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A Diagnostic Survey on Methods Used to Predict Land Used for Shifting Cultivation Using Satellite Images

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***Abstract:** Shifting cultivation and its practice are said to be pernicious and eco-hostile from the standpoint of dependence of tribal people on forest-clad hill slopes. In this farming, the soil bone diseases are also reduced significantly. This is an example of subsistence, extensive, and arable farming. In the rainforest, it is one of the traditional forms of agriculture. The Amazonian Indians mostly do this farming in South America. They use the land for 2 to 3 years before moving to another area. There is a huge part of land which is used for Shifting cultivation for several years. Because of its spread, growing loss of potential green cover and related imbalance in eco-habitat, the Forest Policy, 1952 and the National Commission on Agriculture, 1976 suggested that shifting cultivation be banned, providing the tribal practitioner alternative systems of livelihood support. In this paper we are going to look at different methods and algorithms used to build AI models to predict Land used for Shifting Cultivation.*

***Keywords:** Shifting Cultivation, Remote Sensing, LULC, Image Processing, Neural Networks.*

I. INTRODUCTION

The history of shifting cultivation can be traced back to about 8000 B C in the Neolithic period which witnessed the remarkable and revolutionary change in man's mode of production of food from hunters and gatherers to food producers. Shifting cultivation since its inception is identified with rotation of fields rather than rotation of crops, absence of draught animals and manuring, use of human labor only, employment of dibble sticks or hoe, and short period of occupancy alternating with long fallow periods to assist the regeneration of vegetation, culminating in secondary forests. Many social scientists have described shifting cultivation as a way of life of the societies practicing it.

It is found that the shifting cultivation fields and their surrounding forests provide two alternative sources of subsistence to the dependent population. In case the crops are not good or fail, the forest resource aid the farmer by augmenting their food supplies in addition to the provision of house building material, fuel wood and timber.

Shifting Cultivation is a process to utilize land to grow crops, then abandon it after taking the plant products. This process takes place for several years by tribal communities. Because of its spread, there is a loss of potential green cover, there is an imbalance in eco-habitat.

Thus, on the consideration of the Forest Policy-1952 and the National Commission on Agriculture-1976, suggested that the Shifting Cultivation be banned, providing Tribal partitioner alternative systems of livelihood. Immediate implementation isn't that easy because this leads to many issues like Crop diversity and food availability, Challenges to the ecosystem and many more.

To solve these issues Indian Council of Agricultural Research (ICAR) needed the updated and accurate data related to land used for shifting cultivation to conduct research on it. As we know, Managing transformations in shifting cultivation areas and bringing shifting cultivators into the mainstream of economic development was a complex process. This issue was addressed to NITI Ayog, they suggested some actions to be taken in immediate, medium and long-term time frame. Bridging Data Gaps was one of them, for this data was advised to collect using Remote Sensing and Village Survey.

Remote sensing is a useful source to collect data from satellites and to classify land using Artificial Intelligence. Satellite images are pre-processed using image analysis tools like ERDAS to understand the Land Use Land Cover under specific areas. This data is further used to design

ML algorithms to classify land used for shifting cultivation.

A. General Procedure

In this section we will describe workflow of the research papers covered in this survey, using flowchart:

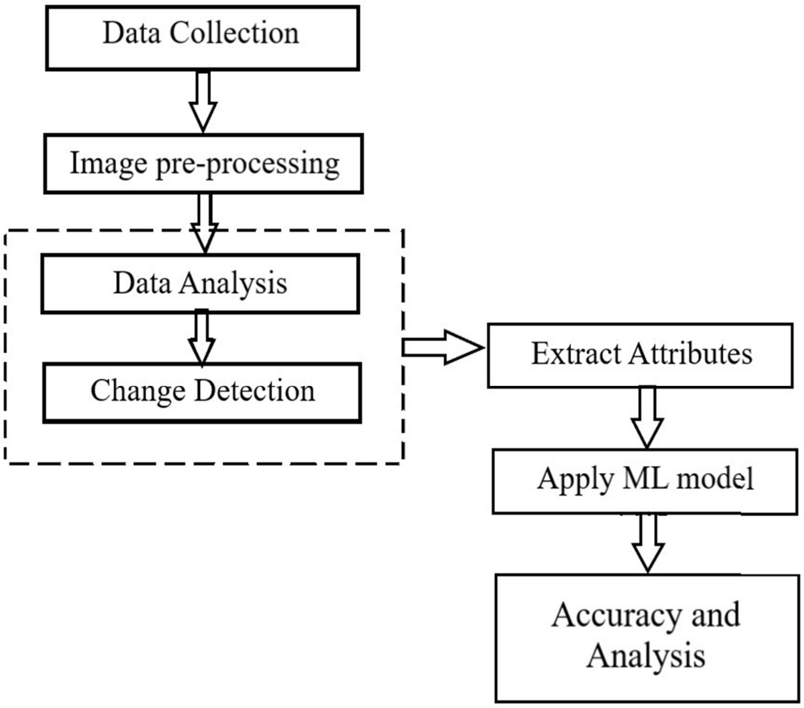

Fig.1

1) *Data Collection:* During research datasets were being used for predicting areas under shifting cultivation or to produce future LULC analysis of specific areas. In this process scientists have collected satellite images of their study area. Satellite images are collected from different sources based on the year and area of focus. While collecting images it was ensured that the images collected were from different years, which helped in change analysis.
2) *Image Pre-processing:* Satellite images consist outlier like cloud image or shadow of cloud, which interrupts land observation through satellite. To remove such interruption images are pre-processed. We can observe various pre-processing techniques were used to obtain the required data for the research.
3) *Data Analysis:* ERDAS software was used to classify land into different categories using colors. Few research papers include the calculated area under LULC observation. This observation helps in model selection to conduct research and to understand features of the area under study.
4) *Change Detection:* This phase helps to recognize the increase or decrease of features of areas like agriculture, deforestation and other classification. As we know Shifting Cultivation is a process which is performed for 7 to 20 years, thus it is necessary to know the changes in quality of land under study. Data analysis and Change detection are very useful phases to know the key parameters of land to recognize the part of land used for Shifting Cultivation. In this survey we will come to know that it is not necessary for every land to have the same feature to recognize Shifting cultivated areas.
5) *Extract Attributes:* Attributes help to classify land using observation made and helps in computing formulas or deriving algorithms. From the observation made from earlier 2 phases, it was easy to select input parameters for the model and to know attributes for change detection.
6) *Apply Model:* In this phase an algorithm is finalized and a suitable ML model or algorithm is chosen, best for the data. On execution an output image of the map is obtained. In this survey two types of output will be seen, from the model an output image is obtained showing the area used under shifting cultivation along with that some other observations were also made.
7) *Accuracy Measure and analysis:* Accuracy is calculated using statistical data and Kappa Coefficient. Statistical data was used to know the cause of accuracy. Kappa coefficient was used for limited algorithms.

B. Challenges

Dataset for the experiment was collected from the satellite, thus there were few images consisting of clouds or its shadow[2]. Due to this the images were not clear, there was noise in the data. Statistical data was used to get the information of land used under agriculture, deforestation and area used to grow crops like rice[3]. These data were useful to create scenarios and to know the feature of land with respect to shifting cultivation. Some parameters include human interference, like population density, the higher the density the more frequent land use change[4]. Creating an ML model considering these parameters was a bit challenging.
Different land surfaces were used for mapping shifting cultivation but this method was found to be time consuming and biased[9]. Thus through all these observations it was necessary to go towards more scientific parameters like NDVI ratio.

C. Motivation

The Government of India is working on a project to study areas under shifting cultivation. Through this project we get an opportunity to contribute to their efforts. While working on this project an individual gets an exposure to open source technologies, used to collect satellite images. Much research has been conducted on this topic. Still it was observed that the remote sensing mapping is unable to provide correct data, as it doesn't reach the root cause of shifting cultivation[13]. Government is expecting organizations to look for all of these issues. Through this project a person gets knowledge of various ML algorithms for image classification, we can also see few scientists have integrated ML algorithms to get the result. ISRO organization has also worked on this. Thus they have built a few websites through which a person can get related data for the project. Bhuvan is used for data collection and Vedas for data analysis. Through these sources a student can carry forward the project.

II. LITERATURE REVIEW

1) Adhikari et al. with his team worked on an experiment to predict land under shifting cultivation. His study area was Koraput District of Odisha which is a mountainous part of EGH region. In this experiment they used a dataset for long term analysis and to analyze decadal change of LULC. They collected images from SOI and satellite images of IRS P6 LISS III. To classify shifting cultivation land from other forest areas they used Ratio vegetation index and fuzzy c-means classification. Finally they got an accuracy of 86%. Through their experiment it was concluded that there was a shift in shifting cultivation land towards upper elevation.
2) Fujiki, S. et al. proposed a procedure for distinguishing bound-aries and identifying stand ages within vegetation patches at shorter intervals of time using remote sensing techniques. The vegetation patches in this study formed a component of a vegetation matrix consisting of protected areas and slash-and-burn fields in north Borneo. They aimed to develop an approach which combines object-based analysis using a high-resolution satellite image with time-series analysis using moderate-resolution Landsat images. They used that approach to analyze spatiotemporal patterns among small and complex vegetation patches in a shifting cultivation area in Borneo, and aimed to classify stand ages into intervals shorter than 5 years. They assess the accuracy of this approach-based classification and discuss the ecological implications of the results.
3) Misra, J., & Rajan, K. S. tried to assess the impact of different policy options available on the land use pattern, its choices and its interaction with the local population and its needs. Here they developed four scenarios that have been modeled for a period of 30 years, from 2005-2035, to understand and evaluate how different policies affected the land use pattern at the micro level. For this they had come up with four different scenarios, including the business as usual (BAU) scenario, each representing a specific form of social or policy change. Each of these scenarios were described as simulated for the period of 2005 to 2035. The agent based model was used to explore the effect of social and economic factors on land use and agriculture patterns. All these scenarios were run independently. The scenarios were: 1.Business as usual2.Incentivisation settled agriculture 3. No growth of settled agriculture 4.Doubling of population.
4) Rediet Girma et al. worked on Gidabo River Basin to analyze LULC changes from 1985 to2050 for Business as usual scenarios (BAU). For their work they collected satellite images from Landsat-5, Landsat-7 and Sentinel-2. They used the MLP-NN model for future LULC prediction. Classification result accuracy was above 80% and overall accuracy was 93.52%. They considered technical and human made factors for LULC change. The MLP-CA-MC model was further validated by the VALIDATE and ROC module based on the actual 2021 image.
5) Motivated by the concept of Normalized Difference Vegetation Index (NDVI), Unnikrishnan A et al. utilized the red and near infrared (NIR) band information for classifying the publicly available SAT-4 and SAT-6 datasets. For that experiment they used AlexNet, ConvNet and VGG by hypertuning the network and the input as two band data. The modified architectures with the

two band information along with a reduced number of filters were trained and tested and the model manages to classify the images into different classes. The proposed architectures were compared against the existing architectures in terms of accuracy, precision and trainable parameters. The proposed architecture was found to perform equally efficient by retaining high accuracy with less number of trainable parameters, when compared against the performance of benchmark deep learning architectures for satellite image classification.

6) Pande, C. et al used RS and GIS to categorize and map LULC with different technologies and digital data sets. An attempt was made in this study to map out the status of land use/cover of one of the development blocks of the Uttarakhand state, viz., Hawalbagh block of District Almora (Rawat and Kumar 2015). Boori et al. (2014) analyzed land use/cover disturbances caused by tourism using a number of RS and GIS-based techniques, including supervised classification. Rawatet al. (2013) also applied the same technique for the Ramnagar town area, Uttarakhand, India, to track changes over the period from 1990 to 2010. The key objective of that research was to use multispectral satellite images to distinguish the extent of changes in the arid area of the Akola district, Maharashtra, India. They collected data from the United States Geological Survey (USGS), Global Visualization Viewer (GloVis) and the National Remote Sensing Centre. Finally the model accuracy was 94.10% for 2008 and 88.14% for 2015.

7) P S Royet al. were informed that the preparation of resource maps was a basic requirement in developing a proper management plan. So far, no map has been produced which delineates the forest cover with respect to the type, areal extent and layout in relation to the non-forest areas. Satellite remote sensing has shown great promise to be able to survey such areas (NRSA1979, RoyandUnni1980). The North-Eastern Council, Shillong, sponsored an integrated survey of forest-cover and land-use pattern and also drainage details for the lower reaches of Arunachal Pradesh using remotely sensed multispectral data from LANDSAT (NRSA1982).

8) Shifting Cultivation: towards transformation Approach was a report on shifting cultivation presented by National Institute of Rural Development & Panchayati Raj of North Eastern Region. In this report they presented problems to be faced when the government tried to immediately stop shifting cultivation. To avoid those issues there were many steps taken by the government which included scientific approach, government policies and steps to be taken by the people. In this draft we get detailed information of efforts of the government for the benefit of tribal communities and preserving land quality for sustainable use of land.

9) Pulakesh Daset al. worked in all seven states of North East India. One of the reasons to conduct the study in NE India was to optimize crop production on available land sources. They used Landsat data of three different sensors to map shifting cultivation land in different time periods from 1975 to 2018. Method used to identify, classify and map the shifting cultivation land is Decision tree based multi-step threshold model [DTMT]. Overall accuracy obtained in this research was >85%. They used the GEE platform to generate the shifting cultivation maps for broader dissemination and replicate the process at desired time intervals. Using the GEE platform the output maps can be accessed using a simple internet browser without any specialized software.

10) Quantitative assessment of changes in LULC was one of the most efficient means to understand and manage the land transformation, Swapan Talukdar et al. Decided to examine different algorithms for LULC mapping. In his proposed paper he used six different algorithms to map LULC land. The aim of this experiment was to suggest a best classifier. They selected the landscape of the river Ganga from Rajmahal to Farakka barrage in India emphasizing three major dynamic river islands (locally, charland) dominated by patches as the area of study. Landsat 8 Operational Land Imager (OLI) image was downloaded from the United States Geological Survey (USGS) website to map the LULC using different machine-learning algorithms. Six algorithms used were, ANN, SVM, Fuzzy ARTMAP, Spectral Angle mapper, Random Forest and Mahalanobis Distance. After executing the model few observations and conclusions were made i) Accuracy of a classification varied with methods, techniques, time and space. ii) Results of experiment suggested that the area under each LULC class varied under different classifiers. The maximum variation was observed for the agricultural and fallow lands, while the minimum for the water bodies and wetlands. iii) Kappa coefficient and index-based analysis showed that the Random Forest has the highest accuracy of all classifiers applied in the study.

11) G.Venkat Rao et al. conducted an experiment to analyze variation in shifting cultivation land in perspective of area and topographical factors. In their study, they considered the area of shifting cultivation lands in 1996, 2001, 2006, 2011, and 2016 of West Karbi Anglong district of Assam for analysis. They used Temporal images of TM, ETM, and OLI imagery of 30 m, from 1996 to 2016. Images were collected from the United States Geological Survey (USGS) and digital elevation model (DEM) of Cartosat—1 with 2.5 m resolution was obtained from the Bhuvan. To understand the spatio-temporal variations in the district and to detect shifting cultivation land they used 2 approaches - i) Disturbance Index (DI) and ii) possibilistic c-means (PCM) classification. From their experiment certain results obtained showed that, from 1996 to 2016 the area under shifting cultivation had been increased from 149 to 215 km^2 , and was mainly distributed at elevations of 250–500 and 500–750 m.

12) Kaspar Hurni et al. has considered two basic challenges to predict land under shifting cultivation. First one is to distinguish forest on fallow forest classes occurring in shifting cultivation. Second is the dynamic nature of shifting cultivation, which causes problems to the delineation of landscapes where shifting cultivation occurred. Their area of experiment lies in the northern uplands of Laos, extending from the outskirts of the province capital, Luang Prabang, towards the east and covering approximately 3,500 km^2. Dataset used was one georeferenced ALOS AVNIR and two georeferenced ALOS PRISM level 1b2 scenes. To classify the land they used a two step approach. First, they used two different object-oriented image classification approaches. Second they used a set of landscape metrics to delineate shifting cultivation landscapes. Accuracy obtained from this experiment for Land cover classification was 89%. Thus, the presented approach had the potential to assess the dynamics of the shifting cultivation landscapes when performed for two or more points in time. It was a cost-effective alternative to the analysis of a time series of satellite images, while being less dependent on having a dense time series of cloud-free images.

13) J.P. Rout had a study on the problem faced due to shifting cultivation via cumulative impactof different interventions to dissuade the tribal shifting cultivators. J.P.Rout had done analysis on the facts and figures showing the difference in the result obtained by eye-estimation, land to land survey and Remote Sensing mapping of area under shifting cultivation. Where the Remote Sensing data was collected from Orissa Remote Sensing Application Center (ORSAC). In his study he stated that the data and the mapping of ORSAC could have been more systematic and reliable. Finally he made his conclusion by giving his suggestion for the welfare of tribal communities who rely on shifting cultivation.

Below is the table providing an overview of all the Research papers considered in this survey.

SL.NO	PAPER NAME	STUDY AREA	ALGORITHM	ACCURACY
1.	Forest type stratification and delineation of shifting cultivation areas in the eastern part of Arunachal Pradesh using LANDSAT MSS data.	Tirap district in eastern Arunachal Pradesh.	Supervised classification on Multispectral Data Analysis System.	95.2
2.	Shifting cultivation: Towards transformation approach.	North eastern India.	Facilitating transformation:Institutional mechanism.	>50
3.	Land use and land cover dynamics with special emphasis on shifting cultivation in Eastern Ghats Highland of India using remote sensing data and GIS.	Koraput district of Odisha.	Classification using RVI and Fuzzy c-means classification.	86
4.	Shifting cultivation and tribals of Orissa.	Orissa	Remote sensing mapping.	64.22
5.	Estimation of the stand ages of tropical secondary forests after shifting cultivation based on the combination of world-view-2 and time series landsat images.	Kinabalu park and Crocker range park, Sahab, Malaysia.	Regression model with decision tree method using NDVI threshold and LDA.	84.28

6.	Shifting cultivation practices in Barak valley, India- Policy scenarios from a spatially explicit land use model.	Barak valley, districts of some parts of Assam and Mizoram.	Agent-based model based on AGENT-LUC.	
7.	Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift.	Gidabo river, Ethiopian rift valley.	Multilayer perceptron-Neural network-Change analysis-Markov chain.	>80
8.	Deep learning architectures for land cover classification using red and near infrared satellite images.	Barren lands, grasslands, water bodies.	ConvNet AlexNet VGG	>90
9.	Study of land use classification in an arid region using Multi-spectral satellite image.	Akola district, Maharashtra.	Maximum Likelihood Algorithm.for supervised classification	94.13
10.	Automated mapping for long-term analysis of shifting cultivation in North east India.	North east India.	Decision tree based multi-step threshold model.	>85
11.	Land use land cover classification by machine learning classifiers for satellite observations.	River Ganga from Rajmahal to Farakka barrage in India.	Artificial neural network, Random Forest, Multi-layer perceptron, Fuzzy ARTmap.	>80
12.	Spatio-temporal monitoring of shifting cultivation using landsat images: soft classification approach.	West karbi anglongAssam, Nagaon district, Dima hasao district, Jaintia hills district, Meghalaya, Ri-bhoi district.	Disturbance Index and Probabilistic C-means classification.	>70
13.	A texture based land cover classification for the delineation of a shifting cultivation landscape in the Lao PDR using landscape metrics.	Montane mainland southeast Asia, northern highlands of Laos.	Object oriented image classification approach, spectral reflectance of satellite image.	>60

III. DATASET

Images are collected from various satellites and the image collected had huge time gaps so that the changes in land were easily observed. In a few papers we can see that the scientist had considered statistical data of area under LULC classes. Using Bhuvan website data can be collected having classified maps and maps showing NDVI ratio of different areas.

SL.NO	PAPER NAME	DATA SOURCE	DATATYPE
1.	Forest type stratification and delineation of shifting cultivation areas in the eastern part of Arunachal Pradesh using LANDSAT MSS data.	LANDSAT images.	Digital data (images)
2.	Shifting cultivation: Towards transformation approach.	Remote sensing satellite	Digital data (images)
		images. Village survey.	
3.	Land use and land cover dynamics with special emphasis on shifting cultivation in Eastern Ghats Highland of India using remote sensing data and GIS.	Satellite images(ERDAS)	Digital data (images)
4.	Shifting cultivation and tribals of Orissa.	Remote sensing satellite images.	Statistical Data
5.	Estimation of the stand ages of tropical secondary forests after shifting cultivation based on the combination of world-view-2 and time series landsat images.	LANDSAT time-series images. World wide-2 images.	Digital data (images)
6.	Shifting cultivation practices in Barak valley, India- Policy scenarios from a spatially explicit land use model.	Land use maps.	Maps and statistical data
7.	Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift.	Multi-spectral satellite images.	Historical LULC data(dependent variable).
8.	Deep learning architectures for land cover classification using red and near infrared satellite images.	Multi-spectral SAT-4 and SAT-6 images.	Digital data (images)
9.	Study of land use classification in an arid region using Multi-spectral satellite image.	Satellite images using GPS.	Digital data (images)
10.	Automated mapping for long-term analysis of shifting cultivation in North east India.	Landsat images.	Digital data (images)
11.	Land use land cover classification by machine learning classifiers for satellite observations.	Landsat-8 operational land data.	Digital data (images)
12.	Spatio-temporal monitoring of shifting cultivation using landsat images: soft classification approach	Temporal images.	Digital data (images)
13.	A texture based land cover classification for the delineation of a shifting cultivation landscape in the Lao PDR using landscape metrics.	Advanced Land Observing Satellite, Advanced Visible and Near Infrared spectrometer images.	Digital data (images)

IV. CONCLUSION

After going through all this research, we came to know about multiple parameters to classify land under shifting cultivation. To continue this project we have to focus on geographical parameters as well as on human intervention like population density and policies made by the government related to shifting cultivation. It is difficult to come up with an algorithm which can be applied to every area to classify shifting cultivation land, but using the upcoming technologies we can get some common parameters like NDVI ratio. Even after so many practices still in a study it was found that the remote sensing way of mapping can't verify the facts at the grass-root to ascertain the factual realities.

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