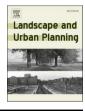


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# Research Paper Does zoning contain built-up land expansion? Causal evidence from Zhangzhou City, China

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# HIGHLIGHTS

• Analysis of causal evidence for effect of zoning on built-up land expansion.

• Zoning effectively contained built-up land expansion in Zhangzhou City.

• We observed a time-lag effect during plan implementation.

Zoning became ineffective at the end of plan implementation.

• Causal inference and the influence of time should be emphasized in plan evaluation.

# ARTICLE INFO

Keywords: Annual effect Land-use change Land-use planning Plan evaluation PSM-DID

# ABSTRACT

The increasing impacts of built-up land expansion on sustainable development have heightened the use of spatial planning as a policy tool to contain built-up land expansion. However, causal evidence for the effect of spatial planning on built-up land expansion has largely remained unexplored. In this study, we used a difference-indifference model with propensity score matching to estimate the average and annual effect of built-up land zoning (subsequently called zoning) on built-up land expansion in Zhangzhou City, China between 2010 and 2020. Results on the average effect show that zoning was effective in containing built-up land expansion. Specifically, zoning prevented 27.02 km<sup>2</sup> of built-up land expansion outside the development-permitted zones between 2010 and 2020, which accounts for 32.46% of the observed built-up land expansion outside the development-permitted zones. We found a time-lag effect, with zoning starting to have an effect after 2013. Furthermore, zoning became ineffective in containing built-up land expansion at the end of plan implementation. Based on our findings, we recommend that future evaluations of the effect of spatial planning on land-use change use causal inference and that they explore the influence of time on the effect of plans in greater detail.

## 1. Introduction

As a salient and rapid human-induced change on the Earth's surface (Gao & O'Neill, 2020; Seto, Guneralp, & Hutyra, 2012), built-up land expansion has been an important sustainability concern (Acuto, Parnell, & Seto, 2018). Spatial planning has been developed as an essential policy tool, with the aim to manage built-up land expansion in an orderly manner (Hersperger, Grădinaru, Oliveira, Pagliarin, & Palka, 2019). However, the causal relationship between spatial planning and built-up land expansion has been largely unexplored. Ideally, the causal effect of spatial planning on built-up land expansion would be conceptualized as the built-up land expansion that is solely attributable to spatial planning (Wong & Watkins, 2009). It is difficult to evaluate such causal effect because we cannot simultaneously observe built-up land expansion in a fixed region both with and without spatial planning. However, plan evaluation based on causal relationships is necessary to enhance the credibility of spatial planning (Oliveira & Pinho, 2010), and it contributes to the understanding of causes and consequences of land-use change (Meyfroidt et al., 2018; Turner, Lambin, & Reenberg, 2007).

China is one of the world's hotspots of built-up land expansion (Seto et al., 2012). To contain built-up land expansion, China's government

\* Corresponding author at: Eidg. Forschungsanstalt WSL, Zürcherstrasse 11, 8903 Birmensdorf, Switzerland. *E-mail addresses:* zhichao.he@student.uni-halle.de, zhichao.he@wsl.ch (Z. He).

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Received 8 March 2021; Received in revised form 16 December 2021; Accepted 18 December 2021 Available online 31 December 2021 0169-2046/© 2021 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/). has implemented land-use planning since 1986, when the government accelerated the reform of the market economy. Land-use plans are compiled at five administrative levels: national, provincial, prefectural city, county, and township (Fig. 1). The national and provincial governments provide guidelines and assign land-use quotas to the lower levels of government. The prefectural city, county, and township governments are responsible for allocating the quotas based on zoning and governing the actual land-use change. Land-use planning has two major targets: built-up land containment and farmland protection, which are both implemented using a "quota with zoning" mode. For example, to contain built-up expansion, the central government set a series of builtup land quotas (e.g., the maximum amount of built-up land, the annual maximum amount of arable land converting to newly-added built-up land) according to the prediction of socioeconomic development. Then these quotas are allocated by the central government to the provincial level and then divided gradually down to the township level based on local socioeconomic characteristics (Fang & Tian, 2020; Zhou et al., 2017). Zoning is used for allocating the quotas into specific locations at the prefectural city, county, and township level based on suitability evaluations of built-up land. Thus land-use plans at the prefectural city, county, and township level mainly consist of several maps showing landuse zoning and a quota system determining the amounts of land-use change. Land-use plans in China are authorized by the Land Administration Law, meaning that land-use plans have legal validity once they are approved. Despite the legal validity of the plans, the effect of landuse planning on containing built-up land expansion is unclear. Many researchers have found a lack of consistency when overlaying zoning with the actual built-up land extent, and they have therefore concluded a failure of land-use planning in China (Guo, Hu, & Zheng, 2020; Liu, Huang, Tan, & Kong, 2020; Shao, Spit, Jin, Bakker, & Wu, 2018; Shen, Wang, Zhang, & Fei, 2021).

In this study, we addressed the research question: does zoning play a causal role in containing built-up land expansion? To get closer to causality, we used a quasi-experimental method (PSM-DID, differencein-difference based on propensity score matching). PSM-DID has been developed to evaluate the causal effect of a policy on the outcome of interest (Abadie, 2005; Wing, Simon, & Bello-Gomez, 2018). In this study, the principle of PSM-DID was to compare the average built-up land expansion of the villages located inside the developmentpermitted zones with that of similar villages located outside the development-permitted zones (with-versus-similar-without difference), before and after plan implementation (before-versus-after difference). PSM-DID, which combines the before-versus-after difference and the

with-versus-similar-without difference, can get closer to causality than either difference alone (Blackman, 2013; Butsic, Lewis, & Ludwig, 2011; Wing et al., 2018). The before-versus-after difference can control for time-invariant factors (e.g., elevation, slope), but it ignores the factors that may influence built-up land expansion over time, such as economic and population growth (Blackman, 2013; Dempsey & Plantinga, 2013). The with-versus-without difference is misleading because zoning is not random (Andam, Ferraro, Pfaff, Sanchez-Azofeifa, & Robalino, 2008; He, Zhao, Fürst, & Hersperger, 2021). For example, urban proximity not only influences built-up land expansion, but also influences zoning. PSM-DID uses the before-versus-after difference to eliminate timeinvariant factors and uses the with-versus-similar-without difference to eliminate the time-variant factors, thereby evaluating the causal effect. Several researchers have applied this method to evaluate the causal effect of construction land quotas on urban expansion (Fang & Tian, 2020) or the causal effect of urban growth boundaries on land development (Dempsey & Plantinga, 2013; Kline, Thiers, Ozawa, Alan Yeakley, & Gordon, 2014). While PSM-DID is an effective method to estimate the causal effect, it is rarely used to evaluate the causal effect of spatial planning on land-use change. One of the challenges is that PSM-DID is data-demanding, because it requires a large amount of longitudinal information to construct the before-versus-after comparison. Spatial planning usually has a timeline of 10 years or more as an implementation period. Evaluating the effect of a 10-year plan on landuse change via PSM-DID requires land-use data spanning over 10 years.

Besides evaluating the causal effect, we made three additional contributions. First, we chose 1662 village-level administrative units in Zhangzhou City as evaluation units. Selecting an appropriate evaluation unit is a fundamental, but often neglected, aspect in the evaluation of the effect of spatial planning on land-use change. In most evaluation research, a grid is chosen with a cell size from 10  $\times$  10 m to 1  $\times$  1 km (Braimoh & Onishi, 2007; Cheng & Masser, 2003; Huang, Zhang, & Wu, 2009; Kasraian, Maat, & Van, 2019). These choices are often arbitrarily determined or match the resolution of the available data. Administrative units are rarely considered (Anthony, 2004; Colantoni, Grigoriadis, Sateriano, Venanzoni, & Salvati, 2016). The ideal evaluation unit must match the plan-implementation unit, which may not be apparent. The village-level administrative units are legalized grassroots units that elect a villagers' committee as the authority, and they are the basic socioeconomic units in China (e.g., census, mail system, land ownership, (Li, Fan, & Liu, 2019)). As the lowest unit in China's top-down administrative hierarchy (nation - province - prefectural city - county township - village), villages are the final administrative unit to put land-

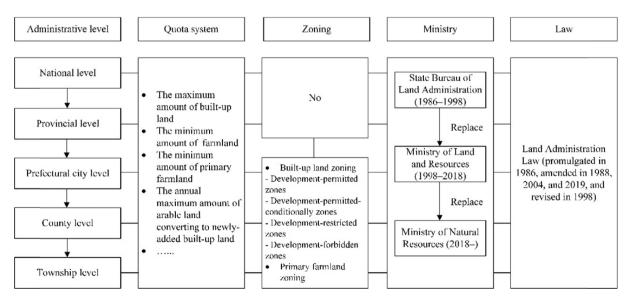


Fig. 1. Land-use planning system in China.

use plans into practice, such as land expropriation, demolition, and farmland protection. Thus, the village-level administrative units are the ideal evaluation unit because they approximate the actual unit of landuse decision-making in China (Huang, Huang, & Liu, 2019).

Second, we used binary and continuous variables to represent zoning. A binary variable is most commonly used to represent spatial planning (Cheng & Masser, 2003; Kasraian et al., 2019; Poelmans & van Rompaey, 2010; Shu et al., 2020). For example, land that is assigned inside protected areas is coded as 1 and other land is coded as 0. A continuous variable is appropriate in our case where the villages have different amounts of area inside the development-permitted zones. The villages with more land area assigned to the development-permitted zones can expand built-up land as they expected, which corresponds to lenient regulation, while the others with more land area assigned to the development-regulations that require them to reduce built-up land expansion. Thus, we

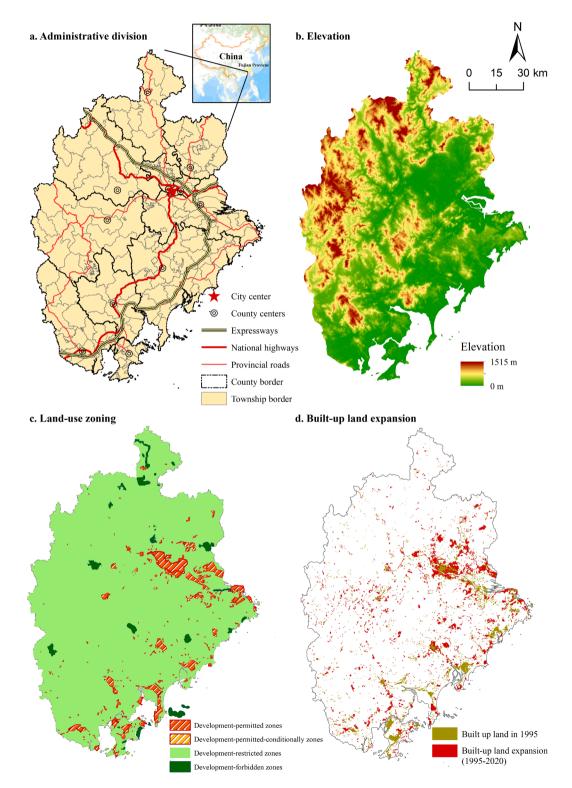


Fig. 2. Study area.

used the binary and continuous planning variables to obtain a robust estimation.

Third, we examined the annual effect of zoning on built-up land expansion. Time influences policy success and failure, and it impacts policy evaluation (Bressers, van Twist, & ten Heuvelhof, 2013). The effect of spatial planning on land-use change may take many years to be visible. (Loh, 2011) suggested that a discrepancy between the actual and planned land-use change may result from a time-lag effect in plan implementation. Moreover; the plan effect varies during the implementation years. In some studies, it has been reported that the plan effect reduced as time elapsed after the plan's implementation (Alterman & Hill, 1978; Padeiro, 2016). Thus, besides the average effect, we explored whether zoning had a time-lag effect on containing built-up land expansion, and how the effect varied over time.

In Section 2 of this paper we present the study area, variables, and data sources; in Section 3 we describe the methodology; in Section 4 we present the empirical results; in Section 5 we discuss the empirical results in depth; and in Section 6 we provide conclusions.

# 2. Study area, variables, and data sources

## 2.1. Study area

Zhangzhou City is located in the southeastern part of China and is a prefectural city in Fujian Province. It has 11 counties which are further divided into 161 townships (Fig. 2.a). The area has strong agricultural roots. It has fertile plains and is highly irrigated (Fig. 2.b), which favors agricultural production (e.g., vegetables, citrus fruits, bananas, and flowers (Huang, Pontius, Li, & Zhang, 2012)). Economic development in this area traditionally depends on arable land and forest land. Since China's Reform and Opening-up Policy in 1978, Zhangzhou City has undergone rapid population and economic development. From 1978 to 2019 its GDP increased from 0.89 billion to 474.18 billion RMB and its population increased from 3.44 million to 5.16 million. Such development is intensifying the contradiction between built-up land expansion and agricultural land protection (Huang et al., 2012; Jiang, Sun, & Zheng, 2019). Our land-use data show that built-up land expanded from 442.39 km<sup>2</sup> in 1995 to 1000.84 km<sup>2</sup> in 2020 (Fig. 2.d). Correspondingly, arable land decreased from 2883.50 km<sup>2</sup> to 2548.08 km<sup>2</sup> and forest land decreased from 6802.45  $\mbox{km}^2$  to 6492.81  $\mbox{km}^2.$  Furthermore, some studies demonstrated that built-up land expansion resulted in environmental degradation in this area. For example, built-up land expansion increased water pollution (Huang, Huang, Pontius, & Zhang, 2015). Ecosystem services have decreased dramatically because a considerable amount of arable land and forest land has been converted into built-up land (Chen, Tang, Qiu, Hou, & Wang, 2020). Thus, answering the causal question - does zoning play a causal role in containing built-up land expansion? - is required for the local government to effectively contain built-up land expansion and to protect the environment.

# 2.2. Variable descriptions

We used panel data comprised of 1622 village-level administrative units with longitudinal information from eight years (1995, 2000, 2005, 2010, 2013, 2015, 2018, and 2020). We chose village as the research unit because it approximates the actual unit of land-use decision-making. We defined a study period that was long enough to contain sufficient longitudinal information. On the one hand, it covers the entire implementation period of the land-use plan in Zhangzhou City (2010–2020). On the other hand, it allows a comparison of built-up land expansion before and after the implementation of the land-use plan.

# 2.2.1. Built-up land expansion

Built-up land expansion was the outcome of interest in our study. We used the percentage of built-up land out of the total land area (excluding waterbody area) to assess built-up land expansion ( $BuLE_{it}$ ) at the village

level during the studied period.  $BuLE_{it} \in [0, 100]$ . Values close to 100 indicate that village *i* was fully developed in year *t*.

## 2.2.2. Planning variables

In Zhangzhou City, the land-use plan divided the territory into four zone types: development-permitted zones, development-permittedconditionally zones, development-restricted zones, and developmentforbidden zones (Fig. 2.c). Built-up land development is allowed only inside the development-permitted and development-permittedconditionally zones, and we therefore combined these two zone types into the development-permitted zone type to form the core independent variable in this study. The delineation of development-permitted zones does not follow the village boundaries. Here, we used two types of planning variables: binary and continuous. We assigned  $Develop_i = 1$  to the villages that were partially or entirely located inside the development-permitted zones, and  $Develop_i = 0$  to the villages that were entirely located outside the development-permitted zones (Fig. 3.A). The reason for using a binary variable is that the villages adopt an aggressive development strategy when they are located inside a development-permitted zone. Considering that the villages have different amounts of area inside the development-permitted zones, we additionally used a continuous planning variable (Intensity<sub>i</sub>) by calculating the percentage of land that was assigned to the developmentpermitted zones in village *i* (Fig. 3.B).

## 2.2.3. Control variables

To improve the explanatory power of our DID model, we used control variables concerning neighborhood, geography, and proximity to urban centers and roads. The census data on socioeconomic characteristics (e. g., population, household, economy) are unavailable at the village level in China, especially for our panel data. The proximity to urban centers and the distance to coastlines can be used as a proxy for socioeconomic characteristics, because urban areas and eastern coastal areas have higher socioeconomic development compared with rural areas and western mountain areas in Zhangzhou City (Jiang et al., 2019). We illustrated the variables in Fig. 4 and summarized the statistical descriptions and data sources in Table 1.

**Neighborhood variables:** The neighborhood effect is an indispensable driver of land-use change (van Vliet et al., 2013; Verburg, de Nijs, van Eck, Visser, & de Jong, 2004). We considered villages that share an edge or a corner of their border the neighboring villages. We calculated the area of built-up land (*Nei\_Built.up*<sub>it</sub>) in the neighboring villages of village *i* in year *t* using the Polygon Neighbor tool in ArcGIS 10.6.

*Geographical variables:* Built-up land tends to expand along rivers and coastlines (le Berre, Maulpoix, Thériault, & Gourmelon, 2016; Tian & Wu, 2015). We measured the distance to waterbodies (*Dis2water<sub>i</sub>*) and to coastlines (*Dis2coastline<sub>i</sub>*) by calculating the Euclidean distance from village *i* to the nearest waterbody and coastline using the Near tool in ArcGIS 10.6. High elevation increases the cost of construction and poses a higher risk of erosion and landslides than lower and flatter areas (Onsted & Chowdhury, 2014; Zhong, Huang, Zhang, & Wang, 2011). We measured elevation (*Elevation<sub>i</sub>*) by calculating the average elevation within village *i* using the Zonal Statistics tool in ArcGIS 10.6.

**Proximity to urban centers:** Proximity to urban centers is an important driver of built-up land expansion (Kasraian et al., 2019; Yin, Kong, Yang, James, & Dronova, 2018). We measured the distance to the city center ( $Dis2city_i$ ) and county centers ( $Dis2county_i$ ) by calculating the Euclidean distance from village *i* to the city center and to the nearest county center using the Near tool.

**Proximity to roads:** Roads are important corridors for built-up land expansion (Poelmans & van Rompaey, 2010; Tian & Wu, 2015). We measured the distance to roads ( $Dis2road_i$ ) by calculating the Euclidean distance from village *i* to the nearest road using the Near tool. We selected expressways, national highways, and provincial roads, because these roads connect all capitals of provinces, prefectural cities, and most of the counties in China.

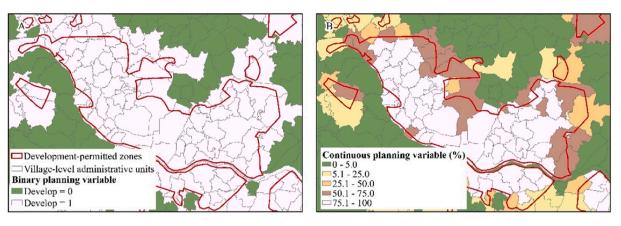
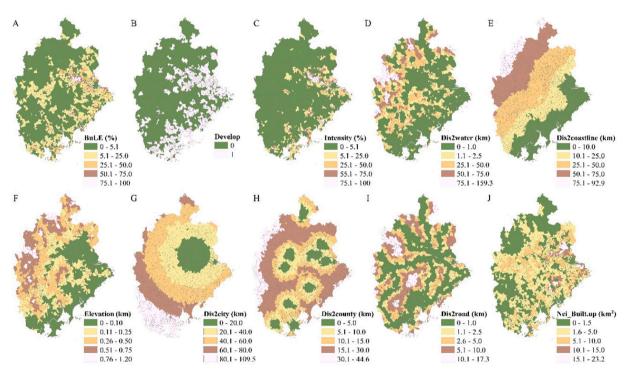


Fig. 3. Illustration of planning variables.



**Fig. 4.** Variables in the DID model: (A) The percentage of built-up land out of the total land area for each village in 2020; (B) binary planning variable; (C) continuous planning variable; (D) Euclidean distance to the nearest waterbody; (E) Euclidean distance to the nearest coastline; (F) elevation; (G) Euclidean distance to the city center; (H) Euclidean distance to the nearest county center; (I) Euclidean distance to the nearest road; (J) area of built-up land in the neighboring villages of village *i* in 2020.

# 3. Methodology

# 3.1. Empirical strategy

# 3.1.1. Average effect

We specified the following DID model to estimate the average effect of zoning on built-up land expansion:

$$BuLE_{it} = \beta(Develop_i * Time_t) + \gamma N_{it} + \sum_{j=2000}^{2020} \phi G_i * Year_j + \sum_{j=2000}^{2020} \varphi P_i * Year_j + u_i + \lambda_t$$
$$+ \varepsilon_{it}$$
(I)

where  $BuLE_{it}$  is the dependent variable, representing built-up land expansion in village *i* in year *t*. *Develop<sub>i</sub>* is a binary planning variable. *Develop<sub>i</sub>* = 0 if the village was assigned as being entirely outside the development-permitted zones, otherwise *Develop<sub>i</sub>* = 1. *Time<sub>t</sub>* is a binary variable. We assigned  $Time_t = 1$  to the years after the implementation of the land-use plan (i.e., 2010, 2013, 2015, 2018, and 2020) and  $Time_t = 0$  to the years before the implementation (i.e., 1995, 2000, and 2005). The coefficient ( $\beta$ ) of the interaction term ( $Develop_i^*Time_t$ ) represents the causal effect of zoning on built-up land expansion. We controlled for the other variables that could affect built-up land expansion.  $N_{it}$  represents the area of built-up land in the neighboring villages of village *i* in year *t* ( $Nei\_Built.up_{it}$ ).  $G_i$  represents geographical variables, such as distance to waterbodies ( $Dis2water_i$ ) and to coastlines ( $Dis2coastline_i$ ), and elevation ( $Elevation_i$ ).  $P_i$  represents the proximity to urban centers ( $Dis2city_i$  and  $Dis2county_i$ ) and to roads ( $Dis2road_i$ ). Because the geographical and proximity variables are time-invariant, we followed the approach proposed by (Nunn & Qian, 2011) to create the interaction terms ( $\sum_{t=2000}^{2020} \phi G_i^* Year_t$  and  $\sum_{t=2000}^{2020} \phi P_i^* Year_t$ ). The dummy variable  $Year_j = 1$  if  $j \in T = [2000, 2005, 2010, 2013, 2015, 2018, 2020]$ , otherwise  $Year_i = 0$ . We used two-way fixed effects to estimate the DID

#### Table 1

Statistical descriptions and data sources for the variables.

Variables	Unit	Mean	Min	Max	S.D.	Data sources
Dependent variable BuLE	%	12.73	0.00	100.00	19.93	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences
Planning variable						
Develop Intensity	- %	0.42 13.50	0 0.00	1 100.00	0.49 27.35	Local government Local government
Control variables	70	10.00	0.00	100.00	27.00	Local government
Dis2water	km	1.50	0.00	15.94	2.30	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences
Dis2coastline	km	26.29	0.00	92.89	23.27	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences
Elevation	km	0.18	0.00	1.05	0.22	Local government
Dis2city	km	49.17	0.00	108.14	27.89	Local government
Dis2county	km	13.51	0.00	42.90	9.48	Local government
Dis2road Nei_Built.up	km km <sup>2</sup>	2.55 2.67	0.00 0.00	17.30 23.21	3.51 2.72	NavInfo company Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences

model, where  $u_i$  and  $\lambda_t$  were the village and year fixed effects, respectively. The two-way fixed effects model can eliminate omitted variable bias arising both from unobserved variables that are constant over years but vary across villages and from unobserved variables that are constant across villages but vary over years (Stock & Watson, 2019). Finally, we clustered the standard errors at the village level to address potential serial correlation and heteroscedasticity.  $\varepsilon_{it}$  is the disturbance term.

Besides the binary planning variable, we explored the average effect of the continuous planning variable on built-up land expansion by specifying the following DID model:

$$BuLE_{it} = \beta(Intensity_i^*Time_t) + \gamma N_{it} + \sum_{j=2000}^{2020} \phi G_i^*Year_j + \sum_{j=2000}^{2020} \varphi P_i^*Year_j + u_i$$
$$+ \lambda_t + \varepsilon_{it}$$
(II)

where  $Intensity_i$  is the percentage of land that was assigned to the development-permitted zones in village *i*.

## 3.1.2. Annual effect

In addition to the average effect, we estimated the annual effect of zoning on built-up land expansion by specifying the following DID models:

$$BuLE_{it} = \sum_{j=1995}^{2020} \beta_j (Develop_i * Year_j) + \gamma N_{it} + \sum_{j=1995}^{2020} \phi G_i * Year_j + \sum_{j=1995}^{2020} \varphi P_i * Year_j + u_i + \lambda_i + \varepsilon_{it}$$
(III)

$$BuLE_{it} = \sum_{j=1995}^{2020} \beta_j (Intensity_i * Year_j) + \gamma N_{it} + \sum_{j=1995}^{2020} \phi G_i * Year_j + \sum_{j=1995}^{2020} \phi P_i * Year_j + u_i + \lambda_i + \varepsilon_{it}$$
(IV)

We used the binary (*Develop*<sub>i</sub>) and continuous (*Intensity*<sub>i</sub>) planning variables to obtain a robust estimation.  $\beta_j$  represents the causal effect of zoning on built-up land expansion in the years 1995, 2000, 2005, 2013, 2015, 2018, and 2020. We considered 2010–2020 the implementation period of the land-use plan in Zhangzhou City and omitted the year 2010 as the baseline year, since the land-use plan in Zhangzhou City was approved by the Fujian Province government in August 2010 (https://www.596fc.com/news/article\_616\_1.html). The other variables were defined above in Section 2.2.3.

## 3.1.3. Parallel trend and selection bias

The key underlying assumption of the DID model is the parallel trend assumption (Wing et al., 2018). This assumption requires that the villages located inside the development-permitted zones had a parallel trend to those located outside these zones in terms of built-up land expansion before the implementation of the land-use plan. Another challenge in plan evaluation is the selection bias inherent in the planning process (Abadie, 2005). The selection bias in our study refers to the systematic differences in the characteristics (e.g., geographical factors, proximity to urban centers) between the villages located inside the development-permitted zones. Before estimating the DID model, we employed PSM to overcome the above two challenges.

In our study, the propensity score refers to the probability of village i being assigned to the development-permitted zones during the planning process, given a series of confounding variables (Rosenbaum & Rubin, 1983). We calculated the propensity score with the following logistic regression model:

$$ps = Prob(Develop_i = 1|X_k) = \beta_0 + \beta_k X_k + \varepsilon_{it}$$
(V)

where *ps* represents the propensity score and *Develop*, is the same as in model I.  $X_k$  are the confounding variables, which include the area of built-up land in the neighboring villages of village *i* in 2010 (Nei\_Built.upi.2010), built-up land expansion in 2010 (BuLEi.2010), distance to waterbodies (*Dis2water<sub>i</sub>*), distance to coastlines (*Dis2coastline<sub>i</sub>*), elevation (Elevation<sub>i</sub>), proximity to urban centers (Dis2city<sub>i</sub> and Dis2county<sub>i</sub>), and proximity to roads (Dis2road<sub>i</sub>). Based on the estimated coefficients  $\beta_k$  , we calculated the propensity score for each village. We carried out 1:1 nearest neighbor matching, where a village assigned as being outside the development-permitted zones was chosen as the matched counterfactual when it was closest to a village assigned as being inside the development-permitted zones in terms of the propensity score. We set up matching without replacement, which can obtain precise estimates in a relatively large dataset (Butsic et al., 2011). We imposed a tolerance level of 0.05 on the maximum propensity score difference (i.e., caliper) to avoid poor matches if the closest neighbor is far away (Caliendo & Kopeinig, 2008).

## 3.2. Robustness checks

#### 3.2.1. Event study

We used an event study to check whether the parallel trend assumption was satisfied. The model for the event study is the same as model III, which is commonly used to test the parallel trend assumption (Jacobson, LaLonde, & Sullivan, 1993).  $\beta_j$  should be non-significant for the pre-implementation years (i.e., 1995, 2000, and 2005) if the parallel trend assumption was satisfied.

# 3.2.2. Balance check

After PSM, the differences in the confounding variables (i.e., selec-

tion bias) should be reduced between the villages located inside the development-permitted zones and those located outside the development-permitted zones (Rosenbaum & Rubin, 1983). We used the standardized mean difference (SMD) to check the extent to which PSM reduced the selection bias (Austin, 2011):

$$SMD = \frac{|\bar{x}_1 - \bar{x}_0|}{\sqrt{\frac{x_1^2 + x_0^2}{2}}}$$
(VI)

where  $\bar{x}_1$  and  $\bar{x}_0$  are the means of the confounding variables of the villages when their *Develop<sub>i</sub>* is equal to 1 and 0, respectively.  $s_1^2$  and  $s_0^2$  denote the sample variances. A higher SMD indicates a larger difference in the confounding variables. The value 0.1 is considered a reasonable threshold for ignoring the selection bias (Austin, 2011; Stuart, Lee, & Leacy, 2013).

#### 3.2.3. Placebo test

We conducted a placebo test using model I. All variables are the same except for  $Time_t$ . Here, we falsely assumed that the land-use plan in Zhangzhou City was approved in 2005, before the actual implementation year.  $Time_t$  equals 1 in the years 2005, 2010, 2013 2015, 2018, and 2020, and it equals 0 in the years 1995 and 2000. Because  $Time_t$  was falsely specified, the coefficient of  $Develop_i^*Time_t$  should be non-significant. A placebo test can also be used to detect an anticipation effect (Fang & Tian, 2020). Stakeholders might have acted in anticipation of the coming regulations. If the coefficient of  $Develop_i^*Time_t$  is significant, the land-use plan in Zhangzhou City might have started to have an effect before 2010.

#### 4. Results

## 4.1. Average effect

The results based on PSM-DID suggest that zoning played a causal role in containing built-up land expansion in Zhangzhou City between 2010 and 2020. The coefficient of  $Develop_i^*Time_t$  indicates a 1.21% increase in built-up land area in the villages assigned to the development-permitted zones (Table 2). To interpret the practical meaning of the coefficient, we assumed that every matched village had the identical total land area (5.74 km<sup>2</sup>), which is the mean of the total land area in the 772 matched villages. The coefficient (1.21%) indicates that each of the matched villages assigned as being outside the development-permitted zones would have expanded by an additional 0.07 km<sup>2</sup> of built-up land if there were no zoning. In aggregate, a total of 27.02 km<sup>2</sup> of built-up land was prevented outside the development-permitted zones during the implementation of the land-use plan, considering that there were 386 matched villages assigned as being outside the development-permitted zones. The actual built-up land expansion outside the

#### Table 2

Average effe	ect of zoning	on built-up	land expansion

	Model I	Model II
$Develop_i^*Time_t$	1.21* (0.67)	
Intensity <sub>i</sub> *Time <sub>t</sub>		0.06** (0.03)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R <sup>2</sup>	0.19	0.19
Hausman test	98.60 ***	103.50***
No. of matched villages ( $Develop_i = 1$ )	386	386
No. of matched villages ( $Develop_i = 0$ )	386	386
No. of years	8	8
No. of observations	6176	6176

**Note:** The clustered standard errors of the coefficients are given in parentheses; \*, \*\*, and \*\*\* denote a significance level of 10%, 5%, and 1%, respectively; a Hausman test shows that a fixed effect model is better than a random effect model; the other coefficients are listed in Table A.1 in the Appendix A.

development-permitted zones between 2010 and 2020 was 83.23 km<sup>2</sup>, with zoning preventing an additional 32.46% of built-up land expansion outside the development-permitted zones. We further controlled for the continuous planning variable and found that an additional percentage of land area assigned to the development-permitted zones increased built-up land expansion by 0.06%.

To compare with the average effect from the PSM-DID approach, we performed an overlay analysis to assess built-up land expansion inside and outside the development-permitted zones. We found that built-up land area increased from 325.48 km<sup>2</sup> in 2010 to 353.19 km<sup>2</sup> in 2020 inside the development-permitted zones. Meanwhile, built-up land area increased from 562.26 km<sup>2</sup> to 645.49 km<sup>2</sup> outside the development-permitted zones (83.23 km<sup>2</sup>) was three times higher than the amount inside the development-permitted zones (27.71 km<sup>2</sup>). These results indicate that much of the built-up land expansion occurred outside the development-permitted zones, despite the fact that zoning played a causal role in containing built-up land expansion as shown above.

# 4.2. Annual effect

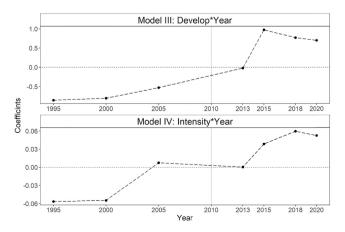
We found a time-lag effect in the initial implementation period of the land-use plan in Zhangzhou City. Zoning did not play a causal role in containing built-up land expansion until 2013, because the coefficients of *Develop*<sub>i</sub>\**Year*<sub>2013</sub> (-0.02, p = 0.50) and *Intensity*<sub>i</sub>\**Year*<sub>2013</sub> (0.0003, p = 0.60) were close to zero and non-significant (Fig. 5 and Table A.2). However, the coefficients of *Develop*<sub>i</sub>\**Year*<sub>2015</sub> (0.97, p = 0.06), *Intensity*<sub>i</sub>\**Year*<sub>2015</sub> (0.04, p = 0.02), and *Intensity*<sub>i</sub>\**Year*<sub>2018</sub> (0.06, p = 0.05) were positive and significant. These results indicate that zoning started to play a causal role in containing built-up land expansion after 2013.

Besides the time-lag effect, we found that zoning became ineffective in containing built-up land expansion as time elapsed. When we used a binary planning variable, the coefficients of  $Develop_i^*Year_{2018}$  (0.77, p = 0.13) and  $Develop_i^*Year_{2020}$  (0.70, p = 0.21) decreased and became nonsignificant. This means that zoning was ineffective in containing built-up land expansion in 2018 and 2020. When we controlled for the continuous planning variable, the coefficient of  $Intensity_i^*Year_{2020}$  (0.05, p = 0.10) also decreased and became non-significant.

### 4.3. Robustness checks

### 4.3.1. Parallel trend test

We conducted an event study (model III) to validate the parallel trend assumption using the unmatched and matched data (Table 3). Before applying PSM, the coefficients of  $Develop_i^*Year_{1995}$ ,  $Develop_i^*$ 



**Fig. 5.** The coefficients of  $Develop_i^*Year_j$  in model III and  $Intensity_i^*Year_j$  in model IV; the other coefficients are listed in Table A.2 in the Appendix A.

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## Table 3

Event study on the parallel trend assumption before and after matching

· · · · · · · · · · · · · · · · · · ·	F F	0
Variable	Before matching	After matching
Develop <sub>i</sub> *Year <sub>1995</sub>	-6.03*** (0.7)	-0.85 (0.81)
Develop <sub>i</sub> *Year <sub>2000</sub>	-5.51*** (0.68)	-0.8 (0.81)
Develop <sub>i</sub> *Year <sub>2005</sub>	-1.53*** (0.37)	-0.53 (0.47)
Develop <sub>i</sub> *Year <sub>2013</sub>	0.04* (0.02)	-0.02 (0.03)
Develop <sub>i</sub> *Year <sub>2015</sub>	0.46 (0.42)	0.97* (0.51)
$Develop_i$ * $Year_{2018}$	0.13 (0.41)	0.77 (0.51)
Develop <sub>i</sub> *Year <sub>2020</sub>	-0.17 (0.44)	0.7 (0.55)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R <sup>2</sup>	0.28	0.19
Hausman test	743.6 ***	138.15 ***
No. of villages ( $Develop_i = 1$ )	692	386
No. of villages ( $Develop_i = 0$ )	970	386
No. of years	8	8
No. of observations	13,296	6176

**Note:** The clustered standard errors of the coefficients are given in parentheses; \*, \*\*, and \*\*\* denote a significance level of 10%, 5%, and 1%, respectively; a Hausman test shows that a fixed effect model is better than a random effect model; the other coefficients are listed in Table A.3 in the Appendix A.

 $Year_{2000}$ , and  $Develop_i^*Year_{2005}$  were significant, which implies that the villages had different trends in terms of built-up land expansion before the land-use plan was implemented (Fig. 6). After implementing PSM, the coefficients of  $Develop_i^*Year_{1995}$ ,  $Develop_i^*Year_{2000}$ , and  $Develop_i^*$   $Year_{2005}$  were non-significant, suggesting that the matched villages followed a parallel trend in terms of built-up land expansion before the implementation of the land-use plan (Fig. 6). Meanwhile, after the implementation of the land-use plan, the coefficient of  $Develop_i^*Year_{2015}$  became significant. Taken together, these results demonstrate that the matched data satisfied the parallel trend assumption, which enabled us to evaluate the causal effect of zoning using a DID method.

## 4.3.2. Balance check

After implementing PSM, we checked the balance of the matched data. All eight confounding variables had a SMD <0.1 after matching (Fig. 7). Moreover, the SMD of the propensity scores decreased dramatically with matching, from 1.53 to 0.03. This indicates that PSM removed the selection bias effectively. The remaining difference in builtup land expansion between the villages located inside the developmentpermitted zones and the matched villages located outside the developmenterne in planning status.

## 4.3.3. Placebo test

In the placebo test, the coefficient of  $Develop_i^*Time_t$  was non-

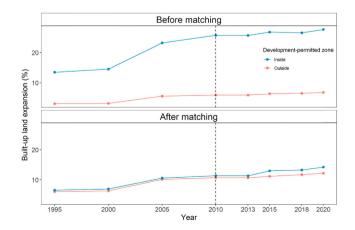


Fig. 6. Trends of built-up land expansion from 1995 to 2020.

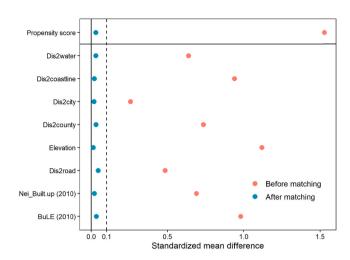


Fig. 7. Standardized mean difference of the confounding variables and the propensity score before and after matching.

significant (1.15, p = 0.13, Table A.4), indicating that zoning had no effect if the land-use plan in Zhangzhou City was approved in 2005. The results of the placebo test enhance the credibility of our findings. In addition, we did not detect an anticipation effect.

### 5. Discussion

# 5.1. Causal effect of spatial planning

While the ineffectiveness of spatial planning on containing built-up land expansion is common around the world (Abrantes, Fontes, Gomes, & Rocha, 2016; Alfasi, Almagor, & Benenson, 2012; Guo et al., 2020; Kleemann et al., 2017; Sharifi, Chiba, Okamoto, Yokoyama, & Murayama, 2014; Wang, Han, & Lai, 2014), most previous research did not answer the question of how built-up land expansion would have differed in the absence of spatial planning. In our study, we used a PSM-DID approach to test the causal effect of zoning in containing built-up land expansion in Zhangzhou City, China between 2010 and 2020. We found that zoning restricted 32.46% of built-up land expansion outside the development-permitted zones. This finding remained robust when we used a continuous planning variable. Our findings are consistent with some research suggesting the effectiveness of spatial planning in containing built-up land expansion via a DID model (Dempsey & Plantinga, 2013; Fang & Tian, 2020). For example, (Fang & Tian, 2020) found that construction land would have expanded by an additional 70 ha annually for each city in the absence of construction land quotas, which have been broken in over one-third of Chinese cities.

The discrepancy between our findings and most previous research, which suggested the failure of spatial planning in containing built-up land expansion, results from how the effect was defined. In previous studies, the effect was commonly evaluated by comparing the actual built-up land expansion with the intended built-up land expansion. We likewise evaluated such effect and found that the amount of built-up land expansion outside the development-permitted zones (83.23 km<sup>2</sup>) was three times as large as the amount inside the developmentpermitted zones (27.71 km<sup>2</sup>) between 2010 and 2020 in Zhangzhou City. In our study, the effect was defined as the difference between the actual built-up land expansion and the counterfactual built-up land expansion that would have occurred without spatial planning. This definition descends from Lewis's theory of causality based on counterfactual thinking (Lewis, 1973). Our results from the PSM-DID approach provide compelling causal evidence for the effectiveness of zoning in containing built-up land expansion. The question of how to define the effect is still controversial in plan evaluation (Alexander, 2009; Baer, 1997; Wong & Watkins, 2009). As (Baer, 1997) suggested, implementation evaluation of spatial planning may fall into either a glass-half-empty or a glass-half-full perspective. The former results in discouragement due to non-conformance between the plan and reality, while the latter is optimistic when reality turns out to be more like the plan than it would have been without the plan.

### 5.2. Time in plan evaluation

Time influences the occurrence and evaluation of plan success or failure (Baer, 1997; Bressers et al., 2013; Loh, 2011). However, empirical evidence for whether and how the effect of spatial planning varies across time is rare. In our study, we quantitively tested the annual effect of zoning on built-up land expansion after the land-use plan was implemented (2010–2020). Our results indicate that a time-lag effect existed in the initial period of plan implementation. Land-use planning is a top-down system in China: planning at lower administrative levels needs to comply with the guidelines set by higher administrative levels. It is inevitable that the lower-level governments spend considerable amounts of time coordinating with the higher-level land-use planning authorities to develop their land-use decision-making. The land-use plan in Zhangzhou City was approved in August 2010. Based on our findings, it is reasonable to observe that zoning started to play a causal role in containing built-up land expansion after 2013.

Besides the time-lag effect, we found that zoning became ineffective in containing built-up land expansion as time elapsed. This finding is consistent with prior research in other countries suggesting that the effect of spatial planning reduces over time (Alterman & Hill, 1978; Feitelson, Felsenstein, Razin, & Stern, 2017; Padeiro, 2016). In our case, the reduced effect of zoning can be explained by three reasons. First, the land-use plan in Zhangzhou City was outdated by 2020, considering that data from 2005 were used as the baseline data in plan-making. Second, the demand for built-up land continued to increase as Zhangzhou City experienced rapid population and economic development. Regulatory plans tend to become less effective over time as development pressures mount (Feitelson et al., 2017). In addition, we attribute the declining effect of zoning in Zhangzhou City to the reform of the spatial planning system in China. In 2018, the Ministry of National Resources was established to replace the Ministry of Land and Resources that had been in charge of land-use planning. In 2019, the National Territory Spatial Planning was proposed to integrate different spatial planning, such as land-use planning, urban planning, and major function-oriented zoning. These changes reduced the causal effect of zoning in containing built-up land expansion at the end of plan implementation.

While results on the average effect show that zoning was effective in containing built-up land expansion between 2010 and 2020, results on the annual effect reveal that the effects of zoning varied during the implementation of the land-use plan. We argue that plan evaluation is insufficient if the temporal dimension during plan implementation is not considered adequately. To ensure rigorous plan evaluation, future work should include a temporal match between the planned and evaluated time horizons, thereby making it possible to look at the entire planning cycle, and should incorporate multiple time points representing detailed dynamics of plan implementation. Such future work will be supported by the digitalization of plan data in public administration (Hersperger & Fertner, 2021) and by publicly available land-use data at a fine spatio-temporal scale.

#### 5.3. Implications for other cities

A 3-year time-lag effect existed during the implementation of the land-use plan in Zhangzhou City, as zoning started to play a causal role in containing built-up land expansion after 2013. While a time-lag effect is expected, it would be interesting to better understand how long it generally takes for the effect of spatial planning on land-use change to become visible. Unfortunately, there are currently few such studies in other cities that can be compared with our case study. Spatial planning is only as effective as the governance capacity to enforce it (le Polain de Waroux et al., 2016; McNeill et al., 2014). The effect of spatial planning on land-use change takes more time to become visible when governance capacity is poor. Taking our findings from Zhangzhou City as a reference, we would expect to observe a time-lag effect of less than 3 years in Shanghai, Beijing, and other provincial capitals, because these cities have a greater governance capacity (Wang, 2020).

Land-use zoning in China is under unprecedented pressure to fulfill the task of containing built-up land expansion resulting from rapid urbanization. Criticism of its effectiveness is prevalent, as discrepancies between zoning and the actual built-up land expansion have been reported in many cities (Guo et al., 2020; Liu et al., 2020; Shao et al., 2018; Shen et al., 2021), and the credibility of land-use planning is therefore declining. We argue, however, that a lack of conformance alone does not mean that causality does not exist. Indeed, our findings suggest that zoning played a causal role in containing built-up land expansion in Zhangzhou City. The causal evidence from our case study can enhance the credibility of land-use planning in other Chinese cities. In addition, there are many similar spatial plans in other countries that regulate the amount and location of built-up land via command-and-control mechanisms, such as urban growth boundaries (Gennaio, Hersperger, & Bürgi, 2009), green belts (Macdonald, Monstadt, & Friendly, 2020; Siedentop, Fina, & Krehl, 2016), and land-use zoning (Alfasi et al., 2012; Sharifi et al., 2014). Our study has implications for the causal evaluation of these plans, especially for developing countries that face severe conflicts between built-up land expansion and natural land protection.

## 5.4. Potential bias from omitted variables

We should be aware that our models and results could be subject to omitted variable bias. Potential variables that also could be used to answer whether zoning plays a causal role in containing built-up land expansion in Zhangzhou City, China are economic and population growth, economic and population size, employment, household size and number, incomes, etc. These variables are important drivers of built-up land expansion and tend to be positively correlated with the planning variables in this study. For example, villages with high economic and population growth are more likely to expand built-up land and to be assigned into the development-permitted zones than those with low economic and population growth. These potential omitted variables usually vary both across villages and over years. Our two-ways fixed effects model is unable to eliminate the bias from omitting these variables, because the two-ways fixed effects model is only immune to omitted variable bias coming from variables that are constant either over years or across villages. Mathematically, a positive covariance of the omitted variables with both the dependent variable and the key independent variables results in the coefficients of the key independent variables being larger than the true value of these coefficients (Wilms, Mäthner, Winnen, & Lanwehr, 2021). That is, if we had been able to include these variables, we would have found smaller effect sizes of zoning in containing built-up land expansion. For example, we expect that we would have found that zoning would have prevented less than 27.02 km<sup>2</sup> of built-up land expansion outside the developmentpermitted zones between 2010 and 2020. However, the omitted variables do not threaten the statistical significance since our sample size is relatively large (Wilms et al., 2021). Taken together, the omitted variable bias does not compromise the validity of our conclusion answering the question whether zoning plays a causal role in containing built-up land expansion.

# 6. Conclusion

As built-up land expansion is emerging as an important sustainability concern, spatial plans to contain built-up land expansion are not lacking. However, causal evidence to support these plans is scarce. The PSM-DID approach applied here can provide causal evidence for the effect of spatial planning on land-use change. In this study, we examined the average and annual effect of zoning on built-up land expansion, taking Zhangzhou City, China as an example. We found that zoning was effective in containing built-up land expansion; specifically, it restricted  $27.02 \text{ km}^2$  of built-up land expansion outside the development-permitted zones between 2010 and 2020. Furthermore, we observed a time-lag effect at the initial implementation period of the land-use plan. Zoning started to play a causal role in containing built-up land expansion only after 2013. Finally, zoning became ineffective in containing built-up land expansion at the end of plan implementation.

In this study, we focused on the causal effect of zoning on the amount of built-up land expansion because the land-use plan in Zhangzhou City mainly aimed to restrict built-up land expansion areas. The causal effect of zoning on built-up land expansion types and forms deserves more attention in future, because zoning may be ineffective in controlling built-up land expansion types and forms, as seen with leapfrog development. In addition, the pattern and the underlying drivers of the nonconforming built-up land expansion need to be explored in future research.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104339.

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