Information extraction and quantifying migration of saltmarsh vegetation in Chongming Dongtan Wetland by integrating multi-source remote sensing data and phenological characteristics during 2017-2022

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Abstract

In this paper, Chongming Dongtan Wetland is taken as the study area, and the multi-temporal Rardarsat-2 full-polarization SAR data and Sentinel-2A medium-resolution optical data are used as the data source. According to the particularity of the estuary wetland in the study area, different characteristic parameters are calculated, including vegetation index, water body index, spectral feature, radar feature, texture feature and time feature. Six multi-dimensional feature data sets containing different feature parameters have been formulated. We perform object-oriented multi-scale inheritance segmentation on six feature data sets, and use segmentation parameter optimization tool to select the optimal segmentation parameters. Combined with field investigation and visual interpretation of high-resolution remote sensing images, we build a classification system of Chongming Dongtan Wetland Saltmarsh Vegetation, which mainly includes three types of wetland saltmarsh vegetation: Phragmites australis, Spartina alterniflora and Scirpus mariqueter. Different vegetation training samples and verification samples are selected on the segmented images, and the information of saltmarsh vegetation is extracted based on the random forest machine learning algorithm. In order to further study the interannual variation characteristics and phenological characteristics of wetland saltmarsh vegetation, this research also uses Sentinel-2, Sentinel-1 and Landsat8 fusion images based on Google Earth Engine(GEE) to construct a medium-resolution long-term median image dataset, to obtain the spatio-temporal distribution results of saltmarsh vegetation in Chongming Dongtan Wetland from 2017 to 2022 and the quantitative migration of saltmarsh vegetation.

Keywords: Chongming Dongtan Wetland; Saltmarsh Vegetation; Multi-source Remote Sensing Image; Phenological Characteristics; Google Earth Engine

1. Introduction

Wetland is known as the "kidney of the earth", and its ecological function, biodiversity, and various values are irreplaceable. However, due to the rapid urbanization process, wetland resources are decreasing day by day, so the investigation of wetland resources is very important. The Yangtze estuarine wetland provides various ecosystem services. However, affected by human activities (upstream sediment reduction) and natural background (sea-level rise, SLR), the saltmarsh of the estuarine wetland is undergoing dramatic changes in recent years.

As one of the important ways of wetland monitoring, remote sensing technology is widely used in wetland monitoring. Traditional wetland monitoring remote sensing technology only uses optical remote sensing data for information extraction, but optical remote sensing data has high requirements for weather and specific characteristics of land cover. For wetland areas with more shallow water and higher rainfall than other areas, it is difficult to effectively obtain information on land cover for long time series using optical images. Comparing with optical remote sensing systems, Synthetic Aperture Radar (SAR) has all-weather, synoptic views of large areas, and day-night imaging capability. Microwave electromagnetic energy can penetrate shallow water and vegetation. In recent years, scholars have conducted extensive research on the information extraction of wetland characteristics based on SAR images.

2. Study Area

Chongming Dongtan is located at the north of Shanghai and east extremity of Chongming Island (31°24′-31°39′ N, 121°43′-122°05′ E) formed by a large amount of sediment accumulation transported by Yangtze River. The study area consists of whole Chongming Dongtan, adjacent agricultural reclamation areas and urbanization areas.

Chongming Dongtan was listed in China Protected Wetlands List in 1992. In 1998, Chongming Dongtan Wetland Reserve was established, and in 2005, it was upgraded to national natural reserve. In 2022, Chongming Dongtan Bird National Nature Reserve has officially become a nominated site for Migratory Bird Sanctuaries along the Coast of Yellow Sea-Bohai Gulf of China (Phase II).

The climate of Chongming Dongtan is subtropical monsoon climate and humid climate. The annual average temperature is 15.3 °C, the annual average rainfall is 1022 mm and the annual average frost-free period is about 229 days.

Chongming Dongtan mainly consists of three wetland vegetation, Phragmites australis, Scirpus mariqueter and Spartina alterniflora which formed the dominate wetland community since Spartina alterniflora was introduced artificially in 1995.

3. Datasets

In this study, we used 2 C-band Fine Quad-Pol Rardarsat-2 (hereinafter referred to as RST2) images from 2021 to 2022, 72 C-band Sentinel-1A (hereinafter referred to as S1A) images from 2017 to 2022, 76 multispectral Sentinel-2A (hereinafter referred to as S2A) images from 2017 to 2022 and 72 multispectral Landsat8 OLI (hereinafter referred to as LAT8) images from 2017 to 2022.

After preprocessing and feature extraction, we combined different features to obtain the following six datasets which are shown in Table 1.

Table 1. Experimental datasets based on different features

Dataset	Description	Acquisition Data
Dataset1	Spectral feature + Vegetation index + Textural feature	2021.9
Dataset2	Spectral feature + Vegetation index + Textural feature	2022.3
Dataset3	Spectral feature + Vegetation index + Textural feature + SAR backscattering feature	2021.9
Dataset4	Spectral feature + Vegetation index + Textural feature + SAR backscattering feature	2022.3
Dataset5	Spectral feature + Vegetation index + Textural feature	2021.9 + 2022.3
Dataset6	Spectral feature+ Vegetation index + Textural feature + SAR backscattering feature	2021.9 + 2022.3

4.Method

After data acquisition, we preprocessed data by ENVI software, SNAP software and GEE platform. Firstly, for multispectral optical images, we conducted radiometric calibration, atmospheric correction and clipping to the range of the study area. For S1A images, we conducted orbit correction, radiometric calibration, deburst, multilooking, speckle filtering and terrain correction. For RST2 images, we conducted multilooking, speckle filtering, terrain correction and coregistration. Secondly, to prove multi-temporal images and SAR images can improve classification accuracy, we combined different features to six datasets. Thirdly, due to traditional classification algorithm based on pixel performing bad, we used multi-resolution object-oriented classification algorithm to improve classification accuracy. Fourthly, training samples and testing samples were extracted from high resolution optical images through region of interest to train and validate the different supervised classifiers.

We utilized the Gray Level Co-occurrence Matrix (hereinafter referred to as GLCM) algorithm to extract texture features from the images. GLCM is a statistical representation of the occurrence of pixel pairs with specific gray-level values at a certain distance within an image.In this experiment, the selected features include homogeneity, contrast, dissimilarity, entropy, angular second moment (hereinafter referred to as ASM), correlation, and variance.

The RF classifier is an ensemble of multiple decision trees. For the input images, n trees will have n classification results. The classification of the RF classifier is determined by the mode value of classifications from decision trees. Since the results of multiple decision trees are integrated, an RF classifier can accept high-dimensional sample input and can evaluate the importance of each feature in the classification with better accuracy than other methods.

5. Results

Table 2. Classification accuracy of different datasets based on random forest

Dataset	OA(%)	Kappa
Dataset1	76.4344	0.6981
Dataset2	78.0738	0.7178
Dataset3	78.4836	0.7246
Dataset4	81.3525	0.7601
Dataset5	81.8648	0.7661
Dataset6	90.2980	0.8606

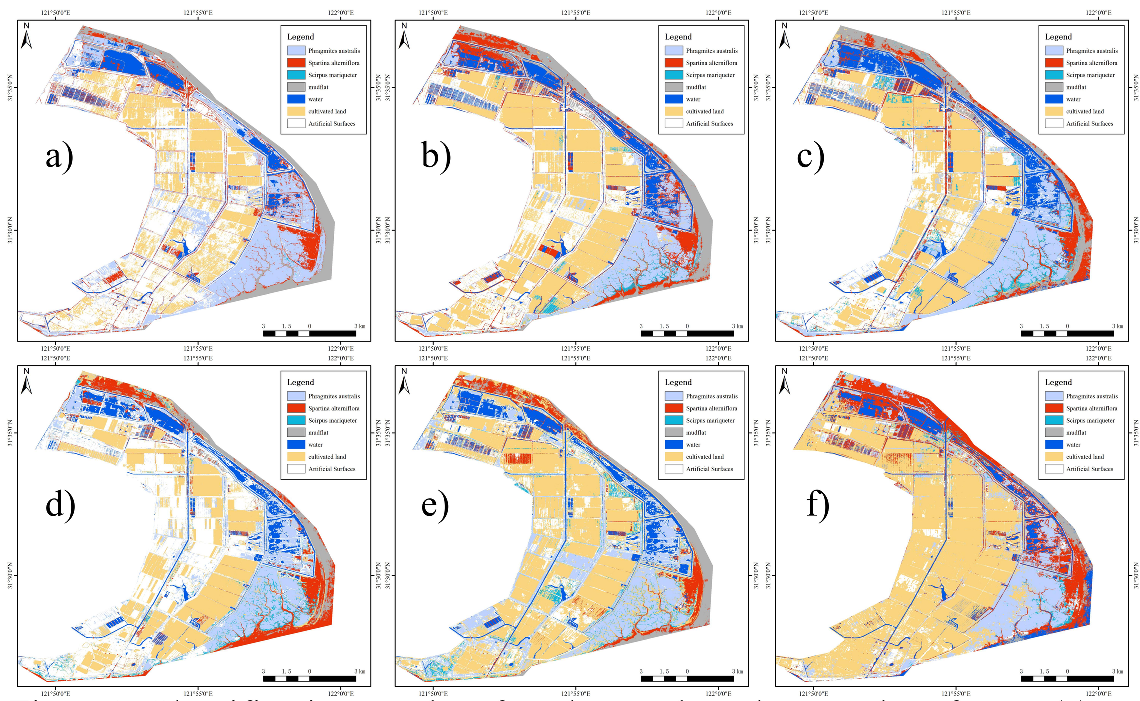

Figure1. Classification results of study area based on random forest. (a) Dataset1, (b) Dataset2, (c) Dataset3, (d) Dataset4, (e) Dataset5 and (f) Dataset6.

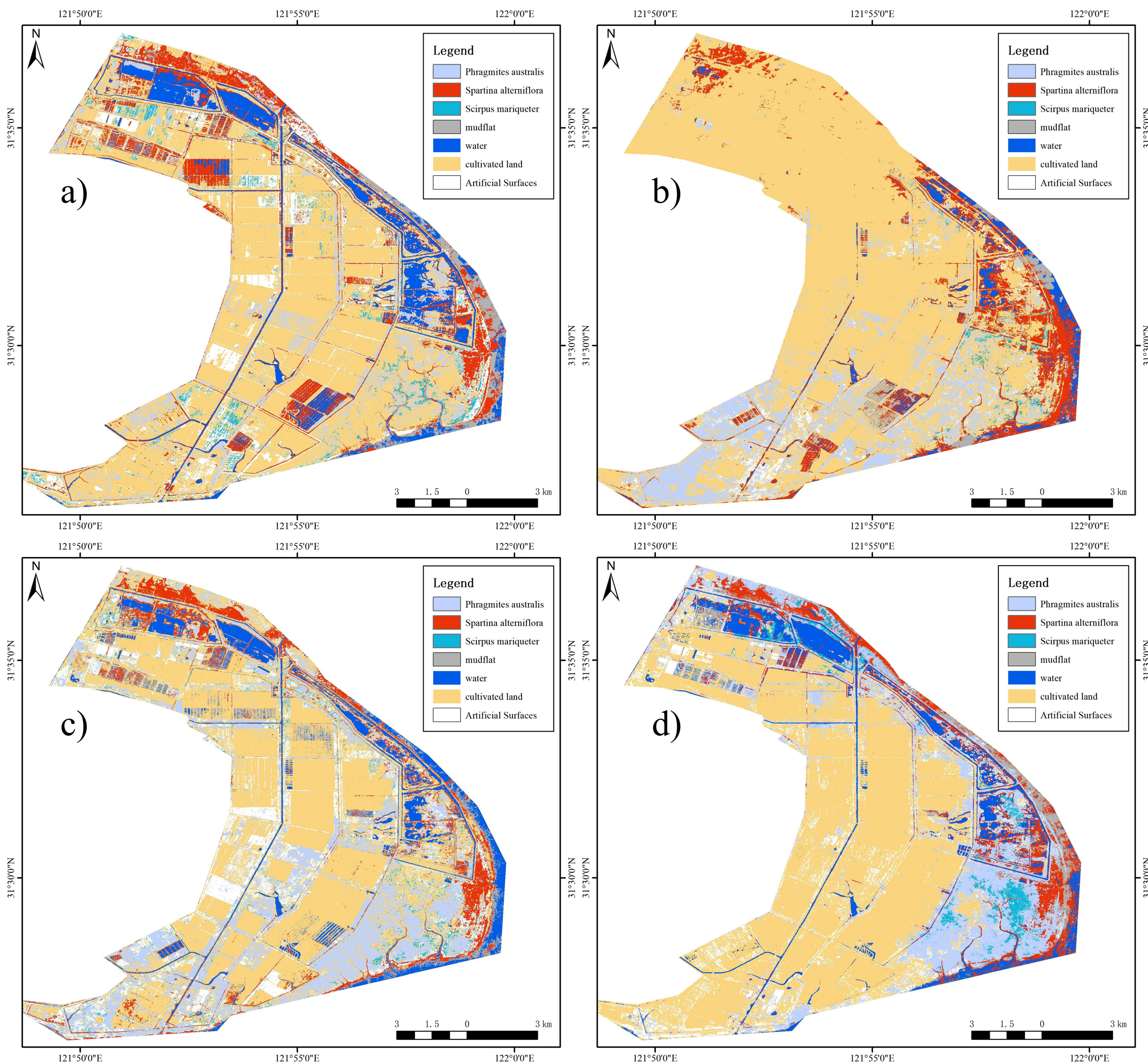

Figure2. Classification results of study area based on random forest. (a) in 2022 spring, (b) in 2022 summer, (c) in 2022 autumn and (d) in 2022 winter.

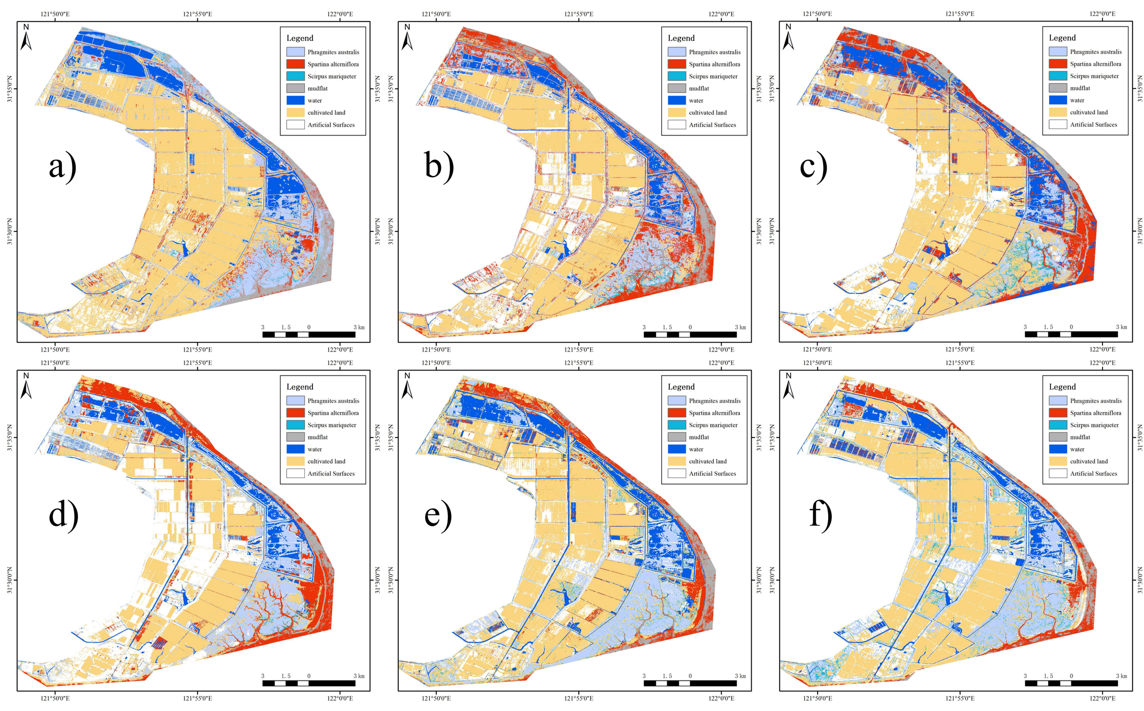

Figure3. Classification results of study area based on random forest. (a) in 2017, (b) in 2018, (c) in 2019, (d) in 2020, (e) in 2021 and (f) in 2022.

6. Conclusion

In this study, we used object-oriented classification algorithm combining phenological characteristics, random forest classification algorithm and time series Rardarsat-2, Sentinel-1, Sentinel-2 and Landsat-8 images to identify and map saltmarsh vegetation.Our case study on Chongming Dongtan shows that annual maps of saltmarsh vegetation track well the expansion and removal dynamics of Spartina saltmarsh during 2017-2022. The resultant annual and multi-year maps of saltmarsh vegetation can be used to support various studies that aim to understand the driving factors of saltmarsh vegetation dynamics and assess the impacts of saltmarsh vegetation expansion on biodiversity, carbon cycle and ecosystem services.

This study provides an accurate reference for the development of remote sensing inversions in different phenological periods and an accurate method for the annual mapping of saltmarsh vegetation. This phenological method can also be used in other areas to extract other vegetation types that exhibit phenological characteristics.

7. Reference

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