Malaysia Architectural Journal

Journal homepage:
https://majournal.my/index.php/maj
e-ISSN : 2716-6139

Generation and Analysis of Urban Morphology in the Qinba Mountains: A GAN-Based Approach for Small Towns in Southern Shaanxi

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ARTICLE INFO

Article history:
Received: 30 April 2024
Received in revised form
Accepted: 15 October 2024
Available online: 22 June 2025

Keywords:

Urban morphology; Gan; Small town; Deep learning; Qinba Mountain area

ABSTRACT

In this study, GAN technology was used to prepare small-town landscape generation and morphological analysis in the Qinba Mountain area. Important for the construction of a standardized dataset, a high-quality remote sensing image and building footprint data vector with adequate diversity and accuracy were utilized. It created exacting, via a GAN model, realistic small town morphologies and gave a sufficiently in-depth quantitative analysis in terms of several morphological indicators of area, perimeter, fractal dimension, longest axis length, circularity, mean distance from centroid to corners, of the convex hull perimeter, and of the aspect ratio. The results showed GAN-generated small town morphologies significantly varying in complexity and diversity. The hierarchical clustering analysis enables to uncover more intrinsic structures of the generated samples and classify the morphological characteristics of different types of towns. Therefore, this research is a verification of the effectiveness of GAN in generating urban morphology, but at the same time, it lays theoretical foundations with proof data for the optimization of GAN models. Therefore, the morphological analysis methods and indicator systems in this paper have a huge reference significance for urban planning and design. In short, this study demonstrated the tremendous potential of GAN technology in the generation and analysis of urban morphology and offered a scientific basis and technical support for small town planning in Qinba Mountain.

1. Introduction

While small towns all over the world may have very different characteristics, unlike big cities they are not marked by their extent. Therefore, there is no specific definition and perception of small towns in the international context, with their definition mostly being determined by the population size

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of the residents, economic activity to a certain degree, and even geography. The international perspective defines small towns in relation to their population size and the function of their economy and locale. However, the governing criteria differ drastically between countries. For instance, Germany considers the towns with a population between 5,000 and 20,000 as small towns(Wolff et al., 2021), whereas the definition according to the United States also refers to "Urban Clusters" creating a total range of 25,000 to 50,000(Urbanska and Levering, 1996). Measurement and classification of urban forms have been one of the important themes in the field of urban geography and urban planning in recent years. By numerically describing urban elements such as buildings, streets, and enclosed spaces, it is intended to reveal the patterns of urban organization and the potential relationships of forms. The measurement of urban form has something in common with the measurement of cellular and organismal morphology. From this point of view, cities can be considered as an analogy to organisms: streets and buildings play the role of cells and tissues, and the city itself is a "tissue structure". In this case, most of the concepts used in urban morphology, such as "urban fabric" and "urban cells," are essentially morphological concepts in biology(Kristjánsdóttir, 2019). GANs have become a breakthrough tool for urban design and urban studies, offering innovative solutions to solve the dynamic and complex problems being thrown up by modern cities. With accelerating urbanization and increasing challenges to sustainability, resource management, and social equity, application of GANs in urban planning represents quite a big jump in analytical and design capabilities. Innovative models—like UrbanGenoGAN—integrate generative adversarial networks with genetic algorithms and geographic information systems to arrive at much-improved urban spatial planning. It generates a lot of different scenarios about towns, optimizes plans of cities, and gives full-scale spatial data analysis. Thus, based on this, UrbanGenoGAN is a game changer in city planning where more efficient, scalable, and sustainable urban development is possible(Cheng et al., 2023). Applications of GANs were also found in different urban studies, such as land use classification and simulation of urban morphology. For example, conditional GANs have already been used in the classification of urban areas by integrating data from multiple sources, demonstrative of its potential to deal with complex urban landscapes(Sirous et al., 2023). Recent studies illustrate practical implementations of GANs in urban planning. For instance, a conditional GAN-based approach was developed to enhance the rendering of hand-drawn park sketches into comprehensive color designs. This method significantly reduces the time required for iterative design processes and improves the overall efficiency of landscape design(Chen et al., 2024). Another study utilized GANs for site planning by integrating urban GIS data, demonstrating improved accuracy and detail in urban planning applications(Tian, 2021). Urban morphology, the study of the form and structure of urban spaces, plays a crucial role in understanding the development, sustainability, and livability of cities. One of the significant advancements in urban morphology is the integration of Earth observation data with morphometric analysis(Zhao and Wu, 2024). Clustering analysis is a statistical method used to group similar objects into clusters, making it an effective tool for urban morphology studies. By grouping areas with similar morphological characteristics, researchers can identify patterns and trends that inform urban planning decisions. For instance, a study in Zurich used clustering analysis to identify distinct urban neighborhoods based on their morphological features, which helped in developing localized strategies for heat mitigation(Joshi et al., 2022). This study integrates Generative Adversarial Network (GAN) technology and urban morphology analysis methods to conduct an in-depth study of small towns in the Qinba Mountain area of southern Shaanxi.

2. Methodology

2.1 Research Framework

The objective of this research is to generate the morphology of small towns in the Qinba Mountain region through generative adversarial networks and then make a detailed morphological analysis for the generated results. Geographical features and architectural characteristics in small towns of the

Qinba Mountain region are peculiar. Their morphology study will help gain insight into the spatial structure of towns in this region and provide a scientific basis for urban planning and building design. During this process, comprehensive links need to be shaped to form a research framework covering data collection, generation of morphology, and morphological analysis. Figure 1 illustrates the overall framework of the research.

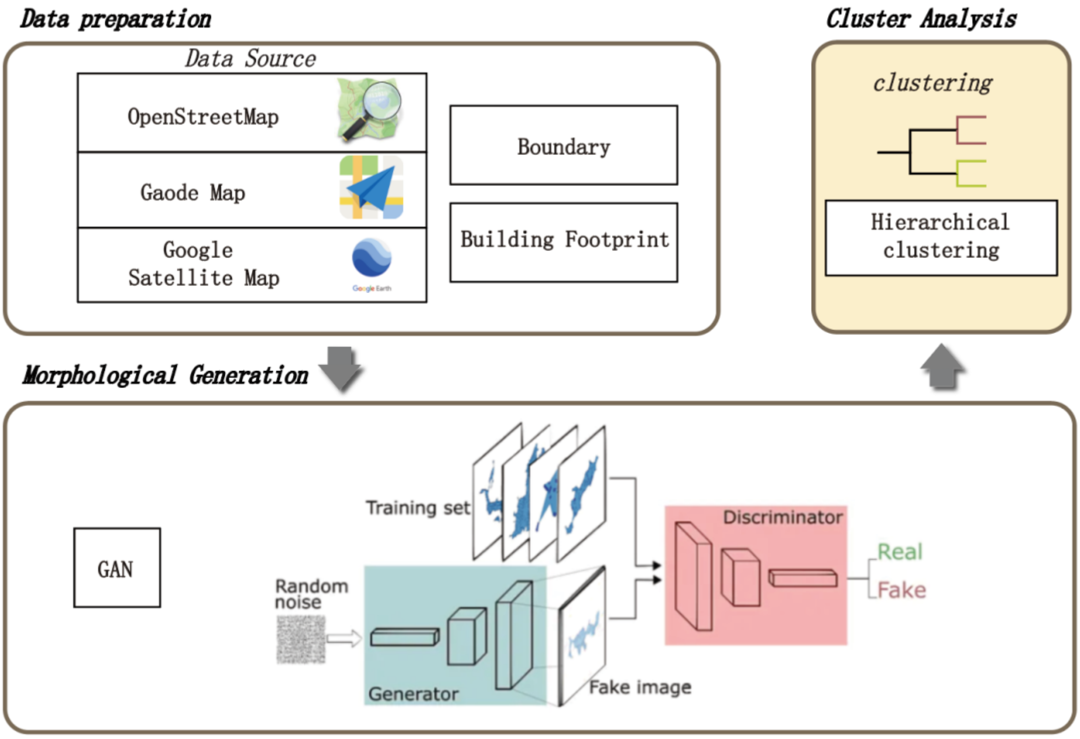

Fig. 1. Research Framework Diagram

Information gathering is the backbone of research. In this paper, we used remote sensing satellite maps from Google and Gaode Maps to get the locations and building footprint data of small towns in the Qinba Mountain region. Using these map data, we could identify the small town boundaries and major building distribution. Location and footprint data were then vectorized to form a standardized dataset, ensuring diversity and accuracy of data. To generate realistic images, it is quite important to have high-quality diverse data.

The next optimization used was the generation of morphology with the Generative Adversarial Network. GANs is comprised of a generator and a discriminator, the generator is responsible for transforming noise into realistic images, and the discriminator distinguishes between real and generated images. During the process of training, the discriminator is first trained using the real and generated images so that it can estimate the probability of the images being real, compute the loss function by backpropagation, and update parameters. In parallel, the generator produces fake images that enter the discriminator, which then calculates the probability of the images being fake. The results of real image discrimination accumulate into the total loss, which is used to update the parameters. To prevent favoring the architecture of the generator and discriminator, the discriminator is updated more often than the generator for each iteration. More explicitly, in each cycle, the parameters of the generator are fixed, and the discriminator is trained to improve its performance in discriminating real samples from generated samples. After that, the parameters which were involved in the training of the discriminator are frozen, and to update the generator, only its parameters are updated. Or in simple words, the generator will produce the fake images associated with a batch and have that batch streamed through the discriminator for the outputs. The loss calculation actually works in such a way that the generator itself, in turn, actively seeks to classify the fake images as real, thus generating images that can fool the discriminator. Both the generator and the discriminator are implemented through the Adam optimizer with a learning rate of 2e-4 and the momentum parameter set at 0.5, 0.999. The optimization criterion for measuring the realism between generated images uses BCELoss. The batch size used during training is 256 for both cases, be it the input of random noise into the generator or real images into the discriminator. Output the weights of the generator and of the discriminator after each epoch of training to be further validated and trained, respectively. This comes to be trained over 500 epochs, it presents one of the highest in quality of generated images, with applications potent and wide in GANs for image generations.

Morphological analysis was then carried out in detail after the generation of the images. Hierarchical cluster analysis classified the generated small town morphologies first. Morphological analysis used a few key indicators, which included the area, perimeter, fractal dimension, length of the longest axis, circularity, mean distance from centroid to corners, convex hull perimeter, and aspect ratio. These indicators present information about the geometric and spatial characteristics of the towns generated at different perspectives. For instance, the area and perimeter dimensions help in quantifying the sizes of a town's layout and boundary complexity. The fractal dimension reflects irregularity or complexity in forms, with the longest axis length giving information about the main directions and extents of urban forms. The circularity and aspect ratio measure compactness and elongation of town shapes respectively. While peripheral distribution with respect to the town's center is measured by the mean distance from the centroid to the corners, convexity is reflected in the perimeter of the convex hull boundary containing the town's layout. It provided the long and short axes of the small town morphologies during the morphological analysis using Grasshopper's C# component programming. The method in effect was rotating the bounding box for calculating the minimum-area bounding box. This approach works precisely to extract the long and short axes of town morphologies, thus providing reliable data for analyses in morphology. These parameters further provide details in quantitative descriptions which ensure that the generated town morphologies are comprehensively evaluated.

2.2 Analysis and Generation of Small Town Morphology in the Qinba Mountain Region Using GANs

2.2.1 Small Town Morphology Generation using GANs in the Qinba Mountains

The Qinba Mountain region small towns morphology dataset offers a great deal of training material, and each image dimension is 96 by 96 pixels. Images capture a good number of boundaries and architectural features that stipulate the quality of small towns. In data collection, images were carefully selected and processed to ensure data diversity and accuracy. The high resolution and clarity of images in the dataset make it a perfect input sample for the training of the GAN. Figure 2 illustrates examples from the morphology dataset of small towns.

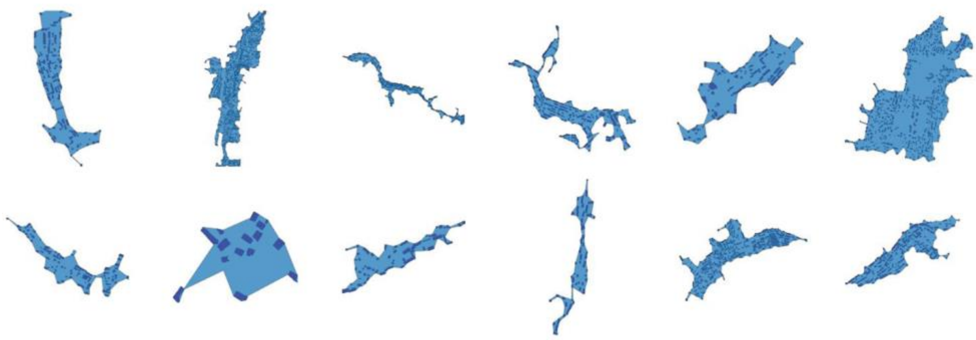

Fig. 2. Examples from the Morphology Dataset of Small Towns in the Qinba Mountain.

In the training process of this Generative Adversarial Network, there has been a strict procedure with detailed parameter settings to guarantee that it generates high-quality images. It involves the training process of two major neural networks: one for generation and one for discrimination. A generator is used to transform random noise into a realistic image, while a discriminator tells between the real and generated images. First, train the discriminator network using both real and generated images. So for each batch of the real image, it will estimate the probability of the images being real, compute backpropagation for the loss, and update parameters of. Simultaneously, let a generator network give fake images to the discriminator, which calculates again the probability that these were fake images. The results of real-image discrimination are combined, and the total loss is then computed for use in updating the parameters. To avoid bias in the structures of the generator versus the discriminator during each iteration, optimization of the discriminator happens more often than optimization of the generator.

First, in each cycle, the generator's parameters are fixed, and the discriminator is trained to increase its chances of differentiating between a real and a fake image. This step is optimizing the model to probably attain more accuracy in detecting fake images. Then, it fixes the parameters of the discriminator and only updates the generator's parameters; that is, the generator produces a batch of fake images and forwards them through the discriminator. The generator should classify the fake images as real according to its loss calculation. In other words, this means that the generator generates images that are so real to hoodwink the discriminator with respect to not being able to tell any difference between them. For both the generator and discriminator, use Adam with a learning rate of 2e-4 and momentum parameters fixed at (0.5, 0.999). Binary cross-entropy loss function BCELoss is also applied to measure the realness of generated images.

The training process is performed using a batch size of 256 for the random noise input to the generator and for the real images fed into the discriminator. Weights for the generator and discriminator are saved after every training epoch for further validation and training. After the generator is trained for 500 epochs, the quality of the generated images will be very high, so GANs must have strong potentials for generating images and wide application prospects. The whole process of training conforms to the requirements of experimental design and scientific methodology in terms of seriousness. Detailed tuning and optimization for parameters demonstrate the effectiveness of the model, offering valuable insights and data support for related research in the future.The image presented in Figure 3 illustrates the variety of small towns generated by the GAN network. The generated images capture the essence and distinctive characteristics of small towns from the Qinba Mountain region, showcasing the model's ability to produce high-quality and realistic depictions that are virtually indistinguishable from actual photographs.

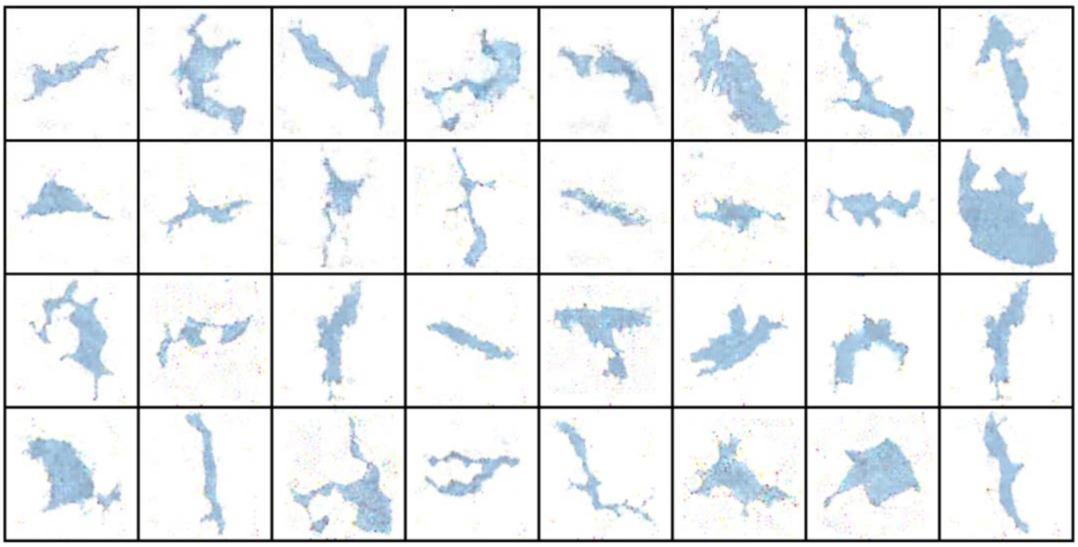

Fig. 3. GAN-Generated Small Towns from Qinba Mountain Region

2.2.2 Small Towns Morphology Measurement

The result of the GAN network in generating new small town morphologies is subject to a morphological analysis using several key indicators. These indicators are dimensions, including area and perimeter, and shape descriptors, such as fractal dimension, longest axis length, circularity, centroid-corners mean distance, hull's perimeter, and aspect ratio. Each of these indicators gives one perspective on the geometric/spatial characteristic of the generated towns. The table 1 lists these indicators as follows.

Table 1
Morphological Feature Indicators for Small Town Urban Form in the Southern Shaanxi Qinba Mountains district

Index	Category
Area	Dimension
Perimeter	Dimension
Fractal Dimension	Shape
Longest Axis Length	Shape
Circularity	Shape
Centroid-corners mean distance	Shape
Hull's Perimeter	Dimension
Aspect Ratio	Shape

For example, area and perimeter dimensions are useful in quantifying total size and boundary complexity for the town layouts. The fractal dimension gives a sense of the irregularity or complexity of forms within the towns. Longest axis length provides information about the primary orientation or main direction and extent of the urban forms. Circularity and aspect ratio are measures of compactness and elongation, respectively, of town shapes. While the centroid-corners mean distance is a measure of the town's periphery distribution in relation to its center, the hull's perimeter reflects how far from convex the boundary containing the town's layout is. These detailed morphological indicators allow doing detailed evaluation about the generated town shapes, whether they fit the characteristic conditions in the real world for small towns in the Qinba Mountain region.

The length of the longest axis is then equal to the length of the longest side of this rectangle. Dimensions and shapes are some of the indicators, but not the only ones, as other parameters connected with density and intensity give a full description of small town morphology. Circularities are among the metrics included in the calculation of the different indicators, calculated as Eq. 1 shows.

$$\text{Circularity} = \frac{4\pi \times \text{ Area}}{\text{Perimeter}^{2}}$$

The application of the fractal dimension concept to delineating small town boundaries is motivated by the experience in the measurement of organisms and cell morphometry. By treating geospatial data as a kind of analyzable morphological structure, we could borrow a similar way to investigate the spatial complexity and structural properties of small towns. Computation of the fractal dimension is an important tool in quantitative analyses related to small town forms, especially to understand the complexity of spatial urban arrangements. The fractal dimension describes the complexity of spaces or structures. Although there are several techniques for its calculation, the box-counting algorithm emerges as the predominant method(Ai et al., 2014). The pivotal formula in this calculation is the computation of the fractal dimension, which is ascertained through the slope of the linear regression, as calculated according to the Eq. 2 shows bellow.

$$D = \lim_{\varepsilon \to 0} \frac{\log(1/\varepsilon)}{\log N(\varepsilon)} \tag{2}$$

This study adopted the rotating method of the bounding box and used C# component programming in Grasshopper in order to obtain the long and short axes of small town morphologies. By using this method, it is possible to obtain a bounding box that could describe more accurately and closely the morphology of small towns, hence extract the long and short axes of morphology quite accurately. The above code calculates the bounding box at every angle by rotating the plane at various angles, then finds the one with a minimum area. Here are the steps to implement it: First of all, define two variables `minArea` and `minBox` which store the minimum area and its corresponding bounding box. The `minArea` is initialized to a very large value to update to the actual minimum value in the subsequent calculation. All the possible rotation angles are iterated from 0 to 180 degrees using a `for` loop. At the beginning of each iteration, the current angle is converted from degrees into radians. The given plane is rotated around its Z-axis to ensure that the bounding box rotates in the two-dimensional plane. Then, the `curve.GetBoundingBox(rotatedPlane)` call calculates the bounding box of the curve on the rotated plane. Obtained BoundingBox is then converted to a Box for easier area calculation. The surface area of the current bounding box is calculated. The formula is the sum of areas of three faces—the X-Y, Y-Z, and Z-X faces—of the bounding box. This current bounding box area is checked versus the minimum recorded area; if smaller, update the minimum area along with its corresponding bounding box. After the loop, it outputs the bounding box with a minimum area, which is the bounding box that best fits and describes the morphology of small towns. In essence, this method relatively digs out the long axis and the short axis of morphology in small towns and obtains basic reliable data for the morphological analysis thereafter. The result of rotating to find the smallest area bounding box is shown in the figure 4 on the next page.

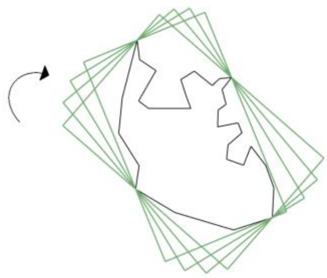

Fig. 4. Bounding Box with the Smallest Area Found Through Rotation

The figure 5 shows the scenario of how all the generated types are iteratively processed. For each type generated, the methodology of bounding box rotation is utilised to obtain the bounding box that can best and most accurately describe its morphological characteristics. By using this methodology, a number of morphological parameters could be estimated, such as the length of the longest axis, the length of the shortest axis, and the aspect ratio, among others describing shape. These parameters further provide a meticulous, quantitative description of the morphologies of the town, ensuring that the generated forms are fully assessed. For each generated form of the town, iterative rotation computes its bounding box and finds one with a minimum area. This bounding box is an important tool in extracting and analyzing the morphological features of the generated towns.

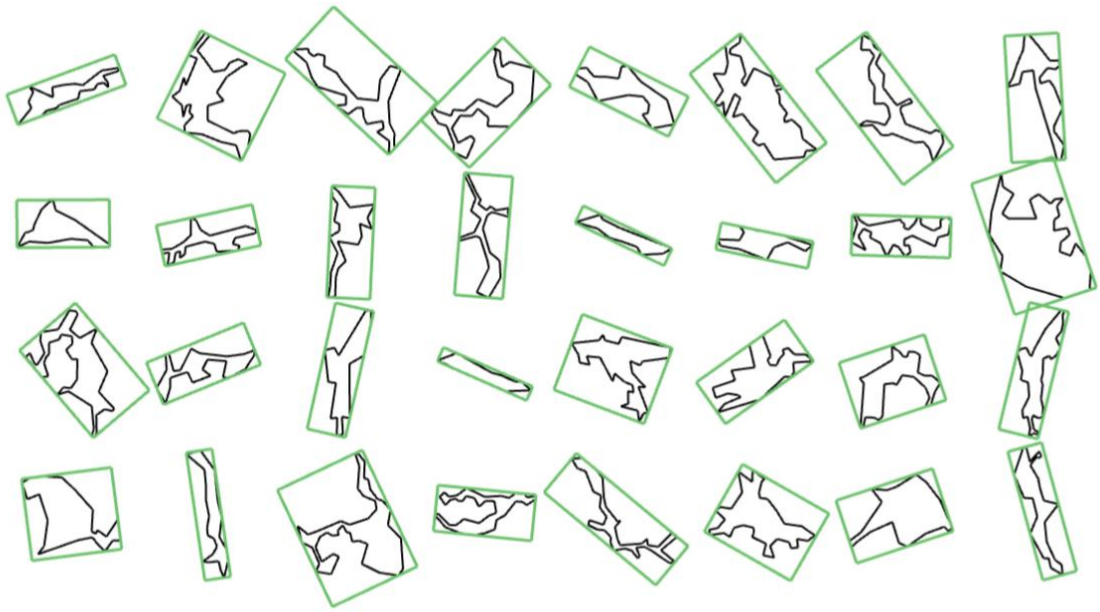

Fig. 5. Bounding Boxes for Morphological Characteristics of All Generated Types.

3. Results

In this paper, a GAN was applied to generate morphological samples for small towns in the Qinba Mountain area and analyzed in depth with regard to distribution characteristics using hierarchical clustering based on multidimensional feature parameters classifying systematically generated samples. The main parameters or features selected for clustering analysis were some of the morphological indicators: the length of the parameters, minimum bounding rectangle area, actual area, roundness, fractal dimension, maximum axis length, and minimum axes length.

The dendrogram depicts the clustering result for this hierarchical relationship of dimensionality with various working parameters for different samples. Hierarchical clustering computes Euclidean distances between a single pair of samples and joins, iteratively, the most similar ones until finally getting a dendrogram. In the dendrogram, each node represents a specific sample or a group of samples where the lengths between link lines represent appropriate clustering distances between samples and groups. To distinguish different clustering categories, color-coding is used where samples in the same category exhibited a similarly high morphological feature parameter value for the same feature.

Cluster results analysis shows the diversity and intrinsic structure of GAN-generated samples with regard to the morphological characteristics. The similarity shown by samples, within each category, concerning length, area, and roundness parameters provides data support and theoretical basis for further optimization of the GAN's generating parameters. The hierarchical clustering method is good at analyzing the internal structure of samples and understanding the multidimensional relationship of complex data. Results: GAN-generated morphological samples of small towns in the Qinba Mountain area, upon hierarchical clustering analysis, expose the sample diversity and feature distribution. This provides scientific guidance and technical support for further improving the GAN model to yield good quality and diverse results. That is to say, through clustering analysis regarding GAN-generated town morphology samples, this research deeply classified and analyzed the results generated by GAN; it is very instrumental and leads with far-reaching theoretical reference and values of practice in related fields of study.

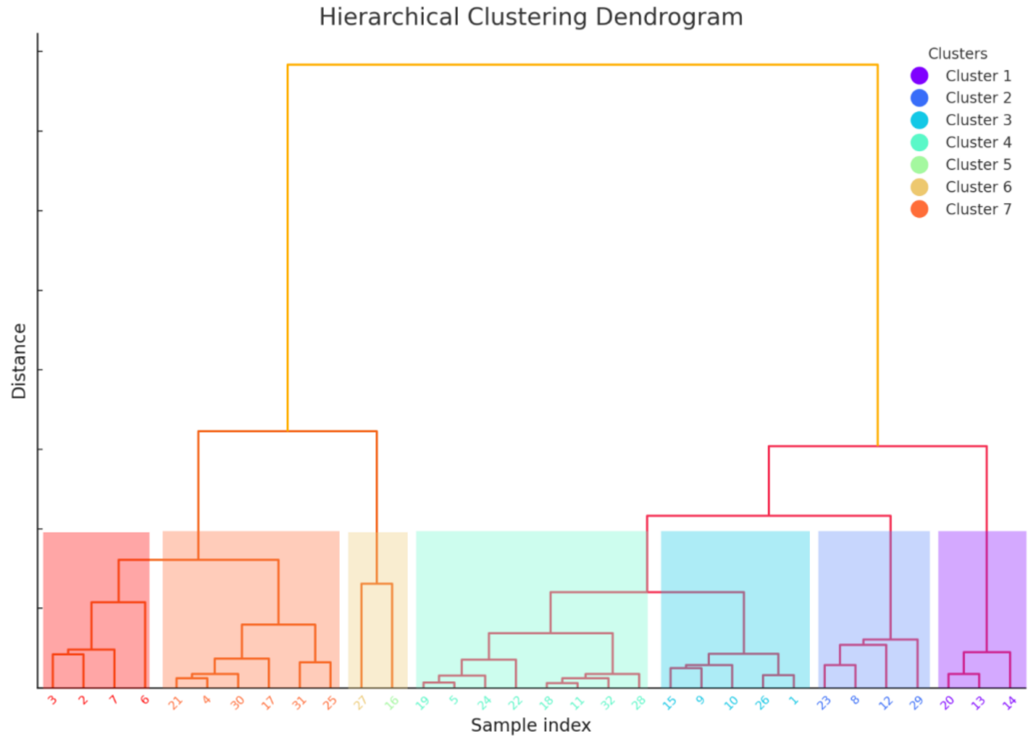

Fig. 6. Hierarchical Clustering Analysis of GAN-Generated Morphological Samples of Small Towns in the Qinba Mountain Area.

It clusters the towns into seven categories according to their morphologic characteristics and summarizes the typical morphological characteristics in each category. The high roundness and fractal dimension reveal smooth boundaries and regular shapes. On the other hand, towns in category 1 are compact and of regular shape. Mean length is relatively small, minimum rectangle area is small, so is total area. Also, the longest and shortest axis length are relatively short, which support their compact morphology, and such towns are usually amenable to high-density building layouts and compact community planning. The towns in category 2 have relatively more complex morphological characteristics with moderate lengths, larger minimum rectangular areas, and areas in general. Their low roundness and fractal dimension also show their irregular shapes. Accordingly, larger values of longest and shortest would suggest elongate and more variegated forms. These towns would possess multiple natural boundaries or would be very irregular in the distributions brought to them by street layouts. The powers of T3 are moderate. They are moderate between regular and irregular morphologies. Their lengths and areas are moderate, and likewise are the minimum rectangular areas. Characteristics of their shape—particularly their roundness and their fractal dimension are of a moderate character—suggesting, therefore, moderate shape regularity. Very similarly, a moderate length is also shown by the longest and shortest axis lengths. This would combine the regularity of main roads with irregularity within secondary streets. Towns of category 4 have the most regular and larger scale of morphological characteristics. They correspond to the longest length, the largest minimum rectangular area, and the biggest overall areas. High values of roundness and fractal dimension indicate very regular shapes. The axis length values are also the largest for both the longest and the shortest axes, thus confirming that their morphology is of large size and regular. These towns are suitable for large-scale unified planning and layout. Category 5 towns display complexity and dispersity in the morphologic characteristics. They are characterized with a relative long length, large area of minimum rectangle, large area in size, and large amount of low roundness and fractal dimension, which both express irregular shapes. The characteristics of the low roundness and fractal dimension express irregular shapes. The longer length of the longest and shortest axes suggests dispersed forms of the towns. It might generally have many natural terrain features or historically inherited street layouts. Category 6 towns have a relatively regular and moderate morphology. Their length, minimum rectangular area, and area are moderate. The roundness and fractal dimension testify to a moderate regularity in their shape. The lengths of the axes are also moderate in their longest and shortest lengths. These towns perhaps combine a regularity of street layout with some landform features. In contrast, Category 7 towns exhibit an elongated and complex morphology. They rank second in length and have large minimum rectangular areas as well as large areas. The roundness and fractal dimension indicate relatively complex shapes. The longest and shortest axis lengths are relatively long, suggesting a large variance in the shape diversity. Such towns could well have diversified street layouts and natural features. Based on the above classification and analysis, it is quite clear that the morphological characteristics of towns have shown great differences. The variations between cities not only relate to the physical characteristics and the planning layout of the towns, but give important references for future urban planning and design.

4. Conclusions

In the present work, GAN technology was used to generate small town morphology in the Qinba Mountain area and analyzed it in great detail. The standardized dataset was constructed with high-quality remote sensing images and building footprint data to guarantee diversity and accuracy. Then, the GAN model was employed for generating fairly true-to-life small town morphologies and conducting detailed quantitative analysis based on several indicators of morphology. These indicators were area, perimeter, fractal dimension, longest axis length, circularity, mean distance from centroid to corners, convex hull perimeter, and aspect ratio. These metrics provided an all-rounded description of the geometric and spatial characteristics of these towns from various perspectives. The results indicated significant differences in terms of complexity and diversity in the GAN-generated small town morphologies. Hierarchical clustering analysis identified and classified the intrinsic structures of the generated samples, indicating that different types of towns have very obvious morphological characteristics. For example, some categories of town morphology are compact and suitable for high-density building layouts, while others show more complex characteristics that can be related to natural terrain slopes or historical street layouts. The results of this study verified the effectiveness of GAN in generating urban morphology and provided theoretical foundations with data support for further optimization of the GAN model. The morphological analysis methods and indicator systems put forward in this research are of significant reference value for urban planning and design. Supervised by rapid urbanization, enormous challenges to sustainable development, and the application of GAN technology in analysis and planning of urban morphology, it provides consolidating analytic and design efficiency while putting into one's disposal new tools and techniques for scientific wording of urban planning. In fact, this research has huge potential for GAN technology in the generation and analysis of urban morphology. It provides a scientific basis and technical support for the planning of small towns in the Qinba Mountain area. Future studies will focus on further optimization of the model parameters and extend to other regions, verifying that the methods put forward are universally effective.

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