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Improved Mapping of Flood Affected Villages in India: A Novel Three-Stage Approach Using PolSAR Polarization Signatures and Ensembled Dilated CNNs

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1 Abstract

2 During floods, updated and accurate information on affected human settlements helps save
3 lives and reduces time to rescue. Therefore, approaches that can provide reliable
4 information during floods via the use of all-weather and real-time functional technology is
5 highly needful. The study presented here attempts to efficiently and precisely map human
6 settlements in the Indian sub-continent during floods via a three-stage approach which uses
7 PolSAR data. However, the segregation of human settlements in India even with PolSAR
8 data is challenging because the built-up structures in the villages of rural India are closely
9 packed and are randomly oriented w.r.t. each other. This condition either hinders their
10 segregation or otherwise induces false alarms during extraction. More descriptive land
11 cover characterization features and powerful feature classifiers may address this challenge.
12 The study in this paper proposes a novel approach to efficiently detect and map flood
13 affected villages which utilize polarization signatures from PolSAR imagery, ensemble-of -
14 dilated-convolutions based CNNs, apriori knowledge, and image morphology. The
15 approach broadly involves three stages; –first, built-up area extraction from a PolSAR
16 image, -second, detection of villages in a built-up area image and, -third, identification and
17 mapping of villages that are affected by the flood. In the first stage, an ensemble of varying
18 dilated-convolutions based novel CNN classifier which directly utilizes PolSAR-2
19 polarization signatures (PSs) in window-mode as features are developed to extract built-up
20 areas. The second stage provides a novel village detection filter based on apriori
21 knowledge and image morphology to detect actual villages and mask out the false objects.
22 Finally, in the third stage, flood affected villages are mapped via a series of morphological
23 operations based degree-of-intersection measure. Experiments are conducted on both;
24 simulated and natural flooded area datasets. Experimental results show 81% detection
25 accuracy and 100% mapping performance of the proposed approach which indicates its
26 potential as an effective flood affected village mapping system.

27 **Keywords**— Fully polarimetric SAR, Polarization Signatures, Ensembled-Dilated-
28 Convolutions.

29

30 **1. Introduction**

31 A significant 65% of the Indian population lives in towns and villages and floods are the most
32 frequent, widespread, and damaging disasters for majority this population (*Flood Affected Area*
33 *Atlas of India - Satellite Based Study 2023*; Jain and Singh 2023). During floods in Indian
34 villages, monitoring and dissemination of rescue operations becomes both critical and
35 challenging at the same time (Mukherjee 2023). Crucial due to the fact that a large proportion of
36 population lives here and challenging because of resource constraints in these regions for
37 frequent update on the situation. A very good example of resource constraints on rural India
38 compared to urban cities is the study done by researchers in (Young et al. 2022). The study
39 highlights the difference in the social media resource exploitation for information and rescue
40 updates between major cities like Kochi and Tiruvananthapuram and other rural districts of
41 Kerala.

42 Therefore, to address this crucial but challenging task, a rapid and reliable monitoring is key to
43 minimize the loss of human lives and property in rural parts of India. An accurate and updated
44 near-real-time information of flood affected rural areas can lead to an efficient disaster
45 mitigation plans.

46 In terms of technologies for flood affected area monitoring in rural India, satellite imaging is one
47 of the most helpful and reliable technology. This resource is geographically and socially
48 unconstrained i.e same fidelity to cities and villages . Especially, the synthetic aperture radar
49 (SAR) imaging modality has proved to be a very effective and all-weather successful technology
50 for monitoring flood affected areas and planning rescue operations (Martinis et al.,
51 2015), (Giustarini et al., 2013)(Sharma et al., 2008).

52 In particular, the ability of satellite PolSAR imaging instruments to remotely sense the changes
53 in polarization states which in-turn are introduced by the “interaction” of EM waves with earth
54 surface objects (in this case, land covers).

55 For example, built-up structures usually show double bounce scattering response. It means that
56 these built-up structures appear bright (high backscattering response) in the “HH” image.

57 Whereas, tall vegetation (e.g. forests) show volume scattering response (bright in in “HV”
58 image), and smooth surfaces such as water show single bounce scattering response.

59 PolSAR imaging has also proved its popularity, significance and unique effectiveness in flood
60 monitoring and mitigation also (Pradhan et al., 2016)(Schnebele et al., 2014)(Dasgupta A. et al.,
61 2017)(Giustarini et al., 2013)

62 However, mapping human settlements during floods in India is difficult even with
63 PolSAR imagery. The built-up structures (e.g.: Houses) in these human settlements (especially in
64 villages of rural India), are closely packed and randomly oriented with respect to reach other.
65 Therefore, these villages show volume scattering response along with double bounce scattering
66 response in a PolSAR image. The mixed scattering response from these villages hinders their
67 segregation from tall vegetation in a PolSAR image (Garg and Singh, 2018; Mishra et al., 2017;
68 Phartiyal et al., 2020). Therefore, the detection and mapping of these villages during a flood
69 event is challenging even with PolSAR imagery as there is high risk of false alarms and hence
70 ineffective rescue operations. To address such challenges, raw PolSAR data has been
71 transformed and represented in different bases and forms namely decompositions, factorizations,
72 coherency, covariance etc. in various flood monitoring studies (Dasgupta A. et al., 2017;
73 Dumitru et al., 2015; Manavalan et al., 2013; Silvana and Laura, 2018). The current study

74 proposes the utilization of PolSAR polarization signatures (PSs) features for the detection and
75 mapping of villages that are affected by flood.

76 Polarization signature (PS) is a two-dimensional or 2D representation depicting
77 backscatter response from any target at a particular polarization state. Polarization signature or
78 PSs are introduced in (Kennaugh and Sloan, 1952) and has been depicted graphically by many
79 researchers in different perspectives (Bielecka et al., 2014; van Zyl et al., 1987). PSs have been
80 proved useful for characterization of land covers (Jafari et al., 2015)(Phartiyal et al., 2020). A
81 comparison of PSs-based features and decomposition-based features for land cover
82 characterization is presented in (Phartiyal et al., 2020). Their study demonstrates the significance
83 of the utilization of PSs over decomposition-based features for land cover characterization and
84 classification in mixed land cover scenarios. This is motivating since a similar scenario is at hand
85 here and therefore, the current study considers PSs as PolSAR features. Theoretical background
86 on PSs is discussed under section 2.

87 A lack of studies that directly utilize the PSs is notable although normalized signature
88 correlation mapper (NSCM), a correlation-based measure, and normalized Euclidean distance
89 (NED), a distance-based measure, are the popular PSs-derived features used in various
90 applications (de Carvalho and Meneses, 2000), (Maurya et al., 2016).. This is because of the fact
91 that PSs are two dimensional features and a two-dimensional feature extractor would be more
92 efficient to exploit it. As of today, convolutional deep neural networks (CNNs) are one of the
93 most popular, efficient, and powerful image (two-dimensional) feature extractors. Their unique
94 characteristic of “local connectivity” and “parameter sharing” makes them best tools to extract
95 complex and localized features from images (Yann LeCun et al., 2015). Authors in (Phartiyal et
96 al., 2019) explored the significance of CNNs as PSs feature extractors and indicated to the

97 potential of PSs and CNN based models in other applications. However, more detailed study is
98 required to this end. Therefore, the current study extensively explores the utilization of CNNs as
99 PS feature extractors in order to map flood affected human settlements with PolSAR imagery.
100 The current study also explores the [p;arization signature sub-space via dilated convolutions and
101 aggregates the different convolutions to achieve better performance.

102 To summarize, this paper presents a novel approach to detect and map villages affected
103 by a flood with the help of PolSAR PSs, CNNs, *apriori* knowledge and image morphology. The
104 novel approach involves three stages. These are;

105 –*first*, design and development of PSs based novel CNN model for extraction of built-up
106 areas from PolSAR image which contains the flooded region,

107 –*second*, development of methodology for design of village detection filters based on *apriori*
108 knowledge and image morphology and,

109 –*third*, development of another methodology for identification, and mapping of flood
110 affected villages using image morphology.

111 This paper is divided into following sections. The fundamentals of the CNNs and the PSs
112 are discussed in section 2. Section 3 provides detailed information on the materials used which
113 involves study areas and datasets considered, and ancillary information collected for the study.
114 Section 4 discusses the three-stage approach development for mapping flood affected villages.
115 Qualitative and quantitative evaluation of the results is also in this section. At last, section 5
116 concludes the study.

117 **2. Theoretical Background**

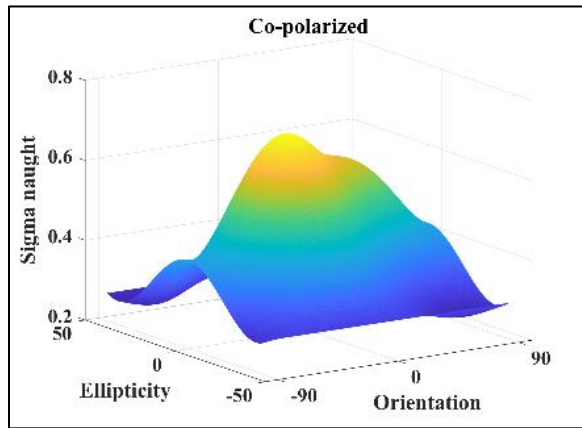
118 *Polarization Signatures*

119 Polarization signature (PS) is a peculiar representation of backscattering behaviour of a target, or
 120 in the case of current study, a land cover. PSs are a two-dimensional in nature. In a polarization
 121 signature representation, the y -axis and the x -axis represent orientation angle and ellipticity angle
 122 respectively and the z -axis represent the received backscattered power coefficient (σ°). The tilt
 123 or orientation angle (ψ) spans from -90° to 90° whereas the ellipticity angle (χ) spans from -45°
 124 to 45° . The signatures are computed using equation (1). The ellipticity angle represents to the
 125 polarization behaviour (i.e. elliptical, circular or linear polarization). On the other hand, the
 126 orientation or tilt angle represents to the polarization states (i.e. either horizontal polarization or
 127 vertical polarization (Jong-Sen Lee et al., 1997)).

128
$$\sigma (\chi_l \psi_l \chi_m \psi_m) = \frac{4\pi}{k} \begin{pmatrix} 1 \\ \cos 2\chi_l \cos 2\psi_l \\ \cos 2\chi_l \sin 2\psi_l \\ \sin 2\chi_l \end{pmatrix} (\mathbf{K}) \begin{pmatrix} 1 \\ \cos 2\chi_m \cos 2\psi_m \\ \cos 2\chi_m \sin 2\psi_m \\ \sin 2\chi_m \end{pmatrix} \quad (1)$$

129 where σ represents backscattering coefficient, suffix m and l represent received and
 130 transmit combinations respectively. Given the polarization characteristics of the receiving
 131 antenna, \mathbf{K} i.e. the Kennaugh matrix, represents the received power (Antenna Laboratory, 1952).
 132 It is alternatively termed as the Stokes scattering operator or the Stokes scattering matrix.
 133 Computation of the kennaugh parameters is done similar to (Harold, 2007). Further, k is the
 134 propagation constant. Two variants of PSs are computed namely co-polarized polarization
 135 signatures and cross-polarized polarization signatures.

136 The co-polarized signature is calculated via a transmit and receive settings of $\psi_l = \psi_m$
 137 and $\chi_l = \chi_m$, whereas the cross-polarized signature is calculated via a transmit and receive
 138 settings of $\psi_l = 90^\circ + \psi_m$, and $\chi_l = -\chi_m$. Figure 1 is the co-polarized PS of a sample of a land
 139 cover.



140
 141 **Figure 1** Land cover class sample co-polarized signature.

142 ***Convolutional Neural Networks***

143 Convolutional neural networks have become a popular neural network type that utilizes the deep
 144 learning technology very well. Fundamental CNN models were proposed in (Ian Goodfellow et
 145 al., 2017)(Ciresan et al., 2012) (Fukushima and Miyake, 1982) (LeCun et al., 1998)(Zhang et al.,
 146 1991) in the early stages but have quite matured now. For the sake of completeness, the building
 147 blocks but not limited to of a conventional CNN are listed here. These are: a convolutional layer
 148 with kernel size, activation function, strides and dilation strategy settings, a pooling layer with
 149 strides and dilation strategy settings, a dropout layer with dropout fraction, a fully connected
 150 layer with node count and activation function, and a loss layer.

151 Imagine a CNN with L layers (including pooling, dropout, or loss), the state vector of the
 152 output of the l^{th} convolutional layer is denoted by \mathbf{o}^l , where $l = \{1, 2, 3, \dots, L\}$ and \mathbf{o}^0 represents
 153 the input. Let's say the input is passed onto to a 1D, 2D or 3D convolutional layer based on
 154 application. The convolution also intakes a kernel size, filter count, stride and dilation strategy,
 155 and activation function. For the sake of reader's interest, a 2D convolution is elucidated here.
 156 The convolution plus pooling in the l^{th} layer is represented in equation (2).

$$157 \quad \mathbf{o}^l = \text{pool}(g(\mathbf{o}^{l-1} \otimes \mathbf{W}_l + \mathbf{b}_l)) \quad (2)$$

158 where, \otimes indicates to the convolution operation and *pool* denotes to a spatial
 159 aggregation strategy. Weights of the links connecting the $(m - 1)^{\text{th}}$ convolutional layer to the
 160 m^{th} layer resides in the matrix \mathbf{W}_l whereas the vector \mathbf{b}_l is the bias term. A non-linear pointwise
 161 activation function $g(\cdot)$ is applied Subsequently. For the selection of dominant features, finally, a
 162 pooling layer is placed with a certain window.

163 If required, any number of convolutional and/or pooling layers queued in any order to
 164 constitute a feature extraction architecture that is hierarchical in nature. The last convolution or
 165 pooling layer features are reprojected to a one-dimensional feature. Further, this feature is input
 166 to a "fully connected" or alternatively termed as "dense" layer which can be perceived as a
 167 typical multi perceptron layer. At the end of a CNN network, the final layer is usually a dense
 168 layer with either a "linear" activation function (for "regression" scenarios) or a dense layer with
 169 a "SoftMax" activation function (for "classification" scenarios) layer. The node count at this
 170 layer matches the number of outputs desired.

171 The weights, $\{\mathbf{W}_1, \mathbf{W}_2, \dots, \mathbf{W}_L\}$ and the biases, $\{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_L\}$ of the CNN represents the
 172 parameters of the model. These are learned iteratively and optimized jointly via objective (e.g.

173 overall accuracy in case of classification) optimization over constraints such as “training” set.
174 Equivalently, models can be realized for 1D or 3D convolution application scenarios.

175 The aforementioned network in whole, still expresses a single differentiable score
176 function from the 2D input on one end to class scores at the other. The property that 2D CNN
177 architectures make the explicit assumption that the inputs are images. As explored and utilized
178 in the case of PSs in this study which allows encoding certain properties into the architecture.
179 This in turn make the proceeding operations and functions more efficient. CNNs with deep
180 learning have found their application in PolSAR data as well (Zhu et al., 2017).

181 **Materials and Methods**

182 *Study Area*

183 For critical analysis, development and evaluation of the proposed three-stage approach, three
184 sites are considered. The first study area is the “Roorkee” city which is situated near the “Rajaji”
185 national park at the foothills of the great Himalayas. This study area spans from $29^{\circ}48'10''N$
186 latitude, $78^{\circ}4'5''E$ longitude to $29^{\circ}57'4''N$ latitude, $77^{\circ}51'54''E$ longitude. It covers around 361
187 km^2 of landscape including multiple land covers. This study area is termed as ‘Roorkee’ study
188 area in this paper. Figure 2(a) shows a true colour Google Earth image of Roorkee. Another
189 study area is the Haridwar city and its neighbouring region. This area extends from $29^{\circ}49'23''N$
190 latitude, $78^{\circ}10'5''E$ longitude to $29^{\circ}58'23''N$ latitude, $77^{\circ}49'52''E$ longitude. The area amounts
191 to about 270 km^2 of landscape again including multiple land covers such as the river Ganges.
192 This second study area is termed as ‘Haridwar’ study area in this article. Figure 3(a) shows a true
193 colour Google Earth image of Haridwar. The third study area is considered for validation of the
194 developed approach. This study area is Patna and neighbouring region which were affected

195 during the ‘Bihar 2016’ floods.

196 *Satellite Data*

197 For the Roorkee and Haridwar study regions, raw single look complex SAR data acquired by the
198 JAXA’s PALSAR-2 L-band fully polarimetric SAR instrument onboard the ALOS-2 satellite on
199 March 13, 2015 is considered. The raw “single look complex” PolSAR data is multilooked,
200 speckle filtered, calibrated, and terrain corrected in that order to obtain backscattering (σ°)
201 coefficients (Phartiyal et al., 2017). Speckle filtering with “Gamma MAP” polarimetric filter is
202 performed analogous to (Mishra et al., 2017) with a 3×3 window size. Calibration and terrain
203 correction are performed in method similar to (Phartiyal et al., 2017). Four features namely HH,
204 HV, VH, and VV are achieved. Intuitively, VH and HV are identical and therefore redundant,
205 only HH, VH, and VV are considered further. Figure 2(b) shows a false colour image of the pre-
206 processed Roorkee dataset and Figure 3(b) shows a false colour image of the pre-processed
207 Haridwar dataset. In addition, for the Patna study area, PALSAR-2 PolSAR image acquired on
208 September 3, 2016 is considered as validation data.

209 *Ground Truth*

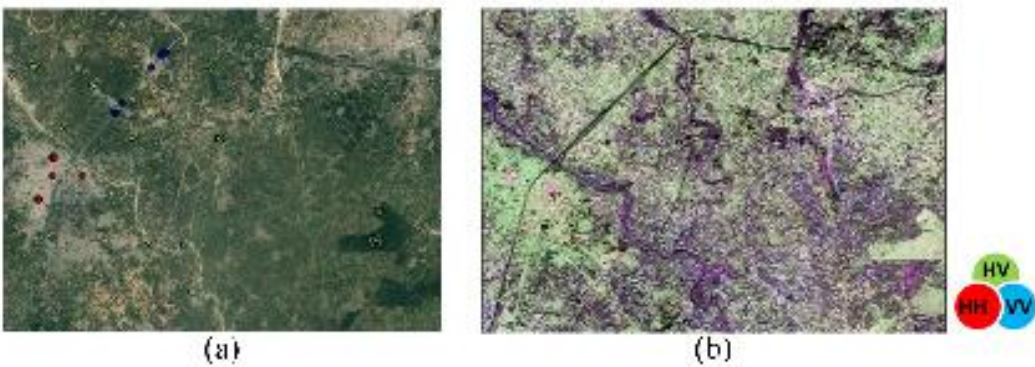
210 Ground truth is collected on two counts. First, ground truth sample points are collected for
211 classifier training and validation. Bare soil (BS), built-up, tall vegetation (TV), short vegetation
212 (SV), and water are the five land cover classes considered. On the basis of visual inspection,
213 ground truth class sample points are measured directly on the terrain. A total of 1200 data points
214 are collected separately for two i.e. Roorkee, and Haridwar study areas. More details of the
215 ground truth survey are shown in Table 1.

216 Second, the total number of villages (a common term opted here to represent all types of
217 human settlements in the study region) in each study area are counted for validation of the
218 proposed approach. Table 1 also lists the actual number of villages in the Roorkee and Haridwar
219 study areas. Further, Figure 4 highlights the villages in the Roorkee and Haridwar study regions
220 captured from Google Earth imagery. Any village in the rural parts of India consists of a
221 minimum of 30 houses and is spread over a minimum area of 5000 m². These physical
222 dimensions help in detection of villages in a PolSAR image

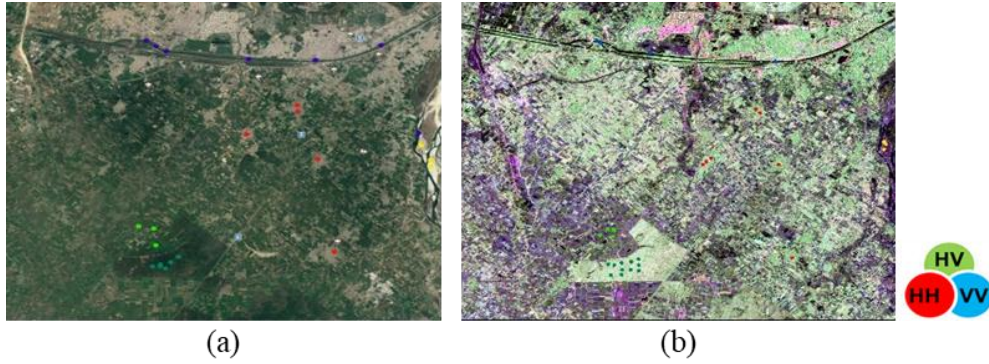
223 It is important to note here that in this paper; different terminologies have been used at
224 different stages to represent different versions of built-up areas. Basic terminologies are defined
225 here.

- 226 • Built-up structure: Man-made structures.
- 227 • Built-up area: A collection of built-up structures.
- 228 • Village or town: Built-up area larger than a predefined size.
- 229 • Object: A connected group of image pixels.
- 230 • Detected villages: Villages that have been successfully detected
- 231 • Flooded villages: Villages that are affected by flood

232 These terminologies help to better understand the different stages of the study.



233
234 Figure 2. (a): Imagery of the Roorkee collected from Google Earth with major land cover classes
235 marked. (b): FCC of the pre-processed March 13, 2015 PolSAR data.



236

237

238

239

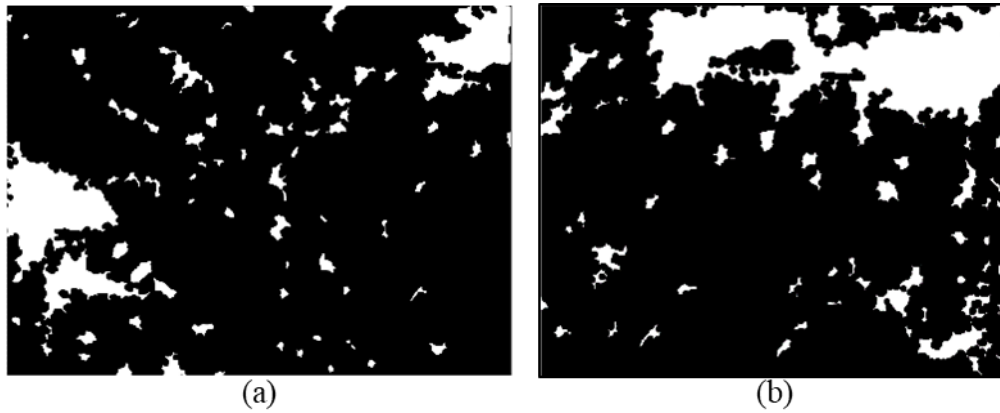
240

Figure 3. (a): Imagery of the Haridwar collected from Google Earth with major land cover classes marked. (b): FCC of the pre-processed March 13, 2015 PolSAR data.

Table 1 Ground survey details. TV = Tall Vegetation, *BS =Bare SOIL, SV = Short Vegetation, BU= Built-Up.

LC Class	Roorkee		Haridwar	
	Training	Testing	Training	Testing
Bare Soil (BS)	201	39	201	39
Tall Veg (TV)	201	39	201	39
Short Veg (SV)	201	39	201	39
Built-Up (BU)	201	39	201	39
Water	201	39	201	39
Total	1005	195	1005	195
Total number of villages in Roorkee region	93			
Total number of villages in Haridwar region	60			

241



242

243

244

Figure 4. Areas highlighted in white are villages in the (a) Roorkee and, (b) Haridwar study area.

245 **Approach, Results, and Discussion**

246 This section discusses the development of the proposed novel approach to detect, identify, and
247 map flood affected villages in a PolSAR image. The overall approach is divided into three
248 stages.

249 In the first stage, design and development of a PSs based CNN model for extraction of
250 built-up areas from PolSAR image is done. This stage is discussed in sections 4.1 and 4.2. Model
251 performance evaluation and comparisons are also discussed in section 4.2.

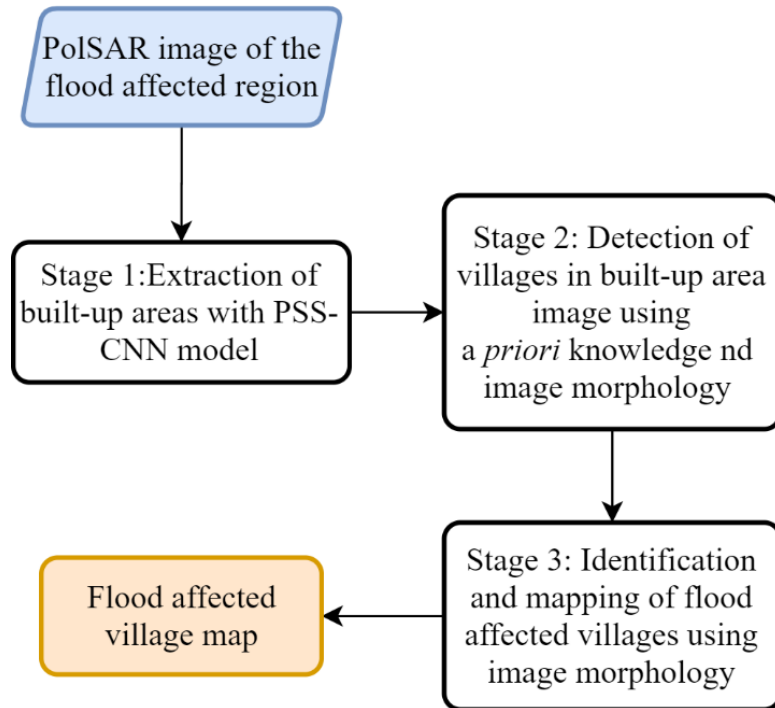
252 In second stage, development of a novel methodology, for designing “village detection
253 filters” based on *apriori* knowledge and image morphology, is discussed. These filters help in
254 detection of villages in a ‘built-up’ class image extracted from classification image (stage-1) and
255 also help suppress false alarms. Section 4.3.1 covers the development of this methodology.
256 Evaluation of the detection performance of this methodology is also covered in section 4.3.1.

257 Finally, in the third stage, development of methodology, for identification and mapping
258 of villages that are affected by flood and masking out villages that are not, is discussed. This
259 methodology exploits the phenomena of ‘enclosed’ that happens when a village is surrounded by
260 water (flooded from all sides). Section 4.3.2 discusses the development of this methodology.
261 Evaluation of this methodology is discussed in section 4.3.2. The three methodologies, proposed
262 in the three stages above, sum up to provide a novel ‘flood affected village detection and
263 mapping’ approach. Flowchart shown in Figure 5 depicts the overall proposed approach.

264 ***Land Cover Polarization Signatures***

265 Based to the discussion in section 2.1, both co-polarized signatures and cross-polarized
266 signatures are computed from PolSAR data using equation (1). Co-polarized PS plots for

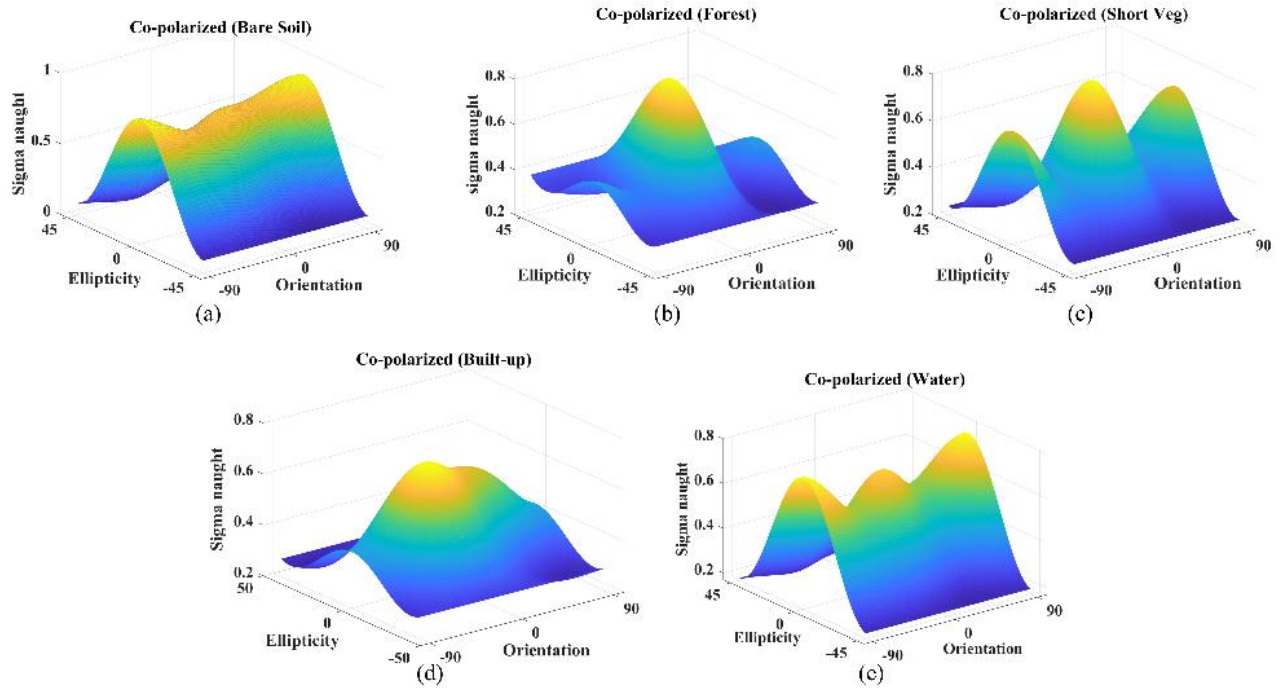
267 considered land cover class (averaged over all class samples, refer to Table 1) are shown in
 268 Figure 6. Backscatter power response shown in Figure 6 is plotted for orientation angle ψ range (
 269 -90° degree to $+90^\circ$) degree and ellipticity angle χ range (-45° degree to $+45^\circ$) degree and a step
 270 size of 5° degree in each direction. This results in a 18×37 two-dimensional feature space. It is
 271 evident from figure 6 that PSs of considered land covers are different from each other.



272

273 **Figure 5.**Flowchart of the proposed approach

274



275

276 Figure 6 Land cover class co-polarized PSs. (a). Bare Soil, (b). Forest, (c). Ground Vegetation,
 277 (d). Built-up, and (e). Water

278 ***Stage 1: PolSig-CNN Classification Model for Built-Up Area Extraction***

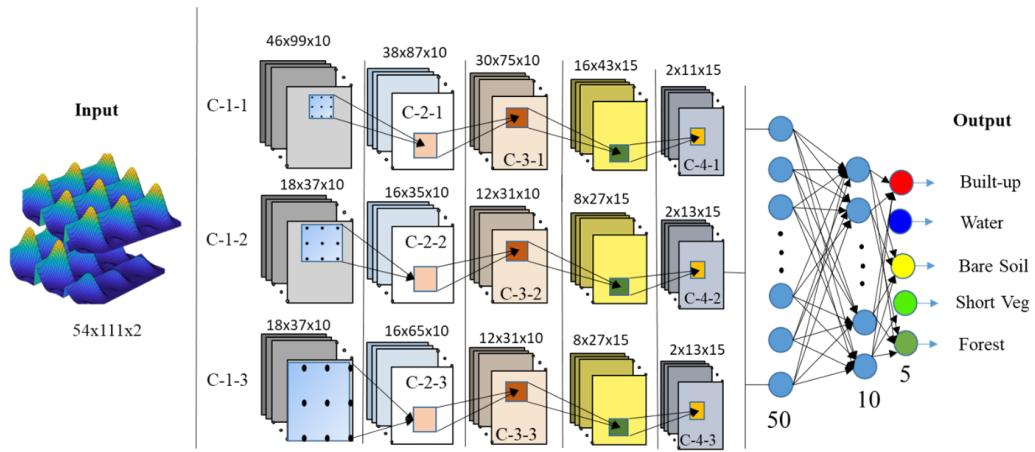
279 PSs based features have been used for land cover characterization and classification in many
 280 studies. Classifiers in (Phartiyal et al., 2017), (Jafari et al., 2015) and (Maurya et al., 2016) used
 281 PSs based distance/correlation one-dimensional features which do not consider the two-
 282 dimensional neighbourhood during classification and therefore PSs remain under-utilized.

283 A PSs based CNN classifier is introduced here which explores and extends to more
 284 effective utilization of PSs directly with CNNs in order to extract built-up areas from PolSAR
 285 images. In this stage, a CNN model is developed to directly utilize PSs as features for built-up
 286 area extraction from PolSAR imagery. The proposed CNN model is termed as ‘PolSig-CNN’
 287 model from here onwards in this paper and, its configuration is provided in Table 2. A two-
 288 dimensional spatial window of PSs is used as input. The window-based approach, via averaging,

289 helps suppresses the random volume scattering responses generated from closely packed built-up
290 structures in built-up areas. This in turn improves the segregation of these built-up areas. A 3×3
291 window of neighbouring PSs is considered. This corresponds to a 54×111 (refer section 4.1)
292 matrix/image as input to the PolSig-CNN model. This 54×111 input image has two channels i.e.
293 *copol*, and *crosspol*. Therefore, the overall size of the input to the PolSig-CNN is $54 \times 111 \times 2$. The
294 PolSig-CNN used five convolutional layers and three parallel convolutions with different
295 dilation rates. The parallel convolutions with varied dilation rates helps to extract localized
296 polarization feature sub-spaces. This should improve classification performance. The output from
297 these varied convolutions are finally concatenated before connecting to fully connected layers.
298 The number of convolution filters and kernel sizes used in each layer are listed in Table 2. *ReLU*
299 activation function and *Dropout fraction* of 10% is used in each convolutional layer. The dropout
300 regularization strategy is employed to reduce overfitting and achieve better generalization
301 (Srivastava et al., 2014). Further, two *Fully Connected* (FC) layers, first with 50 nodes and
302 second with 10 nodes are used. Both FC layers used the *ReLU* activation function and a *Dropout*
303 *fraction* of 10%. Finally, a *SoftMax* classification layer with 5 output labels is used. The five
304 output labels are; built-up (BU), water, bare soil (BS), tall vegetation (TV), and short vegetation
305 (SV). A *batch normalization* process is carried out before the convolutions to speed up the
306 training process and to reduce the network sensitivity. Overall, an eight layered PolSig-CNN
307 classification model is realized as shown in Figure 7.

308 Table 2 Summary of PolSig-CNN model configuration, training and hyperparameter settings. *F = Filters, K = Kernel size, D =
 309 Dilation rate

Layer ↓	Nodes						Hyperparameters settings	
Input ↓	Input image size = $54 \times 111 \times 2$, a 3×3 spatial window with 2 (co- and cross-polarized signatures) Normalization = Batch Normalization						Number of epochs = 200 Learning rate = 0.01 Optimizer = Adam Loss function = Categorical cross entropy	
Convolution	F, K, D*	Convolution	F, K, D*	Convolution	F, K, D*	Activation, DF		
C-1-1	10, 9×13 , 1×1	C-1-2	10, 5×6 , 9×18	C-1-3	10, 3×3 , 18×37	ReLU, 0.1		
C-2-1	10, 9×13 , 1×1	C-2-2	10, 3×3 , 1×1	C-2-3	10, 3×3 , 1×1			
C-3-1	10, 9×13 , 1×1	C-3-2	10, 5×5 , 1×1	C-3-3	10, 5×5 , 1×1			
C-4-1	15, 15×33 , 1×1	C-4-2	15, 5×5 , 1×1	C-4-3	15, 5×5 , 1×1			
C-5-1	15, 15×33 , 1×1	C-5-2	15, 6×15 , 1×1	C-5-3	15, 6×15 , 1×1			
Fully connected	Filters							
FC1	50							
FC2	10							
Output layer	5							SoftMax



310

311 Figure 7 Architecture of the proposed PolSig-CNN model.

312 The developed PolSig-CNN model is trained on labelled samples collected via ground survey
 313 (refer Table 1). The choice of loss function during training is the “*categorical cross entropy*”
 314 function. The *learning rate* is set to 0.01 and the number of training *epochs* is set to 200. For
 315 network weight optimization, “*Adam*” optimizer is chosen. Model architecture and
 316 hyperparameters are set similar for Roorkee and Haridwar datasets for consistency purposes and
 317 are listed in Table 2.

318 Figure 8(a) and figure 8(c) shows the classified image for Roorkee and Haridwar via the
 319 PolSig-CNN model. The model’s classification performance is compared with two popular
 320 feature-classifier pairs that are mostly used with PSs in land cover classification. The first is the
 321 normalized signature correlation mapper (NSCM) feature with maximum value classifier and the
 322 second is the normalized Euclidean distance (NED) feature with minimum distance classifier.
 323 Signature correlation mapper or SCM is a cross correlogram constructed by calculating the
 324 cross-correlation between two polarimetric signatures. The SCM obtained from the Pearson
 325 correlation coefficient and varies from -1 to 1 . The SCM between two signatures p_1 and p_2 is
 326 given by equation (3).

$$327 \quad S(p_1, p_2) = \left(\frac{m \sum_1^m p_1 p_2 - \sum_1^m p_1 \sum_1^m p_2}{\sqrt{\left[m \sum_1^m p_1^2 - \left(\sum_1^m p_1 \right)^2 \right]} \sqrt{\left[m \sum_1^m p_2^2 - \left(\sum_1^m p_2 \right)^2 \right]}} \right) \quad (3)$$

328 where m is the number of polarization states (Jafari et al., 2015)(de Carvalho and
 329 Meneses, 2000). NSCM is obtained by normalizing the range of SCM between 0 and 1 using
 330 equation (4).

$$331 \quad S_N = 0.5*(S + 1) \quad (4)$$

332 Euclidean distance (ED) is the distance metric which provides a quantitative measure of
333 the distance between vectors representing the two polarimetric signatures, and it reflects the
334 dissimilarity between the polarimetric signatures (Gower, 1985) (Jafari et al., 2015). The
335 Euclidean distance between two signatures p_1 and p_2 is given by equation (5).

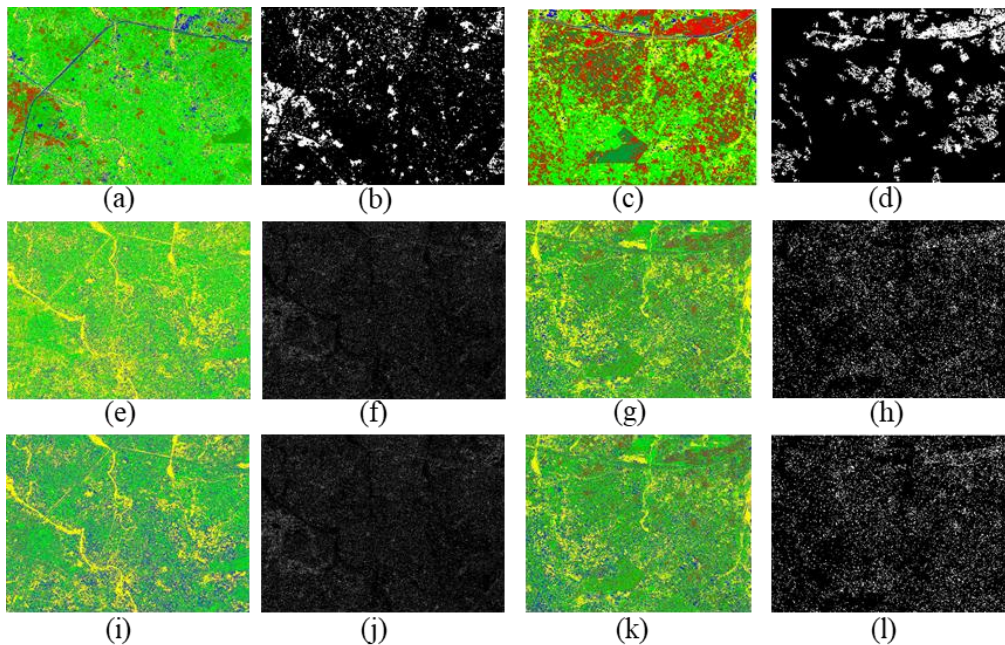
$$336 \quad D(p_1, p_2) = \sqrt{\sum_1^m (p_1 - p_2)^2} \quad (5)$$

337 where m is the number of polarization states. Further, NED is the normalized version of
338 ED. Both NSCM and NED have been utilized for land cover characterization (Jafari et al., 2015)
339 and for land cover classification (Maurya et al., 2016).

340 Figure 8(e) and 8(g) shows classified images using the NSCM as features for Roorkee
341 and Haridwar respectively whereas figure 8(i) and 8(k) shows the classified images using the
342 NED as features for Roorkee and Haridwar respectively. It is evident from Figure 2, Figure 3,
343 and Figure 8(a, c, e, g, i, and k) that the PolSig-CNN classifier outperforms the NSCM-max-
344 correlation classifier and the NED-min-distance classifier on both, the Roorkee, and the
345 Haridwar datasets. Because of the point-wise operability, the limitation of the NED and NSCM
346 classifiers (termed in short) to capture and exploit the two-dimensional neighbourhood
347 relationship of a PS pixel and thereby are not able to efficiently segregate the built-up areas as
348 also discussed in section 1. The developed PolSig-CNN extracts and utilizes the subtle
349 differences in the PSs of built-up and forest and successfully separates the two and hence
350 resolves the issue significantly. It is evident from Figure 8(a) & 8(c) that PolSig-CNN classifier
351 is successful in segregating the two classes. Built-up class is extracted from the PolSig-CNN,
352 NSCM, and NED classified images of and are shown in Figure 8 (b, d, f, h, j and, l). From Figure

353 8 (b, d, f, h, j and, l), it is evident that the PolSig-CNN is able to segregate the built-up class very
354 efficiently.

355 Table 3 summarizes the quantitative assessment of classification performance of the
356 PolSig-CNN, NSCM, and NED classifiers for Roorkee and Haridwar datasets. The PolSig-CNN
357 classifier performs land cover classification with good overall accuracies, i.e. 72% for Roorkee
358 and 75.5% for Haridwar dataset. In contrast, the NED performed the classification with 62.5 %
359 and 59.5% overall accuracy and, the NSCM performed the classification with 64% and 66%
360 overall accuracy for the Roorkee and Haridwar dataset respectively. Both NED and NSCM
361 showed low kappa values (refer table 3) whereas the kappa for PolSig-CNN is satisfactory.
362 Furthermore, the PolSig-CNN classifier successfully segregates the built-up class. The built-up
363 class is segregated with 83.7% user and 77.5% producer accuracies for Roorkee and 82.5% user
364 and 82.5% producer accuracies for Haridwar which supports the visual interpretations.



365
366 Figure 8. Roorkee classified image obtained using; (a). the PolSig-CNN classifier, (e). the NED
367 classifier and, (i); the NSCM classifier. Areas classified as Built-up in Roorkee dataset using;

368 (b). the PolSig-CNN classifier, (f). the NED classifier and, (j). the NSCM classifier. Haridwar
 369 classified image obtained using; (c). the PolSig-CNN classifier, (g). the NED classifier and, (k);
 370 the NSCM classifier. Areas classified as Built-up in Haridwar dataset using; (d). the PolSig-CNN
 371 classifier, (h). the NED classifier and, (l). the NSCM classifier.

372 Table 3 Summary of the classification performance of classifiers for Roorkee and Haridwar
 373 datasets. OA = overall accuracy, UA = user accuracy, PA = producer accuracy

Dataset/Study area	Method	OA (%)	Kappa	Class	UA (%)	PA (%)
Roorkee	PolSig-CNN	72.0	0.69	BS	65.91	72.5
				TV	84.21	80
				SV	56.00	70
				BU	83.78	77.5
				Water	77.42	60
	NSCM	64.0	0.57	BS	59.18	72.5
				TV	72.73	60.0
				SV	50.00	70.0
				BU	75.76	62.5
				Water	75.86	55.0
	NED	62.5	0.53	BS	57.45	69.2
				TV	70.59	60.0
				SV	48.21	67.5
				BU	78.13	62.5
				Water	73.33	55.0
Haridwar	PolSig-CNN	75.5	0.72	BS	65.9	72.5
				TV	75.6	77.5
				SV	72.2	65.5
				BU	82.5	82.5
				Water	82.0	80.5
	NSCM	66.0	0.58	BS	65.9	72.5
				TV	72.9	67.5
				SV	48.1	65.0
				BU	75.8	55.0
				Water	77.7	70.0
	NED	59.5	0.52	BS	54.17	66.6
				TV	70.59	60.0
				SV	45.00	67.5
				BU	75.86	55.0
				Water	71.43	50.0

374 *Detection and Mapping of Flood Affected Villages using Apriori Knowledge and Image*
375 *Morphology*

376 This section presents post classification methodologies based on *apriori* knowledge and image
377 morphology to map the villages affected by flood. Flood affected village maps are obtained
378 using the built-up area image obtained in stage 1. This section covers stage 2 and stage 3 of the
379 proposed approach. The methodology presented under stage 2 detects villages in the built-up
380 area image from section 4.2. This methodology utilizes *apriori* knowledge and image
381 morphology to build village detection filters. Binary morphological image processing is well
382 suited in this case because of the type of outputs produced in stage 1 and the suitability of
383 morphological operations to operate on this data (Zou et al., 2020). These filters detect villages
384 in the built-up area image and significantly remove false alarms or misclassifications.

385 Development of this methodology is discussed under stage 2 in section 4.3.1.

386 Stage 3 presents a methodology which further identifies and maps villages that are
387 affected by flood and mask out villages that are not affected by flood from the total villages
388 detected in stage 2. This methodology also utilizes image morphology to map flood affected
389 villages. Development of this methodology is discussed in section 4.3.2.

390 *Stage 2: Village Detection*

391 The focus of this stage is to detect villages in the built-up area image obtained in stage 1 (refer
392 section 4.2). Here, at first, the built-up area image – a binary image – is cleaned before detection
393 because the image might contain objects (built-up areas) that are close to each other and could be
394 part of same village or, there might be objects with holes in them which is undesirable. These
395 artefacts could lead to inaccurate detection of villages. Therefore, a series of morphological
396 operations are utilized to clean the binary image. The objects or components which are close to

397 each other, are merged together at first using a morphological image *closing* filter provided in
398 equation (6).

$$399 \quad \mathbf{I}_{\text{closed}} = (\mathbf{I} \oplus \mathbf{S}) \ominus \mathbf{S} \quad (6)$$

400 where, $\mathbf{I}_{\text{closed}}$ is the closed image, \mathbf{I} is the image on which the morphological closing
401 operation is to be performed, \mathbf{S} is the structuring element used in the closing operation, and \oplus &
402 \ominus represents the morphological dilation and erosion operations respectively. The vicinity, within
403 which two objects can be merged together is set via the size of the structuring element parameter.
404 The vicinity is set based on an *apriori* knowledge of the approximate minimum distance between
405 two villages and PolSAR image pixel resolution.

406 The approximate minimum distance between two villages is set to 200 meters based on
407 ground surveys, geographical metadata. Since, the ALOS PALSAR-2 PolSAR data considered in
408 this study has 6-meter spatial resolution. Therefore, \mathbf{S} is set as a disc of 15 pixels' diameter (100
409 meters) and two objects within this distance are merged as one. However, similar relationship
410 can be modelled with other PolSAR imagery. Figure 9(b) depicts the effects of closing operation.
411 It can be observed from figure 9(b) that some objects are merged together.

412 Next, the holes in the objects in the $\mathbf{I}_{\text{closed}}$ image are to be filled. The holes are filled
413 using equation (7).

$$414 \quad \mathbf{I}_{\text{filled}} = \mathbf{I}_{\text{closed}} \cup \mathbf{X}_k \quad (7)$$

415 where, $\mathbf{I}_{\text{filled}}$ is the image with holes filled, $\mathbf{I}_{\text{closed}}$ is the image with holes obtained from
 416 equation (6), \cup is the *union* operator, and \mathbf{X}_k is obtained through iterative process governed by
 417 equation (8),

$$418 \quad \mathbf{X}_k = (\mathbf{X}_{k-1} \oplus S) \cap \mathbf{I}_{\text{complement}} \quad (8)$$

419 where again, \mathbf{X}_0 is the $\mathbf{I}_{\text{closed}}$ image, S is the connectivity and, $\mathbf{I}_{\text{complement}}$ is the
 420 negative of $\mathbf{I}_{\text{closed}}$. Figure 9(c) depicts the result of the hole filling operation.

421 Finally, an area limit is set to filter out objects that are not villages. The idea is that if any
 422 object is to be a village, it must have at least 5000 m² of ground area. The area limit is established
 423 based on *a priori* knowledge of the Indian rural human settlements. An area limit (A_L) of 5000
 424 m² (140 pixels approx. in case of PALSAR-2 image considered here) is set. Equation (9)
 425 demonstrates the process of filtering objects based on its area.

$$426 \quad (O_k)_{\text{filtered}} = \begin{cases} 1 & \text{if } (O_k)_{\text{filled}} > A_L \\ 0 & \text{if } (O_k)_{\text{filled}} < A_L \end{cases} \text{ for } k = 1, 2, \dots, N \quad (9)$$

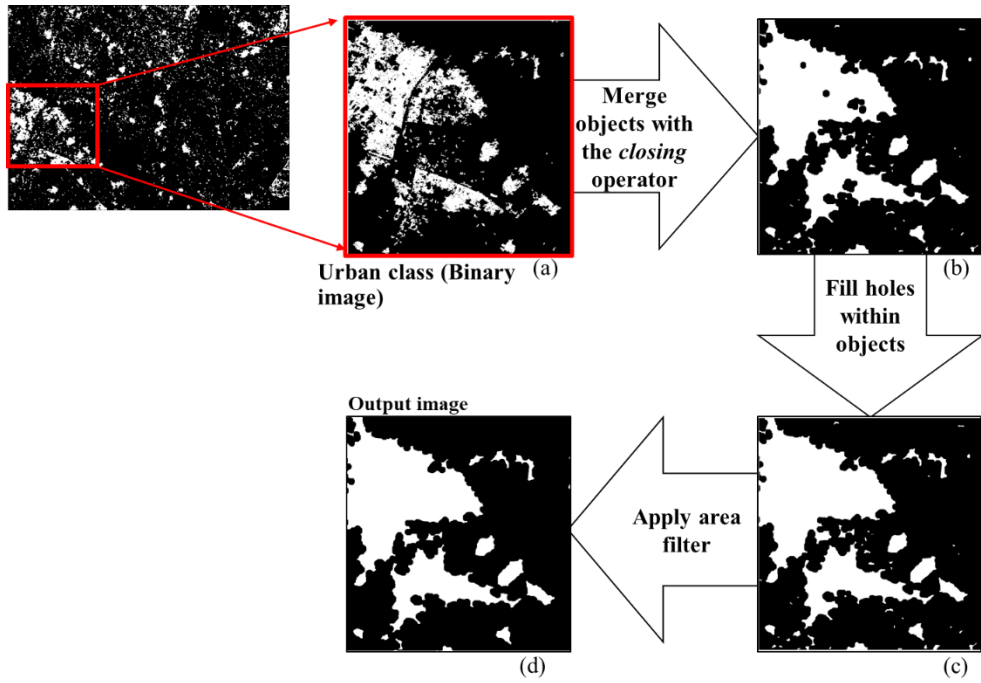
427 where, $(O_k)_{\text{filtered}}$ is the k^{th} object in the filtered image and $(O_k)_{\text{filled}}$ is the k^{th} object in
 428 the $\mathbf{I}_{\text{filled}}$ image, A_L is the area limit and, N is the total number of objects in $\mathbf{I}_{\text{filled}}$ image.
 429 Figure 9(d) depicts output of the area-based filtering. It is observed from Figure 9(d) that many
 430 unwanted objects have been removed successfully. The objects remained in the filtered image
 431 are successfully detected as villages. In summary, the closing, hole filling, and the area filter

432 operations in sequence act as a ‘village detection filter’ which detects villages in a built-up area
433 image and mask out false alarms or misclassifications.

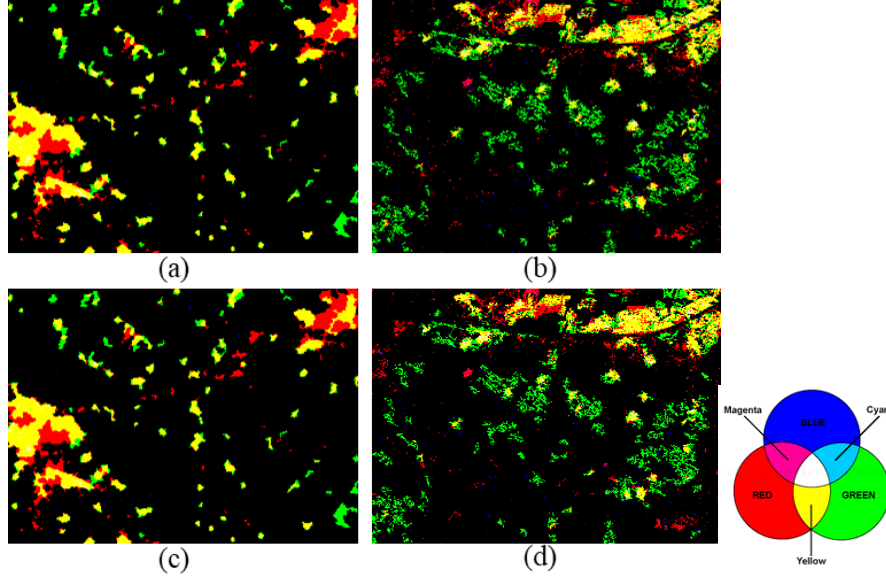
434 This village detection filter is applied to the built-up area images of the PolSig-CNN,
435 NSCM, and NED. Output images after applying the village detection filter are shown in Figure
436 10. These output image(s) contain only the successfully *detected villages* and are termed as
437 “DV” image(s) hereafter in this article. The DV images corresponding to the PolSig-CNN,
438 NSCM, and NED classifiers are assessed using reference images. The reference images contain
439 all the villages in the corresponding study areas. The reference images for both Roorkee and
440 Haridwar are provided in section 3.3. Figure 10 shows false colour composites (FCC) of the DV
441 images for Roorkee and Haridwar areas. In Figure 10(a), red colour objects are objects in
442 reference image (actual villages), green colour objects are villages as per the $DV_{\text{PolSig-CNN}}$, and
443 blue colour objects are villages as per the DV_{NED} .

444 Further, white colour objects are objects which are present in all three images i.e. the
445 reference image, the $DV_{\text{PolSig-CNN}}$ image, and the DV_{NED} image. It means that the object is
446 actually a village and is correctly extracted by both, the PolSig-CNN and the NED classifiers.
447 Yellow colour objects are villages as per the reference and the PolSig-CNN but not as per the
448 NED. Cyan colour objects are villages as per the reference and the NED but not as per the
449 PolSig-CNN. The abundance of yellow colour in Figure 10(a) indicates to the efficient extraction
450 of built-up areas by the PolSig-CNN classifier. Similarly, the $\text{reference-D}V_{\text{PolSig-CNN}}-\text{D}V_{\text{NSCM}}$
451 false colour composite for Roorkee shown in Figure 10(c) evidences the better performance of
452 the proposed PolSig-CNN classifier in built-up area extraction.

453 However, the reference- $D V_{\text{PoISig-CNN}} - D V_{\text{NED}}$ and the reference- $D V_{\text{PoISig-CNN}} - D V_{\text{NSCM}}$ false
 454 colour composites for Haridwar in figure 10(b) and figure 10(d) show numerous green colour
 455 objects. These objects are falsely detected as villages as per PoISig-CNN and indicate false
 456 alarms. A quantitative analysis is therefore required to assess the performance of the classifiers
 457 in more detail.



458
 459 Figure 9 (a). Segment of image shown in figure 6(a). Corresponding segments of: (b). Image
 460 after the *closing* operation, (c) Image after the *holes filling* operation and, (d). image after the
 461 *filtering* operation



462

463 Figure 10 (a) False colour composites for Roorkee using

464 red = reference, green = $DV_{\text{PolSig-CNN}}$, blue = DV_{NED} colour scheme, (b) False colour composites for

465 Haridwar using red = reference, green = $DV_{\text{PolSig-CNN}}$, blue = DV_{NED} colour scheme, (c) False colour

466 composites for Roorkee using red = reference, green = $DV_{\text{PolSig-CNN}}$, blue = DV_{NSCM} colour scheme,

467 and (d) False colour composites for Haridwar using

468 red = reference, green = $DV_{\text{PolSig-CNN}}$, blue = DV_{NSCM} colour scheme.

469 For quantitative evaluation of the DV images corresponding to the PolSig-CNN, NSCM, and

470 NED classifiers, the following method is considered. At first, a bounding box to mark the extent

471 of each object in both; the reference and the test image, is computed. Then, a bounding box

472 overlap ratio (BBOR) is computed using equation (10) for each pair of objects in the reference

473 and the test image. Test image here represents the ‘image under test’ which is the DV image

474 from the classifiers.

475

$$(\text{BBOR}) = \frac{(\text{Overlap Area})_{(\text{test}, \text{reference})}}{\min((\text{Bounding Box Area})_{\text{reference}}, (\text{Bounding Box Area})_{\text{test}})} \quad (10)$$

476 If the BBOR of a particular object pair is above a predefined threshold, then the
 477 corresponding object in the test image is counted a successful detection, otherwise not. The
 478 threshold is set to 0.5 based on experiment and is set identical for both Roorkee and Haridwar
 479 study areas for consistency purpose.

480 True positives (successfully detected villages), true negatives (villages missed), and false
 481 alarms or false positives (objects detected as villages in the test image but are actually not) are
 482 computed using equation (11) through (14).

$$483 \quad \text{True Positive (TP)} = \sum_{i=1}^m \text{logical}(\text{IOU}_i > \text{threshold}) \quad (11)$$

484 Where, m is the total number of objects (villages) in the reference image, and

$$485 \quad \text{logical}(x) = \begin{cases} 1 & \text{if } x > \text{threshold} \\ 0 & \text{if } x < \text{threshold} \end{cases} \quad (12)$$

$$486 \quad \text{False Negative (TN)} = \text{Total number of villages in reference image} - \text{TP} \quad (13)$$

$$487 \quad \text{False Positive (FP)} = \text{Total number of objects in test image} - \text{TP} \quad (14)$$

488 True positives (TP), False negatives (FN), false positives (FP), and intersection over
 489 union (IoU) are computed for Roorkee and Haridwar study areas for PolSig-CNN, NED, and
 490 NSCM. Table 4 summarizes the quantities assessment of the DV images of the PolSig-CNN,
 491 NED, and NSCM classifiers. The PolSig-CNN successfully extracts 75 (out of 93) villages in the
 492 Roorkee study area and 47 (out of 60) villages in the Haridwar study area. Whereas, NED
 493 successfully extracts 26 villages in Roorkee and 20 villages in Haridwar and, NSCM
 494 successfully extracts 22 villages in Roorkee and 27 villages in Haridwar. The low detection rate

495 in case of the NED and the NSCM resonates with their low classification accuracies for built-up
 496 class (refer table 2).

497 The false alarms are also high for the NED and the NSCM. The low values of kappa for
 498 NED and NSCM (refer table 2) indicate to the high false alarms. The PolSig-CNN offers higher
 499 detection rate and low false alarms for both Roorkee and Haridwar study areas.

500 Table 4 Summary of quantitative assessment of performance of PolSig-CNN, NED, and NSCM.

Dataset	Measures	NED	NSCM	PolSig-CNN
Roorkee	Total number of villages in the study area	93	93	93
	TP (Villages successfully mapped)	26	22	75
	FN (Villages missed)	67	71	18
	FP (or False Alarms)	31	41	1
	IoU	0.22	0.16	0.98
Haridwar	Total number of villages in the study area	60	60	60
	TP (Villages successfully mapped)	20	27	47
	FN (Villages missed)	40	33	13
	FP (or False Alarms)	33	39	5
	IoU	0.21	0.22	0.92

501

502 *Stage 3: Mapping flood affected villages*

503 Since, any PolSAR image acquired to monitor a flood may include both, flooded and not flooded
 504 regions. Therefore, it is important here to identify flood affected villages and mask-out non-
 505 flooded villages since the result may impact the planning of a rescue operation. A separate
 506 (stage-3) methodology is proposed to achieve this task. The methodology presented in this
 507 section encompasses stage 3 of the overall approach.

508 Intuitively, the villages that are flooded must be completely enclosed by water and
 509 villages that are not completely flooded should not be enclosed by water. It means that any
 510 village that is completely flooded should appear as ‘hole’ in the ‘water’ class image and any
 511 village that is not completely affected by flood should not appear as a hole and may have

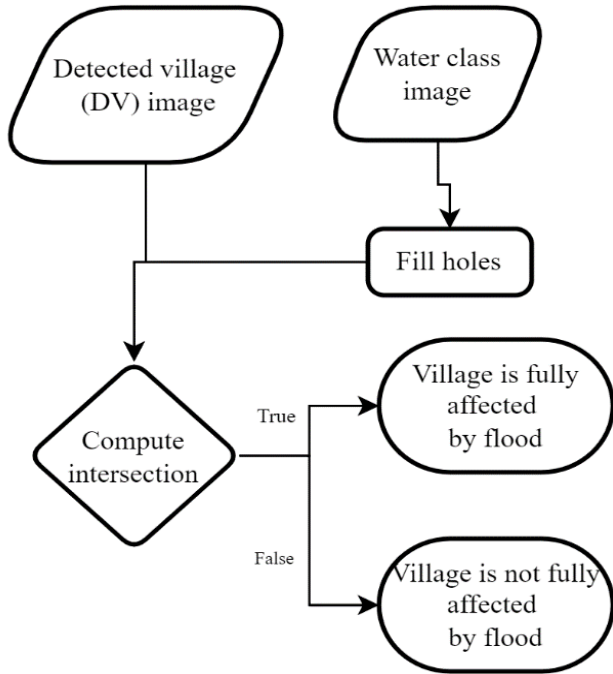
512 presence of other class in the vicinity. Based on this interpretation, a criterion is set i.e. if an
513 object in the DV image obtained from section 4.3.1 is a subset of an object in the water class
514 image, then, that object in the DV image is a flooded village otherwise it is a non-flooded
515 village. This criterion separates flooded villages from non-flooded villages.

516 To realize this criterion, intersection is computed over DV image and the “holes filled”
517 version of water class image. The holes-filled water class image is obtained using equation
518 similar to equation (7). Objects remaining in the intersection image are flooded villages and
519 remaining objects in the DV image is not a completely flooded village. The flowchart of the
520 methodology is depicted in figure 11.

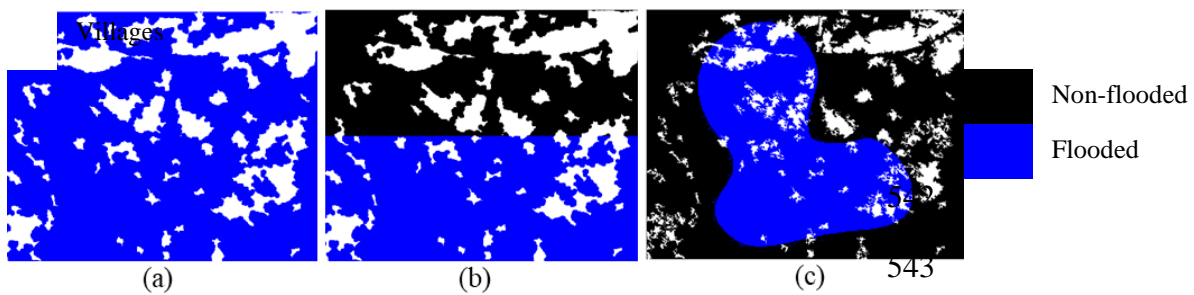
521 In order to evaluate this methodology, three different ‘artificial flood’ scenarios are
522 created. The three flood scenarios are shown in figure 12(a-c). In the first scenario as shown in
523 figure 12(a), flood (highlighted in blue) has affected the whole study region whereas in the
524 second and third scenarios, flood has affected some parts of the study region. For experiment, the
525 DV image of Haridwar corresponding to the PolSig-CNN (refer figure 10(b)) is subjected to
526 these three flood scenarios as shown in figure 12(a-c).

527 In figure 13(a-c), the flood affected villages are marked with yellow colour and the non-
528 flooded villages are marked with red colour. It is evident from figure 13(a-c) that the
529 methodology proposed in this section successfully identifies and maps villages that are
530 completely affected by flood and masks out villages that are not affected by flood. Although, this
531 methodology includes the step ‘generation of artificial flood scenarios’, however, in real flood
532 situation, this step is skipped and flooded villages can be directly be mapped. The methodology
533 is also evaluated on real flood scenario and results are highlighted in section 4.4.

534 Overall, two methodologies are proposed in section 4.3. The stage-2 methodology detects
 535 villages and removes false alarms and misclassifications in a built-up area image. The stage-3
 536 methodology maps flooded villages and masks out non-flooded villages. These two
 537 methodologies in combination with the PolSig-CNN classifier completes the novel ‘flood
 538 affected village detection and mapping’ approach.



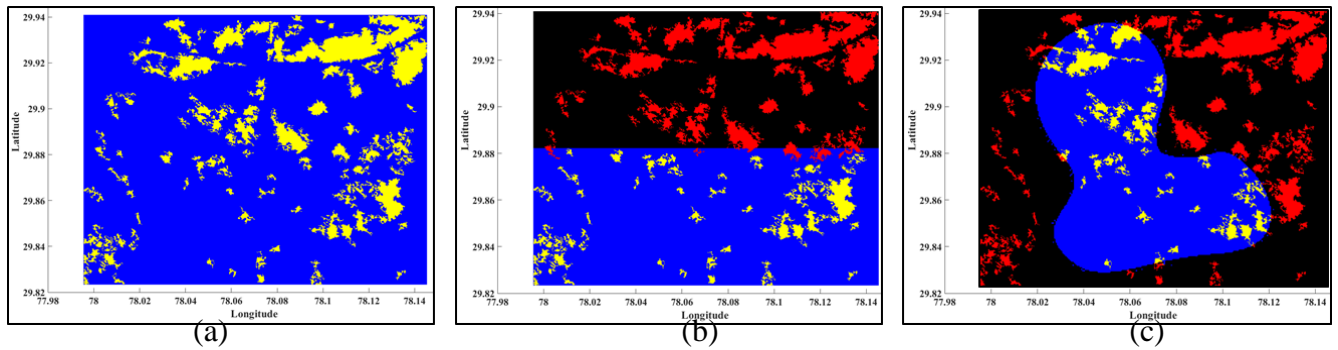
539
 540 Figure 11 Stage 3 methodology flowchart for flood affected village detection.



544 Figure 12 Different artificial flood scenarios; (a) Flood scenario 1, (b) Flood scenario 2 and, (c)
 545 Flood scenario 3.

546

547



548 Figure 13 Flood affected villages (in yellow) and non-flooded villages (in red) under; f(a) Flood
549 scenario 1. (b) Flood scenario 2. (c) Flood scenario 3. Colour scheme: yellow = villages affected
550 by flood, red = non-flooded villages and, blue = flooded region.

551 *Validation on real flood scenario*

552 The novel approach proposed in section 4 is validated on real flood PolSAR dataset of Patna,
553 Bihar, India from August 2016. Patna, Bihar sits up at the banks of the river Ganges. The August
554 2016 Bihar flood affected Patna and neighbouring regions along with other parts of the state.
555 Figure 14(c) shows the FCC of the PALSAR-2 PolSAR data acquired over Patna region on
556 September 03, 2016. The figure clearly highlights the flooded region. The PolSig-CNN classifier
557 used this dataset to create the classification image shown in figure 14(d). The classified image
558 reflects to the flooded situation with presence of ‘water’ class extensively in the area. Further,
559 ‘built-up’ class is extracted using stage-2 methodology from the classified image and is shown in
560 figure 14(e). The resulting image is termed as detected-village (DV) image. It is observed that
561 villages in the area are successfully extracted (both flooded and non-flooded). Finally, flood
562 affected villages are mapped using stage-3 methodology and are highlighted with yellow colour
563 in figure 14(f). The final result indicates to the efficiency and effectiveness of the proposed
564 approach in detection and mapping flooded villages using PolSAR data.

565 **Conclusion**

566 This paper presented an efficient approach to map flood affected villages using fully polarimetric
567 SAR imagery. The approach included three stages i.e. –*stage 1*, built-up area extraction, –*stage*
568 2, village detection and, –*stage 3*, flood affected village mapping.

569 In the first stage, the approach utilized PALSAR-2 PolSAR polarization signatures (PSs)
570 two-dimensional features and dilated convolutions based CNNs to extract built-up areas. A novel
571 five-class classifier namely PolSig-CNN is developed and trained on 3X3 window PSs class
572 samples, the dilated convolutions based CNN classifier provided improved built-up area
573 extraction because of its ability to capture the two-dimensional neighbourhood relationship of a
574 PS pixel. Quantitative results indicate to approx. 83% classification accuracy for built-up
575 averaged over two different study areas which is promising.

576 In the second stage, a novel village detection methodology is developed. The
577 methodology detects whether a particular object in the built-up area image, obtained from stage
578 1, is a village or not using a village detection filter. The detection filter is built on *a priori*
579 knowledge on the minimum average size of rural human settlements in India and image
580 morphology. The detection methodology also significantly removed false alarms and false
581 negatives. A strong detection accuracy of 80% is achieved with this methodology. Qualitative
582 results are also in agreement with the performance.

583 In the third and final stage, flood affected villages are identified and non-flooded villages
584 are masked out using another image morphology-based methodology. This stage-3 mapping
585 methodology computes a degree-of-intersection between successfully detected villages and
586 flooded area masks and utilizes it for identification of flood affected villages. Experiments are
587 conducted on simulated and real flood datasets and performance of the three-stage approach is

588 satisfactory. An average detection accuracy of approx. 80% and further, mapping accuracy of
589 100% is achieved over different study areas. In summary, the three-stage novel approach
590 presented here successfully detects and maps flood affected villages with the help of a PolSAR
591 image. The approach indicates potential to be tested at a real-time.

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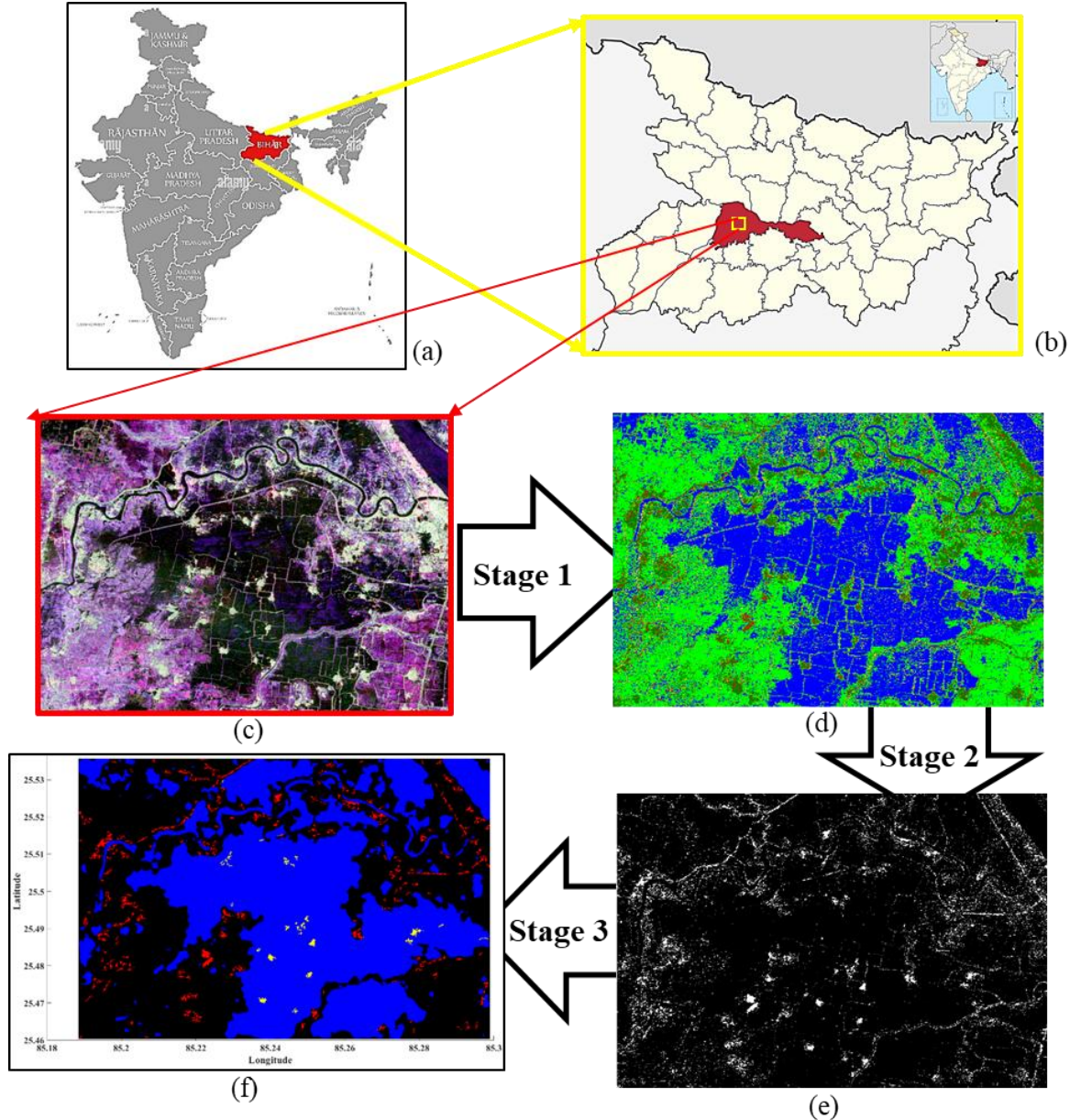
596 **Declaration of Interest Statement**

597 The authors declare that authors have no conflict of interest.

598 **Data Availability Statement**

599 lab, Availability of the data is subjected to be used exclusively uunder the affiliation of Prof.
600 Dharmendra Singh, ECE Department, IIT Roorkee. Collaborations are invited to use the data for
601 impactful studies.

602 **Word Count: 8562**



604

605 Figure 14 Validation of the proposed approach. (a) India's state administrative boundaries
 606 illustration with Bihar highlighted in red, (b) Bihar's district administrative boundaries
 607 illustration with Patna highlighted in red and study area demarcated with yellow box, (c) False
 608 color composite (red = HH, green = HV, and blue = VV) PALSAR-2 PolSAR imagery of the
 609 validation study area, (d) Classification image using the PolSig-CNN classifier proposed in
 610 stage-1, (e) Villages extracted (DV image) using stage-2 methodology, and (f) Flood affected
 611 villages (highlighted in yellow) using stage-3 methodology.

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