Urban Mapping, Accuracy, & Image Classification: A comparison of multiple approaches in Tsukuba City, Japan

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Abstract

The rapid growth of urban space and its environmental challenges require precise mapping techniques to represent complex earth surface features more accurately. In this study, we examined four mapping approaches (unsupervised, supervised, fuzzy supervised and GIS post-processing) using Advanced Land Observing Satellite images to predict urban land use and land cover of Tsukuba city in Japan. Intensive fieldwork was conducted to collect ground truth data. A random stratified sampling method was chosen to generate geographic reference data for each map to assess the accuracy. The accuracies of the maps were measured, producing error matrices and Kappa indices. The GIS post-processing approach proposed in this research improved the mapping results, showing the highest overall accuracy of 89.33% as compared to other approaches. The fuzzy supervised approach yielded a better accuracy (87.67%) than the supervised and unsupervised approaches. The fuzzy supervised approach effectively dealt with the heterogeneous surface features in residential areas. This paper presents the strengths of the mapping approaches and the potentials of the sensor for mapping urban areas, which may help urban planners monitor and interpret complex urban characteristics.

Keywords: LULC, GIScience, land use, land cover, image classification, urban remote sensing, Tsukuba city, ALOS

Introduction

Most of the world population currently lives in urban areas. The worldwide urban population is estimated to be 3.3 billion and is predicted to almost double by 2050 (United Nation, 2008). Persistent dynamic urban change processes, especially the remarkable worldwide expansion of urban populations and urbanized areas, affect natural and human systems at all geographic scales, and are expected to accelerate in the next several decades (Miller and Small, 2003). Worsening conditions of crowding, housing shortages, insufficient infrastructure, and increasing urban climatological and ecological problems require consistent monitoring of urban regions.

Recent advances in remote sensing technologies and the increasing availability of high resolution earth observation satellite data provide great potential for acquiring detailed spatial information to identify and monitor a number of environmental problems of urban regions at desirable spatiotemporal scales (Miller & Small, 2003; Carlson, 2003). Transitions in architecture and building density, vegetation and intensive socioeconomic activities at the block level in cities often transform the urban landscape towards heterogeneity (Cadenasso, Pickett & Schwarz, 2007). Therefore, the urban environment represents one of the most challenging areas for remote sensing analysis due to the high spatial and spectral diversity of surface materials (Herold, Scepan, & Clark, 2002; Maktav, Erbek, & Jurgens, 2005). In recent years, a series of earth observation satellites have provided abundant data at high resolutions (0.6~2.5 m; QuickBird, IKONOS, OrbitView, SPOT and ALOS) to moderate resolutions (15~30 m; ASTER, IRS and LANDSAT) for urban area mapping. Remote sensing data from these satellites have specific potential for detailed and accurate mapping of urban areas at different spatiotemporal scales. The high resolution imagery provides data for monitoring urban infrastructures, whereas moderate resolution imagery can provide synoptic measures of urban growth, surface temperature and more. A wide range of urban remote sensing applications from both sensors is available to date (Carlson & Arthur, 2000; Miller & Small, 2003; Maktav, Erbek, & Jurgens, 2005; Gatrell & Jensen, 2008). These include quantifying urban growth and land use dynamics, population estimation, life quality improvement, urban infrastructure characterization, monitoring land surface temperature, air quality and vegetation, and topographic mapping. Having the potential to monitor human activities at the earth surface, however, the information acquired from remote sensing data could be an additional resource in developed economies, while it might be the only alternative in the developing countries.

Despite advances in satellite imaging technology, computer-assisted image classification is still unable to produce land use and land cover maps and statistics with high enough accuracy (Lo & Choi, 2004). Image analysis techniques are evolving rapidly, but many operational and applied remote sensing analyses still require extracting discrete thematic land surface information from satellite imagery using classification-based techniques (Prenzel & Treitz, 2005). Several image classification techniques, from automated to manual digitization, can be found in the literature. However, these have spanned a broad range of land-surface types and sensors. Very few studies (Carvalho, 2006; Lee & Warne, 2006; Lo & Choi, 2004; Nangendo, 2007; Ozkan & Sunar-Erbek, 2005; Prenzel & Treitz, 2005) have compared different image classification methods with different satellite sensors to determine how the organization of information inherent to the classification scheme influences classification accuracy.

Automated classification procedures of satellite imagery have been based mainly on multi-spectral classification techniques (per-pixel classifiers). These procedures assign a pixel to a class by considering its statistical similarities, in terms of reflectance, with respect to a set of classes (Gong, Marceau, & Howarth, 1992). The unsupervised classification approach provides an automated platform for image analysis, mainly based on surface reflectance and generally ignoring basic land cover characteristics (i.e. shape and size) of landforms (Chust, Ducrot, & Pretus, 2004). The supervised classification approach can preserve the basic land cover characteristics through statistical classification techniques using a number of well-distributed training pixels. However, the maximum likelihood classifier often used in supervised classification has been proven ineffective at identifying land uses at urban fringe areas due to the heterogeneity of urban land cover (Johnsson, 1994; Lo & Choi, 2004). Suburban residential areas form a complex mosaic of trees, lawns, roofs, concrete, and asphalt roadways. Such a complex urban environment develops mixed pixel problems, often causing misclassification of remote sensing images. In this case, the fuzzy supervised classification approach helps reduce mixed pixel problems in the heterogeneous earth surface by using a membership function (Zhang & Foody, 2001; Wang, 1990). However, classification techniques that combine more than one classification procedure improve remote sensing-based mapping accuracies (Lo & Choi, 2004).

Considering the complexity of the urban landscape and the importance of spectral and radiometric resolution to land use and land cover classification accuracies, we discuss the benefits of four approaches: unsupervised; supervised; fuzzy supervised and GIS post-processing. These approaches can address a wide range of mapping problems in urban frontiers and provide alternatives to improve mapping accuracies for urban planners. The objectives of this study are to derive land use land cover maps using four different mapping approaches and to compare the accuracies of the approaches in mapping urban area using Advanced Land Observation Satellite data. Tsukuba city was selected to test the mapping approaches. This city is an interesting place to study remote sensing applications as it includes both heterogeneous and homogeneous anthropogenic landscape patterns.

Methods

Study area: Tsukuba city, urban frontier of Tokyo

Geographically, Tsukuba city is situated within the geographic coordinates 35°59'42" to 36°14'2" North latitudes and 140°0'2" to 140°10'39" East longitudes, northeast of the Tokyo metropolitan fringe (Fig. 1). We considered a rectangular shape strategy covering the city and its adjacent hinterlands to remove administrative biases in mapping spatial patterns. The study site covers 55075 ha of land. The coverage has homogeneous (i.e. paddy field, water, etc.) and heterogeneous (residential, parks, etc.) landscapes. It includes both dense and sparse types of landscape development.

The agricultural landscape of Tsukuba in the 1960s has been transformed into a modern city; in Japan the city is known as Science city. The city is well-planned and developed with a special purpose: to promote science by establishing educational institutes and national-level research institutes. Therefore, it carries a unique perspective of development by absorbing a significant number of educated populations rather than the industrial population. A high-speed train system (Tsukuba Express) was established in 2005. This transportation system makes it easy to commute and reduces the travel time to the Tokyo centre. Due to the establishment of state of the art facilities, improved life quality and reduction in travel time to Tokyo, Tsukuba is becoming the centre of attraction for the residents, even for those who are working in different parts of Tokyo. The population in the business core of Tsukuba and its vicinity is growing, with a density of 730 persons per square kilometre as of 2008; this is 25 heads higher than in 2005 (Statistics Bureau, 2008). New residential and commercial zones are being built. Rapid changes in landscape can be observed, even at a monthly or bimonthly basis.

Physically, the study area is part of the flat Tsukuba-Inashiki Plateau, 20-30 m above sea level, covered with the Kanto Loam Layer. Mt. Tsukuba (elevation of 877 m), one of the major mountains in the Kanto region, is located to the north of the study site (Thapa and Murayama, 2007). Four major rivers (Kokai, Sakura, Higashi Yata, and Nishi Yata) irrigate the area from north to south. Forests and agriculture fields in suburban areas provide natural green spaces to city dwellers. The average annual temperature was 14.2°C with annual precipitation of 1612 mm in the year 2006 (Japan Meteorological Agency, 2006). The city gets fairly cold in the winter; snow falls about twice a year.

(Figure 1 should be around here)

Data sources

Remote sensing image data. We used an ALOS (Advanced Land Observing Satellite) multi-spectral Advanced Visible Near Infra Red 2 (AVNIR2) sensor image acquired on 4th August 2006 (Fig. 2(a)). The ALOS (locally known as 'Daichi') is a new satellite, launched in 2006 (JAXA, 2006). The ground coverage (swath width) of the sensor at nadir is 70 kilometres. This image consists of visible and near-infrared bands (wavebands: Band 1 [blue, 0.42 - 0.50 µm], Band 2 [green, 0.52 - 0.60 µm], Band 3 [red, 0.61 - 0.69 µm], Band 4 [near infrared, 0.76 - 0.89 µm]. The spatial resolution of the image is 10 meters. This image was selected for this study as it provided suitable cloud-free spatial coverage with relatively high spatial and spectral resolutions.

Geometric correction. Accurate registration of multi-spectral remote sensing data is essential for analysing land use and land cover conditions of a particular geographic location. In this study, we carried out geometric rectification using a road network map with the local projection system (i.e., Transverse Mercator, Tokyo GRS 1980 datum). Thirty ground control points were used to rectify the image. A first-order polynomial linear transformation function was used where 0.23 root mean square error was achieved. A nearest neighbourhood re-sampling algorithm was applied, since this does not alter the radiometric values of individual pixels.

Ground reference data. In image analysis, ground reference data play important roles to determine information classes, interpret decisions, and assess accuracies of the results. Substantial reference data and a thorough knowledge of the geographic area are required at this stage. In this study, we adopted both methods (primary and secondary) for collecting ground truth data. Intensive fieldwork was conducted in December 2006 as the primary data collection method. A Personal Digital Assistant (PDA) with built-in Global Positioning System (GPS) equipped with a data entry form and navigation map and a handheld digital camera were used for collecting the geographic data and recording perspective views of the locations for laboratory analysis. A total of 100 geographic locations in points and polygons and their corresponding biophysical attributes were collected in the field. The locations of the collected data represent both the homogeneous and the heterogeneous landscape environments of the study area. In the secondary data collection method, we used higher resolution imagery acquired from airborne and space-borne sensors, as well as city planning maps and other documents. A QuickBird satellite image with 0.6 meter resolution acquired in October 2006 and colour aerial photographs with 0.5 meter resolution acquired in November 2005 of selected areas were used. Using all of these data, detailed ground reference data of the study area were prepared to support the land use class scheming, image classification and subsequent accuracy assessments. Furthermore, the ground reference data used for the image classification were invalid for mapping accuracy assessment purposes.

Classification scheme

Classification schemes provide frameworks for organizing and categorizing information that can be extracted from image data (Thapa and Murayama, 2007). A proper classification scheme includes classes that are both important to the study and discernible from the data on hand (Anderson, Hardy, Roach, & Witmer, 1976). Image enhancement, contrast stretching and false colour composites were worked out to improve the visual interpretability of the image by increasing the apparent distinction between the features. Knowledge-based visual interpretation, texture and association analysis were done at the preliminary stage. Furthermore, field survey data, aerial photographs and the QuickBird image, city planning maps and documents were carefully analyzed while preparing the classification scheme.

A false colour composite (Bands: 4, 3 and 2 as Red, Green and Blue, respectively) of the AVNIR2 image of the study site used as input data is shown in the Fig. 2(a). The false colour image clearly shows the water bodies in black, paddy fields in pink, vegetation in dark red and urban surface materials as light bluish. It is difficult to distinguish dry farm land and exposed field in the false colour image, but this is distinguishable in true colour (Bands: 3, 2 and 1 as Red, Green and Blue, respectively). Separation of asphalt surface from the image is easier, but the association of the surface in the study area makes it difficult to consider it an entity of the urban land use pattern. Most of the roads and parking areas are built out of asphalt, and are associated with residential, facility and industrial areas. Therefore, after analysing the fieldwork information, we decided to combine the roads, parking lots and residential land uses as one class labelled residence/parking/road. The land use categories recommended by the Geographical Survey Institute, sole authority of land use mapping in Japan (GSI, 2008), are also reviewed. After analyzing these information sources, we decided to extract seven types of land use and land cover classes as thematic information from the image (Table 1).

(Table 1 should be around here)

Image classification

Land cover classes are typically mapped from digital remotely sensed data through digital image classification and interpretation. The overall objective of the image classification procedure is to automatically categorize all pixels in an image into land cover classes or themes (Lillesand, Kiefer & Chipman, 2008). In this study, four approaches (unsupervised, supervised, fuzzy supervised and GIS post-processing) were used for image classification and mapping of the urban area. However, the land use prediction methods are constrained by the spatial resolution of satellite imagery, the mapping approach, and expert knowledge of the study area (Thapa and Murayama, 2008).

Unsupervised classification approach. The unsupervised classification approach is an automated classification method that creates a thematic raster layer from a remotely sensed image by letting the software identify statistical patterns in the data without using any ground truth data (Leica Geosystems, 2005; Lillesand, Kiefer & Chipman, 2008). Clusters are defined with a clustering algorithm that uses all pixels in the input image for analysis. After the classification is complete, the analyst then employs a posteriori knowledge to label the spectral classes into information classes. Initially, thirty spectral clusters were formed to separate the image information into a more readable form. The Iterative Self-Organizing Data Analysis Technique (ISODATA) was used to cluster the image pixels into groups. Many more clusters than actual classes (i.e., schemed class in Table 1) were chosen because the exact number of spectral classes in the dataset was unknown. These thirty clusters were carefully judged using expert knowledge and ground reference data. Spectrally similar classes of identical land cover types were merged. These merged clusters were evaluated to whether they belonged to the land use information classes listed in Table 1. Finally, a labelling process was carried out to generate a thematic urban land use and land cover map.

Supervised classification approach. In this approach, the spatial patterns in the image dataset are evaluated by the computer using predefined decision rules to determine the identity of each pixel. Supervised classification requires input from an analyst in order to automate the classification algorithm to associate pixel values with the correct land cover category (Jansen, 2005; Lillesand, Kiefer & Chipman, 2008). We identified homogeneous sample pixels as training pixels in the image that can be used as representative samples for each land use category to train the algorithm to locate similar pixels in the image. For each land use and land cover type (Table 1), five to ten areas of interest were prepared as the signatures of training samples. The training areas were created in order to discriminate the individual classes. The ground reference data were used to prepare the training signatures. After obtaining satisfactory discrimination between the classes during spectral signature evaluation, supervised classification with the Maximum Likelihood Classifier (MLC) was run using all four bands of the image. This classifier quantitatively evaluates both the variance and the covariance of the category spectral response patterns when classifying an unknown pixel (Shalaby & Tateishi, 2007).

Fuzzy supervised classification approach. The fuzzy supervised classification approach works using a membership function, where a pixel's value is determined by whether it is closer to one class than another (Jensen, 2005; Wang, 1990). This approach considers that each pixel might belong to several different classes without definite boundaries. Therefore, it can deal with the mixed pixel problem or the more heterogeneous features representation problem. In this approach, we prepared five to ten training areas for each land use class (Table 1). Instead of delineating training areas that are purely homogeneous, a combination of pure and mixed training sites was used. Mixtures of various feature types defined the fuzzy training class weights. A classified pixel was then assigned a membership grade with respect to its membership in each information class. Two maps (multilayer class map and distance map) were generated. Fuzzy convolution 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 (Leica Geosystems, 2005). Classes with very small distance values remain unchanged, while classes with higher distance values may change to a neighbouring value if there are a sufficient number of neighbouring pixels with class values and small corresponding distance values. The convolution method has a built-in function that creates context-based classification to reduce speckle or salt-and-pepper noise in the classification map.

GIS post-processing approach. A combination of more approaches in mapping provides better results than just using a single approach (Kuemmerle, Radeloff, Perzanowski, & Hostert, 2006; Lo & Choi, 2004). In this study, we propose a GIS post-processing approach that combines the advantages of all three approaches (unsupervised, supervised and fuzzy supervised) to produce an improved land use and land cover map. Here, the maps derived from the unsupervised and supervised approaches were combined using the GIS overlay function. Then, we extracted common land use pixels from the map considering the land use clusters that were identified by both approaches as the best results. The resulting map was carefully evaluated and revealed that the most likely homogeneous features were represented by common pixels, but the more heterogeneous features were left empty. Many studies suggest (Jensen, 2005; Wang, 1990; Zhang & Foody, 2001) that heterogeneous landscape can be better identified by the fuzzy approach. Therefore, the remaining empty pixels were filled by the land use and land cover pixels derived from the fuzzy supervised approach taking into consideration fuzzy strength and rigidness to deal with the heterogeneous landscape. This GIS post-processing approach can represent both homogeneous and heterogeneous areas of the city.

Post-classification smoothing was applied by a 3x3 grid-cell majority filter in the maps generated from unsupervised, supervised and GIS post-processing approaches before the accuracy assessment.

Accuracy assessment

The accuracy of thematic maps derived by image classification analyses is often compared in remote sensing studies. Accuracy assessment is a general term for comparing predicted (i.e., classification) results to geographical reference data that are assumed to be true (Lillesand, Kiefer & Chipman, 2008; Richard & Jia, 1999). This comparison is typically achieved by a basic subjective assessment of the observed difference in accuracy but should be undertaken in a statistically rigorous fashion (Foody, 2004). A set of reference pixels representing geographic points on the classified image is required for the accuracy assessment. Randomly selected reference pixels lessen or eliminate the possibility of bias (Congalton, 1991). A random stratified sampling method was used to prepare the ground reference data. This sampling method allocates the sample size for each land use based on its spatial extent (Shalaby & Tateishi, 2007). A total of 300 reference pixels were prepared for each map as ground truth, using the source data as discussed earlier in the ground reference data section. The minimum representation threshold for each land use land cover class was set to 30.

An error matrix was prepared for each resulting thematic map. The matrix provided the correspondence between the predicted and the actual classes of membership for an independent testing dataset. It made it possible to derive a range of quantitative measures of classification accuracy. Four measures (producer's, user's, and overall accuracy and Kappa statistic) of accuracy assessment were computed to evaluate the accuracy of the thematic maps. The producer's accuracy represents the measure of omission errors that corresponds to those pixels belonging to the class of interest that the classifier has failed to recognize. The user's accuracy, on the other hand, refers to the measure of commission errors that correspond to those pixels from other classes that the classifier has labelled as belonging to the class of interest (Richard & Jia, 1999). 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 agreement that occurs by chance. Consequently, it provides a more rigorous assessment of classification accuracy (Congalton, 1991).

Results and discussion

Each approach produced one thematic land use and land cover map (Fig. 2(b)-(e)). The selection of classification approaches often has an impact in quantitative spatial extent of land uses (Table 2). The land use area statistics derived from the supervised, fuzzy supervised and GIS post processing approaches showed small differences in spatial extent as compared to the unsupervised approach. Automated clustering technique (unsupervised) often failed or overestimated the heterogeneous landscapes, mainly in residential and suburban area. High contrast is observed between the spatial statistics of unsupervised and other approaches, especially in the residence/parking/road class. This may be due to the complexity of the urban environment, which forces the classifier to overestimate land use and land cover area. In this case, the supervised and fuzzy supervised approaches have shown good results because these approaches use signatures of particular surface materials to train the algorithm. However, all classifiers showed very few differences in the spatial extent (within ±2%) of the classes, i.e. urban forest, water and paddy field classes. Natural land covers are separable in all classification processes, so there is no significant change for the corresponding spatial statistical representations. All the classification approaches were able to present dry farmland/exposed field as a major land use in the study area.

(Table 2 should be around here)

Four tables (Tables 3 to 6) were prepared to analyze the accuracy of the mapping results. The reference sample size of land uses in each accuracy assessment table differed depending on its spatial representation at the surface. The same sample size of reference data of the urban forest class derived from the unsupervised approach was not necessarily the same as the sample size of the corresponding class derived from the supervised approach.

In this study, the GIS post-processing approach appeared to be the best approach. This approach showed an overall accuracy of 89.33% (Table 6), which is close to the overall accuracy (87.67%) of the fuzzy supervised approach (Table 5). The fuzzy approach dealt with mixed pixel problems and the heterogeneous representation of land surface features in residential and park areas in the city. The supervised and unsupervised approaches produced lower accuracies (83.67% (Table 4) and 75.33% (Table 3), respectively). Due to the various surface materials in the complex urban system, the unsupervised approach formed several class clusters in images, creating difficulties in interpretation. However, the unsupervised approach provided better insight to identify large space objects in the image (e.g., commercial complexes and industrial plants).

(Figure 2 should be around here)

(Table 3 should be around here)

The kappa indices presented a somewhat clearer picture. The kappa coefficient shows that the GIS post-processing approach can reduce most of the errors during the classification process. The kappa for the approach (Table 6) was 0.87 (87% reduction of error), which is a bit better than the kappa for the fuzzy supervised approach of 0.85 (see, Table 5), with a difference of 1.66% in overall classification accuracy between them. Looking at the kappa, we observed a bigger difference between the supervised and unsupervised approaches, with kappa indices of 0.80 (Table 4) and 0.71 (Table 3), respectively, an increase of 8.34% in accuracy. This signifies that the supervised approach performed better than the unsupervised in mapping of urban area. The overall accuracy and kappa only represent an average result. It is still difficult to determine which approach projected refined mapping results for which surface materials at the class level.

(Table 4 should be around here)

GIS post-processing and fuzzy supervised approaches exhibited high (over 80%) producer's accuracies or low omission errors (Tables 5 and 6) in all classes; similar patterns were observed in user's accuracies (low commission error), except in the Lawn/Grass class.

Urban forest, paddy field, business/industry and water classes have very high user's accuracies (over 89%) in both approaches. With the exception of paddy fields, the user's accuracies of these classes were also similar. Somewhat higher errors of commission occurred in paddy fields. Both the GIS post-processing and the fuzzy supervised approaches did best in extracting urban and natural land covers as both of their producer's and user's accuracies were high.

Because of the mixture of surface materials (i.e., roof tiles, concrete, asphalt and vegetation) in residential areas, the unsupervised (Table 3) and supervised (Table 4) approaches scored the user's and producer's accuracies poorly in the residential/parking/road class. Due to the capacity of dealing with heterogeneous surface features, mapping of such features by the fuzzy supervised approach improved greatly, showing over 82% producer's and user's accuracies in residential land use classifications. The GIS post-processing approach, with a user's accuracy of 85%, appeared to be slightly better than the fuzzy supervised approach (user's accuracy of 83%), an increase of 2% for extracting residential land use. In other words, for the GIS post-processing approach, the producer's accuracy for residential land use was 93%, an improvement of 11% over the fuzzy supervised approach. In both cases, the GIS post-processing approach seems superior for addressing the mapping issues of residential land uses. The user's accuracies show that the supervised approach estimates the lawn/grass class better than the other approaches. A high contrast is observed between the producer's and user's accuracies of the lawn/grass class in all approaches. In the more homogeneous land covers (i.e., paddy field, natural vegetation and water bodies), both the unsupervised and supervised approaches exhibited good producer's and user's accuracies. The unsupervised approach performed better than the supervised approach in clustering the paddy field, with 92% of user's and 83% of producer's accuracy; the supervised approach had 7% lower in user's and 1% higher in producer's accuracies.

(Table 5 should be around here)

In the supervised approach, despite a producer's accuracy of 91% for the business/industry class, there was actually 85% user's accuracy, which means at least 6% of the business/industry land use was classified wrong (Table 4). For the unsupervised approach, the producer's accuracy for this class was 75%, while 73% user's accuracy was actually business/industry land use, making a difference of 2% of wrong classification (Table 3). Here, the unsupervised classifier seems slightly better than the supervised classifier in dealing with big homogeneous parcels characterized by business/industry land use. The supervised approach exhibited a lower difference between the user's and producer's accuracies for urban forest, paddy fields and water, which compared well even with the fuzzy and GIS post-processing approaches.

(Table 6 should be around here)

Conclusions

The urban landscape of Tsukuba city is diverse and complex, comprising both homogeneous and heterogeneous surface features, causing problems of spectral variability in the satellite image data. Assimilating spectral and radiometric properties of image data is more important than spatial resolution in improving computer-assisted land use and land cover classification accuracy. In order to improve mapping accuracies from remotely sensed data, relying on only one approach is not enough. In this study, we examined four approaches (unsupervised, supervised, fuzzy supervised and GIS post-processing) and their accuracies to extract land use and land cover information using an AVNIR2 sensor image of the ALOS satellite. The combination of fieldwork, satellite image data and analysis techniques really improved mapping accuracies. We found that the spatial statistics of land use/cover derived from remotely sensed images mostly depend on the adaptation of mapping approaches. The accuracy assessment report showed that the GIS post-processing approach can predict land use and land cover of the complex urban environment more accurately. The urban woodland, water, business/industry and paddy field mapped by the GIS post-processing were observed more accurately compared to the other approaches. The fuzzy supervised approach presented slightly more accurate results than the traditional supervised approach. This method also shows great potential for dealing with heterogeneous surface features in urban residential areas showing very low difference in the errors of omission and commission. The supervised approach exhibited a lower difference between the user's and producer's accuracies for the vegetation, paddy field and water classes compared to other approaches. In fact, the unsupervised approach greatly helped us understand the land cover structure and identify homogeneous clusters in the imagery. Each classification approach has its special characteristics and benefits to analyse remotely sensed images and mapping of the earth surface. This study explored the strengths of the four approaches for mapping urban area from the AVNIR2 sensor of ALOS, which may significantly help urban planners understand and interpret complex urban characteristics more precisely, as they often cite problems of mapping techniques and spatial resolution (Carlson, 2003).

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Table 1
Land use/cover schemes

No.	Classes	Definition
1.	Urban Forest (UF)	Natural vegetation and planted trees
2.	Lawn/Grass (LG)	Lawn, grass and bush
3.	Paddy Field (PF)	Paddy field
4.	Dry Farmland/Exposed Field (DF)	None irrigated land, vegetables and fruits area
5.	Facility/Industry (FI)	Large space house
6.	Residence/Parking/Road (RP)	Small houses, back/front yards, parking area, road
7.	Water (WA)	Lake, river, wetland.

Table 2
Impact of classification approaches in spatial extent of land use/cover

	Approaches (area in %)			
Land use/cover	Unsupervised	Supervised	Fuzzy supervised	GIS post-processing
Urban Forest	20.97	19.17	17.82	18.74
Lawn/Grass	18.66	13.10	13.71	13.24
Paddy Field	19.75	19.58	18.41	19.27
Dry Farmland/Exposed Field	28.44	21.22	23.25	22.85
Facility/Industry	3.92	5.95	6.01	5.59
Residence/Parking/Road	7.17	19.62	19.51	18.98
Water	1.09	1.36	1.28	1.33
Total	100.00	100.00	100.00	100.00

Table 3
Error matrix of the unsupervised approach for land use/cover classification

Classified data	Reference data								
	UF	LG	PF	DF	FI	RP	WA	Total	U. Acc %
UF	39	1	1	3	1	4	0	49	80
LG	2	33	7	3	0	1	1	47	70
PF	1	2	44	0	0	1	0	48	92
DF	2	3	1	32	2	17	0	57	56
FI	0	0	0	1	24	8	0	33	73
RP	1	0	0	5	5	24	1	36	67
WA	0	0	0	0	0	0	30	30	100
Total	45	39	53	44	32	55	32	300	
P. Acc %	87	85	83	73	75	44	94		
Overall Classification Accuracy = 75.33%									
Overall Kappa Statistics = 0.71									

U. Acc., user's accuracy; P. Acc., producer's accuracy, see table 1 for other abbreviations (number unit is in pixel).

Table 4
Error matrix of the supervised approach for land use/cover classification

Classified data	Reference data								
	UF	LG	PF	DF	FI	RP	WA	Total	U. Acc %
UF	44	2	0	1	0	1	0	48	92
LG	0	33	7	1	0	1	0	42	79
PF	2	3	41	2	0	0	0	48	85
DF	1	3	1	40	1	3	1	50	80
FI	0	0	0	2	29	3	0	34	85
RP	0	4	0	8	2	34	0	48	71
WA	0	0	0	0	0	0	30	30	100
Total	47	45	49	54	32	42	31	300	
P. Acc %	94	73	84	74	91	81	97		
Overall Classification Accuracy = 83.67%									
Overall Kappa Statistics = 0.80									

U. Acc., user's accuracy; P. Acc., producer's accuracy, see table 1 for other abbreviations (number unit is in pixel).

Table 5
Error matrix of the fuzzy supervised approach for land use/cover classification

Classified data	Reference data								
	UF	LG	PF	DF	FI	RP	WA	Total	U. Acc %
UF	43	2	1	0	0	0	0	46	93
LG	3	30	5	3	0	1	0	42	71
PF	0	1	45	0	0	1	0	47	96
DF	0	1	1	43	0	6	1	52	83
FI	0	0	0	1	33	1	0	35	94
RP	2	0	0	1	3	40	2	48	83
WA	0	0	0	0	1	0	29	30	97
Total	48	34	52	48	37	49	32	300	
P. Acc %	90	88	87	90	89	82	91		
Overall Classification Accuracy = 87.67%									
Overall Kappa Statistics = 0.85									

U. Acc., user's accuracy; P. Acc., producer's accuracy, see table 1 for other abbreviations (number unit is in pixel).

Table 6
Error matrix of the GIS post-processing approach for land use/cover classification

Classified data	Reference data								
	UF	LG	PF	DF	FI	RP	WA	Total	U. Acc %
UF	47	0	0	0	0	0	0	47	100
LG	0	27	10	4	0	1	0	42	64
PF	0	1	46	0	0	1	0	48	96
DF	0	3	1	44	2	1	0	51	86
FI	0	0	0	0	33	0	1	34	97
RP	1	1	0	2	2	41	1	48	85
WA	0	0	0	0	0	0	30	30	100
Total	48	32	57	50	37	44	32	300	
P. Acc %	98	84	81	88	89	93	94		
Overall Classification Accuracy = 89.33%									
Overall Kappa Statistics = 0.87									

U. Acc., user's accuracy; P. Acc., producer's accuracy, see table 1 for other abbreviations (number unit is in pixel).

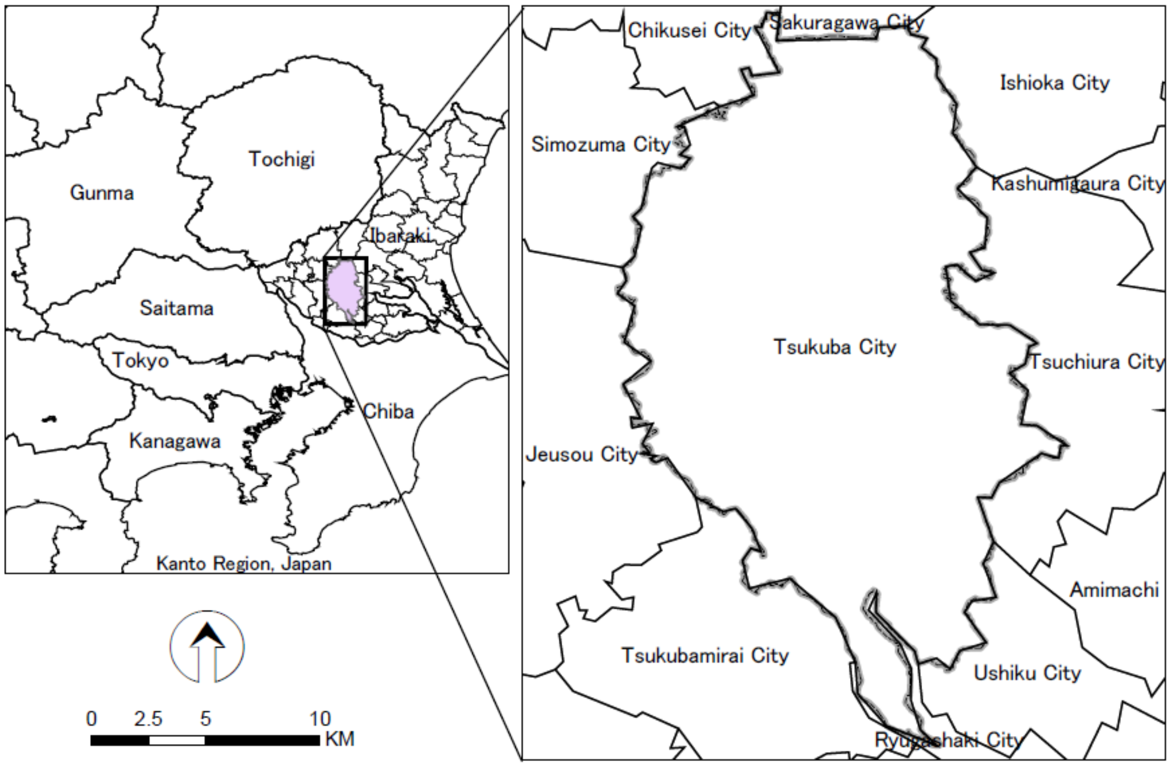

Fig.1. Study area, Tsukuba city, Japan

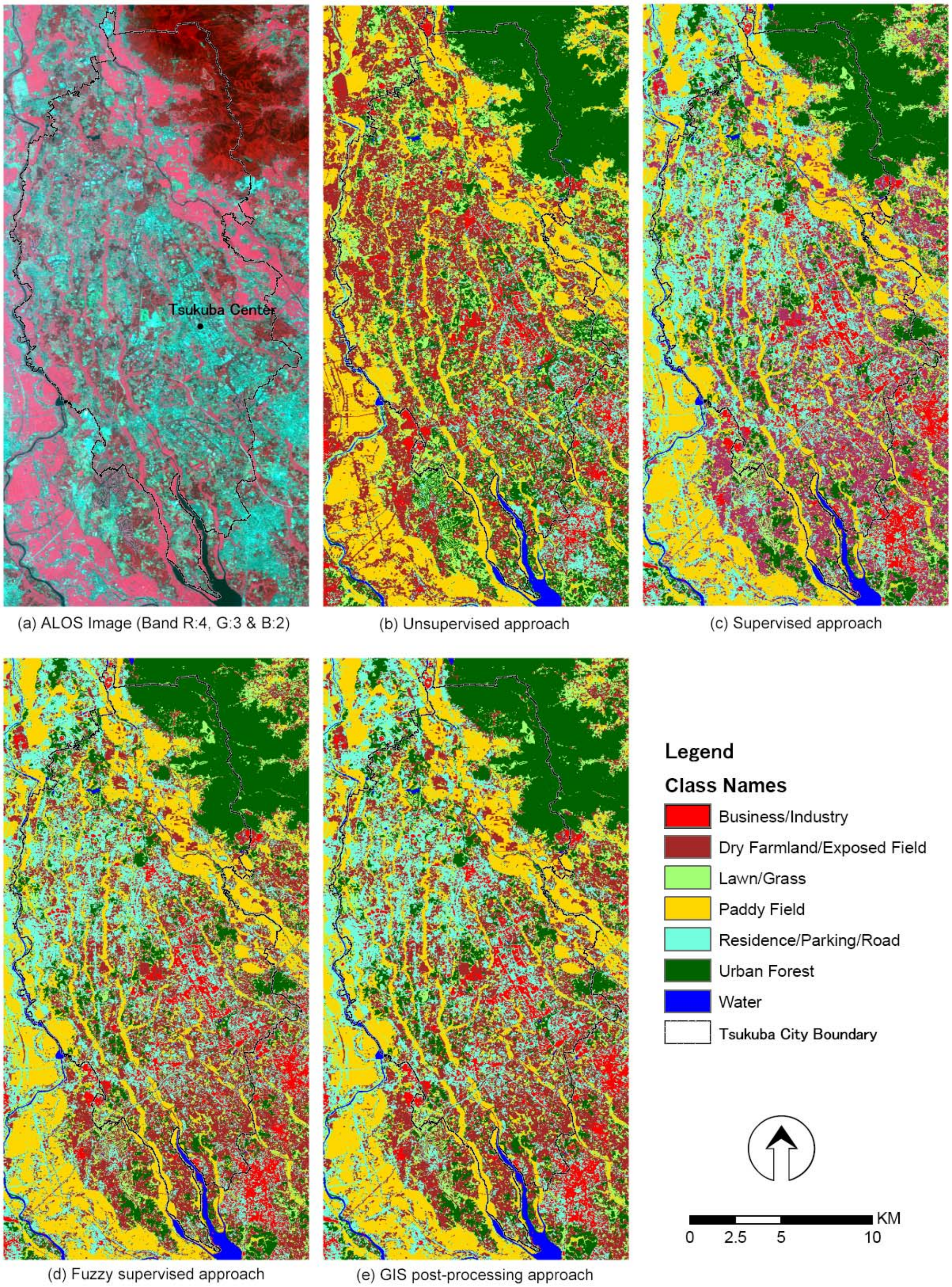

Fig. 2. Image data and land use/cover maps produced by the classification approaches.