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Technical Note

Evaluation of supervised classification algorithms for identifying crops using airborne hyperspectral data

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Sufficient training data must be acquired to classify areas of interest using a supervised classification method and hyperspectral data. However, the relatively small size of agricultural plots in Japan means that there is no training area large enough to represent a feature of interest. In this study, a new method for identifying crops using hyperspectral remotely sensed data has been proposed in order to resolve the problem of identifying training areas in agricultural crops. This method was then compared with conventional methods. The proposed method was found to be most effective for identifying crops using hyperspectral data in an agricultural land area.

1. Introduction

Remote sensing has shown great promise in identifying the crops grown in agricultural land. The resultant information has been found to be useful in the prediction of crop production and of land use change (Myers 1983, Steve and Clark 1990, Owe and D'Urso 2002, Omasa *et al.*, in press). Furthermore, recent advances in agricultural remote sensing include applications in sustainable agriculture, such as precision farming, agroforestry, and land conservation. These are closely related to applications in forestry, ecology, hydrology, and environmental management (Hobbs and Mooney 1990, Rencz 1999, Owe and D'Urso 2002, Omasa *et al.*, in press).

Advancement in sensor technology has led to development of new tool, i.e. mapping spectrometry from air- and space-borne platforms (Campbell 1996, Omasa *et al.*, in press). Although broad categories of interest such as crop, urban, water bodies, and soil areas can be classified using multi-spectral sensors, such as the Landsat Thematic Mapper (TM) and SPOT High Resolution Visible (HRV), identification of crops or soils with subtle differences in spectral response pattern will not be achieved. This is because multi-spectral sensors like TM and HRV have a limited number of spectral channels and coarser spatial resolution. So, imaging spectrometry with very narrow and several spectral bands may offer potential in this endeavour. Currently, airborne hyperspectral sensors, which can acquire hyper-spectral and hyperspatial imagery, are the most effective way to classify various crops and soils in agricultural land.

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In studies using hyperspectral imagery data, arid vegetation has been discriminated (Lewis *et al*. 2001), and green and dry vegetation components have been identified (Datt 2000). Furthermore, Cochrane (2000) has classified vegetation at species level using hyperspectral signatures. He used the discrimination methods proposed by Price (1994) to calculate the root-mean-square difference and shape difference between spectral signatures of a particular vegetation and a reference species. However, the spectral signatures used were not remotely sensed data measured by satellite or aircraft; rather, the data were measured by using a portable spectral radiometer. In addition, these methods were effective for distinguishing specific types of vegetation from each other, but they have not been applied to identify various types of vegetation using hyperspectral remotely sensed imagery.

In this study, a new supervised classification method is proposed for identifying crops at the species level in Japanese agricultural land by using hyperspectral data. In general, it is important to identify a large number of training sets to classify a particular crop or soil category by a supervised classification method using hyperspectral data. However, because agricultural plots in Japan are too small, it is difficult to find adequate number of sufficiently large training area for each category of interest. It calls for development of a new method for accurate classification, even in the absence of sufficient number of training data in the area of interest. The proposed method has also been compared with the existing conventional methods.

2. Study area and data used

2.1 *Characteristics of the Miura peninsula*

The Miura peninsula is located in the south of Tokyo bay (figure 1) and, because of its mild climate, has been developed as an agricultural area devoted mainly to vegetable growing. The main crops are radish and cabbage in the winter and watermelon, melon, and hard squash in the summer. Various fruits, flowers, and animal products are also produced. In addition, the cultivation of vegetation such as marigold (*Tagetes*) has increased recently because this flower is adequate for agricultural or environmental conservation.

2.2 *Hyperspectral data*

Figure 2 shows hyperspectral image used to develop a new supervised classification method and to compare it with conventional supervised classification methods in the agricultural area of the Miura peninsula. The image was acquired on 27 July 2002. The data were measured by Airborne Imaging Spectroradiometer for Application (AISA), which is a hyperspectral sensor with a 2-m spatial resolution, developed by Spectral Imaging Ltd. The wavelength range is 0.43–1.0 μm, with a maximum of 512 spectral bands. In this study, 70 spectral bands were used within the range of 0.43–1.0 μm. The AISA sensor head includes a fibre optic probe (FODIS) for real-time monitoring of downwelling solar irradiance to calculate the apparent reflectance of the Earth's surface (Omasa *et al*., in press).

2.3 *Training and test data for classification*

To determine the training and test areas in which to analyse supervised methods using hyperspectral imagery as shown in figure 2, a ground survey was carried out on 14 August 2002. In this study, a total of seven categories (maize, watermelon,

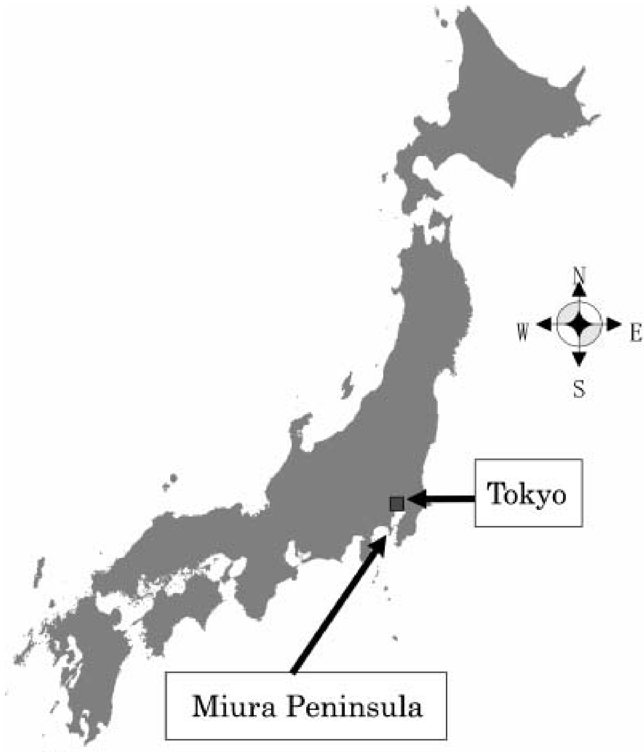

Figure 1. Location of the Miura peninsula in Japan.

tree, marigold, soil 1, soil 2, and building) were used in the evaluation of each supervised method. Figure 2(*a*) and (*b*) shows the training and test areas of each category, and table 1 shows the number of pixels in each category used in the training and test data. Because soil 1 and soil 2 differed in their spectral radiance, we selected these soils as the training data. Figure 3 shows the average spectral radiance of each of the seven categories in the training and test areas.

From table 1, we can see an inability to collect many pixels for each category from the agricultural land area of the Miura peninsula. We need a lot of training data in order to accurately classify land area using conventional supervised methods such as maximum likelihood classification. In particular, more training data are needed when supervised methods with hyperspectral data are used (Malek *et al*. 2002).

3. Classification methods

Four supervised classification methods—(1) maximum likelihood (MLH), (2) Euclidean shortest distance (MED), (3) shape difference (SD), and (4) MED-SD—were selected in this study to evaluate the accuracy of the classification of agricultural land using hyperspectral data. MLH and MED have been used as conventional methods for analysing multispectral data such as Landsat TM and SPOT HRV. SD was recently proposed as a method for hyperspectral data (Price 1994, Cochrane 2000). In this study we propose MED-SD as a new method for analysing hyperspectral data. The characteristics of these methods are described below.

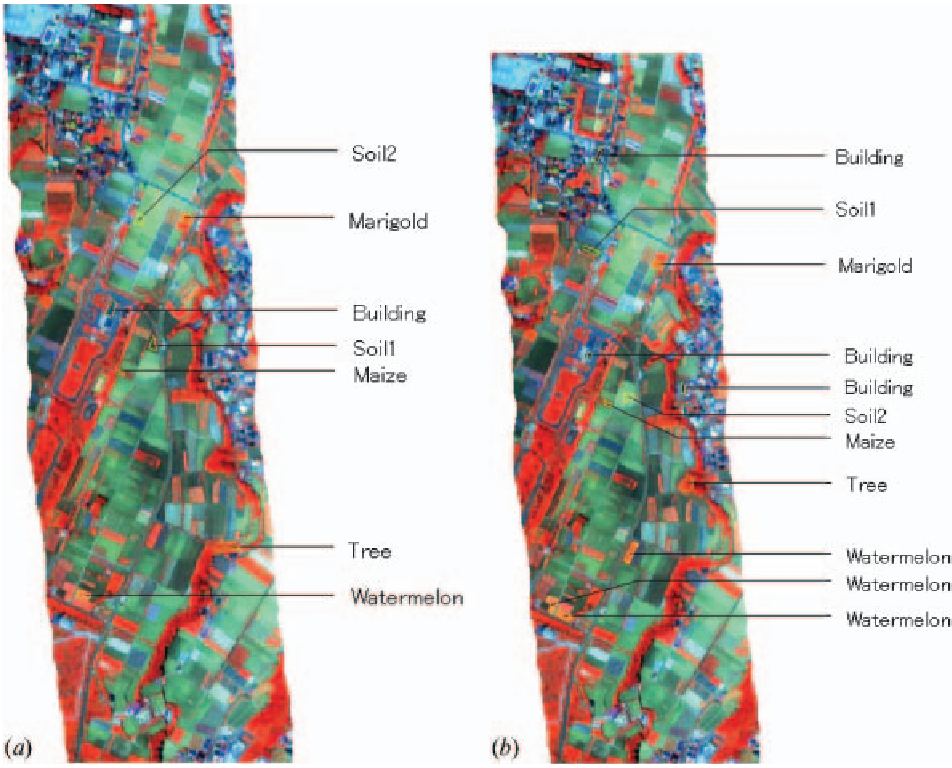

Figure 2. Hyperspectral image of agricultural land of Miura peninsula observed on 27 July 2002.

3.1 *MLH*

The MLH (maximum likelihood) method has been widely used for remote sensing classification. In particular, the method has been used to classify multispectral imagery such as that of the Landsat TM. The principle of MLH is based on Bayes' decision rule. Thus, when spectral radiance data $x=(x_1, x_2\ldots, x_n)^t$ with n bands is classified into k types of categories (w_1, w_2,…., and w_k), the data x is classified into the category w_i, where the value of discriminant function $f_{wi}(x)$ as in the following equation is smallest.

Table 1. Number of pixels in each category used in the training and test data.

	Maize	Watermelon	Tree	Marigold	Soil 1	Soil 2	Building
(a) Training data							
Number of pixels	27	102	176	73	68	85	106
Area (ha)	0.011	0.041	0.070	0.029	0.027	0.034	0.042
(b) Test data							
Number of pixels	41	379	139	64	85	100	136
Area (ha)	0.016	0.152	0.056	0.026	0.034	0.040	0.054

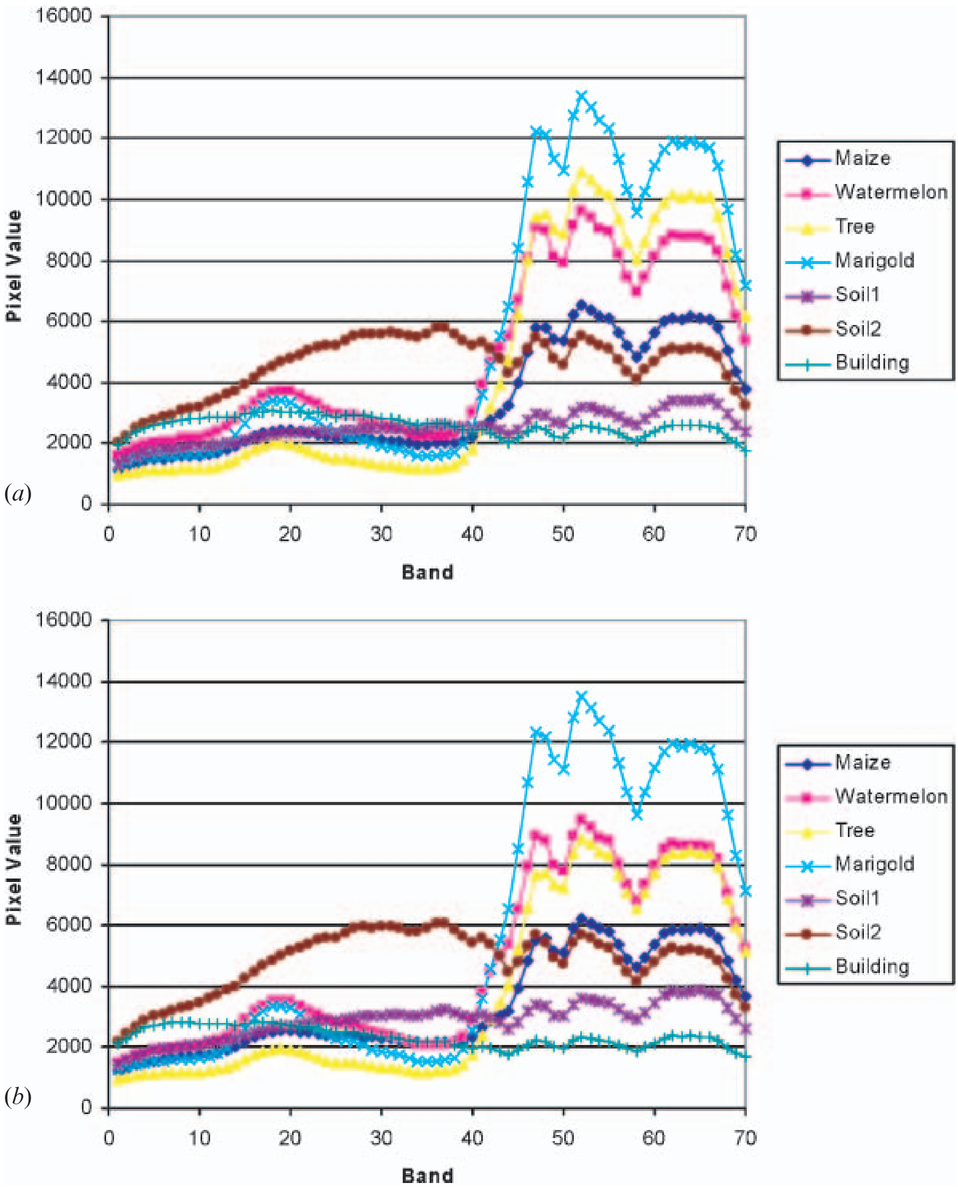

Figure 3. Average spectral radiances of each category in the (*a*) training and (*b*) test areas.

Discriminant function:

$$f_{wi}(x) = (x - m_i)^t S_i^{-1} (x - m_i) + \ln|S_i| \tag{1}$$

where m_i is the average spectral radiance of category w_i calculated from the sample in the training area, S_i is the dispersion covariance matrix of category i, and t stands for transpose.

Because the MLH method is based on statistical theory, it has been used well to classify multispectral imagery. However, it has been reported that an abounding number of samples of each category in the training area is necessary for accurate classification using hyperspectral data (Malek *et al.* 2002). Therefore, it may not be appropriate to use this method for agricultural land, such as that at our study site, with its considerably small numbers of samples in each category (table 1).

3.2 *MED*

Like MLH, the MED (Euclidean shortest distance) method has been used to classify multispectral imagery. The value of discriminant function $f_{wi}(x)$ as shown in the following equation is smallest.

Discriminant function:

$$f_{wi}(x) = (x - m_i)^t (x - m_i) \tag{2}$$

where x is the measured spectral radiance with n bands, m_i is the average spectral radiance of category w_i calculated from a sample in the training area, and t stands for transpose.

It has been reported that the classification result of MED is better than that of MLH when there are few samples of each category, because of the simplicity of MED's discriminant function, which uses only the mean of a sample in the training area as statistical information (Fujimura and Tsubaki 1985). Furthermore, it has been reported that the effects of mixed pixels, which contain various categories within single pixels, are comparatively small when remotely sensed imagery was classified with MED (Ishida and Inamura 2002).

3.3 *SD*

The SD (shape difference) method has been used to identify categories using hyperspectral data (Price 1994, Cochrane 2000). The value of discriminant function $f_{wi}(x)$ as shown in the following equation is smallest.

Discriminant function:

$$f_{wi}(x) = \cos^{-1}\left(\frac{\sum_n x m_i}{\sqrt{\sum_n x^2 \sum_n m_i^2}}\right) \tag{3}$$

where x is the measured spectral radiance with n bands, m_i is the average spectral radiance of category w_i calculated from the sample in the training area.

It is found that SD considers the similarity of spectral radiance to classify each category from equation (3). From equation (3), the spectral radiances of the two categories have identical shapes when the value of the discriminant function is zero, but these categories are not always the same because various effects, such as the angle of view, atmospheric properties, spectral mixture, and illumination angle can change the spectral radiance (Price 1994, Cochrane 2000).

3.4 *MED-SD*

MED-SD is this study's proposed method to classify categories using hyperspectral data. It is considered to combine characteristics of MED and SD. In particular, MED-SD normalizes each value calculated from equations (2) and (3) and adds them together. The value of discriminant function $f_{wi}(x)$ as shown in the following equation is smallest.

Discriminant function:

$$f_{wi}(x) = \frac{D_i - D_{\min}}{D_{\max} - D_{\min}} + \frac{\theta_i - \theta_{\min}}{\theta_{\max} - \theta_{\min}} \tag{4}$$

where $D_{\max}$ and $\theta_{\max}$ are the maximum values of each pixel calculated from equations (2) and (3), respectively, $D_{\min}$ and $\theta_{\min}$ are the respective minimum values of each pixel calculated from those equations, and D_i and θ_i are the respective values of each pixel calculated from those equations.

4. Evaluation of methods

4.1 *Analytical procedure and evaluation*

To compare the accuracy of the four supervised classification methods using hyperspectral data for agricultural land of the Miura peninsula, a set of seven categories, namely maize, watermelon, tree, marigold, soil 1, soil 2, and building was used.

To evaluate the accuracy of each method in seven categories, error matrices have been generated, wherein overall accuracy, Kappa coefficient value, the producer's accuracy, and the user's accuracy were computed (Foody 2002, Keuchel *et al.* 2003, Maxwell *et al.* 2004). Overall accuracy and Kappa coefficient value show the proportion of pixels correctly identified, the producer's accuracy shows the proportion of verification pixels of a category correctly classified, and the user's accuracy shows the proportion of pixels that are classified correctly. Although the user's evaluation of accuracy for each method may be important during the evaluation of the classification map produced over the study site, the user's accuracy evaluation is not important when the classification methods are evaluated. This is because the user's accuracy for each category depends on the number of verification pixels in the test areas. In Japan's typically small agricultural plots, it is difficult to collect sufficient numbers of sample pixels in a training and test area, as shown in table 1, to enable the use of the supervised classification method. Therefore, we used overall accuracy, Kappa coefficient value, and the producer's accuracy of error matrixes to evaluate each of the four supervised classification methods for seven categories.

4.2 *Results and discussion*

Table 2 shows the accuracy evaluation of the four supervised methods for seven categories using error matrixes. In table 2, overall accuracy and Kappa coefficient values of MLH method were not high in comparison with three methods of MED, SD and MED-SD. In particular, the producer's accuracies of MLH were not high for maize, marigold, and soil 2 because there were few pixels for these categories in the training area, as shown in table 1. It has been reported that MLH does not work well when the number of training data are few (Fujimura and Tsubaki 1985, Ishida and Inamura 2002, Malek *et al.* 2002). Therefore, MLH should not be used to classify agricultural land in areas where the collection of training data is difficult, such as the Miura peninsula.

On the other hand, overall accuracy and Kappa coefficient values of MED, SD and MED-SD methods produced almost the same results with higher accuracy. On average, the producer's accuracies of MED-SD were higher for all categories. In comparison with the results obtained with MED-SD, the producer's accuracies of

Table 2. Accuracy evaluation of the four supervised methods for seven categories.

	Maize	Watermelon	Tree	Marigold	Soil 1	Soil 2	Building	User's accuracy (%)
(a) MLH								
Maize	1	0	0	0	0	0	0	100.0
Watermelon	22	369	0	5	0	80	110	63.0
Tree	18	1	139	24	0	0	1	76.0
Marigold	0	9	0	35	0	0	0	79.5
Soil 1	0	0	0	0	85	12	0	87.6
Soil 2	0	0	0	0	0	8	0	100
Building	0	0	0	0	0	0	25	100
Producer's accuracy (%)	2.4	97.4	100.0	54.7	100.0	8.0	18.4	70.1
Kappa coefficient	0.583							
(b) MED								
Maize	41	19	29	0	0	0	0	46.1
Watermelon	0	350	5	0	0	0	0	98.6
Tree	0	0	105	1	0	0	0	99.1
Marigold	0	9	0	63	0	0	0	87.5
Soil 1	0	1	0	0	85	0	0	98.8
Soil 2	0	0	0	0	0	100	19	84.0
Building	0	0	0	0	0	0	117	100.0
Producer's accuracy (%)	100.0	92.3	75.5	98.4	100.0	100.0	86.0	91.2
Kappa coefficient	0.890							
(c) SD								
Maize	34	35	0	0	0	0	1	48.6
Watermelon	0	339	7	0	0	0	0	98.0
Tree	0	0	92	0	0	0	0	100.0
Marigold	0	0	40	64	0	0	0	61.5
Soil 1	0	0	0	0	85	0	0	100.0
Soil 2	7	5	0	0	0	100	23	74.1
Building	0	0	0	0	0	0	112	100.0
Producer's accuracy (%)	82.9	89.4	66.2	100.0	100.0	100.0	82.4	87.5
Kappa coefficient	0.846							
(d) MED-SD								
Maize	35	30	15	0	0	0	1	43.2
Watermelon	0	346	11	0	0	0	0	96.9
Tree	0	0	113	0	0	0	0	100.0
Marigold	0	0	0	64	0	0	0	100.0
Soil 1	0	1	0	0	85	0	0	98.8
Soil 2	6	2	0	0	0	100	24	75.8
Building	0	0	0	0	0	0	111	100.0
Producer's accuracy (%)	85.4	91.3	81.3	100.0	100.0	100.0	81.6	90.5
Kappa coefficient	0.881							

MED and SD were relatively low for trees. Most of the erroneous classifications pertained to maize, watermelon and marigold classified using MED and SD. Table 3 shows the values calculated by equation (2) and (3). The similarity between categories is high when the values of the discriminant function are near zero. From table 3, the values of equations (2) and (3) for maize, watermelon and marigold were relatively similar to that of trees. Furthermore, it can be seen in figure 3 that tree and marigold have most similar spectral radiance shapes. On the other hand, the proposed MED-SD method is considered to combine the merits of MED and SD. Therefore, the classification accuracies for tree were higher using MED-SD.

5. Conclusions

Four supervised classification methods for identifying agricultural crops using hyperspectral data were evaluated. The results showed that MLH should not be used to classify agricultural land where it is difficult to collect training data, such as

Table 3. The values of MED and SD in training and test areas.

	Maize	Watermelon	Tree	Marigold	Soil 1	Soil 2	Building
Training area—SD							
Maize	0	0.102	0.229	0.232	0.317	0.433	0.525
Watermelon	0.102	0	0.154	0.144	0.408	0.520	0.603
Tree	0.229	0.154	0	0.052	0.544	0.660	0.741
Marigold	0.232	0.144	0.052	0	0.547	0.658	0.740
Soil 1	0.317	0.408	0.544	0.547	0	0.136	0.282
Soil 2	0.433	0.520	0.660	0.658	0.136	0	0.269
Building	0.525	0.603	0.741	0.740	0.282	0.269	0
Training area—MED							
Maize	0	14679.26	12371.38	30640.34	10834.57	18340.68	17121.49
Watermelon	14679.26	0	8179.10	16574.36	24642.67	22533.01	31076.83
Tree	12371.38	8179.10	0	19789.59	23135.50	26419.45	29057.59
Marigold	30640.34	16574.36	19789.59	0	41024.76	37245.85	47362.20
Soil 1	10834.57	24642.67	23135.50	41024.76	0	17016.64	7903.43
Soil 2	18340.68	22533.01	26419.45	37245.85	17016.64	0	22690.28
Building	17121.49	31076.83	29057.59	47362.20	7903.43	22690.28	0
Test area—SD							
Maize	0	0.063	0.227	0.183	0.337	0.459	0.549
Watermelon	0.063	0	0.209	0.153	0.370	0.488	0.575
Tree	0.227	0.209	0	0.067	0.562	0.683	0.772
Marigold	0.183	0.153	0.067	0	0.518	0.635	0.724
Soil 1	0.337	0.370	0.562	0.518	0	0.154	0.240
Soil 2	0.459	0.488	0.683	0.635	0.154	0	0.216
Building	0.549	0.575	0.772	0.724	0.240	0.216	0
Test area—MED							
Maize	0	14783.20	19069.36	29131.84	13598.54	17695.83	17418.37
Watermelon	14783.20	0	10158.65	15667.97	27552.76	21826.98	30472.83
Tree	19069.36	10158.65	0	11728.31	32609.87	30729.06	36349.59
Marigold	29131.84	15667.97	11728.31	0	42569.82	36588.98	45804.60
Soil 1	13598.54	27552.76	32609.87	42569.82	0	18397.60	5193.15
Soil 2	17695.83	21826.98	30729.06	36588.98	18397.60	0	18507.12
Building	17418.37	30472.83	36349.59	45804.60	5193.15	18507.12	0

on the Miura peninsula, despite this method's popularity in conventional remote sensing classification.

On the other hand, on an aircraft, the classification accuracies of the proposed MED-SD method in all categories were higher than those derived using other methods. In the future, it is proposed to use data dimensionality for improving the classification accuracy while reducing the time required for analysing hyperspectral measurement.

References

CAMPBELL, B.J., 1996, *Introduction to Remote Sensing* (New York: The Guilford Press).

COCHRANE, M.A., 2000, Using vegetation reflectance variability for species level classification of hyperspectral data. *International Journal of Remote Sensing*, **21**, pp. 2075–2087.

DATT, B., 2000, Identification of green and dry vegetation components with a cross-correlogram spectral matching technique. *International Journal of Remote Sensing*, **22**, pp. 2133–2139.

FOODY, G.M., 2002, Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, **80**, pp. 185–201.

FUJIMURA, S. and TSUBAKI, K., 1985, Classification of multi-spectral remotely sensed imagery. *Journal of the Society of Instrument and Control Engineers*, **24**, pp. 25–30.

HOBBS, R.J. and MOONEY, H.A. (Eds), 1990, *Remote Sensing of Biosphere Functioning* (New York: Springer).

ISHIDA, H. and INAMURA, M., 2002, Evaluation methods for category classification of mixed pixel data. *Journal of Remote Sensing Society of Japan*, **22**, pp. 2–11.

KEUCHEL, J., NAUMANN, S., HEILER, M. and SIEGMUND, A., 2003, Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data. *Remote Sensing of Environment*, **86**, pp. 530–541.

LEWIS, M.M., JOOSTE, V. and DE GASPARIS A.A., 2001, Discrimination of arid vegetation with Airborne Multispectral Scanner hyperspectral imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **39**, pp. 1471–1479.

MALEK, J.E., ALIMI, A.M. and TOURKI, R., 2002, Problems in pattern classification in high dimensional spaces: behavior of a class of combined neuro-fuzzy classifiers. *Fuzzy Sets and Systems*, **128**, pp. 15–33.

MAXWELL, S.K., NUCKOLS, J.R., WARD, M.H. and HOFFER, R.M., 2004, An automated approach to mapping corn from Landsat imagery. *Computers and Electronics in Agriculture*, **43**, pp. 43–54.

MYERS, V.I., 1983, Remote sensing applications in agriculture. In *Manual of Remote Sensing*, 2nd edn, vol. III, R.N. Colwell (Ed.), pp. 2111–2228 (Falls Church, VA: American Society of Photogrammetry).

STEVE, M.D. and CLARK, J.A. (Eds), 1990, *Applications of Remote Sensing in Agriculture* (London: Butterworths).

OMASA, K., OKI, K. and SUHAMA, T., in press, Remote sensing from satellite and aircraft. In *Handbook of Agricultural Engineering, Vol. VI, Information Technology*, A. Munack, (Ed). ASAE.

OWE, M. and D'URSO, G. (Eds), 2002, *Remote Sensing for Agriculture, Ecosystems, and Hydrology III* (Bellingham, WA: SPIE).

PRICE, J.C., 1994, How unique are spectral signature? *Remote Sensing of Environment*, **49**, pp. 181–186.

RENCZ, A.N., 1999, *Remote Sensing for the Earth Sciences* (New York: John Wiley & Sons).