Extraction of the aquaculture farms information from the Landsat-TM imagery of the Younggwang coastal area

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Abstract: The objective of the present study is to compare various conventional and recently evolved satellite image-processing techniques and to ascertain the best possible technique that can identify and position of aquaculture farms accurately in and around the Younggwang coastal area. Several conventional techniques performed to extract such information from the Landsat-TM imagery do not seem to yield better information about the aquaculture farms, and lead to misclassification. The large errors between the actual and extracted aquaculture farm information are due to existence of spectral confusion and inadequate spatial resolution of the sensor. This leads to possible occurrence of mixture pixels or "mixels" of the source of errors in the classification techniques. Understanding the confusing and mixture pixel problems requires the development of efficient methods that can enable more reliable extraction of aquaculture farm information. Thus, the more recently evolved methods such as the step-by-step partial spectral end-member extraction and linear spectral unmixing methods are introduced. The farmer one assumes that an end-member, which is often referred to as "spectrally pure signature" of a target feature, does not appear to be a spectrally pure form, but always mix with the other features at certain proportions. The assumption of the linear spectral unmxing is that the measured reflectance of a pixel is the linear sum of the reflectance of the mixture components that make up that pixel. The classification accuracy of the step-by-step partial end-member extraction improved significantly compared to that obtained from the traditional supervised classifiers. However, this method did not distinguish the aquaculture ponds and non-aquaculture ponds within the region of the aquaculture farming areas. In contrast, the linear spectral unmixing model produced a set of fraction images for the aquaculture, water and soil. Of these, the aquaculture fraction yields good estimates about the proportion of the aquaculture farm in each pixel. The acquired proportion was compared with the values of NDVI and both are positively correlated (R^2 = 0.91), indicating the reliability of the sub-pixel classification.

1. Introduction

Coastal aquaculture such as seaweed beds continues to be the fastest growing sector of the global marine-based aquaculture food industry. It not only plays an important role in coastal marine ecosystem in terms of supporting flora and fauna and increasing coastal fisheries productivity, but also its rapid growth helps boosting the economy of rural people. In the recent years, such environmentally sensitive areas are however under intense pressure due to natural processes, urban growth, resources development and pollution. These processes induce changes in certain environmental factors such as temperature, turbidity and salinity, leading to devastation of aquaculture facilities in many coastal regions around the world. Therefore, it is very essential to map and monitor the aquaculture farms for the sustainable development of marine-based food resources. Until recently, the identification and classification of coastal aquaculture has been a tedious, expensive and time consuming process involving surveys from airborne platforms and manual techniques. The traditional field surveying approaches for mapping the aquaculture farming areas in the coastal zone can only cover small area in detail, can be time consuming, and are often invasive and destructive. Spatially extensive and non-invasive remote sensing data due to its synoptic, repetitive and multispectral nature provide a wide range of information over larger areas in frequent intervals has made remote sensing technology a useful tool in assessing the aerial extent of aquaculture facilities and for coastal mapping and management (Shanmugam, 2002). The aim of the present study is to realize the potential of certain recent and emerging image processing techniques applied to the Landsat-5 TM image data for identifying, positioning and quantifying the aquaculture farms facilities in and around the Younggwnag coastal area.

2. Mapping methods

Several conventional image-processing techniques are attempted on the Landsat-TM imagery and the results are then compared with the recently evolved mapping techniques. The traditional enhancement techniques attempted include contrast enhancement, band ratioing, principal component analysis, density slicing and normalized different vegetation index. More details about these techniques are given (Jenson, 1996 and Shanmugam, 2002). On the other hand, the most widely used method for extracting information on the surface cover from remotely sensed data is image classification. Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands and attempts to classify each individual pixel on the basis of spectral information. Minimum spectral distance and maximum likelihood classifications are superior to all other methods, and therefore attempted using the TM image data. In both of these approaches, a mathematical decision rule is used to assign image pixels to clusters representing surface cover features, in the feature space delimited by the spectral bands of the image (Mather, 1987). A more recently evolved methods such as the step-by-step partial spectral end-member extraction and linear spectral unmixing methods are introduced and the results are then compared with the conventional classification techniques.

3. Results and Discussion

1. Image enhancement techniques

The contrast stretched image brings out valuable information regarding the spatial structure and position of aquaculture farms in and around the study region. Fig. 1a is a color composite image of TM-Band-432 in which the narrow range of brightness values are expanded to a wider range grey levels, showing the contrast between water and aquaculture farms that appear to be arranged in a linear fashion to the north and south direction. The high brightness values (DN) of the pixels of aquaculture farm areas are assigned to the frequently occurring portion of the histogram (Lillesand and Kiefer, 1987). Among all other band ratios, the ratioed image using TM band-1 and- 4 (TM-B4/TM-B1) displays visual interpretability of the aquaculture farms distinguished from the surrounding coastal features. However, the this ratio often produces unrealistic result in shallow coastal region, where occurrence of algal matter is offered to be misinterpreted as aquaculture farms as shown in Fig. 1b. The reason is that the reflected photon not only carries information about algal matter, but also includes information about the shallow sea bottom, resulting in increase of brightness values of the pixels in TM band-4. When these two bands used for ratioing, the pixels of algal matter having high DN values are inevitably highlighted in the ratioed image. However, this effect is minimized greatly in the normalized difference vegetation index (NDVI) image because the difference ratio of near-infrared and red is highly sensitive to the amount of green matter and its density while being moderately sensitive to non-algal matter in a given pixel of an image (Shanmugam, 2002). It is observed that the aquaculture farms appear to be well distinguished compared to that of the ratioed image (Fig. 1c). Other enhancement techniques such as density

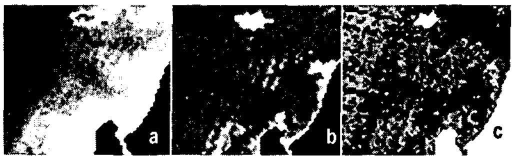


Fig. 1a-c. Result of spectral enhancement techniques. (a) contrast stretched image, (b) ratioed image, and (c) NDVI image.

slicing and filtering were also attempted but they did not yield useful information about the aquaculture farms. This is because the filtering techniques emphasize low frequency features and deemphasize high frequency features of the image data or vice versa.

2. Image classification techniques

Prior to classification, separability analysis using transformed divergence was performed on the signatures of the training classes. Fig. 2 shows an example of spectral profiles for water, aquaculture and muddy area, plotted as a function of TM wavelengths. In separability analysis, low TD values indicate poor separability between water and aquaculture as well as aquaculture and muddy area classes. High separability in TD existed between water and muddy area. The overall minimum separability between water and aquaculture class types decreases when the brightness value of the aquaculture farms decreases in the image. This produces large errors in the classified image (Figs. 3a and b). Of these, maximum likelihood classifier produced broad and less pronounced aquaculture class and introduced more errors in the non-aquaculture areas (Fig. 3a). It should be noted that the maximum likelihood classifier leads to essential overestimation of the aquaculture farms and the

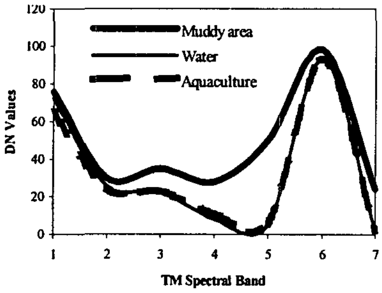
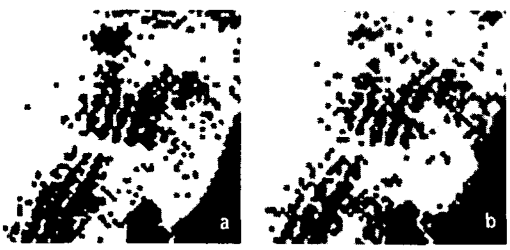


Fig. 2. Spectral profiles of water, aquaculture and muddy area plotted as a function of TM bands.



Figs. 3a and b. results of supervised classifications. (a) MLC and (b) Minimum spectral distance classification.

accuracy of this classification is very poor compared to that obtained from the minimum spectral distance classification (Fig. 3b). Though the classification accuracy is slightly improved in this approach, several water pixels and muddy area pixels appeared to be misclassified. From this study, one visualize that there are two possibilities for this type of misclassification. Firstly, similarity of spectral features is often referred to as the confusing pixel problem. The presence of confusing pixels complicates discrimination and leads to misclassification. The second major factor responsible for the misclassification of the pixels is the inadequate spatial resolution of an imaging sensor. As a result of this, the spectral response observed at a pixel is a mixture of the spectral responses of several surface categories. This is the so-called mixture pixel or "mixel" problem (Shanmugam, 2002). Understanding the above problems requires advanced satellite image processing methods and models that can facilitate more accurate mapping of the aquaculture farms of the study site.

3. Step-by-step partial spectral end-member extraction

This method is quite different from other methods of end-member extraction and assumes that the end-member does not appear to be a spectrally pure form, but rather mixed with the other features at certain proportions. Changing tidal currents, waves and the nature of aquaculture facilities, can elucidate the occurrence of mixture pixels. When pixels of the aquaculture farms are partially intermingled with the pixels of water, performing the step-by-step partial end-member extraction on the appropriate feature space plots can easily pick them up. As it is done on a per-pixel basis, there also exists some uncertainty in the classified image, but the accuracy of the extracted aquaculture farms information can be comparable with the conventional classification approaches (please refer Fig. 5a). The main advantage of this approach is that it could avoid large number of confusing pixels confined in the boundary zone between the aquaculture farms and water. Though this method is superior to the other classification methods, it does not distinguish pixels of the non-aquaculture ponds from the pixels of the aquaculture farming areas. The reason is that the brightness values of thenon-aquaculture areas may often resemble the brightness values of the aquaculture farming areas. When the partial end-member extraction is performed on a step-by-step fashion on the

Landsat-TM imagery, the pixels of the non-aquaculture ponds are inevitably picked up and assigned to as the aquaculture farm class. The similarity in brightness values between the pixels of the aquaculture and non-aquaculture ponds areas occurs due to absorption and reflection of light within the aquaculture farming areas, where currents and waves are less significant. Unmixing the spectral end-member of these areas can reliably distinguish the aquaculture farming areas from the features.

4. Linear spectral unmixing approach

The results of the linear spectral unmixing performed using the Landsat-TM image data are shown in Figs. 4a-c. In the fraction images, each pixel value corresponds to the fraction of aquaculture farm, water and soil in that pixel. Pixels with higher abundance of end-member appear as brighter regions in the corresponding fraction image. In the aquaculture fraction image, brighter tone indicates aquaculture farms with pixels of high proportion at the centre of aquaculture facilities and dull grey pixels correspond to lower proportion of aquaculture farm in the boundary zone between the aquaculture farms and water (Fig. 4a). Similarly, water appears as brighter in water fraction image (Fig. 4b) and the brightness decreases gradually

Figs. 4a-c. Fractions derived from the spectral unmixing model. (a) aquaculture fraction, (b) water fraction, and (c) soil fraction.

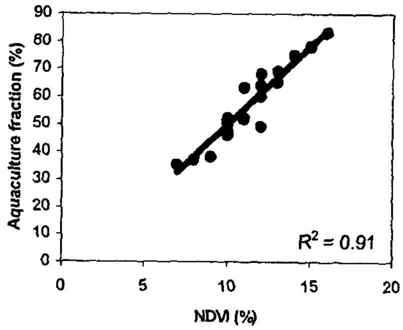


Fig. 5. Relationship between NDVI and aquaculture farm fraction obtained from the linear spectral unmixing model.

Figs. 6a and b. Comparison of per-pixel and sub-pixel classifications. (a) the step-by-step partial spectral end-member extraction. (b) the linear spectral unmixing approach.

towards muddy area, indicating increase of soil proportion, as clearly be seen in Fig. 4c. In order to validate the results of unmixing model, several sample sites (pixels) were chosen in the aquaculture, water and soil fraction images and the average (sub-pixel) proportion of aquaculture, water and soil was computed. The computed aquaculture and soil fractions were then compared with NDVI values. This is one of the ways of validating the accuracy of spectral unmixing model, in the case of absence of such ground-based data (Shanmugam, 2002). It is observed that the aquaculture fraction value increases with increasing NDVI values and the trend line shows one to one correlation for aquaculture farm fraction and NDVI (Fig. 5). The squared correlation coefficient observed is to be 0.91.

Thus, a positively correlated relationship between the aquaculture fraction values and NDVI indicates the correctness of the unmixing model, and the correctness of the derived sub-pixel proportions of aquaculture farms and thus soil and water.

For the sake of comparison of per-pixel and sub-pixel classifications, the fraction image of the aquaculture farms was color-coded and the features that correspond to the classified image produced by per-pixel classification method were displayed. As mentioned in previous section, the per-pixel classification method did not identify the non-aquaculture farm areas surrounded by the region of the aquaculture farm facilities (Fig. 6a). This is essentially due to occurrence of mixed brightness values. In contrast, sub-pixel classification produced more reliable estimates of the fraction of the aquaculture farms and the accuracy was satisfactory compared to all other conventional approaches (Fig. 6b).

5. Conclusion

This study investigated the applicability of certain conventional and recent image processing techniques for the retrieval of aquaculture farms information from the remotely sensed data acquired by the Landsat-5 Thematic Mapper. Compared to other enhancement techniques, band ratioing and NDVI were found to be useful in highlighting the aquaculture farms information. On the other hand, Maximum likelihood and minimum spectral distance produced maps of the aquaculture farm on a per-pixel basis. However, the spectral confusion due to similarity of spectral signatures and inadequate spatial resolution of the sensor occurred between the aquaculture and water class, resulting in misclassification. Such misclassification of the pixels could be avoided by performing the step-by-step partial spectral end-member extraction method on the TM image data of the study site. Though the classification accuracy was improved significantly in this method, misclassification of the pixels within the aquaculture farming areas remains critical. In contrast, the linear spectral unmixing of the Landsat-TM image data produced more realistic and promising results. Validation of such result was facilitated by comparing the estimated proportion of the aquaculture farms with NDVI. It was noticed that the values of the aquaculture fraction and the values of NDVI were well correlated and the squared correlation coefficient (R^2) for this relationship obtained was 0.91, thus indicating the validity of the unmixing model. It gave proportions of the aquaculture farms within a pixel rather than labeling the entire pixel as belonging to one class.

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