Optical Classification of Coastal Water Body in China using Hyperspectral Imagery CHRIS/PROBA

Qing Wang1,3, Zhengke Zhang1,3*, Zengzhou Hao2, Bingling Liu1, Jilian Xiong1
1 Key Laboratory of Coast and Island Development (Nanjing University), Ministry of Education, Nanjing, China
2 State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, State Oceanic Administration, Hangzhou, China
3 Collaborative Innovation Center of South China Sea Studies, Nanjing, China
Email: zhangzk@nju.edu.cn

Abstract. Coastal saltern and aquaculture are vital components of human-made coastal areas and they have immense influence on the coastal water environment in China. Hyperspectral space-borne remote sensing is a significant technology in remote sensing, enabling in-depth identification and discrimination of the spectra from water features on shore. The study uses CHRIS/PROBA images to identify water-bodies and classify six optical water types from artificial and natural water in three sites across regions along China’s coastline. Most of the offshore waters are affected by the inflow of land source materials. The fluorescence peaks appearing at 675 nm can be observed by 5 water types. In addition to Class 1 water which is far from the shore and the Class 4 water whose signals are mainly affected by the algae at its bottom, the other 4 kinds of water show backscattering peak after 800 nm, suggesting that particles are playing an important role in coastal water. For coastal waters in Liushagang, the mangrove forest will transfer the water body signal received by the satellite into the vegetation signal; pools in coastal saltern have rather shallow water during production period when the benthic signal will seriously interfere the reflected signal. In the intertidal area, the hyperspectral characteristics in the same sample also change periodically due to the ebb and flow. The Class 2 and Class 3 water bodies alternately occur in the intertidal zone in the Lianyungang research area. Therefore, it is concluded that optical classification approaches reflect the advantages of remote sensing from Satellite-borne, and our study can be helpful and conductive for follow-up sensors.

Keywords: Optical classification, Water type; Aquaculture, Coastal saltern, CHRIS

1. Introduction
The coastal waters pollution from human activity has long been a problem [1–2]. In China, salt ponds and aquaculture ponds, which have started to mushroom in recent 30 years, are vital components of human-made coastal areas [3–4]. Aquaculture is one of the major human activities that have the negative impact on the nearshore water environment are increasingly recognized [5]. Chemical sediment deposited by seaside salt production may endanger habitat condition and bentonic organism in coastal areas [6]. Therefore, it is necessary to find an effective technical method, which is capable of monitoring and assessing the coastal water-quality in a large-scale and periodic way, so as to study and comprehend the impacts of coastal aquaculture and seaside salt production on the coastal water-quality.

Remote sensing is an effective method for monitoring coastal water-quality and predicting water productivity. It has the capability of acquiring land surface data in a manner featuring large scale, real time, highly efficient and economical [7-8]. At present, there are three main ways of monitoring organic
(phytoplankton chlorophyll a) and inorganic (suspended minerals) constituents of water body by remote sensing. Firstly, known as spectral water index-based approaches, has been proposed in the past few decades [9-10], which makes it easier to separate non-water body features by setting the optimized threshold [11-12]. Although the water indexes are well capable of distinguishing water from land, they were difficult to identify different water types only by the index value [13]. The second way, classical regional approach, is overdeveloped to focus on the optical characteristics of specific coastal waters [14-19]. Lastly, optical-classification approaches cluster spectrums of waters based on similar optical traits. This method originated from the use of ASD hyperspectral spectroscopy by some specialists [20-23], who collected a large amount of hyperspectral data from samples of water bodies in coastal and inland water. And based on the spectrum’s typological characteristics, several typical spectral types of water bodies are summarized.

Hyperspectral space-borne remote sensing, which delivers reflectance information in dozens of bands, is a significant technology development in remote sensing, enabling in-depth identification and discrimination of spectra of water features. Fuchs et al. [24] performed a supervised classification using hyper-spectral CASI data and assessed the influence of tropical shrimp aquaculture on the environment in Indonesia. Koponen et al. [25] classified the lake water according to Secchi Disk, chlo-rophyll-a and turbidity. In recent years, some studies have used hyperspectral imaging to estimate the total dissolved solids (TDS) and colored dissolved organic matter (CDOM) [26-29]. However, applications of optical classification dedicated to the coastal water are very few in China, especially for saltern and aquaculture ponds. Besides, applications of space-borne hyperspectral remote sensing in the optical typology of coastal oceans which aims at monitoring coastal water quality are also relatively scarce in China.

This article intends to provide a better understanding of optical characterization of water bodies in saltern and aquaculture ponds from China’s coastal areas. China has 14, 500-kilometer (about 9, 000 mile) coastline across north and south, which lies within a latitude of 22 degrees. Most of its land is in the subtropical region while a small part of it in the temperate zone. In this case, we asked for CHRIS /PROBA hyperspectral remote sensing data at three research sites along the latitudinal gradient. All images were generated during summer time when the image quality can be free from the effects of sea ice. Oriented in the improved hyperspectral data (CHRIS / RROBA) dimensionality reduction method, two targeted water indexes were established, and a segmentation algorithm, used to extract the optical pixels of complex water bodies in the research areas was deduced. The satellite radiation signals provided by the CHRIS sensor are then clustered to produce a classification of the different water classes spectrally. Finally, the advantages of tracking the spatial and temporal distribution of the optical classes in order for monitoring coastal natural and artificial waters will be illustrated in this article.

2. Research Sites
This study selects three research sites along the latitudinal gradient, which involves (see figure 1) Liaohe Delta, Lianyungang and Liushagang. Liaohe Delta is located in Northeast China. With large areas of the site having been designated as Estuary National Nature Reserve, it embraces wetlands of international importance [30]. Liaohe Delta is belong to Bohai Economic zone and economic and population growth has led to anthropogenic expansion, such as reclaiming farmland and mariculture ponds from sea and littoral wetland.

Most notably, this area is one of the best rice-growing areas of China. Lianyungang is located around the dividing line between South and North China [31]. Its coastal area has been affected by anthropogenic activities, including reclamation, the construction of harbors, channel dredging and aquaculture for a long time. Liushagang, located on the west side of the Leizhou Peninsula in Guangdong Province, is famous for its mudflat aquaculture in farm pond [32]. Sugar cane and shrimp aquaculture are comparatively widely distributed in this area. Particularly, sea salt industry in the site occupied a prominent position in the whole province’s salt production. Furthermore, we can find mangrove forests which grow in there around the subtropical latitudes.
Figure 1. Location and detailed images of the study areas. (a) Liaohe Delta; (b) Lianyungang; (c) Liushagang.

3. Materials and Methods

3.1. Data
Two types of imaging are used in this study. CHRIS (Compact High Resolution Imaging Spectrometer), launched by the European Space Agency (ESA), is a hyperspectral sensor on board the PROBA platform with a revisit time of approximately seven days. CHRIS Mode 1 (34m spatial resolutions) provides 62 bands of spectral information from 410 to 1005 nm. Three CHRIS Mode 1 images were used in this study, acquired on cloud-free days in 2014 and 2016. The central targets of each image are very close to each other with a little overlapping. The image was atmospherically corrected and de-noised using the BEAM toolbox which can be available free of charge on the ESA website. At the same time, our study adopts the Landsat-8 multi-spectrum data in the three research areas to test the performance of CHRIS hyperspectral data. It produces images with 15m panchromatic and 30m multispectral spatial resolutions. Three cloud-free Landsat-8 Level 1T images were used in this study. Table 1 shows the coordinates and dates of images.

Table 1. Dates and center point coordinates of the images used in this study.

| Site            | Center point coordinate | Image type   | Image date   |
|-----------------|-------------------------|--------------|--------------|
| Liaohe Delta    | N41°06′;E122°03′        | CHRIS/PROBA  | 2014/07/19   |
| Lianyungang     | N34°51′;E119°11′        | CHRIS/PROBA  | 2016/08/12   |
| Liushagang      | N20°27′;E110°01′        | CHRIS/PROBA  | 2016/06/02   |
| Liaohe Delta    | N41°06′;E122°03′        | Landsat/ OLI | 2014/09/15   |
| Lianyungang     | N34°51′;E119°11′        | Landsat/ OLI | 2016/09/20   |
| Liushagang      | N20°27′;E110°01′        | Landsat/ OLI | 2016/06/26   |

3.2. Water Index and Segmentation Algorithm
McFeeters (1996) [33] proposed the Normalized Difference Water Index (NDWI) by using the green and Near Infrared (NIR) bands according to that the water body has a high reflectance of water in the green band, and a strong absorbability in the NIR (Near Infrared) band. In light of NDWI, Xu [34] put forward the Modified Normalized Difference Water Index (WNDWI) on the basis of Green band and
SWIR (Short Wave Infrared) band, considering that the water body has a stronger absorbability in the SWIR band. In addition to this, WNDWI can distinguish between buildings and water bodies more effectively. Of the two kinds of dataset mentioned in this article, the band 6 and band 7 of the Landsat OLI can both represent the SWIR band. The spectrum of CHRIS ranges from 410 to 1005 nm, which cannot cover all the SWIR bands, yet it has 10 bands within the range of NIR and 4 in the green band. Therefore, in this article, dimension reduction will be applied to the CHRIS dataset, and then the chosen bands out of the above method will be used to structure NDWI. Meanwhile, band 6 and band 3 will be withdrawn from Landsat OLI to form MNDWI. The threshold value should be determined according to the features of water index values themselves in each spots [35]. In this study, OTSU algorithm [36], a dynamic threshold method with the maximum inter-category variance, was used to determine the optimal threshold $t$ for NDWI and MNDWI extraction.

3.3. Dimension Reduction
There are 62 original bands and information in CHRIS Mode 1 images that means each pixel of CHRIS/Proba image has 62 values corresponding to different bands. Principal component analysis (PCA), the most widely unsupervised method is to solve redundant information from 62 original bands. The study proposes the contribution-based PCA approach, which is based on the degree of contribution from the original space. The degree of contribution of an original band can be calculated as follows:

$$R_{kp} = \lambda_k^2 \times 100\%$$

where $R_{kp}$ is the degree of original band $k$ contributing to PCA band $p$; $\lambda_k$ is the eigenvector of the original band $k$.

Specifically, after converting the original space to the principal component space through PCA, the first several principal components obtain maximum spectral information of the images. Then sort out the original bands in descending order according to the calculated contribution rate to the principal component bands based on eigenvector matrixes. Finally, we filter out the original bands that can represent the green band and NIR band to model NDWI index. The detailed procedures are as follows in figure 2.

![Figure 2. Processing steps of dimension reduction for CHRIS hyperspectral data in the study.](image)

3.4. Optical Classification of Coastal Waters
Cluster analysis is also applied to classify the set of reflectance into several homogeneous groups. To generate clusters, we have chosen non-hierarchical cluster analysis on squared Euclidian distance among data:
where $d_{AB}$ is the squared Euclidian distance between cluster A and B, with $d_{AB} = \sum (g_A - g_B)^2$, $n_i$ and $g_i$ corresponding to the number of sample and the mean vector of the cluster i respectively.

4. Results

4.1. Results of Water Detection

Figure 3 shows the six water indexes maps, including 3 NDWI-CHRIS/PROBA images and 3 MNDWI-Landsat8/OLI images from research sites. All NDWI and MNDWI images clearly confirm the separability of the water bodies. In general, most MNDWI and NDWI values of water bodies are larger than 0.5, except that the average value of the figure 3a water body is obviously lower than 0. In the three research areas, the images of Lianyungang have a large part of built-ups, while those of the other two are dominated by farmland. Comparing figure 3c and 3d, we can conclude that NDWI-CHRIS/PROBA can distinguish between vegetation and built-up more specifically. As is shown in figure 3c, the NDWI value of the vegetation area approaches -0.9, representing dark blue in the image. While the NDWI value of built-ups ranges between -0.5~0.1, representing bluish green in the image. But the southwest area with a high density of buildings shows the color of yellow. However, as in figure 3c, the identification of water bodies is interrupted to some degree by the built-up along the coast. The water bodies with a low NDWI index presents the color of orange, which will be mixed up to some extent with those having a high NDWI index showing yellow, which indicates that the confusion caused by structural features is obviously inhibited and even eliminated in MNDWI images. This phenomenon agrees with previous research results that the NDWI images are often mixed with the information of built-ups, so the scale and area of the extracted water bodies will be enlarged. Besides, MNDWI replacing NIR band with SWIR band will dimish the index of built-ups obviously.

Figure 3. (a) 34m NDWI produced by CHRIS/PROBA in Liaohe Delta; (b) 30m MNDWI produced by Landsat8/OLI in Liaohe Delta; (c) 34m NDWI produced by CHRIS/PROBA in Lianyungang; (d) 30m MNDWI produced by Landsat8/OLI in Lianyungang; (e) 34m NDWI produced by CHRIS/PROBA in Liushagang; (f) 30m MNDWI produced by Landsat8/OLI in Liushagang.
Figure 4 shows the histogram and the corresponding optimal threshold value of each NDWI or MNDWI image calculated by the OTSU algorithm. Almost all histograms have bimodal shapes, and optimal threshold values calculated by the OTSU algorithm are all located at the bottom. In Lianyun-gang and Liushagang, the optimal threshold value of NDWI is much smaller than those of MNDWI, while Liaohe Delta show many differences, representing -0.2960 and 0.7390 respectively. The three peaks in figure 4c fall at -0.9, -0.3 and 0.6, which are also the mean values of NDWI in the farmland, built-ups and water bodies in Lianyungang research area. This can fully illustrate that NDWI-CHRIS/PROBA which is processed through dimension reduction has a better ability of distinguishing between built-ups and vegetation. But we can still see that the NDWI-CHRIS/PROBA histogram has a consecutive platform area between 0 and 0.5, while that of MNDWI-Landsat8/OLI has two peaks and a flat bottom, which mean that the latter can identify water bodies and land more easily than the former.

**Figure 4.** The histograms and optimal threshold values calculated by the OTSU method for the (a) NDWI -Liaohe Delta from CHRIS/PROBA; (b) MNDWI- Liaohe Delta from Landsat8/OLI; (c) NDWI -Liuyungang from CHRIS/PROBA; (d) MNDWI- Liuyungang from Landsat8/OLI; (e) NDWI -Liushagang from CHRIS/PROBA; (f) MNDWI- Liushagang from Landsat8/OLI.
Figure 5. Waterbodies maps extracted from the sub-area NDWI and MNDWI images. (a) NDWI-Liaohe Delta from CHRIS/PROBA; (b) MNDWI-Liaohe Delta from Landsat8/OLI; (c) NDWI-Liuyungang from CHRIS/PROBA; (d) MNDWI-Liuyungang from Landsat8/OLI; (e) NDWI-Liushagang from CHRIS/PROBA; (f) MNDWI-Liushagang from Landsat8/OLI.

Figure 5 shows the extraction of water bodies applying the mask method after the water body segmentation using the threshold method. Images figure 5(a), (c), and (e) are the extractions of water bodies through NDWI-CHRIS/PROBA; images figure 5(b), (d), and (f) are the water bodies in the three research area withdrawn through MNDWI-Landsat8/OLI. In general, the water patches extracted by MNDWI-Landsat8/OLI are more detailed and clearer than those by NDWI-CHRIS/PROBA especially concerning the artificial water bodies. It is mainly because the resolution ratio of Landsat8/OLI within 30 meters is relatively higher than that of CHRIS/PROBA within 34 meters. The biggest difference between the two images lies in the Liushagang research area in Zhanjiang, Guangdong Province,
namely the Maliu State-run Saltern in the lower part of images figure 5(e) and (f). The salt field is divided into a low-salinity evaporation area, a medium-salinity dissolving area and a high-salinity crystallization area. In MNDWI-Landsat8/OLI, the images of three subregions’s extraction are relatively completely reserved, while those of NDWI-CHRIS/PROBA has a deficiency in the medium-salinity dissolving area. This is because the images are produces in different time—those by CHRIS are taken in June 2, 2016 while those by Landsat8/OLI are taken in June 26, 2016—with a gap of 24 days. In June 2, the dissolving area in Maliu salt field was at the end of the whole process, so land features such as beach land or bare land were reflected more in the CHRIS images; while in June 26, the medium-salinity dissolving area had much deeper water, so features as water bodies were reflected in Landsat8/OLI images.

To demonstrate the water body maps, we used the overall accuracy (OA) and kappa coefficient to evaluate the recognition results. The recognition results are shown in table 2, which demonstrate that MNDWI from Landsat8/OLI can better identify water bodies than NDWI from CHRIS/PROBA. Meanwhile, comparing the three research areas, the ability of NDWI and MNDWI in regard to water body identification is much better in Lianyungang than in the other two. However, considering that CHRIS/PROBA has an advantage in hyperspectrum, we extract the water body including artificial water and natural water from NDWI-CHRIS/PROBA to achieve water detection in three research sites.

Table 2. Overall accuracy (OA) and Kappa coefficient.

| Method | Liaohe Delta | Liuyangang | Liushagang |
|--------|--------------|------------|------------|
|        | NDWI         | MNDWI      | NDWI       | MNDWI      | NDWI       | MNDWI      |
| OA (%) | 94.12%       | 95.51%     | 95.88%     | 97.76%     | 94.13%     | 93.98%     |
| Kappa  | 0.8147       | 0.7182     | 0.8943     | 0.8848     | 0.8289     | 0.8478     |

4.2. Classification of Optical Water Type

The sea water from Bohai, the Yellow Sea, the East China Sea and the northern part 'area of South China Sea, belongs to typical turbid ClassII water, which has extremely complicated optical features. The spectral signal acquired by the remote senor mainly comes from the reflection of the water surface, the suspended matter in the water and the material at the bottom of the water body, namely the background. The water bodies have a good ability in absorbing the incident light. Meanwhile, the impurity composition and its concentration in the water have a great effect on the optical characteristics of the water bodies. The optical characteristics of these impurities are combined with the optical features of the water bodies, and thus form the spectral characteristics of different types of water bodies. A total of 126 waters feature spectrums are collected in the three CHRIS/PROBA images, presenting a great variability due to the highly variable water composition of the research areas (figure 6).

The waters feature spectrums from Lianyungang are characterized by a great variability in both magnitude and spectral shape. As is shown in figure 6d, we can tell two kinds of the most widespread water bodies, namely Class 1 in dark blue and Class 2 in light blue, in Lianyungang. Figure 6b shows that the reflectance of the water at different wavelengths is lower than 0.1, and the overall reflectances of all wavelengths are relatively low. Figure 6d tells that the spatial distribution of Class 1 is far away from the estuary or the coast. Therefore, Class 1 is slightly less affected by the coastal matter than Class 2. Comparing the Class 1 water and Class 2 water, a common spectral pattern may be drawn: reflectance increases monotonically from UV to approximately 600 nm, where it starts to decrease, with the peak at 600 nm corresponding to the chlorophyll-a fluorescence. Such results are similar to those of Zhou [37]. The fluorescence peaks of Class 1 and Class 2 appear at 675 nm, while after 800 nm, there shows a backscattering peak, suggesting that particles are playing an important role. We find out the main difference between Class 1 and Class 2 is that from 750 nm to 900 nm, the backscatter of Class 2 is 2 to 3 times stronger than that of Class 1. As we can see in figure 6c, the distribution of most part of Class 2 is near shoreline, so Class 2 are more affected than Class 1 by the suspended sediments. With the increase of sediment content, the spectral characteristics show that the reflection peak will shift from the blue band to the red band, we can see the appearance of red shift in waters dominated by suspended sediment.
Figure 6. Water types distributions observed from the CHRIS/PROBA reflectance data in the Liaohe Delta, Lianyungang and Liushagang (a,d,g); reflectance spectra derived for the non-hierarchical cluster classification applied on Classes 1, 2, 3, 4, 5, 6 (b,e,c,f,i).

Class 3 is a type of water with ultra-high suspended sediment, as is shown in figure 6h. The minimum reflection rate of class 3 water’s spectrum is at 400nm, and the reflectance increases monotonously corresponding to the increase of spectral length. The spectral curve of this water body between 400-675nm is very similar to that of the Class 2. However, Class 2 has a downward trend after the inflection point at 700nm, while Class 3 is affected by the sediment background, causing the backscattering intensity to rise. Figure 6d and 6g shows that in Lianyungang and Liushagang, there exists the distribution of Class 3 type, representing pink. Class 3 water bodies in Lianyungang are concentrated near the offshore line within 2 km of the intertidal area, and are obviously affected by the waves of this zone. This shows the distribution of a large number of tidal channels when receding, and this area is all covered with water when rising tide. The background is soft sand and mud, resulting in much sediment content in water, thus the water color shows brown or yellowish brown. In the Liushagang research area, the distribution of Class 3 is not as large and concentrated as that in the Lianyungang region, but forms a beaded-like shape along the coastline.

The Class 4 and Class 6 water types come from one of the large state-run sea salt industry: Maliu Saltern (see figure 6g). In China, offshore saltern can often be divided into reservoirs, evaporation ponds, dissolving ponds, and crystallization ponds. The reservoir water is used as a source of raw material of the evaporation zone [38]. Considering the optical properties of sites where sea salt production process happens, this paper will divide saltern water bodies into two categories: 1) the dissolving ponds and the crystallization ponds with high reflection rate in all wavelengths (water depth tends to be less than 30 cm); 2) The reservoirs and evaporation ponds of low reflectance. Experiments and field studies show
that [39-40], concerning the dissolving ponds and the crystalization ponds with high reflection rate, their spectral curves are affected by the quantity, type, particle size, and underwater brightness; and the water reflectance in the range of 700-900 nm is sensitive to changes of the density of suspended solids, which makes it the optimal range for remote sensing to detect suspended matters. In figure 6g, the crystalization ponds are located in the saltern closest to the inland side (yellow color in figure 6g). All spectra curves of the crystalization water have a flat reflecting convex peak between 550-750nm, up to 0.27 ultimately. There are a lot of halophilic bacteria in the crystallization ponds. There are a lot of halophilic bacteria in the crystallization pool. Their dead bodies and red excrement make the pool more turbid and the water color dark brown. The concentration of crystals of salt particles is very large in the crystallization ponds. The spectral curves of water in the crystallization pools and water with a lot of suspended sediment are quite different. Compared Class 4 and Class 2, we can see that the main difference between them is that Class 4 still has high reflection rates between the 700-900nm.

Class 6 (see figure 6i) shows the spectral features of the water bodies in the evaporation pool of a typical offshore saltern. It is located in the middle of the whole saltern, presenting the color of orange (see figure 6g). Although the water depth of the evaporation area and reservoir is usually larger than 0.6 meters [41], their water bodies are usually accompanied with a large amount of algae at the bottom of the water, which affects the signals of water’s reflectance and makes the whole water color seems dark green. When there are much algae in the water body, the reflectance of the blue light band decreases while that of the green band increases. The spectral reflectance of algae at different wavelengths is related to the optical activity of the pigments, the geometric shape of the cells and the surface characteristics of the algae cells. However, because algae all contain chlorophyll, the curve of their reflectance spectrum is basically the same. The specific location and the value of reflectivity peaks vary due to their different cell shape and pigment content.

At last, the spectral curve of class 5 is shown in figure 6i, and the distribution map is illustrated in figure 6a: because the study area is in Liaohe delta, where the water flows slowly, the bottom is silted up and covered with sandy soil. We can also observe that there is a large amount of reed in this study area. The image collection time was in mid July, eliminating the interference of the river ice. The spectrum is usually characterized by low values in the short wavelengths (approximately 400 to 500 nm). This is directly related to the high absorbability from C-DOM. After 700nm, the spectral reflectance still maintains a steady state. On the whole, the spectral characteristics of Class5 are similar to those of Class 2 and Class3. More accurately, Class 5 is the intermediate type of transition from Class2 to Class3. However, what is worth noting is that reflectance has some errors between the range of 400-500 nm and 900-950 nm, which are caused by radiometric calibration. Zhang et al. (2006) [42] points out that the inaccuracy of spectral occurs in the range shorter than 498nm and longer than 750, from CHRIS Senor. Similar to the paper of Zhang, the spectrum curve, shorter than 498nm and longer than 750, have some outliers where it should be gradually smooth.

5. Discussion
In our study, classification of inshore natural water bodies are similar to those of previous works. Lubac (2007) and Vantrepotte (2012) collected situ hyperspectral radiometric measurements (3 nm resolution) in English Channel, Southern North Sea and French Guiana, then used clustering method to obtain the type of water body Class D and Class E, which are the same type of optical water as the Class1 and Class 2 obtained by this study. This shows that classification-based approaches is universally applicable. On the basis of the establishment of a spectrum database of global water types, replacing situ measurement with airborne hyperspectral data makes it possible to monitor global offshore water bodies.

The accuracies of natural water detection from Ye et.al (2016) [43] were greater than those calculated in our study perhaps because their data focused on the open water, where there are large water bodies without mixed pixels. Our research area is more complex due to the introduction of artificial water. The form and area of artificial water is much more regular and much smaller than that of natural water. The spatial resolution of CHRIS/PrLandsat8/OLI's model data is 34m, which inevitably leads to the production of mixed pixels. Therefore, in the previous comparison of threshold segmentation with
Water Index, we can see that the water body map extracted by Landsat8/OLI is more detailed than that of CHRIS/PROBA. Compared to CHRIS/PROBA, the 30m pixels of Landsat8/OLI data reduced mixed pixels and their associated omission errors, while the decreased spectral resolution had less discrimination of non-water pixels from water body. We hope that the new type of sensor from ESA, which can make a breakthrough in the image spatial resolution in the future, at the same time of ensuring the hyperspectral advantage like CHRIS/PROBA.

Ye et.al (2016) used MERIS remote sensing reflectance data to monitor seasonal changes in the Yellow Sea, which achieved great results. Classification-based approaches can be applied to the airborne hyperspectral CHRIS/PROBA archive it becomes possible to map the change in water types and their extent over time, which is particular useful in areas belonging to short or periodic regions of dry and submerged condition, such as the salt field, the intertidal zone, etc. Figure 7 shows the variability of Maliu Saltern in Liushagang from June 2nd to June 26th in 2016. The red rectangle represents dissolving ponds, and the ellipse shape outlines an approximate range of the crystallization ponds; a similar situation also appears in Lianyungang, where Class2 and Class3 water bodies appear alternately in the intertidal zone according to the tide.

![Figure 7](image)

**Figure 7.** Variability of Maliu Saltern in Liushagang from June 2nd to June 26th in 2016. The red rectangle represents dissolving ponds, and the ellipse shape outlines an approximate range of the crystallization ponds.

The 6 types based on the optical properties of water bodies can be divided into artificial water and natural water bodies according to the degree of human interference. In three research areas, there are great differences between artificial water bodies and natural ones in their contour, size and shape: natural waters are widely distributed and concentrated (such as class1 water), while the distribution of
artificial water bodies is scattered and dispersed (e.g. class3 and class4). However, it is difficult to completely rely on the optical types of the water bodies to divide the utility situation of them, as in Lianyungang, in the breeding pool the water belongs to the Class 2 type, and large areas of natural water in regions close to the coast area also belong to the Class 2 type. Only when human activities affect the nature of optical water types, we can determine the use of water, such as the crystallization pool in offshore salterns, there are a lot of halophilic organisms caused by human activities, and their dead bodies and the red excrement caused the pool to appear as dark brown, which essentially changes the optical water types. Yao et al. (2016) used the Landsat image data set to analyse the spatial changes in Chinese aquaculture and salt fields from 1985 to 2010, and employed mapping or changed detection approaches without any object features which can provide contour information of artificial water, but there are some gaps in distinguishing aquaculture water bodies from other natural or artificial waters. If we want to identify the coastal artificial water bodies more accurately, we must add object-based image analysis, which promises potential for delineation of artificial water bodies, such as aquaculture ponds and salt fields, on the basis of classification of water’s optical characteristics.

6. Conclusion
Field spectra collection and airborne hyperspectral classification cost huge manpower material resources, using spaceborne hyperspectral sensor can be periodically global coastal water quality monitoring. Prior to the inversion of biochemical parameters in such complex environments, a clustering algorithm was used for CHRIS/PROBA Mode1 reflectance data sets between 410 to 1005 nm to define six water types from three research sites along the latitudinal gradient in China coastline. Based on the study and the works from previous researches, we think that to build a global coastal water type spectral database will play a fundamental and crucial role for the global offshore water environment monitoring, especially in the coastal areas where influenced by sustained and intensive human activities.

Acknowledgments
The work was supported by the ministry of Science and Technology of China (MOST) under (Grant No.2017FY201400). The authors gratefully acknowledge the European Space Agency (ESA) for the provision of the BEAM toolbox. The hyperspectral imagery CHRIS/PROBA were also supplied by the ESA. Landsat8/OLI data were available through United States Geological Survey (USGS). We would like to thank Shengnan Jiang, Minghui Xu and Lixia Chang for their assistance in field investigation.

References
[1] Wang W, Liu H, Li Y, Su J 2014 Development and management of land reclamation in China Ocean Coastal Manage. 102: 415-425.
[2] State Oceanic Administration of China (SOA) 2015 Statistical Bulletin of Oceanic Management http://www.soa.gov.cn/zwgk/hygb/hysyglgb/ (In Chinese)
[3] Mou X, Liu X, Yan B, Cui B 2015 Classification system of coastal wetlands in China Wetland Science 13(1): 19-26.
[4] Yao Y, Ren C, Wang Z 2016 Monitoring of salt ponds and aquaculture ponds in the coastal zone of China in 1985 and 2010 Wetland Science 14(6): 874-882.
[5] Peng Y, Chen G, Li S, Liu Y, Pernetta, J C 2013 Use of degraded coastal wetland in an integrated mangrove–aquaculture system: a case study from the South China Sea Ocean Coastal Manage. 85: 209-213.
[6] Bazylnski D A, Schlezinger D R, Howes B H, Frankel R B, Epstein S S 2000 Occurrence and distribution of diverse populations of magnetic protists in a chemically stratified coastal salt pond Chem. Geol. 169(3): 319-328.
[7] Cao L, Wang W, Yang Y, Yang C, Yuan Z, Xiong S, Diana J 2007 Environmental impact of aquaculture and countermeasures to aquaculture pollution in China Environ. Sci. Pollut. Res. 14(7): 452-462.
[8] Peng Y, Chen G, Li S, Liu Y, Pernetta J C 2013 Use of degraded coastal wetland in an integrated mangrove–aquaculture system: a case study from the South China Sea Ocean Coastal Manage. 85: 209-213.

[9] Du Y, Zhang Y, Ling F, et al. 2016 Water bodies’ mapping from Sentinel-2 imagery with modified normalized difference water index at 10-m spatial resolution produced by sharpening the SWIR band Remote Sens. 8(4): 354.

[10] Xu H 2006 Modification of Normalised Difference Water Index (NDWI) to enhance open water features in remotely sensed imagery Int. J. Remote Sens. 27(14): 3025-3033.

[11] Verpoorter C, Kutser T, Tranvik L 2012 Automated mapping of water bodies using Landsat multispectral data Limnol. Oceanogr. Meth. 10(12): 1037-1050.

[12] Feyisa G L, Meilby H, Fensholt R, et al. 2014 Automated water extraction index: a new technique for surface water mapping using Landsat imagery Remote Sens. Environ. 140: 23-35.

[13] Fisher A, Flood N, Danaher T 2016 Comparing Landsat water index methods for automated water classification in eastern Australia Remote Sens. Environ. 175: 167-182.

[14] O’Reilly J E, Maritorena S, Mitchell B G, et al. 1998 Ocean color chlorophyll algorithms for SeaWiFS J. Geophys. Res.-Oceans. 103(C11): 24937-24953.

[15] Naik, P, Wang M, D’Sa E J, et al. 2015 Bering Sea optical and biological properties from MODIS Remote Sens. Environ. 163: 240-252.

[16] Moore T S, Campbell J W, Feng H 2001 A fuzzy logic classification scheme for selecting and blending satellite ocean color algorithms IEEE Trans. Geosci. Remote Sensing 39(8): 1764-1776.

[17] Doxaran D, Cherukuru N, Lavender S J 2006 Apparent and inherent optical properties of turbid estuarine waters: measurements, empirical quantification relationships, and modeling Appl. Optics 45(10): 2310-2324.

[18] Gohin F, Dronu J N, Lampert L 2002 A five channel chlorophyll concentration algorithm applied to SeaWiFS data processed by SeaDAS in coastal waters Int. J. Remote Sens. 23(8): 1639-1661.

[19] Sathyendranath S, Watts L, Devred E et al. 2004 Discrimination of diatoms from other phytoplankton using ocean-colour data Mar. Ecol.-Prog. Ser. 272: 59-68.

[20] Vantrepotte V, Loisel H, Dessailly D, Mériaux X 2012 Optical classification of contrasted coastal waters Remote Sens. Environ. 123: 306-323.

[21] Tilstone G H, Angel-Benavides I M, Pradhan Y, Shutler J D, Groom S, Sathyendranath S 2011 An assessment of chlorophyll-a algorithms available for SeaWiFS in coastal and open areas of the Bay of Bengel and Arabian Sea Remote Sens. Environ. 115(9): 2277-2291.

[22] Lubac B, Loisel H 2007 Variability and classification of remote sensing reflectance spectra in the eastern English Channel and southern North Sea Remote Sens. Environ. 110(1), 45-58.

[23] Kar S, Rathore V S, Sharma R, et al. 2016 Classification of river water pollution using Hyperion data J. Hydrol. 537: 221-233.

[24] Fuchs J, Martin J L M, Populus J 1998 Assessment of tropical shrimp aquaculture impact on the environment in tropical countries, using hydrobiology, ecology and remote sensing as helping tools for diagnosis.

[25] Zhang Y, Pulliainen J, Koponen S, et al. 2002 Application of an empirical neural network to surface water quality estimation in the Gulf of Finland using combined optical data and microwave data Remote Sens. Environ. 81(2-3): 327-336.

[26] Somdatta C, Chakrabarti S 2011 Pre-processing of hyperspectral data: a case study of Henry and Lothian Islands in Sunderban Region, West Bengal, India International Journal of Geomatics and Geosciences 2(2): 490.

[27] Bhatti A M, Rundquistd B, Schalles J, et al. 2010 Qualitative Assessment of Inland and Coastal Waters by Using Remotely Sensed Data.
[28] Abd-Elrahman A, Croxton M, Pande-Chettri R., Toor G S, Smith S & Hill J 2011 In situ estimation of water quality parameters in freshwater aquaculture ponds using hyperspectral imaging system *ISPRS-J. Photogramm. Remote Sens*. 66(4): 463-472.

[29] Kar S, Rathore V S, Sharma R, et al. 2016 Classification of river water pollution using Hyperion data *J. Hydrol.* 537: 221-233.

[30] Li H, Man W, Li X, et al 2017 Remote sensing investigation of anthropogenic land cover expansion in the low-elevation coastal zone of Liaoning Province, China *Ocean Coastal Manage*. 148: 245-259.

[31] Feng L, Zhu X, Sun X 2014 Assessing coastal reclamation suitability based on a fuzzy-AHP comprehensive evaluation framework: a case study of Lianyungang, China *Mar. Pollut. Bull.* 89(1-2): 102-111.

[32] Li X, Li B, Sun X 2014 Effects of a coastal power plant thermal discharge on phytoplankton community structure in Zhanjiang Bay, China *Mar. Pollut. Bull.* 81(1): 221-233.

[33] McFeeters S K 1996 The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features *Int. J. Remote Sens.* 17: 1425–1432.

[34] Han-Qiu X U 2005 A Study on Information Extraction of Water Body with the Modified Normalized Difference Water Index (MNDWI) *Journal of Remote Sensing* 5: 589-595.

[35] Ji L, Zhang L, Wylie B 2009 Analysis of dynamic thresholds for the normalized difference water index *Photogramm Eng. Remote Sens.* 75: 1307–1317.

[36] Lin K C 2005 On improvement of the computation speed of Otsu's image thresholding. *J. Electron. Imaging* 14(2): 023011.

[37] Zhou L, Liu Y, Guo P 2005 Characteristic of ocean color spectrum in Bohai sea and northern yellow sea *Marine Science Bulletin*. 24(2): 13-19.

[38] Cao K, Ma H W, Suo A N 2017 Analysis of spatial pattern for coastal salt pond engineer based on high spatial resolution satellite remote sensing imagery: a case study in south coast of Yingkou *Journal of Applied Oceanography* 36(2): 286-294.

[39] Zhang Y, Hu P X, Gao J A 2011 reflectance spectra-based approach to mapping salt fields using PCA-fused Landsat TM data *Adv. Space Res*. 47(9): 1490-1496.

[40] Yan F 2004 *Extraction and Production Estimation of Sea Salt Production based on Remote Sensing* Nanjing: Nanjing Normal University.

[41] Wang J J, Zhang Y & Tao F 2005 The research and application of the Salt Pan Water Area classification method by means of remote sensing classification of saltpan water *Ocean Technology* 24(1): 67-71.

[42] Zhang X, Zhang B, Hu F, et al. 2006 Evaluation of radiation and spectral property from CHRIS/Proba *Science in China Ser. E Technological Sciences* 36(B07): 85-93.

[43] Ye H, Li J, Li T, et al 2016 Spectral classification of the Yellow Sea and implications for coastal ocean color remote sensing *Remote Sens.* 8(4): 321.