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MULTI-SCALE EFFECT ON LANDSCAPE PATTERN ANALYSIS USING SATELLITE DATA WITH A RANGE OF SPATIAL RESOLUTIONS

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ABSTRACT

In recent years, identifying the relationship between pattern and scale has emerged as a central issue in ecology and geography. Scale has been defined by grain or resolution but bias in results will occur if the scale is wrongly selected relevant to the landscape evaluation. In this research, satellite data of varying resolution, QuickBird (2.5m), ALOS/AVNIR-2 (10m), Terra/ASTER (15m) and Landsat/ETM+ (30m), were employed to analyze the scale effects of grain size. The research was implemented at Azeta, a typical rural landscape located in Sakura City, central Japan. Land-cover classifications were first implemented using the Maximum Likelihood Method on satellite data of varying resolution. Based on the results of these classifications, a number of landscape metrics imbedded in the FRAGSTATS were extracted for landscape pattern analysis. The results indicate that most landscape patterns show some degree of consistency and scaling relations such as power-law among the various satellite resolutions. The applicability of these various satellite data resolutions for landscape analysis in the target area was also evaluated.
Keywords: LULC classification, extrapolability, landscape metrics, scale effect

INTRODUCTION

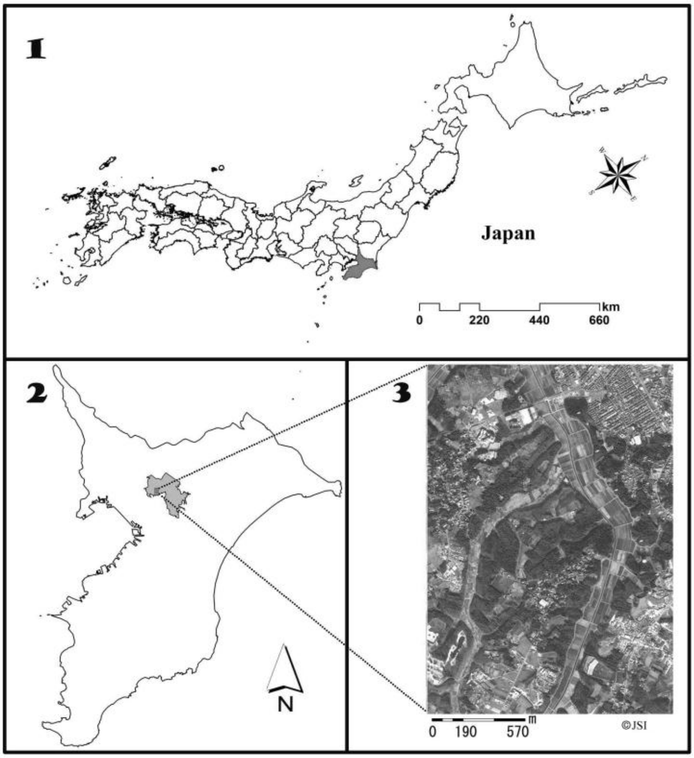
Relations of pattern and scale are central issues in ecology, unifying population biology and ecosystems science, and basic and applied ecology (Levin 1992). Ecological problems often require extrapolation of fine-scale measurements for the analysis of broad-scale phenomena. It is also believed that spatial characteristics could be transferred across scales under specific conditions (Allen and Thomas 1982). It is thus required to shed light on how the spatial information is transferred from a fine scale to a broader scale, and how it supports and complements the transformation as previous knowledge. While the term "scale" here may refer to several definitions, including grain (or resolution), extent, coverage, spacing, and cartographic scale (Wu 2006), the analysis in this paper will only focus on "grain" (the spatial resolution of a particular satellite sensor).

LULC patterns are regarded as important factors in the ecosystem function, and can be considered to represent a spatial aspect of a specific area as determined by both, geographical and biological conditions (Bain and Brush 2004). Therefore, evaluation of landscape patterns based on a multi-scale perspective will provide useful insights for regional conservation, such as how to minimize loss and fragmentation of wildlife habitat due to rapid, widespread human-induced LULC changes. In recent years, remote sensing has become an effective tool to understand LULC characteristics in a variety of scales. This trend is evident in the increased number of research studies related to the issue (Turner et al 1989a; Benson and MacKenzie 1995; Moody and Woodcock 1995; Wu 2004; Zhu et al 2006; Saura 2004; Neel et al 2004; Liu and Weng 2009). Nevertheless, landscape pattern analysis may produce different results when satellite sensors of varied scale are utilized. Recently it has become clear that understanding of the scaling relation among different satellite data can prove useful in producing more efficient land-surface observation based on remote sensing (Quattrochi and GoodChild 1997). Although much work has been done to examine the scaling effect, research on the scaling relations of various satellite sensor with different spatial resolution is still lacking. The major goals of this study are to understand how landscape characteristics respond to changing scale (grain size) and to clarify the inherent scaling relations, such as power-law as found by Wu (2000; 2004), among the various satellite resolutions.

STUDY AREA

This research employs data from a approximately 309 ha area in Azeta (35°42'N, 140°10'E) located in the northwest part of Sakura city in Chiba Prefecture, on the eastern outskirts of Tokyo in central Japan (Fig.1). The area features a typical Japanese rural landscape known as "Yatsu Valley", which consists of narrow, highly-branched valleys cut into level, plateau-like uplands. The area has been selected as a vital habitat for conserving the regional natural environment, and has been designated as a natural park. Although the area is surrounded by densely populated residential zones, the quality of the natural habitats is still high and the area functions as a space where nature can coexist with urban lifestyles. Various wildlife, including species listed as endangered by Chiba Prefecture, inhabit the area. These include the grey-faced buzzard eagle (*Butastur indicus)* and Japanese brown frog *(Rana japonica)* as well as plants such as *Ricciocarpos natans*, *Azolla japonica*, *Ottelia japonica*, and *Penthorum chinense* (Sakura 2006). In recent years, 'Satoyama', as Japanese rural landscapes are known, have been decreasing in area due to such factors as rapid urbanization in some areas, as well as farmland abandonment due to loss of young people from the agricultural sector in others. Conservation of Satoyama landscapes, including the Yatsu Valley environments such as represented by Azeta, is thus now becoming a very important issue in conservation of biological and cultural diversity (Takeuchi et al 2003).

Fig. 1: Study area: Azeta, Sakura city, Chiba prefecture.



MATERIALS AND METHODS

Data preparation

To reveal the scale effect of varying resolution satellite data, images from QuickBird, ALOS/AVNIR-2, Terra/ASTER and Landsat/ETM+ were employed in the analysis. Detailed characteristics of each satellite data are summarized in Table 1. All of the images except for the image from ALOS/AVNIR-2, are in the same area, and have been pre-geo-corrected by the providers. The ALOS/AVNIR-2 was geo-corrected to the Universal Transverse Mercator (UTM) projection with WGS 1984 Zone 54, by referencing the image of QuickBird due to its high visibility. 20 ground control points were chosen for the image. The root mean square errors (RMSEs) for the geo-correction were less than 1 pixel. An additional visually interpreted aerial photograph taken in 2008 of the same area was also utilized as reference data for the LULC classification and accuracy assessment.

Table 1: Detailed descriptions of each four different satellite sensors used for the analysis.

	QuickBird	ALOS/AVNIR-2	Terra/ASTER	Landsat/ETM+
Swath Width	16.5 km^2	70 km^2	60 km^2	185 km^2
Recurrence Period	1〜3.5days	46 days	16 days	16 days
Resolution	2.5m	10m	15m	30m
Observation Date	2009/1/9	2007/11/15	2008/1/8	2006/11/3
Price	25.2 €/1km^2	3.2~6.4 €/1km^2	1.7 €/1km^2	Free
Spectral Bands	B1: .45-0.52µm	B1: 0.45-0.50µm	B1: 0.52-0.60µm	B1: .45-0.52µm
	B2: 0.52-0.60µm	B2: 0.52-0.60µm	B2: 0.63-0.69µm	B2: 0.52-0.60µm
	B3: 0.63-0.69µm	B3: 0.61-0.69µm	B3: 0.78-0.86µm	B3: 0.61-0.69µm
	B4: 0.76-0.90µm	B4: 0.76-0.89µm		B4: 0.76-0.90µm
				B5: 1.55-1.75µm
				B7: 2.08-2.35µm

LULC classification

An image from each sensor was first used to identify six LULC types for the study area based on the ground real data. The classes are: Forest, Grass, Dry Farmland, Paddy Field, Urban Area, and Water Area. Because of absorption in the near-infrared spectrum, the near-infrared spectral band of each satellite imagery was used separately to identify water bodies. In order to avoid misclassification, each image was then subdivided into vegetated area and non-vegetated area according to the normalized difference vegetation index (NDVI). To distinguish vegetated from non-vegetated areas, the original values of NDVI between -1 and 1 were converted into 8-bit unsigned thematic (range 0-255) data. LULC classification was implemented separately for each generated vegetated and non-vegetated area data by using the supervised method of Maximum Likelihood. These analyses were performed using ERDAS IMAGINE 9.3 (Leica Geosystems GIS & Mapping, LLC).

Multi-scale landscape analysis

To investigate the effects of changing scale (grain size), the spatial resolution of four LULC classification maps from each satellite image were systematically changed from their original pixel size to 100 meter at intervals of 5 meters, keeping the spatial extent constant. As the grain size increased, a series of coarser resolution maps were created through a majority rule, which is one of the most commonly used methods for aggregating categorical data in ecology and remote sensing (Turner et al 1989a; Wu 2004; Saura 2004;). Based on these aggregated categorical data, twenty two class-level landscape metrics imbedded in FRAGSTATS 3.3 (McGarigal et al 2002) were employed for landscape analysis. These were: PLAND (Percentage of Landscape), NP (Number of Patches), PD (Patch Density), LPI (Largest Patch Index), TE (Total Edge), ED (Edge Density), LSI (Landscape Shape Index), AREA_MN (Mean Patch Size), GYRATE_MN (Mean Radius of Gyration Distribution), SHAPE_MN (Mean Patch Shape), PARA_MN (Mean Perimeter-Area Ratio), FRAC_MN (Mean Fractal Dimension Index), CIRCLE_MN (Mean Related Circumscribing Circle), CONTIG_MN (Mean Contiguity Index), PAFRAC(Perimeter-Area Fractal Dimension), TCA (Total Core Area), NDCA (Number of Disjunct Core Areas), PROX_AM (Area-weighted Mean of Proximity Index Distribution), ENN_MN (Mean Euclidean Nearest Neighbor Distance), IJI (Interspersion & Juxtaposition Index), AI

(Aggregation Index), COHESION (Patch Cohesion Index). These metrics are often utilized in other research studies for purposes such as examining landscape fragmentation and connectivity (Fahrig and Merriam 1985; Riitters et al 2000; Tischendorf 2001; McAlpine and Eyre 2002; Leitão et al 2006).

RESULTS

Accuracy assessment

The overall accuracies of the classification for each of the four satellite images on their original spatial resolution were 77.23 %, 78.84%, 81.20% and 83.63% (Table 2). The kappa statistics for the images were respectively 0.732, 0.735, 0.749 and 0.749. Although these results show that all of the images were accurately classified, the values increase as the spatial resolution of the satellite becomes coarser. This increase occurs because the so-called 'salt and pepper effect' decreases as image resolution becomes coarser, pulling the classification results closer to the reference data. Grass, Dry Farm Land and Irrigated Paddy Field showed lower accuracies compared to Forest and Urban Area due to their close spectral separability, which caused some difficulties in classification of each satellite data. In addition, the accuracy of the Water Area classifications also performed well with all satellites except Terra/ASTER, but dropped as the spatial resolution of the satellite data become coarser.

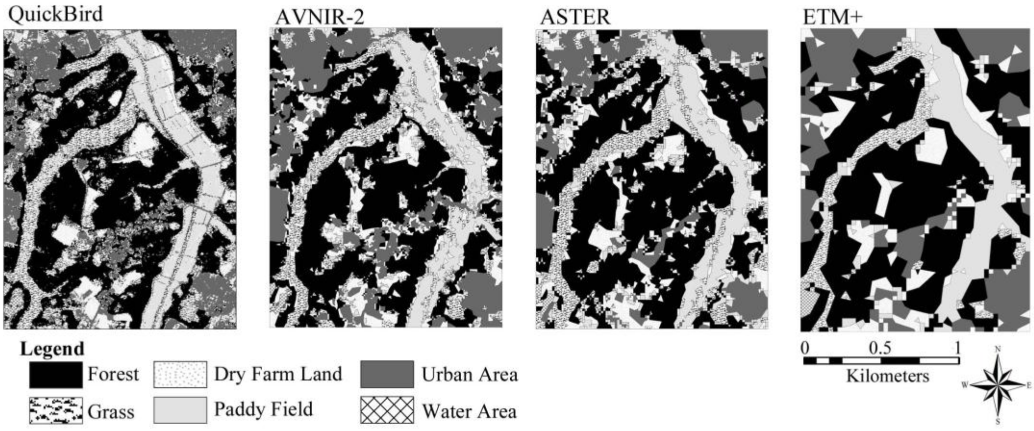
Table 2: Accuracy assessment report of LULC classification for each satellite data.
Fr: Forest, Gr: Grass, DFL: Dry Farm Land, PF: Paddy Field, UA: Urban Area, WA: Water Area.

		Fr	Gr	DFL	PF	UA	WA	Overall Acc(%)	Overall Kappa
QuickBird	Producer's acc (%)	98.40	82.80	63.60	86.10	89.70	42.8		
	User's acc (%)	93.98	75.27	80.30	78.42	93.15	100.00	77.23	0.732
	Kappa (κ) Statistics	0.928	0.703	0.764	0.741	0.918	1.000		
AVNIR-2	Producer's acc (%)	98.60	70.75	55.78%	67.18	98.70	69.49		
	User's acc (%)	88.19	49.10	75.55	75.57	91.13	93.18	78.84	0.735
	Kappa (κ) Statistics	0.847	0.436	0.684	0.685	0.887	0.931		
ASTER	Producer's acc (%)	97.50	80.18	51.18	70.42	92.21	21.21		
	User's acc (%)	85.00	58.19	76.11	80.29	92.61	50.00	81.20	0.749
	Kappa (κ) Statistics	0.759	0.549	0.710	0.759	0.911	0.494		
ETM+	Producer's acc (%)	97.71	48.44	50.65	69.94	94.61	37.50		
	User's acc (%)	89.64	73.81	64.46	88.97	80.61	75.00	83.63	0.749
	Kappa (κ) Statistics	0.772	0.723	0.586	0.838	0.774	0.747		

LULC classification

The classification results showed that Forest is the largest LULC type in the target area, and as mostly surrounded by the Urban Area (Fig.2). Apparently, the most elongated valley areas were covered by agricultural land-use type such as Paddy Field and Dry Farm Land. Although these areas still remained agriculture land, Grass area has increased obviously due to the rapid farming abandonment. These results also show that the areas of different LULC types are distributed sparsely in a typical mosaic pattern.

Fig. 2: Results of LULC classifications for each satellite sensor.



Scaling relations with respect to changing scales (grain size)

Figure 3 shows examples of how different metrics responded to changing grain size for each of the four satellite sensors in the form of scalograms, i.e., plots of landscape metrics against scale (grain size). Due to space limitation, all 22 metrics are not shown in Figure 3. As a resultstronger scaling effect showed in high resolution QuickBird, whereas the effect is less distinctive at a coarser grain size. Nevertheless, most of the metrics responded in a somewhat similar scaling pattern, with the value decreasing as the resolution became coarser. Also, because of mathematical similarity, some metrics such as NP and PD, TE, ED, LSI and PARA_MN exhibited an identical scaling relation.

With changing grain size through spatial aggregation, the responses of the 22 class-level metrics were then divided into four scaling relations; (1) Power-law ($y=ax^b$), (2) Linear function ($y=ax+b$), (3) Logarithmic function ($y=a\ln x+b$), (4) Exponential function ($y=a^x$). All results of these scaling relations between the four satellite sensors are summarized in Table 3, and power-law is considered to be the main scaling relation among the all metrics. The coefficient of determination (R^2) was employed to examine the fitness of each scaling function for each satellite data. As a result, it is evident that power-law is the main scaling relation in case of grain size changing among different satellites. With the spatial resolution of the satellite data increasing, more than one scaling relation emerged to fit the datasets, and the relations became weaker as the value of R^2 become lower. This also means that extrapolability was degraded as the spatial resolution of satellite became coarser.

Based on the above results, the responses of these metrics were further divided into four general groups: metrics showing both consistent and robust scaling relations (Type I) which include 9 indices (NP, PD, TE, ED, LSI, AREA_MN, PARA_MN, ENN_MN, and PROX_AM); metrics showing consistent but less robust scaling relations (Type II) which include 4 indices (PLAND, IJI, COHESION and AI); and metrics showing staircase-like response with change scale (Type III) which include only 2 indices (TCA and NDCA). The rest of the metrics showed an unpredictable scaling behavior (Type IV). Please note that the term "consistent" here refers to the consistence of scaling relations in any forms of linear, power, or logarithmic functions between different satellite sensors, whereas "robust" implies the similarity of scaling relations between different LULC types within the same sensor.

Fig. 3: Examples of landscape metric scalograms with changing grain size

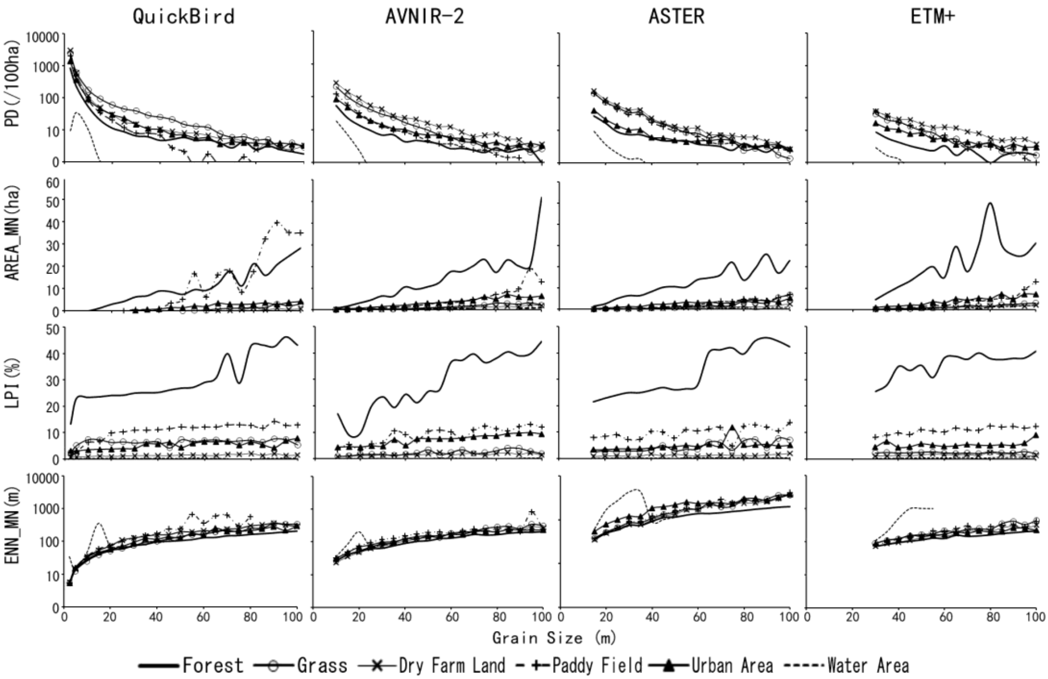


Table 3: Comparison of scaling relations of class-level metrics among different satellite sensors.

landscape metrics	QuickBird	AVNIR-2	ASTER	ETM+
PLAND	unpredictable	unpredictable	unpredictable	unpredictable
NP	power law	power law	power law	logarithmic
PD	power law	power law	power law	logarithmic
LPI	unpredictable	unpredictable	unpredictable	unpredictable
TE	power law	logarithmic or power law	logarithmic or power law	logarithmic or power law
ED	logarithmic	logarithmic	logarithmic	logarithmic
LSI	power law	logarithmic	logarithmic	logarithmic
AREA_MN	power law	power law	power law	power law
GYRATE_MN	power law	power law	power law	power law
SHAPE_MN	unpredictable	unpredictable	unpredictable	unpredictable
PARA_MN	power law	power law	power law	power law
FRAC_MN	unpredictable	unpredictable	unpredictable	unpredictable
CIRCLE_MN	unpredictable	unpredictable	unpredictable	unpredictable
CONTIG_MN	unpredictable	unpredictable	unpredictable	unpredictable
PAFRAC	unpredictable	unpredictable	unpredictable	unpredictable
TCA	staircase	staircase	staircase	staircase
NDCA	staircase	staircase	staircase	staircase
PROX_AM	power law	power law	exponential	exponential or power law
ENN_MN	power law	power law	power law	power law
IJI	unpredictable	unpredictable	unpredictable	unpredictable
AI	unpredictable	unpredictable	unpredictable	unpredictable
COHESION	unpredictable	unpredictable	unpredictable	unpredictable

Note: “*” indicates low fitness of determination coefficient (R^2). The term unpredictable here indicates that the value of R^2 is lower than 0.3.

DISCUSSION

The results showed that the classification from each of the four selected satellite sensor was acceptable. Obviously, satellite data with higher resolution could more delicately reflect landscape characteristics such as patch shape, and distribution status such as canopy gap.

The results of multi-scale landscape analysis showed that more than half of the landscape metrics have significant scaling effects with changing grain size and are predictable across the scale. These metrics may be effective for specific purposes, such as detecting landscape fragmentation or connectivity due to their robust and consistent behavior against satellite data with various spatial resolutions (Saura 2004). In contrast, half of the metrics, including PLAND, LPI, SHAPE_MN, FRAC_MN, CIRCLE_MN, CONTIG_MN, PAFRAC, IJI, COHESION, and AI are independent on grain size and are thus unpredictable across scales in any satellite data. This indicates that a more complex relationship, such as polynomial function or nonlinear relation, may exist between the metrics and scales. From the results of comparison of various satellite sensors, it is evident that power-law is the main and consistent scaling relation among all the landscape metrics which is consistent with previous studies (Wu et al 2000; Wu 2004). This deepens our understanding of hierarchical structure in landscape which follows power laws as in biological and ecological systems (Brown et al 2000; Schneider 2001). The stronger scale effect on satellites with higher resolution indicates that their landscape metrics are highly dependent on the scale and that these satellites have good information extra polability. This may provide a useful insight, that datasets with finer scales of resolution are more appropriate for making an extrapolation from a small area unit to a larger one, due to less information loss as the scale changes. In contrast, sensors with coarser resolution, such as ETM+, showed that most of the metrics are less dependent on the scale because the value of the determinant coefficient are lower than other sensors. This may indicate that due to information loss, the value of metrics from satellite data with coarser resolution is not suitable for investigating the landscape pattern, especially in areas where various types of landscape elements are mixed together in a complicated mosaic pattern. Some natural phenomena may thus be incorrectly interpreted if inappropriate data is used. It is therefore essential for researchers to choose a satellite sensor with appropriate resolution based on the goals for the project and a certain type of the study area.

The Yatsu valley environment researched here is typical of the southern Kanto Region. In this highly developed and heavily populated area the traditional rural landscape usually coexists with suburban residential or commercial development (Takeuchi et al 2003). Quick, efficient monitoring of changes in this landscape is thus essential for preserving a delicate balance between natural habitats and urban lifestyles.

Finally, this study has systematically investigated how landscape metrics respond to changing grain size among various resolution of satellite data. Although our results showed that changing scale (grain size) had significant effects on the metrics, how differences of scale relate to spatial heterogeneity between different satellite data also has to be numerically quantified. In addition, Turner et al (1989a) have noted that the development of methods that will preserve information across scales or quantify the loss of information with changing scales is a critical task. A future goal of this research is thus to construct a statistical model to quantify the scaling relations and detect the break point where landscape pattern may start to change fundamentally using various resolution satellites. This will involve not only focusing on grain size but examining how landscape pattern characteristics respond to changing extent and various types of study area as well.

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