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Integration of Polarimetric Signature-Based Features and Texture Analysis for Accurate Soil Salinity Classification with Sentinel-1

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ABSTRACT

Soil salinity is a major driver of land degradation, and its reliable mapping remains challenging under frequent surface conditions. To address these limitations, this study presents a polarimetric based soil salinity classification framework that integrates dual polarimetric signature with texture information. In this context, an ascending Sentinel-1 dual-polarization (VV/VH) SLC scene acquired on 8 March 2024 was analyzed over the coastal districts of Khulna, Satkhira, and Jessore in southwest Bangladesh, which was deliberately selected to be temporally consistent with the field campaign conducted between 1–9 March 2024. First, texture measures were extracted from VV and VH intensity images using gray level co-occurrence matrix statistics in order to capture salinity related spatial pattern variations associated with surface roughness and crust formation. Next, dual polarimetric signatures were generated by synthesizing polarization states through linear combinations of the available channels, and a set of signature shape descriptors (e.g., pedestal height, extrema-related slopes, skewness, kurtosis, peak intensity, and signature width) was derived to enrich the feature space and improving class separability. Subsequently, to mitigate redundancy among heterogeneous predictors and enhance generalization, a feature selection step was applied to retain the most informative features for salinity discrimination. Finally, soil salinity was classified into three levels (low, moderate, and high) using two non-linear classifiers, support vector machine and multilayer perceptron, and performance was evaluated on an independent test set using confusion matrix metrics. Overall, the best-performing configuration achieved an overall accuracy of 91.6% and a Kappa coefficient of 0.861, thus demonstrating strong agreement with reference labels and underscoring the complementary value of texture and synthesized polarimetric response for dual-pol Sentinel-1 salinity mapping in coastal regions.

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1. Introduction

Soil salinity is one of the most critical environmental threats to agricultural lands, particularly in arid and semi-arid regions. The excessive accumulation of soluble salts in the upper soil layers reduces soil fertility, disrupts water and nutrient uptake by plants, and ultimately leads to a decline in crop productivity and land degradation. Given the increasing demand for food production and the limited availability of cultivable land, the accurate detection and monitoring of salinized areas are essential for sustainable land and water resource management (El Harti et al., 2016).

In this context, remote sensing technology offers an efficient, cost-effective, and scalable solution for soil salinity assessment and monitoring. Satellite imagery enables the identification of salt-affected soils across large geographic areas and over time, thanks to its broad spatial coverage and frequent revisit cycles. By leveraging spectral, spatial, and temporal information, remote sensing allows for the derivation of salinity-related indices and the development of predictive models. The integration of optical, radar, and polarimetric data with machine learning techniques presents a promising path toward improving the accuracy and spatial detail of soil salinity estimations.

Optical satellite imagery has been widely employed in soil salinity studies due to its accessibility, spectral richness, and high spatial resolution. Among various optical sensors, Sentinel-2 (S2) and Landsat-8 (L8) have shown considerable potential for salinity detection, thanks to their multispectral bands in the visible, near-infrared (NIR), and short-wave infrared (SWIR) regions (Bandak et al., 2024; Taghadosi & Hasanlou, 2021).

In a recent study by Bandak et al. (2024), a combination of L8 and S2 imagery was used to estimate soil electrical conductivity (EC) in a 24,000-hectare agricultural region in Northeast Iran (Bandak et al., 2024). Several salinity-related indices derived from these datasets, such as the normalized difference salinity index (NDSI), soil-adjusted vegetation index (SAVI), and topographic wetness index (TWI), were used as inputs for machine learning models including decision tree (DT), random forest (RF), support vector regression (SVR), and XGBoost. The results indicated that the DT model provided the highest accuracy (R^2 = 0.86, RMSE = 10.9 dS/m for Sentinel-2), highlighting the effectiveness of S2 in mapping salinity variations. A time-series analysis further demonstrated the usefulness of optical data in detecting long-term changes in salinity conditions, especially in regions with drainage interventions. Similarly, Taghadosi and Hasanlou (2021) applied Sentinel-2 imagery to monitor surface soil salinity using the geographic weighted regression (GWR) technique (Taghadosi & Hasanlou, 2021). Their study emphasized the importance of local models in capturing spatial heterogeneity, as GWR outperformed traditional global models such as support vector machines (SVM) and multiple linear regression (MLR). Sentinel-2's spectral bands and derived salinity indices were effectively used as predictor variables, achieving high predictive accuracy for surface EC values in saline-affected soils.

While optical remote sensing has proven valuable for detecting surface salinity, its effectiveness can be hampered by vegetation cover, cloud contamination, and a limited ability to probe below the surface. These limitations have prompted increasing interest in radar remote sensing, which offers unique capabilities for soil salinity assessment thanks to its all-weather, day-and-night imaging capacity and its sensitivity to the dielectric properties of soil, which is directly influenced by both soil moisture and salinity levels (Chen et al., 2022; Muhetaer et al., 2022; Taghadosi et al., 2019). In this framework, recent advances in radar technology, especially synthetic aperture radar (SAR) systems with dual or full polarization capabilities, have enabled researchers to extract more detailed information related to soil properties.

Taghadosi et al. (2019) focused on Sentinel-1 dual-polarized data and showed that both intensity and texture features from VV and VH channels could be used to map surface salinity with high precision. By integrating feature selection algorithms such as genetic algorithm (GA) and sequential feature selection (SFS) with SVR, they achieved an R^2 of 0.98 and RMSE of 0.36, confirming the effectiveness of SAR-based methods even without theoretical models for radar backscattering and soil salinity (Taghadosi et al., 2019).

Similarly, Muhetaer et al. (2022) utilized fully polarimetric ALOS PALSAR-2 data to develop quantitative models for mapping soil salinity in the Keriya Oasis, Northwest China. By extracting and evaluating 25 polarimetric features, they constructed two-dimensional radar feature space models (RSDI1–3), achieving correlation coefficients of 0.61–0.63 with observed soil salinity. The study highlighted the advantages of leveraging optimal polarimetric features through decomposition methods such as decomposition to capture scattering mechanisms that relate to the physical and chemical state of the soil (Muhetaer et al., 2022).

In another study, Chen et al. (2022) demonstrated the potential of Sentinel-1 dual-polarized SAR imagery in estimating soil salt content at multiple depths under vegetation. Their study combined radar backscattering indices with advanced machine learning models such as support vector machine (SVM), quantile regression (QR), extreme learning machine (ELM), and partial least squares regression (PLSR). They found that variable selection methods like best subset selection (BSS) substantially improved model accuracy, with SVM providing the highest performance (R^2 up to 0.67 at 10–20 cm depth). Notably, their work extended the capability of radar-based inversion beyond bare soils, showing that under certain conditions, root-zone salinity under crop cover can also be estimated with reasonable accuracy (Chen et al., 2022).

As highlighted in the review of radar-based studies, most existing research on soil salinity estimation has primarily relied on the standard polarizations provided by the sensor and the direct use of their backscattering characteristics. However, this approach can be inherently limited, as it may not fully exploit the rich information contained in the complete polarimetric response of radar systems.

In contrast, research in other fields of radar remote sensing such as forest height estimation, land cover classification, and ground deformation mapping has increasingly moved toward the use of polarimetric signatures and polarimetric optimization methods. These advanced techniques enable the extraction and synthesis of optimal features from the polarimetric data, often resulting in substantial improvements in model accuracy and discrimination power. For example, Jafari et al. (2015) introduced a novel method for land cover characterization and classification using polarimetric signatures derived from the full covariance matrix of PolSAR data. Their approach goes beyond the simple use of fixed polarization channels by generating three-dimensional polarimetric signatures, which offer a more detailed and comprehensive representation of scattering mechanisms in various land cover types. They demonstrated that such signatures, when combined with pattern recognition and object-oriented classification, could outperform conventional supervised classification algorithms by up to 6% in overall accuracy (Jafari et al., 2015).

Similarly, Managhebi et al. (2018) developed a volume optimization method for forest height estimation using PolInSAR data. While the traditional three-stage inversion algorithm uses a fixed polarization (commonly the HV channel) for "volume only" coherence estimation, this study proposed an exhaustive search polarimetric optimization (ESPO) technique to identify the optimal volume coherence across all possible polarization states. The optimized approach led to a significant reduction in height estimation errors, highlighting the impact of polarization basis selection and optimization on the accuracy of biophysical parameter retrieval (Managhebi et al., 2018).

In ground deformation studies, Azadnejad et al. (2020) evaluated the benefits of integrating polarimetric data into persistent scatterer interferometry (PSInSAR) algorithms for subsidence monitoring. By applying amplitude dispersion index (ADI) optimization and exploring several polarimetric optimization strategies (such as ESPO), they demonstrated that the use of optimized polarimetric combinations could substantially increase the density and quality of persistent scatterer (PS) pixels, both in urban and non-urban regions. This improvement, observed in both Sentinel-1 and TerraSAR-X datasets, reinforces the value of polarimetric optimization for enhancing the reliability and spatial coverage of SAR-derived deformation measurements (Azadnejad et al., 2020).

Collectively, these studies underscore the untapped potential of polarimetric signatures and optimization techniques in radar remote sensing. Integrating such methods into soil salinity assessment frameworks could unlock significant improvements in feature space representation and, consequently, in the performance of machine learning-based prediction models. The main idea of this study is to exploit an optimized polarization basis for feature extraction, aiming to enhance the classification and estimation of soil salinity. By leveraging advanced polarimetric optimization and signature analysis, this work seeks to bridge the gap between conventional approaches and the full potential of PolSAR data, ultimately achieving more accurate and robust soil salinity mapping.

2. Study Area and Data

This section describes the study region and the datasets used in this research. It first outlines the geographical and environmental characteristics of the study area, and then summarizes the Sentinel-1 SAR data and the ground-truth information used for model development and validation.

2.1 Study Area

The study area is located in the southwestern coastal region of Bangladesh, encompassing the districts of Khulna, Satkhira, and Jessore. This region, which forms part of the Bengal Delta, is recognized as one of the most vulnerable zones to soil salinity due to its proximity to the Bay of Bengal, frequent tidal intrusion, and declining freshwater inflow. The area covers approximately 6,100 square kilometers, with salinity levels ranging from less than 0.1 to over 9 dS/m and the highest concentrations observed near Debhata and Koyra in the south. The landscape is generally low-lying, with elevations close to sea level, and salinity intensity clearly increases from north to south across the study region (Sarkar et al., 2024). Figure 1 illustrates the location and spatial extent of the study area within the southwestern coastal region of Bangladesh.

2.2 Sentinel-1 Data

Sentinel-1, operated by the European Space Agency (ESA), is a C-band synthetic aperture radar (SAR) mission that provides day and night, all-weather observations. In this study, an ascending-pass Sentinel-1 scene acquired on 8 March 2024 was used because it is temporally consistent with the ground survey period (1–9 March 2024), minimizing potential discrepancies between satellite observations and in situ measurements. The dataset was obtained in dual-polarization (VV/VH) mode, which offers complementary sensitivity to surface scattering behaviour and is therefore suitable for soil salinity mapping in coastal environments. Importantly, the single look complex (SLC) product was selected to preserve both amplitude and phase information, enabling the extraction of conventional intensity based features as well as complex-domain descriptors required for polarimetric signature construction in the subsequent analysis.

2.3 Ground Truth

A total of 130 ground truth points were utilized for model training and validation in this study. Rather than conducting independent fieldwork, we relied on a publicly available dataset produced through a collaborative field campaign organized by researchers from the Massachusetts Institute of Technology (MIT), Khulna University of Engineering and Technology (KUET), and BRAC (Sarkar et al., 2024). The field campaign was conducted between 1–9 March 2024 across the coastal districts of Khulna, Satkhira, and Jessore in southwest Bangladesh.

Sampling locations were selected along survey routes connecting major union centers and were chosen in open, unobstructed areas to ensure compatibility with remote sensing observations. Sites were prioritized in dry, open, and fallow fields and along polders and riverbanks to capture representative soil salinity conditions. At each site, 5–10 subsamples were collected within an approximately 30 m × 30 m area after removing surface disturbances. Samples were obtained from the top 0–30 cm soil layer and homogenized into a composite sample to represent local soil conditions.

The samples were processed and analyzed at the ESSG-WECG laboratory at KUET following the FAO standard procedure for soil electrical conductivity (soil to water ratio 1:5). In the laboratory, samples were air dried, oven dried to reduce moisture content, sieved to remove coarse particles, and mixed with deionized water and finally, the mixture was mechanically stirred, allowed to settle, and electrical conductivity (EC) was measured using a calibrated conductivity meter to ensure measurement consistency and accuracy (Sarkar et al., 2024).

From the original dataset, 106 points were randomly selected for model training and 24 for independent testing, ensuring robust and representative coverage of soil salinity variation across the study region. The complete field dataset is publicly available at https://zenodo.org/records/14560019. Figure 2 illustrates the spatial distribution of the ground truth points used in this study and their coverage across the coastal districts.

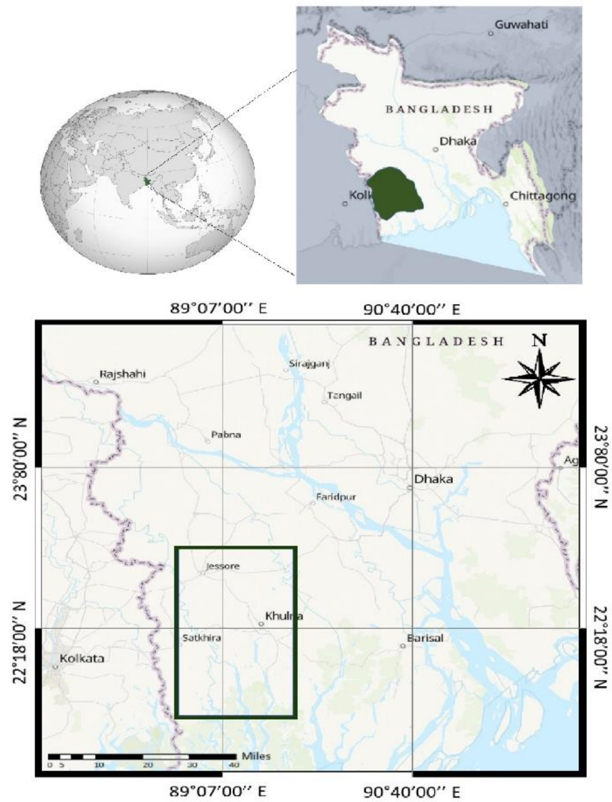

Figure 1. The location and boundaries of the study area

Although the dataset provides valuable field-based observations, several limitations should be acknowledged. The route-based sampling design and site accessibility constraints may not fully capture fine scale spatial heterogeneity of soil salinity. In addition, coverage is limited to selected coastal districts, which may affect broader regional generalization. Laboratory processing steps and instrument precision may introduce minor measurement uncertainties, although standardized procedures and calibration were applied to minimize potential errors.

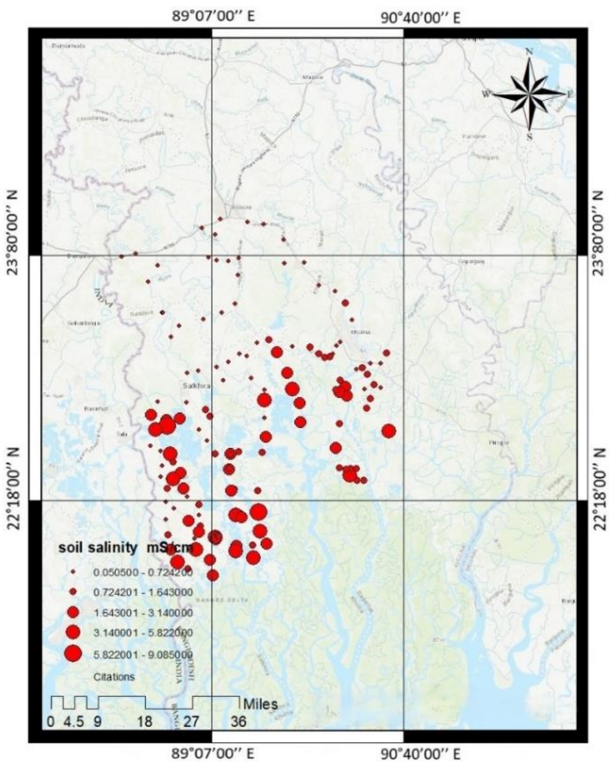

Figure 1. The distribution of ground truth points

3. Methodology

This section presents the methodological framework used for soil salinity mapping with dual-polarization Sentinel-1 SAR data. It begins by introducing the fundamental concepts and dual-pol descriptors, then describes the proposed processing workflow, and finally explains the accuracy assessment procedure used to evaluate the results.

3.1 Fundamental Concept

This part introduces the SAR polarimetric elements required by the proposed framework. We first describe the dual-pol scattering representation of Sentinel-1 and then explain how synthetic polarization responses are generated to form the polarimetric signature.

In dual-polarization SAR systems such as Sentinel-1, each pixel is characterized by a two-component scattering vector containing the complex values for the VV and VH polarization channels. This scattering vector can be written as (Mullissa et al., 2017):

$$S = [S_{VV} \quad S_{VH}]^t \qquad (1)$$

where t represents the transpose operator and S_{VV}, S_{VH} denotes the complex backscattering for the VV and VH polarizations.

In the dual-pol case, the Pauli basis (Pauli vector) is exactly equivalent to this scattering vector, since only VV and VH channels are available. In this study, both the intensity values and the complex values from the VV and VH channels are utilized. The intensity features are used for soil salinity classification, while the complex scattering data serve as the foundation for constructing the polarimetric signature. In this framework, the Sentinel-1 single look complex (SLC) product is used to ensure access to both intensity and phase information required for advanced polarimetric analysis.

A polarimetric signature provides a comprehensive depiction of how a radar target responds to various polarization states, enabling detailed interpretation of scattering mechanisms even in dual-polarization SAR systems (Jafari et al., 2015). In the context of dual-pol Sentinel-1 data, new polarization states can be synthesized mathematically by forming linear combinations of the available VV and VH channels.

A new polarization basis, μ , can be defined as a linear combination of the measured channels as (Navarro-Sanchez & Lopez-Sanchez, 2011):

$$\mu = \omega^t k \qquad (2)$$

where k is the Pauli vector and μ is the unitary projection vector which is defined as (Navarro-Sanchez & Lopez-Sanchez, 2011):

$$\omega = [cos\alpha \quad sin\alpha e^{j\psi}]^t \;, \; \begin{cases} 0 \le \alpha \le \dfrac{\pi}{2} \\ -\pi \le \psi \le \pi \end{cases} \qquad (3)$$

where α and ψ are angular parameters that span the space of possible polarization bases. By systematically varying α and ψ, all possible linear combinations of the available polarizations can be generated, and the intensity of the resulting synthetic channel can be computed for each case. In this framework, the new polarization basis can be calculated by sweeping through values of angular parameters and the dual polarimetric signature can be constructed by calculating the intensity for each synthetic polarization. This yields a two-dimensional signature plot that characterizes the scattering behaviour of each pixel or object under all physically realizable polarization basis.

3.2 Proposed Method

The workflow of the proposed soil salinity estimation framework is illustrated in Figure 3.

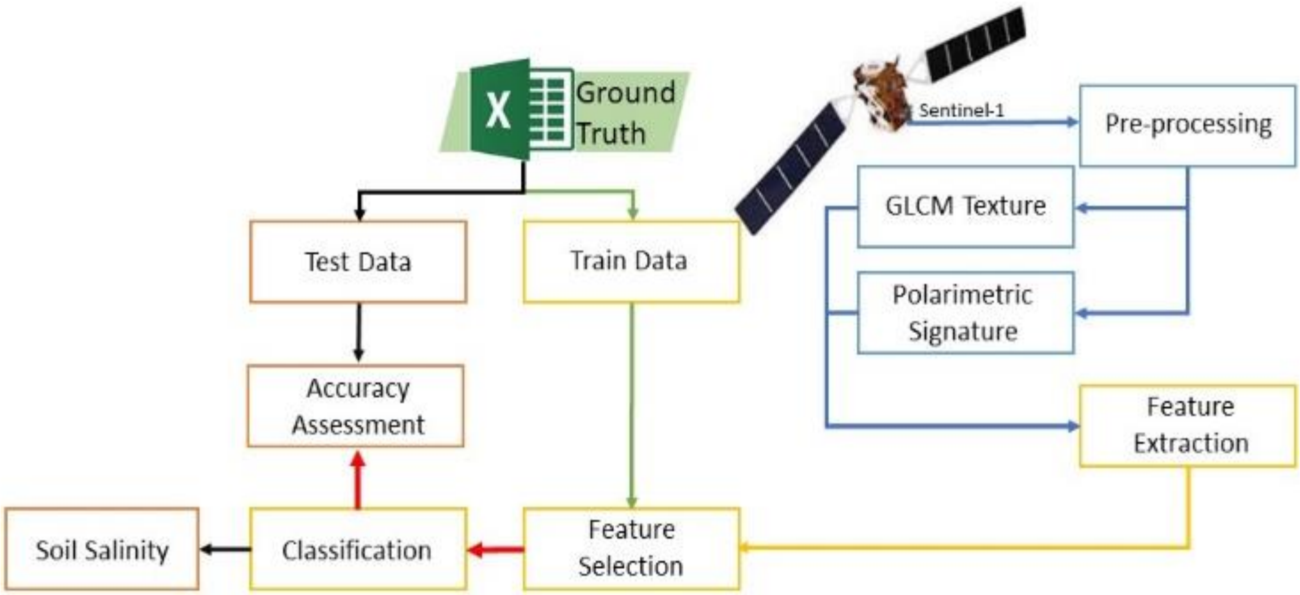

Figure 3. Workflow of the Proposed Method

The main steps are as follows:

3.2.1 Data Pre-Processing

Sentinel-1 dual-polarization SLC images are first pre-processed to generate a geo-referenced SLC image for both VV and VH channels. All pre-processing steps are performed in the ESA SNAP software, following standard SAR workflows. The main steps include: apply the latest precise orbit file to improve geolocation accuracy; TOPSAR de-bursting to seamlessly merge all sub-swaths and remove burst boundaries; and terrain correction based on a digital elevation model to geometric correction and to generate the geo-referenced imagery. The resulting pre-processed SLC products are then imported into Python for subsequent feature extraction and analysis.

3.2.2 GLCM Texture Analysis

In addition to backscattering intensity, incorporating spatial texture information can improve soil salinity classification, because salinity often alters surface roughness, crust formation, and micro structure patterns that are not fully captured by pixel-wise intensity alone. To explicitly model these local spatial variations, GLCM based descriptors are computed to summarize the spatial arrangement of grey levels within a neighbourhood and enrich the feature space with context sensitive information relevant to salinity-driven surface changes. Common texture metrics (e.g., contrast, correlation, entropy, homogeneity, dissimilarity) are computed over sliding windows to capture local spatial patterns and enhance the feature space for soil salinity classification.

3.2.3 Polarimetric Signature Generation

Polarimetric signatures are generated from the dual-pol SLC data by synthesizing new polarization states using linear combinations of VV and VH channels (Navarro-Sanchez & Lopez-Sanchez, 2011). As shown in the Equation (3), synthetic polarization states were produced by systematically varying both α (ellipticity) and ψ (rotation angle) from 0° to 90° and –180° to +180°, respectively, in increments of 5 degrees to generate the polarimetric signatures in each pixel or object. In the proposed method, the scattering intensity was computed over the full grid of α, ψ combinations, resulting in a comprehensive two-dimensional polarimetric signature for each pixel. Afterward, a set of descriptive features was extracted, including pedestal height, surface slope at extrema, skewness, kurtosis, peak intensity, signature width, and other shape-based metrics, for each polarimetric signature.

3.2.4 Feature Selection

The proposed framework produces a relatively large set of candidate features, many of which may be partially correlated or carry overlapping information. Such redundancy can increase model complexity and degrade generalization performance. Therefore, an explicit feature selection step was applied to retain the most informative predictors while removing irrelevant variables.

In this study, feature selection was conducted using a filter-based correlation analysis. The Pearson correlation coefficient was computed between each candidate feature and the electrical conductivity (EC) values representing soil salinity. Features were then ranked according to the strength of their correlation with EC, and those exhibiting stronger relationships were retained, while features with weak associations were excluded. This relevance-driven selection reduces redundancy, improves interpretability, and ensures that the retained predictors are directly related to soil salinity variability.

3.2.5 Classification

Soil salinity classes in real landscapes are typically separated by complex, non-linear boundaries due to the combined effects of soil moisture, roughness, vegetation residue, and heterogeneous surface conditions. As a result, linear decision rules are unlikely to capture the true class separability in the constructed feature space. To account for this non-linearity and to provide a robust comparison, two widely used non-linear classifiers, namely SVM and a multilayer perceptron (MLP) neural network, are implemented. The models are trained using the selected optimal features, and their parameters are tuned via cross-validation to achieve robust classification performance and improved generalization to unseen test samples.

3.3. Accuracy Assessment

The classification performance is verified based on the confusion matrix, which summarizes correct and incorrect predictions across salinity classes and enables error analysis from multiple perspectives, using independent test samples to ensure an unbiased assessment of model generalization. Because no single metric fully captures classification quality, several complementary indices are reported. Overall accuracy (OA) and the Kappa coefficient are used to describe the overall agreement between predicted and reference labels at the map level. In addition, class wise precision and recall are reported to quantify commission and omission tendencies, respectively, while the F1-score is used to provide a balanced measure of performance that accounts for both precision and recall for each salinity class. All metrics are computed using the independent test dataset.

Table 1. Classification results for soil salinity mapping using the proposed method

	SVM		
	Class-specific precision	**recall**	**F1-score**
Low	0.86	1.00	0.92
Mod	0.80	1.00	0.89
High	1.00	0.86	0.92
	MLP		
	Class-specific precision	**recall**	**F1-score**
Low	1.00	1.00	1.00
Mod	0.57	1.00	0.73
High	1.00	0.79	0.88

4. Result and Discussion

In this study, soil salinity was classified into three categories: low (0–0.4 dS/m), moderate (0.4–1.2 dS/m), and high (1.2–9.085 dS/m). The test dataset consisted of 24 samples, distributed as 9 in the low salinity class, 5 in the moderate class, and 12 in the high salinity class.

After feature extraction and optimization, fifteen optimal features were selected for classification. Of these, eight were texture features derived from GLCM analysis of the VV and VH intensity images, while the remaining seven were extracted from the dual-polarimetric signatures. Figure 4 demonstrates the dual polarimetric signature generated for the sample point located at coordinates (89.425, 22.815) with a measured soil salinity of 1.136 dS/m. The signature reflects the backscattering response across synthetic polarization states for this specific location.

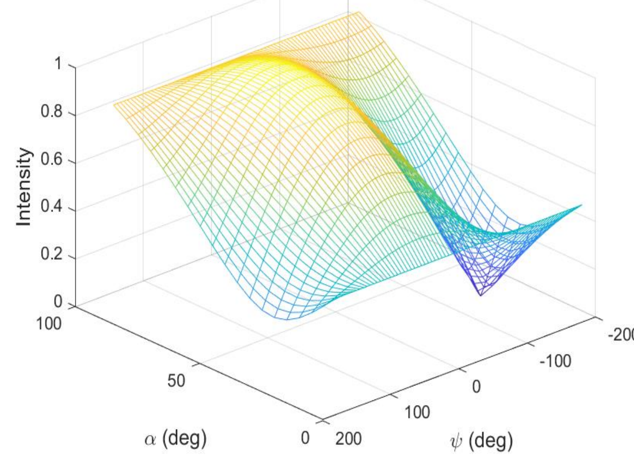

Figure 2. A dual polarimetric signature generated from Sentinel-1 data

The classification models were developed using both SVM and MLP neural network classifiers. The selected features were used as inputs, and model training and evaluation were conducted based on the previously described train/test split. Performance was assessed using standard accuracy metrics, including overall accuracy and kappa coefficient, in addition to class-wise evaluation indices. The best overall accuracy achieved in this study was 91.6%, with a kappa value of 86.1%, indicating a high level of agreement between the predicted and actual salinity classes. Table 1 summarizes the main classification results.

The results demonstrate that the integration of polarimetric signature-derived features with conventional intensity and texture measures lead to a notable improvement in classification performance. In particular, the signature features provided additional discriminatory power for separating moderate and high salinity classes, which are often challenging to distinguish using intensity-based features alone. These findings confirm the utility of dual-pol signature analysis in soil salinity mapping, even with the inherent limitations of dual-polarization SAR data.

Overall, the proposed methodology enabled robust and accurate mapping of soil salinity, showing strong potential for operational monitoring in other salt-affected regions.

Despite the strong classification performance, several limitations should be acknowledged. First, the proposed framework was evaluated in a single coastal deltaic environment (Khulna, Satkhira, and Jessore) using a limited number of in situ samples (130 points), and therefore the transferability of the selected features and trained models to other regions with different soil texture, irrigation practices, topography, and salinity formation mechanisms remains to be verified. Second, the analysis relies on a single date Sentinel-1 dual-polarization (VV/VH) SLC acquisition in an ascending geometry, which constrains generalization across incidence angles, viewing geometries, and alternative sensor configurations (e.g., descending passes, different frequencies such as L-band, or fully polarimetric data). Third, seasonal and short-term surface changes particularly soil moisture variability, surface roughness/crust formation, and vegetation residue can substantially affect SAR backscatter, texture measures, and synthesized polarimetric signatures; although the acquisition date was chosen to be temporally consistent with the field campaign, the robustness of the approach across wet/dry seasons and different phenological stages should be assessed using multi-temporal datasets. Future work will focus on cross-region validation, multi-season experiments, and testing additional SAR configurations to quantify model transferability and operational robustness.

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