Effects of Spatial Resolution to Landcover Classification Accuracies for Spot HRV and LANDSAT TM Data

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ABSTRACT

Utilizations of high resolution image data such as SPOT HRV and Landsat TM data are increasing very rapidly. However the effective analysis techniques, especially in the fields of land-cover/use classifications, have not yet been established for those images.

In order to establish an optimal image processing algorithm, land-cover/use classification capabilities of a conventional classifier for SPOT HRV and Landsat TM data were evaluated from the view point of ground resolutions. In the experiments, several ground resolution images were simulated. Further, texture analyses were conducted to evaluate the spatial feature characteristics. The evaluation of classification accuracy were executed with the aid of digital land-cover/use test site data covering 2km x 10km area.

As a result,if was clarified that the improvement of ground resolutions did not directly bring the improvements of classi- fication accuracies in case of using conventional processing techniques; i.e. supervised training data selection and pixel- wise Baysian classifier. In order to fully utilize the perfor- mance of high resolution sensors, spatial informations in the image should be properly analyzed. However, a simple addition of texture features cannot increase the classification accuracy.

1.Introduction

In the recent years, several earth observation satellites with high resolution sensors were launched. They are Landsat 4, 5 and SPOT 1. They have 30m(TM) and 20m(HRV) ground resolu- tions, respectively which are sufficiently higher than 80m resolution of Landsat MSS image.

As flat areas in Japan are very restricted, landuse has a very detailed pattern and the smallest scale for operational landuse map is 1:50,000. SPOT HRV and Landsat TM data has potential capability for operational use in Japan, because their higher spatial resolution may result generations of 1:50,000 landcover maps.

However, effective analysis techniques in the field of land- cover classifications has not yet been established for those

high resolution satellite images. In order to establish those analysis techniques, it is necessary to evaluate landcover classification capabilities for those images, especially effects of higher ground resolutions.

There has not existed a proper way for the assessment of classification results. In order to solve this problem, we have established a digital land-cover/use test site data which enables a quantitative evaluations of accuracies of digitally classified results.

In this study, several ground resolution images were simulated for Landsat TM data. Those data and SPOT HRV data were classified by using conventional pixel-wise maximum likelihood classification method. And the results were evaluated quantitatively with the aid of digital land-cover/use test site data. At last, texture analyses were conducted to evaluate the effects of utilizing spatial informations in those images.

2.Digital Land-use/cover Test Site Data

The test site covers 2km x 10km area which contains city areas, agricultural areas, forest, rivers and a sea. It locates about 50km west form central Tokyo and Includes the main campus of our university.

The test site data was generated as follows. First, aerial infra-red color photographs over the test site area were taken. A land-cover/use thematic map with scale of 1:2,500 was generated by photo interpretations of these photographs. This thematic map was than improved by highly intensive ground investigations which was conducted from October to November in 1983. The improved thematic map was digitized with ground resolution of 1m. After several preprocessings, each polygons of thematic map were automatically recognized.

Finally, the test site data was resampled with 10m x 10m pixel size. It contains 52 land-cover/use categories. In order to assess classification results of large pixel size images, this basic 10m pixel data were further resampled to 20m, 25m, 50m and 75m using majority law. Figure 1 shows the digital land-cover/use test site data.

3.Test Image Data

Test image data used in this study are as follows;

        a.Landsat TM channel 1-5, 7
          path 107 row 35
          taken on Nov. 4, 1984
          processing level bulk
        b. SPOT HRV(XS) channel 1-3
          path 330 row 279
          taken on Jun. 9, 1986
          product level 1A

After stripe noise elimination, these image data were geometrically corrected using ground control points and registered to the land-cover/use test site data. Images after geometric correction are shown in Figure 2. The resampling sizes of TM and HRV data are 25m x 25m and 20mx20m, respectively.

4.Experiments

Four kinds of data were used. Two types of experiments were conducted. At the first experiment, in order to assess effects of higher ground resolutions for landcover classification accuracy. The first there data were generated from landsat TM data. Two simulated data, i.e. 50m and 75m resolution images were made from the 25m resampled TM image by averaging processings. The last data used for this experiment are HRV image resampled with 20m resolution. Used bands were 6(1, 2, 3, 4, 5, 7) for TM data and 3 for HRV data.

At the second experiment, texture analysis for TM data were conducted to evaluate the spatial feature characteristics. Four texture features, i.e. energy, entropy, homogenuity and inertial moment from co-occurrence matrix for each of six channel data were first extracted. These twenty-four features were then compressed to four features using a principal component analysis (PCA). These four features were merged to the original six channels image data and the second PCA reduced there ten channels (four texture feature + six channels image data) to six channels.

The classification algorithm used in the experiments is a supervised maximum likelihood classifier. The number of training classes used in the TM classification was 90. The same training areas were used for the simulated TM data. For HRV, 50 training classes were used.

Those 90 classification classes were merged to 16 land-cover/use categories after the classification. As the categories used in the land-cover/use test site data differ from those used in image classifications, those land-cover/use categories were further merged to five major categories as shown in Table 1. Accuracy evaluations were performed based upon these 5 major categories.

5.Results and Discussion

1) simulation of ground resolution

Figure 3. shows the classified results for the spatial resolution assessments and table 2, 3, 4 and 5 shows the confusion matrix for each result. Several problems can be pointed out from these tables. First of all, the mean accuracies of these classifications seems to be rather bad compared to existing classification results of TM and HRV.

However, most of reports concerning about classification accuracies use training data for evaluations. The result for

the classification of training data themselves are shown in Table 6. Mean accuracies of 94% and 98% are obtained for the used training data of TM and HRV, respectively. Those results show that the classification accuracies evaluated using training data do not represent the true accuracies.

Second, accuracies for 50m and 75m images are better than those for original data of TM and HRV. The most distinct characteristic related to the resolution difference can be seen in the urban area. In this category, classification accuracies are inversely proportional with the resolutions of images. This phenomena can be interpreted as follows. Urban areas, especially residential areas, are composed of many kinds of surface materials, such as various colored roofs, bare grounds, trees, lawns, concrete, etc. With lower resolutions, these surface materials cannot be resolved in one pixel. Hence, images with low spatial resolutions show rather homogeneous tones in these areas. On the contrary, high resolution images decomposite these surface materials to a certain extent. As a result, pixel values within these areas differ pixel by pixel. Figure 4 shows the difference for classification results between HRV data(20m) and simulated 75m TM data.

Large difference can be seen from Table 2,3,4 and 5 in tree and paddy categories between TM and HRV data. The difference in paddies may be causes by the difference of dates when image were taken. HRV image was taken on June, when paddies are filled with water. On the other hand, TM image was taken on November when rices are already harvested. For trees, the better result for TM data may be caused by higher spectral resolution of TM data.

2) texture features

Table 7 shows the confusion matrix of classified results for image data composed of spectral data and texture data. As can be seen from this table, the addition of texture features has decreased the mean accuracy. However, if one look Table 6 carefully, accuracies of some of the categories have been increased. These results can be interpreted as follows. It is clear that TM data contain much more spatial informations than MSS data. Nevertheless, a simple addition of texture features to conventional classification algorithms cannot fully utilize the spatial informations. Some other kinds of algorithms should be developed to utilize those informations.

6.conclusion

From this study following conclusion were obtained.

a) The real classification accuracies for landcover using maximum likelihood classifier are not so good as estimated by using confusion matrix of training data. Average accuracies may be in the range of 60 to 70%.

b) The increase of spatial resolutions does not necessarily provide higher classification accuracies. This fact means that

a some kind of spatial informations should be used for higher accuracies. However, a simple addition of texture features cannot increase the classification accuracy. A suitable algorithm should be developed to fully utilize the spatial informations.

c) As a whole, TM and HRV data show almost the same classification accuracies for land-cover/use.

Table 1   Classification categories.

middle classification categories		rough classification categories
HRV data (number of training classes)	TM data (number of training classes)	
1 coniferous forest.(2) 2 broad leaved forest.(2) 3 mixed forest.(2) 4 low trees forest.(4)	1 coniferous forest 1.(8) 2 broad leaved forest 1.(7) 3 coniferous forest 2.(2) 4 broad leaved forest 2.(7) 5 shadow (bright).(4) 6 shadow (dark).(5)	vegetation
5 urban.(1) 6 high density urban.(7) 7 low density urban.(5) 8 road.(1) 9 rail way.(1)	7 urban.(3) 8 low density urban area.(3) 9 factories.(3)	urban
10 paddy.(6)	10 paddy.(6)	paddy
11 sea, river.(8)	11 sea, river.(10)	water
12 farm.(2) 13 waste lands.(2) 14 golf courses.(3) 15 grounds.(1) 16 sandy beach.(5)	12 waste lands, sandy beach grounds.(10) 13 rock.(2) 14 farm.(7) 15 grasslands.(10) 16 golf courses.(2)	other

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Table 2 Classification accuracy(HRV 20m).

	TREES	PADDY	URBAN	WATER	OTHER
TREES	40.1	0.4	35.3	0.2	23.9
PADDY	4.5	52.4	28.8	1.8	15.4
URBAN	3.9	1.6	71.2	0.2	13.2
WATER	5.1	3.8	11.7	74.0	5.8
OTHER	16.1	2.9	30.0	0.8	50.2

mean 61.9

Table 3 Classification Accuracy(TM 25m).

	TREES	PADDY	URBAN	WATER	OTHER
TREES	45.7	1.4	23.8	3.2	25.9
PADDY	1.6	32.9	8.4	0.3	56.8
URBAN	3.6	2.6	74.0	3.9	15.9
WATER	4.5	0.8	9.4	76.9	8.5
OTHER	14.5	6.3	27.1	4.2	47.9

mean 61.5

Table 4 Classification accuracy(TM 50m).

	TREES	PADDY	URBAN	WATER	OTHER
TREES	53.3	1.1	22.0	2.4	21.4
PADDY	0.2	41.4	4.3	0.3	53.8
URBAN	4.0	1.0	79.2	2.8	14.0
WATER	3.7	0.2	13.9	75.7	6.6
OTHER	13.3	7.0	25.0	2.6	52.4

mean 68.4

Table 5 Classification accuracy(TM 75m).

	TREES	PADDY	URBAN	WATER	OTHER
TREES	46.2	0.0	25.8	0.8	27.2
PADDY	1.2	39.6	5.4	0.0	53.9
URBAN	2.4	2.6	80.1	2.0	13.0
WATER	1.2	0.8	15.5	72.6	9.9
OTHER	11.2	7.1	24.9	1.8	54.2

mean 66.2

Table 6 Classification accuracies of
training data.(upper:TM, lower:HRV)

	TREES	PADDY	URBAN	WATER	OTHER
TREES	98.4	0.0	0.4	0.3	0.9
	99.4	0.0	0.0	0.0	0.6
PADDY	0.0	95.6	0.0	0.0	4.4
	0.0	99.4	0.6	0.0	4.4
URBAN	0.2	0.2	96.0	0.0	3.7
	1.5	0.0	92.8	0.0	5.7
WATER	0.6	0.0	3.8	95.1	0.6
	0.0	2.1	1.7	95.2	0.0
OTHER	3.7	1.6	7.1	0.0	87.7
	0.0	0.0	0.0	0.0	100.0

mean 94.0(TM), 97.8(HRV)

Table 7 Classification accuracy
(TM 25m+texture features).

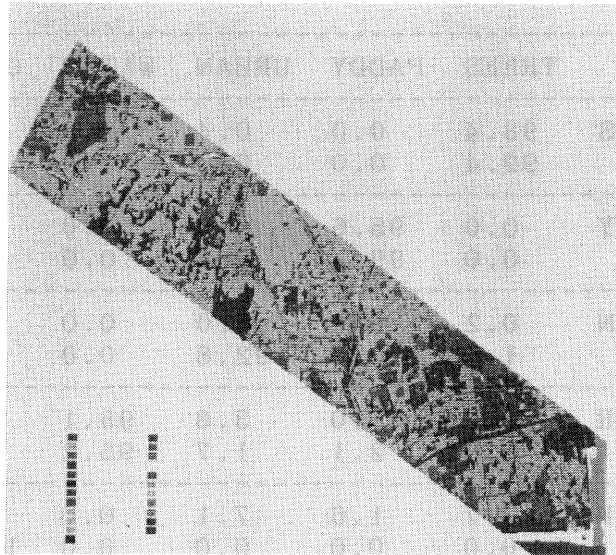|	TREES	PADDY	URBAN	WATER	OTHER
TREES	53.2	0.1	16.0	7.7	23.0
PADDY	3.7	27.2	6.2	1.9	61.0
URBAN	9.2	1.2	62.2	7.7	19.8
WATER	8.4	0.0	4.6	77.0	10.0
OTHER	25.8	2.2	22.7	7.4	41.9

mean 53.9

Fig.1   The digital land-cover/use
test site data.
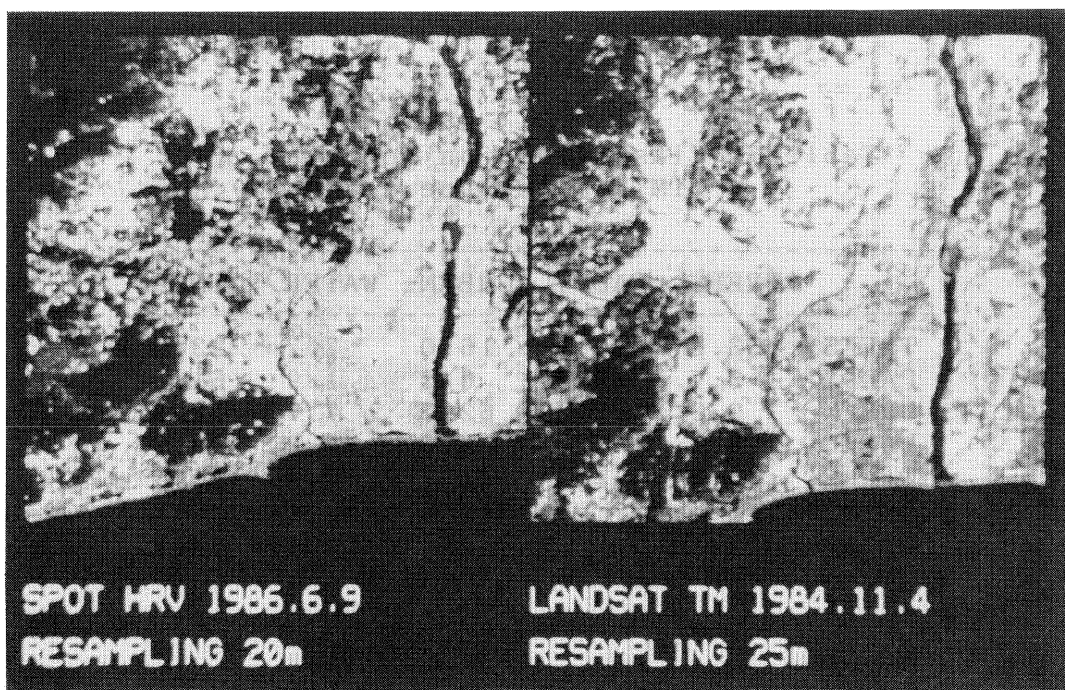

Fig.2   Object images.
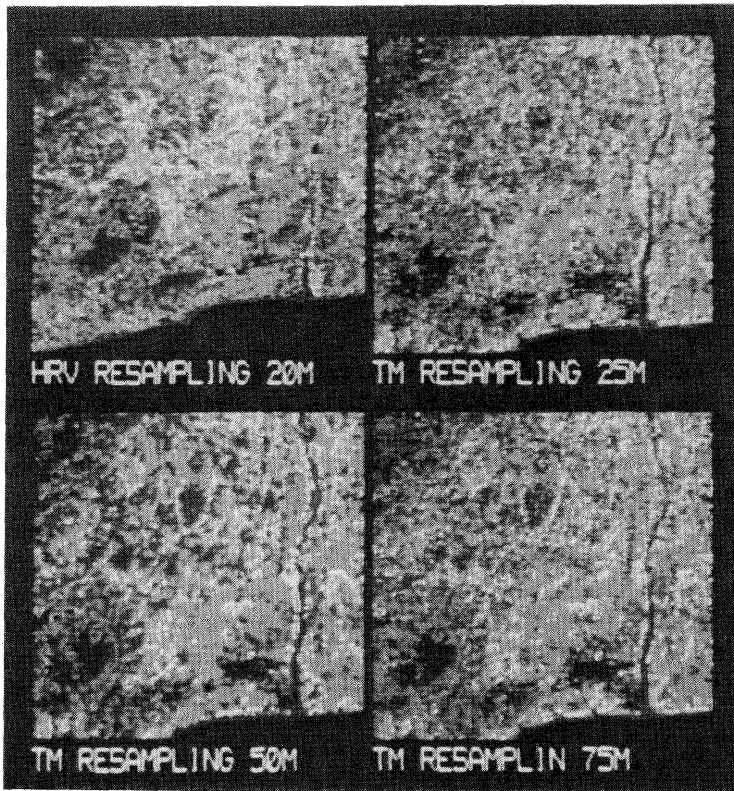
Fig.3   Classification results.
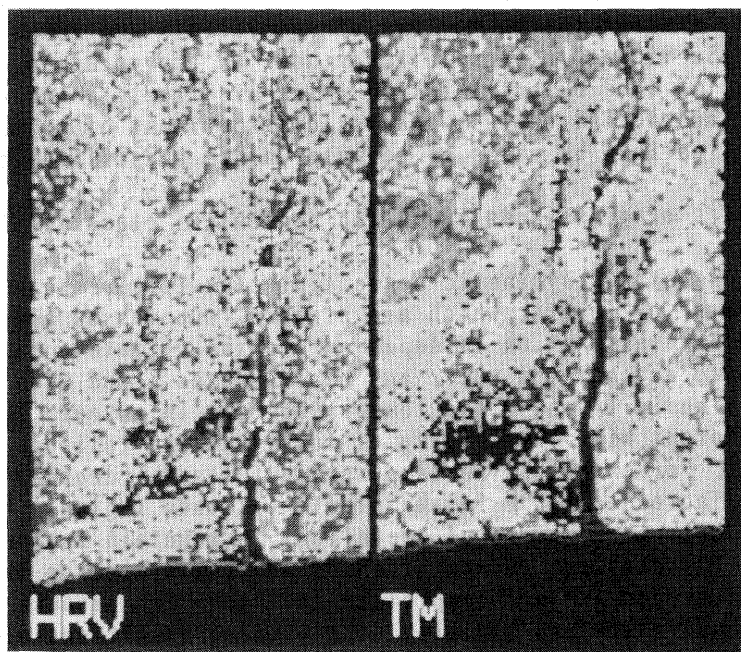

Fig.4   The difference for classification results
        between HRV data(25m) and TM data(75m).
            (HRV data : sampled image)

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