

Novel Clustering Schemes for Full and Compact Polarimetric SAR Data: A Case Study for Rice Phenology Characterization

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Abstract

Information on rice phenological stages from Synthetic Aperture Radar (SAR) images is of prime interest for in-season monitoring. Often, prior in-situ measurements of phenology are not available. In such situations, unsupervised clustering of SAR images might help in discriminating phenological stages of a crop throughout its growing period. Among the existing unsupervised clustering techniques using full-polarimetric (FP) SAR images, the eigenvalue-eigenvector based roll-invariant scattering-type parameter, and the scattering entropy parameter are widely used in the literature. In this study, we utilize a unique target scattering-type parameter, which jointly uses the Barakat degree of polarization and the elements of the polarimetric coherency matrix. In particular, the degree of polarization attributes to scattering randomness from a target. The scattering randomness in crops increases with advancements in its growth stages due to the development of branches and foliage. Hence, the degree of polarization varies with changes in the crop growth stages. Besides, the elements of the coherency matrices are directly related to the crop geometry as well as soil and crop water content. Therefore, this complementarity information captures the scattering randomness at each crop growth stage while taking into account diverse crop morphological characteristics. Likewise, we also utilize an equivalent parameter proposed for compact-polarimetric (CP) SAR data. These scattering-type parameters are analogous to the Cloude-Pottier's parameter for FP SAR data and the ellipticity parameter for CP SAR data. Besides this, we also introduce new clustering schemes for both FP and CP SAR data for segmenting diverse scattering mechanisms across the phenological stages of rice. In this study, we use the RADARSAT-2 FP and simulated CP SAR data acquired over the Indian test site of Vijayawada under the Joint Experiment for Crop Assessment and Monitoring (JECAM) initiative. The temporal analysis of the scattering-type parameters and the new clustering schemes help us to investigate detailed scattering characteristics from rice across its phenological stages.

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Abstract

Information on rice phenological stages from Synthetic Aperture Radar (SAR) images is of prime interest for in-season monitoring. Often, prior in-situ measurements of phenology are not available. In such situations, unsupervised clustering of SAR images might help in discriminating phenological stages of a crop throughout its growing period. Among the existing unsupervised clustering techniques using full-polarimetric (FP) SAR images, the eigenvalue-eigenvector based roll-invariant scattering-type parameter, and the scattering entropy parameter are widely used in the literature. In this study, we utilize a unique target scattering-type parameter, which jointly uses the Barakat degree of polarization and the elements of the polarimetric coherency matrix. In particular, the degree of polarization attributes to scattering randomness from a target. The scattering randomness in crops increases with advancements in its growth stages due to the development of branches and

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foliage. Hence, the degree of polarization varies with changes in the crop growth stages. Besides, the elements of the coherency matrices are directly related to the crop geometry as well as soil and crop water content. Therefore, this complementarity information captures the scattering randomness at each crop growth stage while taking into account diverse crop morphological characteristics. Likewise, we also utilize an equivalent parameter proposed for compact-polarimetric (CP) SAR data. These scattering-type parameters are analogous to the Cloude-Pottier’s parameter for FP SAR data and the ellipticity parameter for CP SAR data. Besides this, we also introduce new clustering schemes for both FP and CP SAR data for segmenting diverse scattering mechanisms across the phenological stages of rice. In this study, we use the RADARSAT-2 FP and simulated CP SAR data acquired over the Indian test site of Vijayawada under the Joint Experiment for Crop Assessment and Monitoring (JECAM) initiative. The temporal analysis of the scattering-type parameters and the new clustering schemes help us to investigate detailed scattering characteristics from rice across its phenological stages.

Keywords: Unsupervised clustering, Entropy, RADARSAT-2, Crop monitoring, PolSAR, Roll-invariant parameter

1. Introduction

Variations in crop phenological stages can be characterized by Synthetic Aperture Radar (SAR) data due to its high sensitivity to the dielectric and geometrical structure of the canopy. However, depending on the frequency of the transmitted electromagnetic (EM) wave, the interaction with crop

6 canopy layers and the underlying soil varies significantly (Davidson et al.,
7 2000). Previous studies reported that phenological changes could be ade-
8 quately captured with high-frequency SAR sensors utilizing backscattered
9 information from vegetation canopy (Wiseman et al., 2014; De Bernardis
10 et al., 2015; McNairn and Shang, 2016; McNairn et al., 2018). In general, the
11 SAR backscatter signal might be affected by the underlying surface during
12 early vegetative growth stages when the canopy was sparse and open (Palos-
13 cia, 2002).

14 In particular, for rice monitoring, Le Toan et al. (1989) investigated the
15 temporal backscatter response of σ_{HH}^0 and σ_{VV}^0 from dual-polarized airborne
16 SAR data. It was noticed that the dynamic ranges of σ_{HH}^0 and σ_{VV}^0 for rice
17 fields were higher (up to ≈ 10 dB) than any other crop fields, possibly due to
18 the flooding condition in those fields. In another study, Kurosu et al. (1995)
19 reported that ERS-1 C-band SAR data had a second-order polynomial rela-
20 tionship of the backscatter values with the number of days after transplant-
21 ing. Besides, a high correlation of rice biomass with radar backscatter values
22 was also apparent. Although these satellites have low revisit time and coarse
23 resolution, the temporal pattern of HH and VV backscatter has been shown
24 to adequately capture the phenological growth of rice (Le Toan et al., 1997;
25 Koay et al., 2007; Bouvet et al., 2009). The discrimination of rice fields from
26 non-rice fields was conducted using the C-band HH/VV ratio, which shows
27 a distinct variation from the beginning of the season until the crop maturity
28 stage. Besides, several other SAR systems (e.g., RADARSAT-2, ALOS-2,
29 TerraSAR-X) have been exploited for crop growth monitoring by correlating
30 the backscatter changes to the crop morphological characteristics (Canisius

et al., 2018; Torbick et al., 2017).

One of the primary parameters associated with the changes in the SAR backscatter coefficient is the crop canopy distribution (e.g., tillers, leaves, and panicles) at each phenological stage. Moreover, this distribution in the crop fields also leads to randomness in scattering (Yuzugullu et al., 2015). In such situations, polarimetric entropy (H) is an important parameter to quantify this randomness. In Cloude and Pottier (1997), an unsupervised classification scheme ($H/\bar{\alpha}$) was proposed using H and the average scattering-type parameter ($\bar{\alpha}$).

Lopez-Sanchez et al. (2011) reported the importance of the $H/\bar{\alpha}$ plane to discriminate phenological stages of rice along with the temporal correlation of HH and VV and their ratio. The clustering results show that at the beginning of the cultivation period of rice, the data cluster was denser in the region with medium entropy and low alpha, which was primarily due to the presence of sparse vegetation in the fields. However, at the advanced phenological stages, the cluster density shifted towards the region of high entropy and high alpha in the $H/\bar{\alpha}$ plane.

In another study, Lopez-Sanchez et al. (2012) utilized the dominant scattering-type information (α_1) instead of $\bar{\alpha}$. In this study, the temporal behaviour of α_1 and the scattering entropy was shown with the phenological stages of rice. At the initial stage, α_1 and entropy were both within low to medium values, and they jointly increased during the plant emergence stage. During the advanced vegetative stage, both parameters show the dominance of multiple scattering from the fields. In contrast, at the harvest stage, $\alpha_1 < 30^\circ$ and the scattering entropy remained high due to the field roughness condition.

56 Praks et al. (2009) proposed alternative scattering-type and randomness
 57 parameters equivalent to $\bar{\alpha}$ and H for clustering PolSAR data. These pa-
 58 rameters can be directly obtained from the elements of the coherency matrix
 59 without utilizing the eigenvalues and the eigenvectors. It was shown that in-
 60 stead of $\bar{\alpha}$ and H , the surface scattering fraction and the scattering diversity
 61 that are equivalent polarimetric descriptors can be utilized for classification,
 62 visualization, or interpretation. Later, Yin et al. (2015) proposed a new
 63 parameter, α_B , defined by the co-polarization ratio and their coherence to
 64 capture various scattering mechanisms. This new parameter was able to dis-
 65 tinguish scattering from oriented and randomly distributed targets. In their
 66 study a new $\Delta\alpha_B/\alpha_B$ plane was proposed which showed better separation ca-
 67 pability than the $H/\bar{\alpha}$ clustering plane. It was also stated that the stability
 68 of the proposed method was better with multi-temporal SAR data.

69 In another work, Ratha et al. (2019) proposed a roll-invariant scattering-
 70 type parameter (α_{GD}), the helicity parameter (τ_{GD}), and the purity param-
 71 eter (P_{GD}) using a geodesic distance between two Kennaugh matrices. A new
 72 P_{GD}/α_{GD} unsupervised classification scheme is proposed whic is analogous
 73 to $H/\bar{\alpha}$. However, the P_{GD}/α_{GD} clustering plane showed better performance
 74 than earlier proposed schemes.

75 The study using compact-polarimetric (CP) SAR data holds promise
 76 due to the upcoming constellation of satellites such as the Canadian RAD-
 77 ARSAT Constellation Mission (RCM), SAOCOM (TOPSAR with experi-
 78 mental CP-mode), and the NISAR (the NASA-ISRO SAR) L- and S-band
 79 mission. Similar to the full-polarimetric (FP) case, scattering-type clustering
 80 assessment using compact polarimetric (CP) SAR data and its decomposition

81 parameters (Raney, 2007; Cloude et al., 2011; Raney et al., 2012) are lately
 82 gaining interest (Ainsworth et al., 2009; Charbonneau et al., 2010; Ballester-
 83 Berman and Lopez-Sanchez, 2011; Sabry and Vachon, 2013). Brisco et al.
 84 (2013) assessed hybrid-compact, circular, and linear polarimetric SAR data
 85 for rice and wetlands mapping. Also, different dual-channel combinations and
 86 $m - \delta$ decomposition parameters for CP data were assessed in their study,
 87 where the classification accuracy for CP data was comparatively better than
 88 linear dual-polarimetric SAR data.

89 Lopez-Sanchez et al. (2014) used the radar backscatter coefficients and
 90 the $H/\bar{\alpha}$ plane to investigate the dynamics of rice phenological changes for
 91 full, dual, and compact polarimetric SAR data. In this study, the dominant
 92 scattering-type parameter (α_s) for CP data is used instead of $\bar{\alpha}$. For CP data,
 93 the entropy, in particular, is equivalent to the Barakat degree of polarization.
 94 It was noticed that the pattern of α_s was similar for full, dual, and compact
 95 polarimetric SAR data for rice crops. Alongside this, it was also observed
 96 that α_s precisely provides similar information like the FP mode, throughout
 97 the phenological cycle of rice. On the contrary, among other decomposition
 98 parameters, δ provides quite noisy information.

99 Subsequently, Yang et al. (2014) showed improved classification accuracy
 100 in discriminating transplanted and direct-sown rice fields. In this study, the
 101 use of the $m - \chi$ decomposition parameters along with α_s , the degree of
 102 polarization (m), relative phase (δ) and conformity coefficient (μ) improved
 103 the classification accuracy from 88 % to 95 %. Besides, the classification
 104 accuracy confirmed the advantage of CP data over other dual-polarized SAR
 105 data. Several other studies (Xie et al., 2015; Uppala et al., 2015; Guo et al.,

106 2018; Kumar et al., 2020) also indicated the potential of CP SAR data for
107 rice mapping and monitoring.

108 Recently, Yin et al. (2019) proposed a new parameter, α_{BCP} , for improve-
109 ment in the clustering results for land-cover features. In particular, α_{BCP} is
110 rotation-invariant and $\Delta\alpha_{BCP}/\alpha_{BCP}$ resembles the existing $\Delta\alpha_B/\alpha_B$ clus-
111 tering for FP SAR data. However, the differences between α_{BCP} and α_B
112 depend on the polarization of the received wave. Moreover, the derivation
113 of specific scattering models is needless for separate CP modes. It was also
114 observed that circular CP data provides almost similar results as FP data
115 for various scattering targets.

116 The literature, as mentioned above, provides a vital foundation for the
117 utilization of H and the scattering-type parameters (i.e., $\bar{\alpha}$ and α_s) for rice
118 crop monitoring and mapping using FP and CP SAR data. Nevertheless,
119 these techniques are formulated either by fitting scattering models or by di-
120 agonalizing the coherency (or covariance) matrix of the received wave. Hence,
121 these techniques might miss the received antenna basis invariant information
122 while characterizing various targets. The importance of the received antenna
123 basis invariant information in terms of the degree of polarization helps to
124 effectively exploit complete information from SAR data (Touzi et al., 2015,
125 2018). In this regard, a new scattering-type parameter is derived by jointly
126 using the received antenna basis invariant information and elements of co-
127 herency (or, covariance) matrix for both FP and CP SAR data.

128 In this study, our main objective is to characterize changes in scattering
129 mechanisms utilizing the temporal series of full- and compact polarimet-
130 ric SAR data across the growth stages of rice. In this regard, we propose

roll-invariant scattering-type parameters using the received antenna basis in-
 variant information along with the elements of the coherency (or, covariance)
 matrices. The received antenna basis invariant information, i.e., in particular,
 the Barakat degree of polarization (Barakat, 1977, 1983) is useful to capture
 changes in scattering randomness due to crop foliage development. At the
 same time, the elements of the coherency (or, covariance) matrices provide
 information about crop canopy geometry as well as the soil and vegetation
 water content. Hence, jointly utilizing these information might be helpful
 in better monitoring the crop growth stages. Alongside this, we present a
 comparative study of the performance of novel clustering schemes for FP and
 CP data for rice phenology mapping.. It is noteworthy that the formulation
 of this new scattering-type parameter is equivalent for both FP and CP SAR
 data. This parameter is comparable to the Cloude and Pottier $\bar{\alpha}$ (Cloude
 and Pottier, 1997) for FP. It may be noted that θ_{FP} consider the Barakat
 degree of polarization in its formulation unlike $\bar{\alpha}$, and hence, it additionally
 utilizes the received antenna basis invariant information. We have proposed
 new clustering schemes using θ_{FP} and θ_{CP} along with H for both FP and
 CP SAR data, respectively. Unlike the H/α plane, the proposed segmen-
 tation scheme utilizes a polar representation, which offers a natural choice.
 Suitable entropy apportionment (radially) together with angular extent of
 $\theta_X \in [-90^\circ, 90^\circ]$ (where X is either FP or CP) provides a reliable target
 discrimination strategy. The segmentation scheme produces 12 feasible clus-
 tering zones that better characterize natural and human-made targets. The
 usefulness and performance of the scattering-type parameters θ_{FP} and θ_{CP} ,
 along with the new clustering schemes, are assessed by utilizing them with

156 the time-series C-band RADARSAT-2 data for monitoring rice.

157 **2. Study area and dataset**

158 The study area is located near Vijayawada in the state of Andhra Pradesh,
159 India ($16^{\circ}24'6.2''N$, $8^{\circ}41'2.4''E$) as shown in Figure 1 (Mandal et al., 2019).
160 The climatic zone of this area varies from sub-humid to humid, with mostly
161 clayey soil texture. Areal coverage of this test site is $\approx 25 \times 25 \text{ km}^2$. Rice
162 is one of the primary and major crops cultivated in this area. The sowing
163 period of rice varies from mid of June to mid of July depending on the
164 variety and cultivation practices. Majorly, the cultivation starts after the
165 pre-monsoon rain and is harvested during mid-December. The average size
166 of each field was $\approx 60 \times 60 \text{ m}^2$, and in each field, two sampling locations
167 were chosen for in-situ measurements. Information about the crop growth
168 stages, management practices, and biophysical parameters was noted during
169 the field campaign from June to December 2018.

170 A total number of 14 in-situ field measurements were considered in this
171 study. We measured soil moisture at each field in two sampling locations,
172 arranged in two parallel transects along the row direction. The separation
173 between each transect was $\approx 80 \text{ m}$. We measured the pointwise soil moisture
174 using theta-probe. Nevertheless, the soil underlying the rice crops was satu-
175 rated during the majority of the growth stages due to irrigation and rainfall
176 events. We measured vegetation samples at two points of each field due to
177 the spatial heterogeneity within the field, which is due to the irregular growth
178 pattern of rice. Vegetation sampling included the measurement of PAI, plant
179 height, and phenology through non-destructive methods. The PAI is mea-

180 sured using the notion of hemispherical digital photography. During each
 181 measurement day, we took ten photos along two transects which are sepa-
 182 rated by 2m in each sampling point, using a wide-angle lens mounted on a
 183 digital camera. All images were post-processed using the CanEYE software
 184 to provide an estimate of PAI. The overall phenology of rice is usually ex-
 185 pressed with three major stages: vegetative, reproductive, and mature (or
 186 ripening). The statistics of bio-physical and soil parameters are given in
 187 Table 1.

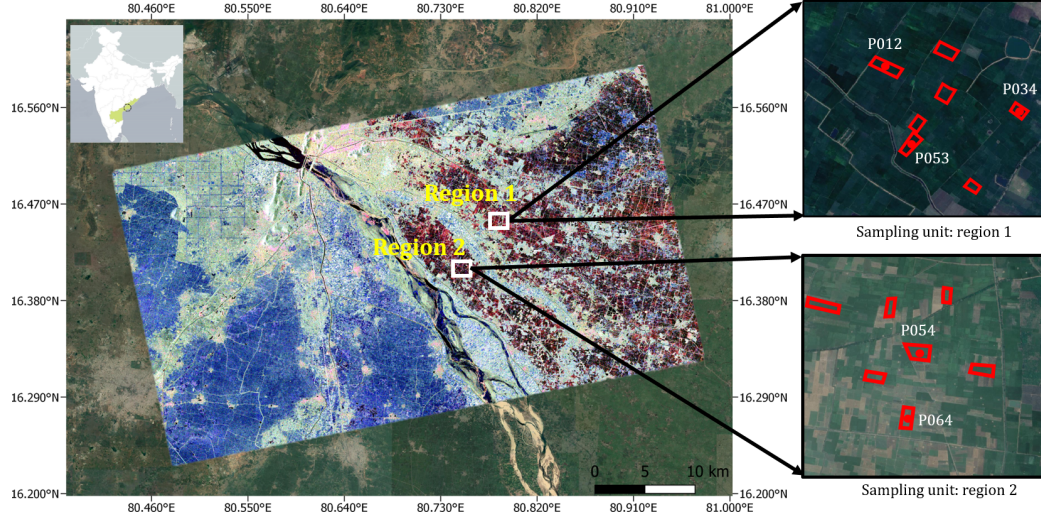


Figure 1: The Google Earth image of the JECAM test site over Vijayawada, India is overlaid with a Pauli RGB image obtained from SAR data acquired on 29 Jul 2018. The samples from region 1 and 2 are used for temporal analysis and clustering. The distribution of five in-situ data points is shown in the sampling unit of region 1 and region 2.

188 3. Satellite data pre-processing

189 We acquired RADARSAT-2 images in Fine Quad (FQ) wide mode from
 190 July to November 2018 over the test site as shown in Table 2. We then
 191 apply a multi-look factor of 2×3 pixels in the range and azimuth directions,

Table 1: Statistics (mean $\pm$ standard deviation) of bio-physical and soil parameters at different phenology stages of rice. Here, PH: plant height, PAI: plant area index, SM: soil moisture and Nan: Not a number

Date	PH (cm)	PAI ($\text{m}^2 \text{m}^{-2}$)	SM(%)	Growth stage
05/07/2018	Nan	Nan	35.92 ± 6.6	Bare field
29/07/2018	26.30 ± 5.21	0.40 ± 0.20	Saturated	Early tillering
22/08/2018	46.26 ± 9.12	1.76 ± 0.26	Saturated	Advanced tillering
09/10/2018	92.16 ± 5.76	4.03 ± 0.20	Saturated	Flowering
02/11/2018	95.93 ± 7.76	4.06 ± 0.16	47.60 ± 0.42	Early dough
26/11/2018	98.32 ± 6.82	3.86 ± 0.22	45.16 ± 6.04	Maturity

192 respectively, to generate $\approx 15\text{m}$ square pixel images. In general, the parcel
193 sizes in this test area are small. However, during rice cultivation, many fields
194 are cultivated alongside the field boundaries. Therefore, the fields seem to
195 be quasi-homogeneous, depending on cultivation practices. Since the area is
196 quasi-homogeneous, we apply a 3×3 boxcar filter (Lee and Pottier, 2009) to
197 each coherency matrix ($\mathbf{T}$) in the images for speckle reduction. Furthermore,
198 we generate simulated compact polarimetric (CP) SAR data from the FP
199 data with 0° orientation angle and -45° ellipticity angle. We co-register all
200 FP and CP images with the $\text{RMSE} \leq 0.25 \text{ m}$.

201 4. Methodology

202 In this section, we present the newly proposed scattering-type parameters
203 for both full- and compact-pol SAR data (Dey et al., 2020) for monitoring
204 rice crop. Alongside this, we propose an unsupervised clustering scheme
205 utilizing these new parameters along with the scattering entropy parameter
206 (i.e., a measure of randomness) derived from full (FP) and compact-pol (CP)

Table 2: Specification of the C-band full-pol RADARSAT-2 acquisitions over the test site during the field campaign (*az*: azimuth resolution and *rg*: range resolution)

Acquisition date	Beam mode	Incidence angle range (deg.)	Orbit	$az(m) \times rg(m)$
05/07/2018	FQ15W	33.73–36.65	Ascending	4.73×5.11
29/07/2018	FQ15W	33.73–36.65	Ascending	4.73×5.11
22/08/2018	FQ15W	33.73–36.65	Ascending	4.73×5.11
09/10/2018	FQ15W	33.73–36.65	Ascending	4.73×5.11
02/11/2018	FQ15W	33.73–36.64	Ascending	4.73×5.11
26/11/2018	FQ15W	33.73–36.64	Ascending	4.73×5.11

207 SAR data.

208 4.1. Full-polarimetry

209 In FP SAR, the 2×2 complex scattering matrix $\mathbf{S}$ encompasses complete
210 polarimetric information about backscattering from targets for each pixel.
211 It is expressed in the backscatter alignment (BSA) convention in the linear
212 horizontal (H) and linear vertical (V) polarization basis as,

$$\mathbf{S} = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \quad (1)$$

213 Each element of the matrix represents the backscattering response of the tar-
214 get at a specific polarization. The diagonal elements of the matrix represent
215 the co-polarized scattering information, while the off-diagonal terms repre-
216 sent the cross-pol information. In the monostatic backscattering case, the
217 reciprocity theorem constrains the scattering matrix to be symmetric, *i.e.*,
218 $S_{HV} = S_{VH}$.

To reduce the speckle effect in $\mathbf{S}$, the multi-looked Hermitian positive

semi-definite 3×3 coherency matrix $\mathbf{T}$ is obtained from the averaged outer product of the target vector $\mathbf{k}_P$ (derived using the Pauli basis matrix, Ψ_P) with its conjugate (Lee and Pottier, 2009).

$$\Psi_P = \left\{ \sqrt{2} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \sqrt{2} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \sqrt{2} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \right\}$$

$$\mathbf{k}_P = \frac{1}{2} \text{Tr}(\mathbf{S}\Psi_P) \implies \mathbf{k}_P = \frac{1}{\sqrt{2}} [S_{HH} + S_{VV}, S_{HH} - S_{VV}, 2S_{HV}]^T$$

$$\mathbf{T} = \frac{1}{N} \sum_{i=1}^N \mathbf{k}_{Pi} \mathbf{k}_{Pi}^{*T}$$

219 where N denotes the square window size for spatial averaging and Tr is the
220 sum of the diagonal elements of the matrix.

221 When a polarized electromagnetic (EM) wave scatters from a random
222 mixture of targets, it becomes partially polarized. The state of polarization
223 of a partially polarized EM wave is characterized in terms of the degree of
224 polarization ($0 \leq m \leq 1$). The degree of polarization is defined as the ratio
225 of the (average) intensity of the polarized portion of the wave to that of the
226 (average) total intensity of the wave. For a completely polarized EM wave,
227 $m = 1$ and for a completely unpolarized EM wave, $m = 0$. In between these
228 two extreme cases, the EM wave is said to be partially polarized, $0 < m < 1$.

229 Barakat (Barakat, 1977) provided an expression of m for the $N \times N$
230 coherency matrix. This expression is used in this study to obtain the degree
231 of polarization m_{FP} from the 3×3 coherency matrix $\mathbf{T}$ for FP SAR data as,

$$m_{\text{FP}} = \sqrt{1 - \frac{27|\mathbf{T}|}{(\text{Tr}(\mathbf{T}))^3}}, \quad (2)$$

232 where $|\cdot|$ is the determinant of a matrix.

233 From the interpretation of the Huynen parameters in terms of certain
 234 general properties of the target geometry, it can be inferred that T_{11} is the
 235 generator of target symmetry and represents the scattered power from a
 236 regular, smooth and convex parts of the scatterer. Similarly, $(T_{22} + T_{33})$ is
 237 the generator of the target structure and represents the scattered power from
 238 an irregular, uneven and non-convex parts of the scatterer (Lee and Pottier,
 239 2009). Therefore, with respect to the total polarized scattered power (i.e.,
 240 $m_{\text{FP}}\text{Span}$) from a scatterer, let us denote,

$$\tan \eta_1 = \frac{T_{11}}{m_{\text{FP}} \text{Span}} \quad \text{and} \quad \tan \eta_2 = \frac{T_{22} + T_{33}}{m_{\text{FP}} \text{Span}}, \quad (3)$$

241 where, $T_{11} = \langle |S_{\text{HH}} + S_{\text{VV}}|^2 \rangle$, $T_{22} = \langle |S_{\text{HH}} - S_{\text{VV}}|^2 \rangle$, and $T_{33} = 4\langle |S_{\text{HV}}|^2 \rangle$
 242 are the diagonal elements of the $\mathbf{T}$ matrix with T_{11} and $T_{22} + T_{33}$ being
 243 roll-invariant quantities. The total power, Span is defined in terms of the
 244 elements of the $\mathbf{T}$ matrix as,

$$\text{Span} = T_{11} + T_{22} + T_{33}. \quad (4)$$

245 We define:

$$\tan \gamma_{\text{FP}} = \tan (\eta_1 - \eta_2), \quad (5)$$

246 where γ_{FP} can be related to the average roll-invariant scattering-type pa-
 247 rameter, Cloude $\bar{\alpha} \in [0^\circ, 90^\circ]$ (Cloude and Pottier, 1997). However, in order
 248 to compare the two parameters within the same range, they are suitably

249 modified as, $\hat{\alpha} = 90^\circ - 2\bar{\alpha}$ and $\theta_{\text{FP}} = 2\gamma_{\text{FP}}$, which is given as,

$$\theta_{\text{FP}} = 2 \tan^{-1} \left(\frac{m_{\text{FP}} \text{Span} (T_{11} - T_{22} - T_{33})}{T_{11} (T_{22} + T_{33}) + m_{\text{FP}}^2 \text{Span}^2} \right) \in [-90^\circ, 90^\circ]. \quad (6)$$

250 It can be noticed from equation (6) that when $T_{11} = 0$ and $m_{\text{FP}} = 1$,
 251 then $\text{Span} = T_{22} + T_{33}$ and $\theta_{\text{FP}} = -90^\circ$. Similarly, when $T_{22} + T_{33} = 0$ and
 252 $m_{\text{FP}} = 1$, then $\text{Span} = T_{11}$ and $\theta_{\text{FP}} = 90^\circ$. Besides, as θ_{FP} approaches 0,
 253 scattering randomness increases and at $\theta_{\text{FP}} = 0^\circ$, the scattering is purely
 254 random (or depolarized).

255 The eigen-decomposition of $\mathbf{T}$ can be expressed as,

$$\mathbf{T} = \mathbf{U}_3 \mathbf{\Sigma} \mathbf{U}_3^{-1} \quad (7)$$

256 where $\mathbf{\Sigma}$ is the 3×3 diagonal matrix with non-negative elements, $\lambda_1 \geq \lambda_2 \geq$
 257 $\lambda_3 \geq 0$, which are the eigenvalues of $\mathbf{T}$. The pseudo probabilities, p_i obtained
 258 from the eigenvalues are defined as,

$$p_i = \frac{\lambda_i}{\sum_{k=1}^3 \lambda_k}, \quad (8)$$

259 which are then used to define the scattering entropy (Lee and Pottier, 2009)

260 as,

$$H_{\text{FP}} = - \sum_{k=1}^3 p_k \log_3 (p_k), \quad (9)$$

261 However, in this study, we use the quantity $\bar{H}_{\text{FP}} = 1 - H_{\text{FP}}$ to suitably
 262 represent the clusters in the $\bar{H}_{\text{FP}}/\theta_{\text{FP}}$ polar plane.

263 The feasible regions for $\bar{H}_{\text{FP}}/\theta_{\text{FP}}$ clustering plane can be represented by

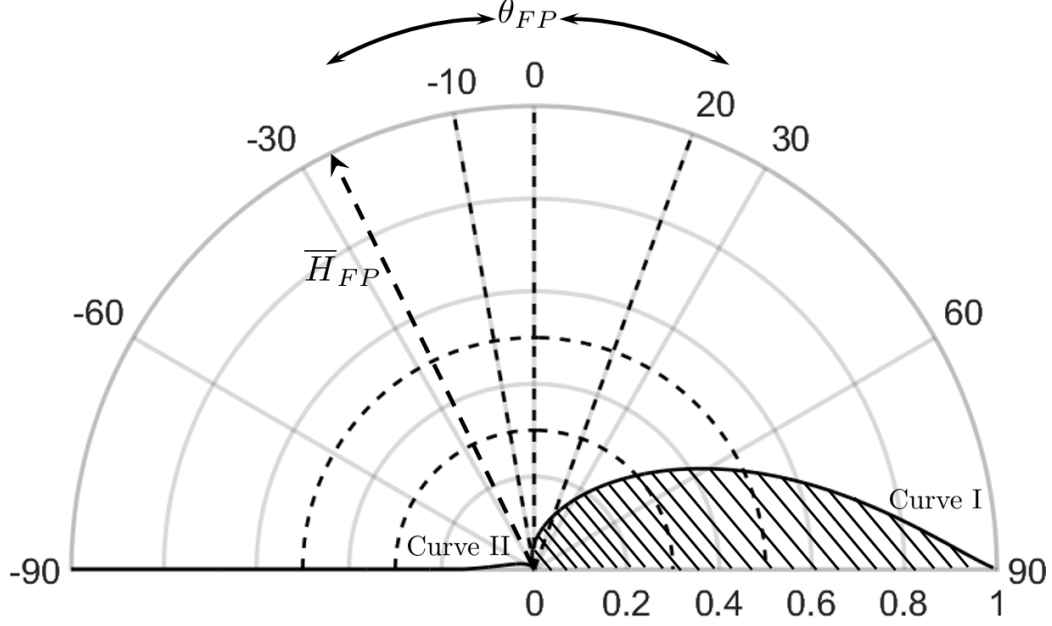


Figure 2: The $\overline{H}_{FP}/\theta_{FP}$ clustering plane displayed in polar plot. Curve I and Curve II represent the azimuthal symmetry lines. No scattering mechanisms exist in the dashed portion of the plane. Two half-circles at 0.5 and 0.7 divide the $\overline{H}_{FP}$ into high, medium and low entropy regions while -90° to -10° represents even bounce scattering, -10° to 20° represents multiple bounce scattering and 20° to 90° represents odd bounce scattering.

264 two bounding curves, Curve I and Curve II as shown in Figure 2.

$$\text{Curve I, } [\mathbf{T}]_I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & m \end{bmatrix} \quad 0 \leq m \leq 1 \quad (10)$$

$$\text{Curve II, } [\mathbf{T}]_{II} = \begin{bmatrix} 2m - 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad 0.5 \leq m \leq 1 \quad (11)$$

265 *4.2. Compact-polarimetry*

266 The CP mode measures a projection of the 2×2 complex scattering
267 matrix $\mathbf{S}$ as,

$$\begin{aligned} \begin{bmatrix} E_{CH} \\ E_{CV} \end{bmatrix} &= \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \begin{bmatrix} 1 \\ \pm i \end{bmatrix} \\ &= \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} \pm iS_{HV} \\ S_{VH} \pm iS_{VV} \end{bmatrix} \end{aligned} \quad (12)$$

268 where the subscript C can be either the left-hand circular (L) transmit with
269 a $+$ sign or the right-hand circular (R) transmit with a $-$ sign. The 2×2
270 covariance matrix is then obtained from the elements of the scattering vector
271 as,

$$\mathbf{C}_2 = \begin{bmatrix} \langle |E_{CH}|^2 \rangle & \langle E_{CH} E_{CV}^* \rangle \\ \langle E_{CV} E_{CH}^* \rangle & \langle |E_{CV}|^2 \rangle \end{bmatrix}. \quad (13)$$

272 For CP-SAR data, the 4×1 Stokes vector $\vec{\mathbf{g}}$ can be written in terms of
273 the elements of the 2×2 covariance matrix $\mathbf{C}_2$ as,

$$\vec{\mathbf{g}} = \begin{bmatrix} g_0 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix} = \begin{bmatrix} C_{11} + C_{22} \\ C_{11} - C_{22} \\ C_{12} + C_{21} \\ \pm j(C_{12} - C_{21}) \end{bmatrix}, \quad (14)$$

274 where $\pm$ corresponds to left and right circular polarization respectively.

275 From the elements of $\vec{\mathbf{g}}$, the backscatter power in the same sense ($SC =$
276 $\frac{g_0 - g_3}{2}$) and opposite sense ($OC = \frac{g_0 + g_3}{2}$) to the transmitted circular polariza-

tion is utilized to derive the roll-invariant scattering-type parameter (θ_{CP}) for the compact-polarimetric SAR data similar to the FP case. Here, OC is the generator of target symmetry and represents the scattered power from a regular, smooth and convex parts of the scatterer. Similarly, SC is the generator of the target structure and represents the scattered power from an irregular, uneven and non-convex parts of the scatterer:

$$\tan \zeta_1 = \frac{OC}{m_{\text{CP}} \text{Span}}, \quad \text{and} \quad \tan \zeta_2 = \frac{SC}{m_{\text{CP}} \text{Span}} \quad (15)$$

where the total power Span is defined as,

$$\text{Span} = SC + OC \quad (16)$$

Similar to FP, we define:

$$\tan \gamma_{\text{CP}} = \tan (\zeta_1 - \zeta_2) \quad (17)$$

where γ_{CP} can be analogously related to the polarization ellipticity parameter $\chi \in [-45^\circ, 45^\circ]$. However, in order to compare, the two parameters within the same range, they are suitably scaled as, $\bar{\chi} = -2\chi$ and $\theta_{\text{CP}} = 2\gamma_{\text{CP}}$ which is given as,

$$\theta_{\text{CP}} = 2 \tan^{-1} \left(\frac{m_{\text{CP}} \text{Span} (OC - SC)}{OC \times SC + m_{\text{CP}}^2 \text{Span}^2} \right) \in [-90^\circ, 90^\circ] \quad (18)$$

Similar to θ_{FP} , it can be noticed from (18) that for a pure dihedral scatterer, i.e., when $OC = 0$ and $m_{\text{CP}} = 1$, then $\text{Span} = SC$ and $\theta_{\text{CP}} = -90^\circ$. Similarly, for a pure trihedral scatterer, i.e., when $SC = 0$ and $m_{\text{CP}} = 1$,

292 then $\text{Span} = OC$ and $\theta_{\text{CP}} = 90^\circ$. Besides, as θ_{CP} approaches 0, scattering
 293 randomness increases and at $\theta_{\text{CP}} = 0^\circ$, the scattering is purely random (or
 294 depolarized).

295 The expression for the Barakat degree of polarization for the compact-
 296 polarimetric case is given as,

$$m_{\text{CP}} = \sqrt{1 - \frac{4|\mathbf{C}_2|}{(\text{Tr}(\mathbf{C}_2))^2}}. \quad (19)$$

297 The eigen-decomposition of $\mathbf{C}_2$ can be expressed as,

$$\mathbf{C}_2 = \mathbf{U}_2 \mathbf{\Sigma} \mathbf{U}_2^{-1}, \quad (20)$$

298 where $\mathbf{\Sigma}$ is a 2×2 diagonal matrix with non-negative elements, $\lambda_1 \geq \lambda_2 \geq 0$,
 299 which are the eigenvalues of $\mathbf{C}_2$. The pseudo probabilities, p_i obtained from
 300 the eigenvalues are defined as,

$$p_i = \frac{\lambda_i}{\sum_{k=1}^2 \lambda_k}, \quad (21)$$

301 which are then used to define the scattering entropy (H_{CP}) for CP-SAR data
 302 as,

$$H_{\text{CP}} = -\sum_{k=1}^2 p_k \log_2(p_k). \quad (22)$$

303 As mentioned earlier for the FP case, we use the quantity $\overline{H}_{\text{CP}} = 1 - H_{\text{CP}}$
 304 to suitably represent the clusters in the $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ polar plane.

305 Similar to FP, the feasible regions for $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ clustering plane can be
 306 represented by two bounding curves, Curve I and Curve II, as shown in

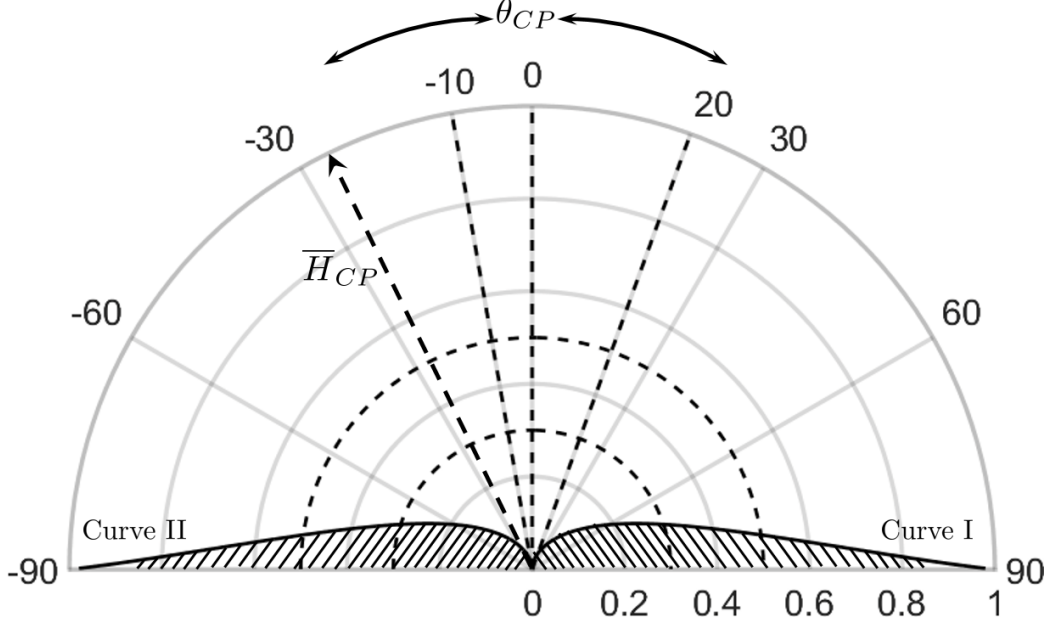


Figure 3: The $\overline{H}_{CP}/\theta_{CP}$ clustering plane displayed in polar plot. Curve I and Curve II represent the azimuthal symmetry lines. No scattering mechanisms exist in the dashed portion of the plane. Two half-circles at 0.5 and 0.7 divide the $\overline{H}_{CP}$ into high, medium and low entropy regions while -90° to -10° represents even bounce scattering, -10° to 20° represents multiple bounce scattering and 20° to 90° represents odd bounce scattering.

307 Figure 3.

$$\text{Curve I, } [\mathbf{C}]_I = \begin{bmatrix} \frac{2m+1}{4} & i\frac{2m-1}{4} \\ -i\frac{2m-1}{4} & \frac{2m+1}{4} \end{bmatrix} \quad 0 \leq m \leq 0.5 \quad (23)$$

$$\text{Curve II, } [\mathbf{C}]_{II} = \begin{bmatrix} \frac{2m+1}{4} & -i\frac{2m-1}{4} \\ i\frac{2m-1}{4} & \frac{2m+1}{4} \end{bmatrix} \quad 0 \leq m \leq 0.5 \quad (24)$$

308 4.3. Clustering

309 Cloude and Pottier (Cloude and Pottier, 1997) proposed a clustering
 310 scheme $H/\overline{\alpha}$, for FP SAR data based on the average scattering-type pa-
 311 rameter ($\overline{\alpha}$) and the scattering entropy (H). The $H/\overline{\alpha}$ plane is sub-divided

312 into nine zones to suitably cluster various scattering mechanisms. The prop-
 313 erties of different scattering mechanisms determine the boundaries between
 314 the zones. Hence certain assumptions are utilized in the proper setting of
 315 these boundaries. Subsequently, the 2D clustering plane is extended to 3D
 316 $H/A/\bar{\alpha}$ space by introducing the scattering anisotropy parameter A . This
 317 parameter, which is complementary to H , is useful to discriminate targets
 318 when $H > 0.7$. However, for lower values of H , this parameter is noisy
 319 and could introduce inaccuracies in determining the clusters. In the litera-
 320 ture, this clustering scheme is extended for dual-pol SAR data (HH-HV or
 321 VV-VH) by suitably modifying the zone boundaries (Ji and Wu, 2015).

322 In our study, we propose a clustering scheme equivalently for both FP
 323 and CP SAR data by utilizing the 2D $\bar{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\bar{H}_{\text{CP}}/\theta_{\text{CP}}$ planes respec-
 324 tively. Besides, the zones and the boundaries of both the clustering planes
 325 are identical. From analysis with scattering model (random volume model),
 326 it has been observed that the scattering-type from vegetation lies approxi-
 327 mately in the range -10° to 20° (Antropov et al., 2011). The upper bound
 328 for multiple scattering ($\theta_X = 20^\circ$) is characterized by equal contributions
 329 from the ensemble of horizontal and vertical dipole scattering components
 330 from vegetation structure. In contrast, the lower bound ($\theta_X = -10^\circ$) is
 331 the characteristic of multiple scattering phenomena predominantly described
 332 by vertical vegetation structure. Hence, this region is subdivided for multi-
 333 ple scattering mechanisms. Unlike the $H/\bar{\alpha}$ plane, the proposed clustering
 334 scheme divides the plane into twelve zones. The scattering-type parameter
 335 θ_X (where X refers to both FP and CP) divides the $\bar{H}_X - \theta_X$ plane into four
 336 sub-planes (P1:(Z1, Z2, Z3); P2:(Z4, Z5, Z6); P3:(Z7, Z8, Z9); P4:(Z10, Z11,

337 Z12)) which consists of (1) pure even-bounce scattering (-90° to -10°) in P1;
 338 (2) even-bounce with multiple scattering (-10° to 0°) in P2; (3) odd-bounce
 339 with multiple scattering (0° to 20°) in P3; (4) pure odd-bounce scattering
 340 (20° to 90°) in P4. The quantity $\overline{H}_X = 1 - H$ divides the plane into (1) high
 341 entropy (0 to 0.3); (2) medium entropy (0.3 to 0.5); (3) low entropy (0.5 to
 342 1). The $H/\overline{\alpha}$ and the $\overline{H}_X/\theta_X$ clustering plane along with the zones are given
 in Figure 4.

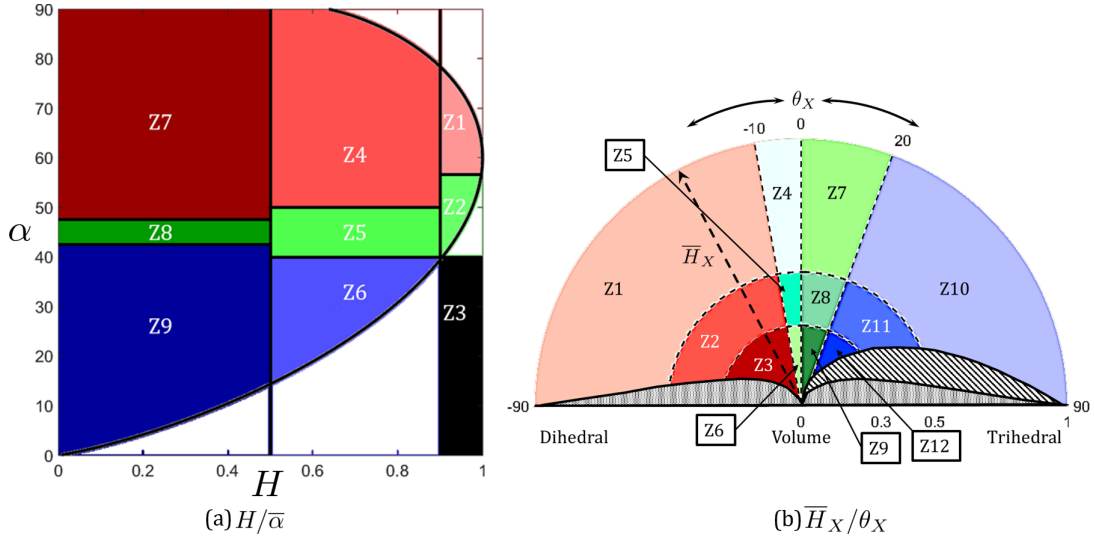


Figure 4: (a) $H/\overline{\alpha}$ clustering plane for FP SAR data and (b) $\overline{H}_X/\theta_X$ plane for both FP and CP SAR data.

343

344 The difference between the geometrical structures of the $H/\overline{\alpha}$ and $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$
 345 2D clustering planes can be observed in Figure 4. As stated earlier, it may
 346 be noted that the parameter $\overline{\alpha}$ is scaled to $\hat{\alpha} = 90^\circ - 2\overline{\alpha}$ solely for the
 347 sake of qualitative comparison. The ability of the two clustering planes, i.e.,
 348 $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ to classify different landcover classes is apparent in
 349 this figure. Region A, B and C in Figure 5 are respectively the oriented
 350 urban area, forest area and ocean areas. The dashed white box in Figure 5

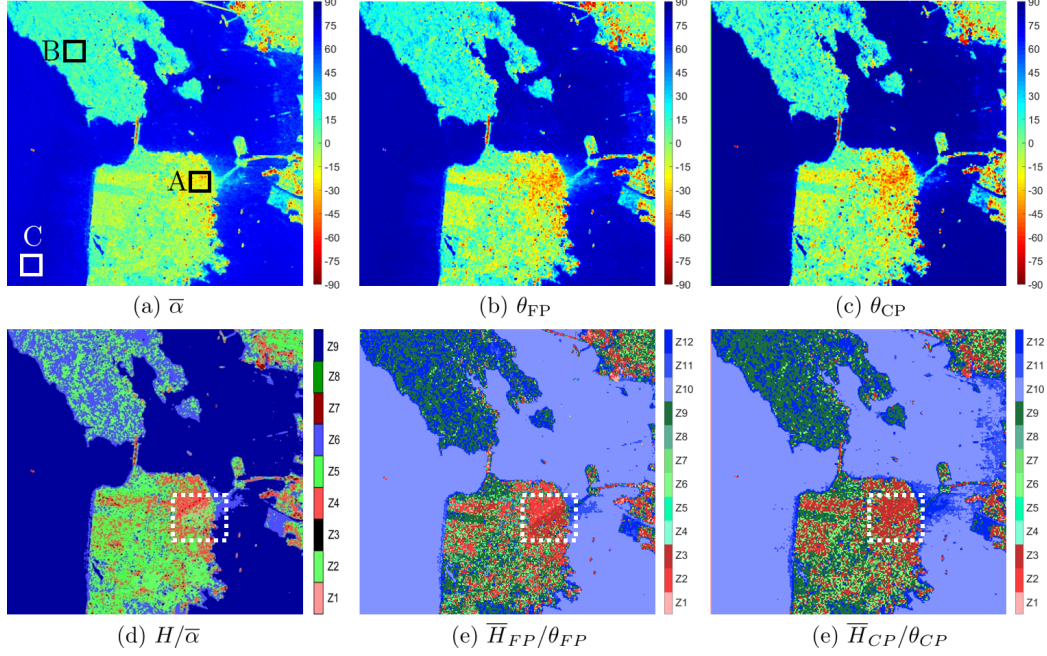


Figure 5: The scattering type parameters, $\bar{\alpha}$, θ_{FP} , θ_{CP} and the $H/\bar{\alpha}$, $\bar{H}_{FP}/\theta_{FP}$, $\bar{H}_{CP}/\theta_{CP}$ clustered image of San Francisco Bay, USA using C-band RS-2 SAR data. Region A represents the oriented urban area, region B and C represents forest and ocean areas, respectively. The white box shows the oriented urban area where the major change during clustering occurred. $H/\bar{\alpha}$ identified it as scattering from vegetation while $\bar{H}_{FP}/\theta_{FP}$ and $\bar{H}_{CP}/\theta_{CP}$ correctly identified it as scattering from urban region.

351 highlights distinct changes in the scattering types as well as the clustering
 352 zones for differently oriented targets.

353 It can be observed from Figure 6 that in the $H/\bar{\alpha}$ plane, the even-bounce
 354 scattering mechanism over oriented urban area (A) is only 17% while the
 355 odd-bounce and multiple-bounce scattering mechanism are 38% and 45%,
 356 respectively. In contrast, the contribution of even-bounce dominant scatter-
 357 ing mechanism in $\bar{H}_{FP}/\theta_{FP}$ and $\bar{H}_{CP}/\theta_{CP}$ are 84% and 79%, respectively. On
 358 the other hand, over the forest area (B), the multiple-bounce scattering mech-
 359 anism is 8% higher for $\bar{H}_{FP}/\theta_{FP}$ and 6% higher for $\bar{H}_{CP}/\theta_{CP}$ as compared

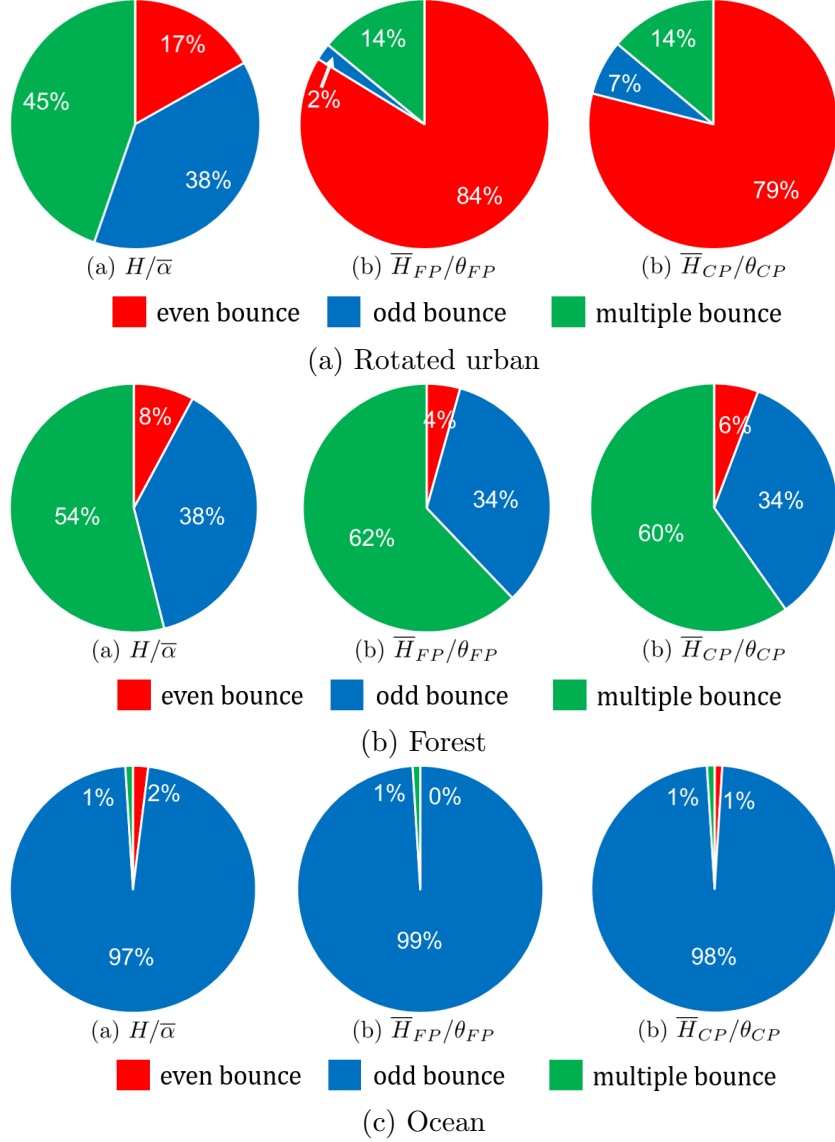


Figure 6: A comparison of the percentages of even, odd and multiple bounce scattering over (a) rotated urban, (b) forest and (c) ocean surfaces for the C-band RS-2 San Francisco Bay area image using $H/\bar{\alpha}$, $\bar{H}_{FP}/\theta_{FP}$ and $\bar{H}_{CP}/\theta_{CP}$ clustering techniques.

360 to $H/\bar{\alpha}$. Similarly, over the ocean area (C) the odd-bounce scattering mech-
 361 anism has increased marginally by 2% and 1% for $\bar{H}_{FP}/\theta_{FP}$ and $\bar{H}_{CP}/\theta_{CP}$,

362 respectively. This suggests that the discriminating ability of $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and
 363 $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ scheme is by and large higher than $H/\overline{\alpha}$. This marked ability might
 364 be due to 1) the joint utilization of the Barakat degree of polarization along
 365 with essential information from elements of the coherency matrix in deriv-
 366 ing the scattering-type parameters, 2) the notion of an extended clustering
 367 procedure (i.e., 12 clusters) using entropy and the scattering-type param-
 368 eters. Hence, we use the proposed clustering schemes with θ_{FP} and θ_{CP} , for
 369 the temporal analysis of two different varieties of rice crops over Vijayawada,
 370 India using FP RADARSAT-2 data and simulated CP SAR data. In this
 371 study, we analyze the phenological changes of rice using these parameters
 372 and the new clustering scheme.

373 **5. Results and Discussion**

374 The study area in Vijayawada is well facilitated with water for crop cul-
 375 tivation throughout the year. The temporal analysis of θ_{FP} and θ_{CP} along
 376 with $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ clustering plane for rice will be discussed in this
 377 section.

378 *5.1. Temporal variation of θ_{FP} and θ_{CP} for FP and CP data*

379 The temporal variation of θ_{FP} and θ_{CP} for FP and CP SAR data, respec-
 380 tively, are shown in Figure 7. As stated earlier, for any deterministic target,
 381 θ_{FP} and θ_{CP} lie at the extremities of the range, i.e., -90° to 90° . For both
 382 θ_{FP} and θ_{CP} , -90° indicates pure dihedral scattering, while 90° indicates
 383 pure trihedral scattering. For pure diffused scattering, θ_{FP} and $\theta_{\text{CP}} \approx 0^\circ$.
 384 However, for any other distributed targets, θ_{FP} and θ_{CP} varies within these
 385 limits.

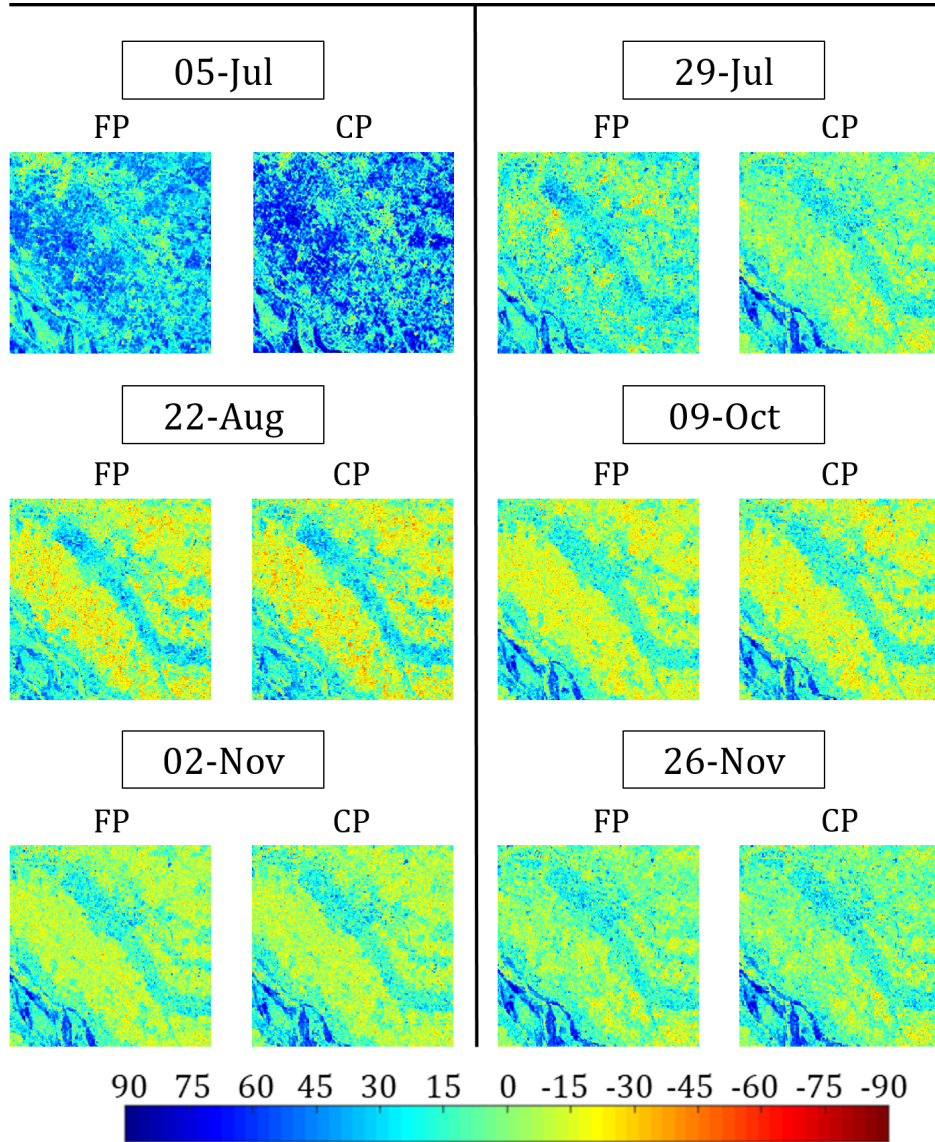


Figure 7: Variation of θ_{FP} and θ_{CP} images for FP and CP over the study area. The growth stages are: 5-Jul: Bare field, 29-Jul: Early tillering, 22-Aug: Advanced tillering, 9-Oct: Flowering, 2-Nov: Early dough, and 26-Nov: Maturity

386 During the first week of July, there was no crop in most of the rice fields.
 387 Hence, the SAR response was primarily dominated by the soil character-

istics in this period. On 29 Jul, a significant difference in θ_{FP} values can be observed in those fields. In that particular area, transplantation of rice was mostly completed, while certain fields entered the early tillering stage. Hence, majority of the rice fields showed even-bounce multiple scattering with θ_{FP} varies from 0° to -20° . Additionally, the rice fields, which were at the end of the tillering stage, showed moderate even-bounce scattering with θ_{FP} varies from -30° to -50° .

On 22 Aug, most of the rice fields were at the advanced tillering stage. Therefore, high even-bounce multiple scattering is prominent in these fields. Around 09 Oct, rice fields reached the end of the vegetative stage, and thus θ_{FP} for the area showed even-bounce multiple scattering mechanisms. On 26 Nov, rice reached the maturity stage. At this time, crop water content got reduced, and the canopy geometry appeared complex due to the randomly oriented stem with grains that are evident from in-situ measurements. Thus, this complex structure generated a random-volume scattering mechanism from most of the fields in that area.

Similarly, θ_{CP} shows changes from high odd-bounce to even-bounce multiple scattering within the growing season of rice. However, few minor differences in the response of θ_{CP} from θ_{FP} can be noticed mainly during the higher phenological growth stages. These differences might be due to the formulation of the compact polarimetric Stokes vector that is obtained from the projection of the scattering matrix with reduced polarimetric information. Due to this reason, for high cross-pol components, the difference between SC and OC powers becomes negligible, and θ_{CP} exhibits high diffused scattering. As stated earlier, on 5 Jul, most of the fields were empty. Hence, like θ_{FP} ,

413 θ_{CP} also exhibits a high amount of odd-bounce scattering in those fields.

414 On 29 Jul, a notable change in the response of θ_{FP} and θ_{CP} for a few
415 fields must be due to different sowing date. During this period, rice was
416 transplanted and progressed to the early tillering stage, which shows dom-
417 inant even-bounce multiple scattering. From 09 Oct to 26 Nov, dominant
418 even-bounce multiple scattering is evident due to numerous branch and fo-
419 liage development with an increase in the plant area index. However, the
420 range of θ_{CP} for even-bounce multiple scattering is higher than θ_{FP} . This
421 high value of θ_{CP} might be because of the high cross-pol component due to
422 which the difference between SC and OC power is almost negligible. For the
423 quantitative temporal analysis of θ_{FP} and θ_{CP} , five different field points were
424 selected from the fields.

425 In this study, both qualitative and quantitative analyses of the temporal
426 variations in θ_{FP} and θ_{CP} utilizing data from five in-situ points (viz., P012,
427 P054, P064, P034, P053) are shown in Figure 8. The values of θ_{FP} and θ_{CP} on
428 05 Jul indicate dominant odd-bounce scattering from bare soil. However, on
429 29 Jul, a sudden change in θ_{FP} and θ_{CP} values are noticed. During this period,
430 θ_{FP} ranges from -17° to -51° while θ_{CP} ranges from -23° to -62° . These
431 sudden changes in the values of θ_{FP} and θ_{CP} are due to the early tillering
432 stage of rice. At this point, the soil was highly saturated, and the vertical
433 stems acted like a dihedral scatterer which leads to even-bounce scattering
434 from the rice fields. A similar response of rice during the tillering phase was
435 also reported by Lopez-Sanchez et al. (2014).

436 Contrarily, we observe an increasing trend in the plots between 22 Aug
437 and 2 Nov due to the reduction in even-bounce multiple scattering. During

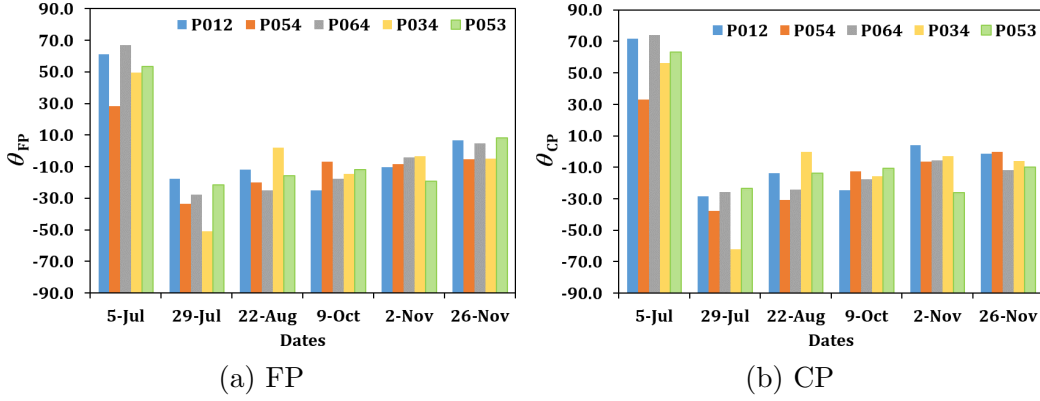


Figure 8: Temporal variation of θ_{FP} and θ_{CP} for rice using FP and CP data. The growth stages are: 5-Jul: Bare field, 29-Jul: Early tillering, 22-Aug: Advanced tillering, 9-Oct: Flowering, 2-Nov: Early dough, and 26-Nov: Maturity

438 this time, rice advanced from advance tillering to early dough stage, and
 439 hence, we observe increased multiple scattering from these fields. Therefore,
 440 the coherence between the co-polarized channels decreased significantly. The
 441 range of θ_{FP} value during this period was 2° to -25° and θ_{CP} value was 0° to
 442 -30° . However, towards the end of the season, randomness in θ_{FP} and θ_{CP}
 443 values are observed due to complex scattering from the rice stem and grains.

444 5.2. $\overline{H}_{FP}/\theta_{FP}$ and $\overline{H}_{CP}/\theta_{CP}$ clustering planes for rice

445 As discussed earlier, the $\overline{H}_{FP}/\theta_{FP}$ and $\overline{H}_{CP}/\theta_{CP}$ planes are divided into
 446 12 zones based on different scattering-type information. In this study, these
 447 clustering zones (Figure 11) are utilized to monitor the growth stages of rice
 448 using full (Figure 9) and simulated compact (Figure 10) polartimetric SAR
 449 data.

450 In Figure 9 and Figure 10, the θ_{FP} and θ_{CP} values are majorly within the
 451 odd-bounce scattering region on 05 Jul due to the nearly smooth soil surface
 452 condition. Hence, dense clusters are seen in Z10, Z11, and Z12, which corre-

453 sponds respectively to low entropy even-bounce scattering, medium entropy
 454 even-bounce scattering, and high entropy even-bounce scattering regions.
 455 Moreover, a few data points lying in region Z3 is due to the early trans-
 456 plantation stage. Besides, tillage operation in some fields has produced soil
 457 surface roughness, which increased the entropy, and hence, a sparse cluster
 458 can also be seen in Z9 and Z6. The proportion of pixels over different scat-
 459 tering regions at each phenological stage is shown in Table 3. To characterize
 460 different changes in scattering mechanisms, we have considered (Z1, Z2, Z3)
 461 as even bounce scattering, (Z10, Z11, Z12) as odd bounce scattering and (Z4,
 462 Z5, Z6, Z7, Z8, Z9) as multiple bounce scattering. High odd bounce scatter-
 463 ing (86.26 %) was noted for FP data. Besides, due to the slight roughness a
 464 small component of multiple bounce scattering (12.24 %) is observed during
 465 this period, whereas even bounce scattering contribution was only 0.90 %.

466 A significant change in the data cluster is seen on 29 Jul. During this
 467 period, most of the rice fields were in the early tillering stage, while other
 468 non-cultivated fields had moist soil with high roughness that is evident from
 469 in-situ data. This highly rough soil surface during this period has generated
 470 a high degree of randomness in the received EM wave, which resulted in
 471 an increased entropy. Hence, a shift from low entropy zone (Z10) to high
 472 (Z12) and medium (Z11) entropy zones is evident on 29 Jul. Also, some data
 473 points in zones Z11 and Z12 are $\theta_{\text{FP}} \leq 30^\circ$, which is due to the scattering from
 474 the water surface in the rice fields (Lopez-Sanchez et al., 2014). However,
 475 compared to θ_{FP} , the values of θ_{CP} are 5° to 10° higher in this period.

476 The density of the data points in Z6 and Z9 zones has also increased
 477 on 29 Jul, while rice transplantation was undergoing in some other fields.

Therefore, a moderately high accumulation of data points can also be seen in Z3 (Figure 9 and Figure 10). Moreover, the previously sown rice fields had achieved a higher vegetative stage due to which the areal coverage by the crop canopy had increased, thereby slightly decreasing the scattering entropy. Due to this aspect, a few data points are sparsely clustered in the Z2 region on 29 Jul. Furthermore, in zones Z2 and Z3, the values of θ_{CP} is 2° to 5° higher than θ_{FP} . Hence, the even bounce scattering had increased by 75.89% and multiple scattering had increased by 16.49%. A noteworthy decrease in the odd bounce scattering (82.38%) is observed which is most likely due to the increase of double-bounce for the presence of stems, which also helps to reduce the surface roughness and the contribution from the ground.

On 22 Aug, dense clusters can be seen in Z3 for FP and CP data, which is due to the tillering stage of rice. During this stage, the fields are flooded with water, and the stems are almost vertical, which acts as dihedral scatterers. During this period, $\overline{H}_{CP}$ is lower than $\overline{H}_{FP}$, which might be due to less polarimetric information content. Similar to 29 Jul, θ_{CP} is higher than θ_{FP} at this time. Additionally, due to the variation in the θ_{CP} and H_{CP} values according to crop morphology, significant change among Z5, Z6, Z8, and Z9 zones can be observed compared to 29 Jul. Moreover, in $\overline{H}_{FP}/\theta_{FP}$ plot, cluster formation in Z5 and Z8 zones is seen, whereas, in $\overline{H}_{CP}/\theta_{CP}$ plot, no such clusters are found due to the high entropy in the CP SAR data.

In general, the occurrence of flooding in rice fields generates even-bounce scattering (Yonezawa et al., 2012). Hence, a significant shift in the scattering mechanism from odd-bounce to even-bounce is visible during 22 Aug.

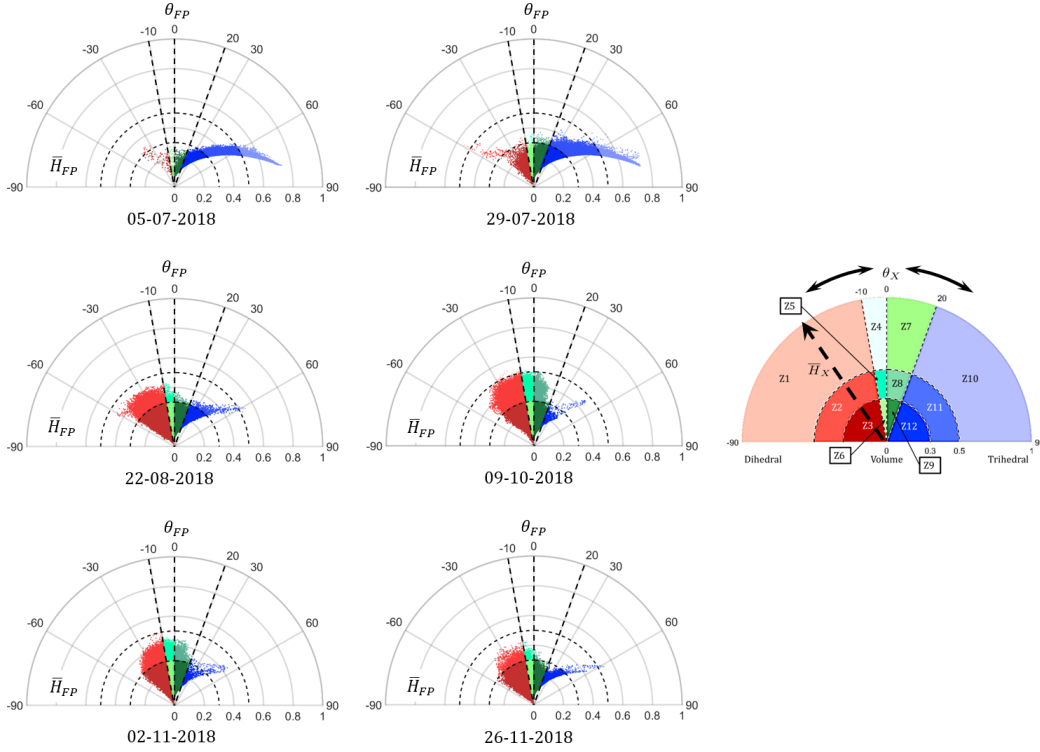


Figure 9: The $\bar{H}_{FP}/\theta_{FP}$ scatter plane for rice fields using FP SAR data. The growth stages are: 5-Jul: Bare field, 29-Jul: Early tillering, 22-Aug: Advanced tillering, 9-Oct: Flowering, 2-Nov: Early dough, and 26-Nov: Maturity

503 However, the orientation, shape, and size of each crop were not the same,
 504 and hence there was also a possibility of rough soil surface stretching out
 505 from the water surface. Therefore, these phenomena could induce high ran-
 506 domness in the scattered EM wave. Besides, similar to 29 Jul, some fields
 507 progressed to a higher vegetative stage due to which a cluster can be seen in
 508 Z2. Furthermore, fields that reached the booting stage display even-bounce
 509 multiple scattering with medium entropy characteristics (Z5). However, the
 510 even-bounce scattering mechanism is evident throughout the tillering stage.
 511 Hence, the even bounce scattering power had decreased by 11.19%, while

multiple bounce scattering had marginally increased by 3.67%.

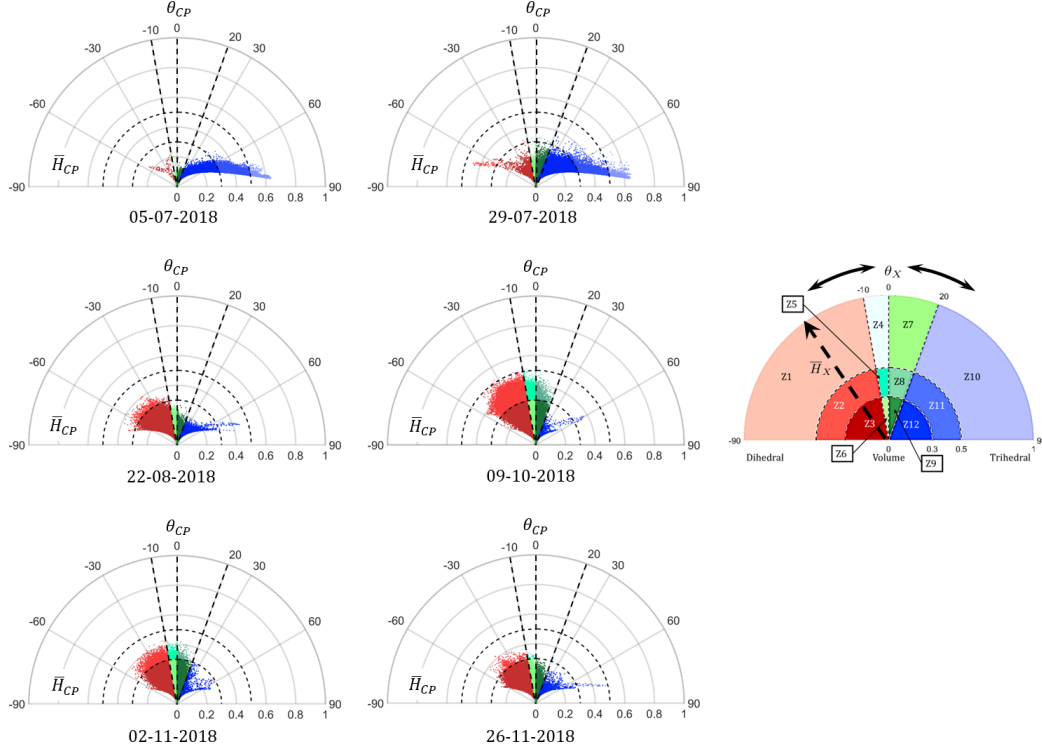


Figure 10: The $\overline{H}_{CP}/\theta_{CP}$ scatter plane for rice fields using simulated CP SAR data. The growth stages are: 5-Jul: Bare field, 29-Jul: Early tillering, 22-Aug: Advanced tillering, 9-Oct: Flowering, 2-Nov: Early dough, and 26-Nov: Maturity

On 09 Oct, both $\overline{H}_{FP}/\theta_{FP}$ and $\overline{H}_{CP}/\theta_{CP}$ planes show a shift towards the medium entropy region (i.e., Z2 and Z5 zones) which is evident in Figure 9. During this period, most of the rice fields were in the inflorescence emergence stage, with θ_{FP} and θ_{CP} indicating even-bounce and even-bounce multiple scatterings. Moreover, the amount of cross-pol components has increased during this period. A similar type of increase in cross-pol components from transplantation to maturity stages was reported by He et al. (2018). The shift towards the Z2 and Z5 zones indicates an even-bounce scattering mechanism

521 of the scattered EM wave. Such a response might be due to the extinction
522 of the vertical polarization due to the canopy structure. Also, the amount of
523 odd-bounce scattering reduced during this period, and rice foliage generated
524 moderate odd-bounce multiple scattering due to which dense cluster in the
525 Z8 zone is noticed in Figure 9 and Figure 10. The contribution of multiple
526 bounce scattering was 40.02 % due to the full-grown rice crop with differently
527 oriented stem, leaf structures and flowers.

528 Around 02 Nov, the rice fields reached the early dough stage, during
529 which, the milky white substance begins to accumulate in rice panicle. Si-
530 multaneously, the crop water content during this period remains very high,
531 while leaf and stem produce overall complex canopy structure, which leads
532 to high randomness in the SAR backscatter. Due to this fact, the values of
533 $\overline{H}_{FP}$ and $\overline{H}_{CP}$ are low, which is apparent in Z2, Z5, and Z8 zones. Moreover,
534 at this point, the clusters in Z3 and Z2 zones are due to the scattering from
535 compound leaf and stem structure. In contrast, clusters in Z6, Z5, Z8, and
536 Z9 zones are due to multiple scattering contribution from the intermediate
537 complex rice canopy layer. The cluster in the Z12 zone corresponds to the
538 scattering of the wave directly from the leaves of the uppermost canopy layer.
539 During this time further decrease in even bounce scattering is evident.

540 On 26 Nov, the rice fields reached the maturity stage, and the grains
541 become firm and heavy. At this point, the crop becomes dry, whereas the
542 moisture content in grains remains $\approx 20\%$. Due to the weight of the grains,
543 lodging of rice is usually visible in the fields due to which the morphological
544 condition becomes further complicated than the dough stage. Hence, an
545 additional increase in the scattering entropy during this period is apparent

for both FP and CP SAR data. High densities of clusters in Z3, Z6, Z9, and Z12 zones can be noticed, which is due to scattering from the complex geometrical structure of rice at this stage. However, a small cluster can also be observed in the Z11 zone, which might be due to fully or partially harvested rice fields. At this stage, the highest contribution of multiple scattering mechanisms (73.23 %) is profound due to the increase in scattering randomness within the SAR resolution cell.

Table 3: Changes in the scattering mechanisms across different dates and between FP and CP data. we have considered (Z1, Z2, Z3) as even bounce scattering, (Z10, Z11, Z12) as odd bounce scattering and (Z4, Z5, Z6, Z7, Z8, Z9) as multiple bounce scattering. The dominant scattering mechanism(s) at each date is highlighted in bold font.

Dates	Modes	Even bounce scattering	Odd bounce scattering	Multiple bounce scattering	Growth Stage
05/07/2018	FP	0.90%	86.86%	12.24%	Bare field
	CP	0.60%	88.28%	11.12%	
29/07/2018	FP	76.79%	4.48%	28.73%	Early tillering
	CP	64.60%	2.10%	33.30%	
22/08/2018	FP	65.60%	2%	32.40%	Advanced tillering
	CP	63.87%	2%	34.13%	
09/10/2018	FP	58.10%	1.88%	40.02%	Flowering
	CP	56.33%	1.88%	41.79%	
02/11/2018	FP	39.40%	3%	57.60%	Early dough
	CP	31.60%	2%	66.40%	
26/11/2018	FP	25.61%	1.16%	73.23%	Maturity
	CP	16.76%	0.92%	82.30%	

It is noteworthy that the differences in the characterization capability between FP and CP SAR data depends on the type and geometry of the targets. Moreover, the spatial heterogeneity induces the changes in the intensity of the co-pol and cross-pol components. Hence, a change in the scattered EM wave is sometimes evident between FP and CP SAR data.

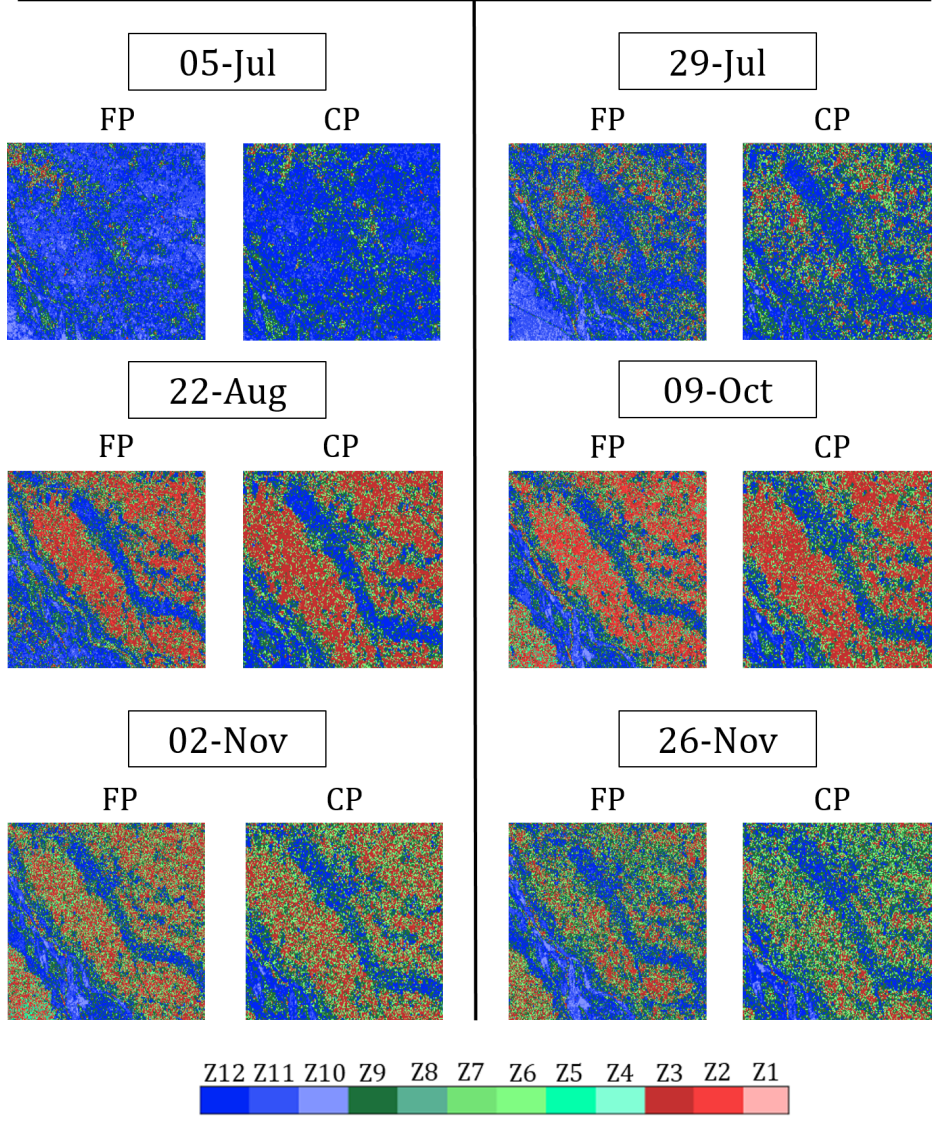


Figure 11: Variation of $\overline{H}_{FP}/\theta_{FP}$ and $\overline{H}_{CP}/\theta_{CP}$ clustered images for FP and CP over the study area. The growth stages are: 5-Jul: Bare field, 29-Jul: Early tillering, 22-Aug: Advanced tillering, 9-Oct: Flowering, 2-Nov: Early dough, and 26-Nov: Maturity

558 6. Conclusions

559 In this study, we have proposed two scattering-type parameters, θ_{FP} and
 560 θ_{CP} for identifying target scattering mechanism for both full (FP) and com-

561 pact polarimetric (CP) SAR data. These quantities are roll-invariant and
 562 vary in the range, -90° to 90° . In particular these two scattering-type pa-
 563 rameters jointly utilize the received antenna basis-invariant parameters, i.e.,
 564 the Barakat degree of polarization and the total scattering power (Span) and
 565 the elements of the coherency matrix. The two extreme values of their range
 566 correspond to even-bounce (-90°), and odd-bounce (90°) scattering mech-
 567 anisms, while $\theta_{\text{FP}} = 0$ and $\theta_{\text{CP}} = 0$ denotes diffused scattering mechanism.
 568 Furthermore, θ_{FP} and θ_{CP} within the range, -10° to 0° indicates even-bounce
 569 multiple scattering components, and 0° to 20° denotes the odd-bounce mul-
 570 tiple scattering components.

571 In this study, we have suitably fulfilled our primary objective to char-
 572 acterize changes in the scattering mechanism with the advancement of crop
 573 phenological stages. We have used the scattering-type parameters for the
 574 temporal analysis of rice over the Vijayawada test site in India using FP and
 575 CP SAR data. The sensitivities of θ_{FP} and θ_{CP} with growth stages of rice
 576 are significantly evident from this study.

577 During the initial period of the growing season, both θ_{FP} and θ_{CP} show
 578 odd-bounce scattering due to bare ground conditions. Subsequently, changes
 579 in the scattering-type from those fields were noticed depending on the sowing
 580 time, and morphological characteristics of rice. Changes in the scattering-
 581 type from odd-bounce to even-bounce at the beginning of the tillering stage
 582 from 29 Jul is adequately captured by θ_{FP} , and θ_{CP} values.

583 We observed the saturation in θ_{FP} and θ_{CP} values during the advanced
 584 reproductive stage, which was due to weak alteration of crop canopy geome-
 585 try. Later, close to the senescence stage, the response of θ_{FP} and θ_{CP} became

586 random due to the complex distribution of crop canopy and partial harvest
587 condition.

588 We have introduced novel new clustering schemes, $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$
589 in this study by utilizing θ_{FP} , θ_{CP} , and the scattering entropies, H_{FP} and
590 H_{CP} . The clustering plane is split into 12 zones, where each zone represents
591 a distinct dominant scattering mechanism. In this regard, the $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and
592 $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ clustering planes provide necessary information about targets with-
593 out any *a priori* knowledge of the scene.

594 In this context, these clustering planes was utilized to characterize phe-
595 nological stages of rice. During the initial period of the growing season, a
596 dominant odd-bounce scattering with high entropy is evident from the clus-
597 ters formed in $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ plots due to the exposed soil layer
598 for those fields. With the completion of the tillering phase, the dominant
599 cluster density moved from the high-entropy odd-bounce scattering zone to
600 the medium and multiple-even bounce high entropy scattering zones. This
601 transition among the zones could be due to the stem water interaction with
602 the incident EM wave and complex morphological characteristics of the crop
603 canopy. At the end of the crop cycle, the entropy started to increase due to
604 the complex canopy geometry. In contrast, the density of the clusters started
605 shifting from even-bounce to odd-bounce zones due to partial harvest of the
606 fields.

607 This study presents a meticulous analysis of θ_{FP} and θ_{CP} individually
608 along with $\overline{H}_{\text{FP}}/\theta_{\text{FP}}$ and $\overline{H}_{\text{CP}}/\theta_{\text{CP}}$ clustering planes for rice phenology anal-
609 ysis. Hence, these parameters are quite useful to monitor the development
610 of rice at each phenological stage. Besides, they also provide information

about changes in the scattering mechanism at different crop phenological stage. These parameters could be beneficial in providing essential information about crop conditions for engaging different cultivation measures. Therefore, further investigation to track and map crop growth stages could be conducted for different crop-types around the globe. The sensitivity of these parameters for different crop geometry could be examined for different incident angles using both FP and CP SAR data. We could adequately utilize these parameters for the newly launched RADARSAT Constellation Mission (RCM) and several upcoming missions.

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