

Developing and evaluating an inversion model for retrieving coastal water quality and benthic coral reef properties from water color

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KEY WORDS: Remote Sensing, Coral Reefs, Coastal Water, Water Quality, Benthic Properties, Inversion

ABSTRACT: Coral reefs prefer to reside in warm, clean, clear waters with high oxygen content. Any deterioration of their environment would affect the life of coral reefs. Therefore, coral reefs serve as an important indicator of the environmental condition. Kenting National Park enjoys the most abundant coral reefs around Taiwan. However, recent extreme weather events, such as Typhoon Morakot in 2009, destroyed 50% of coral reefs in this area. The technique of water color remote sensing is promising in assessing the status of coral reefs at both high spatial and high temporal resolutions. However, to retrieve the water quality and the properties of benthic coral reefs directly from the water color signal requires a robust algorithm that has been validated against comprehensive in situ data and model simulations. In this research, we improve upon a genetic algorithm/semi-analytical model by taking into account the properties of benthic coral reefs, classifying the bottom into six different types; coral reefs, sand, sea grass, and green, red, and brown algae. A spectral library of bottom reflectance is established from in situ data measured in Kenting National Park and data simulated by the HydroLight radiative transfer model. Our new model, Genetic Algorithm and Shallow water Semi-Analytical model (GA-SSA), is able to iterate for an optimized solution of water quality and the properties of the benthic coral reef from the input of bottom reflectance spectrum data. These solutions are then compared to the conditions of water quality and benthic coral reef properties, under which the bottom reflectance spectra are measured in situ or simulated by the HydroLight algorithm. Our results demonstrate that our new model is able to achieve accuracy as high as 80%. In addition, we also used a hyperspectral imager to collect a coral ecosystem spectral database in the Kenting area.

1. INTRODUCTION

Coral reef ecosystem is located at the interface between land and sea, where the sediment loading is low and the water is clear (Ostrand 2000). It is sensitive to the environment change, including temperature ($\pm 3^{\circ}\text{C}$), carbon ion concentration ($\pm 35 \mu\text{mol}\cdot\text{kg}^{-1}$) and pH (± 0.1) (Hoegh-Guldberg et al. 2007). Therefore, coral reefs can serve as an ideal index of environmental change (Eakin, Kleypas, and Hoegh-Guldberg 2008). According to the recent survey of global coral reefs (Boutillier et al. 2009), the decreasing of coral reefs is accelerating, mainly due to the pollution caused by human activity in coastal area. To protect the coral reef ecosystem, various monitoring systems were developed in the past (Eakin et al. 2010). Generally speaking, there are two parts of these monitoring systems: (1) a stable platform with high spatial and temporal resolution, (2) an accurate algorithm to retrieve the water quality and bottom type simultaneously.

If we want to achieve this monitoring system, we can use remote sensing method. There are many studies about the coral reef monitoring method by remote sensing. For examples: CASI (compact airborne spectrographic imager) (Mumby et al. 1998), IKONOS satellite images (Andrefouet 2003) and Ocean PHILLS (Ocean Portable Hyperspectral Imager for Low-Light) (Lesser and Mobley 2007). In this study, we used the underwater platform: V-Fin to carry the hyperspectral imager. When the depth was 10m, we could have 5 cm resolution hyperspectral image. We can use this advantage to improve the accuracy of coral reef ecosystem classification.

Except the platform, the algorithm is the important method that we have to develop. The algorithm could retrieve the water quality and bottom type classification. In this study, we combine the GA-SA (Genetic Algorithm and the Semi-Analytical model) (Chang, Liu, and Wen 2007) with SSA (Shallow water Semi-Analytical model) (Lee et al. 1998, 1999) to build the GA-SSA (Genetic Algorithm and the Shallow water Semi-Analytical model). By GA-SSA

we can achieve accuracy as high as 80%. Either the bottom types classification or the retrieval of IOPs (Inherent Optical Properties). At next will begin to describe how to build this model.

2. MATERIAL AND METHOD

There are two parts of data in this study, simulated data and in situ data. The simulated data that we need in this study is the spectral library. The spectral library has 11250 *Rrs* (remote sensing reflectance) data. We used the radiation transmission model: HydroLight to build the database. The database build is according to the bio-optical model and IOCCG (International Ocean Colour Coordinating Group) report (IOCCG 2003). The detail of the simulated data is at table 1.

Table 1 Simulated data set

Condition	Data set range
<i>Chl</i> (mg/m^3)	0.03~1 (0.03、0.05、0.07、0.1、0.15、0.2、0.3、0.5、0.7、1、2、3、4、5)
Optical model	Case 1 water
Bottom Types	5 different bottom types (Coral Sand, Clean Seagrass, Green Algae, Red Algae, Brown Algae)
Depth(m)	5, 10, 15
Zenith angle	60°
Wind speed m/s	5
Cloud coverage %	0
Wavelength nm	400~700(Once per 10nm)

These conditions are considered the coral reef ecosystem. According to these data sets can make our model near the *in situ* data. The original spectral is according to the reference (Maritorena, Morel, and Gentili 1994).

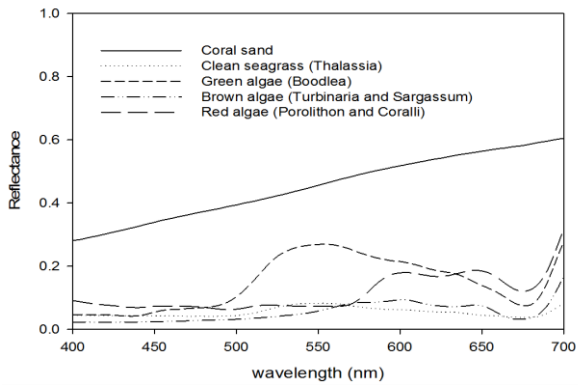


Fig. 1 The original spectral of 5 different bottom types.

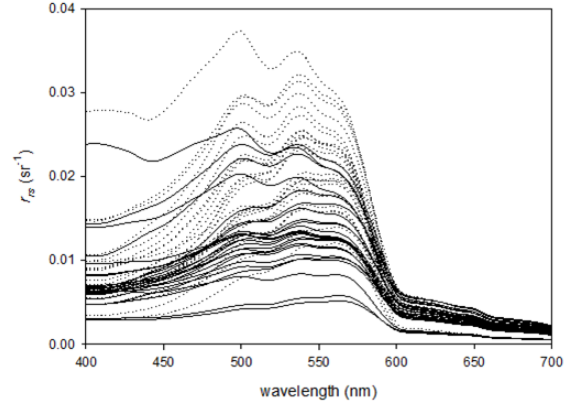


Fig. 2 The database set at the same depth, and the same *Chl* concentration. (Coral sand)

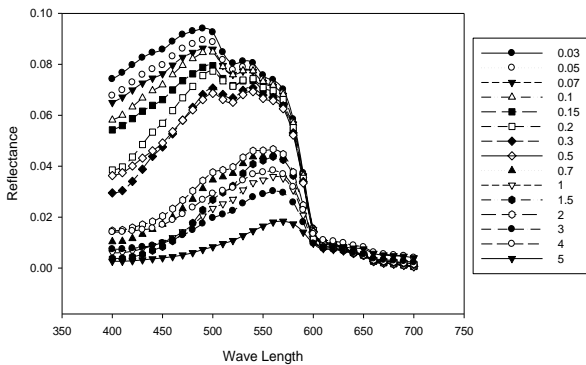


Fig. 3 The database set at the same depth, different *Chl* concentration (mg/m^3). (Coral sand)

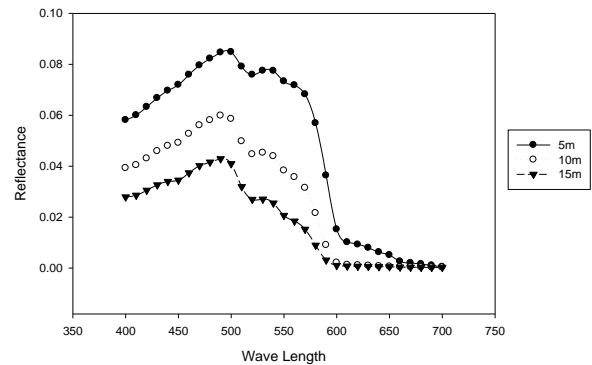


Fig. 4 The database set at the same *Chl* concentration, different depth. (Coral sand)

From Fig.1 to Fig.4, we can find out that even the bottom have the same depth and *Chl* concentration, it still have very different spectral. It shows there have a lot of noise in the nature world. The problem that we try to solve is a complex one. So we combine the GA-SA with SSA to form the GA-SSA. By the GA-SSA, we can solve the complex non linear problem.

Then we went to Kenting National Park in Taiwan to collect the in situ data. We towed the underwater platform V-Fin that carried the hyperspectral imager at the coral reefs area. At first, we used the IARR (Internal Average Relative Reflectance) method to correct the image. Then we calculated the fourth deviation to this hyperspectral image. After that we defined 6 different areas (A area to F area). We used a supervised classification method (Jia and Richards 1999) to classify underwater hyperspectral image data. The hyperspectral image that we processed will show in the result chapter.

3. RESULT

3.1 Simulated data

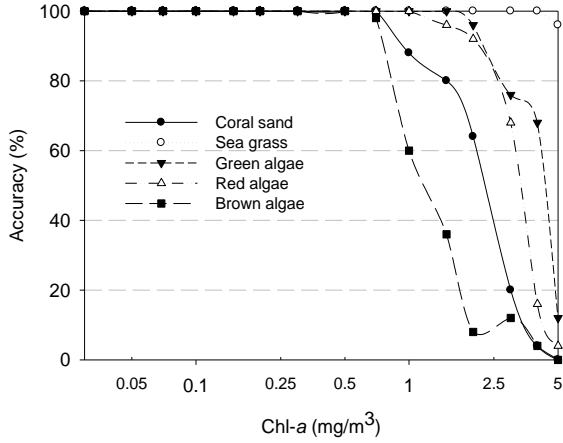


Fig. 5 When the water depth is 5 m. The accuracy of bottom types retrieving.

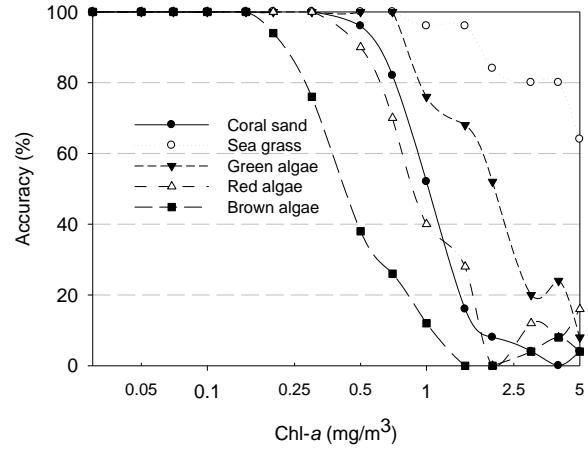


Fig. 6 When the water depth is 10 m. The accuracy of bottom types retrieving.

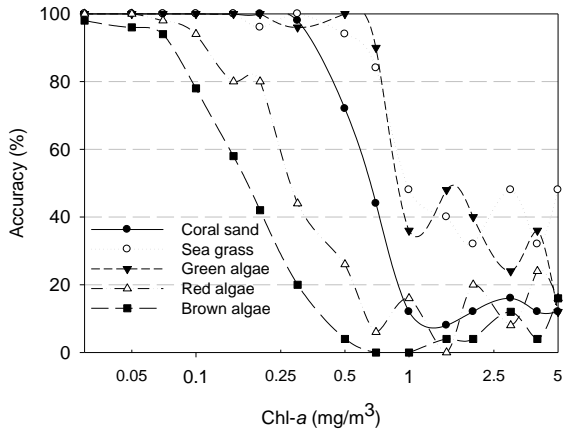


Fig. 7 When the water depth is 15 m. The accuracy of bottom types retrieving.

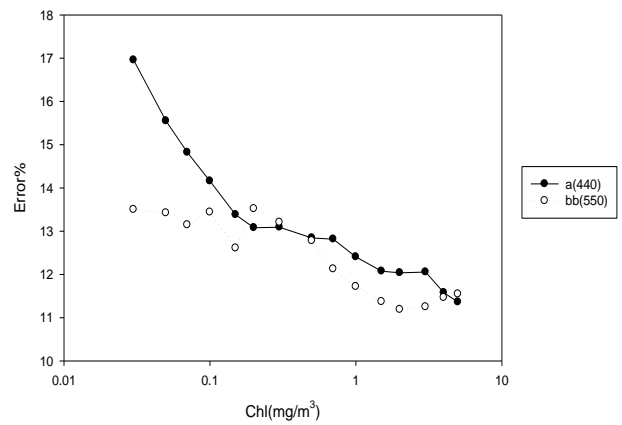


Fig. 8 The linear percentage error of IOPs (absorption coefficient and backscattering coefficient) retrieving.

The accuracy that we use is defined: $Accuracy \equiv \frac{\text{Retrieving Correctly Samples}}{\text{Total Samples}} \times 100\%$ (Eq.1)

The linear percentage error that we use is defined: $\varepsilon = 10^{RMSE-1}$ (Eq.2)

The root mean square error is defined: $RMSE = \left(\frac{\sum_{i=1}^N [\log_{10}(IOP_i^{derived}) - \log_{10}(IOP_i^{known})]^2}{N - 2} \right)^{1/2}$ (Eq.3)

From Fig.5 to Fig.7, we can find out that when the depth deeper and *Chl* concentration higher will cause the accuracy become lower. In particular *Chl* concentration has high correlation with accuracy. But we don't need to worry about the effect by the *Chl* concentration. In many studies indicate that *Chl* concentration at coral reef

ecosystem is lower than 0.2 mg/m^3 , for example: Bahamas ($23^{\circ}46.5_N$, $76^{\circ}05.5_W$) (Lesser and Mobley 2007). If we followed this standard (concentration less than 0.2 mg/m^3), the accuracy will as high as 80%.

The Fig.8 shows that the linear percentage error became lower when the *Chl* concentration became higher. Because of that *Rrs* is producing from combine water column signal with bottom signal. At low *Chl* concentration, the detector will receive more signals from the bottom. Because of that the signal from water column will not enough to determine the IOPs data. In other words, at high *Chl* concentration situation, the detector will receive the less signals from the bottom. Because of that the signal from water column will be stronger, so we can have the better result in retrieving IOPs.

3.2 In situ data



Fig.9 In this hyperspectral image we selected 6 areas (area A to area F). Then we used a supervised classification method to classify this underwater hyperspectral image data.

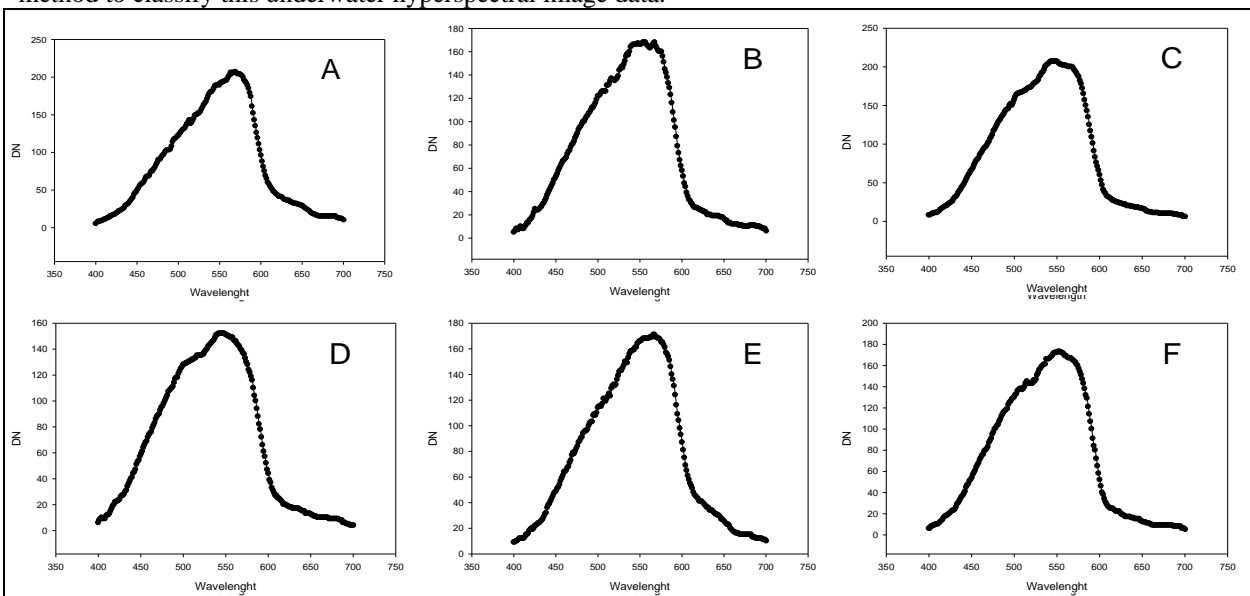


Fig. 10 This image shows the original radiance that we collect by hyperspectral imager. It was hard for us to find out the different between these 6 areas by this image. So we have to use the IARR (Internal Average Relative Reflectance) method to correct this image.

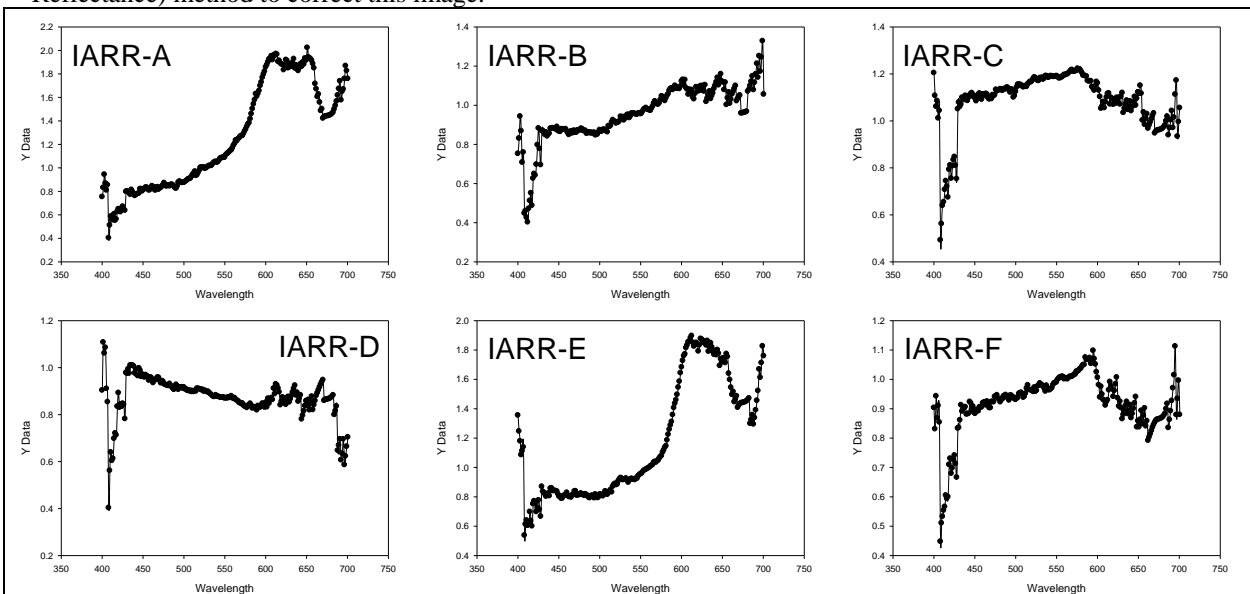


Fig. 11 We used the IARR (Internal Average Relative Reflectance) method to correct this image. After that, it was becoming easier for us to find out the different between these 6 areas by this image. But it was not enough for this

study. If we want to get the better result, we have to use the fourth deviation method to enhance the spectral characteristic.

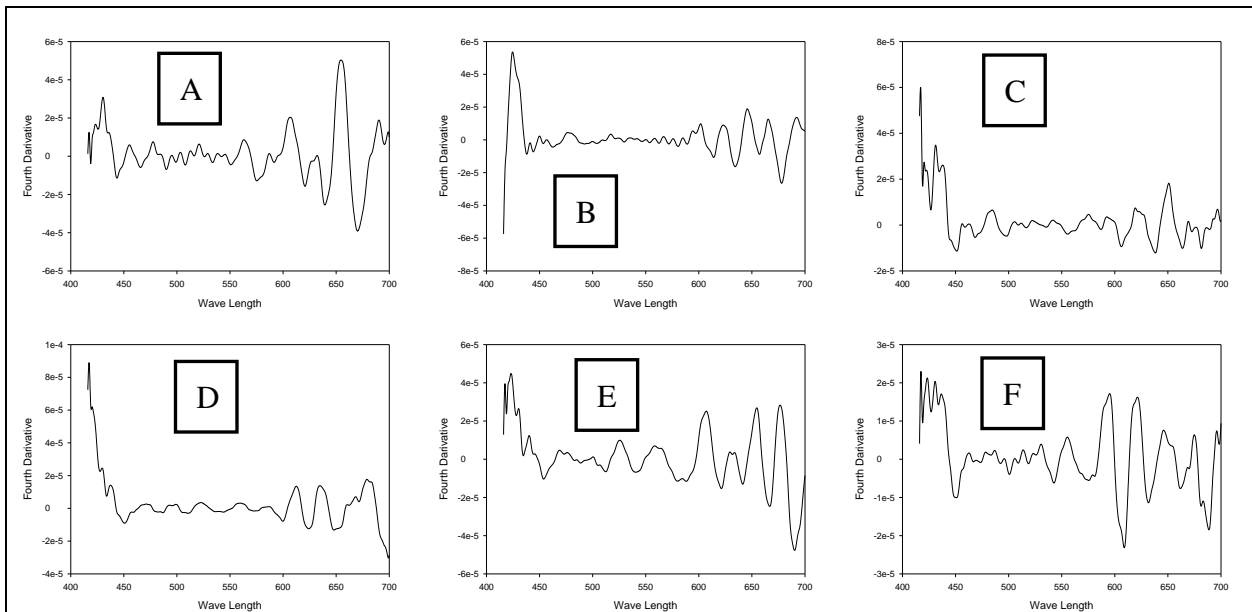


Fig. 12 This image shows the result after the fourth deviation method. After that, it showed the characteristic wavelength bands between these 6 areas by this image. We got 22 characteristic wavelength bands(nm): 451、595、606、607、609、613、620、624、631、634、638、639、645、648、655、667、670、677、678、679、688、690 (22Bands).

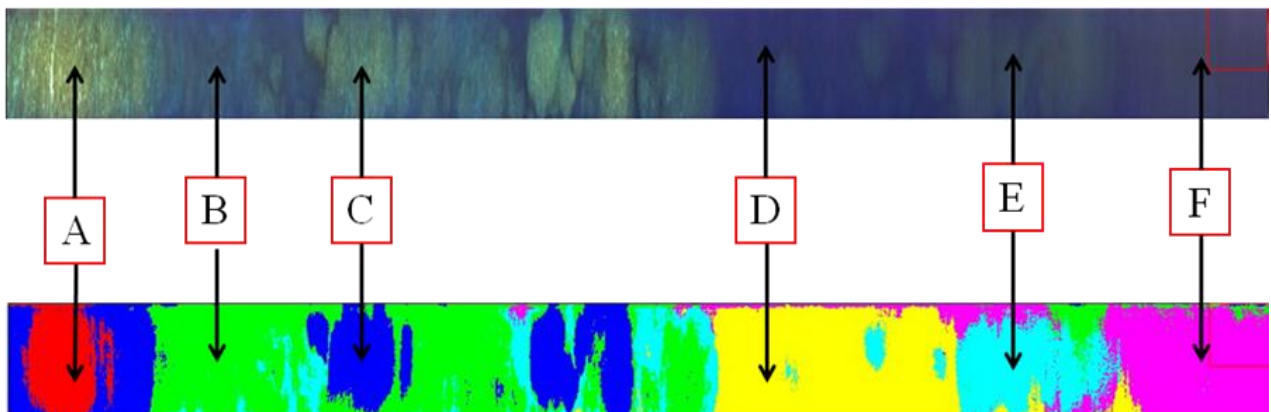


Fig. 13 We used 22 characteristic wavelength bands and classified the image by supervised classification method. The result of this study showed that we can classify the hyperspectral image by supervised classification method easily.

The image that we have is with radiance data, not the remote sensing reflectance. So we can't enter these hyperspectral images data into GA-SSA. The goal in the future is going to collect the remote sensing reflectance. We will set the whiteboard under the sea and use the signal from the whiteboard to be the upwelling radiance. Then we can get upwelling radiance and down welling radiance. Finally we can use the ratio of upwelling radiance and down welling radiance to calculate the reflectance.

4. DISCUSSION

The establishment of a database can be applied to future research. This study is also the first time in the Kenting area in Taiwan where a towed underwater vehicle (V-Fin) was used to collect underwater hyperspectral imaging. We use a supervised classification method to classify underwater hyperspectral data and assess the coral reef condition in Kenting National Park. In the future, we will continue to improve the technology of underwater image collection and use GA-SSA to retrieve the water quality and bottom type classification. Once established, this system will enable us to monitor and address changes in our valuable coral reef ecosystem.

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