A shape-based approach to spatio-temporal data analysis using satellite imagery

by

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Abstract—Many socio-environmental aspects manifest themselves over space and time, interacting at varying scales of these dimensions. Satellite imagery, available repetitively over a region, provide important clues of these observations across these dimensions. But, also pose enormous challenges in terms of data processing, extracting significant patterns (indicating the underlying processes) and be able to further model them as scientific knowledge of the environmental process. In this paper, an effort has been made to propose a time-variant analysis method based on the shape characteristics of the vegetation response over time to help identify regions of significant changes. The study covers four agricultural-year periods between 2008 and 2012 over the district of West Godavari, in south of India. This approach shows that the effect of 2009 drought year on the agricultural practices vary spatially depending on the access to resources and the time-lag that manifests itself in such processes. In this study, we also find that nearly 80% of the region is well endowed and hence resilient to the climatic vagaries.

Keywords-MODIS; vegetation index; time-series data; phenological cycle; temporal signature.

I. INTRODUCTION

Study of spatial distribution of various vegetation covers and changes occurring in it over time for a region provides crucial environmental information. The information plays a vital role in understanding complex ecosystem processes, climate change studies, deforestation studies and many policy applications. Thus, there is a dire need for improved monitoring of vegetation resources. For regions dominated by agricultural land cover, such information is very valuable and critical to the field of agronomics [1]. The agricultural component of the vegetation landscape is of specific interest because it is intensively managed and continually modified. It also has direct impact on the ecological processes, hydrological resources, and the economy [2], [13]. For example, a region hit by drought could suffer from fall in agricultural production which would be evident from change in its corresponding vegetation cover as observed through satellite imagery. Another example could be the introduction of new irrigation infrastructure (e.g., a canal), which can lead to significant changes in vegetation cover over the surrounding regions. Post analysis of such impacts could be conducted via studying changes in the vegetation cover, which can enable us to analyze effectiveness of such infrastructure and what kind of shifts it introduced in cropping practices of that region. It can also provide base for improved structuring of future economic development strategies. Such an analysis provides dual benefits in itself. This can lead to better management and distribution of irrigation facilities by laying emphasis on water-deprived areas and at the same time studying its corresponding socio-economical impacts.

Environmental changes either natural or man-made can majorly be categorized into large scale and small scale. Large scale environmental changes, such as the introduction of new irrigation infrastructures, deforestation, drought, or floods, cause abrupt or sudden changes in vegetation cover. Whereas small scale changes happen over a prolonged period of time. For example, a region showed change from double cropping to single cropping practice over a time span of 10-15 years. These shifts are gradual, but detecting such changes could help us analyze underlying environmental factors like soil degradation, or long-term change in rainfall pattern etc. Thus, the study of various vegetation covers and changes occurring in it over the spatio-temporal space can provide a holistic perception of where and when those changes occurred, give an insight to the possible drivers that triggered such changes, and their corresponding impacts.

Satellite based imagery with its wide and repetitive coverage can provide a good set of samples to assess terrestrial regions. Every pixel of this satellite imagery represents a certain parcel of land on earth. For each such parcel, at a given time, the satellite image gives a snapshot of its current status. This might be in terms of vegetation growth, rate of urbanization, water spread, or any such dynamic phenomena. Such responses captured over frequent intervals helps generate the time-series of the region, which when analyzed over time and space dimension can help understand various phenomena. For an area, represented by a pixel, the time-series generated using vegetation response - captured in the satellite imagery - is referred to as the temporal signature of that particular region. It captures the variation of greenness attribute over time and indicates its phenological progression.

Phenological cycles represent the greening and senescence characteristics in the temporal signature of vegetated land surfaces. In heterogenous landscapes, these
provide valuable clues on various practices. Each vegetation class has a distinct phenological cycle and describes a unique shape in time [3], [4]. Although vegetations tend to vary their annual phenological cycles - may be irregular in timing of greening and senescence phase, length of growing period, maximum vegetation growth etc - because of different geographic and climatic conditions, these variations are not extreme and shape can remain similar. The shape-characteristic of the temporal signature is exploited in the proposed approach for classification of different vegetation cover. Detecting changes over time for such regions can help in understanding the underlying processes that trigger these changes.

Our aim is to detect major changes occurring in vegetation covers with emphasis on agricultural landscape using the time-series data, while disregarding phenological changes i.e. intra-variations in phenological cycles of a particular agriculture class. These variations are bound to be present due the high degree of variability between years, across different geography, that are caused due to short-term climatic fluctuations in temperature and rainfall patterns etc [8].

Given a satellite data spanning across space and time, several time-series analysis techniques have been used to study various environmental phenomena, characterize vegetation cover, and variations occurring in it over time. Satellite time-series data have been used to map forest disturbance [5], for land cover classification [6], fourier analysis to monitor seasonal variations in vegetation phenomenologies and their inter-annual change [7], for detecting trend and seasonal changes [8], wavelet analysis for crop expansion and intensification [9], wavelet analysis in conjunction with time-series models to understand relationship between climate and vegetation dynamics that vary at inter-annual and intra-seasonal scales [10], environmental anomaly indicator system at continental scale using fuzzy approach [11]. For classification of vegetation cover, a number of techniques have been developed using spectral responses and temporal information available from satellite images. Traditional approaches used satellite responses captured at specific periods of time for classification using different separability measurements [12] [13], but shortcoming of such single-scene or multi-scene satellite imagery is that it cannot describe the dynamic process of vegetation growth and does not provide any insight to such phenomena. In majority of other studies, features derived from satellite based time-series data have been used with conventional classification techniques like decision tree etc, for classifying vegetation cover [14]. Features are extracted to capture the information contained in the phenological cycles of vegetation time-series curve [15] [16], but the full temporal detail is not exploited [7] i.e. to say time-series in itself has not been used as an inherent class identifier. Another drawback of such feature-based approaches is that they require adequate training sample that represents full range of variability, and are highly dependent on the feature-selection techniques used to characterize the phenology.

The objective of this research is to exploit the shape-characteristics of time-series and develop an approach for improved sampling of training data and classification of vegetation cover over large regional scale. And this process when applied over time and across space can help in providing valuable clues to understand major changes in vegetation covers and regions of change.

II. DATA AND STUDY AREA

A. Data

In the present study, we used moderate-resolution imaging spectroradiometer (MODIS) 250-m resolution vegetation index product - MOD13Q1. The MOD13Q1 product provides Enhanced Vegetation Index (EVI) data. This dataset is composited at 16-day intervals and so it provides 23 observations per year, at a spatial resolution of 250-m. The MODIS data used in this study cover 5-year period from 2008 to 2012, consisting of 23 images per year, giving 115 datasets in total. Sample MODIS dataset image covering southern part of India is shown in Fig. 1.

Figure 1. Sample MODIS dataset image covering southern part of India and West Godavari district is highlighted.

A vegetation index is a simple numerical indicator that can be used to analyze remote sensing measurements and assess whether the target being observed contains green vegetation or not. EVI value is an empirical measure of vegetation activity at the land surface [17]. As per the MOD13Q1 product description, EVI value varies in range -0.2 to 1.0.

National land cover dataset produced on an annual basis by National Remote Sensing Centre (NRSC), Indian Space Research Organisation, Hyderabad, India with 16 classes and spatial resolution of 56-m was used as a reference data for evaluating classification results.

B. Study Area

In the present work, the study area covers the West Godavari district of Andhra Pradesh state, located in Southern India (highlighted in Fig. 1). The district is located
in delta region of the Godavari river and has large extent of fertile agricultural land. It covers an area of 7,742 km². The district is situated between 80° 52′ and 82° 28′E, of eastern longitudes and 16° 32′ and 17° 50′N, of northern latitudes.

C. Vegetation Classes

In India, agricultural-year is from June to May. The Indian cropping season is classified into three main seasons - (i) Kharif (ii) Rabi and (iii) Zaid. The kharif cropping season is from June to Oct/Nov during the south-west monsoon (monsoon crops) and the rabi cropping season is from Oct/Nov to Mar (winter crops). The crops grown between Mar and June are zaid crops (summer crops). In agriculture, single-cropping is the practice of growing only one crop, whereas multi-cropping is the practice of growing two or more crops in the same piece of land during a single agricultural-year. In the present study, along with these four agriculture classes (kharif, rabi, zaid, and double cropping), two more major vegetation classes were considered, which are plantation and forest. Remaining set of classes such as urban land, fallow land, and waterbody were combined into a single class labelled as no/low vegetation class. Representative temporal signature of each vegetation class can be seen in Fig. 5.a and Fig. 5.b.

III. Methodology

The flow chart depicted in Fig. 2 and Fig. 4 represents the systematic approach adopted in the present study.

Figure 2. Steps to preprocess the raw time-series data.

A. Data Preprocessing

1) Data Extraction

Sequence of contiguous satellite images were stacked to construct raw time-series data using EVI value for each pixel over a period of time. In the present study, time-series were split into segments according to the agricultural-year of India (June to May). A time-series can be thought of as a transition from one agricultural-year to the next. The vegetation pattern for each agricultural-year is processed separately.

2) Curve Smoothing

In case of multi-temporal satellite data, atmospheric influences and sensor malfunctioning often lead to data gaps and data anomalies. The anomalies need to be corrected before any further processing. In the present study, Adaptive Savitzky-Golay filter technique devised in [18], was used to smoothen the raw time-series data and reduce the noise hence preserving the original shape and features of the time-series curve better than other approaches. A window size of 7 with polynomial order 4 was found appropriate for this dataset. In Fig. 3, for a sample pixel, its raw time-series and derived time-series curve are shown.

Figure 3. For a pixel, its raw time-series curve formed using 23 data points for agricultural-year 2010-11 and derived time-series curve obtained after the smoothing step is shown.

Figure 4. System pipeline depicting steps for refining training data and for vegetation cover classification.

In Fig. 4, system pipeline of the proposed approach for classification of different vegetation classes is shown. We perform classification and study spatial distribution of various vegetation covers over the West Godavari district for the agricultural-year 2010-11.
B. Ground Truth Information

The next step is to gather a database of time-series patterns that represents the ground truth information. MODIS data along with the NRSC reference data of previous agricultural-year was used to construct the database. For each vegetation class, representative ground truth data i.e. samples of time-series curves were collected. The database of collected temporal signatures representing the ground truth data will later be required as a training sample in the classification step of our methodology. Temporal patterns corresponding to different vegetation classes in the database need to be error-free as they dictate the accuracy of the classification step.

For each vegetation class, the ground truth data was collected from the homogenous regions in order to avoid any inclusion of outliers i.e. time-series curves belonging to any other vegetation class. However, due to a coarser resolution of MODIS satellite data, the extracted time-series pattern may not correspond to the ground truth information obtained from NRSC reference data which is at a higher resolution. Moreover, we assume NRSC reference data to be error-free. Therefore, even though homogenous regions were used to collect the ground truth data, outliers may still be present which need to be eliminated. The next step is to identify and extract only the core samples for each vegetation class. We viewed this problem as a time-series clustering problem. For each vegetation class, we perform clustering and select those temporal patterns which are relatively closer to the cluster center and eliminate rest of the samples from temporal signature library by claiming them as potential outliers.

In time-series clustering, it is crucial to decide what kind of similarity is important for the clustering application. Accordingly, an appropriate clustering algorithm and an appropriate distance measure should be chosen. In the next section, we discuss the distance metric and the clustering algorithm used in our methodology.

C. Distance Metric and Clustering

1) Dynamic Time Warping

Dynamic Time Warping (DTW) proposed in [19] [20] is a ubiquitous tool that has been used in various time-series applications. For satellite based time-series analysis, DTW has been used in research studies [22], [23] and [24]. For time-series based applications, DTW is an accurate similarity measure and it tends to perform better than traditional distance metrics like euclidean distance, etc [21]. In the present study, DTW which reflects similarity in shape was used as a distance metric. DTW algorithm finds an optimal alignment between two given time-sequences, by explaining variations in Y-axis (curve) by warping X-axis (time) and provides a distance measures that quantifies the similarity between the two sequences. But the crucial observation is that standard DTW algorithm totally disregards the time dimension while finding alignment between two time-sequences. In our study, this can lead to unintuitive alignments, for instance temporal pattern of a monsoon crop shown in Fig. 5.a (Kharif) can match to the temporal temporal pattern of a winter crop shown in Fig. 5.b (Rabi), as both are similar in shape but shifted in time.

To avoid these temporal inconsistencies, we use variant of DTW that introduces a temporal constraint, namely the Constrained Dynamic Time Warping (CDTW) method. CDTW introduces a window size on temporal axis that essentially constrains the possible warping allowed only within that window [20]. Also, CDTW significantly reduces the computation time as compared to DTW. In the present study, time-series are indicative of the annual phenological cycles of different vegetation types. For each vegetation class, cycles tend to be irregular - in terms of timing of greening and senescence phase, length of growing period etc, but irregularities are not extreme and typically temporal shift of one to two months is observed. Thus, in the present study, owing to this fact we use +/-2 as the window size which basically allows matching within the temporal shift of two months overcoming the problem of DTW.

2) K-medoids Clustering

For time-series clustering, k-medoids clustering technique was adopted, being one of the standard approaches [25] [27]. For time-series data, traditional k-means clustering technique tends to fail - in capturing the shape-characteristics of time-series curve - as it is modeled to work in the euclidean space [26]. k-medoids finds new cluster centers by choosing an existing data member within each cluster that best represents its cluster center, instead of calculating the cluster members’ average. k-medoids aims at minimizing the intra-cluster sum of squares, by using the proximity of objects to the medoids of the clusters formed by the algorithm. For each vegetation class, k-medoids clustering technique along with CDTW as a distance metric was used for the refinement of ground truth data to extract core samples.

D. Classification

We have viewed the classification of time-series data as a curve matching problem, comparing the unknown time-series curve of a particular pixel to the temporal signatures available in the library derived from the ground truth data. For classification of time-series data, k-NN with DTW/CDTW as a distance metric is a viable solution and in
Figure 5. Representative temporal signature for one agricultural-year of class: Urban, Fallow, Water, Kharif. For each class, vertical spectrum at 23 data points is also shown, that denotes the variation in time-series curves that were present in the core samples. (a)

Figure 5. Representative temporal signature for one agricultural-year of class: Rabi, Double, Plantation, Forest. For each class, vertical spectrum at 23 data points is also shown, that denotes the variation in time-series curves that were present in the core samples. (b)
several cases it outperforms other classification techniques [21]. However, this approach has one drawback, it is computationally too expensive for any real time application with large database.

1) Optimization

To deal with the problem of expensive computational complexity, we reduce the size of training data. In our study, for time-series analysis purpose, this can be done by constructing a representative curve for each vegetation class using core samples (extracted earlier); and then later use the representative curves for the classification (Fig. 5.a and Fig. 5.b). Here, we take advantage of two critical facts that each vegetation class has distinct temporal pattern and core samples belonging to a particular vegetation class typically have similar shape-characteristics.

In the present study, DTW Barycenter Averaging (DBA) technique demonstrated in [28] was deployed to construct the representative time-series curves. DBA is an averaging method for time-series data based upon DTW distance metric. Furthermore, application of such techniques and its relevance for time-series classification has been shown in [29]. Temporal signature of different vegetation classes using representative curves (obtained using DBA) are shown in Fig. 5.a and Fig. 5.b. For each class, vertical spectrum at 23 data points is also shown in Fig.5.a and Fig.5.b, that denotes the variation in time-series curves that were present in the core samples.

2) Nearest Neighbour Classification

Finally, for the classification of input data, NN-CDTW i.e. Nearest neighbour with CDTW as a distance metric was used. As each class is represented by a unique representative curve, each pixel’s time-series curve is classified based on its CDTW distance threshold to these. NN is computationally less demanding than others, given the data vector size.

IV. RESULTS

A. Vegetation Cover Map

The time-series curve of each pixel was labelled using the proposed approach. Fig. 6 shows the vegetation cover map generated with the MODIS time-series data for the agricultural-year 2010-11 over the West Godavari district. The derived vegetation cover map shows the extent and spatial distribution of different vegetation covers - seven vegetation classes were considered.

B. Validation

Results generated were compared with the land cover reference dataset obtained from NRSC. The NRSC data with 16 classes at a resolution of 56m was merged and resampled to obtain the 7 classes at 250m, to match the MODIS data (Fig. 7). Classes with similar temporal characteristics in NRSC data were grouped together as they exhibit similar vegetation temporal patterns. No/low vegetation included Built-up, Wasteland, Rann, Current Fallow, Grassland, Littoral Swamp, Snow Cover and Water Bodies, while Forest covered Evergreen, Deciduous, and Scrub Forest. The rest were unaltered. In the down-scaling, statistical mode was considered as the class in non-homogenous regions.

Thus, after rescaling of NRSC reference data, pixel-based comparison was carried out with the derived vegetation cover map to evaluate the accuracy using confusion matrix. The confusion matrix shows cross-validation results for 6 classes, as ‘zaid’ class was not present in West Godavari district. The results derived from the confusion matrix (Table 1) yield an overall accuracy of 81.43%.

Based on spatial visualization it can be empirically observed that major classification error occurs at marginal regions that are heterogenous or transitional in nature. The errors can be attributed to mixed pixels, i.e., where pixels in MODIS data contain a mixture in surface reflectance due to its coarse resolution. Another reason for misclassification could be due to rescaling and resampling of NRSC reference data. It can be observed (Fig. 6 and Fig. 7) that our proposed approach performs better in classifying regions that are relatively homogenous in nature. Error between water body (no/low vegetation) and plantation can be attributed to littoral swamps present in wetland regions. Whereas error between plantation and forest could be due to high correlation between their phenological cycles. And temporal signature of other no/low vegetation classes tends to be irregular, as EVI is not designed for such land covers, which can also lead to errors.

Figure 6. Vegetation cover map generated for agricultural-year 2010-11 using proposed approach and labels of seven classes are shown.
Figure 7. Rescaled and resampled NRSC reference data for agricultural-year 2010-11 used for validation.

Figure 8. Vegetation cover map generated using proposed approach for agricultural-year 2009-10.

Table 1. Confusion Matrix of results obtained from the proposed approach against statistics obtained from NRSC reference data for agricultural-year 2010-11.

<table>
<thead>
<tr>
<th>Predicted (No. of pixels (relative %)) (Agri. year 2010-11)</th>
<th>No/low vegetation</th>
<th>Kharif</th>
<th>Rabi</th>
<th>Double Plantation</th>
<th>Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>No/low vegetation</td>
<td>85.99</td>
<td>2.92</td>
<td>3.95</td>
<td>1.07</td>
<td>5.39</td>
</tr>
<tr>
<td>Kharif</td>
<td>3.23</td>
<td>89.43</td>
<td>1.17</td>
<td>0.22</td>
<td>4.71</td>
</tr>
<tr>
<td>Rabi</td>
<td>4.47</td>
<td>2.54</td>
<td>75.31</td>
<td>5.93</td>
<td>10.63</td>
</tr>
<tr>
<td>Double</td>
<td>0.96</td>
<td>4.69</td>
<td>2.84</td>
<td>85.98</td>
<td>4.24</td>
</tr>
<tr>
<td>Plantation</td>
<td>4.51</td>
<td>4.83</td>
<td>10.06</td>
<td>0.65</td>
<td>68.90</td>
</tr>
<tr>
<td>Forest</td>
<td>1.05</td>
<td>1.18</td>
<td>0.62</td>
<td>0.14</td>
<td>15.15</td>
</tr>
</tbody>
</table>

C. Change Detection

The proposed approach was used for classification of West Godavari district for four agricultural-year periods between 2008 and 2012. Derived vegetation cover maps for agricultural-year 2009-10 and 2010-11 are shown in Fig. 8 and Fig. 6 respectively.

The vegetation cover map generated provides detailed spatial distribution of various vegetation classes - with emphasis on agriculture classes - over West Godavari district.

The generated maps can help infer pixel-wise change for each vegetation class, which is crucial in capturing frequently occurring agricultural shifts over the region. Further, to analyze change detection over any two consecutive agricultural-years, we perform quantitative and qualitative analysis using vegetation cover maps. To capture significant changes in agricultural practices and corresponding region of interests, we define seven major changes: (1) Decrease in vegetation - regions that lost their forest or plantation cover, (2) Decrease in cropland - agricultural regions that converted to fallow land, (3) Increase in cropland - fallow regions that started agriculture, (4) Single to Double, (5) Double to Single, (6) Shift in single (monsoon to winter crop or winter to monsoon crop) - denoting shifts in cropping practices, and (7) No changes - regions that showed no significant change. The percentage distribution of the defined classes during all transitions for four agricultural-year periods between 2008 and 2012 are shown in Table 2.a and Table 2.b. (Transitions are 2008-09 to 2009-10, 2009-10 to 2010-11, and 2010-11 to 2011-12).

The classes defined are helpful in analyzing underlying processes such as rainfall patterns, human activity and irrigation access to the area. For instance, major changes can be observed around agricultural-year 2009-10 (Table 2), which is indicative that some event might have occurred during that period. As a case study, a visual representation depicting regions of change for transition from agricultural-year 2009-10 to 2010-11 is shown in Fig. 9.
Figure 9. Region of changes for transition from agricultural-year 2009-10 to 2010-11 are shown. Region A (green), Region B (brown) and Region C (yellow and orange) are highlighted.

Table 2.b Change analysis (Statistics of No change regions) for agricultural-years from 2008-09 to 2012-13.

<table>
<thead>
<tr>
<th>No change (No. of pixels in %)</th>
<th>2008-09 to 2009-10</th>
<th>2009-10 to 2010-11</th>
<th>2010-11 to 2011-12</th>
<th>2011-12 to 2012-13</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008-09 to 2009-10</td>
<td>80.12 %</td>
<td>71.83 %</td>
<td>82.7 %</td>
<td>86.26 %</td>
</tr>
</tbody>
</table>

V. OBSERVATIONS

Table 2 and Fig. 9 helps us to detect spatial clusters - regions under which similar trends and changes are exhibited. We can observe two major clusters, marked as region A and B. Region A depicts change from single to double cropping pattern, whereas region B shows shift from kharif (monsoon crop) single cropping practice to rabi (winter crop) single cropping practice. Similar changes were also evident from the temporal signatures of the regions (Fig. 10 and 11). Fig. 10 shows the corresponding change for one such pixel that changed from kharif to double while transitioning from year 2009-10 to 2010-11 via its time-series curve.

Fig. 10, shows cropping pattern for years 2008-09 to 2011-12 (double-single-double-double) in region A. The change from double to single are observed to revert back in the year 2010-11 and continue to remain the same thereafter. Thus, we detect anomaly only in the year 2009-10 (detected in Fig. 9). Similar trend can be observed in region B (kharif-rabi-kharif-kharif) - where shift in cropping practices occur and is reverted back - as depicted by Fig. 11.
It is known that the agricultural-year 2009-10 was a drought year as reported by Indian Meteorological department. Given our observational data Fig. 10 and 11 along with this prior information, it can be deduced that it is plausible that the abrupt changes were triggered due to lack of irrigation water in drought year. Since they reverted back (region A back to double cropping and region B back to monsoon crop as shown in Fig.10 and 11) in year 2010-11 (detected in Fig. 9), we can use this observation to further infer that these spatial clusters are rainfall dependant regions for their agricultural practices.

As opposed to observations obtained from region A and B, region C showed different trend capturing two major changes (double-double-single-double) and (rabi-fallow-rabi) while transitioning between agricultural-years 2008-09 to 2011-12. In Fig. 12, we can observe that the pixels from region C did not undergo any change in the drought year, but anomaly in these pixels are observed in the next agricultural-year 2010-11 (major being double to single cropping - yellow and other from single to fallow land i.e. decrease in cropland - orange as detected in Fig. 9). As no change is observed in the drought year, it suggests that the regions may not be rainfall dependant and the source of irrigation could be ground water. And also, the fact that despite 2009-10 being a drought year, there is an increase in double cropping practice from single cropping (6.17 %) during transition from 2008-09 to 2009-10 (from Table 2.a), which could be attributed to excessive use of groundwater resources during drought year. But it is a well known fact that rainfall patterns can affect groundwater levels, due to which it is plausible that the effect of drought year (2009-10) was seen later (2010-11), where groundwater resources depleted enough for cropping practices to shift from double to single and from single to fallow land i.e. decrease in cropland ( as shown in Table 2.a).

We are also able to detect regions that are temporally homogenous i.e. regions that remained consistent over time and did not undergo any significant change (Table 2.b). Even in the drought year, no abrupt changes were detected (white portion in Fig. 9). For instance, in Fig. 13 we can observe the time-series curve of a particular pixel having forest cover that shows no change over the span of four years.

VI. CONCLUSION

In this paper, we propose a systematic approach to continuously extract relevant information from the satellite imagery which serves as a knowledge base for many real-time applications. The method enumerated in this paper enabled us to study and identify spatial distribution of various vegetation covers spanning over a large area by taking advantage of high temporal resolution of satellite data and exploiting the distinct shape-characteristics of time-series curve of different vegetation cover.

Using the vegetation cover maps obtained from our approach, we were able to identify different type of changes
along with their location and time instants. We also detected spatial clusters which showed similar kind of trend over a period of time. Further, this can also help us in capturing information regarding episodic and periodic events. The data regarding rainfall pattern, climate change, irrigation facilities, land use management, etc. gathered over a period of time can be combined with the time-series data to detect the possible drivers that trigger such events.

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