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Abstract:
Mapping wetlands and monitoring spatiotemporal variabilities in wetland regions are useful for providing basic ecosystem-monitoring data that are necessary for the protection and management of wetlands. The main objective of this work was to propose a new approach for monitoring the spatiotemporal patterns and reclamation of coastal wetlands in the Liaohe Delta region from 1987 to 2017. With the proposed approach, we aimed to improve the classification accuracy by using integrated classification and a preferred features method. First, after preprocessing the remote sensing data representing the four years of 1987, 1997, 2007 and 2017, we extracted the first component of the principal component analysis (PCA1), normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), soil index (SI), index-based build-up index (IBI), and tasseled cap transformation (TCT) values of the characteristic parameters, such as the brightness component, and then used the maximum likelihood classifier (MLC) and decision tree (DT) methods to classify the preprocessed image landscapes. Finally, we combined the results of the two classification methods with the optimal characteristic parameter band to form new data images and applied the MLC method to perform landscape classification. The analytical results showed that the proposed method can obtain a high average accuracy of 87.71% and a kappa coefficient of 0.85, reflecting a 16.50% higher average accuracy and a 20.72% higher kappa coefficient than the MLC results (average accuracy of 75.29% and kappa coefficient of 0.71). These results indicate that the proposed method is effective and feasible for long-term landscape dynamics research. By using this method, the landscape distributions of the Liaohe Delta wetlands in 4 periods were obtained. We found that although the
area of reed wetlands in the Liaohe Delta region was reduced from 1987-1997 (from 1284.44 km\(^2\) in 1987 to 1006.70 km\(^2\) in 1997), the results were very good in the later periods, indicating optimized wetland protection (from 1040.20 km\(^2\) in 2007 to 1275.53 km\(^2\) in 2017). The coastal zone changed significantly throughout the study period, especially from 2007-2017; during this period, the coastline was significantly affected by human activities, and large areas of tidal flats and coastal suaeda were converted into salt pans and aquaculture areas, while ports, piers, and urban construction areas also continued to extend to the shallow-sea areas (resulting in the coastline land area increasing by 263.24 km\(^2\)).

**Keywords:** maximum likelihood classifier, decision trees, image classification, coastal wetlands, Liaohe Delta.

1. **Introduction**

Wetlands are unique ecosystems with abundant biodiversity found worldwide. Wetlands are not only rich in resources but also perform functions to vastly regulate and control the environment; by impeding floods, conserving water, preventing soil erosion, regulating the climate and purifying the environment, wetlands can improve human living environments. In particular, wetlands can protect many rare and endangered animals and plants around the world and represent a natural gene pool containing many species. In addition, the high biological productivity and harmonious environments provided by wetlands also create good conditions for the sustainable development of humanity and leisure tourism (Lv and Wang 1996). Affected by many factors, such as the actual situations in various study areas, the selected data sources and classification algorithms, and the spectral characteristics of surface features, the accuracies of automatic and intelligent extractions and interpretations regarding coastal wetland information are still lacking due to the scarcity of effective data-fusion and data-mining algorithms (Liu et al. 2017). It is important to accurately grasp wetland ecological health monitoring and evaluations using long-term remote sensing image data to classify wetland landscapes and to carry out studies on the evolution of wetland landscape patterns.
Mapping wetlands is a common remote sensing application in wetland evolution research. With the increasing amount of available global satellite data, remote sensing big data are used in many fields, including in studies exploring marine geology, river channel evolution (Wu et al. 2021), and coastal changes (Yang et al. 2020); in addition, wetland observations based on remote sensing images and field survey data can also be highly effective. Satellite data, field observation data and other relevant data can be collected from different sources and analyzed in geographic information system (GIS) platforms to study the spatial dynamics of wetlands (Sivakumar and Ghosh 2016). Spatially heterogeneous wetland communities can be classified using machine learning algorithms and spectral and textural features, which have been shown to produce statistically significantly higher accuracies than the decision tree (DT) or maximum likelihood classifier (MLC) methods (Szantoi et al. 2015). Yan et al. (2017) pointed out that no one method could be applied to all situations representing a complex wetland environment, so using a combination of different methods to improve the accuracy of the results has become a common phenomenon. Land use types have been classified through visual interpretations of Landsat images; however, the land cover types (associated with several reclamation activities) representing the 1960s were derived from vectorizations of topographic maps and local land use maps (Chen et al. 2018). Jin et al. (2017) used a combination of supervised classification and manual visual interpretation techniques to obtain the main land use/cover types of their study area in different periods from 1979 to 2015 and studied the dynamic changes in wetland reclamation and the invasion influences in the coastal area of central Jiangsu. Zhang et al. (2017) investigated the impacts of temporal land use and land cover changes to evaluate the current status of the environment using multisensor, multitemporal satellite and field observation data using an MLC method. Zhou et al. (2018) applied the support vector machine (SVM) algorithm to train the model on different land types and constructed a category discrimination function to automatically distinguish between the cultivated land types and noncultivated land types. In addition to spectral bands (Gu et al. 2019), the normalized difference vegetation index (NDVI), normalized difference
build-up index (NDBI), modified normalized difference water index (MNDWI), second component of the principal component analysis (PCA2), PCA5, digital elevation model (DEM), slope and aspect features were analyzed, and the classifier accuracies were then assessed using the 4 methods to classify the above features: an artificial neural network (ANN), DT, SVM, and random forest (RF). Liu et al. (2017) classified Yancheng coastal wetlands using supervised classification, DT classification and object-oriented methods. The research results showed that in terms of the classification accuracy and effect, the object-oriented method provided the best classification results, especially for serious spectral confusion. Wu et al. (2019) obtained four land use/cover types based on the iterative classification and regression trees (CART) algorithm, which can improve the classification accuracy by setting up the number of iterations and extracting the NDVI, brightness, NDWI, and hue components based on a hue-intensity-saturation (HIS) transformation and the custom NDVI, near-infrared (NIR), and b-features. Jiang et al. (2019) analyzed the spatiotemporal variabilities in wetlands over 10 years using the CART method, and the object-based CART algorithm produced a higher accuracy (with kappa coefficients of 0.84) than the pixel-based CART algorithm (with kappa coefficients of 0.77). Xiao et al. (2013) constructed a coastal wetland cover classification model based on a BP neural network and applied the model to perform natural wetland cover classification in the core area of the Yancheng Coastal Wetland, obtaining a classification kappa coefficient of 0.83. Chang et al. (2014) obtained wetland classification data using supervised classification algorithms and DT algorithms on the basis of a tasseled cap transformation (TCT), and the results showed that the classification kappa coefficients obtained for the two methods were 0.89 and 0.86, respectively.

At present, the ground object classification methods based on remote sensing images mainly include supervised classification methods, DT methods, neural network methods, SVM methods, and object-oriented methods (Zhou et al. 2016; Yao et al. 2008; Li et al. 2020). Among supervised classification methods, the MLC method is a common classification method with the advantages of a high accuracy and small error. This method can be used to determine the fate of a feature
point by judging the probability that the pixels in the training sample belong to each category, comparing the probability of pixels falling within each category, and determining the fate of the feature point according to the established classification system to determine the main feature types to be partitioned. The advantages of the DT method include its ability to combine multiple input data sources (for example, spectral index data, other classification results, auxiliary data, and active RS measurements from synthetic aperture radar (SAR) or light detection and ranging (LiDAR)), its high computational efficiency, and its strong flexibility.

In contrast from the traditional single classifier and the classification methods without feature parameters, in this paper, we combine multiple feature parameters, use multiple classifiers, and combine methods to extract 13 features and improve the accuracy of the three-level feature classification results. Based on Landsat remote sensing data representing the 4 years of 1987, 1997, 2007, and 2017, in this study, we use the abovementioned high-precision classification methods to extract and classify information characterizing the Liaohe Delta and to study the evolution of the regional Liaohe Delta wetlands over the past 30 years.

2. Methodology and Data

2.1 Study area

The study area is located within Liaohe Delta, from 121°25'~122°30' E and 40°40'~41°25' N (Fig. 1), and includes the Daling River, the Xiaoling River, Linghe, the Shuangtaizi River, the Daliao River and the Daqing River. Liaohe Delta has a flat terrain and fertile soil. It is an important estuary wetland region in China, the largest reed wetland in Asia, and the second-largest reed field in the world. The area belongs to a warm, temperate continental semihumid monsoon climate; the area experiences four distinct seasons, contains diverse vegetation types, and is rich in animal and plant resources. Reeds and Suaeda are the main plant communities, forming a unique landscape of reeds and red beaches, while *Grus japonensis*, *Ciconia boyciana*, *Larus saundersi*, etc., live in the area; these species not only have economic
value but also have important ecological and scientific research value (Zhou et al. 2016).

Due to the influence of drought, upstream interception, and the multiple effects of industrial, agricultural and domestic water usages, the water source guarantee rate of the reed marshes has been maintained at a low level in the study area. At the same time, due to the development of production activities such as petrochemical industry activities, rice planting, and aquaculture, human interference is becoming increasingly intense in this region. The surrounding people are engaged in production activities and do focus on wetland protection, resulting in great impacts on wetland health. Moreover, the *Suaeda salsa* community faces the succession of the reed community, and local *S. salsa* communities, such as those found in *Larus saundersi* breeding regions and on red beaches, are being degraded (Ma 2016). In recent years, different scholars have carried out extensive research on the wetland landscape changes and ecological health of Liaohe Delta from different perspectives. Li et al. (2020) performed an artificial interpretation of 1986-2012 images and analyzed the degradation of the reeds and *Suaeda* from 1986-2012. Liu et al. (2017) and others used human-computer interactive interpretation methods to analyze the changes in the Liaohe Delta wetland from 1982 to 2015; Yin et al. (2019) used the supervised classification method to extract five types of wetland classification information representing Liaohe Delta from 2000 to 2013 and analyzed the dynamic changes in these data. However, most of the preprocessed remote sensing images used in these past studies were constructed based on a single classifier or with classification methods lacking fusion feature parameters during the information-extraction process. To address this problem, we propose combining optimized feature parameters and two classifiers to extract remote sensing image information. Based on this proposed method, in this paper, we classify remote sensing images using a combination of MLC and DT classification methods while combining feature parameters. Thirteen types of features were extracted from each (processed) image; then, the evolution of the landscape in the Liaohe Delta region over the past 30 years was shown using land cover transfer matrices.
2.2 Data sources

The data used in this work were collected from the geospatial data cloud (http://www.dsac.cn) and included Landsat 8 Operational Land Imager (OLI), Landsat 5 Thermal Mapper (TM) and GDEMV2 data, as shown in Table 1. The specific data sources used in this paper included 6 Landsat 5 TM scenes, 2 Landsat 8 OLI scenes and 4 Advanced Spaceborne Thermal Emission and Reflection (ASTER) GDEMV2 images, all with a spatial resolution of 30 meters. The satellite images were taken from September to October, were basically free of cloud cover in the study area and were of good quality. Therefore, 2 scenes from September 21, 1987, 2 scenes from October 18, 1997, 2 scenes from September 28, 2007, and 2 scenes from September 7, 2017, were used in the research. The ASTER GDEM V2 global DEM data were officially released on January 6, 2015, and we used this data source in the information extraction and classification processes as one of the parameters of the decision tree. This DEM of Earth’s land surface contains 1.3 million stereo images collected by Japan’s ASTER satellite. Its horizontal accuracy reaches 30 meters. ASTER's accurate terrain data can be used in the fields of natural resource inclusion, environmental management, geology and urban planning.

2.3 Data processing

A radiometric correction, an atmospheric correction, and splicing and cropping steps were performed on the downloaded remote sensing images and DEM data representing 2017, 2007, 1997, and 1987; in addition, we applied a ground reflectivity extraction on the cropped remote sensing data and a feature extraction. The characteristic parameter bands were combined, and the specific technical route describing the methodology is shown in Fig. 2.

2.3.1 Image preprocessing and feature parameter extraction

(1) Image preprocessing

The preprocessing of the remote sensing images used herein mainly included a sensor radiation correction, an atmospheric correction, stitching and clipping. The radiation correction performed herein mainly included a radiation calibration involving the process of converting the
voltage or digital value recorded by the sensor into an absolute radiance value, that is, by converting the recorded original DN value into a value indicating the reflectivity of the outer surface of the atmosphere. The purpose of this step was to eliminate the errors generated by the sensor itself. The atmospheric correction involved converting the radiance or apparent reflectivity into the actual reflectivity of Earth's surface, and the purpose of this step was to eliminate the errors caused by atmospheric scattering, absorption, and reflection. The radiometric calibration module in ENVI software was used to convert the original image DN values into apparent radiance values; then, the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) atmospheric correction module was used to convert the apparent radiance data into surface reflectance data. For the investigated study area, all available cloud-free, level-1, terrain-corrected imagery with universal transverse Mercator (UTM) map projections were obtained under world geodetic system (WGS) 84. Moreover, considering the specific aim of this work and the given geolocation uncertainty corresponding to circular errors below 12 m in the OLI and TM data products, it was not necessary to improve the geographic location characteristic of the Landsat imagery (Modica et al. 2016).

(2) Feature parameter extraction

The characteristic parameters selected in this study are listed in Table 2 below, including the first component of the principal component analysis (PCA1), TCT brightness component, NDVI, MNDWI, red-band spectral value (RED), NIR spectral value (NIR), soil index (SI), and urban building index (Index-based Build-up Index, or IBI).

PCA is widely used in related research on vegetation coverage (De Almeida et al. 2015), in the remote sensing monitoring of ecological changes (Liu et al. 2017; Yang et al. 2019), and in ground feature classifications (Gu et al. 2019; Xu 2005). PC variables can be repeated (to indicate relationships) for all the originally proposed variables. Similar variables indicate redundancy, and PCA can establish as few new variables as possible and ensure that these new variables are pairwise-unrelated, allowing them to retain the original information to the greatest possible extent.
when reflecting information on the subject. The contributions of PCA1 in 1987, 1997, 2007 and 2017 were found to be 89.18%, 92.47%, 85.93%, and 83.53%, respectively, representing most of the information of each band, and the synthesized PCA1 was used to replace each component index. The PCA data were converted using the PCA module in ENVI software.

The TCT, also known as the KT transformation or Kauth-Thomas transformation, is an empirical linear orthogonal transformation of images based on the information distribution structure of soil and vegetation; this transformation is applied in multispectral remote sensing research performed in a multidimensional spectral space. After the transformation, the first three components are named "brightness", "greenness" and "moisture"; these components reflect the soil rock, vegetation, and moisture information in soil and vegetation, respectively. The PCA data were converted using the Tasseled Cap module in ENVI software.

The NDVI is one of the most commonly used indexes for indicating the growth status of vegetation. It is widely used in the fields of vegetation growth and ecological environmental quality monitoring and can be expressed as shown in Formula (1):

$$NDVI = (\rho(\text{nir}) - \rho(\text{red}))/ (\rho(\text{nir}) + \rho(\text{red}))$$  

(1)

The improved normalized difference water index (MNDWI, or modified NDWI) was used to extract water body information from images. The MNDWI can effectively distinguish shadows and water bodies and solves the difficult problem of removing shadows during the water body extraction process; its equation is shown in Formula (2):

$$MNDWI = (\rho(\text{green}) - \rho(\text{mir}))/ (\rho(\text{green}) + \rho(\text{mir}))$$  

(2)

Bare soil is the main surface landscape in the soil erosion area. This datum thus plays an extremely important role in the monitoring and management of soil erosion. The calculation formula of the bare soil index SI (Zhou et al. 2016) is shown in Formula (3):

$$SI = [\rho(\text{swir1}) + \rho(\text{red}) - (\rho(\text{bule}) + \rho(\text{nir}))]/ [\rho(\text{swir1}) + \rho(\text{red}) + (\rho(\text{bule}) + \rho(\text{nir}))]$$  

(3)

The calculation formula of the urban building index IBI $^{[25,27]}$ is shown in Formula (4):

$$IBI = \frac{2\rho(\text{swir2})/ (\rho(\text{swir1}) + \rho(\text{nir})) - [\rho(\text{nir})/ (\rho(\text{red}) + \rho(\text{nir})) + \rho(\text{green})/ (\rho(\text{swir1}) + \rho(\text{green}))]}{2\rho(\text{swir2})/ (\rho(\text{swir1}) + \rho(\text{nir})) - [\rho(\text{nir})/ (\rho(\text{red}) + \rho(\text{nir})) + \rho(\text{green})/ (\rho(\text{swir1}) + \rho(\text{green}))]}$$
In formula (1)-formula (4), $\rho$(blue) represents the reflectance value of the blue wave band, $\rho$(nir) represents the surface reflectance value of the near-infrared wave band, $\rho$(green) represents the surface reflectance value of the green wave band, $\rho$(red) represents the red-band surface reflectance value, $\rho$(swir1) represents the surface reflectance value of the shortwave infrared 1 band, and $\rho$(swir2) represents the surface reflectance value of the shortwave infrared 2-band.

The remote sensing image information extraction and classification processes mainly included determining the classification system, selecting samples, performing the MLC (supervised classification) and DT classification, and obtaining the band combinations of the two classification results and the characteristic parameters listed in Table 3. Then, the MLC was performed again. The specific process is described as follows: the data sources used for the first MLC and decision tree classification were the Landsat 5 and Landsat 8 OLI data (band 1-band 5 and band 7 of the Landsat 5 data, band 2-band 7 of the Landsat 8 data) after the radiation correction and atmospheric correction were completed. By combining these two classification results with the feature parameters listed in Table 3 through a band combination process, it can be understood that the first MLC results can be regarded as a band, the DT classification results can be regarded as a band, and the parameter characteristics listed in Table 3 can each be considered a separate band (for a total of 9 bands). Then, the 11 bands described above (1+1+9) can be combined through the LayerStack function module of the ENVI software to form 11 bands of new image data. It should be noted that no matter which method is used for landscape classification, the same sample data are used.

(1) Classification system

Wetland classification is the basis of wetland research. The classification schemes of wetland ecosystems differ according to the purpose of the study, the characteristics of the study area, and the local land use/cover characteristics. The Liaohe Delta region contains diverse landforms,
including large areas of natural wetlands such as reeds and beaches and large areas of rice fields and dry lands. At the same time, as a coastal area, the development of the coastal zone has formed a large artificial wetland area. The first-level classification results were divided into three categories based on the hydrologic and surface soil conditions: natural wetlands, constructed wetlands, and nonwetlands; on the basis of the first-level classification results, in the second-level classification, the natural wetlands were subdivided into waters, swamps and beaches and the nonwetlands were subdivided into forestlands, farmlands, industrial and mining buildings, residential lands and unused lands. To better analyze the wetland evolution process in the Liaohe Delta region, the classification results were further refined. In this paper, the wetlands were divided into 13 three-level types, as shown in Table 3. On the basis of the secondary classification results, the water areas were subdivided into rivers and shallow-sea areas, and the marshes were subdivided into reed lands and Suaeda wing areas. Due to the developmental needs of the local economy, artificial wetlands have been continuously developed and expanded, and this land type was subdivided into salt fields, aquatic product breeding areas and reservoirs. As Liaohe Delta produces rice, the farmlands were divided into paddy fields and dry lands.

(2) Selection of training and validation samples

The original images, PCA feature images, TCT feature images, and field survey data were all referenced when drawing training samples. The number of selected samples is shown in Table 5. A total of 479 samples were selected for 1987, 495 samples were selected for 1997, 723 samples were selected for 2007, and 621 samples were selected for 2017. To test the accuracy of the remote sensing interpretation results in the Liaohe Delta region, field survey data were used as verification samples, resulting in a total of 232 verification points, the distribution of which is shown in Fig. 3.
(3) Classification method

Regarding the remote sensing image of Liaohe Delta in 2007, by comparing the single-decision tree classification results with the single maximum likelihood classification results and the maximum likelihood classification effect of the combined method, we found that the classification results obtained with the combined method were the most accurate.

We selected appropriate samples and automatically extracted ground feature classification information using supervised classification (using the maximum likelihood method). The advantages of this method included its high accuracy and low errors. However, practical operations have found that the maximum likelihood method classification results obtained from a single data source still contain certain errors (field verification points were obtained through field surveys, and the overall classification accuracy was 75.29% with a kappa coefficient of 0.71). Reeds also appeared in the dry-land regions.

The DT used a variety of input data to automatically classify the data, and its advantages include its high calculation efficiency and flexibility. For classification tasks using DTs, appropriate parameters need to be selected. Based on the research results of predecessors (Zhang et al. 2017; Zhou et al. 2018; Gu et al. 2019; Liu et al. 2017; Wu et al. 2019; Jiang et al. 2019; Chang et al. 2014), six feature parameters, including the brightness, NDVI, MNDWI, NIR, SI, and DEM, were selected here, and DTs were used. This method classified wetland landscapes using the parameter settings shown in Fig. 4 (the parameter thresholds were determined according to the critical values reflected in the wave spectrum histogram jumps corresponding to different objects). However, the DT method could not distinguish between forestlands and dry lands. Rice and reeds were also not distinguished, nor were bare lands and residential areas (as shown in Figure 5); in addition, 13 classification effects could not be obtained. For example, the DT separated water bodies but did not divide water bodies into rivers, reservoirs, and other water bodies. This resulted in the shallow-water area classification accuracy being relatively low;
the calculated overall classification accuracy reached 56.82%, and the kappa coefficient was 0.57. Therefore, the DT classification method was not suitable for this three-level classification task; that is, it could not be used in situations with higher-level landscape categories.

The classification results obtained using the DT method, the classification results obtained using the first maximum likelihood method and the 9 extracted feature parameters (Table 3) were combined with the bands; then, the second information-extraction task was performed. The effect of this second task was obviously better; the overall classification accuracy reached 87.71%, and the kappa coefficient was 0.85, thus proving that the interpretation method used in this article was appropriate.

2.4 Postprocessing and accuracy evaluation of the classification results

In this article, we use the overall classification accuracy and kappa coefficient indicators to verify the classification accuracy. Regarding these metrics, the overall classification accuracy refers to the ratio of the number of correctly classified category pixels to the total number of categories; the kappa coefficient is the ratio between the error reduction caused by the classification task and a completely random classification. The formula used to calculate the kappa coefficient can be expressed as follows:

$$k = \frac{p_0 - p_e}{1 - p_e}$$

where $p_0$ is the sum of the number of samples correctly classified in each category divided by the total number of samples, which is also the overall classification accuracy, and $p_e$ is the sum of the "product of the actual and predicted numbers" corresponding to all categories divided by the "square of the total number of samples"; this indicator can reflect the "bias" of the model. According to the kappa coefficient calculation formula, the more unbalanced the confusion matrix is, the higher the kappa value is, and the more balanced the confusion matrix is, the lower the kappa value is.
Assuming that the number of real samples in each category can be expressed as $a_1, a_2, ..., a_c$, that the predicted number of samples of each category can be expressed as $b_1, b_2, ..., b_c$, and that the total number of samples is $n$, the following equation can be obtained:

$$p_e = \frac{a_1 \times b_1 + a_2 \times b_2 + \cdots + a_c \times b_c}{n \times n}$$

(6)

2.5 Extraction of coastlines

The definition of a coastline generally refers to the limit reached at high tide during a certain period of time. The natural coastline of the Liaohe Delta estuary region includes river ports and silty coastlines, and the artificial coastlines include the aquaculture dike coastlines, salt field dike coastlines, construction dike coastlines and port coastlines. The river port lines are determined based on the first road, bridge, or gate met by the estuary area from the sea direction landward. Due to the sudden widening of the estuary along the river, silty shorelines are generally located along this estuary and form the dividing line between the lushness and sparseness of the plants in the images (Wang et al. 2015); the outer edge of this artificial shoreline is used as the dike line. Therefore, the tidal-flat and shallow-sea areas were set to type 1, while the other classifications were set to type 2, meaning that each of the 13 classifications were classified into 2 categories and that the boundary between these two categories was the coastline. Coastlines were automatically extracted from the 1987, 1997, 2007, and 2017 images. The coastline extracted from the 2017 image was compared with the 2017 coastline released in the 2019 National Geographic Information Resource Directory Service System (NGIRDSS). As shown in Fig. 6, these artificial coastlines are basically the same, but the silty coastline of the Shuangtaizi estuary differs (the red circle in Fig. 6). The 2017 coastline released by the NGIRDSS is bounded by an aquaculture area, but the coastline automatically extracted in this paper was extracted according to the silty coastline at the Shuangtaizi estuary, corresponding to the dividing line between lush and sparse plants. Notably, in the coastline extractions conducted in this paper, the tide problem is not
considered, and the coastline extractions are mainly performed based on the information available at the time each image was taken.

3. Results and Analysis

3.1 Analysis of dynamic landscape area changes

3.1.1 Analysis of wetland area changes

Fig. 7 shows the extraction results obtained for 1987, 1997, 2007, and 2017. Fig. 8 shows the statistical histograms obtained for various types of land areas. Fig. 7 shows that large areas of reed lands were mainly distributed along the Shuangtaizi River. The area of reeds in 1987 was approximately 1,284.44 km$^2$. However, from 1987-1997, this area was reduced to 1006.70 km$^2$. The implementation of the government's protection policy later expanded this area from 1,040.20 km$^2$ in 2003 to 1,275.53 km$^2$ in 2007. It is not difficult to see that the reed wetland area has been effectively restored. *Suaeda aptarius* grows in saline-alkali soil and often forms single colonies on beaches and lakes. The area of *S. aptarius* is decreasing annually in the study area. In 1987, this area was approximately 227.48 km$^2$. In 1997, it was reduced to 35.23 km$^2$, exhibiting a reduction rate of 84.51%, before increasing to approximately 39.70 km$^2$ in 2007 and then decreasing again to 30.52 km$^2$ in 2017. As a kind of intertidal zone between sea and land areas, tidal flats are affected by both the sea tide level and the local activities. Fig. 7 shows that from 1987-1997, a large area of tidal flats was transformed into aquaculture areas, but the tidal flat area then increased by 2007. The reason for this was twofold: the *Suaeda striata* area was transformed into tidal flats, and a certain degree of seawater erosion occurred along the shoreline from 1997 to 2007, thus increasing exposure and causing tidal flats to form. The aquaculture area changed significantly throughout the study period. From its sporadic distribution (approximately 91.63 km$^2$) in 1987, a large aquaculture area gradually developed. In 1997, the aquaculture area was as large as 358.11 km$^2$. By 2007, the number of aquaculture areas on land decreased, and the overall
aquaculture area was reduced to 242.39 \text{ km}^2; the aquaculture industry in the coastal zone was revitalized by 2017, and some salt fields were even converted into aquaculture areas, resulting in an overall aquaculture area of 307.93 \text{ km}^2. In the study area, the area of salt fields basically showed a decreasing trend year by year. The area of salt fields was approximately 309.60 \text{ km}^2 in 1987 and approximately 315.47 \text{ km}^2 in 1997. That is, the area of salt fields basically remained stable from 1987 to 1997, but then started to decrease to 251.86 \text{ km}^2 (2007) and then to 212.79 \text{ km}^2 (2017). 

Fig. 8 shows that the area of reservoirs in the study area increased year by year, but the river area decreased year by year. Excluding 1997, the salt pan, tidal flat, and *Suaeda pubescens* areas all decreased year by year, while the aquaculture area increased year by year.

### 3.1.2 Analysis of nonwetland area changes

The area of paddy fields was approximately 1,936.71 \text{ km}^2 in 1987. Due to the intensification of human activities, the paddy field area increased significantly to 2,448.71 \text{ km}^2 in 1997, reflecting an increase of approximately 512 \text{ km}^2 and a growth rate of 26.44\%. However, this area decreased annually in the later period. Industrial and mining areas and construction lands expanded significantly throughout the study period, occupying a large area previously occupied by rice fields. However, this area decreased to 2298.99 \text{ km}^2 in 2007 and to 2120.20 \text{ km}^2 in 2017 as a result of the implementation of the “returning farmland to reeds” project. In short, the area of rice fields showed a small trend in which it first increased and then decreased before demonstrating a steady decreasing tendency in the later period. The areas of industrial and mining buildings and residential areas (including urban villages, industrial and mining buildings, roads, protection dikes, areas without buildings and meadows) in 1987 was approximately 732.40 \text{ km}^2, but in 1997, this area was reduced to 494.11 \text{ km}^2. The main reason for this decrease was that large areas lacking buildings and meadows in 1987 and earlier were considered among these areas (these areas were developed into rice fields and dry lands in the later period). However, the area of industrial and mining buildings and residential areas expanded from 882.38 \text{ km}^2 (2007) to
1307.31 km$^2$ (2017), showing an increase of 574.91 km$^2$ over the 1987 area, with a growth rate of 78.5%. Bare lands (including tamarisk-tamame meadows and other meadows) and mountain forests (shrub meadows) showed decreasing trends overall (except under special circumstances in 1997); these areas decreased from 330.39 km$^2$ and 754.84 km$^2$, respectively, in 1987 to 123.48 km$^2$ and 367.45 km$^2$, respectively, in 2017, exhibiting reduction rates of 62.63% and 51.31%, respectively. The area of dry lands increased year by year. In 1987, the dry land area was approximately 1028.60 km$^2$. However, in 1997, the dry land area was as high as 1529.79 km$^2$, reflecting a growth rate of 48.72%. Later, because of the conversion of a portion of these dry lands into rice fields and woodlands, the dry land area decreased. As of 2017, the dry land area was approximately 1223.55 km$^2$, exhibiting a growth rate of approximately 18.95% compared to the 1987 area. Fig. 8 shows that the areas of rice fields and dry lands increased greatly in 1997, by approximately 511.99 km$^2$ and 501.20 km$^2$, respectively, but the areas of residential construction, bare lands and mountain forests decreased greatly, by approximately -238.19 km$^2$, -257.17 km$^2$, and -276.26 km$^2$, respectively.

Therefore, because human activities have intensified, land use types such as residential areas, industrial and mining construction lands, and dock lands have appeared in the coastal areas; moreover, the coastal zone has continued to expand into the shallow-sea area. Throughout the study period, the Liaohe Delta area as a whole showed a trend in which the area of constructed wetlands expanded annually, the area of natural wetlands decreased, and a trend reflecting the internal transfer of nonwetland areas appeared.

### 3.2 Analysis of transfer characteristics

Fig. 8 shows that the landscape types that had increased in area by 1997 compared to 1987; these landscape types included reservoirs, salt pans, aquaculture areas, rice fields, and dry lands. Table 5 shows that the reservoir areas were mainly transformed from mountain forests, covering an area of approximately 1.13 km$^2$, as a new reservoir was built near mountain forest villages; salt
fields were converted from areas of approximately 25.57 km², 14.14 km², 13.01 km², and 11.48 km² of bare lands, aquaculture, beaches, and reed lands, respectively. Aquaculture areas were mainly transformed from bare lands, *Suaeda sylvestris* areas, paddy fields, and tidal flats, taking over areas of approximately 140.09 km², 40.94 km², 35.25 km², and 26.52 km², respectively. Rice fields were mainly transformed from reed meadows, dry lands, residential areas, industrial and mining areas (mainly referring to cultivated lands without buildings), and bare lands, with areas of approximately 279.36 km², 125.61 km², 124.13 km², and 54.88 km², respectively. Dry lands were mainly transformed from mountain forests (mainly including shrub meadows), reeds meadows, meadows, residential areas, industrial and mining areas, and rice fields, with areas of 347.49 km², 156.85 km², 146.22 km², and 72.64 km², respectively.

Fig. 8 shows that the landscape types that had increased in area by 2007 compared to 1997 included reservoirs, residential areas, industrial and mining areas, bare lands, mountain forests, reeds and meadows, and beaches. Table 6 shows that the reservoirs were mainly transformed from reed meadows and salt fields, with transformed areas of approximately 8.35 km² and 5.01 km², respectively, where pond potholes were constructed in reed fields and salt fields were abandoned. Residential areas and industrial and mining areas were mainly transformed from rice fields and dry land, with transformed areas of approximately 170.73 km² and 149.63 km², respectively. Bare lands were mainly distributed in areas that were previously salt pans, aquaculture areas, residential industrial and mining areas, rice fields, and dry land; these areas were not necessarily transformed but instead often coexisted with bare lands. Mountain forests were mostly converted from dry lands, with an area of transformation of approximately 292.59 km², because dry lands that were not cultivated were instead converted to shrub meadows (which were classified as mountain forests). Reeds and meadows were mainly transformed from rice fields and dry lands, with transformed areas of approximately 94.46 km² and 94.46 km², respectively. The tidal flats were mainly transformed due to seawater erosion over an area was approximately 102.47 km², but
these tidal flats were usually distributed together with rivers, aquaculture areas, and *S. pubescens* areas.

Fig. 8 shows that the landscape types that had increased in area by 2017 compared to 2007 included reservoirs, aquaculture areas, residential and industrial and mining areas, dry land, reeds, and meadows. Table 7 shows that reed meadows, salt pans, and aquaculture areas were transformed from reservoirs. Aquaculture areas were mainly transformed from beaches, shallow-sea areas, and salt pans because of the coastal zone development driven by human activities. On the one hand, these changes reveal the transformation of economic activities. The changes in residential areas and industrial and mining areas were large because the growth of urban residents took up large areas previously occupied by paddy fields, dry lands, and woodlands. On the other hand, industrial and mining areas developed in what were previously reed grasslands, salt pans, and aquaculture areas. In addition, ports and piers were built in tidal flat areas. Dry lands were mainly transformed from forestlands, with an area of 309.52 km², because of the reclamation of shrubs and meadows. Reeds were effectively restored; the “returning farmland to reeds” project aimed at rice fields transformed an area of 205.18 km², and moreover, reed fields arose with withdrawal of industrial and mining activities.

3.3 Coastline changes

The coastlines of the Liaohe Delta wetland region extracted in this article in 1987, 1997, 2007, and 2017 are shown in Fig. 9. Fig. 9 shows that from 1987-2017, the land area of the Liaohe Delta coastline increased by 263.24 km², and the coastline length in 2017 was approximately 329.886 km, reflecting an increase of 92.294 km compared to the 1987 coastline length. In the figure, the coastline area within the red circle was mainly transformed from a silty coastline to aquaculture and salt pan areas, and the coastline area within the green circle was mainly a silty coastline region transformed into a port coastline region and a bank line for the construction of dikes. The coastline region indicated by the black thin circle was eroded to a
certain extent from 1987-2007, but from 2007-2017, the area in the large black circle basically
developed into an aquaculture area, while that in the small black circle developed into a paddy
field.

4. Discussion

The information extraction and landscape classification of the Liaohe Delta region were
realized in this work by combining the MLC and DT techniques with specific bands from Landsat
remote sensing image data collected in 1987, 1997, 2007, and 2017. The classification was
performed at three levels, and 13 landscape types were considered. Using field validation data to
evaluate the accuracy of the classification results, the overall classification accuracy was found to
be 87.71%, and the kappa coefficient was 0.85; however, when only the supervised classification
method was used, the overall classification accuracy was 75.29%, and the kappa coefficient was
0.71. Moreover, considering the DT classification results alone, the overall classification accuracy
reached 66.82%, and the kappa coefficient was 0.57; this method alone could not perform the
13-type classification task. Therefore, the classification method suggested in this work effectively
improves the resulting classification accuracy.

In the Liaohe River Delta region, an area containing natural wetlands including rivers, reeds,
suaeda plants, and tidal flats generally first declined and then increased throughout the study
period (Fig. 10). Among the land types, the river area decreased annually, mainly due to the
decreasing precipitation, the decreasing river water level and the encroachment of the riverbanks,
tidal flats and meadows. Although reed wetlands were destroyed by anthropogenic activities from
1987-1997, thus greatly reducing their area, the reed wetland area was effectively repaired in the
later period. By 2017, this area was basically the same as that in 1987; this finding differs from
the analysis results of Li et al. (2020). The area of *Suaeda wingans* decreased year by year and
was mainly transformed into aquaculture areas, rice fields, and reed meadows. In general, *S. wingans* was affected by human activities and greatly reduced throughout the study period. The
Tidal flats were developed into aquaculture areas and salt pans as a result of human activities; on the other hand, large areas of new tidal flats formed due to the impact of seawater erosion, but the overall area generally decreased. Constructed wetlands showed an overall trend of first declining and then growing; these regions mainly included salt pans, aquaculture areas, and reservoirs. The salt field area increased from 1987 to 1997 but continuously decreased in the later period. Aquaculture was vigorously developed in 1997. Although the aquaculture area decreased in the later period, it remained relatively stable. The reservoir area increased year by year and was basically consistent with the analysis results of Liu and Ji (Liu et al. 2017; Ji et al. 2010). Nonwetland areas occupied a large expanse and showed an increasing trend year by year. The main types of nonwetlands included paddy fields, woodlands, dry lands, residential and industrial areas and mining lands. In addition to the mutual transformation among rice fields, dry lands and reed meadows, a mutual transformation relationship was observed among the nonwetland areas; this was mainly reflected in the conversions of rice fields, dry lands, and forestlands to residential, industrial and mining lands and in the mutual transformations among rice fields, dry lands, and woodlands. The residential areas and industrial and mining lands increased throughout the study period, while the area of woodlands decreased (Li et al. 2020).

However, during the classification process, in this article, we classified cattail meadows and deer meadows as reeds, shrub meadows as woodlands, and tamarisk-tamame meadows as bare lands. Areas without buildings and meadows were classified as construction lands. Although there was no problem with the above classification scheme in terms of the land use types, and all land use types were either natural wetlands or nonwetlands, a technicality remains to be discussed. In this article, we tried to use a deep learning method (based on the U-NET algorithm) for the classification task, but because it was a three-level classification task (with the number of categories reaching 13), the classification effect of this algorithm was not ideal; an in-depth exploration of this issue will be included in future work.
5. Conclusion

In this paper, referring to the existing wetland classification system and by comprehensively considering the characteristics of the Liaohe Delta wetland, a three-level classification system for coastal wetland landscapes in the Liaohe Delta region was established. Landsat remote sensing images taken on 4 instances in 1987, 1997, 2007, and 2017 were used to extract landscape information and landscape dynamic change information to perform a quantitative analysis of wetland and coastline change characteristics. The following conclusions were obtained in this work:

(1) The combination of the supervision classification method, DT classification method and band combination method effectively improved the classification accuracy. The classification results obtained for the Liaohe Delta area were verified by field verification points. The overall classification accuracy was 87.71%, and the kappa coefficient was 0.85; the resulting classification data could thus be used to analyze the dynamic evolution of the landscape.

(2) In this paper, we obtained the Liaohe River Delta landscape classification results for 1987, 1997, 2007, and 2017 and analyzed the annual changes in 13 land use types. The long-term data analysis results revealed that compared to the wetland area in the Liaohe River Delta region in 1987, wetlands were reduced by 1997, but wetlands were effectively protected in the later period, especially reed wetlands. This finding is inseparable from the implementation of the environmental protection policy promoted by the local government. The coastal zone changed considerably, especially during the 2007-2017 period, and the coastline was significantly affected by human activities during this period. In addition to the areas of tidal flats and coastal suada resulting from the conversion of salt pans and aquaculture areas, the port, wharf, and urban construction areas also continued to extend into the shallow-water regions.

(3) Because the data used in this article were 30-meter resolution data, certain interpretation errors inherently arose, and the problem of the different objects having the same spectra remained.
For example, there was some confusion between salt pans and aquaculture areas. The classification method thus needs to be further explored in depth. However, the overall change trends have a certain reference significance and can serve as a reference for monitoring the coastal wetland ecosystems in the Liaohe River Delta region.

**Declarations**

**Fundings**

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**Competing Interests**

The authors have no relevant financial or non-financial interests to disclose.

**Author Contributions**

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Jihong Sun and Huairong Song. The first draft of the manuscript was written by Huairong Song and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Ethical Approval**

This work is not applicable for both human and or animal studies.

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**Figures**

Figure 1

Mosaicked image of the study area in the Liaohe Delta, Liaoning Province, China

Figure 2

Technical route used in this study
Figure 3

Verification points of remote sensing interpretation results in Liaohe Delta

![Decision Tree Diagram]

**Figure 4**

Parameter setting of decision tree
Figure 5

Classification results of 2007 were compared by DT (a), MLC (b), combination of them (c) and object-orientated (d)
Figure 6

2017 coastline released in 2019 was compared with the 2017 coastline extracted in this article.
Figure 7

Landscape distribution map of Liaohe Delta in 1987, 1997, 2007 and 2017
Figure 8

Landscape area change of Liaohe Delta in 1987, 1997, 2007 and 2017
Figure 9

Changes of coastline in 1987-2017

Figure 10

Graph showing changes in non-wetland and artificial wetland areas from 1987 to 2017.
Change trend of the first class classification of Liaohe Delta

Supplementary Files

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