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ANALYSIS OF RELATIONSHIP BETWEEN VEGETATION DISTRIBUTION AND LAND PRICE USING MULTITEMPORAL DATA

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ABSTRACT:

Japanese cities are facing a rapidly aging society with birthrates, lower than the average rates of developed world. Population decline generates many problems such as depopulation in rural areas. One of the measures implemented is to define core areas for maintaining sufficient population density given current and predicted population dynamics. On the other hand, there is a potential for the surroundings of the core areas to be run-down because vacancies generate many problems such as crime, susceptibility to fire, and other negative events. There have been, however, few measures concerning the spatial distribution of parks and open spaces around the core areas. We applied a hedonic approach with a Geographically Weighted Regression (GWR) to the analysis of the relationship between the assessed values of land and geographical information in order to estimate the importance of landscape factors: the spatial continuity of vegetation distributions, public parks, and the local averages of NDVI. It was shown that the number of points where the spatial continuity of vegetation distributions makes positive impacts on nearby land prices is gradually increasing during years 2000 and 2015, while the average of land price continues to fall.

1. INTRODUCTION

Japanese cities are facing a rapidly aging society with birthrates, lower than the average rates of developed world. Population decline generates many problems such as depopulation in rural areas, expansion of lower population density in urban areas, as well as a boost in spending for the maintenance of infrastructure under the pressure of lower revenue. One of the measures implemented is a land use strategy for living space and urban function. In this measure, Residence Attraction Districts and Urban Function Attraction Districts are defined as core areas for maintaining sufficient population density given current and predicted population dynamics. The core areas are expected to play a key role as the fundamental building blocks of future cities in an aging society facing population decline. On the other hand, there is a potential for the surroundings of the core areas to be run-down because vacancies generate many problems such as crime, susceptibility to fire, and other negative events. The government has developed several measures to address the deterioration of the fringe regions of the core areas through the creation of some systems that encourage conversion from vacancies into allotments, citizens' parks, open spaces, and other green spaces. There have been, however, few measures concerning the spatial distribution of parks and open spaces around the core areas. We have developed an advanced analysis method for detecting the spatial continuity of vegetation distributions covering parks and open spaces through the statistical testing of the spatial features of a Normalized Difference Vegetation Index (NDVI) derived from remotely sensed data. The method can achieve the detection of the spatial continuity of vegetation distributions in accordance with the types of land use: a completely urbanized area, a suburban area, a rural area, and a mountainous area. In this study, we identify the economic impacts of the spatial continuity of vegetation distributions through applying several data acquired in 2000, 2008 and 2015. We apply a hedonic approach with a Geographically Weighted Regression (GWR) to the analysis of the relationship between the assessed values of land and geographical information in order to estimate the importance of landscape factors: the spatial continuity of vegetation distributions, public parks, and the local averages of NDVI.

2. METHIDS AND MATERIALS

2.1 Study Area

The whole area of the Osaka prefecture was adopted as the area of interest. This area is located in the Kansai district in the western part of Japan. It covers about 1900 krn^2 and contains 33 cities, 9 towns, and 1 village. There are also watercourses consisting of several rivers and many streams in the area.

2.2 Remote Sensing and Geographical Data

We applied the Landsat series of remote sensing data: ETM+ data from August 2000, TM data from September 2008, and OLS data from September 2015. The data covers the whole area of interest since the observation swath of Landsat sensors is wide enough (185 km). We applied atmospheric corrections based on the MODTRAN for this study. We defined the NDVI calculated from the Landsat data as the proxy of vegetation abundance. Figure 1 shows NDVI derived from the Landsat OLS data as an example. In Figure 1, it is shown that the urbanized areas are bounded on three sides by mountainous areas covered with high NDVI. National Land Numerical Information is used to a hedonic approach including GWR for studying the relationship between the land prices and the attributes of landscape.

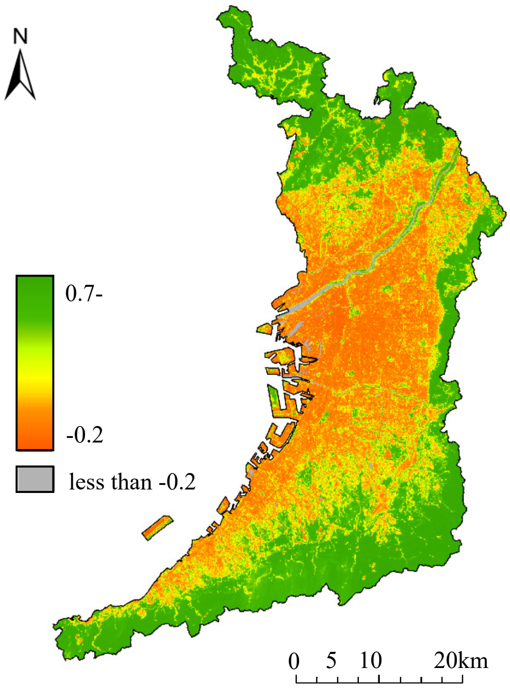

Figure 1. NDVI derived from Landsat OLS data from 2018

2.3 Methods

2.3.1 Generation of SSCs and Ridgelines: The spatial analysis method of vegetation distribution we have developed is composed of a spatial autocorrelation analysis based on G statistics, an overlay analysis, and a hydrological analysis (Getis 1992, Ord 1995, Kumagai 2011). Figure 2 shows procedure of the spatial analysis of vegetation distributions. We overlaid the positive autocorrelation areas generated with the fluctuation of distance *d*: from a widest range to a narrowest range. The area which consists of the multiple layers of the positive autocorrelation area has been called the Spatial Scale of Clumping of vegetated areas (SSC). We also detected the ridgelines from the SSC as the backbones of the high spatial continuity of the vegetated areas by interpreting the SSC as topographic features. The ridgelines play an important role in acting as bridges between the widely dense distribution areas and sparse areas of vegetation, such as the areas (a) and (b) in Figure 2.

Moreover, the application area of the spatial analysis was expanded through the iteration of the procedure with respect to no autocorrelation areas (Kumagai, 2017). Firstly, we applied the spatial analysis method to the area of interest, as mentioned above. The results of this application were renamed SSCl and ridgeline 1. Secondly, we applied the spatial analysis method to the area excluding SSCl, which was initially detected as no spatial autocorrelation area. SSC2 and ridgeline 2 were then generated. Finally, we iterated this procedure to define successive SSCs.

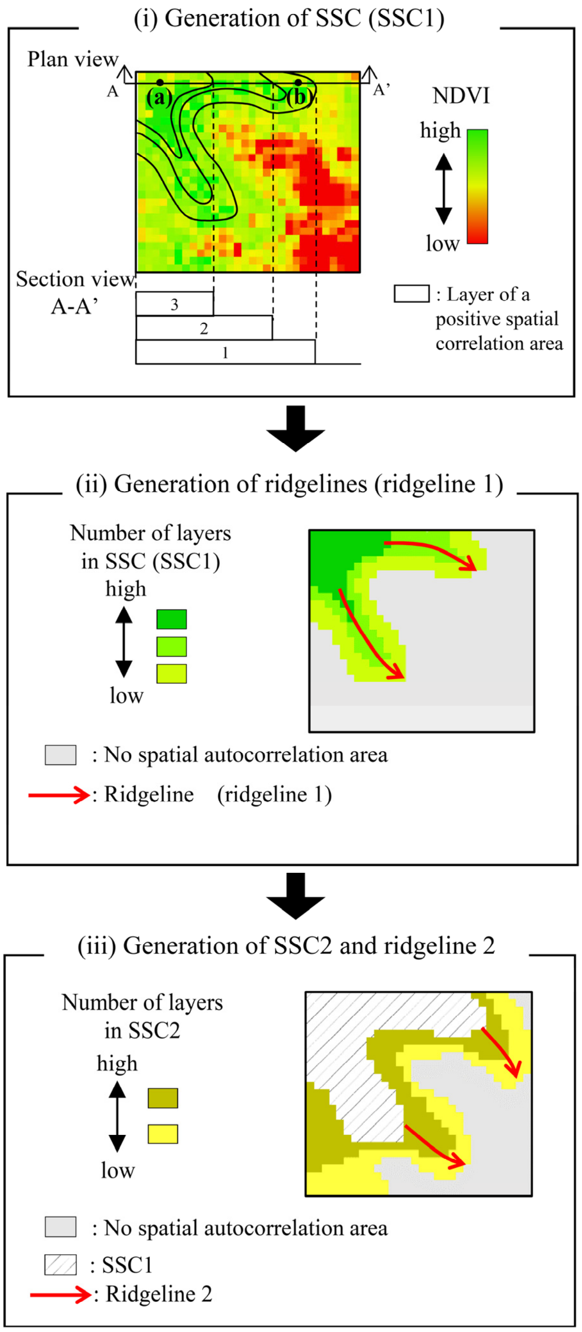

Figure 2. Procedure of the spatial analysis of vegetation distribution

2.3.2 Hedonic method with GWR: To avoid land deterioration around the core areas experiencing population decline in the near future, it is also desirable to be able to conduct a suitable changeover in land use: the substitution of parks and open spaces for vacancies. The changeover should contribute to the maintenance and improvement of the spatial continuity of vegetation distributions. If spatial continuity plays a role in ensuring a rise in value with respect to its surroundings, it will be a good motivating factor to encourage an appropriate changeover of land use. We therefore used a hedonic method with GWR to measure the relationship between the spatial continuity of vegetation distributions and land prices (Brunsdon et al. 1998, Harris et al. 2013, Mulley et al. 2016, Yoo et al. 2016, Hu et al. 2016).

3. RESULTS AND DISSCUSSION

3.1 Results of the Spatial Analysis

Figure 3 indicates the results of the spatial analysis. The study area is divided into 3 SSCs and no autocorrelation area, being common to 2000, 2008, and 2018. The patterns of ridgelines also are slightly different between these results.

3.2 Applicability of GWR

Table 1 shows the variables that we applied to GWR. We adopted the shortest distance from the ridgeline to the point as the factor of spatial continuity of vegetation distributions. The shortest distance to public parks was used as one of the factors of urban facilities. We also calculated the local average of NDVI within 2 km of the point as the local feature of vegetation distributions. These landscape factors are divided into each SSC: SSC1, SSC2, and SSC3 because it appeared that the division could contribute to make an appropriate model to explain land prices (Kumagai 2017).

Before the application of GWR, we examined the relationship between the variables by calculating the VIF. It has been confirmed that there is no multi-collinearity between the variables of Table 1. Initially, we examined the validation of GWR using the statistics of F_1, F_2, and F_3 (Leung et al. 2000). The variables in Table 1 are applied to both OLS and GWR for this examination. The small value of F_1 means that the GWR model has a better goodness of fit than the OLS model, while the large value of F_2 means that the GWR model and the OLS model do not describe the data equally well. F_3 is the test statistic F_k of the spatial differences among the terms of variables. The large value of F_3 means that not all terms are equal. Table 2 shows the results of the validation of GWR. The p values of F_1 and F_2 show less than 0.001 in 2000, 2008, and 2015, respectively. The proportions of significance F_k in F_3 among the three results show more than 70%. Thus, the validity of the GWR model is clarified.

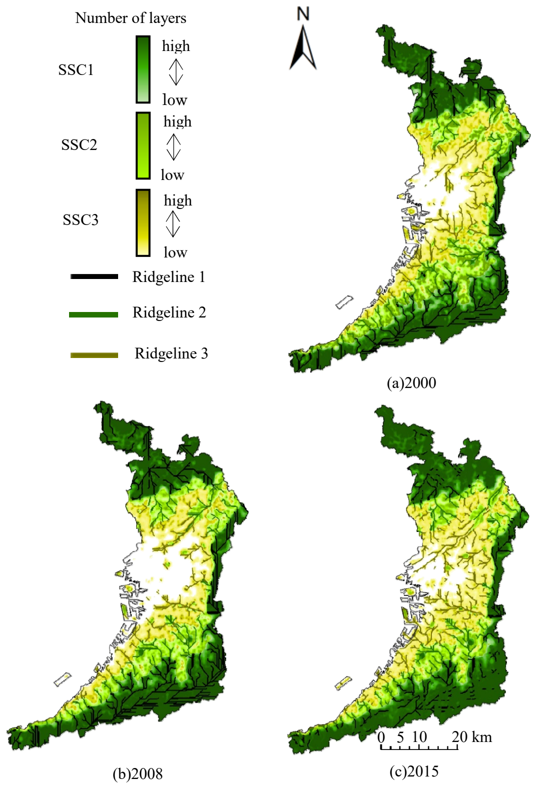

Figure 3. Results of the spatial analysis

	Variables
GI	Acreage [m^2]
	Shortest distance to a railway station [m]
	Building coverage [%]
	Floor area ratio [%]
	Commercial area [dummy]
	Industrial area [dummy]
	Fire protection area [dummy]
	Gas supply [dummy]
	Sewerage [dummy]
Landscape factors	Shortest distance to the ridgeline derived from SSC [m]
	Ridgelines 1, 2, 3, and 4
	Local average of NDVI
	Shortest distance to public parks [m]
	Woods, Small park, and Large park

Table 1. Variables we applied to GWR

Year	F_1	F_2	F_3 (Proportion of F_k (%)) p<0.001	p<0.01
2000	0.735 (p<0.001)	13.11 (p<0.001)	68.0	72.0
2008	0.475 (p<0.001)	9.72 (p<0.001)	88.0	88.0
2015	0.539 (p<0.001)	7.74 (p<0.001)	84.0	84.0

Table 2. Results of the validation of GWR

Year	R^2	AIC	Band width(m)
2000	0.853	210	17088.4
2008	0.896	296	8680.7
2015	0.879	414	9619.3

Table 3. Results of GWR

3.3 Results of GWR

Table 3 displays the results of GWR. R^2 of all the cases are more than 0.85, while AIC and band width seem to depend on the cases. Table 4 shows the proportions of t values of the variable for landscape factors on the basis of the significance level of 5%. The direction (e.g. positive or negative) of an impact on land prices depends on the type of variables. In the variables of shortest distance to public parks, the woods and small parks in SSC2 and SSC3 mostly provide a positive impact on nearby land prices in all years. Especially, the number of t of the small parks in SSC3, showing a positive impact on nearby land prices, gradually increases from 2000 to 2015. NDVI in SSC1 and SSC2 nearly indicates a negative impact in all cases, while the number of t showing a negative impact in SSC3 increases by degrees during these periods. It is also indicated that there are few points in all SSCs, where NDVI shows a positive impact, in all years. On the other hands, in shortest distance to the ridgeline derivied from SSC, the number of t values of the ridgeline 3 in SSC3, making positive impacts on

	t > 1.960 (p(>t)=0.025)	1.960 >= t >= -1.960	-1.960 > t (p(<t)=0.025)
Shortest distance to the ridgeline derived from SSC [m]			
Ridgeline 1 in SSC1	90.69	9.31	0.00
Ridgeline 2 in SSC2	0.00	91.95	8.05
Ridgeline 3 in SSC3	0.00	99.85	0.15
Local average of NDVI			
NDVI in SSC1	0.00	0.00	100.00
NDVI in SSC2	0.00	33.62	66.38
NDVI in SSC3	0.00	100.00	0.00
Shortest distance to public parks [m]			
Woods in SSC1	53.50	20.18	26.32
Woods in SSC2	0.00	17.41	82.59
Woods in SSC3	0.00	2.47	97.53
Small park in SSC1	0.00	0.96	99.04
Small park in SSC2	0.00	6.24	93.76
Small park in SSC3	0.00	59.03	40.97
Large park in SSC1	30.60	69.25	0.15
Large park in SSC2	72.32	20.38	7.30
Large park in SSC3	78.86	21.14	0.00

(a)2000

	t > 1.960 (p(>t)=0.025)	1.960 >= t >= -1.960	-1.960 > t (p(<t)=0.025)
Shortest distance to the ridgeline derived from SSC [m]			
Ridgeline 1 in SSC1	47.72	38.10	14.18
Ridgeline 2 in SSC2	13.67	77.73	8.60
Ridgeline 3 in SSC3	0.00	79.72	20.28
Local average of NDVI			
NDVI in SSC1	3.69	32.87	63.44
NDVI in SSC2	0.00	51.46	48.54
NDVI in SSC3	0.00	26.01	73.99
Shortest distance to public parks [m]			
Woods in SSC1	15.46	48.23	36.30
Woods in SSC2	0.00	74.81	25.19
Woods in SSC3	0.56	54.58	44.85
Small park in SSC1	0.00	2.82	97.18
Small park in SSC2	0.00	15.21	84.79
Small park in SSC3	0.00	56.89	43.11
Large park in SSC1	60.68	36.82	2.51
Large park in SSC2	35.54	45.21	19.25
Large park in SSC3	54.02	45.98	0.00

(b)2008

	t > 1.960 (p(>t)=0.025)	1.960 >= t >= -1.960	-1.960 > t (p(<t)=0.025)
Shortest distance to the ridgeline derived from SSC [m]			
Ridgeline 1 in SSC1	0.00	90.79	9.21
Ridgeline 2 in SSC2	0.00	100.00	0.00
Ridgeline 3 in SSC3	4.02	15.96	80.01
Local average of NDVI			
NDVI in SSC1	0.00	33.08	66.92
NDVI in SSC2	0.00	30.08	69.92
NDVI in SSC3	0.00	21.83	78.17
Shortest distance to public parks [m]			
Woods in SSC1	10.30	59.35	30.35
Woods in SSC2	0.00	16.71	83.29
Woods in SSC3	0.00	47.61	52.39
Small park in SSC1	5.53	86.43	8.05
Small park in SSC2	0.00	76.33	23.67
Small park in SSC3	0.00	20.94	79.06
Large park in SSC1	0.00	71.83	28.17
Large park in SSC2	39.22	51.57	9.21
Large park in SSC3	66.58	33.42	0.00

(%)

(c)2015

Table 4. Proportions of t values of the variable in landscape factors are indicated on the basis of the significance level of 5%

nearby land prices, is gradually increasing during years 2000 and 2015.

3.4 Comparison between Land Prices and Results of GWR

Figure 4 shows the fluctuation of land prices in SSC3 during years 2000 and 2015. In Japan, economic bubble occurred from the mid-1980s to the early 1990. After this periods, land prices generally had declined for about 20 years on the basis of economic slump. We can see the distributions of land prices being on the decrease during years 2000 and 2015 in Figure 4.

Figure 5 displays the distributions of t values in SSC3. Warm

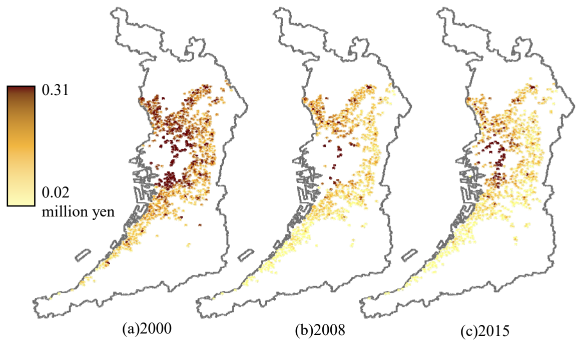

Figure 4. Distribution of land prices in SSC3

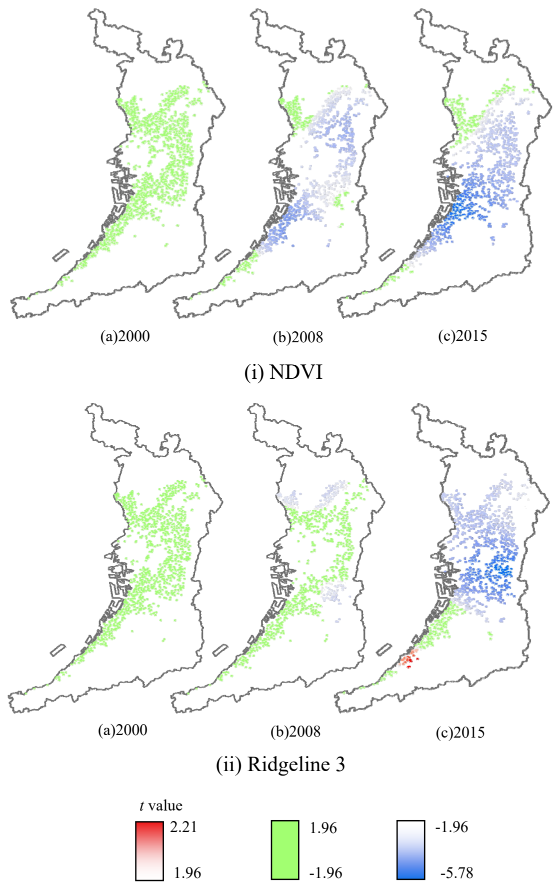

Figure 5. Spatial distribution of t values in SSC3

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colour points mean that the t value is above the significance level of 5%, while cold colour points mean that the t value is below the significance level of 5%. It is apparent that the number of t values of the shortest distance to ridgeline 3, being below the significance level of 5%, increases as the land prices decrease during years 2000 and 2015. Likewise, the number of t value of NDVI, being below the significance level of 5%, increases. The local averages of NDVI in 2015 seem to perform a general role in this model: usually, the land prices of urbanized areas including very few green spaces are relatively high, while the land prices of rural areas surrounded by large green spaces are relatively low. The local average of NDVI, however, does not make a positive / negative impact on nearby land prices in the case where land prices are relatively high. The shortest distance of ridgeline 3 also does not make a positive / negative impact on nearby land prices in 2000. The number of points where the shortest distance of the ridgeline 3 makes a positive impact on nearby land prices is increasing as land prices are decreasing during years 2000 and 2015. In other words, the spatial continuity of vegetation distributions seems to play a more important role in contributing to a substantial extent to predict the land prices of suburban areas around the core areas as land prices decrease.

4. CONCLUSOIN

In this study, we applied the multitemporal analysis of the relationship between assessed values of land and landscape factors by using geographical information data and remotely sensed data acquired in 200, 2008, and 2015. On the basis of the application of hedonic method with GWR, the landscape factors derived from NDVI hardly have a positive / negative impact on nearby land prices in case where the average of land prices are relatively high. It was shown that the number of points where the spatial continuity of vegetation distributions makes positive impacts on nearby land prices is gradually increasing during years 2000 and 2015, while the average of land price continues to fall.

REFERENCES

Brunsdon, C., Fotheringham, A. S., and Chariton, M., 1998. Geographically weighted regression-modelling spatial non-stationarity. *The Statistician*, 3(47), pp.431-443.

Getis, A., and Ord, J. K., 1992. The analysis of spatial association by use of distance Statistics. *Geographical Analysis*, 24(3), pp.189-206.

Harris, R., Dong, G., and Zhang, W., 2013. Using Contextualized geographically weighted regression to model the spatial heterogeneity of land prices in Beijing, China. *Transactions in GIS*, 17(6), pp.901- 919.

Hu, S., Yang, S., Li, W., Zhang, C., and Xu, F., 2016. Spatially non-stationary relationships between urban residential land price and impact factors in Wuhan city, China. *Applied Geography*, 68, pp.48- 56.

Kurnagai, K., 2011. Verification of the analysis method for extracting the spatial continuity of the vegetation distribution on a regional scale. *Computers, Environment and Urban Systems*, 35, pp.399-407.

Kumagai, K., Uematsu, H., and Matsuda, Y., 2017. Advanced Spatial Analysis for Vegetation Distributions Aimed at Introducing Smarter City Shrinkage. *Planning Support Science for Smarter Urban Futures, Lecture Notes in Geoinformation and Cartography*. Springer International Publishing, pp.469-489.

Leung, Y., Mei, C., and Zhang, W. X., 2000. Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A*, 2000(32), pp.9-32.

Mulley, C., Ma, L., Clifton, G., Yen,·B., and Burke, M., 2016. Residential property value impacts of proximity to transport infrastructure: An investigation of bus rapid transit and heavy rail networks in Brisbane, Australia. *Journal of Transport Geography*, 54, pp.41- 52.

Ord, J. K., and Getis, A., 1995. Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis*, 27(4), pp.286-306.

Yoo, J., and Ready, R., 2016. The impact of agricultural conservation easement on nearby house prices: Incorporating spatial autocorrelation and spatial heterogeneity. *Journal of Forest Economics*, 25, pp.78-79.