International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307 (www.ijsrcseit.com)
doi : https://doi.org/10.32628/CSEIT206443

A Geo-spatial Classification Time Series Change Detection Using Remote Sensing Images of Seshachalam Region

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Article Info
Volume 6, Issue 4
Page Number : 167-175
Publication Issue :
July-August-2020

Article History
Accepted : 20 July 2020
Published : 25 July 2020

ABSTRACT

Time series is a scientific process of determining an ordered sequence of values of a variable within equally spaced time intervals. Mostly this is applied when looking at technical data and its influences on the neighboring surroundings. This type of scientific analysis that can be applied twofold. Firstly, it can be used to obtain a knowledge of the triggering forces and structure that produced the observed data. Additionally, it can be used to fit a model and to predict, monitor the area of interest.

This scientific form of analysis can be applied in various sectors so long as the data can be measured over time. The following are some of the applications: Economic and sales forecasting, Crop Yield prediction, Forest cover changes, urbanization, among many other uses. In this analysis, we will focus on time series change detection using image differencing of a classified image and representing the outcome area in a bar graph. The area of study is Seshachalam Hills, Tirupathi an ecological zone in Andhra Pradesh, India.

Keywords : Time series change Analysis, Geo-spatia,l Landsat Time Series, Seshachalam Region, Multi-Temporal, Supervised Classification.

I. INTRODUCTION

The techniques of classification involved in this analysis have various uses, going from data classification, prediction, clustering, and prescription. These techniques are usually application-specific. However, the concepts are equally pertinent to any other application area of research.

Using various remote sensed data, one can perform a time series analysis to determine a particular trend in a feature of interest. Despite Remote sensing data being expensive to acquire, there has been free data available on platforms such as USGS Earth Explorer. For instance, Landsat Satellite has unceasingly provided earth observation data for the past 41 years.

Since 2008, the provision of free, robust data products has stimulated a revitalization of interest in Landsat time series (LTS) for multitemporal categorizations. The efficacious launch of Landsat-8 has seen a steadiness of measures at scales of particular relevance to the management of scientific activities ensured in the short term. Mainly, forest monitoring benefits from LTS, where baseline conditions can be interrogated for both abrupt and gradual changes and attributed to different drivers.

In this study, various Landsat images are acquired at a five year time interval to facilitate the project. Landsat imageries for the years 2000, 2005, 2010, 2015 and 2020 are acquired. Subsequently, image classification is done to identify the underlying classes. An accuracy assessment is then done to determine the accuracy of the classification. It is important to note that supervised classification was utilized because it is easier to determine the accuracy and the quality of the classification. Moreover, the various areas of the individual classes are calculated to investigate and establish the trend.

Seshachalam Hills, Tirupathi is an area that is predominantly covered with trees, natural vegetation, and animals. Forest is an essential resource in nature. They can be majorly classified as Natural or human-made forests. However, there is a narrower classification of forests, some of which includes the following: Tropical Evergreen Forest, Temperate Deciduous Forests, Temperate Coniferous Forests, Taiga Forests. These are classified differently depending on their soil, climate, location, and plant type characteristics.

For instance, Tropical evergreen is located around the equator between 23.5 degrees latitude and longitude with warm temperature. Temperate deciduous forests are located in the Eastern United States and Canada, western parts of Europe, and other parts of China, Russia, and Japan. Temperate Coniferous Forests are located in the coastal area with warm winters and heavy storms, for example, Southwest America and Southern Japan. Additionally, Taiga Forests are a type of northern forest that lies between 50 and 60 degrees latitude. They include the Boreal forests in North Asia, Canada, and Scandinavia.

The importance of Seshachalam Hills, Tirupathi is un ignorable. No human can dispute the fact there is proper livelihood s depended on the functional status of Forests. According to the Panda organization, statistics show that over 2 billion people depend on forests directly as forests provide shelter, livelihoods, food, water, and fuel security. These activities, either directly or indirectly, depend on Forests. Also, over 300 million people across the world live in forests, including sixty million indigenous people. Furthermore, forests are the second world's largest storehouse of carbon after oceans.

Seshachalam Hills, Tirupathi provide ecosystem services that are essential to human welfare, which include: Absorbing harmful greenhouse gasses that are responsible for climate change. Secondly, they provide clean water for drinking, bathing, and other household needs. Also, forests protect watersheds and reduce the amount of erosion and chemicals that reach waterways. Furthermore, forests are a source of food and medicine and serve as a buffer in natural disasters like floods and rainfalls. Forests also provide habitat to more than half of the world's land-based species.

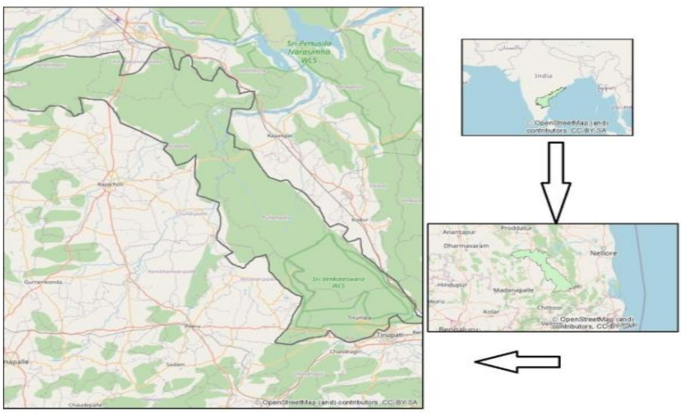
Seshachalam Hills, Tirupathi is the most widely distributed terrestrial vegetation type, and thus play an essential role in providing the environmental context and shaping the dynamics of regional and global ecosystem processes. Recording of variation in data in data values for time is the most common way to read and process real-time data. The recorded values usually show the variance of the data samples of one particular area in accordance to its temporal properties, and thus can be used to predict and analyze the inherent properties of the area under test. A strong classification engine is needed to make a proper inference from recorded temporal data. Various classifiers and land areas are tested to evaluate the forest cover time series data, and probability is assessed to check for the effect of deforestation in the regions under test. Using time-series data. Some researchers have evaluated the Normalized Difference Vegetation Index (NDVI), Vegetation Cover Proportion (VCP), Soil Adjusted Vegetation Index (SAVI) and Normalized Difference Water Index (NDWI). Their research claims to have more than 95% accuracy using machine learning-based classifiers for different types of land cover forest classes.

Some researchers have claimed to be using bi-temporal detection of change by using geometric processing, the discovery of clouds, and change vector analysis (CVA). CVA method usually relies on multi-dimension feature reduction along with expectation maximization (EM) to detect the changes in the vegetation of a specific area. They have also predicted seasonal trend decomposition to predict the seasonal changes in data.

1.2 JUSTIFICATION

Though temporal monitoring of forest cover, environmental-related data such as the rate of deforestation environmental degradation and land encroachment can be analyzed from the data presented above. Therefore this project is essential. The use of Landsat data is a quick way to carry out the analysis and obtain meaningful results. Detecting trends in forest disturbance is also an application of the data obtained and recovery using yearly

1.3 STUDY AREA MAP



II. LITERATURE REVIEW

In this section will be reviewing multiple algorithms for forest cover change detection as an application for time-series change detection. Most of the discussed techniques either use Long-Term trends. In the LandTrends approach, we use relative radiometric normalization and simple cloud screening rules to create on-the-fly mosaics of multiple images per year and extract temporal trajectories of spectral data on a pixel-by-pixel basis. We then apply temporal segmentation strategies with the both regression-based and point-to-point fitting of spectral indices as a function of time, allowing capture of both slowly-evolving processes, such as regrowth, and abrupt events, such as forest harvest. Therefore, we also developed a companion interpretation approach founded on the same conceptual framework of capturing both long and short-duration processes and developed a software tool to apply this concept to expert interpretation and segmentation of spectral trajectories (TimeSync, described in a companion paper by (Frank et al., 2010). These data were used as a truth set against which to evaluate the behavior of the LandTrendr algorithms applied to three spectral indices. We asked the LandTrendr algorithms to several hundred points across western Oregon and Washington (USA). Because of the diversity of potential outputs from the LTS data, we evaluated algorithm performance against summary metrics for disturbance, recovery, and stability, both for the capture of events and longer-duration processes. Despite the apparent complexity of parameters, our results suggest a simple grouping of parameters along a single axis that balances the detection of abrupt events with the capture of long-duration trends.

Landsat data, LiDAR data, or similar standard time-series datasets are applied for prediction, clustering or classification purposes. Landsat data has been used for more than 18 years to analyze the bi-temporal changes in the datasets. The analysis is based on image processing where change detection for the datasets was obtained and the overall accuracy, which serves as a baseline for any image processing application which might need to perform time-series detection. This method can be further improved by using a machine learning or fuzzy logic rule engine. Still, the final evaluation will only be clear after the implementation of the suggested modifications.

While Landsat is one of the standard sets of imagery analysis in time series change detection for forest covers, another dataset, namely corona, is used by researchers to map change in forest cover in eastern US and central Brazil. They have analyzed data from the mid-1960s to the 2000s for achieving the results. As per the claim, the second-order polynomial transformation on corona images resulted in good geometric accuracy as obtained by using Landsat-7 imagery. The following studies were consulted.

Time-Series Analysis of multi-resolution optical imagery for quantifying forest covers loss in Sumatra and Kalimantan, Indonesia. In this paper, we analyzed all Landsat 7 imagery with <50% cloud cover and data and products from the Moderate Resolution Imaging Spectroradiometer (MODIS) to quantify forest cover loss for Sumatra and Kalimantan from 2000 to 2005. We demonstrated that time-series approaches examining all useful land observations are more accurate in mapping forest cover change in Indonesia than change maps based on image composites. Unlike other time-series analyses employing observations with a consistent periodicity, our study area was characterized by highly unequal observation counts and frequencies due to persistent cloud cover, scan line corrector off (SLC-off) gaps, and the absence of a complete archive. Our method accounts for this variation by generating a generic variable space. We evaluated our results against an independent probability sample-based estimate of gross forest cover loss and expert mapped total forest cover loss at 64 sample sites. The planned gross forest cover loss for Sumatra and Kalimantan was 2.86% of the land area, or 2.86 Mha from 2000 to 2005, the highest concentration having occurred in Riau and Kalimantan Tengah provinces.

Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — Temporal segmentation algorithms. The method brings together two themes in time-series analysis of LTS: the capture of short-duration events and smoothing of long term trends.

III. ANALYSIS AND RESULT

3.1 General Characteristics

Classification Design

The zonal areas below show the distribution of the mapping theme. Bare rocks were the most dominant class with the least class is the cloud cover. It is impossible to filter off all the cloud cover from an image resulting in pixels that be unclassified. Supervised classification was adopted by using the maximum likelihood classified. Four thematic classes were identified, and using the text editor signature points with pure pixels were picked and used to assign the remaining classes to thematic classes. To investigate the accuracy of classification, the following methodology was adopted.

Accuracy analysis

Using confusion matrices generated from the classification, the accuracy was obtained, as discussed below.

- Using the trained data, supervised classification was carried out using the maximum likelihood algorithm.
- Using a more precise image from Google Earth, ground truth points were picked and assigned the appropriate class to which it belongs

- Using the conversion tool, the points were converted from points to raster from this point the statistics of the classification can be determined
- Using the combined tool, the point raster is combined with the output raster of the classification
- The result can then be inputted in a pivoting tool to obtain the confusion matrix as a table
- From the confusion matrices, the accuracy of the classification can be computed by the summation of the pixels in the main diagonal and the total pixels of the image.

The average accuracies obtained was 89% with a consideration of all the years. The accuracy matches the traditionally accepted level of accuracy reported by (Masek et al. 2013).

Monitoring data that proved no forest cover loss attribution or that fail to distinguish forest area loss/gain from forest cover loss/gain can lead to a misunderstanding regarding the nature of the observed forest changes. The area of forest present in a given jurisdiction is a function of how a forest is defined. The presence of natural and human disturbances as well as regionally unique successional processes and life cycles of trees results in a situation where a location with forest land use may not have tree cover. Annual land cover products are now available from time-series satellite data representing multiple decades of land cover and dynamics. These data sources offer categorical and temporal insights to determine the context of land cover at a given point in time. The historical information provided by satellite-derived time-series data makes it possible to identify areas that are temporarily occupied by the non-treed land cover as a result of their current stand development stage following stand-replacing disturbances. Even techniques based on satellite imagery detection and leaf-based forest cover detection, which are two extremes in terms of the source of data, yield similar accuracies in detection and analysis of time series forest cover datasets. Researchers can work on multiple datasets to improve the accuracy of time series analysis systems and due to the ease of availability of the data. Datasets like Landsat, LiDAR, MODIS, PALSAR, and others have proven good quality data for forest cover sets to the researchers for analysis. As an extension of the current work, the researchers can use soft computing algorithms like fuzzy logic, genetic algorithm, reinforcement learning based on machine learning, and deep net-based classification, which should improve the accuracy of clustering, classification, and prediction in the system for time series analysis.

Accuracies in percentages

The accuracy of classification is obtained from a confusion matrix generated from the correctly classified pixel and the pixel count expressed as a percentage.

Confusion Matrices

2000

Rowid	OID		Forest	Riverbasin	Farmland	Barerocks	Water Body
1	1	Forest	29	0	0	0	1
2	32	River Basin	0	47	0	0	0
3	33	Farmland	1	0	31	4	0
4	52	Barerocks	11	0	4	44	0
5	67	Waterbody	0	0	0	0	23
			41	47	35	48	24

Correctly classified Pixels	174
Pixel Count	195
Accuracy	89.23%

2005

Rowid	OID		Forest	Riverbasin	Farmland	Barerocks	Water Body
1	1	Forest	32	0	1	0	0
2	32	River Basin	0	46	0	1	0
3	33	Farmland	0	0	32	2	0
4	52	Barerocks	9	1	2	45	0
5	67	Waterbody	0	0	0	0	24
			39	47	37	48	24

Correctly classified Pixels	179
Pixel Count	195
Accuracy	91.79%

2010

Rowid	OID		Forest	Riverbasin	Farmland	Barerocks	Water Body
1	1	Forest	29	0	0	0	1
2	32	River Basin	0	43	0	1	0
3	33	Farmland	0	0	34	5	0
4	52	Barerocks	7	0	5	47	0
5	67	Waterbody	0	0	0	0	23
			36	43	39	53	24

Correctly classified Pixels	176
Pixel Count	195
Accuracy	90.25%

2015

Rowid	OID		Forest	Riverbasin	Farmland	Barerocks	Water Body
1	1	Forest	29	0	0	0	0
2	32	River Basin	0	43	0	1	0
3	33	Farmland	0	0	36	5	0
4	52	Barerocks	5	1	5	47	0
5	67	Waterbody	0	0	0	0	23
			34	44	41	53	23

Correctly classified Pixels	178
Pixel Count	195
Accuracy	91.28%

2020

Rowid	OID		Forest	Riverbasin	Farmland	Barerocks	Water Body
1	1	Forest	25	0	0	1	0
2	32	River Basin	0	43	0	1	1
3	33	Farmland	0	0	37	5	0
4	52	Barerocks	4	2	5	48	0
5	67	Waterbody	0	1	0	0	22
			29	46	42	55	23

Correctly classified Pixels	175
Pixel Count	195
Accuracy	89.74%

Data Acquisition

Landsat data was obtained from USGS and preprocessing was done i.e layer stacking, subsetting and then pansharpening. The table below represents the dates of acquisition of the image in correspondence to the years

Year	Date of acquisition	Sensor
2000	07/June/2000	Landsat 5
2005	23/May/2005	Landsat 5
2010	01/July/2010	Landsat 7
2015	14/June/2015	Landsat 8
2020	19/May/2020	Landsat 8

Table 1. Date of data acquisition

IV. DATA REPRESENTATION AND ANALYSIS

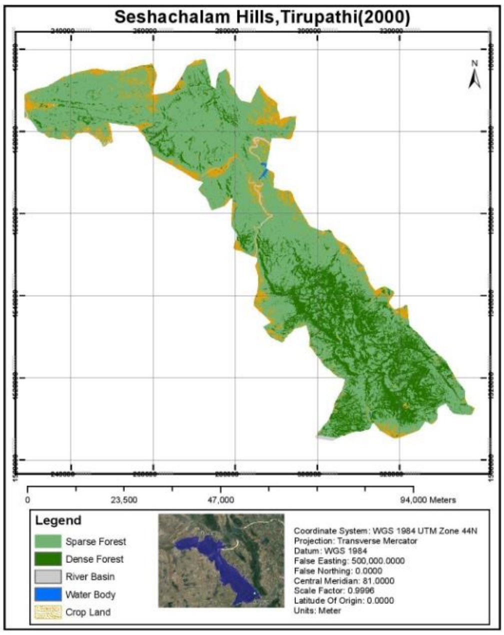


Image 1. Supervised classified map of the year 2000

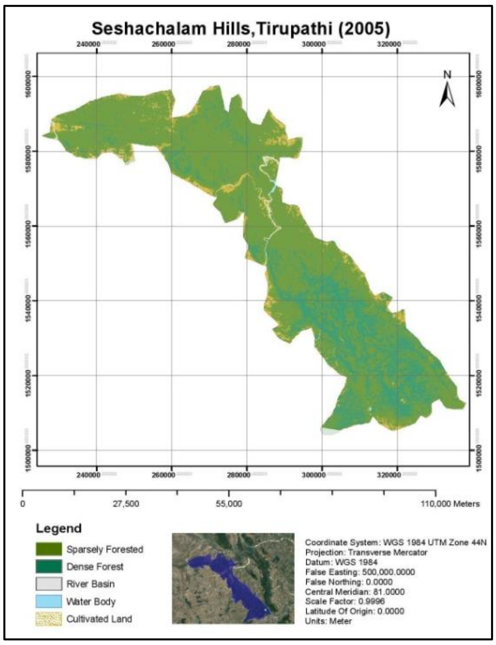


Image 2. Supervised classified map of the year 2005

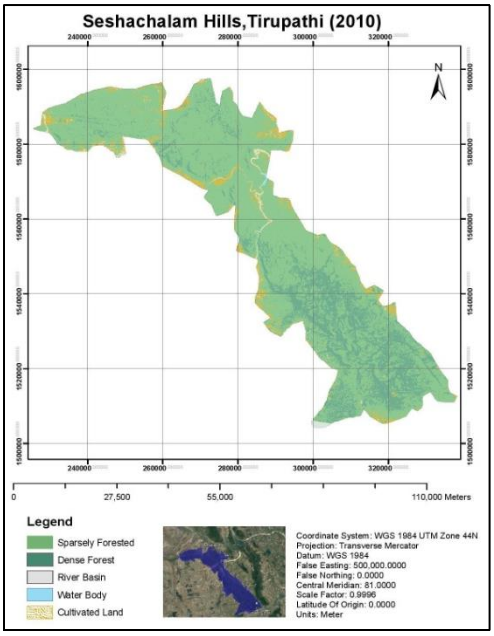


Image 3. Supervised classified map of the year 2010

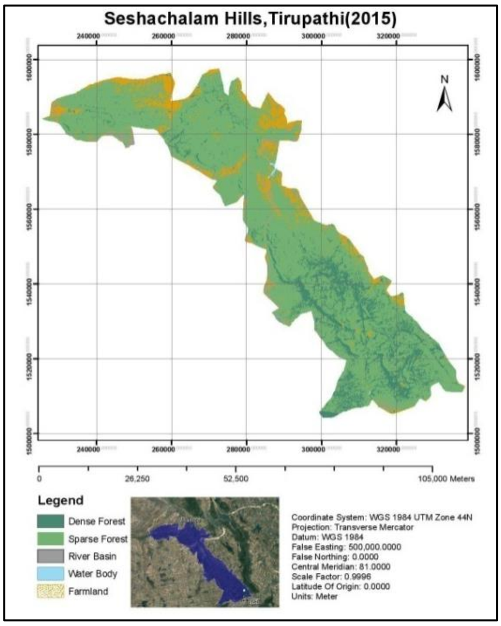


Image 4. Supervised Classified map of the year 2015

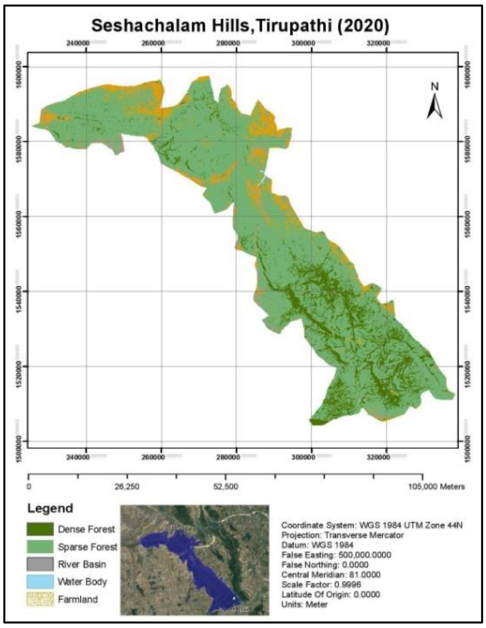
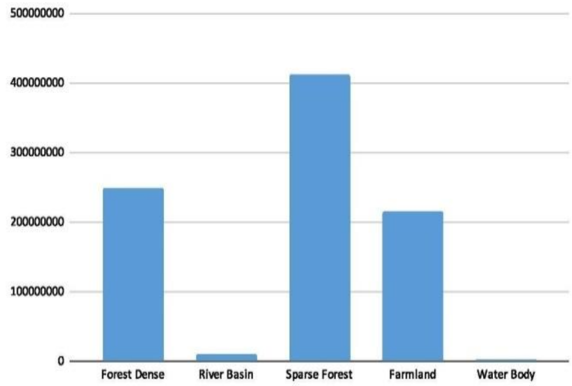


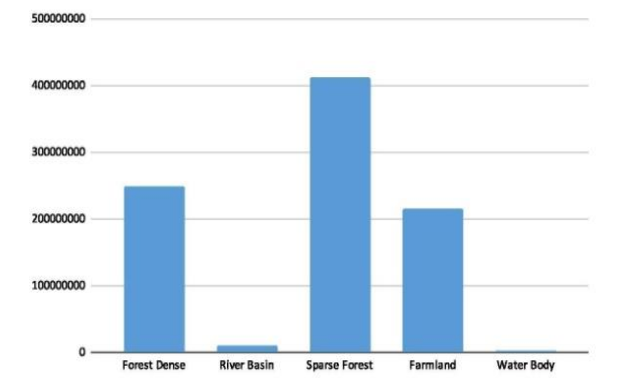
Image 5. Supervised Classified map of the year 2020

Histogram Representation of Areas

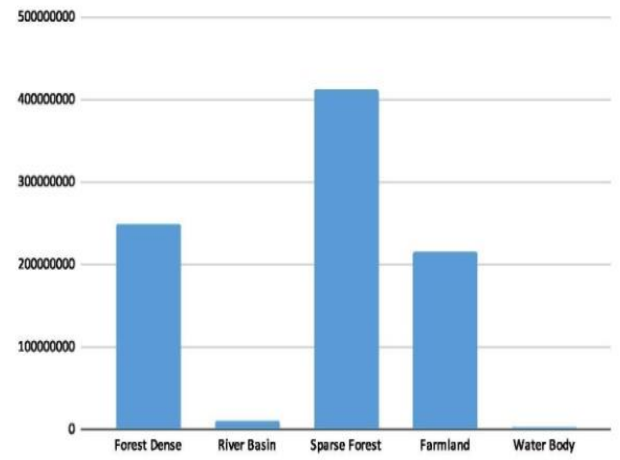
For better visualization, the result of the classification and to easily deduce the trend the data above was represented in graphical format as shown below the area is in meters square .



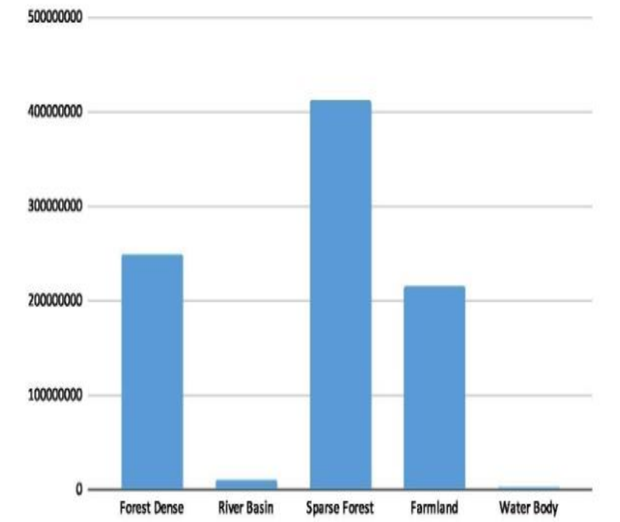
Graph 1 Histogram showing areas against class for 2000 classified map



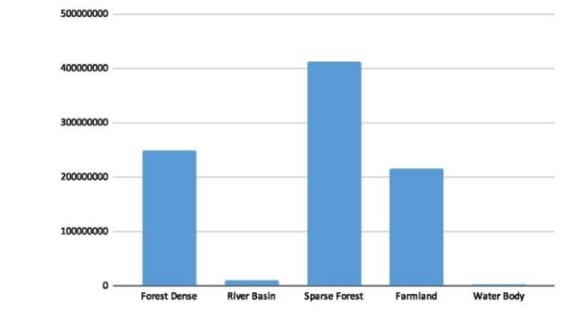
Graph 2 Histogram showing areas against class for 2005 classified map



Graph 3 Histogram showing areas against class for 2010 classified map



Graph 4 Histogram showing areas against class for 2015 classified map



Graph 4 Histogram showing areas against class for 2015 classified map

Examining the graph shows that the dense forest reduced with time over the years while the level of sparse forest increases over the years this is attributed to the presence of forest fires. The water body reduced with time as a result of evaporation and probably deforestation. The river basin was increasing as the river was drying up.

V. CONCLUSION

Even though carrying out Land-Use Land-Cover time series classification is a hefty task future recommendation necessitate the adoption of dividing the entire time series period into subsequences and then classifying the subsequence will improve the LULC efficiency. An integration of Convoluted Neural Network into the classification algorithm improves the accuracy of a classification and is able to detect mixed pixels and classify them appropriately depending on their spectral signatures. The latter approach is useful in classifying images of low spatial resolution like the Landsat image in this case. Measuring the accuracy via the confusion matrix proves to be less accurate as compared to methods of statistical learning which evaluates the accuracy of every pixel as opposed to the sampling technique pf confusion matrix i.e. not all pixels are considered in the classification sample. However, the accuracy of classification is dependent on the spatial resolution and spectral resolution of the classified pixels .

VI. REFERENCES

[1]. Masek, J., Goward, S., Kennedy, R., Cohen, W., Morrison, G., Schleeweis, K., and Huang, C. 2013. "United States forest disturbance trends observed using Landsat time series." Ecosystems, Vol.16(No. 6): pp. 1078-1184. doi:10.10007/s10021-013-9669-9.

[2]. Frank Thonfeld, Antje Hecheltjten& Gunter Menz, Bonn, "Bi-temporal Change Detection, Change trajectories and Time Series Analysis for Forest Monitoring", PFG 2/2015,0219-0141, Stuttgart, April 2015.

[3]. Cook, Diane. "A Survey Of Methods For Time Series Change Point Detection". International Journal On Remote Sensing, vol 45, no. 34, 2017, pp. 5-6., Accessed 22 July 2020.

[4]. Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W. and Campbell, L.B.2016 Mass data processing of time series Landsat imagery: pixels to data products for forest monitoring. Int. J. Digit. Earth 9, 1035-1054.doi: 10.1080/17538947.2016.1187673.

[5]. Yan, Jining. "A Time-Series Classification Approach Based On Change Detection For Rapid Land Cover Mapping". Journal Of Photogrammetry And Remote Sensing, vol 158, no. 3, 2019, pp. 249-262., Accessed 22 July 2020.

Cite this article as :

R.Sanjeeva Reddy, Dr. Anjan Babu G, Dr. A. Rama Mohan Reddy , "A Geo-spatial Classification Time Series Change Detection Using Remote Sensing Images of Seshachalam Region", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 6 Issue 4, pp. 167-175, July-August 2020. Available at doi : https://doi.org/10.32628/CSEIT206443
Journal URL : http://ijsrcseit.com/CSEIT206443