EVALUATION OF FRACTIONAL GREEN VEGETATION COVER IN RESIDENTIAL AREA

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ABSTRACT:

Green vegetation plays rather important role in urban environment. Recently, re-vegetation in urban residential area is becoming important policy for urban planners from the view point of climate change measures. That is, by maintaining and regenerating green vegetation, both mitigation and adaptation can be achieved. In this regard, establishment of accurate assessment and evaluation methods for the green vegetation in urban environment is urgently needed. This research demonstrates such a method by using remote sensing technique and economic model with the case study of Tokyo metropolitan area. First, a high resolution green cover map is created by the classification of remotely sensed images (Landsat ETM+) using subspace method. Our past research have shown that the method performed better than conventional algorithms such as: Maximum Likelihood Classification (MLC), Self Organizing Map (SOM) neural network, and Support Vector Machine (SVM) methods. Then, we have projected the future distribution of green vegetation using a Computable Urban Economic (CUE) model developed recently. CUE model are often used for urban planning practitioners, but here we have developed a simplified CUE model focusing only on land-use changes but employing a higher ground resolution of the micro district level zones. This new model allows us to evaluate realistic/spatially finer green vegetation scenarios. We have created two extreme land-use scenarios: concentration and dispersion scenarios, and correspond changes as green cover map are created. The results show that the method demonstrated in this study has high applicability to the countries where conducting field survey of land cover is difficult.

1. INTRODUCTION

Green vegetation plays rather important role in urban environment. Recently, re-vegetation in urban residential area is becoming very important policy for urban planners from the view point of climate change measures. That is, by maintaining and regenerating green vegetation, both mitigation (absorb CO_2) and adaptation (decrease heat island) can be achieved. In this regard, establishment of accurate assessment and evaluation methods for the green vegetation in urban environment is urgently needed. This research proposes such a method by using remote sensing technique and economic model with the case study of Tokyo metropolitan area in Japan.

First, we create a high resolution green cover map. In Japan, there has already been prepared many freely available sources for land cover data, such as, "National-land numerical information" by Ministry of Land, Infrastructure, Transport and Tourism. However, such an officially provided data is sometimes too old for analysis to give sensible results as current land-cover estimates. More importantly, we hope our proposing method will be applicable to the counties where there have no available land cover maps. Hence we create green cover map by the classification of remotely sensed images (Landsat/ETM). This method has high applicability to other countries where conducting field land cover survey is difficult. Many advanced methods have been applied in remote sensing image classification. Recent research shows that subspace method provides better classification accuracy than the MLC, SOM, and SVM methods (*e.g.*, Yamagata, 1996; Bagan *et al.*, 2008, 2010a). Hence, we adopt the improved modified subspace method for land cover classification described in Bagan and Yamagata (2010b).

Second, the spatial distribution of green vegetation in the feature is predicted by using economic model called "Computable Urban Economic (CUE) model" (*e.g.*, Takagi and Ueda, 2001; Ueda *et al.*, 2009) developed in Japan. Some of the merits of CUE model are, it is economically sound, easy to understand for even urban practitioners, and high predictive accuracy. CUE model is usually constructed at the municipality zone level, while this research uses micro district (around $1km^2$) as the zone, which leads to the realistic/spatially finer green vegetation scenarios.

Since early times, enormous numbers of literatures have suggested the importance of linking remote sensing techniques and social science researches (*e.g.*, Liverman., 1998). However, to the best our knowledge, such a research actually performed is surprisingly few, and no research has conducted creating the feature scenario of green vegetation distribution utilizing both the remote sensing techniques and economic models. This paper is a new and unique challenge from this perspective.

2. CREATING HIGH RESOLUTION GREEN COVER MAP USING SUBSPACE METHOD

Tokyo metropolitan area is in Kanto region in Japan (Fig. 1). The dominant land cover types in the area are forests, residential areas, paddy fields, croplands, golf courses, and urban areas. We employed three almost cloud-free Landsat ETM+ images of the area. We employed the 7-band ETM+ images for land-cover mapping. The ETM+ data resolution is 30 meters for Bands 1-5, and Band 7. ETM+ Band 61 (thermal infrared) was acquired at 120 meter resolution, but is resampled to 30 meters done by U.S. Geological Survey. The main part (about 80%) of the Tokyo metropolitan area was covered by 2002/06/07 ETM+ data. The rest parts were covered by the 2001/09/24 ETM+ data (south) and 2002/10/04 ETM+ data (west). Therefore, we employed a mosaic of the 2002/06/07, 2001/09/24, and 2002/10/04 ETM+ images to obtain full area coverage. For this mosaic, the 2002/06/07 data were used as the base image and the 2001/09/24 and 2002/10/04 data were color balanced to match the 2002/06/07data range.

Based on our field knowledge, IKNOS, ALOS AVNIR-2 mosaic images (2.5-m spatial resolution), Google earth, Land cover map (50 m spatial resolution; published by the Geographical Survey Institute, Japan), and Digital Map 2500 (Spatial Data Framework) at a scale of 1:2500 which also published by the Geographical Survey Institute, Japan, eight ground cover types were selected in this experiment as shown in Table 1.

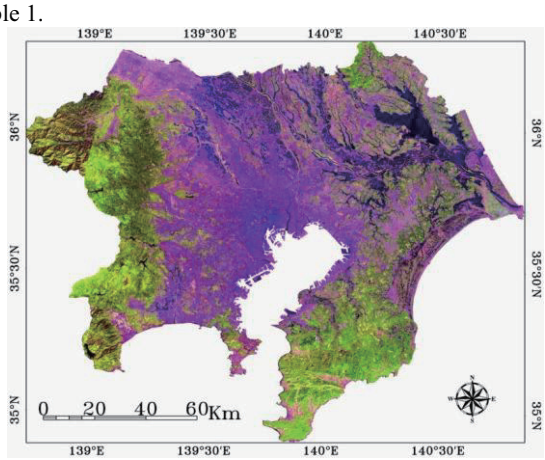

Figure 1. Location of the false-color composite ETM+ image (RGB = bands 5, 4, and 2) of the Tokyo metropolitan area, Japan

Table 1. Description of the land-cover classes and their pixel counts in Tokyo metropolitan area

Land-cover class	Class description	Training pixel count	Test pixel count
1. Forest	Forests with canopies greater than 50%	2316	1183
2.Urban/build-up	Buildings, concrete, asphalt paved road, and other human-made structures	2336	1029
3. Paddy	Paddy rice fields	1857	865
4. Cropland	Cultivated lands for crops	2125	709
5. Grassland	Dominated by density grass, mainly reeds, etc	1392	424
6. golf course	Parks, golf course, playing fields, and other neatened garden	1007	512
7. Water	Water bodies	1470	533
8. Bare soil	Exposed soils without recognizable plant life	376	278
Total		13954	5533

As mentioned in section 1, we adopt the improved modified subspace method for land cover classification described in Bagan and Yamagata (2010b). In this research, the subspace dimension is fixed at 3, the optimal learning parameters are fixed at 0.11, and the MSM parameter were fixed at 0.011, and the corresponding number of training iteration was 135. After obtain the optimal parameters, we implement the modified subspace method to generate class subspaces. Then classify the entire mosaic ETM+ image.

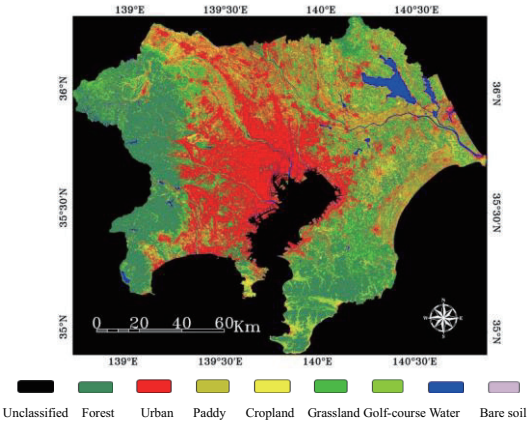

Figure 2. Land-cover classification maps obtained by modified subspace method in Tokyo metropolitan area

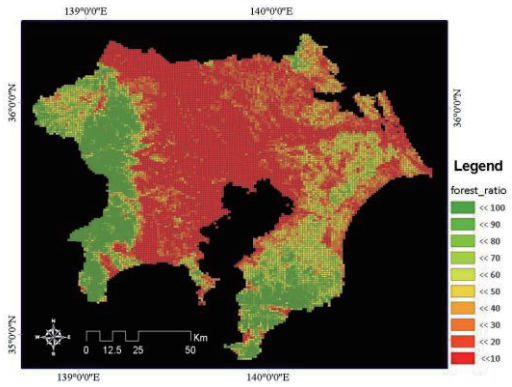

Figure 3. The percentage of the forest class (green cover map) in Tokyo metropolitan area

Fig.2 shows the land cover map obtained by modified subspace method. Our accuracy assessment of the Landsat ETM+ classification indicates a reasonable well overall accuracy of 86.1% with Kappa coefficient of 0.8366. Fig 3 shows the percentage of the forest class in each approximately 1km by 1km mesh which is labeled by $h \in H = \{1,...,H\}$. We define this map as "*green cover map*" in this paper. It must be notable that with respect to the majority of the study area, the percentage of the forest occupancy is less than 20.

3. CUE MODEL

According to Fisher *et al*. (2005), Land cover is determined by direct observation while land use requires socio-economic interpretation of the activities that take place on that surface. Predicting feature land cover including green vegetation directly by using present land cover map is of course possible. However, it is difficult to expect high predictive accuracy of that because the feature land cover is influenced by the economic activities of humans. Hence predicting feature land cover distribution by modeling human behavior and measuring its effect on land use is one of the major approaches. The regional impact of transport is significant in particular (*e.g*, Tsutsumi and Seya, 2009), and vice versa; hence modeling the interaction between them is very important for creating reliable land use change scenarios. In this regard, "land use transport interaction" (LUTI) model has been developed in the field of infrastructure planning, urban economics, and regional since 1980's, and large amount of models have been applied to real urban policy and the creation of land use change scenarios.

In Japan, also large amount of LUTI models including economically ad hoc ones have been proposed since later 1980's. The relationships among them are summarized by Ueda *et al*. (2009). CUE model is an advanced form of traditional LUTI model, and fully based on micro-economics foundation. The structure of the CUE model is explained below. Fig. 4 shows the structure of our CUE model. For simplification, following assumptions are made: [1] There exists a spatial economy whose coverage is divided into zones labeled by $i \in I = \{1,...,I\}$. [2] There are land markets in each zone and transport market. The markets will reach equilibrium simultaneously. [3] The society is composed of two types of agents: household and absentee landowner. [4] The behavior of each agent is formulated by micro-economic principle: household's utility maximization and landowner's land rent maximization. [5] Seven types of households labeled by $k \in K = \{1,...,K\}$ exist, and the household in each type has identical preference. [6] Total numbers of households $\overline{N}$ are given exogenously.

The characteristic of our model is that it considers seven types (groups) of households, while the existing researches on CUE model have considered only one "representative" household, which is typically assumed in micro-economic literatures. With this assumption, our model reflects the behavioral difference among households, which leads to creating more realistic feature land use scenarios. The types of households are shown in table 2. Below, we formulate the household's utility maximization behavior, landowner's land rent maximization behavior, the market equilibrium condition, and the structure of transport model.

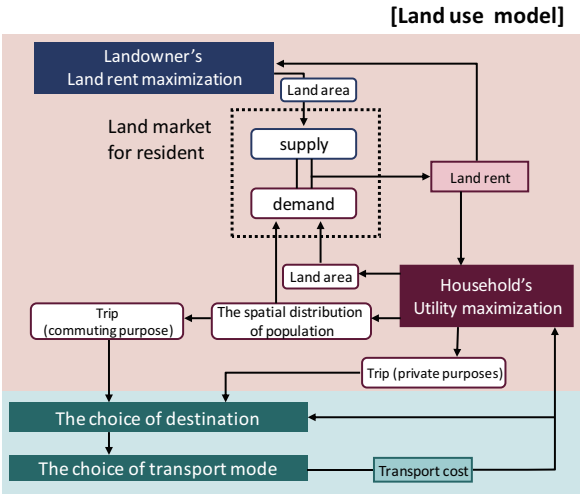

Figure 4. The structure of the CUE model

Table 2. Seven household types

Household types
1. One-person households (in 65 years of age or over)
2. One-person households (in under 65 years of age)
3. A married couple only (either of them in 65 years of age or over)
4. A married couple only (neither of them in 65 years of age or over)
5. A married couple with child(ren)
6. Father and child(ren) / Mother and child(ren)
7. The other types

Figure 5. The spatial distribution of the municipalities in Tokyo metropolitan area

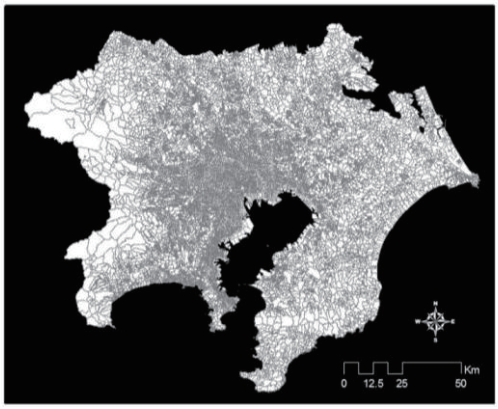

Figure 6. The spatial distribution of the micro district level zones

[A] household's utility maximization under the budget constraint

$$V_i^k = \max_{Z_i^k, A_i^k, Q_i^{k,pr}, L_i^k} \left[\alpha_Z^k \ln Z_i^k + \alpha_A^k \ln A_i^k + \alpha_Q^{k,pr} \ln Q_i^{k,pr} + \alpha_L^k \ln L_i^k \right], \quad (1)$$
$$s.t. \quad Z_i^k + r_i A_i^k + c_i^{k,pr} Q_i^{k,pr} + wL_i^k = w(T^k - c_i^{k,co} Q_i^{k,co}),$$

where V denotes indirect (maximized) utility; Z, consumption level of composite goods (whose price is assumed to be one); A, consumption level of residential land space; Q^{pr}, consumption level of transport service for private purpose; L, consumption level of leisure time; Q^{co}, consumption level of transport service for commuting purpose; r, residential land rent (identical for all the types); c^{pr}, transport cost for private purpose; w, wage rate ; c^{co}, transport cost for commuting; T, total available time. α is the parameter which indicates the characteristics of each household.

Any households in the economy select the zone to locate where the highest level of expected utility can be attained. The location choice behavior is formulated as the logit model. In this research, households's hierarchical decision making toward location is assumed as:

[*First step*]: A locator (household) select municipality (Fig. 5) to locate.

[*Second step*]: The locator choose the sub-municipality-district termed "*cho-cho-moku*" in Japanese in the municipality (Fig. 6).

This assumption seems reasonable and realistic; moreover, it reduces the computation cost drastically compared to the direct choice of cho-cho-moku case. Apart from the existing researches on CUE model, we define cho-cho-moku as the zone in this research instead of municipality. The number of the

municipalities in 2000 year is 333, while the zones 22,368. This difference enables us to build spatially finer resolution model.

Let the municipalities are labeled by $m \in M = \{1,..., M\}$. Then suppose v_i^k, composed of two factors e_i^k and V_i^k, *i.e*, $v_i^k = e_i^k + V_i^k$, where e_i^k is the location specific variable. We identify $e_i^k = \rho^k \ln Y_i$, where Y is available area of residential land supply, and ρ is a parameter. The hierarchical decision by the households lead to the nested logit model presented in the following manner:

$$P_m^k = \frac{\exp[\theta^k s_m^k]}{\sum_m \exp[\theta^k s_m^k]}, \tag{2}$$

$$P_{i|m}^k = \frac{\exp[\phi^k v_i^k]}{\sum_i \exp[\phi^k v_i^k]}, \quad s_m^k = \frac{1}{\phi^k} \ln\left[\sum_i \exp\left[\phi^k v_i^k\right]\right];$$

where θ and ϕ denote parameters, respectively. s is a so-called log-sum variable (*e.g.*, de Jong *et al.*, 2007).

[B] absentee landowner's residential land rent maximization

Generally, the absentee landowner may be defined as the "house hold" that owns the land but does not live there (Morisugi and Ohno, 1992). This assumption is useful for modeling landowner's behavior; hence typically assumed in urban economic literatures.

The absentee landowner in each zone is assumed to behave for maximize revenue given by the following equation:

$$\pi_i = [r_i y_i - c(y_i)], \tag{3}$$

where y denotes the residential land supply, and $c(\bullet)$ denotes the cost function which indicates the maintaining cost of the land. $c(\bullet)$ is identified as:

$$c(y_i) = -\sigma_i Y_i \ \ln\left[1 - \frac{y_i}{Y_i}\right], \tag{4}$$

where Y denotes the available area of residential land supply, σ is a parameter.

[C] market equilibrium condition

The market equilibrium condition is two folds. First is as to the number of locators in each zone presented in the following manner:

$$\sum_i \sum_k N_i^k = \overline{N}, \tag{5}$$

where N_i^k is the number of households belonging to the household type *k*, locating to the zone *i*.

Second is as to the land market equilibrium presented in the following manner:

$$\sum_k A_i^k N_i^k = y_i \cdot \tag{6}$$

[D] transport model

First, transport mode choice model is formulated as the logit model presented in the following manner:

$$P_{i,j}^{k,o}(r) = \frac{\exp[-\upsilon C_{i,j}^{k,o}(r)]}{\sum_r \exp[-\upsilon C_{i,j}^{k,o}(r)]}, \tag{7}$$

where $i, j \in I$ denotes the origin zone (O) and destination zone (D), respectively, o = [*co*, *pr*], *i.e.*, commuting or private purpose, $r \in R = \{1,..., R\}$ indicates the transport mode, C denotes the transport cost between the OD zones, υ is a parameter (assumed to be identical for all the types). As the transport mode, this paper considers the following four: car, train, bus, and walking. Those four modes occupy approximately 80% of the modal share in the area according to the results of fourth nationwide person trip survey implemented by MLIT implemented in 1998 year. Subsequently, the destination choice model is formulated as the aggregate logit model given by:

$$P_{i,j}^{k,o} = \frac{\exp[-\lambda^o c_{i,j}^{k,o}]}{\sum_j \exp[-\lambda^o c_{i,j}^{k,o}]}, \tag{8}$$

$$C_{i,j}^{k,o} = -\frac{1}{\upsilon^o} \ln\left[\sum_r \exp\left[-\upsilon^o C_{i,j}^{k,o}(r)\right]\right], \quad c_{i,j}^{k,o} = C_{i,j}^{k,o} - \gamma^o \cdot f(S_j); \tag{9}$$

$$c_i^{k,o} = -\frac{1}{\lambda^o} \ln\left[\sum_j \exp\left[-\lambda^o c_{i,j}^{k,o}\right]\right]. \tag{10}$$

where $C_{i,j}^{k,o}$ is the minimum expected cost between the OD zones, S_j denotes the attraction of zone *j*, such as, area of the zone, zonal population, and so on. γ, η, λ are parameters, respectively (assumed to be identical for all the types). $f(S_j)$ is the function of S_j, we specify the function form of that as the box-cox form presented in the following manner:

$$f(S_j) = \begin{cases} \dfrac{S_j^{\tau^o} - 1}{\tau^o}, & for\ \tau^o \neq 0, \\ \ln S_j^{\tau^o}, & for\ \tau^o = 0 \end{cases} \tag{11}$$

where τ is a parameter which takes the value between 0 and 1. As the attraction variable, we adopt labor population. $c_{i,j}^{k,o}$ indicates generalized transport cost, and it is inputted to the land use model.

4. PREDICTING GREEN VEGETATION IN TOKYO METROPOLITAN AREA IN THE FEATURE BY USING CUE MODEL

In this section, the spatial distribution of the green cover in the feature is predicted by using CUE model. The procedure is shown in Fig. 7. First, each land cover's occupancy area in the mesh h is calculated. The occupancy area of each class is denoted as z_h^{class}, where classes are indicated in table 1. Second, the actually observed residential land supply data in the zone is interpolated into the mesh simply weighted by its area (Areal weighting interpolation). Third, the relationship between z_h^{urban} and y_h is identified by a simple regression model as:

$$z_h^{urban} = \psi + y_h \beta + \varepsilon_h, \tag{12}$$

where ψ is an intercept, β is a regression coefficient, ε_h is an *iid* error term. Fourth, the residential land supply in the feature is predicted by using CUE model, and the output is interpolated into the mesh by areal weighting interpolation. Fifth, the changes in the residential supply, *i.e*, $\Delta\hat{y}_h$ is calculated, and the change in the urban land cover is calculated based on $\Delta\hat{y}_h$ as:

$$\Delta\hat{z}_h^{urban} = \hat{\psi} + (y_h^* + \Delta\hat{y}_h^*)\hat{\beta} + e_h - \hat{z}_h^{urban}, \tag{13}$$

where e_h denotes the residual by the regression model. The parameter estimates of regression model is shown in table 3.

Finally, $-\Delta\hat{z}_h^{urban}$ is allocated to the other land cover classes, and feature land covers are derived. We employ multinomial logit model for identifying the factors affecting the occupancy probability of each class in each mesh. The dependent variable is the highest occupancy class in each mesh, and the explanatory variables adopted are "*height*," which

represent a height above sea level, "*gradient*," which represent a topographical gradient, "*station*," which represent a distance to the nearest train station, "*tokyo*," which represent a distance to the Tokyo station. The parameter estimates of multinomial logit model are shown in table 4 (the bare soil class is eliminated from the model because there was no mesh in which the highest occupancy class is bare soil; the parameters of cropland class are standardized to zero). The social economic data which we use in this research is described in Table 5. The parameters of the CUE model are estimated by non-statistical calibration with repeated trial and error. The result is shown in table 6.

Table 3. The parameter estimates of the regression model

	Coef.	Std. error	*t*-value	P(>|*t*|)
Intercept	3.794×10^4	1.81×10^3	20.9	0.00
y_h	0.4415	0.00415	106	0.00
Adjusted R^2		0.444		

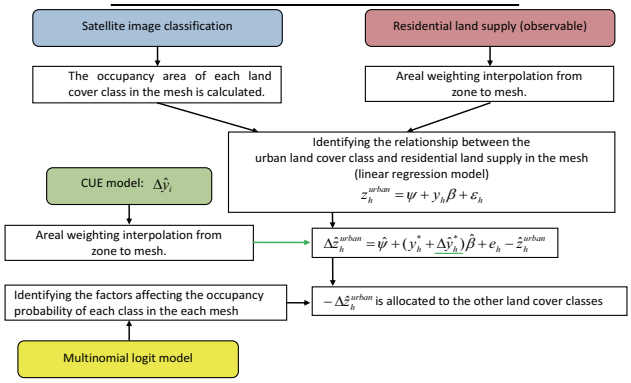

Figure 7. The procedure for predicting land use change using the CUE model

Table 4. The parameter estimates of the multinomial logit model

		Coef.	Std. error	*t*-value	P(>|*t*|)
Intercept	forest	–0.6532	0.130	–5.0	0.00
	golf	–7.248	0.889	–8.2	0.00
	grass	0.2815	0.184	1.5	0.13
	paddy	2.266	0.146	16	0.00
	urban	5.279	0.116	46	0.00
	water	–4.095	0.393	–10	0.00
Height	forest	–0.002026	0.000455	–4.5	0.00
	golf	–0.002469	0.000881	–2.8	0.01
	grass	–0.0009014	0.000830	–1.1	0.28
	paddy	–0.09996	0.00461	–22	0.00
	urban	0.002778	0.000742	3.7	0.00
	water	0.001147	0.000770	1.5	0.14
Gradient	forest	0.2362	0.00804	29	0.00
	golf	0.2431	0.0227	11	0.00
	grass	0.08367	0.0133	6.3	0.00
	paddy	–0.01980	0.0171	–1.2	0.25
	urban	–0.08766	0.0101	–8.7	0.00
	water	0.04501	0.0191	2.4	0.02
Station	forest	0.08989	0.0131	6.8	0.00
	golf	0.2190	0.0535	4.1	0.00
	grass	0.01641	0.0232	0.71	0.48
	paddy	0.009200	0.0170	0.54	0.59
	urban	–0.3435	0.0179	–19	0.00
	water	–0.03153	0.0372	–0.85	0.40
Tokyo	forest	–0.008831	0.00212	–4.2	0.00
	golf	0.005239	0.0142	0.37	0.71
	grass	–0.03939	0.00358	–11	0.00
	paddy	–0.02047	0.00241	–8.5	0.00
	urban	–0.07485	0.00216	–35	0.00
	water	0.02096	0.00578	3.6	0.00
	Log-Likelihood:		–12080		
	McFadden R^2		0.378		

Table 5. Social economic data used for calibrating the CUE model

Data	Data sources	Year	Agency
Population	National census	2000	MIC
Total available time/ Leisure/Wage rate	Surveys on time use and leisure activities	2006	MIC
Income	Statistical survey of actual status for salary in the private sector	2007	National tax agency
Land rent	Officially assessed land price	2005	MLIT
Transportation	The fourth nationwide person trip survey, Tokyo/ National integrated transport analysis system (NITAS)	1998	MLIT
Height above sea level/ Topographical gradient	National-land numerical information	1981	MILIT
Residential land area	Fixed property tax cadastre/ Z map town II (field survey data)	2005	MIC/ Zenrin Co, Ltd
Available area of residential land supply	National census: inhabitable area	2000	MIC

※MLIT: Ministry of Land, Infrastructure, Transport and Tourism, Japan
※MIC: Ministry of International Affairs and Communications, Japan

Table 6. The calibrated parameter estimates for the CUE model

w	υ^{co}	υ^{pr}	γ^{co}	γ^{pr}	τ^{co}	τ^{pr}	λ^{co}	λ^{pr}
2691	0.002	0.002	48	49	0.33	0.27	0.0005	0.0004

	α_Z	α_A	α_Q^{pr}	α_L	ρ	θ	ϕ
Type1	0.2570	0.0106	0.0242	0.7082	0.050	13	13
Type2	0.6530	0.0170	0.0342	0.2958	0.11	6.0	6.0
Type3	0.4746	0.0181	0.0457	0.4616	0.060	10	10
Type4	0.8594	0.0213	0.0477	0.0716	0.13	5.0	5.0
Type5	0.8221	0.0291	0.0824	0.0664	0.13	5.0	5.0
Type6	0.6709	0.0159	0.0681	0.2451	0.13	5.0	5.0
Type7	0.6023	0.0171	0.0766	0.3040	0.13	5.0	5.0

In this paper, we test two extreme land-use scenarios (concentration and dispersion) for showing possible range of future land-use changes. As the concentration scenario, we assume the case that households cannot use a car. This assumption will raise the transport cost, resulting in the increase of household's preference to live near the train station. This is an extreme case of compact city concept. With respect to the dispersion scenario, we assume that households work at their own homes, and do not need to commute to their offices. This assumption will raise real income as commuting cost can be saved, and resulting in the increase of household's preference to live in suburb areas where large residential land area is available. The other spatial land use scenarios distribution in the future can be assumed to lie between these two extreme scenarios.

Fig. 8 shows the green (forest class) land cover distribution of the concentration scenario. It is interesting to observe that the projected future green land cover distributions changes are not so large. This is caused by the probability of the forest occupancy (calculated by multinomial logit model, Fig. 9) is low in the high urban occupancy area; hence the allocation of the changes in urban class, *i.e.*, $-\Delta\hat{z}_h^{urban}$ to the forest class is little. Fig 10 shows the ratio of green land cover to the present in the case of concentration scenario (includes train stations), whereas Fig. 11 shows the case in the dispersion scenario. (In the both Figs, –99999 indicate that the mesh does not include green cover in the present case). With respect to the concentration scenario, green land covers around the some of the train stations are decreased very *locally*, which means only the nearest one mesh from the stations. This is caused by households tend to prefer to locate nearest place from the stations because of the increase of commuting cost. On the other hand, Fig 11 shows that the green vegetation in the suburb area is decreased because of the increase of the urban land cover. The spatial distribution of the green cover would be significantly different between the scenarios especially in the suburb areas. Therefore regional climate change impacts in the area must be considered in particular.

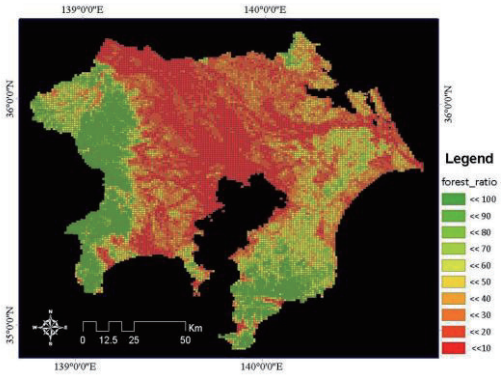

Figure 8. Spatial distribution of the green cover in the future (concentration scenario)

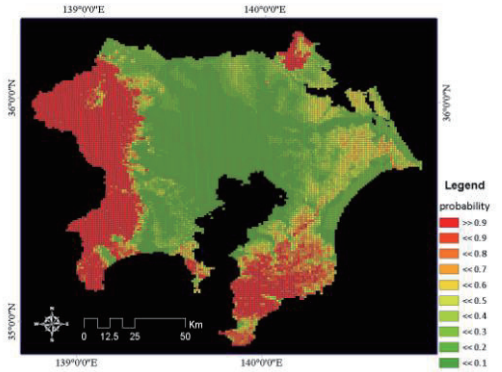

Figure 9. The probability of forest occupancy calculated by the multinomial logit model

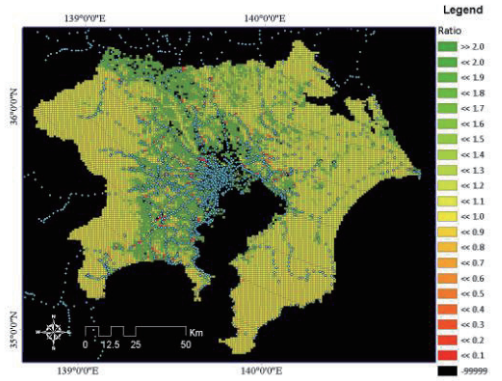

Figure 10. The ratio of the green land cover to the present and train stations (concentration scenario)

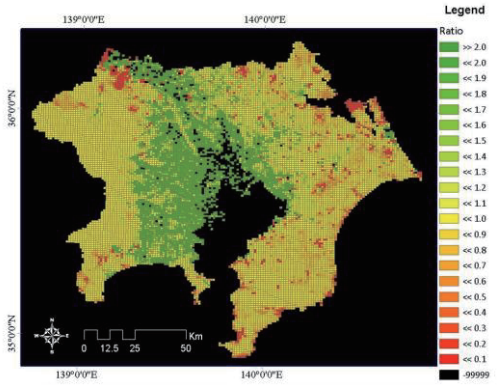

Figure 11. The ratio of the green land cover to the present (dispersion scenario)

5. CONCLUSIONS

This research has developed a method for projecting future green cover distribution by combining remote sensing and urban economic (CUE) modeling. The method is applied to the case of Tokyo metropolitan area. Two extreme future land-use scenarios (concentration and dispersion) are projected and the corresponding green cover maps in the future are created. this method developed is applicable even to the countries where the accurate land-use mapping data is not available.

The projected results of the future land-use are critically dependent on the classification accuracy of satellite images and the CUE model assumptions. In this study, we have focused only on land-use scenarios. Firstly, we must improve the model with regard to the parameter estimation procedure. Secondly, we will consider firm behaviors in the building market in the near future. We are also going to simulate the effect of various urban policy measures which will impact on land-use and green vegetation changes, *e.g.*, flood risk adaptation scenario, compact city policy, load pricing policy, and so on. By considering more diverse scenarios settings, the projected results will be able to provide more important information to the urban planners.

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