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Trade-Off Relationship of Arable and Ecological Land in Urban Growth When Altering Urban Form: A Case Study of Shenzhen, China

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Abstract: Over the last few decades, rapid urban expansion has spread over a great deal of arable and ecological land, leading to severe social and environmental issues. Although different urban growth scenarios cause varying types of urban forms to emerge, there is currently a lack of empirical studies and other research on these different forms. Therefore, it is important for decision-makers to have an improved understanding of the relationships between arable land and ecological land under different urban form conditions in order to implement sustainable urban development policies. This study utilized a patch-based, multilevel stochastic urban growth model to simulate Shenzhen's urban growth until 2035. To determine the impacts of urban forms and population density on land use, we established five scenarios to simulate urban expansion and land-use changes at the sub-regional scale. The results revealed the trade-off relationships that emerge when altering the urban forms or population density, which shows that no single policy can conserve arable land and ecological land simultaneously. The results also revealed that sub-regions have distinct responses to alternative urban form scenarios compared with an entire region. Decision-makers and planners should consider the urban form in order to optimize development projects that fit local conditions and achieve more sustainable development.

Keywords: FUTURES; urban growth simulation; scenarios analysis; Shenzhen

1. Introduction

According to the United Nations 2019 population report, the world's population will reach 11.2 billion by 2100 [1]. Due to this rapid population increase, the urban area demands for humans living around the world are expanding rapidly [2]. However, disordered and uncontrolled urban growth has caused a series of ecological, environmental, and socio-economic problems throughout the world, such as the erosion of arable land and forests, air pollution, heat island effects, water pollution, and traffic congestion [3–7].

In order to resolve those global challenges, urban growth procedures and sustainable urban development has attracted much attention from researchers in various disciplines [8]. Many emerging countries have experienced rapid urban growth during the last few decades. These developing nations face severe problems in their attempts to achieve arable land protection and ecological land recovery, leading to major conflicts between urban growth and environment conservation [9,10]. Hence, determining an approach to scientifically control urban expansion and balance the relationships between ecological land, arable land, and urban land has become a significant challenge.

On the one hand, the demand for urban land is expected to continuously grow in the future [11,12]. On the other hand, strict arable land protection policies and policies for improving environmental requirements are also being implemented [13]. Unfortunately, most of the arable land loss is located on the urban fringe of various cities [14]. Urban growth also impacts the urban morphology and ecosystem services by altering the landscape configuration [15]. Ecological land (e.g., waterbodies, grasslands, forests, and wetlands) provides essential ecosystem services, therefore ecological land protection has become a vital issue for sustainable land use.

The ways in which the urban form affects land-use systems lacks investigation and discussion in China, however, even though this topic has long attracted the attention of scholars and governments in Western developed countries [16–18]. Extensive research carried out in Western countries has investigated the impact of urban forms on ecosystem services [15,19], greenhouse gas emissions [20], and human behavior [21,22]. Moreover, governments have developed urban planning programs such as "Compact City" [23] in the U.K. and "Smart Growth" [24] in the U.S. that encourage the development of a compact urban form. In China, although the urban form is receiving more attention due to its influence on air pollution [25,26] and population density [27], thus far, only a limited number of studies have focused on the urban form and land-use changes. Additionally, the role of the urban form in China's New Urbanization Plan needs more empirical research.

We selected and compared the neo-traditional urban, compact city, and sprawling urban forms [28] in order to evaluate the impacts of various urban forms on land-use systems. The compact city is generally accepted as a sustainable urban form, because it reduces traveling times, increases population density, and improves social interactions [28]. However, the overly compact variation of the compact city urban form increases pressure on prime arable land and resident density [29]. Under certain urban development circumstances, the sprawling urban form provides various benefits for ecosystem services which compact urban forms do not possess [30]. A compact urban form should certainly not be embraced as the preferred urban growth strategy without a full assessment of alternative options [31]. Besides, many of China's cities have already developed with low compactness levels in the past few decades, meaning that increasing the level of compactness may not be the most efficient and cost-effective option to achieve urban sustainability [32]. Thus, there should be more discussion focusing on the alternative sprawling urban form.

Another critical factor impacting urban growth is population density, an essential indicator for evaluating urban sustainability [33]. At the same time, population density and urban form have a coupled relationship with urban growth [34]. Hence, population density also needs to be compared during urban development planning considerations.

Furthermore, specific land-use/land-cover responses to urban growth on the sub-regional scale need further discussion, especially in rapid urbanization regions. The regional scale indicates the spatial and administrative range of an entire city or metropolis. In China, cities usually consist of many sub-regions, referred to as "districts", which constitute the first-level administrative subdivision of a city or metropolis [35]. However, previous evaluations of urban growth on land use/land cover mostly focused on the entire regional scale rather than on sub-regions. The negative implications of urban expansion on arable land productivity and green vegetation land cover at global and national scales have previously been revealed in some studies [8,36,37]. The trade-off relationships between arable land and ecological land change in rapidly developing cities have not been thoroughly compared and evaluated, however. In addition, the socio-economic conditions and land surface features of China's cities display significant spatial heterogeneity, which is still causing a knowledge gap between land-use changes on the regional scale and the sub-regional scale. Moreover, the sub-regions of China's cities exhibit typical urban–rural gradients in the shift from downtown residents to rural residents. The differences in urbanization levels and urban–rural dual structures make it very important to discuss the land-use changes in sub-regions.

At present, researchers have developed several models to simulate land-use change and predict urban growth. These models are classified as quantitative prediction models, spatial pattern prediction models, and coupling models [38]. Firstly, the quantitative models are usually used in forecasting the numerical area change of land use, which is mainly established using mathematical equations or statistical models. Users employ typical methods such as grey prediction models [39], system dynamics models [40], Markov models [41–43], and artificial neural networks [44] to predict the acreage demands of various land-use types [45]. Quantitative prediction models cannot simulate the spatial distributions of land types, however. Secondly, the spatial models can forecast spatial land-use changes. For example, the Integrated Model to Assess the Greenhouse Effect (IMAGE) is a global land-use change system concerned with human society's connections, climate variables, and the biosphere [46]. Another representative and popular spatial model is the cellular automata (CA), a powerful tool for analyzing complex systems and environments that has been widely used in simulating urban development [47–50]. Finally, coupling models have demonstrated their superiority in promoting the accuracy of simulation results, especially the combinations of CA and multifarious quantitative models. Researchers have improved the CA model parameter estimation by coupling it with various methods such as the multicriteria evaluation method [51], a genetic algorithm [52], an artificial neural network [53], logistic regression [54], and a Markov chain [55]. With the development of machine learning and deep learning, some complex parameter estimation methods have been coupled with CA models. Okwuashi et al. used the support vector machine (SVM) method to generate the CA model's transition parameters. They then used the SVM-CA model to simulate the land-use changes in Lekki, Nigeria [56].

Similarly, decision trees, random forests, and genetic algorithms have been coupled with the CA model [57]. Zhou et al. coupled the bat algorithm (BA) and deep belief network (DBN) with the CA model to simulate the urban development of Jiaxing, Zhejiang, from 2015 to 2024, and then compared it with the Artificial Neural Network-CA model, revealing that the DBN-CA model has high stability and accuracy [58]. Moreover, the agent-based model (ABM) has been applied to land-use simulation and forecasting in order to analyze and simulate social impacts on land-use change [59]. Koch et al. constructed a hybrid ABM and CA model to analyze private individuals' decision-making influences on urban landscape forms [60]. Kaviari et al. developed an agent-based model (ABM) to explore the effects of agents at different temporal resolutions on land-use change processing and predicted the urban development of Zanjan City from 2011 to 2016 [61].

This study's purposes were twofold: (1) to employ the land-use model to simulate and investigate future urban development under different urban form scenarios; and (2) to observe and evaluate the impact of urban form on arable land and ecological land at regional and sub-regional scales. To achieve these goals, we first employed scenario-based methods to simulate urban growth under different urban forms and population densities, and then evaluated and compared land-use patterns and changes in arable land and ecological land. Finally, we analyzed each sub-region's responses to the overall urban development policies and formulated the localized development strategies in all districts. Generally, we expect that these findings will clarify future conditions in order to provide thoughtful advice for decision-makers to form precise urban development planning.

The remainder of this manuscript is organized as follows. In Section 2, we describe the information concerning our research extent and the parameters of the simulation models. Section 3 presents the simulation results for Shenzhen. Following that, Section 4 includes a discussion of the simulation results. Section 5 concludes the article.

2. Materials and Methods

2.1. Study Area

Shenzhen is located in the southern part of Guangdong Province, China. It covers a land area of 1952.84 hm^2 and contains 10 administrative districts (Figure 1). The permanent urban population of Shenzhen reached 12.53 million by 2017. As the first exclusive economic zone in China's economic reform and opening-up process, Shenzhen has experienced rapid population growth and urban expansion since 1978 which has caused significant land-use/land-cover changes. Therefore, dealing with the series of ecological and environmental problems associated with the urbanization process and realizing harmonious urban growth remain great challenges for Shenzhen's decision-makers.

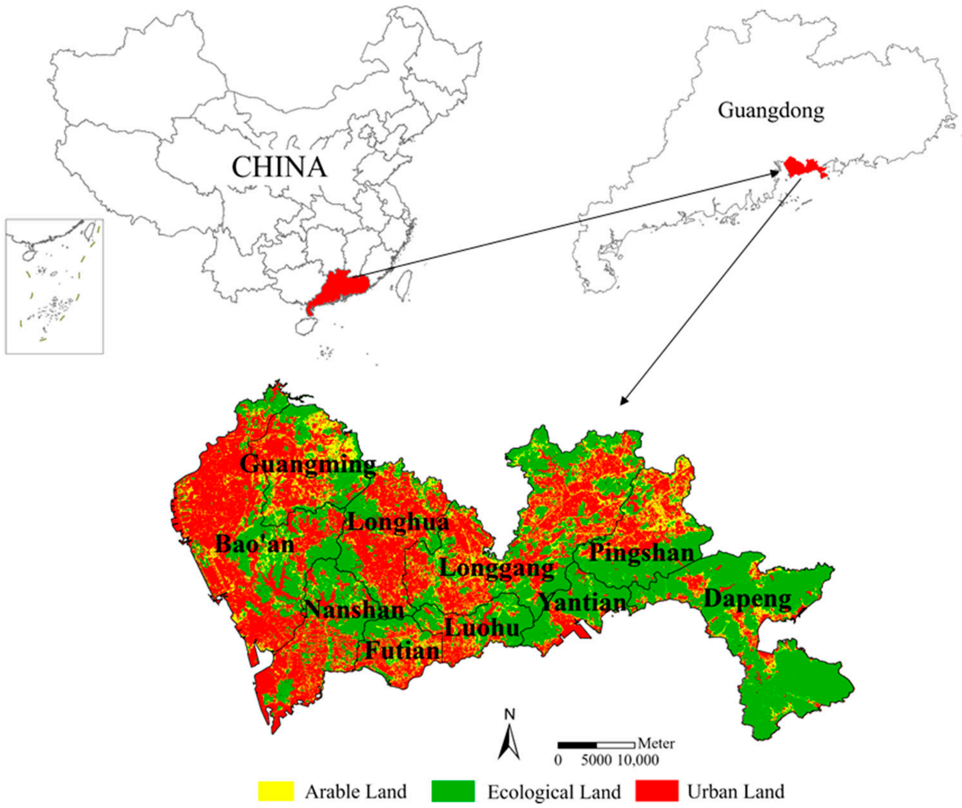

Figure 1. Shenzhen's 2017 land-use map with 10 administrative districts.

Given each district's unique development history, conditions, and potential, and to study sub-regional responses to urban development and expansion, we split Shenzhen into 10 sub-regions based on its jurisdictional boundaries for use as basic units of local development planning.

We reclassified the land-use/land-cover types into three categories—arable land, ecological land, and urban land. Arable land indicates cultivated land or farmland. Meanwhile, forest, grassland, shrubland, waterbodies, and barren land constitute ecological land. In addition, urban land consists of urban or rural residential areas and industrial land.

Furthermore, we used the unsupervised K-means clustering method to classify the developing actualities of Shenzhen's 10 districts. K-means' essential principles are to make the samples in similar clusters connect closely and make the distances between clusters as large as possible. In this study, we set Shenzhen's 10 districts as the clustering samples. Each sample's eigenvectors are area ratios of arable land, ecological land, and urban land in individual districts. Based on the results of clustering, the 10 districts were divided into three types: "urban," "peri-urban," and "rural" (Figure 2). A district was defined as urban when its proportion of urban land-use area was >40%. When it was <20%, the district was classified as rural. When it was >20% but <40%, the district was considered peri-urban. Figure 2 shows the three sides of an equilateral triangle calibrated by the area proportion of arable land, ecological land, and urban land for each district. The horizontal lines within the triangle correspond to the area proportion of ecological land. The 45-degree and 135-degree diagonal lines indicate the area proportions of arable land and urban land, respectively. For example, district 2 is an urban district consisting of 41% urban land, 33% ecological land, and 26% arable land.

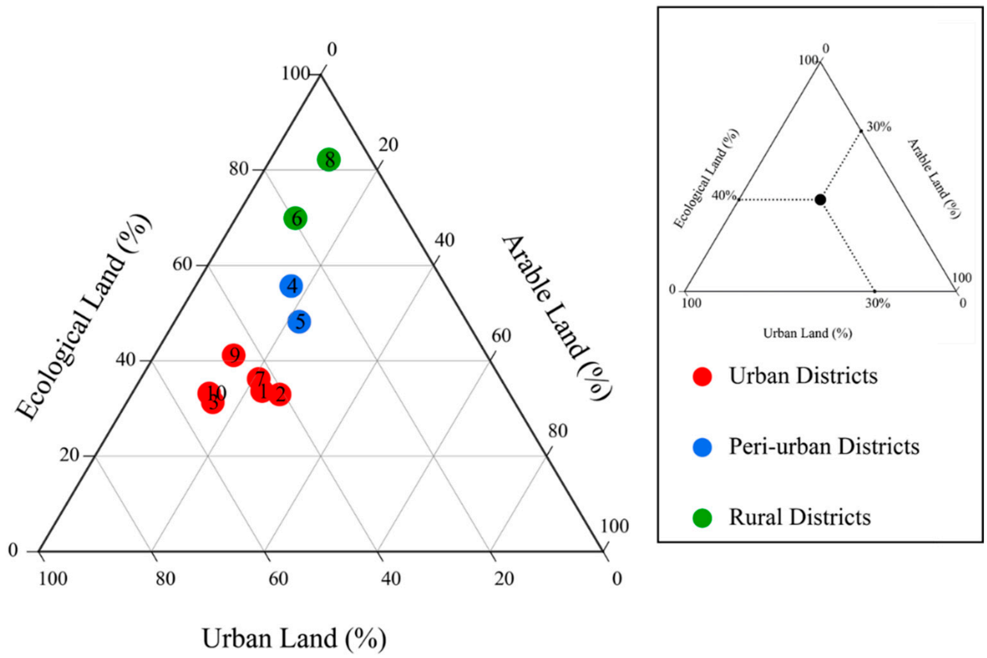

Figure 2. Land-use clusters of the 10 districts (2017).

2.2. Data

The land-use data were derived from fine-resolution (30 m) observation and monitoring global land-use data (http://data.ess.tsinghua.edu.cn). The digital elevation data (DEM) data (30-m resolution) were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn). The necessary geographic information data (1:250,000) were obtained from China's national catalog of geographic information (www.webmap.cn). The points of interest data, such as subway stations, railway stations, land ports, and seaports, were collected from the map service application interface of AMAP (https://ditu.amap.com). The ecological reserve, demographic, and economic statistical data came from Shenzhen's statistical yearbooks and Shenzhen's statistical bulletin on national economic and social development (http://www.sz.gov.cn). Finally, all the geographic data we collected were resampled or converted to 30 m resolution raster data.

2.3. Urban Development Simulation

2.3.1. Modeling Application

This study used the FUTure Urban-Regional Environment Simulation (FUTURES) model to simulate Shenzhen's urban growth from 2017 to 2035. The FUTURES model was developed by Meentemeyer et al. in 2013 [62] and published as an open-source add-on of GRASS GIS software (https://cnr.ncsu.edu/geospatial/research/futures) [63]. The FUTURES model integrates a multilevel regression model to determine the probabilities of urban development in sub-regions and a patch-based stochastic growth algorithm to simulate future landscape patterns in urbanizing regions [15,63]. FUTURES allows researchers to modify the initial data or control parameters to construct different urban growth scenarios [62]. This model has been employed to forecast urban development in several previous studies [30,60,64–66].

The FUTURES model contains three sub-models—DEMAND, POTENTIAL, and PGA (patch-growth algorithm). To increase simulation accuracy, FUTURES uses the corresponding sub-models to ensure the quantities of pixels, the allocation of patches, and the configuration of land-use types [65]. Furthermore, the entire model's running processing could be summarized as three stages: firstly, the DEMAND sub-model projects the amount of urban land consumption in the future, which provides a quantitative constraint for urban growth simulation. In this sub-model, the relationship between historical population and developed land is primarily estimated using regression analysis. Based on this relational expression, we could utilize prospective population data to calculate land area demand for each future year. Secondly, the POTENTIAL sub-model appraises the development suitability score of each pixel based on several socio-economic predictors. This sub-model takes advantage of a multilevel logistical regression model to establish contact among land-use changes and those predictors. Thirdly, the PGA sub-model eventually anticipates the positions and distributions of newly developed regions based on the quantity constraint and formation probability surface. More details of the FUTURES model are described in [62].

2.3.2. Parameterization of Sub-Models

This research adopted land-use maps of 2010, 2015, and 2017 to determine Shenzhen's urban historical development trends. Accordingly, for the DEMAND sub-model, the historical population data were derived from Shenzhen's statistical yearbooks. The predicted population data from 2018 to 2035 were assessed based on the average annual growth rate during the last 15 years. The patch quantities of developed urban areas were extracted from land-use data. The relationship between these two variables was then estimated using a linear regression method. Finally, future urban land consumption demands were calculated based on the predicted population from 2018 to 2035.

For the POTENTIAL sub-model, we selected indicators that influenced the urban growth to build up a valuation model for measuring the patches' development suitability probability. A multilevel logistic regression method was implemented to construct the relationship between land-use change and the drivers of urban development. The response variable was a binary value indicating whether a patch converted to the development type from 2010 to 2017. The explanatory variables driving urban development include geographical indicators (e.g., slope and forest area) and socio-economic indicators (e.g., development pressure, road density, amount of foreign capital used, distance to land ports, distance to ship ports, distance to subway stations, distance to railway stations, and distance to ecological reserves). To improve program running efficiency and to save computation resources, we used a stratified sampling approach to randomly select about 7000 patches as samples. In this sub-model, all the input explanatory variables were combined randomly and repeatedly to obtain multiple regression equations. Finally, the multilevel regression model that resulted in the lowest Akaike Information Criterion (AIC) score was chosen as the ultimate multilevel regression model. The lower the AIC value, the better the model [67]. The AIC can measure and compare the fitness and performance of different models, encourage the goodness of model fitting but avoid overfitting, and find the best model with the least free parameters, therefore it is commonly used for regression model selection [68,69].

The fixed effects coefficients are listed in Table 1, while Table 2 lists the random effects coefficients for the eventual multilevel regression model. It should be noted that the final regression model did not contain all the initial input explanatory variables. This is because any insignificant impact factors were removed when calculating the equations.

Table 1. Estimated fixed effects coefficients of the multilevel logistic regression model.

	Estimate	Std. Error	Pr (>|Z|)
Intercept	−1.988	0.210	<0.001
Development pressure	0.028	0.003	<0.001
Distance to ship port	0.020	0.010	0.042
Forest	−0.041	0.003	<0.001
Slope	−0.027	0.013	0.032
Amount of foreign capital actually used	0.012	0.003	<0.001

Table 2. Estimated random effects coefficients of the multilevel logistic regression model.

District	Intercept
1 Futian	−2.088
2 Guangming	−2.090
3 Longhua	−1.750
4 Luohu	−2.229
5 Pingshan	−1.808
6 Yantian	−1.773
7 Longgang	−2.213
8 Dapeng	−1.961
9 Nanshan	−1.971
10 Baoan	−1.975

There is a calibration program in the FUTURES model designed to improve the PGA sub-model's simulation accuracy. The calibration method ensures that new patches fit historical development trends and patterns by using the histogram comparison method to compare patch size and shape distributions. The shape of a patch is defined as $shape = P_k / min\_P_k$, where the P_k is the perimeter of patch k, and min_P_k is the perimeter of a circle with the same patch area [62]. Based on a comparison of the simulated results of new patches with traditionally arising patches, the model receives the corrective parameters to rectify the patches' spatial sizes and shapes. Notably, in the calibration of this sub-model, we made the strong assumption that future urban expansion will maintain the historical development modes, meaning that the urban expansion scheme is similar to past conditions. In the end, the parameters derived from the calibration program are used as the input parameters of the PGA sub-model in order to control the urban development simulation.

2.3.3. Urban Growth Scenarios

Five scenarios—Business as usual (BAU), Infill, Sprawl, Increase, and Decrease—were used to simulate the urban expansion in Shenzhen from 2017 to 2035. These scenarios helped us to analyze the transformation of arable land and ecological land to urban land and to explore how the urban form and population density would affect urban growth and land-use/land-cover changes.

The BAU scenario was the baseline condition in this study, and indicates the urban form of neotraditional development. In the BAU scenario, we assumed that Shenzhen's development would follow the historical growth trends from 2010 to 2017. The urban form and population density were kept as they were in 2017.

In the Infill scenario, the newly developed patches are closer to the original city regions, revealing the urban form of a compact city. Based on [62], we set the Infill scenario by changing the evenness of the development suitability surface and altering the spatial dispersion of the development events' probability in the PGA sub-model [30]. Meanwhile, the population density and other parameters were maintained at their BAU values.

In contrast, the Sprawl case encourages urban growth in some undeveloped areas, indicative of a sprawling urban form. We altered the incentive parameter to 0.25 in the Sprawl scenario and held the population increase rate, demand for land consumption, population density, and urban morphology constant with BAU. The incentive parameter is used to adjust the distribution of the urban development probability surface. When the incentive value is high, the cells with high probability become aggregated, resulting in the newly formed urban cells gathering in a particular region. In contrast, when the incentive value is low, the newly formed urban cells are widely dispersed [62].

Next, we devised the Decrease and Increase scenarios in order to explore the influence of population density on urban expansion. We kept the population increasing trend, landscape configuration, and urban morphology constant with BAU in these two scenarios. However, the population density of developed urban patches each year was adjusted in the Demand sub-model. Based on the experience of previous FUTURES model studies [30,63,65], we implemented the increasing population density scenario (Increase) by decreasing the number of patches of newly developed urban land by 40% each year compared with BAU. Similarly, we set the decreasing population density scenario (Decrease) by increasing the number of patches of newly developed urban land by 40% each year compared with BAU.

2.4. Sensitivity Matrix

Based on the various responses of arable land and ecological land across sub-regions, we introduced a sensitivity matrix to identify and evaluate how sensitive the land-use changes are to the urban form and population density (Figure 3).

We concluded that the individual sensitivities of arable land and ecological land fall within three levels: insensitive, density-sensitive, and urban form-sensitive. Insensitivity indicates that the changes in arable land or ecological land are insensitive to changes in urban form and population density. Density sensitivity and form sensitivity mean that the changes in arable land or ecological land are sensitive to population density changes and changes in urban form, respectively. It is noteworthy that in the urban form effect (form-sensitivity), the population density followed the BAU scenario. Conversely, in the population density effect (density-sensitive), the urban form followed the BAU scenario.

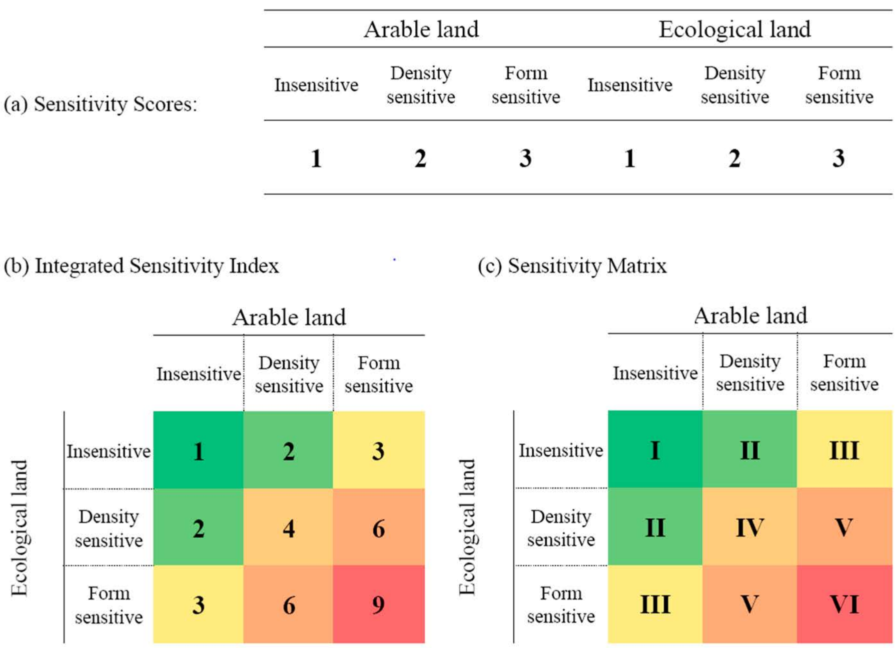

Figure 3. Introduction of sensitivity matrix: (**a**) sensitivity scores for insensitive, density-sensitive, and form-sensitive arable land and ecological land; (**b**,**c**) integrated sensitivity index consisting of the sensitivity scores of arable land and ecological land

Due to the unpredictability and diversity of policies, we regarded form sensitivity as the most sensitive. We assigned the insensitive, density-sensitive, and form-sensitive responses the scores 1, 2, and 3, respectively (Figure 3a). The sensitivity matrix provides the two-dimensional coordinates of arable land sensitivity and ecological land sensitivity, whereas the product of the two-dimensional coordinates represents the integrated sensitivity index (Figure 3b).

Therefore, based on the integrated sensitivity index, the sensitivity matrix of arable land and ecological land in a region can be divided into six categories (Figure 3c), with sensitivity increasing from Sensitivity I to Sensitivity VI. Hence, Sensitivity I indicates the least sensitive districts, in which the arable land and ecological land are insensitive to both urban form and population density, while Sensitivity VI indicates the most sensitive districts, in which the arable land and ecological land are sensitive to both urban form and population density.

3. Results

3.1. Calibration and Validation of the Model

We calibrated the FUTURES model using the standard process mentioned in Section 2.3.1. This calibration program derived the urban patches' size and shape adjustment parameters for that period by comparing the changing characteristics of urban distribution in 2010 and 2015. We then used the argument optimizing model to predict the urban distribution of Shenzhen in 2017 under the BAU scenario. Next, the predicted 2017 result was compared with the actual 2017 situation according to the frequency distribution of the urban patches' area and shape. As displayed in Figure 4, the blue lines and orange lines represent actual and predicted situations, respectively. The subfigures (A) and (B) are the frequency distributions of patch shape while (C) and (D) are the frequency distributions of patch area. This comparison demonstrates that the calibration model could enhance the model's ability to simulate the form changes and areal expansion of Shenzhen as well. Notably, the predicted curves exhibit close agreement with the actual distributions, which may be due to the fact that the urban area changed little during this short period. On the other hand, it could also illustrate the reliability of this model in maintaining urban historical growth patterns.

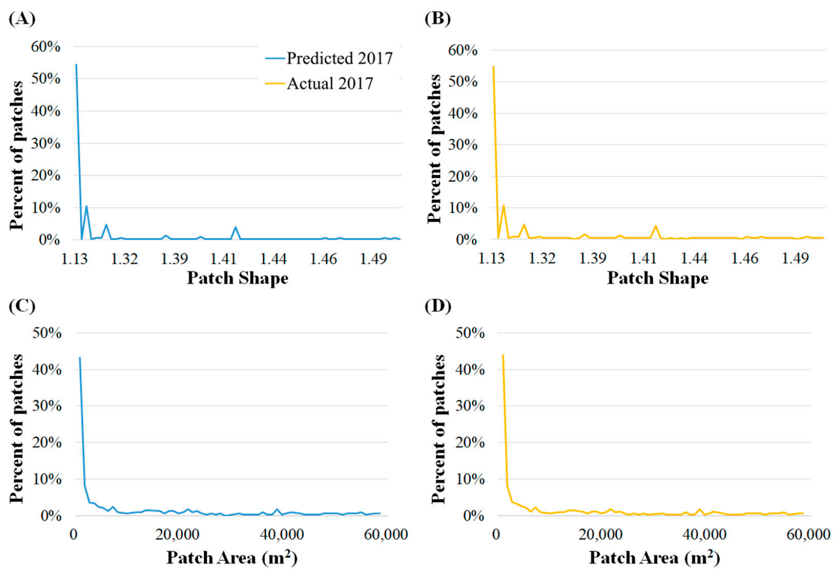

Figure 4. Frequency distributions of calibration results. The blue lines represent the urban simulation results in 2017, and the orange lines represent the actual urban patches in 2017. Subfigures (**A**,**B**) are the frequency distributions of patch shape; subfigures (**C**,**D**) are the frequency distributions of patch area.

Furthermore, in order to examine the reliability of the FUTURES model simulation results, we selected three other models to perform land-use change simulation, including the Multi-criteria CA (MCA) model [70], Future Land Use Simulation (FLUS) model [50], and Land Use Scenario Dynamics (LUSD) model [71]. We set 2015 as the initial year, and used the four models to predict the land use patterns in 2017, after which we compared the simulation results with the actual land-use conditions in 2017. This comparison focused on the amounts and shapes of urban patches, such as the number of urban cells, as the quantitative comparison index. Furthermore, the landscape shape indicators were calculated using FRAGSTATS v4 [72], including the Largest Patch Index (LPI), Mean Patch Area (MPA), and Mean Shape Index (MSI), to describe the shape characteristics of patches.

As shown in Table 3, for the number of urban cells, the FUTURES simulation result was closest to the actual urban cell amount in 2017, while the MCA, FLUS, and LUSD were lower than the actual amounts by 0.135%, 0.914%, and 0.135%, respectively. For the urban patch shape, the MSI of the FUTURES result was closest to the actual situation, indicating that the FUTURES model provided a better prediction for urban shapes. Additionally, the LPI of FUTURES was the maximum value of the four models, although its MPA was the second-closest to reality. These results indicate that the FUTURES model produced the largest urban patches, and the remainder of the patches had shapes that were similar to those of the actual patches.

Table 3. Comparison of urban simulation results of four models

	2017	MCA	FLUS	LUSD	FUTURES
Mean Shape Index	1.8261	1.8123	2.0206	1.8123	1.8168
Largest Patch Index	16.5482	18.0035	16.3603	16.4965	20.6616
Mean Patch Area	500.5899	558.4000	604.1227	502.5581	492.8274
Number of Cells	1,056,801	1,055,372	1,047,146	1,055,372	1,056,841

Based on the comparison results, the FUTURES model demonstrated its reliability and advantages when simulating the quantities and shapes of urban patches. It is true that the FUTURES model merely focuses on simulating urban growth and only considers the changes and allocation of urban patches. For this reason, it can obtain more reliable urban predictions than the models considering multiple land-use class changes. Therefore, the urban simulation results of the FUTURES model could potentially be utilized as input data for other models in order to remedy their urban prediction weaknesses.

3.2. Land-Use Projections for Shenzhen

The urban simulation results under five scenarios in 2035 are shown in Figure 5. Generally, Shenzhen's urbanization process is projected to invade arable land and ecological land in order to generate a large amount of impervious urban land in the future. These simulated land-use maps indicate that the northwest region is forecast to be the primary development area of Shenzhen, while the southeast area is predicted to experience less urban development. The Infill scenario's result displays a compact growth pattern in which new urban patches develop along the original city area's fringes. Conversely, in the Sprawl scenario, the urban development exhibits a fragmented pattern. The Increase scenario creates the least urban land of all the scenarios, while the Decrease pattern creates the most.

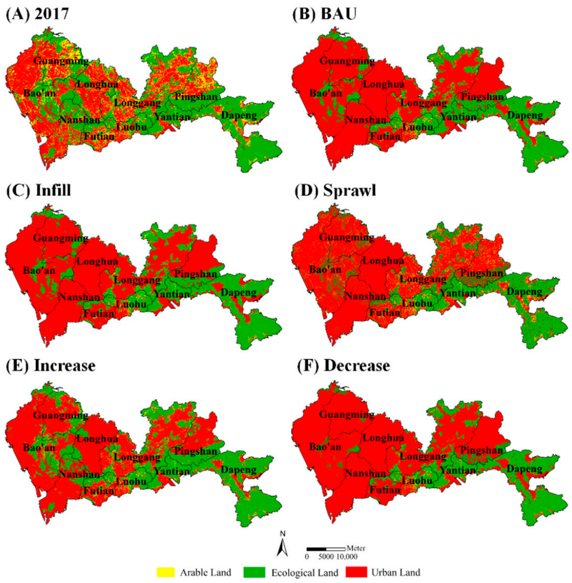

Figure 5. Simulation results of urban development under five scenarios in 2035.

3.3. Comparison of Ecological Land and Arable Land Changes

Additionally, there were a few distinctions in the proportions of different land-use categories under different results of the simulation scenarios. Table 4 shows the land use changes of Shenzhen from 2017 to 2035 under the five scenarios. Comparing the simulation results of the BAU, Infill, and Sprawl scenarios, it is evident that their urban region areas are roughly the same. The Infill scenario's ecological land increases by 10% compared to Sprawl, however the area of arable land decreases by 48%. The arable land area in the Infill scenario and the ecological land area in the Sprawl scenario are higher than in BAU, resulting in the aggregate urban pattern consuming more arable land and the diffuse pattern losing more ecological land. Hence, in the process of urban expansion, when the area of urban land is equal, the decrease in the losses of arable land or ecological land in one area will lead to increased losses in other areas, and vice versa. This phenomenon indicates a trade-off relationship between arable land and ecological land in urban expansion.

Table 4. Changes in land use under the five scenarios from 2017 to 2035.

Land Use	BAU		Infill		Sprawl		Increase		Decrease	
	Area (km^2)	Change (%)	Area (km^2)	Change (%)	Area (km^2)	Change (%)	Area (km^2)	Change (%)	Area (km^2)	Change (%)
Arable	81.79	−78.13	61.58	−83.53	126.28	−66.23	148.10	−60.40	47.26	−87.36
Ecological	655.47	−34.67	654.06	−34.81	591.02	−41.10	822.96	−17.98	562.41	−43.95
Urban	1480.57	76.16	1502.18	78.73	1500.54	78.54	1246.78	48.34	1608.17	91.34

Notably, when changing the demand for urban land, due to the 40% reduction in urban land consumption associated with increasing the population density, the Increase scenario saves the most ecological land and arable land of the five scenarios. Similarly, the Decrease scenario results in the most extensive urban region and maintains the least ecological land and arable land. Overall, in the future, if the population density does not increase, the urban areas will continue to expand and will occupy more ecological land or arable land. This result may be due to the limitations of the administrative regions as well as existing land-use patterns, making future urban areas only available from transformed ecological or arable land.

3.4. Sub-Regional Response to Alternative Urban Growth Scenarios

In order to investigate the differences in land-use patterns among sub-regions (i.e., 10 districts) under the five scenarios, we calculated and compared the arable land and ecological land changes in the different districts.

3.4.1. Comparison of Sub-Regional Ecological Land and Arable Land Changes

Figure 6 shows the percentage of lost arable land and ecological land area in Shenzhen's 10 districts under the five simulation scenarios from 2017 to 2035 (for details, please refer to the Supplementary Material Tables S1 and S2). In Figure 6, the color coding of district names represents the district type, i.e., the red, blue, and black font colors represent the urban regions (Figure 6a–f), peri-urban regions (Figure 6g,h), and rural regions (Figure 6i,j), respectively. The ordinate represents the proportion of loss of ecological land and cultivated land in 2035 relative to 2017.

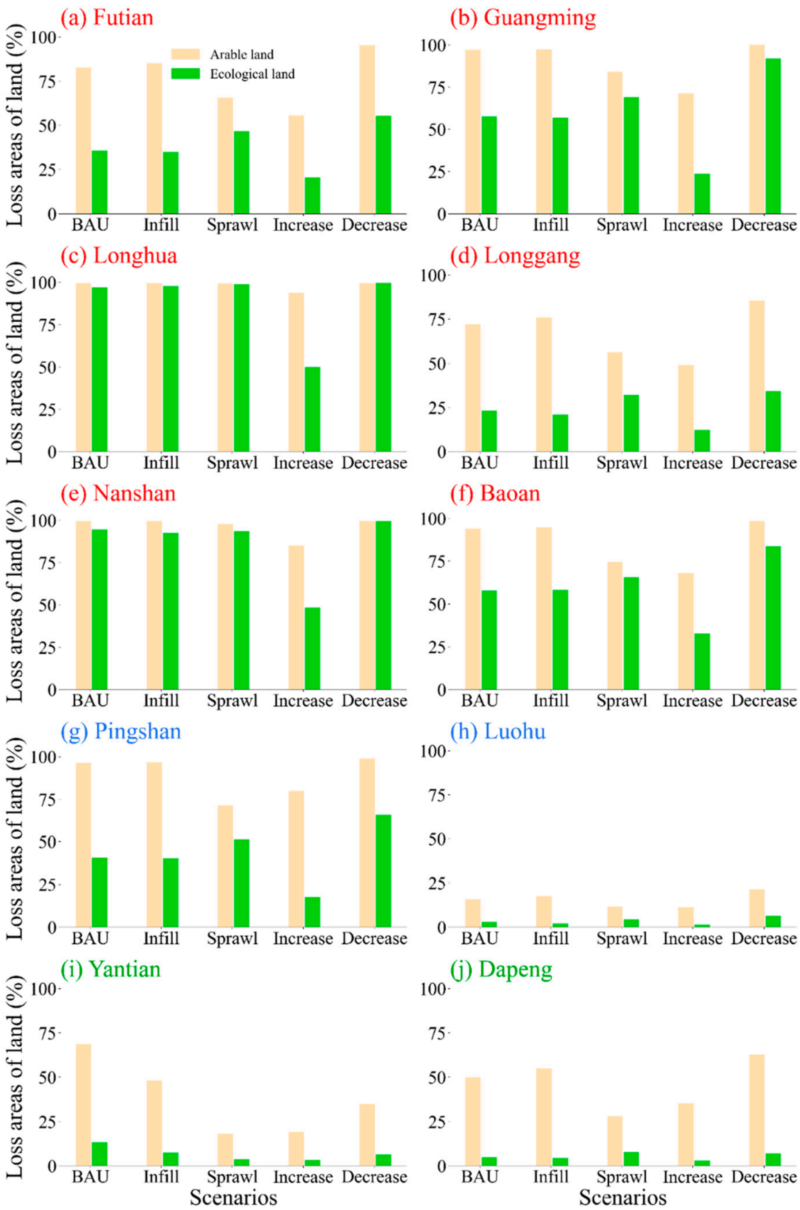

Figure 6. Loss of arable land and ecological land in different districts under the five scenarios from 2017 to 2035. The color-coding of the district names represents their types, which correspond to the colors of the circles representing the districts in Figure 2, with red indicating urban districts, blue indicating peri-urban, and green indicating rural.

Under the BAU, Infill, and Sprawl scenarios, the arable land and ecological land also exhibit trade-off relationships in most districts. This result illustrates the trade-off relationships between the arable land and ecological land in the context of the same or similar urban land demand. In addition, all districts significantly reduced their losses of arable land and ecological land in the Increase scenario. Meanwhile, most districts' consumptions of arable land and ecological land are significantly more in the Decrease scenario than in the other scenarios. This contrast indicates that increasing urban population density while reducing low-density urban land development is critical for China's urban development.

Only in the Yantian district could all four urban development scenarios simultaneously reduce the loss of arable land and ecological land compared with the BAU scenario (Figure 6i). For the other districts, the assumed artificial adjustment scenarios may cause more loss of either arable land or ecological land than the BAU scenario based on historical trends.

Moreover, the simulation results of Yantian revealed that the adjacent Pingshan district exerts a direct impact on the urban land development potential of Yantian. Under the BAU scenario, there is newly developed urban land on the border of Yantian and Pingshan (Figure 5B), and more arable and ecological land converts to urban land in Yantian's northeast region (Figure 6i). Therefore, the southwest expansion of urban land from the Pingshan district influences the land-use change in Yantian. In contrast, in the other four scenarios, the urban areas in Pingshan are more likely to expand within its extent.

Shenzhen's urban growth is incapable of maintaining arable land or ecological land at the full city scale. Nevertheless, a sub-region (Yantian district) can keep ecological land, retain arable land, and meet urban growth demand. The population of rural districts migrate to the urban districts which transfers the urban land demand to the urban districts. This result indicates that the city system cannot simultaneously keep both the arable land and ecological land without land resources from other administrative regions. This goal may be maintained at the sub-regional scale, however, due to the urban land demand being transferred to other sub-regions.

3.4.2. Sub-Regional Arable Land Changes in Response to the Alternative Urban Growth Scenarios

Furthermore, the responses of arable land in different sub-regions to alternative urban growth policies represent regional discrepancies. Overall, the Sprawl and Increase scenarios could reduce more arable land loss than the other three scenarios. From the sub-region perspective, for the six urban regions, the Increase scenario retains most arable land in Futian, Guangming, Longgang, Nashan, and Bao'an. In terms of the rural and peri-urban districts of Pingshan, Luohu, Yantian, and Dapeng, however, the Sprawl method retains more arable land than all other policies. The specific modeling results reveal that the regional heterogeneity of policy implementation differs from the result of the entire city.

In addition, the differences between the scenarios are significant among the 10 districts. For the Longhua, Nanshan, and Luohu districts, their arable land losses are similar under the various scenarios. This similarity indicates that their arable land changes are less sensitive to the alteration of development policies. For the Futian, Guangming, Longgang, Bao'an, Pingshan, and Dapeng districts, the losses of arable land under the Sprawl and Increase scenarios are significantly less than those of other scenarios. This result implies that the arable land of these districts is sensitive to the sprawling urban form or land resource demand. Interestingly, the Yantian district exhibited various responses to all scenarios.

3.4.3. Sub-Regional Ecological Land Changes in Response to the Alternative Urban Growth Scenarios

In terms of ecological land, the predicted amounts are presented in Figure 6. For all districts, ecological land is most significantly conserved under the Increase scenario. This result indicates that the ecological land in different districts largely depends on the demand for urban land. Additionally, the Infill scenario displays its advantage of retaining more ecological land than Sprawl's simulated consequences.

Moreover, based on the analysis of the remnant areas of ecological land, we discovered three response modes of ecological land for the 10 districts in different urban development approaches. The first mode is that the policy-setting could prominently affect the preservation of ecological land. For example, in the Futian, Guangming, Longgang, Bao'an, and Pingshan districts, their ecological land areas are distinctly disparate under the five scenarios. Conversely, the second situation is that there are fewer differences under the five development scenarios because there are few ecological land changes, as exemplified by the Luohu, Yantian, and Dapeng districts. In the third mode, only the Increase policy could significantly impact the saving of ecological land, mainly in the Longhua and Nanshan districts.

3.4.4. Classification of Sub-Regional Responses

Based on the previous analysis results as well as each district's specific sensitivity index, Figure 7 illustrates the spatial distribution of the 10 districts' sensitivity to population density and urban forms.

According to the loss area of ecological land and arable land (Figure 6), we compared the simulation results of the Sprawl, Infill, Decrease, and Increase scenarios to that of the BAU scenario. We then assigned a sensitivity value to each district based on the degree of land-use changes.

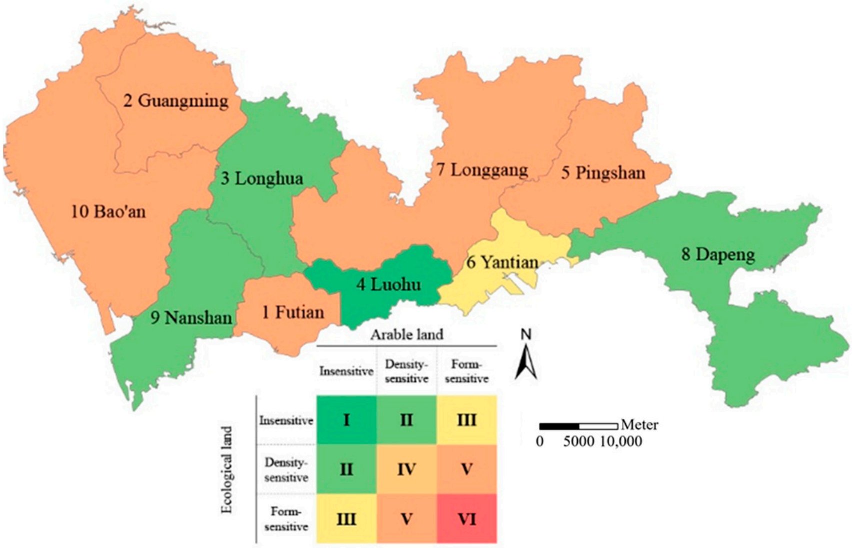

Figure 7. Sensitivity distribution of the 10 districts in Shenzhen.

From Figure 7, it can be seen that the Luohu district is the least sensitive. Meanwhile, the urban and peri-urban districts of Guangming, Bao'an, Futian, Longgang, and Pingshan are the most sensitive sub-regions, all designated as Sensitivity V, indicating that their arable land is sensitive to population density while their ecological land is sensitive to urban form. This distribution indicates that the policymakers need to pay more attention to the impact of population density and urban form on the urban and peri-urban districts.

4. Discussion

4.1. Inevitable Choice Between Arable and Ecological Land When Altering Urban Forms

Overall, this study predicted Shenzhen's urban development from 2017 to 2035 under five specific presupposed policy scenarios using the FUTURES model. Previous urban simulation research has proven that the expansion of cities will inevitably lead to a decrease in other types of land [73,74]. As shown in Table 4, when the built-up areas of cities are similar between different scenarios, significant distinctions emerge for the proportion between arable land and ecological land under alternative scenarios. Due to urban growth expansion, the decrease in the losses of arable land or ecological land in one area will increase those in other areas because the overall demand for urban land remains unchanged or similar. We call this the trade-off relationship between arable land and ecological land in urban development, which is also an inevitable choice for city planners and policymakers.

This finding is in line with previous research results, indicating that there is multi-functional use of land, and the trade-off relationship mirrors the competition among various land-use types [45]. Additionally, the trade-off relationships of distinct urban growth policies have previously been uncovered in different study cases and locations. In our research, we defined five scenarios: "Business-as-usual," "Infill," "Sprawl," "Increased density," and "Decreased density." These five scenarios are similar to those from the previous research of Shoemaker et al. [30]. Their simulation focused on the urban development of Charlotte, North Carolina, U.S.A. from 2007 to 2030 and also revealed a trade-off between urban expansion and conversion of cropland and forest land. Dorning et al. created three hypothetical urban growth scenarios—"Increase density," "Encourage infill," and "Constrain development"—to simulate the urban growth of the North Carolina Piedmont region from 2006 to 2030. They also found that one individual policy cannot achieve all urban development goals [64]. One likely explanation for the trade-off relationships is that urban growth is a type of game behavior on the existing land stock of a region without external land resources such as extending the administrative range or a sea-filling project. Therefore, extending its administration region can be a practical and ecologically protective way to preserve Shenzhen's ecological land and arable land.

Given the trade-off between arable and ecological land, we used scenario analyses to clarify the effects of alternative policies on that relationship. As shown in Figure 5, the assumed urban expansion scenarios exert pronounced spatial effects on their simulation results. For example, the Infill scenario creates newly formed patches close to the original urban area, thereby reducing the fragmentation of arable land near urban regions. Conversely, in the Sprawl scenario, some urban patches are interspersed among arable and ecological land in the suburbs. In addition, the Increase scenario contains areal increments of urban land and maintains most arable and ecological land. As a result, some urban renewal policies implicated in original residential and commercial land to enhance the urban space utilization could help realize sustainable urban development [75]. On the other hand, the Decrease scenario indicates that unlimited urban development demand will lead to uncontrolled urban expansion patterns.

Importantly, as previously mentioned in Section 3.2, there is the counterintuitive result that Infill's policy can maintain more ecological land but less arable land than the Sprawl scenario. This result may be due to the Infill scenario emphasizing that newly built zones are close to the first urban fringe, occupying vast previously high-quality arable land surrounding urban areas. Furthermore, the Sprawl scenario encourages urban growth in some underdeveloped locations, causing more ecological land to be reclaimed as urbanized areas rather than utilizing the original arable land. Therefore, under the inevitable urban growth trend, the choice between arable and ecological land could be an unavoidable problem for policymakers when deciding upon urban development approaches for realizing sustainable urbanization.

4.2. Response of Sub-Regions to Alternative Scenarios

Traditional studies usually simulate individual urban development for scenario analysis at the regional scale [73]. In this study, however, we observed that some sub-regions exert distinctive responses to alternative scenarios rather than the entire city. As displayed in Figure 5, for the rural Yantian district, both the sprawling and compact urban forms could save more arable land than BAU, which is opposite the result for some urban areas such as the Bao'an, Futian, and Nanshan districts. These results serve as a proof-of-concept that the formulation of urban forms needs to be adapted to local conditions instead of pursuing the same policy measures for all sub-city administrative districts.

In light of predicting the model's consequences, we suggest considering sub-regional conditions and development goals in order to optimize urban growth approaches. For the districts with high urbanization levels, planners can design more sustainable and efficient city development with a strategy that increases high urban population density and decreases current land consumption. For those peri-urban and rural regions with great ecological resources, implementing dispersed development strategies can avoid producing a concentrated urban area. For example, the Increased population density scenario plays the primary role in protecting arable and ecological land at the regional scale. Nevertheless, in the Increase scenario, we enhance population density to reduce land consumption, although the exorbitant concentration of residents may result in various urban living and ecological problems [30,61]. When we consider the sub-regional scale, for those peri-urban and rural regions such as Pingshan, Yantian, and Dapeng, the sprawling urban form protects more arable land than other scenarios.

4.3. Limitations

Some limitations of this study also need to be addressed and pointed out. China uses a state-owned land system, therefore individual land rights usually obey the macroscopic plan and administrative authorities. Because we simulated and forecast Shenzhen's development on the large scale, individual land rights were not considered. In addition, land value was indirectly represented by road density, investment, and distance to the city center.

In order to reduce the difficulty of modeling and simulation in this research, we assumed future urban growth based on historical development trends and past natural, social, and economic influencing factors. Land-use change is a non-stationary, unstable, and complex process, however. Although the simulation results were derived against an ideal and linear background, they still provide a helpful benchmark and reference for urban planners to compare the impact of different urban form choices.

5. Conclusions

In this study, we focused on the relationship between arable land and ecological land in the continuous and rapid urbanization region of Shenzhen, China. Based on the analysis of various scenarios and with the help of the prospective urban development simulation model FUTURES, we revealed the effects of different urban expansion forms and policies on the loss of arable and ecological land. The main findings and conclusions of this study are summarized as follows:

Firstly, there is a trade-off relationship between arable land and ecological land when altering urban forms. According to the model simulation results, urban forms exert a significant impact on land use. Specifically, the sprawling urban form could conserve more arable land, while the infilling urban form retains more ecological land than the sprawling form. In the ecological-production-living space theory, arable and ecological land exhibit typical trade-off relationships in the context of urban growth. Nevertheless, previous researchers have mostly concentrated on the contrast between urban land and arable land, while the status of ecological land has received little attention. It is necessary to consider the effects of ecological land as well as the competitive relationship of various land-use types in future urban growth.

Secondly, when carrying out a similar development policy, the responses may vary on sub-regional scales with different characteristics. This phenomenon reflects the practical function of multilevel frameworks in analyzing the geographical processes of non-stationary and overlapping sub-regions. Moreover, these results provide the useful realization that the formulation of an urban development plan cannot use the "one size fits all" approach. Each district should choose appropriate development approaches on the grounds of its actual conditions, rather than merely obey superior instructions and planning.

Thirdly, by increasing urban population density, new urban growth urban areas could be contained. As our results revealed, the low population density urban growth pattern will lead to a massive reduction in both arable and ecological land. In contrast, high population density in an urban area could appreciably reduce urban areas. Shenzhen is a typical city with scarce land resources and is currently experiencing a sustained population aggregation process. Both the population growth and land demands of human living and production are driving Shenzhen to massively expand. Therefore, in order to protect current arable and ecological land during urbanization, the government should attempt to increase the urban population density and land utilization efficiency and reduce the vacancy rates of residences.

This study lets us foresee alternative future urban developments of Shenzhen. The simulation results of the various scenarios indicate the massive pressure Shenzhen is under to simultaneously achieve the goals of saving arable land and maintaining ecological land during urbanization. As a result, we suggest that Shenzhen's policymakers take a two-pronged approach: firstly, to cooperate with surrounding cities (e.g., Dongguan and Shantou) to acquire more development space. Secondly, the city should phase out labor-intensive industries and encourage the development of high R&D-intensive industries, based on the reallocation of the urban area, in order to increase the efficiency of urban land use, thereby reducing the formation of urban patches.

Finally, future research should comprehensively consider the potential effects of more political and economic factors on urban development, such as the land-use rights of individuals, the market or ecological values of different land-use types, and the surrounding living environment of residents. More empirical studies of cities in China and other countries are required in the future.

Supplementary Materials: The following are available online at http://www.mdpi.com/2071-1050/122/31/0041/s1, Table S1. Loss areas of arable land from 2017 to 2035 in five scenarios; Table S2. Loss areas of ecological land from 2017 to 2035 in five scenarios.

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