**RESEARCH ARTICLE** 



# Spatio-Temporal Monitoring of Shifting Cultivation Using Landsat Images: Soft Classification Approach

G. Venkata Rao<sup>1</sup> · Anil Kumar<sup>2</sup> · A. Sentil Kumar<sup>2</sup> · M. Shashi<sup>1</sup>

Received: 10 March 2017/Accepted: 14 March 2018/Published online: 23 May 2018  $\ensuremath{\mathbb{C}}$  Indian Society of Remote Sensing 2018

#### Abstract

The practice of shifting cultivation has been increased due to an increase in population and is affecting the global issues, such as land use/land cover, biodiversity loss and environmental degradation, etc. In this study, the area of shifting cultivation lands in 1996, 2001, 2006, 2011, and 2016 were analyzed in West Karbi Anglong district of Assam by using time series imagery of Landsat Thematic Mapper, Enhanced Thematic Mapper Plus, and Operational Land Imagery with 30 m. The results showed that, from 1996 to 2016 the area under shifting cultivation has been increased from 149 to 215 km<sup>2</sup>, and was mainly distributed at elevations of 250–500 and 500–750 m and on slopes of < 10°, 10°–20° and 20°– 30°. The area under permanent cultivation was increased from 10 to 72 km<sup>2</sup>.

Keywords Disturbance Index · PCM · Shifting cultivation · Area · Temporal Index

## Introduction

The tribes in Assam State have their own cultural life intertwined with forests, wildlife and shifting cultivation. It is a form land use with a rotation of cultivation and fallow in the same unit of land (Hossain 2011; Kafle 2011) and is a resource management strategy by shifting the fields rather than the crop rotation (Mertz et al. 2008).

West Karbi Anglong district is situated in Assam of North East India and is bounded by Nagaon district on North, Dima Hasao district on East, Jaintia Hills district, Meghalaya on South, and Ri-Bhoi district, Mehalaya on West and is mostly covered by medium hills and medium rainfall. The average rainfall in the district is 1120 mm per

Anil Kumar anil@iirs.gov.in

G. Venkata Rao grao9493@gmail.com

A. Sentil Kumar director@iirs.gov.in M. Shashi

mes.shashi@gmail.com

<sup>1</sup> National Institute of Technology, Warangal, India

<sup>2</sup> Indian Institute of Remote Sensing, ISRO, Dehradun, India

year and is unevenly distributed in the district over a period of 6 months from April to September. It lies between  $25^{\circ}30'N-26^{\circ}10'N$  latitude and  $92^{\circ}10'E-93^{\circ}0'E$  longitude. Its geographical area is 2940 km<sup>2</sup> out of which 2500 km<sup>2</sup> area is covered by hilly terrain. The altitude of the hills varies from 0 m in North to 1250 m in South and the geographical location of the study area is shown in Fig. 1.

As per the Report of the Evaluation Study on Hill Area Development Programme in Assam and West Bengal-2010, almost all the people in the district are practicing shifting cultivation for their livelihood purpose and it produces enough grains and vegetables for the entire year. The practice needs large workforce for a series of activities from clearing the forest for cultivation, cropping, and harvesting (Teegalapalli and Datta 2016). The current practice of shifting cultivation has been identified as one of the anthropogenic and unscientific form of land use which resulted in degrading the environment, deforestation, and soil and nutrient loss, etc. (Bera and Namasudra 2016; Deka and Dinesh 2010; Mandal 2016; Rahman et al. 2012). The understandings of dynamics of shifting cultivation has significant importance for the better assessment of socio environmental impacts. However much information about the distribution, scale, and changing rate are remains unknown (Li et al. 2014).



Fig. 1 Geographical location of the study area

Exact figures on the area of shifting cultivation North– East India (NEI) do not exist. But different organizations estimated the area under shifting cultivation in NEI and is different from each other. In 1975 FAO estimated that, the area under shifting cultivation was 7.4 million ha. But as per taskforce planning commission in 1983, it was 3.81 million ha and as per FSI in 1999, it was 1.73 million ha (Sarma et al. 2015).

In earlier days, empirical studies were used to monitor the shifting cultivation lands. Field observations of shifting cultivation lands were generally based on particular plot and involves continuous observation including house hold survey (Liao et al. 2015). But studies were time consuming and cost effective. Since 1970, various earth observing satellites are providing the data for continuous monitoring of biophysical changes on the earth's surface. Among the various satellites, time series satellite data of Landsat imagery with a 16 days' receptivity is most commonly used for monitoring shifting cultivation. The factors that supports the extensive use of Landsat imagery were, long acquisition record with spatial resolution of 30 m (Petropoulos et al. 2011).

But medium spatial resolution remotely sensed data encounters with mixed pixel problem. The problem of mixed pixels can be handled through the soft computing techniques. The principle constituents of the soft computing techniques are fuzzy logic (FL), neural networks (NN), evolutionary computation (EC) and machine leaning (ML), etc. (Musande et al. 2012).

### **Data Source and Preprocessing**

Temporal images of TM, ETM+, and OLI imagery of 30 m resolution is acquired in fallow season from 1996 to 2016 were obtained from United States Geological Survey (USGS) and digital elevation model (DEM) of Cartosat—1 with 2.5 m resolution was obtained from Bhuvan. Details of the data used for this research is listed in Table 1. Considering the ETM+ Scan Line Corrector Off problem after May 31, 2003, a data filling method of focal analysis provided by ERDAS Imagine was used to fill in the gaps in Landsat-7 SLC-off data. Using ArcGIS software, geo-graphic information on aspect, elevation, and slope were extracted from the DEM. The elevation, and slope maps of the study area is shown in Fig. 2a, b respectively.

# Mapping of Shifting Cultivation Lands

In West Karbi Anglong, shifting cultivation is the dominant form of land use/land cover and major source for the forest disturbance. To understand the spatio-temporal variations in the district, we detected the shifting cultivation lands from Landsat imagery using two approaches such as, Disturbance Index (DI) (Tarun 2013) and possibilistic c-means (PCM) (Krishnapuram and Keller 1993) classification to handle the missed pixel problems from 1996 to 2016. In this paper, spatio-temporal changes of shifting

Table 1	Details of Landsat TM,
ETM +	and OLI imageries used
in this s	tudy

Path/row	Date	Sensor	
136/42	Jan-96	ТМ	
	Jan-97	ТМ	
	Jan-98	TM	
	Jan-99	TM	
	Jan-00	ТМ	
	Jan-01	TM	
	Jan-02	ETM+	
	Jan-03	ETM+	
	Jan-04	TM	
	Feb-05	TM	
	Jan-06	TM	
	Mar-07	TM	
	Mar-08	TM	
	Feb-09	TM	
	Jan-03	ETM+	
	Jan-10	TM	
	Feb-11	ТМ	
	Feb-12	ETM+	
	Jan-13	ETM+	
	Jan-14	OLI	
	Jan-15	OLI	
	Jan-16	OLI	

cultivation were analyzed in relation to the topographic factor such as aspect, elevation, and slope.

#### **Disturbance Index (DI)**

Remote Sensing data is the major source for the detection disturbances on the land surface (Masek et al. 2008). Tasseled cap indices (TCI) are commonly used for the detection of disturbances on the land surface (Ozdogan 2014; Potter 2015; Sulieman and Buchroithner 2007). Because, the transformations reduce the reflectance bands of Landsat in three orthogonal bands such as brightness, greenness, and wetness (Ozcan et al. 2012). The coefficients for the calculation of TCI are given in Table 2 (Huang et al. 2002).

DI was calculated from a linear combination of normalized three tasseled cap indices, which was specially designed for detecting the changes in land cover types. After generating the DI, thresholding technique can used separate the specific class (Healey et al. 2005). The mathematical expression for the DI is given in Eq. (1),

$$\begin{split} &\text{Disturbance Index} = B_r - (G_r + W_{r)}) \\ &\text{where } B_r = \big(B - B_\mu\big)/B\sigma, \ G_r = \big(G - G_\mu\big)/ \end{split} \tag{1} \\ &\text{G}\sigma, W_r = \big(W - W_\mu\big)/W\sigma \end{split}$$

where  $B_r$ ,  $G_r$ , and  $W_r$  are the normalized (rescaled) brightness, greenness, and wetness indices and  $B_{\mu}$ ,  $G_{\mu}$ ,  $W_{\mu}$ are the means of three tasseled cap indices and  $B_{\sigma}$ ,  $G_{\sigma}$ ,  $W_{\sigma}$ are the standard deviation of the tasseled cap indices. Instead of finding the individual mean and standard deviation of each image, overall mean and standard deviation was calculated and used in the Eq. (1).



Fig. 2 a Slope map of the study area. b Elevation map of the study area

Table 2TCI coefficients forLandsat

	Blue	Green	Red	NIR	SWIR-1	SWIR-2
Brightness (B)	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness (G)	- 0.3344	- 0.3544	- 0.4556	0.6966	-0.0242	- 0.2630
Wetness (W)	0.2626	0.2141	0.0926	0.0656	- 0.7629	- 0.5388

# **Temporal Vegetation Index**

It was observed that, the classification approach takes only one dimension of data. But, the temporal data has two dimensions i.e., spectral and temporal. The solution to the problem is generation of temporal vegetation indices which reduces the spectral dimensionality of the data (Aggarwal et al. 2014). The temporal vegetation indices help to identify and discriminate shifting cultivation lands from rest of the features present on ground. Simple Ratio (SR) or Ratio Vegetation Index (RVI), was proposed by Birth and McVey in 1968 has been used in this study for shifting cultivation identification. Because, it has the maximum value for vegetation and minimum value for soil, ice and water, etc. The mathematical expression for SR is given in Eq. (2),

Simple Ratio = 
$$\frac{\rho_{\text{nir}}}{\rho_{\text{red}}}$$
 (2)

To monitor the spatial extent of shifting cultivation lands, fuzzy based Possibilistic c—means classification proposed by Krishnapuram and Keller in 1993 was used to separate the target class from the non-interest classes. The classification of temporal vegetation images was carried out using in—house JAVA based image processing package; Sub-Pixel Multi-Spectral Image Classifier (SMIC) with a membership value of 2.1. Classification of vegetation indices generates fractional images, in which each membership value assigned with it. The classified images were validated using testing data and evaluated for optimum weighted component and best temporal data combination.

Shifting cultivation lands were identified based on the visual interpretation on the satellite images with ground truth data. Shifting cultivation lands were separated from the rest of the features on the image by applying a threshold value using ERDAS Imagine software. Aspect, elevation and slope maps were used to calculate the area under shifting cultivation and its distribution. Methodology adopted for this research is shown in Fig. 3.

# **Results and Discussions**

The spatial extent of shifting cultivation in West Karbi Anglong in 1996, 2001, 2006, 2011, and 2016 were analyzed. From 1996 to 2001, the area of shifting cultivation is increased from 149 to 184 km<sup>2</sup> and decreased to 160 km<sup>2</sup> in the year 2006. From 2006 to 2016, there is a gradual increment in the area from 160 to 215 km<sup>2</sup>. The maximum area under shifting cultivation was found to be 266 km<sup>2</sup> in the year 2015. The distribution of area under shifting cultivation is shown in Fig. 4.

The change in area of shifting cultivation lands were analyzed in relation topographical factors such as elevation, slope and aspect. The range of slope was divided into five categories:  $< 10^{\circ}, 10^{\circ}-20^{\circ}, 20^{\circ}-30^{\circ}, 30^{\circ}-40^{\circ}, > 40^{\circ},$ elevation was divided into five categories: 0-250, 250-500, 500-750, 750-1000 and > 1000 m, and aspects was divided into 8 types: North (N), North-East (NE), East (E), South-East (SE), South (S), South-West (SW), West (W), North–West (NW). Firstly, shifting cultivation lands were distributed at elevations of < 250, 250-500 and 500-750 m. The distribution of shifting cultivation in 1996, 2001, 2006, 2011 and 2016 at an elevation of < 250 m was increased from 25 to 79 km<sup>2</sup> and in 2011 it was found to be 102 km<sup>2</sup>. At an elevation of 250-500 m, it was varying from 28 to 43 km<sup>2</sup>, and in 2001 it was maximum. Finally at 500-750 m it varies from 48 to 66 km<sup>2</sup>, minimum area and maximum area was found in the years 2011 and 2001. Distribution of cultivation area at different elevation is shown in Fig. 5.

Secondly, most of the shifting cultivation was distributed on slopes of  $< 10^{\circ}$ ,  $10^{\circ}-20^{\circ}$ , and  $20^{\circ}-30^{\circ}$ . The results showed that from 1996 to 2016, the area under shifting cultivation was increased on slope  $< 10^{\circ}$  from 48 to 93 km<sup>2</sup>, at  $10^{\circ}-20^{\circ}$  it was varying from 52 to 75 km<sup>2</sup>, and at  $20^{\circ}-30^{\circ}$  it was varying from 27 to 39 km<sup>2</sup>. Distribution of cultivation area on different slopes is shown in Fig. 6.

Finally, shifting cultivation lands were distributed in all the aspects with an equal proportions of shifting cultivation lands.

## Conclusions

In this study, spatio-temporal variation of shifting cultivation in West Karbi Anglong was analyzed in perspectives of area and topographic factors. From the results it is summarized that, the area under shifting cultivation was increased at an elevation < 250 m and on slope  $10^{\circ}$ . It indicates that, there is an increment in settled cultivation.



Year Fig. 4 Distribution of area under shifting cultivation



Fig. 5 Area under shifting cultivation at different elevations

Acknowledgements The authors would like to thank sponsors such as United State Geological Survey (USGS) for providing time series data of Landsat—5 and 7 imageries and National Remote Sensing Center,

Fig. 6 Area under shifting cultivation at different slopes

India for providing digital elevation model of Cartosat—1 of West Karbi Anglong district, Assam, India. The first author is thankful to Indian Institute of Remote Sensing ISRO, Dehradun and National Institute of Technology, Warangal for allowing the research.

## References

- Aggarwal, R., Kumar, A., Raju, P. L. N., & Krishna Murthy, Y. V. N. (2014). Gaussian kernel based classification approach for wheat identification. *ISPRS The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-8,* 671–676. https://doi.org/10.5194/isprsarchives-xl-8-671-2014.
- Bera, A., & Namasudra, P. (2016). Impact of shifting cultivation on the environmental changes in Gumti River Basin, Tripura. *International Journal of Recent Scientific Research*, 7, 11771–11774.
- Deka, P. K., & Dinesh, S. (2010). Shifting cultivation and its effects in regarding of perspective in Northern India. *International Journal of Commerce and Business Management*, 3, 157–165.

- Healey, S. P., Cohen, W. B., Zhiqiang, Y., & Krankina, O. N. (2005). Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, 97, 301–310. https://doi.org/10.1016/j.rse.2005.05.009.
- Hossain, M. A. (2011). An overview on shifting cultivation with reference to Bangladesh. *Scientific Research and Essays*, 6, 6509–6514. https://doi.org/10.5897/SRE11.1282.
- Huang, C., Wylie, B., Yang, L., Homer, C., & Zylstra, G. (2002). Derivation of a tasselled cap transformation based on Landsat 7 at-satellite reflectance. *International Journal of Remote Sensing*, 23, 1741–1748. https://doi.org/10.1080/01431160110106113.
- Kafle, G. (2011). An overview on shifting cultivation with reference to Nepal. Scientific Research and Essays, 6, 6509–6514. https:// doi.org/10.5897/SRE11.1282.
- Krishnapuram, R., & Keller, J. M. (1993). A possibilistic approach to clustering. *IEEE Transactions on Fuzzy Systems*, 1, 98–110. https://doi.org/10.1109/91.227387.
- Li, P., Feng, Z., Jiang, L., Liao, C., & Zhang, J. (2014). A review of swidden agriculture in Southeast Asia. *Remote Sensing*, 6, 1654–1683. https://doi.org/10.3390/rs6021654.
- Liao, C., Feng, Z., Li, P., & Zhang, J. (2015). Monitoring the spatiotemporal dynamics of swidden agriculture and fallow vegetation recovery using Landsat imagery in northern Laos. *Journal of Geographical Sciences*, 25, 1218–1234. https://doi.org/10. 11821/dlxb201504007.
- Mandal, R. K. (2016). Jhum cultivation and environment in Arunachal Pradesh. *Journal of Basic and Applied*, 2, 94–101.
- Masek, J. G., Huang, C., Wolfe, R., Cohen, W., Hall, F., Kutler, J., et al. (2008). North American forest disturbance mapped from a decadal Landsat record. *Remote Sensing of Environment*, 112, 2914–2926. https://doi.org/10.1016/j.rse.2008.02.010.
- Mertz, O., Wadley, R. L., Nielsen, U., Bruun, T. B., Colfer, C. J. P., de Neergaard, A., et al. (2008). A fresh look at shifting cultivation: Fallow length an uncertain indicator of productivity. *Agricultural Systems*, 96, 75–84. https://doi.org/10.1016/j.agsy. 2007.06.002.
- Musande, V., Kumar, A., & Kale, K. (2012). Cotton crop discrimination using fuzzy classification approach. *Journal of the Indian Society of Remote Sensing*, 40, 589–597. https://doi.org/10.1007/ s12524-012-0201-z.

- Ozcan, O., Bookhagen, B., Musaoglu, N., Sensing, R., Faculty, C. E., Index, D., et al. (2012). Impact of the atatürk dam lake on agrometeorological aspects of the southeastern anatolia region using remote sensing and gis analysis. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXIX,* 305–310.
- Ozdogan, M. (2014). A practical and automated approach to large area forest disturbance mapping with remote sensing. *Public Library of Science*, 9, 1–13. https://doi.org/10.1371/journal.pone. 0078438.
- Petropoulos, G. P., Kontoes, C., & Keramitsoglou, I. (2011). Burnt area delineation from a uni-temporal perspective based on Landsat TM imagery classification using support vector machines. *International Journal of Applied Earth Observation* and Geoinformation, 13, 70–80. https://doi.org/10.1016/j.jag. 2010.06.008.
- Potter, C. (2015). A case study of forest and woodland habitat loss to disturbance and development in an ex-urban landscape: Santa Clara County, California 1999–2009. *Current Urban Studies*, 2, 18–24.
- Rahman, S. A., Rahman, M. F., & Sunderland, T. (2012). Causes and consequences of shifting cultivation and its alternative in the hill tracts of eastern Bangladesh. *Agroforesty Systems*, 84, 141–155. https://doi.org/10.1007/s10457-011-9422-3.
- Sarma, P. K., Hudae, A., Baruah, B., Mipun, B. S., & Talukdar, B. K. (2015). Assessment of changing trends of shifting cultivation in Garo Hills landscape of Meghalaya-a geo-spatial approach. *International Research Journal of Environment Science*, 4, 1–7.
- Sulieman, H. M., & Buchroithner, M. F. (2007). Multi-temporal classification of abandoned agricultural land in Gadarif Region, Sudan, using original bands, indices and feature components of spaceborne imagery. *Analysis of Multi Temporal Remote Sensing Images*. https://doi.org/10.1109/MULTITEMP.2007.4293032.
- Tarun, T. (2013). Land use and vegetation mapping of tropical forests using remote sensing and GIS techniques: A review. *International Journal of Research in Chemistry and Environment, 3*, 10–14.
- Teegalapalli, K., & Datta, A. (2016). Shifting to settled cultivation: Changing practices among the Adis in Central Arunachal Pradesh, north-east India. *Ambio*, 45, 602–612. https://doi.org/ 10.1007/s13280-016-0765-x.