A NEW METHOD OF VEGETATION MAPPING BY OBJECT-BASED CLASSIFICATION USING HIGH RESOLUTION SATELLITE DATA

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ABSTRACT:

Continuous monitoring and updating of distribution maps is essential for conservation and management of plant communities, especially in regions where change and development are rapid. Traditional methods of vegetation mapping rely on interpretation of aerial photographs and follow-up field research, and are expensive, time-consuming and labor-intensive. Remote sensing, using high resolution data such as IKONOS, offers the potential for streamlining the process of producing and updating vegetation maps. In this research, three types of classification; pixel-based maximum likelihood, pixel-based ISODATA and object-based minimum distance, were used to classify IKONOS images obtained for typical countryside landscape in Chiba Prefecture. The results from each of these classifications was compared to a master map based on standards used by the Ministry of the Environment in their physiognomical vegetation maps. The object-based classification outperformed the two pixel-based methods in terms of overall accuracy and Kappa index. In the maximum likelihood classification, over-classification resulted in identification of too many tiny areas; while in the ISODATA method, clustering caused the system to classify several different categories into a single area. The object-based classification, however, produced results that compared well with the master map, indicating that remote sensing can contribute to reduction of the work load and standardization of quality in the early stages of producing and updating vegetation maps.

1. INTRODUCTION

Plant communities all over Japan are changing rapidly due to global warming and shifts in land management policies. In addition, in recent years, fragmentation of plant communities due to urbanization and development has become a major issue. Continuously updated vegetation maps, showing the current distribution of the various communities, are required for proper management and conservation. Representative vegetation maps are those produced by the Ministry of the Environment since 1973. These maps, however, rely on detailed analysis of aerial photographs coupled with substantial field research, and as such require great amounts of time and labor. In addition, the accuracy of the maps varies with the skill and experience of the researchers. The need for a more efficient, less labor-intensive methodology has become even more urgent since the Ministry switched from 1/50,000 scale maps to 1/25,000 scale for the 6th National Survey on the Natural Environment (1999~2004).

Recently, new technologies, employing Geographic Information Systems (GIS) and remote sensing technology, are being examined as tools for efficient vegetation mapping (Alexander and Millington, 2000). The Japanese Ministry of the Environment is also considering the use of remote sensing in future vegetation mapping projects (Biodiversity Center of Japan, 2005). The recent widespread availability of high resolution satellite data, such as IKONOS, which is capable of extracting forest crowns and classifying vegetation elements even in areas with mixed patterns of vegetation, has increased expectations for remote sensing as a tool for producing and updating vegetation maps. Still, at this stage, due to technical problems in pixel-based classification, such as misinterpretation of shadows and variable-shaped individual crown trees, vegetation mapping by remote sensing has not quite reached the practical level. Recent research (e.g. Wang et al, 2004; Marçal et al, 2005), however, has focused on object-based classification programs as a means of overcoming these problems.

In this research, the practicality of vegetation mapping by object-based classification using IKONOS high resolution remote sensing data, is examined and compared with two types of extant pixel-based classifications methods.

2. OBJECT-BASED CLASSIFICATION IN VEGETATION MAPPING

The extant vegetation mapping process is outlined in Figure 1. To begin with, aerial photographs are studied, and boundaries

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of the major vegetation types are mapped out according to appropriate scale, producing a draft physiognomical vegetation map. Next, on site field research is implemented to correct and verify the boundaries drawn on this draft map. Data on vertical and horizontal distribution density of individual species is also collected at this time. The field data is then compiled and analyzed to identify precise plant communities. Finally, these results, combined with additional fieldwork, are used to produce a phytosociological vegetation map based on associations of particular species (Suzuki et al, 1985).

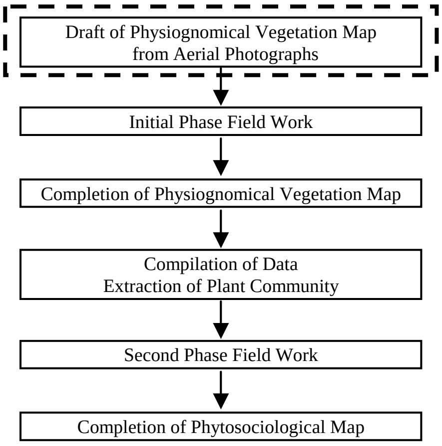
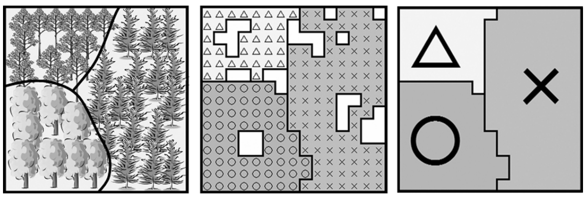


Figure 1. Steps in production of Phytosociological Vegetation Map (Suzuki et al., 1985)
(Remote Sensing can contribute to the First step, encased in a dotted line.)

Remote sensing, which its limited in its ability to identify understory vegetation, can not be expected to generate or update the completed phytosociological vegetation map. Figure 2 shows the differences among traditional hand-mapping using aerial photographs (2a); pixel-based classification of remotely-sensed data (2b) and object-based classification of remotely sensed data (2c). As shown in the figure, the pixel-based classification approach, which does not consider the relationship of each pixel data with its adjacent units, tends to divide the area up into finer divisions than is called for. Small gaps or shadows in a relatively homogeneous forest, for example, show up as different vegetation categories. In the object-based approach, on the other hand, the program can be set to filter out these minor inconsistencies, producing results very similar to those generated by the traditional method. Thus object-based classification should have potential for streamlining and standardizing the initial phase work of vegetation mapping.



(a) (b) (c)

Figure 2. Classification of vegetation types
(a): based on visual interpretation
(b): pixel-based (over classifies)
(c): object-based (result, similar to visual interpretation)

3. EXPERIMENTS

3.1 Study Area

This research was implemented on a 2 km by 2 km test area, located in an agricultural area of Sosa City, located in eastern Chiba Prefecture, central Honshu (Figure 3). The target area consists of narrow, highly-branched alluvial valleys, called ‘Yatsu’, which are cut deeply into flat-topped, plateau-like uplands. The height of the uplands is only 30-40 meters, limiting the effect of terrain on the analysis. Forest communities in the target area consist of deciduous broadleaved woodlands (*Quercus - Carpinus*); evergreen broad-leaved woodlands (*Castanopsis - Quercus*); bamboo groves (*Phyllostachys*) and conifer plantations (*Cryptomeria - Chameocyparis*). These vegetation types border each other in a complicated patchwork pattern. In addition, some deciduous broadleaved woodlands have been invaded by bamboo or dwarf bamboo (*Pleioblastus*).

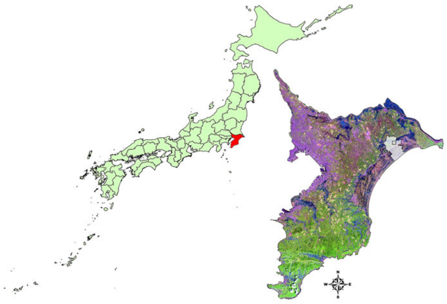


Figure 3. Location of study area

3.2 Methods

The research utilized multi-spectral, 4 square meter grid remotely-sensed data from IKONOS (Space Imaging, Japan), obtained on 1 April 2001 (Figure 4). Physiognomical vegetation maps were produced, using three types of classification; object-based minimum distance method, pixel-based using maximum likelihood method, and pixel-based ISODATA method. The results of these three classifications were compared against a master vegetation map (Figure 5), based on standards used by the Ministry of the Environment in their physiognomical vegetation maps. Only vegetated areas were considered. The vegetation community categories employed in this research follow those of the Ministry map: Evergreen broad-leaved forest; Deciduous broad-leaved forest; Secondary Grassland; Post-cutting secondary growth; Wetland vegetation; Coniferous plantation; Other plantation; Bamboo grove; Fruit orchard.

Figure 4. IKONOS true color image of study area (2000m x 2000m)

The object-based classification employed eCognition software (Definiens). Initial segmentation was a multi-resolution, bottom-up system based on the method of Baatz and Schape (2000). In object-based classification, object size, shape and other parameters can be adjusted to fit the needs of the research. In this case, the basic parameter was set at the level of the plant communities as noted above. Texture and color of the image data were used to classify each unit, and integration of areas was accomplished by increasing the scale parameters. The study area was divided by segmentation processing, and each segment identified was considered to be one object. Aerial photography and the master map were used to establish ground truth and set training data for the different vegetation types. For vegetation categories that showed individual variation in terms of mixture and crown shape, 2 to 10 classes were initially established for recognition purposes, and these were consolidated into a single category in the final analysis. Similar classes were established for the maximum-likelihood and ISODATA classifications.

For evaluating the accuracy, the master map was converted from vector data to 4 meter square raster data, and stratified random sampling was employed to choose sampling points from each category. Using the master map as a base, producer accuracy, user accuracy and Kappa index were calculated for each vegetation category in each of the classification methods. The Post-cutting secondary growth, Other plantation and Fruit orchard categories, however, rarely showed up in the data, and were thus excluded from the accuracy analyses.

4. RESULTS AND DISSCUTIONS

The image results generated by the three classification methods are shown is Figures 6 (object-based), 7 (maximum-likelihood) and 8 (ISODATA); and the classification accuracy for these three methods are shown respectively in Tables 9, 10 and 11.

In terms of overall classification accuracy, the object-based results (64.17%) scored higher than both the maximum-likelihood (60.17%) and the ISODATA (53.64%). In terms of overall Kappa index as well, object-based (0.551) outscored maximum likelihood (0.497) and ISODATA (0.388).

Comparing the ISODATA image with the master physiognomical map, a high number of pixels were classified as Coniferous plantation. As shown in the figure on the vegetation map, whole areas are completely classified in this category. This result can be attributed to clustering of Coniferous plantation and Evergreen broad-leaved forests into the same category. There is thus a large difference in the producer and user accuracies for these two categories, and the Kappa index is low as well.

The maximum likelihood method produced better results, in terms of classification accuracy and Kappa index, than the ISODATA method. Indicating at the vegetation map, however, it can be seen that the results consist of an extremely large amount of scattered categories. A comparison with the master map shows that this classification method has over-divided the data. In addition, the producer accuracy and user accuracy for

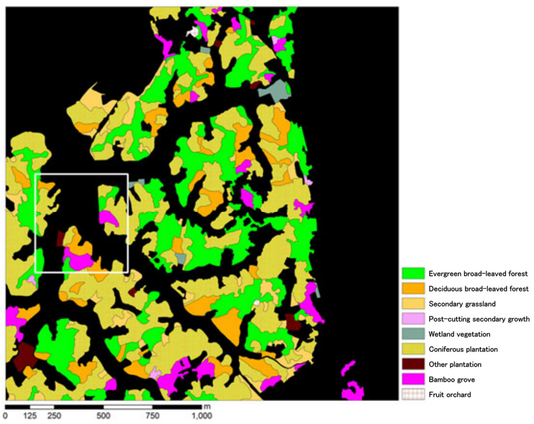


Figure 5. Master Map

White area shown in expanded view in Fig 9

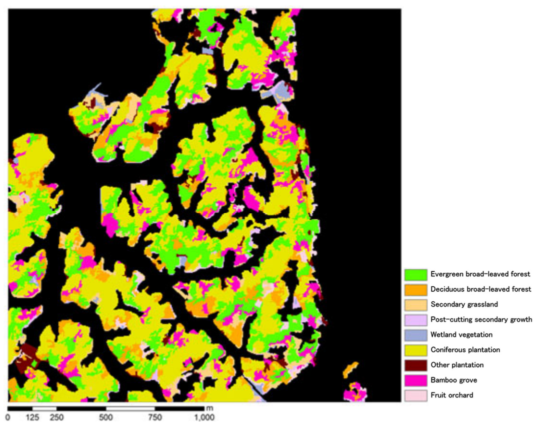


Figure 6. Result of Object-based Classification

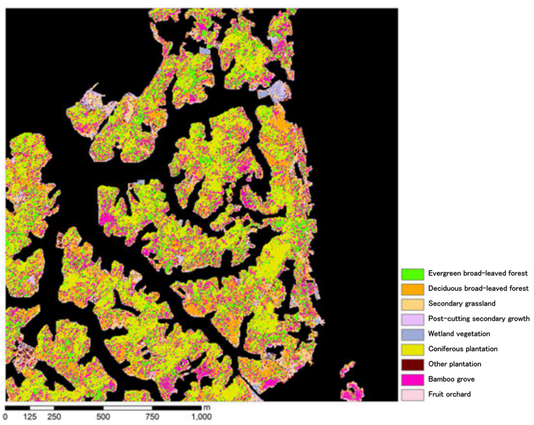


Figure 7. Result of Maximum Likelihood Classification

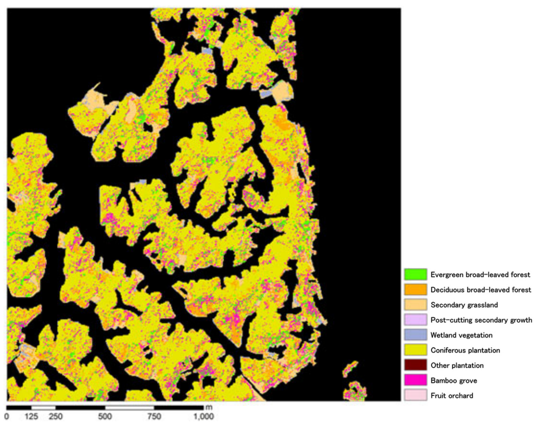


Figure 8. Result of ISODATA Classification

each category shows a fairly large gap, indicating that much of the consistency between this classification and the master data is due to chance.

The object-based classification results, with the exception of the Bamboo grove category, showed high classification accuracy. Also, for all categories the difference between the producer and user accuracies is small, and the Kappa index is higher than that for the two pixel-based methods. From experience, a Kappa index of less than 0.40 is considered indicative of low correspondence, from 0.40~0.80 as medium level matching, and over 0.80 as high (Landis and Koch, 1977). This research showed that object-based classification produces a higher level of correspondence than pixel-based.

Figure 12 shows an expanded view of one section of the master map (a) and object-based classification results (b), maximum likelihood (c) and ISODATA (d). In these figures the scattered, sprinkled results produced by the maximum likelihood method, and the clustering of the ISODATA method can be clearly seen. Comparing the object-based method with the master map, although there has been some mislabeling of categories, the boundaries can be seen to be fairly accurate.

5. CONCLUSIONS

The results of this research show that object-based classification is more accurate and useful than pixel-based for generation of vegetation maps. This sort of high resolution remote sensing data shows a high potential for practical use in producing and updating the vegetation maps required for proper conservation and management of countryside landscapes. In the future, classification accuracy can be improved even further using image variables such as texture and shape. In addition, new advanced classification methods should include such features as segmentation optimization and use of multi-temporal data.

Table 9. Accuracy Result: Object-based classification

		Master map category							Accuracy		
Classification category	Points	Evergreen broad-leaved forest	Deciduous broad-leaved forest	Secondary Grassland	Wetland vegetation	Conifer plantations	Bamboo groves	Match Points	Pruduser Accuracy	User Accuracy	K*
Evergreen broad-leaved forest	133	82	6	1	0	28	16	82	67.21%	61.65%	0.49
Deciduous broadleaved forest	68	11	36	6	0	12	3	36	56.25%	52.94%	0.46
Secondary Grassland	56	0	6	39	1	0	10	39	68.42%	69.64%	0.66
Wetland vegetation	48	0	0	9	39	0	0	39	97.50%	81.25%	0.80
Conifer plantations	125	15	4	0	0	104	2	104	63.80%	83.20%	0.75
Bamboo groves	64	14	12	2	0	19	17	17	35.42%	26.56%	0.19
Total	494	122	64	57	40	163	48	317			

* K = Class Kappa Index
Overall Accuracy = 64.17%
Overall Kappa Index = 0.551

Table 10. Accuracy Result: Maxmum likelihod classification

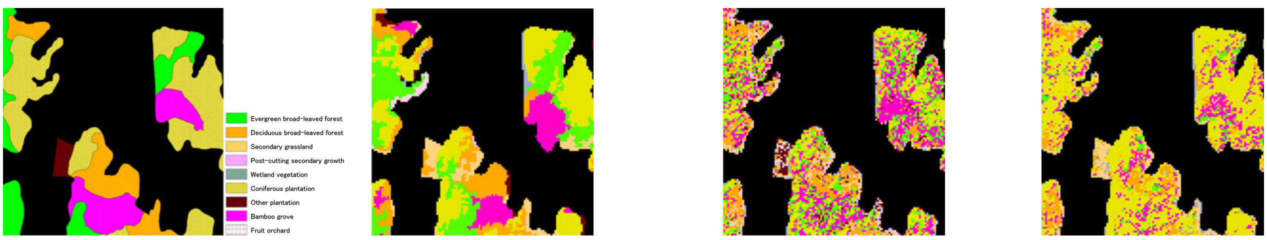
		Master map category							Accuracy		
Classification category	Points	Evergreen broad-leaved forest	Deciduous broad-leaved forest	Secondary Grassland	Wetland vegetation	Conifer plantations	Bamboo groves	Match Points	Pruduser Accuracy	User Accuracy	K*
Evergreen broad-leaved forest	76	46	6	0	0	19	5	46	38.02%	60.53%	0.47
Deciduous broadleaved forest	84	15	44	9	0	12	4	44	69.84%	52.38%	0.45
Secondary Grassland	30	1	3	24	2	0	0	24	53.33%	80.00%	0.78
Wetland vegetation	28	0	0	7	21	0	0	21	91.30%	75.00%	0.74
Conifer plantations	141	26	2	2	0	108	3	108	66.26%	76.60%	0.64
Bamboo groves	103	33	8	3	0	24	35	35	74.47%	33.98%	0.27
Total	462	121	63	45	23	163	47	278			

* K = Class Kappa Index
Overall Accuracy = 60.17%
Overall Kappa Index = 0.497

Table 11. Accuracy Result: ISODATA classification

		Master map category							Accuracy		
Classification category	Points	Evergreen broad-leaved forest	Deciduous broad-leaved forest	Secondary Grassland	Wetland vegetation	Conifer plantations	Bamboo groves	Match Points	Pruduser Accuracy	User Accuracy	K*
Evergreen broad-leaved forest	42	26	1	1	0	3	11	26	21.31%	61.90%	0.49
Deciduous broadleaved forest	52	7	30	9	0	5	1	30	46.88%	57.69%	0.51
Secondary Grassland	73	1	1	35	36	0	0	35	61.40%	47.95%	0.41
Wetland vegetation	6	0	0	2	4	0	0	4	10.00%	66.67%	0.64
Conifer plantations	268	76	24	4	0	149	15	149	91.41%	55.60%	0.34
Bamboo groves	53	12	8	6	0	6	21	21	43.75%	39.62%	0.33
Total	494	122	64	57	40	163	48	265			

* K = Class Kappa Index
Overall Accuracy = 53.64%
Overall Kappa Index = 0.388



(a) Master map (b) Object-based (c) Maximum likelihood (d) ISODATA

Figure 12. Expanded comparison of Master Map with result of three classification methods

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