Does Urban planning affect urban growth pattern? A case study of Shenzhen, China

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A B S T R A C T

It is essential to understand how urban plans affect urban growth patterns in order to improve current urban planning and management systems. Few studies have been conducted to analyse urban growth patterns of Shenzhen, an international megacity located in southern China, but none of them revealed the relationships between urban planning and urban growth patterns. This study explores the effects of urban master plans on urban growth patterns in different plan periods in Shenzhen. We first quantified the urban growth patterns comparing pixel- and patch-based methods. Three methods resulted in different quantities and spatial characteristics of urban growth. We then explored the relationships between urban growth patterns and urban planning in Shenzhen through multinomial logistic regression models. Across two planning periods, the master plans together with other socio-economic, physical, proximity, accessibility and neighbourhood factors shaped the urban growth patterns of Shenzhen. Out of the master plan elements, planned main roads in the Master Plan of Shenzhen 1996–2010 and the planned built-up zone in the Master Plan of Shenzhen 2010–2020 had stronger effects on urban growth patterns but contributed less than most other factors, e.g. distance to ocean. The importance of the other influence factors also varied over time. This changing effect suggests that we need to consider carefully whether driving factors might change in their importance over time when investigating future scenarios of urban land use change. Overall, this approach could also be applied to monitor progress in the paradigm shift towards an integrated urban-rural development in China.

1. Introduction

More than half of the world population is now living in urban areas, and this figure will likely increase to 60 % by 2030 (United Nations, 2014). Until 2030, the urban land cover is likely to increase to 1.2 million km² which is nearly triple of the urban land in 2000 (Seto et al., 2012). Even though urbanisation brings ample economic and technological benefits (Runde, 2015), the increase in built-up land has manifold negative environmental impacts, such as encroaching on natural areas and agricultural fields (Huang et al., 2017). Some of the environmental impacts are related to specific spatial patterns of urban growth, such as leapfrogging that increases travel demand and energy consumption (Transportation Research Board and National Research Council, 2009).

Spatial planning is assumed to direct urban land change (Couclelis, 2005; Hersperger and Bürgi, 2010). According to the conceptual role of spatial planning in urban land change proposed by Hersperger et al. (2018), urban plans intend land use changes, that are implemented under the territorial governance processes and external conditions. Thus, plan implementation can eventually lead to land change. However, so far little attention has been paid to analysing the impacts of urban planning and policy on urban landscape change (Hersperger et al., 2018). Identifying urban growth patterns and their relations with urban plans can be one step in that direction.

China is a crucial case for analysing the effect of urban plans on urban growth patterns, since it has experienced unprecedented urban growth during the transition from a centrally planned economy towards a market economy over the last decades (Zhu et al., 2019). The share of the population living in urban areas has grown from about 20 % in 1982 to almost 60 % nowadays (Shi and Zhong, 2019). Key drivers are an intense rural-urban migration and rapid economic development (Zhu et al., 2019) as well as strong population growth (Liu et al., 2018). Implications of such fast urbanisation include the loss of agricultural land (Liu et al., 2019) as well as the loss of ecologically sensitive areas (Liu, 2018). These rapid changes require continuous updates of mapped urban built-up areas (Li et al., 2020) to inform land management.

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Various land use policies have been implemented over the years to address the negative effects of urbanisation (Liu et al., 2014). At each level of the Chinese land administration system, from central to township, a land use master plan is supposed to coordinate all building activities with the lower tiers translating the setting of the upper tiers into concrete terms for their territory (Shao et al., 2020). These master plans are intended to direct development in intended urban promotion areas and avoid urban developments in defined protected areas (Wang et al., 2017). The urban master plan is a very important instrument for Chinese cities to manage the development of the city, whereas “Chinese cities do not follow a single standard to identify the boundaries of urban built-up areas” (Li et al., 2020, p.1). It is prepared by the local planning department and is supposed to determine the city size, the urban structure and the spatial distribution of the population over the planning period (Tian and Shen, 2011). It is a comprehensive plan which encompasses various other plans, such as spatial zoning plan, land use plan, physical infrastructure plan, transportation plan and housing plan. Until 2017, sectoral plans could also implement different types of ecological protection zones (Guo et al., 2018). Also, economic development zones have been implemented to foster urban development in specific locations (Liang et al., 2020).

However, doubts have been raised whether the urban growth management is effective in controlling urban expansion (Shao et al., 2020). Also, Liu et al. (2018) suggest a strategic adjustment of land use policies in China under the current slowing down of the economic growth termed the “new normal”, including a better integration of the multiple planning instruments of the various planning tiers. With our study, we aim at providing scientific evidence on how far the urban master plans and Special Economic Zone were able to steer urban growth patterns in a Chinese case study in order to inform the adjustment of land use policies in China.

A striking example for the potential influence of spatial planning onto urbanisation in China is Shenzhen in Guangdong Province: it was promoted as a city in 1979, and the first Chinese Special Economic Zone (SEZ) was established in Shenzhen in 1980 but then cancelled in 2010 (Fig. 1). After the establishment of the SEZ, Shenzhen has developed from a small city of about 300,000 inhabitants to a megacity with approximately 15 million people by 2015 (UN-Habitat, 2015). Urban land increased from 3.6%–41.8% of the whole city (Dou and Chen, 2017). This increase is, especially at the city fringe, due to the continuously growing informal peri-urban settlements (Sumari et al., 2017).

Still, the urban population growth between 2000 and 2018 has been faster than urban land growth in the same period (Yu et al., 2019). Also, rapid urbanisation has led to “urban villages”, i.e. formerly rural villages which have been encircled by industrial, commercial, and residential areas (Jiang et al., 2020). Consequently, issues like agricultural land loss, traffic congestion and air pollution were registered. In response to these issues, urban planning (e.g. spatial zoning) was frequently employed by Shenzhen’s urban planning department (Deng et al., 2018). Given the rapid urban growth in Shenzhen, it can serve as a testbed to investigate to what extent urban plans have actual influence in the resulting urban growth patterns.

Many studies have already elaborated on the spatial and temporal patterns of urban growth in Shenzhen. For instance, Lv et al. (2009) found outlying growth to be the main growth pattern during 1979 and 2005. Li et al. (2005) described the urban growth from 1978 to 1999 as

Fig. 1. The geographic location of Shenzhen and the Special Economic Zone (The map of China comes from Resource and Environment Data Cloud Platform (http://www.resdc.cn/data.aspx?DATAID = 200)).
at first fragmented, then expanded and finally amalgamated. Furthermore, they logically deduced with their background knowledge of Shenzhen that the changes in urban landscape patterns were the consequences of both urban planning and disordered human disturbances (e.g., economic activities). Dou and Chen (2017) investigated a later period (1988–2015) and determined extensive urbanisation being the main urban growth pattern. The authors hypothesized that the extensive growth was probably caused by foreign capital investment and government policies of introducing satellite towns and industrial parks. The study by is—to our knowledge—the only study that quantitatively investigated the effects of spatial planning on urban growth. The authors focused on urban growth in the sense of land use/cover change and found that urban planning in the master plan of Shenzhen posed no significant effects on guiding urban development from 2000 to 2010. Since their focus was urban growth as such instead of the spatial patterns of urban growth, the effects of spatial planning on urban growth patterns is still an open question. Three master plans have been implemented in Shenzhen and are claimed as “significant directors” of the development of Shenzhen (Urban Planning and Land Resources Commission of Shenzhen Municipality, 2017). Therefore, this study aims to investigate the effects of master plans on urban growth patterns in different master plan periods in Shenzhen. Three sub-objectives help to achieve this purpose: 1) to identify the urban growth patterns in Shenzhen over time; 2) To identify the effects of urban master plans on urban growth patterns in Shenzhen and 3) to differentiate whether these effects varied in different plan periods.

2. Data and methods

2.1. Land cover data acquisition and processing

We build our analysis on the land-use/land-cover data set provided by Dou and Chen (2017) of Shenzhen in 1988, 1993, 1999, 2001, 2005, 2008, 2011, 2013 and 2015 based on Landsat imagery. Since one of the purposes of this study was to analyse the urban growth patterns in Shenzhen, the land cover types were reclassified to urban (built-up area) and non-urban (forest, cultivated land, water body, grassland and bare land). Also, we needed to exclude permanent or temporary shrinkage of the built-up area. In brief, we treated urbanisation as irreversible which means that once the urban pixels were urbanised, they remain urbanised forever. Appendix A describes the procedure in detail, and Table 1 compares the total extent of urban area in the original data set compared to the one employed here. All data processing was conducted in ArcMap 10.5.

2.2. Identification of urban growth patterns

Urban form and growth patterns have been widely studied in many different disciplines, such as urban planning, landscape ecology, and urban modelling (Reis et al., 2016). Urban form metrics such as complexity, density or compactness (e.g. Huang et al., 2007) describe urban spatial patterns for a specific point in time. Urban growth patterns, on the contrary, describe the spatial patterns of urban expansion over time. Following Pham et al. (2011); Yue et al. (2013) and Liu et al. (2016), we distinguish three urban growth patterns: infilling, expansion and outlying, since other patterns can be regarded as variants or hybrids of these three basic patterns (Wilson et al., 2003; Xu et al., 2007; Liu et al., 2010). Infilling is characterised by new urban area filling up gaps between exiting urban areas. Expansion is characterised by new urban area spreading unidirectionally in more or less parallel strips from the urban edge. Outlying refers to new urban area that has no spatial connection with the existing urban areas.

Many studies have been conducted to quantify urban growth patterns, using either pixel-based or patch-based methods. For our study, we decided to choose one representative for each of these two approaches to provide a solid basis for our analysis. Both Wilson et al. (2003) and Pham et al. (2011) provide pixel-based methods by combining a moving window approach and spatial metrics. For our study, we chose the method proposed by Wilson et al. (2003) since their five patterns provide more diversity than the patterns proposed in other studies (e.g. Pham et al., 2011). Xu et al. (2007) and Liu et al. (2010) have employed patch-based methods to characterise the infilling, expansion and outlying patterns. Out of those two, we chose the approach proposed by Liu et al. (2010) since it was frequently applied by scholars to study urban growth in Chinese cities that have experienced fast urbanisation (Liu et al., 2016; Ou et al., 2017).

Thus, two major methods were adopted for urban growth pattern identification in this study: the pixel-based urban growth model developed by Wilson et al. (2003) and the patch-based Landscape Expansion Index (LEI) developed by Liu et al. (2010). The latter approach requires creating patches, and these can be computed with two different types of neighbourhoods (see Section 2.2.2 for details). Therefore, we distinguish two sub-types for the LEI: LEI 4-cell and LEI 8-cell. Fig. 2 provides examples of urban growth patterns and their classification according to Wilson’s model, the LEI 4-cell and the LEI 8-cell methods.

2.2.1. Urban growth model proposed by Wilson et al. (2003)

The urban growth model proposed by Wilson et al. (2003) classifies infilling, expansion and outlying patterns, the latter consisting of isolated, clustered and linear patterns. Wilson et al. (2003) employed a moving window method to identify the urban growth patterns base on the proportion of non-urban pixels in the moving window. The authors classify the five urban growth patterns from categorized land cover maps in three steps:

- Step 1: Each non-urban pixel (date 1) is assigned a fragmentation category based on its neighbouring pixels in a moving window.
- Step 2: Each urban pixel (date 2) changed from a non-urban pixel with a fragmentation category (date 1) is assigned one of the three basic urban growth patterns (i.e. infilling, expansion and outlying).
- Step 3: Each outlying pixel is reclassified into isolated pattern, linear branch and clustered branch.

Fig. 2 visualises exemplary urban growth pattern classifications according to Wilson’s urban growth model. Compared to other methods, it further differentiates diverse outlying patterns. Appendix B provides the details on how the urban growth model proposed by Wilson et al. (2003) was implemented for this study.

2.2.2. Urban growth pattern classification based on Landscape Expansion Index proposed by Liu et al. (2010)

The LEI index is computed based on patches, thus, it is essential to determine which neighbourhood rule should be used to aggregate the pixels to patches. There are two neighbourhood rules for this purpose: 4-cell neighbourhood (von Neumann neighbourhood; sharing an edge with the focal cell) and 8-cell neighbourhood (Moore neighbourhood; sharing an edge or corner). In this study, both rules were applied in the process of classifying urban growth patterns since we did not know
upfront which neighbourhood rule works better in the context of this methods used in this study. The classification procedure proposed by Liu et al. (2010) is based on the LEI in a buffer zone around the new urban patch (Eq. (1)).

\[
\text{LEI} = 100 \times \frac{A_0}{A_0 + A_v}
\]  

- LEI is the landscape expansion index for a new urban patch;
- \(A_0\) is the intersection between the buffer zone of the new urban patch and existing urban patches.
- \(A_v\) is the intersection between the buffer zone of the new urban patch and vacant land.

The rules for identifying the three urban growth patterns are the following:

1. If the buffer zone of a newly grown patch mostly intersects with the existing urban patch, then this newly patch is classified as infilling (LEI larger than 50).
2. If the area in the buffer zone of a newly grown patch mixes vacant land (or other landscapes) and existing urban landscape, then the newly grown patch is assigned as edge-expansion (LEI between 0 and 50).
3. If the buffer zone of a newly grown patch composes of vacant lands, the newly grown patch is assigned as outlying (LEI equals 0).

Fig. 2 indicates that the LEI 4-cell and LEI 8-cell methods largely provide the same urban growth pattern – differences occur in cases where urban pixels only share corners, but not edges, with other pixels. In these cases, the different definitions for neighbourhood when defining a patch matter. The detailed process of classifying the urban growth patterns based on LEI is provided in Figure C.1 in the appendix. In this study, we used the “LEI tool” developed for ArcGIS desktop, available from http://www.geosimulation.cn/LEI.html. The LEI tool computes the LEI based vector data for the original (previous) area and the newly added area. Users also need to determine the buffer distance.

2.3. Potential influence factors from planning

This study focuses on the urban master plans of Shenzhen. So far, three master plans were developed by the Shenzhen urban planning department, covering the three periods of 1986–2000, 1996–2010 and 2010–2020. As the Master Plan of Shenzhen SEZ 1986–2000 was not accessible, the study periods are only 1999–2011 and 2011–2015 in this study. After reviewing these master plan maps and documents as well as checking their data availability, the land use plan and transportation plan have been considered as the plans which have the potential to influence urban growth patterns. According to the plan documents, the land use plans are responsible for controlling the spatial locations and the quantity of new urban constructions and transportation plans aims to connect the existing or planned urban clusters. In other words, these two types of plans are meant to steer the process of non-urban land becoming urban land. Due to the availability of plan-related data, only specific elements in those plans have been selected as the factors considered in logistic regression (Table 2): the planned built-up zones and the fundamental ecological protection zones (see also Guo et al., 2018) in the land use plan; and the planned highways and planned main roads in the transport plan. From 1980–2010, also the SEZ as a national planning instrument was implemented in Shenzhen. To be able to test whether this national instrument also has an influence on urban growth patterns, we also included it in our analysis (Table 2).

2.4. Other potential influence factors

Although we were mainly interested in the effects of urban master plans on urban growth patterns in Shenzhen, we also included other potential factors influencing urban growth patterns into our regression models. We did so to disentangle the effects of the urban master plans from other potential influence factors: Should the urban master plan elements and other potential influence factors be correlated, the regression models might falsely attribute more importance to the urban master plans if no other influence factors were included in the models.

We distilled potential influence factors other than urban planning from the literature on urban growth in Shenzhen. The studies by Seto and Kaufmann (2003); Chen et al. (2014); Chen et al. (2016a, 2016b); Li et al. (2018) and Deng et al. (2018) suggested potential influence factors in the dimensions of socio-economic, physic, proximity, accessibility and neighborhood dimensions. Given the large amount of potential influential factors, we decided to focus on those factors that lie within the case study area, and skip those that lie outside the case study area. With this approach, we cover most of the major factors also identified by Aburas et al. (2016) in their review of urban growth models. The rationales of choosing them and the data sources are stated in Table 3.

Due to the data availability of the selected potential influential
Table 2
Plan elements, factors considered in logistic regression and plan intentions.

| Plan element | Factor considered in logistic regression | Plan intention | Link to urban growth pattern |
|--------------|----------------------------------------|----------------|------------------------------|
| Planned built-up zones (inside or outside) | Planned built-up zones shall restrict construction outside and encourage to increase the density of urban areas inside the zone. | We translate this plan intention in a way that infilling and expansion (by LEI 4-cell, LEI 8-cell and Wilson’s method) are more likely to happen inside the planned built-up zone. | Hypothesizing that any urban growth happening inside an ecological protection zone should be limited and thus outlying (by LEI 4-cell and LEI 8-cell) or isolated, linear and clustered (by Wilson’s method). |
| Ecological protection zones (inside or outside) | Ecological protection zones shall prohibit urban development inside the zone. | We translate this plan intention into new highways encouraging expansion (by LEI 4-cell, LEI 8-cell and Wilson’s method) and linear patterns (by Wilson’s method). | Hypothesizing that any urban growth happening inside an ecological protection zone should be limited and thus outlying (by LEI 4-cell and LEI 8-cell) or isolated, linear and clustered (by Wilson’s method). |
| Planned highways (distance to) | The newly planned highways shall connect with the existing roads and make the current or planned socio-economic centres more accessible. | We translate this plan intention into new highways encouraging expansion (by LEI 4-cell, LEI 8-cell and Wilson’s method) and linear patterns (by Wilson’s method). | Hypothesizing that any urban growth happening inside an ecological protection zone should be limited and thus outlying (by LEI 4-cell and LEI 8-cell) or isolated, linear and clustered (by Wilson’s method). |
| Planned main roads (distance to) | The newly planned main roads shall connect with the existing roads and make the current or planned socio-economic centres more accessible. | We translate this plan intention into new highways encouraging expansion (by LEI 4-cell, LEI 8-cell and Wilson’s method) and linear patterns (by Wilson’s method). | Hypothesizing that any urban growth happening inside an ecological protection zone should be limited and thus outlying (by LEI 4-cell and LEI 8-cell) or isolated, linear and clustered (by Wilson’s method). |
| SEZ (inside or outside) | The SEZ encourages the foreigners to invest in the constructions of factories, enterprises and other business inside SEZ by promising them private property rights protection, tax incentives and exemption of land use fees. | If a place is inside SEZ, it will have more opportunity to be fast-developed, the patterns of growth are likely infilling and expansion. | Hypothesizing that any urban growth happening inside an ecological protection zone should be limited and thus outlying (by LEI 4-cell and LEI 8-cell) or isolated, linear and clustered (by Wilson’s method). |

Note: Parts of the documents and related maps can be reviewed on: http://www.szpl.gov.cn/.

Table 3
Rationales of selected other potential influence factors.

| Dimension | Factors | Rationale | Data source |
|-----------|---------|-----------|-------------|
| Proximity | Distance to lakes | It is hard to build on high slope areas. | Raster, 30 m spatial resolution; It is derived from elevation (calculated by Slope tool in ArcMap 10.5). |
| Distance to ocean | It affects urban development by two means. On the one hand, it prevents the urban from expanding towards the water. On the other hand, it offers a scenic view to the buildings nearby (Luo and Wei, 2009) and access to facilities such as ports. | Vector; The ocean areas were digitized based on Google Earth satellite image |
| Distance to city centre | Distance to city centre offers abundant socioeconomic resources to residents (Li et al., 2018). | Raster, 30 m spatial resolution; The city centre is from National Geomatics Centre of China, NGCC (https://ngcc.sbsm.gov.cn/). |
| Distance to ports | The ports in Shenzhen were constructed for attracting foreign investment and they provide access to other cities, e.g. Hong Kong (Chen (2017)) | Raster, 30 m spatial resolution; The ports were digitized based on Google Map and Google Earth |

Note: Parts of the documents and related maps can be reviewed on: http://www.szpl.gov.cn/.

In the literature, various factors have been considered to influence urban growth. Some of these factors, such as the foreign direct investment (Seto and Kaufmann, 2003), the relative ratio of productivity generated by land associated with agricultural and urban uses (Seto and Kaufmann, 2003) and the distance to railway (Braimoh and Onishi, 2007), are well-known. However, for instance, the foreign direct investment (Seto and Kaufmann, 2003) could not be considered in this study. Some potential other influence factors are: (1) population density, (2) GDP, (3) elevation, (4) slope, (5) distance to ocean, (6) distance to lake, (7) distance to city centre, (8) distance to ports, (9) distance to existing highway, (10) distance to existing main road, (11) percentage of existing urban areas within 1 km².

Factors, some of the factors mentioned in the literature could not be considered, for instance the foreign direct investment (Seto and Kaufmann, 2003), the relative ratio of productivity generated by land associated with agricultural and urban uses (Seto and Kaufmann, 2003) and the distance to railway (Braimoh and Onishi, 2007). The factor density of neighbouring urban areas has been replaced by its proxy measurement (percentage of existing urban areas within 1 km²). The final set of studied potential other influence factors are: (1) population density, (2) GDP, (3) elevation, (4) slope, (5) distance to ocean, (6) distance to lake, (7) distance to city centre, (8) distance to ports, (9) distance to existing highway, (10) distance to existing main road, (11) percentage of existing urban areas within 1 km².
2.5. Statistical approach to test the relationships between urban planning and urban growth patterns

Logistic regression is known as a helpful method to reveal the relationship between one categorical variable and one or more nominal, ordinal, interval or ratio-level independent variables. Logistic regression plays an important role in urban modelling studies since this technique can test the effects of different factors onto a spatial phenomenon such as urban development (Cheng and Masser, 2003). In this study, we focussed on the different urban growth patterns as the dependent variable, i.e. a categorical variable, and the selected influential factors as independent variables. Since there are more than two urban growth patterns, a multinomial logistic regression model has been employed in this study. The relationships between the dependent variable and independent variables are revealed by the following Eq. (2):

$$\ln \left( \frac{P(Y = k_1)}{P(Y = k_0)} \right) = \alpha_{k_1} + \beta_{k_1} X_1 + \beta_{k_2} X_2 + \ldots + \beta_{k_n} X_n + \epsilon_n$$

(2)

$$\ln \left( \frac{P(Y = k_{n-1})}{P(Y = k_0)} \right) = \alpha_{k_{n-1}} + \beta_{k_{n-1}} X_1 + \beta_{k_{n-2}} X_2 + \ldots + \beta_{k_1} X_n + \epsilon_n$$

where n is the total number of categories of outcome variable; k_0, k_1, …, k_{n-1} are the categories of outcome variable; k_0 is the reference category; P(Y = k_{n-1}) is the probability of the category k_{n-1}; X_i is the i-th predictor variable; as the intercept; $\beta_{k_{n-1}}$ is the coefficient of X_i when comparing category k_{n-1} with reference category k_0.

Sampling points of new urban land within Shenzhen serve as data points in the multinomial logistic regression. The minimum distance between the random sampling points was set as 200 m to avoid spatial auto-correlation between points but still cover all the urban growth patterns in Shenzhen. Outliers with large values on distance-related-factors and near Dongguan, which can bias the model coefficients estimates, were excluded. The final numbers of sampling points for the period 1999–2011 and the period 2011–2015 are 1346 and 611, respectively. In each analysis, the sampling points have been equally separated into training and test data by a ratio of 1:1. The distributions of these two sets of samples are provided in Figure D.1 in the appendix.

Prior to the multinomial regression modelling, multicollinearity among continuous predictor variables was checked to avoid errors in the estimation of parameters of individual predictors. We used the Variance Inflation Factor (VIF) to detect statistical multicollinearity among the predictor variables (Midi et al., 2010). The VIF is a measure of how much the variance of an estimated regression coefficient increases if the predictor variables are correlated, with higher VIF values indicating greater collinearity. In line with Myers (1990), we used a threshold value of VIF > 10 to indicate multicollinearity. An initial screening of multicollinearities among predictor variables indicated that multicollinearity existed for planned ecological control zone and planned built-up zone in 1999–2011 and for the GDP per capita and inside or outside SEZ in 2011–2015 (Appendix D). Thus, the planned ecological control zone was removed from the logistic regressions for the time period 1999–2011; and GDP per capita has been removed from the regression in favour of inside or outside SEZ for the time period 2011 and 2015. All VIF values were less than 10 after that (Table D.1).

An automated stepwise model simplification based on Akaike’s Information Criterion (AIC) was employed. The AIC is a goodness-of-fit measure that also takes the number of predictors into account and can be used to compare different model versions (Field, 2017). A smaller AIC indicates higher goodness-of-fit. Stepwise regression by AIC is a model fitting method in which every variable is considered for addition or subtraction from the set of predictors based on AIC. A predictor variable can remain in the regression when it contributes to a smaller AIC than others. After the multinomial regression modelling, the spatial autocorrelation among model residuals was quantified with Moran’s I to check the spatial autocorrelation of the model results.

3. Results and discussion

3.1. Urban growth patterns in Shenzhen

Fig. 3 illustrates urban growth in Shenzhen during the three planning periods. In 1988, only a small area of Shenzhen was built-up, mainly in the southern part where the SEZ was located. Most of the urban growth from 1988 to 2015 occurred in the west and east of Shenzhen close to the sea and the SEZ. The urban growth during the last 37 years was enormous, especially between 1988 and 1999. However, the development of non-SEZ areas was chaotic and gradually became a threat to the coordinated development in the entire city region (Huang and Xie, 2012). One reason could be the ambitious economic development goals set up by the local governments who benefited more from building constructions than from protecting agricultural land (Liu et al., 2014).

As it can be seen from Fig. 4, the three classification methods led to different quantities of basic urban growth patterns in the three planning periods. During 1988–1999, expansion was the dominant urban growth pattern covering more than 60% of the new urban development according to the LEI 4-cell and LEI 8-cell methods (Fig. 4a). In contrast, outlying was the main pattern in this period based on Wilson’s method. In 1999–2011, the percentages of the area of infilling growth patterns classified by all the three methods increased compared to 1988–1999 while the other two patterns declined. However, the amount of infill was still smaller than expansion in that period (Fig. 4b). These findings are in line with results by Yu et al. (2019) who found fast and loose expansion to be the dominant expansion pattern from 2000 to 2004, followed by a brief period of fast and compact expansion (2004–2006) and then again loose (until 2016). For the third period (2011–2015), all three methods found that the amount of infilling pattern increased even more compared to the previous periods (Fig. 4c); nevertheless, expansion

| Dimension                  | Factors                                      | Rationale                                         | Data source                                      |
|----------------------------|----------------------------------------------|---------------------------------------------------|-------------------------------------------------|
| Distance to existing        | Accessibility                                | It is closely connected to transportation time and costs (Braimoh and Onishi, 2007). |
| highways                   |                                               |                                                   | Raster, 30 m spatial resolution; Existing highways were digitized based on the transportation maps from Urban Planning and Land Resources Commission of Shenzhen Municipality |
|                           | Neighbourhood                                | It is the proxy of spatial interaction with existing urban land use. It can influence land rent and cultural preference (Braimoh and Onishi, 2007). |
|                           |                                               |                                                   | Raster, 30 m spatial resolution; Existing main roads were digitized based on the transportation maps from Urban Planning and Land Resources Commission of Shenzhen Municipality |
|                           |                                               |                                                   | Calculated upon the urban areas from land cover dataset from Dou and Chen (2017). |

Note: All the distance maps were calculated as Euclidean distance in ArcMap 10.5.
patterns of urban urban growth still cover about the same amount of urban growth for both LEI methods, while outlying pattern are only found to contribute to urban growth at the same order of magnitude as expansion following Wilson’s method. The decrease of expansion pattern and the increase of infilling corresponds with findings of Dou and Chen (2017) who found a slowing down of expansion after 2005 due to a shortage of urban land resources, which in turn can also explain the increase of infilling patterns.

Table 4 presents the percentage of urban growth patterns of sub-classes of outlying patterns (i.e. clustered, isolated and linear pattern)
according to Wilson’s method. The clustered pattern was the major component of outlying pattern in all three planning periods, while the isolated pattern was least frequent. The percentages of the area of the subclasses in 1988–1999 and 1999–2011 were similar but differ from the period 2011–2015, when the outlying pattern only occupied 63% of total outlying urban area. In both the LEI 4-cell and LEI 8-cell methods, many of these outlying patterns were classified as expansion (see example in Fig. 5).

The geographical distributions of the identified urban growth patterns in the three planning periods are shown in Fig. 6 for LEI 4-cell; the results for LEI 8-cell and Wilson’s method are provided in Figure E.1 and Figure E.2 in the appendix. In 1988–1999, infilling mostly took place in the north-western part (i.e. close to Dongguan) and in the south (i.e. in the SEZ). On the contrary, expansion and the outlying urban growth patterns were spreading over the whole city. In the second master plan period (1999–2011), the infilling pattern became more intensive and mostly distributed in the north-west and mid parts of Shenzhen; and the expansion pattern was closely linked with the infilling growth. In 2011–2015, all three patterns were fragmented over the city. The LEI 8-cell method (Figure E.1) showed a similar spatial distribution of urban growth patterns. The growth patterns classified by Wilson’s method (Figure E.2) distinguish three sub-types of outlying patterns. The clustered pattern dominated in 1988–1999 was mainly located in the middle and northern parts of Shenzhen. In 1999–2011, the expansion and clustered patterns were mainly around the existing urban in 1999. The spatial distribution of the urban growth patterns in 2011–2015 seems to be evenly distributed across the city.

Lv et al. (2009) also distinguished infilling, edge-expansion, and outlying urban growth at the patch level in Shenzhen. However, their rule to define a patch, i.e. 4-cell neighbourhood rule or 8-cell neighbourhood rule, was not mentioned in the paper. They concluded that outlying growth dominated in 1985–1990, 1990–1995 and 1995–2000. The findings largely correspond to the results provided here except for the time period 1988–1999, where we detected expansion as the most frequent pattern. Different reasons might be responsible for this difference, among them the different underlying time intervals, potentially different criteria to quantify the spatial patterns or the data correction method we used to exclude temporary shrinkage.

3.2. Relationship between urban planning and urban growth patterns

In total, six multiple linear regressions were run for the two time periods of 1999–2011 and 2011–2015 and for each of the three methods of quantifying urban growth pattern, respectively. Model
quality indicators as well as regression coefficients are provided in Appendix F. The parameters estimated in the six models are not biased by spatial autocorrelation (see Moran’s I test on residuals in Appendix G).

Model quality indicators suggest that using urban growth patterns based on LEI lead to higher explained variance as well as higher prediction accuracies than using urban growth patterns based on Wilson’s
method (see details in Table F.1 and Table F.2 in Appendix F). This is to be expected, since Wilson’s model differentiates between five urban growth patterns in total, making prediction harder than predicting only three different patterns. Moreover, visual inspection indicated that Wilson’s method did not distinguish well some of the clustered and linear outlying patterns (example in Appendix H). The differences in model quality between the logistic regressions for LEI 4-cell and LEI 8-cell are small, with model quality indicators slightly higher for LEI 4-cell in the second time period. After the stepwise model simplification, the LEI 8-cell model contained more urban planning factors than the LEI 8-cell model in both time periods. 

Fig. 7 presents an overview of the regression coefficients for those factors that stayed in the models after automated model simplification (the detailed information about the coefficients can be found in Table F.3 and Table F.4). Clearly, the effects of urban planning factors on urban growth pattern vary between the urban growth patterns and also the planning periods: The Wilson-based urban growth patterns are only related with the presence of the ecological protection zone, and only in the second planning period. For the LEI-4-cell-based and LEI-8-cell-based urban growth patterns, the distances to planned highways and planned main roads remained more frequently in the models.

The factors stemming from land use plans, i.e. planned built-up zone and planned ecological protection zones, did not influence the coalescence or diffusion of the built-up area in Shenzhen in the planning period of 1999–2011. Considering the number of the relations remained in the models based on Wilson’s approach for the second period, the ecological protection zones seemed to be more relevant than the planned built-up zones. Overall, urban growth within ecological protection zones is less likely an infill pattern compared to expansion and outlying patterns; only the linear outlying urban growth pattern is less likely to happen than the infill pattern within the zone. The intention stated for the ecological protection zone is to prohibit urban growth at all in the zone. Thus, the mere fact that urban growth happened within the zone contradicts its intention.

The regression coefficient for the planned built-up zones in the Master Plan of Shenzhen 2010–2020 suggests that infilling patterns (LEI 4-cell) are less likely inside the planned built-up zones compared to expansion or outlying patterns, and thus, are associated with densification of the existing urban area. However, other urban growth patterns, i.e. expansion and also outlying patterns quantified with different methods, were not affected by the planned built-up zones, suggesting an unstable relationship between this planning element and urban growth patterns. This is also related to the finding of Deng et al. (2018) who did not find a significant relationship between the planned built-up zones and urban growth in Shenzhen. Both market forces and potentially contradicting other sectoral plans could have weakened the implementation of these master plans. Shao et al. (2020) found that the local implementation of the land use master plan for Nanjing deviated from the land use master plan at the national level as it is challenged by a combination of decentralization, marketization and globalization. In a similar vein, according to Tian and Shen (2011), not all land needs to be developed as planned in the master plan after required legal procedures, i.e. the planned residential land might be developed for other uses according to the market situations. Also, the plans compiled for different themes and different time phases contradicted the master plans to some extent. For example, the Land Use Plan of Shenzhen 2006–2020 designated a different amount of urban area in 2020 (976 km²) compared to the Master Plan of Shenzhen 2010–2020 (890 km²). In addition, Liu et al. (2014) assume that irresponsible behaviors of local governments, e.g. ignoring requested legal land acquisition procedures, can also lead to unplanned land conversion. The factor whether an area is inside or outside the SEZ was hardly relevant in the statistical models. For the period of 2011–2015, this is no surprise since the SEZ was abolished in 2010, i.e. immediately beforehand. Our statistical results suggest that the SEZ also was not effective in steering urban growth patterns before its abolishment. In fact, the study by Deng et al. (2018) even showed that urban growth was more likely outside the SEZ than inside. The authors believed that the dual land management system in SEZ and non-SEZ did not coordinate with the needs of rapid urban development of Shenzhen, and rather resulted in the chaotic urban construction throughout the non-SEZ zone (Deng et al., 2018).

The transport plan contained the planned highways and planned main roads. For the planned highways, the direction of effects depends on the planning period and the pattern. For planned main roads, the coefficients are always negative, indicating that it is more possible for a new urban patch to be expansion or outlying relative to being infilling for lower distance to planned main roads. Thus, results are in line with our translation of the original plan intention that planned main roads are associated with expansion and outlying growth instead of infilling and encouraged further urban sprawl and connected the existing urban clusters, e.g. different towns.

3.3. Role of other influence factors

When looking at the role of covariates in the regression models, the most striking pattern is the relationship of the share of existing built-up in 1 km² with almost all growth patterns. The regression coefficients are consistently negative, indicating that this covariate can differentiate urban growth patterns into infill and all other patterns, with infill being more likely in highly built-up areas. This finding is not surprising since urban growth is only considered as infill if surrounded by existing urban areas. For this covariate, Deng et al. (2018) also found a negative regression coefficient with urban growth, indicating that a higher share of existing built-up within 1 km² is associated with a lower likelihood of additional urban growth – mostly likely due to the fact that little land for further development is available.

Population density’s regression coefficients in the models based on LEI 4-cell and LEI 8-cell methods are mostly positive, indicating that a higher population density is associated with a higher likelihood of infilling patterns rather than expansion or outlying patterns. The underlying reason here could again be the presence of built-up areas (leading to overall higher population density): a higher share of built-up area leads to urban growth being classified as infill.

Factors such as distance to lake and distance to ocean show clear temporal differences: The distance to lakes is exclusively relevant in 1999–2011. The regression coefficients for distance to ocean are consistently switching directions from positive to negative from the first to the second time period: A higher distance to the ocean is associated with a higher likelihood for non-infill in the first time period, but a higher likelihood for infill in the second time period. Such unstable relationships would hamper studies that build future land use/cover change scenarios based on regressions (Musa et al., 2017; Noszczyk, 2019). These approaches typically assume that these processes are stationary, i.e. do not change over time (Veldkamp and Lambin, 2001). Thus, such changes over time limit the applicability of purely regression-based approaches.

3.4. Reflections on the approach and limitations of the study

The limitations of this study first and foremost stem from the land cover dataset and the digitalization of the urban plan maps. The land cover dataset used in this study was adapted from the land cover data classified by Dou and Chen (2017) in order to study the grown urban areas instead of shrinkages or urban renewal, as for instance also done by Deng et al. (2018). However, this resulted in unrealistically high urban growth since any errors of the land cover classification have cumulated in the correction process (see the example in Appendix Figure H.2). The maps within the urban plans needed to be digitized, thus, the resulting spatial data have limited accuracy due to the quality of the plan maps and errors occurring during their digitization.

The comparison of the LEI-based and the pixel-based approach
(Wilson’s method in this study) of urban growth patterns indicated that Wilson’s method is not directly usable in a fast-growing city such as Shenzhen. The application of this method led to very high proportions of outlying patterns but a low proportion of infilling and expansion although both were picked up better by the LEI approach.

Another limitation of the study is the fact that only factors influencing urban growth patterns that lie inside the study area were taken into account. In fact, also factors located outside the area of Shenzhen can have an influence on the urban growth inside the Shenzhen area, as shown by Zhang et al. (2019) who analysed urban land use change in the Guangdong-Hong Kong-Macao Great Bay Area megaregion. In fact, the infilling patterns in 1988–1999 found in this study were mainly located in the north-western part, which is close to the city of Dongguan. Moreover, also the impact of the reclamation area on the coastline of the Shenzhen area was not considered in the study, because exact the data was not available, and the reclamation areas are close to the three ports already considered in the study.

Finally, other, more detailed urban growth patterns in Shenzhen could be considered in future studies. For instance, the transformation of urban villages of Shenzhen could be investigated, since urban regeneration programs are under way (Jiang et al., 2020).

4. Conclusions

The objective of this study was to understand the relationship between urban master plans and urban growth patterns in Shenzhen. To this end, we first quantified the urban growth patterns comparing pixel- and patch-based methods. The results show that the patterns classified by the three methods are different in terms of both quantity and spatial distribution of urban growth pattern. Next, we identified a set of both models on urban growth patterns in Shenzhen between 1988 and 2015. While this is beyond the scope of our study, other scholars have, for instance, pointed out the limited implementation of the land use master plan for the case of Nanjing likely due to decentralization, marketization and globalisation overruling planning regulations (Shao et al., 2020). Also, limited coordination and contradictions between sectoral and integrated plans of the various tiers (Du et al., 2019; Wang and Liu, 2012) or a weak monitoring system not being able to detect illegal constructions for instance in ecological protection areas could be important reasons.

In order to overcome these shortcomings and introduce a rural vitalization strategy (Liu, 2018), Liu et al. (2018) propose an optimization of the urban-rural spatial structure and urban-rural coordinated development by means of multiple plans integration, a uniform database, and consolidation of inefficient and vacant land. In fact, this implies a paradigm shift towards an integrated urban-rural development in China (Zhu et al., 2019), also more explicitly taking into consideration rural land transitions and their relation with land management (Long and Qu, 2018). It remains to be seen whether the National New Urbanisation Plan (2014–2020) (Chen et al., 2019, 2016) from a land-centered to a people-centered policy can be a first step into that direction. Future research will be needed to investigate evidence of a more profound impact of planning onto urban growth patterns and integrated urban-rural development.

Discovering the instability for several factors – both planning-related and covariates – is of high relevance for land use/cover change modelling. In which contexts can we make use of, for instance, regression models based on one time period to simulate urban growth in another one? For Shenzhen, the answer seems to be that the relevance of some influence factors changes over time, introducing large uncertainties into scenarios based on such modelling approaches.

Future studies on urban growth patterns should consider using several methods for quantifying urban growth patterns in parallel to check which method(s) work best in the specific context, given available data and their spatial resolution, but also the speed of the urban growth process.

With our study, we hope to partly follow up on Hersperger et al. (2018) who ask for going beyond rather simplistic conceptualisations of planning by a binary variable in regression for conservation or designated growth areas. Although we also used binary (inside or outside a specific zone) or metric variables (distance to planned main roads or highways), we tried to interpret the plans’ intentions in the light of specific urban growth patterns. There is considerable uncertainty associated with our interpretation, and we hope to foster a discussion on how such an interpretation can be further improved. Future evaluations of urban planning will clearly need more insights also into the implementation process. Since the land space has been limited due to the rapid increase of urban area in China, urban development in Shenzhen as well as many other cities is not only taking place horizontally but also vertically. The two-dimensional land use intensity researches affect the understanding of the evolution of the urban and probably influence the land use laws making (Qiao et al., 2019). Therefore, the increase or decrease of the building height (e.g. Mahatta et al., 2019) can also be part of the criteria to define the urban growth patterns in further research.
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