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A Comparative Review of Seven-Component Decomposition and Neural Network Approaches for Mangrove Detection Using L-Band PolSAR Data

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Abstract – **Mangrove forests play an important role in coastal protection, biodiversity conservation and carbon sequestration by making their accurate and reliable mapping important for sustainable environmental management. However cloud cover and/or atmospheric interference limit optical remote sensing; however, Polarimetric Synthetic Aperture Radar (PolSAR) is important for all-weather, day and night observations. The objective of this review is to explore the potential for mangrove detection using L-band PolSAR and Seven-Component Decomposition (7SD) and to highlight the polarimetric scattering features and the neural-network-based classification. It critically reviews the existing research related to mangrove mapping, SAR processing, scattering decomposition techniques and machine-learning techniques with emphasis on Multilayer Perceptron (MLP), Radial Basis Function Network (RBFN) and Cascade Forward Network (CFN) classifiers. Important methodological issues such as speckle filtering, feature scaling, class imbalance, quality of the reference labels, spatial autocorrelations, and information leakage when evaluating models are also discussed. Moreover, it offers a comparable framework for assessment that is reproducible and includes consistent data partitions, spatially independent assessment, confusion matrices, overall accuracy, precision, recall, F1 score and Kappa statistics. Research opportunities are identified in the synthesis of feature ablation, multi-temporal analysis, sensor fusion, and cross-region validation. This review focuses on evidence-based model selection, transparent reporting and generalisation assessment for the support of robust and reproducible mangrove monitoring using PolSAR.**

Keywords - L-band PolSAR, Mangrove Detection, Seven-Component Decomposition (7SD), Neural Network Classifiers, Polarimetric Scattering Features

I. INTRODUCTION

The accurate mapping of mangrove forests is essential for their sustainable management, given their important functions in protecting coastal environments, conserving biodiversity and sequestering carbon [1]. But cloud and atmospheric conditions frequently limit the use of conventional optical remote sensing. Polarimetric Synthetic Aperture Radar (PolSAR), which is able to be operated in all weather conditions and at night, is an effective alternative. The L-band PolSAR data and Seven-Component Decomposition (7SD) provide important scattering characteristics that can be used to discriminate mangroves [2] from adjoining land classes. This review explores the use of 7SD-derived features along with Multilayer Perceptron (MLP), Radial Basis Function Network (RBFN) and Cascade Forward Network (CFN) classifiers, pointing out challenges, gaps, and evaluation methods for accurate mangrove detection.

II. REVIEW SCOPE AND APPROACH

The source base emphasizes peer-reviewed publications as well as a methodological review that is well established, a review of mangrove remote-sensing that is accessible, and a contribution to IGARSS 2024 directly related to neural-network optimisation for mangrove detection. The focus is on

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sources that are used for the processing and evaluation decisions in a 7SD-based PolSAR workflow.

The studies are contrasted in terms of the sensor/data type, representation, classification approach, validation design, and limitations reported, when available. The difference between reporting findings found in the literature and drawing implications from those findings as well as recommendations for the proposed study, is maintained. The reported results of datasets that are not directly related are not considered as direct numerical comparison results due to the fact that scene composition, prevalence of classes, spatial resolution and ground truth can be very different.

III. Mangrove Mapping and SAR Observation

A. Ecological and Mapping Challenges

The detection of mangroves is a spatial classification problem where mangroves can be present as a narrow shoreline band, in fragmented patches, or mixed pixels. The tides, wet soil, shadow, surrounding terrestrial vegetation and urban development create complex class boundaries [3]. If all but a few pixels are not mangrove, it's possible for a map to have high overall accuracy and poor accuracy in mangrove patches. Apparent change can also be caused by variation in sensor geometry, tide, season, preprocessing, or the quality of labels and not necessarily by ecological change, for monitoring change.

B. Why L-Band and Full Polarimetry?

The SAR backscatter is a function of the geometry of scattering and dielectric properties of targets. Possible contributions include surface scattering from exposed ground or water, volume scattering from vegetation, and/or double bounce scattering from vertical structures and with a nearby surface. These mechanisms are not exclusive to the individual classes of land cover; they can take place in different land cover environments. The beauty of polarimetry is that multiple channels and their intricate relationships give rise to a more comprehensive feature space than a single intensity image.

The longer the wavelength the more useful it can be for woody vegetation as some of the longer wavelengths can penetrate further into some vegetation structures and interact with larger canopy elements than shorter wavelengths. However, its assertion that L-band always penetrates a canopy, or that L-band always separates mangroves is too strong. Penetration and class separability are related to biomass, water content, canopy architecture, acquisition configuration, and the reference classes [4]. An evaluation should include the identification of the sensor, date of acquisition, polarization channels, incidence angle information (if available), spatial resolution, and radiometric and/or terrain corrections performed.

C. Polarimetric Matrices and Decomposition

In the case of fully polarimetric data, the scattering matrix will hold complex numbers for the various combinations of polarisation for the transmitters and receivers [5]. Covariance and coherency representations form second-order relationships between the channels and are often used as inputs to the polarimetric analysis. Decomposition methods decompose the observed matrix into scattering contributions that are modelled. The Freeman–Durden approach is a well-known three-component decomposition method and the Yamaguchi family generalises the model-based description by incorporating other scattering components such as helix-like scattering. These approaches are considered as an approximation or proxy of the actual labels and not as a direct ground-truth.

IV. Related Works

A. Remote Sensing Approaches for Mangrove Mapping

In recent years, remote sensing is recognised as an effective tool to monitor mangrove distribution, diversity and changes in mangrove ecosystems over time. Study [6] used 36 years of Landsat satellite images (1987–2022), along with low-tide Sentinel-1 SAR and Sentinel-2 MSI data, and combined these with 257 field plots to classify six mangrove communities, and monitored restoration results using a simplified version of the Automatic Regrowth Monitoring Algorithm (SARMA). Study [7] had focused on scalable national-level mapping using Sentinel-1, Sentinel-2 and SRTM data in Google Earth Engine (GEE), while this one emphasised long-term ecological changes and species diversity. Further studies proposed the effects of spatial resolution and feature selection on classification performance of Landsat-8, Sentinel-2, ZiYuan-3 (ZY-3) and GaoFen-1 (GF-1) images [8]. Compared to traditional Random Forest techniques, the U-net-based technique improved the quality of mangrove mapping by cutting the classification noise to observe the smaller patches of mangroves. Along with these classification studies, study [9] used Landsat to study the mangrove expansion, densification of mangrove canopy, and fragmentation of mangroves in the Indus Delta and Sandspit of Pakistan over the period of time. Overall the above studies show that the synergy of multi-source satellite-derived data and suitable classification algorithms, together with ecological indicators, can help reinforce mangrove monitoring, but tidal variations, resolution of the satellite images and limited field validation are important challenges.

B. SAR and Fully Polarimetric SAR Data

Although synthetic aperture radar (SAR) has given good radar information in target recognition, classification and environmental monitoring, exploitation of the polarimetric information remains one of the main challenges in various

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applications. To resolve this issue, Study [10] proposed a visualisation method to investigate the contribution of individual polarimetric elements and proposed a feature called polarimetric correlation, which was based on features of both the target and typical scatterers. In this paper, the polarimetric relations were used to enhance target discrimination, but [11] took the next step in polarimetric exploitation by developing a unified framework for full and compact polarimetric SAR data. It integrates, into the same products, feature-based, machine-learning-based, and phenomenology-based approaches to facilitate target detection, classification and change analysis in multimodal and multisensor data. In addition to target-oriented applications, [12] showed the feasibility of fully polarimetric SAR for quantitative environmental assessment, using a study of soil salinity in arid areas. The authors used the Gaofen-3 data and field measurements of Yutian Oasis to select the saline monitoring characteristic parameters of polarimetric decomposition and establish a radar salinisation monitoring index (RSMI). The usefulness of its use was further tested with data acquired through RADARSAT-2, as shown in Table I.

C. Seven-Component Scattering Power Decomposition (7SD)

The seven-component scattering power decomposition (7SD) has become a valuable tool to represent forest structure and enhance aboveground biomass (AGB) estimation from polarimetric synthetic aperture radar (PolSAR) data. Study [13] showed that seven-component scattering power decomposition (7SD) is effective for forest aboveground biomass (AGB) estimation, combining the scattering powers with random forest regression (RFR) using fully polarimetric ALOS-2/PALSAR-2 data in Shivamogga, India. The method accounted for forest heterogeneity, and there was a strong correlation between the volume scattering and biomass. This was extended in Study [14] to a mixture of scattering powers derived from 7SD with forest height derived from PolInSAR: L- and X-band fully polarimetric data were combined to include complementary structural information. The first study evaluated the transferability by testing the validation at the Tundi Forest, while the second study emphasised significant spatial variation of biomass.

TABLE I. SUMMARY TABLE

Study	Proposed approach / technique	Dataset(s)	Key results	Key contributions
[6]	SARMA for regrowth monitoring; hierarchical clustering and Random Forest for species classification.	Landsat (1987–2022); low-tide Sentinel-1 SAR and Sentinel-2 MSI; 257 field plots.	Mangrove extent increased by 1,518 ha (21.59%), from 7,030 ha to 8,548 ha. Six mangrove communities were identified; classification accuracy was 83.57%.	Developed a systematic framework linking long-term mangrove expansion with species diversity and restoration outcomes, revealing the limited structural complexity of rehabilitated monoculture stands.
[7]	Google Earth Engine-based mapping using GTB, RF, CART, and SVM classifiers.	Sentinel-1, Sentinel-2, and SRTM; 10,000 data points acquired in 2018; Thailand mapping from 2016–2022.	GTB achieved 96.75 ± 0.63% overall accuracy. Mangrove area in Thailand increased by 11% between 2016 and 2022.	Established a scalable, semi-automated workflow for national-level mangrove mapping that can be adapted to other geographical regions.
[8]	Comparison of pixel-based RF, object-oriented RF, and U-Net with ResNet-34 using spectral, texture, and terrain features.	Landsat-8 (15 m and 30 m), Sentinel-2 (10 m), ZY-3, and GF-1 (2 m); Beibu Gulf.	U-Net with Sentinel-2 and terrain features achieved an F1-score of 96.45%. Terrain features improved the Landsat-8 F1-score by 1.91%, while texture features improved the ZY-3/GF-1 F1-score by 2.99%.	Demonstrated that optimal feature selection depends on spatial resolution and that deep learning can reduce classification noise and improve detection of small mangrove patches.
[9]	Long-term land-cover classification, NDVI-based canopy-density assessment, fragmentation analysis, and transition analysis.	Landsat (1988–2024); Sentinel-2 (2019 and 2024); Google Earth imagery for visual validation.	Sandspit mangrove cover increased from 10.22 to 15.64 km², while Indus Delta cover increased from 305.54 to 1,002.82 km². Thick vegetation at Sandspit increased approximately ninefold to 10.08 km². Overall classification accuracy exceeded 96%, with kappa values above 0.93.	Integrated mangrove extent, canopy density, and fragmentation analysis to assess long-term ecosystem changes and provide evidence to support coastal conservation and climate adaptation policies.
[10]	Channel-wise convolutional visualization and a polarimetric correlation feature integrating target and typical scatterer	Synthetic and real datasets; specific names not provided in the supplied abstract.	Demonstrated advantages of polarimetric information over single-polarization intensity. The proposed feature achieved intra-class compactness and inter-class	Explained polarimetric element contributions and developed a feature reflecting physical scattering and target geometry.

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	characteristics.		separation.	
[11]	Unified framework combining hybrid feature-based, multichannel machine-learning-based, and phenomenology-based classification, detection, and change-detection products.	Multimodal and multisensor SAR data; specific sensor and dataset names not provided in the supplied text.	Kappa coefficients of 0.8768 and 0.8436 for two compact polarimetric classification methods, indicating good agreement with ground truth. Some confusion remained between volume and odd/even-bounce scattering classes.	Enabled customized, multiaspect, and multisensor SAR exploitation for target detection, classification, and anomalous change analysis.
[12]	Two-dimensional Yamaguchi4_vol–Freeman3_vol feature space and radar salinization monitoring index (RSMI).	Gaofen-3 SAR and field measurements from Yutian Oasis, Xinjiang, China; RADARSAT-2 SAR data from Weiku Oasis for validation.	Yutian: correlation coefficient 0.85, (R2=0.72), RMSE = 7.28 dS/m. Weiku validation: (R2=0.70), RMSE = 9.29 dS/m.	Developed a quantitative soil salinity retrieval method and demonstrated its transferability across two environmentally similar arid regions.
[13]	Integrated seven-component scattering power decomposition (7SD) with random forest regression (RFR) to estimate aboveground biomass (AGB).	Fully polarimetric ALOS-2/PALSAR-2 data and field-measured AGB from Shivamogga, India; cross-validation in Tundi Forest.	RMSE: 21.94 Mg/ha; relative RMSE: 19.46% in Shivamogga. Relative RMSE in Tundi Forest: 22.9%.	Developed the 7SD-RFR-AGB model, demonstrating the usefulness of volume, compound, and double-bounce scattering powers for capturing forest heterogeneity and improving AGB estimation compared with existing backscatter-based models.
[14]	Combined 7SD-derived scattering powers and PolInSAR-derived forest height with random forest regression for AGB estimation.	L- and X-band fully polarimetric SAR data and field measurements from Shivamogga forest.	RMSE: 29.18 Mg/ha; relative RMSE: 25.88%. High spatial variability in biomass was observed.	Extended scattering-based biomass estimation by incorporating forest height as a complementary structural predictor, demonstrating the potential of combining PolSAR decomposition and PolInSAR information for tropical forest biomass retrieval.

V. Preprocessing and Feature Representation

A. Speckle and Filtering

Coherent radar imaging is related to the variation, known as speckle [15]. Filtering can enhance the visual interpretability of the data but may also create some boundary clearing, may remove small patches of data, or may change the texture and statistics of the polarimetric data. The polarimetric workflow needs to be clear on whether it is filtering a particular type of data, filtering all channels, and the preservation of the relationships required for the subsequent matrix decompositions.

It should be recorded how the filter was configured (window size, handling of the edges, etc. and any equivalent number of looks assumed). It is good practice to perform a sensitivity check with at least one alternative filtering setting as a classifier can seem to perform better under one particular pre-processing choice. Filtering needs to be based on the test accuracy, but not by repeatedly looking at the final test accuracy, which will leak information out of the test set into the model development process.

B. Feature Extraction from 7SD

The seven decomposition powers can be used to create a feature vector, and if warranted, additional polarimetric or contextual variables can be added. The review suggests that exact component names, units/scaling, treatment of negative/invalid components, use of log transformation (if applicable), and no-data pixels should be reported. If it is only the 7SD outputs that are being used, this should be clearly set out, and, if texture, intensity or ancillary features are introduced [16], then the comparison should distinguish the contribution of the decomposition features and the ancillary features.

Pre-processing of missing and extreme values, along with the elimination of redundant and differently scaled variables, should be performed before training of neural networks. Parameters used for standardisation must be determined using the training subset and remain the same for the validation and test sets. This prevents the use of observations not used for training the feature transformation. Useful ablation design entails comparing a baseline, which includes a small, pre-determined feature set, to the full 7SD feature vector. If this ablation isn't present, it's not possible to say that the enhanced classification is due to 7SD.

VI. Neural-Network Classifiers

A. Multilayer Perceptron

An MLP consists of an input layer, one or more hidden layers and an output layer [17]. This can be used to approximate the complex decision boundaries between mangrove and other land-cover classes by using nonlinear activation functions.

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Though flexible and widely used, there are several parameters that affect the performance of MLPs, such as the size of the hidden layers, regularisation, input scaling, initialisation, class imbalance, and stopping criteria. If the model contains too many parameters, it can fit the local patterns or 'label-noise' in the data, and if it contains too few parameters, it may underfit the data.

The size of the layers and type of activation functions used in the MLP must be determined from the training/validation data only and should be kept constant when evaluating the final MLP. For multiclass classification the representation and decision rule should be given, in some regression-style encodings it is possible to use a linear output layer, but the decision rule for the classes, and the loss function must be explained.

B. Radial Basis Function Network

The basic structure of an Radial Bais Function Network (RBFN) is inspired from a hidden layer of radial basis functions, usually Gaussian [18], whose activation is based upon the distance between an input vector and a collection of centres. The output layer is used to combine all these activations to make predictions of class scores. Hidden units (HUs) process the data locally in feature space making RBFNs suitable for modeling the possible nonlinear class structure. In some situations, where centre selection and width estimation are appropriate, RBFNs can be efficient in training. They have a number of limitations including number and location of centres, distance scaling and coverage of rare classes.

C. Cascade-Forward Network

A Cascade-Forward Network (CFN) is similar to a FFN, except that it has connections from the input to later layers in the network and from earlier to later processing stages [19]. Additional paths provide network with the ability to use original inputs as well as transformed inputs. The increased connectivity can also be beneficial for the fitting of non-packetized relationships which are hard for a traditional layered network, but can lead to an increase in the number of trainable parameters and the risk of overfitting, particularly if there aren't many independent training samples.

The settings used for the CFN experiment, including the layer sizes, connection pattern, transfer functions, loss function, optimiser, stopping criteria and policy about the random seeds used to initialise the problem, should be documented. But having direct connections doesn't necessarily mean that they are more accurate or more quickly converge. These statements need to be repeated and a consistent comparison budget should be used.

D. Levenberg–Marquardt Optimisation

The Levenberg–Marquardt (LM) algorithm is an optimisation method for damped least-squares optimization [20], and is a commonly applied algorithm for training small feed-forward networks when the objective is to minimise a sum of squared errors. It is a mix of gradient descent and Gauss–Newton update and can converge rapidly for certain problems [21], but has memory and computation requirements proportional to the number of parameters. Not always optimal for all architectures, data set size or loss function.

The difference in the achievable values should be due to architecture and not optimiser. The comparison is not strictly between three networks that have been optimised in the same way, because MLP and CFN are trained with LM while the RBFN are trained with a centre-based procedure and a linear fit on the output. It's a valid applied question but it needs to be worded exactly. An alternative approach is to perform a separate optimiser experiment to compare methods in architectures in which each method is appropriate.

VII. Evaluation Design and Reporting

A. Data Split and Spatial Independence

There are spatial auto-correlations among the pixels of a remote sensing image: adjacent pixels are likely to have similar land cover, acquisition conditions, and texture. Similar neighbours can easily be placed in both the training set and the test set because of a random pixel split. Ideally separate areas or polygons should be allocated to training, validation and testing. The test set should not be modified until model selections are made. When only a single scene is available, the restrictions of within-scene evaluation need to be recognised and cross-site generalisation needs to be stated explicitly as an experiment for the future.

B. Metrics Beyond Overall Accuracy

Overall accuracy is the percentage of samples correctly classified, but may mask low recall for a small mangrove class. This confusion matrix should therefore be complemented with the precision, recall and F1-score per class. Sensitivity is the percentage of reference mangrove pixels detected, and specificity is the percentage of non-mangrove pixels rejected. The Kappa can be included as a supplementary agreement statistic, but should not be used as a substitute for measures at the class level or uncertainty analysis. When continuous class scores are available, the use of ROC curves and area under the ROC curve (AUC) may be helpful, and precision–recall curves may be more informative when the positive class is rare. In the case of multiclass tasks, report macro-averaged metrics and weighted metrics or micro-averaged metrics and explain the averaging scheme. Provide sample counts so that each score can be interpreted. If a probability threshold is tuned, then the threshold is to be chosen from the validation set and not the final test set.

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VIII. Recommended Experimental Design for Future Studies

It is important to have a defensible experimental design, in which the target classes are identified prior to modelling, and the class scheme is uniform across the paper. Where the task is a binary classification of mangrove vs. non-mangrove, all training labels, figures, metrics and objectives should be in accordance with that definition. If more than one land-cover class is kept, it is important to explicitly mention a multiclass task and to report the results per class. This is significant since a multiclass workflow cannot be reduced to a binary detection without specifying a conversion step.

The same partitionings of the data, the same families of classifiers, and the same data-scaling procedure should be used in a controlled experiment. For isolating effects of features, fix the split for comparing different decomposition sets; for estimating the robustness, repeat the training across various seeds/folds that retain spatial independence. The hyperparameters need to be tuned using training/validation data, and the test data should be used only by the end of the tuning process. Apart from accuracy, precision, recall, F1 score, confusion matrix, kappa (when applicable), ROC/AUC (when applicable), runtime, and model complexity. Provide a clear description of the source of the ground truth data, and its temporal relationship with the SAR acquisition.

For operational relevance, test a different geographic area or acquisition date to make the test relevant in the operation. When no such information is available, make sure to state only what you have evaluated, and not make broad general statements. A good results table should include the experimental results, but it should also distinguish between what the results mean and what it is an anticipated result of an experiment.

IX. Conclusion

The use of L-band PolSAR and seven component decomposition (7SD) for mangrove detection by extracting informative polarimetric scattering features is pointed out. The modelling of nonlinear relationships between these features and land-cover classes is available in different ways, such as by using MLP, RBFN, or CFN networks. Yet, in order to make reliable comparisons, the preprocessing must be uniform, the classification classes must be clearly defined, the samples must be representative, and the validation samples must be independent in space. In addition to the overall accuracy, precision, recall, F1 score, confusion matrix and Kappa statistics should be used. Future studies could focus on feature ablation, multi-temporal data, sensor fusion, and cross-region validation to improve the performance of PolSAR-based mangrove monitoring systems and their practical applicability.

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