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Synthetic Aperture Radar Remote Sensing for Crop Classification

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

This Study proposes the approach for crop classification using the Grey Level Co-occurrence Matrix feature of Synthetic Aperture Radar (SAR) images. The method utilizes the SAR Images acquired by Sentinel 1A SAR Data and extract textural features using GLCM. In this study, we investigate the potential of Grey Level Co-occurrence Matrix (GLCM)-based texture information for horticulture crop classification with SAR images in Kharif and cloud weather condition. A study on Synthetic Aperture Radar (SAR) satellite imagery was conducted in Chhattisgarh with the objective to evaluate the potential of different texture parameters among crop. The SAR data were pre-processed for textural analysis having entire angle and equal distance quantization. The results were categorized among different parameters showing significant variation for horticulture crops for Contrast, Dissimilarity, Homogeneity, ASM, Energy, Entropy and GLCM Mean. The statistical analysis was done for fruit crop along with major kharif crop of study area. The results shows that mean backscatter value was lowest for banana (99.12 dB) and highest for Mango (198.26 dB) regarding contrast textural property in VH Channel whereas mean backscatter value in VH Channel w.r.t to energy was maximum for banana (0.60 dB) followed by papaya (0.49 dB) and guava (0.45

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dB) and least for mango (0.44 dB). The mean backscatter value for GLCM mean textural property in VH channel was shown maximum by banana (51.24 dB) followed by papaya (41.96 dB) and mango (32.98 dB). These results indicate the usefulness of texture information for classification of SAR images, particularly when acquisition of optical images is difficult in Kharif and cloud weather condition for crop classification. Thus GLCM feature of SAR Data proven to be significant for the classification of horticulture crops.

Keywords: Classification; horticultural crops; GLCM; synthetic aperture radar.

1. INTRODUCTION

Remote Sensing technology is a valuable tool that plays a significant role in evaluation, monitoring, management and classification of land, water and crop resources. It offers a wide range of applications in various field such as agriculture, forestry and monitoring vegetation. In agriculture sector it is used to monitor health of crops, estimate yield, and classify crops based on land cover and monitor water stress [1]. However, among all the applications of remote sensing, crop classification is a challenging task because of the similarity in texture and colour of crops in their initial stages [17-21]. High resolution images have advanced discrimination capabilities, but obtaining time series datasets that cover the entire growth cycles of crops is challenging [3-7]. This is due to the dependence of optical satellite image acquisition on atmospheric conditions, which often results in contaminated and cloud masked images, particularly in Kharif crops and fruit trees [12-16,26-29]. Synthetic Aperture Radar data sets offer an advantage in this regard.

Texture, the intrinsic spatial variability of SAR tone is recognized as an important interpretive tool for discriminating different land-cover and land-use types and is a function of spatial resolution or scale [8-11]. Texture is dependent on three variables: (i) size of the area being investigated/processed; (ii) the relative sizes of the discrete tonal features; and (iii) spatial distribution of discrete tonal features [2]. Gray level co-occurrence matrix (GLCM) has proven to be a powerful basis for use in texture classification [22-25].

In this paper, GLCM textural features derived from Sentinel-1A SAR data are examined and compared with respect to their utility for discriminating fruit crop types (banana, guava, mango and papaya) having difference in canopy and plant height.

1.1 Study Area

Kawardha District in Chhattisgarh, India is located at 22.02°N 81.25°E. The total area is 798 square miles (2,070 km^2). The state consists of hill and forest. It has an average elevation of 353 metres (1,158 ft).

1.2 Satellite Data and Software Used

Freely available Sentinel-1A C-band IW GRD SAR data of recorded characteristics (Table 1) from the European Space Agency through Sentinels Scientific Data Hub were used for the study.

2. METHODOLOGY

2.1 Flow of Methodology

Flow of methodology shown in Fig. 2.

Table 1. Main characteristic of acquired sentinel-1A data

S. No	Parameter	IW
1	Polarization	Dual (VV + VH)
2	Access(Incidence Angle)	31º - 46º
3	Azimuth resolution (m)	< 20
4	Ground Range resolution (m)	> 5
5	Swath (Km)	>250
6	Maximum NESZ (dB)	-22
7	Radiometric Stability (dB)	0.5
8	Radiometric accuracy (dB)	1
9	Acquisition Dates	Single Scenes (29/08/2020)

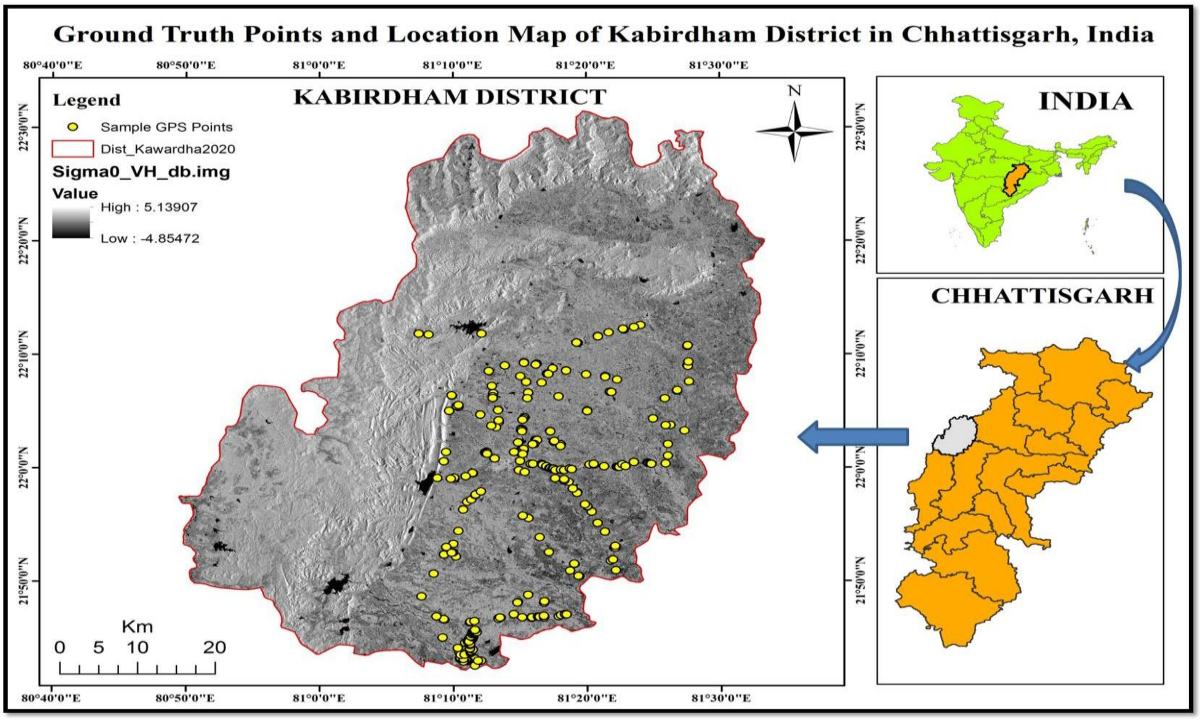

Fig. 1. Location map of study area

Table 2. Number of sample points covered during field visit

S. No	Feature class	No of sample points covered
1	Banana	30
2	Guava	1
3	Mango	8
4	Papaya	18
5	Paddy	62
6	Soybean	29
7	Pigeon pea	42
8	Sugarcane	60
9	Vegetable Crop	45
	Total points	295

2.2 Field Visit

Field visit was performed with scene date for ground truthing of four major fruit crop classes namely banana, guava, mango and papaya and major kharif crop including paddy, pigeon pea, soybean, sugarcane and vegetable crop in study area. Nearly 295 sample points is covered having 57 GPS points of Fruit Crop including 30 for Banana, 01 for Guava, 08 for Mango and 18 for Papaya during field visit (Fig. 3) as shown in Table 2.

2.3 Ground Truth Points during Field Visit

The sample points covered during field visit has been depicted in Table 2.

2.4 Grey Level Co-occurrence Matrix Analysis

Finally, the GLCM texture analysis was performed on the time series stacks in both polarizations VV+VH. In order to discriminate between the S1 SAR images pixel spatial relationships, all eight GLCM texture measurements were obtained. The employed GLCM module configuration parameters were the following: Windows Size = 5X5, Angle = All Quantizer = Probabilistic Quantizer, Quantization Level = 32, Displacement = 4.

- Contrast
- Dissimilarity
- Homogeneity
- Angular Second Moment (ASM)
- Energy
- MAX
- Entropy
- Variance
- Correlation

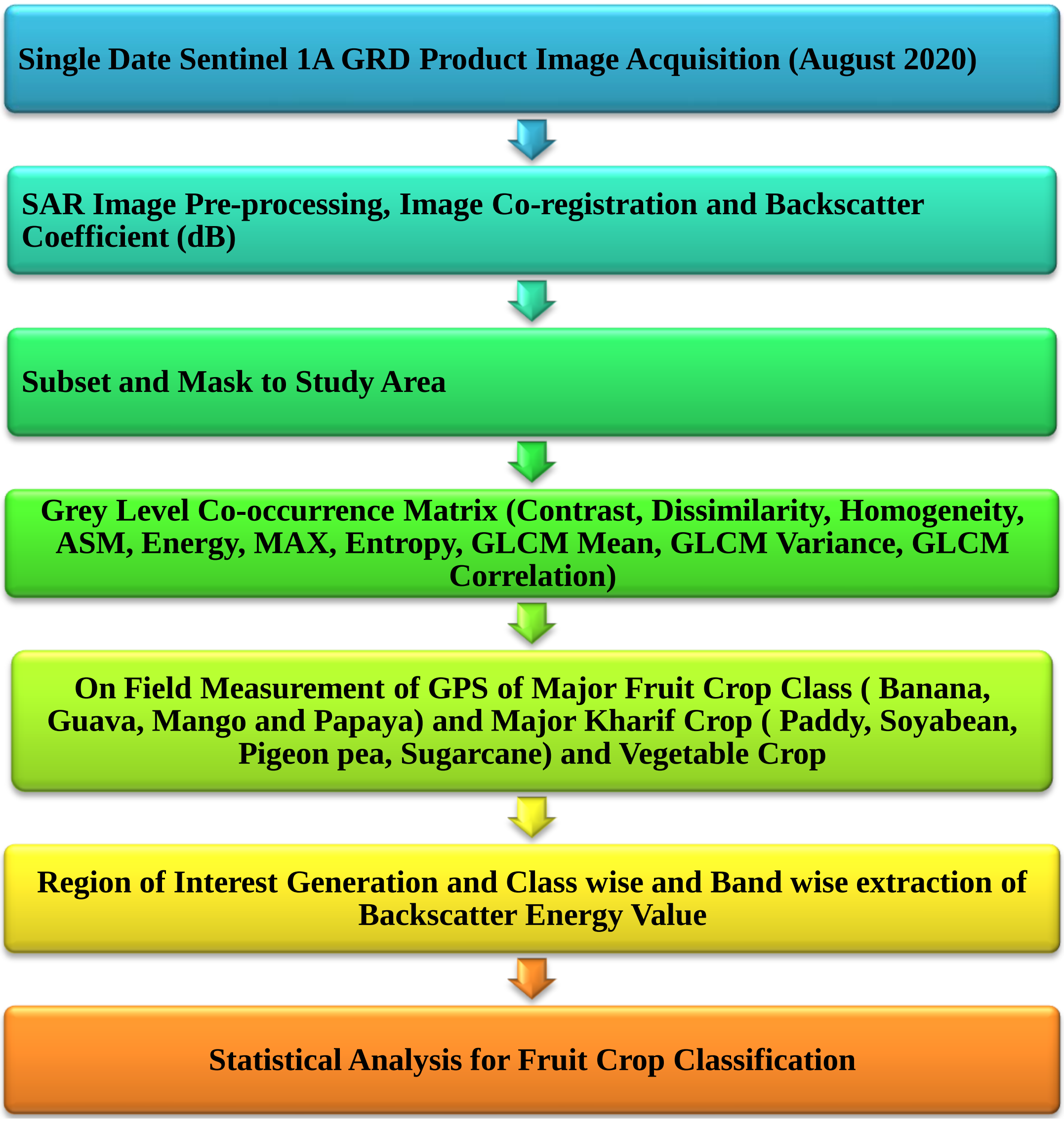

Fig. 2. Flow of methodology

Fig. 3. Sample points collection & identification (A) banana, (B) papaya, (C) guava & (D) mango

3. RESULTS AND DISCUSSION

3.1 Textural Analysis

3.1.1 Contrast

The mean backscatter value was lowest for banana (99.12 dB) and highest for Mango (198.26 dB) regarding contrast textural property in VH Channel, whereas papaya (140.48 dB) and Guava (173.37 dB) was showing intermediate value. Probable reason was smooth coverage of ground due to dense canopy by banana than other fruit crop. In case of VV Channel lowest backscatter value was shown by Guava (0.17 dB) and highest by Mango (6.67 dB) whereas banana (4.78 dB) and papaya (3.43 dB). (This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.)

3.1.2 Dissimilarity

The mean backscatter value was found lowest for banana (9.27 dB) and highest for mango (16.14 dB) whereas guava (14.94 dB) and papaya (13.18 dB) was showing intermediate value for dissimilarity textural property in VH Channel of Sentinel 1A data. In case of VV Channel lowest energy value was shown by guava (0.47 dB) and highest by mango (1.53 dB) w whereas banana (1.30 dB) and papaya (0.84 dB) remain in between among fruit crop.

3.1.3 Homogeneity

The mean backscatter value was lowest for mango (0.23 dB) and highest for banana (0.60 dB) whereas guava (0.26 dB) and papaya (0.30 dB) was in between for VH channel. In case of VV Channel very minute difference among value was seen for all fruit crop as banana (1.98 dB), papaya (1.98 dB) followed by mango (1.94 dB) and guava (1.91 dB), but value gradually decreases for pigeon pea (1.91 dB) and vegetable (1.84 dB) with lowest for sugarcane crop with 1.83 dB backscatter value. (This statistic is also called as Inverse Difference Moment. It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant).

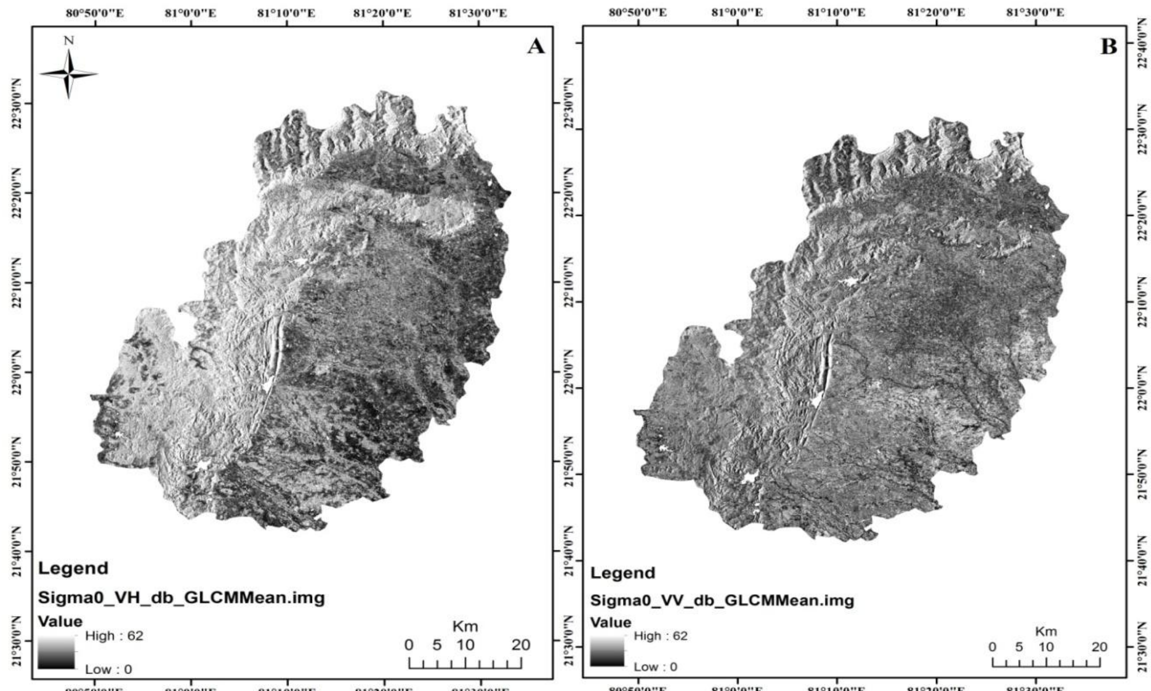

Fig. 4. GLCM mean of crop in VH (A) and VV (B) channel of sentinel 1A data

3.1.4 Angular Second Moments (ASM)

The mean backscatter value was maximum for banana (0.42 dB) and minimum for mango (0.20 dB) and very slight difference was shown for papaya (0.22 dB) and guava (0.21 dB). In case of VV Channel, very slight difference was shown for the entire crop.

3.1.5 Energy

The mean backscatter value in VH Channel w.r.t. to energy was maximum for banana (0.60 dB) followed by papaya (0.49 dB) and guava (0.45 dB) and least for mango (0.44 dB). In case of VV Channel the mean backscatter value was shown maximum for banana (1.98 dB) followed by papaya (1.97 dB) and mango (1.92 dB) and least for guava (1.84 dB). (It measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normalized range. The GLCM of less homogeneous image will have large number of small entries.)

3.1.6 MAX

The mean backscatter value of VH channel for MAX property was shown by banana (0.32 dB) followed by papaya (0.16 dB) and guava (0.15 dB) whereas least value was shown by mango (0.14 dB). Other Kharif crop shows very little difference ranging from 0.14 dB – 0.18 dB for kharif crop. In case VV Channel a typical up down curve was seen showing maximum value for banana (1.97 dB) followed by papaya (1.96 dB) and mango (1.91 dB), whereas least value was shown for guava (1.82 dB).

3.1.7 Entropy

The mean backscatter value for entropy in VH channel was maximum for mango (4.73 dB) followed by guava (4.68 dB) and papaya (4.59 dB) and least for banana (3.80 dB). Whereas entropy lies between 4.68 dB – 4.59 dB for other kharif crops. In case of VV channel maximum value was shown by guava (-0.87 dB) followed by mango (-1.11 dB) and papaya (-1.28 dB) whereas least value was shown for banana (-1.31 dB). (This statistic measures the disorder or complexity of an image. The entropy is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy.)

3.1.8 GLCM mean

The mean backscatter value for GLCM mean textural property in VH channel was shown maximum by banana (51.24 dB) followed by papaya (41.96 dB) and mango (32.98 dB) whereas for kharif crop maximum value was shown by vegetable crop (34.38 dB) followed by soybean (34.53 dB), pigeon pea (32.64 dB) and sugarcane (30.56 dB). Minimum value of GLCM mean was shown by paddy (20.57 dB). In case of VV Channel of GLCM mean textural property 61.97 dB – 61.89 dB with very little significant difference to differentiate among crops (Fig. 4).

3.1.9 GLCM variance

Similarly mean backscatter value for GLCM variance in VH channel was shown maximum by banana (51.24 dB) followed by papaya (41.96 dB) and mango (32.98 dB) whereas least variance was shown by guava (22.72 dB). In Kharif crop maximum value was shown by vegetable crop (34.38 dB) and minimum by paddy (20.57 dB). In case of VV channel very slight difference was observed among crops to find suitable for differentiation. (This statistic is a measure of heterogeneity and is strongly correlated to first order statistical variable such as standard deviation. Variance increases when the gray level values differ from their mean.)

3.1.10 GLCM correlation

The mean backscatter value in VH channel for GLCM correlation was shown maximum by banana (0.93 dB) followed by papaya (0.91 dB) and mango (0.81 dB) and least by guava (0.71 dB). In case of field crop least correlation was observed in case of paddy (0.70 dB) and maximum for soybean (0.86 dB). In case of VV Channel very little difference was seen in all crop except vegetables (0.97 dB) (The correlation feature is a measure of gray tone linear dependencies in the image).

4. CONCLUSION AND SUMMARY

Response of backscatter coefficient was found to be varies with different classifier used. Statistical analysis of the classification revealed that the distribution of the Banana, Guava, Mango and

Papaya can be very significantly classified using textural characteristics of Sentinel-1A data.

1. Thus combination of one or more textural property can be used to classify fruit crop significantly.
2. The dense and smooth canopy of banana as well as light and rough canopy of papaya can be significantly classified using a combination of textural property.
3. Mango and guava not showing significant difference due to less number of GPS points.
4. Kharif crop except vegetables shows a consistent similar textural value in GLCM.

Energy and contrast are the most significant parameters in terms of visual assessment and computational load to discriminate between different textural patterns.

Thus Sentinel-1A SAR Data was effectively utilized for the classification of field as well as horticultural crops.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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