

Article

Mangrove Extraction from Compact Polarimetric Synthetic Aperture Radar Images Based on Optimal Feature Combinations

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Abstract: As a polarimetric synthetic aperture radar (SAR) mode capable of simultaneously acquiring abundant surface information and conducting large-width observations, compact polarimetric synthetic aperture radar (CP SAR) holds great promise for mangrove dynamics monitoring. Nevertheless, there have been no studies on mangrove identification using CP SAR. This study aims to explore the potential of C-band CP SAR for mangrove monitoring applications, with the objective of identifying the most effective CP SAR descriptors for mangrove discrimination. A systematic comparison of 52 well-known CP features is provided, utilizing CP SAR data derived from the reconstruction of C-band Gaofen-3 quad-polarimetric data. Among all the features, Shannon entropy (SE), a random polarimetric constituent (V_B), Shannon entropy (SE_I), and the Bragg backscattering constituent (V_G) exhibited the best performance. By combining these four features, we designed three supervised classifiers—support vector machine (SVM), maximum likelihood (ML), and artificial neural network (ANN)—for comparative analysis experiments. The results demonstrated that the optimal polarimetric feature combination not only reduced the redundancy of polarimetric feature data but also enhanced overall accuracy. The highest accuracy of mangrove extraction reached 98.04%. Among the three classifiers, SVM outperformed the other classifiers in mangrove extraction, while ML achieved the highest overall classification accuracy.

Keywords: mangrove identification; compact polarimetric SAR; polarimetric features; image classification; Gaofen-3



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1. Introduction

Mangrove forests are primarily tidal wetland woody communities that grow in the upper part of tropical and subtropical low-energy coastal intertidal zones [1], subject to periodic tidal inundation, and composed of evergreen shrubs or trees, with mangrove plants as the mainstay [2]. Mangrove ecosystems are special ecosystems situated at the transition from land to sea, providing valuable resources for local residents and coastal zone environmental protection and serving as breeding sites for diverse flora and fauna and for storing large amounts of carbon [3–6].

However, since the 1950s, mangroves have endured more extensive damage, which is driven by both natural factors and human interference; the main threats to mangrove wetlands include pollution, polder, overfishing, dredging, infrastructure, urban construction, and invasive alien species [7]. Therefore, conducting remote sensing monitoring of

mangroves and accurately grasping their area and distribution can provide crucial scientific support for the effective management, conservation, and ecological restoration of mangroves in the future.

As mangroves are distributed in shallow mudflats at the junction of land and sea, their growth environment is complex and variable. Traditional survey methods are limited by issues such as large workloads and low efficiency, so it is difficult to obtain mangrove information on a large-scale basis and with high accuracy. In recent decades, the rapid development of remote sensing technology has enabled large-scale monitoring of mangrove forests. Remote sensing technology has the following advantages [8]: wide monitoring range, short repetition period, and high timeliness. Currently, multispectral, hyperspectral, LIDAR, and radar remote sensing technologies are mainly employed for mangrove monitoring. Among them, multispectral remote sensing technology has the highest spatial resolution and can finely classify mangroves, whereas hyperspectral remote sensing technology has the highest spectral resolution and can easily identify different kinds of mangroves. Because mangroves mainly grow in cloudy and rainy tropical and subtropical areas, the application of optical remote sensing in these areas is greatly limited by complex and changeable weather conditions. However, radar remote sensing can obtain data under all weather conditions without being affected by clouds, fog, and rain. Therefore, compared with optical remote sensing, it is more valuable to use it in mangrove distribution areas affected by clouds and rain for a long time.

Currently, radar is widely used in mangrove research. The main sensors employed for mangrove monitoring are ALOS, JERS-1, Envisat ASAR, Radarsat-1 SAR, and Sentinel-1A SAR [9–13] (Table 1). In recent decades, numerous studies on the application of SAR in mangrove identification and classification have been carried out. Thomas et al. utilized JERS-1 SAR and ALOS PALSAR data to monitor mangrove changes in nine regions worldwide from 1996 to 2010. Subsequently, they studied the global mangrove change distribution in the past five years based on expert interpretation [14,15]. Singh et al. employed an expert decision tree method based on JERS-1 (L-band HH polarimetric) and ERS-1 (C-band VV polarimetric) data for dynamic monitoring of mangroves in the western region of Gabo [16]. Bui et al. used Landsat and ALOS data to extract a land classification map of the Vietnamese region. In the region, mangroves were replaced mainly by shrimp ponds, resulting in a decrease in the area [11]. Simard et al. classified mangroves, grasslands, woodland, and swamps in the coastal area of Gabon based on JERS-1 and ERS-1 data using a decision tree method. They showed an 18% improvement in multi-band classification accuracy compared with that in a single band [17].

Table 1. Radar sensors used in mangrove study.

Sensor	Start Year	Band	Polarimetric Mode	Resolution (m)	Ref.
AIRSAR	1985	P C L	Quad-polarimetric	/	[18–20]
ERS-1	1991	C	VV	30	[17,18,21]
SIR-C	1994	C L X	Quad-polarimetric	10–200	[18,22,23]
JERS-1	1992	L	HH	18	[15,18,22]
ERS-2	1995	C	VV	30	[24,25]
Radarsat-1	1995	C	HH	10–100	[26–28]
Envisat	2002	C	Dual-polarimetric	28	[29–31]
ALOS	2006	L	Dual-polarimetric	10–100	[14,15,32,33]
TerraSAR-X	2007	X	Dual-polarimetric	1–40	[34]
Radarsat-2	2007	C	Quad-polarimetric	1.5–100	[35–37]
Sentinel-1	2014	C	Dual-polarimetric	5–40	[38–40]
ALOS-2	2014	L	Quad-polarimetric	3–100	[41–44]
GF-3	2017	C	Quad-polarimetric	1–500	[45]

With the development of radar technology, quad-polarimetric (QP) SAR and dual-polarimetric (DP) SAR can obtain more comprehensive polarimetric information than

single-polarimetric (SP) SAR [46]. Hence, they have been widely utilized for mangrove identification and classification. Rao et al. conducted research on Wishart supervised and unsupervised classification based on H/A/ α decomposition using SIR-C, ALOS, and ENVISAT data. They reported that ALOS has a higher classification accuracy (96%) than SIR-C (92%), accurately distinguishing between water, mangrove, and seawater [23]. Wang et al. investigated the classification of land cover classes, including mangroves in the Pearl River Delta, using multitemporal Envisat ASAR data. The decision tree method was used for classification, with an overall accuracy of 80% and a kappa coefficient of 0.77. They demonstrated that multi-temporal data helped improve the classification accuracy and that the radiation variation in mangroves exhibited normal seasonal fluctuations, with no obvious life cycle [30]. Wong et al. used Hyperion optical data and Envisat radar data to classify mangroves in Hong Kong. They selected hyperspectral and radar features and evaluated the accuracy of each class of combination by using Wrapper-based Feature Selection. Finally, comparing the maximum likelihood, decision tree, artificial neural network (ANN), and support vector machine (SVM) classification algorithms, they reported that the feature selection method can identify salient features, which is the best ANN among the classifiers [30].

Although QP SAR can provide more polarimetric information to enrich the information content of SAR data, it encounters issues such as lower resolution and smaller amplitude. Additionally, the system structure is complex and expensive, leading to higher application costs and significantly constraining the application of QP SAR. For instance, the QP SAR data width of RADARSAT-2 is only 25 or 50 km, whereas the width of the SP ScanSAR mode is 500 km.

As a polarimetric SAR mode capable of simultaneously acquiring abundant surface information and large-width observations, CP SAR has drawn increasing attention from researchers over the past decade. Following the successful launch of the Indian RISAT-1 satellite, CP SAR has made progress in a series of application studies [47]. However, no research has been conducted on mangrove identification using CP SAR. To develop a CP SAR mangrove monitoring technology, the response characteristics of CP SAR to mangroves need to be fully understood. In this study, we reconstructed GF3 QP SAR data to obtain CP SAR data, extracted 52 CP features based on various polarimetric decomposition methods, analyzed the performance of the 52 polarimetric features in distinguishing mangroves from other feature types using the Euclidean distance method, and filtered out the features with the best performance for mangrove identification and feature type differentiation, thereby obtaining the most optimal polarimetric feature combination. Finally, supervised classification methods such as the SVM classifier, maximum likelihood method, and artificial neural network were used for mangrove extraction and feature classification experiments.

The remainder of this paper is organized as follows: Section 2 presents an introduction to the study area and data; Section 3 elaborates on the theory of compact polarimetric, feature extraction, optimal feature selection, and supervised classification methods; Section 4 showcases optimal polarimetric feature selection and the results of mangrove identification and feature type classification experiments; Section 5 discusses the obtained results; Finally, Section 6 concludes with a summary.

2. Study Site and Data

2.1. Overview of the Study Site

The Leizhou Peninsula is situated at the southernmost tip of mainland China and belongs to the north tropical and south subtropical monsoon climate zone. It has an average annual temperature ranging from 22.8 to 23.4 °C and an average annual water temperature of 25 to 27 °C. The average annual total solar radiation is 4500–5600 MJ·m⁻², and the average annual precipitation is 1534.6 mm. These are prerequisite conditions for mangrove growth. The study area is located in the coastal area of Annex Town (Figure 1a). The mangrove forest is distributed in a strip from the east embankment of Shaoshan Village

in the north to the mouth of the Nandu River, with a total length of 13.5 km. The average width of the forest belt is 50–100 m, and the widest area reaches 300 m.

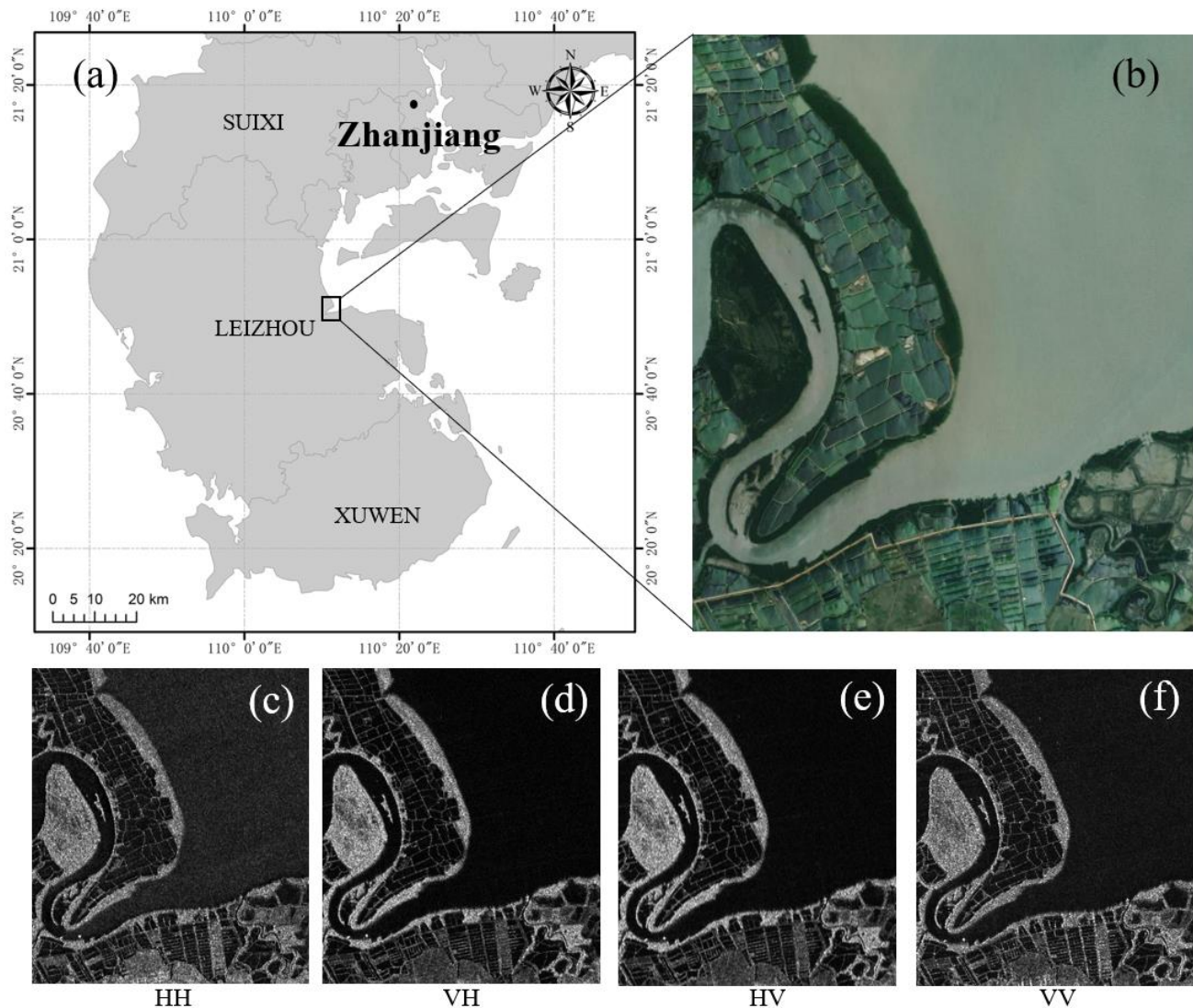


Figure 1. Study area and data images. (a) Geographical location of the Leizhou Peninsula; (b) optical satellite image; (c) SAR data image in HH polarimetric mode; (d) SAR data image in VH polarimetric mode; (e) SAR data image in HV polarimetric mode; (f) SAR data image in VV polarimetric mode.

The main mangrove tree species in the area are mainly white bone loam, tung flower tree, and autumn eggplant, with an average height of 1.2 to 1.5 m. Under the influence of wind and waves, from the shore to the sea, most mangroves exhibit the distribution characteristics of being from high to low and from dense to sparse. In the 1990s, *Sonneratia apetala* was successfully introduced, and its growth area gradually expanded. Currently, the area of *Sonneratia apetala* accounts for approximately 50% of the mangrove area. It has good growth and an average tree height of 8–9 m [48]. The optical image interpretation and field surveys revealed that there are various other classes of land cover in the region apart from mangroves, mainly including water (rivers and fishponds), land (bare land, roads, and cultivated land), and seawater. Since the scattering characteristics of rivers, fishponds, bare land, roads, and cultivated land are similar in SAR images (Figure 1c–f), these classes of land cover were classified into one category (water and land).

2.2. Data Source and Pre-Processing

The data in this study were selected from the QP SAR data of Gaofen-3, the first Chinese satellite capable of acquiring multi-polarimetric C-band SAR data, developed by the China National Space Administration, which was launched in August 2016. GF-3 has 12 imaging modes, with resolutions ranging from 1 to 500 m, data widths from 10 to 650 km, and conventional incidence angles from 20 to 50° [45]. The rich polarimetric information enables the identification of mangroves from complex and diverse land-cover classes. The data used in this study originated from the Guangdong Data and Applications Center of the High-Resolution Earth Observation System of Systems (http://gdgf.gd.gov.cn/GDGF_Portal/index.jsp (accessed on 2 July 2022)). This study employs C-band SAR data. Although the wavelength of the C-band is relatively short and its penetration ability is relatively weak, C-band SAR has certain advantages in data acquisition and multi-source data fusion. It can provide an effective means for estimating mangrove biomass, classifying communities, and monitoring distributions. Thus, it is of great significance in mangrove monitoring.

In particular, a GaoFen-3 QP SAR data image acquired on 7 March 2017 (Figure 1c–f) was used, and the product used was an L1A level single-look complex image, operating in quad-polarimetric strip I imaging mode and containing four polarimetric modes as follows [49]: (1) horizontal emission horizontal reception (HH); (2) horizontal emission vertical reception (HV); (3) vertical emission horizontal reception (VH); and (4) vertical emission vertical reception (VV), with a resolution of 8 m. PIE-SAR 7.0 software was employed to preprocess the GaoFen-3 data for radiometric calibration, complex data conversion, multi-look processing, Lee filtering, and geocoding (Table 2).

Table 2. Data details.

Scene ID	Image Area	Incidence Angle	Date (UTC)	Band	Polarimetric Mode	Resolution
3405430	Zhanjiang, China (20.836 N, 110.263 E)	48.845°–49.887°	7 March 2017, 10:55	C (5.4 Hz, center frequency)	Quad-polarimetric strip I	8 m

3. Methods

3.1. Compact Polarimetric SAR Data Acquisition and Feature Extraction

A compact polarimetric SAR fundamentally operates as a dual-polarization (DP) system. In contrast to the quad-polarization (QP) SAR, it features a simpler design and maintenance process, along with a wider imaging width. At present, several main modes for CP SAR have been introduced: (1) the $\pi/4$ Mode [50]; (2) the dual circular polarimetric (DCP) mode [51]; (3) the hybrid polarimetric (HP) mode [52]. Compared with conventional linear DP SAR, CP SAR has the capability to store the phase of the echo signal, allowing for greater flexibility in signal combination methods. Therefore, CP SAR can capture more detailed scattering information and often produces results comparable to those obtained from QP SAR data in various applications.

3.1.1. Compact Polarimetric SAR Data Acquisition

As actual CP data are unavailable in most cases, most research has depended on QP SAR data to simulate CP SAR data. Since the CTLR mode shows rotational invariance and has a simpler and more stable system structure, it is less prone to noise compared to the DCP mode [53]. Therefore, this study mainly focused on the CTLR mode. The CP scattering vector k derived from the polarimetric scattering matrix is represented by Equation (1). [54]:

$$k = \begin{bmatrix} E_{HC} \\ E_{VC} \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} & S_{VH} \\ S_{HV} & S_{VV} \end{bmatrix} \begin{bmatrix} 1 \\ \pm i \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} \pm iS_{HV} \\ S_{VH} \pm iS_{VV} \end{bmatrix} \quad (1)$$

where E is the electric field vector, H and V indicate horizontal and vertical polarization, C denotes circular polarimetric, S_{HH} , S_{VH} , S_{HV} , and S_{VV} are elements of the scattering matrix, while the symbols + and − indicate that the system transmits a left-hand circular (LHC) or right-hand circular (RHC) polarimetric wave, respectively.

This study employed a right-hand circular polarimetric wave (i.e., CTRL) since circular transmission is conducive to more effective reconstruction of pseudo-QP information [53]. According to Equation (1), the covariance matrix for the right CP can be expressed as shown in Equation (2):

$$C_2 = \langle \vec{k} \vec{k}^{*T} \rangle = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} \langle |E_{RH}|^2 \rangle & \langle E_{RH} E_{RV}^* \rangle \\ \langle E_{RV} E_{RH}^* \rangle & \langle |E_{RV}|^2 \rangle \end{bmatrix} \quad (2)$$

where R represents circular polarimetric, T indicates the matrix transpose operation, $*$ signifies the complex conjugate, and $\langle \rangle$ denotes the spatial average.

3.1.2. Feature Extraction

Based on the CP data simulation theory described in Section 3.1.1, GF3 QP SAR data were reconstructed to obtain CP SAR data. PolSARpro [55] was employed to extract CP features. A total of 52 features were analyzed, mainly derived from a combination of polarimetric components and decomposition techniques. Features $f1$ – $f4$ represented elements of the covariance matrix of CP SAR, while additional features were obtained from polarimetric decomposition techniques. The key features are detailed as follows (Table 3).

Table 3. Polarimetric features used in this study.

No.	Feature	Ref.	Description
$f1$ – $f4$	$C11$, $C12_imag$, $C12_real$, $C22$	[56]	Covariance matrix components
$f5$ – $f11$	Linear representation of the wave anisotropy ($Stokes_A$), circular polarimetric ratio (CPR), degree of circular polarimetric ($DoCP$), degree of linear polarimetric ($DoLP$), linear representation of the wave entropy ($Stokes_H$), linear polarimetric ratio (LPR), linear representation of the wave polarimetric contrast ($Stokes_Contrast$)	[57]	Stokes decomposition
$f12$ – $f15$	$g0$, $g1$, $g2$, $g3$	[57]	Stokes components
$f16$ – $f19$	Orientation angle (ϕ), ellipticity angle (τ), Poincaré planisphere ($Stokes_xp$, $Stokes_yp$)	[57]	Stokes Angles
$f20$ – $f22$	Dbl (V_G), Odd (V_R), Rnd (V_B)	[57]	m – χ decomposition
$f23$ – $f25$	m , χ (χ), δ (δ)	[57]	
$f26$ – $f29$	Eigenvalues ($l1$, $l2$) and probabilities ($p1$, $p2$)	[52]	
$f30$ – $f31$	Entropy (H) and anisotropy (A)	[56,58]	
$f32$ – $f34$	α , $\alpha1$, $\alpha2$		
$f35$	λ	[59]	H/α decomposition
$f36$ – $f38$	Δ , $\Delta1$, $\Delta2$		
$f39$ – $f41$	Shannon entropy (SE , SE_I , SE_P)	[60]	
$f42$ – $f45$	Combination (H , A): $1mH1mA$, $1mHA$, $H1mA$, HA	[61]	
$f46$ – $f48$	Dihedral component power (Pd), surface-scattering component (Ps), volume power (Pv)	[56]	Three-component compact decomposition
$f49$ – $f52$	α_s , m_s , m_v , ϕ	[56]	Compact RVoG (random volume over ground) decomposition

3.2. Optimal Feature Selection

To quantitatively compare the ability of the above-mentioned 52 CP features to extract mangroves and classify land cover classes, we used Euclidean distances to measure the contrast between mangroves and other land cover classes in the study site. The Euclidean distance is defined as follows:

$$D = \frac{|m_1 - m_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad (3)$$

where m and σ^2 represent the sample mean and variance, respectively; $|\cdot|$ denotes the absolute value; and $D > 0$. A greater Euclidean distance signifies a higher degree of differentiability between two samples, while a smaller distance indicates lower separability. According to Equation (3), a larger mean difference combined with a smaller variance result in a greater Euclidean distance between regions, leading to better separability. The Euclidean distance is commonly applied across various fields, including sea ice classification, ship target identification [62] and marine oil spill detection [63].

To evaluate the importance of the 52 CP features among various classes and identify those with the highest differentiation performance for each land cover class in the study area, a polarimetric feature analysis was carried out using Euclidean distance. The feature values used in this analysis were obtained from sample calculations of different classes within the polarimetric feature images.

In order to precisely represent the characteristics of the features, samples were chosen based on specific criteria. First of all, each sample class represents the typical nature of the corresponding feature. Secondly, the sample size is adequate to ensure the reliable estimation of the features, with the selection roughly corresponding to the area proportion of each class, aiming for approximately 20% of the total number of pixels of that class [64]. The spatial distribution of four land cover classes—mangroves, water, land, and seawater—was analyzed. The mean and variance of samples from each area in the CP feature images were calculated, and the Euclidean distances between each area were determined according to Equation (3). The distance between mangroves and the other three classes was utilized to assess the identification capability of each feature for mangroves, while the distances among the other three classes were used to evaluate the classification ability of each feature. Eventually, the polarimetric features were combined to identify the optimal set of features, as illustrated in Figure 2.

3.3. Supervised Classifications

3.3.1. SVM Classification

An SVM is a pattern recognition method based on statistical learning theory. According to Mercer's kernel expansion theorem, the sample space is mapped to a high-dimensional or even infinite-dimensional feature space (Hilbert space) through a nonlinear mapping Φ . In this way, the method of linear learning machine can be applied in the feature space, thereby addressing problems such as highly nonlinear classification and regression in the sample space. Its advantages and characteristics lie in its ability to effectively address the issue of small sample size, enhance generalization ability, and exhibit superior robustness and noise immunity. It has been applied in fields such as computer science, bioinformatics, and environmental science. It is currently one of the most widely used methods in remote sensing image classification [65]. In this study, radial basis functions were used as kernel functions. The principle of model construction is as follows:

Let the training sample set be $\{x_i, y_i\}_{i=1}^n$, where n is the sample capacity. Let the input sample data be $x_i \in R^n$ and the output sample data be $y_i \in R$. The idea of SVM is to map the samples to a high-dimensional feature space $F(\varphi : R^n \rightarrow F)$ through a nonlinear mapping $\varphi(\cdot)$. In the feature space $F(\varphi : R^n \rightarrow F)$, a classification problem is constructed as follows:

$$\min_{A, \xi} \frac{1}{2} \|A\|^2 + \frac{C}{2} \sum_{i=1}^n \xi_i^2 \quad (4)$$

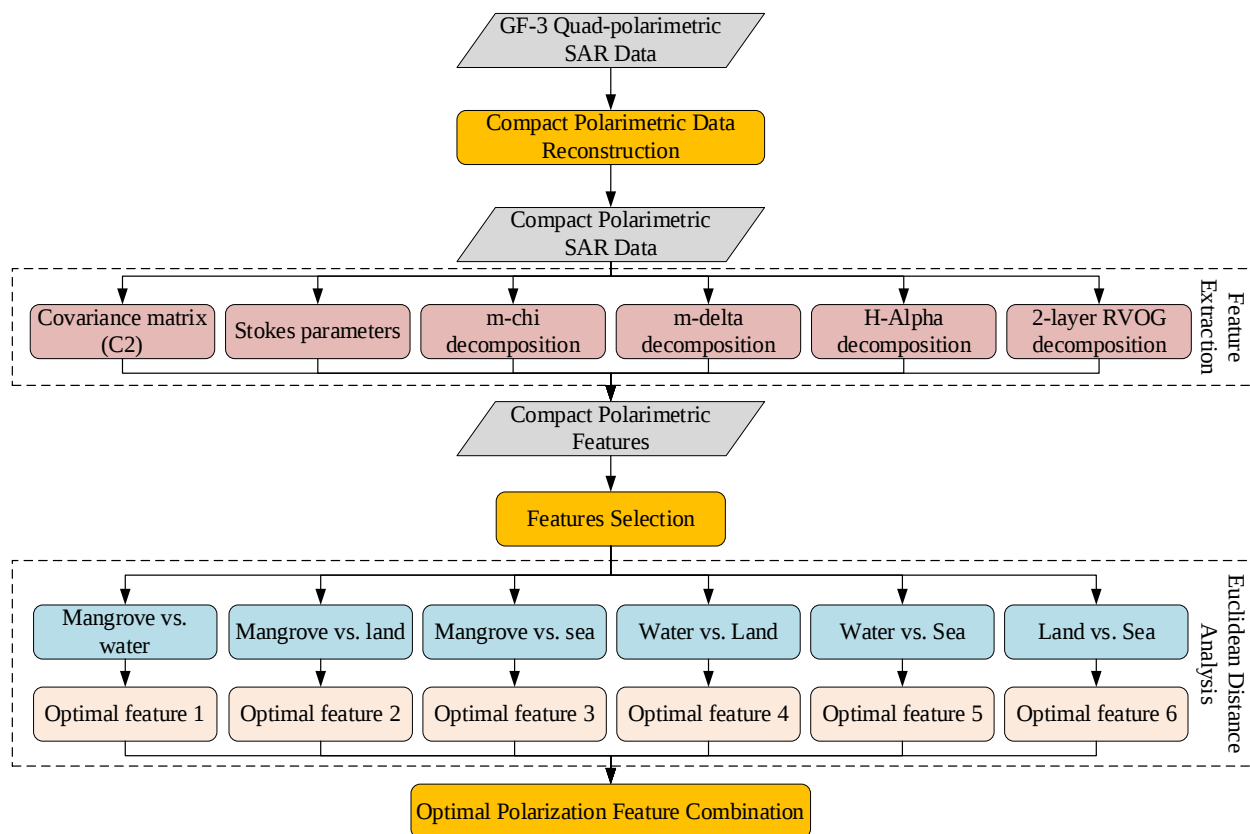


Figure 2. Optimal polarimetric feature selection flow.

Here, ξ_i is the slack variable, representing the degree of misclassification of the training samples. C is the penalty constant, which controls the degree of penalty for misclassified samples. A and b are, respectively, the weight and threshold of the function $f(x) = A \cdot \varphi(x) + b$. The decision function is obtained by using the Lagrange method.

$$f(x) = \text{sgn} \left(\sum_{i=1}^n \alpha_i^* y_i R(x, x_i) + b^* \right) \quad (5)$$

Among them, α_i^* is the weight corresponding to the SVM-optimized sample, and b^* is the threshold of the optimized SVM classifier. Radial basis function:

$$R(x, x_i) = \exp(-g|x - x_i|^2) \quad (6)$$

x_i is the center of the kernel function, g is a free parameter, and $|x - x_i|^2$ is the squared Euclidean distance between two feature vectors.

3.3.2. ML Classification

The ML classifier is a classical classifier widely used in various remote sensing interpretations [66]. It obtains parameters such as the mean and variance of each category through statistics and calculations on the sensing area to determine a classification function. Then, each image element in the image to be classified is substituted into the classification function of each category. The category with the largest return value of the function is used as the attribution category of the scanned image element to achieve the classification effect.

The basic principle is as follows: Given a probability distribution D , assuming its probability density function (for continuous distribution) or probability mass function (for discrete distribution) is f_D , and a distribution parameter θ , A sample data with n values

$x_1, x_2, \dots, x_n$ can be extracted from this distribution, and its probability P can be computed by utilizing f_D :

$$P = (x_1, x_2, \dots, x_n | \theta) \quad (7)$$

Then, these sampled data x are used to estimate θ . Maximum likelihood estimation will search for the most probable value of θ (that is, among all possible values of θ , find a value that maximizes the “likelihood”).

The likelihood is defined as

$$lik(\theta) = f_D(x_1, x_2, \dots, x_n | \theta) \quad (8)$$

Furthermore, maximize this function across all possible values of θ . The value that yields the maximum likelihood is referred to as the maximum likelihood estimate of θ .

3.3.3. ANN Classification

Neural networks are designed based on the nervous systems of animals [67]. This can be used to estimate complex unknown functions based on a large number of inputs. ANNs have adaptive properties and are often used for supervised classification. They achieve a better performance when the training samples are sufficiently large.

This paper uses a three-layer feedforward neural network, where each neuron (or ‘unit’) in the network contains a transfer function. The neurons in the hidden and output units perform a nonlinear sigmoid function, whereas those in the input units perform a constant transfer function. The layers are then interconnected using a weighting system that multiplicatively scales the values of the traversal links. The weights and biases of these links in the network are initialized randomly and fine-tuned through a back-propagation process. Its architecture is as follows.

- Input layer: receive external input data and pass it to the next layer.
- Hidden layer: The middle layer. The number of neurons in it can be adjusted as needed. The hidden layer introduces nonlinearity through linear transformation and activation function so it can handle complex nonlinear relationships.
- Output layer: responsible for outputting the prediction results of the model.

Then, each layer is interconnected through a weight system. The weight system multiplicatively scales the values traversing the links. The weights and biases of these links in the network are first randomly initialized and then fine-tuned through the backpropagation process.

4. Results

4.1. Feature Analysis and Selection of Optimal Polarimetric Feature Combination

The Euclidean distances between mangroves and water (E_{M-W}), mangroves and land (E_{M-L}), mangroves and seawater (E_{M-S}), water and land (E_{W-L}), water and seawater (E_{W-S}), and land and seawater (E_{L-S}) for each polarimetric feature map are shown in Figure 3a–f. E_{M-S} was relatively large (mean 2.027, maximum 8.754), whereas E_{W-L} was relatively small (mean 0.962, maximum 8.754) for most features. For each figure in Figure 3, an analysis of the differentiation performance between different classes showed the following:

- Figure 3a: the best performance in differentiating mangroves from water was $f39(SE)$, with $E_{M-W} = 8.937$, followed by $f40(SE_I)$, $f22(V_B)$.
- Figure 3b: the best performance in differentiating mangroves from the land was $f22(V_B)$, with $E_{M-L} = 2.596$, followed by $f39(SE)$ and $f40(SE_I)$.
- Figure 3c: the best performance in differentiating mangroves from seawater was $f39(SE)$, with $E_{M-S} = 8.754$, followed by $f40(SE_I)$, $f22(V_B)$.
- Figure 3d: the best performance in differentiating water from land was $f40(SE_I)$, with $E_{W-L} = 5.728$, followed by $39(SE)$, $f22(V_B)$.
- Figure 3e: the best performance in differentiating water from seawater was $f20(V_G)$, with $E_{W-S} = 2.079$, followed by $f40(SE_I)$ and $f26(I1)$.

- Figure 3f: the best performance in distinguishing land from seawater was $f39(SE)$, with $E_{L-S} = 4.972$, followed by $f40(SE_I)$ and $f22(V_B)$.



Figure 3. Euclidean distances between different classes in CP feature images. (a) denotes the Euclidean distance between mangrove and water; (b) denotes the Euclidean distance between mangrove and land; (c) denotes the Euclidean distance between mangrove and seawater; (d) denotes the Euclidean distance between water and land; (e) denotes the Euclidean distance between water and seawater; (f) denotes the Euclidean distance between land and seawater.

The largest Euclidean distance indicates the best classification performance. Therefore, the above four optimal features are combined to form the optimal feature combination: $C_{f39, f22, f40, f20}$. Figure 4a–d present the images of the above features. There are significant visual differences between mangroves and other classes, indicating that these features can be used for mangrove detection. In addition, the three features— $f39(SE)$, $f40(SE_I)$, and $f22(V_B)$ —not only had the best differentiation performance for the two classes but also had better classification ability for other inter-classes, especially $f39(SE)$. Moreover, $f12(g_0)$ and $f48(P_v)$ possessed good comprehensive abilities (Figure 4e,f).

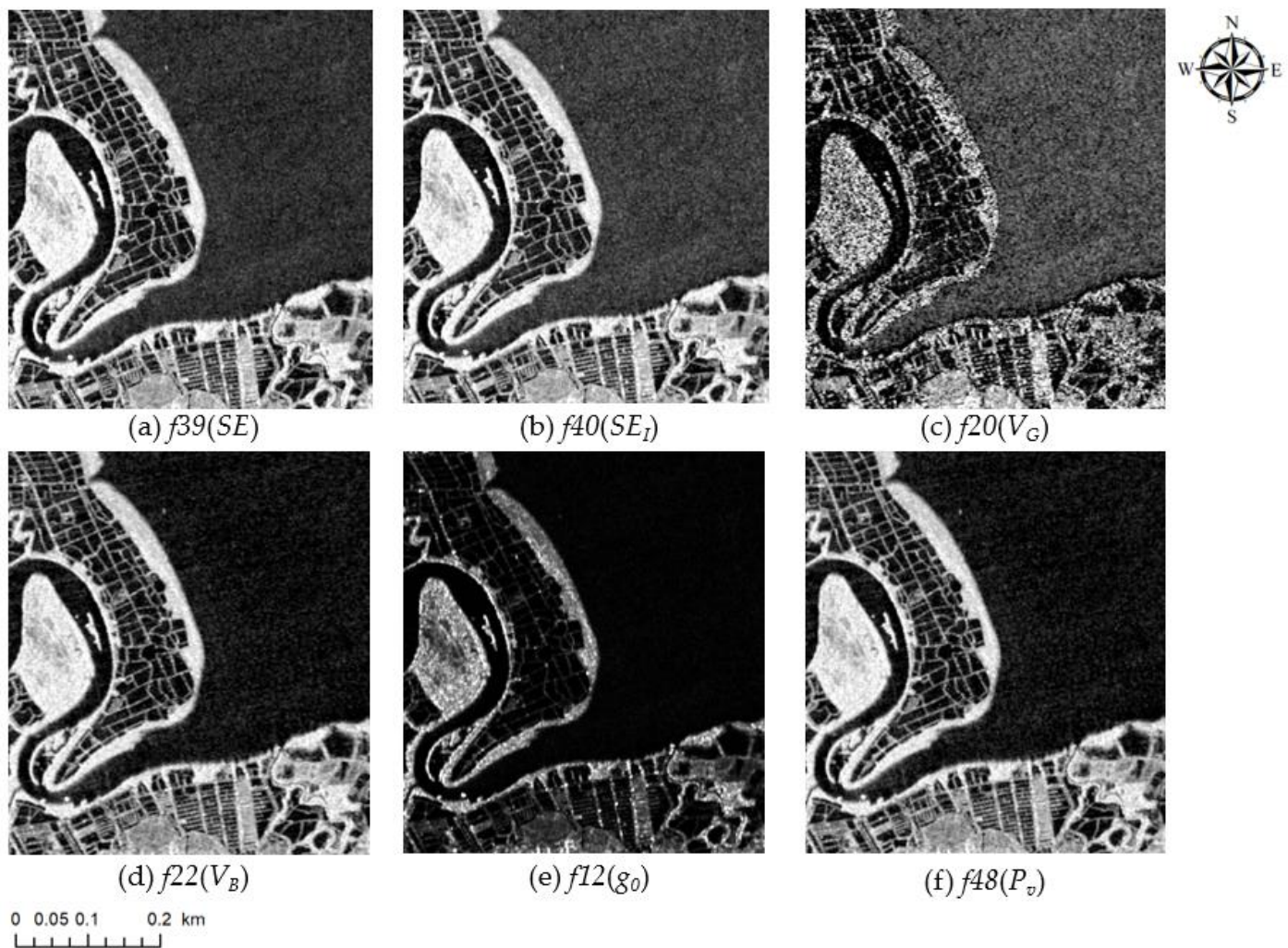


Figure 4. CP feature image.

To verify the reliability of the above six polarimetric features— $f39(SE)$, $f40(SE_I)$, $f22(V_B)$, $f20(V_G)$, $f12(g_0)$, and $f48(P_v)$ —with comprehensive classification performance, each feature value of the four cover classes—mangroves, water, land, and seawater—samples was normalized to yield the difference in the response of the four classes under different features (Figure 5). Among the six polarimetric feature images, the response difference in mangrove is the most significant compared with the other three cover classes, and there were no overlapping intervals in the eigenvalue distributions, indicating good mangrove differentiation. The differences in the eigenvalue responses of the four classes in $f39(SE)$ and $f40(SE_I)$ were relatively evident, and there were no overlapping intervals in their distribution, including that of mangroves. For example, the range of mangrove eigenvalues in the $f39(SE)$ feature image was 0.57–0.62; that of land eigenvalues was 0.43–0.5; that of water eigenvalues was 0.12–0.17; and that of seawater eigenvalues was 0.22–0.26.

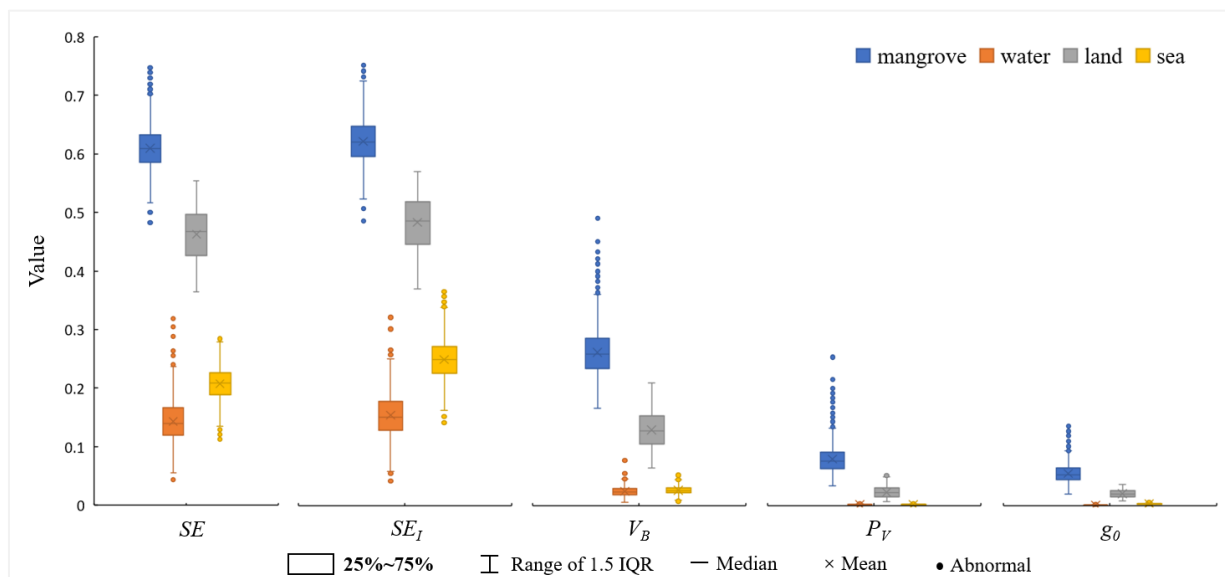


Figure 5. Differences in eigenvalue responses between mangroves and other cover classes in feature images with enhanced combined performance.

As a result, the Euclidean distances between the different classes in the $f39(SE)$ and $f40(SE_I)$ feature images were also larger, providing a better comprehensive classification performance for multiple classes. However, the distribution of eigenvalues of water and seawater in the three feature images of $f22(V_B)$, $f48(P_V)$, and $f12(g_0)$ overlapped heavily, and the Euclidean distance between different classes in the feature images was relatively small but relatively better than those of the other polarimetric features.

In the following section, a comparative analysis of the classification experiments was conducted for the above features that have a relatively comprehensive classification performance.

4.2. Mangrove Identification and Land Cover Classification Results

Here, supervised classification experiments were conducted for the above features. The confusion matrix method was employed to evaluate the accuracy of classification results. The specific evaluation indicators include overall accuracy (OA), which represents the proportion of correctly predicted samples to the total number of samples, that is, the probability that the classification result is consistent with the actual category corresponding to the sample. The Kappa coefficient is an indicator used for consistency inspection and is often utilized to measure the effectiveness of classification. The specific formulas are as follows:

$$OA = \sum_{i=1}^n \frac{x_{ii}}{N} \quad (9)$$

$$Kappa = \frac{N \sum_{i=1}^n x_{ii} - \sum_{i=1}^n (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^n (x_{i+} x_{+i})} \quad (10)$$

Before the experiments, all features were normalized to the range of 0–1, and the results of the above features in mangrove extraction and class classification were compared and analyzed. In the experiments, training samples from four research areas, including mangrove, water, land, and seawater were selected. Test samples containing the same number of pixels as the training samples were selected, and the training and test samples were not included in each other, and these pixels were visually identified as the four cover classes.

4.2.1. Classification Results Based on a Single Feature Input

To compare and analyze the performance of mangrove extraction and classification of other classes with different features, SVM classifiers were designed to perform classification experiments for six features, namely $f39(SE)$, $f40(SE_I)$, $f22(VB)$, $f20(V_G)$, $f12(g_0)$, and $f48(P_v)$. The classification results are presented in Figure 6. The classification accuracy confusion matrix is provided in Table 4. Mangrove extraction results are shown in Figure 7.

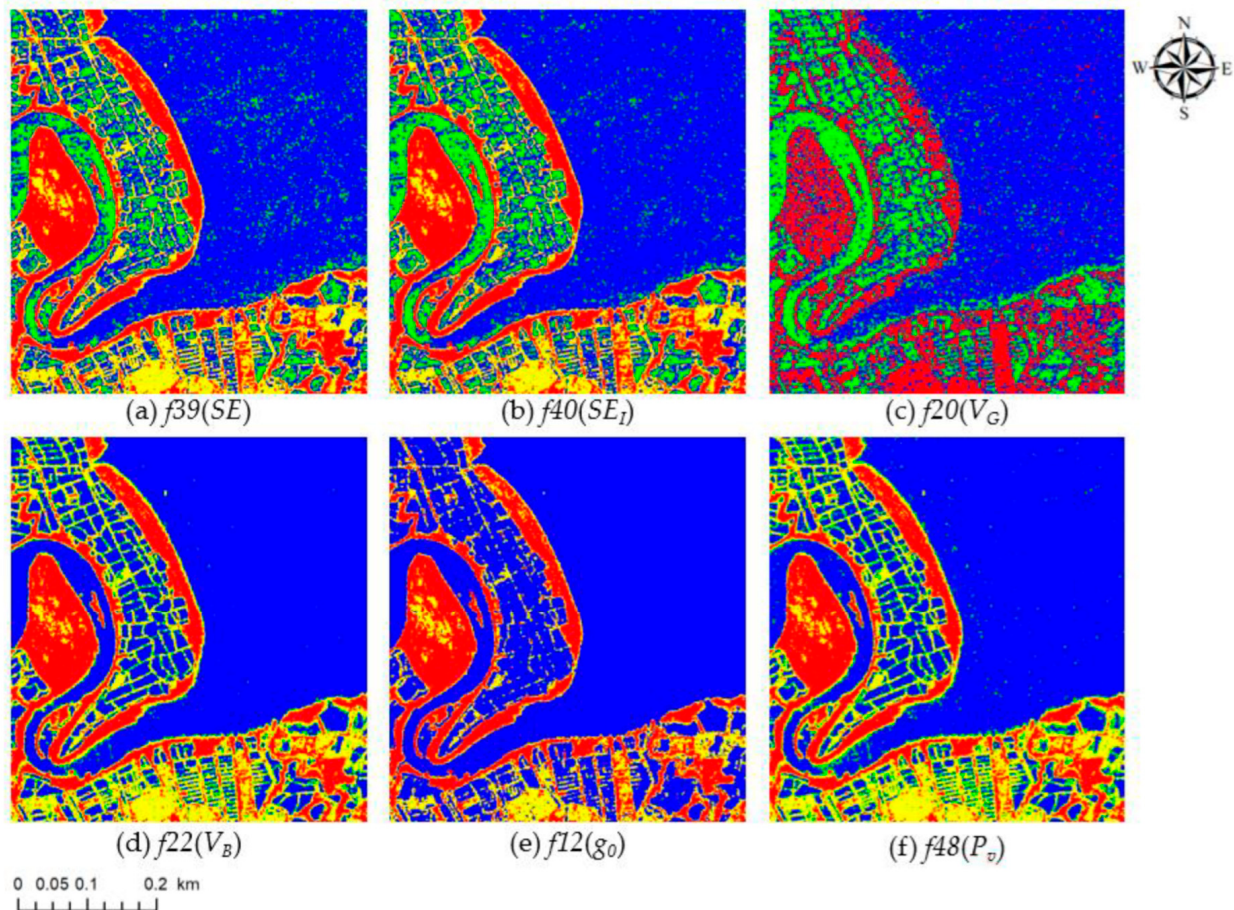


Figure 6. SVM classification results are based on a single polarimetric feature input. Mangroves are shown in red, water in blue, land in yellow, and seawater in blue.

Table 4. Accuracy of classification results based on a single feature input.

Input	Class	Mangrove	Water	Sea	Land	Overall Accuracy (%)	Kappa Coefficient
SE	Mangrove	97.97%	0.00%	0.00%	6.69%	0.8548	0.80632
	Water	0.00%	66.08%	11.74%	0.00%		
	Sea	0.00%	33.92%	88.26%	3.73%		
	Land	2.10%	0.00%	0.00%	89.58%		
SE _I	Mangrove	97.90%	0.00%	0.00%	8.87%	0.88345	0.84455
	Water	0.00%	78.44%	8.49%	0.00%		
	Sea	0.00%	21.56%	91.51%	5.77%		
	Land	2.03%	0.00%	0.00%	85.36%		
V _G	Mangrove	66.57%	0.00%	2.69%	76.57%	0.59776	0.46309
	Water	6.99%	82.65%	8.08%	2.32%		
	Sea	26.43%	17.35%	89.23%	21.11%		
	Land	0.00%	0.00%	0.00%	0.00%		

Table 4. Cont.

Input	Class	Mangrove	Water	Sea	Land	Overall Accuracy (%)	Kappa Coefficient
V_B	Mangrove	97.69%	0.00%	0.00%	5.21%	0.72113	0.62763
	Water	0.00%	0.07%	0.48%	3.38%		
	Sea	0.00%	99.93%	99.52%	0.77%		
	Land	2.31%	0.00%	0.00%	90.64%		
g_0	Mangrove	96.85%	0.00%	0.00%	6.40%	0.68915	0.58484
	Water	0.00%	0.00%	0.00%	0.00%		
	Sea	0.00%	100.00%	100.00%	15.41%		
	Land	3.15%	0.00%	0.00%	78.18%		
P_v	Mangrove	97.48%	0.00%	0.00%	4.57%	0.7234	0.63068
	Water	0.00%	1.33%	1.73%	3.45%		
	Sea	0.00%	98.67%	98.27%	0.21%		
	Land	2.52%	0.00%	0.00%	91.77%		

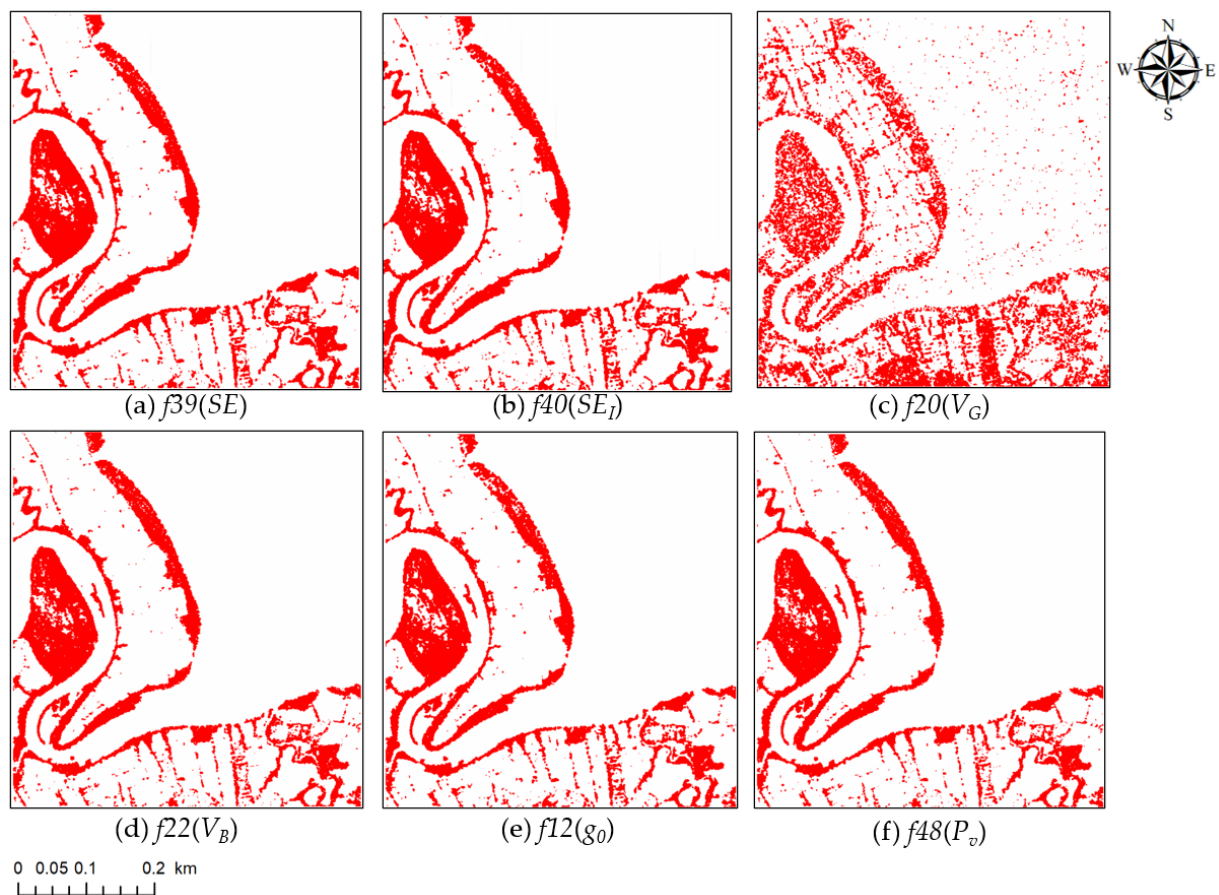


Figure 7. Mangrove extraction results are based on a single polarimetric feature input.

Regarding mangrove extraction, with the exception of $f20(V_G)$, the other five polarization features all exhibit excellent mangrove extraction capabilities. The average accuracy stands at 97.58%. Among them, $f39(SE)$ achieves the highest accuracy of 97.97%. From the classification results, it can be seen that most mangrove areas can be detected, and the edge details of mangrove regions can be effectively preserved, suggesting that these features possess relatively strong mangrove recognition abilities (Figure 7). However, the accuracy of $f20(V_G)$ is merely 66.57%. The mangrove classification result shows an obvious “pretzel” phenomenon (Figure 7c), and it fails to distinguish between land and mangroves. Consequently, 76.57% of the land is misclassified as mangroves, which might be attributed to the similar polarization response of these two classes in the feature image. Nevertheless,

the distinguishing performance of $f20(V_G)$ for water and seawater is relatively satisfactory, with the classification accuracy reaching 82.65% and 89.23%, respectively. On the contrary, $f22(V_B)$, $f12(g_0)$, and $f48(Pv)$ cannot effectively distinguish between water and seawater. In particular, in the case of $f12(g_0)$, all water areas are classified as seawater (Figure 6e). $f39(SE)$ has a relatively strong capability to distinguish between mangroves and land as well as between mangroves and seawater. In terms of its discriminatory ability, the next is between mangroves and water. $f40(SE_I)$ has a similar classification effect to $f39(SE)$. It also has a relatively strong capability to distinguish between mangroves and seawater as well as between mangroves and land. In terms of its discriminatory ability, the next is between mangroves and water bodies. By looking at Figure 6, it is not hard to see that this is mainly because the response differences between mangroves and water, seawater, and land at the features of $f39(SE)$ and $f40(SE_I)$ are relatively significant. Utilizing these two features can distinguish mangroves from other ground objects more effectively.

In general, among the six features, $f40(SE_I)$ achieved the highest overall classification accuracy of 88.34%, with a kappa coefficient of 0.845, followed by $f39(SE)$ (OA = 85.48%, K = 0.806), which not only has better mangrove extraction ability but can also effectively distinguish between the other three classes. However, $f22(V_B)$, $f20(V_G)$, $f12(g_0)$, and $f48(Pv)$ all have classes that cannot be distinguished.

4.2.2. Classification Results Based on Optimal Feature Combination Input

For the classification experiments with the input of optimal polarimetric feature combinations $C_{f39,f22,f40,f20}$, in this study, three main supervised classifiers, including SVM, ML, and ANN, were considered, and separate comparison experiments were carried out.

The parameters of the three classifiers are adjusted multiple times. When the classification accuracy tends to be stable, it is output as the final result. For SVM, the Radial Basis Function (RBF) is selected as the kernel function, which contains two parameters: penalty coefficient and gamma. The parameter of ML is the likelihood threshold. For ANN, the default relu activation function is selected. The main adjusted parameters are the learning rate and penalty parameter (alpha). The algorithm parameter settings of each group of experiments are shown in Table 5.

Table 5. The parameter settings for the three classifiers.

Classifier	Parameter
SVM	Kernel Type: 'RBF'; Penalty = 100; gamma = 0.0001
ML	Probability Threshold = 0.7
ANN	learning rate = 0.05; alpha = 0.0001

Figure 8 presents the classification results of the three classifiers, and the classification accuracy confusion matrix is shown in Table 6. All three classifiers have an accuracy higher than 95% for mangrove identification. Among them, SVM has the highest accuracy for mangrove extraction at 98.04%, followed by ANN (97.76%) and ML (95.80%).

Table 6. Accuracy evaluation of classification results based on optimal polarimetric feature combination input.

Feature	Class	Mangrove	Water	Sea	Land	Overall Accuracy (%)	Kappa Coefficient
C_{SVM}	Mangrove	98.04%	0.00%	0.00%	4.29%	91.60%	0.888
	Water	0.00%	83.08%	6.98%	0.07%		
	Sea	0.00%	16.92%	93.02%	3.38%		
	Land	1.96%	0.00%	0.00%	92.26%		
C_{ML}	Mangrove	95.80%	0.00%	0.00%	2.11%	91.99%	0.893
	Water	0.00%	86.66%	11.12%	0.70%		
	Sea	0.00%	13.34%	88.88%	0.49%		
	Land	4.20%	0.00%	0.00%	96.69%		

Table 6. Cont.

Feature	Class	Mangrove	Water	Sea	Land	Overall Accuracy (%)	Kappa Coefficient
C-ANN	Mangrove	97.76%	0.00%	0.00%	5.84%	91.61%	0.888
	Water	0.00%	86.45%	10.43%	0.00%		
	Sea	0.00%	13.55%	89.57%	1.48%		
	Land	2.24%	0.00%	0.00%	92.68%		

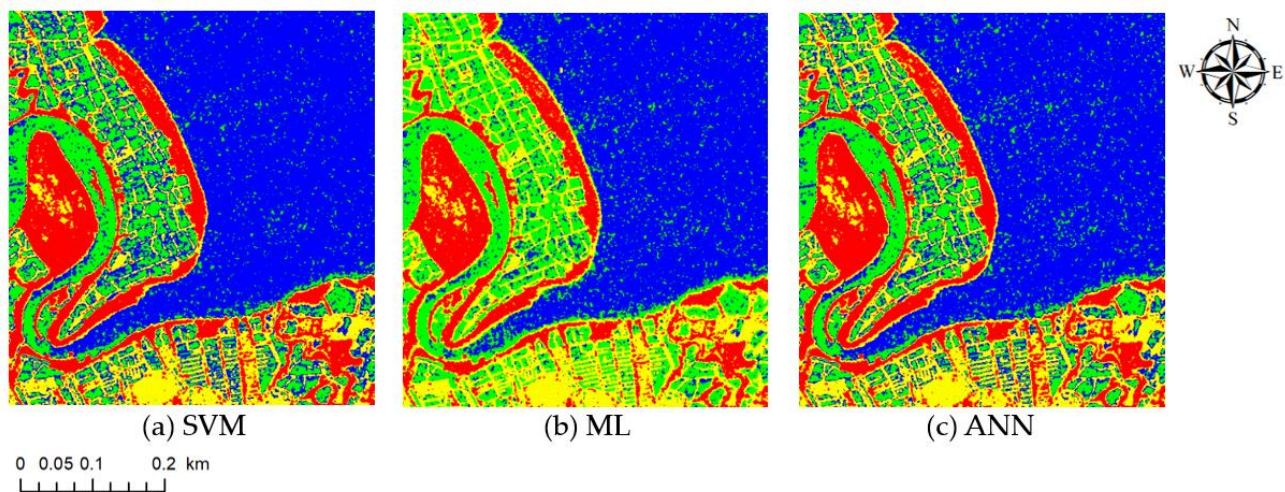


Figure 8. Classification results based on optimal polarimetric feature combination input. Mangroves are in red, water in blue, land in yellow, and seawater in blue.

The results of mangrove segmentation are displayed in Figure 9. Most mangrove areas were detected, and their edge details were effectively maintained, indicating that all three classifiers have a good mangrove recognition ability.

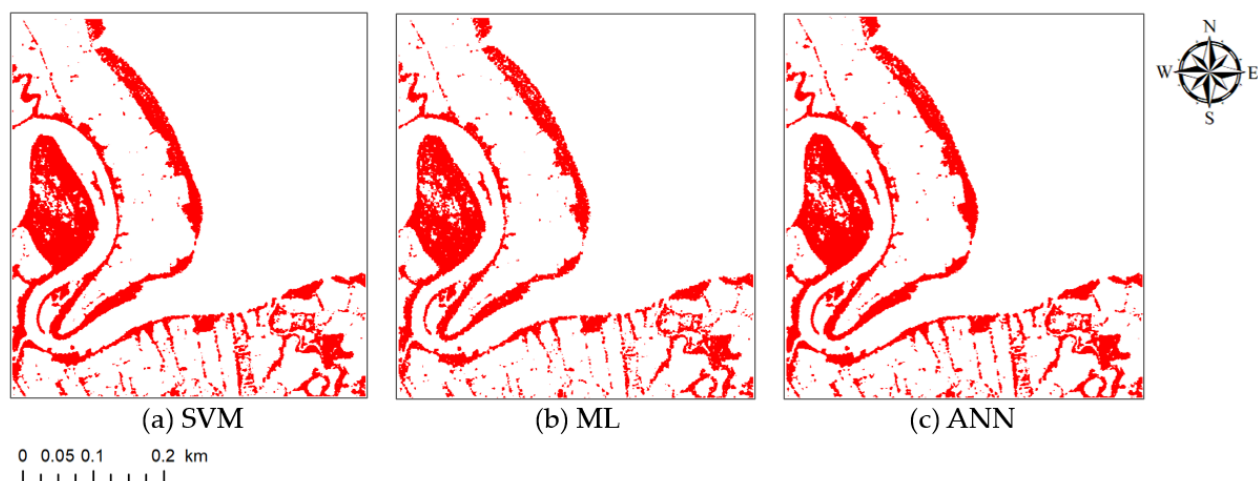


Figure 9. Mangrove extraction results based on optimal polarimetric feature combination input.

Figure 8 indicates that the three classifiers can effectively distinguish mangroves from water and seawater. However, mangroves were mainly confused with land due to their similar scattering mechanisms. Mangrove fringe areas are often classified as land, probably because the polarimetric response characteristics of mudflats near the mangrove fringe are similar to those of land. ML had the best performance in classifying water and land, with classification accuracies of 86.66% and 96.69%, respectively. SVM has the highest accuracy for seawater extraction at 93.02%. The OA and Kappa coefficients are listed in Table 6.

The difference in OA among the three classifiers was not significant. All were higher than 90%, with ML being the highest at 91.99%, followed by SVM and ANN, with OA values of 91.60% and 91.61%, respectively. The Kappa coefficients of the three classifiers exceeded 0.8, indicating a high level of agreement among them. Overall, SVM has the optimal mangrove extraction performance, and ML has a strong performance in differentiating water and land.

5. Discussion

Based on Euclidean distance analysis (Figure 3), among the 52 CP features, $f_{39}(SE)$ is the most optimal for distinguishing mangroves from water and land from seawater; $f_{22}(V_B)$ is optimal for distinguishing mangroves from land; $f_{40}(SE_I)$ is optimal for distinguishing water from land; and $f_{20}(V_G)$ is optimal for distinguishing water from seawater. Comparing the classification results of the single-feature and optimal-polarimetric-feature combination SVM (Figure 10), the latter has higher OA and Kappa coefficients. The optimal polarimetric feature combination combines the advantages of $f_{39}(SE)$, $f_{40}(SE_I)$, $f_{22}(V_B)$, and $f_{20}(V_G)$. It can leverage the advantages of each feature in distinguishing different classes of ground objects, compensate for the deficiency in the comprehensive extraction ability of mangroves relying solely on a single feature, and enhance classification accuracy while effectively reducing the redundancy of polarization features.

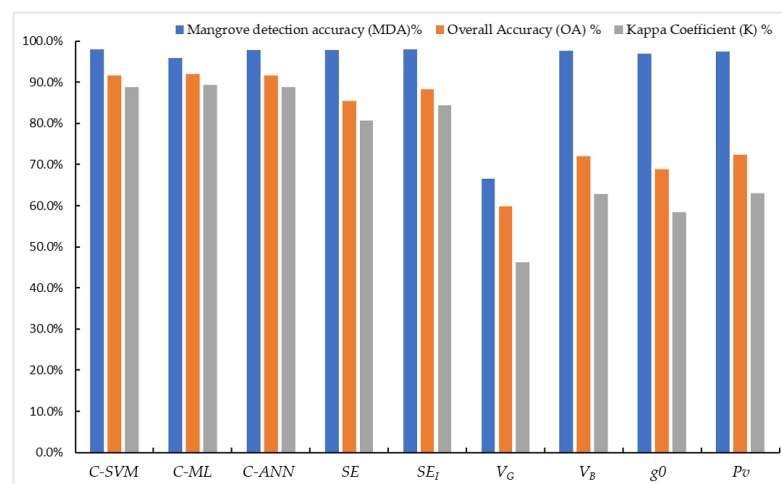


Figure 10. Comparison of mangrove extraction accuracy, OA, and Kappa coefficient values of the different classifiers and features.

By comparing the extraction effects of mangroves by the SVM classifier with a single feature and the optimal feature combination, it can be observed that the optimal features mainly enhance the OA and Kappa indicators. Since OA and Kappa can balance the classification results of all categories and are comprehensive indicators, the improvement of OA and Kappa intuitively reflects that the optimal feature combination enhances the classifier's comprehensive discrimination ability for different land cover classes.

The selection of the four classes was effective in identifying mangrove areas, enabling the separation of mangroves from the other classes. However, there might have been some inaccuracies, as many lands were incorrectly classified as mangroves according to the classification confusion matrix (Tables 4 and 6). When using optimal polarimetric feature combinations and employing the SVM classifier, the overall classification accuracy reached 91.6%, and the Kappa coefficient reached 0.888, showing high consistency. The actual mangrove areas were correctly classified as mangroves at a rate of 98.04%, and only 1.96% were classified as land. One possible explanation for the confusion between land and mangroves is that the double-bounce scattering caused by ground-trunk interactions in the flooded environment of mangroves may be similar to that of land; this double-bounce scattering mechanism similarly increases the energy intensity of the returned radar in both

environments. For the classification of water and seawater, the polarimetric responses of these two classes are extremely similar. Only 16.92% of water regions are misclassified as seawater, and 6.98% of seawater regions are misclassified as water. The classification accuracy distributions of water and seawater regions reach 83.08% and 93.02%, respectively. Additionally, $f20(V_G)$ has a significant advantage in differentiating between water and seawater. The accuracy of the classification results based on a single polarimetric feature input can reach 82.65% and 89.23%, respectively. This may be because seawater is greatly influenced by wind and surge, and its Bragg backscattering intensity is greater than that of water and aquaculture ponds.

The results of the Euclidean distance calculation were compared with classification accuracy and found to be consistent. The variation in Euclidean distance and classification accuracy of CP features with better performance in mangrove extraction and land cover class classification is shown in Figure 11a. The classification accuracy of CP features for mangroves and land is closely related to the Euclidean distance, proving the reliability of using the Euclidean distance to analyze the mangrove extraction and cover class classification performance of CP features. However, the classification results of water and seawater in $f22(V_B)$, $f12(g0)$ and $f48(Pv)$ were inaccurate (Figure 6d–f), and most water areas were misclassified as seawater. Moreover, the classification accuracy of seawater was very high, reaching up to 100%. These findings indicate that the three features of $f22(V_B)$, $f12(g0)$ and $f48(Pv)$ cannot distinguish between water and seawater. Therefore, detection accuracy did not produce the same trend of change as the Euclidean distance (Figure 11b); nevertheless, this did not affect the conclusion that Euclidean distance is effective for the classification of surface cover classes.

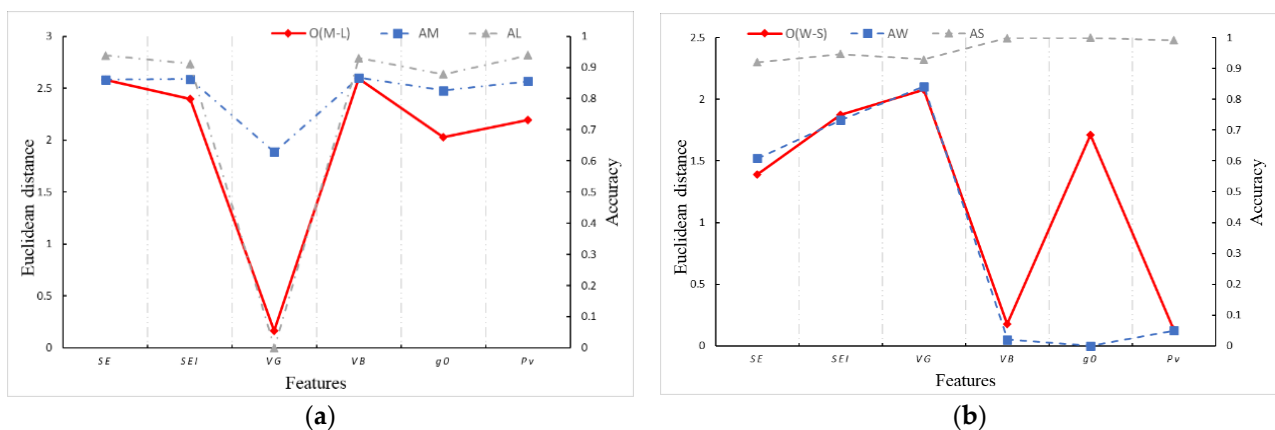


Figure 11. Euclidean distance and classification accuracy. (a) Euclidean distance and classification accuracy between mangrove and land, where O(M-L) denotes the Euclidean distance between mangrove and land in the feature image, and AM and AL denote the classification accuracy of mangrove and land, respectively. (b) Euclidean distance and classification accuracy between water and seawater, where O(W-S) denotes the Euclidean distance between water and seawater in the feature image, and AW and AS indicate the classification accuracy of water and seawater, respectively.

CP SAR, as a polarimetric SAR mode that can simultaneously obtain relatively rich surface information and achieve large swath observation, compared with QP and SP SAR, combines the advantages of all-weather and all-weather observation of radar remote sensing, and can also reduce the cost of large-scale observation of mangroves while ensuring the high-precision identification of mangroves, showing a very good application prospect in the global mangrove dynamic monitoring research. In addition, CP SAR also has great application potential in forest aboveground biomass inversion and vegetation height inversion.

In future research, more in-depth research is needed on the mangrove scattering model. On this basis, it is necessary to make full use of various features provided by the radar, combine prior knowledge and the advantages of multi-source remote sensing, and integrate

time series data to achieve more breakthroughs in mangrove classification and identification and biophysical parameter inversion research. In addition, in terms of surface information acquisition, how to effectively integrate compact SAR data with other data sources to obtain more comprehensive and accurate surface information is also an urgent problem to be solved. Secondly, a perfect model and method need to be established for the interpretation of CP SAR data to give full play to the advantage of its multi-polarization information. In short, CP SAR has important application value in mangrove monitoring, but it also needs to continuously overcome challenges and provide more reliable technical support for remote sensing and surface information acquisition. In order to provide a reference for the application of the actual CP SAR data obtained by platforms such as ALOS-2-PALSAR-2, RCM, and the See-Earth SAR constellation planned to be launched in China.

6. Conclusions

As an emerging field of polarimetric SAR, CP SAR has great potential for application in large-scale dynamic mangrove monitoring. To better utilize CP SAR for mangrove monitoring, this study addressed the issues of mangrove extraction and surrounding cover class classification feature selection in CP SAR. In this study, 52 CP features were extracted, and the optimal features were filtered based on the Euclidean distance between the four classes in the feature image as follows: mangrove, water, land, and seawater. Using the optimal polarimetric features as input, three classifiers (SVM, ML, and ANN) were designed, and classification results were obtained and compared with those of the SVM classifier based on a single feature input. The effectiveness of the optimal polarimetric feature combination in improving the classification accuracy and reducing the redundancy of polarimetric features was verified, and the application potential of CP SAR in mangrove monitoring was explored. The main findings of this study can be summarized as follows:

- Among the 52 CP features, $f_{39}(SE)$ is the most optimal for distinguishing mangroves from water and land from seawater; $f_{22}(V_B)$ is optimal for distinguishing mangroves from land; $f_{40}(SE_I)$ is optimal for distinguishing water from land; and $f_{20}(V_C)$ is optimal for distinguishing water from seawater.
- Comparison of the classification results of different features shows that $f_{22}(V_B)$ has the best performance in mangrove extraction and that $f_{40}(SE_I)$ has the best comprehensive performance in the classification of the four classes.
- Compared with the SVM classification results based on a single polarimetric feature input, the results of the optimal polarimetric feature combination, selected based on Euclidean distance analysis, not only reduced data redundancy and computational effort but also improved classification efficiency and accuracy. The feature combinations included $f_{39}(SE)$, $f_{40}(SE_I)$, $f_{22}(V_B)$ and $f_{20}(V_C)$. Among the three supervised classifiers (SVM, ML, and ANN), SVM has the best performance in mangrove extraction, and ML has the best performance in overall classification accuracy.

In the near future, more CP SAR data will be available for monitoring natural resource dynamics. The polarimetric observation capability of these sensors will significantly enhance the efficiency and reliability of SAR mangrove detection and classification applications.

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