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Image classification techniques in mapping urban landscape: A case study of Tsukuba city using AVNIR-2 sensor data

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Abstract

Although several techniques to extract the land uses from remotely sensed data have been evolving, mapping urban landscape with enough accuracy is not completely achieved. This paper aims to evaluate image classification methods for mapping the urban landscape of a fast growing city in the Tokyo metropolitan fringe using Advanced Land Observing Satellite (ALOS) data. Three image classification methods: unsupervised, supervised and fuzzy supervised were evaluated. An AVNIR-2 sensor image of ALOS satellite covering Tsukuba city was used for the study. Field survey data including high resolution satellite image and aerial photographs were used for scheming land use types, selecting training samples and assessing accuracies of the classification results. Seven types of land uses: forested land; lawn/grass; paddy field; dry farmland/exposed field; facility/industry; residence/parking/road/upland bare field and water were extracted using the methods. Error matrix and Kappa index were computed to measure the map accuracy. The fuzzy supervised method improved the mapping results showing highest overall accuracy of 87.7% as compared to supervised and unsupervised methods. The fuzzy method effectively dealt with the mixed pixels that appeared in the residential area. The study also revealed that the image classification method greatly influences the spatial statistics of land use types.

Key words: land use, urban landscape, image classification, unsupervised, supervised, fuzzy, ALOS, Tsukuba.

1. Introduction

Urban land uses represent one of the most challenging areas for remote sensing analysis due to high spatial and spectral diversity of surface materials (Thapa et al., 2007). In recent years, series of earth observation satellites are providing enormous data from high (0.6 m) to moderate (30 m) resolution for urban area mapping. Remote sensing data from these diverse resolutions have a specific potential for mapping urban landscape. Despite advances in satellite imaging technology, computer-assisted methods of image classification are still unable to produce urban land use maps and statistics with enough accuracy. Although the image analysis techniques are evolving rapidly, many operational and applied remote sensing analyses still require the extraction of discrete thematic land surface information from satellite imagery using classification-based techniques. Several image classification techniques from automated to manual digitization can be found in various literature to date.

Classification procedures of satellite imagery have been mainly based on multi-spectral classification techniques (per pixel classifiers). These procedures assign a pixel to a class through considering its statistical similarities, in terms of reflectance in respect to a set of classes (Gong et al., 1992). Unsupervised classification method provides an automated platform for image analysis, which is mainly based on surface reflectance and generally ignores basic land cover characteristics (i.e., shape and size) of landforms (Chust et al., 2004). Urban areas typically exhibit a spatially heterogeneous land cover and there is probability of similarity in spectral response from the different land cover and land uses. Supervised classification method helps to solve such problems through the statistical classification techniques using a number of well-distributed training pixels (Jensen, 2005; Racolt et al., 2005; Thapa and Murayama, 2007). Johnsson (1994) claimed that the traditional multi-spectral image classification techniques have proven to be ineffective at identifying built-up areas especially at the peri-urban area, due to the heterogeneity of urban land covers. The suburban residential areas consist of a complex mosaic of trees, lawns, roofs, concrete and asphalt roadways. Such complex urban environment develops mixed pixels problem often causing misclassification of remote sensing imagery. Supervised fuzzy classification method allows multiple and partial class membership properties for mixed pixels classification (Zhang and Foody, 2001). Thus, the heterogeneous urban land uses may be addressed using the fuzzy approach. However, the accuracy of the classification and the spatial statistics are usually controlled by many factors, i.e., classification method, nature of the land use type, spatial and radiometric scales of remotely sensed data and topography of study area.

Considering the complexity of urban landscape and the importance of spectral and radiometric resolution to land use classification accuracies, three image classification

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methods, i. e., unsupervised, supervised, and fuzzy supervised were examined in this paper. The paper aims to discuss usefulness of urban remote sensing application using newly borne Japanese satellite ALOS and evaluate image classification methods for mapping urban landscape of a city in the Tokyo metropolitan fringe.

2. Methods

2.1. Geography of study site

Tokyo metropolitan area has experienced rapid urbanization since the 1950s, the beginning period of high economic growth led to a massive migration population from rural to urban area. Based on population projection, the trend continues in the years to come. With the establishment of modern transportation infrastructures and forward-looking government policies, the rural landscapes in the metropolitan fringe are being agglomerated in unprecedented ways. Tsukuba city (Fig. 1) located in the south of Ibaraki Prefecture (50 km northeast from central Tokyo) is one of the emerging peri-urban cities in Tokyo metropolitan region. The city landscape, currently known as science city in Japan, used to be agriculture land in the 1960s. With the aim of promoting science and technology and to become the centre of advanced research and higher education based on national institutes, the science city was planned in the early 1960s (Tsukuba City Hall, 2005). The agricultural landscape duly transformed into modern city with the state of the art infrastructure establishments. It is noteworthy to study Tsukuba city as a case of urban remote sensing application because it has carried very unique perspectives of development in the metropolitan region in the past more than four decades.

The study site covers a rectangular area of 55,000 hectares. The area has a flat geographical feature laid on the Tsukuba-Inashiki Plateau, 20-30m above sea level, which is covered with Kanto Loam Layer. Mt. Tsukuba (an elevation of 877 meters), one of the major mountains in Kanto region, is located in the north of the study site. Forests and agriculture fields in suburban area provide natural green spaces to the more than 200,000 city dwellers.

2.2. Data sources

2.2.1. Remote sensing data. An ALOS multi-spectral AVNIR-2 sensor image covering Tsukuba city was acquired on 4th August 2006. The ALOS (locally known as 'Daichi') is a new satellite, which was launched in 2006 (JAXA, 2006). This image consists of visible and near-infrared bands (Band 1: blue, 0.42 - 0.50 µm, Band 2: green, 0.52 - 0.60 µm, Band 3: red, 0.61 - 0.69 µm and Band 4: near infrared, 0.76 - 0.89 µm. The spatial resolution of the image is 10 meters. This sensor was

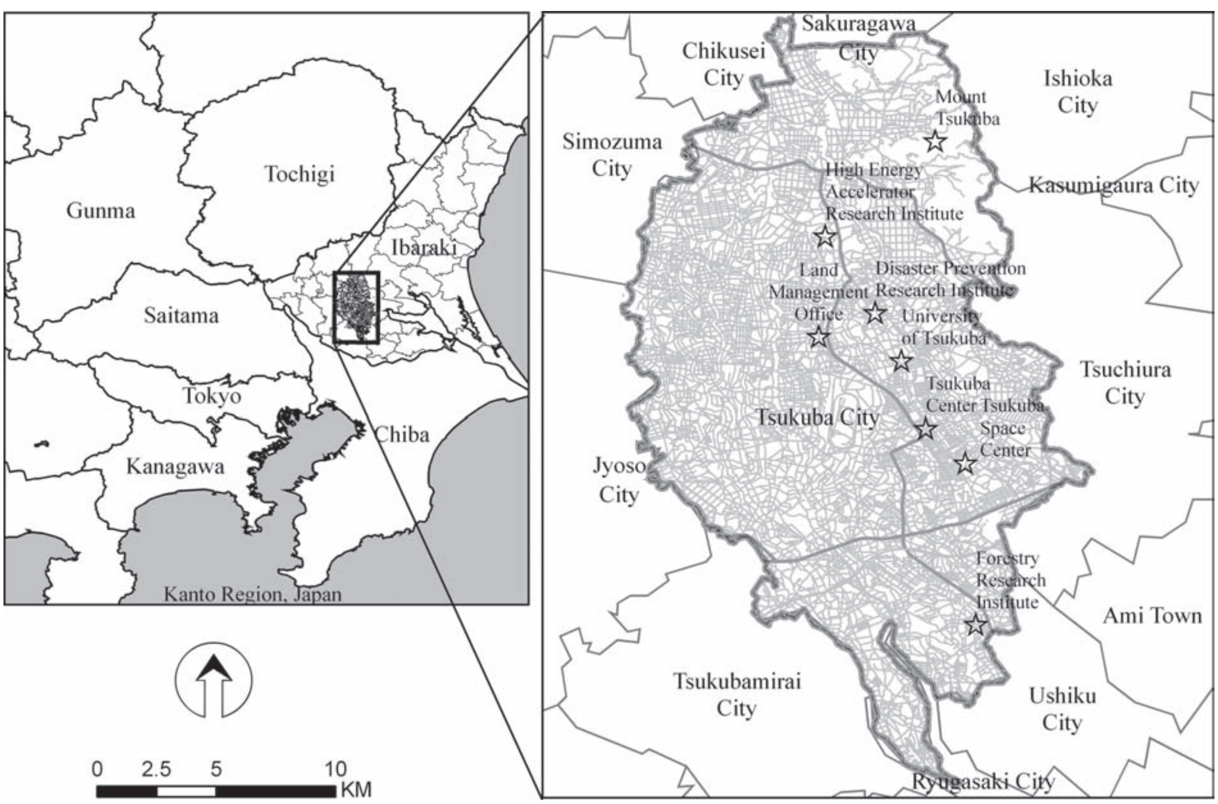

Fig. 1 Study area, Tsukuba city, Japan.

selected for this study since it provided suitable cloud free spatial coverage with relatively high spatial and spectral resolutions.

2.2.2. Ground reference data. Detail ground reference data in support of the classification and subsequent accuracy assessment were obtained from aerial photographs (November 2005), QuickBird image (October 2006) and field work (November 2006). These ground references were used in preparing signatures of classification training samples as well as evaluating the accuracy of the classified maps. Although the aerial photographs and the QuickBird image used for the training samples acquired in different time periods, the seasonal variation observed on the data, especially in the paddy field and dry farmlands, were verified by field work.

2.3. Classification scheme

Usually, classification is performed with a set of target land use types in mind. Such a set is called a land use classification scheme (plan). The purpose of such a scheme is to provide a framework for categorizing the information that can be extracted from the data (Gregorio and Jansen, 1998; Jensen, 2005). Knowledge-based visual interpretation, vegetation analysis using normalized differential vegetation index (NDVI), texture and association analysis were carried out. Field survey data, aerial photographs and QuickBird satellite image were employed in preparing the classification scheme. After interpretation of these data sources, seven types of land use (Table 1) were to be extracted as thematic information from the AVNIR-2 sensor image.

2.4. Image processing

Researchers involved in land use classification studies using satellite images data have conceived a large range of methodologies for preparing thematic maps. In this study, we selected three classification methods: unsupervised, supervised, and fuzzy supervised to classify the image. Professional software (Erdas Imagine 9.1) was used for the data processing and image analysis. Initially, we performed geometric rectification process in order to fit the image data to the local projection system (Transverse Mercator, Tokyo GRS 1980 datum). After this pre-processing phase, we classified the image using following methodologies.

2.4.1. Unsupervised method. Unsupervised classification method creates a thematic raster layer from remotely sensed image by letting the software identify statistical patterns in the data without using any ground truth data. After the classification is completed, the analyst employs a posteriori knowledge in labeling the spectral classes into information classes. Clusters are defined with a clustering algorithm, which often uses all pixels in the input image for analysis (Lillesand and Kiefer, 1994). Initially, thirty spectral clusters were formed using unsupervised ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering to separate the image information into more readable form. Much higher number of clusters than the actual classes was chosen because the exact number of spectral classes in the data set was unknown. Spectrally similar classes of identical land use type were merged. Additionally, these merged clusters were carefully interpreted and labeled into seven land use types (Table 1) to generate thematic land use map. Modal filter with 3x3 pixels window was run as a post classification tool to remove the salt and pepper noises in the resulting map.

2.4.2. Supervised method. Supervised classification method is the procedure most often used for quantitative analysis of remote sensing image data. In this technique, the analyst identifies sample pixels in the image that can be used as representative samples for a particular land use category and then the sample pixels are used to train the algorithm to locate similar pixels in the image (Laba et al., 1997; Jansen, 2005; Thapa and Murayama, 2007). For each land use type (Table 1), 5-10 areas of interest were selected as signature of training samples. After obtaining a suitable indication for satisfactory discrimination between

Table 1 Urban land use types.

No.	Classes	Definition
1.	Forested Land	Artificial forest and natural vegetation
2.	Lawn/Grass	Lawn, grass, bush and gulf course
3.	Paddy Field	Paddy field
4.	Dry Farmland/Exposed Field	None irrigated land, vegetables and fruits cultivated area
5.	Facility/Industry	Large scale buildings, i.e., big residential unit, shopping mall, industrial and office buildings
6.	Residence/Parking/Road/Upland Bare Field	Small houses, back/front yards, small residential unit, parking area, road, new construction area and upland bare field
7.	Water	Lake, river and wetland

the classes during spectral signature evaluation, supervised classification with Maximum Likelihood Classifier (MLC) was run. A 3x3 modal filter was applied to remove the small pieces of noise in the map.

2.4.3. Fuzzy supervised method. Fuzzy classification method works using a membership function, wherein a pixel's value is determined based on proximity of one class to another (Wang, 1990; Jensen, 2005). In this method, we used the same class signatures that were prepared for supervised classification method. Two maps (i.e. land use and distance) were generated using the fuzzy classification method. Fuzzy convolution operation was then performed to create a single classification layer by calculating the total weighted inverse distance of all the classes in a 3x3 window of pixels. This operation assigns the centre pixel in the class with the largest total inverse distance summed over the entire set of fuzzy classification layers. Classes with a very small distance value remain unchanged while classes with higher distance values may change to the neighboring value if the neighboring pixels are sufficient in number. The convolution method has built-in function that creates context-based classification to reduce the speckle noise in the classified map.

2.5. Accuracy assessment

Accuracy assessment is a general term for comparing the classification results to geographical reference data that are assumed to be true (Richard and Jia, 1999). A set of reference pixels is usually used in accuracy assessment. Reference pixels represent geographic locations on the classified image for which actual data are known (Thapa et al., 2007). Randomly selected reference pixels lessen or eliminate the possibility of biasness (Congalton, 1991). Based on stratified random sampling method, total 300 independent reference locations for each thematic map were prepared in order to assess the accuracy of the maps.

An error matrix for each map was computed that made it possible to derive a range of quantitative measures of classification accuracy. Four measures (producer's accuracy, user's accuracy, overall accuracy and Kappa statistic) of accuracy assessment were computed for assessing the accuracy between the thematic map and independent set of reference pixels. The producer's accuracy, known as a measure of omission errors, corresponds to those pixels belonging to the class of interest where the classifier has failed to recognize. The user's accuracy, known as a measure of commission errors, corresponds to those pixels from other classes where the classifier has labeled as belonging to the class of interest. The overall accuracy is the percentage of correctly classified samples. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process. Kappa accounts for all elements of the confusion matrix and excludes the agreement that occurs by chance (Congalton, 1991; Steele et al., 1998).

3. Results and discussions

A false color AVNIR-2 image of the study site as an input data is shown in Fig. 2(a). The false color image clearly shows the water bodies in black color, paddy field in pink, vegetation in dark red and urban surface materials as light bluish color. Fig. 2(b) further confirms the land cover showing the gradient of vegetation distribution in the city. Separation of dry farm land and exposed field in false color image is difficult but it can be clearly distinguished in true color combination. Although it is easier to separate asphalt surface from the image, the association of the surface makes it difficult to classify the surface as a unique entity of the urban land use pattern. In the study site, roads and parking lots are built using asphalt materials. Roads and parking area are greatly associated with residential, facility and industrial. In some places, the upland bare field and new construction areas also reflected relatively same energy. Therefore, after analyzing the field survey data, we decided to combine roads, parking lots, small residential and upland bare field as one land use type which is labeled as residence/parking/road/upland bare field. The three classification methods produced three thematic land use maps (Fig. 2(c)-(e)).

The selection of classification methods often has impact in quantitative spatial extent of land use (Table 2). The land use statistics derived from the supervised and fuzzy supervised method showed small differences in spatial extent as compared to the unsupervised method. Automated clustering technique (unsupervised) often failed or overestimated the heterogeneous landscapes mainly in residential and peri-urban areas. High contrast is observed between the spatial statistics of unsupervised and other methods especially in the residence/parking/road/upland bare field type. It may be due to the complexity of the urban environment which forces the classifier to overestimate the land use area. In this case, supervised and fuzzy supervised methods seem superior because these methods use signatures of particular surface materials to train the algorithm. All classifiers showed very few differences in the spatial extent (within ±2%) of the land uses vegetation, water and paddy field. Natural land covers are separable in all classification processes, so there is no significant impact on corresponding spatial statistics. All classification methods confirmed that the dry farmland/exposed fields cover larger area compared to the other land uses.

Error matrix including user's accuracy, producer's accuracy, overall accuracy and kappa coefficient were analyzed for each map to reveal the accuracy of the classification results. Based on the overall accuracies of the error matrices, the fuzzy supervised method of image classification appeared to be the best classifier among the methods. Due to dealing capacity of mixed pixels problem in residential area, the fuzzy supervised method shows an overall accuracy of 87.67% (Table 3). The supervised method presents an overall accuracy of 83.67% whereas the unsupervised approaches produce the lowest accuracy (75.33%). The unsupervised ISODATA clustering approach fully depended on the digital value of

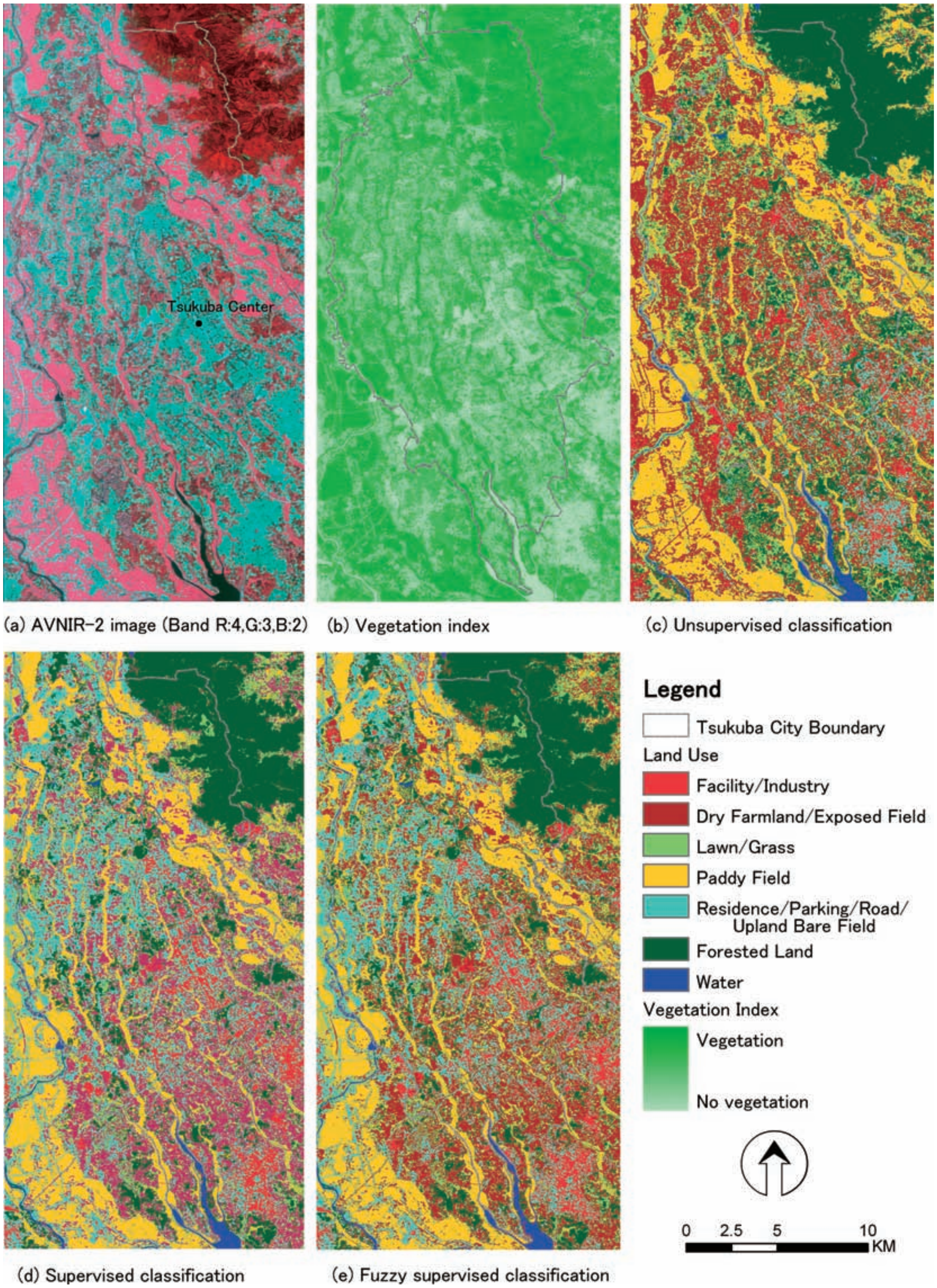

Fig. 2 Image data (a), NDVI (b) and land use maps (c, d and e).
Sources: ALOS satellite, 4th August, 2006.

the image data, which required being further interpreted. Due to various surface materials in complex urban system, the unsupervised method formed several classes cluster in the image, creating difficulties in interpretation. However, the unsupervised approach provided an overall idea about interpretable land use/cover classes in the image.

The fuzzy supervised method is able to avoid greater percentage of errors during the classification process. The Kappa index for the fuzzy method (Table 3) was 0.8555 (85% reduction of error), compared to a kappa index of 0.8085 for the supervised method, which represented an increase of 4.7% in overall classification accuracy agreement. The unsupervised method with the Kappa index of 0.7114, a decrease of 8.34% accuracy compared to supervised method, performed poorly among the methods. The Kappa indices presented somewhat clearer picture.

Error of commission occurs when incorrectly classified pixels are added to a certain land use type, resulting in a more than actual representation of that particular land use type. On the other hand, error of omission occurs when pixels that belong to a land use type are incorrectly classified as some other land use and subtracted from their actual land use, thus resulting in a less than actual representation. Because of mixture of surface materials (i.e., roof tiles, concrete, asphalt and vegetation) in residential area, the unsupervised and supervised methods poorly scored in the user's and producer's accuracies (Figs 3 and 4). Due to dealing capacity of mixed pixel problems in fuzzy method, the results greatly improved, showing over 82% producer's and user's accuracies in residential land use classification (Fig. 5). The user's accuracies show the supervised method better estimates the lawn/grass land use compared to other methods. However, high contrast is observed between the producer's and user's accuracies of lawn/grass class in all methods. Both unsupervised and supervised methods exhibited good producer's and user's accuracies in natural land covers (i.e., paddy field, vegetation and water bodies). Unsupervised method performed better in clustering the paddy field showing 92% of user's and 83% of producer's accuracy while the supervised method shows 7% lower in user's and 1% higher in producer's accuracies. Fuzzy supervised method exhibited high (over 80%) producer's accuracies or low omission error (Fig. 5) whereas similar results showed in the user's accuracies (very low commission error) except in lawn/grass land use type. Forested land, paddy field, facility/industry and water types have very high user's accuracies (over 89%) in the method. With the exception of paddy field, the user's accuracies of these types are also similar.

In the supervised method, despite a producer's accuracy of 91% for the facility/industry land use, there was actually 85% user's accuracy in the land use type which means at least 6% of the facility/industry land use was wrongly classified. As for unsupervised method, the producer's accuracy for facility/industry uses was 75% while user's accuracy was 73%, making a difference of only 2% (Fig. 3). Herein unsupervised classifier seems slightly better than the supervised classifier in dealing with homogenous large parcels characterized by the facility/industry land use. However, supervised method exhibited a lower difference between the user's and producer's accuracies for vegetation, paddy field and water, which compared well even with the fuzzy method.

4. Conclusions

Urban landscape typically exhibits a spatially heterogeneous land uses giving similar spectral responses from the different land uses. The complex urban system also greatly enhanced

Table 2 Spatial statistics of urban land use types.

Land use	Unsupervised	Supervised	Fuzzy supervised
Forested Land	20.97%	19.17%	17.82%
Lawn/Grass	18.66	13.10	13.71
Paddy Field	19.75	19.58	18.41
Dry Farmland/Exposed Field	28.44	21.22	23.25
Facility/Industry	3.92	5.95	6.01
Residence/Parking/Road/Upland Bare Field	7.17	19.62	19.51
Water	1.09	1.36	1.28

Table 3 Map accuracies and Kappa statistics

Classification method	Overall accuracies	Kappa statistics
Unsupervised	75.33%	0.7114
Supervised	83.67	0.8085
Fuzzy supervised	87.67	0.8555

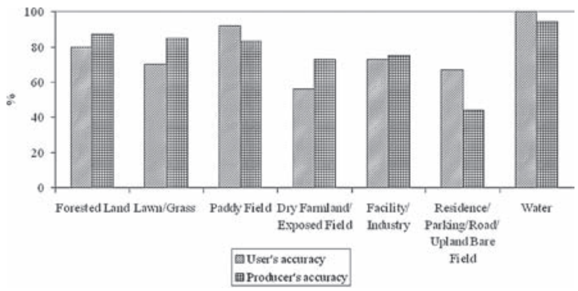

Fig. 3 Accuracies of the unsupervised method for urban land use classification.

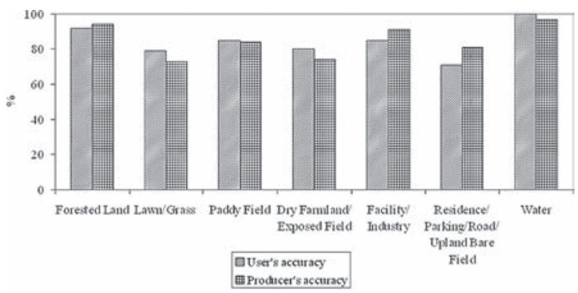

Fig. 4 Accuracies of the supervised method for urban land use classification.

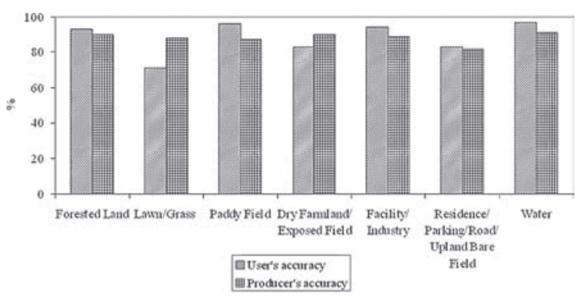

Fig. 5 Accuracies of the fuzzy supervised method for urban land use classification.

the mixed-pixel problems in image data. These problems still remain the most challenging in urban remote sensing, although significant advancement has been observed in remotely sensed image analysis techniques. Therefore, in order to derive accurate urban classifications, it is necessary to utilize data acquired by high spatial resolution sensors as well as field survey in conjunction with more sophisticated classifiers. In this study, we examined three classification methods: unsupervised, supervised and fuzzy supervised and their accuracies to extract the urban land uses using AVNIR-2 sensor image of ALOS satellite. The fuzzy supervised method had shown to be more effective in detecting land uses of the complex urban environment. The method mapped the urban woodland, water followed by facility/industry and paddy field more accurately as compared to other methods. This method also showed great potential to deal with the mixed pixel problems represented by the urban residential and dry farmland land uses. The results show also that the supervised method was better than the unsupervised in identifying the land use type more accurately. In fact, the unsupervised approach greatly helped us to understand the image information in the initial phase of the analysis, which eventually led to the classification schemes. The study also revealed that the spatial statistics depend on classification method even from the same input image data.

In this research, the study site is almost flat and it is a newly developed city in the north of the Tokyo metropolitan fringe. The potential of ALOS data needs to be further explored in old cities as well as complex topography. Finally, the study is able to explore the strength of the three classification methods in mapping urban landscape from the AVNIR-2 sensor of ALOS, which may help to understand and interpret the complex urban characteristics more precisely.

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References

Chust, G., Ducrot, D, Pretus, J. L., 2004. Land cover mapping with patch-derived landscape indices. *Landscape and Urban Planning*, **69**, 437-449.

Congalton, R. G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, **37**, 35-46.

Gong, P., Marceau, D. J., Howarth, P. J., 1992. A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data. *Remote Sensing of Environment*, **40**, 137-151.

Gregorio, A. D., Jansen, L. J. M., 1998. *Land Cover Classification System (LCCS): Classification Concepts and User Manual*. Rome: FAO, United Nations.

JAXA, 2006. About ALOS. Earth Observation Research Center. Available online at: http://www.eorc.jaxa.jp/ALOS/about/about_index.htm (accessed 1 December 2006).

Jensen, J. R., 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*. New Jersey: Prentice Hall.

Johnsson, K., 1994. Segment-based land-use classification from SPOT satellite data. *Photogrammetric Engineering and Remote Sensing*, **60**, 47-53.

Laba, M., Smith, S. D., Degloria, S. D., 1997. Landsat-based land cover mapping in the Lower Yuna River watershed in the Dominican Republic. *International*

Journal of Remote Sensing, **18**, 3011-3025.

Lillesand, T. M., Kiefer, R. W., 1994. *Remote Sensing and Image Interpretation*. New York: Wiley.

Raclot, D., Colin, F., Puech, C., 2005. Updating land cover classification using a rule-based decision system. *International Journal of Remote Sensing*, **26**, 1309-1321.

Richard, J. A., Jia, X., 1999. *Remote Sensing Digital Image Analysis*. Berlin: Springer.

Steele, B., Winne, J., Redmond, R., 1998. Estimation and mapping of misclassification probabilities of thematic land cover maps. *Remote Sensing of Environment*, **66**, 192-202.

Thapa, R.B., Murayama, Y., 2007. Land evaluation for peri-urban agriculture using analytical hierarchical process and geographic information system techniques: a case study of Hanoi. *Land Use Policy*, doi: 10.1016/j.landusepol.2007.06.004.

Thapa, R.B., Murayama, Y., Bajimaya, M., 2007. Monitoring land cover change in Kathmandu city using spatial metrics and remote sensing techniques. *Nepalese Journal on Geoinformatics*, **6**, 76-84.

Tsukuba City Hall, 2005. Overview of Tsukuba science city. Available online at: http://www.city.tsukuba.ibaraki.jp/hp/e_hp/guide/geography.html (accessed 20 November 2006)

Wang, F., 1990. Improving remote sensing image analysis through fuzzy information representation. *Photogrammetric Engineering and Remote Sensing*, **56**, 1163-1169.

Zhang, J., Foody, G. M., 2001. Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical and artificial neural network approaches. *International Journal of Remote Sensing*, **22**, 615-628.

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