LOCAL SPATIAL STATISTICS FOR REMOTELY SENSED IMAGE CLASSIFICATION OF MANGROVE

LIU Zhi-gang [a], LI Jing b, LIM Boon-leong [c],
SENG Chung-yueh [c], INBARAJ Suppiah [c], SUN Zhichao[a]

[a] State Key Laboratory of Remote Sensing Science (Beijing Normal University), Beijing, 100875, China;
[b] College of Resources Science and Technology, Beijing Normal University, Beijing, China;
[c] Cilix Corporation Sdn Bhd, 1st Floor Resource C, Tech Park Malaysia 57000, Kuala Lumpur

KEY WORDS: Mangrove, Remotely Sensed Image, Classification, Texture, Local Spatial Statistics

ABSTRACT:

As the spatial resolution improvement in remotely sensed imagery, more detail spatial information of mangrove forest can be shown. It is important to find a method, which can effectively use the spatial information to improve the accuracy of mangrove forest classification. In the study, SPOT-5 image of Matang Mangrove Forest Reserve in Malaysia has been used in the mangrove forest classifications, to study the influence of different spatial features. It is shown that influence of first-order （including entropy-1） and second-order texture features (including entropy-2, energy and homogeneity) to classification with Maximum Likelihood Classifier (MLC) and Support Vector Machine (SVM) are different. The involvement of texture features will reduce the classification accuracies with SVM. Meanwhile, the classification accuracies with MLC will mostly improve slight, if texture features (except the energy texture) are involved. In this research, a local spatial statistics, local Moran's I index, was also tested. The Moran index are different from texture features, because the distance between pixels is considered in their calculation. The results shown that the Moran index calculated from multispectral image and panchromatic image can all improve obviously the classification accuracy of both MLC and SVM. For example, when the Moran index calculated from multispectral image with 7x7 kernel window are involved in the classification of SVM and MLC with spectral features, the accuracies will become 75.2% and 77.5% respectively, which are improved about 3.5% and 6.9% respectively. Our results show that it is necessary and important to find effective spatial features from high resolution remotely sensed image to improve the mangrove classification accuracy.

1. INTRODUCTION

1.1 General Instructions

Mangrove forest is an essential ecological coastal zone area of ecology with high-productivity, high-return and high decomposition rate. It is an ideal habitat that not only provides marine life food and shelter but also protects shoreline from erosion and purifies wastewater containing pollutant concentration. Mangrove forest therefore has important ecological, environmental and economical values (Zhang, 2001; Green, 1998). However, mangrove area is of drastic reduction as a result of the human caused pollution and irrational development. According to the statistics, approximately 73% (Zhang, 2001) of natural mangrove forest in China has been reduced since the 1950s. Consequently, the monitoring and protection mangrove forest should be given the top priority.

In order to prompt a timely and effective monitoring and management of mangrove forest resource, an immediate, accurate and cost reasonable mangrove forest cartography technique is necessary. Remote sensing technology is capable to realize the mangrove forest information gathering in wide range scale. However, a key point always been concerned and studied among scientist researches in this sophisticated technology is the method to enhance the accuracy of remote sensing image and the level of automation in mapping. At early time, remotely sensed data utilized in mangrove forest investigation was aerial photos, which mainly depended on manual interpretation. In 1980s, Landsat and SPOT satellite imageries were used for the researche of mangrove forest remote sensing mapping (Green, Clark, 1998). Researchers have attempted different methods to obtain ideal classification accuracy. Gao (1998) proposed a "two-tiered" classification methodology to utilize SPOT imagery to classify mangrove forest located at New Zealand Waitemata port, where 81.4% accuracy of mangrove and non-mangrove forests has been assessed . Green et al. (1998) examined five classification methods using TM, SPOT, airborne hyperspectral data (CASI) and the accuracies to differentiate mangrove and non-mangrove forests using SPOT XP and TM data are approximately 25% and 80% respectively. Accuracy to differentiate 9 mangrove forest types obtained from TM and SPOT XP are less than 25%, where higher classification accuracy has been obtained from CASI by about 80% accuracy . Gao (1999) research revealed that if only utilize SPOT XS data in high dense and low mangrove forest cartography, accuracies of 77.5% and 67.5% were obtained respectively, and accuracy increased to 80% when fused with 10m resolution SPOT PAN data. This indicated spatial resolution is important to enhance accuracy in mangrove forest remote sensing classification.

With existence of high resolution satellite imagery such as SPOT-5, IKONOS and Quickbird and so on, the spatial resolution of remote sensing image have been significantly improved, much detailed mangrove forest spatial information could be manifested from imagery. That provides an opportunity to improve the accuracy of mangrove forest classification .Wang et al. (2004) analyse the impacts of the classification accuracy by adding texture features, when they utilized IKONOS and Quickbird image to classify three kinds of mangrove, black, white and red. The results show that the involvement of first-order texture features can improve the classification accuracy at a certain extent, but the adding of second-order can not improve classification accuracy efficiently. The researches indicated that it is important to find a method, which can effectively use the spatial information in remote sensing image of high spatial resolution to improve the accuracy of mangrove forest classification cartography. In this study, SPOT-5 image of Matang Mangrove Forest Reserve in Malaysia has been used in the mangrove forest classifications. In order to make the best use of local spatial characteristics, not only the first-order/second–order texture features but also a kind of local spatial statistics –local Moran's I index (Getis, 1992) were used in this study. This paper analyses the influence of the classification accuracy with different spatial features based on the experiment.

2. STUDY AREA AND DATA PROCESSING

2.1 Study Area

Matang mangrove forest located at West Coast Peninsula of Malaysia with North latitude 4^{o}15'- 5^{o}1' and East longitude 100^{o}2'-100^{o}45'. Matang mangrove forest reserve systematized management started as early as 1904, and gazetted as the best conserved mangrove forest reserve in the world. This mangrove forest reserve is divided into four sub-areas from North to South: North Kuala Sepetang, South Kuala Sepetang, Kuala Trong and Sungai Kerang. Among these sub-areas, Sungai Kerang is formed as an island, where its interior is consists of inland vegetations and surrounded by different mangrove forests. Sungai Kerang has been chosen as study area since its mangrove types is abundant comparing other three sub-areas (Figure 1).

Figure 1. SPOT-5 image of Sungai Kerang

2.2 Data

SPOT multispectral (XP) and panchromatic (PAN) image data were used in the experiment. These data gained on 30th January 2005 with both 10m multispectral image and 2.5m panchromatic image. Firstly, multispectral and panchromatic images were fused by advanced HIS fusion algorithm [13] before correction conduction using control points gathered from DGPS and topographic map. The multispectral image was rectified based on corrected fusion image. In order to achieve higher accuracy, both geometric correction mean square errors were maintained within a single pixel.

This study divided study area landcover into 9 classes, after referred to forest classes defined in Matang mangrove forest reserve plan and combined with field investigation circumstances. These classes are including 6 mangrove forest types: accreting *Avicennia* forest, transitional new forest, *Bruguiera cylindrica* forest, *Bruguiera parviflora* forest, *Rhizophora* forest and dryland. Table 1 has described specification of each class and their abbreviation. The study chose training and test samples separately, according to the results of Matang mangrove forest reserve management information and field investigation (Table 2).

Class Name (Abbreviation)	**Specification**
Accreting Avicennia Forest (Avic)	These forests are characterised by young stands of *Avicennia* species invading the mud flats of estuaries and foreshores. Common species include *Avicennia alba* and *A. marina* that are sometimes interspersed with *Sonneratia*, *Rhizophora* and *Brugguiera* species.
Transitional New Forest (T-New)	This type consists of the older accreting *Avicennia* forest, which carries in it intermittent stands of both *Rhizophora* and *Bruguiera* species in varying proportions.
Bruguiera cylindrica Forest (B-Cyl)	These forests usually consist of pure stands of *Bruguiera cylindrica* with small populations of *Rhizophora* and other *Bruguiera* species.
Bruguiera parviflora Forest (B-Pav)	These forests usually comprise a mixture of *Brugguiera parviflora* with *Rhizophora* species towards the mainland and *Bruguiera cylindrica* towards the seafront.
Rhizophora Forest (Rhiz)	The forest is the major forest type in Matang Mangroves. It consists predominantly of *Rhizophora apiculata* and *R. mucronata*, two main commercial species. This forest is characterised by trees with straight boles and even canopy heights.
Dryland Forest (Dryland)	This type consists of two sub-types: "transitional dryland forest" and "true dryland forest". The former contains a mixture of sparse stands of *Rhizophora* species and a large population of relic *Bruguiera* species with a dense crop of *Acrostichum* ferns on the forest floor. The later denotes the final stage of mangrove succession and the transition into inland forest type. Structurally, it consists of three canopy layers, namely emergent, main canopy and understorey.
Inland Vegetation (Inland)	This type mainly consists of coco and pineapple, which distribute in interior area of the island, where never covered by sea water.
River	Rivers.
Others	This type consists of bare land and building area.

Table 1. Classes definitions and their abbreviation

Type	Training sample (pixels)	Test sample (pixels)
Avic	203	4354
T-New	140	540
B-Cyl	254	2358
B-Pav	151	955
Dryland	302	939
Rhiz	276	5208
Inland	306	1368
River	131	318
Others	122	337

Table 2. Training and test sample size for SPOT-5 XP images

3. CLASSIFICATION METHOD

3.1 Classification features

Both spectral and spatial features have been used in classification experiments. All features have been normalized. Value of each image band pixel is considered as spectra feature. The spatial features include texture features and local spatial statistics. The study adopted the first-order and second-order texture features which are in common use (Baraldi, 1995). The first-order texture feature includes entropy-1(Et-1), whereas second-order texture consist homogeneity (Hm), energy (En) and entropy-2 (Et-2). The general definition of local spatial statistics is as follows (Anselin, 1995; Getis, 1992):

$$\Gamma_i = \sum_{j=1}^{N} \omega_{ij} \xi_{ij} \tag{1}$$

Where Γ_i is the measure for location i defined in terms of spatial similarity in one matrix ω_{ij} and value similarity ξ_{ij} which capturing the interaction between the attribute values at locations i and j. N is the number of pixels within the neighbourhood of pixel i. ω_{ij} is usually defined as the reciprocals of distance between pixel i and pixel j. The definition of ξ_{ij} is of multiplicity. In this paper, ξ_{ij} is defined as (Getis, 1992):

$$\xi_{ij} = \left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right) \tag{2}$$

Where $\bar{x}$ is the average property of pixels within the neighbourhood. The feature based on the formula (1) (2) is named as “local Moran’s Index” (Getis, 1992), hereinafter referred to it as Moran (abbreviated as Mo). Moran’s I is a kind of local spatial statistics indicator, which reflect the level of cluster in the image. If the index is positive, then the property values of local pixels are similar. Contrarily, if the index is negative, then the property values are of large difference. First-order/second-order texture features consider the pixels in one window as equality, but the Moran index is different from texture features, because the distance between pixels is considered in their calculation.

3.2 The Classification Schemes

To study the effectiveness of different spatial features, spectral features were firstly used in classification experiments. Then, different spatial features calculated with multispectral images (XS) and panchromatic image (PAN) were included respectively. When calculated the multispectral image texture feature, 3 different window sizes selected are 3x3, 5x5 and 7x7. Larger window sizes of 5x5, 9x9 and 13x13 were replaced during panchromatic image texture calculation. Classification was implemented using maximum likelihood (MLC) and support vector machine (SVM) classifiers (Cortes, 1995; Vapnik, 1998). SVM implemented RBF kernel function, its penalty coefficient and kernel function width through cross-validation method to obtain best value (Anguita, 2000; Vapnik, 1998). One-versus-Rest multiple classification strategies were implemented in SVM classification (Bottou, 1994).More details of the classification scheme are shown in Figure 2.

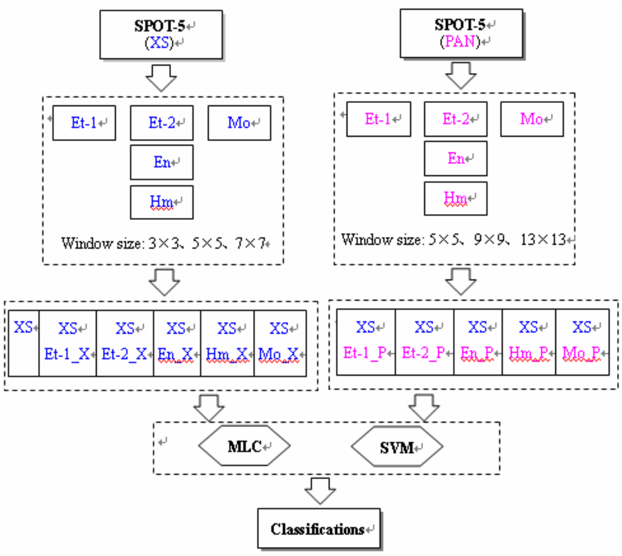

Figure 2. Classification Schemes

4. RESULTS AND DISCUSSION

Table 3 shows the classification accuracies of different classification schemes. It is shown that the influences of texture features to classification with the two classifiers are different. For MLC, all kinds of texture features except energy increased the classification accuracy, and the highest increment is 2.1% which owe to Hm. The classification accuracies of SVM with just spectral feature are 5.6% higher than MLC. However, the accuracies for SVM classification method decreased obviously when any texture features were included. The influence of second-order to classification is obviously larger than first-order. When energy calculated with multi-spectral image (window size of 3x3) is included, the classification accuracy of SVM dropped from 73.9% to 62.6%, even lower than the accuracy of MLC.

However, the involvement of local spatial statistic Moran’s I enhance the classification accuracies obviously both with MLC and SVM. For example, when the Moran index calculated from multispectral image with 7x7 kernel window are involved in the classifications of SVM and MLC together with spectral features, the accuracies will become 75.2% and 77.5% respectively, which are improved about 3.5% and 6.9% respectively (Table 3 and Figure 3). For MLC classification method, the increment of classification accuracy of Moran index calculated from multispectral image is larger than that from panchromatic image. But for SVM classifications, the improvements are similar.

Window Size	Feature	Accuracies MLC	SVM
-	XS	68.3	73.9
3×3	XS + Et1_X	69.1	72.1
	XS + Et2_X	67.6	67.2
	XS + Hm_X	69.3	64.2
	XS + En_X	65.7	62.6
	XS + Mo_X	73.3	75.5
5×5	XS + Et1_X	71.0	70.1
	XS + Et2_X	69.7	69.4
	XS + Hm_X	70.4	69.5
	XS + En_X	66.6	67.6
	XS + Mo_X	74.1	76.8
7×7	XS + Et1_X	71.0	72.2
	XS + Et2_X	70.0	67.0
	XS + Hm_X	70.3	69.2
	XS + En_X	67.4	67.6
	XS + Mo_X	75.2	77.5
5×5	XS + Et1_P	69.6	71.3
	XS + Et2_P	68.8	72.5
	XS + Hm_P	69.0	73.3
	XS + En_P	67.9	72.8
	XS + Mo_P	69.1	75.8
9×9	XS + Et1_P	69.2	72.1
	XS + Et2_P	69.1	73.2
	XS + Hm_P	70.4	71.5
	XS + En_P	69.3	71.8
	XS + Mo_P	69.1	76.1
13×13	XS + Et1_P	69.7	72.5
	XS + Et2_P	69.1	73.0
	XS + Hm_P	70.4	71.7
	XS + En_P	69.3	71.8
	XS + Mo_P	69.1	76.1

Table 3. Classification Accuracies
(The features with "_X" are calculated with multispectral images. The feature with "_P" are calculated with panchromatic image.)

5. CONCLUSION

In this study, SPOT-5 image of Matang Mangrove Forest Reserve in Malaysia has been used in the mangrove forest classifications, to study the influence of different spatial features. It is shown that influence of first-order (including entropy-1) and second-order texture features (including entropy-2, energy and homogeneity) to classification with MLC and SVM are different. The involvement of first-order/second-order texture features reduced the classification accuracies of SVM. However, the classification accuracies of MLC mostly improved, if texture features are involved. Also, the study adopted a local spatial statistic—Moran's Index which is different from texture features, because the distance between pixels is considered in their calculation. The results shown that the Moran index calculated from both multispectral image and panchromatic image can all improve obviously the classification accuracy of both MLC and SVM.

The results show that different spatial features have different role in the classification. Moreover, the influences are different for different classifiers. The increment of the classification accuracy with Moran is much higher than the commonly used texture features. Therefore, we can reach two conclusions: 1) Local Moran Index is an effective spatial feature to improve the performance mangrove classification; 2) it is necessary and important to find effective spatial features from high resolution remotely sensed image.

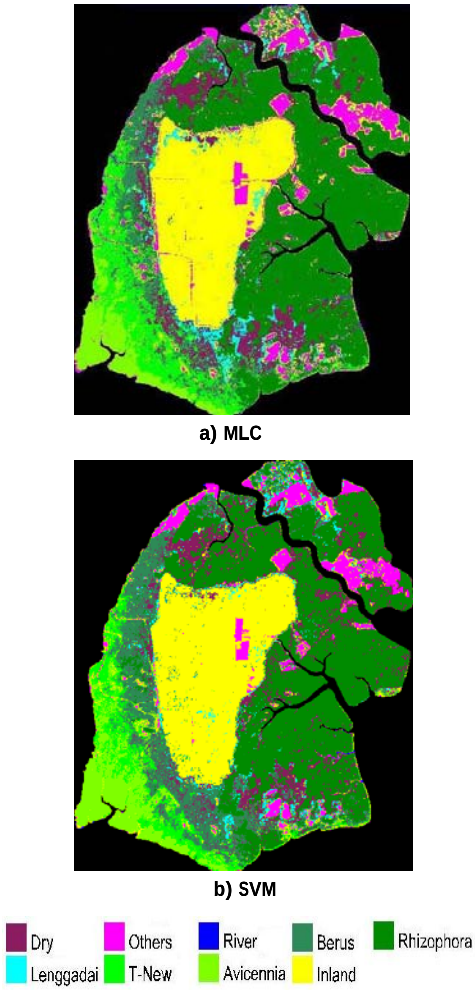

Figure 3. Classification Results (SPOT5 XS + Moran7x7)

REFERENCES

Anguita, D., Boni, A., Ridella, S.,2000. Evaluating the generalization ability of support vector machines through the bootstrap. *Neural Process*, 11, pp. 51-58.

Anselin, L.,1995. Local indicators of spatial association – LISA. *Geographical Analysis*, 27(2), pp. 93-115.

Anys, H., Bannari A., He, D.C., and Morin, D.,1994. Texture analysis for the mapping of urban areas using airborne MEIS-II images. *Proceedings of the First International Airborne Remote*

Sensing Conference and Exhibition, Strasbourg, France, 3, pp. 231-245.

Baraldi, A., Parmiggiani, F.,1995. An investigation of the textural Characteristics associated with gray level cooccurrence matrix statistical parameters. *IEEE Trans. On Geoscience and Remote Sensing*, 33(2), pp. 293-304.

Bottou, L., Cortes, C., Dcnkcr, J., Druckcr, H., Guyon, I., Jackcl, L., Cun, Y., Muller, U., Sackingcr, E., Simard, P., and Vapnik, V.,1994. Comparison of classifier methods: A case study in handwriting digit recognition. In: *International Conference on Pattern Recognition.* IEEE Computer Society Press, 77-87.

Cortes, C., Vapnik, V.,1995. Support Vector Networks. *Machine Learning*, 20, pp. 273-297.

Gao, J.,1999. A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. *International Journal of Remote Sensing*, 20(14), pp. 2823-2833.

Gao, J.,1998. A hybrid method toward accurate mapping of mangroves in a marginal habitat from SPOT multispectral data. *International Journal of Remote Sensing*, 19(10), pp. 1887-1899.

Getis, A., Ord, J K.,1992. The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), pp. 189-206.

Green, E.P., Clark, C.D., Mumby, P. J., Edwards, A. J., Ellis, A.C.,1998. Remote sensing techniques for mangrove mapping. *International Journal of Remote Sensing*, 19(5), pp. 935-956.

Siddiqui, Y.,2003. The modified IHS method for fusing satellite imagery. ASPRS Annual Conference Proceedings, Anchorage, Alaska.

Vapnik, V.N.,1998. *Statistical Learning Theory*. New York, Wiley.

Wang, L., Wayne, P.S., Gong, P., Gregory, S.B.,2004. Comparison of Ikonos and Quickbird Images for Mapping Mangrove Species on the Caribbean Coast of Panama. *Remote Sensing of Environment*, 91, pp. 432-440.

Zhang, Q.M., Sui, S.Z.,2001. The mangrove wetland resources and their conservation in China. *Journal of Natural Resources*, 16(1), pp. 28-36.

Zhang, X.L., Li, P.Y., Xu, X.Y.,2005. Present conditions and prospects of study on coastal wetlands in China. *Advances in Marine Science*, 23(1), pp. 87-95.

ACKNOWLEDGEMENTS

We thank Malaysia Centre for Remote Sensing (MACRES) for providing data and arrangement of field survey. We also thank Matang Mangrove Forest Reserved Department for assistance in the field survey and reports of the study area. This work is partially supported by the National Natural Science Foundation of China (40701101), The National High Technology Research and Development Program of China (2006AA12Z145), National Key Project of Scientific and Technical Supporting Programs(2006BAJ09B01), National Key Basic Research Program (2007CB714403), Open Research Fund of State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (WKL(07)0103).