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VecLI: A framework for calculating vector landscape indices considering landscape fragmentation

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A R T I C L E I N F O

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A B S T R A C T

Currently, raster-based landscape indices (LIs) that measures the landscape pattern of raster-format land-use data, can be easily computed by relevant software (e.g., Fragstats). Unfortunately, open-access software for vector-based LIs often implement a small variety of metrics, which cannot meet the growing demand of the GIS and landscape design research. The common approach often results in a loss of accuracy. Hence, this paper presents the state-of-the-art VecLI framework for computing 217 vector-based LIs. A parcel merging algorithm is proposed to address the impact of landscape fragmentation on vector-based LIs by considering the neighborhood effect. A case study was conduct in Shunde, China. The result shows that 80% of the LIs from VecLI are strongly correlated to Fragstats's LIs. The patch perimeter-related metrics from VecLI portray a more realistic geographical pattern compared to those from Fragstats. Moreover, the VecLI-based software is developed for use by the GIS and landscape design researchers.

1. Introduction

Landscape indices (LIs), also call landscape metrics, are the important basis in the field of landscape ecology (Frazier and Kedron 2017). In landscape-related studies, landscape modeling often applies LIs to measure landscape spatial patterns and analyze their temporal evolutions (Liu and Yang 2015; Sklenicka and Zouhar 2018). With the application of LIs in geographic information system (GIS) and remote sensing, more and more LIs have been proposed to quantify the configuration of landscape patterns (Del Castillo et al., 2015; Zhang and Atkinson 2016; Yu 2021). It has also driven the continuous development of related software for computing LIs, with rich types of LIs implemented (Turner and Gardner 2015).

Currently, the most popular software for LI computation available is Fragstats (McGarigal 2015; Frazier and Kedron 2017). Fragstats is a stand-alone software for raster-based LIs, with detailed instructions and metric descriptions. As the pioneer of LI software, Fragstats was the first to classify LIs into three geographic scales, i.e., Landscape, Class and Patch scales. Also, to evaluate the similarities among LIs, Fragstats classifies them into six classes, including Area_edge, Shape, Core area, Contrast, as well as Aggregation. To date, Fragstats still provides the largest number of raster-based LIs, with 251 metrics in version 4.2 (McGarigal 2015; Yu et al., 2019). In second place is a package called "landscapemetrics", which only implements a total of 134 metrics (Hesselbarth et al., 2019).

However, to date open-access Vector-based software for computing LIs still only offers a paucity of vector-based metrics. These vector-based solutions are mainly presented in the form of plug-ins for GIS software, e.g., ArcGIS-based V-late, Patch Analyst 5 and Arc_Lind. Among them, V-late and Patch Analyst 5 only provide a small number of LIs, mainly for quantifying ecological landscape conservation, such as biodiversity (Lang and Tiede 2003; Rempel et al., 2012). And Arc_Lind provides 195 metrics and some solutions for the problems of computing vector-based LIs but is not currently open for use (MacLean and Congalton 2013; Yu et al., 2019).

Currently, raster-based LIs are widely used for studying landscape pattern. Land use and land cover (LULC) data are a prerequisite for the computation of LIs (Gustafson 2019). LULC data are represented in two forms in geographic information system (GIS), i.e., raster and vector formats (Mõisja et al., 2016). And in the past the vast majority of LULC

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data was produced in the form of raster data, with lower computing performance requirements and higher efficiency (Bober et al., 2016). This is the reason why most of the existing LIs computing frameworks are based on raster-format LULC. However, most existing studies based on vector-format LULC must follow the raster-based routine by rasterizing the vector-format data (Bosch 2019; Fu et al., 2021). Data rasterization is prone to loss of graphical data, resulting in loss of accuracy (Boongaling et al., 2018; Zhou et al., 2018). The scale-related parameter of the data rasterization can also make a significant difference to the results (Pan et al., 2019). With the development of fine-grained land use simulations, vector data is valued for its ability to describe topographic data in great detail and accuracy (O Festus et al., 2020). Hence, it is an urgent need for software to compute LIs based on vector-format LULC data.

In the past, the development of vector-based LIs has encountered many limitations. First, vector-based LIs are much less efficient than raster-based methods limited by the development level of computer technology (Lausch et al., 2015). Second, vector data are prone to topological errors and cumbersome data processing when representing landscape patterns (Bubenik and Dłotko 2017). At the same time, parcel-based vector landscape patterns are susceptible to landscape fragmentation due to human activities such as urban expansion and road construction, which is not conducive to quantifying vector landscape patterns (Dadashpoor et al., 2019; Kumar et al., 2018). Nowadays, the efficiency of vector data processing has been guaranteed thanks to the development of computer hardware and specialist vector data processing packages (Hesselbarth et al., 2019), and common topological errors of vector data can be easily corrected via GIS software (Kukulska et al., 2018; Martinez-Llario et al., 2017). Landscape fragmentation causes excessive fragmentation of parcels and affects the quantification of vector landscape patterns (Yao et al., 2021). Due to the lack of research on this issue, this becomes an urgent problem for the current computation of vector-based LIs.

This paper proposes a new unifying computational framework for vector-based LIs (VecLI), which provides three scales and six types in total 217 LIs with reference to Fragstats. We adopt a parcel merging approach to address the problem of excessive land parcel fragmentation in the vector format. A case study is conducted taking Shunde, Guangdong Province, China as the study area, computing 40 LIs at the landscape scale, to compare them with the current mainstream raster LI software, Fragstats V4.2. The efficiency of VecLI framework is verified by conducting a consistency analysis with Pearson coefficients and t-tests.

2. Methodology

The proposed VecLI framework in this paper can be divided into two steps. (1) First, the optimal neighborhood radius of the study area will be obtained. And then a parcel merging algorithm based on this radius will be implemented to eliminate the effects of landscape fragmentation. Next, the new landscape pattern will be quantified as vector-based LIs based on the merged vector LULC data. (2) The vector-format LULC will be rasterized and a set of its raster-based LIs will be computed via Fragstats V4.2 as a baseline. (3) A consistency analysis will be conducted between the vector- and raster-based LIs by using two-tailed paired t-tests and Pearson R correlation coefficients. Specifically, the impacts of three aspects on the consistency, i.e., the spatial resolutions of the rasterization, the types of LIs and individual metrics, will be analyzed respectively.

2.1.1. Parcel merging algorithm considering landscape fragmentation

Landscape fragmentation often causes over-division of parcels (Li et al., 2017; Yao et al., 2021). Particularly, parcels are the basic spatial unit of the vector-based landscape patterns. And the effect of landscape fragmentation makes it difficult to accurately quantify vector-based landscape patterns. Hence, it is important to merge the adjacent parcels of the same land-use type before quantifying the vector landscape patterns.

Here, we propose a parcel merging algorithm to address the effect of landscape fragmentation as follows (Fig. 1). First, a breadth-first search is conducted to collect the adjacent parcels of a parcel by setting up a searching radius. The indices of the adjacent parcels are recorded if they are of the same land-use type. At the end of these parcels are merged in order.

It is readily apparent that the searching radius significantly affects the result of the parcel merging algorithm. To investigate the optimal searching radius, we first compute the number of patches (NP) within the completed landscape pattern for different neighborhood radius before performing merging, based on the pre-defined neighborhood extent and interval.

To extract the optimal searching radius, we also introduce the concept of the number of patches within the neighborhood (NPN) to assess the effect of the neighborhood on the parcel merging. As it is necessary to determine whether the patches within the neighborhood are contiguous during this process, an increase in NPN means that more parcels are considered and more time is required to complete the process.

2.2.2. Comparison with VecLI's metrics and raster-based LIs via Fragstats

This paper compares two types of LIs, i.e., vector- and raster-based LIs, for the study area. We used the field of the land-use type as the raster value field to rasterize the vector-format LULC data. And then the Fragstats is used to compute the raster-based LIs. To investigate the effect of the spatial resolutions of the rasterization on the result, we also obtained raster-format LULC data with diverse spatial resolutions to compute the corresponding raster-based LIs. And VecLI framework is also used to directly quantify the vector-based landscape pattern of the study area.

In this paper, 217 vector-based LIs are implemented in the VecLI framework with reference to Fragstats (Table 1). Three scales of LIs are included, of which 14 LIs are at Patch scale to describe patches' patterns, 98 LIs are at Class scale to quantify land use types, and 105 LIs are Landscape level describing the whole landscape patterns. The LIs can also be classified into six types. Area_edge metrics and Shape metrics are computed based on the area and perimeter of the patch. The former describes the basis of the landscape structure, while the latter measure the complexity of the patch shape. Core area metrics and Contrast metrics are calculated based on the patch boundaries, describing the area without the edge effects, and the quantification edge effects, respectively. Aggregation metrics are computed based on the distance between patches. They reveal the distribution and aggregation of patches on the landscape. Diversity metrics are calculated based on the number and area of patches. They are used to measure landscape structure (McGarigal et al., 2012; Park and Guldmann 2020; Slattery and Fenner 2021).

Among them, some of the Shape and Aggregation metrics contain parameters related to the raster-format structure (Table 2), which indicates that they cannot be directly computed from vector-format LULC data. Here, the metrics in Table 3 are not included in the VecLI framework, leaving a total of 217 metrics.

In addition, some of the indices need corrections when computing based on vector-format LULC data. The radius of gyration (GYRATE) of Area_edge metrics is strongly raster-format related. Here, we proposed a vector formula based on the definition of the GYRATE and modified the meaning of the parameter (Table 4). Also, SHAPE, FRAC, LSI of Shape and Aggregation metrics contain the raster-based adjustment parameter of 0.25 was changed to 0.282 (Table 5) in reference to Yu's approach (Yu et al., 2019). PROX and SIMI of Aggregation metrics need to compute the edge-to-edge distance between patches, while the raster-based method is based on the centers of raster pixels, and this distance is

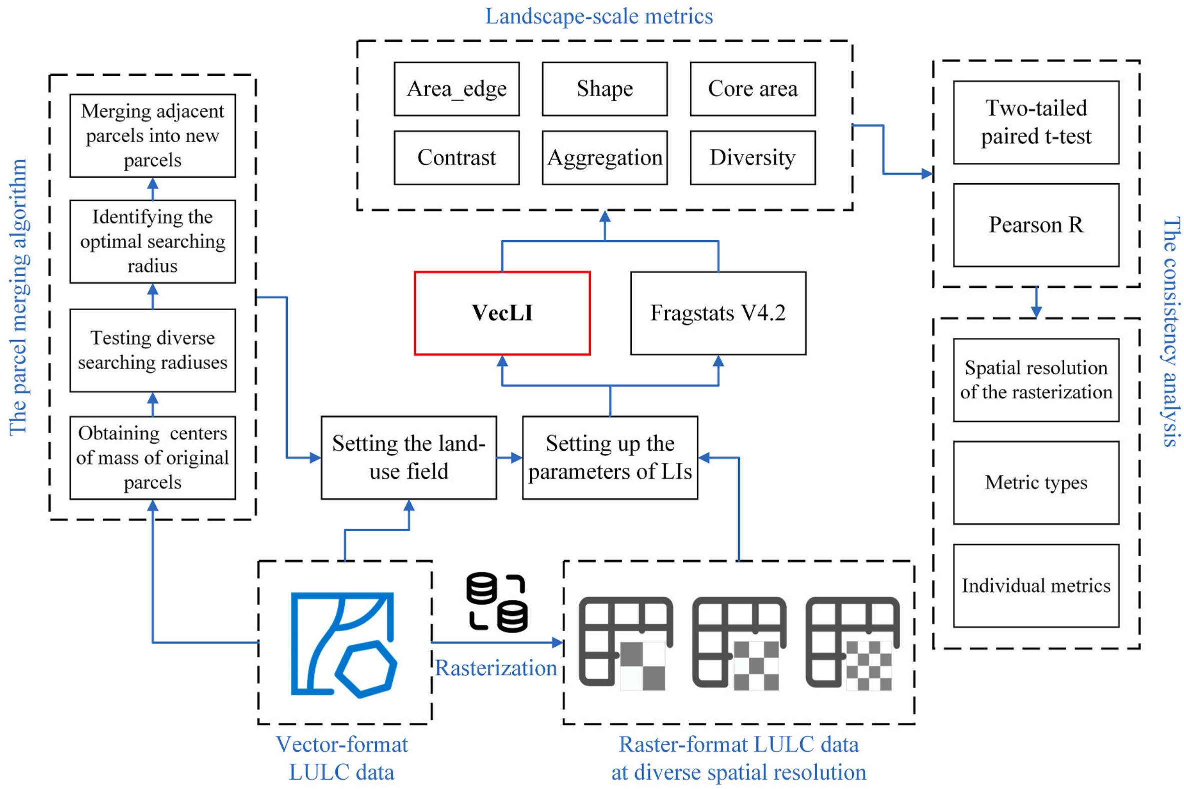

Fig. 1. VecLI framework for computing vector-based landscape indices considering landscape fragmentation.

Table 1
Numbers of metrics applied for comparison from VecLI and Fragstats V4.2

Metric type	Scale	Fragstats	VecLI
Area_edge	Patch	3	3
	Class	17	17
	Landscape	16	16
Shape	Patch	5	4
	Class	37	25
	Landscape	37	25
Core area	Patch	3	3
	Class	22	22
	Landscape	21	21
Contrast	Patch	1	1
	Class	8	8
	Landscape	8	8
Aggregation	Patch	3	3
	Class	31	26
	Landscape	30	26
Diversity	Landscape	9	9
Sum		251	217

taken as 1 by default when using Fragstats. In the VecLI framework, the parameter is calculated directly based on the edge-to-edge distance. And when plaque adjacency is present, the, and the parameter in VecLI is also set as 1.

Table 2
Parameter related to raster format.

Parameter	Description
c_{ijr}	contiguity value for Pixel *r* in Patch *ij*.
v	sum of the values in a 3-by-3 pixel template (13 in this case).
a_{ij}	area of Patch *ij* in terms of number of pixels.
b	average pixel value of the medial axis transformation of a patch.
g_{ii}	number of like adjacencies (joins) between pixels of Patch Type (Class) *i* based on the *double-count* method.
g_{ik}	number of adjacencies (joins) between pixels of Patch Type (Class) *i* and *k* based on the *double-count* method.
g_{ij}	number of like adjacencies (joins) between pixels of Patch Type (Class) *i* based on the *single-count* method.
$max \rightarrow g_{ii}$	maximum number of like adjacencies (joins) between pixels of Patch Type (Class) *i* based on the *single-count* method.
e_i	total length of edge (or perimeter) of Class *i* in terms of number of pixel surfaces; includes all landscape boundary and background edge segments involving Class *i*.
$min\ e_i$	minimum total length of edge (or perimeter) of Class *i* in terms of number of pixel surfaces.
$max\ e_i$	maximum total length of edge (or perimeter) of Class *i* in terms of number of pixel surfaces.
p_{ij}^{*}	perimeter of Patch *ij* in terms of number of pixel surfaces.
a_{ij}^{*}	area of Patch *ij* in terms of number of cells.
Z	total number of pixels in the landscape.

2.3.3. Consistency analysis between the vector and the raster-based landscape indices

A consistency analysis is conducted for the evolution of the landscape pattern in the study area. T-tests and Pearson R correlation coefficients are applied to measure the consistency between the vector-based LIs and the raster-based LIs at diverse scales.

The two-tailed paired *t*-test is a method used to measure the average difference between two sets of samples (Doehl et al., 2017). This paper applies this test to detect whether there is variability between the means of the vector-based LIs and the raster-based LIs. Here, a two-tailed p-value of less than 0.05 is regarded that significant variability existed.

The Pearson R correlation coefficient is a commonly used to measure the correlation between two sets of samples (Weaver and Wuensch 2013). Here, we use it to analyze the correlation between the vector-based LIs and the raster-based LIs. When the absolute value of Pearson R is greater than 0.8, between 0.6 and 0.8 or less than 0.6 we consider the correlation to be strong, moderately strong, or weak, respectively.

Table 3
The landscape indices of Fragstats that are not included in VecLI.

Indices name	Indices type	Parameter related to raster format	Index of the index
CONTIG	Shape	c_{ijr} , v , a_{ij}^{*}	P5,C32–C37,L32-L37
Linear	Shape	a_{ij}^{*} , b	C20–C25,L20-L25
PLADJ	Aggregation	g_{ii}, g_{ik}	C2,L3
AI	Aggregation	$g_{ij}, max \rightarrow g_{ij}$	C3,L4
CLUMPY	Aggregation	g_{ii}, g_{ik}	C4
nLSI	Aggregation	$e_i, \mathrm{min} e_i, max\ e_i$	C6
COHESION	Aggregation	p_{ij}^{*} , a_{ij}^{*} , Z	C7,L6
CONTAG	Aggregation	g_{ik}	L1

3. Results

3.1.1. Study area

Shunde, Guangdong Province, China is selected as the study area. Shunde covers an area of approximately 806 km^2, with four streets and six towns under its jurisdiction. Shunde shows an increasing trend of land-use parcels' number, with a total of 16,611, 20,865 and 23,336 parcels in 2012, 2015 and 2018, an increasing ratio of 25.61% and 11.84% respectively. Because the rapid land use changes have resulted in a heavily fragmented landscape in Shunde.

According to Shunde's statistical yearbook, Shunde has been ranked as the first of the top 100 districts in terms of comprehensive strength since 2012 to 2018. The diverse industries there has led to a variety of land use types in Shunde. Here, we summarize the land use types of LULC data into four classes, i.e., unused land, farmland, road and construction land. We also rasterize the vector-format LULC data into raster-format data at three spatial resolutions of 10m, 20m and 30m in Shunde.

3.2.2. The optimal searching radius based on the NP and NPN metrics

This section explores the optimal searching radius of Shunde in 2012, 2015 and 2018. We first calculated the NP and NPN of the landscape pattern from a range of 0–3000 m searching radius at a 50 m interval (Fig. 2). trends of NP and NPN in the study area.

As shown in Fig. 3, the trends of NP and NPN in Shunde both remains basically the same in different years. As the radius increases, the NP gradually decreases and tends to converge. The NPN gradually increases and at an ever-increasing rate. Because the number of adjacent parcels increases as the area of the predefined neighborhood grows. However, the actual neighborhood is fixed, which indicates that the NP eventually remains constant.

In this paper, the searching radius when the NP is just constant is regarded as the optimal searching radius. By setting the optimal searching radius, the result of parcel merging algorithm as well as the computational efficiency are both the best. The optimal radiuses in 2012, 2015 and 2018 are 1750 m, 1700 m and 1500 m, respectively, which indicates that the parcels are gradually concentrated, and the urban functional areas show the trend of clustering. It verifies that the parcel merging algorithm adopted in this paper can eliminate internally fragmented parcels by accurately quantifying the neighborhood effect. And it can also effectively mine the landscape pattern of urban functional areas.

Table 4
Vector-based equation of GYRATE based on vector-format LULC data.

	Equation	Description of the parameters
For raster format	$\mathrm{GYRATE} = \sum_{r=1}^{z} \frac{h_{ijr}}{z}$	z : number of pixels in Patch *ij*. h_{ijr} : distance (m) between Pixel *ijr* [located within Patch *ij*] and the centroid of Patch *ij* (the average location), based on cell center-to-cell center distance.
For vector format	$\mathrm{GYRATE} = \sum_{r=1}^{z} \frac{h_{ijr}}{2z}$	z : number of vertices of Patch *ij*. h_{ijr} : distance (m) between Vertice *ijr* and the centroid of Patch *ij* (the average location), based on Euclidean distance.

3.3.3. Consistency between vector- and raster-based LIs

The vector-based LIs of Shunde are compared with the raster-based LIs at different scales via the consistency analysis. For the same metrics, Pearson correlation coefficients and p-values for t-tests are computed based on the results of 2012, 2015, and 2018. (see Table 9)

For the null values in Table 6, we compare them with the ground-truth for the analysis (Table 7). It can be noticed that the metrics of the PR, PRD and RPR for all three years maintain constants. Moreover, the vector-based metrics are the same as the raster-based LIs. Thus, these metrics are not considered in the following analysis.

74.7% of the results obtained from Fragstats and VecLI are significantly different, but 79.3% are strongly correlated. It indicates that there is an objective quantitative difference between the vector- and raster-based LIs due to different data structures. However, they show a high degree of consistency in the linear relationship, reflecting the validity of the proposed VecLI framework.

In terms of the spatial resolutions of the rasterization, p values and r values always vary with the resolutions (Table 8), which indicates that almost all metrics except PR, PRD and RPR are sensitive to the spatial resolution-related parameter of the data rasterizations. At the same time, variability is minimally affected by changes in resolution, but correlation is strongly affected and proportional to resolution. Thus, although the raster-based LIs differ numerically from the vector-based metrics, the higher the spatial resolution is set, the more the landscape pattern described is correlated with the vector-based landscape due to its ability to portray geographic entities. It suggests that the VecLI framework for vector-based LIs is significantly more realistic than the conventional raster-based way.

In terms of index type, both Area_edge and Diversity metrics show a higher variability in average values compared to the other types, with 38.9% and 55.6% significant as weak differences, respectively. It suggests that the mean values of the raster- and vector-based LIs are closer to each other in measuring the pattern of the landscape. In terms of the linear correlation, both Core area and Contrast have a strong correlation of 100.0%, indicating that the metrics based on patch edges are almost independent of the structure of the data.

In terms of individual metrics, the range of SPLIT and MESH is limited by the number of raster pixels. Although their vector-based metrics are achievable, the correlation between vector- and raster-based metrics fluctuates significantly as the parameter of spatial resolution changes. The metrics related to the perimeter of the parcels, e.g. PAFRAC, PARA _MN, FRAC, show low correlations and their significance fluctuates greatly. Because the raster data structure represents the parcel in such a way that the edges are described as larger than the reality due to the jaggedness. And the lower the resolution of the raster data is set, the greater the edge length of the pixel, leading to a greater lack of accuracy. While the vector-format data can more accurately portray the edge of the parcels, and their edge lengths are more closely

Table 5
Modified equation of vector-based SHAPE, FRAC, LSI.

Metric	Metric type	Original	Modified
SHAPE	Shape	$\mathrm{SHAPE} = \frac{.25^{*}p_{ij}}{\sqrt{a_{ij}}}$	$\mathrm{SHAPE} = \frac{.282^{*}p_{ij}}{\sqrt{a_{ij}}}$
FRAC	Aggregation	$\mathrm{FRAC} = \frac{2\ln(.25p_{ij})}{\ln a_{ij}}$	$\mathrm{FRAC} = \frac{2\ln(.282p_{ij})}{\ln a_{ij}}$
LSI	Aggregation	$\mathrm{LSI} = \frac{.25E^{*}}{\sqrt{A}}$	$\mathrm{LSI} = \frac{.282E^{*}}{\sqrt{A}}$

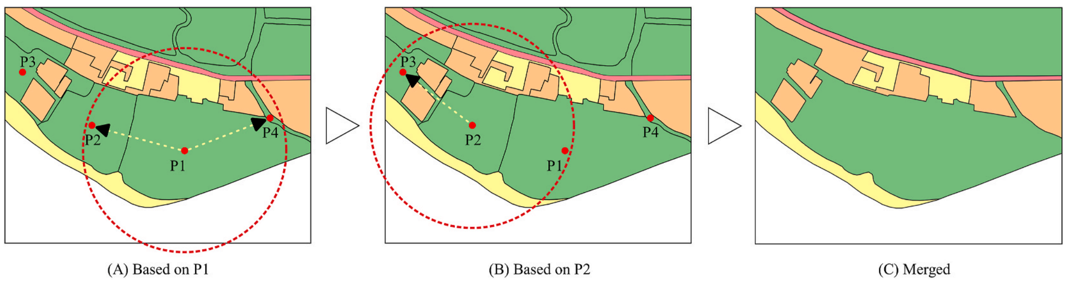

Fig. 2. Process of merging the adjacent parcels with the same land-use type. Diverse colors indicate diverse land-use type.

matched to the ground-truth. It highlights VecLI's excellent ability to quantify the edge of the parcels finely.

4. Discussion

We summarize the existing limitations of LIs, and propose an effective solution for the issue of landscape fragmentation. Previous studies often overlooked this problem. This paper is the first to presents the NP and NPN-based parcel merging algorithm. It considers the neighborhood effect by merging adjacent parcels of the same land-use type. We find that the searching radius of neighborhood tends to decrease year by year as the clustering trend of urban functional area becomes more apparent. It is consistent with the results of previous studies (Yao et al., 2017; Zhai et al., 2020), indicating the feasibility of our idea.

This paper provides reasonable corrections for vector-based LIs computation. Referring to the framework of raster-based LIs provided by Fragstats, this paper proposes new equations for metrics without vector-based equations and adjusts some of the metrics' parameters by combining the study of Yu et al. and the equations of Fragstats (Yu et al., 2019). Currently, the proposed VecLI framework provides the most

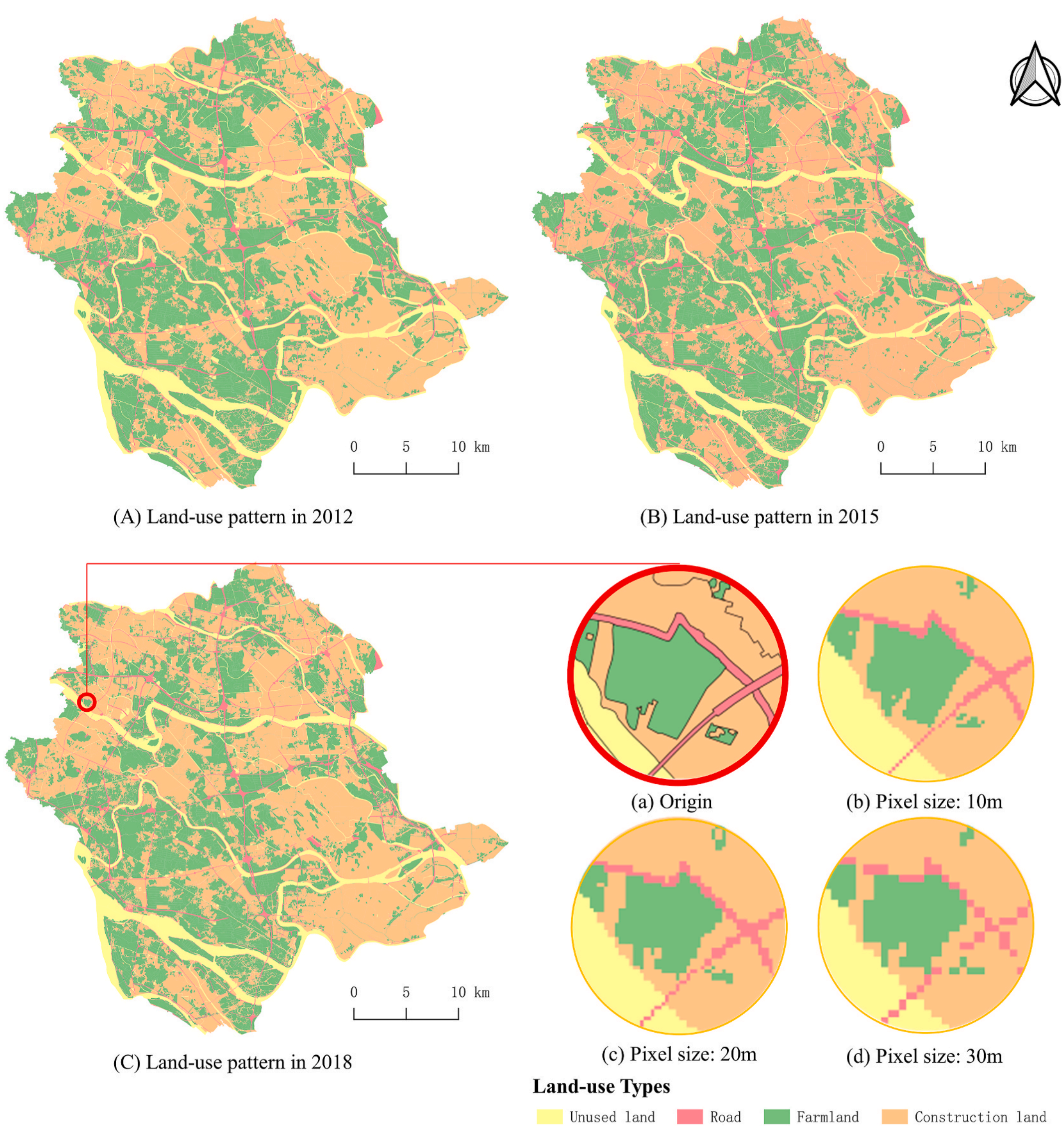

Fig. 3. Land use and land cover data of Shunde.

Table 6
Result of the consistency analysis.

Metric type	Metric	t-test (p-value)			Pearson r		
		10m	20m	30m	10m	20m	30m
Area_edge	TA	0.170	0.168	0.170	−0.906	−0.993	−0.956
	LPI	0.026	0.024	0.023	−0.197	0.203	0.376
	TE	0.002	0.001	0.016	0.998	0.998	0.999
	ED	0.001	0.000	0.053	1.000	1.000	1.000
	AREA_MN	0.006	0.038	0.092	0.999	0.999	0.999
	GYRATE_MN	0.007	0.396	0.920	0.999	0.998	0.996
Shape	PAFRAC	0.065	0.031	0.020	−0.572	−0.787	−0.779
	SHAPE _MN	0.506	0.017	0.009	−0.902	−0.820	−0.817
	PARA _MN	0.000	0.000	0.000	−0.734	−0.661	0.733
	FRAC_MN	0.001	0.001	0.001	0.949	0.813	0.675
	SQUARE_MN	0.035	0.036	0.036	−0.388	−0.624	0.000
Core Area	TCA	0.008	0.001	0.001	0.947	0.947	0.945
	NDCA	0.003	0.015	0.003	0.999	0.997	0.996
	DCAD	0.002	0.007	0.004	0.999	0.999	0.998
	CORE_MN	0.004	0.051	0.165	0.998	1.000	1.000
	DCORE_MN	0.002	0.002	0.001	0.992	0.995	0.996
	CAI_MN	0.009	0.026	0.026	0.999	0.999	0.999
Contrast	CWED	0.001	0.000	0.053	1.000	1.000	1.000
	TECI	0.024	0.026	0.028	−1.000	−1.000	−1.000
	ECON_MN	0.076	0.063	0.059	0.992	0.995	0.996
Aggregation	IJI	0.043	0.005	0.001	1.000	1.000	1.000
	LSI	0.000	0.027	0.120	0.999	0.999	1.000
	NP	0.018	0.001	0.029	0.999	1.000	1.000
	PD	0.016	0.001	0.034	0.999	1.000	1.000
	DIVISION	0.002	0.004	0.001	0.906	0.906	0.906
	SPLIT	0.013	0.012	0.009	0.921	−0.808	0.255
	MESH	0.001	0.003	0.001	0.946	−0.768	0.316
	ENN_MN	0.019	0.037	0.003	0.999	0.752	0.977
	PROX_MN	0.004	0.004	0.004	−0.918	−0.986	−0.984
	SIMI_MN	0.024	0.022	0.022	0.679	0.601	0.607
	CONNECT	0.009	0.166	0.064	0.998	0.999	0.998
Diversity	PR	/	/	/	/	/	/
	PRD	/	/	/	/	/	/
	RPR	/	/	/	/	/	/
	SHDI	0.004	0.004	0.004	0.262	0.285	0.338
	SIDI	0.726	0.726	0.007	1.000	1.000	1.000
	MSIDI	0.318	0.781	0.001	1.000	1.000	1.000
	SHEI	0.426	0.425	0.429	0.926	0.937	0.919
	SIEI	0.045	0.517	0.015	1.000	1.000	1.000
	MSIEI	0.452	0.635	0.004	1.000	1.000	1.000

Table 7
Result of the null value of the three metrics.

Metric	Year	VecLI	Fragstats		
			10m	20m	30m
PR	2012	4.000	4.000	4.000	4.000
	2015	4.000	4.000	4.000	4.000
	2018	4.000	4.000	4.000	4.000
PRD	2012	0.005	0.005	0.005	0.005
	2015	0.005	0.005	0.005	0.005
	2018	0.005	0.005	0.005	0.005
RPR	2012	1.000	1.000	1.000	1.000
	2015	1.000	1.000	1.000	1.000
	2018	1.000	1.000	1.000	1.000

Table 8
Impact of the spatial resolution on p-value and r-value.

	$p \geq 0.05$	$p < 0.05$	$\lvert r\rvert \in [0, 0.6]$	$\lvert r\rvert \in [0.6, 0.8]$	$\lvert r\rvert \in [0.8, 1]$
10m	8	29	4	2	31
20m	10	27	2	6	29
30m	10	27	5	4	28
Sum	28	83	11	12	88

index types and the richest number of vector-based LIs in a reasonable computation framework.

This paper examines the effect of data rasterization on the accuracy of LIs and considers the relationship between the parameter of raster resolution and the vector-based landscape pattern. We found that all metrics vary with raster resolution, except for a few indices of Diversity where the results are constant. This result is consistent with previous studies. We also found that the higher the raster resolution is set, the stronger the correlation between the calculated LIs and the vector-based LIs. It indicates that the refined raster landscape pattern is closer to the vector landscape pattern, proving the authenticity of VecLI in the representation of landscape patterns.

Table 9
Impact of index types on p-value and r-value.

	$p \geq 0.05$	$p < 0.05$	$\lvert r\rvert \in [0, 0.6]$	$\lvert r\rvert \in [0.6, 0.8]$	$\lvert r\rvert \in [0.8, 1]$
Area_edge	7	11	6	0	12
Shape	2	13	11	2	2
Core area	2	16	0	0	18
Contrast	4	5	3	0	6
Aggregation	3	30	7	4	22
Diversity	10	8	0	3	15

Overall the VecLI and Fragstats results are significantly different in mean values of LIs but maintain a high correlation. 74.7% of the landscape indices are significantly different in mean values. However, the metrics measuring the overall structure of the landscape from VecLI and Fragstats both are close in mean values, which is different from the overall trend. There is an extremely high correlation between the vector-and raster-based LIs in terms of linearity, with strong correlations reaching even 100% in the metrics related to the parcel edge effect.

According to the overall trends of LIs' variability and correlation, we found that the patch perimeter-dependent metrics are mainly influenced by edge jaggedness, with raster data describing patch edge lengths that are larger than the actual edge lengths and proportional to the size of the raster pixel. The vector-based LIs are more realistic because the vector data structure accurately describes the geographic entity, and the calculated perimeter matches the ground-truth accurately. Thus the vector-based LIs implemented by VecLI framework compensates for the lack of Fragstats.

The lack of open-access software for computing vector-based LIs has been considered in the design of the VecLI framework and the development of its software. Firstly, a wide range of LIs is a prerequisite for the software to be widely used. The VecLI-based software can implement 217 indices, which is perfectly suitable for the main scenarios of Fragstats. Secondly, the software should be architecturally independent and free to use. The VecLI-based software has its own underlying layer and the user does not need to obtain any commercial license. We also provide comprehensive documentation and index descriptions to further help users understand and access the LIs they need.

The proposed VecLI framework still has shortcomings. First, the efficiency of the algorithm is still lacking compared to Fragstats when dealing with vector-format LULC data with more than 100,000 parcels at once. Thus, the algorithm still needs to be optimized in the future. Second, in terms of the richness of the LIs, considering that the variety of LIs will be diversified in the future and not only limited to Fragstats, but we will also consider opening up the software code and provide the interface of the corresponding functions in the future, so that users can develop the indices they need. Finally, with the increasing demand for LIs from disciplines such as urban planning, resources and environment, and biological sciences, it is a direction of our later research to adapt the quantification of metrics to diverse application scenarios.

5. Conclusion

This paper proposes a framework for computing the vector-based LIs (VecLI) considering the effect of the landscape fragmentation. In this paper we not only summarize the vector-based LIs and make vector-based corrections in conjunction with previous research, but also innovatively propose a parcel merging algorithm that considers the neighborhood effects, effectively solving the problem of landscape fragmentation on quantifying vector-based landscape patterns.

The overall experimental results from the consistency analysis show both consistency and variability between results of VecLI and Fragstats. The consistency is evidenced by a strong linear relationship between the results for 2012, 2015 and 2018, while the variability is evidenced by a significant difference in the mean values of the metrics. Specifically, vector-based LIs are more accurate in measuring the perimeter of patches compared to raster-based LIs. Therefore, the perimeter-based LIs should be implemented through a vector-based way. The VecLI software for computing vector-based LI released in this paper makes up for the shortcomings of the existing vector-based software. The independent architecture and rich landscape indices of VecLI can meet the needs of the geographic information and landscape design fields, making it a professional software for computing vector-based LIs.

CRediT authorship contribution statement

Yao Yao: Conceptualization, Methodology, Project administration, Resources, Funding acquisition, Writing – original draft, Software. **Tao Cheng:** Writing – original draft, Writing – review & editing, Software, Methodology. **Zhenhui Sun:** Writing – original draft, Writing – review & editing, Software, Methodology. **Linlong Li:** Writing – original draft, Writing – review & editing, Software, Methodology. **Dongsheng Chen:** Writing – original draft, Supervision, Conceptualization, Software. **Ziheng Chen:** Writing – review & editing, Software, Validation. **Jianglin Wei:** Writing – review & editing, Software, Validation. **Qingfeng Guan:** Supervision, Funding acquisition, Data curation.

Declaration of competing interest

No conflict of interest exists in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part.

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Software availability

Software name VecLI v2.0.0
Developer Yao Yao, Tao Cheng, Zhenhui Sun, Linlong Li, Dongsheng Chen
Year first official release 2021
Hardware requirements PC
System requirements Windows
Program language C++
Program size 159.4 MB
Availability this paper the version (2.0) mentioned in this paper: https://urbancomp.net/archives/vecli200, the lastest version (3.0 beta): https://www.urbancomp.net/archives/vecliv3beta
License GPL-3.0
Documentation Documentation can be downloaded from the website: https://urbancomp.oss-cn-hangzhou.aliyuncs.com/blog/VecLI_v2_manuals_en_1629191061075.pdf

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2022.105325.

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