Landscape Ecol
https://doi.org/10.1007/s10980-019-00937-1

RESEARCH ARTICLE

Spatial scaling of multiple landscape features in the conterminous United States

Chunxue Xu · Shuqing Zhao · Shuguang Liu

Received: 1 December 2018 / Accepted: 25 November 2019

Abstract
Context Spatial heterogeneity is scale-dependent. Understanding the scaling rules of spatial features across wide ranges of scale is a major challenge in landscape ecology. The lack of scientific justification in choosing proper scale may lead to unexpected outcomes in landscape pattern analysis and result in biases in subsequent process analysis.
Objectives The goal is to provide an extensive analysis on scaling relationships for a variety of landscape metrics as functions of grain size and extent. Specific research objectives are to: (1) identify scaling relationships of landscape metrics as functions of grain size, (2) define scale domains of these scaling relationships, and (3) explore how scaling relations of landscape metrics with respect to grain size would change with spatial extent.
Methods Expanding the approach of Wu and Hobbs (Landsc Ecol 17:355–365, 2002) and Wu (Landsc Ecol 19:125–138, 2004) using a much bigger dataset and covering a wider range of scales, we examined the patterns of scalograms of 38 landscape metrics within 96 sampled landscapes ranging from 2^5 to 2^{21} km^2 in the conterminous United States. Scaling models were derived from the scalograms as a function of grain size, and the scale domains of these models were identified as the critical scales along the dimensions of grain size and spatial extent where the performance of the models fell below a given error limit.
Results The responses of landscape metrics with respect to changing resolutions fall into three categories: predictable across the whole spectrum of grain size investigated (Type I), predictable in a limited range of grain size (Type II), and unpredictable (Type III). For Type II metrics, the critical aggregation resolutions were identified based on the predefined error limit, and scale-invariant power-law scaling relationships were found between critical resolutions and spatial extents. All the scaling exponents are positive, suggesting that critical aggregation resolutions can be relaxed as the spatial extent expands. Furthermore, the coefficients of scaling relations for Type I and II metrics vary with spatial extents, and robust scaling functions between the coefficients and the extent can be observed for some metrics.
Conclusions This study addresses a fundamental scale issue in landscape ecology: how a particular spatial pattern would change with scale and how information could be adequately transferred from one

C. Xu · S. Zhao (✉)
College of Urban and Environmental Sciences, and Key Laboratory for Earth Surface Processes of the Ministry of Education, Peking University, Beijing 100871, China
e-mail: sqzhao@urban.pku.edu.cn

S. Liu
National Engineering Laboratory for Applied Technology of Forestry & Ecology in South China, and College of Biological Science and Technology, Central South University of Forestry and Technology,
Changsha 410004, China

Published online: 02 December 2019

scale to another. A variety of scaling relationships exist on the spatial patterns of landscape metrics, and they could provide guidance to researchers on how to select an appropriate scale for a study of interest. In addition, the findings support the empirical perception that coarser grain size might be used for a larger spatial extent.

Keywords Spatial heterogeneity · Landscape metrics · Scale effect · Scale domain · Spatial resolution · Geospatial extent

Introduction

Scale is a central but challenging concept describing the hierarchical organization of the earth system (McGarigal and Marks 1995; Marceau 1999). It refers to spatial and temporal dimensions of the phenomenon (Turner et al. 1989a; Wu and Qi 2000), and the spatial dimension is most frequently characterized as grain size (the finest spatial resolution of the dataset) and extent (the size of the study area) in ecology and other earth sciences (Wu et al. 2006). Scale issues principally deal with two fundamental questions. One is how a particular spatial pattern or process would change with scale and what is an appropriate scale for a study of interest (Kotliar and Wiens 1990; With and Crist 1995; Keymer et al. 2000; Buyantuyev et al. 2010). And the other is scaling, that is, how information could be adequately and precisely transferred from one scale to another (Wiens 1989; Schneider 2001; Spence 2009; Argañaraz and Entraigas 2014).

Landscape metrics for spatial pattern analysis have been widely used in the measurement and interpretation of spatial heterogeneity, and the scale issue has been explored through observing the behaviors of landscape metrics with changing scales. Considerable effort has been devoted to exploring scale effects (Turner et al. 1989b; Qi and Wu 1996; Cain et al. 1997; Saura 2002; Alhamad et al. 2011), hierarchy or scale breaks (Wu 1999; Rutchey and Godin 2009; Wheatley 2010), and scaling (Wiens and Milne 1989; Costanza and Maxwell 1994; Nikora et al. 1999; Shen et al. 2004). It has been generally accepted that spatial data tends to lose details when coarsen the grain size, and the response of landscape metrics with changing scales can be grouped into predictable and unpredictable types. Scalograms are often used to capture how landscape metrics respond to changing resolution or extent. Previous studies (e.g. Wu et al. 2002; Wu 2004; Alhamad et al. 2011) have found that the responses of landscape-level metrics fall into three categories as predictable (i.e., simple scaling relations), stair-like and erratic types for real landscapes. The responses of class-level metrics present predictable and unpredictable behaviors. Furthermore, scaling relations are more consistent and predictable with changing grain size than with changing extent for both-level metrics. Similar patterns have also been found for simulated landscapes (Shen et al. 2004).

The multi-scale perspective allows us to observe the scale-dependence of spatial heterogeneity, whereas our ability is still limited in determining whether a spatial resolution is proper to a study of interest. In practice, the spatial resolution is usually chosen based on grain size of the spatial dataset. The lack of scientific justification in the choice of scale may lead to unexpected outcomes in landscape pattern analysis and result in further biases in subsequent process research. As multiple aspects of the landscape structure respond to changing scale in different ways, there is no single ‘optimal’ scale for the representation of the landscape features (Wu 2004). However, it is possible to obtain specific scaling relations for some spatial characteristics with respect to changing scales. The scaling relation suggests that the multiscale characteristics of landscape pattern could be quantified in a precise and concise way, presenting practical implication in spatial analysis (Wu 2004).

However, the scaling functions of landscape metrics have not been examined thoroughly. First, we have limited knowledge about the scope of the scaling functions. If some landscape metrics present simple scaling relations, more understanding is needed around whether regression functions fit well over the whole spectrum or limited range of scale. Second, there is a lack of quantitative understanding of the interactive effects between resolution and extent, covering a wider range of scales, with the goal of identifying some general guiding principles for study design. Most previous efforts on examining the behaviors of landscape metrics have emphasized the effect of changing grain size while keeping the same extent, or changing extent with grain size remained the same. To explore the generality of the scaling functions across different landscapes with various extents, the scaling functions should be disclosed so that we can understand if the function type would change with scale, or how the parameters of the functions would change if the functions type remains the same across scales.

To address the issues raised above, we expanded the approach of Wu et al. (2002) and Wu (2004) in this study with much wider ranges of grain size and extent to explore and quantify the scaling behaviors of the landscape metrics. Specifically, we explored the scale effects of landscape pattern metrics in 96 landscapes across the conterminous United States with various extents ranging from 2^5 km^2 to 2^{21} km^2 along with a wide spectrum of resolutions. The aims of this study were to address the following research questions: (i) what are the scaling relationships of landscape metrics as functions of grain size for landscapes with a certain extent? (ii) how do scaling relations of landscape metrics with respect to grain size change with the spatial extent? (iii) how can the aggregation domain of the scaling relationships be identified?

Data and methods

Study area

The study area is the conterminous United States (CONUS), covering an area of about 8,059,023 km^2. A total of 96 sub-regions varying in size were sampled across CONUS with areas ranging from 2^5 km^2 upwards to 2^{21} km^2 (Fig. 1). All sampled landscapes were square in shape, and six samples of each size were chosen except for the extents of 2^{20} and 2^{21} km^2 of which only four and two could be sampled, respectively, due to their large sizes. The 90 sub-regions with extents ranging from 2^5 to 2^{19} km^2 were sampled non-overlappingly to capture various spatial patterns and increase the generality of results.

Data

The land cover maps for CONUS were derived from the National Land Cover Database (NLCD) created by the Multi-Resolution Land Characteristics Consortium (Homer et al. 2012). We used the land cover product NLCD 1992 at a resolution of 30 m with a 21-class land cover classification scheme for our study. The NLCD 1992 product includes four forest classes (deciduous, evergreen, mixed forest and woody wetlands) covering about 32.1% of the total area, agricultural lands (pasture/hay, row crops, small grains, fallow and orchards/vineyards) with a coverage of about 26.4%, and urban areas (low and high intensity residential, commercial/industrial/transportation) occupying a small fraction (approximately 3%) of the total area (Vogelmann et al. 2001).

Methods

Resampling of input data

To investigate the effect of changing grain size, the original datasets were systematically resampled from a resolution of 30 m (i.e., one-pixel size) upwards to 60 m (two-pixel size), 90 m (three-pixel size) and so on till the coarsest possible within a given extent. The largest grain size should be the same as the spatial extent. However, the number of rows or columns of the spatial data could not always be wholly divided by the grain size. In this case, the size of resampled data for the same extent would change as the grain size coarsened progressively. In this study, the coarsening of grain size didn't continue for a certain extent once the change rate of extent size for the resampled data exceeded 10%.

Two widely used resampling approaches, the nearest neighbor and majority algorithms, were both used in this study to compare their performances. The nearest neighbor resampling assigns the value of the center cell within the filter window to the new one, while the majority resampling determines the value of the cell based on the most popular value in the window. The resampling was accomplished in ArcGIS Spatial Analyst.

Methods for investigating the scale effect

We chose 38 landscape-level metrics to quantify the effects of changing grain size on landscape patterns (Table 1). The metrics were calculated from the computer software program FRAGSTATS version 4.2 using an eight-neighbor rule for patch delineation (McGarigal et al. 2012). The calculations were applied to each extent with different grain sizes and repeated over all 96 extents, and were performed using the workstations with CPU processors (32 GB RAM, up

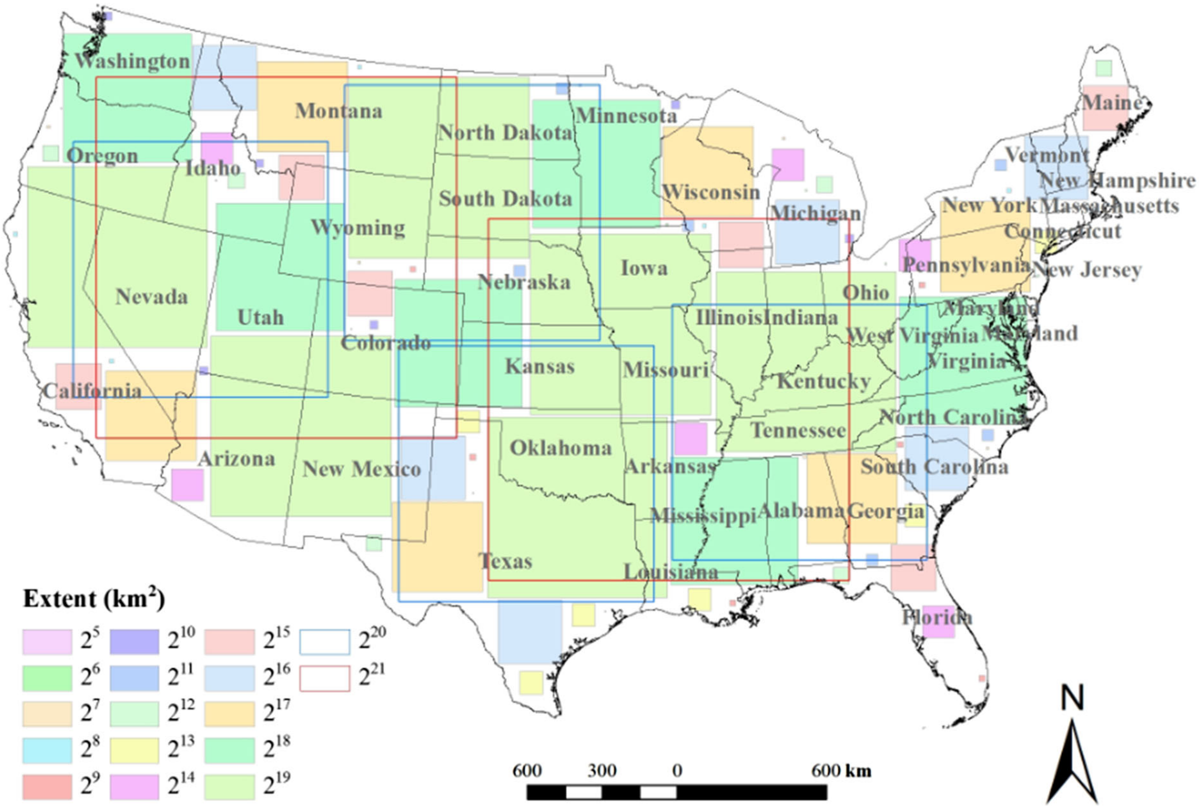

Fig. 1 Locations of the 96 square-shaped landscapes in this study. The spatial extent ranges from 2^5 km^2 upwards to 2^{21} km^2. The sub-regions are sampled randomly to capture various landscape patterns, and they cover almost the entire conterminous United States

to 3.9 GHz). Due to the memory constraint of FRAGSTATS (McGarigal et al. 2012), the spatial pattern analysis began from 30 m for the landscapes with extents smaller than 2^{18} km^2, 60 m for the landscapes with extents of 2^{18} and 2^{19} km^2, 90 m for the landscapes with extents of 2^{20} km^2, and 120 m for the landscapes with extents of 2^{21} km^2.

Scalograms were used to show the behaviors of landscape metrics in response to changing grain size, and regression analysis was performed to model their scaling functions. Based on previous studies (Wu et al. 2002; Wu 2004; Alhamad et al. 2011), we chose five potential functions including linear, exponential I ($y = ae^{bx}$, $a > 0$) and II ($y = ae^{b/x}$, $a > 0$), logarithmic, and power law functions and used the Corrected Akaike Information Criterion (AICc) to measure the goodness of fit for the models. AICc is a correction of AIC (Akaike information criterion) for small sample sizes (Cavanaugh 1997) and has been widely used in statistical model selection. The model with the lowest AICc was selected as the optimal one.

Methods for investigating the dependence of scaling functions on grain size and extent

To investigate whether there exist critical resolution thresholds for scaling functions during aggregation, we examined the performance of the model with respect to changing resolutions. As scaling functions vary with grain size (Argañaraz and Entraigas 2014), we first obtained scaling relations from metric-scalograms starting with 15 input data points (e.g. grain sizes ranged from 30 to 450 m for landscapes with the extent smaller than 2^{18} km^2), and the scaling relations were re-examined by extending the scaling resolution scope gradually to 480 m (resulted in a total of 16 input data points), 520 m (a total of 17 input points) till the coarsest. The behaviors of goodness of fit (R^2) with respect to changing resolution scope were examined.

To identify the critical aggregation resolution at which the scaling relationship breaks, the relative difference was first estimated between the observed and predicted values as follows:

Table 1 List of 38 landscape metrics used in the study

Group name	Name	Acronym
Aggregation	Aggregation Index	AI
	Contagion	CONTAG
	Division Index	DIVISION
	Euclidean Nearest Neighbor Distance distribution	ENN_MN
		ENN_AM
		ENN_SD
	Interspersion Juxtaposition Index	IJI
	Landscape Shape Index	LSI
	Number of Patches	NP
	Splitting Index	SPLIT
	Proportion of Like Adjacencies	PLADJ
Area–edge metrics	Patch Area distribution	AREA_MN
		AREA_AM
		AREA_SD
	Radius of Gyration distribution	GYRATE_MN
		GYRATE_AM
		GYRATE_SD
	Largest Patch Index	LPI
	Total Edge	TE
Diversity	Patch Richness	PR
	Shannon's Diversity Index	SHDI
	Shannon's Evenness Index	SHEI
Shape metrics	Related Circumscribing Circle distribution	CIRCLE_MN
		CIRCLE_AM
		CIRCLE_SD
	Contiguity Index distribution	CONTIG_MN
		CONTIG_AM
		CONTIG_SD
	Fractal Dimension Index distribution	FRAC_MN
		FRAC_AM
		FRAC_SD
	Perimeter-Area Fractal Dimension	PAFRAC
	Perimeter-Area Ratio distribution	PARA_MN
		PARA_AM
		PARA_SD
	Shape Index distribution	SHAPE_MN
		SHAPE_AM
		SHAPE_SD

The definition and algorithm of each metric can be found in FRAGSTATS HELP. For the landscape distribution statistics, mean (MN), area-weighted mean (AM) and standard deviation (SD) were selected

$$\propto_i = \frac{\left|C_{scaling} - C_i\right|}{\left|C_i\right|} \times 100\%,$$

where $\propto_i$ is the relative bias in percentage, C_i is the observed value of landscape metrics at given resolution i (i = 30 m, 60 m, 90 m, …), and $C_{scaling}$ is the predicted value based on the specific scaling function. We define the critical aggregation resolution (i.e., the threshold or the bounds of the scale domain) as the resolution beyond which a given scaling relationship does not hold anymore at a given error limit (e.g.,

$\propto_i$ = 10%, 15% and 20%, respectively) in aggregation.

To further investigate whether the responses of landscape metrics to changing grain size would be influenced by the spatial extent of the dataset, the above analysis was repeated over the 96 sampled extents. The scaling functions were obtained based on the first 15 values (e.g. the grain size ranges from 30 m to 450 m for landscapes with the extent smaller than 2^{18} km^2). The scaling parameters and critical aggregation thresholds were calculated, so that their relationship with the spatial extent could be observed.

Results

Effects of changing grain size

The spatial patterns of the landscapes differ greatly in composition and configuration at the original resolution (i.e., 30 m). Six randomly-selected diverse landscapes (L1–L6) corresponding to the extent of 2^{15} km^2 (Fig. 2) were used to illustrate the impact of grain size on landscape metrics. As the grain size coarsens, detailed spatial features in land cover map lose gradually (Fig. 3) and landscape metrics change dramatically. Here we take Aggregation metrics as examples to show the selection of the regression model for the scalograms of the 38 metrics when the data was resampled from the grain size of 30 m to 450 m by the nearest neighbor algorithm (Table 2). The behaviors of AI, CONTAG, ENN_MN, ENN_AM, ENN_SD, LSI, NP, and PLADJ exhibit specific scaling functions among the six landscapes. The R^2 for the models amounts to 1, which indicates perfect fit of the scaling relationship. No specific scaling function can be found for DIVISION, IJI, and SPLIT among different landscapes, and unstable R^2 implies bad fit of the selected function.

The 26 metrics from the Aggregation, Area-Edge and Shape groups exhibit specific scaling functions among all landscapes, and the other 12 metrics behave staircase-likely or erratically. Figures 4, 5 and 6 illustrate the scaling functions for metrics in each group. The scaling functions could be summarized into three types: increasing power-law relation, decreasing power-law relation, and decreasing logarithmic relation. Although scaling functions are not identical for two resampling approaches, the responses of the metrics to changing grain size have similar scaling patterns and regression model types. However, the scaling functions of some metrics start at 60 m instead of 30 m, and a rise from 30 to 60 m can be observed for the majority algorithm. These metrics include AI, CONTAG, and PLADJ in the Aggregation group, and CIRCLE_MN, PAFRAC, CONTIG_MN, CONTIG_AM, and CONTIG_SD in the Shape group.

Performance of the scaling function with respect to changing grain size

As shown in Figs. 4, 5 and 6, the scaling performance becomes unstable with increasing grain size, and the regression function varies with the number of input data. The behaviors of the goodness of fit (R^2) with respect to coarsening resolutions present two types in general, and Fig. 7 shows the Aggregation metrics as an example. As the resolution coarsened, R^2 of the scaling model for ENN_MN, LSI, and NP remains almost 1, indicating that the scaling functions fit well on the whole spectrum of spatial resolutions, whereas R^2 values for AI, CONTAG, ENN_AM, ENN_SD, and PLADJ decrease as the resolution scope extended, suggesting deterioration of the scaling models.

Based on the scaling performances (i.e., whether regression functions are robust on the whole spectrum or limited range of resolution), we group the behaviors of the 38 metrics into three types (Table 3). Type I are those showing consistent scaling relations across the whole spectrum of scale, that is, the scaling relations do not show abrupt change. There are 13 metrics in Type I. Type II metrics have specific functions fitting well only in a limited range of resolution, and beyond the range (i.e., resolution thresholds) the responses change erratically. A total of 13 metrics falls into this group. Type III metrics respond to changing grain size either staircase-likely or erratically, and no consistent scaling relationships could be identified for them. Specifically, CIRCLE_SD and SHAPE_SD perform erratically when the spatial data is resampled using the majority algorithm.

Identification of the critical resolution for Type II metrics

Although most landscape metrics are sensitive to changing grain size, the scaling function makes it possible to extrapolate spatial features across

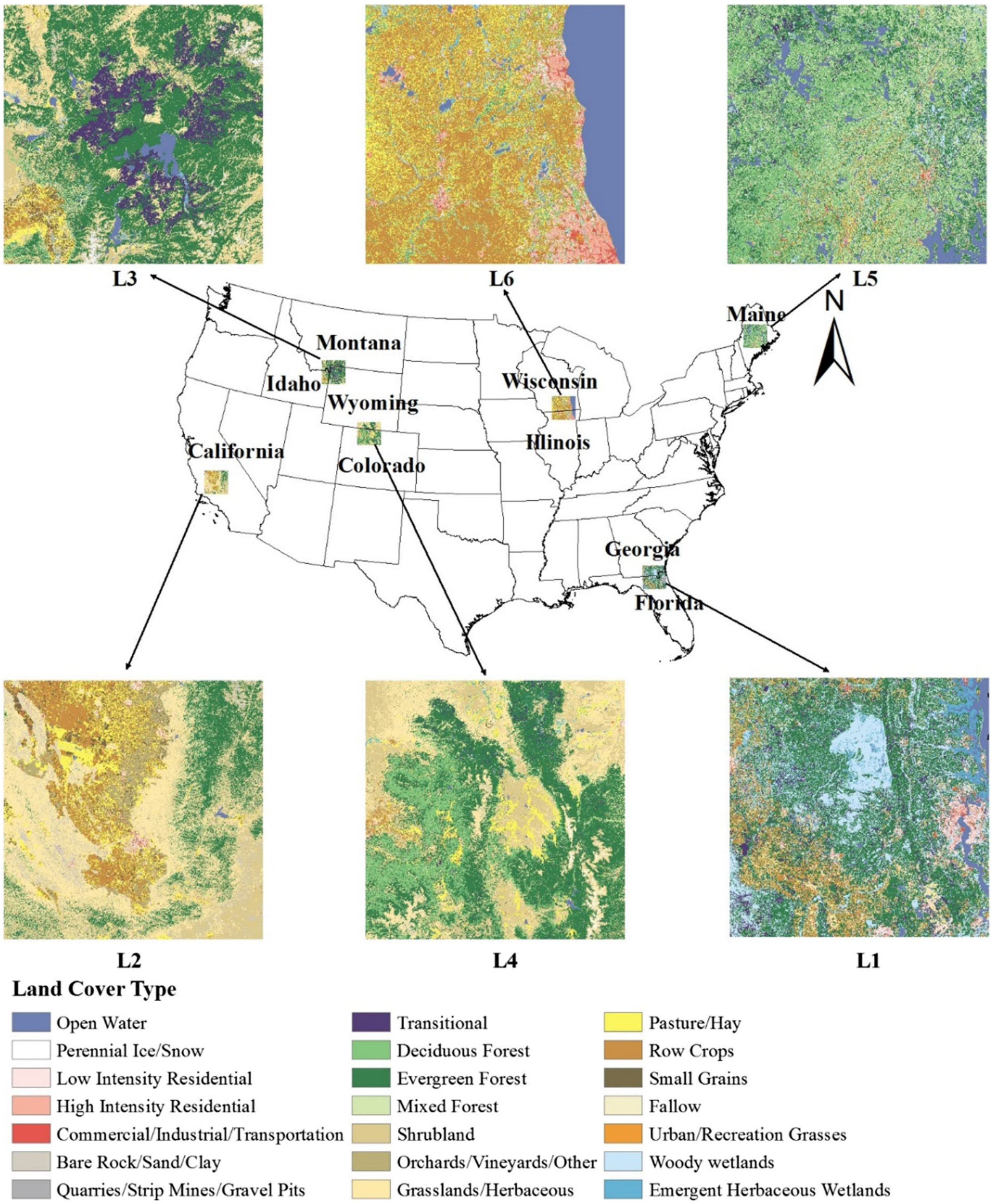

Fig. 2 Maps of the six landscapes with extent of 2^{15} km^2 in this study

scales (Wu 2004). As Type II metrics tend to exhibit scaling relationships in a limited range of grain size, it indicates more variation or disorder in the scaling relationships as the resolution coarsened. The identification of the critical aggregation resolution is therefore important to the

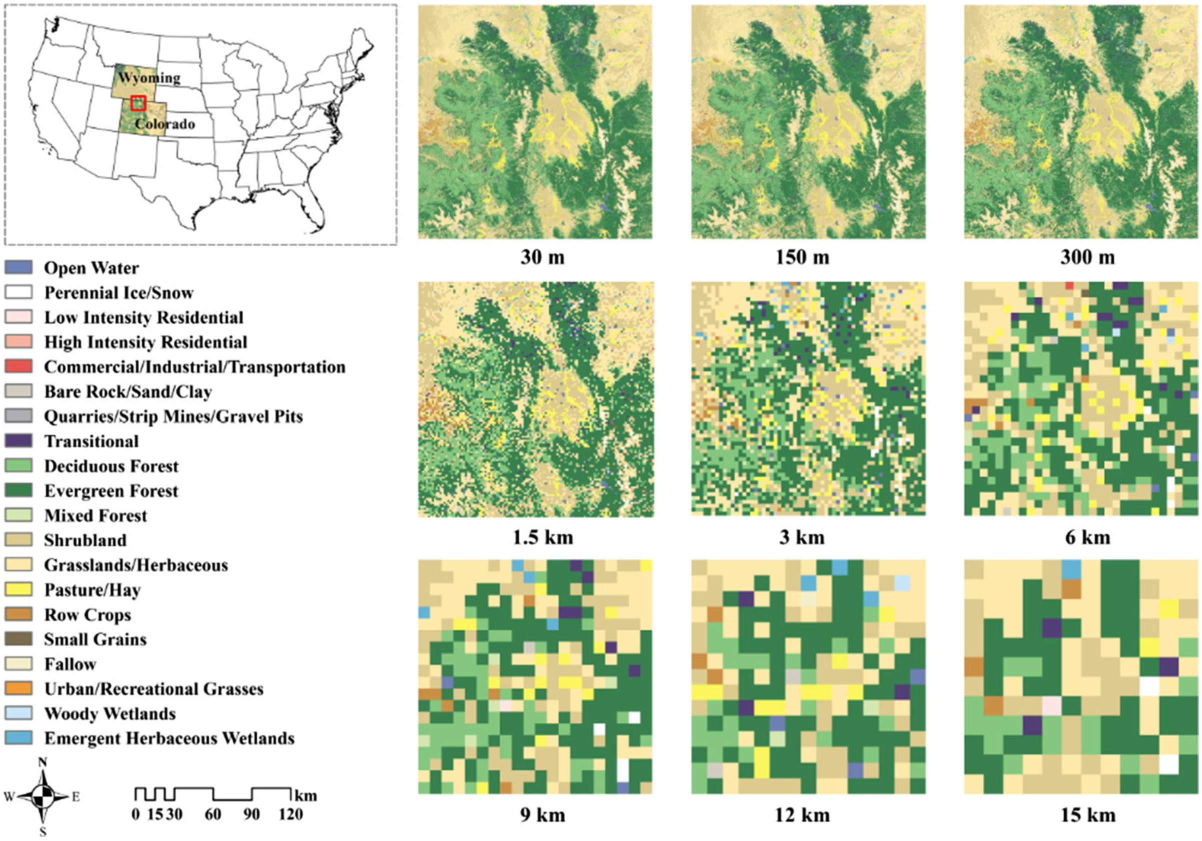

Fig. 3 The loss of detailed spatial information as the resolution coarsens using the nearest neighbor algorithm

understanding of the scaling of the spatial patterns.

To identify whether there exists critical resolution of the scaling function, regression functions were obtained from the metric scalograms, and relative differences were estimated between the observed and predicted values. Here we take the metric AI as an example to illustrate the derivation of the critical resolution within a given error limit of 20% during aggregation. The scaling function was first obtained from 15 input data with resolutions ranging from 30 m to 450 m. As is shown in Fig. 8b, the predicted value agrees well with the observed value when AI is higher than 50, and biases tend to be obvious at coarser grain sizes. The grain size constraining the error within 20% is 9930 m (Fig. 8c). Furthermore, as the fitted curve varies with the selection of input data, the number of data points for modeling fitting was gradually and sequentially increased to examine the behavior of the fitted model. From Fig. 8d, we can see that the goodness of fit of the scaling relationship declines as more values at coarser resolutions are included for modeling. The equations for curve fitting demonstrate no significant change and the corresponding relative differences remain about the same when the number of input data was < 350 (i.e., the maximum grain size is about 10 km) (Fig. 8d). Although the critical resolution constraining the error within 20% can be relaxed to around 13,500 m if more data at coarser resolution are included for regression, the overall performance of the model becomes poorer. Here we identify the critical scaling resolution as 9930 m when R^2 is high to ensure the selected scaling model has better fit for most data in smaller grain sizes. The identification of critical aggregation resolution was processed for the 13 metrics in Type II. The existence of critical resolution in scaling indicates that spatial resolution must be chosen carefully to avoid the "unpredictable" behavior when coarsening beyond the critical point in aggregation.

Table 2 Regression models for Aggregation metrics when the dataset is resampled by the nearest neighbor algorithm

Metrics	Landscape	AICc					R^2
		Linear	Power law	Exponent I	Exponent II	Logarithmic	
AI	L1	87.13	**− 119.10**	−41.03	−35.20	29.61	1.00
	L2	78.93	**− 121.35**	−48.18	−48.96	31.33	1.00
	L3	77.30	**− 144.41**	−52.83	−51.23	21.28	1.00
	L4	80.75	**− 104.87**	−48.48	−54.29	39.55	1.00
	L5	95.52	**− 102.38**	−30.44	−31.91	58.00	1.00
	L6	80.57	**− 113.25**	−49.88	−41.89	6.50	1.00
CONTAG	L1	62.04	**− 100.04**	−54.92	−65.86	24.53	0.99
	L2	48.15	**− 98.76**	−68.33	−67.00	15.51	0.98
	L3	54.44	**− 97.34**	−66.36	−67.05	22.34	0.98
	L4	54.18	**− 103.96**	−66.74	−84.09	20.76	0.98
	L5	68.06	**− 80.06**	−49.17	−74.09	41.64	0.97
	L6	50.67	**− 101.87**	−69.79	−67.66	16.20	0.98
DIVISION	L1	−83.42	−94.49	−82.23	**− 120.14**	−95.53	0.96
	L2	−109.25	−108.68	−108.13	**− 109.94**	−109.81	0.12
	L3	−60.13	−57.91	−56.19	−60.97	**− 61.90**	0.24
	L4	−144.05	−153.66	−142.68	−151.42	**− 155.08**	0.81
	L5	−167.21	−174.11	−167.09	−172.56	**− 174.24**	0.69
	L6	−69.17	−78.36	−66.36	−68.34	**− 81.26**	0.86
ENN_MN	L1	90.51	**− 74.01**	7.37	13.69	198.47	1.00
	L2	96.49	**− 92.51**	9.27	13.89	198.78	1.00
	L3	98.73	**− 72.95**	7.75	14.08	198.51	1.00
	L4	112.93	**− 64.65**	7.81	15.16	199.71	1.00
	L5	78.86	**− 74.71**	7.04	13.21	196.84	1.00
	L6	90.83	**− 86.03**	8.16	13.33	199.73	1.00
ENN_AM	L1	81.08	**− 85.08**	8.99	14.18	190.06	1.00
	L2	91.52	**− 105.48**	10.40	13.88	189.63	1.00
	L3	87.48	**− 107.42**	10.07	14.07	188.70	1.00
	L4	72.85	**− 102.38**	9.78	14.14	188.69	1.00
	L5	61.07	**− 104.70**	9.45	13.70	189.54	1.00
	L6	64.35	**− 127.31**	10.25	13.96	189.42	1.00
ENN_SD	L1	140.67	**− 45.45**	2.30	12.61	195.92	1.00
	L2	183.25	**− 32.59**	3.75	13.74	208.78	0.99
	L3	189.55	**− 23.10**	2.04	13.58	211.02	0.98
	L4	178.10	**− 31.02**	6.22	15.72	211.85	0.99
	L5	154.05	**− 50.52**	1.29	9.22	195.11	1.00
	L6	178.07	**− 27.92**	6.64	9.17	197.56	0.99
IJI	L1	22.49	−110.16	−101.38	**− 128.19**	13.70	0.88
	L2	20.80	−99.84	**− 100.35**	−81.78	22.30	0.91
	L3	32.88	**− 90.27**	−86.28	−79.11	29.09	0.81
	L4	2.92	**− 147.44**	−113.95	−101.01	−28.49	0.99
	L5	−5.29	−100.90	**− 124.16**	−83.00	18.73	0.97
	L6	47.71	−77.82	−71.76	**− 86.55**	41.54	0.69

Table 2 continued

Metrics	Landscape	AICc					R^2
		Linear	Power law	Exponent I	Exponent II	Logarithmic	
LSI	L1	181.86	**− 45.30**	−7.06	7.85	152.11	0.99
	L2	189.71	**− 55.89**	−0.95	9.38	165.52	1.00
	L3	178.57	**− 49.68**	−4.29	8.32	151.27	1.00
	L4	179.88	**− 43.54**	−4.95	9.60	151.37	0.99
	L5	182.99	**− 33.39**	−9.98	10.07	147.67	0.99
	L6	175.72	**− 49.53**	−7.00	6.66	146.69	1.00
NP	L1	430.15	**− 32.77**	18.87	30.02	416.73	1.00
	L2	434.68	**− 35.38**	21.63	31.54	422.35	1.00
	L3	417.33	**− 31.78**	18.92	30.18	403.76	1.00
	L4	419.43	**− 25.97**	18.79	31.54	405.69	1.00
	L5	434.06	**− 33.39**	19.37	30.16	420.71	1.00
	L6	423.18	**− 39.77**	19.71	29.19	410.14	1.00
SPLIT	L1	135.44	13.21	21.82	**− 8.12**	128.89	0.91
	L2	92.38	−10.19	−9.08	**− 12.19**	90.51	0.21
	L3	69.96	2.03	4.16	**− 2.06**	67.44	0.43
	L4	43.49	**− 62.53**	−50.41	−61.24	30.22	0.83
	L5	186.14	−6.33	5.53	**− 10.74**	173.33	0.84
	L6	82.52	**− 7.29**	5.52	−0.61	69.50	0.85
PLADJ	L1	87.18	**− 115.84**	−41.02	−34.58	28.23	1.00
	L2	78.98	**− 125.93**	−48.17	−47.90	29.73	1.00
	L3	77.36	**− 149.73**	−52.82	−50.24	19.02	1.00
	L4	80.79	**− 107.88**	−48.46	−53.22	38.35	1.00
	L5	95.55	**− 105.04**	−30.43	−31.39	57.61	1.00
	L6	80.63	**− 110.36**	−49.86	−41.19	3.55	1.00

The lowest AICc values are marked in bold, indicating the scaling relation types for Aggregation metrics

Dependence of the critical resolution on extent for Type II metrics

To further demonstrate whether the scale effect of changing grain size would vary with the extent of spatial data, the critical resolution was estimated within the given error limit (i.e., 10%, 15% and 20%) across various extents, and the relationship between the critical resolution (G) and the extent (E) are shown in Figs. 9 and 10 for Type II metrics. In general, the critical resolution can be relaxed with extending the spatial extent, indicating that there is more room for scaling within a given error for a larger extent.

Furthermore, a power-law scaling relationship between critical aggregation resolution (G) and spatial extent (E) could be found when spatial data were resampled by the nearest neighbor algorithm as follows:

$$G_\alpha(E) = k_\alpha E^{\gamma_\alpha} + \varepsilon,$$

where α is the given error limit, k is a proportionality constant, γ is the scaling exponent of the power law scaling relationship, and ε is an error term representing uncertainty in estimating the critical resolution. The power law relationship signifies the scale invariance between the critical threshold and the extent of the landscape. That is, scaling the spatial extent E by a constant factor c, the original power law relationship would simply be multiplied by the constant c^{γ_α}.

$$G_\alpha(cE) = k_\alpha (cE)^{\gamma_\alpha} = c^{\gamma_\alpha} G_\alpha(E)$$

The change of FRAC_MN or PAFRAC is subtle within the whole spectrum of scaling (< 5% and 20%, respectively), and would not be further discussed here. Similar to the scale effect when resampling by the nearest neighbor approach, power-law scaling

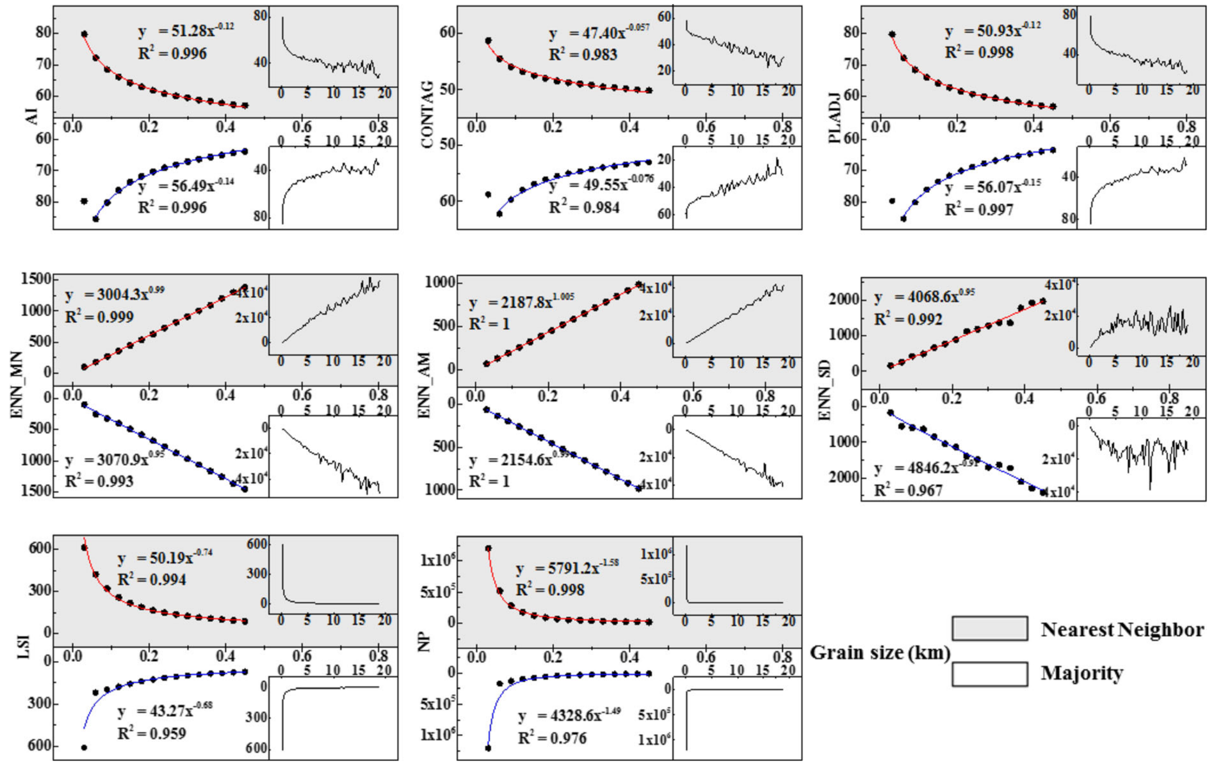

Fig. 4 Scalograms and scaling functions of Aggregation metrics. Insert graphs are scalograms over the whole spectrum of grain size, and the main graphs are zoomed-in window over a range of [30 m, 450 m] in grain size (X-axes are grain size (km), and y-axes are metric values, which are same for Figs. 5 and 6). Among them, ENN_MN, ENN_AM and ENN_SD present increasing power-law scaling relations, while others present decreasing power-law relations. The scaling relationships exhibit more variation when coarsening grain size for AI, CONTAG, ENN, and PLADJ

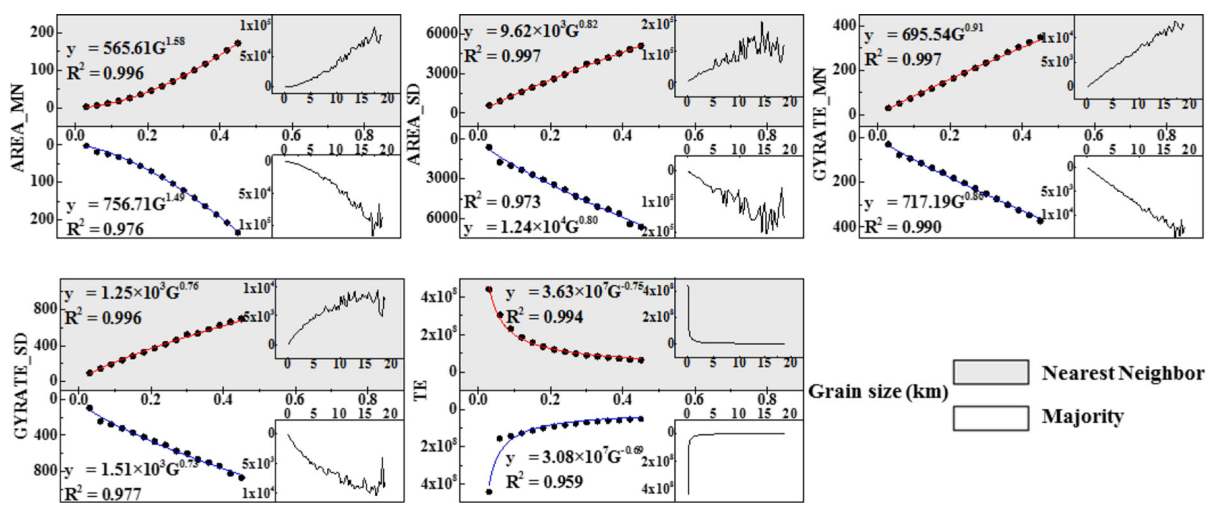

Fig. 5 Scalograms and scaling functions of Area–Edge metrics. Among them, TE presents decreasing power-law relations, and others present increasing power-law relations. Their scaling relationships exhibit more variation when coarsening grain size except for TE

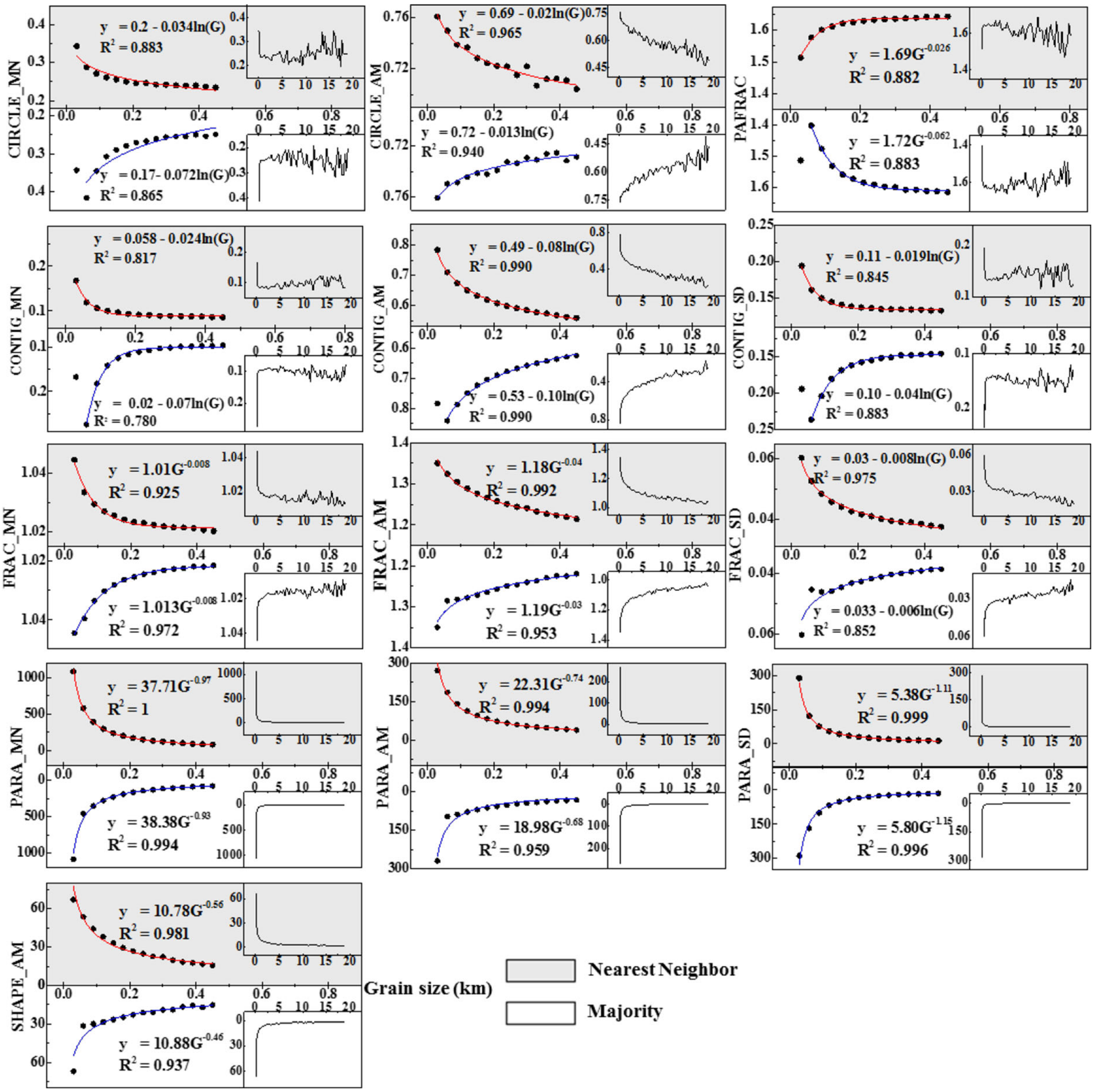

Fig. 6 Scalograms and scaling functions of Shape metrics. Among them, PAFRAC, FRAC_MN, FRAC_AM, PARA and SHAPE_AM present power-law scaling relationships, and other metrics present logarithmic scaling functions. Their scaling relationships exhibit more variation when coarsening grain size except for FRAC_AM, PARA and SHAPE_AM

relationship could also be found when resampling by the majority algorithm. Figures 9 and 10 show the power law relations presented between critical aggregation resolutions and extents for most Type II metrics. However, there are exceptions. For example, the graphs for GYRATE_SD uniquely show erratic behaviors; ENN_SD shows two scale domains: a flatter relationship for smaller extent and then a sudden shift to higher values of critical resolution in aggregation; CONTIG_MN shows similar behavior when calculated by the majority algorithm. These results show that most landscape metrics have consistent

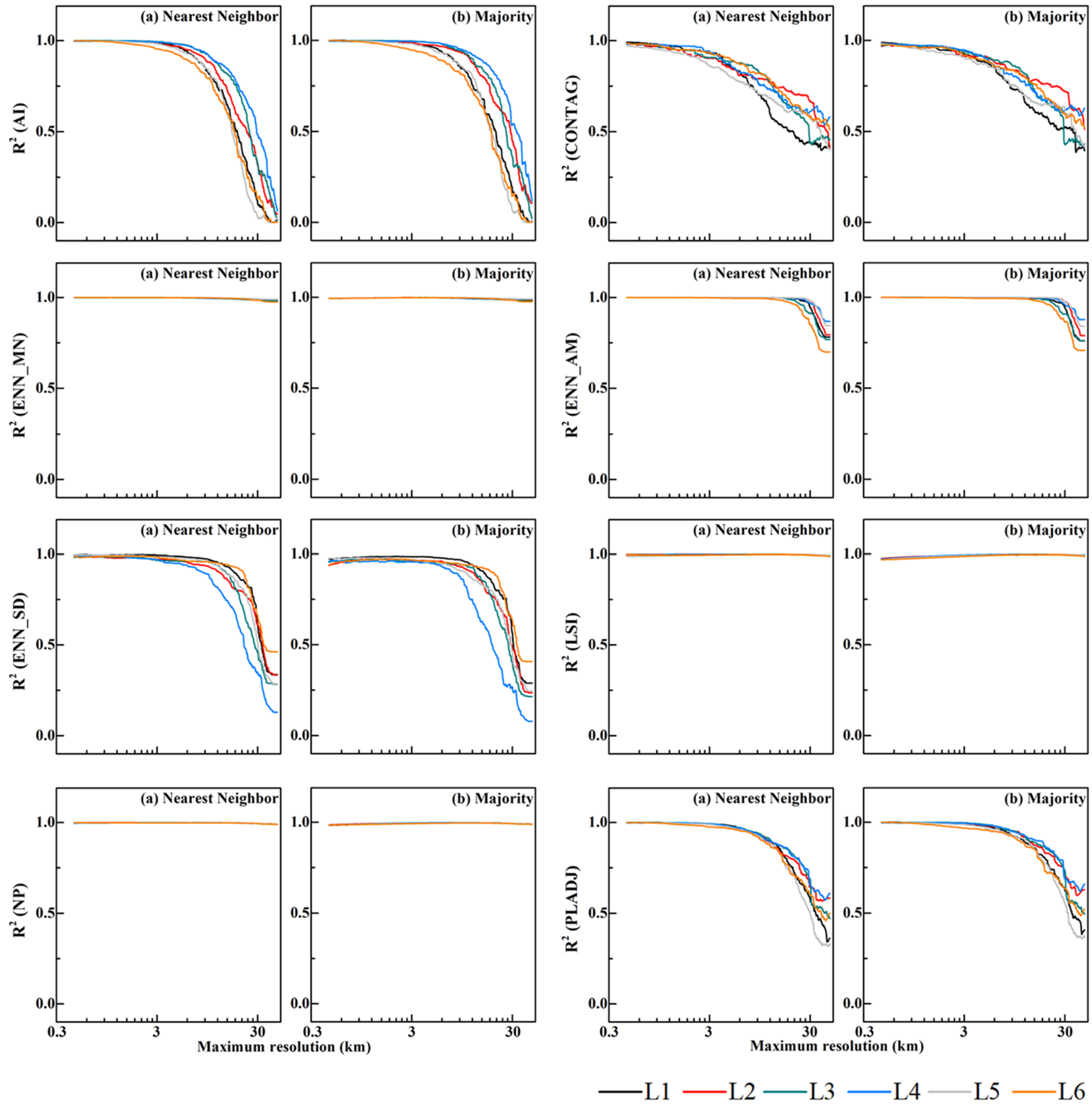

Fig. 7 The behavior of R^2 of scaling relations for Aggregation metrics in changing the range of grain size

power-law scaling relationships and only a few present more than one scale domains.

Dependence of scaling coefficients on extent for Type I and II metrics

The coefficients of scaling relations for metrics in Type I and Type II vary with spatial extents. For Type I metrics whose responses to changing grain size exhibit power law functions, the absolute value of scaling exponent β increases with the spatial extent, and logarithmic scaling relationship was found between β and the extent (Figs. 11 and 12).

$$\beta = a' \log_2 E + b',$$

where a' and b' are constants, and E is the spatial extent.

Table 3 Three types of landscape metrics and their scaling relations with respect to changing grain size

Group name	Metrics	Scaling relationship
Type I metrics: predictable across the whole spectrum of grain size.		
Aggregation	ENN_MN	An increasing power function:
	ENN_AM	$y = \alpha x^{\beta}$, $\alpha > 0$, $\beta > 0$
Area–Edge metrics	AREA_MN	
	AREA_SD	
	GYRATE_MN	
Aggregation	LSI	A decreasing power function:
	NP	$y = \alpha x^{\beta}$, $\alpha > 0$, $\beta < 0$
Area–Edge metrics	TE	where y is the value of the metric, x is the grain size, α is the proportionality constant, and β is the scaling exponent of power law function.
Shape metrics	FRAC_AM	
	PARA_MN	
	PARA_AM	
	PARA_SD	
	SHAPE_AM	
Type II metrics: predictable within a limited range of grain size.		
Aggregation	ENN_SD	An increasing power function:
Area–Edge metrics	GYRATE_SD	$y = \alpha x^{\beta}$, $\alpha > 0$, $\beta > 0$
Shape	PAFRAC	
Aggregation	AI	A decreasing power function:
	CONTAG	$y = \alpha x^{\beta}$, $\alpha > 0$, $\beta < 0$
	PLADJ	where y is the value of the metric, x is the grain size, α is the proportionality constant, and β is the scaling exponent of power law function.
Shape	FRAC_MN	
Shape	CIRCLE_MN	A decreasing logarithmic function:
	CIRCLE_AM	$y = a\ln(x) + b$, $a < 0$, $b > 0$
	CONTIG_MN	where a and b are constants.
	CONTIG_AM	
	CONTIG_SD	
	FRAC_SD	
Type III metrics: unpredictable across scales.		
Aggregation	DIVISION	These metrics behave staircase-likely or erratically. The response curves of other metrics demonstrate various forms, like no obvious changes or fluctuations. No consistent behaviors emerge across landscapes, or specific scaling functions could not be identified. Specifically, PR and SHEI tend to decrease while scaling functions could not be extracted.
	IJI	
	SPLIT	
Area–Edge metrics	AREA_AM	
	GYRATE_AM	
	LPI	
Shape	CIRCLE_SD	
	SHAPE_MN	
	SHAPE_SD	
Diversity	PR	
	SHDI	
	SHEI	

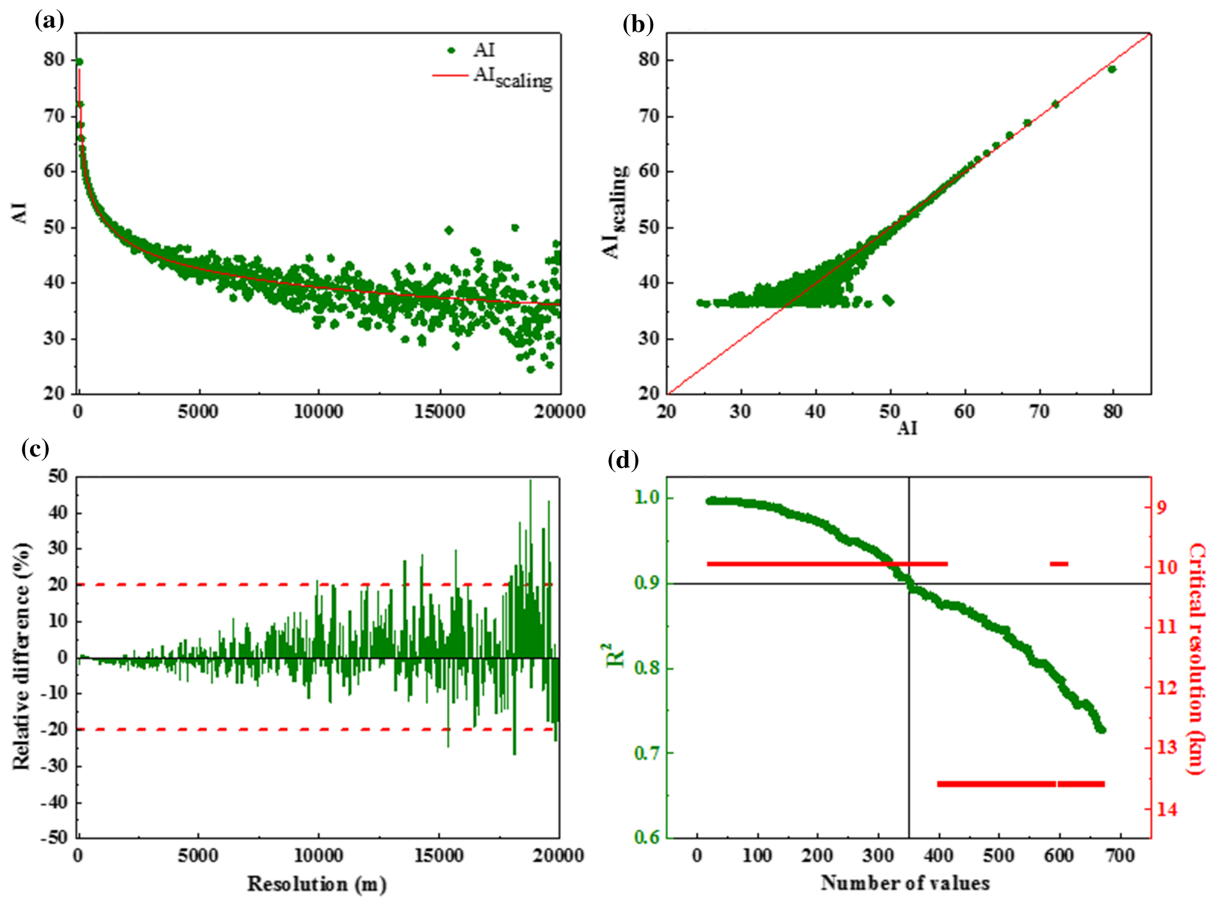

Fig. 8 The identification of critical resolution at which the relative differences of predicted values deviating from the observed value by more than 20%. **a** The scalogram of AI and the predicted curve. **b** Pairs of observed and predicted values of AI. The straight line is reference 1:1 line. **c** The relative differences between observed values and estimates. **d** The goodness of fit and critical thresholds derived from the corresponding regression for different input data

The changes of the constant α of the scaling functions are more complicated. The constants α exhibit similar increasing trends among the Type I metrics except for the scalograms of GYRATE_MN, PARA_SD, and PARA_AM. In general, a power law or logarithmic scaling relationship was found between α and E.

$$\alpha = \gamma E^{\theta} \text{ or } \alpha = \gamma \log_2 E + \theta,$$

where γ and θ are constants, and E is the spatial extent.

For Type II metrics, the scale effects with respect to changing grain size exhibit power-law functions or logarithmic functions. The ranges of the scaling coefficients are relatively small. And compared to Type I metrics, no obvious and consistent patterns could be observed between the parameters of the scaling function and spatial extents (Figs. 13 and 14). In general, for AI, CONTAG, ENN_SD, GYRATE_SD, and PLADJ, whose responses to changing grain size exhibit power-law function, and for CIRCLE_AM and CONTIG_AM whose responses to changing grain size exhibit logarithms functions, all parameters increase a little bit as the spatial extent increases, and logarithmic scaling relationship was found among them. Considering the variations among different landscapes with certain spatial extent, the scaling relationships are not robust.

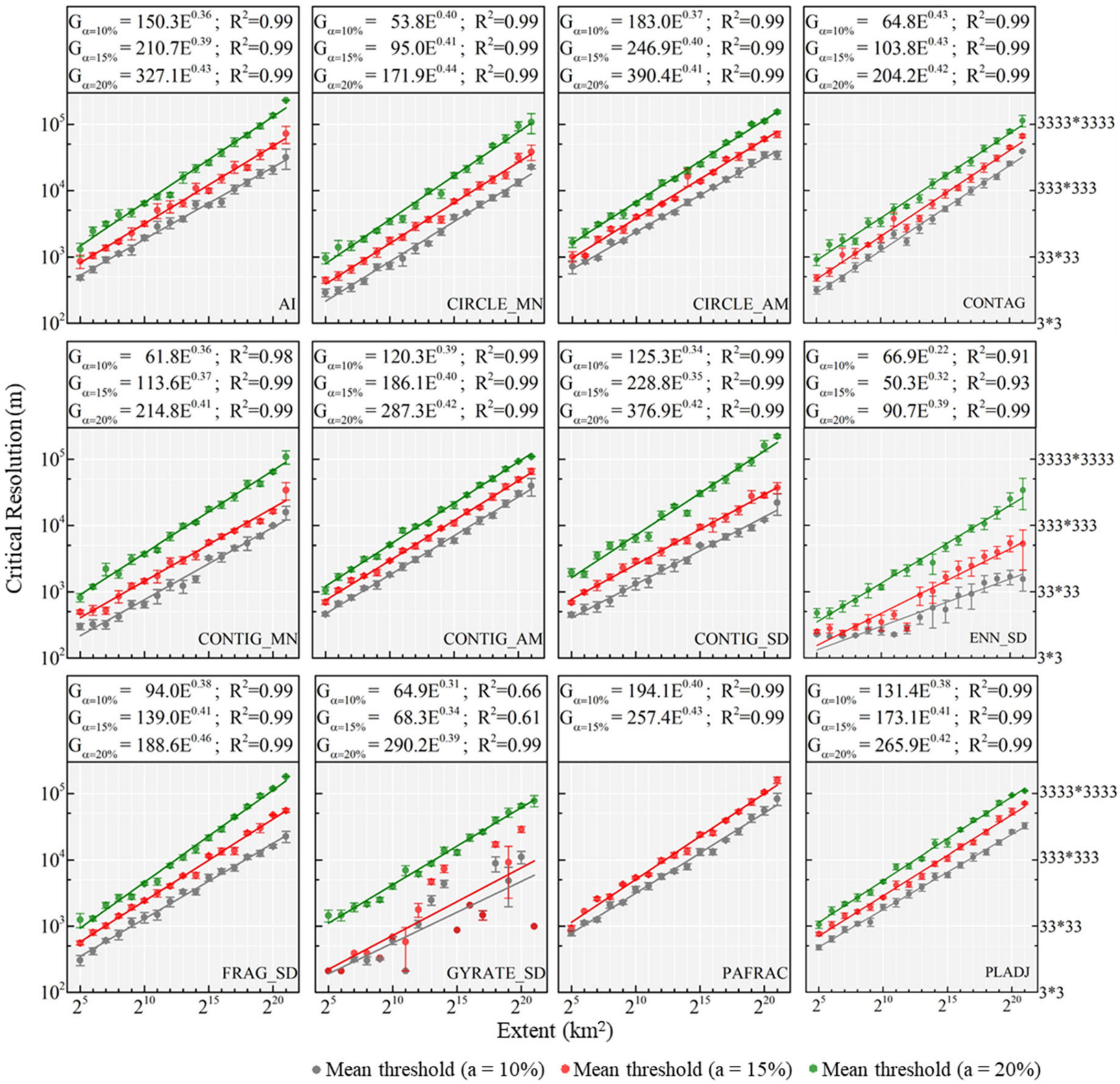

Fig. 9 Power–law relationships between critical aggregation resolution of scalograms and spatial extent for Type II metrics at given error limits (i.e., 10%, 15%, and 20%) when the dataset is resampled by the nearest neighbor algorithm. The mean value and standard error were derived from thresholds of six landscapes with the same extent, and the regression curve was obtained accordingly

Discussion

Although increasing attention has been placed on how to effectively characterize the spatial patterns across scales, our ability to precisely quantify the scaling relations remains limited. For a specific landscape, the pattern and the underlying process are specific, so the challenge lies in how we represent it and how to transfer the knowledge to other scales. It has been perceived empirically that if a study area is larger, coarser spatial resolution could be acceptable for study. Whether the empirical perception is valid or not is still an open question. In addition, if behaviors of certain metrics suggest that the spatial resolution can be coarsened, the quantitative functions to transfer the knowledge from one resolution or extent to others need to be identified.

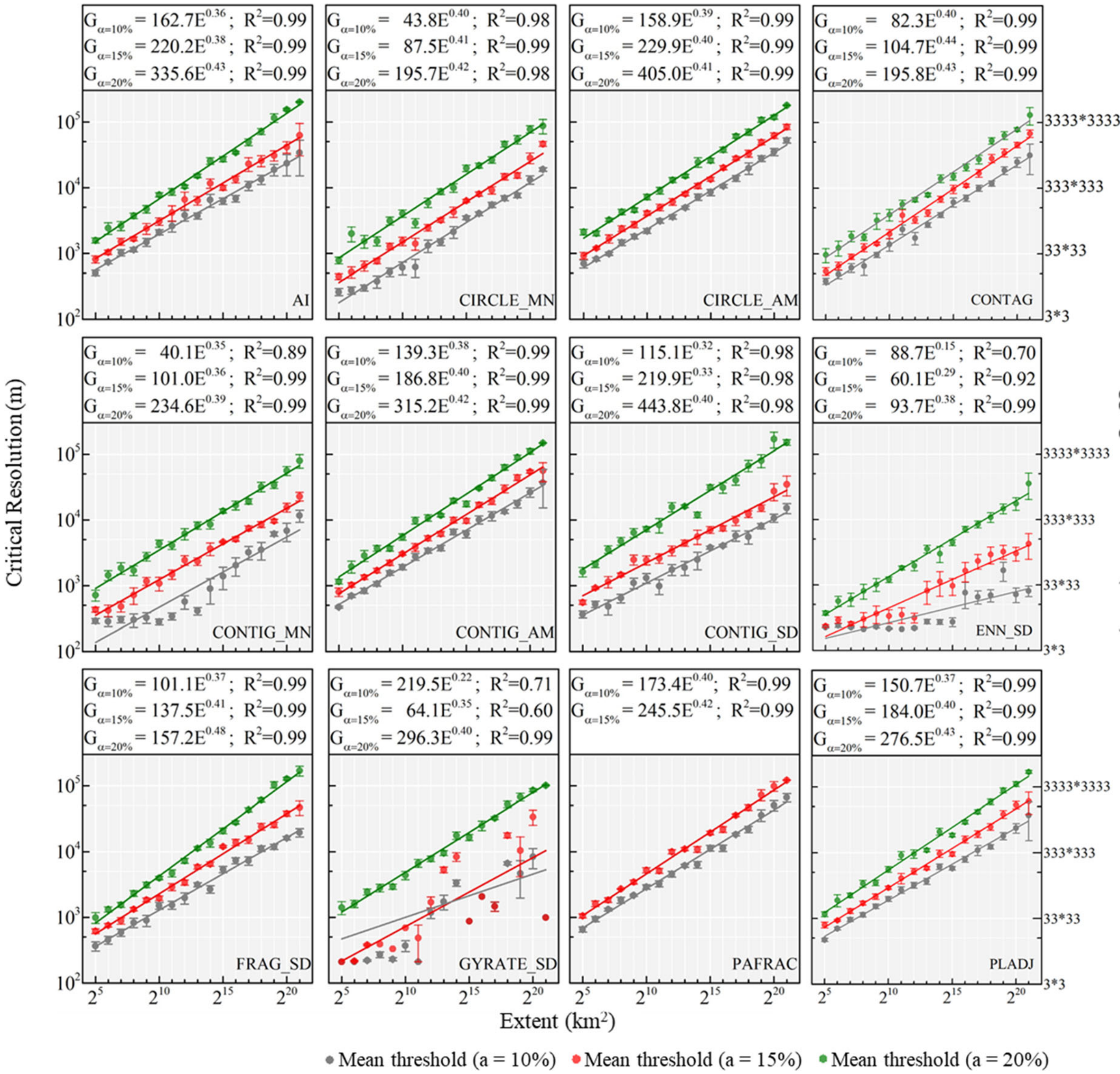

Fig. 10 Power–law relationships between critical aggregation resolution of scalograms and spatial extent for Type II metrics at given error limits (i.e., 10%, 15% and 20%) when dataset is resampled using the majority algorithm

In this study, we expand the approach of Wu et al. (2002) and Wu (2004) by performing a much more extensive investigation on the scaling of landscape parameters over wider ranges of grain size and extent. Results show that the behaviors of landscape metrics with changing resolution can be grouped into three types, which are consistent with previous studies that generally classified the scale effects of landscape metrics as predictable and unpredictable (Wu and Hobbs 2002; Uuemaa et al. 2005; Alhamad et al. 2011; Feng and Liu 2015). Previous studies have suggested that a metric should behave insensitively or predictably sensitively to changing resolution on the premise that it could efficiently measure the spatial features as designed (Frohn and Hao 2006). Type I and Type II metrics are predictably sensitive. For example, NP drops dramatically due to the way the raster image represents the edge or perimeter. Because of the stair-step outline of the edge, the length is biased upward and the magnitude of the bias varies with resolution (McGarigal and Marks 1995). It is essentially fractal, similar to the typical measurement of the length of

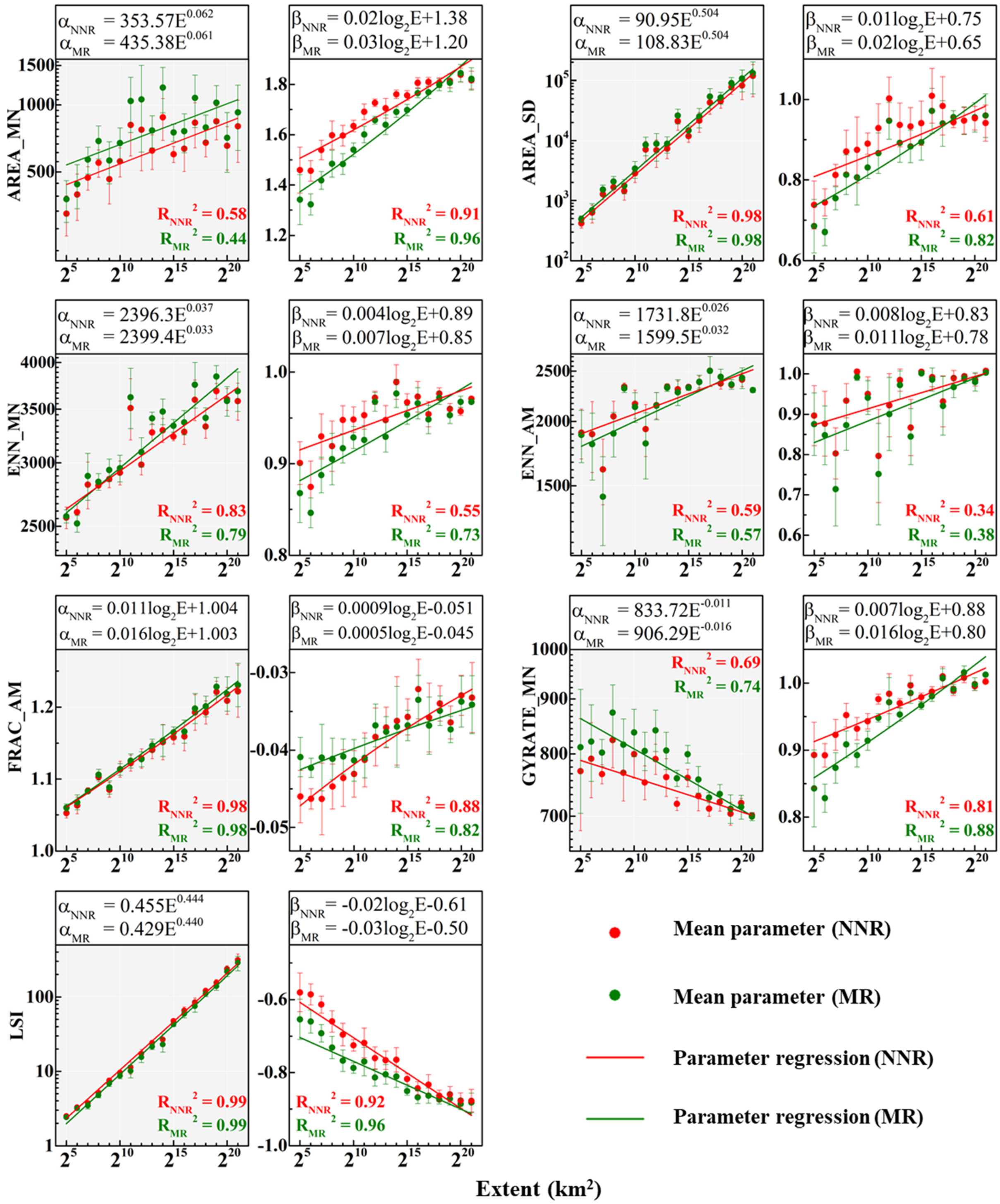

Fig. 11 Relations between the parameters (α and β) of the power law scaling function (i.e., $y = \alpha x^{\beta}$) with changing grain size and the spatial extent (E) for Type I metrics when resampling with the nearest neighbor (NNR) and the majority algorithm (MR). The absolute value of scaling exponent β increases with E, and logarithmic scaling relationship was found between β and E. A power law or logarithmic scaling relationship was found between the constant α and E. (Part 1)

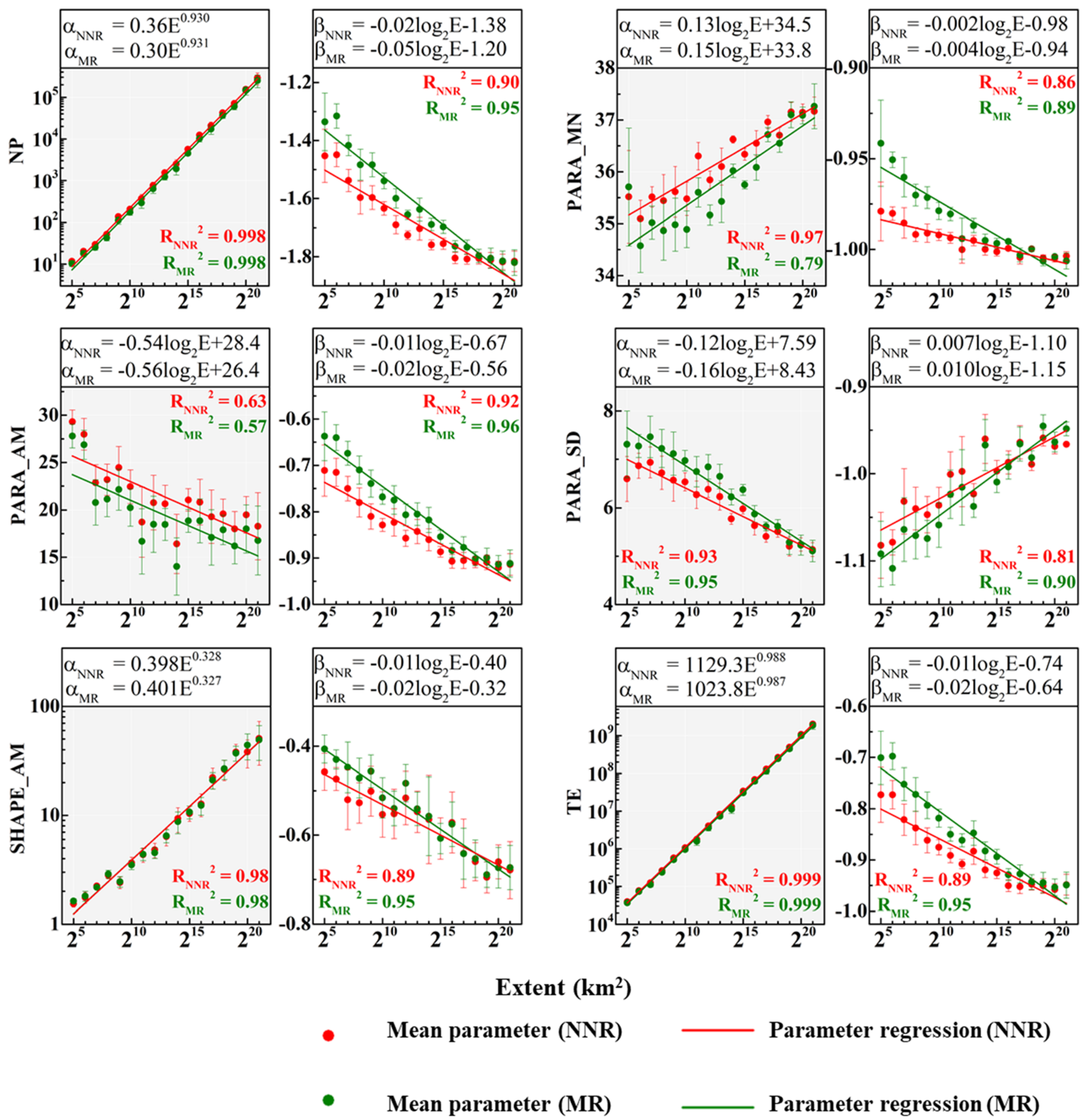

Fig. 12 Relations between the parameters (α and β) of the power law scaling function (i.e., $y = \alpha x^{\beta}$) with changing grain size and the spatial extent (E) for Type I metrics when resampling with the nearest neighbor (NNR) and the majority algorithm (MR). The absolute value of scaling exponent β increases with E, and logarithmic scaling relationship was found between β and E. A power law or logarithmic scaling relationship was found between the constant α and E. (Part 2)

Britain's shoreline using different rulers (Mandelbrot 1967). A fractal system is statistically self-similar without a characteristic scale (Mandelbrot and Wheeler 1983), suggesting that scale-independence is an important property of geographic phenomena (Goodchild and Mark 1987). Most Type I metrics involve perimeters and size of the patches as input, and some of them are highly correlated. For example, NP and AREA_MN, LSI, and TE mimic each other when spatial extent remains the same in scaling. Together with PARA and SHAPE_AM, these metrics exhibit power law scaling relationships due to the fractal

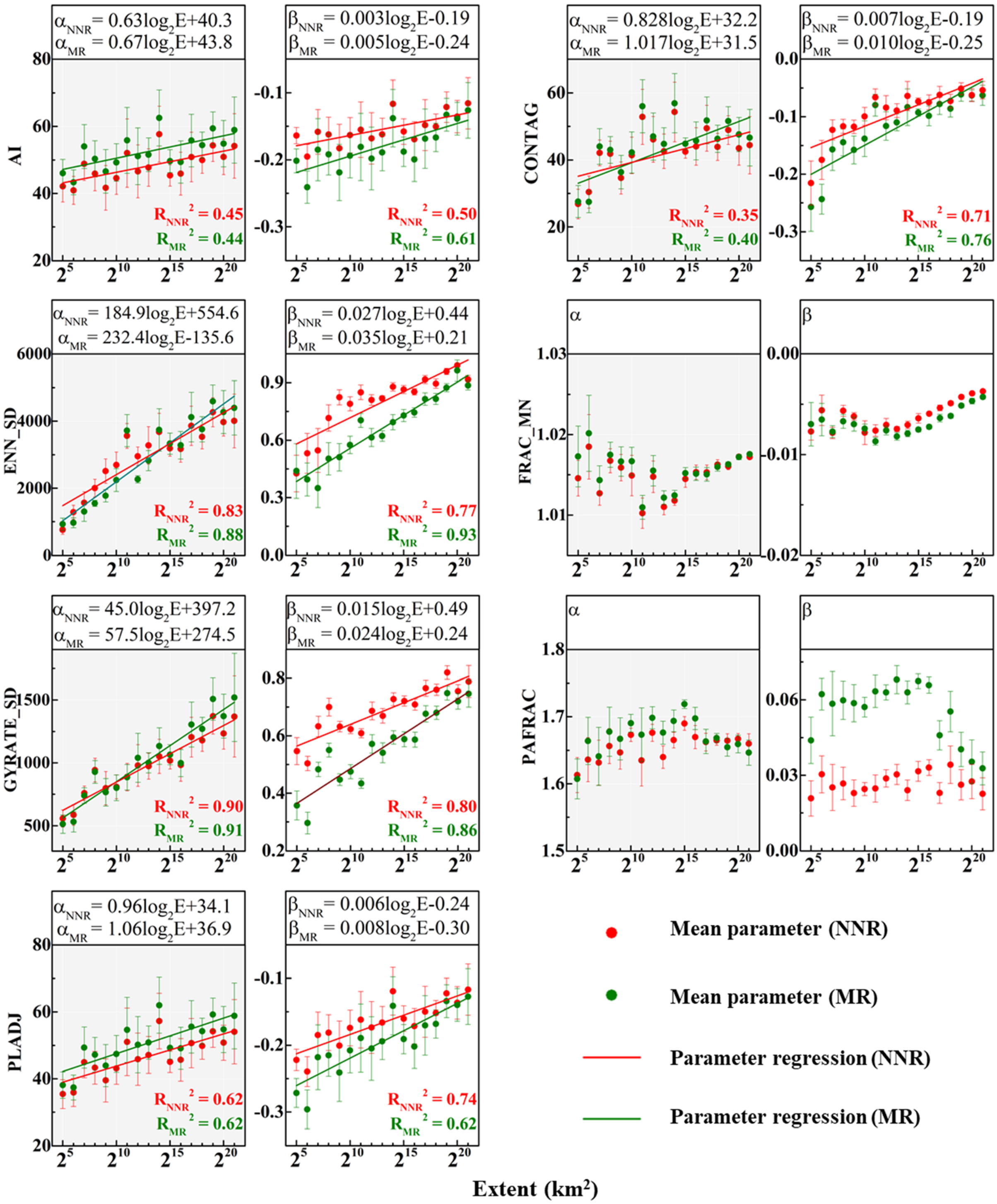

Fig. 13 Relations between the parameters (α and β) of the power law scaling functions (i.e., $y = \alpha x^{\beta}$) with changing grain size and the spatial extent (E) for Type II metrics when resampling with the nearest neighbor (NNR) and the majority algorithm (MR). The parameters present logarithmic relations with respect to changing extent for AI, CONTAG, ENN_SD, GYRATE_SD, and PLADJ

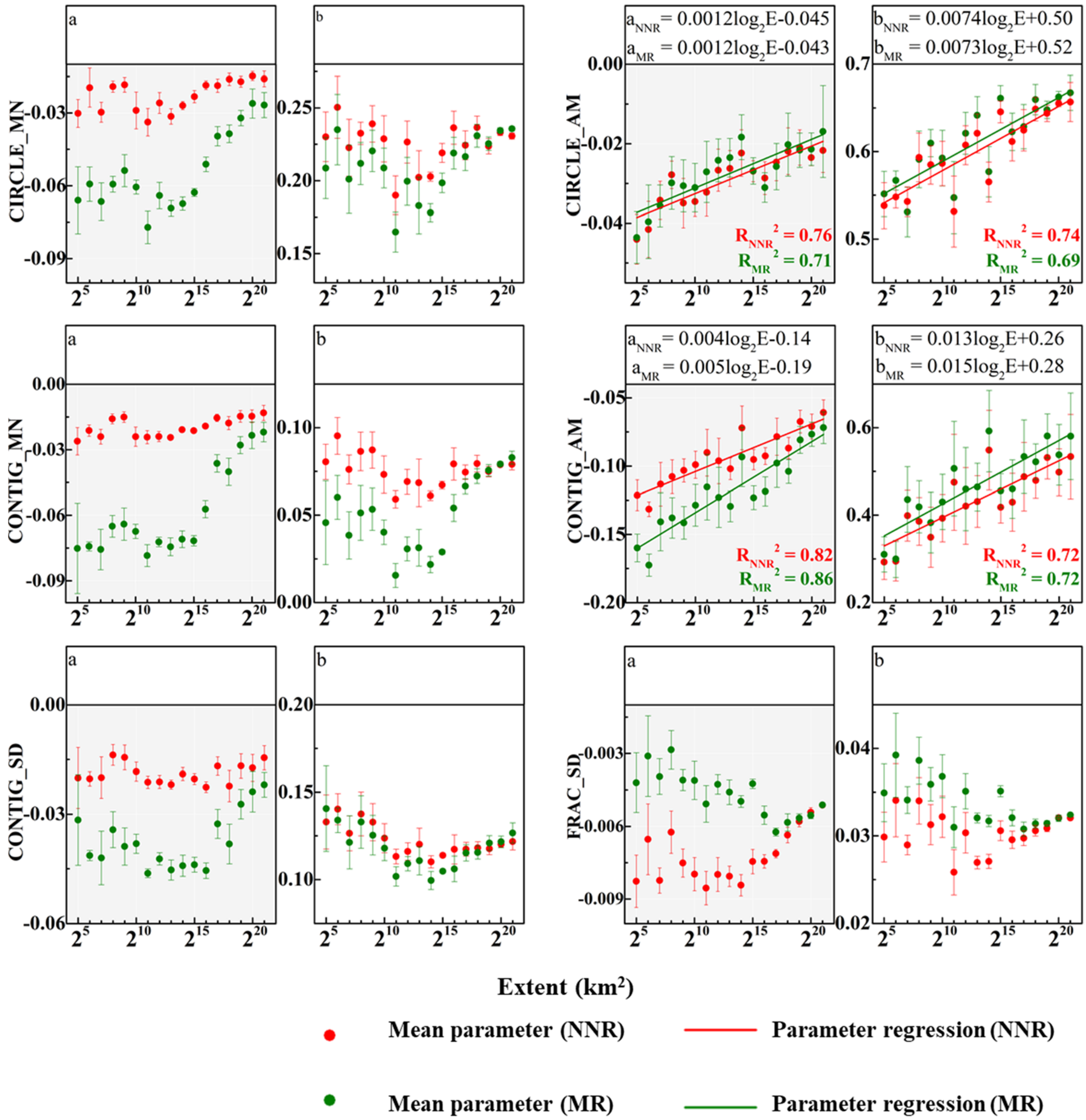

Fig. 14 Relations between the parameters (a and b) of the logarithmic scaling functions (i.e., $y = a\ln(x) + b$) with changing grain size and the spatial extent (E) for Type II metrics when resampling with the nearest neighbor (NNR) and the majority algorithm (MR). The parameters present logarithmic relations with respect to changing extent for CIRCLE_AM and CONTIG_AM

nature of the patch edges. Although robust across the whole spectrum of scales, the scaling relations provides limited information at coarse resolutions when number of patches decreases dramatically. For Type III metrics, their responses to changing grain size are more complicated. We suggest that Type III metrics should be used with more caution as no consistent or stable patterns are found either among different landscapes or for multi-scale analysis.

For Type II metrics, the existence of aggregation threshold calls for further examination on the change of the scaling relationship beyond the critical resolution. It is important to know if the scaling relationship shift from one type of function to another (e.g., from power law to logarithmic) or become erratic beyond the threshold. It is therefore important to specify not only the set of scaling functions but also the corresponding valid ranges of resolutions. Results show that scaling relations of Type II metrics exhibit increasing variation with coarsening grain size. We suggest that the scaling functions are used only in their corresponding limited domains of scales with the following two considerations. First, spatial information would gradually get lost as the resolution coarsened, and there would be more uncertainty due to the greater variation using one aggregated pixel to present the spatial heterogeneity of an area at coarser resolution. Second, more caution is needed in the interpretation of the landscape pattern with the metrics of big variation, as the uncertainty in the aggregation process and the chaos beyond the threshold would prevent us from identifying the scaling relation.

We found power-law scaling relationships between the critical aggregation resolution and spatial extent for Type II metrics, and three features can be found in the relations (Figs. 9 and 10). First, all the scaling exponents (γ) are positive, suggesting that the critical aggregation resolutions for these landscape metrics can be relaxed as the spatial extent expands. This finding supports the empirical perception that coarser grain size might be allowed for the spatial data of a larger extent. Second, most exponents of the power-law functions vary within [0.35, 0.45], regardless of error limit or landscape metric. The particular ranges of scaling exponents might suggest a deeper origin of an underlying mechanism generating the power law relation (Zhao and Liu 2014). Third, the critical resolutions of various metrics are inconsistent with one another for a certain landscape and at a given error limit. The inconsistency is reasonable considering the differences in meanings and algorithms of these landscape metrics. Critical aggregation resolutions of different landscapes for a certain spatial extent are also different, suggesting that spatial heterogeneity inherent in all landscapes should not be ignored in quantifying landscape patterns. Although most Type II metrics follow the power law function relating extent to critical resolution, exceptions exist. For example, GYRATE_SD exhibits erratic behaviors when the error limit is set to 10% or 15%. The critical aggregation resolution remains small for ENN_SD and shifts to higher value when the spatial extent is larger than about 2^{15} km^2. A similar pattern appears for CONTIG_MN when resampling with the majority algorithm. The low critical aggregation resolutions for landscapes with smaller extents suggest that the scaling relations with respect to changing grain size are not consistent throughout the entire spectrum of resolutions for these metrics, and the scaling relationship derived for one segment of resolution should be used with caution in practical analysis. In addition, we group FRAC_MN and PAFRAC into Type II based on the performance of R^2 of the scaling functions; however, the parameters of the scaling functions remain in a relatively narrow range and do not show logarithmic relationships with extent as other metrics do (see Fig. 13). This might be related to the fact that the perimeter is adjusted for correcting the raster bias in their calculations, overcoming the major limitations of the straight perimeter-area ratio as a measure of shape complexity (McGarigal and Marks 1995).

Furthermore, this research investigated how scaling functions with changing grain size vary with the spatial extent, which has seldomly explored in previous studies. The relationships between the scaling function parameters and spatial extents show how the landscape metrics would change with scales (i.e., both the resolution and extent) to formally represent the spatial heterogeneity mathematically. Among all the metrics, SHAPE_AM, TE, LSI, and NP present the robust scaling relationships between the parameters and spatial extents, especially for the constant α. These four metrics are highly correlated in their definitions and formula, and the simple scaling relationships suggest that these spatial features can be accurately extrapolated or interpolated across scales. However, the scaling relationships of other landscape metrics should be used with caution for interpolation or extrapolation as no robust and consistent scaling relationships can be identified when changing both resolutions and extents.

The scaling functions found in this study and previous studies present a set of complicated nonlinear relationships among landscape metrics, resolution, and extent. Power-law scaling relationship has been found ubiquitous in physics and biology (Milne et al. 2002; Newman 2005; Spence 2009; Humphries et al. 2010). The most notable one is the allometric scaling of organism form or function to body size (Kleiber 1947; Gould 1966; West et al. 1997). For the landscape system, Wu (2004) suggested that the power law of landscape metrics could be considered as an extension of spatial allometry (Schneider 2001). That is, the power law can be applied to represent the scaling relationship between ecological attributes and extent of landscape. Though the underlying mechanisms remain unclear, the power-law scaling relationships could contribute to the identification of general guiding principles in spatial pattern analysis, and our study takes a small step in that direction.

The major difference between the two resampling methods is that rare patch types are more likely to be preserved when spatial data are aggregated with the nearest neighbor algorithm. Rare patch types are significant for characterizing some ecological phenomena such as the locations of urbanization, disturbances, and endangered species, and therefore should be preserved during scaling. With the majority resampling scheme, only the dominated patch type would be assigned to the aggregated pixel, and some spatial information like number of patches, total edges and patch type degrades dramatically. For example, the NP for L1 drops from 1,203,960 at 30 m to 520,763 and 172,742, respectively, when resampled to 60 m using the nearest neighbor and majority algorithm, indicating that spatial information degrades faster with the majority algorithm. On the other hand, the dominated patch type is widely used in many ecological studies because the dominated landscape usually plays a significant role in determining the landscape process. As the general patterns of scale effects and critical resolution-extent relationships are similar when resampled by these two aggregation methods, we suggest that the selection of the aggregation method should primarily consider the purpose of the studies.

It should be noted that the large landscape extents and grain sizes investigated in our study are far beyond what would be considered by most landscape ecologists, and we believe it is worthy to investigate the scaling issues beyond the traditional boundaries as larger extents or coarser resolutions can reveal the continuity or discontinuity of scale effects in the whole spectrum of scales. In this regard, our analysis goes beyond but contains the traditional landscape scale. In practice, spatial information aggregated up to 20 km is useful for global climate models (Kumar et al. 2013), and the behaviors of landscape metrics can provide insight into whether the land cover or other spatial datasets can be aggregated into large extents. In addition, the power-law scaling relationship between the critical aggregation resolution and spatial extent found in this study could provide a concrete quantitative relationship guiding the choice of spatial resolution according to the variation of spatial metrics for a given extent and error limit, which has further implications for studying ecosystem processes. For example, we found a similar power law relationship in scaling carbon cycle processes in an earlier study (Zhao and Liu 2014), which signifies the criticality of the disturbance scale in the carbon cycle. Our present study shows that power-law relations in pattern scaling across scales is an intrinsic part in the representation and interpretation of landscape pattern, and future research should investigate the implications of these relationships to underlying ecological processes and their scaling. In addition, we investigated the existence and scale domains of scaling relationships across ranges of resolution and extent, which could be seen as an upscaling effort as coarser resolutions are sequentially added during the calculation process. Our calculations do not necessarily have to go from fine to coarse resolutions, and therefore the scaling results are in fact directionless. Nevertheless, downscaling is often more challenging and more important since sub-grid information is often unknown and has to be generated (Riitters 2005; Argañaraz and Entraigas 2014; Frazier 2014), and the intrinsic scaling relationships presented in this study may help guide the downscaling processes. It should be realized that our findings may be specific to the dataset or geographic regions used in our study; it is therefore necessary to assess the generality of these rules using different research areas and datasets, in particular, those related to ecological processes such as plant canopy structure, evapotranspiration, and ecosystem productivity.

Acknowledgements This study was supported by the National Natural Science Foundation of China (#41771093 and 41571079 and #31621091).

References

Alhamad MN, Alrababah MA, Feagin RA, Gharaibeh A (2011) Mediterranean drylands: the effect of grain size and

domain of scale on landscape metrics. Ecol Indic 11:611–621
Argañaraz JP, Entraigas I (2014) Scaling functions evaluation for estimation of landscape metrics at higher resolutions. Ecol Inform 22:1–12
Buyantuyev A, Wu J, Gries C (2010) Multiscale analysis of the urbanization pattern of the Phoenix metropolitan landscape of USA: time, space and thematic resolution. Landsc Urban Plan 94:206–217
Cain DH, Riitters K, Orvis K (1997) A multi-scale analysis of landscape statistics. Landsc Ecol 12:199–212
Cavanaugh JE (1997) Unifying the derivations for the Akaike and corrected Akaike information criteria. Stat Probab Lett 33:201–208
Costanza R, Maxwell T (1994) Resolution and predictability: an approach to the scaling problem. Landsc Ecol 9:47–57
Feng Y, Liu Y (2015) Fractal dimension as an indicator for quantifying the effects of changing spatial scales on landscape metrics. Ecol Indic 53:18–27
Frazier A (2014) A new data aggregation technique to improve landscape metric downscaling. Landsc Ecol 29:1261–1276
Frohn RC, Hao Y (2006) Landscape metric performance in analyzing two decades of deforestation in the Amazon Basin of Rondonia, Brazil. Remote Sens Environ 100:237–251
Goodchild MF, Mark DM (1987) The fractal nature of geographic phenomena. Ann Assoc Am Geogr 77:265–278
Gould SJ (1966) Allometry and size in ontogeny and phylogeny. Biol Rev Camb Philos Soc 41:587–640
Homer CH, Fry JA, Barnes CA (2012) The national land cover database. US Geol Surv Fact Sheet 3020:1–4
Humphries NE, Queiroz N, Dyer JR, Pade NG, Musyl MK, Schaefer KM, Fuller DW, Brunnschweiler JM, Doyle TK, Houghton JD, Hays GC, Jones CS, Noble LR, Wearmouth VJ, Southall EJ, Sims DW (2010) Environmental context explains Lévy and Brownian movement patterns of marine predators. Nature 465:1066–1069
Keymer JE, Marquet PA, Velasco-Hernández JX, Levin SA (2000) Extinction thresholds and metapopulation persistence in dynamic landscapes. Am Nat 156:478–494
Kleiber M (1947) Body size and metabolic rate. Physiol Rev 27:511–541
Kotliar NB, Wiens JA (1990) Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. Oikos 59:253–260
Kumar S, Dirmeyer PA, Merwade V, DelSole T, Adams JM, Niyogi D (2013) Land use/cover change impacts in CMIP5 climate simulations: a new methodology and 21st century challenges. Journal of Geophysical Research: Atmospheres 118:6337–6353
Mandelbrot B (1967) How long is the coast of Britain? Statistical self-similarity and fractional dimension. Science 156:636–638
Mandelbrot B, Wheeler JA (1983) The Fractal Geometry of Nature. Am J Phys 51:286–287
Marceau DJ (1999) The scale issue in the social and natural sciences. Can J Remote Sens 25:347–356
McGarigal K, Cushman S, Ene E (2012) FRAGSTATS v4: spatial pattern analysis program for categorical and continuous maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at: the following web site: http://www.umass.edu/landeco/research/fragstats/fragstats.Html
McGarigal K, Marks BJ (1995) FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Gen Tech Rep PNW-GTR-351 Portland US Dep Agric For Serv Pac Northwest Res Stn 122 P 351. https://doi.org/10.2737/pnw-gtr-351
Milne BT, Gupta VK, Restrepo C (2002) A scale invariant coupling of plants, water, energy, and terrain. Écoscience 9:191–199
Newman MEJ (2005) Power laws, Pareto distributions and Zipf's law. Contemp Phys 46:323–351
Nikora VI, Pearson CP, Shankar U (1999) Scaling properties in landscape patterns: New Zealand experience. Landsc Ecol 14:17–33
Qi Y, Wu J (1996) Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. Landsc Ecol 11:39–49
Riitters KH (2005) Downscaling indicators of forest habitat structure from national assessments. Ecol Indic 5:273–279
Rutchey K, Godin J (2009) Determining an appropriate minimum mapping unit in vegetation mapping for ecosystem restoration: a case study from the Everglades, USA. Landsc Ecol 24:1351
Saura S (2002) Effects of minimum mapping unit on land cover data spatial configuration and composition. Int J Remote Sens 23:4853–4880
Schneider D (2001) Spatial allometry: theory and application to experimental and natural aquatic ecosystems. In: Gardner RH, Kemp WM, Kennedy VS, Petersen JE (eds) Scaling relations in experimental ecology. Columbia University Press, New York, pp 113–154
Shen W, Darrel Jenerette G, Wu J, Gardner RH (2004) Evaluating empirical scaling relations of pattern metrics with simulated landscapes. Ecography 27:459–469
Spence AJ (2009) Scaling in biology. Curr Biol CB 19:R57–R61
Turner MG, Dale VH, Gardner RH (1989a) Predicting across scales: theory development and testing. Landsc Ecol 3:245–252
Turner MG, O'Neill RV, Gardner RH, Milne BT (1989b) Effects of changing spatial scale on the analysis of landscape pattern. Landsc Ecol 3:153–162
Uuemaa E, Roosaare J, Mander Ü (2005) Scale dependence of landscape metrics and their indicatory value for nutrient and organic matter losses from catchments. Ecol Indic 5:350–369
Vogelmann JE, Howard SM, Yang L, Larson CR, Wylie BK, Van Driel N (2001) Completion of the 1990s National Land Cover Data set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. Photogramm Eng Remote Sens 67:650662
West GB, Brown JH, Enquist BJ (1997) A general model for the origin of allometric scaling laws in biology. Science 276:122–126
Wheatley M (2010) Domains of scale in forest-landscape metrics: implications for species-habitat modeling. Acta Oecologica 36:259–267
Wiens JA (1989) Spatial scaling in ecology. Funct Ecol 3:385–397

Wiens JA, Milne BT (1989) Scaling of 'landscapes' in landscape ecology, or, landscape ecology from a beetle's perspective. Landsc Ecol 3:87–96

With KA, Crist TO (1995) Critical thresholds in species' responses to landscape structure. Ecology 76:2446–2459

Wu J (1999) Hierarchy and scaling: extrapolating information along a scaling ladder. Can J Remote Sens 25:367–380

Wu J (2004) Effects of changing scale on landscape pattern analysis: scaling relations. Landsc Ecol 19:125–138

Wu J, Hobbs R (2002) Key issues and research priorities in landscape ecology: an idiosyncratic synthesis. Landsc Ecol 17:355–365

Wu J, Jones KB, Li H, Loucks OL (eds) (2006) Scaling and uncertainty analysis in ecology: methods and applications. Springer, Dordrecht

Wu J, Qi Y (2000) Dealing with scale in landscape analysis: an overview. Geogr Inf Sci 6:1–5

Wu J, Shen W, Sun W, Tueller PT (2002) Empirical patterns of the effects of changing scale on landscape metrics. Landsc Ecol 17:761–782

Zhao S, Liu S (2014) Scale criticality in estimating ecosystem carbon dynamics. Glob Change Biol 20:2240–2251