

Deforestation Mapping Using MODIS Tree Cover Mask and Sentinel-1 Images



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Abstract Forests are an essential resource that needs to be conserved. Excessive cutting of trees for urbanization and growth has led to rapid deforestation in parts of Haryana and its neighboring areas. In this study, tree cover mapping is done over a period of five years (2015–2019) using Sentinel-1 ground range detected band-C images. To distinguish between the land cover classes, a rich set of features play an important role. Based on the second-order statistics, gray level co-occurrence (GLCM) features are extracted from the image to study the uniformity between the pixels. A binary classification of the study area into tree and non-tree area is carried out by supervised random forest algorithm. According to the analysis, the net rate of reduction of the tree cover in parts Haryana and its neighboring areas, i.e., parts of New Delhi, is calculated as 3.1% in successive years.

Keywords Deforestation · SAR · Random forest · GLCM · Sentinel-1 · MODIS

1 Introduction

Deforestation and forest degradation are a result of the urban development in the state of Haryana. Haryana's economic development has led to the increase in the number of industries, construction of high-rise buildings for residential use, especially in districts of Gurugram and Faridabad. New industries have been set up by cutting large number of trees thereby thinning the tree cover. Due to the deforestation, the amount of rainfall has also been reduced. There has been substantial fall in the ground water level in the past twelve years which has adversely affected the farmers for irrigation of crops. The farmers in Haryana depend on the freshwater from the

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wells and rainfall for irrigation purpose. Over the years, Haryana has witnessed a sharp fall in annual production of crops such as cotton, bajra, basmati rice, and paddy.

In this study, some parts of Haryana and New Delhi are analyzed over a period of five years (2015–2019) using Sentinel-1 images to map the extent of deforestation in these areas. There have been various studies on the deforestation mapping using different bands of the synthetic aperture radar. To enlist few studies, Rahman et al. [1] mapped the tropical forest cover and deforestation using SAR-C (band-C) and ALOS PALSAR (band-L) images classifying forest and non-forest areas by maximum likelihood classifier. Delgado et al. [2] derived the degradation status of Sumaco Biosphere Reserve Ecuador due to deforestation with the use of Terra SAR (band-X) and Sentinel-1 (band-C). The backscatter from the active radar is fed as input to the random forest algorithm to classify the areas as forest and non-forest. The fusion of RADAR data and optical data (Sentinel-2, Landsat, MODIS) has been used to produce accurate forest maps. Ritchiee et al. [3] used a combination of Sentinel 1, ALOS2 PALSAR, and Landsat time series to detect near real-time deforestation. In another paper, Ritchiee et al. [4] also used a combination of Landsat and ALOS PALSAR (band-L) to extract relevant feature for decision tree classifier.

Saatchi et al. [5] used L- and C-band SAR data for the classification of the deforestation area by the Bayesian classifier with an accuracy of 87%. This study also highlights the comparison between the data acquired in the wet and dry season. Almeida Filho et al. [6] shows an analysis based on the stages of deforestation (slashing, burning, terrain, and clearing) using Landsat images. The wood pieces left after cutting the trees initially act as corner reflectors, but as the debris is removed the backscatter decreases. Kuntz et al. [7] talks about the capability of the ESA ERS satellite for the land monitoring applications. The texture features are created which discriminates among various land cover classes in tropical rain forests. Barreto et al. [8] proposes the use of the two segmentation approaches like iterative clustering and object correlation image segmentation for the X-band synthetic aperture radar images. A. Bouvet [9] in his paper has exploited a new indicator of the shadows which form due to the acquisition of images in slant range to detect deforestation by the use of Sentinel-1 images.

In the proposed work, we present a robust method to find deforestation mapping using Sentinel-1 images. The next section discusses the methodology for calculating the rate of deforestation.

2 Material and Methods

2.1 Acquisition of Image Dataset

Five Sentinel-1A level-1 ground range detected (GRD) products for a period of Aug 2015 to June 2019 are downloaded from Copernicus Open Access Hub [10] for the study area which comprises some parts of Haryana and New Delhi. The time series

dataset from Aug 2015 to June 2019 cover parts of Haryana (Panipat, Hisar, Rohtak, Bhiwani, Rewari, and Gurugram) and New Delhi. The SAR-C synthetic aperture radar instrument operating at a central frequency of 5.404 GHz fitted on the Sentinel-1 Satellite has all weather, day, and night imaging capability. It can capture high-resolution remote-sensing images for land and ocean monitoring. Interferometric wide swath (IW) mode with a swath of 250 km at 5 m by 20 m spatial resolution is preferred as it is suitable for land cover classifications as it acquires the image with detail and resolution. Five datasets with the same geographical coordinates and orbit number (136), VV and VH bands but different time frames (2015 to 2019) are used to map the change in the tree cover using the Sentinel-1A images as given in Table 1.

2.2 Methodology

The reduced percentage of tree covers is due to rapid growth in urban development. It has been observed that National Capital Region (NCR) has a larger rate of deforestation. The methodology for the derivation of tree cover to analyze the rate of deforestation in major parts of Haryana and New Delhi is divided into several steps. The initial step requires preprocessing of Sentinel-1 data, calculation of GLCM features, derivation of training samples using land cover MODIS 2007 mask, classification using random forest algorithm, and change detection to calculate the change in forest cover from August 2015 to June 2019.

Preprocessing of Sentinel-1A images

Level-1 Sentinel-1 GRD multi-temporal images are preprocessed using the SNAP Tool box (Version 6) [11]. To improve the geo-coding and the SAR processing results, the first step of preprocessing [12] is to apply orbit file correction. The next step is calibration to Sigma naught values to map the pixel values directly to the backscatter of the radar. After calibration a 7*7 window size Lee speckle filter is applied to reduce the amount of the grainy noise in the images to further improve the classification results. The last preprocessing step is to convert the data type of the product into int8 for both bands (Sigma0_VH, Sigma0_VB). The converted product is an input parameter for the GLCM texture analysis.

Texture Analysis

A rich set of features in the high-resolution images are essential for understanding the correlation between the sigma backscatter return and texture signatures by landforms in the image. Second-order descriptive statistical features from the image are calculated by the gray level co-occurrence matrix (GCLM) operator available in the SNAP [11] tool. The texture information like mean, variation, contrast, and energy is calculated for the image. It calculates the frequency of the occurrence of the pair of pixels with the particular value in spatial domain. For the analysis purpose, only six GLCM features are calculated, i.e., SigmaVH_Contrast,

Table 1 Image dataset in classification study

Year	Data product	Date of acquisition
2015	S1A_IW_GRDH_1SDV_20150308T005141_20150308T005207_004933_0062A3_5838	08/03/2015
2016	S1A_IW_GRDH_1SDV_20161004T005151_20161004T005216_013333_01542A_4C79	04/10/2016
2017	S1A_IW_GRDH_1SDV_20171128T005158_20171128T005223_019458_02103B_D789	28/11/2017
2018	S1A_IW_GRDH_1SDV_20180819T005203_20180819T005228_023308_0288EB_FEA8	19/08/2018
2019	S1A_IW_GRDH_1SDV_20190603T005205_20190603T005230_027508_031AA0_C615	03/06/2019

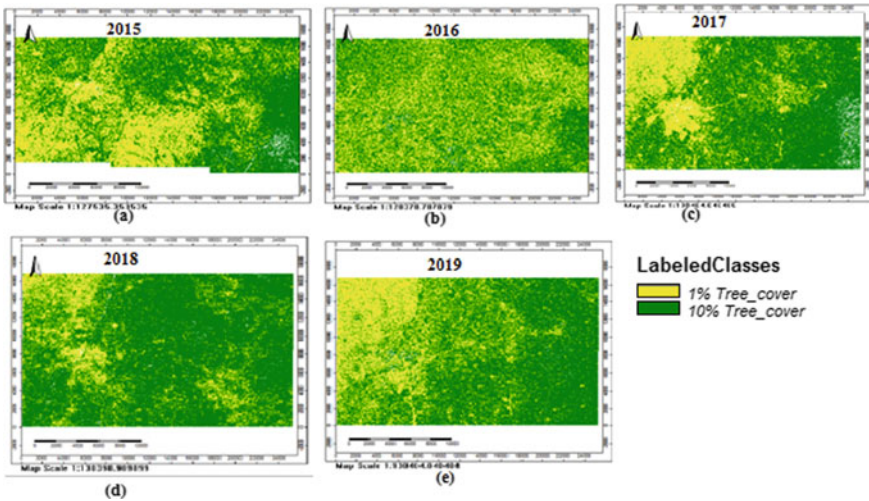


Fig. 1 Classification results from 2015–2019

SigmaVH_Mean, SigmaVH_Variance, SigmaVV_Contrast, SigmaVV_Mean, and SigmaVV_Variance, with respect to each band VH and VV. This information is used for the image classification done in the next step. These features are widely used to compute the second-order statistical features in the satellite images.

Training Samples and Classification

The GLCM features calculated in the previous steps are used as an input in the classification using random forest algorithm. The training sample for 1% tree cover and 10% tree cover are used for supervised classification. The land cover mask, MODIS 2007 Tree cover percentage as shown in Fig. 1, is added on the preprocessed image. The training vectors are selected for the regions having tree cover percentage ranging from 1 to 3% under the label of 1% tree cover. This percentage gives an idea that an area has only 1–3% of area covered by trees, and there is increase in deforestation. The other areas having tree cover percentage more than 35% (median value of the data) are named with the label of 10% tree cover to give an area that the area has more than 35% of the tree cover. These shape files are used as training samples for random forest algorithm. The random forest algorithm is effective in mapping the deforestation in the area on the basis of the training samples as shown in Fig. 1.

3 Experiments and Results

Table 2 presents detailed results for the classification of the study area in two classes of 1% and 10% tree cover in form of percentage change and area change by random

Table 2 Classification results using random forest algorithm

Year	1% tree cover	10% tree cover	1% area cover (Km ²)	10% area cover (Km ²)
2015	60.309	39.691	23,466	15,377.120
2016	65.703	34.297	25,421	13,297
2017	69.642	30.358	27,651	12,080
2018	82.235	17.765	33,026.102	7146
2019	68.205	31.795	27,427	12,809

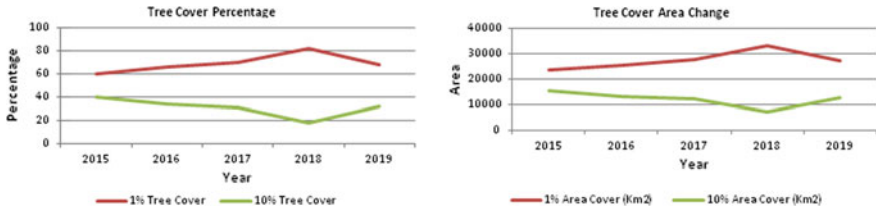


Fig. 2 Graphical representation of tree cover random forest results

forest algorithm. The results are visually represented in the line graphs to show the time series change (see Fig. 2).

The analysis of the results is done on the basis of Formula (1) given in Eq. (1):

$$P_n = P_0(1 + r)^n \tag{1}$$

where P_n is the percentage value after n year.

P_0 is the initial percentage value and r is the rate of growth.

Formula Used for Finding NET Average Rate

$$G = \text{AntiLog}\left(\frac{\sum \log X}{n}\right) \tag{2}$$

where G is the average rate, $x = 100 + r$

$$\text{NET Rate} = G - 100 \tag{3}$$

Table 3 presents the results of random forest algorithm in the form of frequency of the labeled classes (1% tree cover, 10% tree cover). The classifier is trained by the training samples and the GLCM features which classifies the input image of each year into two classes (1% tree cover and 10% tree cover). It is clearly evident from Table 3 that the percentage of 1% tree cover is growing successively every year from 2015 to 2019. The deforestation rate is increasing at a rapid rate. The percentage of tree cover with more than 10% of the trees is decreasing with an alarming rate. For

Table 3 Chain-based method

Year	1% tree cover		1% tree cover	
	Rate %	Rate % (Area)	Rate %	Rate % (Area)
2016	8.94	8.33	- 13.59	- 13.53
2017	6.00	8.772	- 11.48	- 9.152
2018	18.08	19.43	- 41.48	- 40.8
2019	- 17.06	- 16.95	78.98	79.24
NET	3.1	4	- 5.39	- 4.46

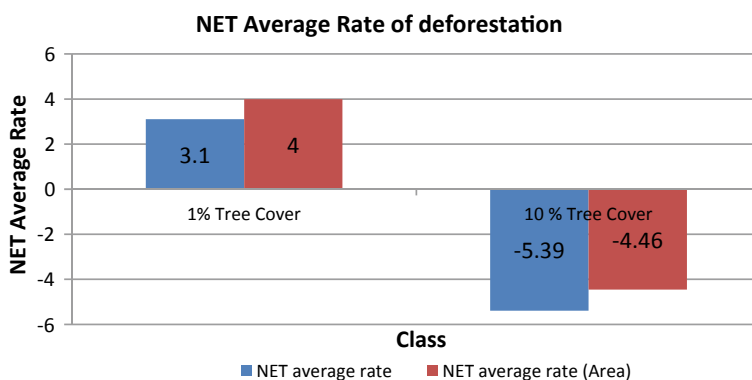


Fig. 3 Net rate of deforestation

analysis, the net rate of deforestation has been calculated using chain-based method described in the next subsection.

Chain-Based Method

This method computes the relative difference in the growth of deforestation. The net rate of growth for the year 2016 is calculated with respect to year 2015; year 2017 is calculated with respect to year 2016 and so on using Eq. (1). The total net growth of deforestation in five years is calculated as 3.1%, and the decrease in the area under 10% tree cover is 5.39% using Eqs. (2) and (3). The rate of deforestation is increasing day by day as it can be clearly seen from Fig. 3 that a considerable decrease in the tree cover is observed from the year 2015–2018. So, some efforts are made by the government agencies to check this alarming situation of deforestation.

4 Conclusion

The results presented in this study suggest that dual polarization (HV and VV) of Sentinel-1 can be used for mapping change in tree cover over a time-series data. The

analysis show that in many parts of Haryana, the tree cover is decreasing at a rate of 3.1% successively every year. Hence, there is a need to plan out some strategies to improve the tree cover in some of the parts of Haryana and New Delhi.

References

1. Rahman MM, Sumantyo JT (2010) Mapping tropical forest cover and deforestation using synthetic aperture radar (SAR) images. *Appl Geomatics* 2(3):113–121
2. Delgado-Aguilar MJ, Fassnacht FE, Peralvo M, Gross CP, Schmitt CB (2017) Potential of TerraSAR-X and sentinel 1 imagery to map deforested areas and derive degradation status in complex rain forests of Ecuador. *Int Forest Rev* 19(1):102–118
3. Reiche J, Verbesselt J, Hoekman D, Herold M (2015) Fusing Landsat and SAR time series to detect deforestation in the tropics. *Remote Sens Environ* 156:276–293
4. Almeida-Filho R, Shimabukuro YE, Rosenqvist A, Sanchez GA (2009) Using dual-polarized ALOS PALSAR data for detecting new fronts of deforestation in the Brazilian Amazônia. *Int J Remote Sens* 30(14):3735–3743
5. Saatchi SS, Soares JV, Alves DS (1997) Mapping deforestation and land use in Amazon rainforest by using SIR-C imagery. *Remote Sens Environ* 59(2):191–202
6. Almeida-Filho R, Rosenqvist A, Shimabukuro YE, Silva-Gomez R (2007) Detecting deforestation with multitemporal L-band SAR imagery: a case study in western Brazilian Amazonia. *Int J Remote Sens* 28(6):1383–1390
7. Kuntz S, Siegert F (1999) Monitoring of deforestation and land use in Indonesia with multitemporal ERS data. *Int J Remote Sens* 20(14):2835–2853
8. Barreto TL, Rosa RA, Wimmer C, Nogueira JB, Almeida J, Cappabianco FAM (2016) Deforestation change detection using high-resolution multi-temporal X-Band SAR images and supervised learning classification. In: 2016 IEEE international geoscience and remote sensing symposium (IGARSS). IEEE, pp 5201–5204
9. Bouvet A, Mermoz S, Ballère M, Koleček T, Le Toan T (2018) Use of the SAR shadowing effect for deforestation detection with Sentinel-1 time series. *Remote Sens* 10(8):1250
10. European Space Agency Copernicus Open Access Hub. <https://scihub.copernicus.eu/>. Online Accessed on date 14 Mar 2020
11. Matthieu Bourbigot Sentinel-1. <https://sentinel.esa.int/documents/247904/1877131/Sentinel-1-Product-Definition>. Accessed on 14 Mar 2020
12. Kaushik P, Jabin S (2018) A Comparative study of pre-processing techniques of SAR images. In: 2018 4th international conference on computing communication and automation (ICCCA). IEEE, pp 1–4. doi: <https://doi.org/10.1109/CCAA.2018.8777710>