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Monitoring Cotton Crop Temporal Profile Using Cloud Computing Paradigm

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Abstract

Satellite-based NDVI requires optical satellite data, and the main challenge lies in acquiring clear-sky (cloud-free) images for regional agricultural crop monitoring during the monsoon season over the Indian subcontinent. Unfortunately, persistent cloud cover during that time frequently results in significant data gaps that reduce optical-based monitoring to varying degrees. Overcoming this aspect of NDVI, a study emphasized the alternative to NDVI for cotton crop growth monitoring, in the name of Radar Vegetation Index (RVI). Multi-temporal Sentinel-1 SAR and Sentinel-2 optical data were processed using the cloud-based geospatial processing platform Google Earth Engine (GEE) for the Musi watershed in Telangana, India, over the period from March 1, 2020, to March 31, 2021. Using GEE for scalable processing, we were able to generate time-series NDVI and RVI automatically without requiring dedicated local storage or high-end computing resources. From time series analysis, it was possible to notice that NDVI values were stable after the flowering cotton stage by the second week of October; however, despite stabilization of NDVI until November, coincident with boll formation in cotton. This longer-range sensitivity makes RVI a critical metric to track for later-stage growth. The study concluded that RVI can provide a robust and fast substitute for cotton monitoring concerning NDVI, particularly in cloudy regions. Operational large-scale crop monitoring will perform flawlessly, even in the peak monsoon season, by utilizing the GEE cloud computing environment.

Keywords: Radar Vegetation Index, Normalized Difference Vegetation Index, Sentinel-1, Sentinel-2, Cloud Computing.

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1 Introduction

India is one of the major cotton growers in the world, cultivating 13 million hectares of land, which accounts for 38% of the total cotton cultivated areas. The Indian cotton industry employs millions of people in Gujarat, Maharashtra, Andhra Pradesh, Telangana, Haryana, Rajasthan, Madhya Pradesh, and Punjab, producing a revenue of around 90,000 crore rupees per year (approximately 12 billion US dollars). Factors such as crop yields, weather conditions, global demand and supply, and government policies all contribute to determining cotton yield every year (Mustapha et al., 2017). So, the Normalized Difference Vegetation Index (NDVI) is an essential tool in monitoring cotton growth, used for providing a range of information about the status of plant development and plant health, physiological characteristics, and photosynthetic effectiveness (Xun et al., 2022; Wu et al., 2018).

There are some remote sensing-driven vegetation indices to monitor the growth of cotton, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Chlorophyll index (CI), and Leaf Area Index (LAI) (Ren et al., 2020; Yin et al., 2021). The NDVI is one of the most frequently used parameters, computed from reflectance in near-infrared and visible spectral bands for satellite images Rouse Jr et al., 1974). The VI calculates the green vegetation content in each area and is designed to detect higher values that indicate increased vegetation density and photosynthetic activity. For example, it can assist in the evaluation of how drought or heavy rain has affected cotton crops in a particular region through NDVI analysis throughout the crop growing season. NDVI values evolved in cotton plants, which indicates the variation in vegetation density and photosynthesis as they mature. This data is crucial for decision-makers to determine harvesting and crop yields (Balavandi, 2017).

For the Indian subcontinent, monsoon and optical data have their limitations, as our country experiences a distinct weather pattern known as the monsoon, which occurs from June to September. This makes it impossible to calculate NDVI during this period using optical data (Becker-Reshef et al., 2010; Qadir & Mondal, 2020). All this means finding cotton fields growing during the final days of their development has proven very difficult. The Radar Vegetation Index (RVI) is suggested as an alternative vegetation monitoring index for the mitigation of these controversies to NDVI, especially in the monsoon season covered by clouds (Kumar et al., 2013; Qadir & Mondal, 2020; Sahadevan et al., 2019).

Unlike NDVI, which uses near-infrared and visible bands in satellite image data, the RVI is based on radar only. On the contrary, radar signals have an advantage over optical sensors as these can penetrate clouds and vegetation canopy, which provides detailed information about the spatial composition or structure of vegetation based on density (Hosseini et al., 2019).The RVI, which uses the degree of randomness in radar signals returned from vegetation scattering, as explained earlier, to estimate vegetation density and structural complexity, using cloud security with larger values corresponding to denser and complex vegetative structures (Gatla et al., 2025; Mokhtari et al., 2025). It occurs as vegetation grows and matures; the random scattering in radar signals from plants increases significantly, which translates into higher RVI values. RVI: RVI provides information about vegetation patterns and health, enabling us to analyze cotton crop growth and yield for agriculture (Satapathy et al., 2025; Mustapha et al., 2017).

It is important to understand the relationship between RVI and cotton growth stages to interpret the RVI values and monitor cotton growth. As mentioned earlier, the RVI value only has any real significance from stem elongation onwards (i.e., after canopy closure). Therefore, RVI values should be compared across different growth stages to identify changes in the growth rate.

2 Study Area

The Musi watershed is located in the southern Indian state of Telangana, covering an area of 2108 Sq.km (Figure 1). The study area is gently undulating, with the elevation ranging from 520 m to 730m above the Mean Sea Level. The elevation is high in the western part and slowly decreases towards the eastern part. The average rainfall of the study area is 875 mm/year, with the highest being in the NW portion of the watershed, which recorded higher rainfall (~ 1000 mm) in comparison to the SE, which receives 700 mm. The majority of the area covered by the Pedi plain pediment complex of denudational origin, covering 85% of the study area, makes this terrain more suitable for agricultural activity. According to the analysis of the Resourcesat-1 LISS IV data sets, the majority of the study area is devoted to agriculture, covering a total of 1852 sq km. Specifically, the western portion of the area is well-suited for growing cotton crops due to the presence of Deccan traps. The prevalence of loamy soil in the western region compared to the eastern region makes it more conducive to agricultural activity, resulting in the majority of the double crop regions being located in the western part of the study area. The majority of areas are rain-fed regions and cultivated with cotton, Maize, and vegetables.

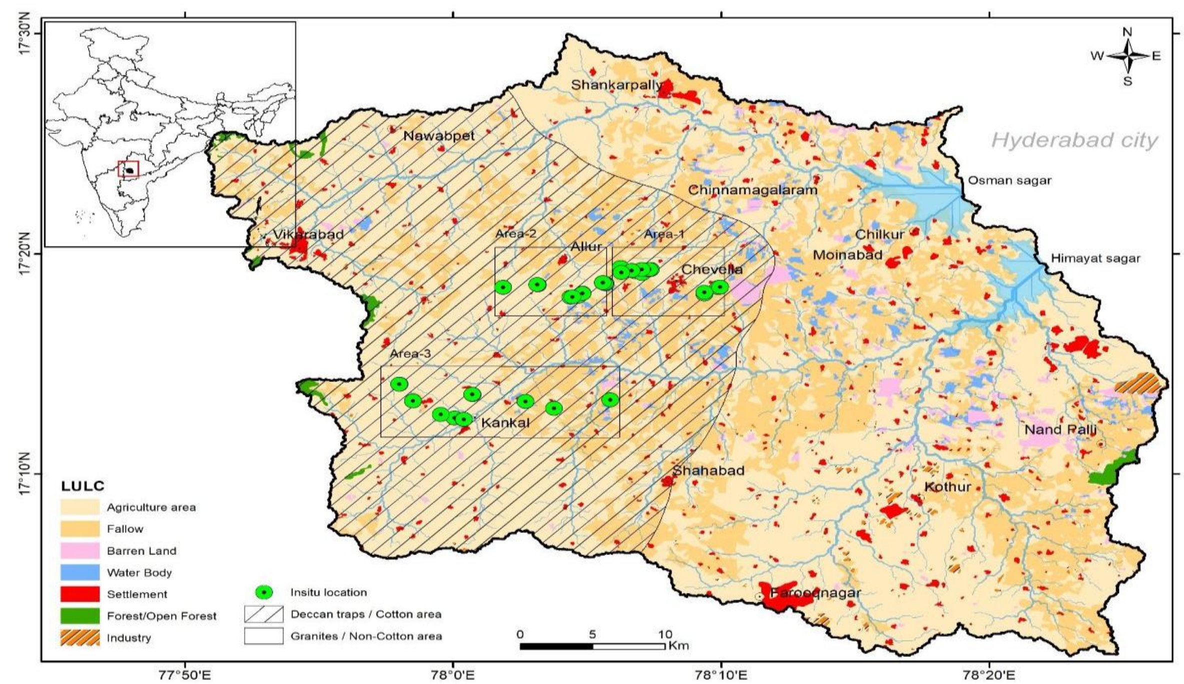

Figure 1: Study Area Located in the West of Hyderabad City, Telangana. The LULC was Derived from Resourcesat-2 LISS IV Data in 2019 using Semi-automated Classification. The Streams and Watershed were Derived from Cartosat-1 DEM. The Ground Truth Regarding Cotton Growth was Collected from Areas 1, 2, and 3. The Geology Information (Deccan Traps) was Derived from the Geological Survey of India Map

3 Data and Methods

The satellite data, Sentinel-1 and Sentinel-2, were used in this study to derive RVI and NDVI, respectively. In addition to satellite data, ground truth information (crop height, type, stage), soil moisture, and tilling height were collected at 30 ground points during the same time of data acquisition in three different clusters (1-3) of the study area. The ground points were chosen in such a way that the field is almost unique for more than 60*60 meters. The Sentinel-1 mission operates a C-band Synthetic Aperture Radar (SAR) instrument, working in the 5.4GHz frequency at a dual polarization configuration.

Sentinel-2 is a wide-swath, high-resolution, multispectral imaging mission supporting Copernicus Land Monitoring studies. Data are collected from March 2020 to March 2021 for India across the Kharif season (southwest monsoon). COPERNICUS/S1_GRD ground range detected (GRD) scenes were processed in Google Earth Engine to calculate the backscatter coefficient from Sentinel-1 data. Here, the backscatter coefficient was obtained after applying the orbit file, GRD border noise removal, thermal noise removal, radiometric calibration values, and terrain correction. The backscattering coefficient is converted to RVI using models proposed by (Kim et al., 2012; Kim & Van Zyl, 2004; Kim & Van Zyl, 2009). One should have σHH, σVV, and σHV quad polarization data to use the model.

$$RVI = \frac{8\sigma_{vh}}{\sigma_{vv} + 2\sigma_{vh} + \sigma_{hh}} \tag{1}$$

Where σ HV is the polarization coefficient and σ HH and σ VV are like polarized backscattering coefficients in power units. However, as of today, no satellites are providing quad-polarization data on an operational basis with sufficient temporal resolution and swath. Researchers have modified the above equation, assuming σvv ≈ σvv (KUMAR Sahadevan et al., 2013; Trudel et al., 2012). It is valid when the interaction between vegetation and soil terms is negligible (Trudel et al., 2012), which holds in our case. The truncated equation after the approximation (Eqn 2) can provide RVI for a larger area on an adequate interval.

$$RVI = \frac{4\sigma_{vh}}{\sigma_{vv} + \sigma_{vh}} \tag{2}$$

Once the backscattering coefficient was calculated, the RVI is computed by taking the ratio of the backscatter values from two polarizations, VV and VH (Eqn 2). The RVI value was calculated for every pixel of the SAR image, and thus, time series RVI (ranging from March 2020 to March 2021) were developed to monitor the growth of the cotton canopy. When the crop reaches a smooth surface after plowing, the RVI is almost zero (maximum reflection) and becomes greater than 1 as the crop grows. The NDVI was computed with NIR and Red bands from the Sentinel-2 (Eqn. 3).

$$NDVI = NIR - RED/NIR + RED \tag{3}$$

The NDVI was derived for the 30 ground truth coordinates in Google Earth Engine using the JavaScript API. A total of 157 images from Sentinel-2 satellites have been processed, covering March 2020 to March 2021. Due to challenges in obtaining data under cloud cover in optical seasons, the number of observations was unevenly distributed over the cotton growth cycle. The NDVI and RVI were derived from available data sets, correlated with each other, and compared with the ground truth information.

4 Results and Discussion

For displaying the SAR parameters trends during the growing season in a visual way, RVI responses were generated for sample cotton fields, including data from March 2020 and extended to March 2021, covering the full plant growth cycle from pre-seeded bare soil till cotton harvest. The area was segregated into three parts to examine the degree of variability across the study area, considering factors such as rainfall and soil texture variance. Due to the landscape and corresponding textural differences, the crop seeding period shows very high ranges in soil moisture across all study areas 1, 2, and 3. This range depends on wetting and drying events for the given seeding period.

Preparation of cotton fields, such as clearing of the existing straw, tilling, and levelling, had happened during June 2020. The surface texture differences within and among fields were relatively minor as farmers plowed and readied the soil for planting cotton seeds. The lowest backscattering was observed during May-June because the scattering came from levelled flat fields with less moisture and no vegetation. The median RVI for these smooth bare fields with no moisture condition was at 0.24, 0.25, and 0.36 for areas 1, 2, and 3, respectively, during June (Figure 2a, b, c). Expectedly, mean NDVI also recorded the lowest of 0.18, 0.2, and 0.25 in areas 1, 2, and 3, respectively, during April-June 2020 (Figure 2a, b, c and Figure 3a, b, c). The NDVI registers its lowest in May, coinciding with the lowest greenness in the cotton field, whereas RVI registers its lowest in the first week, coinciding with a leveled dry field (Figure 2a, b, c and Figure 3a, b, c). This NDVI and RVI relation could be used to delineate the cotton areas that initiated the cultivation process after the onset of the Kharif season.

Cotton was seeded between the last week of June and the first week of July, with variations across the study area. Once the cotton seedlings emerge, the crop canopy starts to grow, and the cotton leaves start developing. During this time, the backscattering contribution comes from a mixture of soil-vegetation interactions (Figure 2b). The RVI backscatter shows very minimal increase during early stage of leaf development, the median RVI increased to 0.24-0.34 in area-1, 0.20-0.36 in area-2, 0.17-0.31 in area-3 between first week July to first week of August although the cotton height increased to 0-40cm (Figure 2a, b, c). However, the mean NDVI values were doubled during the same period in all the areas. The values are increased from 0.27 to 0.57, 0.24 to 0.42, and 0.15 to 0.40 in areas 1, 2, and 3, respectively (Figure 2a, b, c and Figure 3a, b, c). The increase in NDVI is attributed to the spread of greenness in the cotton fields; however, the volume of cotton is not increased as much as greenness, hence a lower increase in the RVI was observed.

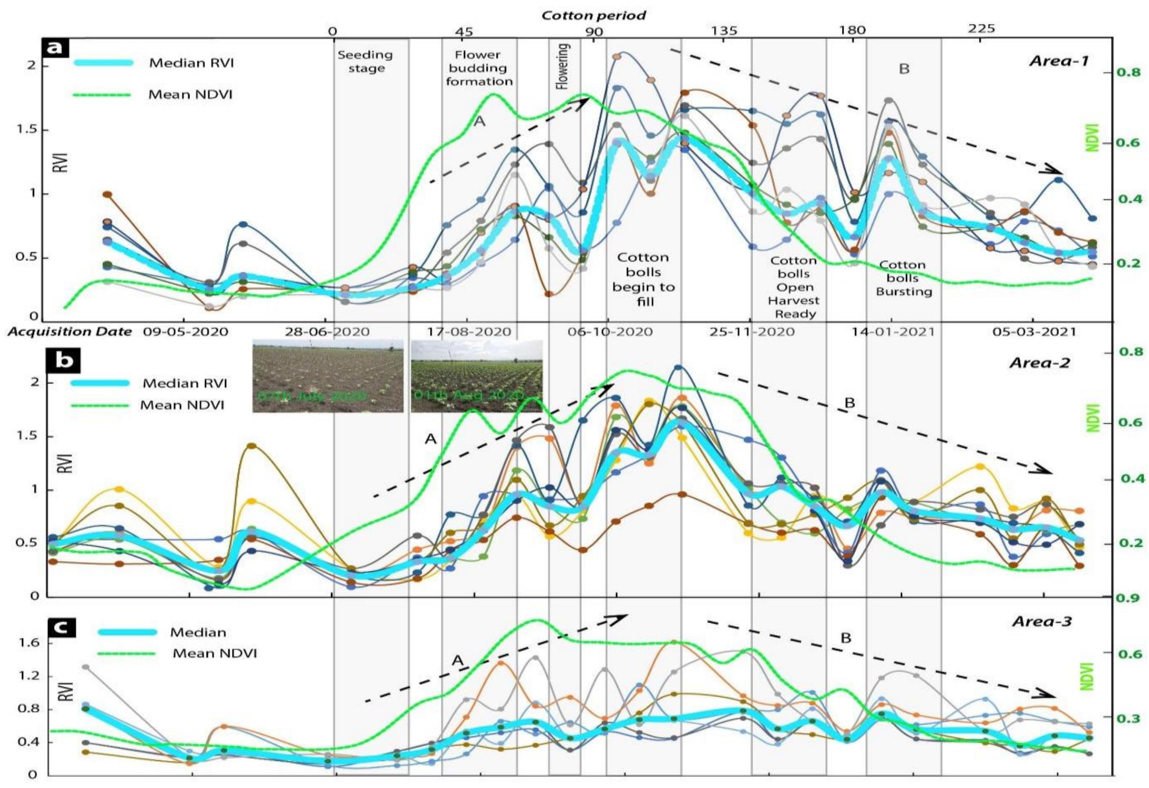

Figure 2: The RVI plotted against the date of the satellite from March 2020 to March 2021 at study areas a, b, and c. The locations of study areas a, b, and c are shown in Figure 1. Cotton period information was obtained from the ground truth data. A&B indicate an increase and a decrease of RVI concerning the cotton growing stage, respectively. The mean NDVI was derived from Sentinel-2 satellite data for the corresponding locations of a, b, and c. The photographs in Figure 2b indicate the exposure of soil and cotton in July-August 2020, responsible for mixed scattering during the period

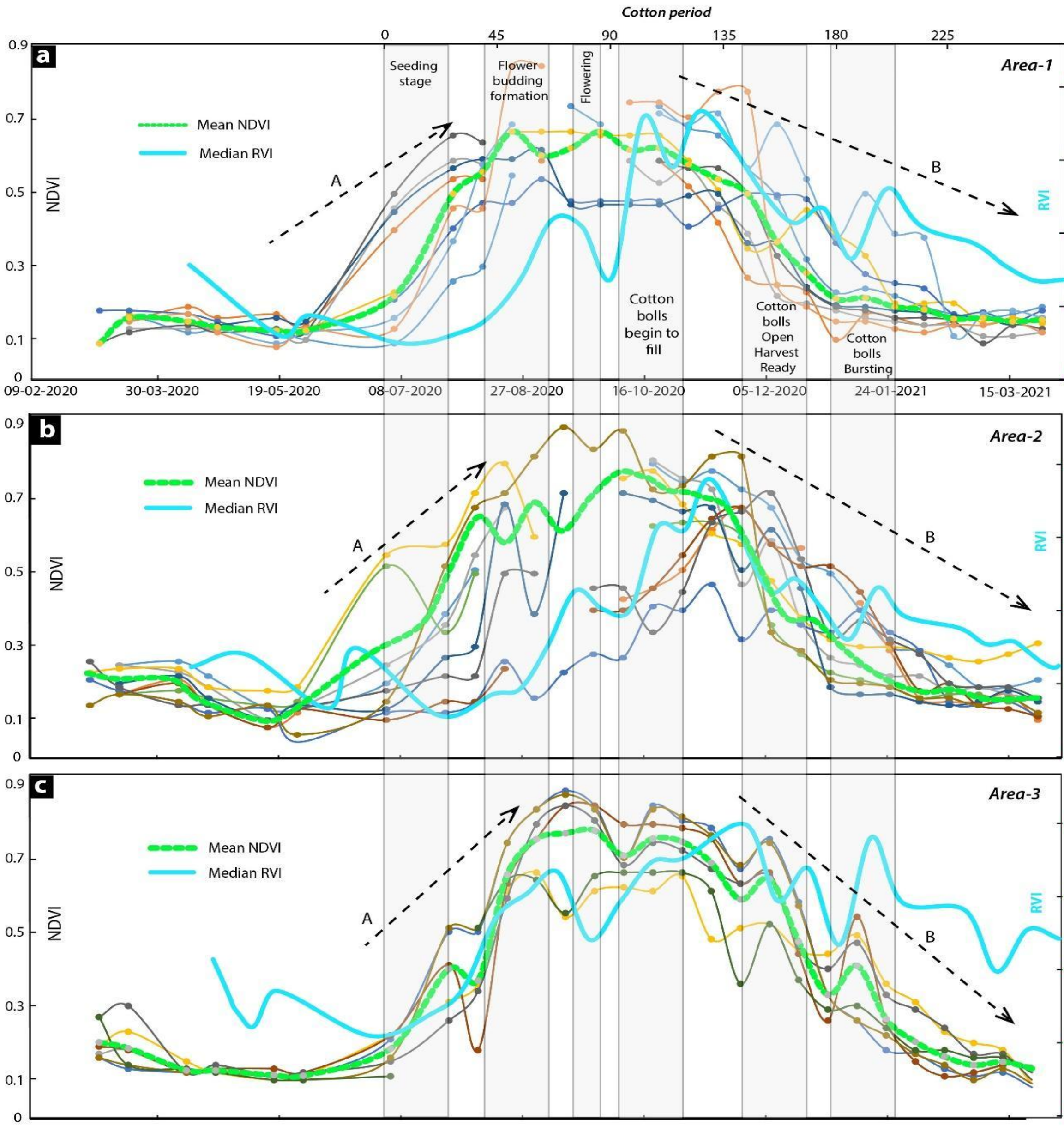

Figure 3: The NDVI plotted against the date of pass of the satellite from March 2020 to March 2021 at study areas a, b, and c. The locations of study areas a, b, and c are shown in Figure 1. Cotton period information was obtained from the ground truth data. A&B indicate an increase and a decrease of NDVI concerning the cotton growing stage, respectively. The median RVI was derived from Sentinel-1 backscattering data. The mean NDVI was derived from Sentinel-2 satellite data for the corresponding locations of a, b, and c

The RVI backscatter exhibits sensitivity to growth after the first week of August, once cotton plants start developing side shoots and flower buds. Volumetric scattering increases rapidly and follows a logarithmic increase between August and September. The RVI rose from 0.34 to 0.86, 0.36 to 0.84, and 0.31 to 0.64 in areas 1, 2, and 3, respectively, during the period from August to September (Figure 2a, b, c). The significant rise in RVI is because, as the cotton canopy collects more leaves, stems, and clusters of flower buds, the structure of the canopy becomes increasingly intricate and disordered, resulting in the occurrence of multiple scattering within the canopy volume and random scattering events. During this period, NDVI increased marginally from 0.57 to 0.63, 0.42 to 0.55, and 0.40 to 0.66 in areas 1, 2, and 3, respectively, and approached its maximum value by the end of September (Figure 2a, b, c and Figure 3a, b, c). The response of maximum increase in the RVI and minimum increase in the NDVI can be attributed to an enormous volumetric increase in cotton during this period.

The RVI peaked in its response during the cotton bolls filling stage by the end of October 2020. Between the October-November period, within 90 to 150 days of the crop cycle, the RVI increased from 0.86 to 1.2, 0.84 to 1.33, and 0.64 to 0.84, in study areas 1, 2, and 3, respectively (Figure 2a, b, c). During this period, the cotton plant grew from the budding stage to the fruit stage, increasing in height from about 120cm to 180cm, and its growth doubled horizontally. Although a tremendous increase was witnessed in the RVI, the NDVI values were decreased slightly from 0.63 to 0.55, 0.55 to 0.54, and 0.66 to 0.59 in areas 1, 2, and 3, respectively (Figure 2a, b, c and Figure 3a, b, c). The RVI increase is due to a volume increase in the cotton crop, whereas the NDVI decreased due to a drop in greenness.

The cotton canopy undergoes a maturation process that progresses from ripening towards senescence; consequently, RVI decreases rapidly from a peak of 1.4 to 0.6 in area 1, 1.63-0.66 in area 2, and 0.96-0.44 in area 3, till 225 days (Figure 2a, b, c). Both canopy biomass and water content are powerful drivers for the decrease in RVI. While the cotton bolls are ripening, their foliage and flowers can naturally fall off, leading to a reduced canopy biomass. Moreover, as the seed pods senesce and fill with seeds, the seeds naturally dry out over time, which reduces water in the canopy. The RVI did not reach the pre-seeding stage (~0.3) due to the presence of cotton straw in the field. During the same period, the NDVI also decreased rapidly to ~ 0.2 (Figure 3a, b, c), equivalent to the pre-seeding stage, which can be attributed to the loss of greenness due to senescence of cotton.

The RVI measures the randomness of scattering, with a low sensitivity to ambient conditions but sensitivity to biomass and vegetation water content. NDVI offers valuable insights into crop condition, health, growth, and phenology. RVI values have not been saturated like NDVI in the October-November period, because it is directly proportional to volumetric scattering, which grows when the scattering contribution increases from cotton branches. However, the health of the cotton can be better monitored with NDVI than RVI. The combined use of NDVI and RVI can help in identifying the cotton areas and their developmental stage.

5 Conclusions and Further Work

The study concludes that variations in RVI are notable during the crop's shift from one phenological stage to another, making it a viable substitute for NDVI in cotton monitoring when cloud-free optical data is unavailable, provided that SAR data can be collected regularly. Unlike NDVI, RVI does not saturate until cotton bolls begin to fill. However, it cannot accurately depict any deficiency in the greenness of cotton, which is helpful for the health monitoring of cotton.

RVI values provide a valuable means of comparing cotton growth rates across different growth stages. Typically, RVI values are low during the early growth stages when the canopy is sparse and gradually increase as the canopy becomes denser and more complex. It is important to mention that the correlation between RVI and crop growth stages may differ based on factors like crop variety, soil conditions, and weather conditions. Despite the variability in the relationship between RVI and crop growth stages, monitoring RVI values can help identify changes in growth rate and inform decision-making around crop management. To monitor the growth of the cotton crop, the study suggests using RVI in conjunction with NDVI whenever available. By fusing NDVI and RVI vegetation indices, the temporal resolution would increase, reducing the dependence on interpolation, and it helps in identifying more accurate phenology metrics. Further study can be performed by combining Sentinel-2 NDVI and

Sentinel-1 RVI using a machine learning data fusion approach to identify cotton areas and monitor them more effectively.

Acknowledgement

There is no acknowledgement.

Conflicts of Interest

There are no conflicts of interest.

Supporting Materials

The GEE code used to generate the cropland is available to the public at https://github.com/Benazir88/rvialternativendvi.git.

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Authors Biography

Benazir Meerasha is a researcher specializing in Earth Observation, Remote Sensing, and Artificial Intelligence, with over a decade of academic and professional experience. She holds a Bachelor's degree in Electronics and Communication Engineering, a Master's in Remote Sensing, and is pursuing a Ph.D. in Earth Observation and Machine Learning. Her expertise spans geospatial data analysis, satellite image processing, machine learning model development, and advanced computer vision techniques for agricultural monitoring, environmental assessment, and land use mapping. She has extensive experience working with multispectral, radar, and hyperspectral datasets and is proficient in cloud-based platforms such as Google Earth Engine for large-scale geospatial analytics. Benazir has contributed to research on multi-sensor data fusion, vegetation monitoring, and climate-resilient agricultural systems. She has also worked on applied projects involving GIS, carbon stock assessment, and spatial data management. Passionate about innovation, she aims to bridge technology and sustainability through impactful scientific research.

Dr. Martin Sagayam is an accomplished academic and researcher in the field of Computer Science and Engineering, specializing in Artificial Intelligence, Machine Learning, and Internet of Things (IoT) applications. He holds a Ph.D. in Computer Science and has extensive experience in developing intelligent systems for real-world challenges, including smart agriculture, healthcare monitoring, and environmental sensing. His research focuses on integrating AI algorithms with IoT-enabled devices to create efficient, scalable, and sustainable solutions. Dr. Sagayam has published numerous papers in reputed international journals and conferences, contributing to advancements in deep learning, image processing, and data analytics. He is also actively involved in mentoring students, guiding research projects, and collaborating with interdisciplinary teams. Passionate about technology for societal benefit, he is committed to bridging the gap between academic research and practical implementation, fostering innovation that addresses both local and global needs.

Dr.M. Lavanya obtained her B.E. degree in Information Technology in 2004 from Madras University and M.E. degree in Computer Science and Engineering in 2009 from Anna University. Right from 2009, she has been working as an Assistant Professor in the Department of Computer Science & Engineering under Anna University-affiliated colleges. She started her full-time Time Research work in 2017 and completed her PhD under Anna University in 2023. Presently, she is working as an Associate Professor in the Department of Artificial Intelligence and Data Science at Adhiparasakthi College of Engineering, Kalavai, Tamil Nadu, which is affiliated to Anna University. Her research interests include Cloud Computing, Network Security, Image Processing, and Blockchain.