Crop Phenology Study Based on Multispectral Remote Sensing

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Abstract The study identifies various growing stages of rice crop using multispectral data through red edge analysis. The maximum reflectance values for 35, 66, 76, and 96 days which indicate vegetative phase, reproductive phase, reproductive phase and ripening phase are 0.17, 0.228, 0.231, and 0.266 respectively at the test site 1. For the test site-2, the same trends are followed. When the crop is in vegetative stage the reflectance values are less whereas, when the stage of crop is reproductive, adjacent to the vegetative, the values of reflectance are increasing significantly due to increase in trend in canopy. This type of spectral analysis approach can be adapted to generate spectral library which can be beneficial for future research purpose.

Keywords Multispectral · Phenology · Rice crop · Red edge · Sentinal-2 Spectral analysis · Spectral library

1 Introduction

Most significant components in foundation of Indian economy include agriculture. As agriculture is one of the major concerns, the crop monitoring should be taken cared properly to maintain good crop health. If crop misses possessing good health

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even any at least in one stage of its growth then also the overall growth and required yield will not be considered as proper as usually it should happen to be [1]. The comprehensive study is demanded to understand the growth and progress to improvement along with grain yield of a crop plant [2]. Study on crop phonology includes the factors serving as age of the crop, variety of the crop, genes along with environmental factors acting as weather conditions and climate, water supply may be natural or artificial and diseases can also be counted as influence for plant phenology [3]. Understanding crop phenology is also important for proper irrigation management, proper fertilization, yield prediction, and policy planning [1]. Spectral and temporal profiles which are extracted from the fields regarding same crop type can show some intra-yearly fluctuations (early or delayed phonological stages) even for local scales [4–7].

The stages of natural cyclic incidents of a crop can be observed practicing field observation, but when it comes to large areas it is very difficult to maintain the same procedure and due to this reason for large areas, remote sensing time series datasets are important for figuring out the phonological stages of crops [1].

Remote sensing and GIS approach plays a crucial role to the cost beneficial agricultural applications and practices [8]. One of the significant implementation is the spectral classification of the crop types from the satellite-based multispectral imageries, with which it is possible to form or update crop inventories when the field data is limited [9]. In vegetation, different species may show utterly similar spectral behavior, distinctively for some specific phonological stages and at the usual bandwidth along with spectral resolution of satellite-based multispectral imageries [10, 11]. So the issue can strongly limit accuracy of the crop types if classified by a single imagery dates [12–15].

Normalized Difference Vegetation Index (NDVI) imageries are often helpful to interpret crop biomass [16]. NDVI is formed by a red band (R) which is sensitive to content of foliar chlorophyll, and by a near infrared (NIR) band which is sensitive to canopy foliage amount or simply NDVI can be expressed as (NIR-R)/(NIR + R) [9]. Intra-yearly fluctuation in amplitude of NDVI profiles (temporal) of the two fields for the same crop type (when stage unaltered) point out several vegetation condition [9]. At the same time, intra-yearly fluctuations in the stage of the temporal profiles (when amplitude altered) of the fields of same crop type point out shifts in uplifting stages [17].

To enhance along with supporting the crop type categorizing which is based on NDVI temporal profiles, field data on crop phenology have been adopted as reference [8, 18–22].

But it has been explored that the NDVI saturates for high biomass and dense vegetative areas [23, 24]. In addition to the mentioned discovery, NDVI is critical to the canopy background and this comes with significant errors when the vegetation characteristics estimation is being done [25]. Furthermore, the utilization of NDVI values which can be derived from the multispectral spatial resolution sensors is limited for their blended pixels problems despite their huge utilization at the regional scale [26, 27].

The application of red edge is more effective [28] than the conventional ones such as contrast between NIR and Red bands [29].

The new favorable circumstances for the vegetation analysis include the availability of the extension of spectral ranges for instancing the red edge band which emerged with Rapid Eye and WorldView-2 launching [29]. The red edge reflectance possesses better sensitivity to the fluctuations of chlorophyll content and has been projected in the experimental studies as more effective for analyzing stress in vegetation [30, 31].

When it needs to be most accurate on earth observational data, vegetation structure estimating attributes for instance canopy storage capability and LAI hyper spectral data are the most preferable [25]. Hyper spectral data can detect even little vegetation traits which can be merged with mixed pixels while using broadband sensors with its narrow spectral pathways [32]. Due to being expensive, unavailable most of the time, limited with spatial coverage and complex for analysis due to low knowledge of skills such datasets are not agreeable all the time [33, 34]. Landsat datasets remain the most optimal source of the spatial data for the regions which have limited resources and it possesses the longest historic datasets, its readily available and free, with less complexities while processing and analyzing [25]. Enhanced Landsat 8 operational land imager, Landsat balanced spatial resolution along with the inadequacy of spectral channels for instance red edge, and sensitive vegetation mapping limits its benefits [35]. So the important was to search for other sensors which are having comprehensive spatial and spectral information and which could be utilized while mapping and the understanding sensitive water relevant issues like as canopy water storage capability and interception [25].

In this study, two test sites with rice crop fields taken near Vellore. The rice test fields variety is the same, i.e., ADT 43. Most of the nearby crop fields are farmed with the same variety of rice. The spectral analysis has been done with the data collected for the two crop fields. The different phonological stage of the crop has been analyzed with the utilization of red edge band.

2 Study Area

The study area (Fig. 1) is located in Vellore district, Tamil Nadu, India. The latitude and longitude of margining the study area are 12° 58′ 34″N to 12° 58′ 35″N and 79° 9′ 8″E to 79° 9′ 10″E, respectively. The maximum and minimum temperatures are 40.2 °C and 14.6 °C respectively for the plain areas of the districts [36]. The normal rainfall due to northeast monsoon is 392 and 501.3 mm due to southwest monsoon [36].

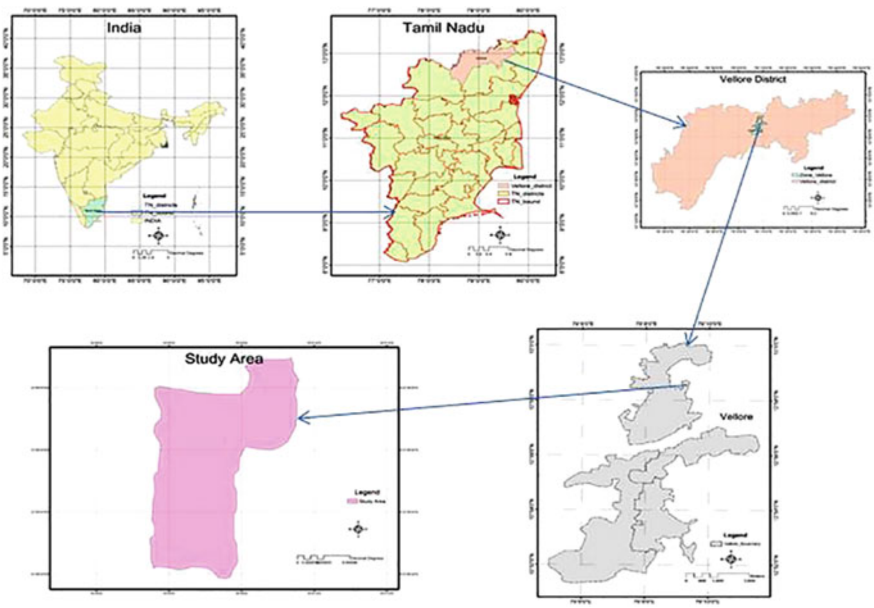

Fig. 1 Study area for the current work

3 Data Used and Methodology

Sentinel-2A satellite data has been used for this study which was launched in June of 2015. It is assembled with the identical multispectral instruments (MSI) a very wide field of view (a swath width of 290 km), which is skillful to acquire data with 13 bands in various spatial resolutions (within the range of 10–60 m). Estimated fact is sentinel-2A can supply at least one cloud free data image in each month on average

The MSI on Sentinel-2A can record data within the red edge spectral domain for vegetation which is one of the most useful remote sensing based description holders for chlorophyll content [37]. A 5-day Sentinel data has been taken for analysis consecutively for two test sites.

4 Red Edge Analysis

Red edge is the rapid transition zone within 680–760 nm as there occur a sudden increase from low red region of spectra to high infrared region of spectra due to intense pigment absorption close to 680 nm and high canopy scattering near 760 nm [38, 39]. Test site 1 had been taken for experimenting. The red edge first observed as for the vegetation analysis with satellite data red edge is more significant. Then the cross verification is done by the other test site. The spectral signature of both the lands shows the same pattern when it comes to red edge portion.

5 Results and Analysis

5.1 Field Survey

The significant information pertinent with the experimental study was inventoried such as farming style, harvesting, composting, etc. The field inventoried data will not create any difference as the information about two test sites is similar only and the crop type is of short duration variety.

5.2 Spectral Analysis

Spectral signature of test site 1 for four available consecutive days is shown in Fig. 2. It shows the reflectance at visible and near infrared and the various stages pattern at difference growth stage, i.e., 5–96 days.

Figure 3 is similarly showing spectral signature of test site 2 and how the reflectance is changing and how this change is presenting different stages of rice (Tables 1 and 2).

In tropical environment, growth phases of rice plant take first 60 days as vegetative stage, next 30 days as reproductive phase, and last 30 days as ripening phase for a short duration variety [40]. So the reflectance is less in vegetative phase as the presence of water takes the absorption higher. In vegetative phase, tillers and more leaves are formed, plant heights increase whereas in reproductive stage, the plant is more matured and panicle formation takes place and in ripening stage the

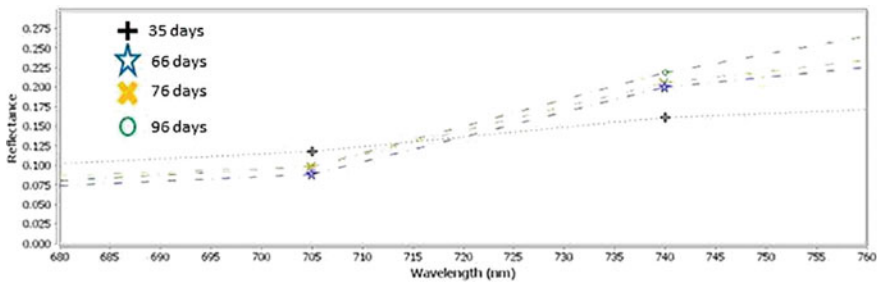

Fig. 2 Spectral signature of test site-1 for 4 days

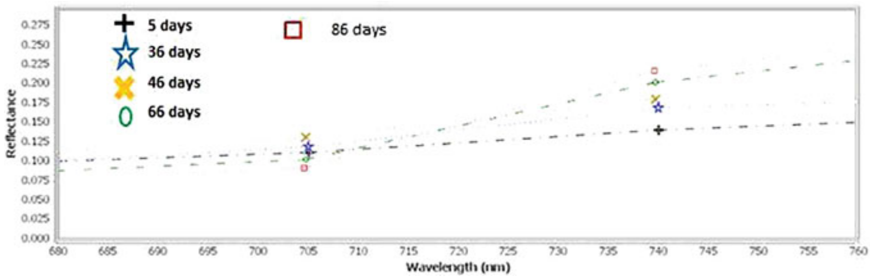

Fig. 3 Spectral signature of test site-2 for 5 days

Table 1 Phonological stages (daywise) analysis of test site 1

Age of the crops (in day)	Maximum reflectance	Growing stage
35	0.170	Vegetative phase
66	0.228	Reproductive phase
76	0.231	Reproductive phase
96	0.266	Ripening phase

Table 2 Phonological stages (daywise) analysis of test site 2

Age of the crops (in day)	Maximum reflectance	Growing stage
5	0.148	Vegetative phase
36	0.175	Vegetative phase
46	0.192	Vegetative phase
66	0.231	Reproductive phase
86	0.246	Reproductive phase

rice plant is in totally matured phase [40]. So the water absorption is no longer dominating in matured stages.

6 Conclusion

The study shows that depending on change in the age of the crop, the canopy of the crop also changes and based on this canopy change, remote sensing can identify crop stages with the red edge analysis. Current study's fruition is a new approach when it comes to crop monitoring. It is shown that multispectral data is also helpful for red edge analysis. This study shows the biophysical parameters analysis for the distribution of fertilization and nutrients through red edge concept. Further, the creation of spectral library can be considered which identifies the stressed vegetation, i.e., deceased crops for various rice varieties. This multispectral spectral library can be compared with hyper spectral datasets for the further developmental implementation possibilities.

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