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Discrimination of maize crop with hybrid polarimetric RISAT1 data

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ABSTRACT

Microwave remote sensing provides an attractive approach to determine the spatial variability of crop characteristics. Synthetic aperture radar (SAR) image data provide unique possibility of acquiring data in all weather conditions. Several studies have used fully polarimetric data for extracting crop information, but it is limited by swath width. This study aimed to delineate maize crop using single date hybrid dual polarimetric Radar Imaging Satellite (RISAT)-1, Fine Resolution Stripmap mode (FRS)-1 data. Raney decomposition technique was used for explaining different scattering mechanisms of maize crop. Supervised classification on the decomposition image discriminated maize crop from other land-cover features. Results were compared with Resourcesat-2, Linear Imaging Self Scanner (LISS)-III optical sensor derived information. Spatial agreement of 91% was achieved between outputs generated from Resourcesat-2, LISS-III sensor and RISAT-1 data.

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1. Introduction

Maize (*Zea mays*) is the most important crop in the world after wheat and rice. It is grown for food, feed, and as an industrial crop; it is a major food grain crop supporting food security in several countries. The area under maize crop has increased several fold and Asia recorded the fastest growth of around 4% in the past decade (Prasanna et al. 2014). The demand is likely to increase further till 2050. However, constraints in the maize productivity are limiting the growth. In India, maize crop is the third most important food grain crop after wheat and rice. It is grown in diverse production environments from a cool, dry area of Chitradurga, Karnataka, to warm, wet plateau of Chindwara, Madhya Pradesh. The annual production of maize in India has increased at a compound annual growth rate (CAGR) of 5.5% over the last 10 years from 14 million tonnes in 2004–2005 to 23 million tonnes in 2013–2014. Demand for maize is driven by the poultry and starch industries apart from food additives sector and exports. India exported five million tonnes of maize in 2012–2013, which is valued at Rs 70 billion (Anonymous 2014a, b). Water scarcity and

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government's policy of crop diversification is also promoting the growth of maize crop in non-conventional areas. Availability of region-specific hybrids equal/near-equal minimum support price for maize and rice crop is also encouraging farmers to cultivate maize crop, which can be grown round the year.

Access to timely and reliable data on crop distribution and its condition assumes importance for enabling decision-makers to make informed decisions with respect to imports, exports, and other policy matters. Satellite remote sensing can be used as a suitable tool for monitoring agriculture and land surface changes (Bastiaanssen et al. 2000; Kalluri, Gilruth, and Bergman 2003; Seelan et al. 2003; Gumma et al. 2014, Gumma et al. 2011). Within the range of on-board sensors in different satellites, those that functioning in the microwave domain have twofold advantage acquiring in all weather conditions as well as offering a high degree of sensitivity to surface parameters (Ulaby et al. 1986). In the microwave domain, many studies have been conducted using spaceborne data from (European Remote Sensing Satellite (ERS)-1/2, EnviSat, Radarsat-2 and others) associated with ground-measurement campaigns. These studies have addressed the sensitivity of multi-frequency, multi-polarization, and multi-incidence data to surface parameters (Dobson and Ulaby 1981). The backscatter coefficient's influence for different levels of topsoil moisture, surface roughness and texture have been widely analysed since 1980s (Ulaby et al. 1979; Ulaby et al. 1978; Dobson and Ulaby 1981; McNairn et al. 2012) showing the importance of sensor configurations. These studies addressing sensitivities of vegetation parameters are mainly based on data acquired during specific phenological stages (Ulaby Fawwaz, Bradley, and Dobson 1979; Brown et al. 2003; Balenzano et al. 2011; Gumma et al. 2015).

Mapping of maize crop by successfully using optical remote sensing has been demonstrated (de la Casa et al. 2014; Sibanda et al. 2012), but it is not possible over areas of continuous cloud cover. Very few studies have reported the use of SAR data for maize crop using amplitude and fully polarimetric data (Soria-Ruiz et al. 2007; Smith et al. 2006; Van der Sanden 2004; McNairn et al. 2014).

RISAT-1 is the first satellite among spaceborne earth observation missions operating in hybrid polarimetric mode. This satellite operating in C-band, was intended for agricultural studies. RISAT-1 SAR has all-weather capability in HH, VV, HV VH, and hybrid polarization. It covers a swath of 25 km in fine mode to 220 km in course resolution mode with an incidence angle range of 12°–55°. It captures images every 25 days (Tapan et al.2013). The system is capable of acquiring data in both right and left looks (Table 1).

Hybrid polarimetric SAR is one in which the transmitted field is circularly polarized, and the resulting backscatter is received in two mutually coherent linear polarizations (either horizontal or vertical). The resulting backscatter RH, RV, LH, and LV is less susceptible to noise than the other dual-polarization SAR systems operating in circular transmission and reception mode (RR, RL, LR, and LL). The frequently used circular dual-

Table 1. Sensor specifications of RISAT-1.

Mode	Polarization	Spatial resolution (m)	Swath (km)
Coarse Resolution ScanSAR (CRS)	HH/HV or VH/VV or RH/RV	36	223
Medium Resolution ScanSAR (MRS)	HH/HV or VH/VV or RH/RV	18	115
Fine Resolution Stripmap (FRS)-2	HH, HV,	10/4.6	25
Fine Resolution Stripmap (FRS)-1	HH/HV or VH/VV or RH/RV	3.3/2.3	25

polarization SAR is RR and RL. The hybrid polarimetric architecture is much simpler than conventional circular dual-polarized SAR (Touzi 2009). Hybrid SAR was mainly promoted by Raney (2007b). It facilitates large swath coverage than full polarimetric SAR systems (Charbonneau et al. 2010). The hybrid polarimetric data has shown potential for crop discrimination using single date data (Uppala et al. 2015). Lee et al. (2000) earlier reported that fully polarimetric data is preferred for crop classification in all the frequencies studied (P, C, and L). Simulated compact polarimetry is widely used for rice crop discrimination. Acknowledging the importance of maize in Indian food security mission, utility of RISAT-1 SAR data can be well emphasized to fill the gap in generating such information. The current study attempts use of RISAT-1 SAR microwave hybrid polarimetric data for maize crop discrimination and monitoring.

2. Study area

The study area is located in Guntur district of Andhra Pradesh, India (16°13′17.42″N, 80° 42′35.57″E) covering an area of 835 km^2 (Figure 1). The climate is warm moist semi-arid/ dry sub-humid eco-sub-region with medium to deep loamy to clayey mixed red and black soils. In this region, maize is the major crop during *rabi*. It is sown during last week of December or first week of January and harvested in last week of March or first week of April. Apart from maize, pulses such as green gram and black gram were also grown. However, these crops were harvested by the time the data was acquired.

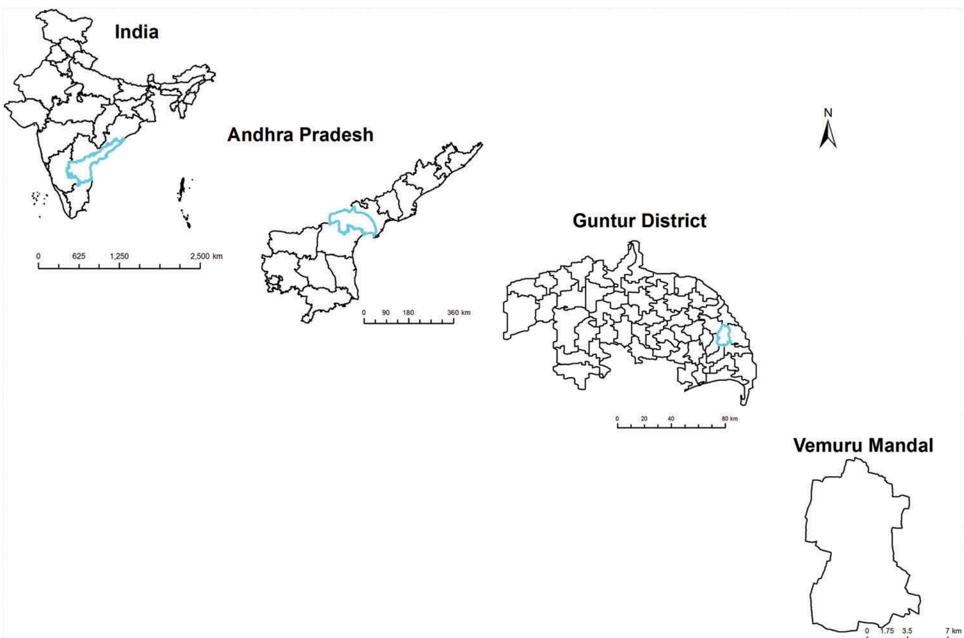

Figure 1. Study area.

3. Methodology

3.1 *Data collection*

A single date hybrid polarimetric (RH, RV) data set acquired from RISAT-1, C-band is used for this study. Fine Resolution Stripmap (FRS)-1 data acquired on 25 March 2014 with incidence angle 38.7° and spatial resolution of 3.3 m in azimuth and 2.3 in range directions was used. RISAT-1 operates in hybrid polarimetric mode covering a swath of 25 km in FRS mode. Resourcesat-2, LISS-III data is used to compare the output from RISAT-1 and assess the accuracy of area. The Resourcesat-2 satellite was launched on 20 April 2011 by Indian Space Research Organization (ISRO). It carries three sensors. LISS-III, IV, and Advanced Wide Field Sensor (AWiFS) with respective resolution of 23.5, 5.8, and 56 m. LISS-III sensor images the earth in four spectral bands: Green (0.52–0.59 µm), Red (0.62–0.68 µm), near-infrared (0.77–0.86 µm) and short-wave infrared (1.55–1.70 µm) (Dave et al. 2006; Pandya, Murali, and Kirankumar 2013). The present study selected data acquired on 01 April 2014 with spatial resolution of 23.5 m.

Ground measurements consisting of qualitative parameters were collected for 205 locations. Land-use information is also collected such as crop type, stage, and height, synchronous to the satellite date of pass.

3.2 *Data processing*

Single look complex (SLC) of RISAT-1 hybrid polarimetric data was used for the study. Backscattering coefficient analysis was performed on filtered RISAT-1, FRS data by using Equation 1 (RISAT-1 Manual):

$$\sigma_0(\mathrm{dB}) = 20 \times \log_{10}\left[(\mathrm{DN})_p\right] - K_{\mathrm{dB}} + 10 \times \log_{10}\left[\sin(i_p)/\sin(i_{\mathrm{centre}})\right], \tag{1}$$

where $\sigma_0(\mathrm{dB})$ is radar backscatter coefficient, $\mathrm{DN_p}$ is digital number or the image pixel grey-level count for pixel p, K_{dB} is calibration constant in dB, i_p is incidence angle for the pixel position p, and i_{center} is incidence angle at the centre.

In order to compare the accuracy of RISAT-1 with LISS-III, the RISAT-1 (RH, RV) data was multi-looked seven times in azimuth and 10 times in range direction to arrive at the pixel resolution of 24 m × 24 m and C2 matrix was generated. A refined Lee filter was applied with 3 × 3 window size to reduce the speckle noise. To discriminate different features through scattering mechanism, Raney decomposition was applied on the filtered data. Raney proposed parameters, such as Degree of polarization (m), relative phase (δ), degree of circularity (χ). Based on these parameters Raney suggested $m - \delta$ and $m - \chi$ as two decompositions and their applicability is discussed in Raney (2013). Double, Odd, and Volume/Diffuse scattering mechanisms were computed by using m and χ (Raney 2007a, 2007b; Raney et al. 2011). Hybrid polarimetric decompositions and sigma naught images were geometrically corrected using LISS-III data. Five test locations, representative of the type of land use present in the scene were selected. Training sites for maize, plantation, fallow, settlement, and water were selected based on the ground data. Finally decomposition parameters were introduced into classification gradually according to their sensitivity to maize crop information. Supervised parallelepiped minimum distance classifier was used to delineate the maize area from hybrid

Table 2. Comparison of land-use classes in Vemuru Mandal.

	Area (ha)	
Class name	RISAT-1	LISS-III
Maize	8374	8268
Plantation	1375	905
Fallow	301	797
Water	37	224
Settlement	160	55

polarimetric data. For assessing accuracy of hybrid polarimetric data, LISS-III imagery was also classified by using supervised Maximum Likelihood Classifier. The spatial distribution of both classified results are compared in Table 2.

4. Results and discussions

4.1 *Response of maize crop*

Mean and standard deviation of backscatter coefficient from RH and RV polarizations for various features is shown in Figure 2. Water exhibits low backscatter than other features and settlements exhibit the highest backscatter. Even though these classes exhibited separation at mean values, the high standard deviation leads to overlapping of classes. For example, the backscatter coefficient of RH in peak vegetative stage of maize crop varies between −2 and −10 dB and it overlaps with standard deviation of rough surface from fallow and plantation.

Backscattering (Figure 3(*a*)), Raney decomposed (Figure 3(*b*)), and Resourcesat-2 (LISS-III) images (Figure 3(*c*)), covering Vemuru Mandal are shown in Figure 3. Maize crop dominates the area, followed by fallow, plantations, and other land-cover features. In LISS-III imagery maize crop is manifested in different shades of dark red colour due to wet fields and light red tone indicates maize at the harvest stage due to low moisture content in the field and dry vegetation.

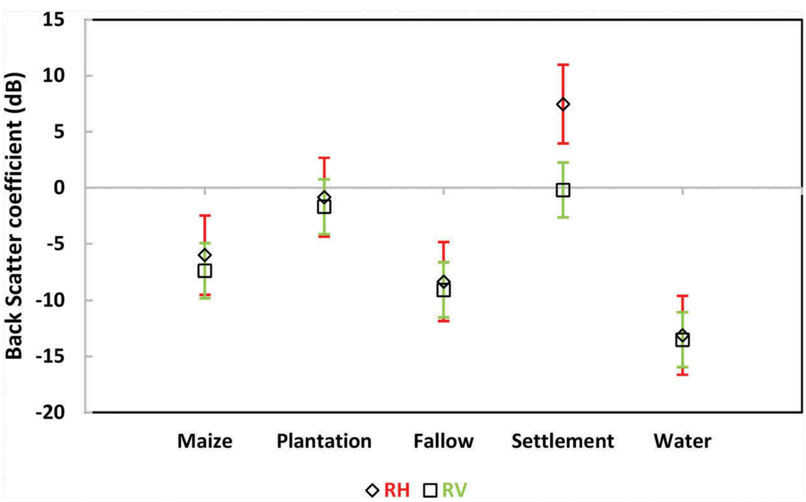

Figure 2. Mean and standard deviation of backscatter coefficient (σ_0).

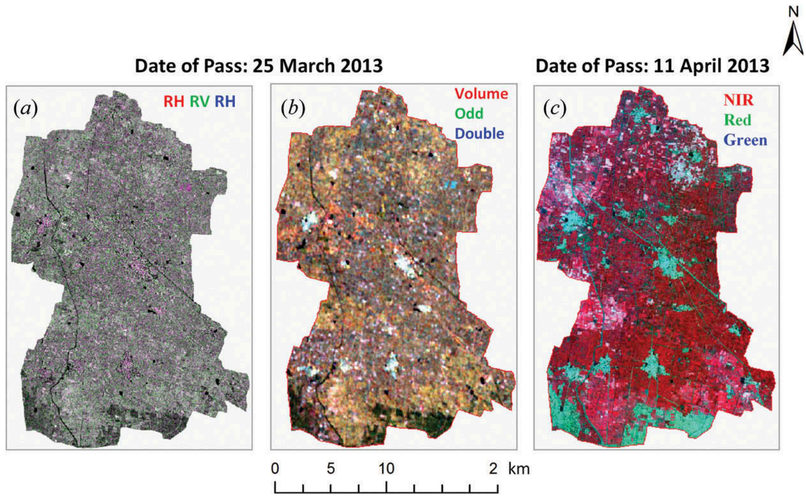

Figure 3. FCC images of RH, RV intensity data, Raney composition and Resourcesat-2 (LISS-III). (*a*) Amplitude data, (*b*) Raney decomposition, (*c*) Resourcesat-2 (LISS-III).

Raney decomposed image (Figure 3(*b*)) reveals that none of the scattering mechanisms is dominant, but it found that the magnitude of volume scattering mechanism is slightly higher than odd and double scattering mechanisms in maize crop at peak vegetative stage and harvesting stage. Degree of polarization is a vital parameter for decomposition (Charbonneau et al. 2010) and higher values indicate the purity of scattering mechanism. Degree of polarization is higher in settlement class than other land-use classes. Other land-use classes illustrate mixing up (Figure 4(*b* and, *c*)). Relative phase, a sensitive indicator of double bounce, is positive when odd scattering is dominant and negative if double bounce scattering is dominant (Kausika 2013). For settlement class relative phase values are negative, which indicates that double bounce is dominant. All other classes have positive phase value because of less contribution from double bounce (Figure 4(*a*,*c*)). Degree of circularity is a sensitive indicator of double and odd bounce scattering. Settlement class shows high degree of circularity because of double bounce scattering. Maize crop and water also shows high degree of circularity than plantation and fallow due to more contribution of volume scattering from maize crop and odd bounce scattering from water (Figure 4(*a*,*b*)).

All three decomposition parameters clearly separate core settlement class from all other land use and land cover (LULC) classes. In order to separate these LULC classes, even, odd, and double scattering mechanisms were derived from these three decomposition parameters. The peak vegetative stage of maize crop shows high magnitude of volume bounce scattering than odd and double bounce scattering (Figure 5). The two-dimensional cluster diagram of volume and double scattering, volume and odd scattering, double and odd scattering for various classes prevalent in the study area show that maize crop, plantation, settlement, fallow and water classes were clearly separable. Settlement class shows high magnitude in volume, odd and double bounce scattering because of heterogeneity. Plantation and maize crop exhibit high magnitude of volume scattering than water and fallow because of geometric structure. Maize crop at peak

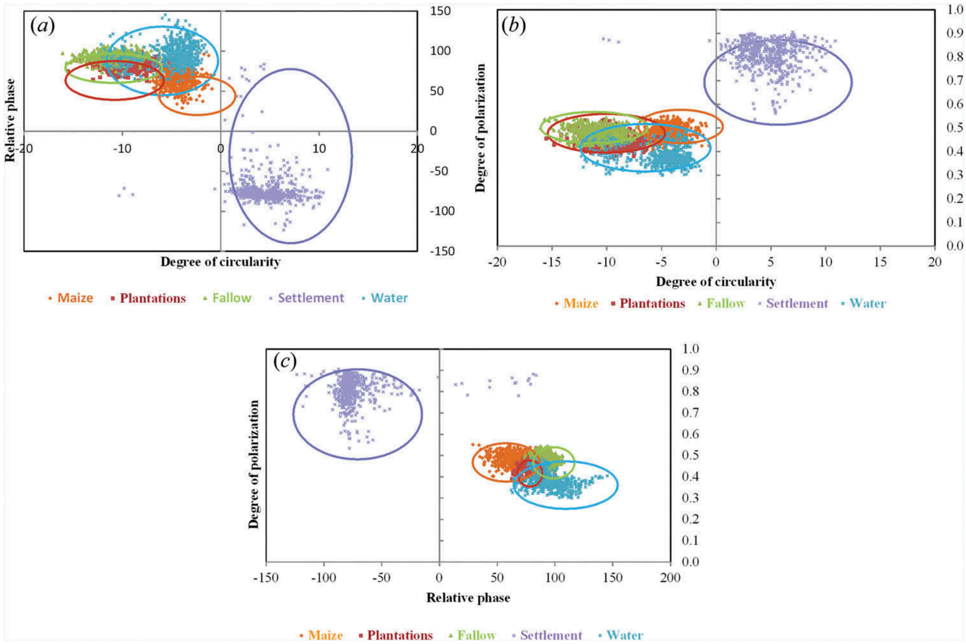

Figure 4. The degree of polarization, degree of circularity, and relative phase of the Raney decomposition.

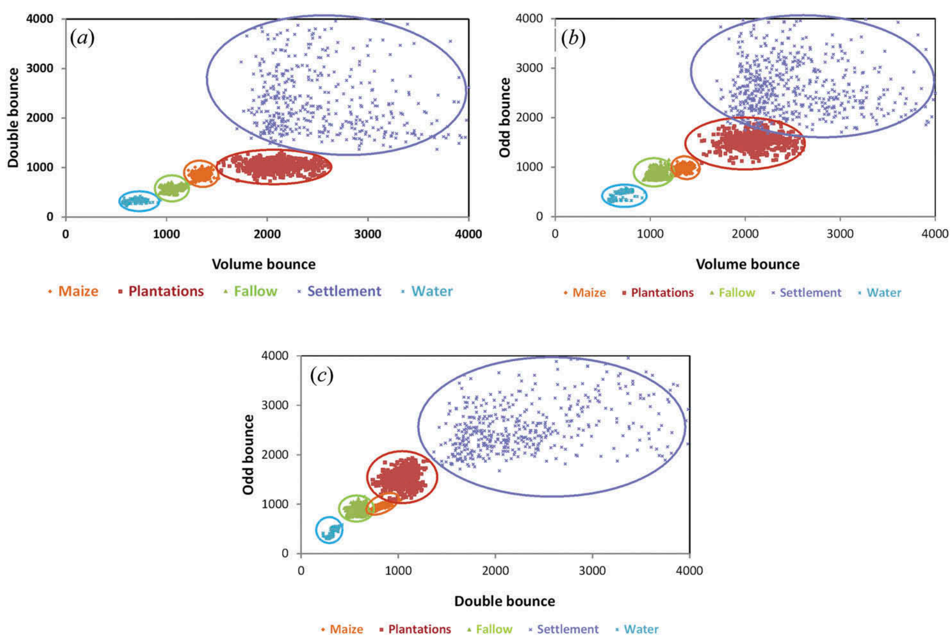

Figure 5. Double, odd, and volume bounce parameters of the Raney decomposition.

vegetative stage is likely to have a scattering mechanism similar to plantation class in double vs odd bounce scattering. It is clearly separable when compared to volume vs double bounce scattering and volume vs odd bounce scattering mechanisms (Figure 5(*a*,*b*)). Plantation class has larger canopy than maize, which creates multiple reflections from plantation canopy than maize crop. Because of these reasons, high magnitude of volume bounce scattering was observed in plantation class than maize.

4.2 *Classification*

All decomposition parameters (degree of circularity, relative phase, degree of polarization, double bounce, odd bounce, and volume bounce) were introduced into parallelepiped minimum distance classifier according to their sensitivity to maize crop. To classify the decomposition image, a small area of interest is selected and 100 training sites from that area. Resourcesat-2 LISS-III (Figure 6(*a*)), Raney decomposition (Figure 6(*b*)), and classified images (Figure 6(*c*)) are depicted in Figure 6. The misclassification of maize is observed due to harvest of maize on 01 April 2014, which is highlighted with circles (Figure 6). Scrub present in the field bunds is also classified as maize in RISAT-1, shown in the left corner of Figure 6(*c*). In order to compare statistics from these two data sources classification, the harvested maize fields are masked out in RISAT-1 data also.

For assessment of accuracy of RISAT-1 FRS data, LISS-III data was also classified by using supervised Maximum Likelihood Classifier. Since supervised minimum distance classifier can be applied on any data independently of data distribution, Maximum Likelihood Classifier was used for LISS-III data as it follows normal distribution. The administrative boundary of Vemuru Mandal was selected for comparison. The classification outputs for Vemuru Mandal using RISAT-1 and LISS-III are illustrated in Figure 7.

From Figure 7, it was observed that in optical imagery, settlement is classified as fallow but in RISAT-1 it is classified as settlement. Also, settlement class mixes with plantation class because of volume scattering mechanism in RISAT-1 data. The

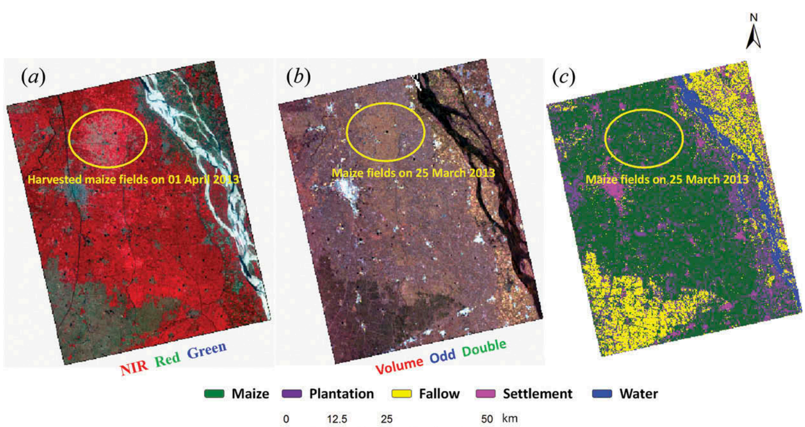

Figure 6. Decomposition and classified images of RISAT-1. (*a*) Resourcesat-2 (LISS-3), (*b*) decomposition image of RISAT-1, (*c*) classified image of RISAT-1.

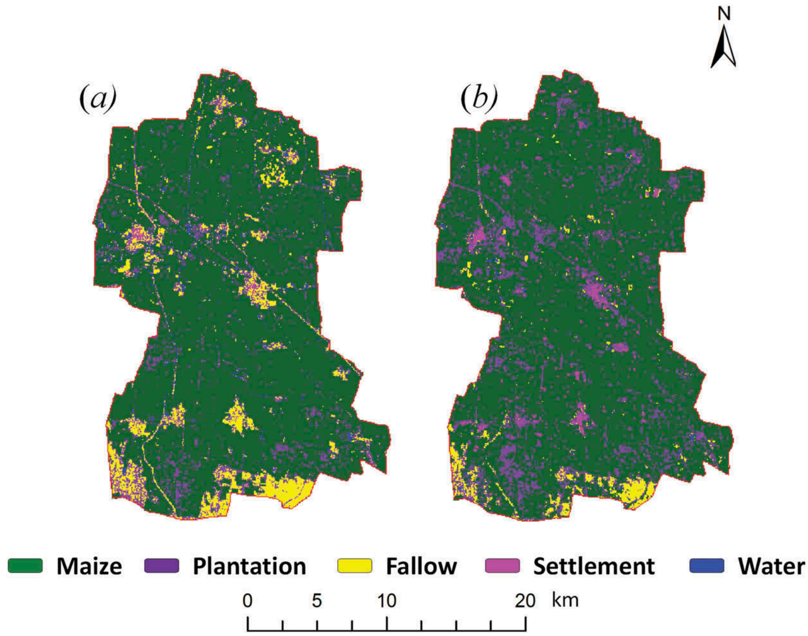

Figure 7. Classified images of LISS-III and decomposed image. (*a*) Resourcesat-2 LISS-III, (*b*) RISAT-1.

misclassification observed in optical imagery is due to some harvested fields around settlement, which was not masked because it was occupying a small geographical area.

4.3 *Accuracy assessment*

The overall accuracy of LISS-III and RISAT-1 FRS data is 92.00% and 89.33%, respectively (Table 3). Producer's accuracy of maize crop is 94 and 91 from LISS-III and RISAT1 data, respectively. Maize cropped area was estimated to be 8268 and 8374 ha from LISS-III data and RISAT-1 hybrid polarimetric data, respectively. However, it should be noted that maize cropped area is overestimated from RISAT-1 data because of the similar backscatter of scrub present on the field bunds. The spatial agreement between maize class derived from LISS-III and RISAT-1 is 91%, which indicates the potential of single date hybrid polarimetric data for maize crop mapping and monitoring.

Table 3. The accuracies of decomposition and LISS-III classifications.

	LISS-III			RISAT-1		
Class name	Producer's accuracy (%)	User's accuracy (%)	Kappa coefficient	Producer's accuracy (%)	User's accuracy (%)	Kappa coefficient
Maize	93.75	96.77	0.9437	90.63	87.88	0.7886
Plantation	88.89	88.89	0.8737	88.89	100.00	0.9101
Fallow	100.00	76.47	0.7154	69.23	81.82	0.7801
Settlement	81.82	100.00	1	100.00	91.67	0.9023
Water	90.00	100.00	1	100.00	90.91	0.8951
Total		92.00	0.8914		89.33	0.8541

5. Conclusion

Results clearly show the benefit of using single date hybrid polarimetric data for discrimination of maize crop. The RH/RV combination shows similar results as obtained from fully polarimetric data and it offers a good compromise between resolution, swath width, incidence angle coverage, cost, and information content. Hybrid polarimetric data provides a basis for classifier based on the structural characteristics of the target and it was suited for maize crop discrimination. Very good spatial agreement 91% is observed between maize crop derived from Resourcesat-2, LISS-III, and RISAT-1 hybrid polarimetric data for Vemuru Mandal. Maize cropped area was estimated to be 8268 and 8374 ha from LISS-III and RISAT-1 hybrid polarimetric data. Overall classification results show that Raney decomposition provides effective information from single-date data for maize crop. The inclusion of relative phase in classification scheme did not yield any ambiguous results, even though χ is already included. This result shows that hybrid polarimetric data, specifically FRS-1 mode data, from RISAT-1 was suitable for maize crop discrimination and mapping in mono-cropped areas.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Anonymous. 2014a. "India Maize Summit 14." Proceedings of Maize in India, FICCI, Federation House, New Delhi, March 20–21, 2014.

Anonymous. 2014b. *Maize Production Growing Faster in India on Higher Demand*. http://www.businesstoday.in/magazine/features/cargill-india-ceo-siraz-chaudhury-maize/story/205721.html

Balenzano, A., F. Mattia, G. Satalino, and M. Davidson. 2011. "Dense Temporal Series of C- and L-band SAR Data for Soil Moisture Retrieval over Agricultural Crops." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 4 (2): 439–450. doi:10.1109/JSTARS.2010.2052916.

Bastiaanssen Wim, G. M., D. J. Molden, and I. W. Makin. 2000. "Remote Sensing for Irrigated Agriculture: Examples from Research and Possible Applications." *Agricultural Water Management* 46 (2): 137–155. doi:10.1016/S0378-3774(00)00080-9.

Brown Sarah, C. M., S. Quegan, K. Morrison, J. C. Bennett, and G. Cookmartin. 2003. "High-Resolution Measurements of Scattering in Wheat Canopies-Implications for Crop Parameter Retrieval." *IEEE Transactions on Geoscience and Remote Sensing* 41 (7): 1602–1610. doi:10.1109/TGRS.2003.814132.

Charbonneau, F. J., B. Brisco, R. K. Raney, H. McNairn, C. Liu, P. W. Vachon, J. Shang, R. DeAbreu, C. Champagne, and A. Merzouki. 2010. "Compact Polarimetry Overview and Applications Assessment." *Canadian Journal of Remote Sensing* 36 (sup2): S298–S315. doi:10.5589/m10-062.

Dave, H., C. Dewan, S. Paul, S. S. Sarkar, H. Pandya, S. R. Joshi, A. Mishra, and M. Detroja. 2006. "Awifs Camera for Resourcesat." Proc. SPIE 6405, Multispectral, Hyperspectral, and Ultraspectral Remote Sensing Technology, Techniques, and Applications, 64050X, December 22. doi:10.1117/12.693971.

de la Casa, A. C., G. G. Ovando, A. C. Ravelo, E. G. Abril, and H. Bergamaschi. 2014. "Estimating Maize Ground Cover Using Spectral Data from Aqua-MODIS in Córdoba, Argentina." *International Journal of Remote Sensing* 35 (4): 1295–1308. doi:10.1080/01431161.2013.876119.

Dobson, M. C., and F. Ulaby. 1981. "Microwave Backscatter Dependence on Surface Roughness, Soil Moisture, and Soil Texture: Part III-Soil Tension." *IEEE Transactions on Geoscience and Remote Sensing*, no. 1: 51–61. doi:10.1109/TGRS.1981.350328.

Gumma, M. K., P. S. Thenkabail, I. V. Muralikrishna, M. N. Velpuri, P. T. Gangadhararao, V. Dheeravath, C. M. Biradar, S. Acharya Nalan, and A. Gaur. 2011. "Changes in Agricultural Cropland Areas between a Water-Surplus Year and a Water-Deficit Year Impacting Food Security, Determined Using MODIS 250 M Time-Series Data and Spectral Matching Techniques, in the Krishna River Basin (India)." *International Journal of Remote Sensing* 32 (12): 3495–3520. doi:10.1080/01431161003749485.

Gumma, M. K., D. Uppala, I. A. Mohammed, A. M. Whitbread, and I. R. Mohammed. 2015. "Mapping Direct Seeded Rice in Raichur District of Karnataka, India." *Photogrammetric Engineering & Remote Sensing* 81 (11): 873–880. doi:10.14358/PERS.81.11.873.

Gumma, M. K., K. Rao Pyla, P. S. Thenkabail, V. Murthy Reddi, G. Naresh, I. A. Mohammed, and I. Rafi. 2014. "Crop Dominance Mapping with IRS-P6 and MODIS 250-M Time Series Data." *Agriculture* 4 (2): 113–131. doi:10.3390/agriculture4020113.

Kalluri, S., P. Gilruth, and R. Bergman. 2003. "The Potential of Remote Sensing Data for Decision Makers at the State, Local and Tribal Level: Experiences from NASA's Synergy Program." *Environmental Science & Policy* 6 (6): 487–500. doi:10.1016/j.envsci.2003.08.002.

Kausika, B. B. 2013. *Polarimetric Modeling of Lunar Surface for Scattering Information Retrieval Using Mini-Sar Data of CHANDRAYAAN-1*. Enschede: University of twente in partial fulfilment of the requirements.

Lee, J. S., M. R. Grunes, T. L. Ainsworth, E. Pottier, E. Krogager, and W. M. Boerner. 2000. "Quantitative Comparison of Classification Capability: Fully-Polarimetric versus Partially Polarimetric Sar." Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000 International, Piscataway, NJ.

McNairn, H., A. Kross, D. Lapen, R. Caves, and J. Shang. 2014. "Early Season Monitoring of Corn and Soybeans with Terrasar-X and RADARSAT-2." *International Journal of Applied Earth Observation and Geoinformation* 28: 252–259. doi:10.1016/j.jag.2013.12.015.

McNairn, H., A. Merzouki, A. Pacheco, and J. Fitzmaurice. 2012. "Monitoring Soil Moisture to Support Risk Reduction for the Agriculture Sector Using RADARSAT-2." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 5 (3): 824–834. doi:10.1109/JSTARS.2012.2192416.

Pandya, M. R., K. R. Murali, and A. S. Kirankumar. 2013. "Quantification and Comparison of Spectral Characteristics of Sensors on Board Resourcesat-1 and Resourcesat-2 Satellites." *Remote Sensing Letters* 4 (3): 306–314. doi:10.1080/2150704X.2012.727491.

Prasanna, B. M., B. Vivek, A. R. Sadananda, D. P. Jeffers, P. H. Zaidi, C. Boeber, O. Erenstein, R. Babu, S. K. Nair, and B. Gerard. 2014. *12th Asian Maize Conference and Expert Consultation on Maize for Food, Feed, Nutrition; and Environmental Security*. Bangkok, August 30–November 1.

Raney, K., P. D. Spudis, B. Bussey, J. Crusan, J. Robert Jensen, W. Marinelli, P. McKerracher, C. Neish, M. Palsetia, and R. Schulze. 2011. "The Lunar Mini-Rf Radars: Hybrid Polarimetric Architecture and Initial Results." *Proceedings of the IEEE* 99 (5): 808–823. doi:10.1109/JPROC.2010.2084970.

Raney, R. K. 2007a. "Decomposition of Hybrid-Polarity SAR Data." PolIn-SAR 2007: Proceedings of the 3rd International Workshop on Science and Applications, Esrin, Frascatti.

Raney, R. K. 2007b. "Hybrid-Polarity SAR Architecture." *IEEE Transactions on Geoscience and Remote Sensing* 45 (11): 3397–3404. doi:10.1109/TGRS.2007.895883.
Seelan Santhosh, K., S. Laguette, G. M. Casady, and G. A. Seielstad. 2003. "Remote Sensing Applications for Precision Agriculture: A Learning Community Approach." *Remote Sensing of Environment* 88 (1–2): 157–169. doi:10.1016/j.rse.2003.04.007.
Sibanda, M., and A. Murwira. 2012. "The Use of Multi-Temporal MODIS Images with Ground Data to Distinguish Cotton from Maize and Sorghum Fields in Smallholder Agricultural Landscapes of Southern Africa." *International Journal of Remote Sensing* 33 (16): 4841–4855. doi:10.1080/01431161.2011.635715.
Smith, A. M., P. R. Eddy, J. Bugden-Storie, E. Pattey, H. McNairn, M. Nolin, I. Perron, M. Hinther, J. Miller, and D. Haboudane. 2006. "Multipolarized Radar for Delineating Within-Field Variability in Corn and Wheat." *Canadian Journal of Remote Sensing* 32 (4): 300–313. doi:10.5589/m06-026.
Soria-Ruiz, J., H. McNairm, Y. Fernandez-Ordonez, and J. Bugden-Storie. 2007. "Corn Monitoring and Crop Yield Using Optical and RADARSAT-2 Images." Paper presented at the Geoscience and Remote Sensing Symposium, 2007. IGARSS 2007. Barcelona: IEEE International.
Tapan Misra, S. S., N. M. Rana, D. B. Desai, R. Dave, R. K. Arora, C. V. N. Rao, B. V. Bakori, R. Neelakantan, and J. G. Vachchani. 2013. "Synthetic Aperture Radar Payload On-Board RISAT-1: Configuration, Technology and Performance." *Current Science* 104 (4): 446.
Touzi, R. 2009. "Compact-Hybrid versus Linear-Dual and Fully Polarimetric SAR." Proceedings of POLinSAR 2009, Frascati.
Ulaby, F., P. Batlivala, and M. C. Dobson. 1978. "Microwave Backscatter Dependence on Surface Roughness, Soil Moisture, and Soil Texture: Part I-Bare Soil." *IEEE Transactions on Geoscience Electronics* 16 (4): 286–295. doi:10.1109/TGE.1978.294586.
Ulaby Fawwaz, F., G. A. Bradley, and M. C. Dobson. 1979. "Microwave Backscatter Dependence on Surface Roughness, Soil Moisture, and Soil Texture: Part II-Vegetation-Covered Soil." *IEEE Transactions on Geoscience Electronics* 17 (2): 33–40. doi:10.1109/TGE.1979.294626.
Ulaby Fawwaz, T., R. K. Moore, and A. K. Fung. 1986. *Microwave Remote Sensing Active and Passive-Volume III: From Theory to Applications*. Norwood, MA: Artech House.
Uppala, D., R. V. Kothapalli, S. Poloju, S. S. V. R. Mullapudi, and V. K. Dadhwal. 2015. "Rice Crop Discrimination Using Single Date RISAT1 Hybrid (RH, RV) Polarimetric Data." *Photogrammetric Engineering & Remote Sensing* 81 (7): 557–563. doi:10.14358/PERS.81.7.557.
Van der Sanden, J. J. 2004. "Anticipated Applications Potential of RADARSAT-2 Data." *Canadian Journal of Remote Sensing* 30 (3): 369–379. doi:10.5589/m04-001.