Combing Sentinel-1 and Sentinel-2 image time series for invasive Spartina alterniflora mapping on Google Earth Engine: a case study in Zhangjiang Estuary

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Abstract. As one of the most threatening invasive alien species to mangroves in China, Spartina alterniflora (S. alterniflora) has broadly existed along the Chinese tropical and subtropical coasts. Monitoring S. alterniflora with remote sensing is urgent and requisite for scientific invasive plant control and management. However, given the spectral similarity between S. alterniflora and other wetland types, such as mud covered by algae and the optical image coverage gaps due to cloud and tidal inundation in coastal areas, accurate and timely mapping of S. alterniflora is challenging. Using the extended Jeffries–Matusita distance (J Bh), we first explored the best time window for detecting S. alterniflora with satellite data in Zhangjiang Estuary, Fujian, China. Then we presented a hierarchical classification framework to alleviate the spectral confusion problem, combining cost-free Sentinel-1 synthetic aperture radar (SAR) and Sentinel-2 multispectral image time series on the Google Earth Engine platform. Specifically, we integrated the inundation frequency map derived from the SAR time series, elevation, and slope criteria to calculate the potential areas of S. alterniflora and mangroves, then used the random-forest classification algorithm to identify S. alterniflora, and finally refined the classified map with a year-long water mask. The optimal time windows of one month, two months, and three months identified by J Bh were January, November, and January, and November, January, and August, respectively; we got the high classification accuracies with corresponding overall accuracies of 99.35%, 99.63%, and 99.63%, respectively. The results suggested classification accuracy could be improved with a wider temporal window, but would saturate with 3-month imagery. The generated 10-m mangrove and S. alterniflora maps of 2017 and 2018 clearly showed the relatively stable spatial pattern of mangroves and the rapid expansion of S. alterniflora. The thriving S. alterniflora in Zhangjiang Estuary suggests the necessity of high-frequency and large-scale monitoring of invasive species along the coastal estuaries of China. © The Authors. Published by SPIE under a Creative Commons Attribution 4.0 Unported License. Distribution or reproduction of this work in whole or in part requires full attribution of the original publication, including its DOI. [DOI: 10.1117/1.JRS.14.044504]

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1 Introduction

Biological invasions pose a primary threat to global biodiversity and the economy.1 Invaders can entirely alter a species composition and ecosystem function through outcompeting native species. Invasive species also exert important socio-economic impacts, with economic losses estimated at more than 200 billion Chinese Yuan per year in China.2 Spartina alterniflora (S. alterniflora), one of the most threatening invasive alien species to mangroves in China, was the only coastal saltmarsh vegetation among the 16 most serious invasive alien species released by the State Environmental Protection Administration of China in 2003. Researchers suggested that, without intervention, S. alterniflora could gradually replace mangroves in China’s coastlines of moderate salinity.3 Methods used to control invasive S. alterniflora include biological, chemical, and mechanical controls, and they all require the invaders’ distribution information as the precondition.4 Accurate and timely mapping of S. alterniflora is urgent and requisite for the scientific invasive plant control and management.

Satellite sensors provide repeated and cost-effective observations over inaccessible areas, which supports efficient and reliable information for monitoring invasive S. alterniflora and complements traditional time-consuming and labor-intensive field surveys.5 Medium spatial resolution (10 to 30 m) optical satellite imagery has been extensively used to monitor S. alterniflora at national,6–9 regional, and local10 levels due to easy-access, low-cost, and long-time historical data archives. But it is still challenging to use optical satellite imagery for routine S. alterniflora monitoring. First, the commonly used Landsat satellite imagery has a moderate spatial resolution (30 m), which results in mixed pixel problems.11 Second, commercial high-resolution satellite imagery has a comparatively high cost and is generally acquired on demand rather than at regular temporal intervals.12 Third, persistent cloud cover and tidal inundation in tropical and subtropical coastal regions prevents the acquisition of high-quality optical data.11,13,14 Finally, the spectral similarity between S. alterniflora and mud covered by biofilm or algae leads to S. alterniflora misclassification.15–17

Investigating the optimal temporal window for invasive plant detection and image selection is an efficient way to lessen the number of images required while maintaining accurate detection.18,19 Studies have indicated that the optimal temporal window for S. alterniflora detection varies from region to region. For instance, Ouyang et al. (2013)18 pointed out that the germination and early growth stage, as well as the flowering stage, were the best time windows to identify S. alterniflora through measuring the field spectra of S. alterniflora and neighboring saltmarsh plants in Shanghai Chongming Dongtan National Nature Reserve. Sun et al. (2016)20 classified saltmarsh vegetation species with high temporal Chinese HJ-1 satellite data (30 m) in Xinyang Estuary, Jiangsu, China, and suggested that November was a good time for the identification of S. alterniflora there. Liu et al. (2018)7 pointed out that early spring and winter are good times for S. alterniflora identification in the south of China. Assuming different phenological features of S. alterniflora in different latitudes,20 optimal timing assessment with local time-series data is necessary. Sun et al. (2016) used the C5.0 decision tree classifier and the importance ratio of variables method to identify the best period for S. alterniflora identification. Evangelista et al. (2009)21 and Liu et al. (2017)22 applied the Maxent model to study the important periods for invasive plant detection. Rajah et al. (2018) used classification accuracy as the criteria to determine the optimal season for detecting invasive American Bramble.23 Furthermore, different methods of optimal temporal window analysis, which have been applied for crop mapping,24–27 such as the extension of Jeffries–Matusita (JM) distance26 and classification accuracy-based methods,24,25,28 could also be applied for invasive plant identification.

Although the combination of optical and synthetic aperture radar (SAR) imagery offers great potential for invasive plant remote sensing,23 few studies have integrated the use of time-series imagery to map invasive plants in complex coastal wetlands.10,23,29 Invasive plants usually have distinct phenological characteristics from native species in order to occupy ecological niches better.23 Reflectance variations due to phenological fluctuations in leaf pigmentation, water content, and structure provide opportunities for mapping invasive plants with optical image time series.23 SAR is a powerful tool for inundation extent mapping, providing valid measurements for cloudy and rainy days.30 SAR image time series can be used to estimate inundation frequency, an important factor determining saltmarsh zonation patterns.31 S. alterniflora is

a perennial deciduous grass, while the biofilm or algae on mud is ephemeral. Thus SAR-based inundation frequency data could contribute to the discrimination of *S. alterniflora* from ephemeral biological structures on mud, potentially addressing the misclassification problem of *S. alterniflora*. Rajah et al. (2018)\textsuperscript{23} fused Landsat-8, Sentinel-2, and Sentinel-1 imagery at the feature level and detected a harmful invasive alien plant, American Bramble, with support vector machine algorithm. But *S. alterniflora* usually lives in intertidal wetlands, which are heterogeneous and dynamic. The difficulty of simultaneously collecting SAR and optical satellite imagery at low tide limits the application of the method by Rajah et al. (2018)\textsuperscript{23} in identifying *S. alterniflora*. Image fusion at the decision level,\textsuperscript{32} a hierarchical classification method integrating optical, SAR and other ancillary data, is required to regularly map *S. alterniflora* in a cost-effective manner.\textsuperscript{33}

In recent years, the cloud-based platform Google Earth Engine (GEE), providing a multi-petabyte catalog of remote sensing data and machine learning algorithms, offers a new choice for researchers interested in geospatial big remotely sensed data analysis.\textsuperscript{34,35} GEE has gained broad applications, and enabled time series analysis of wetlands\textsuperscript{35-37} and mangroves,\textsuperscript{38,39} facilitating our ability to monitor *S. alterniflora*.

In this study, we choose Zhangjiangkou National Mangrove Nature Reserve (ZNMMNR), a representative mangrove and *S. alterniflora* ecotone, as the study region to identify the invasive *S. alterniflora* using remote sensing imagery on the GEE. The objectives of this paper are: (1) to investigate the optimal temporal window to identify *S. alterniflora* with Sentinel-2 optical image time series; (2) to apply a hierarchical classification framework through integrating Sentinel-1 SAR and Sentinel-2 multispectral image time series to map mangroves and *S. alterniflora*; and (3) to monitor *S. alterniflora* and mangroves in Zhangjiang Estuary from 2017 to 2018.

2 Materials and Methods

2.1 Study Area

The ZNMMNR is located at Zhangjiang Estuary, Fujian province, China (117°24′07″E~117°30′00″E, 23°53′45″N~23°56′00″N, Fig. 1). It has the northernmost and largest concentrated natural mangrove forests in China and has been included in the List of Wetlands of International Importance since 2008. *S. alterniflora* is distributed on the tidal flats in both the eastern and western parts of the reserve. The elevation range of the estuary is −6 to 8 m above the mean

![Fig. 1](a) The Sentinel-2A false-color image of the study area on January 12, 2018, the spatial distribution of the sample data (colored polygons), and the black rectangle denotes the study area (the band combination of the Sentinel-2A image is the NIR band, red band, and green band); (b) the location of Fujian province; and (c) the location of ZNMMNR (the red polygon highlights the location of the study region).
The climate is a subtropical maritime monsoon climate with an annual average temperature of 21.2°C. The maximum (minimum) temperature is 38.1°C (0.2°C). The annual average rainfall is 1714.5 mm, with the rainy season from April to September. The annual average relative humidity is 79%. The annual average sunshine hours are 2125.1 h.

2.2 Data

2.2.1 Satellite data

Cloud-free Sentinel-2 Level-1C top of atmosphere reflectance data\textsuperscript{40} in the GEE (ImageCollection ID: COPERNICUS/S2) with the highest quality and lowest tide level in each month from 2017 to 2018 were selected by visual inspection (Table 1). We used data from December 2017 to November 2018 for optimal temporal window selection analysis. The wide-swath multispectral imager of the Sentinel-2A/2B satellites has 13 spectral bands with 4 bands at 10 m, 6 bands at 20 m, and 3 bands at 60 m spatial resolution. This study used blue, green, red, near-infrared (NIR), and short-wave infrared (SWIR) bands. The spatial resolution of blue, green, red, and NIR bands is 10 m. The SWIR band was resampled at a 10-m pixel size.

We also used Sentinel-1 C-band Ground Range Detected SAR data\textsuperscript{41} from GEE (ImageCollection ID: COPERNICUS/S1) and collected a total of 29 and 28 scenes covering the study region in 2017 and 2018, respectively. The data are of the Interferometric Wide swath mode with dual-band vertical transmit/horizontal receive (VH) polarization and a pixel size of 10 m.

2.2.2 Digital elevation model and vector maps

We used the 30-m SRTM digital elevation model (DEM) data and the derived variable (slope) to mask out regions of high elevation or steep slope where \textit{S. alterniflora} and mangroves are not likely to exist.\textsuperscript{38} We also applied the boundary vector data of the reserve to mask out regions outside of the reserve.

2.2.3 Sample data

We used \textit{in situ} data derived from the Global Geo-Referenced Field Photo Library\textsuperscript{38} and Google Earth very high-spatial resolution satellite images from 2017 to 2018 as the background reference to create regions of interests (ROIs) for algorithm training and accuracy assessment. Sample polygon ROIs of five land covers, namely mangroves, \textit{S. alterniflora}, water, mud flats, and other vegetation, were delineated by visual interpretation. Note that other vegetation here corresponded to other vegetation species except \textit{S. alterniflora} and mangroves in the ZNMNR, mainly distributed around aquaculture ponds. The number of sample polygons for training and
validation of the random forest classifier in 2017 and 2018 are listed in Table 2. For the optimal temporal window analysis of different vegetation species in the study area, we independently collected another ROI dataset of mangroves, *S. alterniflora*, and other vegetation to limit the tidal inundation influence.

### 2.3 Optimal Time Window Selection

We used the JM distance to measure the period-by-period separability for each pair of vegetation species and applied the extension of JM distance ($J_{Bh}$) to calculate the optimal time window when considering the separability of multiclasses, refer to Hao et al. (2014) for details. The JM distance was widely used to quantify the separability of different bands, different vegetation categories, different crops, etc. Hao et al. (2014) applied JM distance and $J_{Bh}$ to learn how separability of different crops changes over the growing season and to calculate the optimal time period combination order for crop classification. As crops are also plants, the method from Hao et al. (2014) applies to the situation of detecting *S. alterniflora* from mangroves and other vegetation here. Normalized difference vegetation index (NDVI) is a measure of vegetation density and condition and is widely used for vegetation phenology studies. We used NDVI for optimal time window analysis here. We first calculated the JM distance of the collected ROI dataset every month for all pair-wise vegetation species and selected the single month with the highest JM distance. Then by comparing any one of the other months to the selected month, we calculated the $J_{Bh}$ distance of all possible combinations and selected the combination with the largest $J_{Bh}$ as the optimal time period. By repeating the process, we obtained the optimal month combination order, which can guide image selection for vegetation classification.

The phenological patterns over the course of a year are of particular interest for annual vegetation mapping in this study. To verify that NDVI values derived from 1-year imagery (Table 1) could represent the phenological trends of different vegetation species, we used 4-year Sentinel-2 imagery to produce phenological data for comparison. Based on image time series from 2016 to 2019, we calculated NDVI values of *S. alterniflora*, mangroves, and other vegetation. Then we removed the outliers due to factors such as clouds, cloud shadows, and tidal inundation by visual inspection of each image. Finally, we adopted the harmonic analysis of time series (HANTs) algorithm to get high-quality phenological data.

### 2.4 *S. Alterniflora* and Mangrove Detection

The proposed hierarchical classification framework mainly comprises three steps: (1) calculate the potential areas of mangroves and *S. alterniflora*; (2) apply random forest classifier to detect mangroves and *S. alterniflora*; and (3) use the yearlong water mask and the criterion of interaction with the sea to refine the distribution of mangroves and *S. alterniflora* (Fig. 2).

#### 2.4.1 Detecting potential areas of *S. alterniflora* and mangroves

Features including tidal inundation and topography (elevation and slope) were used to calculate potential areas of *S. alterniflora* and mangroves, which mainly existed near coastlines inundated by tides. We used the Sentinel-1 SAR image time series in each year to produce the inundation frequency map $F_{VH<19}$ (e.g., Fig. 3 based on imagery in 2018). $F_{VH<19} < 90\%$ was applied to create the inundation mask where *S. alterniflora* and mangroves possibly exist. We used the criteria DEM < 10 m and slope < 10 deg to mask out uplands and steep-slope regions, and

### Table 2 The number of samples for random forest classifier in this study.

<table>
<thead>
<tr>
<th>Type</th>
<th>Mangroves</th>
<th><em>S. alterniflora</em></th>
<th>Water</th>
<th>Mud flats</th>
<th>Other veg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>2017 and 2018</td>
<td>40 (10.13)</td>
<td>44 (1.64)</td>
<td>15 (22.06)</td>
<td>24 (5.68)</td>
<td>22 (0.66)</td>
</tr>
</tbody>
</table>

Note: The first number is the polygon number, the second number in the bracket is the area of the sample (unit: hm$^2$).
the criterion intersection with the inundation mask was applied to produce the potential areas of mangroves and *S. alterniflora*.

### 2.4.2 Random forest classification

Up to now, the random forest classifier has been widely applied in different remote sensing research fields, such as land use and land cover, wetlands, and forests.\(^{15,37,45-51}\) We used both spectral and texture features as classification inputs. The spectral features include the red, green, blue, NIR, and SWIR bands, normalized difference water index (NDWI),\(^{52}\) modified normalized difference water index (mNDWI), NDVI, enhance vegetation index (EVI),\(^{53}\) and land surface water index (LSWI).\(^{54}\) The texture feature is the standard deviation of NDVI in a box with a radius of 5 pixels. Note that before running the random forest classifier, the potential areas of mangroves and *S. alterniflora* were used to mask the spectral and texture features. As to the parameters for the random forest classifier, the number of trees was 100, and the number of variables per split was the square root of the number of variables. The sample data were randomly divided into training (70%) and validation (30%). We quantified classification accuracy...
using overall accuracy, confusion matrix, user accuracy, producer accuracy, and kappa coefficient.

To further investigate the optimal month combination order in the ZNMR, we tested the 1-month (January), 2-month (January and November), and 3-month (January, November, and August) imagery in 2018 with the random forest classifier. When the optimal time window was greater than 1 month, the inputs of the random forest classifier were all Sentinel-2 images in the calculated optimal time window.

2.4.3 Refining the *S. alterniflora* and mangrove map with the intersection-with-sea criterion

We assume vegetation that does not interact with the sea is not *S. alterniflora* or mangroves to further refine the classification results. Impervious surfaces were removed with the reserve boundary vector data and no sand beaches existed in the study region, thus we used frequency map $F_{VH<19} > 80\%$ to calculate the yearlong water body mask. We deleted mangrove patches and *S. alterniflora* patches with pixel numbers smaller than 1 to lessen problems such as too fragmented vegetation patches.

3 Results

3.1 Separability Analysis and Optimal Time Window Selection

Based on the mean and standard deviation of the monthly NDVI data (Fig. 4), we can see that the NDVI seasonal variation of mangroves was not as distinct as that of *S. alterniflora* and other vegetation, corresponding to the fact that mangroves are evergreen species. The NDVI value of mangroves was larger than those of *S. alterniflora* and other vegetation in almost every month, suggesting that the separation of mangroves from other two categories was much easier than the identification of *S. alterniflora* and other vegetation. We could infer from Fig. 4 that January and November were the optimal periods for *S. alterniflora* identification and separation from other vegetation in the ZNMR. Comparing Figs. 4 and 5, NDVI time series derived from 12-month imagery here can approximately reflect the phenological curves of different plants, especially

![Fig. 4](image-url) NDVI curves for the three categories (mangroves, *S. alterniflora*, and other vegetation). The nodes denote the mean values and error bars represent the standard deviations. ("Dec-17" means December in 2017).
S. alterniflora, based on 4-year dataset. Our results also showed a similar phenological spectral behavior of S. alterniflora to that of Li et al. (2019). They demonstrated that months in winter and spring, such as January, were the most important months for the classification of mangrove species and S. alterniflora in Zhangjiang Estuary. Our results were in line with Li et al. (2019), suggesting that the workflow utilized here was reliable and could be applied to other regions.

We used the JM distance to quantify the differences between the three vegetation categories in the study region (Fig. 6). The JM distance ranged from 0 to 2, with excellent separability for JM distance values >1.9. The JM distance values between mangroves and S. alterniflora in every month from December 2017 to November 2018 were mostly >1.99 [Fig. 6(a)], suggesting that one scene in any month was sufficient for the discrimination of mangroves from S. alterniflora. The JM distance values between mangroves and other vegetation were >1.90 from January to May and from November to December, and deteriorated from June to October. These indicate the discrimination of evergreen mangroves from other vegetation is also feasible with one scene, especially in spring and winter in the ZNMNR. The JM distance values between S. alterniflora and other vegetation were >1.5 only in November and January and increased with NDVI data of more months [Figs. 6(a)–6(c)]. Every vegetation class showed good separability at some time, indicating the possibility of high overall accuracy using multitemporal classification. This has been confirmed by previous studies about crop discrimination.

As to the separability of multiclases, the first two maximum $J_{Bh}$ distance values of each month were 2.54 in January and 2.51 in November [Fig. 6(d)]. By comparing image data in January with other months, we found that the maximum $J_{Bh}$ distance value was 2.66 in November. By combing image data in January and November with other months, we learned that the maximum $J_{Bh}$ distance value was 2.70 in August. The maximum (minimum) $J_{Bh}$ distance values were 2.54 (2.19) with 1-month data, 2.66 (2.60) with 2-month data, 2.70 (2.67) with 3-month data, respectively. The $J_{Bh}$ variations with 2-month and 3-month data were much smaller compared with that of 1-month data. Thus, January was the optimal month; January and November were the optimal 2-month combination; January, November, and August were the optimal 3-month combination for the detection of S. alterniflora and mangroves in the ZNMNR. We did not calculate the optimal 4-month combination, because the separability did not increase much when adding other images ($J_{Bh}$ increased by <0.1 from 2-month to 3-month combination).

3.2 Classification Accuracy Assessment

The overall accuracies of 1-month (January), 2-month (January and November), and 3-month (January, November, and August) imagery in 2018 were 99.35%, 99.63%, 99.63%, respectively,
suggesting that classification accuracy could be improved with a wider temporal window, but would saturate with 3-month imagery. We focused on the classification results with 1-month and 2-month data (Table 3). The producer accuracy and user accuracy of mangrove, mud flat, and water were >90%, whereas the user accuracies of other vegetation were lower than 90% with either 1-month or 2-month imagery. The classification accuracy of other vegetation was lower than the remaining land covers. The producer accuracies of mangrove and mud flats were improved from 1-month imagery to 2-month imagery, suggesting the identification of mangrove and mud flats benefits from adding seasonal signals with more images from different months.

### 3.3 Importance of Features

We calculated the variable importance scores for all features with a random forest classifier. The top 10 features of each image combination in 2018 were presented in Fig. 7. Implementing a random forest classifier with one image in January or November 2018, the two most important features were texture feature and NDVI. When two images in January and November 2018 were used in the model, the five most important features were January NDVI, January NIR, January NDWI, January red, and November texture bands, respectively. Using three images in January, August, and November 2018 in the model, the five most important features were January NDWI, January NDVI, August texture feature, January NIR, and January blue bands, respectively. Although we used the 11 features as inputs, the features with high importance scores changed when using imagery of different periods, especially when multiperiod imagery was used. The variable importance score also decreased when the number of features increased, which was due to how the importance was measured.27

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**Fig. 6** JM distance values of all pair-wise vegetation comparisons for (a) each month; (b) two months, one of which is January, and (c) three months, two of which are January and November using the ROI dataset; and (d) $J_B$ distance values of one month, two months (one is January), and three months (two are January and November). (“Dec-17” means December in 2017). The blue line representing the JM distance values of Mangrove—$S. alterniflora$ pair, overlapped with the red line representing the JM distance values of Mangrove—Other vegetation pair in (b) and (c).
Table 3  Accuracy assessment with 1-month image on January 2, 2-month images on January 2
and November 23 in 2018; and 2-month images on January 2 and November 10 in 2017 for the
study region.

<table>
<thead>
<tr>
<th>Year</th>
<th>Time</th>
<th>Type</th>
<th>Mangrove</th>
<th>SA</th>
<th>Mud flats</th>
<th>Water</th>
<th>OV</th>
<th>PA (%)</th>
<th>UA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>January 2</td>
<td>Mangrove</td>
<td>264</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>98.51</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SAa</td>
<td>0</td>
<td>49</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mud flat</td>
<td>0</td>
<td>0</td>
<td>108</td>
<td>0</td>
<td>2</td>
<td>98.18</td>
<td>99.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>631</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OV</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>17</td>
<td>94.44</td>
<td>73.91</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy = 99.35%, kappa coefficient = 0.989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2017</td>
<td>January 2 and November 23</td>
<td>Mangrove</td>
<td>267</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>99.63</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SAa</td>
<td>0</td>
<td>48</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>97.96</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mud flat</td>
<td>0</td>
<td>0</td>
<td>109</td>
<td>0</td>
<td>1</td>
<td>99.09</td>
<td>98.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>631</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OV</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>17</td>
<td>94.44</td>
<td>89.47</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy = 99.63%, kappa coefficient = 0.994</td>
<td></td>
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<td></td>
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</tr>
</tbody>
</table>

| 2017       | January 2 and November 10 | Mangrove | 268      | 0   | 0         | 0     | 0   | 100    | 100    |
|            |                     | SAa      | 0        | 48  | 1         | 0     | 0   | 97.96  | 100    |
|            |                     | Mud flat | 0        | 0   | 108       | 0     | 2   | 98.18  | 90.76  |
|            |                     | Water    | 0        | 0   | 10        | 621   | 0   | 98.42  | 99.84  |
|            |                     | OV       | 0        | 0   | 0         | 1     | 17  | 94.44  | 89.47  |
|            | Overall accuracy = 98.70%, kappa coefficient = 0.978 |

*aSA and OV represent S. alterniflora and other vegetation, respectively.

Fig. 7 Feature importance scores of the 10 most important features for each image combination.
(a) January in 2018; (b) November in 2018; (c) January and November in 2018; and (d) January,
August, and November in 2018.
3.4 Monitoring S. alterniflora and Mangroves in Zhangjiang Estuary in 2018 and 2017

Figures 8(a)–8(d) present the inundation frequency map, inundation frequency mask, random forest classification map based on three-month imagery, and yearlong sea water mask in the study region in 2018. The mangrove and S. alterniflora maps based on 1-month, 2-month and 3-month imagery in 2018 are displayed in Fig. 9. Obviously, mangroves were distributed in the southwest of the study areas, whereas S. alterniflora were distributed on both sides of the north and south of the Zhangjiang River. The spatial distribution patterns of mangroves and S. alterniflora are similar based on data of different months in 2018 (Fig. 9). But comparing the enlarged views of the mangrove and S. alterniflora maps, we can see that classification results derived from 1-month imagery missed some small patches of S. alterniflora (the red circle in Fig. 9) compared with those derived from 2-month or 3-month imagery. Similarly, the areas of S. alterniflora and mangroves based on 1-month data in 2018 were 114.07 and 58.63 hm², respectively, clearly underestimated in comparison with results from 2-month data and 3-month data (Table 4).

Comparing results based on 2-month imagery from 2017 to 2018 (Table 4), we can see that the mangrove area was relatively stable, whereas S. alterniflora area increased quickly. Verified in Figs. 9(d) and 9(j), S. alterniflora in the southwest of the study region occupied the whole mud flat area in 2017 and further enlarged in 2018. The red rectangles in Figs. 9(f) and 9(l) clearly presented the expansion of the S. alterniflora extent from 2017 to 2018.

4 Discussion

4.1 Potential of Time Series Sentinel-1 and Sentinel-2 Imagery to Monitor S. alterniflora and Mangroves

The areas of mangroves and S. alterniflora are not always in consensus with literature due to differences in classification methods and satellite images including the spatial, spectral, and temporal resolutions. Researchers presented that mangrove and S. alterniflora areas were 116.11 hm² (Ref. 55) and 62.19 hm² (Ref. 38) in 2015, and 117 and 60 hm² in 2016. The magnitude of S. alterniflora and mangrove area in our study (Table 4) was comparable.
Fig. 9 The distribution maps of *S. alterniflora* and mangroves based on 1-month, 2-month, and 3-month Sentinel-2 satellite imagery in 2018 and 2-month imagery in 2017. (a), (d), (g), and (j) are the overviews, whereas (b), (c), (e), (f), (h), (i), (k), and (l) are the enlarged views of the red rectangles on the left.

### Table 4 Areas of mangroves and *S. alterniflora* in 2018 and 2017.

<table>
<thead>
<tr>
<th>Year</th>
<th>2018</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mangroves</td>
<td>58.68</td>
<td>58.52</td>
</tr>
<tr>
<td><em>S. alterniflora</em></td>
<td>140.77</td>
<td>139.60</td>
</tr>
</tbody>
</table>
with previous research, and the invasion of *S. alterniflora* also contributed to the discrepancies of *S. alterniflora* area. By comparison with other studies, the expansion of *S. alterniflora* in both the southwestern and northwestern parts of the study area from 2015 to 2018 was obvious. The distribution of *S. alterniflora* was more scattered in comparison to the research of Chen et al. (2019), in 2016, probably because *S. alterniflora* expanded as time went on, and the spatial resolution of Sentinel-2 imagery is higher than that of Landsat imagery, contributing to the detection of small-area *S. alterniflora* clumps. *S. alterniflora* can reproduce both sexually and clonally by seed, rhizome, or vegetative fragmentation. Its seeds are dispersed by currents and tides, which can be transported long distances. We suggest that the clonal growth of *S. alterniflora* mainly contributed to its area increase in this study [red rectangles in Figs. 9(f) and 9(l)]. In Sec. 3.4, we found the area of the detected *S. alterniflora* based on 1-month data in 2018 was smaller than those derived from 2-month and 3-month imagery. The reasons for this might be that (1) January is not the growth month for *S. alterniflora* in the ZNMNR when biomass and leaf greenness is relatively low, leading to confusion between *S. alterniflora* and mud flat; (2) by adding seasonal signals with 2-month or 3-month imagery, the random-forest algorithm can identify *S. alterniflora* better; and (3) in the period of several months, *S. alterniflora* expanded.

Although different methods and datasets have been used to map *S. alterniflora* in the ZNMNR, our study outperforms them in terms of higher image spectral resolution and temporal resolution. Liu et al. (2017) used Google Earth RGB imagery, which might degrade the performance of the classification method. Their overall accuracies were no larger than 90%, and the *S. alterniflora* producer and user accuracies were smaller than 92%. Li et al. (2019) processed 24-month Sentinel-2 NDVI time series from 2017 to 2018 as a whole to map mangrove species and *S. alterniflora*, which might introduce *S. alterniflora* distribution bias due to its dynamic invasion process. The overall accuracy of their method was 84%, whereas the classification accuracy of *S. alterniflora* was 77%. Our study produced *S. alterniflora* maps with higher classification accuracy and shorter time intervals, contributing to the timely monitoring of invasive plants. As to the optimal time window analysis, period-by-period JM distance values efficiently demonstrate class separability through time. Different from other studies that used the Maxent model or classification accuracy criteria, the JM distance and $J_{FL}$ method can effectively provide the optimal time window results with less computation resources and is suitable for routine large-scale *S. alterniflora* monitoring.

### 4.2 Inundation Frequency Map for Discriminating *S. alterniflora* from Ephemeral Biological Structures on Mud

Our study demonstrated the inundation frequency map derived from SAR time series could be used to effectively reduce the spectral confusion between *S. alterniflora* and ephemeral biological structures on mud flats. For instance, Fig. 10(a) presents a Sentinel-2 optical image on February 11, 2017, in which large patches of green ephemeral biological structures were visible. Figure 10(b) shows the corresponding inundation frequency mask. The red circles in Figs. 10(c)–10(f) highlighted the nonpersistent biological structures. The inundation frequency mask effectively deleted areas where ephemeral structures existed and retained areas where *S. alterniflora* and other land covers persisted. In addition, from Fig. 10(g), the nonpersistent biological structures of *S. alterniflora* cannot be discriminated by NDVI, and the NDVI confusion between mud flats and *S. alterniflora* is evident.

It should be noted that the mixed pixel problem, the spectral confusion between *S. alterniflora*, mud flats, and other vegetation is still a challenge. For example, the boundary between mangroves and *S. alterniflora* in Fig. 8(c) was mixed with mud flat and other vegetation. It is possible to solve the mixed pixel problem by detecting *S. alterniflora* with very-high-resolution multispectral remote sensed imagery, thereby contributing to identifying invasive *S. alterniflora* in the early invasion stage.

### 4.3 Factors Affecting the Mapping Accuracy

Multisource images have uncertainties such as different spatial resolutions, scanning systems, and angular effects, affecting the detection accuracies of *S. alterniflora*. Our study used...
Sentinel-1 SAR imagery to calculate an inundation frequency map and yearlong water body, and used Sentinel-2 imagery for vegetation classification, which could limit the multisensor related uncertainties to some degree. The algorithm was also used on the GEE, which was efficient, reproducible, and recommendable. We do not need to do extensive visual interpretation of the entire satellite image except for the sample data collection.

The parameters of the method, such as features used in the random forest classifier, land cover types, thresholds, and data sources, can affect the mapping accuracy of *S. alterniflora* and mangroves. Löw et al. (2013) set the number of trees to a relatively high number of 500, and pointed out that a higher number of trees did not improve the performance of the random forest classifier.59 We tested the importance of this parameter by changing it from 20 to 50, 100, and 500, whereas other parameters were set the same in our study area. The overall classification accuracies based on 2-month imagery with the number of trees set as 20, 50, 100, and 500 were 99.35%, 99.63%, 99.63%, and 99.63%, respectively, consistent with the viewpoints from Löw et al. (2013).59 In addition, we used 11 features including red, green, blue, NIR, and SWIR bands, NDWI, mNDWI, NDVI, EVI, LSWI, and one texture feature as inputs for the random forest classifier in this study. We did not apply feature selection, whereas most researchers tried to select the most important features from tens to hundreds of features.59 We tested our method with subsets of the feature set and 2-month imagery in 2018. According to the overall accuracies with different feature sets listed in Table 5, the 20-m SWIR band could degrade the classification accuracy to some degree in our relatively small test area. In addition, the water indices mNDWI and LSWI were related to the SWIR band. The mNDWI, LSWI, and SWIR bands were not among the four most important features (Fig. 7). On the other hand, researchers highlighted the contribution of the SWIR band in vegetation species discrimination.12,60 and mNDWI ranked fifth out of top 10 most important features based on imagery in November 2018 here. More features could not further improve the accuracy of the classification model.

**Table 5** The overall classification accuracies with different feature sets and 2-month imagery in 2018.

<table>
<thead>
<tr>
<th>Feature set</th>
<th>Blue, green, red, NIR, and SWIR</th>
<th>Blue, green, red, and NIR</th>
<th>NDVI</th>
<th>NDVI, NDWI, and texture feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy (%)</td>
<td>99.16</td>
<td>99.63</td>
<td>97.77</td>
<td>98.88</td>
</tr>
</tbody>
</table>

Fig. 10 (a) The overall view of the original Sentinel-2 image; (b) inundation frequency mask; (c)–(f) the corresponding enlarged views of the two red rectangles in the overview figure; and (g) NDVI of different land covers, including *S. alterniflora*, mangroves, mud flats, water, nonpersistent biological structures, and other vegetation (OV) in the study region on February 11, 2017.
In this study (Table 5). In the last step of the algorithm, we deleted mangrove and
*S. alterniflora* patches with pixel number <1; researchers interested in smaller vegetation patches
can ignore these criteria.

It is worth noting that the premise of using our algorithm is that mangroves and *S. alterniflora*
are affected by the tidal flood, and vegetation that is not connected to seawater is not considered
as mangroves or *S. alterniflora*. However, in a few areas of the world, such as China’s Hainan
Province, Australia, and Bangladesh, some mangroves live on land without a connection to
the ocean, so our algorithm may not be applicable there.

5 Conclusions

In this study, we estimated the optimal time window using the extended JM distance and mapped
mangroves and *S. alterniflora* integrating Sentinel-1 and Sentinel-2 image time series with
a hierarchical classification framework. Our main conclusions are summarized as follows.
(1) Mangroves and *S. alterniflora* show clear differences on the monthly NDVI time series
curves due to different phenology and coverages. January, November and January, and
November, January, and August were the optimal time windows for the identification of *S. alter-
niflora* and mangroves in the ZNMNR. The 2-month imagery (January and November) could
provide a very high classification accuracy, and additional images could not significantly
improve the overall accuracy. (2) The proposed hierarchical classification framework produced
annual *S. alterniflora* and mangrove maps with high overall accuracies of 98.70% and 99.63%
based on 2-month imagery in 2017 and 2018, respectively. (3) The generated 10-m mangrove
and *S. alterniflora* maps of 2017 and 2018 clearly showed the relatively stable distribution
pattern of mangroves and the rapid expansion of *S. alterniflora*.

*S. alterniflora* thriving in the ZNMNR suggests the necessity of high-frequency and large-
scale monitoring of estuaries along the coast of China. The proposed workflow and generated
mangrove and *S. alterniflora* datasets here may provide resource managers, government
officials, and ecologists guidelines for remote sensing data collection and processing for
*S. alterniflora* monitoring.

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