Characteristics of Multi-Spatial Resolution Satellite Images for the Extraction of Urban Environmental Information

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ABSTRACT

The coefficients of variation obtained from three typical vegetation indices of eight levels of multi-spatial resolution images in urban areas were employed to identify the optimum spatial resolution in terms of maintaining information quality. These multi-spatial resolution images were prepared by degrading 1 meter simulated, 16 meter ADEOS/AVNIR, and 30 meter Landsat-TM images. Normalized Difference Vegetation Index (NDVI), Perpendicular Vegetation Index (PVI) and Soil Adjusted Ratio Vegetation Index (SARVI) were applied to reduce data redundancy and compare the characteristics of multi-spatial resolution image of vegetation indices. The threshold point on the curve of the coefficient of variation was defined as the optimum resolution level for the analysis with multi-spatial resolution image sets. Also, the results from the image segmentation approach of region growing to extract man-made features were compared with these multi-spatial resolution image sets.

INTRODUCTION

It is expected that the availability of high spatial resolution with multi-spectral images could greatly expand our capability to collect urban environmental information. These images are expected to provide much more information compared to existing sensors, but their usefulness for the extraction of urban environmental information could be restricted by its huge data volume and limited ground coverage [1]. Therefore it is essential to investigate the potential for information extraction from multi-spatial resolution image sets of our urban environment.

The ability to detect, identify, and monitor ground cover types with remote sensing is depend on the relationship between the spatial resolution of the sensor and the surface feature [2]. Therefore a sampling system can be optimized with respect to particular characteristics of the geographical phenomena [3]. The choice of an appropriate scale, or spatial resolution level, for a particular application depends on several factors. These include types of information desired to extract from the scene, the analysis methods to be used, and the spatial structure of the scene itself [4].

In this context, objectives of this study were to investigate characteristics of multi-spatial resolution satellite image sets and to compare the results by the extraction of urban environmental information from multi-spatial resolution image sets. Urban environmental information in this study are divided into two groups; natural features such as vegetation, water, etc. and man-made features such as buildings, roads, etc.

METHODS

This study is composed of two parts. The first part is to search for the optimum resolution level by using the coefficients of variation of typical vegetation indices for the Forest Park and residential area. The second part is to compare the results from the image segmentation approach of region growing for the extraction of man-made features with multi-spatial resolution image sets.

Numerous vegetation indices have been proposed for vegetation mapping and monitoring. They can be categorized into three groups according to the types of computational operations they involve (Table 1) [5]. The mathematical transformations for the vegetation indices used in this study are given below. The formulae and parameters are based on Richardson and Everitt [6].

(1) Perpendicular Vegetation Index (PVI):

$PVI = (NIR - a*RED - b) / SQRT(1+a^2)$

(2) Soil Adjusted Ratio Vegetation Index (SARVI):

$SARVI = NIR / (RED+b/a)$

(3) Normalized Difference Vegetation Index (NDVI):

$NDVI = (NIR - RED) / (NIR+RED)$

Where RED= reflectance value in red band, NIR= reflectance value in near infrared band, a = the slope of the soil line (0.96916) and b = the intercept of the soil line (0.084726).

Table 1. Vegetation Indices Groups

Computational Groups	Vegetation Indices
Subtraction Group	Difference Vegetation Index (DVI) Perpendicular Vegetation Index (PVI)
Division Group	Ratio Vegetation Index (RVI) Soil Adjusted Ratio Vegetation Index (SARVI)
Rational Transform Group	Normalized Difference Vegetation Index (NDVI) Soil Adjusted Vegetation Index (SAVI)

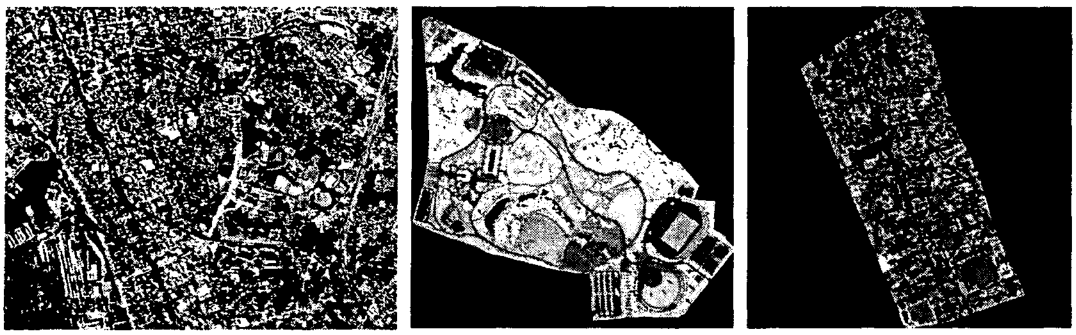
	Transformed Soil Adjusted Vegetation Index (TSAVI)

Three kinds of vegetation indices, PVI, SARVI, and NDVI were selected from each group. PVI and SARVI can remove soil background effects and provide better estimates of plant biomass and cover. PVI is a good index for bright soils in arid and semi-arid locations where vegetation cover is relatively poor and where the ratio vegetation indices are not as sensitive [7].

Next, the image segmentation approach of region growing to extract information was applied, using the natural boundaries between objects to determine their size and shape [8]. In this study, the conventional region growing was used to multi-spatial resolution image sets from vegetation indices that could eliminate the data redundancy, and these results were investigated whether the limit resolution level was coincident, or not.

Image Data Experiment

The study site is located in the southern part of Chiba City, Japan, and the Forest Park and residential area are included (Figure 1 (a)). Three kinds of images were used; PASCO, a Japanese mapping corporation, produced the 1- meter resolution simulated image by scanning color IR films (KODAK #2443) obtained on Oct. 17, 1995. The spectral ranges were centered to green, red, and near infrared. The ADEOS/AVNIR image with three visible bands (0.42-0.50, 0.52-0.60, 0.61-0.69 um) and one infrared band (0.76-0.89 um) of Nov. 17, 1996 were used. The Landsat-TM image of Nov. 19, 1995 was also used. The 1-meter simulated image was geometrically registered to the digital map scaled 1 to 2,500. After this, the ADEOS/AVNIR and the Landsat-TM image were registered to this rectified image. Atmospheric correction was also implemented.



(a) whole area (3750x3030) (b) Forest Park (1024x1024) (c) residential area (1024x1024)

Figure 1. Images of the study site (1 meter simulated images from NDVI)

All of image data were used to produce multi-spatial image sets of consecutively lower resolution of 1, 2, 4, 8, 16, 32, 64, and 128 meter by combining a certain number of neighboring pixels. Table 2 shows the concept of this multi-spatial resolution image sets at each level. After this degradation, the Forest Park and residential area (Figure 1 (b) and (c)) were extracted and vegetation indices for all levels of spatial resolution were computed. The values of computed vegetation indices were truncated and converted to 8-bit data.

Vegetation indices of all resolution levels were statistically compared with each other to find out the optimum level of the resolution. At this time, the coefficient of variation, calculated by dividing the standard deviation by the mean, was used. It is the most commonly used measure of relative variability. Since the target is the same, the mean value in all resolution levels must be same theoretically. But this is not true in reality. To compensate this effect, the coefficient of variation was applied. If the resolution level were similar to the size of objects in the image, the variance would be high. And when adjacent pixels were consecutively merged to produce lower resolution images, the coefficient of variation would decrease accordingly. The optimum spatial resolution level for ground cover types can be located on the curve of the coefficient of variation. The threshold point can be operationally defined as the point where the slope changes the most dramatically. Thus we can conclude the optimum resolution level where the least amount of data volume required to keep the information contained on the original image.

Finally, the acceptability of the optimum resolution level identified at the previous stage was tested with the region growing approach. This segmented approach depends on a piecewise homogeneous area around the observation point and therefore uses a varying local neighborhood [9]. For this experiment, three RGB band images were concentrated to the single gray level image by the vegetation indices.

RESULTS AND DISCUSSION

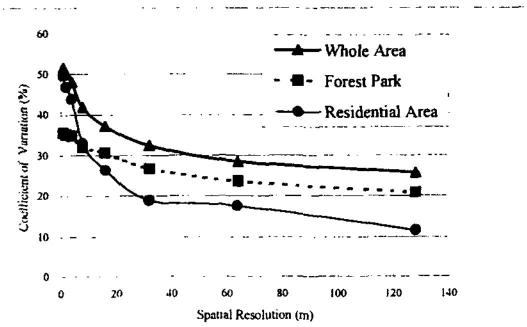
The spatial structure of a scene is closely related to the size of objects and the spatial resolution of the image. The dispersion in the different resolution levels, as measured by the coefficient of variation, decreases gradually in accordance to the degradation of spatial resolution.

Table 2. Description of the multi-spatial resolution image sets

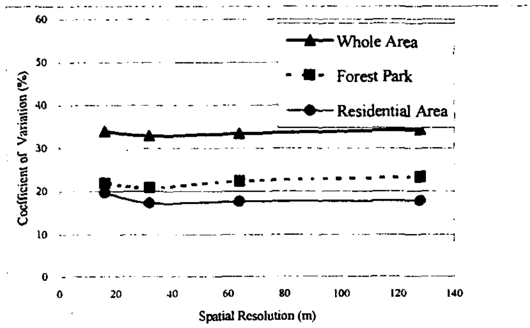
Level	Image Size		Cell Size (m)	Data
	Pixels	Lines		
0	3750	3030	1	Simulated Image
1	1875	1515	2	
2	938	758	4	
3	469	379	8	
4	235	190	16	ADEOS/AVNIR
5	118	95	32	Landsat-TM
6	59	48	64	
7	30	24	128	

The coefficients of variation of NDVI at different levels of spatial resolution are shown on Figure 2. It shows that the degradation of spatial resolution results in the decrease of the coefficients of both cover types, but the decreasing trend of the coefficient of the residential area is greater than that of the park at the level 3. Such difference of trends is due to the difference of ground cover types. At the level 0, 1 and 2, the coefficients of the residential area are greater than those of the park.

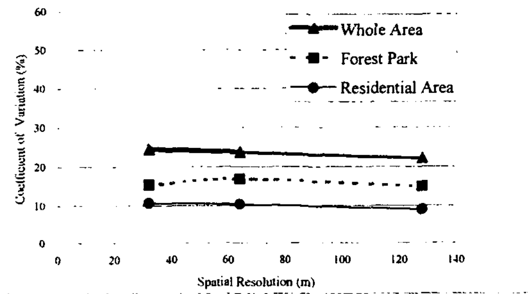
This means that ground cover types of the residential area are much more complex than the park. On the other hand the coefficients of the park show little change along the same resolution levels for the opposite reason. At the level 3, spatial resolution of 8 meter, the degree of change of the coefficient of the residential area is greater than that of the park. This phenomenon is caused by the diminishing heterogeneity of the scene by merging pixels with diverse buildings and roads. This resolution level is the point where the balance between information quality and the requirement for data volume could be achieved. The coefficients of Landsat-TM image are smaller than higher resolution images and are relatively constant at all levels of spatial resolution, which means it is unsuitable for information extraction in such urban areas.



(a) 1 meter simulated image



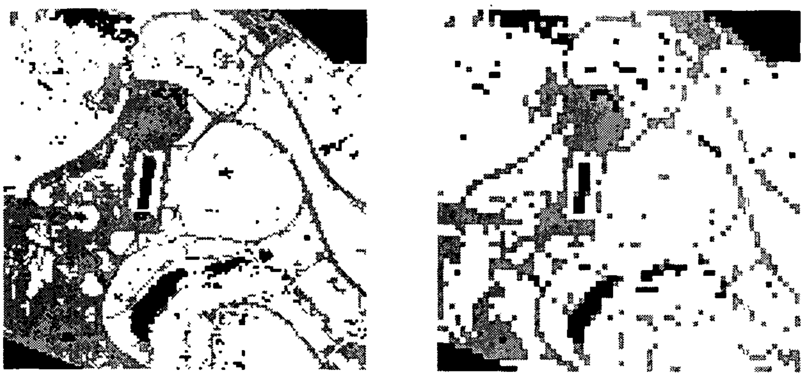
(b) ADEOS/AVNIR image



(c) Landsat-TM image

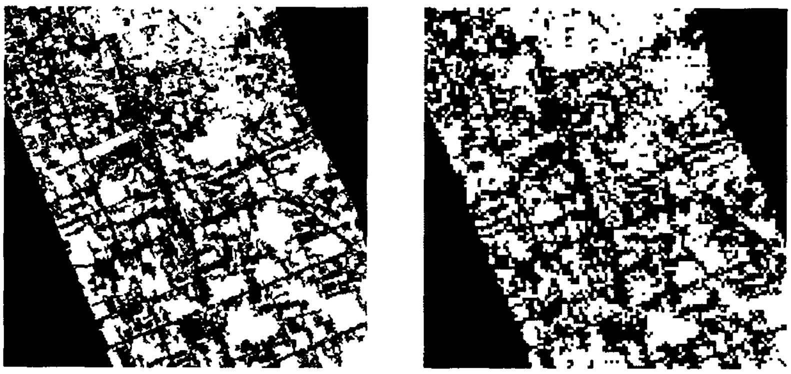
Figure 2. Changes of the coefficients of variation for NDVI at eight levels

Figure 3 shows the results of region growing at level 2 and 3 in the Forest Park, and level 1 and 2 in the residential area. These levels are the points where the coefficients of variation decrease the most dramatically. Man-made objects in the Forest Park can easily be extracted owing to the relatively large size of the objects. But most of the narrow roads in the Forest Park could not be connected at level 3. In the residential area, details were diminished at the level 2, and it is nearly impossible to classify the ground objects at level 3.



(a) Level 2 in the forest park (b) Level 3 in the forest park

Road Vegetation Water



(c) Level 1 in the residential area (d) Level 2 in the residential area

Road Built-up area

Figure 3. Results of the image segmentation approach of region growing

CONCLUSIONS

Multi-spatial resolution data sets of eight levels of spatial resolution with vegetation indices in urban areas were compared to identify optimum resolution levels in terms of maintaining information quality. It was found that higher resolution is required to analyze residential areas than an urban park. Owing to the object size and the spatial resolution, it could be concluded there were different optimum resolution levels between Forest Park and residential area. Typical vegetation indices and the segmentation approach of region growing were applied to get the optimum level in this study

It is expected that the results of this research could provide essential information to overcome the limitations of low spatial resolution images and to exploit full potential of high spatial resolution images.

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