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Extracting Meso- and Microscale Patterns of Urban Morphology Evolution: Evidence from Binhai New Area of Tianjin, China

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Abstract: Understanding and recognizing urban morphology evolution is a crucial issue in urban planning, with extensive research dedicated to detecting the extent of urban expansion. However, as urban development patterns shift from incremental expansion to stock optimization, related studies on meso- and microscale urban morphology evolution face limitations such as insufficient spatiotemporal data granularity, poor generalizability, and inability to extract internal evolution patterns. This study employs deep learning and meso-/microscopic urban form indicators to develop a generic framework for extracting and describing the evolution of meso-/microscale urban morphology. The framework includes three steps: constructing specific urban morphology datasets, semantic segmentation to extract urban form, and mapping urban form evolution using the Tile-based Urban Change (TUC) classification system. We applied this framework to conduct a combined quantitative and qualitative analysis of the internal urban morphology evolution of Binhai New Area from 2009 to 2022, with detailed visualizations of morphology evolution at each time point. The study identified that different locations in the area exhibited seven distinct evolution patterns: edge areal expansion, preservation of developmental potential, industrial land development pattern, rapid comprehensive demolition and construction pattern, linear development pattern, mixed evolution, and stable evolution. The results indicate that in the stock development phase, high-density urban areas exhibit multidimensional development characteristics by region, period, and function. Our work demonstrates the potential of using deep learning and grid classification indicators to study meso-/microscale urban morphology evolution, providing a scalable, cost-effective, quantitative, and portable approach for historical urban morphology understanding.

Keywords: urban morphology evolution; meso- and microscale; deep learning; visualization; urban planning



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1. Introduction

Since the beginning of the 21st century, continuous urban expansion and construction activities have caused significant changes in urban form. Numerous social, economic, and environmental problems have come to the fore, including population density [1], traffic congestion [2], social injustice [3], decline in biodiversity [4], and urban heat island effects [5,6]. In response to these challenges posed by urbanization, urban historical cognitive data have become particularly important. For instance, in the United Nations ‘Sustainable Cities and Communities’ initiative, a fundamental premise for guiding sustainable urbanization is the recording and monitoring of urban morphology. This aids in understanding the developmental history of cities, monitoring current urban conditions, optimizing resource allocation, and guiding future urban planning and management efforts [7–9].

Urban morphology focuses on the physical form of urban elements such as plots, streets, and buildings over space and time [10]. Urban morphology evolution is a complex, dynamic, and multidimensional process that includes the formation, transformation, growth, and changes of urban forms [7,11,12]. Since the 20th century, the recording and tracking of urban morphology have been ongoing in urban studies. The focus of research has gradually shifted from simple documentation of urban changes to the extraction and analysis of urban morphology evolution patterns. The research methods largely depend on the state of urban development and technological limitations. Early studies primarily involved detailed mapping of urban morphology changes on maps. The interrelated roles of urban elements such as streets, plots, and buildings are revealed with the aim of tracing and documenting the evolution of urban form [13–17].

With the rapid development of remote sensing technology, many scholars have started to use remote sensing imagery from platforms like Landsat and Sentinel to study large-scale urban morphology evolution [18,19]. These technologies not only provide new avenues for extracting urban evolution patterns but also greatly expand cross-disciplinary research between urban morphology evolution and fields such as urban disaster prevention [20], urban heat island effects [21–23], and air and noise pollution [24]. Compared with traditional methods, remote sensing technology has the advantages of quickly acquiring large-scale urban morphology information, being economical, easily accessible, globally covering, and having rich temporal data [25,26]. However, these approaches also have limitations. Firstly, the low spatial resolution makes it impossible to identify microscopic urban changes, so the method is not applicable to cities where sprawl is strictly controlled [27]. Secondly, it is not possible to delineate patterns of development within cities and is only suitable for detecting the evolution of simple urban forms, such as the transformation between urban and non-urban areas [28].

In the context of sustainable urban development, modern city planners and stakeholders seek innovative, energy-efficient, and cost-effective development models. Smart growth strategies are more likely to be adopted in this context [29], and the pattern of urban development has shifted from rapid sprawl to more focused infill and edge-jumping. Therefore, in modern urban evolution research, the evolution of urban morphology at the meso- and microscale has gradually begun to be paid attention to in order to meet the needs of smart city planning and fine-grained urban management [2,30,31]. Studies at this scale typically use multi-source data to map and analyze urban morphology evolution, such as population density [32], urban elements [33,34], nighttime lighting [35], and elevation [36], featuring high data accessibility, controllable scale, and innovative methods. The technology related to deep learning algorithms has matured in recent years and has become very efficient in processing complex real-world images, such as high-resolution remote sensing. It is becoming a common method in the remote sensing community for extracting various urban morphological information [7,37,38]. Recent work employs computer vision techniques in deep learning to open new technical pathways for studying micro-scale urban morphology changes to cover areas such as identifying urban morphology changes [39,40], types of urban morphology change [27], and specific urban functions and historical development types of urban morphology [41]. However, these studies focus on identifying ‘changes’ in urban morphology without distilling the process of ‘evolution’. Additionally, they lack the extraction and interpretation of evolution patterns suitable for urban planning, making it challenging to integrate with other data like macro-scale studies, limiting the expansion of research [42].

Despite the significant expansion in urban morphology evolution research, challenges remain in studying meso- and microscale urban morphology evolution due to the current state of urban development and uneven resource distribution: (1) Meso- and microscale urban morphological changes are often subtle and complex, and traditional data and analysis methods often lack sufficient spatiotemporal resolution. This makes it difficult for them to accurately capture the continuous evolution of urban form over time and to reveal the intrinsic patterns of urban form evolution. (2) Many published meso- and microscale urban

morphology evolution mapping techniques are highly localized and require extensive data annotation, resulting in high research costs and a lack of reproducibility and scalability. (3) The data structures of related urban morphology studies are complex, the analytical processes are highly specialized, and they often lack mapping processes for evolution, ignoring the historical and logical features of urban spaces that visual interpretation can reveal. This limits their widespread application in urban planning and management practices.

To address these limitations, this study proposes a comprehensive analysis framework for urban morphology evolution based on computer vision technology and the TUC classification system. The framework includes three parts: Dataset construction, urban form extraction, and indicators describe the evolution of urban form Figure 1. It utilizes accessible high-resolution remote sensing imagery, open-source deep learning technologies, and pixel abstraction methods to understand urban morphology evolution. The innovations include the following: (1) Enhanced spatiotemporal granularity of urban morphology evolution research; (2) Generalizability of the workflow; (3) Ease of visual interpretation for planners using data mapping methods. This study aims to provide urban planners and decision-makers with an accurate and timely understanding of urban forms, facilitating the formulation of more scientific and sustainable urban development strategies.

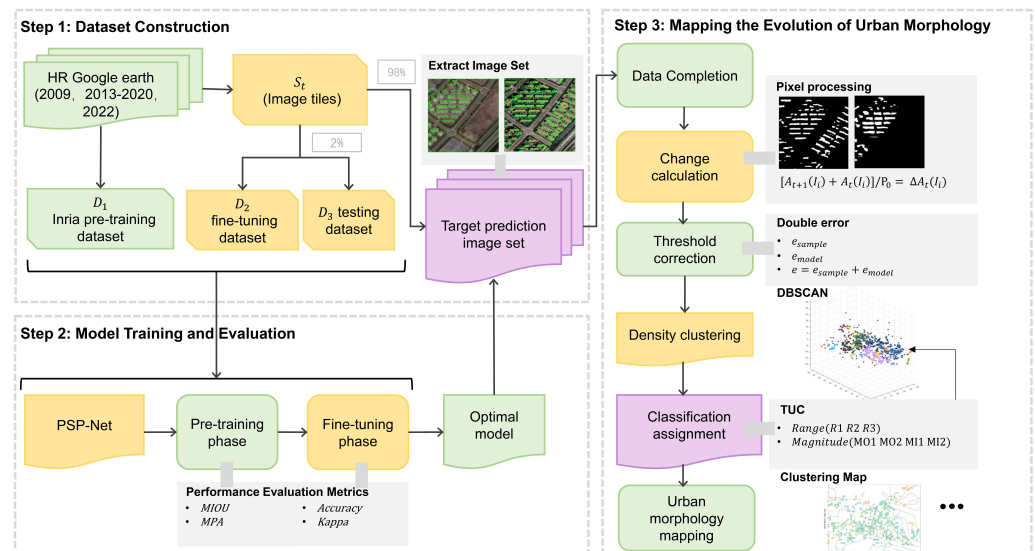


Figure 1. The framework of mapping urban morphology evolution based on image tiles.

2. Materials and Methods

2.1. Study Area and Datasets

2.1.1. Study Area

This research focuses on the Binhai New Area in Tianjin, China, a district under the jurisdiction of Tianjin and functioning as a satellite city. It is located in the eastern part of mainland China along the Bohai Sea area Figure 2. As the third major economic growth zone in China, following the Shenzhen Special Economic Zone and Shanghai Pudong New Area, Tianjin's Binhai New Area has experienced a period of rapid economic and population growth. The population increase is concentrated in the central part around the Haihe River, stretching from east to west along the downstream of the river. We strategically selected the central urban area of this district as the subject of this study. It meets our research needs well: (1) The city is mainly in the stage of stock development, but at the same time accompanied by a certain degree of urban expansion. Therefore, the city shows a diverse urban form, which is highly representative of the study. (2) The study area is designated as a high-density urban center, usually one of the first developed areas of a city. Compared to other parts of the city, changes in these central urban areas are smaller in scale. So this is an

ideal test environment to evaluate the recognition accuracy of the deep learning model and the robustness of the framework for analyzing the evolution of urban form.

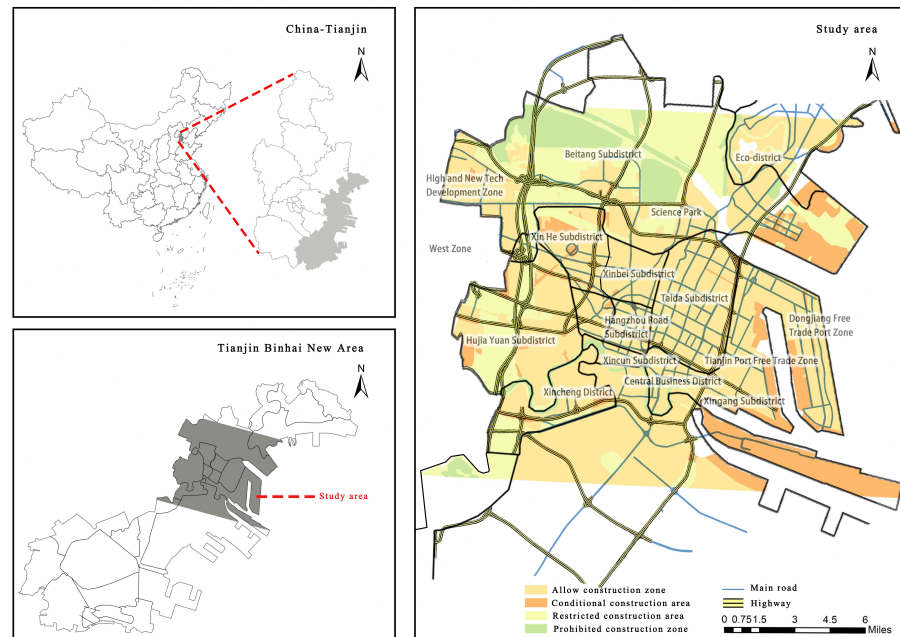


Figure 2. The left side shows the location of the study area, while the right side depicts the current land use status of the study area, from the Tianjin Binhai New Area Land Use Master Plan (2015–2020).

The chosen study area covers the most densely populated zones, as populations are typically concentrated in the central areas of cities. The specific geographic bounding parameters are 117°30'36" E–117°49'12" E, 38°57'34" N–39°03'36" N.

2.1.2. Data Preparation

There are several products available globally that provide satellite remote sensing imagery, including the Landsat Program [43], Google Earth [44], and Digital Globe [45]. Multiple requirements need to be considered, including the need for high resolution, broad data coverage, rich historical information, relatively low data acquisition costs, etc. Based on these considerations, the Google Earth historical satellite image data source is considered to be a more appropriate solution.

Since Google Earth does not support downloading images for specific ranges or choosing image resolution levels, we utilized the third-party open tool SAS.Planet3 [46] to download images from the Google Earth web platform. To avoid dealing with excessively large VRAM loads during data processing, we pre-cut the images into tiles of the same pixel size. However, the edge region of a tile may lead to recognition error due to the lack of information on the neighboring regions. To mitigate the edge effect on image recognition, a part of the overlapping region is set between neighboring tiles. We define all image tiles at all time points in the entire study area as S_t .

2.1.3. Dataset Construction

Our deep learning model training strategy consists of two stages: First, we conduct generalized training with a large-scale pre-training dataset to enhance the model’s generalizability. Next, we perform task-specific training with a targeted fine-tuning dataset to improve performance on specific tasks. The dataset structure is organized based on this training strategy and consists of three parts: $\mathcal{D}_1$, $\mathcal{D}_2$, and $\mathcal{D}_3$, representing the pre-training, fine-tuning, and testing datasets, respectively. The pre-training dataset, $\mathcal{D}_1$, is designed to broaden the model’s generalization capabilities, requiring a large data volume with diverse

morphological coverage. The fine-tuning dataset, $\mathcal{D}_2$, is aimed at enhancing segmentation accuracy for specific study locations, necessitating similar urban morphology and image characteristics as the study site. Finally, the testing dataset, $\mathcal{D}_3$, is entirely independent of the training and validation process, composed of real data from the study site, and serves exclusively to assess model performance.

The pre-training dataset $\mathcal{D}_1$ uses the Inria aerial image labeling dataset, which covers a wider range of human settlements and urban building types than the other datasets. It was created in 2017, initially to “enhance the training generalization of building extraction models” [47], in line with our training goals. These images were taken under different lighting conditions and shooting seasons and cover an area of 810 km². The labels in the dataset are classified into building and non-building categories with a spatial resolution of 0.3 m/pixel.

However, the Inria dataset primarily covers urban areas in Europe and the United States. The lack of morphological data specific to our study area may reduce the model’s accuracy in identifying buildings in this region. To address the issue of high generalizability but low specificity following pre-training, we designed the $\mathcal{D}_2$ and $\mathcal{D}_3$ datasets. $\mathcal{D}_2$ and $\mathcal{D}_3$ consist of annotated data from the study site itself, aiming to achieve the required segmentation results with minimal effort. We manually annotated the 2% satellite images in S_t . These images were drawn equally from the image data for each year separately, covering a variety of urban form, image qualities, color shades and types of light and dark variations. Data augmentation proved to be an effective strategy in many previous studies [48,49]. This enables the model to better handle a wide range of first-time data and complex task challenges (e.g., aerial images with different color hues, qualities, and shades, and blurred by clouds). The fine-tuned dataset $\mathcal{D}_2$ uses 70% of the data in the annotated dataset and performs data enhancement. The original dataset was rotated, flipped, blurred, pretzel noise added, and hue and brightness adjusted. This measure resulted in the number of images in the original dataset being augmented by a factor of 10. The remaining 30% of the images serve as the test set $\mathcal{D}_3$. These images are equally distributed in number in each year, and this test set is independent of the training and validation process of the model.

2.2. Model Training and Evaluation

2.2.1. Overview of the Model

In this study, we employed the PSP-Net (Pyramid Scene Parsing Network) [50] as the model for data extraction. The network architecture of the PSP-Net is illustrated in Figure 3. The input image for the model is an original raw image captured by remote sensing satellites, containing various targets. The feature map is obtained through a backbone network that utilizes a dilated ResNet from the DeepLab algorithm. The pyramid pooling module performs pooling operations at four different scales: 1×1 , 2×2 , 3×3 , and 6×6 , to capture feature maps of multiple sizes. These feature maps are then subjected to 1×1 convolution to reduce the number of channels, followed by up sampling through bilinear interpolation, and concatenated along the channel dimension. Ultimately, the model outputs the final prediction results. Although the PSP-Net was designed as a general-purpose recognition model, we recognized the need to enhance its capability in identifying buildings. To this end, we introduced a segmented training approach, employing specific training strategies to improve the model’s performance in building recognition.

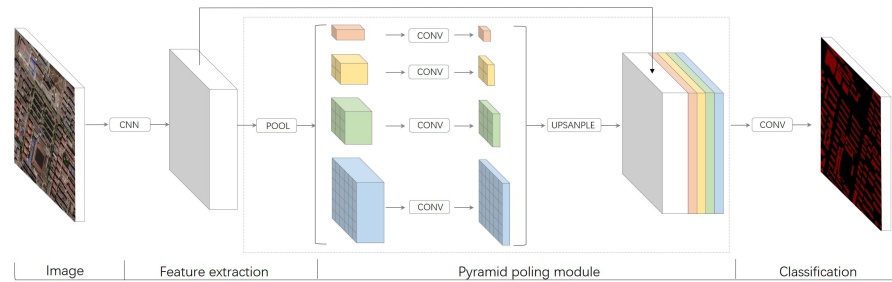


Figure 3. Structure of the PSP-Net algorithm: PSP-Net captures multi-scale contextual information and achieves high-precision image semantic segmentation by combining features extracted by the convolutional neural network with a pyramid pooling module.

2.2.2. Training Process

Our training strategy is devised to address the challenges associated with using mid- to high-resolution historical satellite imagery. Due to influences from satellite sensors and atmospheric conditions, these images often exhibit inconsistencies in resolution, color tones, and noise levels. These factors place high demands on the generalization ability and robustness of deep learning models [27]. To tackle these challenges, we propose a two-phase training strategy for our deep learning model: pre-training followed by fine-tuning. Initially, the model is pre-trained using the pre-training dataset $\mathcal{D}_1$. Then the fine-tuned dataset $\mathcal{D}_2$ is used for the fine-tuning training of the model. This can improve the image extraction ability of the deep learning model for the study area. Training is conducted on a platform equipped with an Intel Xeon Gold 6346 CPU and NVIDIA A40 GPU. The optimal model is selected based on the accuracy metrics calculated on the test samples $\mathcal{D}_3$ after each complete training cycle. Below is a detailed introduction to the training process.

Pre-training phase

$\mathcal{D}_1$ dataset was used to train the semantic segmentation model, where 70% of the data is randomly divided into a training set $\mathcal{D}_{1tra}$, and 30% into a validation set $\mathcal{D}_{1val}$. The model is trained for 1000 epochs, with evaluations performed at the end of each epoch using the validation dataset $\mathcal{D}_{1val}$. Adam is chosen as the optimization algorithm with binary cross-entropy as the loss function. The maximum learning rate is set to 0.001.

Fine-tuning training phase

The best-performing model from the pre-training phase was transferred to the $\mathcal{D}_2$ dataset for training, with 70% of the data randomly divided into the training set $\mathcal{D}_{2tra}$ and 30% of the data divided into the validation set $\mathcal{D}_{2val}$. We continue to use the Adam optimization algorithm and binary cross-entropy as the loss function. The starting learning rate is set at 0.0001, with a batch size of 16. The learning rate is halved every 50 epochs, and a model checkpoint is created every 100 epochs for a total of 1000 epochs of training. This phased approach ensures that the model can effectively adapt to and perform well with the unique data characteristics and challenges posed by the satellite imagery of the study area.

2.2.3. Model Performance Evaluation

To evaluate the segmentation effectiveness of our model within the dataset of this study, we employ the following methods for validation within the $\mathcal{D}_3$ dataset: (1) Utilizing *IoU* (Intersection over Union) and *Recall* to measure the discrepancies between actual categories and those predicted by the model [37,51]. (2) Using *Accuracy* and the *Kappa* coefficient to assess the precision of the model [27]. For ease of computation, all formulas are represented using a confusion matrix (see Table 1). Below are the calculation formulas for each metric used to validate the model.

The Intersection over Union (*IoU*) measures the degree of overlap between the predicted segmentation and the actual segmentation. The formula for calculation is

$$IoU = TP / (TP + FP + FN) \quad (1)$$

Recall is the proportion of correctly retrieved results that should be detected. The formula for calculation is

$$Recall = TP / (TP + FN) \quad (2)$$

where *TP*, *FP*, and *FN* represent the number of true positives, false positives, and false negatives. The values of *IoU* and *Recall* range between $[0, 1]$. The closer these values are to 1, the better the segmentation performance.

Accuracy primarily calculates the proportion of correctly classified pixels to the total number of pixels. The formula for calculation is

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (3)$$

The value of *Accuracy* ranges between 0 and 1. The closer it is to 1, the better the segmentation performance.

The *Kappa* Coefficient is a metric used to measure the consistency of observations. Especially in the case of unbalanced data, the coefficient takes into account the possibility of random agreement. The calculation of the *Kappa* Coefficient is based on the confusion matrix, with results ranging from -1 to 1 , though typically they fall between 0 and 1. The range of *Kappa* values and their corresponding interpretative standards are shown in Table 2. The formula for calculating the *Kappa* Coefficient is

$$\begin{cases} P_o = \frac{TP+TN}{P_0}, \\ P_e = \frac{(TP+FN) \cdot (TP+FP) + (FP+TN) \cdot (FN+TN)}{P_0^2}, \\ Kappa = \frac{P_o - P_e}{1 - P_e} \end{cases} \quad (4)$$

Table 1. Confusion Matrix.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (<i>TP</i>)	False Negative (<i>FN</i>)
Actual Negative	False Positive (<i>FP</i>)	True Negative (<i>TN</i>)

Table 2. Interpretation of *Kappa* Values.

<i>Kappa</i> Value Range	Interpretation
0.01–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–0.99	Almost Perfect

P_0 refers to the total number of pixels in an image tile sample, P_o is the observed agreement, i.e., the actual proportion of pixels correctly classified by the model, and P_e is the chance agreement, representing the probability of correctly classifying pixels when predictions are made at random.

After completing the model testing, we selected the best-performing deep learning model to extract urban morphology from the remaining 98% of unannotated satellite imagery data in S_t .

2.3. Mapping the Evolution of Urban Morphology Using Image Tile

In this section, we adopted a method based on image tiles for mapping the evolution of urban morphology. This method aims to enhance analytical efficiency and make the analysis results concise and easy to interpret. The method can also reduce the impact on interpretation caused by errors in satellite images due to factors such as the tilt angle of buildings and the shooting angle. We employed a workflow of change threshold calculation and extraction of change patterns. Below, we provide a detailed introduction to these two steps.

2.3.1. Calculation of Change Threshold

Data Completion

Due to the incomplete temporal data in high-resolution historical satellite imagery, it is common for certain regions to lack data for specific periods. Therefore, we use the Compound Annual Growth Rate (CAGR) to estimate data for missing years. CAGR provides an average growth rate between two time points, assuming that the growth during this period is smooth and constant. The formula for calculating CAGR is as follows:

$$\text{CAGR}(t_1, t_2) = \left(\frac{A_{t_2}(I_{i,t_2})}{A_{t_1}(I_{i,t_1})} \right)^{\frac{1}{t_2-t_1}} - 1 \quad (5)$$

where $I_{i,t_1} \in S_{t_1}, I_{i,t_2} \in S_{t_2}, i = 1, \dots, N$

A is a mapping of the image feature extraction, where the input is an $n \times m$ image and the output is the extracted d -dimensional features; $t \in T$ is the time, representing our sampling interval; and $I_{i,t} \in S_t, i = 1, \dots, N$ denotes the image of the i th image at t moment, while S_t denotes the set of images at t moment; N denotes how many images there are in total.

In order to obtain the urban floor area occupancy ratio at any moment t . We can deform the above equation to obtain the following formula.

$$A_t(I_{i,t}) = A_{t_1}(I_{i,t_1}) \cdot (1 + \text{CAGR}(t_1, t_2))^{t-t_1}, \quad t_1 < t < t_2 \quad (6)$$

Change Calculation

This study focuses on the changes in urban morphology within each time period, which can be represented by the variation over time in the proportion of building pixels within an image tile.

We define all image tiles at all time points in the entire study area as $S_t = \{I_i \mid i = 1, 2, \dots, N_t\}, t \in T$. The set of all image tiles is represented by $S: S = \bigcup_{t=1}^T S_t$. where T is the total time series of the study, t represents one of the time points, I represents an image, N is the number of images in the set at each time point, and $A_{i,t}$ represents the number of building pixels in the i -th image tile in year t .

To quantify changes in urban morphology within image tile and facilitate the calculation of changes over time, we compute the change rate of building coverage area from time t to $t + 1$. The formula for this calculation is as follows:

$$\Delta_{A_t}(I_i) = \frac{A_{t+1}(I_i) - A_t(I_i)}{P_0} \quad (7)$$

To perform more precise calculations on the images, the following formula can be used to express our calculation process:

$$I_q = \begin{bmatrix} \Phi_q(1, 1) & \dots & \Phi_q(1, m) \\ \dots & \dots & \dots \\ \Phi_q(n, 1) & \dots & \Phi_q(n, m) \end{bmatrix} \quad (8)$$

where $\Phi_i(x, y)$ is a mapping from image positions to corresponding location information, with x and y representing the horizontal and vertical coordinates of a pixel.

Threshold Correction

The purpose of this section is to eliminate the effects of sampling noise, which may originate from changes in satellite shooting angles or the tilting of buildings. To this end, a method has been designed to calculate and correct interannual errors. This method specifically involves calculating the sampling error e_{sample} and the model error e_{model} and correcting the dataset by setting threshold values e . The specific steps are as follows:

1. Sampling error:

We use the formula for determining sample size to ascertain the minimum number of samples required to obtain overall characteristics under conditions of acceptable marginal error:

$$M = \frac{Z^2 \cdot p \cdot (1 - p)}{E^2} \quad (9)$$

$$M_{\text{corrected}} = \frac{M}{1 + \frac{M-1}{|S|}} \quad (10)$$

Here, M represents the theoretical sample size uncorrected; $M_{\text{corrected}}$ is the sample size after correction for a finite population; Z is the standard score corresponding to the required confidence level; p is the estimated value of the population proportion; E is the accepted marginal error; $|S|$ denotes the total number of images or samples contained in the image set S .

To obtain the sampling error, we draw $M_{\text{corrected}}$ elements from the entire image set S to form a subset S' , where $S' \subseteq S$ and $|S'| = M_{\text{corrected}}$:

$$\begin{aligned} e_{\text{sample}} &= \max_{s \in S'} (\|I_{s,t_1} - I_{s,t_2}\|) \\ &= \max_{s \in S'} \left(\sqrt{\sum_{x \in X} \sum_{y \in Y} (\Phi_{s,t_1}(x, y) - \Phi_{s,t_2}(x, y))^2} \right) \end{aligned} \quad (11)$$

The formula above indicates that to estimate the error of the whole set S using the sample S' , we perform error analysis on each pair of drawn samples (I_{i,t_1}, I_{i,t_2}) .

2. Model error:

For each grid from time point t_1 to t_2 , calculate the pixel proportion change correction value e_{model} :

$$e_{\text{model}} = \frac{(FP_{t_2} - FN_{t_2}) - (FP_{t_1} - FN_{t_1})}{P_0} \quad (12)$$

3. Threshold setting:

Combine the actual error e_{sample} and the calculated model error e_{model} to set a threshold e , covering both types of errors:

$$e = e_{\text{sample}} + e_{\text{model}} \quad (13)$$

4. Error correction:

Thus, through error analysis, the threshold e is obtained. If the A value of any point satisfies $A \leq e$, it indicates that the change at that point is likely due to error. Therefore, we perform an error removal operation on the data. The formula is as follows:

$$A = \begin{cases} A, & A > e \\ 0, & A \leq e \end{cases} \quad (14)$$

The range of the e value determined by this algorithm is marked as 0 in the analysis of urban form evolution, thereby enhancing the visualization of change analysis results. Although this method may exclude some image grids where actual changes have occurred, these changes are usually very minor and thus do not significantly affect the overall urban-scale analysis.

2.3.2. Assigning Change Indicators

To enhance the inductiveness and interpretability of image tiles, while also improving analysis efficiency, we use the 'density clustering-classification assignment' method to process the dataset. Through the kernel density clustering algorithm, we map image tiles to data points and group them based on their density in the feature space, identifying and distinguishing clusters with similar geographic locations and change values. Subsequently,

an index assignment strategy is introduced, assigning specific index values to each cluster. This process aims to quantify the features of the clusters and provide them with clear interpretations. Below, we will provide a detailed introduction to our work.

Density Clustering

DBSCAN [52] (Density-Based Spatial Clustering of Applications with Noise) is a density-based spatial clustering algorithm that is robust to noise. The DBSCAN algorithm excels at identifying dense regions within a dataset and interpreting these regions as distinct clusters. It has three main characteristics: (1) it is robust to noise points within urban areas; (2) it does not require prior knowledge of the number of clusters; and (3) it is suitable for clustering three-dimensional non-convex datasets with noise, which aligns with the characteristics of our data. The DBSCAN method is used to cluster the urban morphological change dataset after removing noise. Based on the characteristics of the small dataset, the parameter *MinPts* is set to 3.

Classification Assignment

Change calculations are performed on tile-level images of building footprints. In order to describe the changes inside and outside the tiles, we built the Tile-based Urban Change (TUC) to jointly describe the data. Tables 3 and 4 classify the clusters after clustering. Here is an introduction to the dimensions in TUC:

R: Range, the change range dimension, used to describe changes in building area between tiles. The *R* indicator is divided into three levels, with the classification of levels related to the number of individual clusters: *R1* represents noise points not included in any cluster; *R2* represents clusters that are included but of limited extent, set as $MinPts^2$; *R3* represents clusters with a large number of sample points.

M: Magnitude, the change magnitude dimension, used to describe changes in building area within tile. The *M* indicator is divided into two categories and two levels, with the classification of levels related to the tile occupying more than half of the interval values within the cluster: *MI* represents a decrease in change; *MO* represents an increase in change. The critical value q for the division between the first and second levels is defined by the average of the third quartile $Q3$ of the yearly change difference distribution $\Delta A_t(I_i)$, which allows the second-level indicators *MI2* and *MO2* to exhibit more significant changes compared to the first-level indicators *MI1* and *MO1*.

Table 3. Tile-based Urban Construction Area Change Classification System—Dimension: Range (*R*).

Level	Description
R1	Noise points, not clustered
R2	Small clusters, $MinPts \leq \text{range} < MinPts^2$
R3	Large clusters, $\text{range} \geq MinPts^2$

Table 4. Tile-based Urban Construction Area Change Classification System—Dimension: Magnitude (*M*).

Level	Description
MI2	Significant decrease, $\text{mag} < -q$
MI1	Decrease, $q \leq \text{mag} < 0$
MO1	Increase, $0 < \text{mag} \leq q$
MO2	Significant increase, $\text{mag} > q$

Through the joint description of these two indicators, the overall urban change patterns can be abstracted. For example, in the range indicator, *R1* could indicate small-scale urban renewal projects. *R2* indicates a medium-scale urban development project that may include the mixed-use development of multiple neighborhoods or areas. Such projects may involve the construction or renovation of a residential neighborhood, commercial area, and public facilities. *R3* involves large-scale urban planning and changes, such as the development of new urban districts. In the magnitude indicator, *MI1*, *MO1* indicate slow changes, typically involving small-scale buildings, such as the demolition or construction

of individual buildings or small complexes; $MI2$, $MO2$ indicate significant changes, usually involving large-scale structures, such as the demolition or construction of large buildings like factories.

3. Results

3.1. Dataset and Model Testing

After filtering through the images we downloaded from Google Earth, we finally obtained high-resolution satellite images from 2009, 2013 to 2020, and 2022, with one high-resolution satellite image per year. These images have a resolution of 0.6 m/pixel, a bit depth of 24 bits, consist of 3 bands, and have dimensions of $59,392 \times 36,864$ pixels. The images were pre-cropped into tiles of 1024×1024 pixels, with an overlap area of 100 pixels. After cropping, each year produced 2088 images, covering the entire study area. The S_t dataset totals 20,880 images, saved in a lossless format (tiff) to preserve the original resolution and details. Of these, labeled images constitute 2% of the S_t total, amounting to 420 images, which include images from each year featuring clouds, varying hues, and different seasons. 294 images, accounting for 70%, were extracted from these labeled images for data augmentation, resulting in 2940 images for dataset $\mathcal{D}_2$. The remaining 126 labeled images formed the test dataset $\mathcal{D}_3$.

Pre-Training

The $\mathcal{D}_1$ dataset was input into the PSP-Net for scene parsing and feature learning. The trained deep learning model was subsequently evaluated on the independent test dataset $\mathcal{D}_3$ to test its generalization capability in predicting building structures in the central urban area of Tianjin Binhai New Area. The performance results of the model are summarized in Table 5, with P_0 fixed at 1024×1024 pixels. It was observed that overfitting occurred in training Model 7; hence, Model 6 was chosen for subsequent training. These results indicate that although the model has shown certain generalization abilities after extensive pre-training, the effectiveness recognition ability of the model is still insufficient to support in-depth research on urban form evolution for the urban form segmentation task of this research site.

Table 5. Model Performance Metrics (Pre-Training).

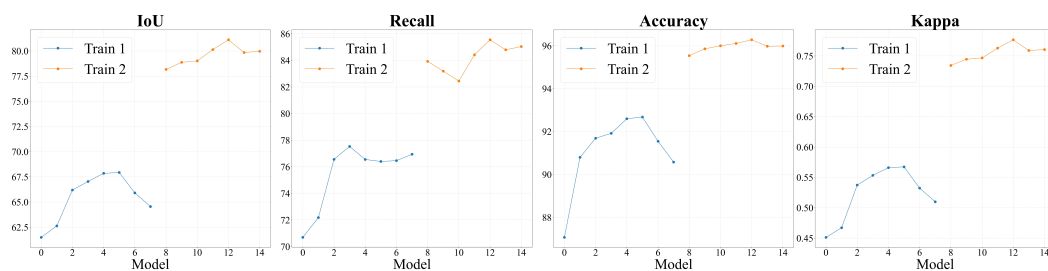
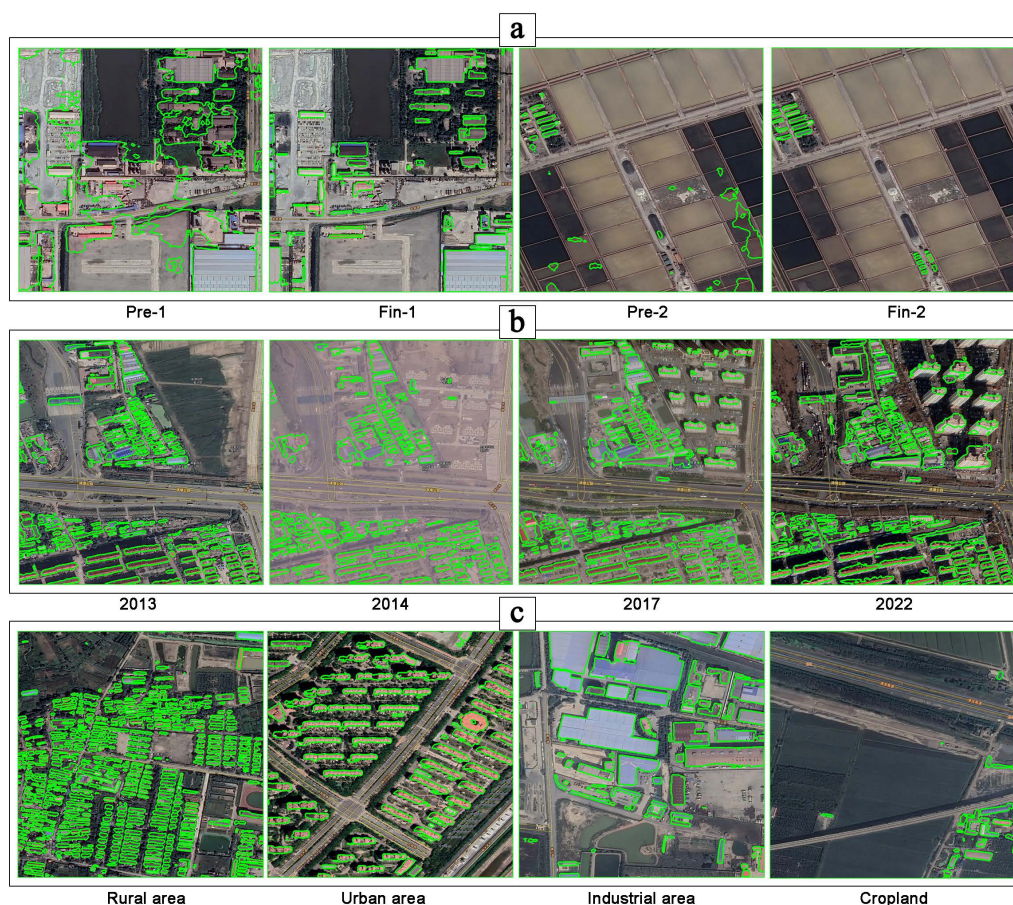
Model	IoU (%)	Recall (%)	Accuracy (%)	Kappa
1	61.49	81.69	87.07	0.4713
2	62.63	72.18	90.8	0.4672
3	66.19	76.56	91.69	0.5374
4	67.04	77.53	91.92	0.5534
5	67.85	76.55	92.6	0.5661
6	67.93	76.4	92.68	0.5674
7	65.91	76.46	91.55	0.5324
8	64.55	76.94	90.58	0.5099

Fine-tuning Training

To further improve the segmentation accuracy of the model on specific sites, the $\mathcal{D}_2$ dataset was used to fine-tune the best-performing pre-trained deep learning model 6. After 1200 training epochs, we observed overfitting in model 14. Consequently, the superior model 13 was selected. The performance of the fine-tuned model is detailed in Table 6. The results show a significant improvement in the performance of the model during our training (Figure 4), with the kappa value of model 13 approaching the “almost perfect” criterion. This model demonstrates excellent performance in processing urban satellite images of different years, seasons, and variations in hue, clarity, and saturation. Additionally, the model effectively handles various types of urban forms, including rural buildings, densely built urban areas, and large industrial facilities Figure 5.

Table 6. Model Performance Metrics (Fine-tuning Training).

Model	<i>IoU</i> (%)	<i>Recall</i> (%)	<i>Accuracy</i> (%)	<i>Kappa</i>
9	78.17	83.93	95.54	0.7344
10	78.87	83.19	95.86	0.7446
11	79.02	82.45	96.00	0.7467
12	80.14	84.42	96.11	0.7629
13	81.11	85.55	96.28	0.7766
14	79.85	84.80	95.98	0.7589
15	79.97	85.04	95.99	0.7605

**Figure 4.** Line chart of model test scores, showing, from left to right, *IoU*, *Recall*, *Accuracy*, and *Kappa* Coefficient.**Figure 5.** Building extraction results of image tiles. (a) Comparison of the effect of the same recognized image after pre-training and fine-tuning training. (b) A comparison of the effects under different years, seasons, hues, saturation, and clarity. (c) A comparison of the results for different types of urban morphology, including rural areas, dense urban areas, farmland, and factories.

Overall, this comprehensive training approach ensures the model's generalizability and applicability in practical applications. The pre-training phase established a robust foundation for generalization, enabling the model to handle a variety of urban morphology images. The subsequent fine-tuning training was specifically optimized for the unique needs of this research site, significantly enhancing the model's performance within this setting, particularly in terms of urban form extraction precision.

3.2. Error Correction and Spatial Clustering

Sampling error: The total sample size N is 18,756 pairs of data, with the estimated population proportion p set at 0.5, confidence level Z at 95%, and error range E set at 5%. Using these parameters, the preliminary calculated sample size M is 384. Considering the finiteness of the total sample, a finite population correction was applied, resulting in a corrected sample size $M_{corrected}$ of 376. We drew 376 pairs of samples, and after virtual visit checks, we found that 193 pairs had errors, taking the largest interval of these error samples e_{sample} to be $[1.9421, -1.7963]$.

Model error: We used the final model to independently predict images from test sets over the past 10 years, and statistical results e_{model} and the calculated combined error e are shown in Table 7. Furthermore, we mapped the evolution of urban morphology and performed threshold correction on the resulting images.

Table 7. Statistics of error values.

ΔA_t	e_{model}		e
9–13	−0.992934604	0.949165396	−2.789234604
13–14	−0.1404782	1.8016218	−1.9367782
14–15	0.45630139	2.39840139	−1.33999861
15–16	−0.476181897	1.465918103	−2.272481897
16–17	0.565098781	2.507198781	−1.231201219
17–18	−0.515700218	1.426399782	−2.312000218
18–19	−0.721515601	1.220584399	−2.517815601
19–20	−0.108421856	1.833678144	−1.904721856
20–22	0.552629224	2.494729224	−1.243670776

We statistically analyzed the change differences for each interval year and presented their distribution through a box plot Figure 6, where the calculated third quartile $q = \overline{Q3} = 2.29$ is obtained.

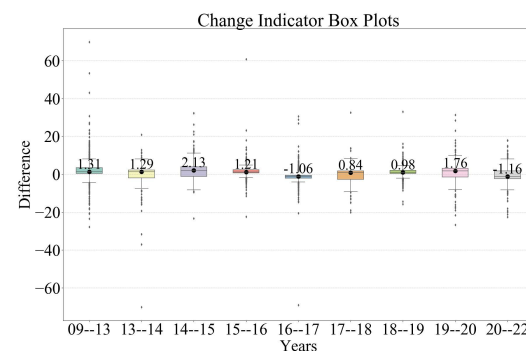


Figure 6. Box plot of the $\Delta A_t(I_i)$ value distribution.

3.3. Characteristics of Urban Morphology Evolution

The characteristics of urban morphology evolution are manifested in two aspects: time and space. Based on this, this article will elaborate on the changes in urban form from two dimensions, time and space, and on this basis, derive the spatiotemporal evolution pattern of urban morphology.

3.3.1. Temporal Evolution

In this Section, we summarize the overall trends and detailed changes in urban development, focusing on two aspects: (1) exploring the trends in urban built-up area changes, dividing them into different development periods; (2) analyzing the distribution changes of various TUC categories over time, revealing the dynamic processes of urban expansion and contraction.

The study period from 2009 to 2022, based on the trend of urban area changes, can be divided into three periods: a rapid expansion period (2009–2016), a turning period (2016–2020), and a slow contraction period (2020–2022) Figure 7. During the rapid expansion period, the urban built-up area significantly increased, with the urban space characterized by apparent scattered and few patchy constructions. During the turning period, with 18 years as the node, there was a brief urban contraction before continuing urban expansion, and the changes in urban space presented complex and ever-changing characteristics. In the slow contraction period, the urban built-up area began to decline, with the urban space showing characteristics of a slow, areal contraction. The overall trend in the central urban area of Binhai New Area is characterized by infill development, accompanied by minor edge expansion and intermittent periods of urban contraction. This is in line with the urban smart growth strategy of large-scale planning and small-scale development. Figure 8 presents the changes over time in the number of each TUC category during the study period, along with the stacked statistical counts of each category.

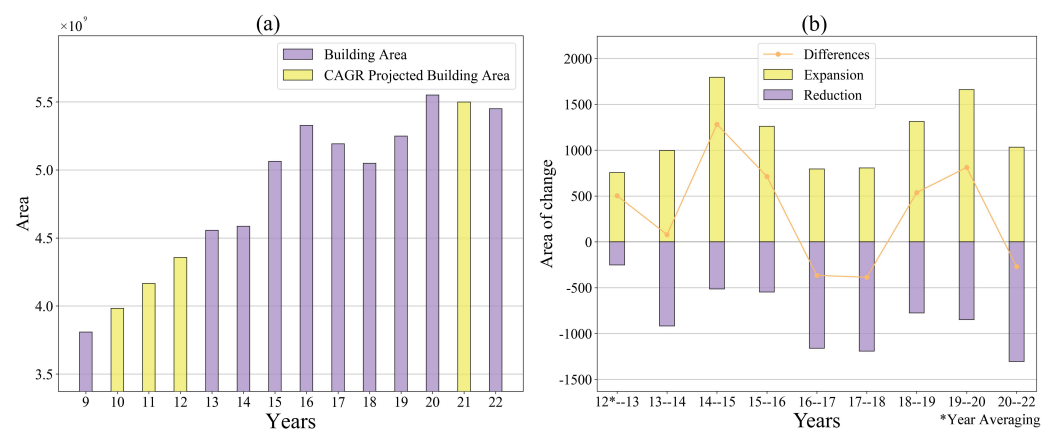


Figure 7. Annual Building Area. (a) The actual building area and the building area calculated by the CAGR algorithm; (b) building area increase and decrease in adjacent years.

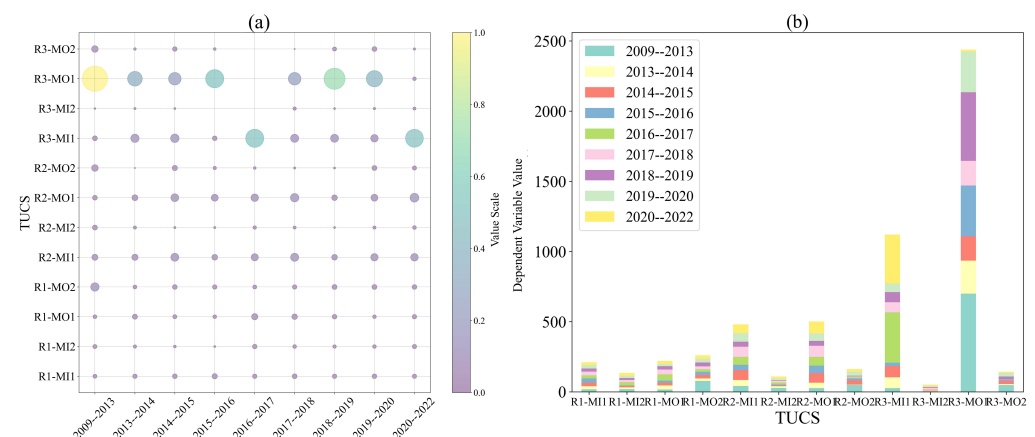


Figure 8. Change classification quantitative statistics. (a) TUC index bubble matrix plot; (b) stacked bar chart of TUC index.

Expansion Period: Between 2009 and 2015, the R3-MO1 category predominated; besides R3-MO1, from 2009 to 2013, the MO2 category was relatively more numerous than other types (MO1, MI1, MI2), and from 2013 to 2015, the MI1 category was more prevalent compared to other types. This indicates that the major trend in urban spatial changes during this period was large-scale and small-degree growth. This reflected that point development areas had become more sustainable due to time overlap, and the growth in urban point changes was greater than demolition.

Transitional Period: Between 2016 and 2020, the dominant type gradually shifted from R3-MI1 to a smaller number of R3-MO1, with a changing area of first increasing and then decreasing. This period is a period of fluctuation, when contraction begins to occur in the city, and then expansion begins to occur and increase, after which the phenomenon is weakened.

Slow Contraction Period: Between 2020 and 2022, the dominant type was R3-MI1, with a decrease in the number of R1-MO1, indicating a reduction in point-like construction and the occurrence of widespread minor contraction phenomena.

3.3.2. Spatial Evolution

In this section, we observe the spatial distribution of significant urban change units and the spatial evolution trends of TUC to deepen our understanding of the spatial dimensions of urban morphology development. Here are the descriptive statistics of the results.

Change Units

Figure 9 visualizes the rate of change in building area from 2009 to 2022 to observe the spatial distribution of significant urban change units throughout the entire study period. Significant change units refer to areas in the graph where significant changes occur. From this, significant growth and decrease, slight growth and decrease, and planar expansion and contraction can be observed as morphological change units in the graph.

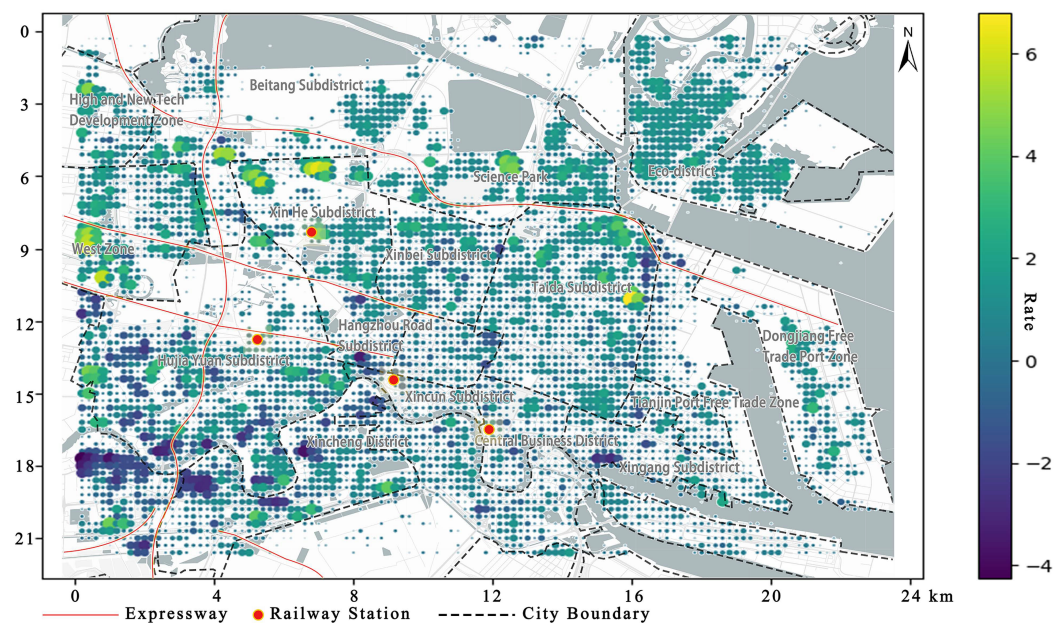


Figure 9. Building Area Change Rate (2009–2022): The graph shows significant change areas, with point size representing the magnitude of change and color indicating positive or negative change, highlighting growth, reduction, and expansion/contraction units.

Observing the overall condition of the scatter plot, the dots on the periphery of the city are relatively larger than those in the city center, indicating that the city is still undergoing slight edge expansion during the study period. The significant growth and change units mainly occur in the northwest part of the city, distributed along the Beijing–Tianjin Expressway Gangcheng Avenue area. This may be because large buildings such

as logistics and warehousing are mainly located in this area, and this type of building occupies a large area, so any changes will be very significant on the map. The significant reduction change units are mainly located in the southwest part of the city, developing horizontally along the Haihe River-Jinbin Expressway. This may be because this area has been designated by urban planning as a new urban development zone for the city with certain developmental potential.

The urban space change timeline Figure 10 shows the distribution of change units in the urban space over the study period, reflecting the development trends of urban change units. The following describes the urban morphology evolution observed in areas affected by significant change units:

The northwest region of the city shows an evolutionary trend of concentrated development and construction at first, and unchanged in the later stage: during the early part of the study period (2009–2015), development intensity was high with repeated occurrences of significant demolition and construction change units; in the later period (2015–2022), there were virtually no significant changes. The southwestern region of the city has shown a development trend of ‘initial intensive demolition, followed by gradual reconstruction’. Between 2009 and 2013, this area experienced significant reductions in buildings, then entered a stable period with almost no significant changes, primarily characterized by sporadic point-like growth along major transport routes. The south-central part of the city (near train stations) is a sensitive area for urban morphology changes. This area has shown a series of complex morphological changes, experiencing a multi-stage development process from reduction to increase, to point-like and large-scale demolitions, and finally to reconstruction and reduction.

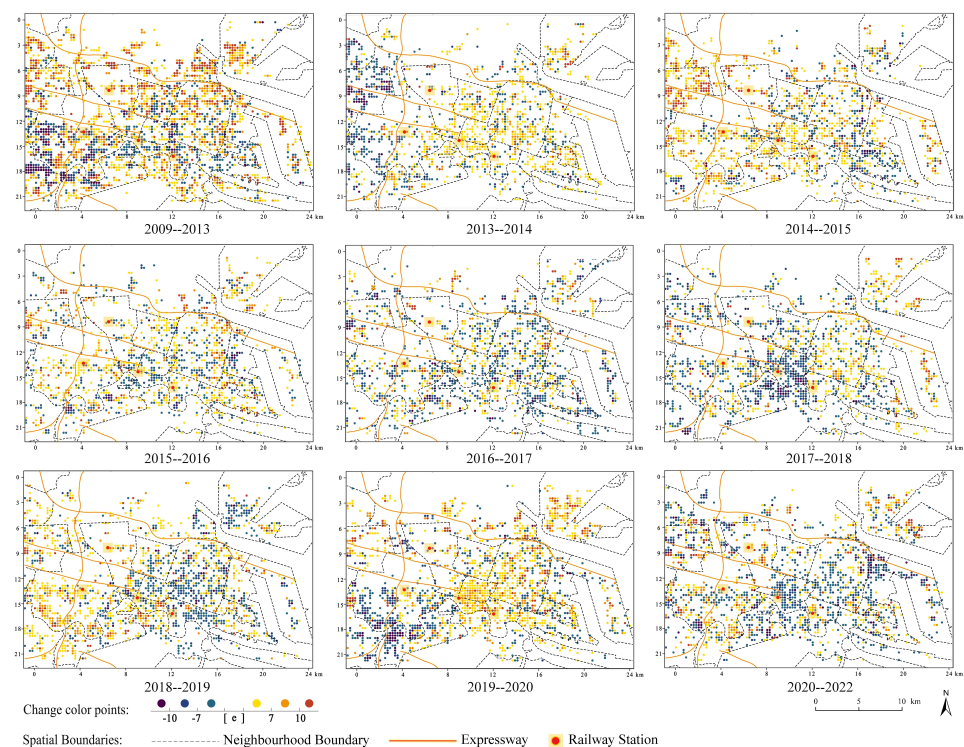


Figure 10. Urban Spatial Change Timeline: This diagram shows urban spatial change units at various time points. Warm color points represent an increase, cool color points represent a decrease, and the darker the color, the more drastic the change. Allowing observation of significant urban changes over time.

Types of Changes

The urban morphology evolution spatial clustering map Figure 11 visualizes the urban morphology changes after mapping the clusters to get the abstract urban morphology changes. Each color corresponds to a type in TUC, and the space is mapped according to the classification. Figure 12 The Sangi diagram calculates the number and type conversion of various types of changes between years, allowing for the observation of the type of location points in the cluster diagram that change over time, and thus analyzing the evolution pattern of urban form.

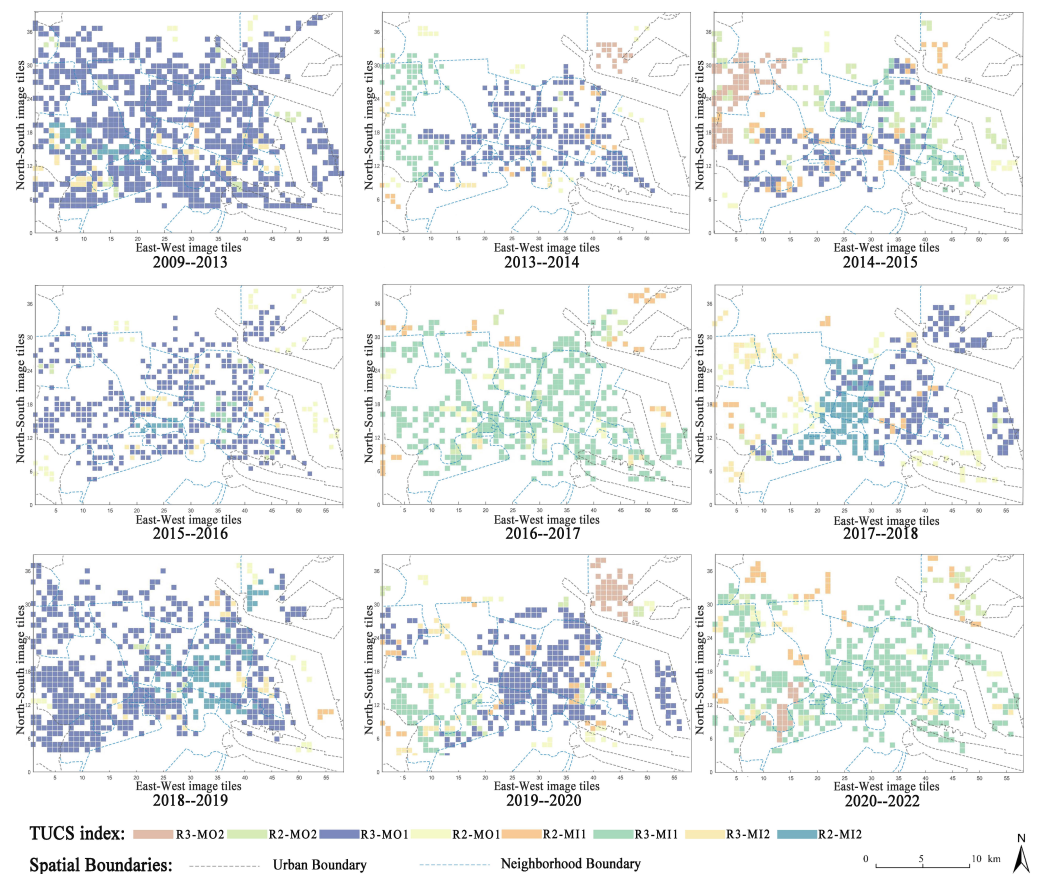


Figure 11. Urban morphology evolution spatial clustering map: each color corresponds to a type in the TUC, mapping these spatial data points according to the classification.

In most periods, the R3-MO1 indicator mainly involves the urban center area. Further observation from the Sangi diagram shows that there are often liquidity changes between the R3-MO1 indicator and the fixedness indicator, indicating that the morphological evolution of the city center area is not limited to expansion or contraction, but also includes flow with stability types.

After an initial rapid expansion, the development of the southern part of the city entered a relatively stable phase. From 2009 to 2013, this region was dominated by R3-MO1 and R2-MO2, experiencing extensive construction. Afterward, slow construction activities continued along the southern edge of the Haihe River, while the further south remained largely unchanged over the next decade. A comparison with land use planning maps reveals that this area was restricted by urban development strategies. The eastern part of the city often experiences medium-scale, high-degree change indicators (R2-MO2, R2-MO1), interspersed with large areas of slow changes (R3-MI1, R3-MO1). A significant pattern of urban expansion can be observed in the northeast part of the city, with the spread of construction from the center to the outside (R3-MO2, R2-MO2, R2-MO1), accompanied by

small-scale dismantling of the peripheral areas (R2-MI1). The central and northern regions of the city exhibit a linear distribution pattern along highways. In this region, the changing units mainly cluster around highways, and most other areas have maintained a relatively stable and slow development state for most of the time.

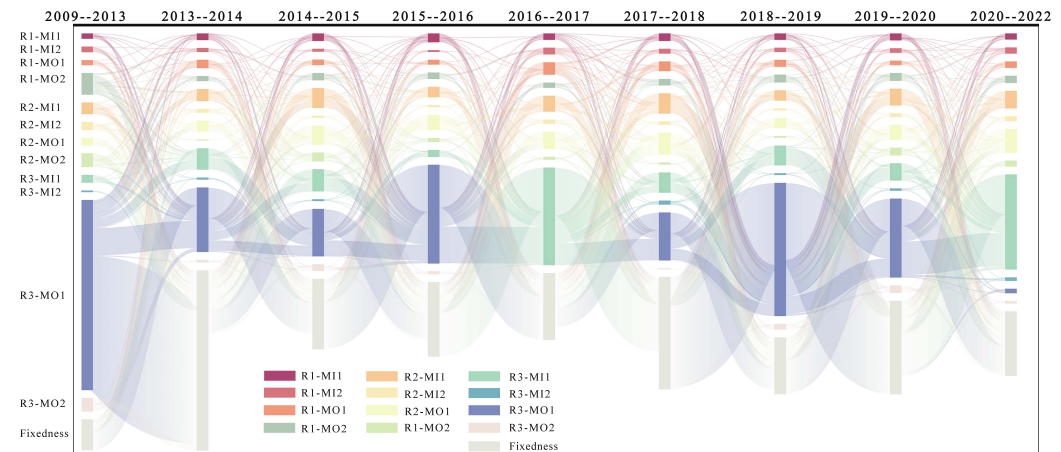


Figure 12. TUC-type transition Sankey diagram: This diagram allows observation of the changes in the types of position points within the clustering diagram over time, thereby facilitating the analysis of urban form evolution patterns.

Overall, the general change pattern across the city is ‘dispersed small-area growth’: the R3-MO1 indicator covers most of the space in most periods of urban development, with only two periods dominated by R3-MI1.

3.3.3. Urban Morphology Evolution

Based on the conclusions above, we can derive the patterns of urban morphology evolution (e.g., Figure 13 and Table 8):

Edge Areal Expansion Pattern: Located in the northeast corner of the research area, as shown in area 1 on the map. Similar to the traditional ‘pancake’ expansion, the city expands outward at a relatively fast rate, accompanied by the areal demolition of old buildings and the point-like demolition of construction buildings. This typically occurs in the rapidly developing urban fringe areas, indicating planned large-scale development and construction in this region.

Preservation of Development Potential Pattern: Located south of the Haihe River, as shown in area 2 on the map. Initially, point-like demolitions of old buildings are carried out, followed by sporadic construction, while also preserving much land for future development. This pattern usually occurs in the inner parts of cities during rapid development phases, preserving undeveloped land to ensure long-term construction potential.

Industrial Land Development Pattern: This pattern is located in the eastern part of the study area, as shown in area 3 on the map. The urban form of this area remained relatively stable during the study period. Because infrastructure such as industrial plants and logistics warehouses were largely constructed by 2019. As a result, only slight scattered changes occurred in the area during subsequent development, with large buildings remaining unchanged. The changes mainly occurred in small factory buildings. Due to the dispersed layout of small factories, the range of changes is relatively wide, but the degree of change involved is relatively small.

Rapid Comprehensive Demolition and Construction Pattern: This pattern involves the area located in the western part of the city, as shown in Area 4 on the map. This pattern of change manifests as a large-scale demolition and construction in space, and their development and construction processes have obvious phased characteristics. This change in pattern reflects the phased planning of construction and has a clear policy-driven character.

Linear Development Pattern: Located in the northern part of the city, as shown in area 5 on the map. The pattern of change in the area is associated with large buildings such as logistics warehouses in this area. The pattern changes linearly along the transportation arteries. And significant change units occur in point form, which is mainly characterized by a small scope of change and a large degree of change. This indicates that the architectural structure of the area is extremely sensitive to changes in logistics demand. Driven by logistics needs, buildings are demolished and reconstructed to adapt to industry requirements.

Mixed Evolution Pattern: Located in the southern part of the city, north of the Haihe River, as shown in area 6 on the map. This area integrates various types of buildings, such as industrial parks, residential areas, and urban villages, with diverse urban functional buildings. In addition, the region also includes three major transportation stations in the city, making them key nodes in urban transportation. This region has undergone a series of complex morphological changes, presenting a multi-stage development process.

Stable Evolution Pattern: Located in the central part of the city, as shown in area 7 on the map. Throughout the entire research period, there was little significant change, and significant units of change did not appear in the area, usually manifested as scattered and subtle changes in small and medium-sized urban buildings.

Overall, urban development presents a multi-dimensional development pattern that is divided into regions and periods. A city is not a homogenous entity that develops completely according to a certain evolutionary pattern. Cities are composed of different areas, which exhibit diverse development paths at different periods based on their own geographical, economic, social, and cultural conditions.

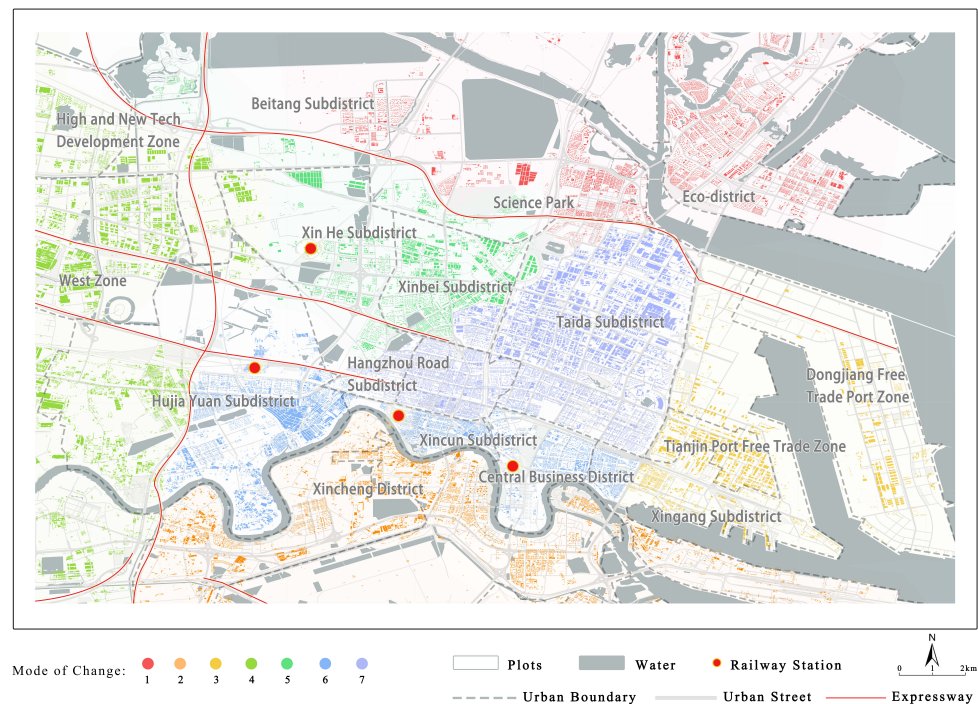
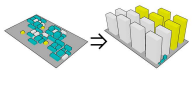
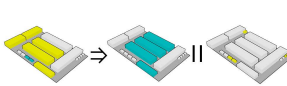
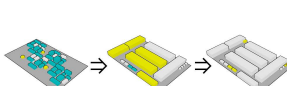
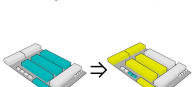
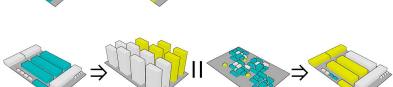


Figure 13. The urban morphology evolution patterns of Tianjin Binhai New Area can be classified into eight distinct patterns, influenced by spatiotemporal changes and geographical location.

Table 8. Overview of landscape and urban morphology evolution patterns.

Number	Pattern	Map	Schematic Diagram
1	Edge Areal Expansion Pattern		
2	Preservation of Developmental Potential Pattern		
3	Industrial Land Development Pattern		
4	Rapid Comprehensive Demolition and Construction Pattern		
5	Linear Development Pattern		
6	Mixed Evolution Pattern		
7	Stable Evolution Patterns		

4. Discussion

4.1. Complexity of Longitudinal Data Extraction on Urban Form

Many scholars believe that the finer the quantitative scale of urban physical forms, the greater its practical significance for urban science research [11,12], because fine-scale analysis can reveal subtle changes in urban structure and function that are not easily perceptible at a macro scale. More detailed observation and analysis of specific elements in a city, such as buildings and streets, can directly solve specific urban problems. This has more practical significance for understanding real-time urban dynamics and targeted urban transformation. However, quantifying the temporal evolution of urban physical forms has always been a complex task, especially at a microscale. Remote sensing images exhibit significant differences in their spatiotemporal distribution, morphology, and environmental context [53,54]. Historical remote sensing images are often composed of different satellite sources, leading to significant inconsistencies in quality, tone, and noise among these images [55]. These differences and inconsistencies greatly increase the complexity of data processing, thereby requiring highly accurate and adaptive extraction methods.

To extract high-quality urban morphology, we adopted a deep learning semantic segmentation approach, which is very common in the field of remote sensing. For example, Google's global building data and the U.S. building footprint data were extracted using this method [31,56]. However, these datasets typically lack temporal sequences, and their coverage and precision are insufficient to meet the needs of general urban studies and high-precision urban morphological evolution research. This is particularly evident when studying the evolution of urban morphology in underdeveloped countries and cities [12,40]. Based on the core findings of previous similar studies, which suggest that the effectiveness of a model depends more on the quality of the dataset [27], we designed our method to be adaptable to the needs of a wide range of urban environments, including data-scarce non-developed cities and high-density urban areas. The advantage of this method is that it uses a wide range of training data and conducts targeted training on the research site, enhancing the model's generalization and robustness to longitudinal satellite image data. In addition,

our method minimizes labor and economic costs as much as possible, improving efficiency and feasibility.

Although our method performs well in most cases, it may perform poorly when dealing with a few urban buildings of special forms. This type of building has a limited number in a wide urban environment, so its impact on the overall research results is relatively small. To enhance the model's adaptability and accuracy, diverse data was used during training to minimize the impact of urban landscape variations. However, factors like tree canopy and cloud shadows can still obstruct building recognition and affect results, which is unavoidable. With the development of more generalized or targeted deep learning semantic segmentation models for building footprints (such as Deeplabv3+ [57]) and the availability of more high-quality public datasets, future researchers will be able to use more optimized algorithms and seek matching or similar urban morphology datasets based on the target city, further enhancing the applicability and precision of the methods. We aim for the model to better adapt to complex urban environments, enhancing urban morphology extraction and accurately reflecting the city's development.

4.2. The Balance of Methodology in Mapping Urban Morphology Evolution

In urban morphology quantification research, it is often necessary to find a balance between theoretical interpretability and practical simplicity. Overly complex theoretical models, although highly explanatory, are poorly operationalized and difficult to adopt widely; whereas simplified models, although easy to use, may not be able to adequately reveal the complex dynamics of internal urban morphology changes [18,58]. To find this balance, we intend to use a method that is both convenient for numerical statistics and easy to visualize its results. This method requires a numerical decomposition of the urban morphology image, which preserves the necessary morphological information while also facilitating the statistics of urban morphology changes.

Based on accurately extracting the form of buildings, we use image tiles to map the changes in the proportion of urban buildings. We call it "Dynamic Analysis of Urban Morphology Based on Image Tiles", highlighting the integration of longitudinal image data for a continuous view of urban development. This method of constructing a continuous urban development view is significantly different from traditional research methods on meso- and microscale urban morphology, which typically focus on binary changes (such as 'unchanged-changed') or ternary urban growth patterns ('unchanged-increased-replaced') [27], and cannot reveal the complex evolution patterns within the city in depth. The reason is that abstracting urban evolution from massive data requires efficient algorithms and handling complex noise. Machine learning can help detect city changes [59], but models often lack robustness, interpretability, and have complex, limited analysis methods, hindering a deeper understanding of urban morphological evolution.

Fine-grained time-series data were used in this study to get a comprehensive picture of the urban evolution process. Spatial clustering and assigning change types based on annual data changes in the urban morphology grid enables a more intuitive presentation of valid information. This method not only reduces the impact of noise data through the use of image tiles but also obtains the multivariate changes of morphological evolution patterns. Future studies will cross-correlate these changes with spatiotemporal data from other urban research areas (e.g., urban equity, green space, heat island). Integrating historical and current data will deepen urban research, uncover root causes of issues, predict trends, and support urban planning decisions. It will also highlight successes and lessons in planning, governance, and infrastructure, helping emerging cities avoid past mistakes and design future-ready development patterns.

However, the research method has limitations: while the square image tile offers easy processing, efficiency, and compatibility, it may experience boundary effects, limited edge continuity, and inadequate visual presentation. To address the limitations of quadrilateral tiles, future research can use image tiles of other shapes, such as geometric shapes with better symmetry or approximate circular shapes. This can reduce deviations caused by

direction, alleviate boundary effects and data distortion, enhance data continuity and accuracy [60], and provide better visual effects [61].

4.3. *The Reality of Urban Evolution Pattern*

This study reveals the historical trends in Binhai New Area's urban development. Spatiotemporal analysis shows diverse patterns in urban morphology evolution, varying across regions and periods, and linked to factors like development time, location, land use policies, and transportation. The following discusses the current patterns of urban morphological evolution.

During the rapid development phase of a city, the edge expansion pattern often emerges on a large scale. However, despite the extended period of urban development in Tianjin Binhai, this pattern remains evident due to its unique characteristics as a new town. There are significant differences in urban development patterns between new districts and main urban areas. Compared to the main urban areas, new districts are more function-oriented, with their development often driven by policy incentives and guidance. Due to the high demand for development and the relatively abundant land resources in new districts, they continue to exhibit pronounced edge expansion patterns even in the later stages of development. In contrast, the main urban areas, constrained by limited land resources and more mature planning, primarily undergo changes through internal renewal and redevelopment rather than edge expansion. This difference reflects how the stage of urban development and the planning context influence the emergence of edge expansion patterns. However, such expansion is often accompanied by the encroachment on ecosystems and the overconsumption of resources, leading to environmental degradation and a decline in urban sustainability. Therefore, in urban planning practice, it is essential to strengthen the monitoring and control of this expansion pattern to ensure the rational use of resources, protect ecosystems, and prevent resource misuse and disorderly urban sprawl during the development process.

The linear development pattern is usually closely related to transportation and logistics demand. The city's geographic characteristics, transportation arteries, and economic activity are important factors in shaping this pattern. For instance, if a city has important development plans in a certain direction, the associated supply chain, services, and housing industry may concentrate in that direction. This clustering effect promotes the development of cities along specific axes, exacerbating the trend of linear expansion [62,63]. Additionally, residential areas in this region, due to their proximity to major transportation and logistics hubs, face environmental pressures such as noise, exhaust emissions, and pollution from frequent construction, which affect the quality of life and health of residents. Therefore, exploring the relationship between linear urban development patterns and residents' quality of life can help improve the living environment and promote rational urban planning. Coincidentally, this area is adjacent to the edge areal expansion pattern on the map. In future research, the interconnections between urban expansion areas and linear urban development patterns can be further explored to optimize urban planning and land use strategies.

The Rapid Comprehensive Demolition and Construction Pattern usually stems from the needs of urban development and policy promotion, especially in the construction stage of new urban areas, through rapid and concentrated demolition and reconstruction to meet the needs of urban function expansion. In Tianjin Binhai New Area, a significant economic and industrial region in northern China, the rapid development has led to notable changes in social structure. This pattern can profoundly impact community residents, leading to displacement, changes in community structure, shifts in the socio-economic environment, and often further intensifying challenges related to social equity, justice, and potential [64,65]. As a result, identifying and studying social changes in these areas, particularly in preventing potential gentrification, becomes a critical breakthrough point in academic research. Future studies may focus on the issues of relocation and resettlement of original residents under the changing economic and social structure of the region,

as well as on the preservation of historical and cultural memory and the protection of community identity.

The Industrial Land Development Pattern occupies a significant area in Tianjin Binhai New Area, indicating the strong development of the region's industrial, logistics, and other secondary sectors. The landscape stability of industrial land reflects that the development strategy in this area places a high emphasis on long-term sustainability and economic stability.

In future urban development, especially in transitional areas between different functional zones, the mixed evolution pattern requires careful planning and management. Implementing refined management strategies, improving land use efficiency, and fully considering the opinions and needs of residents will help minimize potential conflicts in these areas.

The Preservation of Development Potential Pattern involves conserving land and planning for future growth, commonly found in highly functional urban areas. This aligns with the positioning of Binhai New Area in planning documents, reflecting both its current urban functions and foresight for future development potential. Implementing this pattern requires considering factors such as location, strategic positioning, environment, and constraints to maximize land use efficiency and ensure sustainable development. Planners must assess current land use and future potential to optimize resources, meet future urban needs, and achieve long-term development goals.

The stable evolution pattern provides a contrasting perspective, demonstrating the relative stability of development change in the city center area. As the old urban area of the city, land use has reached a relatively extreme state, with fewer large-scale demolition and construction, and only minor changes in building demolition and construction due to urban renewal. By identifying and analyzing this pattern, policymakers can better understand the potential constraints of urban development and evaluate urban renewal policies.

From an overall trend perspective, the primary change in the central urban area of Binhai New Area is characterized by infill construction, accompanied by minor edge expansion and intermittent occurrences of brief urban contraction. This aligns with the "big planning, small development" strategy of smart growth. Additionally, the significant changes in industrial and logistics buildings highlight the distinctive nature of the new urban area, which aims to integrate industry and urban functions into a comprehensive new city, differing from traditional single-function industrial park developments. Notably, potential causes for urban contraction include the 2015 real estate market downturn, whose delayed effects may have led to slow building growth between 2016 and 2018. From 2020 to 2022, the built-up area of the city experienced a net annual reduction of approximately 5.04 billion square meters. This change is likely related to the COVID-19 pandemic, which may have resulted in the suspension or cancellation of construction projects.

4.4. The Interpretive Capability of Meso- and Microscale Morphological Evolution

Meso- and microscale urban morphology evolution involves an in-depth study of the detailed changes in the internal structure and function of cities. This analysis focuses on smaller urban scales or specific urban features such as streets, buildings, and plots, and their dynamic changes over time. However, urban spatial data must be properly contextualized and interpreted in order to be transformed into meaningful information. The development of remote sensing data collection and analysis, spatial statistical techniques, and visualization methods will contribute to the advancement of this process [18,34]. The accurately extracted urban form data through in-depth analysis can be applied to various urban development studies. For example, it can be used to archive intelligent city dynamic data systems, aid in sustainable planning and design for small and medium-sized cities; perform typological measurements using urban morphology masks to distinguish different building or area types within a city; additionally, urban morphology detection can also support social equity studies by identifying deprived areas in cities to promote policy targeting [31,65,66].

The core breakthrough of this study is in enhancing the explanatory power of urban morphology evolution patterns.

(1) **Deepen the Study of Urban Physical Form:** Previous fine-grained studies have generally not involved vertical changes, while studies that do focus on vertical changes often choose a larger scale, causing much information to be hidden within subtle and less noticeable changes. In the future, we hope to reveal hidden urban development trends and potential issues by integrating and analyzing more detailed and comprehensive urban form sequence data. This will allow for more effective guidance in urban planning and policy-making, enabling more accurate and intelligent urban planning and governance.

(2) **Application of the Framework in Various Real-world Scenarios:** In large cities, this framework can help identify complex urban morphological evolution patterns. In medium and small cities, it can alleviate problems related to insufficient urban development data and understanding. It can also facilitate comparative studies of different urban evolution patterns within urban clusters, aiding in the coordination of urban development strategies.

(3) **Achieving More Immediate Urban Monitoring:** This framework enables real-time monitoring of urban morphology by utilizing advanced remote sensing technologies, real-time data collection, and analysis tools. Urban planning can thus stay informed of spatial changes in real time, allowing for rapid responses to various urban issues and challenges. Policymakers can adjust or formulate new policies based on real-time data to address new situations or problems arising in urban development.

(4) **Incorporating More Variables and Interdisciplinary Applications:** Future research on urban morphological evolution can be enhanced by introducing variables from disciplines such as economics, sociology, and environmental science, thereby promoting knowledge integration across different fields. For example, combining economic growth data, population migration patterns, and environmental impact assessments with urban morphology data allows for a comprehensive analysis of the economic drivers, social consequences, and environmental costs of urban expansion.

This framework has certain limitations. We acknowledge that simplifying urban form into architectural elements does not fully capture all physical manifestations of urban morphology. Absolute representation of urban form often faces complexity challenges and cannot be entirely represented by a single category [18,58]. However, because buildings dominate the urban landscape, changes in building area are the most suitable mapping carriers for urban morphology evolution. Compared to plots or roads, it is a more unstable element in cities, showing more significant changes in short sequences. Additionally, as the main carriers of human production and living activities, they offer stronger interpretive power regarding socio-economic activities than other urban elements [67–69].

5. Conclusions

In this study, we divided our workflow into three steps to understand the spatiotemporal evolution of urban morphology at the meso- and microscale. First, we created a method for constructing urban form datasets for evolution analysis. Second, we effectively extracted the urban morphology by training a deep learning semantic segmentation model; Finally, we quantified the changes in urban morphology using the TUC classification system and abstracted the evolution patterns.

The main conclusions of this study are as follows: (1) Google high-resolution satellite imagery longitudinal data, which is not only inexpensive and easily accessible for research, but also effectively supports the study of the evolution of urban morphology. (2) The dataset construction method and two-stage training method we designed can achieve more accurate urban form extraction using computer vision technology even in specific research sites with limited data volume. (3) Using image-tiles mapping and spatial clustering, we can abstract the spatial and temporal evolutionary patterns of micro-urban morphology for a study city. Although the approach in the form of patches may mask some of the physical information about the city, it can simplify the denoising and quantization process.

This paper discusses the importance of fine-grained spatiotemporal methods in understanding urban form. A refined quantitative scale can enhance the practical impact of urban studies, offering better guidance for rapid development [12]. Our research framework

provides urban planners with tools for quantitative assessment, enabling them to develop strategic plans tailored to various urban development patterns, particularly in rapidly expanding areas like new towns.

In practice, we strongly advocate for urban planners to consider the different developmental characteristics of various regions within the city when formulating urban development strategies. Our analysis of evolution patterns reveals a high degree of diversity in the development paths within the city. This finding is particularly important for urban planners, as it reminds us that a city is not a homogeneous entity, but rather a collection of regions with distinct developmental needs and characteristics. For instance, the rapid, comprehensive demolition and construction patterns observed in certain areas indicate the need for more controlled and phased urban renewal policies to avoid the negative impacts of sudden changes in the urban landscape. This differentiated planning strategy can not only help mitigate the challenges brought by rapid urban development but also promote balanced development among different regions of the city, ultimately achieving overall sustainability and livability. In the future, this method combined with other urban spatiotemporal quantitative data will have the advantages of transfer ability and flexible adjustment of spatiotemporal granularity, and it can also be applied to research in the fields of environmental equity, disaster prevention and mitigation, and heritage conservation.

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