

# MODELLING AND UNDERSTANDING MULTI-TEMPORAL LAND USE CHANGES

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## ABSTRACT:

Understanding temporal urban growth is very crucial to the interpretation of urban morphology and a key challenge for the study of rapid urbanization in contemporary China. Previous land use change modelling approaches only consider the spatial complexity that may be indicated by spatial dependence and landscape fragmentation, ignoring the temporal complexity inherent in the process of urban growth. Multi-temporality is a typical characteristic of urban growth and multi-temporal data availability has been much improved due to great advance in geospatial technology particularly remotely sensed imagery. This paper proposes an innovative application of a machine learning method – Maxent for analysing the urban morphology of a fast growing city –Wuhan, China. Multi-temporal data sets for 1955, 1965, 1993 and 2000 were processed from remotely sensed imagery. The results demonstrate that Maxent is an effective exploratory method and tool for understanding urban morphology.

## 1. INTRODUCTION

Rapid urbanisation has stimulated fast urban growth occurring in Chinese cities and other developing countries. Wuhan, a mega city in Central China, has seen its urban built-up areas grow tenfold between 1955 and 2000 (Cheng and Masser, 2003). Understanding temporal dynamics of urban form and urban land cover/land use is a prerequisite to making appropriate sustainable urban development policies and strategies. Stimulated by rapid advances in geospatial technologies, high-resolution remotely sensed imagery has become widely available and at low cost. Such factors have made monitoring urban growth possible and more successful in developing countries. Moreover, various models have been developed and explored for interpreting, predicting and simulating urban development pattern and processes and assisting the decision support of urban growth management and planning. Among these models, logistic regression, cellular automata and multi agent system methods have received a lot of attention. However, most models are only focused on the spatial complexity of urban growth system, not on temporal complexity. Urban growth is a continuous process, which means that new buildings, roads, and commercial centres emerge temporally accidentally. Multi-temporality is a typical characteristic of urban morphology. Three classic theories of urban morphology were developed in the 1970s: the concentric zone theory, the sector theory and the multiple nuclei theory. These theories have defined morphological factors (e.g. distance to city centre(s), distance to main corridors) which affect urban development patterns. Morphology analysis makes it possible to summarise the changes and trends of the urban spatial structure. For example, we need to establish the dominant morphological factors (e.g. proximity and development density) driving urban growth in multi-temporal periods. Such findings can make a useful contribution to the local knowledge of urban development planning.

The availability of multi-temporal data sets offers great opportunity for measuring and understanding urban

morphology. However, previous studies in urban morphology were focused on the measurement of urban morphology using methods such as fractals, density gradient and landscape matrix. These methods only provide single or multiple indicators for spatially measuring urban morphology, instead of, temporally modelling urban morphology. Multi-temporal spatial modelling is still not well developed in geospatial areas. In this paper, we propose an innovative application of a machine learning method – Maxent, for analysing urban morphology of a fast growing city (Wuhan, China). Multi-temporal data sets are available for 1955, 1965, 1993 and 2000, which were processed from remotely sensed imagery. This research has demonstrated that Maxent is an effective exploratory method and tool in helping understand urban morphology.

## 2. DATA & METHODOLOGY

### 2.1 Data sources and processing

Wuhan is located in Central China on the middle reaches of the Yangtze River. Wuhan municipality, the capital of Hubei province, has a total population of about 8 million over an area of 2000 km<sup>2</sup> in 2007. Wuhan is known as ‘Water City’ (*Jiang cheng*) due to the two rivers (Yangtze and Han rivers) that intersect here, and the surrounding lakes. In previous research (Cheng, 2003), temporal urban growth of Wuhan from 1955 to 2000 has been mapped (see figure 1) based on primary data sources composed of aerial photographs from 1955 (scale 1:25000) and 1965 (scale 1:8000), SPOT Pan/XS images taken in 1986 and 2000, and secondary data sources (e.g. land use map of 1993, topographic maps of 1993, traffic and tourism maps and master plan schemes). Land conversion was detected and classified using the maximum likelihood method (SPOTs) and visual interpretation (photographs).

## 2.2 Maxent method

Maxent is a general-purpose method for characterizing probability distributions from incomplete information based on the principle of maximum entropy. In urban and transport geography, the maximum entropy principle has been successfully applied to model spatial interactions, such as the flows of trips, immigrants, and vehicles. Maxent's strength was first discovered in the successful applications for natural language processing. Recently Maxent methods have been widely explored and applied in species distribution modelling where only presence data is available for prediction (e.g. Phillips et al., 2006; Loiselle et al, 2008.). The main advantages of Maxent include, as summarized by Phillips et. al. (2006): no requirement of independence between predictor variables, only presence data, easy and efficient deterministic algorithm. Maxent is a generative approach, rather than discriminative. Many researches have shown Maxent has higher efficiency in learning and testing over support vector machine.

This paper aims at explore potential application of Maxent for urban morphology analysis using multi-temporal data sets. We use the presence-only (or called growth-only) data in multi-temporal periods. This application is different from urban growth pattern analysis, in which the probability of land conversion is calculated for both presence and absence (no land conversion) areas in the same period of urban growth. Logistic regression (conditional version of Maxent) has been widely applied for urban growth pattern modelling (Cheng and Masser, 2003). However, in most cases, it is hard to define an explicit boundary within which we can sample absence sites. This urban morphological analysis attempts to temporally compare the growth-only data distributions among multi-temporal periods.

Supposed that we have  $n$  urban morphological variables (called environmental variables in species distribution modelling) that are treated as features in Maxent, and  $m$  pixels in the study area, which defines a probability space, we denote the  $n$  variables as function  $f_i$  ( $i=1$  to  $n$ ) and their values at pixel  $j$  ( $j=1$  to  $m$ ) as  $f_i(j)$ . The probability space is split into two parts: sample ( $k=1$  to  $m1$ ) and background ( $k=1$  to  $m2$ ). i.e.  $m1+m2=m$ . The sample part is composed of the growth pixels occurring in period  $p1$ , i.e. the areas converted from non-urban into urban in a single specific period (e.g. 1965-1993). Background is composed of the growth pixels occurring in another period  $p2$  (e.g. 1955-1965) and provides reference sites for comparisons. The unknown probability distribution over the entire space ( $m$  pixels) is denoted as  $X$ . Then the probability being present at site  $j$  is  $X(j)$ .

The maximum entropy principle aims to estimate the probability distribution function  $X$  given the constraints that the expected value of each feature  $f_i$  under this estimated distribution matches its empirical average. The empirical average of each feature  $f_i$  ( $i=1$  to  $n$ ) over the sample part ( $m1$  pixels) is known and represented as  $g_i$ , that is based on a uniform distribution. The expectation of the feature  $f_i$  under  $X$  is defined as  $\sum X(j)f_i(j)$  and denoted by  $h_i$ , contrasting with  $g_i$ . We assume  $h_i$  can be approximately estimated by  $g_i$ . By the maximum entropy principle, therefore, we seek the probability distribution  $X$  of maximum entropy subject to the constraints that each feature  $f_i$  has the (or nearly) same mean as observed, i.e.  $h_i=g_i$ . The implementation of maxent uses a sequential-update algorithm (Dudik et al., 2007) that iteratively picks a weight and adjusts it so as to minimize the resulting regularized log loss.

Maxent uses the receiver operating characteristic (ROC) analysis to evaluate the performance of a model. A ROC plot is created by plotting sensitivity values against 1-specificity for all probability thresholds. The sensitivity is the fraction of all positive instances (sample part) representing absence of omission error, while 1-specificity is the fraction of all negative instances (background part) representing commission error. The area under the curve (AUC) is a single number to assess model accuracy, which usually ranges from 0.5 (random or similar) to 1.0 (perfect discrimination). The higher the AUC value is; the more distinct morphological characteristic between the periods of  $p1$  and  $p2$  it informs us.

## 2.3 Exploring and selecting features

In this paper, urban form, or morphology is classified as compact development (higher density of built-up area in its neighbourhood), road-led development (better proximity to main roads), polycentric development (better proximity to main commercial centres), industrial centric development (better proximity to industrial centres) and river-led development (better proximity to rivers). To explore the dominant urban morphology in multi-temporal periods, several spatial explanatory variables corresponding to these morphological factors (proximal or density oriented) have been incorporated into Maxent models for spatio-temporal exploration. They are denoted as Deve\_Density (neighbourhood density of urban built-up areas), Dist\_MainRoad (distance to main roads), Dist\_Centres (distance to main commercial centres), Dist\_Industrial (distance to industrial centres) and Dist\_River (distance to rivers). Change5565, change6593 and change932000 are used to represent the urban growth occurring in the periods of 1955-1965, 1965-1993 and 1993-2000 respectively. Then all morphological factors are measured on these growth-only pixels based on right temporal correspondence. It means that Dist\_MainRoad for Change5565 will measure the distance of each pixel in the layer of Change5565 to the closest main road of 1965 and Deve\_Density measuring the density of developed areas of 1955, and so on. In order to save computational time, all raster layers are re-sampled in ArcGIS from original 10-m resolution to 100-m resolution. Neighbourhood density was calculated as the percentage of built-up area to the total developable area (e.g. excluding water body and protected areas) in a circle with a radius of 100 pixels (10km). Then log transformation of the four proximal variables is taken in order to make them follow a normal distribution as much as possible. Finally these raster data are converted into MOS-DOS text file format (.csv) for use in the Maxent modelling software.

## 3. RESULTS

### 3.1 Measuring temporal urban growth

The temporal urban growth of Wuhan from 1955 to 2000 is mapped in figure 1. Due to space constraints, only the morphological indicator of main roads in the three periods is mapped in figure 2. The information dimension of fractal measuring the evenness degree of spatial distribution was calculated as 1.67034, 1.7134, 1.740, 1.753 and 1.78 for the urban built-up areas of 1955, 1965, 1986, 1993 and 2000 respectively (Cheng, 2003). The information dimension shows a general trend of increasingly even distribution which can be theoretically explained by the spatial process from leap-forward development to compact development pattern. However, the

fractal measure of spatial complexity still lacks adequate interpretation capability for urban morphology due to the fact that the same value of a fractal dimension may represent different forms or structures. Using linear regression analysis, the spatial impact of each morphological factor on urban growth can be quantified as a kind of density (or probability) gradient that represents the negative exponential relationship between the probability values of land conversion from non-urban to urban and the distance rings in relation to the morphological factor. Cheng and Masser (2003) previously explored the density gradient values of main road, main commercial centres, industrial centres, rivers and developed area density for the urban growth in the period 1993-2000.

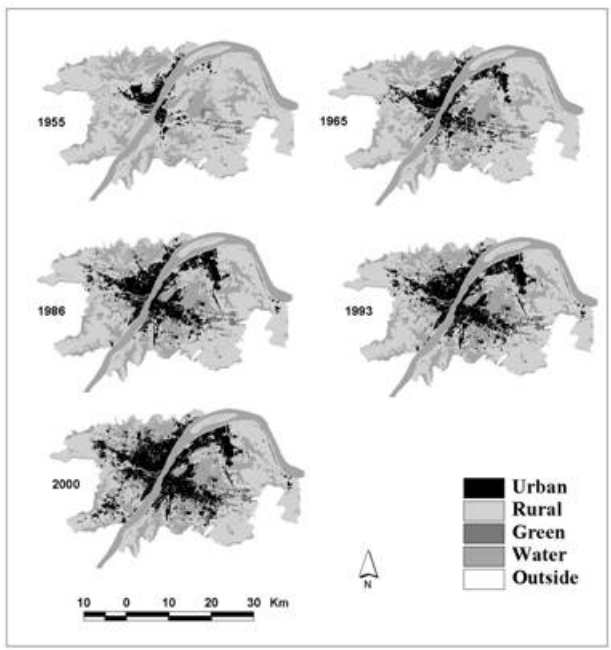


Figure 1. Temporal urban growth of Wuhan 1955-2000

All five factors showed significant spatial impacts and their density gradients were calculated as -0.00076, -0.000225, -0.00013, -0.00003 and 0.465 respectively. For example, the probability of land conversion is the exponential function of  $Dist\_MainRoad$  (i.e. probability value =  $\exp(-1.05 - 0.00076 * Dist\_MainRoad)$ ). The higher the absolute gradient value is, the greater impact it has. As a result, the relative ordering will be proximity to main roads, commercial centres, industrial centres and rivers in terms of their growth density gradient. The spatial impacts of these morphological factors are measurable and comparable. However, density gradient measurement only provides a single indicator for relative comparisons in the same period and is unable to temporally compare the contribution of each morphological factor to urban morphology. Looking at figures 1 and 2, the time-series model of urban expansion offers an intuitive hypothesis that the city gradually changed its development axes from rivers to major roads and also shifted from a mono-centric to multi-nuclear spatial structure. Next, the Maxent method is used to explore the hypothesis. Because of the relatively slight change from 1965 to 1986, only the temporal urban form in the three periods: 1955-1965, 1965-1993 and 1993-2000 is considered here.



Figure 2. Main roads in the years of 1965, 1993 and 2000

### 3.2 Maxent models

The three presence data layers processed are Change5565 (6152 pixels), Change6593 (7233 pixels), Change932000 (6109 pixels), which indicate the total urban growth occurring in the periods of 1955-1965, 1965-1993 and 1993-2000 respectively. 40% random sampling was taken from each of them for the uses of Maxent modelling. An absence-only data layer - Unchange (8317 pixels) was defined by taking a 20% random sample from developable pixels (e.g. agriculture and bare land) in 2000. This layer will serve as a reference for comparison purpose.

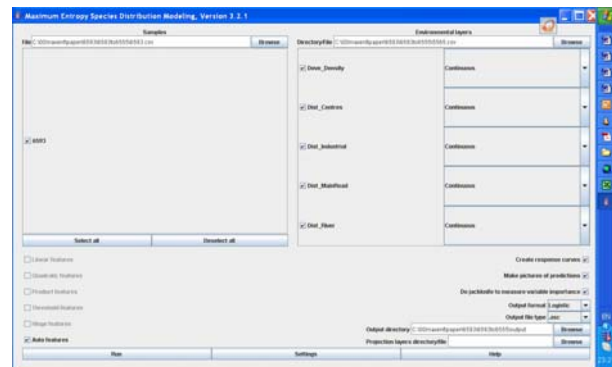


Figure 3. Maxent modelling interface

Maxent was implemented using version 1.8.2 of the software developed by Phillips and colleagues (for free download see: <http://www.cs.princeton.edu/~schapire/maxent/>). 5000 was set up as maximum iterations with convergence threshold 0.00001, and 30% of sample sites (e.g. from Change5565) was taken for training and the remaining 70% for testing. Suitable regularization values, included to reduce over fitting, were selected automatically by the program (see figure 3). The selection of two data sets separately defining sample and background is dependent on the purpose of temporal comparison, e.g. the urban growth in 1955-1965 against that in 1965-1993.

First, a Maxent model (figure 3) is built using two presence data layers - Change6593 as sample and Change5565 as background, which aims to explore the distinct morphological characteristics between urban growth occurring in the periods 1955-1965 and 1965-1993. In Maxent modelling, AUC (see figure 4) is a model performance indicator comparing the probability distributions between sample and background layers. The higher the AUC value is, the more distinct patterns it discloses. The AUC value shown in figure 3 is 94%, well beyond 80%,

which indicates that the morphological characteristics of urban growth can be significantly distinguished between the two periods.

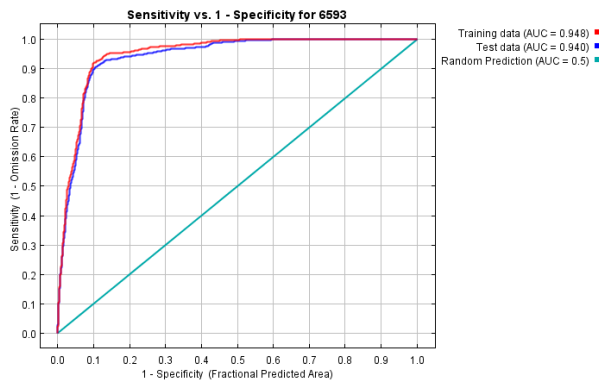


Figure 4. AUC graphic showing model performance

| Models          | Model 1    | Model 2      |
|-----------------|------------|--------------|
| Sample          | Change6593 | Change932000 |
| Background      | Change5565 | Change6593   |
| AUC             | > 0.94     | > 0.90       |
| Dist_Centres    | 5.4 (-)    | 5.1 (+/-)    |
| Dist_MainRoad   | 6.1 (+/-)  | 12.0 (+)     |
| Dist_Industrial | 15.1 (-)   | 41.1 (-)     |
| Dist_River      | 9.3 (-)    | 9.2 (-)      |
| Deve_Density    | 64.1 (+)   | 32.6 (+)     |
| Total (%)       | 100        | 100          |

Table 1. Selected outcome of Maxent modelling

| Models          | Model 3                   | Model 4      |
|-----------------|---------------------------|--------------|
| Sample          | Change932000              | Change932000 |
| Background      | Change5565,<br>Change6593 | Unchange     |
| AUC             | >0.94                     | >0.90        |
| Dist_Centres    | 0.8 (+/-)                 | 30.8 (+)     |
| Dist_MainRoad   | 8.9 (+)                   | 62.8 (+)     |
| Dist_Industrial | 42.6 (-)                  | 5.2 (+/-)    |
| Dist_River      | 10.0 (-)                  | 5.0 (+/-)    |
| Deve_Density    | 37.7 (+)                  | 6.2 (+/-)    |
| Total (%)       | 100                       | 100          |

Table 1. Selected outcome of Maxent modelling (continued)

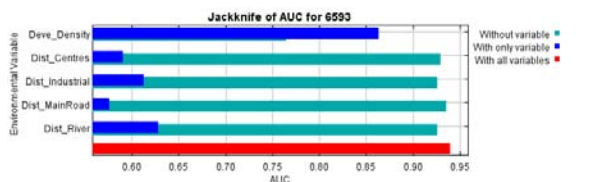


Figure 5. Detail of relative contributions (65/93 and 65/55)

The five rows from Dist\_Centres to Deve\_Density in table 1 measure the relative contribution of each morphological factor to the AUC value. Figure 5 explains the detail of what is meant by relative contribution, which graphically confirms the

contribution values declining from Deve\_Density down to Dist\_Industrial, Dist\_River, Dist\_Centres and Dist\_MainRoad. However, relative contribution alone is not sufficient to conclude on the dominant urban morphology characteristics – e.g. compact or leap forward development (by the highest contribution - Deve\_Density), because of the lack of information concerning the direction or nature of contribution: positive (the higher value, the greater probability of conversion) or negative (the higher value, the smaller probability of conversion). It should be noted that positive or negative is a relative term, depending on which side you are standing on, 1955-1965 or 1965-1993. If it is positive to 1965-1993, then it must be negative to 1955-1965 as sample and background data sets can swap in Maxent model of this particular application. Figures 6-8 show the responses of Change6593 to three morphological factors with higher relative contribution. Figure 6 indicates a positive response to Deve\_Density; Figure 7 the negative response to the proximity of industrial centres (proximity is opposite to distance, the higher the Dist\_Industrial is, the lower the proximity is, so do other proximal variables); and Figure 8 the negative response to the proximity of rivers (Dist\_River) again. To help interpret the dominant morphological characteristics in each period, the direction of contribution was added to each explanatory variable in Table 1, in which plus (+) indicates positive and minus (-) negative. As a result, the relative contributions in Table 1 exhibit that urban growth in 1965-1993 was dominated by relatively compact development as indicated by Deve\_Density (+64.1%) and conversely urban growth in 1955-1965 was dominated by leap forward development (-64.1%) expanding out from industrial centres (+15.1%) and rivers (+9.3%).

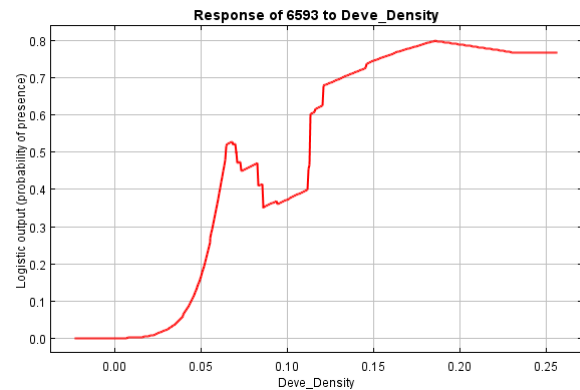


Figure 6. Response of Change6593 to Deve\_Density

Second, two other Maxent models (see table 1) were built by changing the data sets of sample and background, which allow different morphological analysis varying with urban growth periods to be compared. Model 2 enables us to conclude that urban growth in 1993-2000 was dominated by relatively compact development (Deve\_Density +32.6%) and road led development (Dist\_MainRoad +12%), conversely urban growth in 1965-1993 was dominated by industrial centric development (+41.1%) and rivers along development (+9.2%). Model 3 enhances the conclusion with dominant morphological characteristics of urban growth 1993-2000 through comparing it with the total urban growth 1955-1965 and 1965-1993.

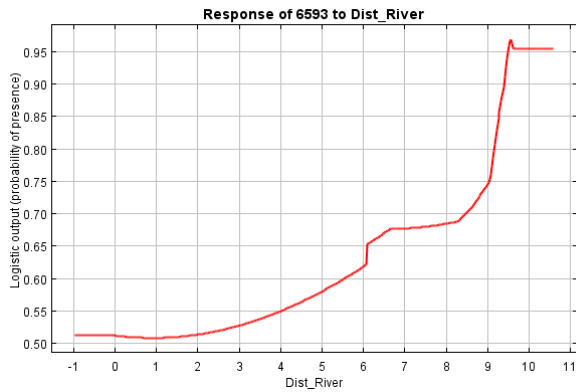


Figure 7. Response of Change6593 to Dist\_Industrial

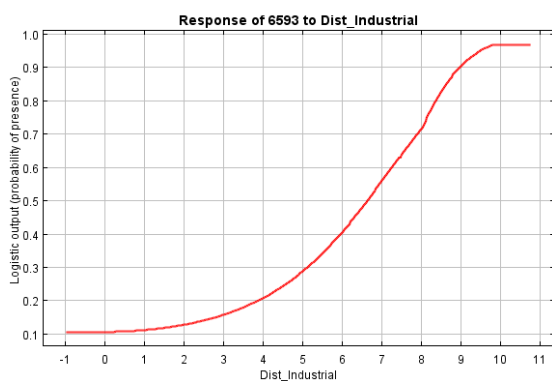


Figure 8. Response of Change6593 to Dist\_River

Finally, a Maxent model (model 4 in table 1) was built with Change932000 as sample and Unchange as background. Model 4 exhibits a morphological trend of multiple centric and main roads led development, which is consistent with the current urban development strategies of mega cities in China. Integrating the findings from these four models, a general conclusion can be made that urban morphology of Wuhan city from 1955 onwards shifted from leap forward development to industrial centric compact development, to the mixture of road led development and multi-centric development. Such quantitative evidence is highly consistent with the visual perception of local experts and other theoretical understanding (e.g. Wu, 1998) and therefore, Maxent modelling provides an effective exploratory environment (e.g. figures 4-8) for interpreting urban morphology.

#### 4. DISCUSSION AND CONCLUSIONS

When applying traditional regression analysis for spatial issues, we usually need to take spatial autocorrelation into account, such as spatial logistic regression (Cheng and Masser, 2003), which is a typical requirement for modelling urban growth patterns. In this paper, for testing the effect of spatial autocorrelation on urban morphology analysis, model 1 (in table 1) was modified by taking all pixels (instead of 40% or less random sampling) into the sample and background data sets. This should obviously result in stronger spatial autocorrelation of each explanatory variable in both sample and background layers. Applying Moran' I method (neighbourhood is defined as a circle with a radius of 1000 metre), the spatial autocorrelation

values calculated range from 0.51 up to 0.97. However, the relative contributions as calculated as Deve\_Density (66.7%), Dist\_Centres (5.7%), Dist\_Industrial (15.6%), Dist\_MainRoad (5.6%) and Dist\_River (6.4%), exhibit no significant changes in terms of amount and direction. The AUC of this model is > 0.95, nearly the same as model 1. Consequently it can be claimed that Maxent modelling is not sensitive to spatial autocorrelation. This is particularly beneficial to urban morphology analysis in which morphological factors (e.g. proximal and neighbourhood density variables) always exhibit strong spatial autocorrelation as being different from the environmental features in species distribution modelling.

The Maxent application for urban morphology, compared to those for species distribution modelling (e.g. Phillips et al. 2006), is characterized by rich rather than sparse data of presence sites, no sample selection bias, more uses for understanding instead of predicting and at metropolitan scale not global scale. This paper has demonstrated Maxent's strong capacity for exploratory analysis which can be easily used for communication with local planners. In future work, we will compare the Maxent method with other machine learning methods such as support vector machine. We will also continue the morphological analysis of Wuhan with the data set of newly emerging urban growth from 2000 onwards.

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