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Relationships between the Visual Quality and Color Patterns: Study in Peri-Urban Forests Dominated by *Cotinus coggygria* var. *cinerea* Engl. in Autumn in Beijing, China

Yujuan Cao, Yanming Li, Xinyu Li *, Xing Wang, Ziyun Dai, Minjie Duan, Rui Xu, Songting Zhao, Xiuping Liu, Jiale Li and Junfei Xie

Beijing Key Laboratory of Ecological Function Assessment and Regulation Technology of Green Space, Beijing Urban Ecosystem Positioning Observation and Research Station, Beijing Academy of Forestry and Landscape Architecture, Beijing 100102, China
* Correspondence: lxy09618@163.com; Tel.: +86-010-6473-5225

Abstract: The spatial pattern of color patches plays a crucial role in affecting the visual quality of peri-urban forests dominated by *Cotinus coggygria* var. *cinerea* Engl. in autumn. The impact mechanism has been studied to facilitate algorithm-based automatic visual quality estimation. The color patterns of 120 photographs were calculated after color quantization and automatic color substitution. The scenic beauty of the forest was estimated by 698 respondents. Multiple correlations between visual quality and color pattern metrics were explored with stepwise regression. Principal component analysis (PCA) was also employed to investigate the impact mechanism of color patterns on visual quality. Number of patches (NP), largest patch index (LPI), mean patch area (AREA_MN), patch size standard deviation (AREA_SD), and Shannon's evenness index (SHEI) were the main factors affecting the visual quality of the *Cotinus coggygria* forest. AREA_MN correlated positively with visual quality, while NP, LPI, AREA_SD, and SHEI correlated negatively. Moreover, AREA_SD had the most significant impact on the visual quality of the landscape, while SHEI, LPI, and AREA_MN had the second-highest impact. The evenness and the size of color patches significantly affected the visual quality of the forest landscapes. Balancing the diversity and evenness of color patches plays a decisive role in creating a forest landscape with high visual quality.

Keywords: aesthetic preference; color patch; spatial pattern; visual perception; urban forestry

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1. Introduction

The living environment has to face urgent challenges with global urbanization, and the life-quality of urban residents has been declining with the city population increasing yearly [1]. Peri-urban forests near cities are becoming necessary for people to experience nature due to the satisfactory ecological conditions, excellent recreational facilities, and beautiful scenery. It has become an effective way to meet the residents' urgent demand to enjoy ecological products and handle the living environment crisis [2]. As cities expand, peri-urban forests draw close to the city's edge, and townspeople could easily see it from a distance. Due to difficulty in identifying details such as tree shapes, peri-urban forests are typically presented as a whole picture. Improving the scenic quality of forests viewed from intermediate distances is, therefore, of the most significant interest for recreational development in peri-urban forests.

Leaves of autumn-color trees turn yellow, red, or orange from September to October in China, and the red autumnal leaves become bright spots in peri-urban forests. As the most visually striking feature, color produces about four times the intensity of visual stimulation than other elements, such as texture [3] and has a significant bearing on the scenic beauty. In recent decades, the colors of urban forest landscapes have been explored from several perspectives. The color of the leaves of most trees in Sweden was determined by the NCS (natural color system) [4], and coleus plants suitable for different areas were listed, which made a valuable reference for improving the visual quality of urban forest landscapes. Serpa and Muhar [5] analyzed the relationship between colors and residents' perceptions of the scenic quality of the trees in urban parks. Lev-Yadun et al. [6] revealed the correlation between the leaf color of trees in spring and autumn after conducting a comparative analysis of forest communities in Finland, Japan, and Israel. Through field investigation and in-depth interviews, Hoyle et al. [7] found that the aesthetic preference reached the highest level when the coverage rate of coleus plants in urban public spaces exceeded the critical threshold of 27%. Mu et al. [8] proposed a method to improve the visual quality by optimizing tree species configuration after investigating the relationship between visual quality and percentage of hue of natural slope forests.

In mixed coniferous forests, trees of different species are planted next to each other. As the spatial position of trees varies, resulting in a variety of color patterns, the visual quality of different color patterns varies considerably when the color ratios are the same [9]. However, the relationship between color patterns and visual quality has barely been studied, and little mature theory or method to improve the visual quality of established peri-urban forest parks has been developed yet.

Beijing, the capital of China, is a typical international metropolis with a resident population of 21,886,000 at the end of 2021. In the past 20 years, the Beijing government has proposed a series of policies to increase the planting area of coleus plants in peri-urban forests. The Mountain Beautification Project was proposed by the Beijing Government and the Capital Afforestation Commission in 2002, which accelerated the planting of coleus plants on mountain road sides, scenic spots and other places in the city, to expand the area of red autumnal leaf scenery before the 2008 Beijing Olympic Games. The scientific and technological innovation project of "color enhancement and green extension" plans to promote more than 80 new species and build a livable city of "colorful in three seasons and evergreen in four seasons" from 2015 to 2022. However, the lack of mature and targeted scientific management techniques after afforestation and the mismatch of tree species, color, and mingling intensity considerably reduces the scenic beauty [10–13]. After extensive planting practices, *Cotinus coggygria* has become a rational autumn color tree species in Beijing. Red, orange, yellow, and green become the prominent hues in an autumn forest landscape and keep relatively stable.

The typical peri-urban forests dominated by *Cotinus coggygria* in Beijing, China, were studied. Moreover, the forest landscape's color patterns and visual quality were comprehensively analyzed. In the study, we focused on solving the following problems:

1. To solve the low efficiency and poor stability of manual visual interpretation of color patches, an automatic and rapid method for calculating the spatial color pattern of extensive peri-urban forests was explored.
2. To study the correlation between spatial color patterns and visual quality of peri-urban forests and provide theoretical support for optimizing forest management strategies.
3. To analyze the possibility of improving the aesthetic quality by changing the spatial color pattern of peri-urban forests through planting and replanting trees on a small scale.

The visual quality of peri-urban forests is affected by various factors, and only spatial color patterns were investigated in this study. To avoid interference by additional factors, we based the research on the following three fundamental assumptions:

4. In the established urban forest park, adjusting the spatial color pattern through replanting trees on a large scale would be resource-intensive, which would not be accepted by forest managers.
5. The autumnal leaves were dominated by colors such as red, yellow, green, and gray. Moreover, only a tiny fraction of new colors could be seen.
6. During the normal evolution of urban forests, birth, aging, illness, and death of trees make much-needed space for planting and replanting some current tree species.

2. Materials and Methods

2.1. Study Area

The study was conducted in Beijing (40°20′46.01″ N, 116°0′52.20″ E), a typical urbanized metropolis located in northern China, with a total area of 16,410,54 hectares. The terrain in Beijing is elevated in the northwest and low in the southeast, with an average altitude of 43.5 m. The mountainous area with an altitude between 1000 m and 1500 m accounts for 62% of the total area, and the plain with an altitude between 20 m and 60 m accounts for 38%. Beijing experiences a continental monsoon climate zone with semi-humid and warm temperate climates. Compared with areas on the same latitude, the temperature in summer is higher, and in winter, it is lower. A mean 12.3 °C annual temperature occurs with a 160-day frost-free period and 572 mm average annual precipitation, mainly concentrated from June to August.

Cotinus coggygria var. *cinerea* Engl. is a short deciduous tree of *Cotinus* in the family Anacardiaceae. It is light-loving (mainly planted on sunny or semi-sunny slopes), cold-tolerant, drought-resistant, tolerant of infertile and alkaline soils, and not tolerant of water and moisture [14,15]. With branching and stemming habits and low branching points, it is an ideal autumnal color tree species for landscape planting in northern and southwestern China. In late autumn, the leaves of *Cotinus coggygria* shift from green to red, which are bright and eye-catching. Therefore, spatial color pattern plays a dominant role in affecting the scenic quality of the *Cotinus coggygria* forest.

Consistent with the growth habit, most *Cotinus coggygria* are planted in high terrain areas in Beijing. Only a few sites are located in southeastern Beijing where the terrain is gentler. Mixed with conifer and broadleaves, most *Cotinus coggygria* were planted in the 1960s and 1970s, and some have been replanted in recent years. The 1966 ~ 1970 Urban Greening Plan formulated by the Beijing Landscape Bureau proposed to plant trees in order to achieve universal urban greening in 4~5 years, "from the need of war preparedness, rectify the needs of the city appearance, and increase the needs of production". In 1974, the Beijing Landscape Bureau proposed to carry out greening adjustment according to the principle of "combining deciduous trees with evergreen trees, combining arbors with shrubs, combining fast-growing trees with slow-growing trees, and combining gardens with production", and began to renew roadside trees [16]. Red dots in Figure 1 represent the sites where *Cotinus coggygria* trees were planted (Table 1).

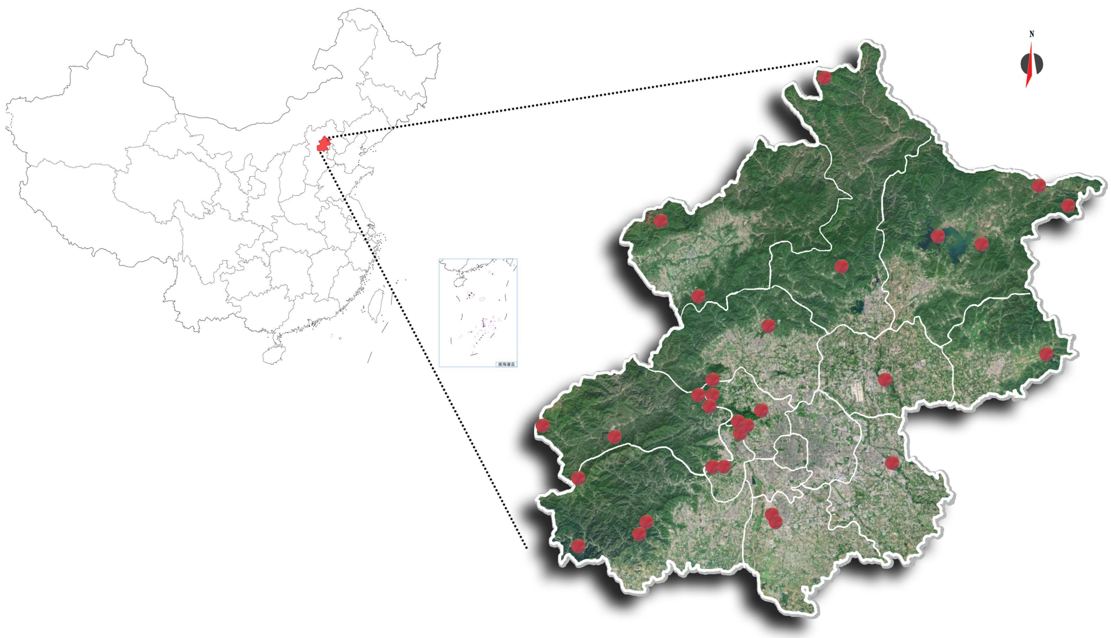


Figure 1. Relief map of Beijing. Red dots represent the sites where *Cotinus coggygria* var. *cinerea* Engl. were planted.

Table 1. Main sites to plant *Cotinus coggygria* var. *cinerea* Engl. forest in Beijing.

Municipal District	Distribution Location	Municipal District	Distribution Location
Haidian District	Xiangshan Park Xishan National Forest Park Yangtaishan Natural Scenic Area	Fangshan District	Youlanshan Pofengling Scenic Area Shangfangshan National Forest Park Shidu Scenic Area
	Fenghuangling Natural Scenic Area Baiwangshan Forest Park	Yanqing District	Badaling National Forest Park Yudushan Scenic Area
	Jiufeng National Forest Park	Daxing District	Daxing New City Riverside Forest Park
Miyun District	Yunxiugu Hunting Natural Scenic Area		Niantan Park
	Miyun Reservoir Bailongtan Natural Scenic Area	Huairou District	Mutianyu Section of the Great Wall Labagou Original Forest Scenic Area
	Simatai Great Wall	Fengtai District	Beigong National Forest Park
Mentougou District	Shuanglongxia Scenic Area		Qianlingshan Scenic Area
	Xiaolongmen National Forest Park	Changping District	Mangshan National Forest Park
	Baihuashan National Nature Reserve	Pinggu District	Jinhaihu Scenic Area
	Miaofengshan Forest Park	Shunyi District	Gongqing Riverside Forest Park
Shijingshan District	Badachu Park	Tongzhou District	Grand Canal Forest Park

2.2. Photograph Acquisition

Chen et al. [17] indicated that most visitors viewed the landscape along roads and paths. Thus, the photographs used in the study were taken along roads during the best ornamental period of the *Cotinus coggygria* landscape from 2018 to 2020 in the planting sites in Beijing. Under different lighting conditions, the color, shape, surface, contours, and boundaries of the same landscape shift to some degree [18], which the human visual system can easily perceive. To reduce the influence of weather, visibility, light intensity, light direction, and other factors such as photographic equipment, we selected the points where the landscape can be viewed positively to take photographs and objectively recorded the actual situation of the scenery from a normal viewing angle. Additionally, some principles were followed during photograph acquisition. (1) All photographs were taken from 8:00 am to 11:30 am with clear weather and visibility more significant than 10 km; (2) All photographs were taken using a Nikon D3S camera and a Nikon AF-S 24–70 mm f/2.8 ED lens with 35 mm focal length; (3) All photographs were taken from the best viewpoint under front lighting conditions with a tripod. (4) Efforts were made to avoid non-landscape factors in the frame. Some could not be avoided, such as the sky and the Great Wall, and walking trails should be under 20% of the field. (5) The distance between the camera and landscape was kept greater than 100 m, which the Nikon 550 AS laser rangefinder could measure. Finally, we selected 120 well-focused photographs with no color deviation from 304 photographs to create a questionnaire to estimate the scenic beauty of the *Cotinus coggygria* forest landscape. Three randomly selected example photographs are shown in Figure 2.

(**a**) (**b**) (**c**)

Figure 2. Randomly selected example photographs. (**a**–**c**) The photographs of *Cotinus coggygria* var. *cinerea* Engl. forest.

2.3. Assessment of Visual Quality

The visual quality of forest landscapes is the subjective estimation after visual perception, which is a comprehensive combination of people's judgment and visual characteristics. Scenic beauty estimation (SBE) [19] is a reliable technique for landscape perception assessment, which is widely accepted. In the study, questionnaires [20–23] were employed to acquire people's visual perceptions of the forest landscape and it is a pretty reasonable method to qualitatively process people's attitudes towards the quantitative visual characteristics of a forest landscape.

The survey was conducted on a professional form-making website and spread randomly to undergraduates, army soldiers, and tourists by the project team with a QR code. Of course, it was open to people from all walks of life. First of all, a total of 18 experts, including professors, researchers and experienced landscape forest managers in urban forestry were selected randomly and the Delphi method [24] was employed to choose 12 photographs with mean visual quality from 120 photographs as the "baseline". In every questionnaire, 27 normal photographs and 3 "baseline" photographs were randomly selected from 120 photographs. Furthermore, each photograph was shown for 8 seconds to give enough time for the respondents to perceive the scene in the photograph. To prevent repeat participation, the users with the same IP address, the same computer, or the same account would receive a newly generated questionnaire with photographs different from the ones that had appeared in the previous questionnaires and could not get more than four questionnaires in total. A 7-point scale [25] was used in the questionnaires. Consistent with people's habits, the positive and negative numbers were used to indicate degree of preference. In detail, -3, -2, -1, 0, 1, 2, and 3 were used to indicate the perceptions of landscape as least preferable, not preferable, relatively not preferable, no preference, relatively preferable, preferable, and most preferable, respectively. After 30 days, landscape photographs were evaluated by 698 respondents. We sorted and checked the filled forms, eliminated invalid ones and finally obtained 678 valid questionnaires. Then, the data collected in the survey were statistically processed.

Although the differences in landscape aesthetic perception caused by economic conditions, living environment, educational background of respondents [26] are not statistically significant [27], some certain less technically skilled groups may have been underrepresented in the online survey. To reduce the influence of background of respondents, the scores of all photographs in the questionnaire minus the average scores of the "baseline" photograph was performed to obtain the adjusted scores for each photograph. After adjusting all the questionnaires, the SBE of each photograph was calculated with Formulas (1) and (2) for all respondents [28].

$$MZ_i = \frac{1}{m-1}\sum_{k=2}^{m} f(cp_{ik}) \tag{1}$$

$$SBE_i = (MZ_i - BMMZ) \times 100 \tag{2}$$

where MZ_i is the average Z score of the photograph i; cp_{ik} is the frequency at which the participator gives a rating of k or greater than k to photograph i; $f(cp_{ik})$ is the cumulative frequency normal function distribution; m is the total scale of the rating; k is the rating scale; SBE_i is the original SBE value of photograph i, and $BMMZ$ is the average Z score of the "baseline" photograph.

2.4. Color Pattern of Forest Landscape and Metrics Selection

Based on the meaning of patches in landscape ecology, we referred to color patches to represent a relatively homogeneous non-linear area composed of similar colors that differ from the surroundings. Color patches form various color spatial patterns when area, shape, and combination change. With a complex spatial pattern, the *Cotinus coggygria* landscape forest mainly presents red, brown, and green colors, with scattered purple, yellow, and gray patches [29]. The color of leaves, species, location, and density of trees, as well as the exposed soil in the forest affect the spatial color patterns.

As landscape metrics describe the characteristics of spatial patterns could accurately quantify spatial color patterns [30], we chose six metrics with intense sensitivity to color pattern changes by a sensitivity ranking method [29], which screened metrics with linear correlated and overlapping meanings. The selected metrics were mean patch area (AREA_MN), largest patch index (LPI), patch size standard deviation (AREA_SD), number of patches (NP), patch richness (PR), and Shannon's evenness index (SHEI). PR and SHEI were used to depict the composition characteristics quantitatively; AREA_MN and AREA_SD were used to depict the patch area characteristics quantitatively; NP was used to analyze the degree of patch fragmentation, and LPI was used to analyze the shape characteristics (Table 2).

Table 2. The selected metrics for describing the characteristics of spatial color patterns.

Metrics	Abbr.	Definition	Comments
Number of Patches [a]	NP	The number of patches in the landscape.	NP conveys the same information as patch density or mean patch size, if total landscape area is held constant. It is used as a measure of landscape fragmentation.
Largest Patch Index [a]	LPI	The percentage of the landscape comprising the largest patch.	Largest patch index at the class level quantifies the percentage of total landscape area comprising the largest patch. As such, it is a simple measure of dominance.
Mean Patch Area [a]	AREA_MN	The sum of the patch area divided by the total number of patches, across all patches in the landscape.	AREA_MN expresses the legibility of color patterns. When AREA_MN is large, it is easier for people to see the color of each patch, and to form a better perception.
Patch Size Standard Deviation [a]	AREA_SD	Standard deviation of patch area, across all patches in the landscape.	AREA_SD is a measure of absolute variation; it is a function of the mean patch size and the difference in patch size among patches.
Patch Richness [b]	PR	The number of different types of patches, independent of the number of patches of each type.	High-richness values indicate a high number of different patches. It can, therefore, be referred to as the compositional dimension of landscape diversity.
Shannon's Evenness Index [a]	SHEI	This measures the distribution of areas among patch types and is independent of richness.	Shannon's evenness index is expressed such that an even distribution of area among patch types results in maximum evenness. As such, evenness is the complement of dominance.

[a] Cited from https://github.com/kmcgarigal/Fragstats (accessed on 15 October 2022). [b] Cited from [31].

2.5. Color Quantization and Color Pattern Calculation

Taking advantage of the inertia of the human visual system, the color quantization process combines similar colors that are less significant in the original image into one to reduce the total number of colors, which facilitates automatic color processing by computer programs. The HSV (hue, saturation, value) model in Munsell's color system [32] quantifies the color with hue, saturation, and value components consistent with the color perception in the brain. Therefore, this study used the HSV model to quantize and classify colors.

Regarding the results of previous studies [33–35], the color space was quantized into 256 colors, shown in Figure A1 in Appendix A. Considering the color similarity and characteristics of *Cotinus coggygria* forest, the 256 colors are combined into 25 categories [29] (Table A1 in the Appendix A).

A Python program (version 1.0, Yujuan Cao, Beijing, China) for automatic interpretation of color patches was developed to facilitate the spatial color pattern calculation, the specific details of which could be found in Appendix B. All the 120 photographs were compressed to 400 × 600 resolution respectively, and the color of each pixel in every photograph was replaced with the color of the highest ratio in the classification. Then the patches with similar colors were fused, and some detail information was discarded so that the size, edge, shape, richness, and uniformity of color patches became evident. The processed photographs were used to interpret the color patches and calculate the metrics. We randomly selected one photograph and visualized it, as shown in Figure 3.

(**a**) (**b**)

Figure 3. Visualization of *Cotinus coggygria* var. *cinerea* Engl. forest photograph. (**a**) The original landscape photograph; (**b**) the photograph after color quantization.

As the Python program was used for automatic color substitution, the pixel was represented by the classification number to generate a rasterized file in IDF_ASCII format. Moreover, the six selected metrics of each photograph were calculated by Fragstats (version 4.2, McGarigal, University of Massachusetts, USA) for every 120 photographs, which were used to statistically analyze the overall color patterns of the *Cotinus coggygria* landscape forest.

2.6. Mechanisms of Color Patterns on Visual Quality

The SBE of each photograph was treated as the dependent variable, and the six color pattern metrics were treated as the independent variables. Using the stepwise regression, multiple correlations between visual quality and the color pattern metrics were explored by IBM SPSS Statistics (version 26.0, IBM, Chicago, IL, USA). The correlation coefficients, complex correlation coefficients, and residual standard deviations of each metric were calculated, and the correlation coefficient test was also conducted. Finally, principal component analysis (PCA) was employed to further explore the effect of color patterns on visual quality. Normalization and equalization were performed on the variables to eliminate the effects of dimensionality and order of magnitude. Then, the eigenvectors, eigenvalues, principal components and contribution rates of the correlation coefficient matrix were calculated on the normalized metrics. After that, all the principal components were ranked by their contribution rate, and ones with eigenvalues greater than 1.0 were selected. We scattered the SBE of each photograph with the selected principal components and fitted the surface with a locally weighted regression (Lowess) algorithm to express the influence mechanism of color patterns on visual quality. As PCA is a mature method commonly used for data compression and dimension reduction, its specific calculation and analysis processes can be found in the relevant literature [36,37].

3. Results

3.1. Color Patterns of Cotinus coggygria Forest

After carrying out color quantification and pattern metric calculations, we performed a statistical analysis of each metric. The general color pattern of a *Cotinus coggygria* landscape in Beijing is summarized in Table 3. The p values of Kolmogorov–Smirnov test were larger than 0.2, which indicated that values of all six metrics were subject to a normal distribution.

The color patches of the *Cotinus coggygria* forests in Beijing were relatively rich, as the mean of NP was 467. The range of NP was extensive, and the CV (coefficient of variation) reached 42.54%, indicating that the number of color patches varied a lot in different sites. As for PR, the minimum was 13.00, the mean was 19.52, and the CV was only 15%, which indicates that the color patch types of the *Cotinus coggygria* forest in Beijing were abundant, and the color patch richness of different sites was kept on a specific scale.

Table 3. Metrics values of landscape color structure of the *Cotinus coggygria* var. *cinerea* Engl. forest.

Metrics	Mean	Max.	Min.	Standard Deviation	Coefficient of Variation	Sig. of K-S Test [a]
AREA_MN	0.34	0.69	0.08	0.12	36.08%	0.463
LPI	21.34	41.05	7.68	8.58	40.21%	0.552
AREA_SD	3.56	8.90	0.36	2.28	63.92%	0.470
NP	221.92	467.00	74.00	94.40	42.54%	0.788
PR	19.52	24.00	13.00	2.97	15.00%	0.326
SHEI	0.65	0.84	0.55	0.06	8.67%	0.523

[a] The significance of Kolmogorov–Smirnov test.

As for the size of color patches, the mean of LPI was 21.34, and the maximum was 1.9 times the mean. Additionally, the CV reached 40.21%, indicating that the distribution of the largest color patch remained relatively concentrated in *Cotinus coggygria* forests. Moreover, the largest color patch accounted for 40% of photographs in some sites. The mean of AREA_MN was 0.34, and the maximum was 8.6 times the minimum, but the standard deviation was tiny, and the CV was 36.08%. Meanwhile, the mean of AREA_SD was 3.56, and the CV was 63.92%, indicating that the areas of different color patches varied significantly in most sites. What is more, the mean of SHEI was 0.65, and the CV was only 8.67%, indicating that most of the area of the *Cotinus coggygria* forest was composed of several major color patches.

3.2. Multiple Correlations between Visual Quality and Color Spatial Pattern Metrics

As spatial pattern metrics quantified the number, size, extent, shape, and other specific aspects of the spatial arrangement of color patches [38], the overall features of color patterns used to be described by various metrics from different aspects. Based on the relation between the visual quality of a forest landscape and the overall color pattern, we calculated the correlation between the SBE of photographs and the above six metrics by stepwise regression. Moreover, the procedure is given in Table 4. In the first run, PR was removed due to a negligible correlation with visual quality. Moreover, in the second run, NP, LPI, AREA_MN, AREA_SD, and SHEI had significant multiple correlations with R = 0.915 on the aesthetic quality.

Table 4. Stepwise regression process and partial correlation coefficient.

Factors	The First Run		The Second Run	
	Partial Correlation Coefficient	Sig.	Partial Correlation Coefficient	Sig.
NP	−0.912	0.059	−0.514	0.047
LPI	−0.976	0.026	−0.496	0.009
AREA_MN	0.911	0.021	0.186	0.003
AREA_SD	−0.983	0.004	−0.733	0.001
SHEI	−0.991	0.011	−0.579	0.004
PR	0.721	0.312		

In the results of multiple correlation analysis (Table 5), NP, LPI, AREA_MN, AREA_SD, and SHEI affected the visual quality to different degrees. We performed normalization and equalization on the variables to eliminate the effects of dimensionality and order of magnitude. Moreover, we presented the standardized coefficients for each metric to compare the magnitude of their effect on visual quality. The standardized coefficients for AREA_MN, NP, LPI, AREA_SD, and SHEI were 0.116, −0.303, −0.298, −0.797, and −0.337, respectively, indicating that AREA_SD had the most significant impact on landscape quality, while AREA_MN had the most negligible impact relatively. Moreover, the visual quality was negatively correlated with NP, LPI, AREA_SD, and SHEI and positively correlated with AREA_MN.

Table 5. Analysis of multiple correlations coefficients of *Cotinus coggygria* var. *cinerea* Engl. forest.

Factors	Unstandardized Regression Coefficients		Standardized Regression Coefficients	t	Sig.
	B	Standard Error	Beta		
Constant	4.764	0.418		11.405	0.001
NP	−0.002	0.000	−0.303	−6.870	0.001
LPI	−0.025	0.004	−0.298	−6.093	0.001
AREA_MN	0.673	0.333	0.116	2.020	0.046
AREA_SD	−0.251	0.022	−0.797	−11.492	0.001
SHEI	−4.259	0.562	−0.337	−7.581	0.001

3.3. Impacts of Color Patterns on Visual Quality

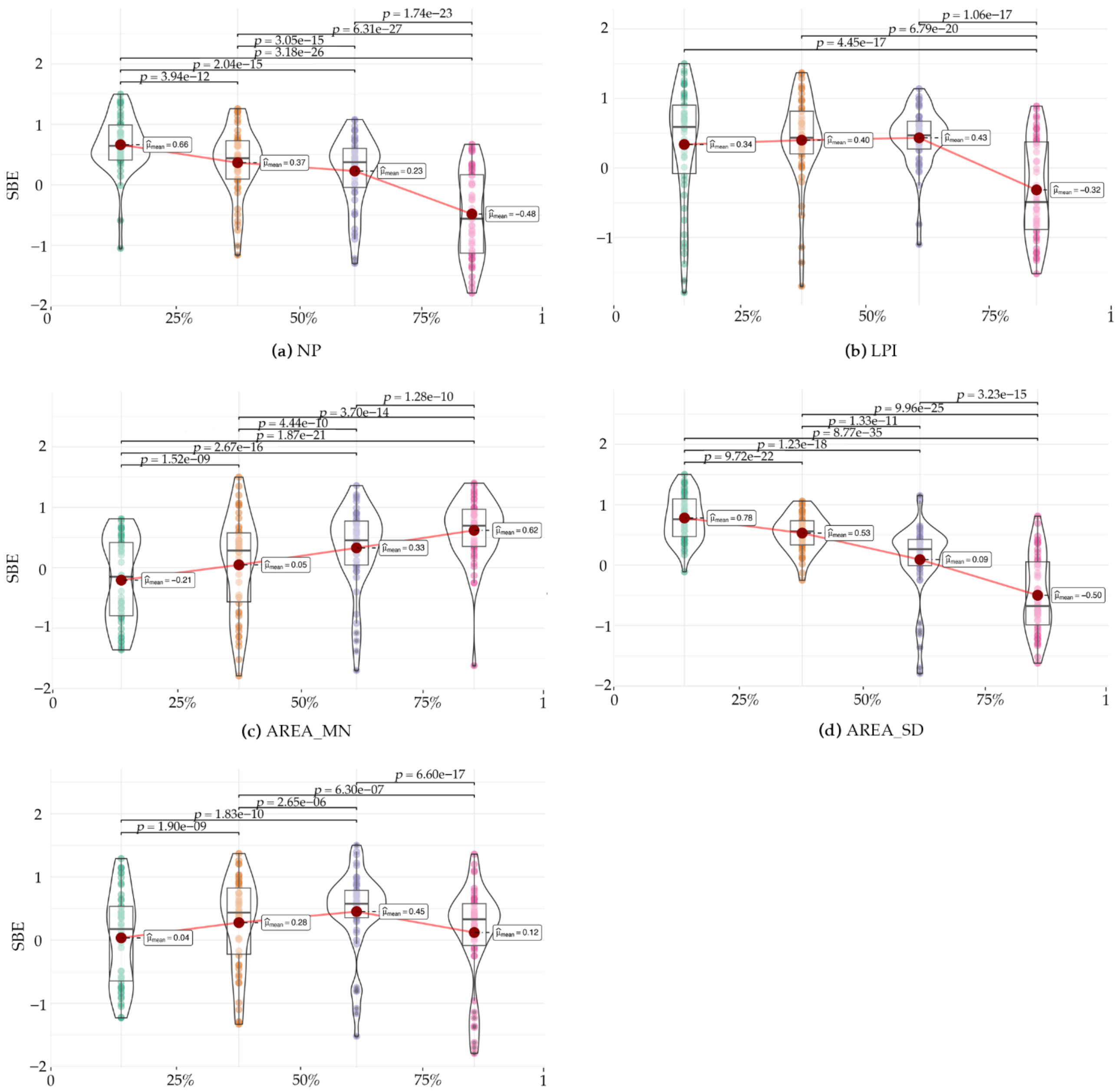
NP, LPI, AREA_MN, AREA_SD, and SHEI were significantly correlated with the visual quality of the *Cotinus coggygria* forest, suggesting that differences in the color pattern may account for the visual quality variations. The values of metrics were numerically continuous, and it was difficult to represent them in terms of order. To explore the impact mechanism of each metric on visual quality, we divided the metric into four intervals by the quartiles, therefore, every interval included 30 photographs. We depicted a box plot to represent the distribution of the SBEs and the red dots represented the mean of SBEs in each interval. The line connecting the red dots across all the boxes expressed the correlation between the color pattern metrics and visual quality. The p values of mean comparisons of the SBE in each quartile was plotted above the boxes. All the p values shown in the figures were less than 0.05, which indicated that the means of the SBEs in the different quartiles were significantly different. Some p values that were larger than 0.05 are not shown in the figures, indicating that the means of the SBEs in two quartiles were not significantly different.

As shown in Figure 4, NP was negatively correlated with the SBE of the photographs. When the NP was small, its effect on the visual quality was not apparent, but a large NP resulted in a significant reduction in the visual quality. The correlation between LPI and SBE was similar to that between NP and SBE. In the first quartile the difference in the SBE was the most prominent, and in the fourth quartile, the difference in the SBE decreased a bit. When the LPI was small, the visual quality changed a lot, but a large LPI caused a sharp drop in the visual quality.

AREA_MN was positively correlated with the SBE. The SBE of most of the photographs in each box increased with AREA_MN. However, except for the outliers, the minimum value of the SBE significantly increased, indicating that enlarging AREA_MN for low-visual quality forests was considerably more effective in improving scenic beauty. AREA_ SD was negatively correlated with SBE. In the fourth quartile the difference in SBE was the most prominent. As AREA_SD accounts for the difference in the size of the color patches across the photographs, its impact mechanism on the visual quality was somewhat different from that of LPI. The effect of SHEI on the visual quality was insignificant. However, the median of SBE was significantly improved in the second and third intervals, and the mean of the SBE was also slightly increased, also in the fourth quartile the difference in SBE was the most prominent, indicating that harmonious color patch patterns typically permit superior visual quality.

3.4. Comprehensive Effects of Spatial Color Pattern on Visual Quality

The color pattern metrics correlated to each other to some degree, and all the metrics subsequently changed when the pattern varied. The correlation between an individual metric and visual quality cannot sufficiently reveal the influence mechanisms of color patterns on the visual quality of *Cotinus coggygria* forest. Therefore, principal component analysis (PCA) was employed to further explore the effect of color patterns on visual quality, and the results are presented in Table 6.



(a) NP **(b)** LPI **(c)** AREA_MN **(d)** AREA_SD **(e)** SHEI

Figure 4. Correlation between color pattern metrics and visual quality of the *Cotinus coggygria* var. *cinerea* Engl. forest. The 25%, 50%, and 75% of the coordinate on the horizontal axis of each subplot represent the 1st quartile, median, and 3rd quartile of each metric. (**a**) Correlation between number of patches (NP) and SBE; (**b**) correlation between largest patch index (LPI) and SBE; (**c**) correlation between mean patch area (AREA_MN) and SBE; (**d**) correlation between patch size standard deviation (AREA_SD) and SBE; (**e**) correlation between Shannon's evenness index (SHEI) and SBE.

The first principal component (PC1) mainly characterized the color patches in terms of evenness, with the most significant factor loading of AREA_SD (0.918) and a negative factor loading of SHEI with an absolute value of 0.686. Moreover, the factor loadings of LPI and AREA_MN were more prominent than 0.5. The second principal component (PC2) primarily characterized the color patches in terms of area, with the most significant factor loading of NP (0.633) and a negative factor loading of LPI with an absolute value of 0.719. Moreover, AREA_MN had a factor loading of 0.609. The top two principal components had eigenvalues greater than 1.0, and the cumulative contribution of both was 71.47%.

Therefore, the first and second principal components were chosen as the two variables to analyze the mechanism of impact on the visual quality. The factor loadings of each principal component are shown in Figure 5d.

Table 6. Principal component analysis of color pattern metrics of the *Cotinus coggygria* var. *cinerea* Engl. forest.

Item	1st Principal Component	2nd Principal Component	3rd Principal Component	4th Principal Component	5th Principal Component
NP	0.099	0.633	0.607	−0.421	0.210
LPI	0.634	−0.719	0.241	0.098	0.118
AREA_MN	0.671	0.609	−0.196	0.302	0.220
AREA_SD	0.918	0.258	0.131	−0.006	−0.272
SHEI	−0.686	0.210	0.496	0.483	−0.081
Eigenvalue	2.175	1.399	0.728	0.511	0.187
Contribution Rate	43.50%	27.97%	14.56%	10.22%	3.75%
Accumulated Contribution Rate	43.50%	71.47%	86.03%	96.26%	100.00%

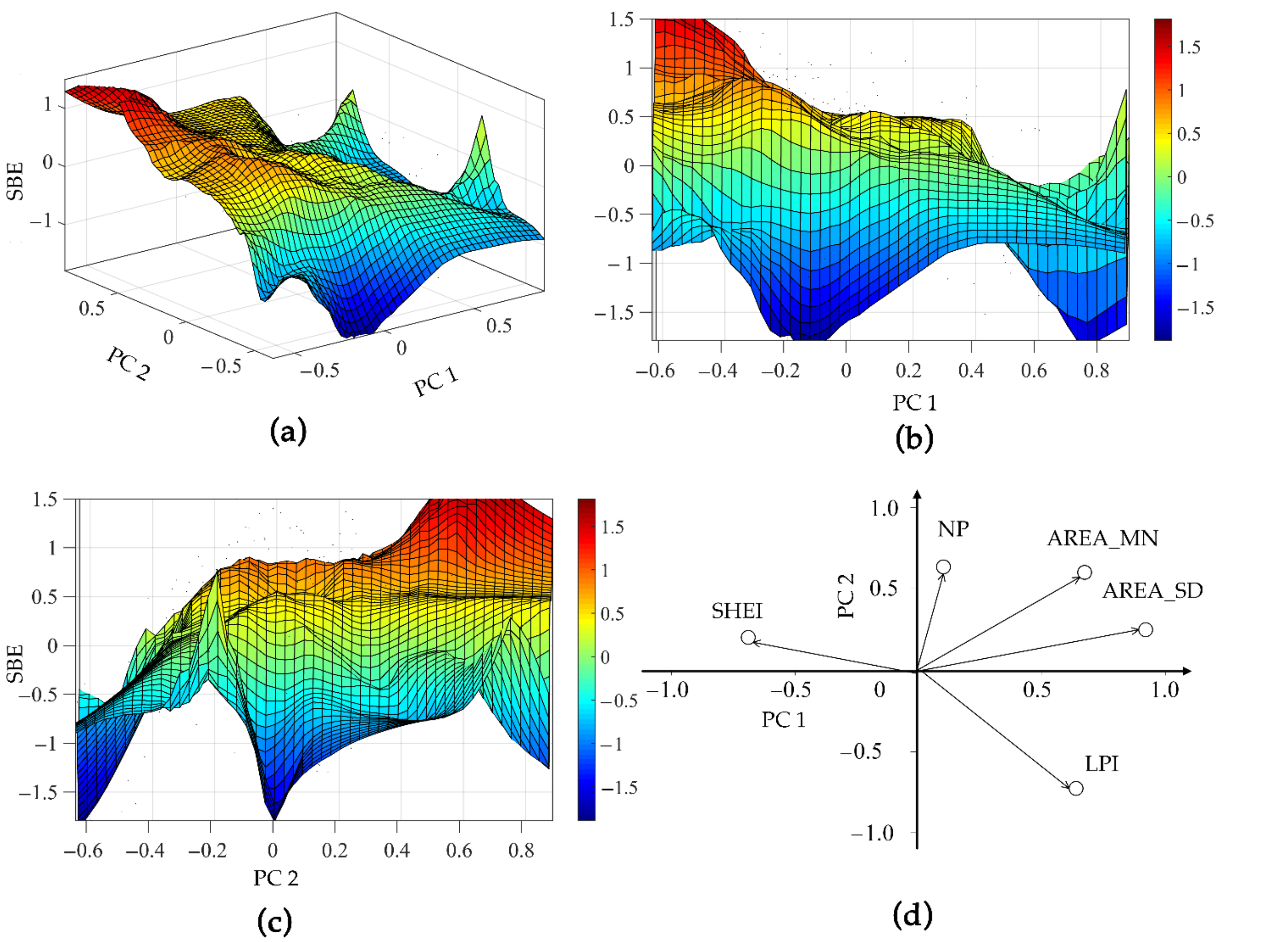


Figure 5. The influence trend of color pattern metrics and visual quality of the *Cotinus coggygria* var. *cinerea* Engl. forest. (**a**) The scattered plot and fitted surface of SBE with the first principal component (PC1) and the second principal component (PC2); (**b**) the projection of the fitted surface in the plane of PC1 and SBE; (**c**) the projection of the fitted surface in the plane of PC2 and SBE; (**d**) the factor loadings of metrics on PC1 and PC2.

We analyzed the spatial patterns of the color patches and SBE of 120 photographs, as well as scattered SBE with PC1 and PC2. The fitted surface is shown in Figure 5. As revealed by the trend of surface, the visual quality of *Cotinus coggygria* landscape increased sharply and then decreased slowly as the two principal components increased (Figure 5a). We obtained the lowest SBE when the PC1 was close to 0 and the PC2 was minor, indicating a large LPI, a minor NP, and a moderate SHEI. That is, the landscape had few color patches and consisted mainly of a limited number of color patch types with relatively dull colors.

The projection of the fitted surface in the plane of PC1 and SBE is shown in Figure 5b. It mainly remained stable, showing a specific downturn trend. When PC1 was around −0.6, the SBE reached its maximum; when PC1 was around −0.1, the SBE achieved the minimum; when PC1 was larger than 0.6, the SBE decreased dramatically. This indicates that the color patch area and uniformity had a more significant impact on the visual quality of the *Cotinus coggygria* forest. As PC1 increased, the degree of fluctuation in the visual quality first increased and then decreased. The visual quality was significant when the patch size and uniformity were moderate. However, the visual quality decreased when the patch size was too large and the main color patch was overly abrupt.

In the projection of the fitted surface in the plane of PC2 and SBE (Figure 5c), with the increase in PC2, the SBE showed a moderately upward trend, and the SBE obtained the minimum value when PC2 was near 0, and the degree of fluctuation gradually increased. It indicated that the visual quality would be high when the number of color patches was coordinated with the patch size. In contrast, the patch layout began to fragment when the number of patches was large, and at this time, the visual quality showed a significant difference due to the different patch areas. Therefore, keeping the diversity and uniformity of color patches coordinated and balanced with each other, while properly reducing the number of tiny miscellaneous color patches is key to improving the visual quality of the landscape of *Cotinus coggygria* forests. It is not easy to comprehensively improve the visual quality only by changing one metric.

4. Discussion

4.1. Pattern Metrics and Visual Attributes

Countless spatial metrics have been proposed to quantitatively characterize the landscape's spatial and temporal variability and current state [39–41]. Studies have shown that some of the ecological spatial metrics could be used as indicators for evaluating visual quality [42,43]. In this paper, NP, LPI, AREA_MN, AREA_SD, SHEI, and PR were selected to quantify the pattern of color patches from different aspects.

Because landscape composition metrics were more closely related to scenic values than the configuration metrics [44], and considering the stability of the color composition of autumn *Cotinus coggygria* forests and the immutability of tree planting locations, we ignored the metrics expressing the spatial configuration of patches and selected only the composition metrics quantifying the proportion, richness, evenness, and diversity of color patches [31].

Together with NP, PR expresses the diversity of color patches and the complexity of color patterns. SHEI expresses the diversity of patch arrangement styles, and AERA_SD expresses the diversity of patch area variations, both of which characterize the diversity of color patterns from different perspectives. Variety and complexity, as one of the most influential predictors of visual preference [45,46], show a significant correlation with the variety of elements in the landscape [47]. Heterogeneity, variety, diversity, and complexity are attributes consistently interpreted by subjects similarly [45,48,49]. However, since the color of the autumn *Cotinus coggygria* forest mainly covers red, brown, green, and purple, and the minimum value of color patch richness at the site of this study is 13, and 13 color patch types could combine to form a rich and diverse landscape color pattern, resulting in PR being screened out in the first run of multiple linear regression.

The LPI expresses the dominance of the largest color patch and the overall coherence. The more significant the LPI, the more prominent the largest color patches are, and the less the overall coherence is. AREA_MN expresses the legibility of color patterns. When AREA_MN is large, it is easier for people to see the color of each patch, and to form a better perception. Both coherence and legibility reflect the viewer's perception of the landscape and play a crucial role in interpreting the landscape structures [50]. Herzog and Leverich [51] argued that landscapes with higher legibility tend to be preferred in many studies.

4.2. Relationship between Pattern Metric and Visual Quality

The results suggested that the visual quality could be expressed to some extent by the spatial pattern of the color patches when the *Cotinus coggygria* forest was seen at intermediate distances. Moreover, this is consistent with previous studies related to agriculture [52,53] and rural landscapes [54]. The results of the multiple correlations showed that five landscape metrics, NP, LPI, AREA_MN, AREA_SD, and SHEI, were the main factors affecting the visual quality of the landscape.

NP was negatively correlated with visual quality, indicating that as the number of color patches increases, the complexity of spatial color structure increased sharply while the legibility of the color patches decreases [46,55]. The minimum NP in this study was 74, and the probability of an overly dull color pattern was low; however, when it was too complex to be discernible [46], it caused a fragmented and confusing spatial structure and a sharp decline in visual quality. Color patterns with great complexity may suffer from low legibility when multiple color patches failed to form a periodic structure [31].

LPI was negatively correlated with visual quality. When the LPI is small, the uniformity of the whole picture increase, there are no apparent dominant color patches, and the picture has strong coherence. The landscape quality is less affected by the LPI at this time. Hunziker and Kienast [52] showed that the uniformity of landscape patches was positively correlated with visual quality. However, the visual quality would be sharply reduced when the uniformity decreases to a certain threshold. In this study, when the LPI exceeded a certain threshold, the dominant color patches occupied a more significant proportion of the picture, the color patterns became monotonic and less coherent, and the visual quality decreased dramatically. The present results suggested that although the uniformity of the color pattern had a positive effect on preference [56,57], the relationship was not purely linear.

AREA_MN was positively correlated with visual quality. Color patches with large average areas tend to be noticed at intermediate distances. The human visual system is much more efficient at processing clear and concise pictures than processing pictures full of details, especially when the details are overly complex. People find it easy to perceive pictures with patches of considerable size. That is, the SBE appears high.

AREA_SD was negatively correlated with visual quality. When the patch area remains relatively homogeneous, the complexity of the spatial pattern is low, and the AREA_SD is modest. As the minimum value of SHEI in the study was 0.55, there were no oversimplified color patterns at the sites. Different color patches were distributed relatively uniformly, so the SBE stayed high. With the increase in AREA_SD, the heterogeneity and complexity of pictures increased. According to Kaplan and Kaplan [50], significant heterogeneity is commonly thought to be negatively related to scenic value [54].

The correlation between SHEI and visual quality was not apparent. In this study, the visual quality of the landscape photographs did not change significantly as the SHEI of the photographs within a narrow range, with a CV of only 8.3% of the SHEI. When the SHEI was around 0, the inhomogeneous distribution of the color patches led to confusion in the landscape graph. However, when the SHEI was around 1, the uniform distribution of color patches led to monotony of the graph and the lack of natural dynamism. Both of these scenarios led to a drop in visual quality. This was consistent with that more fantastic perceived scenic beauty attributed to landscapes with greater spatial evenness [54].

Overall, the spatial patterns of color patches are correlated with people's perception of the scenic beauty of a landscape forest. From the results presented in this paper, the spatial pattern of color patches was a dimension of the autumn *Cotinus coggygria* seen at intermediate distances, which affected the perception of autumn-colored leaves to a certain extent.

4.3. Influence Intensity of Visual Attributes and Optimal Color Pattern

The degree to which different color patterns affect visual quality varied. In terms of the standardized coefficients, AREA_SD and SHEI had the most significant impact on visual quality. These two metrics express both the complexity and diversity of color patterns. Since the selected sites were natural landscapes with minor human intervention, the probability of entirely homogeneous or unusually heterogeneous patterns was relatively small, and heterogeneity in patch regions was more easily perceived at intermediate distances. Moreover, the complexity and diversity of the color patches remained the most influential factors for visual perception.

The influence of NP and LPI on visual quality remained essentially the same and slightly less than SHEI on landscape quality. In landscapes with NP $\geq$ 74 and PR $\geq$ 13, the color pattern had a certain complexity that increased significantly with increasing NP, while increasing LPI decreased global coherence, which simultaneously degraded visual quality. Similar parallels exist between the effects of uniformity and diversity [55] and order and complexity [58] on visual quality.

Due to the correlation between color pattern metrics, each metric changed accordingly when the color pattern changed. In the principal component surface plot, the SBE reached its maximum at PC1 = 0.6 and PC2 = $-$0.6. At this time, SHEI was large, NP and LPI were moderate, and AREA_SD was tiny. The color patches were uniformly distributed, and the number of color patches was just right. This was consistent with color harmony theory. In a natural environment, deliberately creating a landscape that conforms to the optimal color pattern could be severely costly and unstable. Computer modeling software (such as Blender) can be used to determine whether the landscape design is reasonable. In built-up urban landscapes, landscape color layouts could be altered by interleaving and replanting a modest number of different trees. Additionally, it indicated the reasonability to improve the aesthetic quality by changing the spatial color pattern of peri-urban forests through planting and replanting trees on a small scale. At this point, feasibility simulations could also be performed with the help of computer modeling to reduce the transition risk effectively.

At intermediate distances, it is difficult to accurately distinguish the visual forms such as crown width, height, and crown length of trees in the landscape. Moreover, the heterogeneity of tree height, crown width, and forest stand density is easily overlooked or obscured. However, the effect of these features on the color pattern and visual quality cannot be ignored entirely in practice. In a follow-up, we will continue to investigate the mechanisms of influence between individual trees, stands, and landscape color structures as well as the overall mechanisms of influence on the visual quality of landscape forests.

5. Conclusions

This study focused on spatial color patterns of the forest while other aspects such as voice and smell that are connected to real forest experiences were not considered. Based on 120 photographs of the *Cotinus coggygria* forest and six color pattern metrics, we explored the spatial patterns of color patches in terms of composition, area, shape, and degree of fragmentation. Following the SBE approach, a questionnaire on scenic beauty was conducted, and 678 valid questionnaires were used to analyze the multivariate correlation between color pattern metrics and visual quality. NP, LPI, AREA_MN, AREA_SD, and SHEI were found to be the main factors affecting the visual quality of the *Cotinus coggygria* forest.

AREA_MN was positively correlated with visual quality, while NP, LPI, AREA_SD, and SHEI correlated negatively with visual quality. Moreover, AREA_SD had the most significant impact on the visual quality of the landscape, while SHEI, LPI, and AREA_MN had the second-highest impact. In other words, the area of color patches and uniformity of color pattern had a more significant impact on the visual quality of the landscape, especially when the patch area was large and the dominant color patch was overly abrupt, the quality of the landscape was significantly reduced. NP had minimal impact on the visual quality, and the visual quality of the landscape was higher when the number of patches was coordinated with the patch area. However, if the number of patches was overly considerable, the layout of color patches became highly fragmented and the visual quality decreased. Thus, keeping the diversity and uniformity of color patches in the landscape in harmony with each other while appropriately reducing the number of minor miscellaneous color patches plays a decisive role in creating a forest landscape with high visual quality.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to confidentiality.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The process of color quantization, substitution, and classification in the study was carried out as follows.

First, the hues were non-uniformly quantized into 16 categories, labeled H1 to H16. The saturation and the value were quantized into four categories, marked as S1~S4 and V1~V4, respectively, so that the color space was quantized into 256 ($16 \times 4 \times 4$) colors (Figure A1).

Moreover, supervised color substitution and classification were performed to quantize the photograph into 256 colors. The images were converted from the RGB color model to the HSV color model, and the colors of each pixel were tallied. Based on the frequency of each color appearing in the 120 photographs, some colors with visual similarity were combined into one category.

In Figure A1, the colors corresponding to V1 had low values and were mainly composed of tree shadows and tree trunks in the forest. These were grouped in the black category. The colors corresponding to S1 had low saturation and were organized into the gray category, except those already classified as black. Moreover, the grey category shows mainly the color of the leafless crowns of shrubs, herbs, and trees and the exposed soil of forests. The red, yellow, and green colors with high frequencies were grouped into 21 categories, except for the black and gray categories. The colors with low frequency (0.1%~0.5%) were merged into the 21 categories with similar visual appearances. Colors with tiny frequencies (less than 0.1%) were classified into the additional category. It was not easy to keep all non-experimental factors out of the range, so the sky and the Great Wall appeared in some photographs. These perturbed colors were replaced by colors with frequency 0 and treated as background colors, which were neglected in the calculation of pattern metrics. As shown in Table A1, 256 colors were divided into 25 categories.

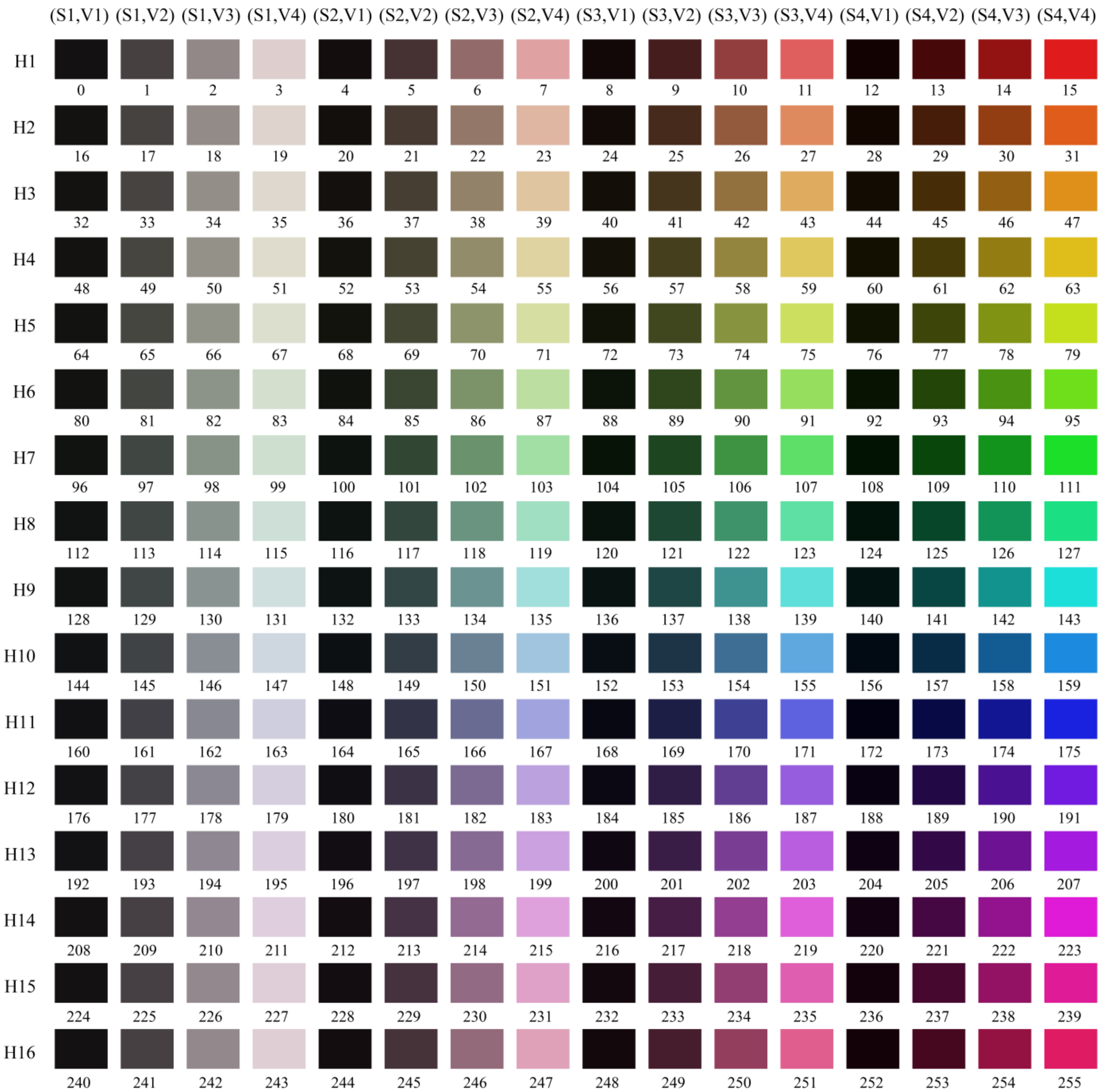


Figure A1. Non-uniform quantization of color in the HSV model.

Table A1. The classification of 256 colors.

Category Number	Colors in The Category	Color Code	Main Color	Hex of Main Color
1		7		#DFA1A2
2		23		#DFB6A2
3		11		#DF5F5E
4		10, 14		#923E3E
5		5, 25, 9, 13		#463233

Table A1. *Cont.*

Category Number	Colors in The Category	Color Code	Main Color	Hex of Main Color
6		30, 31		#923E12
7		27		#DE8A5E
8		6, 246		#926A6A
9		22, 245, 229, 213, 181		#937769
10		39, 55		#DFC5A0
11		43, 59, 47		#DFAB5F
12		58, 71		#93853E
13		57		#453F1D
14		74, 73, 86, 85		#87933F
15		70, 54		#8D946B
16		53, 69		#454231
17		26, 29		#935A3D
18		42, 46, 62		#92713E
19		38		#928269
20		41, 45, 61		#45351C
21		21, 37		#463931
22		34, 66, 50, 2, 18, 65, 33, 1, 161, 49, 17, 162, 81, 82, 177, 97, 225, 209, 242, 241, 226, 19, 35, 3, 51, 67, 83, 98, 99, 113, 114, 115, 129, 130, 131, 145, 146, 147, 163, 179, 193, 194, 195, 210, 211, 227, 243		#919388
23		165, 36, 68, 0, 4, 8, 12, 16, 20, 24, 28, 32, 40, 44, 48, 52, 56, 60, 64, 72, 76, 80, 84, 88, 92, 96, 100, 104, 108, 112, 116, 120, 124, 128, 132, 136, 140, 144, 148, 152, 156, 160, 164, 168, 172, 176, 180, 184, 188, 192, 196, 200, 204, 208, 212, 216, 220, 224, 228, 232, 236, 240, 244, 248, 252		#14100D
24		155, 158, 159		#5FA8DF
25		149, 178, 101, 89, 249, 197, 151, 90, 77, 75, 133, 117, 150, 169, 166, 230, 153, 63, 15, 78, 217, 250, 214, 167, 182, 198, 253, 154, 87, 185, 157, 173, 201, 134, 102, 170, 171, 237, 93, 118, 234, 137, 247, 135, 79, 254, 183, 231, 91, 105, 138, 251, 94, 103, 215, 95, 106, 107, 109, 110, 111, 119, 121, 122, 123, 125, 126, 127, 139, 141, 142, 143, 174, 175, 186, 187, 189, 190, 191, 199, 202, 203, 205, 206, 207, 218, 219, 221, 222, 223, 233, 235, 238, 239, 255		#3D4509

Appendix B

The Python program for automatic interpretation of color patches was developed to facilitate the spatial color pattern calculation, which could be accessed at https://github.com/chunhv/color-patches-automatic-interpretation/, accessed on 14 October 2022. The procedure steps and how them works were explained as follows.

Step 0: Image prepossessing. The perturbed colors in the images were replaced by the colors never appeared in all photographs by Adobe Photoshop manually. The processed images were the inputs to the programs of automatic interpreting color patches.

(**a**) (**b**)

Figure A2. The sample of original photograph and processed one. (**a**) The original landscape photograph; (**b**) the photograph after color replacement.

In programming, the original photograph was treated as a three-dimensional matrix of $6000 \times 4000 \times 3$, where 6000×4000 was the width and height of the photo, and 3 represented the values of RGB of pixels. Therefore, an original photograph was represented as an orderly combination of $6000 \times 4000 \times 3$ numbers.

Step 1: Image compression. To improve the processing speed, we resample and compress the photograph using pixel area relation with resolution of $600 \times 400 \times 3$, which could reduce the processing time by 100 times.

Step 2: Color space conversion. The color space of photograph was converted from RGB to HSV based on the algorithm A1~A4.

$$\begin{cases} R' = R/255 \\ G' = G/255 \\ B' = B/255 \\ C_{\max} = \max(R', G', B') \\ C_{\min} = \min(R', G', B') \\ \Delta = C_{\max} - C_{\min} \end{cases} \tag{A1}$$

$$Hue = \begin{cases} 0^\circ & ,\Delta = 0 \\ 60^\circ \times (\frac{G'-B'}{\Delta} + 0), & C_{\max} = R' \\ 60^\circ \times (\frac{B'-R'}{\Delta} + 2), & C_{\max} = G' \\ 60^\circ \times (\frac{R'-G'}{\Delta} + 4), & C_{\max} = B' \end{cases} \tag{A2}$$

$$Saturation = \begin{cases} 0 & ,C_{\max} = 0 \\ \frac{\Delta}{C_{\max}} & ,C_{\max} \neq 0 \end{cases} \tag{A3}$$

$$Value = C_{\max} \tag{A4}$$

Step 3: Compress the color space. Each pixel in the photograph was compressed into 256 colors from full color (16,777,216 colors) based on the algorithm A5~A7.

$$H' = \begin{cases} 0, \ H \le 7.5 \ or \ H > 172.5 \\ 10, \ 7.5 < H \le 12.5 \\ 18, \ 12.5 < H \le 22.5 \\ 25, \ 22.5 < H \le 27.5 \\ 34, \ 27.5 < H \le 40 \\ 47, \ 40 < H \le 54 \\ 62, \ 54 < H \le 70 \\ 76, \ 70 < H \le 82.5 \\ 89, \ 82.5 < H \le 95 \\ 103, \ 95 < H \le 110 \\ 119, \ 110 < H \le 127.5 \\ 133, \ 127.5 < H \le 137.5 \\ 141, \ 137.5 < H \le 145 \\ 151, \ 145 < H \le 157.5 \\ 161, \ 157.5 < H \le 165 \\ 169, \ 165 < H \le 172.5 \end{cases} \tag{A5}$$

$$S' = \begin{cases} 19, \ 0 \le S < 38.25 \\ 70, \ 38.25 \le S < 102 \\ 147, \ 102 \le S < 191 \\ 223, \ 191 \le S \le 255 \end{cases} \tag{A6}$$

$$V' = \begin{cases} 19, \ 0 \le V < 38.25 \\ 70, \ 38.25 \le V < 102 \\ 147, \ 102 \le V < 191 \\ 223, \ 191 \le V \le 255 \end{cases} \tag{A7}$$

Step 4: Further compression of the color space. Replace the color of every pixel with the highest ratio color in the classification which were listed in Table A1. The photograph was compressed into 25 colors from 256 colors. In Figure A3, photograph (a) has 256 colors and photograph (b) has 25 colors, and some details especially the dark part of the photo was optimized in photograph with 25 colors.

(**a**) (**b**)

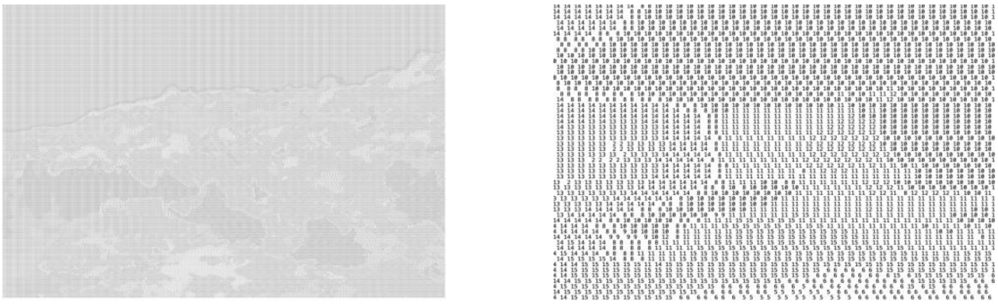
Figure A3. The sample photograph with 256 colors and 25 colors. (**a**) The photograph with 256 colors; (**b**) the photograph with 25 colors.

Step 5: Gaussian blur. To lower the impact of noises on color patch division, Gaussian Blur Algorithm was used to smooth the photos. The step size of blurring used in the paper was 8 × 8, and it should be adjusted according to contents and resolutions of photographs.

Processed from Step 0 to Step 5, the color patches in the photographs had been basically interpreted as shown in Figure A4.

Figure A4. The automatic interpreted color patches in photographs.

Step 6: Generate IDF_ASCII files. Fragstats (version 4.2, McGarigal, University of Massachusetts, Amherst, MA, USA) was used to calculate the metrics of color patches patterns. The photograph was not supported as the input files, and it should be converted to the files in IDF_ASCII format. In this step, every pixel was replaced by the number of its color category, and a two-dimensional matrix formed of 600 × 400 numbers was generated. As shown in Figure A5, the pattern of patches in IDF_ASCII file was similar to that in Figure A5a, and the IDF_ASCII file was formed by numbers as shown in (b).



(**a**) (**b**)

Figure A5. The IDF_ASCII files shown in the text editor. (**a**) It was the full vision; (**b**) It was the local part.

Step 7: Calculate the metrics. The landscape scale was selected in the Fragstat, and the values of metrics of color patterns were calculated.

Step 8: Repeat from Step 0 to Step 7 until all the photographs were processed. And the metrics were calculated photograph by photograph.

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