An enhanced landscape aggregation index

SHU Bo \(^1\), JIA Liu-qiang \(^2\)

\(^1\) Faculty of Architecture, Southwest Jiaotong University, Chengdu 610031, P. R. China
\(^2\) Sichuan Institute of Urban Planning and Design, Chengdu 610081, P. R. China

Abstract: The aggregation index (AI) is a classical ecology calculation method, which has been widely used for measuring the aggregation level of spatial patterns within a landscape scale in landscape ecological studies. However, it has certain limitations. For instance, identical results can be obtained by AI even when the shape and number of landscape patches are totally different in two landscape units. Furthermore, the value of AI approaches to 1 if the landscape patch is large enough. To solve these problems, a logical limitation of the original AI equation was revised firstly. Secondly, an improved AI-J was developed based on the awareness of the effects of spatial distribution characteristics of patches and changing spatial scale on AI operation. Finally, the accuracy of AI and AI-J results were evaluated through a case study of city green patches in Chengdu, P. R. China. The results show that the calculated result of AI-J is more precise than that of AI and AI-J can be used to compare a certain landscape class under different spatial scales.

Keywords: landscape indices; aggregation index; landscape ecology; green patch; spatial scale

1 Introduction

Landscape ecology is one of the most dynamic and influential subjects in modern ecological studies. \(^{[1-3]}\) It has the most extensive research area and keeps developing new research interests. Spatial heterogeneity, the relationships between ecological process and its spatial scale currently attract the most attention of ecologists. \(^{[3]}\) Landscape indices are widely used to analyze spatial heterogeneity. These indices not only enable us to quantify spatial patterns of landscape, but also produce scientific data for comparison study of landscape patterns under different scales and monitoring landscape structure developing process. \(^{[4-5]}\) Although landscape indices provide scientific support to understanding the trends under landscape pattern formation and development, their limitations have been pointed out by some researchers. For example, not all indices are able to reflect the true composition and structural character of a landscape pattern; \(^{[5-7]}\) and the analysis results from certain index are often affected by the spatial pixels and spatial resolutions. \(^{[8-9]}\) Therefore, it is a challenge for us to interpret the landscape indices and their results more precisely in landscape ecological research. \(^{[10-11]}\)

Aggregation index (AI) is a landscape index which reflects the aggregation level of certain landscape class. \(^{[12]}\) It can represent the connectivity of a landscape pattern with certain ecological process. \(^{[13-14]}\) Thus it becomes a very important aspect in landscape ecological research. AI has been widely used to describe urban spatial morphology, city green patches and the spatial aggregation/scattering level of a certain species. It was first introduced by O’Neill and other 11 scholars in 1988 under the name ‘Contagion Index’ (CI). \(^{[15]}\) Li and Eeynolds \(^{[16]}\) improved CI to CI-Li in 1993. Until 2000, He et al. \(^{[14]}\) developed AI to address the problem of discrepancy when using CI and CI-Li in aggregation level analysis. AI is available for
producing more reasonable results in quantity analysis, but it has limits such as 1) identical number of landscape patches leads to identical AI regardless of their spatial distribution; and 2) when the landscape patches are too big comparing with the space they are in, the AI results always approach 1.

Based on these findings, we revised and improved the AI operation method and validated it by comparison with the analysis results of green patches’ aggregation level in Chengdu, P. R. China.

2 Samples and methods

2.1 Research data collection and preparations

The paper is focused on the improvement of AI operation method and does not involve any analysis of the ecological process. Since AI results will be affected under different spatial scales like other landscape indices, a certain spatial scale has to be identified before data collection.

A certain number of green patches within Chengdu’s 3rd ring road in 2000 were chosen as the research subject. They formed a certain landscape pattern with relevant spatial units (which are called thermal elements, characterized by their even temperature inside) that were defined by the surface temperature at that time, which provided statistic data for this research. The pattern reflects an ecological process, which represents the influence from the aggregation level of green patches on ground surface temperature.

Green patches data was collected on 10th May 2000 in Chengdu using Landsat ETM (enhanced thematic mapper) and remote sensing devices (spatial resolution 28.5 m). It was then revised based on the information from citywide survey database (97 data collection points with spatial resolution at 1.0 m, Beijing 54 coordinate system). EREAS, ARCGIS and visual check were adopted to identify green patches. Surface temperature was first recorded by ERDAS MODELER, using radiation equation method. After that, we processed recorded data into a remote sensing image processing software (Definens Developer 5.0) to produce image sample by defining various parameters, including scale parameter, color and shape heterogeneity (smooth and aggregation heterogeneity). The results of overlapped green patches image and thermal image are shown in Fig. 1. There were 294 identified green patches in 73 spatial thermal units.

Fig. 1  A certain landscape pattern with relevant spatial units (study samples)

2.2 Revision and improvement of AI

2.2.1 AI and its limits

AI is a class-level index developed from raster data. AI approaches 1 when landscape pixels shared most edges; it tends to 0 when there is no shared edge between pixels. Hence, the basic rule of AI operation is dividing the length of shared edges between pixels by the max shared edge length in theory. The original operation process is shown as follows. [13]

In raster data, a landscape element is disaggregated into square-shaped pixels. When \( e_{i,j} \) represents the number of shared edges between landscape class \( i \) and class \( j \), \( e_{i,j} \) represents the number of shared edges within class \( i \) and thus reflects its aggregation level. There comes \( \max_e_{i,j} \) when all pixels within one class aggregate into one patch of area \( A_i \):

\[
\max_e_{i,j} = \begin{cases} 
2n(n-1), & m = 0, \\
2n(n-1) + 2m - 1, & m < n, \\
2n(n - 1) + 2m - 2, & m \geq 0,
\end{cases}
\]

where \( n \) is the side length of inscribed square and \( m = A_i - n^2 \); \( \max_e_{i,j} \) is only defined by the size of the
landscape patch and not affected by its shape or number. The AI of landscape class $i$ is then calculated by

$$\text{AI}_i = \frac{e_{ij}}{\max_e_{ij}},$$

(2)

In general, AI provides better and more reasonable results than CI and CI-Li when dealing with different number of patches under different spatial resolution. Since AI is a ratio variable, map units do not affect the calculation. However, it has following limits:

1) When there are equal numbers of landscape patches of the same shape distributed differently into spaces, AI results are the same. For example, AI is 0.8 in Figs. 2a and 2b, but it is obvious that there is a higher aggregation level in Fig. 2a.

2) When there is no shared edge between pixels, AI always equals 0. For example, AI is 0 in Figs. 2c and 2d, but their aggregation levels are different by visual observation.

3) When the size of a landscape patch is too big compared with its spatial setting, AI always approaches 1.

4) The original $e_{ij}$ calculation was undertaken by computer programming, which might hinder its wide use.

5) There is a logical limitation in Eq. (1). There is no equation when $m \geq n$, whereas two equations exist when $m = 0$.

2.2.2 Revision and improvement of AI operation method

1) Revision

As any two neighboring pixels share only one edge, the total perimeter of all pixels in a landscape patch equates to the sum of the perimeter of this patch and twice the length of the shared edges inside the patch. As the perimeter/area ratio of all pixels in raster data is 4, a mathematical representation of this relationship can be defined as

$$\frac{S + 2e_{ij}}{A} = 4,$$

(3)

where $S$ is the total perimeter of all landscape patches in landscape class $i$ and $A$ is the total area of all landscape patches in landscape class $i$.

Eq. (3) can be rearranged to derive the total number of shared edges in landscape class $i$ based on Eq. (4).

$$e_{ij} = 2A - \frac{S}{2}.$$  

(4)

Analysis of Eq. (1) suggests that $\max_e_{ij}$ consists of two parts. One is the total number of shared edges in an $n \times n$ square patch, which equals to $2n(n-1)$. The other is the number of shared edges between the square patch and another landscape patch of area $m$. A revision of Eq. (1) is

$$\max_e_{ij} = \begin{cases} 
2n(n-1), & m = 0, \\
2n(n-1) + 2m - 1, & 0 < m \leq n, \\
2n(n-1) + 2m - 2, & n < m < 4n + 4.
\end{cases}$$

(5)

Three discreet choices are defined in Eq. (5). When $m = 0$, the landscape patches of class $i$ is a square so there are no other shared edges. When $0 < m \leq n$, the area of the landscape patch is greater than that of its inscribed square and its shared edges with the square is lower than $n$. Therefore, the increased number of shared edges is $2m-1$. When $m > n$, the area of the landscape patch is greater than that of its inscribed square and its shared edges with the square is greater than $n$. Thus, the increased number of shared edges is $2m-2$. In theory, the value of $m$ should be less than $4n+4$. Otherwise, the size of the inscribed square will increase by 1 when $m \geq 4n+4$.

![Fig. 2 Examples of aggregation index limits](image-url)
For example, there are 9 pixels in a certain landscape class as shown in Fig. 3a. The size of its inscribed square is $3 \times 3$. In this case, $n = 3$ and $m = 9 - n \times n = 0$. The value of $\text{max}_i \ e_{ij}$ is 12 according to Eq. (5). When there are 10 pixels in the landscape class (Fig. 3b), $n$ remains unchanged but the value of $m$ is 1 (lower than $n$). The value of $\text{max}_i \ e_{ij}$ is therefore 13 according to the second equation in Eq. (5). When there are 12 pixels, $n$ remains unchanged, $m = 3 = n$, and $\text{max}_i \ e_{ij} = 17$; When there are 13 pixels, $n$ remains unchanged, $m = 4 > n$ and $\text{max}_i \ e_{ij} = 18$. All the results are displayed in Fig. 3.

In practice, the size of the inscribed square of a landscape patch can be estimated by rounding down the square root of its area to the nearest integer. The value of $m$ can therefore be calculated by $2 \sqrt{A} - n$. The value of $\text{max}_i \ e_{ij}$ can be derived by $m$ and $n$ according to Eq. (5) and this eventually leads to the value of AI using Eqs. (4) and (2). The calculation process is as given in Fig. 4.

2) Improvement

Since the unity of opposites is the fundamental law of the universe, it is meaningless to discuss aggregation/disaggregation level of landscape patches without considering the spatial scale. [19] This principle will help to solve the problem displayed in Fig. 2.

Assuming the total area of a spatial unit (with landscape patches of a given class) is $A_0$ and the area of the maximum polygon, whose vertices connect the centers of all landscape patches of the same class in the spatial unit, is $A_1$, the difference between $A_0$ and $A_1$ is inversely proportional to the level of aggregation of the given landscape class in the spatial unit. That is, the difference approaches $A_0$ when the maximum level of aggregation is reached, but is 0 if the landscape patches are evenly distributed. A scaling coefficient $k$ is introduced to revise the value of AI as

$$k = \frac{A_0 - A_1}{A_0}, \quad (6)$$

where the value of $k$ is directly proportional to the level of aggregation but falls in the range between 0 and 1.

There are two exceptions to the value of $k$. When there is only one landscape patch in a spatial unit, $k = 1$. If the number of patches increases to two, the value of $k$ is equal to 1 minus the ratio of distance between the two patches over the length of the major axis of the spatial unit. Assuming the coordinates for the centers of $n$ ($n > 2$) patches are $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$, the calculation of $A_1$ is

$$A_1 = \frac{1}{2} \sum_{i=1}^{n-1} (x_i y_{i+1} - x_{i+1} y_i). \quad (7)$$

The revised aggregation index (AI-J) is

$$\text{AI-J} = k \times \text{AI}. \quad (8)$$

3 Results and analysis

3.1 Comparison of AI-J and AI operation results

We conducted a numerical test to compare the AI and AI-J of green landscape patches for 73 spatial units in Chengdu. The results are shown in Fig. 5.
Fig. 4 Calculation flow chart of AI (aggregation index), where \( n \) is the side length of inscribed square and \( m = A_i - n^2 \), in which \( A_i \) is the area of patch \( i \), and \( e_{ij} \) is the number of shared edges within class \( i \) and thus reflects its aggregation level.

Fig. 5 Comparison of AI-J (revised aggregation index) and AI (aggregation index) operation results

It is clear that AI-J reflects the different aggregation level of these green patches, while AI results are always around 1 due to large patch size.

3.2 AI-J verification

Since there is no absolute index to measure the aggregation level of landscape patches, intuitive analysis is often used to provide a reasonable estimate of the relative aggregation levels between different samples. This approach was adopted to estimate the relative aggregation level order of green patches within the 73 spatial units in the aforementioned example. The estimated result was then compared against those derived from the calculated AI and AI-J values.

Rules applied during the intuitive analysis process are:
1) Single patch has higher aggregation level than multiple ones;
2) Square shaped patch has higher aggregation level if there is only one patch in each spatial unit;
3) Clustered patches produce higher aggregation level than evenly distributed ones, while evenly distributed patches have higher aggregation level than peripheral ones;
4) Skip the unit if none of above rules applies.

The relative aggregation level order for 67 spatial units was determined through the intuitive analysis and numbered in ascending order. This was then compared against its counterparts derived from the calculated AI and AI-J values for the same group of spatial units as shown in Fig. 6.

It can be observed from Fig. 6 that the order derived from AI-J values closely matched that from the intuitive analysis with a high correlation coefficient of 0.995. On the contrary, the correlation coefficient between results from AI values and intuitive analysis is only 0.161. It demonstrates that AI-J is a much better representation of the aggregation level of landscape patches.

4 Conclusion

AI is an important index in landscape ecological research [4,12,13] but has certain limits. Its accuracy is variable under different spatial scales [8-9]. In addition to revise the logical limitation in original AI equation, we developed AI-J by introducing a scaling coefficient \( k \) to improve the accuracy of AI analysis result. Therefore, AI-J is not only able to provide more precise and reasonable results than CI and CI-Li as AI is, but also able to compare the aggregation level under different spatial scale. It has better performance than AI in reflecting the actual aggregation level of certain landscape class, which has been proved in our case study.
However, by adopting visual observation into this research, there is a risk that certain human factor may affect the result. Further research is required to test the reliability of AI-J in practice.

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References


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