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A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones

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A B S T R A C T

This study assesses the performance of the support vector machine image classification technique in the context of a tropical coastal zone exhibiting low to medium scale development. The overall and individual classification results of this approach were compared to the maximum likelihood classifier and the artificial neural network techniques. A 15-m spatial resolution ASTER image of Koh Tao in Thailand was used for the test, and support vector machine was found to offer only limited improvements in classification accuracy over the other methodologies. The support vector machine did, however, show promise in dealing with the difficult challenge of separating human infrastructure such as buildings from other land cover types such as coastal rock and sandy beach which have very similar spectral signatures. The medium resolution ASTER image also proved highly suited to classifying coastal landscapes with this mix of land cover types. Additional research is needed to assess the full potential of the support vector machine in a weighted or layered classification, and to explore potential applications of this classification tool in other tropical environments.

Introduction

Data from satellite sensors has become an important tool for researchers studying land use and land cover change. Remote sensing offers the advantage of rapid data acquisition of land use information at a lower cost than ground survey methods (Pal & Mathur, 2004) and the analysis of this data can provide critical insights into the evolving human–environment relationship. In particular, the analysis of multispectral imagery to detect coastal land cover and land use change (LCLUC) is growing in importance. Over 50% of the world's population now lives within 100 km of the coast and coastal environmental systems are facing increasing pressure from multiple stressors ranging from human economic development activities to sea level rise associated with global warming (Hwang, 2005). Given the scale and pace of change in the coastal zone, particularly in tropical regions, the development of tools which can both monitor coastal change and model the dynamics of future growth is critically important.

A number of techniques exist to classify coastal land use or land cover categories in remotely sensed images. Maximum likelihood classification (MLC) represents the most established approach (Jensen, 2005). This technique assumes a normal Gaussian data distribution of multivariate data with pixels allocated to the most likely output class, or a posterior probability of membership and dimensions equal to the number of bands in the original image (Richards and Jia, 2006). This requires users to carefully determine the classification scheme so that each class follows a Gaussian distribution, and MLC ideally has to be performed at the spectral class level. Recent coastal examples of MLC include: a study of land use change in China which utilized Landsat Thematic Mapper imagery (Ding et al., 2007); an investigation of land use change of the Majahual region of Mexico (Berlanga-Robles & Ruiz-Luna, 2002); and the analysis of landscape change produced by tourism and agriculture development in Egypt (Shalaby & Tateishi, 2007).

Artificial neural networks (ANN) are a more recent non-parametric classification technique (Lu & Weng, 2007) which does not depend upon an assumption of normally distributed data (Dixon & Candade, 2008; Foody, 2004). In contrast to MLC, ANN can classify land cover and land use types that are multi-mode or not linearly separable in the original spectral space. Accurately describing processes that translate input data into output classes can, however, be difficult due to the combined use of multiple nonlinear activation functions at different layers (Kavzoglu & Mather, 2003). For this reason ANN is often referred to as a "black box" technique (Qiu & Jensen, 2004). In a coastal context ANN has been used to produce "fuzzy" maps of land use change in Mexico (Mas, 2004)

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and wetland vegetation coverage in Florida (Filippi & Jensen, 2006). ANN utilizing a layered thematic classification approach has also been used to map coastal Argentina (Kandus, Karszenbaum, & Frulla, 1999) and examine coastal areas of the Gulf of Mississippi (O'Hara, King, Cartwright, & King, 2003).

Support vector machine (SVM) is one of the latest additions to the existing catalog of image classification techniques that support coastal LCLUC analysis. Recent research has demonstrated that SVM compares favorably with more established classification techniques (Gualtieri & Cromp, 1998), but the application of this approach in coastal environments is comparatively understudied. The purpose of this research is, therefore, to test the applicability of SVM in a coastal environment and compare the statistical accuracy of this approach in classifying land cover types against both ANN and MLC using medium spatial resolution imagery. Tropical coasts typically include a variety of land cover types such as coral, wet and dry sand, rock and developed areas. These land covers often possess very similar spectral signatures and transitions between types can be extremely gradual which creates significant problems in defining class separations. SVM utilizes a user-defined kernel function to map a set of non-linear decision boundaries in the original dataset into linear boundaries of a higher-dimensional construct (Huang, Davis, & Townshend, 2002). This approach could be particularly applicable to the suite of problems related to class separation that researchers typically encounter in attempting to assess coastal LCLUC and may be particularly suited to applications in tropical regions.

Study area

The study area for this research is the small Thai island of Koh Tao which is located approximately 70 km east of the mainland in the western Gulf of Thailand at 10° 05′ latitude and 99° 50′ east longitude (Fig. 1). Included are the main island of Koh Tao and several smaller surrounding islets which possess a total land area of approximately 19 km^2. The island is 4.5 km at its widest point and 7.5 km in length, and is dominated by steep granitic hills that rise to a maximum of 379 m above sea level. A coastal plain exists at the base of these hills in western and southern areas, with sandy beaches sporadically located along the island's rocky northern and eastern coastline. Land cover is dominated by secondary tropical forests in the highlands and coconut plantations at lower

Fig. 1. Koh Tao Study Area.

elevations. The island is now known as one of the busiest scuba diving centers in Southeast Asia with close to one million foreign and Thai tourists visiting annually (Prince of Songkhla University, 2005). Development has been rapid with over 2500 hotels and bungalow rooms constructed on the island since the early 1990s, and a significant percentage of this development has occurred in close proximity to the coastline.

Methods

Support vector machines

Support vector machines are based on statistical learning theory as described in Vapnik (1995). The primary objective of the SVM method is the generation of a hyperplane that represents the optimal separation of linearly-separable classes in decision boundary space. Most SVM applications involve the separation of only two classes by a decision boundary termed the optimal separating hyperplane (OSH). While many hyperplanes may exist that provide effective separation, the OSH minimizes classification generalization errors by maximizing the distance between itself and the planes representing the two classes. Discovering the OSH therefore requires an optimization solution. The *support vectors* are the data points that lie at the edge of each individual class hyperplane in feature space and are closest to the OSH (Pal & Mather, 2005; Sanchez-Hernandez et al., 2007). Suppose a set of training data with k number of samples is represented by the equation:

$$\{x_i, y_i\},\ i = 1 \ldots k \tag{1}$$

where $\mathbf{x}\ \varepsilon\ \mathbf{R}^n$ is an n-dimensional vector and $y\ \varepsilon\ \{-1, +1\}$ represents the label of each class. This set of training data can be linearly separated by a hyperplane if a vector $\mathbf{w}$ and a scalar b can satisfy the following two inequalities:

$$\mathbf{w} \times \mathbf{x}_i + b \geq +1 \quad \text{for all y} = +1 \tag{2}$$

$$\mathbf{w} \times \mathbf{x}_i + b \leq -1 \quad \text{for all y} = -1 \tag{3}$$

The two equations can also be combined in the following equation which represents a constraint that must be satisfied to achieve a hyperplane that completely and linearly separates the two classes:

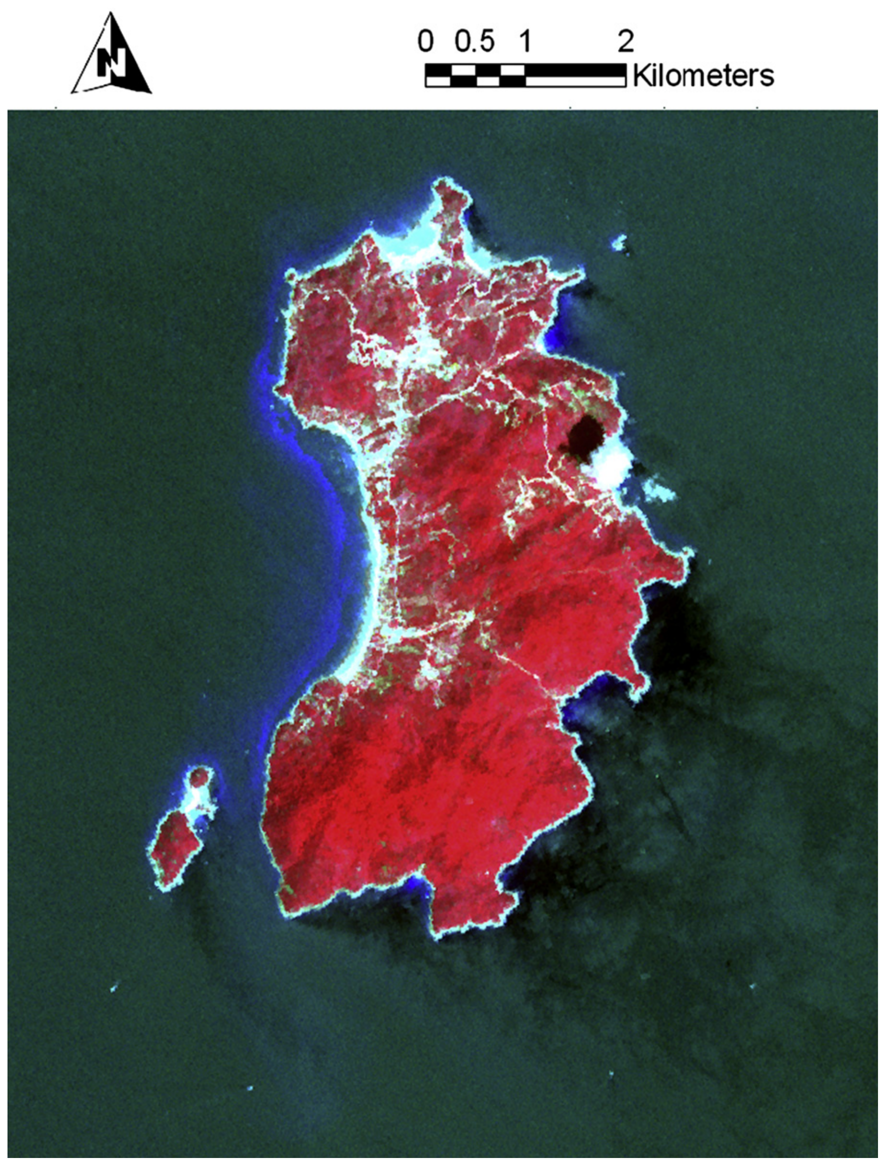

Fig. 2. False Color Composite ASTER Image.

$$\mathbf{y}_i(\mathbf{w} \times \mathbf{x}_i + b) - 1 \geq 0 \tag{4}$$

The primary objective of SVM is to find the *optimal* separating hyperplane (OSH) among all the possible hyperplanes which is accomplished through an optimization problem utilizing Lagrange multipliers and quadratic programming methods (Pal & Mather, 2004). For cases where the two classes are not linearly separable, a set of slack variables $\{\xi_i\}_{i=1}$ is introduced in order to maximize the distance between class hyperplanes and the OSH while minimizing the number of classification errors where pixels are classified onto the wrong class hyperplane:

$$\mathrm{y}_i((\mathrm{w} \times \mathrm{x}_i + b)) \geq 1 - \xi_i, \xi_i \geq 0 \tag{5}$$

Since this constraint can be met by continually increasing the value of ξ_i, a function $C\Sigma_{i=1}\xi_i$, is added to penalize solutions which exhibit a large value for ξ_i. The constant C is used to control the degree of the penalty administered for pixels that occur on the wrong side of the separating hyperplane and, as such, the optimization problem becomes:

$$\mathrm{Min}\left[\left(\left\|\mathrm{w}\right\|^2/2\right) + C\Sigma_{i=1}\xi_i\right] \tag{6}$$

In order to map nonlinear data into a higher-dimensional space for the generation of a linearly separating hyperplane, a mapping function Φ is used. Input data is therefore represented as $\Phi(x)$, which is the conversion of input vector x in feature space into a constructed space of n dimensions. This can be computationally expensive as n increases, so a kernel function is chosen:

$$K(x_i, x_j) = \Phi(x_i) \times \Phi(x_j) \tag{7}$$

This kernel function allows for the training data to be projected in a larger space where it may be increasingly possible to discover a superior separating margin for the OSH. Two commonly used kernels utilized today in SVM solutions are the polynomial-based and radial basis function (RBF) kernels. The choice of kernel used for a problem and the parameters selected can have an effect on the speed and accuracy of the classification. Previous research has demonstrated tradeoffs between different levels of performance between polynomial-based and RBF kernels (Zhu & Blumberg, 2002).

Imagery

An image from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor mounted on NASA's Terra satellite was acquired for this research. This sensor incorporates three subsystems scanning visible and near infrared, shortwave infrared, and thermal infrared spectral regions with spatial resolutions of 15–90 m. A 15-m resolution visible and near infrared image acquired on 22 June 2004 of the study area was available and selected for use in this study (Fig. 2). ASTER data has previously been used to obtain high overall accuracy using support vector machines (Zhu & Blumberg, 2002) and this platform was chosen because of its spatial and spectral resolution characteristics and the availability of a relatively cloud-free image. Clouds did obscure a small portion of the study area necessitating the creation of a limited cloud mask in the eastern portion of the island to prevent this area from being used in the training process. Red areas in the image represent the near infrared band that exhibits high reflectivity and is heavily vegetated.

Classification scheme, fieldwork and analysis

Although support vector machines typically adopt binary classification schemes (Hsu & Lin, 2002; Melgani & Bruzzone, 2004), more recent studies have investigated its use in multiclass approaches that more accurately reflect the presence of multiple land cover categories. This study adopts a multiclass scheme consisting of seven land cover types based on representativeness in the image, identified spectral differences and knowledge of the study area (Table 1). Fieldwork conducted during November 2007 produced 98 GPS points that facilitated the selection of training and testing pixels from the ASTER image. A majority of these sites were located in developed areas of the island based on this study's focus on human activities in the coastal zone. Specific areas of interest included Sai Ree on the west coast of Koh Tao and Chalok Ban Kao which is situated in the south. Both areas have hotels and tourist bungalows constructed on either rocky coastlines or on a sandy coastal plain that was previously dominated by coconut plantations. Spectrally and spatially diverse areas were chosen for training and testing to improve the validity and accuracy of classification results. A summary of pixel selection is provided in Table 1.

Table 1
Land cover and land use classification scheme and class descriptions.

Class	Description	Training pixels	Testing pixels
Coastal rock	Granitic rock formations	256	65
Vegetation	All vegetation types including tropical forest and coconut plantation	1510	85
Deep water (>3 m)	Seaward of nearshore reefs	3400	103
Shallow water (1–3 m)	Nearshore areas with sandy bottom	125	41
Sandy beach	Exposed subaerial beach	128	50
Sandy ocean bottom	Along reef edge in medium-depth water	101	45
Developed	Residential areas, commercial development, roads and infrastructure	111	90

Library for Support Vector Machines (LIBSVM) software was adopted for the SVM analysis because it has produced high-quality results and required limited training time in previous studies (Pal & Mather, 2005). Binary executables were used to create and test the training model, while analysis of the SVM parameters utilized a Python script written by the LIBSVM authors (Chang & Lin, 2001). ENVI 4.2 imagery analysis software was used for the MLC and ANN classifications. Identical training and testing pixels were used in all three classifiers to minimize evaluation bias, and an individual search for ideal parameters was conducted to obtain optimum classification results. Ground-truthing with separate testing pixels was employed to calculate overall accuracies and to produce confusion matrices. Comparisons of classification results for both computed accuracy and visual accuracy utilized *a priori* knowledge of the study site from both *in situ* fieldwork and communication with local residents. Historical aerial photography and the original ASTER image were also used for this purpose. Areas of focus for the visual search included roads, smaller developed areas embedded within larger homogenous forest classes, and developed areas along rocky and sandy coastlines which possess spectral similarities.

Results

Land cover classification maps for the 15-m resolution ASTER image were produced using MLC, ANN and SVM supervised classification techniques. Confusion matrices for each classification technique were produced to analyze class separation performance for each technique with overall accuracy assessed at 93.95%, 94.99% and 94.15% for MLC, ANN and SVM respectively (Table 2). The

Table 2
Land cover and land use classification accuracy (%) of three classifiers.

	MLC		ANN		SVM	
	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
Coastal rock	80	86.67	83.08	87.1	93.85	79.22
Vegetation	100	100	100	100	100	100
Deep water	99.03	100	100	100	100	96.26
Sandy beach	100	91.11	100	89.13	100	95.35
Shallow water	86	87.76	92	100	86	93.48
Sandy ocean bottom	100	100	100	100	93.33	100
Developed	91.11	88.17	90	88.04	84.44	96.2
Overall accuracy	93.9%		94.99%		94.15%	

similarity in overall accuracy is likely due to a combination of the land cover classification scheme utilized as well as the medium spatial resolution of the image. MLC exhibited highly accurate overall results, yet was markedly less effective in the separation of coastal rock, developed and shallow water classes. Only 52 of 65 coastal rock test pixels were classified correctly with most misclassified pixels in the developed class. This was both expected and understandable as these classes are often not definitively separated on the ground. While coastal rock that surrounds the island is usually dry, dampening can often occur as a result of wave splash and run-up. Both of these processes can encircle dry rock features in a thinly submerged layer of ocean water (Fig. 3a) and potentially affect NIR reflectivity of the entire pixel. Less densely developed coastal areas of the island can also produce spectral signatures similar to coastal rock as a result of their limited spatial footprint and use of reflective construction materials.

Results of the neural network classification paralleled those of the MLC after the training threshold contribution was reduced from 0.9 to 0.1 in ENVI (Table 2). Multiple iterations of the network proved this threshold to be the optimum value for maximizing classification performance. Only five additional pixels were correctly classified compared to MLC with deep water, vegetation and sandy oceanic bottom classes all perfectly classified. ANN did outperform MLC for both coastal rock and shallow water classes which is significant given the objectives of this study. A noticeable difference between ANN and MLC also occurred with respect to the classification of the shallow water class. These areas are unique in their potential complexity with non-uniform surface conditions, changing water depth, and particle suspension characteristics resulting from wave energy in the surf zone. The neural network classification technique performed admirably on this class, and it would appear that the dynamic and unpredictable physical nature of the surf zone is well suited to a non-parametric classification approach.

Support vector machine also produced a high overall accuracy and minimal errors for the vegetation, deep water, sandy beach and sandy ocean bottom classes (Table 2). It is, however, interesting to note that this approach performed differently than the other two classifiers with respect to the separation of developed and coastal rock areas. While there was some misclassification between the two classes in both directions for all three classifiers, commission errors for both classes using SVM were substantially less than those of MLC and ANN. Omission rates for MLC and ANN were also higher than SVM for the developed and coastal rock classes. These results indicate that the optimal separating hyperplane integral to the SVM method was oriented in a different position in feature space than the decision boundaries generated by the MLC and ANN algorithms. SVM did not, however, identify sandy

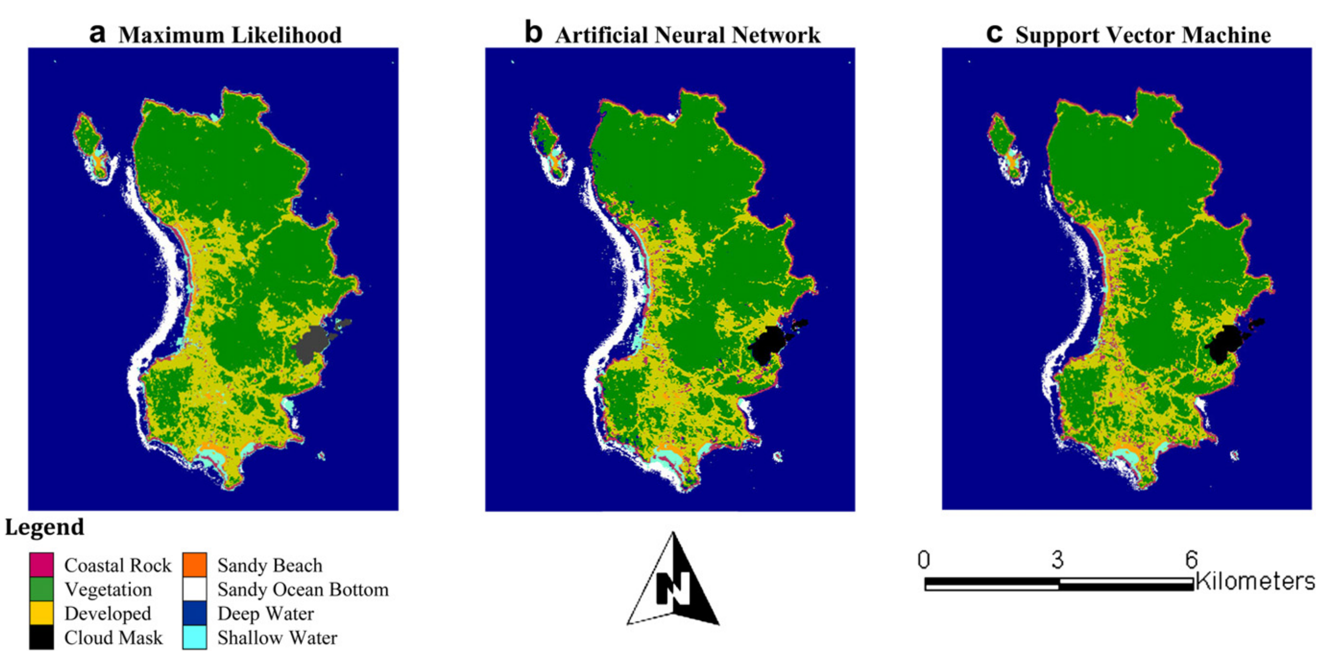

Fig. 3. Classification Images.

ocean bottom as well as the other two classifiers (Fig. 3). This error stems from a misclassification of sandy ocean bottom as deep water by SVM which is evident in the lower producer accuracy for sandy ocean bottom and lower user accuracy for deep water (Table 2). Understanding the differences in performance and trade-offs involved for each classifier is important when choosing the optimum classification tool for a given scene or application. The "correct" or "most appropriate" classifier is ultimately a subjective decision that reflects both research objectives and characteristics of the data.

Discussion

Overall classification performance

The high overall classification accuracy generated by the support vector machine in this study suggests that this approach may be useful in conducting rapid land cover analyses in coastal areas characterized by low to moderate rates of development. SVM did not, however, significantly outperform the maximum likelihood or artificial neural network classification techniques in this comparison. All three techniques were able to separate developed areas from surrounding land cover types exhibiting similar spectral signatures and generate similarly high accuracies (~94%) for the land cover classification scheme utilized in this study. Three main factors likely produced the uniformly high performance levels for all three classification techniques in this test. First, the prevalence and high separability of the deep water class undoubtedly contributed to uniformly high overall accuracy levels. An examination of the scatter plots of near infrared and visible red energy showed no spectral overlap between deep water and the other classes which supports this assumption. Second, the limited spatial representation of other classes (shallow water, sandy beach, sandy ocean bottom, developed) also likely contributed to high overall performance scores by restricting both the amount and spectral diversity of test pixels. This situation likely led to an "overfitting" of the data. Third, a single developed class was used in this study which encompassed land cover pixels representing both low density tourist bungalows surrounded by vegetation and the more urbanized small villages on Koh Tao. Small island study areas such as Koh Tao typically possess a relatively small number and diversity of pixels exhibiting different development types, and this limits opportunities to create valid multi-class tests for the developed class. Future research utilizing finer resolution imagery situated in a more heavily developed coastal area could focus on this particular issue, and could potentially reveal additional significant differences between the three classification techniques with respect to overall classification accuracy.

Individual class performance

Evaluations at the individual class level were also performed to compare the performance of support vector machine against maximum likelihood and artificial neural network techniques in classifying coastal environments with similar spectral signatures and gradual class transitions (Table 2). Specific class comparisons included:

- developed areas versus coastal rock,
- developed areas versus vegetation, and
- developed areas versus sandy beach.

The support vector machine performed well in separating the developed and coastal rock classes. Coastal rock was correctly classified for 93.85% of the test pixels while the developed class was correctly classified for 84.44% of all test pixels. Each classified set of this binary pair also included incorrectly classified test pixels which suggests that support vectors for each class were not linearly separable with one hyperplane due to spectral similarities. Examination of the scatter plot (Fig. 4a) of visible red and near infrared bands clearly reveals significant overlap in feature space of these two land cover types. MLC misclassified an equal number of test pixels incorrectly as compared to SVM while ANN misclassified just three additional pixels. These results suggest no clear advantage of SVM for this particular binary class separation, but visual inspection of the classified images (Fig. 3) revealed that MLC misclassified substantially fewer inland developed areas as coastal rock than either ANN or SVM.

The pattern of development between Sai Ree along the western coast to Chalok Ban Kao in the south portion of Koh Tao was also effectively separated from the adjacent vegetation and coastal rock perimeter in all three classifications. It was expected that high density developed areas such as Mae Haad would be easily separable, but we anticipated some degree of misclassification between areas of vegetation and those possessing lower density development (e.g., bungalows and small-scale construction interspersed

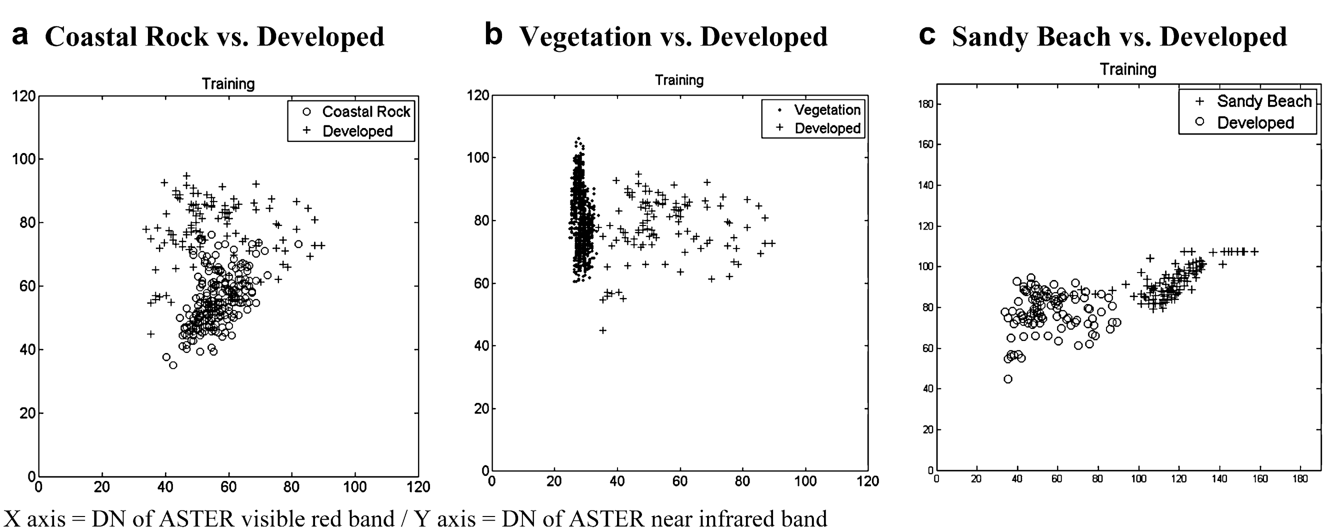

Fig. 4. Scatter Plots of Training Pixels. X axis = DN of ASTER visible red band/Y axis = DN of ASTER near infrared band.

among grass and trees). Surprisingly, all areas of development irrespective of density were accurately separated from vegetation by all three of the classification techniques. This result was produced by a clear separation in feature space and training pixel selection (Fig. 4b). Analysis of post-classification confusion matrices suggest that the support vector machine is somewhat better suited to separating areas of low to medium development from coastal rock and sandy beach, but minimal differences in accuracy existed between the three techniques for this class comparison. It would be useful to perform additional analysis on other images at the same site over different time periods to support this result. This would confirm whether our findings are indicative of a true performance advantages for the support vector machine as opposed to random data noise or imagery error.

Tropical coastal areas that host significant tourism infrastructure typically display a significant amount of development along sandy beaches and Koh Tao is very representative of this generalization. The analysis of confusion matrices once again revealed no significant performance advantage for SVM over the other techniques with respect to the separation of the development and sandy beach classes. All three techniques proved highly accurate in this test with very few misclassified pixels in either direction. Examination of the scatter plot (Fig. 4c) and visual inspection of the classified images revealed that SVM misclassified fewer pixels as sandy beach in the southern road confluence than either MLC or ANN. This suggests a slight performance improvement associated with the support vector machine in this particular class separation, but it would be useful to test this potential performance advantage against a larger data set from similar shorelines to confirm these results.

Conclusions

Coastal areas in the tropics often display a fragmented, heterogeneous landscape arising from absent or ineffective local planning or planning directed from geographically distant institutions (Olsen & Christie 2000). Monitoring land cover to detect development trends is, therefore, highly useful in this context and remote sensing technology can certainly play an important role in the analysis of land use and land cover change. The findings of this study suggest that the support vector machine can perform adequately as coastal land cover classification tool using medium-scale imagery. Although SVM did not produce significantly better results than the MLC or ANN techniques, it did produce a “tighter” fit for classifying coastal rock and produced fewer commission errors in classifying developed areas than either MLC or ANN. The support vector machine also performed slightly better than MLC and ANN with respect to important binary separations such as developed versus coastal rock and developed versus sandy beach. These distinctions may be important for future studies monitoring coastal change in tropical coastal environments similar to Koh Tao. Although the focus of this study was the relative performance of the support vector machine image classification technique in a tropical coastal environment, a combination of classification rules from multiple classifiers could also potentially produce excellent classification accuracies. This approach is not uncommon in LCLUC studies (Li, Hu, & Li, 2008) and future research could specifically target the relative benefits of including SVM in a multiple classifier approach situated within a tropical coastal environment. As coastal development continue to increase as a result of current population trends, it is important that future studies in applied geography continue to investigate classification tools such as SVM which support planning efforts that attempt to balance socioeconomic needs and conservation goals.

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