

Deep Learning-Driven Morphological Dataset and Analysis Methods for Chinese Campuses

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Abstract

Modern campuses in China display distinct morphological characteristics, evolving to form unique patterns as subsystems within the urban environment. Hence, the approaches for comprehensive analysis for those urbanized Chinese campus morphology (UCCM) are important. This study proposes a framework for dataset construction and morphology recognition of UCCM, using visual representing learning methods. Computer vision technologies are used to acquire the morphology patches of 1257 campuses. We analyse the campus morphology with our proposed multi-dimensional morphometrics. Then, we constructed multiple morphological cluster maps for UCCM in terms of road, building and landscape, respectively. The cluster maps show significant compliance with human visual perception. Compared with classic morphometrics, our approach excels in learning implicit morphological characteristics with lower data processing demands and less reliance on expert experience.

Keywords: Urbanized Chinese campus morphology, Morphometric, Visual Representation, Self-organizing Map, Unsupervised learning

Abstract

Modern campuses in China display distinct morphological characteristics, evolving to form unique patterns as subsystems within the urban environment. Hence, the approaches for comprehensive analysis for those urbanized Chinese campus morphology (UCCM) are important. This study proposes a framework for dataset construction and morphology recognition of UCCM, using visual representing learning methods. Computer vision technologies are used to acquire the morphology patches of 1257 campuses. We analyse the campus morphology with our proposed multi-dimensional morphometrics. Then, we constructed multiple morphological cluster maps for UCCM in terms of road, building and landscape, respectively. The cluster maps show significant compliance with human visual perception. Compared with classic morphometrics, our approach excels in learning implicit morphological characteristics with lower data processing demands and less reliance on expert experience.

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1. Introduction

With the expansion of higher education in this century, more universities and campuses have been established in Chinese cities, especially in suburban and nascent urban areas. These new campuses occupying larger footprints than their initial forms, responding to expanding enrolment and diversified functions. These urbanized Chinese campus morphology (UCCM) are often isolated from surrounding urban areas, evolving into a distinct subsystem within the broader urban network. They have changed the pre-existing urban fabric and ecological landscape to a significant extent.

A comprehensive recognition about morphology of those urbanized campus is required, since their form not only contributes to the shape of the city but also links to the efficiency of teaching and learning (Kenney, Dumont and Kenney, 2005). At the master planning level, modern campus morphology study involves various aspects such as campus circulation, built environment, spatial compactness, contextual responsiveness, and increasingly, landscape ecological patterning (Dalton, Hajrasouliha and Riggs, 2018). Most studies proposed strategies for campus urbanization based on practical experiences or comparative analyses of various campuses (Xu, Zhang and Rong, 2012; Zhang, Fisher, and Gang Feng, 2020; Meng *et al.*, 2023). There is a lack of specific classification criteria and a comprehensive morphological recognition framework, especially for these newly urbanized campuses in China. Urban morphology characteristics are twofold, encompassing both measurable and immeasurable aspects, such as quantifiable metrics and abstract prototypes. This complexity adds significant challenges to digital morphological classification for campus.

In this context, this study proposes an approach of the dataset construction and morphology recognition based on visual representation learning approach for the new urbanized campus form in China. We gather images and data on 1257 medium to large-scale higher education campuses in China from open-source mapping platforms. Image processing techniques are applied on high-resolution map tiles to address the challenge of incomplete data on campus, converting them into vector geographic graphics. Based on the dataset, we firstly analyse the UCCM with morphometrics in multiple dimensions, including site and context, roads, buildings and density, and landscape ecology. Furthermore, we deploy deep learning techniques to deal with visual features which are challenging-to-quantify. Utilizing the unsupervised Self Organizing Map (SOM), morphological cluster maps for Chinese campus are constructed, which facilitate to discover similarities and characteristic among campuses. Our research offers insights into the understanding of the morphology of campuses in China in two different ways, morphometrics and visual representation using deep learning. Morphological recognition based on visual representation methods has unique advantages, and integrating the two methods will be the focus of subsequent research.

Related work

Representing Campus Form

The Morphometrics approach has gained strong momentum in urban research, with the advent of new geospatial data and tools. It dedicates to describe the form through the quantification of geometry and relationship of urban elements. Separated dimensions are considered in multi-scale urban form, which often includes intensity, distribution, proximity, connectivity, complexity, diversity and form, etc. (Salat, 2011). Existing studies have proposed multiple metrics through interdisciplinary approaches and validated their effectiveness in characterizing urban form (Clark, Martin and March, 1975; Marshall, 2004; Berghauer Pont and Haupt, 2005). Morphometric on blocks and blocks assemblage hierarchies inform medium to large scale campus morphology studies, for their similar scales.

Researches on campus form focus more on the certain elements like buildings, roads or open space, using case studies and comparative studies (Dalton, Hajrasouliha and Riggs, 2018). Hajrasouliha proposed a framework for campus form dimension and campus score, based on the dataset of campuses in the United States. The form dimensions of campus can be categorized into seven: land use, compactness, connectivity, configuration, habitability, greenness, and cultural heritage, which are summarized in the three perspective of urbanity, greenness, and habitability of the campus (A. H. Hajrasouliha, 2017(a)). It was confirmed that campus scores based on morphometrics were associated with the quality of teaching and learning (A. Hajrasouliha, 2017(b)). As for campus planning in China, the Architectural Design Sourcebook (Volume 4, 2017) summarizes exemplary campus designs and standards, serving as a pivotal reference. The sourcebook provides a qualitative categorization of certain dimensions of campus morphology, while does not address the quantification of morphology or provide comprehensive data support.

Unsupervised Learning and Clustering

Morphological features are those connected with human visual and can usually be easily understood through visual interpretation (Wang, Huang and Biljecki, 2024). The recognition of images is highly inspired thanks to advances in computer vision (CV), while convolutional neural networks (CNN) led breakthroughs on learning features that entail the intrinsic characteristics from imagery data. The visual representation learning facilitates the simulation of human visual interpretation of morphology patches based on sample training with provided training objective. Based on figure-ground maps, unsupervised learning has been applied on morphological feature extraction and clustering of residential plots (Cai *et al.*, 2021) and village patterns (Wang, Tang and Cai, 2023), as well as retrieval of urban blocks (Mo *et al.*, 2024). The recognition of urban network is also widely studied based on images or graphs (Kempinska and Murcio, 2019; He and Aliaga, 2023).

SOM is a general-purpose nonlinear data clustering and visualization method, which creates continuous visual patterns on top of high-dimensional data (Vahid Moosavi, 2015). It has been

proved with high efficiency in architectural form clustering (Jiang *et al.*, 2023). A structured form-map is output, in which each grid unit represents a cluster of similar data, and the spatial distance between the grids expresses the distance of the feature embeddings of the data. It has been applied on the construction of structure form map (Fuhrmann *et al.*, 2018), as well as retrieval of residential based on multimodal features (Cai, Zaghoul and Li, 2022). Considering there is no consensus in the categorization of Chinese campus morphology, unsupervised learning is applied and an atlas of campuses are constructed with SOM.

2. Morphological Dataset Construction

We comprehensively gather images and data on 1257 medium to large-scale higher education campuses in China from open-source mapping platforms (Figure 1). The amalgamation of graphical, imagery, and quantitative data is constructed and processed for four aspects: context, roads, buildings, and green spaces.

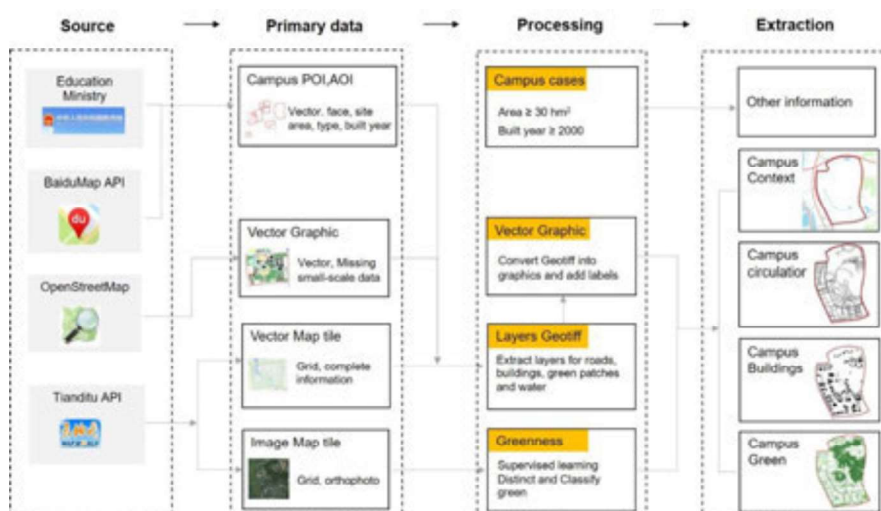


Figure1 Morphological Dataset Construction framework for urbanized Chinese university campus morphology.

2.1 Campus Selection

China's higher education institutions include both higher universities and higher vocational and technical colleges, which include private or public, vary in size, and have one or more campuses. In China's campus construction standards, campuses are classified as small, medium, large and extra-large according to their size (Figure 2). Among them, small campuses are those under 30 hectares, most of which were constructed earlier, with simple road networks and consist of a limited number of buildings. This study focuses on medium-sized campuses and above, which

Among them, the campus divided by a county road with functionally intact parts will be treated as two. As a result, 1257 campus with area larger than 30hm² are selected (Figure 3).

2.2 Imagery Data Acquisition and Processing

There is a significant missing for geometric data of campuses in China, especially those located in suburbs or new towns, on widely-used open map platforms like open Street Map(OSM). To address this issue, we propose a method to extract information from map tiles acquired from online map platforms. After comparing different map platforms through experiments, it is founded that the Map World API provided by CNGISP (China National Geographic Information Public Service Platform: World Map, no date) excels for high timeliness and comprehensive data with zoom level up to 17.

The exact map tiles for campus are pinpointed and crawled with their geometrical information. Specifically, the column and row indexes of map tiles are calculated by longitude and latitude, according to the rules of Mercator projection transformations:

$$\begin{aligned}I_{row} &= \text{Floor}[2^{\text{zoom}} \cdot ((lon + 180)/360)]; \\ I_{col} &= \text{Floor}\left[2^{\text{zoom}-1} \cdot \left(1 - \frac{1}{\pi} \log(a)\right)\right] \\ a &= \tan(lat \cdot \pi/180) + 1/\cos(lat \cdot \pi/180);\end{aligned}$$

In which the value of zoom is 17. A 9*9 matrix of tiles around the centre point of each campus is crawled, which covers exactly the largest campuses.

The imagery data are then converted to GeoTiff format attached with geography data using GDAL, in order to interact with geographic elements, such as being clipped by campus boundary. Image processing techniques are applied to classify and extract data from them. From the vector map, roads, buildings, green and river regions are extracted by colour and converted to binary image using OpenCV separately. They also support further vectorization and analysis on ArcGIS. Meanwhile, the plant types are roughly distinct from the image map by mature supervised classification tool, labelling part of each type manually and then generating the whole results. Overall, our campus morphology patched consists of geometric elements of boundary, roads, buildings, water systems, and green spaces in and around the campus. (Figure 4)

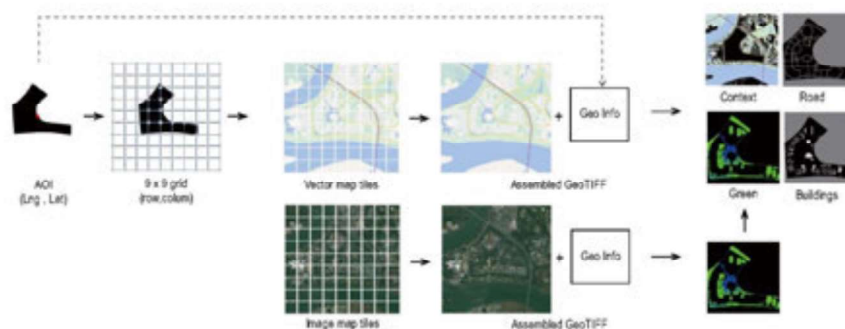


Figure 4 The acquisition and combination process of campus tiles, constructing the campus geometric data with multiple layers

3. Morphometrics for Campus

3.1 Dimensions and Metrics

Based on the characteristics of campuses in Chinese cities, this study attempts to focus on the campus form from four perspectives: site and context, roads, buildings and density and landscape ecology. Medium-and large-scale campuses in China are usually clustered, with a clear demarcation from the city. With the expansion of cities, neighbourhood of early campuses have developed into high-density region, while the new campuses built in this century, due to the tight urban land use, are mostly located in the outskirts of the city with more natural landscape. As a result, the site forms and contextual elements are quite different. Despite continued advocacy for school-city integration, most campuses have separate road systems which support vehicular traffic but not directly connected to urban roads. The buildings are laid out according to functional zoning, with the teaching area, dormitory area and sports area forming the core functions of the campus. At the same time, ecology is gradually being paid attention to in campus planning, considering the organization of green patches, the configuration of plants, and the relationship between green spaces and buildings. Therefore, from the four perspectives proposed in the previous section, nine dimensions of campus morphology can be delineated as shown in Figure 5.

Referring the method of urban morphometric, we summarize the metrics corresponding to each dimension as well as their calculations and the morphology element data required for the analysis. A case study has been conducted to verify the representation of this metrics.

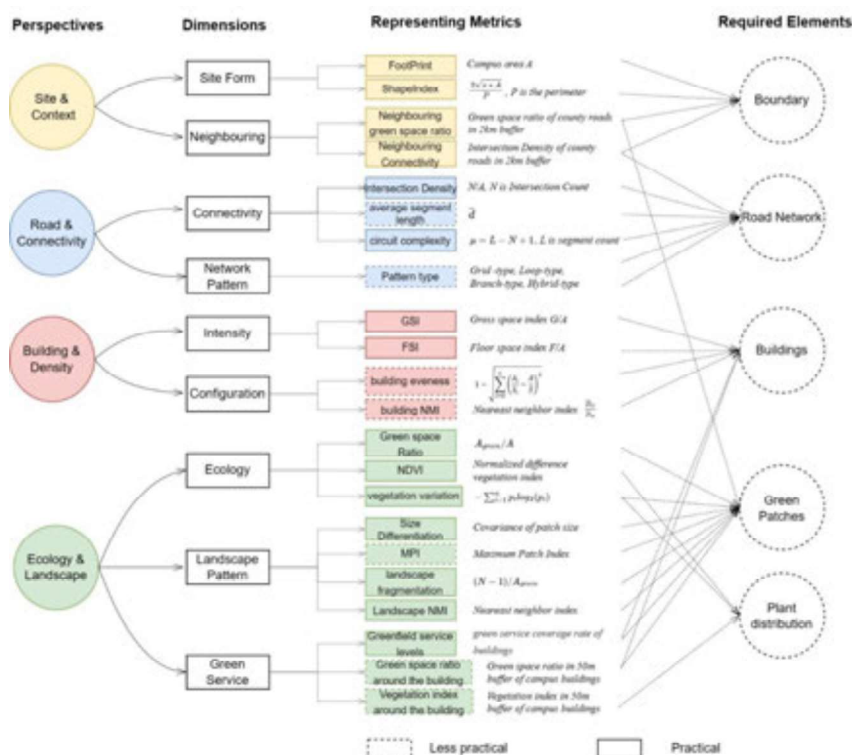


Figure 5 Morphometrics for Chinese university campus with multiple dimensions.

3.2 A case-study of Nanjing

For case study, 38 Campuses in Nanjing are selected to practice the analysis approach applying morphometrics (Figure 6). In order to obtain the geometry for the analysis, the binary image data of the various elements in the dataset are vectorized and assigned with attributes on ArcGIS. It is necessary to classify the road elements according to their width, to integrate water areas with green space patches and to give them a type definition, as well as to extract urban roads and landscapes within a certain range around the campus. Possible missing parts are supplemented and elemental attributes are refined in conjunction with the vector data acquired by OSM.

Figure 7 illustrates the ordering of morphological elements according to morphological metrics, which shows the coincidence of the metrics with human cognition.



Figure 6 The results of morphometrics of the 37 campuses in Nanjing

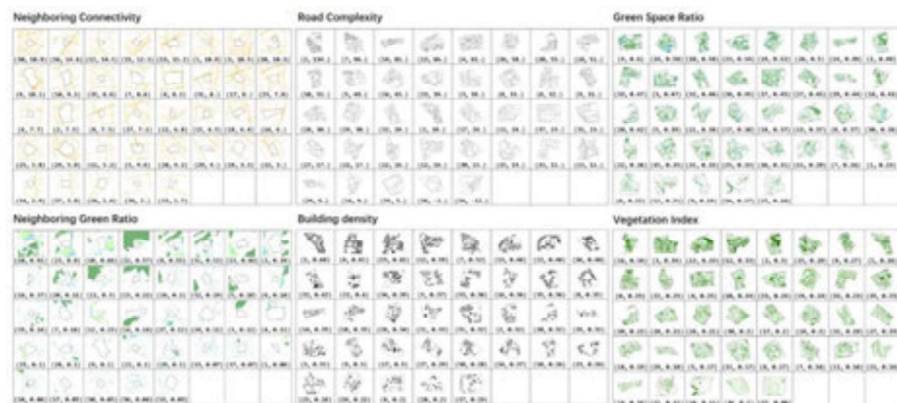


Figure 7 Sorting the selected 37 cases according to the morphological metrics, with the visualizations of corresponding geometric data.

The result implies that intensity-related metrics such as building density, road density, and green space rate are usually consistent with human cognition, while those related to spatial

distribution are relatively ambiguous. The calculation results of shows significant differences and some errors due to the choice of calculation units, differences in campus sizes, and localized missing data. Meanwhile, there are still some implicit features difficult to quantified, such as street pattern, and porosity of building groups, which are usually summarized qualitatively into categories with visual inspection by experts. Though some researches attempt to integrate them into the score system by assigning points, there is no uniform standard and requires considerable human labour.

4. Visual Representing Learning and Clustering

4.1 Visual Representing and data space

In contrast to 3.2 which vectorizes geographic images into geometric data, this section uses neural networks to extract features from morphological patches containing a single type of elements in image format. Among the four types of image patches of the campus, the cultural patches reflect the information of the campus site boundaries and the surrounding urban environment at a uniform scale, while the road, building, and landscape patches are scaled to fill the image at different scales to reduce the distraction of the campus scale and focus on the distribution of the elements. All image patches were scaled down to 256 x 256 pixels. We train feature extractors to extract high dimensional vectors from images for each type of campus patches separately, applying the neural network model. The training data is augmented with affine transformations including rotation and mirroring, resulting in eight times the amount of data compared to the original dataset.

The data space is visualized in 2-D with dimension reduction methods (Figure 8). Nonlinear dimension reduction methods, which have been proven to be efficient for high dimensional features, including UMAP, TSNE and Autoencoder, are tested separately to visualize extracted features. The results exhibit that the campus form gradients rather than falling into simplistic categories, which can be explained by the gradient distribution of both the size and form of Chinese campus. Therefore, compared with classic linear clustering methods like k-means, SOM is applied to achieve continuous visualization as a spectrum in a 2D space.

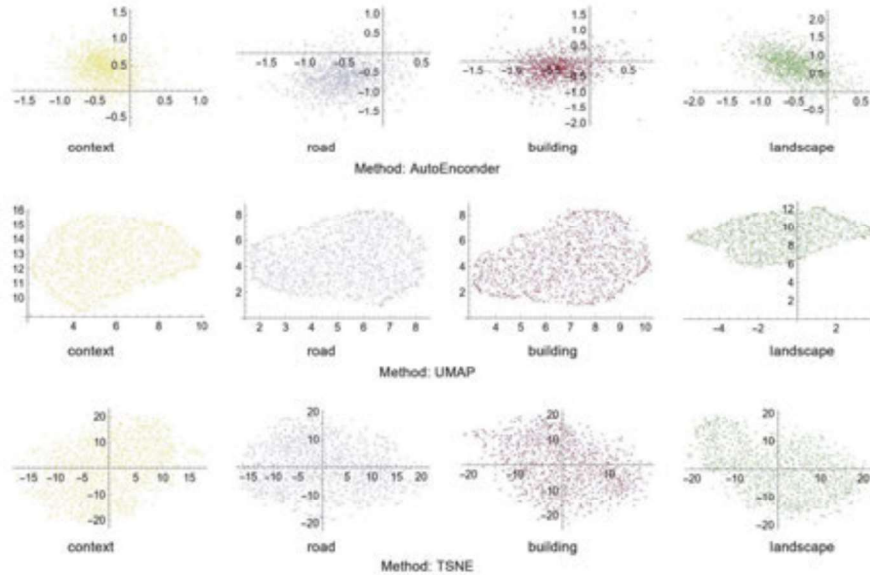


Figure 8 Visualization of High-dimensional vectors in 2D space after dimension reduction using 'Autoencoder' (top), 'UMAP'(middle), and 'TSNE' method (bottom).

4.2 Data Clustering using SOM

To achieve it, a fixed grid is first initialized with random real weights for each node. Then, the SOM is trained with randomly selected examples in the dataset. For each turn of the irritation, the best-matching unit (BMU) of each example is searched, which has a minimum Euclidean distance between its weight to the vector of example. Then the weight of BMU and its neighbours are updated according to Gaussian Neighbourhood Function, and the neighbourhood radius σ shrinks as iteration increasing:

$$g(i, j) = e^{-\frac{(c_x - i)^2 + (c_y - j)^2}{2\sigma^2}};$$

$$\sigma = \left(1 - \frac{u}{ite+1}\right) \times 0.6 \times d/2;$$

where c is the coordinates of BMU, u is the current generation and d is the counts of nodes in each dimension.

For our study, we build SOM for contexts, road, green and building configuration separately. After several parameter tests, a 15*15 SOM is trained by 12 iterations and 40000 examples are

selected for each turn. Then, we represent each grid cell with its most representative sample, to form a morphological cluster map. As a result, the characteristic distribution of UCCM is visualized.

In the campus context map, the combined effects of site scale, surrounding road distribution, and the distribution of natural and artificial landscapes on similarity can be observed. From left to right, there is a trend of increasing road network density and decreasing campus size, reflecting that large-scale campuses are more commonly situated in low-density urban areas. Several typical clusters and corresponding campus cases are extracted, with characteristics including: (1) adjacent to extensive natural landscapes, (2) situated in high-density urban environments with regular boundaries formed by orthogonal road networks, (3) with low surrounding development intensity and absence of natural landscapes, (4) relatively high development intensity with rich urban landscapes and irregular campus boundaries, and (5) coexistence of high-density urban landscapes and surrounding natural landscapes.

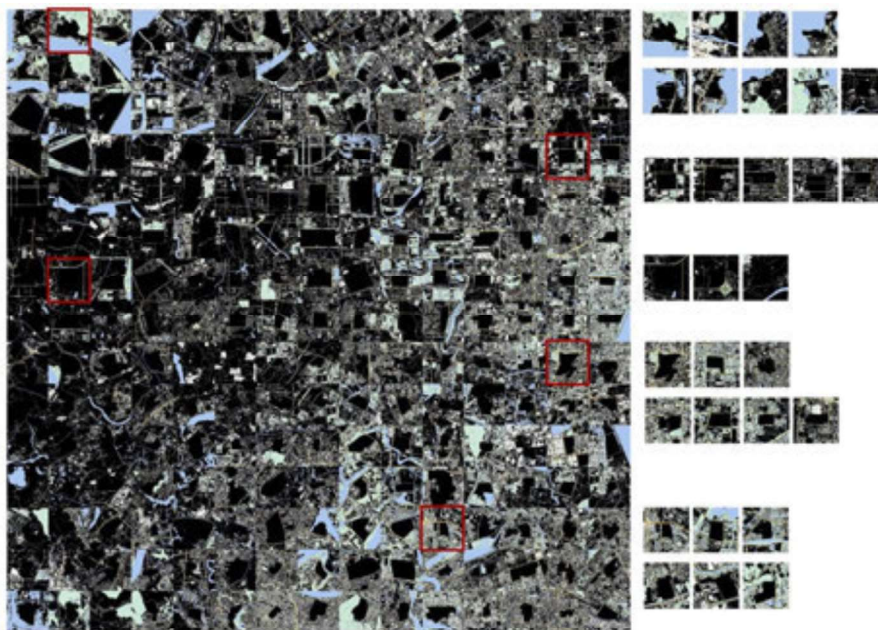


Figure 9 Representation of campus context cluster map and exemplary clusters selected from the map.

The cluster maps, reflecting the morphology of the campus park, are trained with uniformly sized masterplans in order to concentrate on learning of the structure. In the road map (Figure 10), there is a trend of transition from structured to natural from left to right. Grid and ring roads are commonly used features in organized campuses, with grid features particularly prominent

in large-scale campuses. In natural campuses, some exhibit branching structures, while others form irregular campus loops, showing a greater degree of freedom in form. The distribution of data in the building map is associated with both campus shape and building density, although differences in building distribution characteristics are not yet clear (Figure 11). From left to right, there is a trend of gradually regularizing campus shapes, while from top to bottom, there is a trend of decreasing density and organization. In the landscape map (Figure 12), campus landscapes become increasingly rich from top to bottom, while designed landscape water bodies is quite common in the overall campus layout. The campus in the upper-left corner of the map providing valuable references on landscape organization, with high diversity, fragmentation and equilibrium.

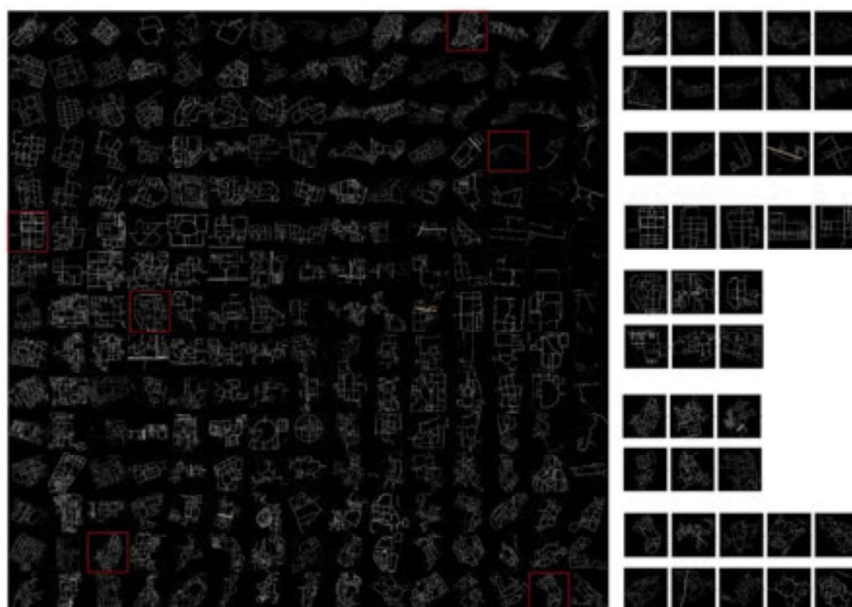


Figure 10 Representation of campus road cluster map and exemplary clusters selected from the map.

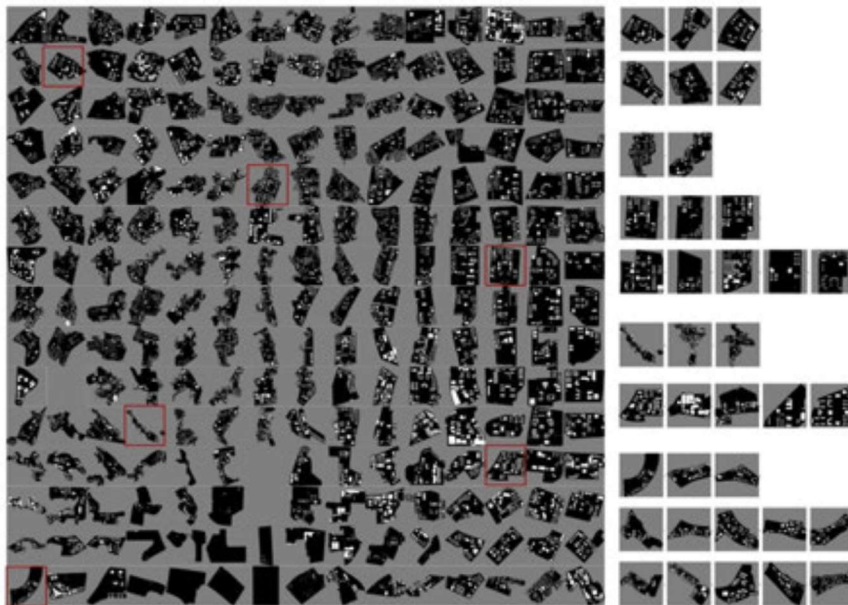


Figure 11 Representation of campus building cluster map and exemplary clusters selected from the map.

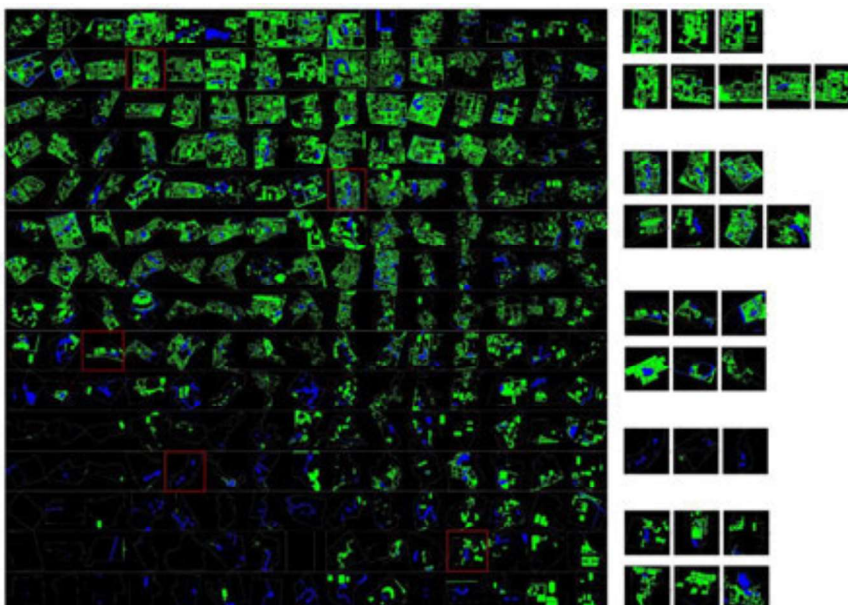


Figure 12 Representation of campus landscape cluster map and exemplary clusters selected

from the map.

Furthermore, these four morphological cluster maps can be correlated with campus objects, enabling multi-perspective linked analysis. For instance, the retrieval of corresponding morphology patches for campuses with similar context is supported.

5. Discussion

5.1 Comparison and Discussion

This study summarizes perspectives and form dimensions of Chinese campus and proposes a framework for morphology recognition based on deep learning. Through case studies, a comparison between visual representation learning methods and classical morphometric methods reveals the advantages and challenges of this framework.

Data Requirements and Technical Difficulty: Traditional morphometric methods rely on geometric data for specific algorithms, necessitating high accuracy and involving complex pre-processing. However, there is a notable deficiency in vector data availability for Chinese campuses on open-source platforms like OSM, while nationwide vectorization of geographical imagery poses significant challenges. Additionally, errors, omissions, or improper unit selection can result in substantial inaccuracies, as evidenced by our experiments. In contrast, visual representation learning extracts intricate knowledge from extensive image datasets, requiring lower data processing demands and exhibiting greater tolerance to data imperfections. Therefore, achieving a comprehensive understanding of nationwide campus morphology is more attainable through visual representation learning.

Representation Advantages of High-dimensional Features: The high-dimensional features extracted through visual representation learning cover multiple form dimensions of campus morphology, resulting in morphological cluster maps that align with human visual perception. This approach excels in capturing intricate feature characteristics such as structure, patterns, and shapes, which are often challenging to quantify. Furthermore, it reduces the dependency on expert experience and minimizes redundancies and incompleteness in indicator representations. However, classical morphometrics, as a foundational approach in morphological research, continues to play an essential role. Its algorithms are grounded in extensive human experience and have been empirically validated in numerous studies. Classical morphometrics advances in the assessment and grading of specific dimensions, facilitating the analysis of broader morphological issues spanning demographics, society, economy, and other domains.

Randomness and Interpretability: Traditional morphometrics produces a unique result for each indicator when employing the same data and algorithms. Conversely, variations in feature extraction methods and training parameters result in diverse outcomes during visual feature learning. This approach inherits the typical challenge of unsupervised learning, where training outcomes display a level of randomness, and optimal parameter configurations rely on experimental expertise. Furthermore, unlike single-dimensional indicators, the comparability

and interpretability of the obtained high-dimensional features and cluster maps are relatively constrained.

5.2 Future Opportunities

Inspired by limitations mentioned above, we proposed several directions for future work.

Integrating visual representing learning and morphometric methods. Classic morphometrics relies on human ingenuity and prior knowledge, among which manually selected metrics representing different dimensional features are integrated into multidimensional vectors. In contrast, visual representation learning relies on machine learning to extract high-dimensional embeddings from images. While these two approaches offer distinct advantages in morphological quantification, merging the two types of vectors is not straightforward. Exploring the integration of metrics and image feature extraction methods is also a significant focus in the current trajectory of urban morphology research (Cai *et al.*, 2021; Qin and Zheng, 2023).

Improving Feature Extraction Methods. Image features extraction based on neural network has been widely applied in various fields. However, compared to common real-world photos, feature extraction for campus patches requires additional understanding of campus morphology. Therefore, fine-tuning and refining neural networks to address specific issues related to campus morphology recognition will significantly enhance the validity of visual representation. Recent studies have endeavoured to enhance models for urban morphology recognition research. For example, SimCLR is employed to guide feature extraction by maximizing mutual information agreement between different versions of the same image (Chen *et al.*, 2020; Wang, Huang and Biljecki, 2024). In subsequent research, we will integrate new model methods to experiment and validate the effectiveness of feature extraction.

Supporting generative design of campus. Existing design principles for campuses are often derived from a limited number of case studies, with the Architectural Design Sourcebook serving as a primary reference. By leveraging the nationwide campus dataset and the morphological analysis conducted in this study, it becomes feasible to systematically compile a set of rules and design methodologies for Chinese campuses. Furthermore, recent researches have been conducted to explore the generation of campus masterplans using advanced deep learning technologies, such as Generative Adversarial Networks (GAN), based on hundreds of Chinese campus cases. (Liu *et al.*, 2021; Chen, Zheng, and Wu, 2022). The efficacy of the generation model could be significantly enhanced by expanding the dataset to encompass a nationwide range. Consequently, future endeavours will focus on integrating rule-based and case-based generative design methods to expedite the process of early-stage campus designs and provide decision-making support.

6. Conclusion

This paper proposes a deep learning driven framework for morphological dataset construction and analysis methods of Chinese Campuses. We compared the differences between deep

learning-based visual representation methods and classical morphometrics methods in the recognition of campus morphology. Firstly, by utilizing web data scraping and computer vision techniques, combined with integrating multiple sources of data such as map tiles and geographic information, we addressed the challenge of obtaining data on the morphology of Chinese university campuses. Secondly, based on the characteristics of Chinese university campus morphology, we integrated campus research with urban morphology indicators and landscape ecological indicators at similar scales. We proposed perspectives, dimensions, and measurement methods for the campus morphology, which were validated across 38 university campuses in Nanjing. In response to the limitations of traditional statistical methods, such as high data processing difficulty and limited visual representation, we introduced deep learning-based visual representation and morphological clustering methods. Using SOM, we developed morphological cluster map of Chinese university campuses, enabling morphological analysis and similarity retrieval across the entire dataset. This method provides important insights into the characteristics and issues of university campus morphology in the context of China's urbanization process, while also offering case support for the construction of new campuses.

However, we also discovered that traditional morphometrics methods still possess advantages that are difficult to replace, while deep learning methods suffer from low interpretability and the need for model optimization. In future research, we will further explore the potential integration of these two types of methods and focus on the discovery of patterns in campus morphology features based on datasets, as well as generative design.

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