological evolution, with mean values progressing from 0.07 during the crop establishment phase in December to a peak of 0.47 in February, followed by a decline to 0.31 in March and reaching a low of 0.13 by April, marking the onset of senescence and harvest-readiness. Further, spatial assessments of NDVI revealed variability in crop health within and among the selected fields, with higher heterogeneity apparent during early and peak growth phases indicating localized stress factors such as moisture deficits or nutrient imbalances. The later uniformity in NDVI across fields, while indicative of synchronized senescence, also raised concerns for areas that consistently underperformed during peak growth.

Overall, the findings of the present study underscore the efficacy of satellite remote sensing as a cost-effective and scalable solution for monitoring and assessing crop health. Moreover, this technology underpins precision agriculture by enabling timely, targeted interventions that optimize crop management and sustain yield potential.

Keywords: Satellite Remote Sensing, Vegetation Index, NDVI, Precision Agriculture, Crop Health Monitoring, Wheat Cultivation, Spatial Variability, Early Stress Detection.

1. Introduction

Timely stress detection in crops is critical for ensuring that appropriate remedial actions can be implemented before stress factors lead to irreversible damage. Early identification of stress whether due to water deficits, nutrient imbalances, pest infestations, or disease is essential for minimizing yield losses and sustaining crop productivity. Remote sensing has revolutionized the monitoring of crop health by providing timely, large-scale, and non-invasive data that surpasses the capabilities of conventional field surveys. Unlike traditional methods where visual inspections and manual sampling are labour intensive and often limited to discrete areas, remote sensing uses multispectral imaging to capture continuous data across extensive agricultural fields. This allows for early detection of stress indicators, such as changes in canopy reflectance, which can signal water deficits, pest infestations, or nutrient imbalances before these issues become visible to the naked eye. As a result, farmers and agronomists can rapidly implement targeted interventions, thereby reducing the risk of substantial yield losses and enabling more precise management of inputs and resources.

Furthermore, remote sensing offers high temporal resolution, which is critical for monitoring the dynamic growth stages of crops. Continuous data acquisition from aerial or satellite platforms not only enhances spatial coverage but also delivers consistent, objective measurements over time. This is particularly advantageous when tracking the subtle physiological changes that occur during early crop development and throughout the growing season. The pioneering work by Rouse et al. (1973) and subsequent advancements by Tucker (1979) laid the foundation for such techniques, demonstrating that spectral data not only can be used for monitoring crop growth through its various stages but also to pinpoint areas of early stress with considerable accuracy.

The amount of radiation reflected/absorbed by crop canopies varies due to the presence of certain pigments such as chlorophyll (an indicator of plant vigour/health) and the wavelength of incident radiation. Chlorophyll absorb radiation strongly in the visible spectrum (400 – 700 nm). In contrast, the reflectance is high in the near infrared (700 - 1300 nm) region as a result of leaf density and canopy structure effects. The level of chlorophyll in crops changes/decreases due stress and these changes can alter/reduce the reflectance in crops. By combining the response of crop reflectance in visible and near infrared regions a measure of crop health and/or an early detection of various stresses can be obtained. Based on such principles, vegetation indices such as the Normalized Difference Vegetation Index (NDVI) can be instrumental in providing near real-time indicators of crop health (Rouse et al., 1973). Such indices can reveal subtle changes in plant vigour long before visual symptoms appear, thereby alerting growers to emerging issues and allowing for prompt, targeted interventions.

NDVI is based on ratios of reflectance values of crops in the visible and NIR regions and have been widely utilized for agricultural mapping and monitoring (Maselli et al., 1992; Rasmussen, 1992; Benedetti and Rossini, 1993). NDVI is developed directly from multispectral satellite images and can be used throughout the growing season to not only detect problems, but also to monitor the success of the treatment. Kogan (1995) and Bastiaanssen et al. (2000) were among the pioneers in applying remote sensing techniques to irrigated agriculture and demonstrated how satellite imagery combined with indices such as NDVI can effectively monitor crop water stress and assess field conditions. Expanding on the reliability of NDVI, Sims and Gamon (2003) investigated the relationships between leaf pigment content and spectral reflectance across a diverse range of species and developmental stages. Their study validated the accuracy of NDVI derived assessments across different crop types and under varying environmental conditions, thereby reinforcing its widespread application in agricultural monitoring.

Mulla (2007) provided a comprehensive review of progress in the application of remote sensing within precision agriculture, with a detailed focus on the evolution of NDVI-based techniques. While foundational research established NDVI as a robust proxy for vegetation health, subsequent studies such as those by Funk et al. (2009), Jone et al. (2010), Mkhabela et al. (2011) and Li et al. (2013) have expanded its use from crop monitoring to drought monitoring and yield estimation/forecasting. Advances in satellite sensor resolution and data processing in exemplified works by Zarco-Tejada et al. (2014) and Johnson et al. (2015) continue to enhance the granularity and applicability of NDVI assessments.

The present study utilizes satellite remote sensing for monitoring the growth and health of wheat crops in the study area. By harnessing NDVI-derived insights along with comprehensive spatial and temporal evaluations, the research aims at capturing critical stages of crop development from early growth to maturation and detect variations in plant vigour. The study area for this investigation encompasses the wheat-growing regions within Allahabad district, a vital segment of Uttar Pradesh's extensive agricultural landscape. Uttar Pradesh is a cornerstone of India's wheat production, playing a pivotal role in ensuring its substantial yield contributions. Within this framework, Allahabad district has long been recognized as a key wheat-producing region, consistently delivering a significant share of the state's overall output thanks to its fertile alluvial soils, favourable climatic conditions, and well-established irrigation infrastructure.

Given the district's strategic importance, leveraging advanced technologies to monitor crop health is critical for optimizing yield potential. Modern remote sensing techniques, for instance, enable the timely detection of stress factors and precise assessment of crop vigour, which in turn supports targeted agronomic interventions and more efficient resource management. This approach not only enhances the reliability of yield estimates but also helps ensure that the region continues to meet its pivotal role in sustaining both regional and national wheat demands.

2. Methodology

Satellite images were acquired on five distinct dates: December 24, 2015; January 24, 2016; February 10, 2016; March 21, 2016; and April 14, 2016. The satellite data utilized in the present study included raster images in visible and near-infrared bands of the electromagnetic spectrum acquired by the Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) sensors, onboard Landsat 7 and Landsat 8 satellites respectively. For each image, the NDVI was computed using the following formulation, originally introduced by Rouse et al. (1973):

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{Red}}{\mathrm{NIR}+\mathrm{Red}} \quad (1)$$

Where, NIR represents the reflectance captured in the near-infrared band, while Red stands for the reflectance in the red band of the electromagnetic spectrum. Before applying Equation 1, the raw satellite data, represented as Digital Numbers (DN), is first converted into spectral radiance and subsequently into Top-of-Atmosphere (TOA) reflectance. A comprehensive methodology for this conversion from DN to spectral radiance and, ultimately, TOA reflectance is available on the USGS website and documented in key literature, including works by Chavez (1988), Vermote et al. (1997), and Huang et al. (2001). A brief conceptual summary of this methodology is provided below:

The raw Digital Numbers (DN) of Landsat 7 satellite data utilized in the present study were converted into spectral radiance using a linear transformation with calibration coefficients provided in the satellite image metadata (Equation 2):

$$\mathrm{L}_{\lambda} = \mathrm{M}_{\mathrm{L}}\mathrm{Q}_{\mathrm{cal}} + \mathrm{A}_{\mathrm{L}} \quad (2)$$

Where L_λ is the TOA spectral radiance (Watts/(m^2 srad µm)); M_L is band-specific multiplicative rescaling factor from the metadata; A_L is the band-specific additive rescaling factor from the metadata and Q_{cal} is the quantized and calibrated standard product pixel values (DN). Further, the TOA spectral radiance is converted into TOA reflectance. This step normalizes the radiance by accounting for solar geometry and Earth–Sun distance variations, ensuring consistency across different acquisition dates (equation 3):

$$\rho_\lambda = \frac{\pi \times L_\lambda \times d^2}{ESUN_\lambda \times \cos\theta_S} \quad (3)$$

Where ρ_λ is the unitless planetary reflectance; L_λ is the spectral radiance (from equation 2); d is Earth-Sun distance in astronomical units; $ESUN_\lambda$ = mean solar exoatmospheric irradiances and θ_s = solar zenith angle.

The TOA reflectance for Landsat 8 satellite data utilized in the present study was computed as (equation 4):

$$\rho_\lambda' = M_\rho Q_{cal} + A_\rho \quad (4)$$

Where ρ_λ' = TOA planetary reflectance, without correction for solar angle; M_ρ is the Band-specific multiplicative rescaling factor from the metadata; A_ρ is band-specific additive rescaling factor from the metadata and Q_{cal} is quantized and calibrated standard product pixel values (DN). The TOA reflectance with a correction for the sun angle wasestimated as (equation 5):

$$\rho_\lambda = \frac{\rho_\lambda'}{\cos(\theta_{SZ})} = \frac{\rho_\lambda'}{\sin(\theta_{SE})} \quad (5)$$

Where ρ_λ is the TOA planetary reflectance; θ_{SE} is the local sun elevation angle and θ_{SZ} is the local solar zenith angle (θ_{SZ} = 90° - θ_{SE}).

The NIR and Red bands are particularly important because healthy vegetation strongly reflects near-infrared light and absorbs red light, making NDVI a robust indicator of vegetation vigour. The computed NDVI values range from -1 to +1, where higher values typically signify healthier and more robust vegetation. In practical applications however, areas exhibiting dense, vigorous vegetation typically show NDVI values in the range of 0.6 to 0.9, whereas values closer to zero indicate sparse or stressed vegetation, and negative values often correspond to non-vegetated surfaces such as water or urban areas. This sensitivity makes NDVI a reliable metric to distinguish between healthy and compromised vegetation across various landscapes.

By processing each satellite image with the aforementioned methodology, a temporal series of NDVI maps were obtained with an aim to capture the dynamic changes in crop conditions over the growing season. For selected wheat fields, the maximum, mean, and minimum NDVI values were extracted. Additionally, spatial distribution was analysed, and statistical measures such as standard deviation and median values were calculated to assess variability within and among the fields.

Trends in NDVI over the study period were examined to confirm the progression of the crop's growing season.

3. Results

In agricultural settings, comprehending NDVI values can offer critical insights into crop vitality throughout different growth stages. For instance, during the early stages of crop development, NDVI values might be modest, reflecting lower biomass; however, as crops mature and green biomass increases, NDVI values naturally rise. A sudden drop or unexpected variation in NDVI across a field can serve as an early indicator of stress factors such as pest infestations, water stress, or nutrient deficiencies.

In the present study NDVI trends over time were analysed for 110 contiguous wheat fields spanning all the eight tehsils of Allahabad district—Phulpur, Soraon, Koraon, Meja, Handia, Karchana, Bara, and Allahabad. Figure 1, illustrates the maximum, mean, and minimum NDVI values extracted from satellite images acquired on five distinct dates: December 24, 2015; January 24, 2016; February 10, 2016; March 21, 2016; and April 14, 2016. The mean NDVI values on these dates were recorded as 0.07, 0.41, 0.47, 0.31, and 0.13, respectively. These NDVI values provide a quantitative reflection of the wheat crop's phenological evolution as captured via remote sensing over the full growing season.

In Figure 1, the initial NDVI value of 0.07 on December 24, 2015, corresponds to an early stage of crop establishment, where minimal green biomass and widespread exposed soil are typical. As the season advances, the marked increase in mean NDVI to 0.41 on January 24, 2016, and further to 0.47 on February 10, 2016, clearly indicates a progression into the growth/developmental phase. This period sees an expanding of chlorophyll-rich canopies and vegetation cover, which are in line with established baseline values for healthy

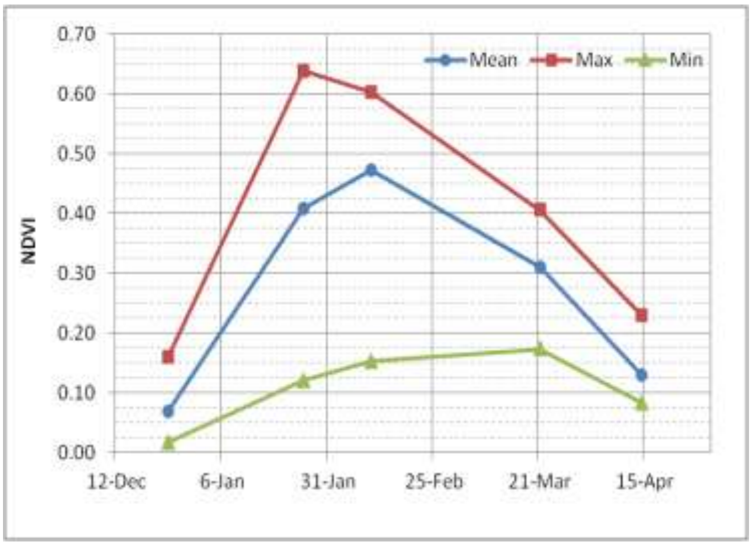

Figure 1 Maximum, Minimum and Mean NDVI For Selected Wheat Fields

wheat crops (typically ranging between 0.45 and 0.6). The graph further reveals that the maximum and minimum NDVI values moved in concert with the mean, highlighting both the overall improvement in crop vigour and the underlying spatial variability across the fields.

By March 21, 2016, the NDVI values begin to decline, with the mean dropping to 0.31, signalling the onset of senescence as the crop shifts from active vegetative growth to maturation. The final image on April 14, 2016 shows a further decrease in the mean NDVI to 0.13, indicating that the fields have largely completed senescence and are harvest-ready. This steady decline in NDVI after the peak growth period underscores the end of the active growing season and transitioning toward crop maturity.

Spatially distributed NDVI maps corresponding to the respective image dates were generated and utilized to evaluate the spatio-temporal variability of NDVI for wheat cultivation in the study area. (Figure 2). These NDVI maps reveal a clear spatio-temporal dynamics in the wheat fields over the growing season. In the earliest observation from December 24, 2015, the maps show a relatively low NDVI values overall, which is consistent with the early stages of crop establishment when green biomass is minimal. As the season progresses to January 24 and February 10, 2016, there is a marked increase in NDVI values that reflects vegetative growth and higher chlorophyll content indicative of optimal metabolic activity.

This upward trend aligns closely with the established baselines for healthy wheat crops, typically ranging between 0.45 and 0.6. Moving into the later stages, the maps from March 21 and April 14, 2016, begin to exhibit either a slight stabilization or a decline in NDVI values. This change likely represents the transition towards crop maturation or the onset of early senescence, a phase during which vegetation vigour naturally diminishes. Spatially, the NDVI maps also expose critical variability within the fields.

While many areas maintain NDVI values that meet or exceed baseline levels indicating zones of robust growth there are distinct patches where the values fall significantly below the normative range. These anomalies may point to localized stressors such as water deficiencies, pest outbreaks, or nutrient imbalances. Such discrepancies underscore the value of integrating remote sensing into crop management practices, allowing for precision interventions. By continuously comparing the observed NDVI values with baseline standards, agronomists can quickly identify underperforming zones and implement targeted remedial strategies, thereby mitigating potential yield losses and ensuring more efficient resource utilization.

The distribution of NDVI for the selected fields on individual image dates was also assessed (Figure 3). The NDVI distribution apparent in Figure 3 offers a detailed view of the variability in vegetation health across the selected wheat fields on different image dates. The relative frequency distribution of NDVI for the selected fields are shown vertically along the axis of each image date as a means of visualizing the variability and how often specific NDVI ranges occur on each date. For December 24, 2015, the narrow spread of NDVI values with a standard deviation of 0.03, minimum of 0.02, and maximum of 0.16 indicates a high concentration of pixels around low NDVI values. The median value of 0.06 further confirms that over half of the observed pixels exhibit very low levels of vegetation vigour, which is characteristic of the initial stage of the wheat growing season. At this early phase, the sparse vegetation and the predominance of exposed soil are expected, reflecting the limited canopy development immediately after planting.

As the growing season unfolds, subsequent image analyses reveal significant shifts in the distribution of NDVI values that reflect the evolving state of crop health. On January 25, 2016, the median NDVI reached 0.41, with values ranging between 0.12 and 0.64. The apparent

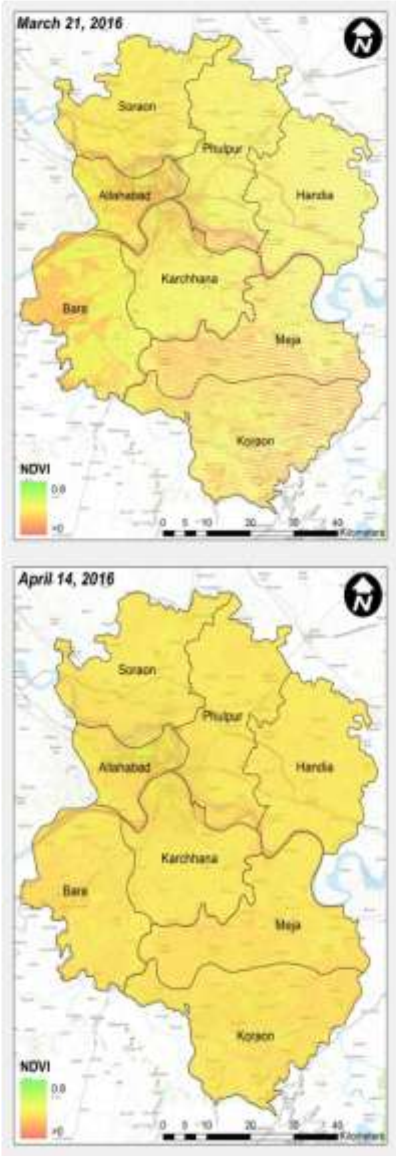

Figure 2 Spatial Distribution of NDVI for The Study Area on Selected Image Dates

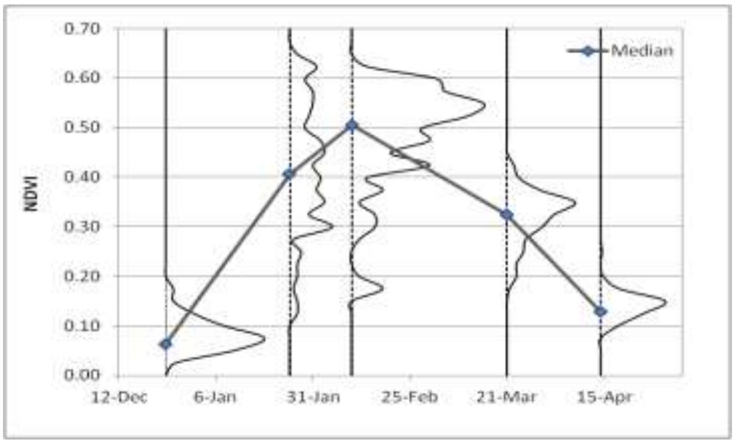

Figure 3. NDVI Distribution and Median values For Selected Wheat Fields

increase in the median value signals an overall enhancement in vegetation cover and vigour, indicative of crop growth as the plants begin to develop dense, chlorophyll-rich canopies. However, the observed standard deviation of 0.13 on this date also highlights notable variability among the selected fields, suggesting that the crop growth is not uniform.

A similar pattern in NDVI variability is evident on February 10, 2016. On this date, an increase in overall crop vigour is reflected by a higher median NDVI of 0.50, with the minimum and maximum values recorded at 0.15 and 0.60, respectively. Despite this encouraging increment indicative of enhanced vegetative cover the standard deviation remains relatively high at 0.11. This persistent variability suggests that, although the selected fields are exhibiting improved growth, there is still significant heterogeneity in canopy development. Ideally, by early February, one would expect most fields to have achieved full canopy cover, resulting in a more uniform NDVI distribution. However, the elevated standard deviation signals that some areas/fields are not keeping pace with the overall growth trends observed on January 25, 2016.

By March 21, 2016, the NDVI data reveal a significant shift in crop dynamics, signalling the onset of senescence. The median NDVI value has declined to 0.32, with overall values ranging between 0.17 and 0.41—a notable decrease from the higher readings observed during peak growth in January and February. This reduction in NDVI reflects the loss of greenness and chlorophyll content typical of crops transitioning from active growth to the senescence phase. Further, the NDVI values had approached their lowest levels by April 14, 2016 with a median of 0.13 and an overall range from 0.08 to 0.23, marking the culmination of the senescence phase and indicating that the fields are harvest-ready.

This represents a marked change compared to earlier assessments: while the earlier dates showed higher values during the peak growth phase (with median NDVI values of 0.41 in January and 0.50 in February), the substantial decline in NDVI by April signifies the complete loss of canopy greenness as the crop matures. The progressive decline in NDVI values from the vigorous growth observed in January and February, through the gradual uniformity noted in March, to this final, low value stage on in April, effectively illustrates the complete phenological cycle of the wheat crop.

Moreover, the low variability observed on March 21 and April 14—with standard deviations of 0.05 and 0.02 respectively, highlights a uniform transition across the selected fields into the senescent stage, aligning with expected phenological progress. In contrast to the higher variability seen in previous observations, this minimal spread indicates that nearly all areas of the fields have synchronized in their progression towards maturity. Such uniformity is critical for optimizing harvest operations, as it confirms that conditions conducive to harvest have been reached across the entire study area.

However, this uniformity in the senescence phase also underscores a potential concern: fields that never reached optimal vigour during earlier stages may now be exhibiting consistently low NDVI values. These areas, which failed to achieve the higher NDVI benchmarks characteristic of vigorous growth, signal poorer overall crop health and may ultimately suffer from reduced yield potential. This comparative analysis from the heterogeneity observed during peak growth to the uniform decline now highlights the importance of continuous monitoring and targeted interventions to mitigate the adverse effects of non-uniform development.

Overall, the temporal NDVI trends captured in Figure 3 not only demonstrate how satellite remote sensing effectively tracks the phenological stages of crop development—from establishment and peak growth to senescence—but also offer critical insights into spatial variability across diverse agricultural landscapes, thereby enabling targeted management interventions for optimizing yield.

4. Discussion

The NDVI trends derived from the satellite images acquired on five distinct dates provide a clear narrative of the wheat crop's phenological evolution over the growing season in Allahabad district. In the initial phase on December 24, 2015, the NDVI values were uniformly low, indicating the early stage of crop establishment when green biomass is minimal and exposed or bare soil is predominant in the selected fields. This early-stage condition is expected, as the fields are still in the initial phases immediately following planting.

As the season progressed into January 2016, a marked increase in vegetation vigour was observed. This significant increase in the median value reflects the onset of vegetative growth and development of chlorophyll-rich canopies across the fields. However, the relatively high standard deviation also points to a noticeable heterogeneity in crop growth. Such variability could be attributed to local differences in soil moisture, nutrient availability, or other micro-environmental factors that cause some fields to thrive while others lag behind.

The trend of increasing crop vigour continues into February 2016. Although this heightened NDVI suggests overall enhanced vegetative cover, the persistence of variability indicates that full canopy cover was not uniformly achieved across the study area. This ongoing heterogeneity, despite an overall trend towards increased greenness, implies that certain patches may be under stress or experiencing suboptimal growth conditions compared to their neighbouring fields, highlighting the necessity for targeted agronomic interventions in such areas.

By March 21, 2016, a substantial shift is evident in the NDVI data, marking the onset of crop senescence. The overall NDVI declined along with a significant drop in variability. This reduction in NDVI—the loss of canopy greenness and decreased chlorophyll content—corresponds to the natural progression from active growth to the senescence phase. The much lower variability on this date suggests that the majority of the fields are synchronously transitioning towards maturity, although areas that never reached optimal vigour remain a concern, as their lower NDVI values could forecast reduced yield potential.

Finally, the NDVI values on April 14, 2016, reached their lowest levels with an extremely low variability. This stage signifies the completion of the senescence phase and confirms that the fields are harvest-ready. The uniformity at this late stage, in stark contrast to the earlier observed heterogeneities, indicates that nearly all fields have synchronized their development towards harvest maturity. While uniform senescence is beneficial for coordinated harvest operations, the consistent low NDVI readings also draw attention to fields that may have underperformed during peak growth stages, implying that these areas could have suffered from prolonged stress or suboptimal agronomic conditions.

In summary, the temporal evolution of NDVI values from initial low values at crop establishment, through a phase of vigorous yet heterogeneous growth, to a uniform decline at senescence not only illustrates the complete phenological cycle of wheat but also underscores the utility of remote sensing for continuous crop monitoring. The comparative insights provided by these NDVI trends emphasize the need for timely, location-specific interventions to minimize yield losses and ensure resource efficiency across diverse agricultural landscapes.

5. Conclusion

This research demonstrates that satellite-derived NDVI can reliably monitor the progression of wheat growth, providing crucial insights into crop health dynamics. Satellite remote sensing, through the application of NDVI, has proven to be a robust and efficient tool for monitoring and assessing wheat crop health in Allahabad district. The temporal analysis—from the initial low NDVI values indicative of sparse vegetation during crop establishment in December, through the increasing vigour observed in January and February, to the uniform senescence stage captured in March and April demonstrates the capability of this approach to accurately track the complete phenological cycle of the crop.

By continuously monitoring these changes, NDVI not only provided real-time insights into crop development but also underscored the spatial variability within and among the fields, enabling the identification of underperforming areas that may be at risk due to stress factors. The temporal increase and subsequent decrease in NDVI values reflect the natural development cycle of wheat, while spatial analysis confirms the variability in crop conditions across the study area.

This level of detailed, objective, and timely information is pivotal for precision agricultural practices, allowing for targeted interventions that can mitigate yield losses and optimize resource utilization. Ultimately, the integration of satellite remote sensing with NDVI analysis offers significant advantages over traditional monitoring methods, ensuring that crop management decisions are well-informed, proactive, and effective.

These findings support the further integration of remote sensing tools into precision agricultural practices, enhancing decision-making processes and resource management. Future studies may expand upon this work by incorporating additional spectral indices and higher temporal resolution data to refine crop health diagnostics further.

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