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High or low? Exploring the restorative effects of visual levels on campus spaces using machine learning and street view imagery

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A R T I C L E I N F O

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A B S T R A C T

According to the Attentional Restoration Theory (ART), cognitive restoration (e.g., Fascination) may occur when the physical environment exhibits high restorative quality. However, these studies usually ignore the effect of different levels of visual features on restoration quality, and small-scale questionnaires are difficult to use to comprehensively evaluate the restoration quality of a space. In this study, we propose a machine learning based method for high-resolution, large-scale assessment of the restoration quality of campus environments using Street View Images (SVIs). First, visual features are extracted from campus SVIs using computer vision method. Second, an online survey using the PRS-11 questionnaire (containing four indicators: Being-away, Coherence, Scope, and Fascination) was conducted to label the images. Finally, we developed a regression model to predict campus restorative quality and to model the non-linear relationship between the visual features of SVIs and this quality. We studied 1088 SVIs in the Lihu campus of Jiangnan University (JNU) to verify the feasibility of our method, and the results showed that SVIs can accurately help us predict the restoration quality of the campus environment on a large scale ($R^2 = 0.726$). Next, we examined the variance in visual features between campus spaces with different levels of restorative quality, and investigated the effect of different levels of visual features on restoration quality. We found that contributions of high-level visual features to restoration, such as trees, are robust (Adj $R^2 = 0.504$) compared to low-level visual features (Adj $R^2 = 0.032$) that included such as color information. This provides a new perspective for assessing recovery environments and designing healthy campus environments. The code is shared at: https://github.com/MMHHRR/Restorative_Quality

1. Introduction

Reports from universities and colleges around the world indicate that college students are suffering from mental health problems (Karyotaki et al., 2020). According to statistics from the Institute of Psychology of the Chinese Academy of Sciences' 2022 Survey Report on College Students' Mental Health,[1] nearly 80,000 college students in China between the ages of 15 and 26 have experienced varying degrees of mental health issues as a result of the stress of studying and pursuing higher education. 21.48% of college students may be at risk for depressive disorders and 45.28% of college students may be at risk for anxiety, and they have higher levels of anxiety and poorer sleep quality than before. Despite the availability of mental health classes and mental health counseling services in schools, stigma (e.g., shame about attending mental health counseling center appointments) and avoidance (e.g., social anxiety) persist (Cuijpers et al., 2019). Therefore, there is an urgent need to provide students with effective ways to adequately alleviate mental fatigue.

Restoring focus through contact with the environment is an effective way to deal with this condition (Hipp et al., 2016). According to previous studies, students who frequent green places tend to be less stressed and have better moods overall (Holt et al., 2019a). A campus space with a natural environment can create an enjoyable experience and increase students' willingness to learn and actively participate on campus (Hajrasouliha, 2017; Carrus et al., 2015). This can improve students' attention span and academic performance (Kweon et al., 2017;

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Matsuoka, 2010) while also helping them to manage their emotions, maintain their mental health (Wang et al., 2018), and lead more fruitful, self-disciplined lives (Taylor et al., 2002). However, existing research tends to focus on particular campus space restorative qualities, such as the design of water spaces and public squares. They do not provide a comprehensive understanding of the restorative qualities of campus environments from perceived dimensions (Lu and Fu, 2019; Wang et al., 2021). Due to that the use of questionnaires, interviews and other survey methods is very time consuming and resource intensive (Zhang et al., 2018). It is also clear that the differences in geographical locations, which result in environmental variations (spatial heterogeneity), there are consequent differences in the perception of restoration. In order to influence the restorative design of campus environments from a more comprehensive perspective, a more affordable and effective way of assessing the restorative quality of campus environment is needed.

Attention Restoration Theory (ART) proposes four factors (namely: being away, fascination, compatibility, and extent) that evaluate the restoration environment, providing important theoretical insights into the restorative cognition of physical environments (Kaplan and Peterson, 1993). However, related studies have overlooked the differential impact of low and high-level visual features on the restoration quality. Low-level visual features refer to the primitive components of scene perception, such as color and edges. These features combine to form complex scenes and constitute high-level visual content (Kandel et al., 2000). Recent studies have found associations between natural or emotional content and different levels of visual features (Redies et al., 2020; Rhodes et al., 2019). Furthermore, Celikors and Wells (2022), Menzel and Reese (2022) have preliminarily explored the impact of low-level visual features on the perception of environmental restoration, but it is not yet sufficiently clear. On the contrary, high-level visual features typically encompass attribute features such as trees and buildings (Kandel et al., 2000). These features have been shown to be significantly related to human perception, such as safety (Kang et al., 2023). (Nordh et al., 2009) has validated that these features could predict the restorative of parks, and similar studies have been conducted by (Han et al., 2023; Yin et al., 2023). However, these studies often neglect low-level visual features in the same images. Therefore, it is great significance to validate the effects of low-level and high -level visual features on the perception of campus restorative environments.

This study aims to achieve three primary objectives centered around enhancing the prediction and understanding of the restoration quality of campus spaces. Firstly, our study's basic research objection is to propose an efficient and comprehensive method for predicting the restoration quality in campus spaces. Secondly, exploring the visual feature differences in the restoration quality of campus spaces. Lastly, investigate the impact of different levels of visual features on the restoration quality of campus spaces. The following questions guide this study:

(1) How can we accurately predict the restoration quality of campus spaces?
(2) Are there discernible disparities in visual features among distinct levels of restoration quality in campus spaces?
(3) To what extent do both high and low-level visual features impact the restoration quality of campus spaces?

By addressing these questions, we aim to provide valuable insights into predicting and enhancing the restoration quality of campus spaces, ultimately contributing to the advancement of both practical applications and theoretical frameworks in this domain.

2. Related work

2.1. Restorative study of campus spaces

Kaplan's research shows that people consume a certain amount of physical, psychological, and social resources constantly in their daily life, study, and work, which leads to the need for recovery when physically and mentally exhausted (Kaplan, 1983). A restorative campus environment can effectively help students recover their consumed attention, relieve mental stress, and produce a series of positive changes in their physical and mental state (Guo et al., 2020). The tree coverage and greening window view are significantly positively correlated with the health, happiness, and academic performance of university students (van den Bogerd et al., 2018; Browning and Rigolon, 2019). Water features are also seen as a positive restorative visual component, and people prefer to walk or ride a bike in areas with rich water features to relieve stress (Massoni et al., 2018). More natural banks in the campus environment attract university students to engage in activities such as reading, meditation, and viewing (Markevych et al., 2017). Additionally, landscapes with hard pavements attract students who enjoy dynamic exercise such as walking and running and tend to be more energetic and less susceptible to stress (Holt et al., 2019b).

Although these studies tend to examine specific areas or plants on campus as spaces with restorative qualities, campuses exhibit distinct spatial variations. For instance, the same waterfront space has significantly different visual characteristics due to differences in spatial location, thereby influencing perceptions of restoration. In addition, most research has used small samples to explain the association between campus environment and restorative effects (Sun et al., 2021; Lu and Fu, 2019; Moll et al., 2022). For example, the (Nordh et al., 2009) study used only 74 images to determine the restorative quality of environment. This is not a convincing result. Additionally, questionnaires have often been used as the main research method in previous studies. Distributing questionnaires is time-consuming and labor-intensive, and it is difficult to collect data promptly (Ha and Kim, 2021; Malekinezhad et al., 2020). It is also difficult to cover the whole campus scale as the survey results either provide general cross-sectional conclusions (Foellmer et al., 2021) or focus on specific locations (Lu and Fu, 2019). As a result, previous studies are insufficient to provide a comprehensive picture of campus restoration.

2.2. Effect of visual features on restoration quality

ART provides a framework for understanding the psychotherapeutic benefits of environmental interactions (Kaplan, 1995). Being away, extent, fascination, and compatibility are the high-level healing features that a restorative helpful environment embodies (Kaplan and Berman, 2010; Berman et al., 2008). Bing away could help us maintain a certain distance from common mental fatigue in daily life (Kaplan and Kaplan, 1989). For example, taking breaks by looking at the scenery outside could provide mental rest (Lee et al., 2015). Extent contributes to cognitive recovery by making people feel involved and immersed. Some studies divide this into coherence and scope. Coherence refers to the organization of scene elements and their interconnectedness, while scope refers to the opportunities for exploration and involvement that the environment provides, creating a sense of depth (Hartig et al., 1997). Both contribute to creating a psychological map of the environment that promotes immersion and engagement (Kaplan, 1984; Kaplan and Kaplan, 1989). Fascination is described as being attracted by the environment without depleting attentional resources or replenishing depleted cognitive resources (Kaplan, 1995). Compatibility refers to the consistency between a person's intentions and the activities offered by the environment, which depends on an individual's propensity for environmental fit and can easily change (Kaplan, 1995; Celikors and Wells, 2022). As this study aims to examine visual features of the environment as potential restoration mechanisms, compatibility is not included in this study. Despite the theoretical importance of ART, restoration quality, e.g., the relationship with visual features, has not been the subject of sufficient evidence.

Scene perception is a complex process that takes into account the dynamic interactions between several levels of visual features (Groen et al., 2017). Color, brightness, contrast, and edges are examples of low-level visual properties that are typically processed early in the visual system (Epstein and Baker, 2019). They combine to create a sophisticated scene (high-level visual properties). Previous studies have shown that people's preferences for natural environments are influenced by low-level color and spatial features (Kardan et al., 2015). Green and yellow plants can make students feel comfortable and calm, alleviate stress and attention fatigue, and improve work efficiency (Guo et al., 2020). Furthermore, a variety of low-level visual attributes, such as measures of hue and edge features, appear to be associated with preferences for specific settings (or levels of naturalness) (Berman et al., 2014). However, removing higher-level visual features appears to reduce this correlation (Kotabe et al., 2017). Indeed, higher-level visual features, such as water and buildings, are better predictors of scene naturalness and scene preference, which are somewhat independent of lower-level visual features (Kotabe et al., 2017). However, current research only considers the effect of visual features on restoration from one side (low or high), ignoring the effect of the interaction between different levels of visual features on perceived restoration.

2.3. Street view imagery and machine learning

Street View imagery has been widely used due to its rich visual information and wide coverage, providing an opportunity for spatial studies at multiple scales. (Biljecki and Ito, 2021). This includes quantifying the blue-green space of the city (Labib et al., 2020), healthy (Feng and Jiao, 2021; Wang et al., 2019), extracting architectural features (Zhang et al., 2021), building a city knowledge graph (Zhang et al., 2023), especially measuring perceptual metrics (Zhang et al., 2018). Research on urban perception often involves using SVIs to explore participants' subjective experiences and quantifying them into humanly perceived attributes such as safety, lively, beauty, and wealth. One influential work is the research by MIT, which provides the Place Pulse 2.0 dataset, which consists of 110,988 urban streetscape images (Dubey et al., 2016). It has been widely used around the world (Wei et al., 2022; Wang et al., 2022). Furthermore, SVIs have been demonstrated to have virtually no deviation from actual perception when it comes to predicting the human sense of security (Kang et al., 2023). Therefore, we use SVIs as the primary spatial data in this study due to their various advantages.

Computer vision techniques are used to process SVIs (Wang et al., 2022; Liang et al., 2023). Image feature extraction models based on convolutional neural networks, such as YOLO (Redmon et al., 2016), SegNet (Badrinarayanan et al., 2017), and VGG (Simonyan and Zisserman, 2014), extract visual features at multiple levels (such as semantic features). These supervised models are trained on datasets such as Cityscape (Cordts et al., 2016), which categorizes urban elements into 19 classes (such as roads, cars, vegetation, and sky). Allowing automatic analysis of highly scalable image features and appearances. However, these models are limited by the categories in the dataset, only recognizing the classes included in the dataset, and their inference speed is limited (Vaswani et al., 2017). To extract features from Street View images, we use state-of-the-art (SOTA) models in this study. For example, the pre-trained model MaskFormer, provided by Meta, recognizes 150 object categories, which could include all the elements that are present in the campus scenes. It also offers fast processing speed (Cheng et al., 2021).

SVI features are typically modeled in a non-linear way using machine learning techniques to identify the relationship between spatial features and human perception (Zhang et al., 2018; Zhao et al., 2023). Unlike traditional linear regression, machine learning not only predicts perception but automatically discovers patterns and structures within large datasets (Zhou, 2021), such as random forests (Breiman, 2001) or decision trees (Kotsiantis, 2013). Machine learning is more accurate and efficient in predicting human perception (Zhang et al., 2018; Wang et al., 2022; Ibrahim et al., 2020). To our knowledge, no research has used this method to assess the environmental restoration quality on campus. Therefore, by combining SVI with machine learning, this research has great potential to propose an affordable and effective technique for assessing the quality of campus restoration.

3. Data and methods

3.1. Research framework and study area

We propose a large-scale and high-resolution method for spatially restorative quality assessment of campuses using SVIs. The method consists of three steps (Fig. 1). (1) Construction of campus restorative quality assessment indicators. We used the PRS-11 questionnaire, which contains four assessment indicators (namely, being-away, coherence, scope and fascination). Each indicator was labeled using a large-scale online survey; (2) extracting visual features of SVIs from pixel-level features, semantic-level features, and scene-level features of SVIs based on computer vision algorithms; (3) building a campus restorative quality prediction model. The SVIs features and campus restorative quality assessment metrics are used as inputs to train the gradient-enhanced regression tree (GBDT) model. And the SVIs features of the campus are input into the training model for prediction and mapping the high restoration quality space on the campus.

Our study area is the Lihu campus of Jiangnan University (JNU) located in Wuxi, Jiangsu Province (Fig. 2). There are 32,219 students enrolled on the campus, which has a total area of 2166 square kilometers and a building area of 1.1 square kilometers.[2] According to the Jiangnan University Centre for Psychological Education, every academic year at least 1550 people report experiencing various levels of research and work pressure.[3] Since we cannot overlook restorative approaches to alleviating stress through the physical environment, it is necessary to analyze the restorative quality of campus spaces in addition to counseling and mental health course knowledge. We collected a total of 1088 panoramic SVIs along the road network at 50 m intervals from the Baidu Street View API,[4] with 4 street view photos (512 *512 pixels) taken from different angles at each location in March 2023 (Fig. 2d).

3.2. Collecting four subjective perceptions of restorative quality

ART served as the basis for the restorative quality assessment matrix used in this study (Kaplan and Peterson, 1993). ART proposes four components for restorative contexts: being away, fascination, extent, and compatibility. Compatibility indicators are not included in this study as it examines the physical characteristics of the environment as a potential mechanism for restoration (Hartig et al., 1997). In addition, because extent is a combination of coherence and scope, it was split into two constructs and measured separately in the PRS (Hartig et al., 1997). PRS (Perceived Resilience Scale) was proposed based on restorative attention theory and has been widely used in research on assessing environmental restorative quality (Hartig et al., 1997). In this study, we used the PRS-11, which assesses being away, coherence and scope, to assess the effectiveness of campus restoration (Laumann et al., 2001). Unlike the PRS scale, the PRS-11 provides two descriptors for scope, and three descriptors for being away, coherence and fascination. Following the work of (Celikors and Wells, 2022), we selected the best phrase to describe each quality and asked participants to rate how strongly they agreed or disagreed with the description of each image (Table S1).

200 campus SVIs (≈20%) were randomly selected for the study (Fig. S1a). Through a one-week online survey in March 2023, a total of 123 student evaluations were collected, including 62 females and 60 males between the ages of 20 and 24 years (mean age = 21.7 years). Based on the PRS-11 questions, participants were asked to select the

[2] www.jiangnan.edu.cn

[3] http://jdxl.jiangnan.edu.cn/

[4] https://map.baidu.com/

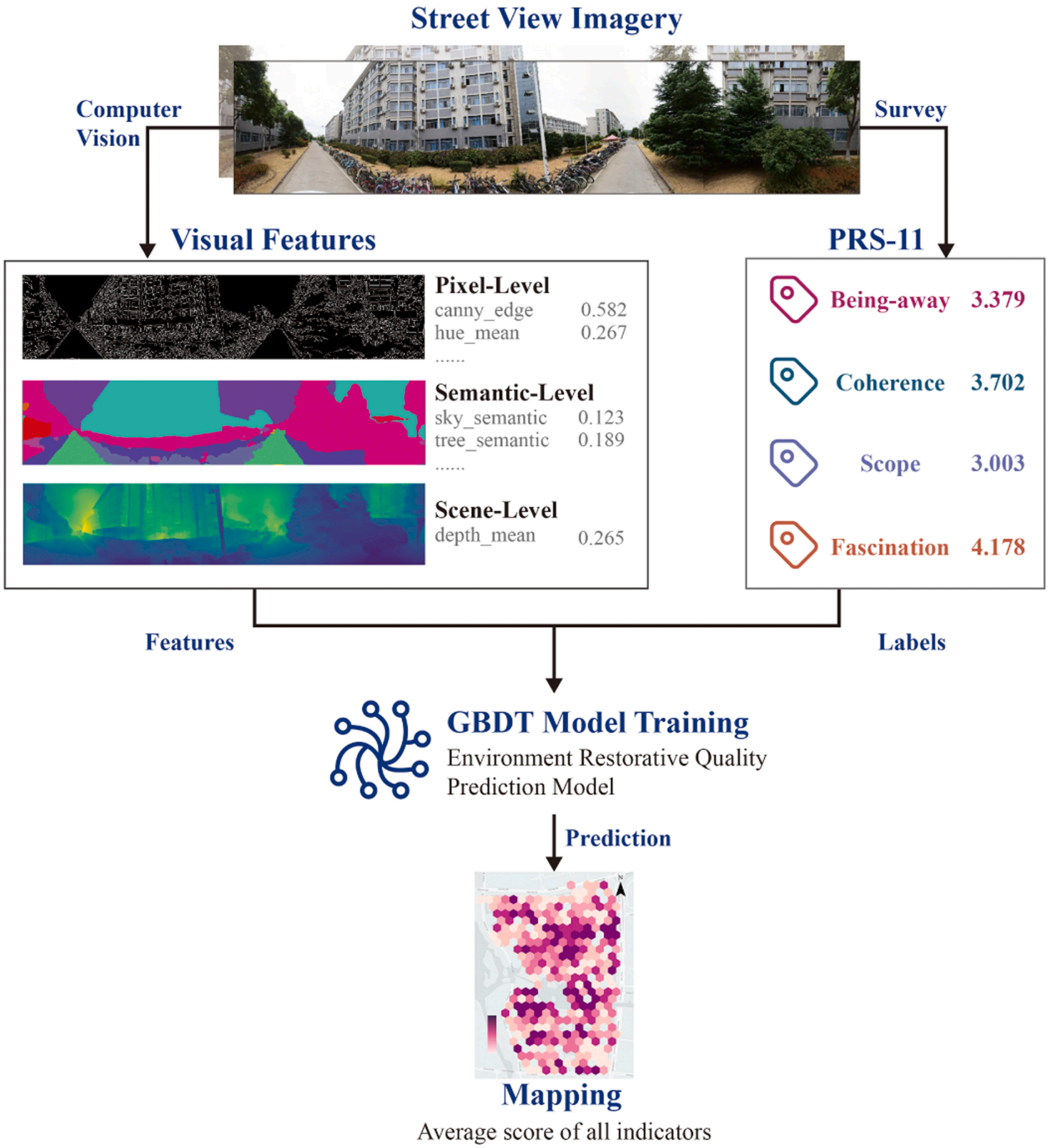

Fig. 1. Overview of our workflow to assess walking space on university campus restorative quality comprehensively from street view imagery.

image that most closely matched the description on our platform (Fig. 3). After five rounds of evaluation, the number of times each image was selected was recorded, the results were sorted using the Trueskill calculation method (Allouche et al., 2006), and the converted into a score between 1 and 7. Consistent with the 7- point Likert scale used below. Each SVI was evaluated at least fifty times on average, with a time limit of 45 min per evaluation. Table S2 presents descriptive statistics of the scores for each restorative indicator.

In addition, 100 randomly selected survey sites at JNU were provided for the validation dataset (Fig. S1b). PRS-11 was used to evaluate the "immersive perceived" of scene restoration quality in real scenes. Table 1 describes the questionnaire content of offline survey. Participants were asked to rate each image on a 7-point Likert scale, with 1 being strongly disagree and 7 being strongly agree. The classification method is commonly used to measure attitudes or perceptions, allowing for more nuanced responses than a simple binary choice (Ki and Lee, 2021). 56 students aged between 20 and 24 years (mean age = 22.6 years) were invited to each survey site to complete the questionnaire in March 2023. There were 30 males and 26 females. On average, each site received more than five ratings. We obtained a perceptual validation dataset for each survey site by calculating the mean (Table S3).

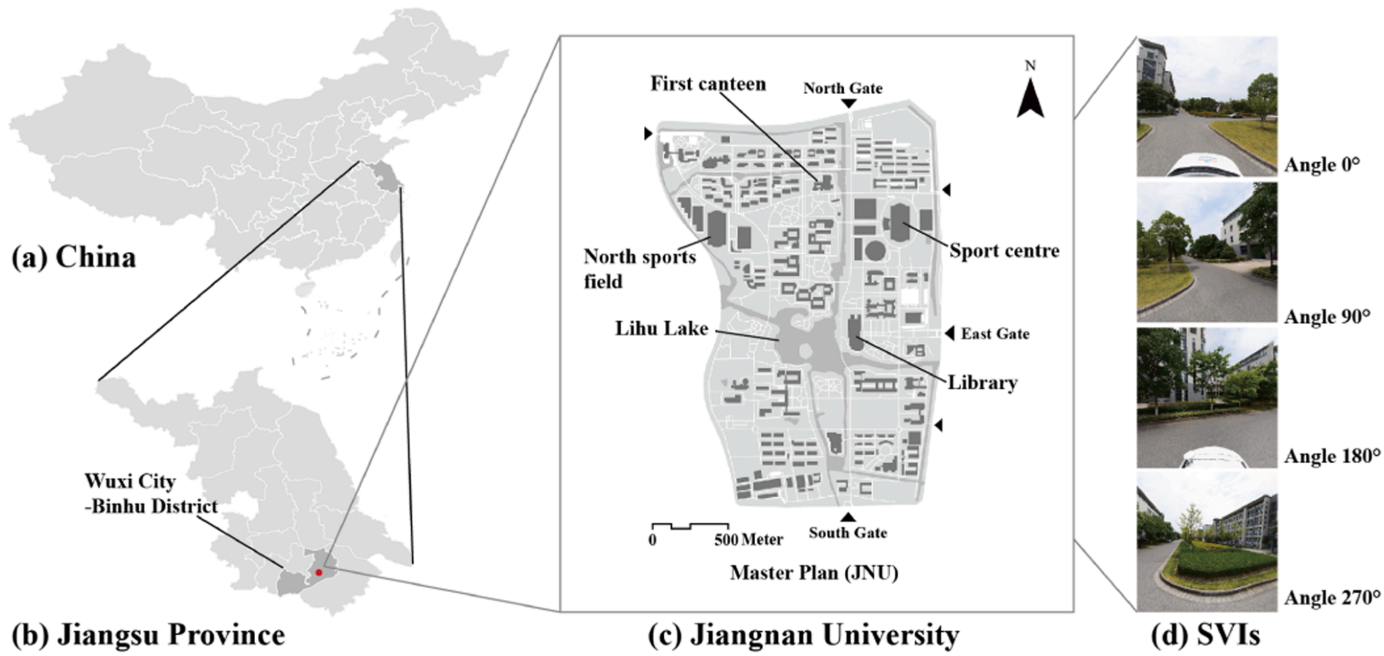

Fig. 2. Overview of the study area for the present study: (a) location of Jiangsu Province in southern China, (b) location of Wuxi within Jiangsu Province, (c) Jiangnan University campus master plan. (d) SVIs samples.

Fig. 3. Interface of campus space restoration evaluation platform.

Table 1
Questionnaire for campus restoration quality evaluation.

Restorative quality	Descriptions	Score (7-point Likert scale)
Being-away	"To stop thinking about the things that I must get done I like to go to places like this."	Very poor 1–7 Very good
Coherence	"It is easy to see how things are organized in this place."	Very poor 1–7 Very good
Scope	"This place is large enough to allow exploration in many directions."	Very poor 1–7 Very good
Fascination	"In this place, my attention is drawn to many interesting things."	Very poor 1–7 Very good

Note. Definition and function of each restorative quality and measurement based on (Pasini et al., 2014; Celikors and Wells, 2022).

3.3. Potential features to support restorative experiences and processes

Computer vision techniques were used to extract visual features at the pixel, semantic, and scene levels. Restoration quality is influenced by different level visual features (such as sematic-level) (Berman et al., 2017). Semantic-level features, such as the percentage of sky, vegetation, and other semantic elements in an SVI, capture the weight of pixel points for each semantic element (Ma et al., 2021). These features have been shown to influence restorative quality (Han et al., 2023). Scene-level elements relate to the depth information of in the environment, which indicates the openness of the scene (Cai et al., 2022). According to Table 2, three pre-trained deep learning models extract visual features. OpenCV algorithms are used to obtain hue, saturation, brightness, and value edge detection properties, which are available at the pixel level. Because it has excellent performance in shallow feature extraction from images and has been widely used in environmental and perception studies (Middel et al., 2019; Rossetti et al., 2019). Meta's faster and more accurate MaskFormer model is used for the semantic-level feature extraction task (sky, vegetation, architecture, etc.). MaskFormer, which is more SOTA than traditional methods (such as SegNet), can recognize 150 categories trained on the ADE20K dataset (Cheng et al., 2021). Finally, the scene depth information (RGB-D) of

Table 2
Summary of feature extraction models and algorithms.

Feature	Model	Pretrained Dataset	Variables
Pixel-level features	OpenCV	–	hue, saturation, lightness, canny edge, threshold…
Semantic-level features	MaskFormer	ADE20k	32 categories (road, sky, tree, etc.)
Scene-level features	DPT-Large	MIX 6	Scene-Depth (RGB-D)

SVIs is inferred using the DPT-Large model provided by Intel. Estimating depth from a single view is commonly considered a dense regression problem. But the appearance of DPT-Large can solve this question to a considerable content, and it could accurately infer the visual depth information with a 28% improvement in performance (Ranftl et al., 2021).

3.4. GBDT based campus restoration quality prediction model

It is conceived as a supervised regression task to predict each environmental quality indicator on campus. Gradient Boosting Decision Tree (GBDT) is a machine learning technique based on tree models that perform well in regression problems (Natekin and Knoll, 2013). Unlike general tree models, the GBDT provides a practical way to manage high-dimensional information and generate accurate predictions without hyperparameter tuning. The basic idea behind the GBDT is to perform each computation by creating a new model in the direction of the lowered gradient to minimize the residuals from the previous computation. The data set consists of $D = \{(x_1,y_1),(x_2,y_2),\ldots,(x_N,y_N)\}$, and $L(y,f(x))$ is the loss function. The number of leaf nodes of each regression tree is J. The input space is divided into J disjoint regions $R1m, R2m, \ldots, Rjm, bjm$. The regression tree generic $g_m(x)$is expressed as follows:

$$
\begin{aligned}
g_m(x) &= \sum_{j=1}^{J}\left(b_{jm}I\right) \\
I(x) &= \begin{cases} 1, x \in R_{jm} \\ 0, else \end{cases}
\end{aligned} \tag{1}
$$

The number of regression trees (M) and the learning rate have the greatest effect on the prediction accuracy of the GBDT model. The prediction accuracy of the model increases as M increases, but too many trees can lead to overfitting and more processing. The SVIs' visual features served as input variables for the training data, and the associated campus environmental quality measures served as target values.

4. Analysis of experiment results

4.1. Model performance and prediction bias

We evaluated Decision Trees Regression (DTR), Support Vector Regression (SVR), Random Forest Regression (RFR), and K-Neighbor Regression (KNR) algorithms to verify the effectiveness of the GBDT predictions with the same parameter settings. The dataset was created using a sample of SVIs used to evaluate the restoration quality of campus scenes, with 20% serving as the test set and 80% serving as the training set. K-fold worse validation, which divides the data into K-folds and uses each of them as a test set, was used to validate the model. In this research, K = 10 was used. In addition, we assessed the effectiveness of the model using the mean square error (MAE) and the coefficient of determination (R^2). For each metric, we calculated the mean of the results from ten replications. Table 3 provides an overview of the results of the study. Overall, the GBDT model performed best for each of the predictions made by the restorative quality scores, with R^2 of 0.633–0.748 and MAE of 0.030–0.246. The DTR model performed the worst across all metrics.

The expected indicators of restorative quality are human perceptions of SVIs. To confirm the sensitivity of using the SVIs to predict the restorative quality of the campus, we evaluated the relation between the expected results of the SVIs and individuals' perceptions of the actual scenes. As outlined in Section 4.3, questionnaires were distributed in the field, and immersive perception results were gathered to evaluate the restorative quality of the campus. The correlation between human and prediction results (all indicators) is shown in Fig. 4(a), with $R^2 = 0.726$. Fig. 4(b) illustrates the differences between the predicted results and the perceptual validation data. Except for the "Fascination" indicator (human=4.136, predict=4.218), the median of the GBDT model predictions was somewhat lower than the "immersive" perceptual scores for all other indicators. However, the difference was small, and for each indicator, the range was quite narrow (3.756–4.358). Although three outliers were observed in the direct perception ratings for the "Coherence" indicator, it is reasonable to conclude that this variation can be attributed to individual differences. The results of these analyses indicate the accuracy of SVIs in assessing the campus restorative quality.

4.2. Restorative distribution of campus space and differences in visual features

Fig. 5a shows the spatial distribution of the quality of campus space restorative predicted by the GBDT model. We projected the average of the four restoration perception scores (PRS-11) onto hexagons with a radius of 50 m. Hexagonal grid cells share more adjacent edges and have equal distances between neighboring center points, which makes the distribution of restoration results smoother. In addition, hexagons can represent the overall situation of each small area, effectively avoiding erroneous results in individual areas and guiding updates or renovations in different regions. Areas with better restoration quality are represented by darker colors.

As shown in Fig. 5a, spaces with high-quality restoration are mainly distributed around Lihu Lake, the east gate, and the sports center. These spaces have attractive scenery and broad views. Waterfront spaces have more significant restoration, producing a cool and refreshing feeling in the summer, and providing a comfortable environment for meditation or sightseeing (Burmil et al., 1999). Additionally, sports fields in the campus environment are a preferred space for student activities, and engaging in outdoor sports can help release learning stress and aid in attention restoration (McCormack et al., 2010). Interestingly, the east gate, as an important entrance, with abundant plants and open views, seemed to have produced high-quality restoration. By contrast, the university dormitory area surrounded by buildings seemed to have insufficient restoration, and the low-level blue-green space visibility greatly reduces the attractiveness of the space and affects the perception of restoration (Labib et al., 2020).

According to predicted results, we used Jenks Natural Breaks to classify the restoration quality of campus spaces into three categories: low, medium, and high (Fig. 5b). Jenks Natural Breaks is best for groups with similar values and maximizes the differences between classes (Liu et al., 2023). We found that green plants were generally lacking in low-quality campus restoration spaces, and building density was high. In medium-quality campus restoration spaces, more shrubs appeared, which to some extent, increased the space's storability. In high-quality

Table 3
Restorative quality prediction accuracy in different models.

Models	Being-away		Coherence		Scope		Fascination	
	MAE↓	R2↑	MAE↓	R2↑	MAE↓	R2↑	MAE↓	R2↑
DTR	0.724	0.306	0.777	0.432	0.753	0.482	0.794	0.468
KNR	0.647	0.401	0.647	0.419	0.705	0.311	0.558	0.484
SVR	0.481	0.536	0.568	0.530	0.521	0.555	0.456	0.577
RFR	0.359	0.583	0.329	0.547	0.254	0.632	0.254	0.587
GBDT	0.212	0.655	0.246	0.633	0.090	0.748	0.030	0.677

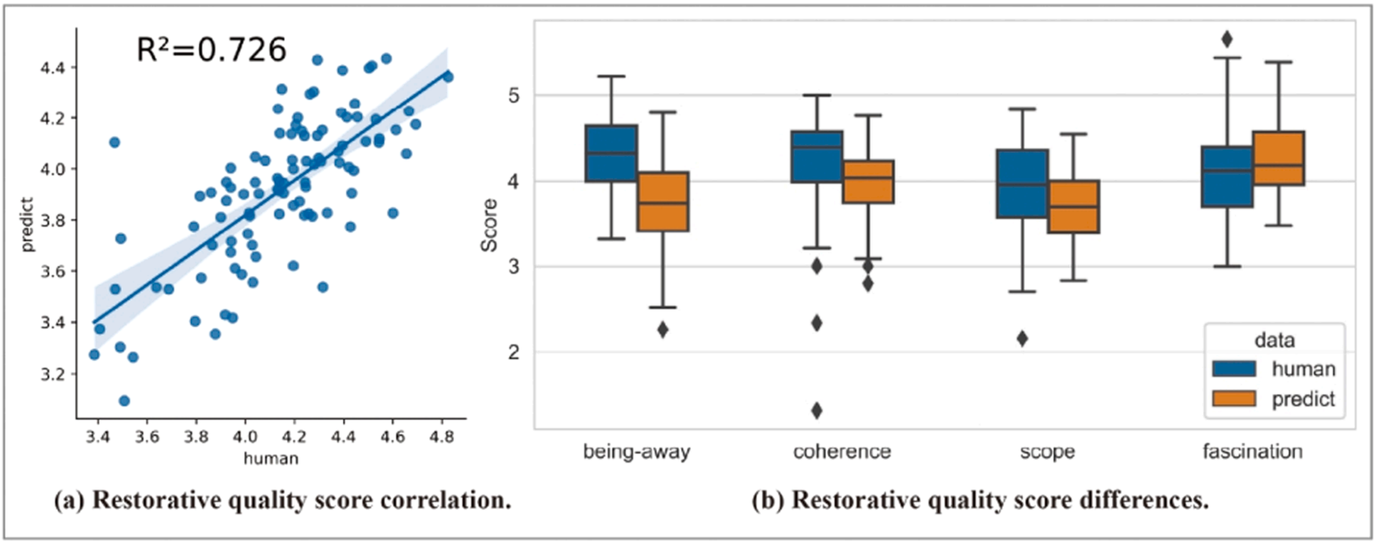

Fig. 4. Prediction results validation: (a) restorative quality score correlation (all indicators), (c) restorative quality score differences between human and model prediction on each perception.

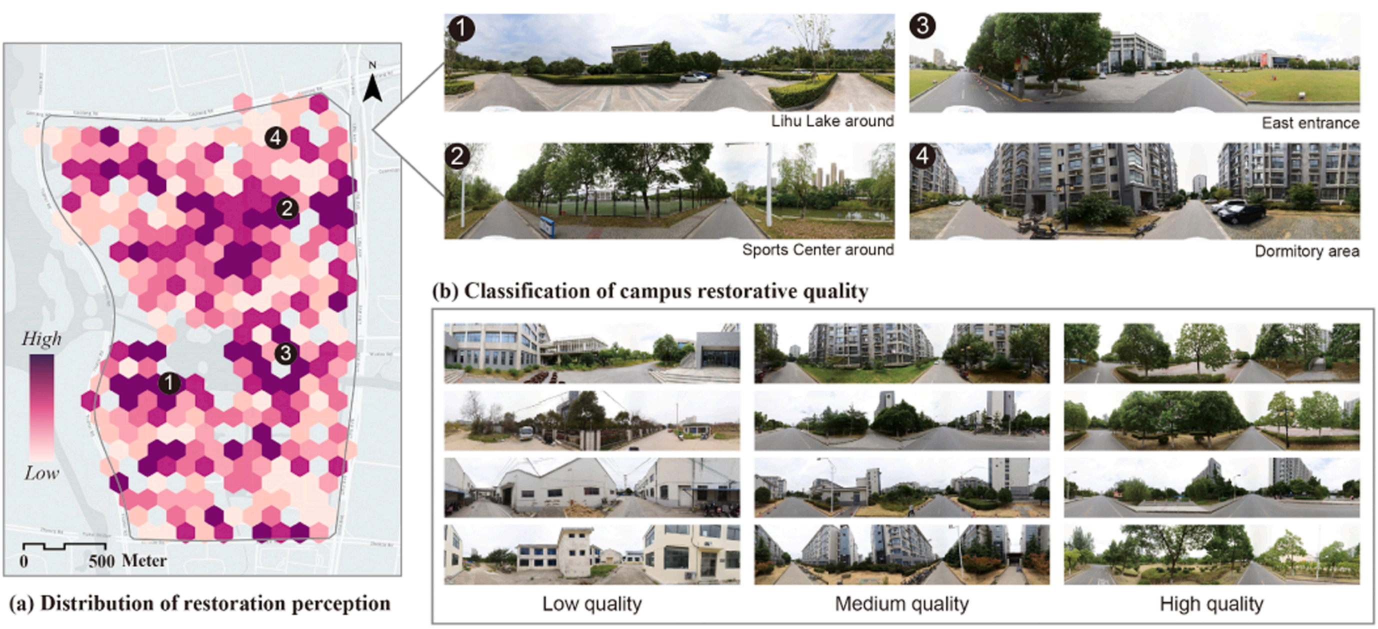

Fig. 5. Distribution of restoration perception and classification of campus restorative environmental quality predicted using the GBDT model.

restoration spaces, a comfortable road ratio and abundant trees added to the space's affinity and charm. To more clearly observe the visual differences of campus spaces with different restoration levels, we selected 17 visual features based on the GBDT model feature importance Gini index (Table S4). These include six low-level features and 11 high-level features.

Interestingly, although the restoration levels of these three types of spaces differ, we found that the median values of low-level visual features were similar (Fig. 6). Upon closer inspection, the median values of threshold, entropy, and brightness were very close. There were still small differences, such as the median saturation of campus spaces with high-quality restoration being higher than those with low and medium-quality restoration, especially on the edges. Additionally, the differences in median values of high-level visual features were significant among the three-level restoration quality spaces. Low-quality campus restoration spaces contained more buildings, fences, and ground features, and the average scene depth was generally much higher than the others. Higher depth values are associated with spatial variability, which affects students' sense of safety and lowers their restoration expectations (Cai et al., 2022). In high-quality campus restoration spaces, the median values of trees and roads were significant. Trees are undoubtedly conducive to the release of potential stress, and roads with hard paving can also promote students' outdoor activities (Guo et al., 2020; Guo et al., 2023). There were few differences in the sky, rivers, and plants between the three spaces. Blue-green spaces have a positive effect on human health, but they seemed to need to be considered in the context of other environmental features. In conclusion, we could find a preliminary research conclusion: the impact of low-level visual features on judging the quality of campus space restoration is minimal, while the impact of high-level visual features is more pronounced.

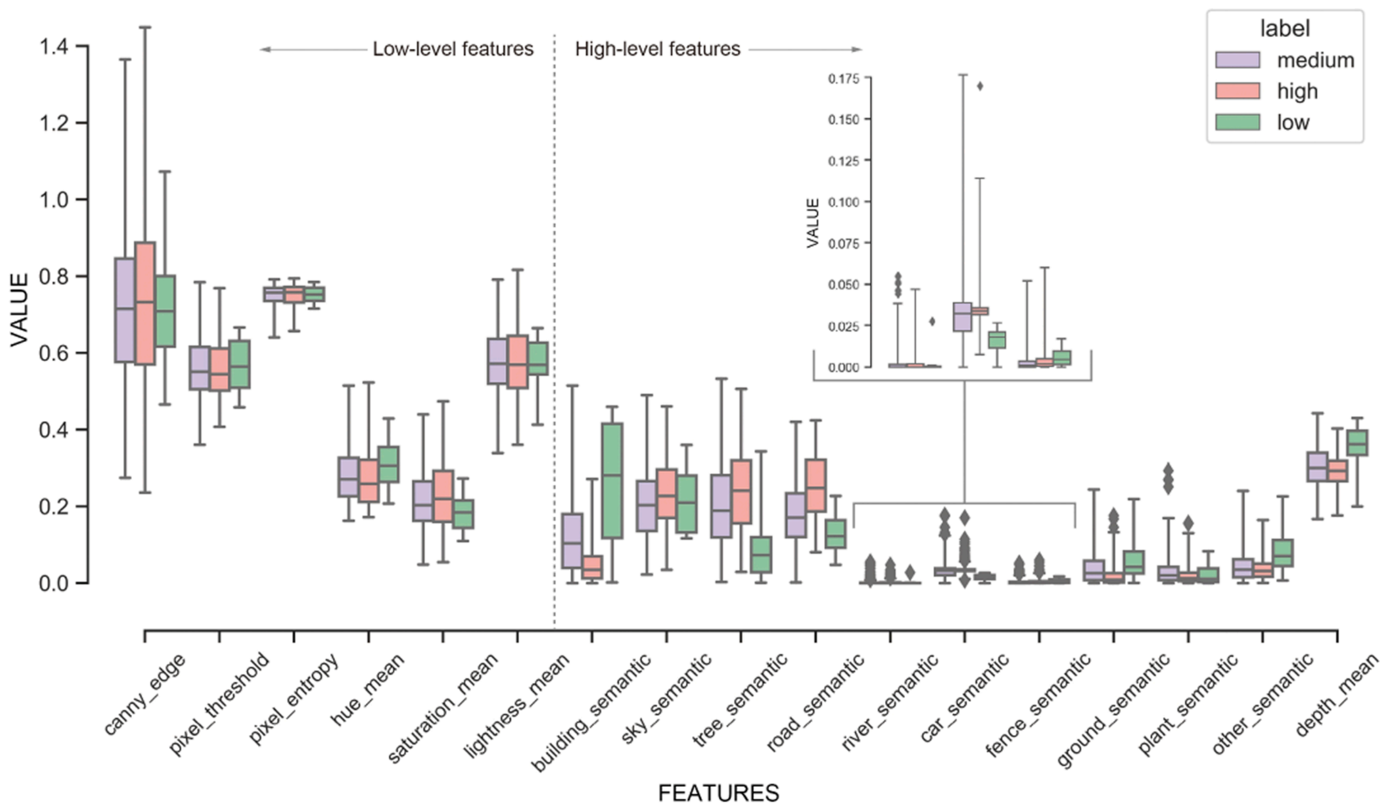

Fig. 6. Differences in visual characteristics of campus spaces at different restoration levels.

4.3. Restorative differences and correlations between high and low visual features

To further verify the accuracy of the conclusion, campus restoration spaces with high scores were separately analyzed. First, we constructed a correlation matrix to understand the potential relations between visual features (Fig. 7). Warm-colored dots represent positive correlations, and cool-colored dots represent negative correlations. The larger dots size, the stronger the correlation. And the cross means those variables didn't pass the significant correlation test ($p > 0.1$). Upon close examination, there are correlations between visual features of different levels. For example, the color saturation of high-quality restoration scenes is positively correlated with the sky, trees, and plants. The scene's brightness is correlated with the sky, roads, ground, and plants. These results are consistent with our expectations. Additionally, there are also significant negative correlations between these features, but only between the same level of visual features. In low-level visual features of high-quality restoration spaces, brightness is negatively correlated with saturation and edge density is negatively correlated with brightness. It can be explained that higher edge density represents a higher level of scene complexity, which accordingly reduces the brightness of the scene. Furthermore, in high-level visual features, trees, ground, and plants are significantly negatively correlated with the sky. This corresponds to common sense, where the number of trees can obstruct the visibility of the sky. In conclusion, there are correlations between visual features of different levels in high-quality campus restoration spaces. Therefore, the conclusion that low-level visuals have a weak impact on campus space restoration quality needs further discussion.

We constructed three multiple regression models to verify the preliminary conclusion in Section 5.2 and compared the explanatory differences between high and low-level visual features on the perception of high-quality restoration (Table 4, Table S5). Due to the high correlation between these variables, we examined the Variance Inflation Factor (VIF) values of the variables (Weisberg, 2005). We found that only the VIF values of building (13.327), sky (15.276), and tree (20.494) were greater than 10 (high multicollinearity), which means we need to remove them. The VIF values of pixel-level features and several semantic-level features (such as car_semantic) are all below 10 (no multicollinearity). Although the VIF is used to measure multicollinearity, it is not absolute. Previous research has shown that these three variables have a significant effect on restoration (Zhou et al., 2022; Yakınlar and Akpınar, 2022). Additionally, these variables also have a high Gini rank (Table S4). Therefore, we retained these three variables. We calculated Standardized Bayesian regression coefficients for different levels of visual features. The adjusted coefficient of determination (Adj R^2) was used to evaluate the performance of the models.

Overall, in Model 1, we found that shallow visual features had poor explanatory power for the restoration quality evaluation indicator, with an Adj R^2 of 0.032. Low-level visual features such as threshold and hue had no significant impact on high-quality restoration environmental perception. On the contrary, when considering high-level visual features of semantic and scene levels in Model 2, the model's explanatory power became higher, with an Adj R^2 of 0.504. This validates the preliminary conclusion we drew in Section 4.2. We found that buildings, ground, and average scene depth were significantly negatively correlated with high-quality restoration perception. The average depth of the scene has never been discussed in previous restorative studies. In our study, the beta coefficient for scene depth in model 3 is − 0.127. The higher average depth is associated with spatial variability, which affects students' sense of safety and reduces their expectations of recovery (Cai et al., 2022). Interestingly, in Model 3, we tried to include all-level visual features in the model and calculated the Adj R^2 values for each restoration quality evaluation indicator. The Adj R^2 values were very close to the results of Model 2, and brightness was no longer significant. Therefore, we can conclude that low-level visual features have a weak impact on judging the quality of campus space restoration and have poor explanatory power for high-quality restoration perception.

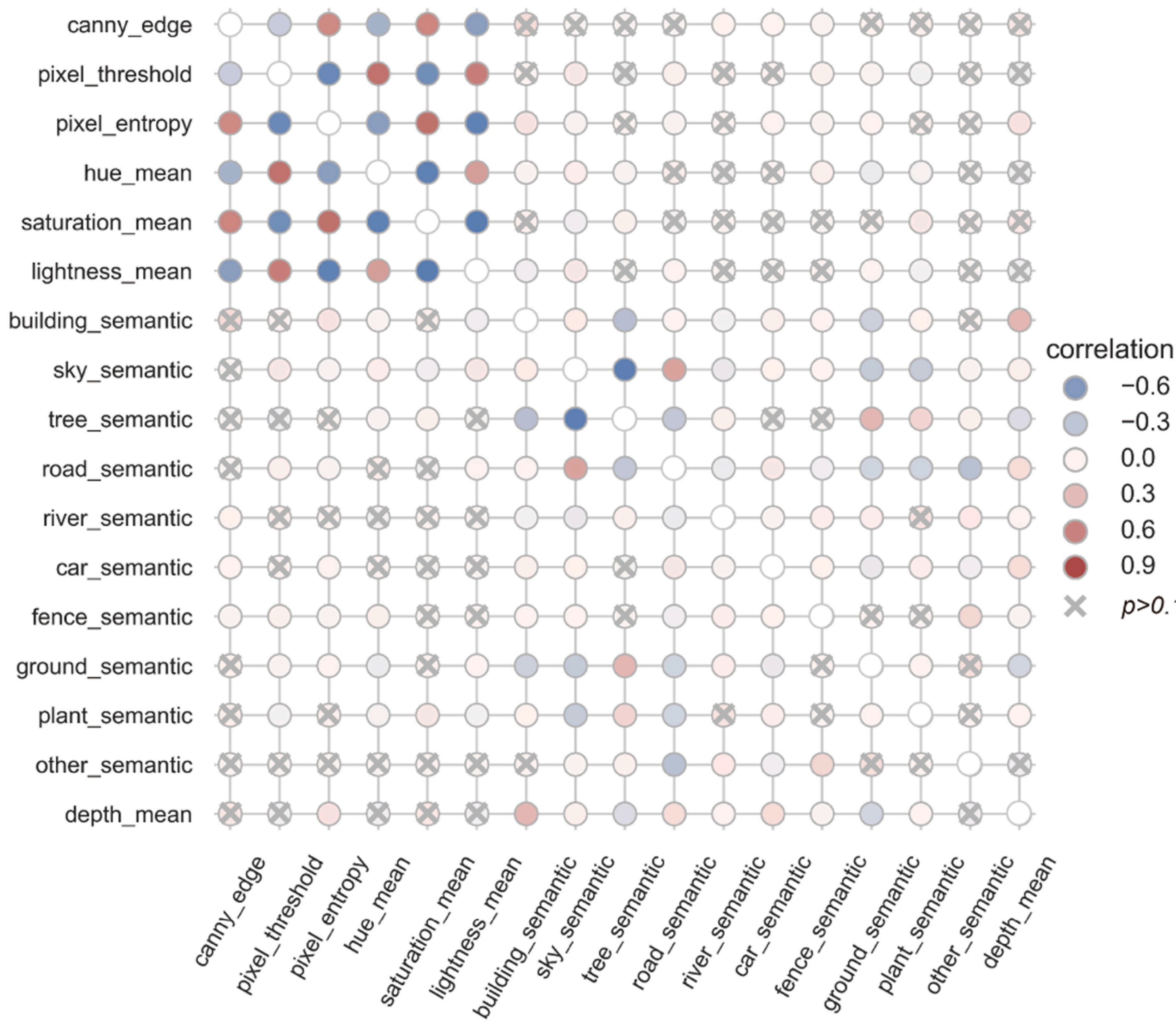

Fig. 7. Correlation matrix of campus high-quality restorative spatial visual features.

Table 4
Regression results in different visual levels and high restorative qualities of campus space.

Feature	Variable	Model 1 (Low-level feature effect)		Model 2 (High-level feature effect)		Model 3 (Total feature effect)		VIF
Pixel-level	canny_edge	0.065	*	/	/	0.055	* *	1.863
	pixel_threshold	0.004	–	/	/	-0.011	–	3.066
	pixel_entropy	-0.127	* **	/	/	-0.060	*	2.877
	hue_mean	-0.004	–	/	/	-0.009	–	2.866
	saturation_mean	0.243	* **	/	/	0.121	* **	4.070
	lightness_mean	0.128	* *	/	/	0.053	–	2.950
Semantic-level	building_semantic	/	/	-0.126	* **	-0.115	* **	13.327
	sky_semantic	/	/	0.185	* **	0.186	* **	15.276
	tree_semantic	/	/	0.418	* **	0.419	* **	20.494
	road_semantic	/	/	0.389	* **	0.383	* **	2.561
	river_semantic	/	/	0.113	* **	0.113	* **	1.129
	car_semantic	/	/	0.178	* **	0.172	* **	1.158
	fence_semantic	/	/	0.057	* *	0.064	* **	1.137
	ground_semantic	/	/	-0.277	* **	-0.275	* **	1.639
	plant_semantic	/	/	0.022	–	0.018	–	1.399
	other_semantic	/	/	0.091	* **	0.085	* **	1.574
Scene-level	depth_mean	/	/	-0.131	* **	-0.127	* **	1.475
Adj R^2		0.032		0.504		0.563		

Note: p values are shown in parentheses; * <0.1, * *< 0.05, * ** <0.01. Although the three variables (building_semantic, sky_semantic, and tree_semantic) have high VIF values, based on the experience of Yakınlar and Akpınar (2022), Zhou et al. (2022), and Gini features rank (Table S4), they are still retained.

5. Discussion

5.1. Restorative differences of high-low level visual features in campus space

This study investigates for the first time the explanatory differences between high and low-level visual features on high-quality campus restorative spaces. It can be affirmed that low-level visual features have little impact on judging the restorative quality of campus space, and have poor explanatory power for high-quality restoration perception. Firstly, low-level visual features will dynamically affect people's judgment of the environment restoration quality depending on the image content. Subjectivity may be more likely to occur when the physical characteristics of the environment are reduced. For example, two images of the same beach taken on a sunny day and a rainy day will have very similar spatial visual characteristics but different judgments on whether the scene is restorative (Celikors and Wells, 2022). Such surveys based on visual characterization information often require participants to respond very quickly to images, and therefore low-level visual features are more powerful in predicting preferences (Kardan et al., 2015). Secondly, prior knowledge will affect the judgment of the restorative quality of the campus environment. For example, certain image attributes may amplify activity from low-level to high-level processing areas after the object is recognized, or through feedback loops from high-level to low-level areas (Andrews et al., 2015; Rice et al., 2014). This is supported by the brain's prior knowledge of imaging data. Simply put, low-level visual features do not have the attributes of real objects, so the brain's prior knowledge intervenes in the judgment when perceiving these contents. Additionally, high-level SVIs features have a significant impact on restorative quality. High-level visual features have the attributes of objects, which can regulate the relationship between higher-level processing, evaluation, and restoration. At the same time, there is continuous bidirectional feedback between top-down prediction and bottom-up information to minimize energy consumption (Schertz and Berman, 2019; Friston, 2005). Our findings support the development of restorative campus spaces, where high-level visual features should be prioritized in terms of physical environment design and landscape setting. Therefore, our conclusion is valid, and these results can provide practical significance for the design of healthy campuses and interventions that are conducive to students' psychological restoration.

5.2. Measuring restorative quality to promote healthy campus construction

In the study of restorative campus environments, creating an attention-restoration space with a preference for space would be effective. First, improving the visual experience is necessary. Plant species and colors are landscape elements that enhance the visual experience for college students. In campus space design, the different colors and shapes of vegetation should be fully utilized to create a comfortable and pleasant space environment. Second, in campus space design, water should be a priority landscape type, although it may be limited by economic conditions, the geographical location of the campus, water resources, and climate region (Bulut and Yilmaz, 2009). Water scenery produces a fresh and cool feeling in summer, providing a comfortable environment for people to meditate or appreciate the scenery (Kaplan and Kaplan, 1989). Moreover, natural water scenery is more easily integrated into the surrounding natural landscape, thereby enhancing aesthetic quality. Third, the design of campus sports space should be considered. The increase in the number, type, and color of vegetation in sports fields is significantly related to enhancing psychological restoration (Kelz et al., 2015). At the same time, reasonable planning of the service radius and spatial layout of sports facilities in the student living area can provide a wider range of sports opportunities for students. Fourth, the most unpopular campus space is the one enclosed by dense buildings. The low-level visibility of blue-green space greatly reduces the attractiveness of the space, while also affecting the quality of perceived restoration (Nordh et al., 2009; Halecki et al., 2023). For campuses with a large number of individual buildings, improving the vegetation space in front of the buildings may have a positive effect. For example, the arrangement of deciduous trees can provide privacy and reduce direct contact between indoor and outdoor visual stimuli. Fifth, creating micro-spaces on campus can create a restorative environment suitable for students to read, meditate, or appreciate the scenery. Increasing trees can improve reading ability, especially natural vegetation, which will encourage students to study in a comfortable environment (Hodson and Sander, 2017).

5.3. Advantage of street view imagery in measuring environmental restorative quality

The SVIs data has been shown to have great advantages in research to achieve a large scale and economical assessment of the restorative qualities of campus environments. It comprises many elements and is a comprehensive and easily accessible source of data (Zhang et al., 2022). They consist of (1) Reliable geospatial coordinate data. Commercial mapping companies such as Google and Baidu can provide extremely accurate coordinate data collection with errors of less than ten meters (Anguelov et al., 2010). They lack comprehensive coordinated information and consideration of the restoration environment as a whole compared to randomly collected test image data of the restoration environment. (2) Both timely updates and comprehensive coverage are achievable. Compared to other data, data from crowdsourced SVI platforms (such as Mapillary and KartaView) offer many important advantages in terms of data availability, coverage, and update rates (Mahabir et al., 2020). (3) With little perceptual difference. Human-centric scene images can effectively avoid the discrepancy between model predictions and actual scene perception. This has been verified in the study of Kang et al. (2023). Furthermore, our study verifies the minimal difference between the predicted restorative quality of campus spaces using street view images and the restorative perception assessment in real-life settings.

5.4. Limitations and future work

We acknowledge that this study possesses some limitations. Firstly, the restorative qualities of the environment are subject to variations. For instance, distinct seasons of the campus landscape may evoke distinctive psychological responses. Additionally, soundscape may impact the restorative qualities of the campus environment, and this has been supported by previous studies (Ratcliffe et al., 2013; Ratcliffe, 2021). However, SVIs data only contains images of campus scenes at a specific time and does not contain any sound information. Consequently, a perceptual difference may arise, as explained in Section 4.3. The effect of scene depth features on perceptual restoration also requires more evaluation. Secondly, this research employed the environmental restoration scale (PRS-11) and only selected the most descriptive term for each category, potentially undermining the precision of the evaluation. Thirdly, the study solely focuses on Jiangnan University, neglecting environmental disparities among other universities. Future studies should incorporate diverse data sources, such as audio, video, and social media, and select more campuses to better inform the findings.

6. Conclusion

The discussion surrounding the correlation between environmental restorative quality and physical environmental attributes has been a longstanding subject of exploration. However, a comprehensive evaluation of environmental restorative quality on a significant scale and with a high level of detail within the university campus, as well as an analysis of the varying impact of visual characteristics of different tiers on restorative quality, remains relatively unexplored. This article proposes a method based on machine learning with large scale and high resolution to address those gaps, establishing a non-linear relationship model between the PRS-11 scale and campus SVIs' visual features, using the GBDT model to predict high-quality restorative campus environments and analyze their spatial distribution. The study also examines the differences in visual features between campus spaces with different restoration quality levels and the impact of diverse visual features on high-quality campus space restoration. Three conclusions were drawn from this study. Firstly, low-level SVIs features have little impact on the evaluation of campus space restorative quality (such as hue, saturation, etc.), although their medians are very similar in three different levels of campus restorative spaces. In contrast, high-level SVIs features have a significant impact on restorative quality (such as semantic features and scene features). Secondly, the restorative quality of campus space has significant spatial heterogeneity, with campus spaces that have natural elements such as water and plants and sports spaces having greater potential for restoration. Thirdly, it is feasible to use SVIs for large-scale prediction of campus space restorative quality. Our study extends to the realm of constructing health-oriented campuses and holds the potential for broader application in the design of health-centric spaces at the community and urban levels.

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CRediT authorship contribution statement

Haoran Ma: Conceptualization, Methodology, Software. **Haoran Ma, Qing Xu:** Data curation, Writing – original draft preparation. **Haoran Ma, Qing Xu:** Visualization, Investigation. **Yan Zhang:** Supervision. **Haoran Ma, Yan Zhang:** Writing – reviewing and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The numerical calculations in this paper have been done on the supercomputing system in the Supercomputing Center of Wuhan University.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.128087.

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