CHANGE DETECTION OVER MULTISPECTRAL IMAGES USING MACHINE LEARNING TECHNIQUES: A CASE STUDY ON RUSHIKONDA

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Abstract— The ability to identify the amount of change observed in Land is needed and it is necessary to describe how human actions impact/affect the environment. The Rushikonda, which is located in the Andhra Pradesh district of Visakhapatnam, has seen changes in the land use, according to observations. The goal is to examine and comprehend how, over the course of the last six years, land use and cover has changed in the Rushikonda(2015-2021). The current study has demonstrated how changes in agricultural patterns, industry, and land use have always had an impact on the environment[11-15]. The findings of the present study have revealed that how risk to nature, industry, change in crop patterns, and land usage are already influenced by the lack of water resources. The paper's conclusion is that recent approaches help to understand how land is being used generally and that the observation of a 28% land shift helps with the planning of construction projects close to the Rushikonda.

Keywords— Remote Sensing, Principal Component Analysis, K-Means, Change Detection, Classification, Image Processing, Multi-Spectral Images, Normalized Difference Vegetation Index, Geospatial Data Abstraction Library.

1. Introduction

Change detection" is used to identify changes that have occurred in remote sensing data over two time periods. It finds applications in a variety of fields, including surveillance videos and medical imaging. Its research goal is to separate out unwanted data and gather information on changes in the study area.

The most popular algorithms nowadays are those that involve machine learning. It will be applied in categorization, clustering, and various other applications. [16] The different types of machine learning algorithms are reinforcement, semi-supervised, unsupervised, and supervised.
Researchers believe that remote sensing is the most efficient and trusted environment for detecting changes on the earth's surface. The examination of the Land use and Land change information provides urban planners some advantage in making appropriate choices for managing land resources. To categorize the satellite images, researchers used a number of categorization algorithms..

2. Literature Review

In [1] The author discussed how to compute and assess the efficiency of both implementation options for change identification using ML/DL algorithms. [2] mentioned that initially, the photos are enhanced, and then the change detection using Fuzzy C-Means Clustering approach is used, which will result in better outcomes.[3] author employed the well-known K-Means clustering method, which improves the single-channel intensity band ratio and is difficult to determine the K value. [4] author employed the Edge Enhancement approach, which has a lower computational cost, does not require prefiltering, and gives results directly to the wavelet domain; however, the image may begin to look less natural as the overall sharpness advances. [5] author utilised the IR-MAD approach, which when using the suggested initial change mask may converge to a better no change backdrop even in the face of big changes but fails to converge when there are a lot of change pixels. [6] the author employed K-means clustering tends to produce fewer errors but results in thicker boundaries on the derived change map. [7] CNN, Sharp Mask, U-Net, and ResNet methods were used by the author to provide fast and precise image segmentation. Deeper networks are computationally expensive and require weeks to train, but they can be learned fast without increasing the error rate. [8] By analysing satellite images, the author employs image processing techniques that employ machine learning to identify changes in the pattern. Based on Convolutional Neural Networks, authors present a methodology for automatically detecting change in multispectral satellite data. [9] The author utilizes K-Means clustering and principal components Analysis, which first calculate Eigen Vector Space and then generate Future Vector Space, which is then subjected to K-Means clustering with two clusters, one stating change and the other stating no change in the Satellite Image. [10] The author uses two wavelet-based image enhancement approaches, the discrete wavelet transform (DWT) and the dual tree-complex wavelet transform (DT-CWT), to increase the image quality. Following image enhancement, Support Vector Machines are used to classify the land use of the pictures. An evaluation of accuracy based on a confusion matrix is used to evaluate the accuracy of land-use categorization.

3. Proposed Method

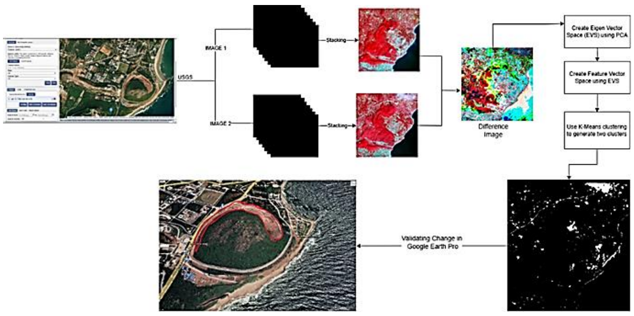

fig 1: Architecture of the proposed method

2.1 Input data collection

In this stage, we will download data from the United States Geological Survey (USGS) website for the Rushikonda area for two different time periods, 2015 and 2021, onto our local computer. The downloaded image will be divided into bands.

And then, we will perform stacking, which is the process of combining multiple images of the same resolution into a single image, where the images with higher resolution will be resampled into the target resolution.

2.2 Calculating the Difference Image

The difference image between the stacked images obtained in the previous step will be calculated in the third step

```
FOR xi=1 to length(stacked_image1)
        FOR xj=1 to length(stacked_image2)
                Diff_image=abs(xi-xj)
        END FOR
 END FOR
```

2.3 Dimensionality reduction and feature Extraction

In this step, we will examine how to compute Eigen vectors using Principal Component Analysis and Kernel Principal Components Analysis. These are non-zero vectors that do not change direction when subjected to a linear transformation. It only varies by a single scalar factor.

The kernel PCA enables the analysis of more complex data patterns that would not be visible using only linear transformations.

$$\mathrm{COVR} = \frac{1}{\mathrm{M}} \times \sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{I} \times \mathrm{I}^{\mathrm{T}}$$

And then we use the Eigen Vector that we obtained in the previous step, sorted in decreasing order, to assemble the feature vector space when PCs are acquired.

After that the future vector obtained in the previous step is applied into the K-Means Clustering algorithm with the K value set to 2 because there are only two possibilities: change or no change.

K-Means algorithm

Step-1: K clusters will be formed (here we take 2 clusters)
Step-2: Centroids were formed based on the cluster.
Step-3: Assign points to the centroid that are close to the cluster.
Step-4: Centroids of newly formed clusters were recomputed
Step-5: Previous two steps are repeated until the value of the centroid will be constant for the next two computations.

2.4 Validating the Results

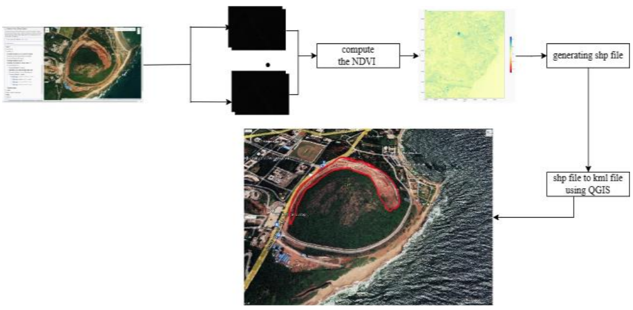

Fig 1.1 Validating the Results in Google Earth Pro

After obtaining the change map, the validation process began with the use of the Geospatial Data Abstraction Library (GDAL), which is primarily used to handle data in the raster and geospatial formats.

The inputted data will be downloaded from the USGS earlier and extracted, and this data will be used to calculate the Normalized Difference Vegetation Index (NDVI). Researchers must observe the amount of green on a given area of land is observed by looking at the various wavelengths of visible and near-infrared sunlight reflected by the plants.

Following that, a shape file will be generated and exported, allowing us to import and display the change map in Google Earth Pro.

Now launch Google Earth Pro, navigate to the menu, and select the option called open. Then you will be prompted to specify the shape file location, select the exported shape file, and click open. The change map will then be displayed in Google Maps.

4. Result Analysis

In this experiment, we obtain various outputs after performing various tasks, and each output represents a specific output in each step.

The first output is a stacked image of two timeline periods, 2015 and 2021, obtained with the QGIS tool.

Fig 2. Color Infrared Image of 2015

fig 3. color Infrared Image of 2021

The images above are the final images obtained after applying stacking in the QGIS tool, and they are used to generate the change map.

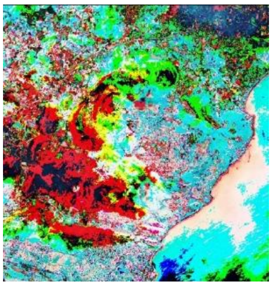

Fig 4. Difference Image of Kernel PCA

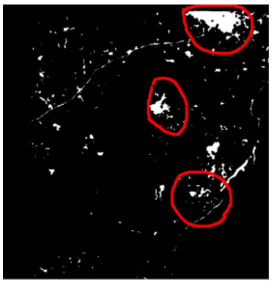

Fig 5. Change Map with K-Pca & K-means

The above images represent the difference image that we obtained and the change map obtained using Kernel PCA and K-Means.

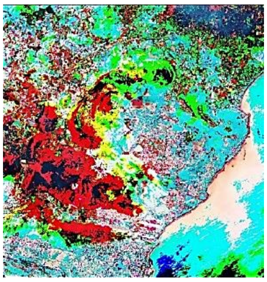

Fig 4. Difference Image of PCA

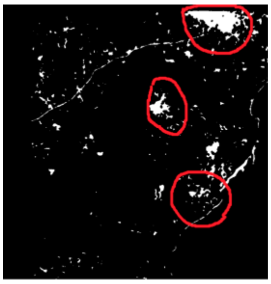

Fig 5. Change Map with Pca & K-means

The above images depict the difference image and the change map obtained using PCA and K-Means.

The images above depict the change map at two different time periods: 2015 and 2021. The normal PCA algorithm produces less accurate results than the Kernel PCA algorithm, and the results are shown above.

The outputs obtained after applying PCA and Kernel PCA are compared, with PCA producing a change in percentage of 21.06 and Kernel PCA producing a change in percentage of 18.76. According to the results, PCA produces more change than Kernel PCA.

Further to that, the obtained NDVI data reveal that there is 39.03 Vegetation Index available near Rushikonda, indicating that the green health vegetation is present.

Fig 6. Rushikonda Before 2015

Fig 7. Rushikonda after 2021

As a result, the obtained changes are validated in Google Earth Pro. The area that is automatically marked in red by Google Earth Pro near Rushikonda is as the change is obtained in the preceding process.

Algorithm	Percentage of change obtained during the year 2015 and 2021
PCA & K-Means	21.06
Kernel PCA & K-Means	18.76

Table 1. Comparing the results of PCA and Kernel PCA with K-Means

5. Conclusion

We have analysed the two algorithms PCA and Kernel PCA for better accurate results. Since the proposed method is unsupervised, there is no need for expensive training data sets catered to change detection. It is designed to detect change in land use/cover of Rushikonda. The years 2015 to 2021 were used to detect land cover changes using remote sensing, satellite imagery, and image processing techniques.

References

1. T. Vignesh; K. K. Thyagharajan; K. Ramya: Change Detection using Deep Learning and Machine Learning Techniques for Multispectral Satellite Images.
2. M. H. Kesikoglu; U. H. Atasever; C. Ozkan: Unsupervised Change Detection In Satellite Images Using Fuzzy C-Means Clustering And Principal Component Analysis.
3. Debanshu Ratha, Shaunak De, Student Member, Turgay Celik, Member, and Avik Bhattacharya, Senior Member, IEEE “Change Detection in Polarimetric SAR Images Using a Geodesic Distance Between Scattering Mechanisms”.

4. M.N. Sumaiya; R. Shantha Selva Kumari; “Unsupervised Edge Enhancement algorithm for SAR Images using Exploitation of Wavelet Transform Coefficients”.
5. Prashanth Reddy Marpu; Paolo Gamba; Morton J. Canty; "Improving change detection results of IR-MAD by eliminating strong change".
6. Turgay Celik “Unsupervised Change Detection in Satellite Images Using Principal Component Analysis and k-Means Clustering”.
7. de Bem, Pablo Pozzobon, Osmar Abílio de Carvalho Junior, Renato Fontes Guimarães, and Roberto Arnaldo Trancoso Gomes. 2020. "Change Detection of Deforestation in the Brazilian Amazon Using Landsat Data and Convolutional Neural Networks".
8. Greeshma Katarki; Harivijay Ranmale; Indira Bidari; Satyadhyan Chickerur; "Estimating Change Detection of Forest Area using Satellite Imagery".
9. Christopher Munyati: “Use of Principal Component Analysis (PCA) of Remote Sensing Images in Wetland Change Detection on the Kafue Flats, Zambia".
10. Karan, Shivesh Kishore, and Sukha Ranjan Samadder. "Accuracy of land use change detection using support vector machine and maximum likelihood techniques for open-cast coal mining areas".
11. Polykretis, C.; Grillakis, M.G.; Alexakis, D.D. Exploring the impact of various spectral indices on land cover change detection using change vector analysis: A case study of Crete Island, Greece.
12. Panuju, Dyah R., David J. Paull, and Amy L. Griffin. "Change detection techniques based on multispectral images for investigating land cover dynamics".
13. Minu, S., and Amba Shetty. "A comparative study of image change detection algorithms in MATLAB."
14. Rathindra Nath Biswas, Md. Nazrul Islam, M. Nazrul Islam, Md. Juel Mia, Md Nasrat Jahan, Mir Fahim Shaunak, Md. Motiur Rahman, Md. Yachin Islam. (2022) Impacts of morphological change on coastal landscape dynamics in Monpura Island in the northern Bay of Bengal, Bangladesh.
15. Saha, S.; Bovolo, F.; Bruzzone, L. Unsupervised deep change vector analysis for multiple-change detection in VHR images.
16. Abijith, Devanantham, and Subbarayan Saravanan. "Assessment of land use and land cover change detection and prediction using remote sensing and CA Markov in the northern coastal districts of Tamil Nadu, India." Environmental Science and Pollution Research (2021): 1-13.
17. Aldhshan, Shaban RS, and Helmi Zulhaidi Mohd Shafri. "Change detection on land use/land cover and land surface temperature using spatiotemporal data of Landsat: a case study of Gaza Strip." Arabian Journal of Geosciences 12, no. 14 (2019): 1-14.
18. Talukdar, Swapan, Pankaj Singha, Susanta Mahato, Swades Pal, Yuei-An Liou, and Atiqur Rahman. "Land-use land-cover classification by machine learning classifiers for satellite observations—A review." Remote Sensing 12, no. 7 (2020): 1135.
19. Vali, Ava, Sara Comai, and Matteo Matteucci. "Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review." Remote Sensing 12, no. 15 (2020): 2495.

20. Gong, Maoguo, Yuelei Yang, Tao Zhan, Xudong Niu, and Shuwei Li. "A generative discriminatory classified network for change detection in multispectral imagery." IEEE.