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Spatial Accuracy Assessment for Coral Reef Classifications

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Abstract. This paper illustrates methods of assessment of a supervised classification using the Maximum Likelihood classifier performed for coral reef classifications that explicitly include the spatial pattern of classification errors, and which presents the user with a visual indication of the reliability of the pixel label assignments. Two of Ikonos images covering two coral reef test sites in Thailand were used in this study. Non-spatial statistics such as: overall accuracy, Kappa coefficient, variance, and Z statistics; were computed from the error matrix and thematic images were also generated. None of these statistics explicitly considers the spatial distribution of misclassified pixels. Results show that regardless of statistical accuracy measurements which present outstanding outcome (values), the accuracy is not spatially similar for every pixel through the image (homogeneous). Thus, a considerable amount of research and development needs to be accomplished before the spatial characterization of thematic accuracy associated with remote sensing products can be adequately reported in standardized format and legends.

Keywords: reliability of the remote sensing products; thematic accuracy; coral reef mapping; IKONOS, image classification.

1. Introduction

Coral reefs are often mentioned as ‘rainforests of the sea' because of the extraordinary diversity of life they support. As one of the most complex ecosystems in the world, coral reefs are home to over 4,000 different species of fish, 700 species of coral, and thousands of other plants and animals(ICRAN 2006). The condition, health and diversity of coral reefs are important to socio-economic living of millions of people who depend on coral reefs and other coastal environments. The distribution, types and quality of subtidal marine habitats are largely unknown in shallow waters throughout Thailand’s marine environment. This lack of information holds back the management of marine ecosystems. An essential component of effective management knows where divergent habitats occur so that excellent, unique, productive and sensitive habitat types can receive a higher level of resource assessment for permit review or even be subject to practical protection measures. In order to generate the coral reefs distribution maps for their management, remotely sensed data seems to be a potential source of useful information, especially as these maps require frequent updating which is time consuming and expensive by traditional methods. The process of remote sensing coral reef habitat mapping consists in assigning image pixels to thematic classes based on their spectral properties. This procedure can be achieved with a variety of applications. The supervised classification approach (maximum likelihood (ML) classifier) was embraced here to envisage the output benthic habitat classes. The ML decision rule is considered to be robust given that its estimation depends on the covariance between spectral.

In order to evaluate the reliability of the image classification of a coral reef, the quality of the thematic map needs to be determined. According to Janssen and Van der Wel (1994) there are two different components of accuracy in the context of remote sensing: positional and thematic accuracy. Positional accuracy resolve how closely the position of discrete objects shown on a rectified image (map) or in a spatial database agree with the true position on the ground, while thematic accuracy refers to the non-positional characteristic of a spatial data entity, which are derived from radiometric information. The accuracy of spatial databases goes beyond the issue of thematic accuracy, which is emphasized in this paper, since it is also concerned with lineage, logical consistency, and completeness, positional and temporal accuracy. This paper describes methods of assessment of classifier performance for coral reef classifications that explicitly include the spatial pattern of classification errors, and which presents the user with a visual indication of the reliability of the pixel label assignments.

2. Study Areas and Data

2.1 Study areas

According to Chansang (2003) coral reefs in Thailand territory's waters are found both in the Gulf of Thailand and the Andaman Sea. **Figure 1** shows reef distribution in Thailand waters. In the Gulf of Thailand, most of the reefs are found on leeward side of the islands. On the west side of the Gulf of Thailand, small fringing reefs are found on islands, they are mostly less than 1-2 km^2 in area and less than of 10 metes in the depth , except for the reefs of the large islands group such as reefs of Mu Ko Chang and Mu Ko Ang Tong. On the Andaman side, reefs are found on leeward side of islands facing the predominant Southwest Monsoon wind. These reefs are better developed than the reefs in the Gulf of Thailand. On offshore islands such as Surin Islands and Similan Islands, reefs can develop to 30 meter in depth. The approximated total reef area in Thailand is 153.36 km^2 with 74.8 km^2 in the Gulf of Thailand and 78.56 km^2 in the Andaman Sea.

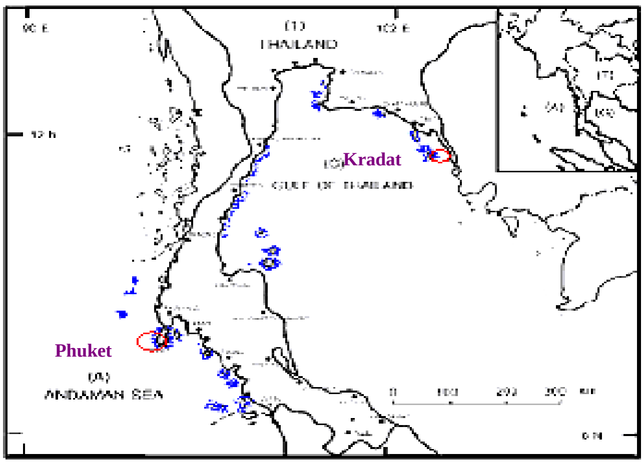

Figure 1. Map of coral reef distribution in Thailand (G) represents distribution of coral reefs in the Gulf of Thailand and (A) the Andaman Sea (source Chansang, 2003).

Ikonos images of two test study sites in Thailand (**Figure 2**) were kindly contributed by Space Imagine Southeast Asia, Had Nai Yang (acquisition date 24/01/2004, 04.09 GMT) in Phuket Island is a representative coverage from the Andaman coastal and Kho Kradat Island (acquisition date 02/04/2001 , 03.42 GMT), of Trat, province in the Gulf of Thailand. The dissimilar nature of the reef system and geomorphology including the climatic and anthropogenic influences, of the two selected areas are make for a suitable and challenging test of the potential of ML classifier for coral reefs habitat mapping.

Figure 2. Study areas, Phuket (left), Kradat (middle) of Ikonos composite image. RGB colors represented with spectral bands 1, 2, and 3 respectively and Kradat (right) after operation Island mark off and deglinted

2.1 Image pre-processing

Image pre-processing operations were performed using ERDAS Imagine (version 8.7), IDRISI (version 3.2) and some in-house programs written by Vieira (2000) in order to carry out specific procedures. Images georeferencing was done by registration to the aerial photograph's ground control data collections from of Ministry of Natural Resources and Environment for Phuket site, (WGS 84 Zone 47 North) and Ortho-rectification photomap of Ministry of Agricultural and Cooperation for Kradat site (WGS 84 Zone 48 North), both were performed using 20 ground control points each. The Nearest Neighbor algorithm was selected to avoid change the original pixel values. The RMS error was 0.465 and 0.534 pixels respectively. Standard atmospheric corrections have been applied to correct for path radiance. *Prior* to bottom - type classification, in order to obtain a depth-independent spectral measurement of the substrate, it is necessary to compensate for the water column effect. As suggested by Mumby et al.(1998a), the influence of the water column, which was accounted for the empirical approaches developed by Lyzenga (1978,1981) "Depth-Invariant Bottom-Indices". Due to the high spatial resolution, sea surface in Kradat Island area appears to have Wave-induced specula reflectance effects of the images (i.e., glint). In order to circumvent the weakness of basing the deglinting on two isolated pixels from the whole image, a linear relationship between NIR and visible bands was established using linear regression based on a sample of the image pixel. The near-infrared radiance is practically totally absorbed in the water, thus the observed radiance can be considered to have an origin either as reflected from the surface or as scattered in the atmosphere. For a more complete understanding of the method and algorithm refer to Hedley et al. (2005).

2.2 Image classification processing

Image classification comprises of assigning image pixels to thematic classes based on their spectral properties. The supervised classification approach was embraced here to predict the output benthic habitat classes from collected ground truth data. The ML decision rule is considered to be robust given that its estimation depends on the covariance between spectral bands for each of the classes. This algorithm has also been widely used by reef remote sensing scientists in similar studies by Mumby et al. (1997), Mumby et al. (1998b), and Andréfouët et al. (2003). Training pixels were defined based on visual image interpretation, with the guidance of field descriptions and underwater photography collected in-situ. Pixels of well-known ground areas were selected as training sites. The benthic class characteristic was assigned following the classification scheme. The four habitat classes are described in **Table 1**. The ML algorithm assumes normality within the training data, and such parametric rule should be approximated by having an appropriate sample size and by checking for deviated spectral values within the samples. Once the statistical characterization was approximated the image classification approach followed using the ML decision rule with equal probabilities of the classes.

Table 1. Benthic community, habitat percentage cover and geomorphological attributes were incorporated in the classification scheme

Habitat Label (class)	Characteristics
Dense coral covered substrate	More than 50 percent is coral-covered substrate.Including hard coral, benthic algae, and sponges mainly over fringing reefs.
Sparse coral covered substrate	Less than 50 percent is coral-covered substrate.Predominantly bare substratum (pavement, dead coral, coral rubble, sand pockets) over patch reefs.
Algae dominate with sparse patches reef	Algae dominate with visibly dominant, with sparse occurrence of patch reef, gorgonians, algae, sponges, coral rubble or small stony corals.
Sand	Carbonate sand/rubble/ mud with occurrence of sparse green algae

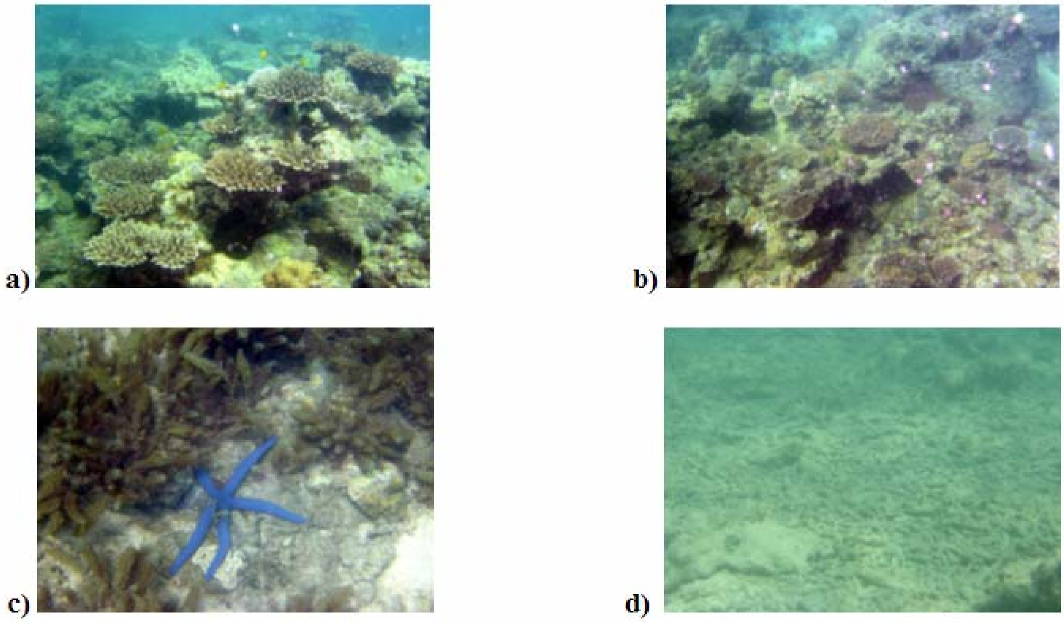

Figure 3. a) Dense coral covered substrate, b) Sparse coral covered substrate, c) Algae dominate with sparse patches reef, d) Sand and rubble

3. Techniques for Estimating Thematic Accuracy

The validation of the reference map was generated from the ground truth data with the guidance of field descriptions and underwater photography collected in-situ. This was used specifically to test the thematic accuracy. Additional information from a previous study of Phuket area from Plathong (2000) was taken into account in order to confirm the reliability of reference map. The number of reference points or ground truth sites was adequate to test the overall classification accuracy of the benthic classification. The accuracy assessment techniques are based on non-spatial statistics derived from the confusion of matrix, which compares the output of a classifier and known test data (**Table 2** and **3**).

Table 2. Confusion or Error of Matrix

Phuket	Reference					
Class [a]	1	2	3	4	Total	ErrorC[c]
1	1465	130	0	0	1595	0.0820
2	148	1684	64	0	1896	0.1118
3	6	136	102	16	260	0.6077
4	0	199	4	922	1125	0.1804
Total	1619	2149	170	938	4876	Overall
ErrorO[b]	0.1149	0.2186	0.4070	0.0233		0.1528
Kradat	Reference					
Class [a]	1	2	3	4	Total	ErrorC[c]
1	9164	129	0	0	9293	0.0139
2	336	1666	275	530	2807	0.4065
3	1	84	1646	84	1815	0.0931
4	53	414	401	1596	2464	0.3523
Total	9554	2293	2322	2210	16379	Overall
ErrorO[b]	0.0503	0.2785	0.2945	0.2846		0.14883

[a] Habitat description refer to **Table 1**
[b] ErrorO = Errors of Omission (expressed as proportions)
[c] ErrorC = Errors of Commission (expressed as proportions)
90% Confidence Interval = +/- 0.0045 (0.1437 - 0.1528)
95% Confidence Interval = +/- 0.0054 (0.1429 - 0.1537)
99% Confidence Interval = +/- 0.0071 (0.1412 - 0.1554)

Table 3. Kappa coefficient

Thematic	**Kappa**	**Z**	**Variance**
Phuket	0.775	104.50	0.000055
Kradat	0.759	184.08	0.000017

These statistics include overall accuracy, individual class accuracy, error of commission and omission, user's and producer's accuracy, and several other statistics. Although these measures are in widespread use, none of them considers the spatial distribution of erroneously classified pixels, either implicitly or explicitly. The comparison of Kappa index of agreement of reference and training pixel among substratum of both study areas are shown in **Table 4**. The thematic images were also generated for both areas, as presented below in **Figure 4**.

Table 4. Kappa index of agreement of reference and training pixel among substratum/benthos

Class	Dense covered substrate	Sparse covered substrate	Algae dominate with sparse patches reef	Sand
Phuket				
Reference	0.8768	0.8009	0.3703	0.7767
Training	0.8304	0.6442	0.5703	0.9711
Kradat				
Reference	0.9666	0.5275	0.8916	0.5927
Training	0.8851	0.6645	0.6692	0.6655

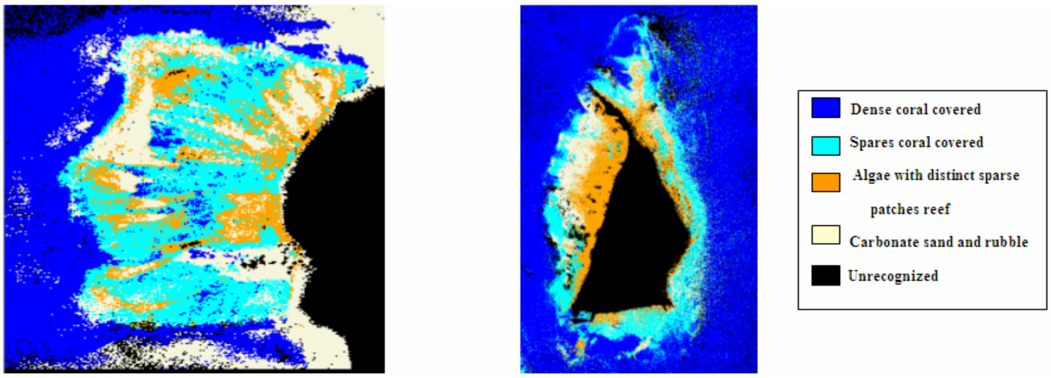

Figure 4. Thematic Images generated using the Maximum Likelihood decision rule for Phuket (left) and Kradat (right)

3.1 Characterizing the Spatial Distribution of the Errors

The determination of the spatial distribution of the errors in a thematic classification is carried out by directly comparing thematic images with their respective ground truth maps. One of the products of this comparison should be an error image (**Figure** 4), in which each point takes the value 0 (unrecognised), 1 (correctly labeled) or 2 (erroneously labeled). By examining the spatial distribution of such pixels in **Figure 5**, we can make a number of observations. It is apparent that misclassified pixels are spatially correlated. These correlation effects are probably due to the presence of mixed pixels at habitat class boundaries, to variation in the reflectance spectrum caused, most probably, by variations in covered substrate within a benthic or variation on the water depth. Spatial analysis measures (e.g., Join Count Statistics) could be used in order to determine whether these correlation effects are random or clustered in their spatial distribution. Looking at the spatial distribution of the remaining errors can help to refine the classification process.

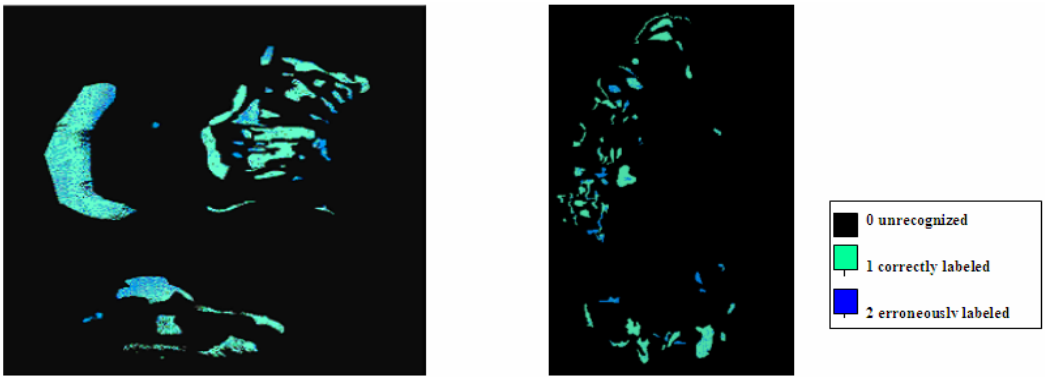

Figure 5 Spatial characterizations of classification errors by comparing the thematic image of Phuket (left) and Kradat (right) area to its respective reference image.

3.2 Visualizing the Reliability

An alternative way of looking at the spatial distribution of the errors present in a classified image is by generating a "distance image" which shows distance from individual pixels to the multivariate means of the classes to which they have been assigned. Either the Euclidean distance or the Mahalanobis distance measure can be used (Vieira 2002). The former, however, implies spherical clusters in feature space, while the latter takes into account the covariance between the features on which the classification is based. The individual distances are scaled onto a 0-255 range, and displayed as a grey scale image. Darker pixels are spectrally "nearer" to their class centroid (in the sense of statistical distance), and are thus more likely to be classified correctly. On the other hand, pixels with higher distance values are spectrally further from the centroid of the class to which they were assigned, and are thus more likely to be misclassified. A threshold can be applied to the distance image to identify those pixels that are most likely to be misclassified.

Figure 6 Visualizing the reliability by distance image of Phuket (left) and Kradat (right) area to its respective reference image.

Any distance measure between the pixel and the mean pixel values (or centroid) of each class can be used to compute a measure of reliability of a pixel's label. These measures of reliability could be then combined to the already assigned class label in order to generate a new thematic value for the pixel, which not only indicates the class to which the pixels was assigned but also the degree of accuracy achieved. A separate color is assigned to each class. Within class levels are also assigned separate shades of that color regarding to the accuracy achieved range form 0 – 20 %, 20 – 40%, 40-60% ,60-80% and more than 80 %, from the light to the dark shade respectively. Thus each class is represented by four shades of the given color (see **Figure 7**). This kind of representation allows the visual appreciation of the degree of accuracy of the classified pixel. Although the final map may look uniform in its accuracy, it is actually a representative assemblage from several image processing procedures and refinements. It is important for the user to known how these accuracies are spatially distributed in the image through a thematic reliability map. In this classification the shade of accuracy achieved in range of 0-20% was not arise that presumably the degree of accuracy is somewhat good.

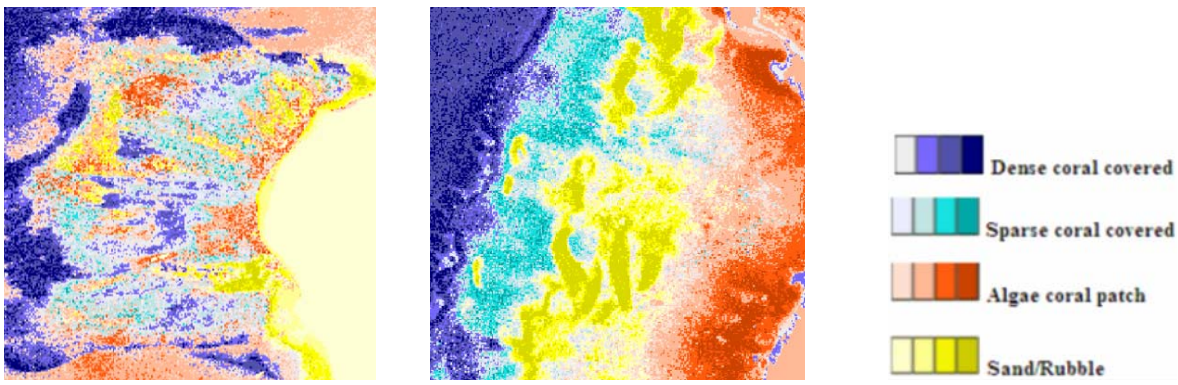

Figure 7 Representation of the thematic reliabilities using a Maximum Likelihood classifier Phuket (left) and subset of Kradat (right)

4. Discussion and Conclusions

Since the study area is relatively small and some of the classes are also spatially small, the accuracies (user and producer) of individual habitat classes cannot be rigorously discussed, given the reduced number of reference points describing benthic classes. However, it is possible to depict some general trends from the omission and commission errors as derived from the resulting error matrices. The IKONOS Image showed contrasting responses with significant confusion in discriminating most of the individual classes. In general, the *sparse coral covered substrate* and *Sand/Rubble substrate* classes seem to be relatively better resolved. The poor discrimination or confusion relates to the degree of spatial patchiness and variability of each benthic habitat class per image spatial resolution. Further more, these results show that a considerable amount of research needs to be undertaken before the spatial characterization of positional and thematic accuracy associated with remote sensing data can be adequately reported in standardized format and legends. The Kappa coefficient indicated is very high value (0.775 for Phuket and 0.759 for Kradat). However the thematic map is prone to spatial error and is not constant over the study areas. The spatial pattern of error is persistently around the boundary between classes The expaination would seem to be that the Kappa coefficient was contributed over the whole image.

The future work is needed for alternative procedures to take into account the characteristics of other current satellite sensors, such as QuickBird which has a very fine spatial resolution (2.44-meters multispectral and 0.61-meters panchromatic): the only space sensor providing such level of footprint detail. QuickBird’s spectral bandwidths are similar to those of Ikonos and ETM+, and the fine spatial resolution may allow it to overcome the difficulties imposed by reef system’s internal structure. In addition, there is now the concurrent development of high capacity of personal computer performance and Airborne Hyperspectral Imagery such as AISA (Airborne Imaging Spectroradiometer for Applications) with the high spatial (1.5 m) and spectral resolution (24 bands between 0.44 and 0.74 nm) and the global dataset from the hyperspectral satellite Hyperion which offers same spatial resolution as ETM+ (30-meters) with 220 spectral bands. It is expected that by means of the enhanced spatial and spectral capabilities of satellite sensors, it will be possible to narrow the gap between the degree of accuracy that can be derived from high resolution airborne and spaceborne sensors for coral reef assessment. It should illustrate as well the relative importance of the spatial and spectral resolutions in terms of thematic map accuracy. Further, any cost-effectiveness report should also include the time and effort effectiveness of using empirical or analytical image correction techniques, in addition to the image classification methods for better map accuracies.

These results show that a considerable amount of research needs to be undertaken before the spatial characterization of positional and thematic accuracy associated with remote sensing data can be adequately reported in standardized format and legends.

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