Abstract: The thermodynamic landscape method is becoming a more popular approach for urban heat island research with the development of remote sensing technology. However, a limited amount of research discusses the theoretical and methodological issues of this method. This paper analyzed the reliability and stability of the results of thermal landscape pattern analysis with six different grading rules through surface temperature retrieval, landscape pattern analysis, and Geographic Information System (GIS) spatial analysis. The results demonstrate the following points. (1) The six grading methods can be categorized into two types: pixel number methods and temperature range methods. The grading results of the two kinds of methods lack comparability, whereas the grading results within one kind of method have high comparability. The temperature range methods have good consistency. The average value of the consistency indices (SI) of thermal landscape levels reaches up to 81.55%. The anomaly temperature method and standard deviation method are recommended for future research. (2) The grading rule significantly affects the stability of landscape indices, and its average variation coefficient reaches up to 22.36%. The authors suggest the use of landscape indices that have strong stability, such as shape index and landscape division index, in future research. (3) The results of the sensitivity analysis show that the change of the temperature range of thermal landscape levels affects landscape indices slightly, whereas the effect of the change of the level number of thermal landscapes on landscape indices is intense. The authors suggest categorizing the thermal landscape into six levels in future research in order to enhance the consistency and comparability among case studies.

Keywords: grading rule; sensitivity; stability; thermal landscape; Hangzhou
pattern of an urban thermal environment from the perspective of landscape ecology [14]. This method has gained significant interest since it was proposed. Meng et al. studied the thermal environment evolution in Beijing, Shanghai, and Guangzhou in the past decade with MOD11A2 and the MODIS land surface temperature (LST) night data and categorized the thermal landscape into five levels by using the equidistant division method [15]. Sun et al. analyzed the spatio-temporal changes of the urban thermal environment in Guangzhou by using a robust statistical grading method [16]; Liu et al. examined the seasonal variations in the relationship between landscape pattern and land surface temperature in Indianapolis, United States (USA) by categorizing the LST data with the standard deviation method [17]. Weng et al. assessed the effects of land use and land-cover patterns on thermal conditions using landscape metrics in Indianapolis, USA [18]. The promotion and improvement of the thermodynamic landscape method led to the transition of the traditional qualitative research of the thermal environment into the quantitative approach [19,20]. On the one hand, the levels, shapes, connectivity, distribution patterns, and other parameters of urban thermal landscape can be obtained by employing landscape ecology analysis, which provides more scientific information for urban planning and landscape design to alleviate UHI. On the other hand, the spatio-temporal evolution and the internal drive mechanism of UHIs can be analyzed by comparing the results of the thermal landscape analysis with that of the multi-temporal approach to gain a better understanding of the development and evolution path of the UHI effect [21].

Thermodynamic landscape analysis is a relatively new research area, and many related theoretical and methodological issues must be resolved. However, a limited amount of research discusses the internal mechanism issues, such as the reliability and stability of thermal landscape pattern analysis, and most studies in this area just employ this approach [22,23]. This research gap significantly reduces the credibility and comparability of the results of case studies and may also result in inaccurate conclusions. Thus, this paper attempts to discuss the effect of grading rule on the results of urban thermal landscape analysis and assess the reliability and stability of the results of thermal landscape pattern analysis to provide suggestions and basis for further research. The following questions are considered in this paper: (1) What are the effects of different grading rules on thermal landscape analysis? (2) What are the effects of the threshold values of thermal landscape levels on thermal landscape analysis with the same grading method? (3) What are the effects of the level number of thermal landscape on thermal landscape analysis with the same grading method? (4) What landscape indices are relatively stable and reliable despite having different grading rules?

2. Data and Method

2.1. Study Area

Hangzhou is the capital of Zhejiang Province, which is situated in the east coast of China. Hangzhou is located in a subtropical monsoon zone, and the city is hot and humid in the summer. Rapid urbanization contributes to the formation of the UHI and urban climate change in Hangzhou [24]. Data provided by China Meteorological Data Sharing Service System and the National Meteorological Information center indicate that Hangzhou has become one of the hottest cities in China in recent years. Determining ways to alleviate the UHI and improve the urban environment has become an important issue in Hangzhou.

2.2. Land Surface Temperature Data

In this study, a land surface temperature map of Hangzhou has been derived as a three-day average (27 July 2016; 28 August 2016; 27 May 2017) using Landsat 8 satellite images taken during hot summer days. The path/row numbers for these images are 119/39, the scene center latitudes are 30.31, and the scene center longitudes are 119.95. The generalized single-channel method was used for land surface temperature retrieval from Landsat 8 imagines [25,26]. MODIS Near-Infrared Total
Precipitable Water Product (MODIS 05) downloaded from the website of National Aeronautics and Space Administration (NASA) was used in the process of retrieval.

2.3. Grading Methods

(1) Equal pixel method. In this method, all of the pixels were sorted based on their surface temperature, and all of the pixels were graded with the same amount of pixels. For the grading result of this method, the area of each thermal landscape level is equal. In this study, 406,235 pixels exist in the study area, which were divided into six thermal levels. Thus, each level contains approximately 67,706 pixels.

(2) Equal temperature method. In this method, all of the pixels were sorted based on their surface temperature, and all of the pixels were graded with the same temperature range. For the grading result of this method, the temperature range of each thermal landscape level is equal. In this study, the lowest surface temperature is 17.5 °C, whereas the maximum temperature is 51.2 °C. We divided all of the pixels into six thermal levels. Thus, the temperature difference in each thermal landscape level is approximately 5.6 °C.

(3) Anomaly temperature method. In this method, the anomaly temperature of all of the pixels was calculated, and all of the pixels were graded with threshold values of \(-10 \, ^\circ\text{C}\), \(-5 \, ^\circ\text{C}\), \(0 \, ^\circ\text{C}\), 5 °C, and 10 °C. This method considers the average temperature as an important basis for grading and comparing thermal landscapes at different times and locations is easier when this method is employed.

(4) Shift average method. In this method, all of the pixels were sorted based on their surface temperature, and all of the pixels were categorized into five classes (the pixel number of each class is equal). The average temperature of each class was calculated. All of the pixels were graded into six levels by employing the five average temperatures, which were stated earlier as the five threshold values.

(5) Standard deviation method. This method considers the average value and standard deviation of all of the pixels as an important basis for grading. Its threshold values are calculated using the following formula: \(T_v = \text{Ave} \pm \text{SD}\); where \(T_v\) are the threshold values of different grades, Ave is the average temperature of all of the pixels, and SD is the standard deviation of all of the pixels. In this study, the average temperature of all of the pixels is 34.09 °C, and the standard deviation is 4.80 °C. Thus, the threshold values in this study were 24.49 °C, 29.29 °C, 34.09 °C, 38.89 °C, and 43.69 °C.

(6) Natural breakpoint method. Some points, such as natural turning points, feature points, and breaking points, exist in every statistical series. These points could be determined by utilizing a frequency histogram and gradient graph. The points are used as the threshold values in the grading process. This method is the preferred spatial data classification and coloring method in Arcgis. The threshold values of each thermal landscape level can be obtained by using Arcgis 10.0 °C; these threshold values are 29.43 °C, 30.92 °C, 32.93 °C, 35.53 °C and 39.08 °C.

2.4. Thermal Landscape Analysis

In this study, the average value, standard deviation, number of pixels, and other statistical parameters of each grading result by Arcgis 10.0 °C were obtained. The thermal landscape indices of each grading result by Frag stats 4.2 °C were calculated.

3. Comparison of Grading Method

3.1. Grading Results

Figure 1 shows that the grading method affects the grading result of the thermal landscape significantly. The six grading methods can be easily categorized into two types. One type is the grading methods, which are based on the number of pixels, including the equal pixel method, shift average method, and natural breakpoint method; these methods are called the pixel number methods. The other type is grading methods, which are based on temperature range, and include the equal temperature
method, anomaly temperature method, and standard deviation method; these methods are called temperature range methods. The two types of methods differ significantly in terms of the value range of each thermal landscape level (Table 1), whereas the differences in each kind of method are lower.

![Grading results of the thermal landscape in Hangzhou by different grading methods.](image)

**Figure 1.** Grading results of the thermal landscape in Hangzhou by different grading methods.
Table 1. Range sets of each level under different grading methods.

| Grading Method       | Level 1       | Level 2       | Level 3       | Level 4       | Level 5       | Level 6       |
|----------------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Equal pixel          | 17.50–30.24   | 30.24–31.99   | 31.99–33.74   | 33.74–35.64   | 35.64–38.52   | 38.52–51.20   |
| Shift average        | 17.50–27.93   | 27.93–31.66   | 31.66–33.72   | 33.72–36.16   | 36.17–40.98   | 40.98–51.20   |
| Natural breakpoint   | 17.50–29.43   | 29.43–30.92   | 30.92–32.93   | 32.93–35.53   | 35.53–39.08   | 39.08–51.20   |
| Equal temperature    | 17.50–23.07   | 23.23–28.70   | 28.70–34.30   | 34.30–39.90   | 39.90–45.50   | 45.50–51.20   |
| Anomaly temperature  | 17.50–24.02   | 24.12–29.09   | 29.09–34.09   | 34.09–39.09   | 39.09–44.09   | 44.09–51.20   |
| Standard deviation   | 17.50–24.45   | 24.53–29.29   | 29.29–34.09   | 34.09–38.89   | 38.89–43.69   | 43.69–51.20   |

3.2. Statistical Feature

The average value, standard deviation, and other statistical parameters of each grading result by Arcgis 10.0 are obtained to discuss the differences of spatial statistical features under the grading methods. Figure 2 indicates that significant differences exist in the average temperature among the six grading methods. (1) First, the largest deviation in the average temperature among the six grading results ranges from 1.12 °C to 7.23 °C; (2) Second, evident differences were observed among the thermal levels. The deviations of the side levels (levels 1 and 6) are higher, whereas those of the middle levels (levels 3 and 4) are lower.

Figure 2. Average surface temperature of each thermal level by different grading methods.

The standard deviation of samples within the levels should be as small as possible based on the principle of clustering [27,28]. Figure 3 shows that significant differences also exist in the standard deviation among the six grading methods. Thus, the pixel number methods and the temperature range methods can be distinguished easily. Generally, the grading results of the temperature range methods are better than those of the pixel number methods.
3.3. Consistency

A consistency index ($S_i$) was defined to discuss the consistency of the six grading results. The formula of $S_i$ is as follows:

$$S_i = \frac{P_i}{m_i}$$  \hspace{1cm} (1)

where $S_i$ is the consistency index of thermal level $i$; $P_i$ is the pixel number that belongs to level $i$ in all six grading results; and $m_i$ is the average pixel number of level $i$ in the six grading results. The $S_i$ of the six grading methods, pixel number methods (including the equal pixel method, shift average method, and natural breakpoint method) and temperature range methods (including equal temperature method, anomaly temperature method, and standard deviation method) were computed. The following results were obtained:

Figure 4 indicates that temperature range methods have the best consistency, and the average consistency index $S_{\text{average}}$ of all six thermal levels is as high as 81.55%. This result demonstrated that the grading results of the three grading methods have higher stability and consistency based on the temperature range. Meanwhile, the other three grading methods, which are based on the pixel number, have lower stability and consistency. The consistency of all six grading methods is the worst, which indicated that significant differences exist between the two types of grading methods. Those differences likely affect the results of thermal landscape analysis, and lead to the incomparability of the different case studies.
Figure 4. Consistency indices of the grading results.

Figure 5 indicates that the spatial distribution of the thermal landscapes with an unchanged level in the six grading methods is scattered. Qian Tang River is the only ground feature that can be identified clearly, and the typical cold island (for example, urban wetlands such as West Lake and Xixi) and heat island (built-up area) were not lumped, which indicated that the inconsistency of the grading rules will affect urban thermal landscape analysis significantly.

3.4. Landscape Index

In this section, the landscape indices of thermal landscape patterns are calculated, which were obtained from six grading methods using Fragstats 4.2, and the effects of the grading rules on thermal landscape pattern analysis are discussed.

On the basis of the division standard of confidence level, which is commonly used in statistics, these landscape indices were divided into four groups by the variation coefficients (CV) of six grading
methods, namely: highly stable (CV < 5%), stable (5% < CV < 10%), unstable (10% < CV < 20%), and highly unstable (CV > 20%). Table 2 illustrates the following points. (1) A significant difference exists among landscape indices, which were calculated using the six grading results. The number of highly unstable (CV > 20%) landscape indices is up to 10, which is substantially higher than that of the pixel number methods and temperature range methods. These results indicate that the findings of two case studies are completely incomparable when the pixel number methods and temperature range methods are adopted to categorize the thermal levels. However, when the case studies employ both pixel number methods and temperature range methods, their comparability increased significantly; as did the numbers of highly stable (CV < 5%) landscape indices increased to 14 and 12, respectively. (2) Significant correlations were found among the three CV groups, which were significantly calculated using the six grading methods, pixel number methods, and temperature range methods. The Pearson correlation coefficients obtained by using all of the approaches are above 0.9. These results demonstrate that the stability of each landscape index is consistent, such that some landscape indices perform stably under any grading rules, and vice versa. Thus, landscape indices, which have higher stability, should be adopted in future research to increase the reliability and consistency of the results of the thermal landscape pattern analysis. Specifically, some landscape indices, such as Mean patch shape index (SHAPE_MN), Mean patch fractal dimension (FRAC_MN), Perimeter area ratio distribution (PARA_MN), Patch cohesion index (COHESION) and Landscape division index (DIVISION), have a higher stability and should be preferred, whereas other landscape indices, including Patch density (PD), Largest patch index (LPI), Mean patch area (AREA_MN), Effective mesh size (MESH), and Splitting index (SPLIT), are not recommended. Particularly, the CVs of Effective mesh size (MESH) and Splitting index (SPLIT) are more than 80%. Thus, the two landscape indices should be avoided in analyzing thermal landscape patterns.

| No. | Landscape Indices                      | Code  | Six Grading Methods | Temperature Range Methods | Pixel Number Methods |
|-----|---------------------------------------|-------|---------------------|---------------------------|----------------------|
| 1   | Patch density                         | PD    | 48.23%              | 8.62%                     | 20.10%               |
| 2   | Largest patch index                   | LPI   | 41.68%              | 15.48%                    | 12.77%               |
| 3   | Landscape shape index                 | LSI   | 23.19%              | 6.45%                     | 6.32%                |
| 4   | Mean patch area                       | AREA_MN | 45.03% | 9.02% | 18.54% |
| 5   | Mean patch shape index                | SHAPE_MN | 2.48% | 0.63% | 0.60% |
| 6   | Mean patch fractal dimension          | FRAC_MN | 0.35% | 0.05% | 0.06% |
| 7   | Perimeter area ratio distribution     | PARA_MN | 2.38% | 0.46% | 1.27% |
| 8   | Contiguity index distribution         | CONTIG_MN | 7.23% | 1.26% | 4.28% |
| 9   | Perimeter area ratio dimension        | PAFRAC | 3.01% | 0.47% | 0.84% |
| 10  | Mean Euclidean nearest neighbor distance distribution | ENN_MN | 12.73% | 1.66% | 3.92% |
| 11  | Contagion                             | CONTAG | 34.73% | 7.29% | 13.98% |
| 12  | Percentage of similar adjacencies     | PLADJ | 11.66% | 2.34% | 4.27% |
| 13  | Interspersion and juxtaposition index | IJI   | 21.14% | 5.79% | 7.19% |
| 14  | Patch cohesion index                  | COHESION | 2.63% | 0.18% | 2.04% |
| 15  | Landscape division index              | DIVISION | 2.11% | 1.15% | 0.21% |
| 16  | Effective mesh size                   | MESH   | 83.53%              | 26.02%                    | 29.77%               |
| 17  | Splitting index                       | SPLIT  | 83.70%              | 22.90%                    | 25.82%               |
| 18  | Shannon’s diversity index             | SHDI   | 15.26%              | 5.39%                     | 3.32%                |
| 19  | Simpson’s diversity index             | SIDI   | 10.95%              | 3.75%                     | 1.98%                |
| 20  | Modified Simpson’s diversity index    | MSIDI  | 23.34%              | 6.84%                     | 5.19%                |
| 21  | Shannon’s evenness index              | SHEI   | 15.26%              | 5.39%                     | 3.32%                |
| 22  | Simpson’s evenness index              | SEI    | 10.96%              | 3.76%                     | 1.98%                |
| 23  | Modified Simpson’s evenness index     | MSSEI  | 23.34%              | 6.83%                     | 5.19%                |
| 24  | Aggregation index                     | AI     | 11.63%              | 2.33%                     | 4.27%                |
|     | Mean value                            |        | 22.36%              | 6.00%                     | 7.38%                |

Note: The formula and ecological meaning of each landscape index are indicated in the help files of Fragstats 4.2.

4. Sensitivity Analysis

The anomaly temperature method has the best reliability and consistency among the six grading methods on the basis of the above comparison. Thus, this section will discuss the effects of the changes in thermal level number and temperature range in thermal levels on the results of thermal landscape pattern analysis based on the anomaly temperature method.
4.1. Temperature Range Change

In this section, we discuss the sensitivity of the landscape indices on the temperature range setting in thermal levels by increasing and decreasing the temperature range of each thermal level by 1 °C (Table 3).

Table 3. Three temperature range settings of thermal landscape levels.

| Range Setting | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 | Level 6 |
|---------------|---------|---------|---------|---------|---------|---------|
| Turn up 1 °C  | <−9     | −9−(−4) | −4−1    | 1−6     | 6−11    | >11     |
| Base range    | <−10    | −10−(−5)| −5−0    | 0−5     | 5−10    | >10     |
| Turn down 1 °C| <−11    | −11−(−6)| −6−(−1)| −1−4    | 4−9     | >9      |

The grading maps of the thermal landscape in Hangzhou under three setting circumstances were determined by using Arcgis (Figure 6). From a qualitative point of view, the change of temperature range affects the thermal landscape pattern, although the effects are not evident.

To quantify the effects of changes in the temperature range on thermal landscape pattern analysis, the thermal landscape indices in the three setting circumstances were calculated by using Fragstats 4.2. The variation was determined when the temperature was increased or decreased by 1 °C.

Figure 7 illustrates the following points. (1) The altered trend of the landscape index is similar when the temperature range was increased or decreased by 1 °C. Its Pearson correlation coefficient is as high as 0.9922. This result indicated that the direction of the temperature range variation (increase or decrease) affects the thermal landscape index slightly. (2) Generally, the effects of the variation of temperature range on thermal landscape indices are not significant. The variations of some landscape indices are unusually large, such as that of Largest patch index (LPI), Effective mesh size (MESH) and Splitting index (SPLIT) (Table 4). Thus, these landscape indices should not be used in future research.
Figure 7. Effects of the changes of temperature range of thermal levels on landscape indices. Variation = (I_a − I_base)/I_base × 100%, where I_base is the thermal landscape index calculated with base range, and I_a is the thermal landscape index calculated with changed temperature range (increased by 1 °C).

Table 4. Changes of thermal landscape indices under three setting circumstances.

| Landscape Indices                  | Code     | Turn Up 1 °C | Base Range | Turn Down 1 °C | CV |
|-----------------------------------|----------|--------------|------------|----------------|----|
| Patch density                     | PD       | 3.75         | 3.85       | 3.69           | 2.20% |
| Largest patch index               | LI       | 17.28        | 10.74      | 18.64          | 27.17% |
| Landscape shape index             | LS       | 87.66        | 86.87      | 83.33          | 2.68% |
| Mean patch area                   | AREA_MN  | 26.63        | 25.96      | 27.12          | 2.20% |
| Mean patch shape index            | SHAPE_MN | 1.31         | 1.31       | 1.30           | 0.33% |
| Mean patch fractal dimension      | FRAC_MN  | 1.04         | 1.04       | 1.04           | 0.02% |
| Perimeter area ratio distribution  | PARA_MN  | 333.57       | 333.97     | 332.93         | 0.16% |
| Contiguity index distribution     | CONTIG_MN| 0.22         | 0.22       | 0.22           | 0.34% |
| Perimeter area fractional dimension| PAFRAC  | 1.50         | 1.50       | 1.49           | 0.22% |

Mean Euclidean nearest neighbor distance distribution | ENN_MN | 308.97 | 307.04 | 309.55 | 0.43% |

Percentage of similar adjacencies | PLAD$|$ | 72.85 | 73.10 | 74.21 | 0.99% |

Interspersion and juxtaposition index | JI | 50.63 | 50.59 | 48.86 | 2.02% |

Patch cohesion index | COHESION | 99.04 | 98.80 | 99.07 | 0.15% |

Landscape division index | DIVISION | 0.94 | 0.96 | 0.94 | 1.24% |

Effective mesh size | MESH | 18,719.15 | 12,223.13 | 19,125.87 | 23.21% |

Simplicity index | SPLIT | 17.58 | 26.92 | 17.20 | 26.76% |

Shannon’s diversity index | SHDI | 1.37 | 1.34 | 1.33 | 1.59% |

Simplicity’s diversity index | SIDI | 0.69 | 0.68 | 0.68 | 0.71% |

McDonnell’s diversity index | MSIDI | 1.17 | 1.14 | 1.15 | 1.33% |

Shannon’s evenness index | SHEI | 0.77 | 0.75 | 0.74 | 1.59% |

Simplicity’s evenness index | SIEI | 0.83 | 0.81 | 0.82 | 0.71% |

McDonnell’s evenness index | MSIEI | 0.65 | 0.63 | 0.64 | 1.33% |

Aggregation index | AI | 73.09 | 73.34 | 74.45 | 0.98% |

Note: The formula and ecological meaning of each landscape index are indicated in the help files of Fragstats 4.2.

4.2. Level Number Change

In this section, the sensitivity of the landscape indices on the thermal level number change at five, six, and seven thermal levels is discussed (Table 5). The base grading method is also the anomaly temperature method.

Table 5. Thermal level number setting and the temperature range of each level.

| Level Number | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 | Level 6 | Level 7 |
|--------------|---------|---------|---------|---------|---------|---------|---------|
| Five levels (°C) | ≤−9 | −9→−3 | −3→−3 | 3→−9 | >9 | – | – |
| Six levels (°C) | ≤−10 | −10→−5 | −5→−0 | 0→5 | 5→10 | >10 | – |
| Seven levels (°C) | ≤−10 | −10→−6 | −6→−2 | −2→2 | 2→6 | 6→10 | >10 |
The grading maps of the thermal landscape in Hangzhou under three setting circumstances were obtained using Arcgis (Figure 8). From a qualitative point of view, the change of the number of thermal level has a more significant effect on the thermal landscape pattern than the change in temperature range. Figure 8 indicates that the thermal landscape pattern with seven thermal levels could exhibit a more exquisite and accurate thermal environment than the other five thermal levels.

![Grading maps of the thermal landscape in Hangzhou with different numbers of levels.](image)

**Figure 8.** Grading maps of the thermal landscape in Hangzhou with different numbers of levels.

To quantify the effects of the changes of thermal level number on thermal landscape pattern analysis, the thermal landscape indices in three setting circumstances were calculated by using Fragstats 4.2. As is shown in Table 6, the variations of some landscape indices are unusually large, such as that of LPI, MESH, SPLIT, and PD. It is worth noting that LPI, MESH, and SPLIT are unstable in Section 4.1 too, which further confirmed that these landscape indices should not be used in future research.
Table 6. Changes of thermal landscape indices under different setting circumstances. CV: variation coefficient.

| Landscape Indices               | Code   | Five Levels | Six Levels | Seven Levels | CV  |
|--------------------------------|--------|-------------|------------|--------------|-----|
| Patch density                  | PD     | 3.10        | 3.85       | 5.16         | 25.79% |
| Largest patch index            | LPI    | 26.50       | 10.74      | 14.80        | 47.18% |
| Landscape shape index          | LSI    | 72.95       | 86.87      | 102.38       | 16.84% |
| Mean patch area                | AREA-MN| 32.26       | 25.96      | 19.39        | 24.87% |
| Mean patch shape index         | SHAPE-MN| 1.27       | 1.31       | 1.34         | 2.45% |
| Mean patch fractal dimension   | FRAC-MN| 1.04        | 1.04       | 1.04         | 0.28% |
| Perimeter area ratio distribution | PARA-MN | 335.07 | 333.97 | 338.70 | 0.74% |
| Contiguity index distribution  | CONTIG-MN| 0.22       | 0.22       | 0.21         | 2.16% |
| Perimeter area fractal dimension | PAFRAC | 1.47        | 1.50       | 1.54         | 2.18% |
| Mean Euclidean nearest neighbor distance distribution | ENN-MN | 312.48 | 307.04 | 293.38 | 3.23% |
| Contagion                      | CONTAG | 42.04       | 41.99      | 38.82        | 4.50% |
| Percentage of similar adjacencies | PLADJ  | 77.46       | 73.10      | 68.23        | 6.34% |
| Interspersion and juxtaposition index | IJI     | 49.76       | 50.59      | 53.94        | 4.30% |
| Patch cohesion index           | COHESION| 99.92       | 98.80      | 98.49        | 0.40% |
| Landscape division index       | DIVISION| 0.90        | 0.96       | 0.97         | 3.78% |
| Effective mesh size            | MESH   | 31,788.80   | 12,223.13  | 10,788.16    | 64.23% |
| Splitting index                | SPLIT  | 10.35       | 26.92      | 30.50        | 47.59% |
| Shannon’s diversity index      | SHDI   | 1.22        | 1.34       | 1.54         | 11.52% |
| Simpson’s diversity index      | SIDI   | 0.64        | 0.68       | 0.74         | 7.34% |
| Modified Simpson’s diversity index | MSIDI  | 1.03       | 1.14       | 1.36         | 14.22% |
| Shannon’s evenness index       | SHEI   | 0.76        | 0.75       | 0.79         | 2.67% |
| Simpson’s evenness index       | SIEI   | 0.80        | 0.81       | 0.87         | 4.04% |
| Modified Simpson’s evenness index | MSEI   | 0.64       | 0.63       | 0.70         | 5.34% |
| Aggregation index              | AI     | 77.71       | 73.34      | 68.48        | 6.31% |

Note: The formula and ecological meaning of each landscape index are indicated in the help files of Fragstats 4.2.

In addition, we calculated the variation of five or seven thermal levels with the six thermal levels. Figure 9 illustrates the following points. (1) The altered trend of landscape indices is not similar when five and seven thermal levels are adopted, and its Pearson correlation coefficient is only $-0.0119$. This result indicated that the direction of the changes in the thermal level number (increase or decrease) affects the thermal landscape indices significantly, unlike the effects of changes in temperature range. (2) Generally, the effects of the changes in the number of thermal level on thermal landscape indices are greater than those of the changes in temperature range. The variation of the five thermal levels is higher than that of the seven thermal levels. Additional research is needed to confirm whether the effects of the changes in thermal level number on thermal landscape indices will converge with the decrease of thermal level number.

Figure 9. Effects of the changes in the thermal level number on landscape indices. Note: Variation = $(I_i - I_6)/I_6 \times 100\%$, $I_6$ is the thermal landscape index calculated with the six thermal levels; $I_i$ is the thermal landscape index calculated with five or seven thermal levels.
5. Discussion

5.1. Implications

The landscape pattern analysis method is widely used in research on land use or cover change [29,30]. The similarities and differences between thermal landscape levels and land cover types must be discussed before introducing the landscape pattern analysis method in the research of urban thermal environments. (1) Similarities: Many studies determined that some land cover types, such as forests, grasslands, and rivers, exhibit apparent negative correlativity with UHI intensity, whereas other land cover types, including paved roads and buildings, show apparent positive correlativity with UHI intensity [31,32]. Thus, the spatial distribution pattern and temporal evolution between thermal landscape levels and land cover types often appear similar [33]. Analyzing the temporal–spatial evolution pattern of thermal landscape levels by using landscape pattern analysis is rational and feasible from this perspective. (2) Differences: The first difference is the classification or grading feature. Land cover types have multi-dimensional classification features, such as vegetation coverage, humidity, impervious surface coverage, and altitude. Many remote sensing classification methods were developed based on the multi-dimensional classification features of land cover types, and the classification accuracy of some methods is as high as 90% [34]. However, thermal landscape levels have only a one-dimensional feature, and surface temperature is the only basis for categorizing the thermal level. Thus, assessing the grading accuracy of thermal levels is difficult. Grading accuracy may not even exist. The second difference is the type or level border. Land cover types are well defined. Thus, the boundaries between land cover types are relatively clear, particularly in urban areas, which have many traces of artificial construction. However, the boundaries of thermal levels are difficult to define clearly. For example, proving that using 35 °C is more accurate than using 36 °C as the lower bound of the high-temperature zone is difficult. It is also a difficult task to verify that dividing the thermal landscape into seven levels will be more accurate than dividing the thermal landscape into six levels. The third difference is the type or level of stability. The main driving force of changes in land cover is human activity in the city area [35]. Changes in land cover usually occur for a long time, and the change frequency is relatively low. However, unlike land cover change, thermal landscape changes are dramatically affected by natural factors, such as weather conditions and seasonal and circadian replacement. Thus, the changes in frequency are significantly faster than in land cover types. Studies have shown that urban wetland appeared as a cold island during the day and a heat island in the evening [36]. This result demonstrated that the stability of the thermal level is far below that of the land cover type.

Thus, thermal landscape levels and land cover types are connected, but their differences are significant. Compared with the grading process of the land cover type, the grading process of the thermal level is more susceptible to a researcher’s subjective judgment, which is evident in research on urban thermal landscapes. The grading method and grading criteria of the thermal landscape are often parallel with different case studies. (1) Level number: Studies differ substantially. The lowest level number of the thermal landscape is three [16], the maximum is 12 [37], and most of the level numbers ranged from five to seven. (2) Grading method: Various grading methods were presented in previous studies, such as the equal temperature method [15], anomaly temperature method [37], standard deviation method [16], and natural breakpoint method [38]. (3) The threshold value of thermal levels in various studies differ significantly. Similar studies that use the same grading method have inconsistent threshold values [17].

The inconsistencies and irregularities in the research process of the UHI effect often result in a lack of comparability among studies and reduce the credibility of research results [39]. This paper discussed the effects of grading rules on the results of thermal landscape analysis from many aspects, such as the number and temperature range of the thermal landscape level and the stability and reliability of thermal landscape indices. These results could provide an important basis and suggestions for further research and help improve the method of analyzing thermal landscape patterns.
5.2. Limitations and Prospect

(1) This study was carried out based on remote sensing images with a single location and sensor. Additional studies with multi-temporal and multi-source remote sensing images in different regions are needed to verify the findings of this paper.

(2) As mentioned earlier, the thermal landscape has only a one-dimensional feature for its classification. Thus, assessing the classification accuracy of thermal landscape levels and determining the number of thermal levels that obtain better results are difficult. Therefore, this paper was focused on the differences among the results of thermal landscape pattern analysis obtained by using different grading methods. Determining a reasonable and objective assessment standard for grading thermal landscape is a key issue that needs to be addressed in follow-up research.

6. Conclusions

6.1. Effects of Grading Methods

(1) The difference among grading methods. Six grading methods can be categorized into two types: the pixel number methods, which include the equal pixel method, shift average method, and natural breakpoint method, and the temperature range methods, such as the equal temperature method, anomaly temperature method, and standard deviation method. The two types of methods differ substantially, whereas the difference in each kind of method is lower. Generally, the grading results of the temperature range methods are better than those of the pixel number methods.

(2) The consistency of grading results. The consistency of the temperature range methods is the best; its average consistency index $S_i$ in all of the thermal landscape levels is 81.55%. However, the average consistency index $S_i$ of the six grading methods is only 20.90%, which indicated that the two types of grading methods differ significantly. Those differences likely affect the results of thermal landscape analysis, and lead to the incomparability of different case studies.

(3) The stability of landscape indices. Landscape indices, which were calculated by the grading results of six methods, are highly different. The differences in stability among landscape indices are also substantial. To increase the reliability and consistency of the results of the thermal landscape pattern analysis, the landscape indices, which are highly stable, must be chosen in future research.

6.2. Sensitivity Analyses

(1) The sensitivity of the changes in temperature range. Generally, the effects of variations in temperature range (including direction and amplitude) on thermal landscape indices are not significant. The variations of some landscape indices are unusually large, such as that of LPI, MESH, and SPLIT. Thus, these landscape indices should not be adopted in future research.

(2) The sensitivity of the changes in thermal level number. Generally, the effects of the changes in the thermal level number on thermal landscape indices are greater than those of the changes in temperature range. The variation value of seven thermal levels is greater than that of five thermal levels. To increase the consistency and comparability among the results of the thermal landscape analysis of different case studies, the thermal landscape must be divided into six levels in future research, which is consistent with the findings of most previous studies.

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