Estimating Resource Distribution Using Satellite Images to Utilize Woody Biomass

Yu Ohya, Katsutoshi Kanamori, and Hayato Ohwada
Tokyo University of Science, Japan
Email: 7414606@ed.tus.ac.jp, {katsu, ohwada}@rs.tus.ac.jp

***Abstract*—This study proposes estimating resource distribution using coarse and comprehensive satellite images in order to utilize woody biomass. Woody biomass has potential and there is a large amount of unused forest. Therefore, determining the location and quantity of forest resources is important. Lfand-cover classification is beneficial for finding forest. For such classification, using high-resolution remote-sensing images has the disadvantages of high cost and narrow range. This study used Landsat 8, which provides free coarse satellite images and employed experimental land-cover classification using the Normalized Difference Vegetation Index (NDVI). In addition, this study selected an optimum combination of satellite images. The proposed method was implemented in order to develop a resource-distribution map reflecting latitude and longitude in an unknown forest region. As a result, this study determined the quantity and location of biomass and demonstrated the capability of coarse satellite images.**

***Index Terms*—woody biomass, resource-distribution map, remote sensing, satellite image, image analysis, GIS**

I. Introduction

Woody biomass has potential for environment and energy issues. Despite the large quantity of uncontrolled forest, woody biomass resources, especially tree biomass, are not used. For harnessing tree biomass, it is important to determine the resource distribution. However, much manpower, money, and time are required. Thus, it is necessary to develop a resource-distribution map that indicates resource location and quantity.

Remote sensing can be used for classifying land cover (e.g., water and urban vegetation) for the purpose of forest preservation. Remote sensing offers such technical advantages as high resolution; however, its narrow range makes it inappropriate for finding biomass.

Therefore, this study attempts to develop a resource-distribution map using free coarse satellite images to classify land cover in order to clarify the quantity and location of resources. In addition, this study seeks to develop optimal transportation using the resource-distribution map. Thus, this study classified satellite images using the object-based maximum-likelihood method. Classification groups (e.g., water, urban, castanopsis, live oak, cryptomeria japonica, and Japanese cypress) were established. In addition, an optimized combination of satellite images was utilized, since the use of coarse satellite images affected classification. This study evaluated precision using a vegetation index. Furthermore, the quantity of woody biomass resources was estimated based on classification results, a resource-distribution map was developed with the addition of location information, and the use of selected biomass resources was investigated.

Manuscript received May 19, 2014; revised August 1, 2014.

II. Related Work

This section presents related literature on woody biomass. With the recent broad array of environment issues promoting nature restoration, the use of biomass has received much attention. The Geographic Information System (GIS) has been used in the development of distribution maps, determination of transportation distance, and analysis of site conditions. GIS reflects characteristics of the region that impact system performance, cost, energy use, and CO_2 emission. Therefore, many previous works used GIS. Moler *et al*. investigated the cost of transporting woody biomass to the Combined Heat and Power (CHP) plant in Denmark [1], and Shi *et al*. reported on biofuel plant locational conditions in Indonesia [2]. There are also such works in Japan [3], [4]. However, no studies have addressed realistic utilizable resource amounts of each tree biomass. Yamamoto *et al*. did propose transport optimization utilizing herbaceous biomass [5].

Moriguchi *et al*. studied the possibility of using logging residue [6]. Japan uses a thinning system for forestry preservation. However, there are many uncontrolled forest areas in Japan. Terada *et al*. proposed a forest administration capability [7]; however, utilizing uncontrolled forest areas requires many people and much money and time. Therefore, this study proposes remote sensing for automatically estimating resource distributions in unused forests.

Alan developed the method of prior probabilities in maximum-likelihood classification of remotely sensed data [8]. In addition, Kamagata *et al*. performed object-based image analysis on Very High Resolution (VHR) remote-sensing data [9]. However, VHR is very expensive and has a narrow range, with no capability for finding woody biomass resources.

Therefore, the objective of this study is to develop a resource-distribution map using free coarse satellite

doi: 10.12720/lnit.2.2.158-162

images to classify land cover in order to clarify the quantity and location of resources. In addition, this study seeks to optimize transportation using the resource-distribution map.

III. METHOD

This section presents methods of developing land-cover classification and estimating woody biomass resources.

Fig. 1 depicts the methods three-part structure: (A) preparing satellite images, (B) developing land-cover classification in categories, and (C) estimating woody biomass resources with the addition of location information.

In the first part, many categories are used in an effort to understand biomass resources. However, classification becomes increasingly difficult with an increase in the number of categories. Therefore, we employ object-based classification, which classifies remote-sensing data object-by-object rather than pixel-by-pixel and is composed of neighboring and similar pixels.

Multi-pixels in an object are likely to be in the same classification group. This resembles human visual recognition. Thus, object-based classification potentially has higher accuracy than pixel-based classification. Moreover, we employ choices using remote-sensing data, eliminating negative impact data, and creating positive impact data for classification, in an effort to increase the accuracy of land-cover classification. Section III-A describes this method of selection in detail.

In the second part, after preparation of remote-sensing data, this study develops land-cover classification using the maximum-likelihood method. Section III-B describes this method of classification in detail.

In the third part, based on classification results, this study estimates woody biomass resources with the addition of location information. Section III-C describes this method of resource estimation in detail.

A. Selection of Satellite Images

This study establishes many categories in an effort to understand biomass resources. Thus, accuracy may be reduced with the use of conventional land-cover classification. Therefore, negative impact data is eliminated and positive impact data is created for classification.

1) Elimination data: A satellite image consists of data acquired at certain wavelengths. The satellite images, called "bands," record reflectance ratios of the wavelengths, and there are many bands. There are some bands which prevent making a classification. In other word, using all bands has possibilities to reduce the accuracy of classification. Thus, the band is likely to have an adverse impact on classification if one band has different features than other bands. Therefore, in a certain classification group, we find a band to band relation, and avoid the use of non-relation bands in all group.

2) Additional data: We add the Normalized Difference Vegetation Index (NDVI) to the remote-sensing data [10]. NDVI has the advantage of a correlated band in the classification of trees, because it indicates the activation level of vegetation. NDVI provides a difference between a band of near-infrared (NIR) wavelengths and a band of visible red (R) wavelengths. Equation (1) calculates the difference.

This method is used to transform the NDVI's range from [-1.0, 1.0] to [0, 2^{16}]. Equation (2) is used for conversion to an integer value.

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

$$NDVI_{int} = (NDVI + 1) \times 2^{15} \tag{2}$$

B. Land-Cover Classification

This study classifies satellite images using the maximum-likelihood method.

$$f_k(x) = ln|\Sigma_k| + (x - m_k)^T \Sigma_k{}^{-1} (x - m_k) \tag{3}$$

Equation (3) uses a discriminant function. Here, variable x is observed data, constant k is classification group, variable m_k is a mean vector, and variable Σ_k is a variance-covariance matrix in class k. This method calculates them as follows.

First, observed data x is a one-dimensional vector consisting of bands at a location. Elements of the vector have four attributes for each band: range, maximum, average, and standard deviation of pixels in a segmentalized area. In this regard, variance-covariance matrixes inverse has a chance of getting into a rank deficient if there are too many vector elements. Therefore, to use four x_i each attribute values i, this method calculates discriminant functions $f_k(x_i)$ and multiplies these functions $f_k(x_i)$ by classificatory influence rates α_i. α_i which is defined the base 10 logarithm of an accuracy added 10. Here, the accuracy is results of a classification by the attribute only.

Second, mean vectors m_k and variance-covariance matrixes Σ_k are vector spaces. They are composed of training data x. Therefore, in order to use correct data, this method calculates the vector spaces of m_k and Σ_k using area data randomly selected from each classification group. In addition, it is necessary to have more than one trial, since classifications influences selected areas. In this study, there are ten trials.

For the above reasons, the maximum-likelihood method in this study is:

$$g_k(X) = \sum^{n} \sum_{i=1}^{4} \alpha_i \, f_k(x_i). \tag{4}$$

When a discriminant function $g_k(X)$ is minimum, the land-cover area is group k.

C. Woody Biomass Resources

This study estimates woody biomass resources with the addition of location information using the classification results. This method regards the annual allowable cut as forest growth increments. In other words, woody biomass resources are less than the amount of forest growth. Based on this idea, this method calculates in the order of pixel number, wood-cover area, forest-growth increments, and woody biomass resources.

First, this method numerates forest cover pixels based on classification results and converts them to the real wood-cover area. The wood-cover area is the product of pixels and the square of resolution performance. However, the reduced scale depends on images sent from artificial satellites. The forest-growth increments are thus calculated using the relationship between wood area and volume. Table I indicates the timber volume per hectare. Next, utilizable resources are estimated based on the relationship between wood volume and mass. Table II indicates the quantity of energy available per cubic meter. Wood mass is assumed to have normal distribution according to median μ and standard deviation σ of Table II, with a confidence level of 95%. NDVI of Equation (3) is in the range [-1.0, 1.0] and activation level; thus, this method regards NDVI as an indicator of deviation from the average value μ. This presents that the higher NDVI the more resources.

TABLE I. RELATIONSHIP BETWEEN WOOD AREA AND VOLUME

Species	I [m^3/ha]
Conifer	6.2
Broadleaf tree	1.2

TABLE II. RELATIONSHIPS BETWEEN WOOD VOLUME AND MASS

Species	μ	σ	Range of Value [kg/m^3]
Conifer	418.6	79.6	262.6 - 574.5
Broadleaf tree	650.0	91.8	470.1 - 829.9

For these reasons, this method estimates woody biomass resources based on real wood-cover area S hectare.

$$W = S \times I(\mu + 1.96\sigma \times NDVI) \qquad (5)$$

IV. EXPERIMENT

This section presents experiments to demonstrate the usefulness of this method. We developed land-cover classification and estimated woody biomass resources with the addition of location information using MATLAB, which is numerical software that allows digital-image processing.

A. Data Set

The target region was Kamakura City, Kanagawa Prefecture, Japan. There were 12 classification groups. Correct data was a vegetation map drafted by a nature conservation research group in 2000. Satellite images were acquired by Landsat 8, launched in 2013. Landsat 8 provided the world's first free satellite images. Its Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. Thermal Bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100-meter intervals. These bands have 16-bit pixel values. They are not hyper spectral images but coarser multi-spectral images.

B. Experiment Details

First, we made a true color image compound from Band 4 (Red), Band 3 (Green), and Band 2 (Blue), and segmented it into small area compounds from similar and neighboring pixels using the Watershed Algorithm [11]. Results indicated that the target region had 11,138 areas. Table III indicates the number of segmentation areas in each classification group.

Second, we selected correlated bands. Based on the result, Bands 1 to 5, 7 to 8, 10 to 11, and added $NDVI_{int}$ were selected.

We then classified the land cover using those bands and estimated woody biomass resources. This study regarded wood-cover areas of less than 4.5ha as having no resources. In addition, this study put Group 8 of Table III as non-biomass resources due to evergreen broad-leaved trees.

TABLE III. RESULTS OF SEGMENTATION

	Classification group	Number of areas
1	Water areas	4,0333
2	Factories	221
3	Urban areas	3,217
4	Residential areas with forest	877
5	Bare ground	75
6	Weed, Grass areas	144
7	Golf course	77
8	Castanopsis, Live oak	163
9	Quercus acutissima Carruth	54
10	Quercus serrate Thunb	1,549
11	Mallotus japonicas, Zanthoxylum	235
12	Cryptomeria Japonica, Japanese Cypress	493

In contrast, this study regarded resources of Group 12 as architectural material, we was able to use 30% of Group 12 as biomass fuel. Based on these assumptions, we developed a resource-distribution map using Google Maps API on MATLAB.

Next, we calculated the kappa coefficient [12], which is one of the most reliable classification coincidence indicators.

TABLE IV. CONFUSION MATRIX

		Classification group											
		1	2	3	4	5	6	7	8	9	10	11	12
Correct data	1	3665	8	3	3	298	3	1	5	16	16	10	0
	2	0	66	28	13	9	18	0	8	17	36	17	3
	3	0	344	1424	320	111	193	34	141	205	291	80	60
	4	3	62	220	129	41	54	26	50	49	138	47	24
	5	4	0	5	2	41	5	6	5	3	4	4	0
	6	0	11	22	9	8	35	18	8	6	15	23	5
	7	0	3	5	0	0	1	38	2	1	15	11	1
	8	0	10	12	7	3	14	5	46	4	43	48	6
	9	0	7	13	5	3	8	0	2	32	16	3	4
	10	0	55	150	42	14	49	29	112	54	458	577	51
	11	0	1	8	3	2	6	6	3	0	4	195	4
	12	0	14	33	15	8	16	13	36	10	76	238	57

kappa coefficient = 0.4454

TABLE V. QUANTITY OF WOODY BIOMASS RESOURCES

Class	Species	Quantity [kg]
9		86,397.29
10	Broadleaf tree	668,846.94
11		763,832.65
12	Conifer	61,922.55

TABLE VI. RESULTS OF ADDED TRANSPORT SCENARIO

Total resources quantity	1,580,999	kg
Generated energy	18,066,868	MJ-HHV
Drying energy	1,861,627	MJ
Recycling energy	1,139,020	kWh
Transportation cost	18,857,205	JPY
Unit cost	16.556	JPY/kWh

Last, we added a transport scenario using the results of estimated resources. This scenario is nearly a real transit plan. Resources were transported to the nearest thermal power plants, the Yokosuka and Minami-Yokohama plants. After transport, the plants dried the resources and generated electricity [13], [14].

C. *Experiment Results*

Fig. 2 depicts a correct vegetation map, Fig. 3 presents the results of land-cover classification, and Table IV indicates the results. In Table IV, rows are correct groups, columns are classification result groups, and elements are the number of areas. Diagonal elements are right classification. Kappa coefficient K is 0.4454 based on the confusion matrix of Table IV. This is moderate due to the range [0.41, 0.60].

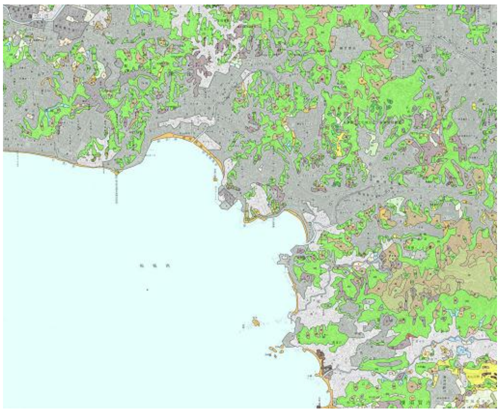

Figure. 2. Correct land-cover data

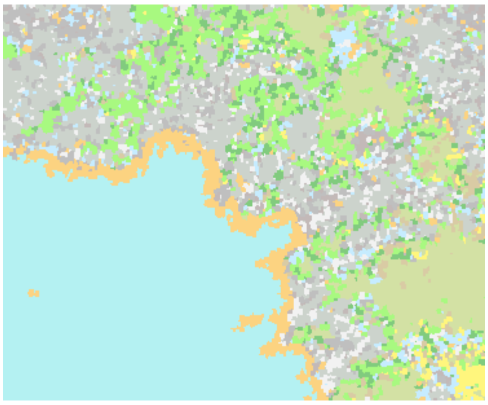

Figure. 3. Results of land-cover classification

Table V indicates the amount of estimated resources, Fig. 4 depicts a resource-distribution map reflecting latitude and longitude, and Table VI presents the results of the transport scenario.

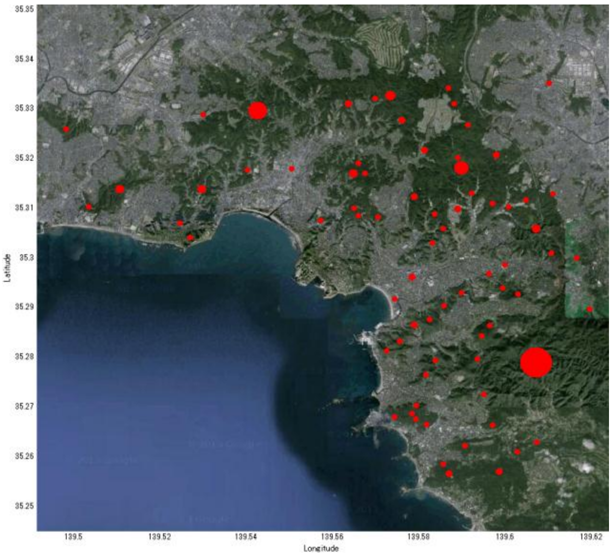

Figure. 4. Resource-distribution map

V. DISCUSSION

Comparing Fig. 2 and Fig. 3, we confirm that the land-cover classification is correct, since there are a lot of area in diagonal elements of Table IV. In addition, Table VII compares the results of Kamagata et al. and those of this study. These two studies had the same coincidence degree, although this study used coarser images and had more classification groups. In a strict sense, this study had a lower kappa coefficient, because it had more difference in time between satellite images and vegetation map.

TABLE VII. COMPARISON WITH PREVIOUS WORKS

	Kamagata	This study	
Target area	Kamakura	Kamakura	
Region	Mountainous	plain	
Area	$25km^2$	$102,724km^2$	larger
Satellite image	IKONOS	Landsat 8	
Spatial resolution	4m	30m	coarser
Classification groups	7	12	more
Kappa coefficient	0.526	0.445	
Degree of coincidence	moderate	moderate	same

Looking at Table IV, much area of Group 3 and 4 was divided into vegetation region because this study focused on vegetation regions and employed NDVI. In addition, much area of Group 8 to 12 was divided into Group 11 because vegetation of Group 11 was a strong tree crown. In either case, in order to use the latest correct data, we must validate the evidence.

This study estimated resources in order to distinguish between conifer and broadleaf trees. However, this reduced this study's advantage of having many classification groups. Therefore, we need to investigate more detailed relationships among wooded areas, volume, and mass.

Regarding the added transport scenario, the recycling energy in Table VI was equal to the annual electrical usage of 316 family units, or 5.3% of the people in Kamakura City. For this reason, woody biomass resources may provide realizable energy to see unit cost of Table VI.

VI. CONCLUSIONS

This study employed experimental land-cover classification by NDVI and selected satellite images. It then estimated woody biomass resources using the results of the classification and relationships among wooded area, volume, and mass. This allowed investigation of a resource-distribution map reflecting latitude and longitude in an unknown forest region.

Today, natural regeneration energy has attracted attention and advances the coefficient of utilization. And, there are a large amount of woody biomass resources as one of the new energy. However, it is necessary to investigate the unknown location of forest resources. This study is able to estimate resources distribution using satellite images to utilize woody biomass, and find resource location quickly and easily. In future work, in order to use realistic biomass quantity, it is necessary to optimize the transport scenario using geographical information.

REFERENCES

[1] B. Moller and P. S. Nielsenb, “Analysing transport costs of Danish forest wood chip resources by means of continuous cost surfaces,” *Biomass and Bioenergy*, vol. 31, pp. 291-298, 2007.

[2] X. Shi, A. Elmore, X. Li, N. J. Gorence, H. M. Jin, X. H. Zhang, and F. Wang, “Analysing transport costs of Danish forest wood chip resources by means of continuous cost surfaces,” *Biomass and Bioenergy*, vol. 32, pp. 35-43, 2008.

[3] M. Iuchi, “Development of the support system for biomass energy business plans-the data base and evaluation models to simulate the collection cost-,” Central Research Institute of Electric Power Industry Report, no. Y03023, 2004.

[4] T. Kinoshita, K. Inoue, K. Iwao, H. Kagemoto, and Y. Yamagata, “A spatial evaluation of forest biomass usage using GIS,” *Applied Energy*, vol. 86, pp. 1-6, 2009.

[5] H. Yamamoto, T. Nakata, and K. Yabe, “Design of biomass co-firing system considering resource distribution and transportation optimization,” *Journal of Japan Institute of Energy*, vol. 89, pp. 42-52, 2010.

[6] K. Moriguchi, Y. Suzuki, J. Gotou, H. Inatsuki, T. Yamagushi, Y. Shiraishi, and T. Ohara, “Cost of comminution and transportation in the case of using logging residue as woody biofuel,” *Japanese Forestry Society*, vol. 86, pp. 121-128, 2004.

[7] T. Terada, M. Yokohari, and N. Tanaka, “Potential of utilizing woody biomass from satoyama woods on plateaus assessed by the estimation of harvesting and collecting costs,” *Landscape Research Japan*, vol.73, pp. 663-666, 2010.

[8] A. H. Strahler, “The use of prior probabilities in maximum likelihood classification of remotely sensed data,” *Remote Sensing of Environment*, vol. 10, pp. 135-163, 1980.

[9] N. Kamagata and K. Hara, “Vegetation mapping by object-based image analysis: Evaluation of classification accuracy and boundary extraction in a mountainous region of central Honshu, Japan,” *Vegetation Science*, vol. 27, pp. 83-94, 2010.

[10] J. R. Dong, R. K. Kaufmann, R. B. Myneni, C. J. Tucker, P. E. Kauppi, J. Liski, *et al.*, “Remote sensing estimates of boreal and temperate forest woody biomass: Carbon pools, sources, and sinks,” *Remote Sensing of Environment*, vol. 84, pp. 393-410, 2003.

[11] K. Saarinen, “Color image segmentation by a watershed algorithm and region adjacency graph processing,” *IEEE Image Processing*, vol. 3, pp. 1021-1025, 1994.

[12] R. G. Congalton, “A review of assessing the accuracy of classifications of remotely sensed data,” *Remote Sensing of Environment*, vol. 37, pp. 35-46, 1991.

[13] K. Yagi and T. Nakata, “Economic analysis on small-scale forest biomass gasification considering regional resource distribution and technical characteristics,” *Journal of the Japan Institute of Energy*, vol. 86, pp. 109-118, 2007.

[14] Y. Makino, T. Kato, and Y. Suzuoki, “Potential of co-firing of woody biomass in coal fired power plant,” *IEEJ Transactions on Power and Energy*, vol. 125, pp. 1129-1135, 2005.

Yu Ohya is a graduate student of Industrial Administration, Tokyo University of Science, Japan. He received a Bachelor of Engineering from Tokyo University of Science 2014. He has been working on Image Analysis and Data Mining.

Katsutoshi Kanamori is an assistant professor of Industrial Administration, Tokyo University of Science, Japan. He received a Doctor of Science from Tokyo University of Science 2009. He has been working on Artificial Intelligence and Formulation of Creativity.

Ohwada Hayato is a professor of Industrial Administration and Director of the Division of Next Generation Data Mining Technology, Tokyo University of Science, Japan. He received a Doctor of Engineering from Tokyo University of Science 1988. He has been working on Machine Learning and Inductive Logic Programming.