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Importance of considering grain and extent for the analysis on spatial dynamics: perspectives from comparison between theory and empirical example on seagrass bed dynamics in Tokyo Bay

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Abstract

The term scale has been used in many ways. In continuous landscape analysis, the spatial scale consists of two components; grain and extent. Most previous studies on the scale issue were conducted in limited range or on one component of the scale. To further step up, we compared theory of scaling by applying indices developed for terrestrial static landscape to underwater vegetation. The result suggested that changing grain shows power-low scaling relationships for the most of landscape indices. Changing extent increased variation of above scaling relationships. We conclude that changing both components reveal the possibility to extrapolate these indices into different scales or places. For the conservation of ecosystems, recognition of scaling relationships is necessary to build more spatially explicit planning and understanding of phenomenon.

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1. Introduction

Seagrass is a marine flowering plant which is known to have important functions such as high primary production, water clarification by nutrient absorption, sediment stabilization, and it provides a nursery area for commercially important fishes [1]. However, seagrass landscapes (so called seagrass beds) are decreasing world widely because of human induced effects [2]. Effective management strategies and detection of driving forces of the vegetation dynamics are required for their conservation. For this purpose, researches considering large spatial area are necessary [3]. By remote sensing approach, we expect to find appropriate indices to measure the state of seagrass dynamics because the spatial pattern is

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the consequence of interaction of local processes affecting those vegetation dynamics [4]. For example, Sleeman et al. [5] quantified spatial patterns of seagrass bed fragmentation by comparison of 23 landscape indices (measurement of landscape structures) which evaluating the patch structures such as area, density, area/perimeter ratio and distance of patches. They detected 8 indices as a representative of fragmentation and they also calculated single axis showing combination of these indices. To apply this approach to the other seagrass vegetation, we need to clarify the generality of these indices across different study area and different resolutions.

Inappropriate extrapolation from one to another scale fails to capture the true process or accurate distribution which is known as spatial transmutation [6]. This causes problems about selecting sampling area and resolution for monitoring and management plans. However, basic rules of spatial scaling (changing scale) were not clearly understood for empirical marine ecosystems [7,8]. The spatial scale is separated into grain (sampling resolution) and extent (range of study area) for the analysis of continuous landscape. Most previous studies on seagrass landscape considered only one of the two components, and over narrow range of variation [9]. For example, if we could not recognize increase of new germination in low resolution satellite image (large grain size) the seagrass possibly increase unexpectedly sudden over wide range of study area (large extent). In case of the situation which we record the rapid elongation of rhizome in a ground survey of seagrass patches in local area (narrow extent and small grain size), it does not always expect rapid increase in all over the area because of spatial heterogeneity. In addition, higher resolution (small grain size) is not always possible to treat in raw values because of a limitation of machine power and research budged. These make it difficult to carry out analyses of spatial dynamics over large extent with fine grain size. Toward the better understanding of scaling, more researches considering both extent and grain simultaneously over wider ranges are necessary. In case of terrestrial vegetation, there is an empirically derived theory which explains how landscape indices vary with changes in both components of the scale [10]. In summary, Wu mentioned that the most indices show linearity and follow the power-low and differing extent shows less robust patterns. It was not clear whether this theory also apply to aquatic vegetation, especially about the indices which previously pointed out as a representative of seagrass bed fragmentation. To answer this question, we first calculate grain and extent dependency of landscape indices. We then discussed about comparison of the scaling pattern of landscape indices between seagrass beds and those in theory. We also discuss the cause of variation of this pattern based on the known temporal dynamics and driving forces.

2. Methods

The analysis was conducted in the Futtsu Tidal Flat, Tokyo Bay which holding the largest seagrass bed in the bay which remaining after rapid land reclamation era from 1960’s to 70’s (Fig. 1). This seagrass bed is located at the north of the sandspit structure at the mouth of the inner part of the bay and known to show different dynamics by the location [9]. The bed consists of dominance species Zostera marina L and two other spices which were not dominate in our quadrats.

For the extraction of the seagrass distribution we used aerial photographs taken during the winter for the purpose of location survey. Supervised classification was applied to extract the vegetation in 0.5m resolution. Extracted dataset was resampled into different grain sizes from 1 m to 128 m resolution directly from original dataset [8]. Four 400 m quadrats (E, F, M, W in Fig. 1) were extracted from the above dataset to represent different extent size. The effect of extent was examined at two scales. One is the each 400m quadrates and the other is all four quadrates averaged as a large extent analysis.

Fragstats [11] was used to calculate a total of 22 landscape indices (Table 1). We chose 12 indices which basically had strong linear scaling relationships based on Wu [10], Nine of these were picked up as indices showing power-low scaling. Among these indices LPI, Area_MN, Area_SD, Area_CV, Shape_AM and Frac_AM were not robustly follow this pattern all the time compares to others. 8 indices (3 overlapped) which represent fragmentation were also chosen from Sleeman et al. [5]. 2 other indices which directly represent fragmentation and dynamics of the bed was also calculated (CONTIG and Veg_size_change). We compared scaling characteristics of each index in three different phases of seagrass dynamics (the decrease phase from 1992 to 1993, no-change in 2000, the increase phase from 2006 to 2007; Fig. 2). Best fit model was selected among linear, logarithm, power-low and exponential scaling relationships by R square value of minimum least square method. We then compared the effect of extent for each index using summed value of all quadrats.

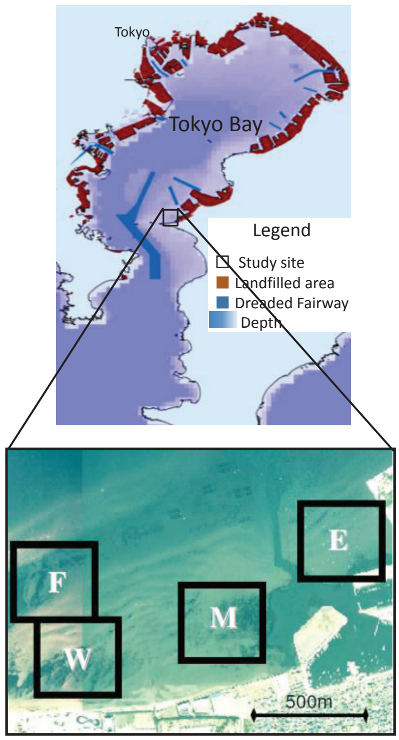

Fig. 1. Location of Futtsu Tidal Flat in Tokyo Bay and quadrats E, F, M, W placed on the aerial photograph.

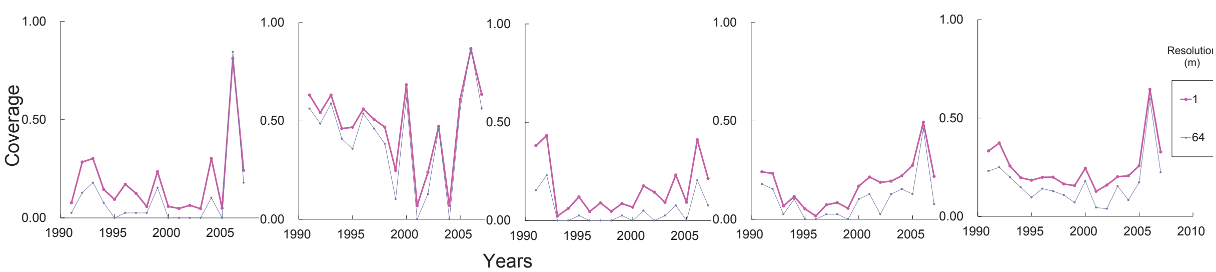

Fig. 1. Annual vegetation dynamics in 1 m and 64 m resolutions at the quadrats E F M W and all area (left to right). (see Yamakita and Nakaoka 2009 for more details).

Table 1. Landscape indices and those characteristics used for the model. Characteristics of each index based on McGarigal et al. (2002) and summary of the selected models by previous researches are also listed.

Abbreviation	Name	Characteristics	Wu 2004	Slee et al 200
AREA_CV	Patch Size Coefficient of Variation (CV)	Coefficient of variation (standard deviation divided by the average) of size of patches.	Power	
AREA_MN	Mean Patch Size	Average size of patches.	Power	
AREA_SD	Patch Size Standard Deviation (SD)	Standard deviation of patch sizes.	Linear	
FRAC_AM	Area-Weighted Mean Fractal Dimension	Representing shape complexity which is calculated by 2 times the logarithm of patch perimeter divided by the logarithm of patch area.	Power	
LPI	Largest Patch Index	Ratio of maximum size of patch and total study area.	Log.	
LSI	Landscape Shape Index	Representative of aggregation. This is calculated by ratio between total length of perimeter and minimum length of perimeter.	Power	
PD	Patch Density	Number of patches divided by the area.	Power	
SHAPE_AM	Area-Weighted Mean Shape Index	The ratio between perimeter of a patch and the most simple shape patch with same area as a correction of perimeter-area ratio.	Power	
TE	Total Edge	Absolute values of total length of patch perimeter.	Power	
Veg_Size	Vegetation size	Total area of the vegetation.	na	Sele
ED	Edge Density	TE divided by total area and multiplied by 10,000 to be per ha value.	Power	Sele
NP	Number of Patches	Counting number of patches.	Power	Sele
DIVISION	Landscape division	Cumulative patch area distribution calculated by 1 minus the sum of patch area divided by total landscape area, quantity squared, summed across all patches of the corresponding patch type.		Sele
ENN_CV	CV of Euclidean Nearest-Neighbor Distance of each patch	CV of distance to the nearest neighbouring patch. The minimum value depends on cell size.		Sele
GYRATE_AM	Area-weighted Mean radius of gyration	See GYRATE_MN.		Sele
GYRATE_MN	Mean radius of gyration	Mean distance of each cell within each patch and the patch centroid which represent patch extent (effected by both patch size and patch compaction).		Sele
PARA_AM	Area-weighted Mean perimeter to area ratio	Area waited mean of the perimeter/ area ratio as a simple measure of shape complexity.		Sele
CONTIG_MN	Contiguity of patches	Used to assess spatial connectedness, or contiguity.		
Veg_Size_change	Changes of the size of vegetation to the following year	Difference of the absolute values from one year to the next year.		

3. Results

The scaling analysis of seagrass landscape selected power-low scaling functions for most landscape indices when we changed the grain size (Table 2; Fig. 3). LPI, a part of DIVISION and Veg_Size_change shown linear relationships among the landscape indices used for this analysis. Fitness of the models was differed in some years and quadrats (Table 3). Best fit model for AREA_MN, PARA_CV and Veg_Size_change was different in some time. The R square values were over 0.9 in most indices but it was low for some indices such as CONTIG_MN, LPI, PARA_CV, Veg_size, and Veg_Size_change (Table 3. Mean).

Variations of these variables were greater at the larger extent in general (Table 3. SD of all years). Amount of the variation was highly depending on years and sites. Especially in AREA_SD, LPI, Veg_size, DIVISION, ENN_CV, GYRATE_AM, CONTIG_MN, Veg_Size_change showed high variance caused by large annual fluctuation of the model fitness because of a low fitness in some quadrats.

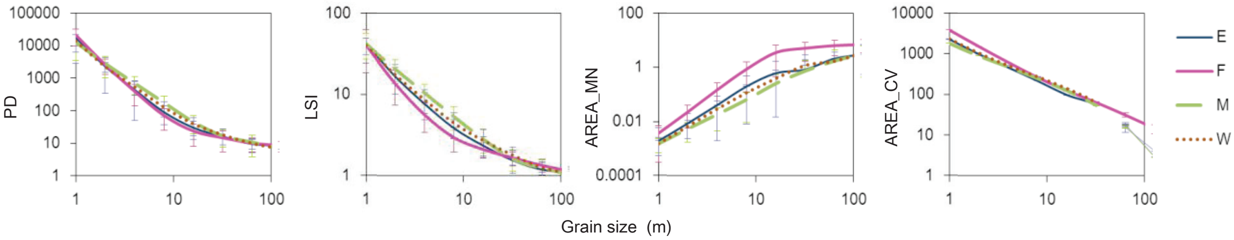

Fig. 3. Examples of scatter plot of landscape indices by different grain size of data at four quadrats (E to W). Lines are smoothing of each plot of average value and error bars showing standard deviation derived from the data of different years.

Table 2. Number of selected scaling relationships in each landscape index. Linear, logarithmic, power-low and exponential relationships was used for the model.

	Types of scaling relationships			
	Linear	Logarithmic	Power-low	Exponential
AREA_CV	0	0	11	0
AREA_MN	4	2	13	0
AREA_SD	0	1	10	0
FRAC_AM	0	0	19	0
LPI	10	2	7	0
LSI	0	0	19	0
PD	0	0	19	0
SHAPE_AM	0	0	19	0
TE	0	0	19	0
Veg_Size	0	5	14	0
ED	0	0	19	0
NP	0	0	19	0
DIVISION	8	4	7	0
ENN_CV	2	3	1	0
GYRATE_AM	2	7	10	0
GYRATE_MN	0	2	17	0
PARA_AM	0	0	19	0
CONTIG_MN	1	1	15	0
Veg_Size_change	6	2	4	0

Table 3. Effect of the extent on the scaling relationships. The mean and standard deviation of R square values of fitted models in each quadrate are shown.

	1992		1993		2000		2006		2007		ALL years	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AREA_CV	0.97	0.01	0.96		0.99		0.98	0.01	0.95	0.06	0.97	0.03
AREA_MN	0.87	0.10	0.89	0.01	0.95	0.06	0.93	0.01	0.96	0.02	0.92	0.06
AREA_SD	0.92	0.02	0.38		0.97		0.89	0.10	0.92	0.07	0.87	0.17
FRAC_AM	0.93	0.03	0.97	0.02	0.95	0.04	0.93	0.02	0.90	0.08	0.94	0.05
LPI	0.50	0.36	0.32	0.06	0.82	0.10	0.87	0.12	0.45	0.39	0.61	0.31
LSI	0.90	0.08	0.92	0.02	0.96	0.06	0.93	0.01	0.95	0.05	0.93	0.05
PD	0.88	0.10	0.88	0.00	0.95	0.07	0.93	0.01	0.95	0.05	0.92	0.06
SHAPE_AM	0.91	0.02	0.95	0.01	0.94	0.04	0.91	0.03	0.87	0.07	0.92	0.05
TE	0.90	0.07	0.91	0.02	0.95	0.06	0.93	0.02	0.95	0.05	0.93	0.05
Veg_Size	0.61	0.15	0.58	0.24	0.89	0.11	0.43	0.36	0.91	0.07	0.69	0.27
ED	0.89	0.08	0.90	0.02	0.95	0.07	0.92	0.02	0.94	0.06	0.92	0.05
NP	0.88	0.10	0.88	0.00	0.96	0.06	0.93	0.01	0.95	0.05	0.92	0.06
DIVISION	0.50	0.34	0.59	0.28	0.86	0.07	0.89	0.09	0.49	0.38	0.67	0.30
ENN_CV	0.41				0.59		0.61		0.89	0.05	0.71	0.21
GYRATE_AM	0.66	0.18	0.36	0.23	0.33	0.36	0.55	0.27	0.44	0.41	0.47	0.30
GYRATE_MN	0.91	0.09	0.92	0.05	0.95	0.05	0.94	0.01	0.96	0.03	0.94	0.05
PARA_AM	0.88	0.08	0.93	0.01	0.95	0.06	0.92	0.01	0.95	0.05	0.93	0.05
CONTIG_MN	0.54	0.45	0.70	0.17	0.52	0.17	0.64	0.13	0.41	0.32	0.56	0.27
Veg_Size_change	0.41	0.21	0.43	0.17	0.59	0.25	0.75	0.09			0.56	0.21

4. Discussion

Most of the indices had linearity and followed power-low function as expected from theory when we changed the grain size of the analysis. Landscape metrics with this simple scaling relationship enable us to extrapolate use of these landscape indices as representative of fragmentation across wide spatial scales. Revealing scaling relationships between broad spatial pattern and local processes is also promising to detect the spatial range of dominant driving forces of the vegetation dynamics [4].

Compare to changing grain, changing extent showed unpredictable scaling pattern, which agreed with the theory by Wu [10]. The variation of study area in the large extent seriously affected this result. The reason of this variance can be either of two types of spatial dependency on the location. One is the different physical setup among these quadrats, the other is the inherent nonlinear scaling reaction of indices refracting the different reaction of the vegetation to the same driving forces. The first reason is not likely during our study term because of similar types of temporal changes are observed in our quadrats (Fig. 2). Because the most indices which have higher variance seem to be related with patch fragmentation/connectivity, latter reason will be the most appropriate. Even if there is no major difference in the physical disturbance itself, the local reaction of vegetation can be different depending on the status of vegetation. Although there is a similar trend of vegetation change in different quadrats, the absolute values of vegetation are totally different depending on the locations (Fig. 2). This can makes different pattern of fragmentation by different locations. For example, in case of dense distribution of the vegetation, intermidiate physical disturbance does not affect to the seagrass landscape. In contrast, in case of sparse vegetation, the disturbance can change the vegetation patterns. This type of different dynamics caused by different status of vegetation has been discussed to be discipline of the complex ecosystem and detected as neighboring effect of the vegetation [4,8]. Asynchronous dynamics between local quadrats in long-term dynamics of the seagrass [9] is rarely a single effect of physical setup itself but possibly caused by interaction of direct physical disturbance and local reaction of the vegetation.

We conclude that changing both components of scale revealed the possibility of extrapolation of landscape indices. This is especially true for changing grain size. Elucidating the cause of the variance component of scaling with different extent remains as important task. However, the variance of extent gives us an insight about the importance of plant-physical interaction to the vegetation dynamics not just from the viewpoint of the vegetation size but from the viewpoint of the landscape structure. This will give some answers to solve the problem that where to plan conservation areas or monitoring sites by using these indices. Revealing the cause of extent variance is also practically important to detect the driving forces of vegetation dynamics. For the conservation of ecosystems, both the recognition of scaling relationships and the use of scaling characteristics as a representative of the status of vegetation are encouraged to develop more relevant spatially explicit planning and to enhance understanding of phenomenon.

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