

# Evaluation of soft classification algorithm for sub-pixel mapping of the shoreline

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**The main objective of this research is to study the potential of different soft classification algorithms to determine sub-pixel composition for shoreline mapping. Sub-pixel composition information is an important element in determining the accuracy of shoreline maps based on sub-pixel analysis. This allows the shoreline to be mapped within image pixels producing an accurate and realistic prediction of shoreline position. In this paper, the potential to map the shoreline at sub-pixel scale from different soft classification of relatively coarse spatial resolution satellite imagery were evaluated. The coarse satellite imagery used were at 5 m and 10 m spatial resolution. Three fuzzy functions were evaluated mainly, the Fuzzy sigmoidal, Fuzzy Linear and Fuzzy J-shaped and preliminary results showed that the different fuzzy functions gives varied accuracy. The fuzzy sigmoidal function produced the most accurate sub-pixel prediction with an  $r^2$  of 0.93 for 5 m pixel, while the Fuzzy J-shaped produced the less accurate prediction  $r^2$  of only 0.47. These predictions were later used to predict sub-pixel shoreline position based on a contouring technique. As expected the Fuzzy sigmoidal produced the most accurate shoreline with RMSE of 2.98 m from the actual shoreline.**

**Keywords:** Soft classification, fuzzy sigmoidal, fuzzy linear, sub pixel, shoreline mapping

## 1. INTRODUCTION

A large percentage of the world's population and industrial activity is concentrated along the coastal zone. These environmentally sensitive areas are under intense pressure from natural processes, urban growth, resources development, and pollution (Gordon et al., 1998). The shoreline data are useful for determining flood zones, creating coastal navigation routes, constructing beach nourishment projects, calculating erosion rates, placing setback lines and denoting jurisdictional boundaries (Moore, 2000). Each of these applications requires a unique combination of datasets, technology and methodology. Conventionally, shoreline maps have often been derived from aerial photography and ground based survey (Camfield and Morang, 1996; Gorman et al., 1998), identification of relative changes among coastal units (Jantunen and Raitala, 1984; Siddiqui, and Maajid, 2004) and extraction of topographic and bathymetric information.

This conventional methods are impractical in mapping large areas as it is time consuming and expensive. (Mckenna et al. 2003, Zuzek et al. 2003). Thus, remote sensing provides an alternatives to mapping shoreline quickly and cost effectively (Ryu et al., 2002; Yamano et al., 2006; Muslim et al., 2007).

Due to the large extent of Malaysian shoreline and limited resources, the shoreline has only been mapped every five years but the shoreline constantly changing in location (Davis et al., 2000; Fletcher et al., 2003). With the development of remote sensing technology, satellites can capture high-resolution imagery with the capability of producing stereo imagery, such as IKONOS and SPOT satellite images.

The main problem for accurate interpretation of remotely sensed data is correlated to the fact that the pixels may contain more than two classes which would only be realised from ground activities (Foody, 1992) because of the complex relationship of land cover types and their spectral reflectance (Richard, 1993). In order to solve this problem, researchers have developed techniques to derive estimation of the sub pixel class composition through the use of mixture modelling (Foody, 1996) and soft or fuzzy classification (Muslim, 2003). Classification is a fundamental image processing task of extracting information from remote sensing data. In a hard classification, each image pixel is assumed pure and is classified to one class. Often, particularly in coarse spatial resolution images, the pixels may be mixed containing two or more classes resulting in inaccurate classification. Soft classifications that assign multiple class memberships to a pixel may be appropriate for images dominated by mixed pixels. Mixed pixels are an important problem in information extraction from remote sensed imagery (Wilma, 2008). A number of alternative techniques such as MLC in soil mode (Foody et al., 1992), linear mixture modelling (LMM) (Settle and Drake, 1993), fuzzy set (Key et al., 1989) and neural network approach (Foody and Arora, 1996; Foody, 1996a; Moody et al., 1996) can be used for the classification of mixed pixels. This research explored different fuzzy set theory classification approaches to improve the sub-pixel class composition thus improve the accuracy.

A fuzzy classification method takes into account that there are pixels of mixed up that is, a pixel cannot be definitively assigned to one category. Fuzzy classifications works using membership function, where in a pixel's value is determined by whether it is closer to one class than another. A fuzzy classification has no boundary and each pixel can belong to several classes (Jensen, 1996). Since multiple and partial class membership is accommodated in a soft classification these techniques may sometimes be a useful means of reducing the mixed pixel problem and acquiring sub-pixel scale thematic information (Fisher and Pathirana, 1990, Foody, 1996).

Previous study done by Muslim (2007) had showed that when the conventional methods such as hard supervised classification were used, the shoreline prediction was unrealistic. These errors were attributed to mixed pixels being assigned to single classes during hard classification and the boundary between the classes being constrained to lie between pixels. The magnitude of the error arising from mixed pixels increased with a coarsening of the spatial resolution. Hence, to solve the problem, a soft classification is used to accurately predict the class proportion of the mixed pixels. This research extends this work by exploring different soft classification algorithm and how it effects the accuracy of the predicted shoreline. Several fuzzy classifications algorithm were explored in this study mainly, sigmoidal, linear and j-shaped type. Two coarse resolution imagery were used at 5m and 10m.

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## 2. TEST SITE AND IMAGERY

### 2.1 Study area

The research focused on the rocky-type shoreline along Kuala Terengganu, Terengganu. The shoreline was located at the river mouth of Kuala Terengganu estuary facing the South China Sea to the northeast and the Terengganu River to the southwest. Attention was focused on the rocky type of shoreline and the area surrounding.

### 2.2 Satellite imagery

The study requires a relatively coarse spatial resolution image data set of a coastal region for which the shoreline location was known. Two data sets used: coarse spatial resolution image from which the shoreline could be predicted and one at a much finer spatial resolution to represent the actual conditions for used as ground data set. In this preliminary study, the SPOT image was degraded spatially by aggregating pixels in order to produce the coarse spatial resolution as an alternative approach. Thus, 10m spatial resolution was produced as showed in Figure 1 (b) and 5m spatial resolution in Figure 1 (a).

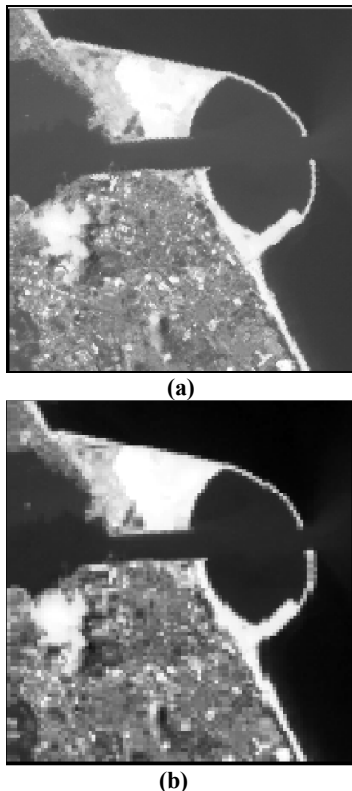


Figure 1. Study area from (a) 5m spatial resolution and (b) simulated image with a 10m spatial resolution.

### 2.3 Benchmark shoreline position

Basically the shoreline reference data was generated from the 2.5m spatial resolution SPOT satellite sensor imagery. From this image, the position of the shoreline was mapped according to a conventional Minimum Distance classification. The shoreline fitted between image pixels that had been allocated to the two difference classes and the resulting classified image was used as the ground data set on shoreline position.

## 3. SHORELINE MAPPING USING SOFT CLASSIFICATION

This research compares different soft classification algorithms accuracy in predicting the shoreline position. A comparison was conducted between the produced shoreline from soft classification and conventional hard classification.

The hard classification operates by allocating each pixel in the image to one of the classes in the set defined by the analyst. In this study, with minimum distance classification technique, each pixel is allocated to the class with which it has the highest posterior probability of membership. Hard classification were used to classify image into different classes mainly as water and land as showed in figures 2(a) and (b) which indicate black as complete water cover and white as complete land water cover.

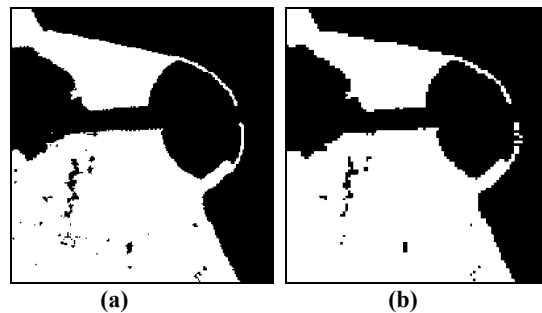
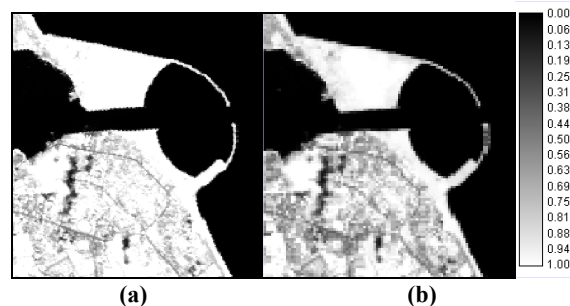


Figure 2. Hard classification (a) 5m and (b) 10 m spatial resolution.

To increase accuracy of the shoreline maps, a soft classification approach was taken. Later a comparison was conducted to determine the most accurate technique. Soft classification was applied to predict the proportional cover of the water and land classes within the pixels of each coarse-spatial resolution image pixel. In this preliminary study, the soft classification were achieved by using three different fuzzy set theory, a sigmoidal, linear and j-shaped membership function and the training site defined previously. The proportion image obtained from the soft classification is shown in Figure 3.

The output were then comprised the strength of predicted membership of each class pixel to the land class. For a pixel with large degree of mixing, this fuzzy membership value derived was treated as representing the proportion of the pixel's area that was covered with land, while the remainder were described to the water class.



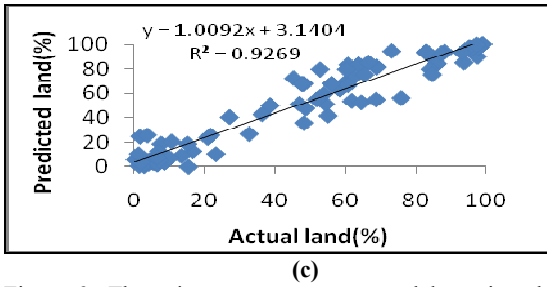


Figure 3. These imagery were generated by using the fuzzy sigmoidal type for (a) 5m spatial resolution and (b) 10m spatial resolution images and (c) relationship between the predicted and actual proportion of land in pixels from the output of the soft classification of fuzzy sigmoidal for 5m spatial resolution image. The accuracy of the soft classification was assessed through a comparison of the predicted coverage of class which derived from the ground data. The predicted coverage and ground data were highly correlated ( $r^2 = 0.93$ (figure 3(c)) and  $r^2 = 0.91$  for 5m and 10 m spatial resolution respectively). Table 1 showed the accuracy of fuzzy membership functions.

Table 1. Proportion for shoreline prediction accuracy for 5m and 10 m spatial resolution

| Soft classification method | 5m   | 10m  |
|----------------------------|------|------|
| Fuzzy sigmoidal function   | 0.93 | 0.91 |
| Fuzzy linear function      | 0.51 | 0.81 |
| Fuzzy j-shaped function    | 0.47 | 0.44 |

From the table, with  $r$  value of 0.93 ( $P < 0.05$ ) and 0.91 ( $P < 0.05$ ) respectively for 5 m and 10 m spatial resolution imagery by using sigmoidal function, it was determined that the output of the soft classification accurately represented the actual proportion of classes within each pixel. On the other hand, the  $r$  value of 0.81 ( $P < 0.05$ ) for 10m spatial imagery derived from fuzzy linear function was also acceptable. Meanwhile, for 5m spatial imagery shows only 0.51  $r$  values indicate that it is not relevance to be used. The same goes to fuzzy j-shaped function which showed  $r$  value below 0.5 and were not reliable. To determine the shoreline at a sub pixel scale, contouring was used to increase the prediction accuracy of the shoreline position from the coarse spatial resolutions (5m and 10m) simulated imagery. The soft classified imagery was contoured at 0.5 intervals as at this point, the pixel contains 50% of water and 50% of land. The shoreline generated from contouring the soft classification output was shown in Figure 4.

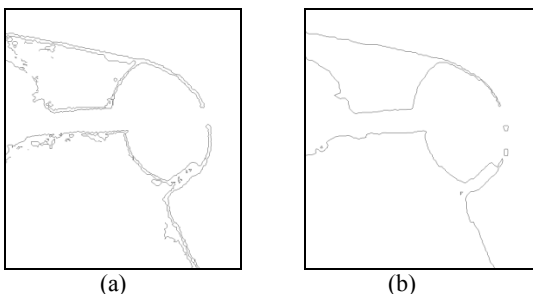


Figure 4. Predicted shoreline position from (a) 5m spatial resolution and (b) 10m spatial resolution

The shoreline predicted from contouring applied to the simulated image was compared with that derived from the

classification of the original 2.5 m spatial resolution image. The distance between the predicted and the actual location of the shoreline mapping was calculated at each 5 metre point along the coast for accuracy estimating.

Table 2. Root Mean Square Error (RMSE) of shoreline prediction

| Mapping method  | 5 m      | 10 m    |
|-----------------|----------|---------|
|                 | RMSE (m) | RMSE(m) |
| Fuzzy Sigmoidal | 2.9      | 3.8     |
| Fuzzy Linear    | 3.6      | 4.5     |

The correlation was calculated based on the Pearson's correlation coefficient. The result showed that for 5 m spatial resolution,  $r$  value was 0.8584 and 0.8440(10m spatial resolution) indicated that by fitting a class membership contour to the soft classification output will provide an indication of where these proportions might be located within each pixel and therefore could provide a refined estimated shoreline position.

The shoreline predicted from the fuzzy sigmoidal classification approach for 5 m spatial resolution provided the most accurate and visually realistic representation (Table 2). The RMSE derived from this analysis was 2.9m and 85.8% of the predicted shoreline lay within 5m of the actual shoreline. Meanwhile the shoreline predicted from 10 m spatial resolution of fuzzy sigmoidal classification showed RMSE of 3.8m and 84.4% of the predicted shoreline lay within 5m of the actual shoreline.

#### 4. DISCUSSION

Boundaries such as the shoreline cannot be represented appropriately in a conventional approach to thematic mapping from remotely sensed data based on hard classification, as their location is constrained by the data's pixel grid. Recently, there is an increasing need for sub-pixel and super pixel assessment of classification analysis made evident by recent remote sensing research (Aidy *et al.*, 2007; Foody *et al.*, 2005; Latifovic and Olthof, 2004; Okeke and Karniele, 2006; Ozdogan and Woodcock, 2006; Shabanov *et al.*, 2005).

Soft classification (Figure 3) can provide an alternative representation for the shoreline mapping. Since this soft classification was the basis for contouring analyses, its accuracy were evaluated by comparing the predicted coverage of a class with that derived from the reference data, the 2.5m spatial resolution image. The correlation between the actual and predicted coverage were  $r = 0.8584$  (Figure 3) for 5m spatial resolution and  $r = 0.8440$  for 10 m spatial resolution and hence the soft classification were taken to be an appropriate based for the contouring. In addition, membership grades of fuzzy classification have been shown to have strong correlation with true class proportions.

The result indicated no simple general trend with the effect of variation in spatial resolution or one method that is always more accurate than another. However, the results do suggest that the fuzzy sigmoidal approach was typically provided the most accurate prediction in comparison with fuzzy linear and fuzzy j-shaped approached. The correlation coefficient derived for the relationship between the actual class proportion cover and with that predicted in the soft classification output showed a local variation in soft classification accuracy and so of the proportion values input to

the contouring mapping process. For instance, the correlation coefficient between 5 m and 10 m spatial resolution were differed slightly but it was apparent that the shoreline prediction accuracy was generally positively related to the magnitude of the correlation coefficient between the actual and predicted coverage of the class.

The shoreline predictions derived from the contouring applied to the output of the fuzzy sigmoidal and fuzzy linear classification provided more realistic and accurate representations than hard classification.

## 5. CONCLUSION

In this context, techniques for improving the soft classification accuracy by using different types of fuzzy classification method showed the potential of using sigmoidal and linear approach at sub pixel scale with relatively coarse satellite sensor imagery. This research concerned the issue of providing the most accurate shoreline mapping by increasing the soft classification accuracy thus increase the overall accuracy. Further research in other soft classification algorithm and their suitability in shoreline mapping need to be explored. Research would also look at different types and shape of shoreline.

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