MARTIN-LUTHER-UNIVERSITÄT
HALLE-WITTENBERG

From spatial planning to built-up land expansion: Plan evaluation in southeastern China

Dissertation

zur Erlangung des

Doktorgrades der Naturwissenschaften (Dr. rer. nat.)

der

Naturwissenschaftlichen Fakultät III

Agrar- und Ernährungswissenschaften,

Geowissenschaften und Informatik

der Martin-Luther-Universität Halle-Wittenberg

Presented by

Mr. **Zhichao He**

Born in 15th Feb. 1991 (Fujian Province, China)

Supervisors:

1. Prof. Dr. Christine Fürst

Martin-Luther Universität Halle-Wittenberg, Institut für Geowissenschaften und Geographie

2. Prof. h.c. Dr. Anna M. Hersperger

Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL

Reviewers:

1. Prof. Dr. Christine Fürst

2. Prof. Dr. Wolfgang Wende

Data of defense: 16 May 2023

Executive summary

Background and motivation

As a salient and rapid human-induced change on the Earth's surface (Gao & O'Neill, 2020; Seto et al., 2012), built-up land expansion has been an important sustainability concern (Acuto et al., 2018). 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 across the world. This dissertation emerged from two gaps between spatial planning and land-system science. The non-conformance of built-up land expansion to spatial planning is common worldwide, most research, however, did not answer the question of (1) how built-up land expansion would have differed in the absence of spatial planning and (2) why non-conforming built-up land expansion happens, persists, and spreads. These two raise doubts on the credibility of spatial planning and hinder theoretical developments in land-system science.

China is one of the world's hotspots of built-up land expansion (M. Li et al., 2022; Seto et al., 2011). China's government has implemented many spatial plans, e.g., land use planning, urban planning, Major Function Oriented Zone (MFOZ), to contain rapid built-up land expansion. However, numerous plan evaluations indicated limited success of these spatial plans in containing built-up land expansion, as rapid expansion of built-up land often did not follow established planning regulations (T. Liu et al., 2020; Shao et al., 2018; Shen et al., 2019; L.-G. Wang et al., 2014; Zhong et al., 2014). Against this background this dissertation evaluates the causal effect of spatial planning in containing built-up land expansion and explores the characteristics and drivers of non-conforming built-up land expansion in southeastern China. The specific methods and findings were published in three peer-reviewed scientific journals, and the contents of this dissertation are based on these three articles as a cumulative format.

Research objectives

This dissertation aims to add valuable new knowledge that can better understand the contribution of spatial planning to land use changes. The two research gaps mentioned above prompt the two key research objectives at the center of this dissertation. The first research objective is to broaden the understanding of how plan effect is defined. This dissertation defines the causal effect as the difference between the actual built-up land expansion and the counterfactual built-up land expansion that would have occurred without spatial planning. The causal effect of spatial planning was estimated in southeastern China (Zhangzhou City and Fujian Province) using two quasi-experimental methods. The second research objective is to improve the understanding of why large amounts of built-up land have expanded in areas that are non-conforming with uses by planning regulations. The quantity, location, expansion types, and drivers of non-conforming built-up land expansion were analyzed in Zhangzhou City between 2010 and 2020, via conformance-based evaluation and spatial autoregressive models

Data and methods

Multiple spatial data were used in this dissertation. Land use data (1995, 2000, 2005, 2010, 2013, 2015, 2018, and 2020) were obtained from Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The land use data had a vector format and were manually interpreted from Landsat TM and 8 images with six land use types: arable land, forest, grassland, water, built-up land, and bare land. The land use plan in Zhangzhou City (2010–2020) and the MFOZ in Fujian Province (2013-2020) were provided by the local government. The digital elevation model (resolution 30 × 30 m), the raster data for GDP and population in 2010 (resolution 1 × 1 km), road network data for 2010 were collected to extract other control variables of built-up land expansion.

Four methods were used in this dissertation. (1) Propensity score matching (PSM) was used to compare the changes in the amount of built-up land in the towns of the development-prioritized zones with the matched towns of the development-restricted zones. (2) Difference-in-difference model with propensity score matching (PSM-DID) was used to compare the average built-up land expansion of the villages located inside the development-permitted 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). (3) Conformance-based evaluation was used to evaluate the extent to which built-up land zoning contained the actual built-up land expansion. (4) Spatial autoregressive models (SAR) were used to estimate the peer effects and other drivers on non-conforming built-up land expansion. The first two methods served to answer whether built-up land zoning (2010-2020) and the MFOZ (2013-2020) played a causal role in containing built-up land expansion in two study areas (Zhangzhou City and Fujian Province) in southeastern China. The third method was used to reveal the quantity, location, and expansion types of the non-conforming built-up land expansion in Zhangzhou City between 2010 and 2020. The last method served to estimate peer effects and other factors facilitating non-conforming built-up land expansion at the village level in Zhangzhou City between 2010 and 2020.

Results

The results from the PSM and PSM-DID provide causal evidence for the effectiveness of built-up land zoning and the MFOZ in containing built-up land expansion. Zhangzhou's built-up land zoning prevented 27.02 km^2 of built-up land expansion in the development-restricted zones between 2010 and 2020, and Fujian's MFOZ prevented a total of 79.31 km^2 of built-up land within the development-restricted zones between 2013 and 2020. In short, built-up land would have expanded by an additional 27.02 km^2 and 79.31 km^2 if there were no built-up land zoning in Zhangzhou City and the MFOZ in Fujian Province.

The results from the PSM and PSM-DID suggest a time-lag effect during plan implementation. The causal effect of the MFOZ varied from ineffective at the start of its implementation (2013-2015) to effective later in its implementation period (2013-2018 and 2013-2020) in Fujian Province. Likewise, built-up land zoning of Zhangzhou City did not play a causal role in containing built-up land expansion before 2013.

The results based on the conformance-based evaluation reveals the quantity, location, and expansion types of non-conforming built-up land expansion in Zhangzhou City between 2010 and 2020. The newly developed built-up land area between 2010 and 2020 covered 144.75 km^2, with non-conforming built-up land expansion accounted for 67.61% (97.87 km^2). These non-conforming expansions occurred mostly through a transition from arable land and forest to industry/mining/transport uses. Edge expansion was the dominant type of non-conforming built-up land expansion, and only a small percentage of the non-conforming built-up land expansion was infill expansion.

The results of the SAR estimated five types of peer effects and other factors facilitating the non-conforming built-up land expansion at the village level. A given village's non-conforming built-up land area increased by 3.9%, 6.2%, 22.5%, 4.7%, and 7.1% if its geographical peers, political peers, economic peers, geographical-economic peers, and political-economic peers increased in non-conforming built-up land area by 10%. Besides the peer effects, the villages with further distance to county centers, lower elevations, more available arable land and grassland in 2010, and less land located inside development-permitted zones, would expand more non-conforming built-up land area between 2010 and 2020.

Discussion

As built-up land expansion has emerged 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. Spatial planning in China often failed to contain built-up land expansion as planned. Criticism of its effectiveness is prevalent, and the credibility of spatial planning is therefore declining. This dissertation argues, however, that a lack of conformance between spatial planning and built-up land expansion does not necessarily mean that causality does not exist. Indeed, the findings suggest that built-up land zoning and the MFOZ played a causal role in containing built-up land expansion in southeastern China. The causal evidence from this dissertation can enhance the credibility of spatial planning in other Chinese cities.

Time influences the occurrence and evaluation of plan success or failure. However, empirical evidence for time-lag effect of spatial planning is rare. Spatial planning is a top-down system in China. It is inevitable that the lower-level planning authorities spend considerable amounts of time coordinating with the higher-level planning authorities to develop their land use decision-making. The built-up land zoning and MFOZ was approved in 2010 and 2013, respectively. It is reasonable to observe that these two plans started to play a causal role in containing built-up land expansion with 2 or 3-year lag.

The large amount of non-conforming built-up land expansion in Zhangzhou City between 2010 and 2020 raises serious concerns. These non-conforming expansions were at the expense of arable land and forest. This pattern may threaten food security, biodiversity, and landscape quality. The prominence of non-conforming industry/mining/transportation development is closely associated with oversupply of industrial land in China. While the extensive non-conforming development of industry/mining/transportation land promotes local economic growth in the short term, it may lead to an overheated economy, excess production capacity, and inefficient land use. Most non-conforming built-up land contribute to reducing landscape fragmentation and improving urban agglomeration via edge expansion.

While the non-conformance between established zoning regulations and built-up land expansion is commonplace around the world, few attempts have been made to analyze spatial interdependencies between local government's land use behaviors of violating established zoning regulations. The findings reveal five positive peer effects driving villages to violate zoning in Zhangzhou City between 2010 and 2020. The primary motivation for villages to violate zoning is to compete for economic growth, which fits the common view that China's local governments, fiercely competing for economic growth, reduce established regulatory rules (e.g., lower environmental standards, lenient land development permissions, lower industrial land prices) to attract investment, thereby leading a "race to the bottom".

Conclusions

This dissertation used quasi-experimental methods to evaluate the causal effect of spatial planning in containing built-up land expansion, used conformance-based evaluation to investigate the characteristics of non-conforming built-up land expansion, and used the SAR to estimate peer effect on non-conforming built-up land expansion in southeastern China. Key findings are: 1) more built-up land would have expanded at the absence of spatial planning; 2) the causal effect of spatial planning varied across time; 3) the large amount of non-conforming built-up land expansion raises serious concerns, e.g., arable land and forest loss, inefficient land use, overheated economy, excess production capacity; 4) the peer effects facilitate non-conforming built-up land expansion. The findings of this dissertation improve better understanding of the contribution of spatial planning to land use changes. I recommend wider applications of causal inference in plan evaluation, greater detailed investigation of the influence of time on plan effect, and closer examination on non-conforming built-up land expansion. To doing so, closer interdisciplinary collaborations between spatial planning and land-system science should be established.

Zusammenfassung

Hintergrund und Motivation

Die Ausdehnung bebauter Flächen ist eine auffällige und rasche vom Menschen verursachte Veränderung der Erdoberfläche (Gao & O'Neill, 2020; Seto et al., 2012) und stellt ein wichtiges Nachhaltigkeitsproblem dar (Acuto et al., 2018). Die zunehmenden Auswirkungen der Ausdehnung bebauter Flächen auf die nachhaltige Entwicklung haben den Einsatz der Raumplanung als politisches Instrument zur Eindämmung der Ausdehnung bebauter Flächen auf der ganzen Welt verstärkt. Diese Dissertation entstand aus zwei Lücken zwischen Raumplanung und Landsystemwissenschaft. Die meisten Forschungsarbeiten gaben jedoch keine Antwort auf die Frage, (1) wie sich die Ausdehnung bebauter Flächen ohne Raumplanung verändert hätte und (2) warum eine nicht konforme Ausdehnung bebauter Flächen stattfindet, fortbesteht und sich ausbreitet. Diese beiden Fragen lassen Zweifel an der Glaubwürdigkeit der Raumplanung aufkommen und behindern die theoretischen Entwicklungen in der Landsystemwissenschaft.

China ist einer der weltweiten Hotspots für die Ausdehnung bebauter Flächen (M. Li et al., 2022; Seto et al., 2011). Um die rasche Ausdehnung der bebauten Fläche einzudämmen, hat die chinesische Regierung viele Raumordnungspläne umgesetzt, z. B. Flächennutzungsplanung, Stadtplanung, funktionsorientierte Hauptzonen (MFOZ). Zahlreiche Planevaluierungen haben jedoch gezeigt, dass diese Raumordnungspläne bei der Eindämmung der Ausdehnung bebauter Flächen nur begrenzt erfolgreich waren, da die rasche Ausdehnung bebauter Flächen häufig nicht den festgelegten Planungsvorschriften folgte (T. Liu et al., 2020; Shao et al., 2018; Shen et al., 2019; L.-G. Wang et al., 2014; Zhong et al., 2014). Vor diesem Hintergrund bewertet diese Dissertation die kausale Wirkung der Raumplanung bei der Eindämmung der Baulandausweitung und untersucht die Merkmale und Triebkräfte der nicht konformen Baulandausweitung im Südosten Chinas. Die spezifischen Methoden und Ergebnisse wurden in drei wissenschaftlichen Fachzeitschriften mit Peer-Review veröffentlicht, und der Inhalt dieser Dissertation basiert auf diesen drei Artikeln in kumulativer Form.

Forschungsziele

Ziel dieser Dissertation ist es, wertvolle neue Erkenntnisse zum besseren Verständnis des Beitrags der Raumplanung zu Landnutzungsänderungen zu gewinnen. Die beiden oben erwähnten Forschungslücken führen zu den beiden zentralen Forschungszielen, die im Mittelpunkt dieser Dissertation stehen. Das erste Forschungsziel besteht darin, das Verständnis für die Definition von Planungseffekten zu erweitern. In dieser Dissertation wird der kausale Effekt als die Differenz zwischen der tatsächlichen Ausdehnung der bebauten Fläche und der kontrafaktischen Ausdehnung der bebauten Fläche, die ohne Raumplanung stattgefunden hätte, definiert. Der kausale Effekt der Baulandausweisung und des MFOZ wurde im Südosten Chinas (Stadt Zhangzhou und Provinz Fujian) mit zwei quasi-experimentellen Methoden geschätzt. Das zweite Forschungsziel besteht darin, das Verständnis dafür zu verbessern, warum sich große Mengen an bebautem Land in Gebiete ausgedehnt haben, die nicht mit den planungsrechtlichen Nutzungen übereinstimmen. Die Menge, der Ort, die Art der Ausdehnung und die Ursachen für die nicht konforme Ausdehnung von bebautem Land wurden in der Stadt Zhangzhou zwischen 2010 und 2020 mittels konformitätsbasierter Bewertung und räumlich autoregressiver Modelle analysiert.

Daten und Methoden

In dieser Dissertation wurden mehrere räumliche Daten verwendet. Die Landnutzungsdaten (1995, 2000, 2005, 2010, 2013, 2015, 2018 und 2020) wurden vom Datenzentrum für Ressourcen und Umweltwissenschaften der Chinesischen Akademie der Wissenschaften (RESDC) bezogen (http://www.resdc.cn). Die Landnutzungsdaten hatten ein Vektorformat und wurden manuell aus Landsat TM- und 8-Bildern mit sechs Landnutzungstypen interpretiert: Ackerland, Wald, Grünland, Wasser, bebautes Land und unbebautes Land. Der Flächennutzungsplan der Stadt Zhangzhou (2010-2020) und das MFOZ der Provinz Fujian (2013-2020) wurden von der lokalen Regierung zur Verfügung gestellt. Das digitale Höhenmodell (Auflösung 30 × 30 m), die Rasterdaten für das BIP und die Bevölkerung im Jahr 2010 (Auflösung 1 × 1 km) und die Straßennetzdaten für das Jahr 2010 wurden gesammelt, um andere Kontrollvariablen für die Ausdehnung der bebauten Flächen zu ermitteln.

In dieser Dissertation wurden vier Methoden verwendet. (1) Mit Hilfe des Propensity Score Matching (PSM) wurden die Veränderungen der bebauten Fläche in den Städten der entwicklungspriorisierten Zonen mit den entsprechenden Städten der entwicklungsbeschränkten Zonen verglichen. (2) Das Differenz-Indifferenz-Modell mit Propensity-Score-Matching (PSM-DID) wurde verwendet, um die durchschnittliche Ausdehnung der bebauten Fläche in den Dörfern innerhalb der Fördergebiete mit derjenigen ähnlicher Dörfer außerhalb der Fördergebiete zu vergleichen (mit-gegen-ähnlich-ohne-Differenz), und zwar vor und nach der Umsetzung des Plans (Vorher-gegen-Nachher-Differenz). (3) Mit Hilfe der konformitätsbasierten Bewertung wurde beurteilt, inwieweit die Ausweisung von Bauland die Ausdehnung der bebauten Flächen eindämmte. (4) Räumliche autoregressive Modelle (SAR) wurden verwendet, um die Auswirkungen von Peer-Effekten und anderen Einflussfaktoren auf die nicht konforme Ausdehnung bebauter Flächen zu schätzen. Die ersten beiden Methoden dienten der Beantwortung der Frage, ob die Baulandausweisung (2010-2020) und die MFOZ (2013-2020) eine kausale Rolle bei der Eindämmung der Baulandausweitung in zwei Untersuchungsgebieten (Stadt Zhangzhou und Provinz Fujian) im Südosten Chinas spielen. Die dritte Methode wurde verwendet, um die Menge, den Standort und die Art der Ausdehnung der nicht konformen bebauten Flächen in Zhangzhou City zwischen 2010 und 2020 zu ermitteln. Die letzte Methode diente der Schätzung von Peer-Effekten und anderen Faktoren, die eine nicht-konforme Baulanderweiterung auf Dorfebene in Zhangzhou City zwischen 2010 und 2020 begünstigen.

Ergebnisse

Die Ergebnisse der PSM- und PSM-DID-Methode liefern kausale Belege für die Wirksamkeit der Zonierung bebauter Flächen und des MFOZ bei der Eindämmung der Ausdehnung bebauter Flächen. Die Zonierung von Bauland in Zhangzhou verhinderte zwischen 2010 und 2020 eine Ausdehnung von 27,02 km^2 bebauter Fläche außerhalb der Zonen mit Entwicklungsgenehmigung, und die MFOZ in Fujian verhinderte zwischen 2013 und 2020 insgesamt 79,31 km^2 bebauter Fläche innerhalb der Zonen mit Entwicklungsbeschränkung. Kurz gesagt, die bebaute Fläche hätte sich um weitere 27,02 km^2 bzw. 79,31 km^2 vergrößert, wenn es in der Stadt Zhangzhou und der MFOZ in der Provinz Fujian keine Bebauungszonen gegeben hätte.

Die Ergebnisse von PSM und PSM-DID deuten auch auf einen zeitverzögerten Effekt während der Planumsetzung hin. Die kausale Wirkung der MFOZ variierte von unwirksam zu Beginn der Umsetzung (2013-2015) bis hin zu wirksam im späteren Verlauf des Umsetzungszeitraums (2013-2018 und 2013-2020) in der Provinz Fujian. Auch die Zonierung bebauter Flächen in der Stadt Zhangzhou spielte keine kausale Rolle bei der Eindämmung der Ausdehnung bebauter Flächen nach 2013. Neben dem Time-Lag-Effekt wurde die Bauleitplanung am Ende der Planumsetzung in der Stadt Zhangzhou unwirksam, was die Eindämmung der Baulandausweitung angeht.

Die Ergebnisse auf der Grundlage der konformitätsbasierten Bewertung zeigen die Menge, den Ort und die Erweiterungsarten der nicht konformen Baulandausweitung in Zhangzhou City zwischen 2010 und 2020. Die neu erschlossene bebaute Fläche zwischen 2010 und 2020 umfasste 144,75 km^2, wobei 67,61 % (97,87 km^2) auf nicht-konforme Bebauung entfielen. Diese nicht-konformen Erweiterungen erfolgten hauptsächlich durch den Übergang von Ackerland und Wald zu Industrie/Bergbau/Verkehrsnutzung. Die Ausdehnung von Randgebieten war die vorherrschende Art der nicht konformen Ausdehnung von bebautem Land, und nur ein kleiner Prozentsatz der nicht konformen Ausdehnung von bebautem Land war eine Ausdehnung durch Auffüllung.

Die Ergebnisse des SAR ergaben fünf Arten von Peer-Effekten und andere Faktoren, die die nicht-konforme Ausdehnung bebauter Flächen auf Dorfebene begünstigen. Die nicht-konforme bebaute Fläche eines bestimmten Dorfes nahm um 3,9%, 6,2%, 22,5%, 4,7%, und 7,1 % zu, wenn die geografischen, politischen, wirtschaftlichen, geografisch-wirtschaftlichen und politisch-wirtschaftlichen Peers ihre nicht-konforme bebaute Fläche um 10 % vergrößerten. Abgesehen von den Peer-Effekten würden die Dörfer mit größerer Entfernung zu den Kreiszentren, niedrigeren Höhenlagen, mehr verfügbarem Acker- und Grünland im Jahr 2010 und weniger Land innerhalb von Baugenehmigungszonen zwischen 2010 und 2020 mehr nicht-konforme bebaute Fläche ausweiten.

Diskussion

Da die Ausdehnung der bebauten Fläche zu einem wichtigen Anliegen der Nachhaltigkeit geworden ist, fehlt es nicht an Raumordnungsplänen zur Eindämmung der Ausdehnung der bebauten Fläche. Kausale Belege zur Unterstützung dieser Pläne sind jedoch rar. Die Raumplanung in China hat es oft nicht geschafft, die Ausdehnung des bebauten Landes wie geplant einzudämmen. Die Kritik an ihrer Wirksamkeit ist weit verbreitet, und die Glaubwürdigkeit der Raumplanung nimmt daher ab. In dieser Dissertation wird jedoch argumentiert, dass eine mangelnde Übereinstimmung zwischen Raumplanung und Baulandausweitung nicht unbedingt bedeutet, dass keine Kausalität besteht. In der Tat deuten die Ergebnisse darauf hin, dass die Flächennutzungsplanung und das MFOZ eine kausale Rolle bei der Eindämmung der Flächenausweitung im Südosten Chinas gespielt haben. Die kausalen Beweise aus dieser Dissertation können die Glaubwürdigkeit der Raumplanung in anderen chinesischen Städten erhöhen.

Die Zeit beeinflusst das Auftreten und die Bewertung des Erfolgs oder Misserfolgs von Plänen. Empirische Belege für den zeitlichen Effekt der Raumplanung sind jedoch selten. Raumplanung ist in China ein Top-Down-System. Es ist unvermeidlich, dass die Planungsbehörden der unteren Ebene viel Zeit damit verbringen, sich mit den Planungsbehörden der oberen Ebene abzustimmen, um ihre Entscheidungen zur Flächennutzung zu entwickeln. Die Zonierung von bebautem Land und die MFOZ wurden 2010 bzw. 2013 genehmigt. Es ist plausibel, dass diese beiden Pläne mit einer Verzögerung von 2 oder 3 Jahren begonnen haben, eine kausale Rolle bei der Eindämmung der Ausdehnung von bebautem Land zu spielen.

Das große Ausmaß der nicht konformen Ausdehnung von bebautem Land in Zhangzhou City zwischen 2010 und 2020 gibt Anlass zu ernster Besorgnis. Diese nicht-konforme Ausdehnung ging auf Kosten von Ackerland und Wald. Dieses Muster kann die Ernährungssicherheit, die biologische Vielfalt und die Landschaftsqualität gefährden. Die starke Ausdehnung von Industrie, Bergbau und Verkehr steht in engem Zusammenhang mit dem Überangebot an

Industrieflächen in China. Während die umfangreiche nicht-konforme Erschließung von Industrie-/Bergbau-/Verkehrsflächen kurzfristig das lokale Wirtschaftswachstum fördert, kann sie zu einer überhitzten Wirtschaft, überschüssigen Produktionskapazitäten und einer ineffizienten Flächennutzung führen. Die meisten nicht-konformen bebauten Flächen tragen dazu bei, die Landschaftsfragmentierung zu verringern und die städtische Agglomeration durch die Ausdehnung der Randgebiete zu verbessern.

Während die Nichtübereinstimmung zwischen den geltenden Flächennutzungsvorschriften und der Ausdehnung bebauter Flächen weltweit gang und gäbe ist, wurden bisher nur wenige Versuche unternommen, die räumlichen Interdependenzen zwischen dem Flächennutzungsverhalten der Kommunalverwaltungen bei Verstößen gegen die geltenden Flächennutzungsvorschriften zu analysieren. Die Ergebnisse zeigen fünf positive Peer-Effekte, die Dörfer in der Stadt Zhangzhou zwischen 2010 und 2020 dazu veranlassen, gegen die Bebauungsvorschriften zu verstoßen. Die Hauptmotivation für die Dörfer, gegen die Flächennutzungsvorschriften zu verstoßen, ist der Wettbewerb um wirtschaftliches Wachstum. Dies passt zu der weit verbreiteten Ansicht, dass Chinas Lokalregierungen im harten Wettbewerb um wirtschaftliches Wachstum etablierte Regulierungsvorschriften (z.B. niedrigere Umweltstandards, großzügigere Erschließungsgenehmigungen, niedrigere Preise für Industrieland) abbauen, um Investitionen anzulocken, und damit einen "Wettlauf nach unten" auslösen.

Schlussfolgerungen

In dieser Dissertation wurden quasi-experimentelle Methoden angewandt, um die kausale Wirkung der Raumplanung bei der Eindämmung der Baulandausweitung zu bewerten, die Merkmale der nicht konformen Baulandausweitung mit Hilfe der konformitätsbasierten Bewertung zu untersuchen und die SAR zur Schätzung des Peer-Effekts auf die nicht konforme Baulandausweitung im Südosten Chinas einzusetzen. Die wichtigsten Ergebnisse sind: 1) ohne Raumplanung hätte sich mehr bebautes Land ausgedehnt; 2) der kausale Effekt der Raumplanung variierte im Laufe der Zeit; 3) die große Menge an nicht-konformer Baulandausdehnung gibt Anlass zu ernsthaften Bedenken, z.B. Verlust von Ackerland und

Wäldern, ineffiziente Landnutzung, Überhitzung der Wirtschaft, Überschussproduktionskapazitäten; 4) die Peer-Effekte erleichtern die nicht-konforme Baulandausdehnung. Die Ergebnisse dieser Dissertation tragen zu einem besseren Verständnis des Beitrags der Raumplanung zu Landnutzungsänderungen bei. Ich empfehle eine breitere Anwendung von Kausalschlüssen bei der Bewertung von Plänen, eine detailliertere Untersuchung des Einflusses der Zeit auf die Wirkung von Plänen und eine genauere Untersuchung der nicht konformen Ausdehnung von bebautem Land. Zu diesem Zweck sollte eine engere interdisziplinäre Zusammenarbeit zwischen Raumplanung und Landsystemwissenschaft aufgebaut werden.

Table of contents

List of tables

List of figures

List of abbreviations

PSM	Propensity score matching
PSM-DID	Difference-in-difference model with propensity score matching
MFOZ	Major Function Oriented Zone
SAR	Spatial autoregressive model

1. Introduction

1.1 Background and motivation

As a salient human-induced change on the Earth's surface, built-up land has expanded at an unprecedented rate over recent decades (M. Li et al., 2022; Seto et al., 2011). This trend is projected to continue in the coming few decades (Gao & O'Neill, 2020). Rapid expansion of built-up land has been emerged as an important sustainable concern (Acuto et al., 2018; Foley et al., 2005; Nagendra et al., 2018; W. Zhou et al., 2022). One the one hand, it drives a series of environment changes from directly encroaching on cropland and natural land (Bren d'Amour et al., 2017; van Vliet, 2019) to indirectly causing biodiversity degradation (Seto et al., 2012). One the other hand, built-up land expansion is strongly correlated to economic development and dramatically promotes human's material living standards (Acuto et al., 2018; C. He, Huang, et al., 2014).

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. In response, governments around the world have deployed a range of policy tools, such as urban growth boundary policies (Gennaio et al., 2009; Long et al., 2013), greenbelt planning (Macdonald et al., 2020; Siedentop et al., 2016), urban planning (Sharifi et al., 2014; M. Wang et al., 2017), and land use planning (Alfasi et al., 2012; Zhong et al., 2014). However, numerous plan evaluations have indicated a lack of conformance of actual built-up land expansion to established planning regulations, and that there was a failure of spatial planning (Abrantes et al., 2016; Alfasi et al., 2012; Guo et al., 2020; Kleemann et al., 2017; Sharifi et al., 2014; L.-G. Wang et al., 2014). Limited success of spatial planning in containing built-up land expansion leads to prevalent criticism, and the credibility of spatial planning is therefore declining.

Land-system science considers spatial planning as one of the drivers of land use changes (Bürgi et al., 2004; Geist & Lambin, 2002). Literature reviews have shown that political drivers (e.g., spatial development policies, nature conservation policies and land use planning) were more frequently mentioned than economic, technological, cultural, and natural drivers, when explaining urban sprawl (Colsaet et al., 2018; Plieninger et al., 2016). However, land-system science still calls for more robust approaches to evaluate the causal effect of spatial planning on land use changes, in particular because driving force frameworks consider spatial planning as a process exogenous to land use system, thus neglecting the potential of selection bias (Meyfroidt, 2016). Furthermore, due to a paucity of planning data, researchers in land-system science often fail to distinguish between conforming and non-conforming built-up land when developing land-change theories and models (Tellman et al., 2020, 2021). A complete understanding of non-conforming built-up land expansion is still lacking in land-system science.

Causal evaluation of spatial planning and analysis of non-conforming expansion of built-up land are urgently required in China, as China has become the one of the world's hotspots of built-up land expansion (M. Li et al., 2022; Seto et al., 2011). To contain rapid built-up land expansion, China's government has implemented a series of spatial plans. However, plan evaluations in China often reported that large amounts of built-up land have expanded in areas that are non-conforming with uses by planning regulations (T. Liu et al., 2020; Shao et al., 2018; Shen et al., 2019; L.-G. Wang et al., 2014; Zhong et al., 2014). Against this background, China is an excellent laboratory to evaluate spatial plans based on causal relationships and investigate non-conforming expansion of built-up land.

This dissertation was conducted as a part of the CONCUR project - From plans to land change: how strategic spatial planning contributes to the development of urban regions, funded by the Swiss National Science Foundation. The author conducted case studies of China in the CONCUR context and this dissertation aims to add valuable new knowledge that can better understand the contribution of spatial planning to land use changes.

1.2 Literature reviews

1.2.1 Evaluation of spatial planning

(1) Conformance-based evaluation

If spatial planning intends to have any credibility as a discipline, plan evaluation is an inseparable part (E. R. Alexander & Faludi, 1989; Guyadeen & Seasons, 2016; Khakee, 1998; Oliveira & Pinho, 2010). Plan evaluation can be performed in different states in plan-making and plan-implementation, such as reliability of plan alternatives, quality of the plans, or achievement of planning intentions (Baer, 1997; Guyadeen & Seasons, 2018). This dissertation focus on the evaluation of plan implementation after plans are adopted and implemented. This type of evaluation aims to discover whether the plan is implemented, and if so, how it affects land use changes. Conformance-based evaluation is mostly used for such evaluation. Conformance-based evaluation proposes that the link between planned and actual land use changes is the "gold standard" in evaluating plan implementation effectiveness (Calkins, 1979; Chapin et al., 2008; Laurian et al., 2004; T. Liu et al., 2020).

In conformance-based evaluation, the effect of spatial planning is measured as the difference of land use changes between before- and after-planning period in the fixed region (Chai et al., 2009; Vorovencii, 2018; Walsh, 2012). Vorovencii (2018) quantified deforestation rates in Apuseni Natural Park (ANP), Romania in the pre- (1986–2002) and post-establishment (2002–2016) periods. The results show that the deforestation rates increased four times, from 0.03% in the pre-establishment period to 0.14% in the post-establishment period, which indicates Natural Park was ineffective in restricting deforestation. In addition, the effect of spatial planning is measured as the difference of land use changes between planning, e.g., inside protected areas, and non-planning regions, e.g., outside protected areas (Alfasi et al., 2012; Barber et al., 2012; Gennaio et al., 2009; Sharifi et al., 2014; Siedentop et al., 2016). Gennaio et al., (2009) analyzed the change of the developed land inside and outside building zones in four Swiss municipalities and found that more than 70% of the total expansion of developed land occurred inside building zones. It indicates that building zones effectively restricted the developed land expansion in Switzerland. Methodological simplicity dramatically promotes wide applications of conformance-based evaluation. Yet, conformance-based evaluation addresses merely correlation rather than causality, since it is unable to control selection bias (Andam et al., 2008; Blackman, 2013; Butsic et al., 2011).

(2) Selection bias

Selection bias is a central problem in the evaluation of the causal effect of spatial planning on land use changes. However, this problem has not been fully acknowledged to date (Blackman, 2013). A thought experiment to illustrate the problem of selection bias is as follow: $Y_i(1)$ and $Y_i(0)$ denote two changes in built-up land area for the same area i in the same period, where 1 indicates that the area i is assigned inside the urban growth boundaries and 0 indicates that the area i is assigned outside the urban growth boundaries. The difference between $Y_i(1)$ and $Y_i(0)$ in this example can only result from a difference in the planned status (inside or outside the urban growth boundaries), as the area i is unchanged. In this case, the effect of the urban growth boundaries on built-up land expansion could be computed as $Y_i(1) - Y_i(0)$ and could be considered as a causal effect.

However in reality, we cannot simultaneously observe $Y_i(1)$ and $Y_i(0)$. If we assume that the area i was assigned inside the urban growth boundaries, we are able to observe $Y_i(1)$, whereas the potential $Y_i(0)$ is missing and can be considered as a counterfactual for $Y_i(1)$. In most circumstances, researchers presume that an area j, outside the urban growth boundaries, is a counterfactual for the area i, and consider their difference ($Y_i(1) - Y_j(0)$) as an effect of the urban growth boundaries on built-up land expansion. However, this is arbitrary due to selection bias inherent in plan-making, in which the most suitable areas are assigned for particular uses. The areas with higher suitability for built-up land are more likely to be assigned inside the urban growth boundaries, and these areas are more likely to experience higher built-up land expansion due to their higher suitability for built-up land use, rather than due to the urban growth boundaries.

(3) PSM-based evaluation

To overcome the evaluation problems associated with selection bias, a PSM-based evaluation was developed as an effective statistical tool for evaluating the causal effect (Imbens & Rubin, 2015; Rosenbaum & Rubin, 1983). It follows counterfactual thinking and regards the causal effect as the difference in the outcome when the characteristics of the evaluated units are identical in all aspects except in the variable of interest (Imbens & Rubin, 2015). Recent studies applied the PSM to evaluate the effect of protected areas or forest conservation policies on forest change (Andam et al., 2008; Bruggeman et al., 2015; Putraditama et al., 2019) or the effect of agricultural land preservation programs on farmland loss (X. Liu & Lynch, 2011). The main principle of the PSM-based evaluation is to find counterfactual units which are close to evaluated units in terms of confounding variables. Confounding variables such as elevation, distance to the nearest urban center, etc. are crucial, as they impact both the planned status (plan-making) and land use changes. However, they are often neglected in causal evaluations of spatial planning and land use changes.

By incorporating confounding variables into evaluations, the PSM-based evaluation enables us to untangle the interplay of spatial planning and confounding variables and to identify land use changes which are solely attributable to spatial planning. The PSM-based evaluation is promising because, aside from handling selection bias, it relies on observational data (such as land use data from remote sensing, socioeconomic data from censuses and big data from social sensing). Additionally, it is less restrictive to model assumption and model specification, as it is based on non-parametric estimations. Despite the above-mentioned strengths of the PSM, it still suffers from the weakness of hidden biases caused by the unobserved confounding variables (Paul R. Rosenbaum, 2002). For example, leaders' judgements often influence the probability of the area to be assigned into a specific zone during the plan-making and the probability of this area to be developed in the actual development. The subjective judgements are the unobserved confounding variable which is out of control of the PSM.

(4) DID-based evaluation

Besides the PSM, the DID has been developed to evaluate the causal effect of a policy on the outcome of interest (Abadie, 2005; Wing et al., 2018). The principle of the DID is to compare the changes in outcome in the evaluated units affected by a policy with that of the evaluated units not affected by a policy (with-versus-without difference), before and after policy implementation (before-versus-after difference). The DID, which combines the before-versus-after difference and the with-versus-without difference, can get closer to causality than either difference alone (Blackman, 2013; Butsic et al., 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 et al., 2008; Z. He et al., 2021). For example, urban proximity not only influences built-up land expansion, but also influences zoning.

The DID uses the before-versus-after difference to eliminate time-invariant factors and uses the with-versus-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 et al., 2014). While the 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 changes. One of the challenges is that the 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 land use changes via the DID requires land use data spanning over 10 years.

1.2.2 Non-conforming expansion of built-up land

(1) A concerning degree of non-conforming built-up land expansion

Rapid expansion of built-up land is widespread and often does not follow established planning regulations. For example, plan evaluation in Lisbon metropolitan region indicates that 46.9% of newly developed built-up land between 1990 and 2007 were not conforming to land use planning (Abrantes et al., 2016). Plan evaluations in developing countries (e.g., China, Brazil, Pakistan, Ethiopia) often reported non-conformance rates of 50–60% (Bulti & Sori, 2017; Hussain & Nadeem, 2021; Liu et al., 2020; Menzori et al., 2021; L. Tian & Shen, 2011; L.-G.

Wang et al., 2014). While the non-conformance of built-up land expansion to spatial planning is commonplace worldwide, an understanding of why this non-conformance happens, persists, and spreads is still lacking yet urgently needed in land-system science and spatial planning. One the one hand, due to a paucity of planning data, researchers in land-system science often fail to distinguish between conforming and non-conforming built-up land when developing land-change theories and models (Tellman et al., 2020, 2021). One the other hand, spatial planning is struggling to manage built-up land expansion in an orderly manner (Domingo et al., 2021; Hersperger et al., 2019). However, plan evaluations have frequently indicated that a large proportion of built-up land expansion was non-conforming and suggested that it is a main cause of plan ineffectiveness (Abrantes et al., 2016; Alfasi et al., 2012; T. Liu et al., 2020; Sharifi et al., 2014; Sobhani et al., 2021).

The non-conforming expansion of built-up land may exacerbate environmental problems. The non-conforming expansion mostly were at the expanse of arable land and forest, thereby threatening food security, biodiversity, and landscape quality (Alfasi et al., 2012; Shen et al., 2019). Non-conforming built-up land expansion will lead to a more fragmented land use pattern than conforming expansion, via leapfrog development (Abrantes et al., 2016; Yue et al., 2013). Furthermore, non-conforming built-up land expansion is often associated with land-related crimes (e.g., corruption and illegal land transactions), not only undermining the credibility of spatial planning but also triggering social conflicts. A better understanding of non-conforming built-up land expansion is crucial to improve the effectiveness of spatial planning in governing built-up land expansion and to enhance the support of land-system science in sustainable development.

(2) Peer effects on non-conforming built-up land expansion

Institutional actors are commonly regarded as playing a formal role in land use changes (Bürgi et al., 2022). However, one interesting phenomenon is that local governments, originally in charge of making spatial plans and implementing them, frequently contribute to non-conforming built-up land expansion (Alfasi et al., 2012; Menzori et al., 2021; Sharifi et al., 2014; Sundaresan, 2019; Tellman et al., 2021). Further, the behavior of local governments in developing the non-conforming built-up land may depend on the behavior of other local governments (J. Wang et al., 2020). Such interdependencies create peer effects, i.e., local governments might consider other local governments' non-conforming built-up land expansion in their own land use activities.

A local government's behavior of developing non-conforming built-up land is influenced by the behavior of contiguous local governments (geographical peer effect). Numerous studies have demonstrated that geographical contiguity has an influence on a local government's land use decisions and behaviors (Christafore & Leguizamon, 2015; Gómez-Antonio et al., 2016; Z. Huang & Du, 2017; Schone et al., 2013; J. Wang et al., 2020). On the one hand, local governments can easily observe what happens in contiguous governments (Schone et al., 2013). On the other hand, the development conditions of contiguous local governments are relatively similar. Consequently, contiguous local governments often adopt similar land use decisions and behaviors.

A local government's behavior of developing non-conforming built-up land is influenced by the behavior of other local governments within the same political jurisdiction (political peer effect). Confinement within a political jurisdiction is a vital channel for influencing a local government's decisions and behaviors (Atella et al., 2014; Cassette et al., 2012; Yu et al., 2016). In China, superior governments have exclusive control over a local government official's promotion, and over the funds and political support that are crucial to local developments (Z. Chen et al., 2017; Z. Huang & Du, 2017). Specifically, to outperform other local governments within the same political jurisdiction, local governments may be more sensitive to non-conforming built-up land expansion of their political peers and less sensitive to the behaviors of local governments in different political jurisdictions.

A local government's behavior of developing non-conforming built-up land is influenced by the behavior of other local governments with similar levels of economic development (economic peer effect). In China, economic competition among local governments is fierce, and local governments with similar economic levels are close rivals (Yu et al., 2016). Because non-conforming built-up land expansion can generate a greater marginal economic return compared with conforming expansion (Z. Chen et al., 2015), local governments are interested in whether and how their economic peers employ non-conforming built-up land expansion to advance economic development, even when they are not contiguous and/or in different political jurisdictions. Finally, a local government's behavior of developing non-conforming built-up land is more likely to be influenced by geographical peers with similar economic levels (geographical-economic peer effect) and by political peers with similar economic levels (political-economic peer effect). Considering the intense economic competition among local governments in China, economic competition would enhance geographical and political peer effects. That is, the geographical-economic and political-economic peer effects in promoting non-conforming built-up land expansion would be greater than the geographical and political peer effects, respectively.

1.2.3 Land use planning and the MFOZ in China

(1) Land use planning in China

China's government 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 town, and have two major targets: built-up land containment and farmland protection. Land use planning is implemented using a "quota with zoning" mode (Figure 1). To contain built-up expansion, the central government set a series of built-up 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 town level based on local socioeconomic characteristics (Fang & Tian, 2020; Y. Zhou et al., 2017). Built-up land zoning is used for allocating the quotas into specific locations at the prefectural city, county, and town level based on suitability evaluations of built-up land. Thus land use plans at the prefectural city, county, and town level mainly consist of several maps showing land use zoning and a quota system determining the amounts of land use changes.

Built-up land zoning is the core tool used to contain built-up land expansion in land use planning. It divides a territory into four zone types: development-permitted zones, development-permitted-conditionally zones, development-restricted zones, and development-forbidden zones. Built-up land expansion is allowed only inside the first two zone types. 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 land use planning on containing built-up land expansion is unclear. Many researchers have found a lack of consistency when overlaying built-up land zoning with the actual built-up land extent, and they have therefore concluded a failure of land use planning in China (Guo et al., 2020; T. Liu et al., 2020; Shao et al., 2018; Shen et al., 2021).

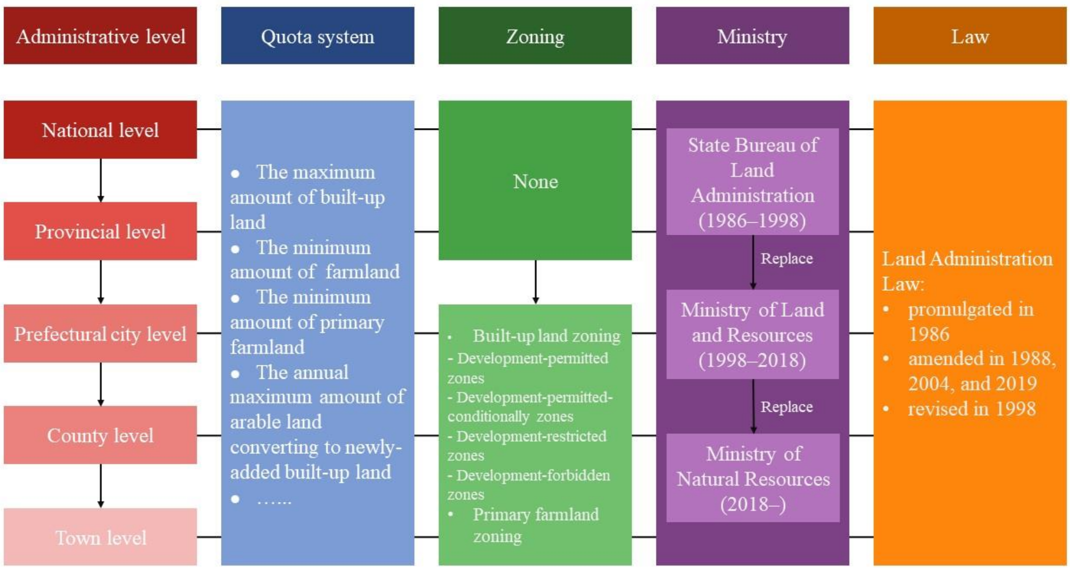

Figure 1. Land use planning system in China

(2) The MFOZ

The Chinese central government released the MFOZ to achieve a coordinated regional development in 2010, through spatial regulation and zoning of development (J. Fan et al., 2012).

The provincial governments then developed the zoning schemes of the MFOZ covering their full provincial territory. The MFOZ divided land into four major function-oriented zones with different planning intentions on built-up land expansion: (a) The development-optimized zones are characterized by a high level of urbanization and industrialization, here land use needs to be optimized due to inefficient uses of built-up land and a decreasing quality of farmland. As a result, built-up land expansion is required to slow down in the development-optimized zones. (b) The development-prioritized zones intend to promote the future regional development through large-scale urbanization and industrialization. Thus, in these zones the demand for built-up land expansion should be accommodated. (c) The development-restricted zones restrict large-scale urbanization and industrialization. It is divided into two types of zones: an agricultural production zones and an ecological security zones. The former are important for food security, the latter aim to restore ecosystems and to protect ecological security. Hence, only small amounts of built-up land expansion are permitted within the development-restricted zones. (d) The development-prohibited zones can be regarded as a natural and cultural heritage protection region, in which built-up land expansion is strictly prohibited.

The government developed an indicator framework in order to delineate the different zones. The framework assessed suitability with 10 indicators addressing such as environmental capacity, ecological vulnerability, ecological importance, natural hazards, population density, economic development, and strategic selection (Y. Liu et al., 2018). Each indicator is comprised of several factors. For example, the indicator of ecological vulnerability included desertification, soil erosion, and stone desertification (J. Fan et al., 2012). The final zoning scheme of the MFOZ was selected based on the suitability evaluation. The MFOZ was developed at the national and provincial administrative levels. The national MFOZ is diagrammatic and lacks an accurate cartographic delineation of the major function-oriented zones (J. Fan et al., 2012). In contrast the provincial MFOZ contains maps with high geographical accuracy and clear boundaries.

1.3 Research objectives, questions, and the structure of the dissertation

This dissertation aims to promote the understanding of how spatial planning contributes to land use changes. The two key research objectives at the center of this dissertation are: 1) evaluating causal effect of spatial planning in containing built-up land expansion; 2) analyzing the non-conforming expansion of built-up land to spatial planning (Figure 2). The first research objective can broaden the understanding of plan effect. It is fulfilled by answering following specific research questions:

RQ1) How to evaluate the causal effect of spatial planning in containing built-up land expansion?

RQ2) Whether and how the causal effect differs with the plan effect that is evaluated by conformance-based evaluation?

RQ3) Whether and how the causal effect of spatial planning varies across time?

The second research objective can generate new knowledge for understanding why large amounts of built-up land have expanded beyond the areas permitted by planning regulations. Thus two specific research questions are as follows:

RQ4) What are the characteristics of non-conforming built-up land expansion?

RQ5) Do peer effects among local governments promote non-conforming built-up land expansion?

The research questions were addressed by three papers have published peer-review scientific journals:

- He, Z., Zhao, C., Fürst, C., & Hersperger, A. M. (2021). Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China? Land Use Policy, 108, 105562. https://doi.org/10.1016/j.landusepol.2021.105562
- He, Z., Ling, Y., Fürst, C., & Hersperger, A. M. (2022). Does zoning contain built-up land expansion? Causal evidence from Zhangzhou City, China. Landscape and Urban Planning, 220, 104339. https://doi.org/10.1016/j.landurbplan.2021.104339
- He, Z, Yu Z, Fürst, C., & Hersperger, A. M. (2023) "Peer effects drive non-conformance between built-up land expansion and zoning: Evidence from Zhangzhou city, China" Applied Geography 152, 102875. https://doi.org/10.1016/j.apgeog.2023.102875

The first two papers focused on evaluating the causal effect of built-up land zoning and the MFOZ in containing built-up land expansion in Zhangzhou City (2010-2020) and in Fujian Province (2013-2020), respectively. The third paper focused on investigating the characteristics and peer effects on non-conforming built-up land expansion in Zhangzhou City (2010-2020).

The following chapters consist of four parts. In the chapter of materials and methods, two study areas in southeastern China and data sources are first presented. Then four methods, including PSM, PSM-DID, conformance-based evaluation and SAR, are described. In the chapter of results, the five research questions were answered specifically. Next, the relations of the findings of this dissertation to previous studies and related policy implications are elaborated in the chapter of discussion. In the chapter of conclusions and outlook, the summary of the key findings and future research directions are provided.

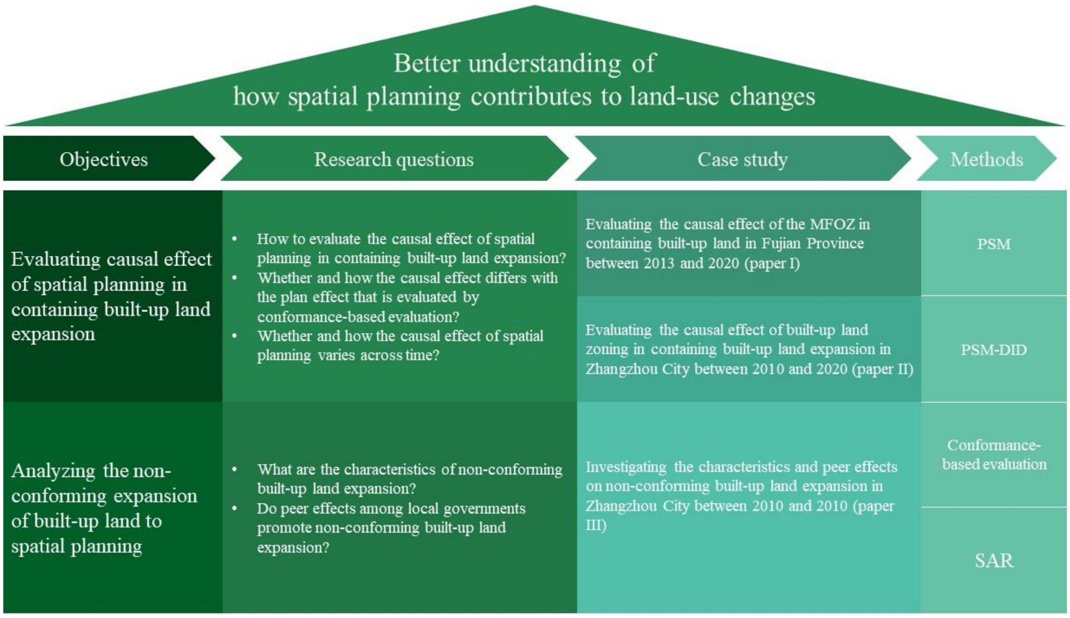

Figure 2. Development process of the doctoral dissertation and the contributions of publications to address research objectives and questions

2. Materials and methods

2.1 Study areas

This dissertation chose Fujian Province and one of its prefectural cites (i.e., Zhangzhou City) as two study areas, where contradiction between built-up land expansion and farmland and forest conservation are serious.

2.1.1 Fujian Province in China and the MFOZ

Fujian Province was chosen as a study area because of its problems of built-up land expansion and farmland and forest conservation. Fujian Province, located in southeastern China, has nine prefectural cities which are further divided into 84 counties (Figure 3.a). The topography of Fujian Province is dominated by mountains and hills (Figure 3b). Western mountainous and hilly areas are mostly forested and provide a wide range of ecosystem benefits (Figure 3.c). Fertile plains are concentrated in the narrow eastern coastal areas which have been highly industrialised and urbanised. A local saying—eighty percent is mountains and hills, ten percent is water and ten percent is arable land—vividly stresses the shortage of areas for farmland and built-up land use. Moreover, the conflicts concerning built-up land and farmland are intensifying as rapid urbanisation and economic development. Since China's Reform and Opening-up Policy in 1978, the urban population in Fujian Province has risen from 13.70% in 1978 to 65.80% in 2018, which exceeded the national average urban population of 59.58%. Furthermore, Fujian Province has experienced rapid economic growth, with its gross domestic product (GDP) increasing from 6,637 million RMB in 1978 to 3,580,404 million RMB in 2018. Such developments were mainly concentrated in the eastern coastal areas (Figure 3.d) where built-up land is consuming the limited fertile plains.

Government of Fujian Province released its MFOZ to governing built-up land expansion to align demands for economic development with farmland conservation and ecosystem protection. The MFOZ divided 974 town-level administrative units (hereafter called towns) into the development-optimized zones, the development-restricted zones, and the development-restricted zones (Figure 3.e). Of the 974 towns, 20, 386, and 568 towns were located within the development-optimized zones, the development-prioritized zones, and the development-restricted zones, respectively. The 20 towns that are located within the development-optimized zones were excluded from the analysis, because it was not possible to find enough suitable matching pairs from the development-prioritized and development-restricted zones

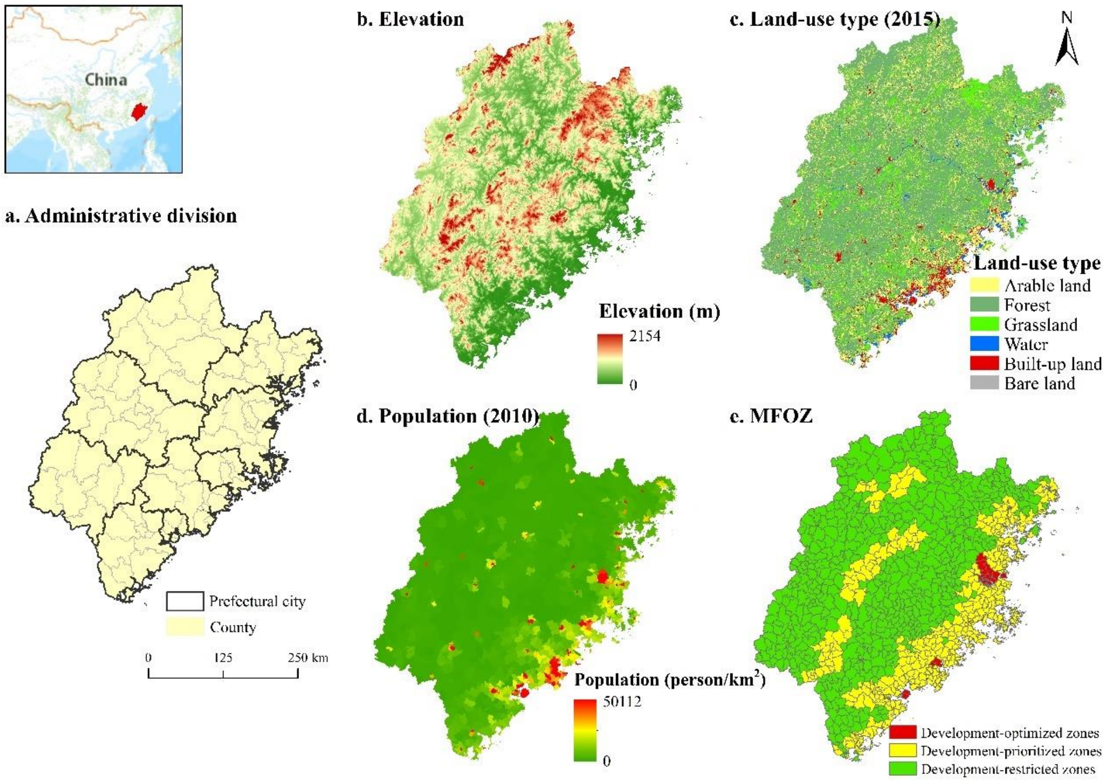

Figure 3. Fujian Province. (a) Location within China and administrative divisions; (b) The topography; (c) The different land use types in 2015; (d) The population density in 2010; (e) The MFOZ

2.1.2 Zhangzhou City in China and built-up land zoning

Zhangzhou City is a prefectural city in Fujian Province in southeastern China (Figure 4.a). It includes 11 counties, which are further divided into 161 towns and finally into 1,662 village-level administrative units (subsequently called villages). The area has strong agricultural roots. It has fertile plains and is highly irrigated (Figure 4.b), which favors agricultural production (e.g., vegetables, citrus fruits, bananas, and flowers (J. Huang et al., 2012)). Economic development in this area traditionally depends on arable land and forest (Figure 4.c). Since

China's Reform and Opening-up Policy in 1978, Zhangzhou City has undergone rapid population and economic development, especially in eastern coastal regions and at the periphery of the city center (Figure 4.d). 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 farmland protection (J. Huang et al., 2012; Jiang et al., 2019). The land use data of this dissertation show that built-up land expanded from 442.39 km^2 in 1995 to 1000.84 km^2 in 2020. Correspondingly, arable land decreased from 2883.50 km^2 to 2548.08 km^2 and forest decreased from 6802.45 km^2 to 6492.81 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 (J. Huang et al., 2015). Ecosystem services have decreased dramatically because a considerable amount of arable land and forest has been converted into built-up land (H. Chen et al., 2020).

The land use plan in Zhangzhou City was approved in August 2010 and came to the end in 2020. Built-up land zoning is the core tool used to contain built-up land expansion in land use planning. It divides a territory into four zone types: development-permitted zones, development-permitted-conditionally zones, development-restricted zones, and development-forbidden zones (Figure 4.e). Built-up land expansion is allowed only inside the first two zone types (subsequently referred to collectively as development-permitted zones). However, large amounts of built-up land were developed outside the development-permitted zones between 2010 and 2020 (Z. He et al., 2022). Thus, Zhangzhou City provides an excellent laboratory to fulfill the research objectives in this dissertation.

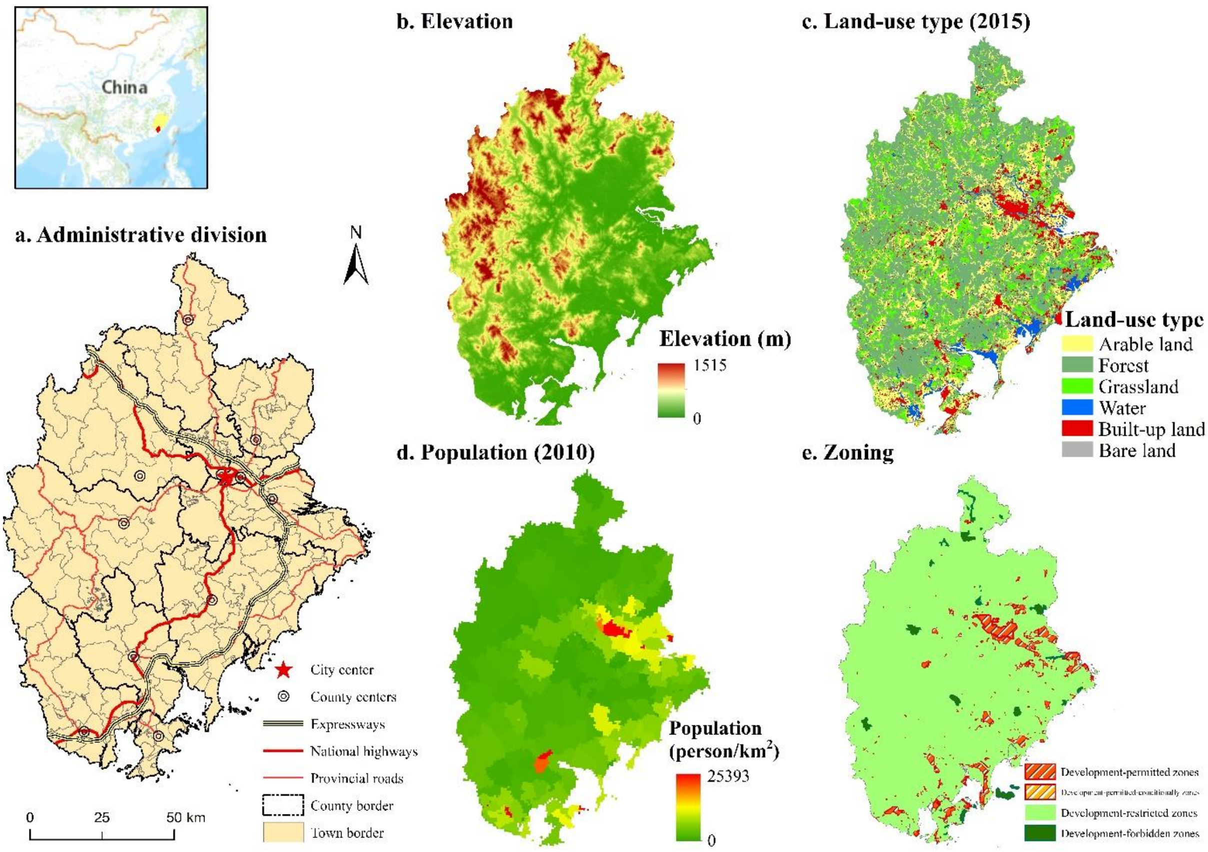

Figure 4. Zhangzhou City. (a) Location within China and Fujian Province and administrative divisions; (b) The topography; (c) The different land use types in 2015; (d) The population density in 2010; (e) The built-up land zoning

2.2 Methods

2.2.1 The PSM

The PSM was used to evaluate the casual effect of the MFOZ in containing built-up land expansion of the 954 towns in Fujian Province between 2013 and 2020. Specifically, the casual effect of the MFOZ was defined as the difference between the changes in the amount of built-up land in the towns of the development-prioritized zones with the matched towns of the development-restricted zones. The PSM-based evaluation consisted of four steps (Figure 5): (1) select confounding variables and estimate propensity scores, (2) execute matching and check balance, (3) evaluate the causal effect, and (4) conduct robustness tests.

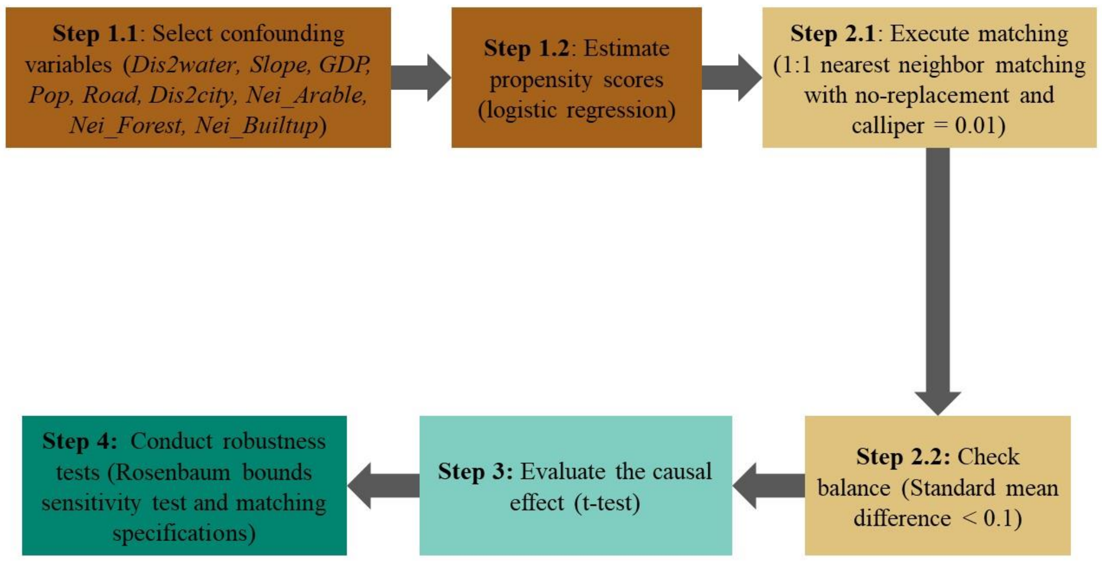

Figure 5. Steps for the PSM-based evaluation

(1) Select confounding variables and estimate propensity score

The confounding variables that determine which the major function-oriented zone a town is assigned to may also affect built-up land change. The following confounding variables was selected in the PSM-based evaluation:

- *Distance to water (Dis2water)*: Fujian Province is topographically dominated by mountains and hills, as a result, settlements have a distinctive distribution pattern in areas close to water. This variable was measured as the Euclidean distance from the town to the nearest waterbody, via a Near tool in ArcGIS 10.6.
- *Slope (Slope)*: Steep slopes increase the cost of construction and pose a higher risk of erosion and landslides than flatter areas (Onsted & Chowdhury, 2014). This variable was measured as the average slope within the town, via a Zonal Statistics tool in ArcGIS 10.6.
- *Economic development (GDP)*: Built-up land expansion is strongly positively correlated to economic development (Acuto et al., 2018; C. He, Huang, et al., 2014). This variable was measured as the average GDP in 2010 within the town, via a Zonal Statistics tool in ArcGIS 10.6.
- *Population growth (Pop)*: Population growth increases the demand for built-up land (van

Vliet et al., 2017). This variable was measured as the average population in 2010 within the town, via a Zonal Statistics tool in ArcGIS 10.6.

- *Road length (Road)*: Transport is usually considered as a determining factor influencing land use change (Kasraian et al., 2019; X. Li et al., 2017). This variable was measured as the length of road within each town in 2010, via a Intersect tool in ArcGIS 10.6.
- *Distance to city center (Dis2city)*: Proximity to urban centers is an important driver for built-up land expansion (Kasraian et al., 2019; Yin et al., 2018). This variable was measured as the Euclidean distance from the town to the nearest prefectural city center, via a Near tool in ArcGIS 10.6.
- *Neighborhood effect*: The neighborhood effect is an indispensable driver of land use change (van Vliet et al., 2013; Verburg, de Nijs, et al., 2004). In general, planners prefer compact strategies for built-up land expansion, in order to avoid the negative impacts of built-up sprawl. Three types of neighborhood effect were used, the area of: arable land (*Nei_Arable*); forest land (*Nei_Forest*) and built-up land (*Nei_Builtup*) neighboring town i in 2010, using a Polygon Neighbor tool in ArcGIS 10.6. A first-order contiguity was used to define the neighborhood relationship, that is, the towns that share an edge or a corner will be considered as the neighboring towns.

Logistic regression was used to calculate the propensity scores via incorporating the confounding variables as independent variables and the planning variable as a dependent variable.

$$ps = Prob(Plan_i = 1|X_i) = \beta_0 + \beta_i X_i + \varepsilon_{it} \quad (1)$$

The propensity score (ps) refers to the probability of the town i being assigned, in the planning process, to the development-prioritized zones, given the selected confounding variables (X_i). The planning variable ($Plan_i$) is a binary variable, where the value 1 was assigned to towns located in the development-prioritized zones and the value 0 for towns within the development-restricted zones.

(2) Execute matching and check balance

I carried out 1:1 nearest neighbour matching. A town from the development-restricted zones was chosen as a matching counterfactual when it was closest to the town of the development-prioritized zones in terms of propensity score. I also set up matching without replacement, as it can yield the most precise estimates in a relatively large dataset (Butsic et al., 2011). Nearest neighbour matching risks poor matches if the closest neighbour is far away (Caliendo & Kopeinig, 2008). To avoid this, I imposed a tolerance level of 0.01 on the maximum propensity score difference (calliper). I imposed a common support by dropping the towns of the development-prioritized zones whose propensity score was higher than the maximum or less than the minimum propensity score of the towns of the development-restricted zones.

After PSM, I obtained 103 matched pairs (Figure 6.a) and checked the balance, that is, the confounding variables between 103 matched towns of the development-prioritized zones and 103 matched towns of the development-restricted zones should be similar as much as possible (Rosenbaum & Rubin, 1983). Standard mean difference can be used as a balance indicator and is defined as (Austin, 2011):

$$SMD = \frac{|\bar{x}_1 - \bar{x}_0|}{\sqrt{\frac{s_1^2 + s_0^2}{2}}} \tag{2}$$

In which $\bar{x}_1$ and $\bar{x}_0$ are the means of the confounding variables of the towns in the development-prioritized zones and development-restricted zones respectively. s_1^2 and s_0^2 denote the sample variances. Standard mean difference is not influenced by sample size and is independent of the unit of measurement, which enables to compare the relative balance among the different confounding variables (Zhang et al., 2019). A higher standard mean difference indicates a higher dissimilarity in the confounding variables. The value 0.1 is considered as a reasonable threshold for ignoring dissimilarity (Austin, 2011; Stuart et al., 2013). The results of standard mean difference show in Annex A.1.

(3) Evaluate the causal effect

The causal effect of the MFOZ in built-up land expansion was estimated by comparing the difference in the mean built-up land expansion between 103 matched towns of the development-prioritized zones and 103 matched towns of the development-restricted zones. To reflect temporal changes in the causal effect of the MFOZ on built-up land expansion, I used three time intervals: 2013-2015, 2013-2018 and 2013-2020 (Figure 6.b-d). I used a t-test to assess the statistical significance of the causal effect, which enabled us to be less restrictive with model specifications and to directly compare the results with the conventional conformance-based evaluation.

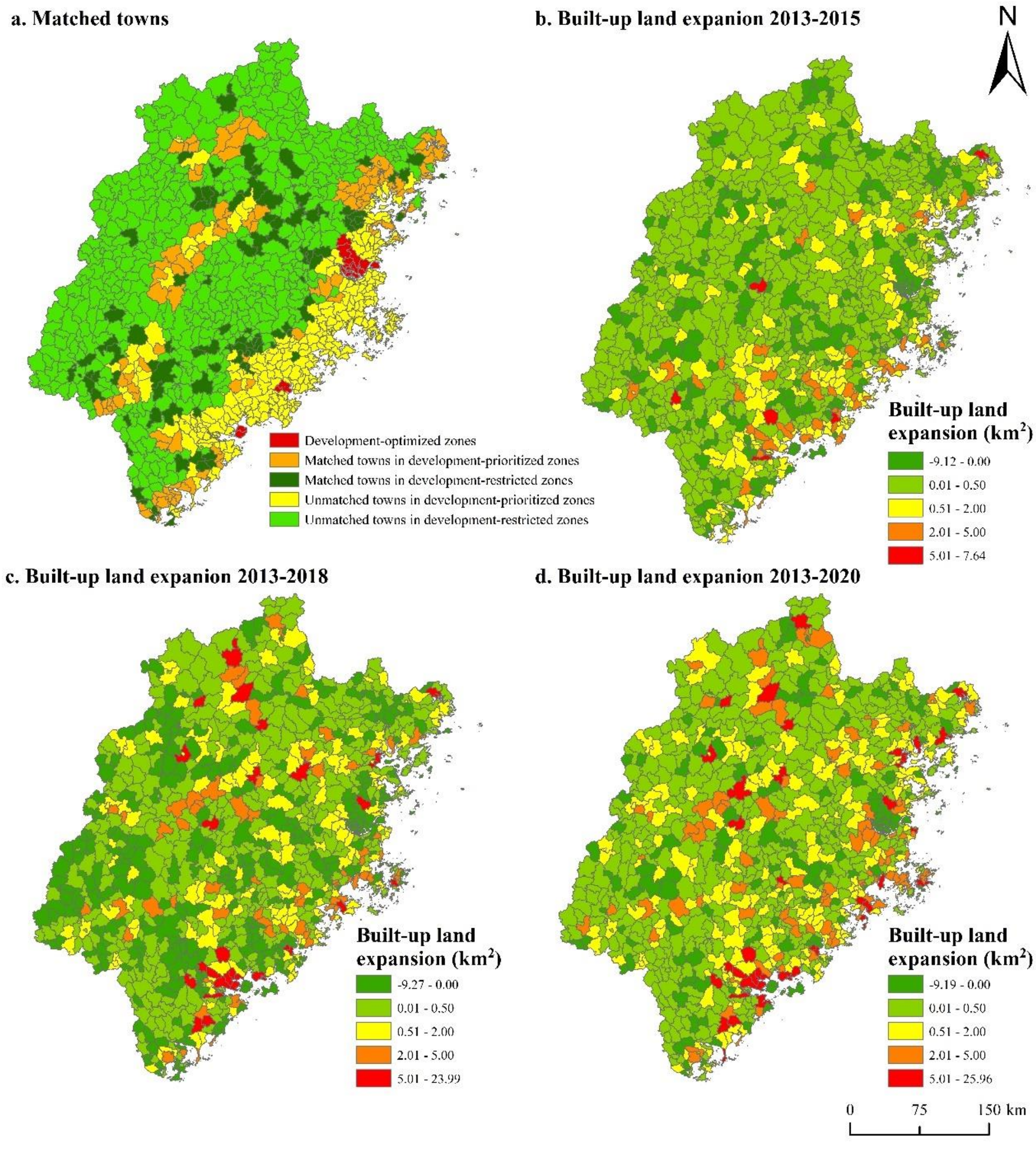

Figure 6. The matched towns and built-up land expansion in 2013-2015, 2013-2018 and 2013-

2020 in Fujian Province

(4) Robustness tests

I tested the robustness of the results in two ways (Annex A2). First, the Rosenbaum bounds sensitivity test was used to check whether the results were robust to potential hidden bias from unobserved confounding variables. Second, the robustness of the matching algorithms was tested by applying the different matching specifications, which included nearest neighbour matching with multiple callipers, radius matching with multiple callipers, and kernel matching.

2.2.2 The PSM-DID

The PSM-DID approach was used to evaluate the causal effect of built-up land zoning in containing built-up land expansion of the 1,662 villages in Zhangzhou City between 2010 and 2020. Specifically, the casual effect of built-up land zoning was defined as the difference between the average built-up land expansion of the villages located inside the development-permitted 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).

(1) Average effect

The DID model to estimate the average effect of built-up land zoning on built-up land expansion was specified as follows:

$$BuLE_{it} = \beta(Develop_i * Time_t) + \gamma N_{it} + \sum_{j=2000}^{2020} \phi G_i * Year_j + \sum_{j=2000}^{2020} \varphi P_i * Year_j + u_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where $BuLE_{it}$ is the dependent variable, representing the percentage of built-up land out of the total land area in village i in year t. $Develop_i$ is a binary planning variable. $Develop_i = 0$ if the village was assigned as being entirely outside the development-permitted zones, otherwise $Develop_i = 1$. $Time_t$ is a binary variable. The value 1 was assigned to the years after the implementation of the land use plan (i.e., 2010, 2013, 2015, 2018, and 2020), and the value 1 to the years before the implementation (i.e., 1995, 2000, and 2005). The coefficient (β) of the interaction term ($Develop_i * Time_t$) represents the causal effect of built-up land zoning on built-up land expansion.

The other variables that could affect built-up land expansion were selected. 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 Euclidean distance from village i to the nearest waterbodies ($Dis2water_i$) and to coastlines ($Dis2coastline_i$), and the average elevation within village i ($Elevation_i$). P_i represents proximity variables, including the Euclidean distance from village i to the city center ($Dis2city_i$), to the nearest county center ($Dis2county_i$), and to the nearest roads ($Dis2road_i$).

Because the geographical and proximity variables are time-invariant, I followed the approach proposed by Nunn and Qian (2011) to create the interaction terms ($\sum_{t=2000}^{2020} \phi G_i * Year_t$ and $\sum_{t=2000}^{2020} \varphi P_i * Year_t$). The dummy variable $Year_j = 1$ if $j \in T$ = [2000, 2005, 2010, 2013, 2015, 2018, 2020], otherwise $Year_j = 0$. I used two-way fixed effects to estimate the DID model, where u_i and λ_t were the individual 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, the standard errors were clustered at the village level to address potential serial correlation and heteroscedasticity. ε_{it} is the disturbance term.

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

$$BuLE_{it} = \beta(Intensity_i * Time_t) + \gamma N_{it} + \sum_{j=2000}^{2020} \varphi G_i * Year_j + \sum_{j=2000}^{2020} \varphi P_i * Year_j + u_i + \lambda_t + \varepsilon_{it} \qquad (4)$$

where $Intensity_i$ is a continuous planning variable by calculating the percentage of land that was assigned to the development-permitted zones in village i.

(2) Annual effect

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

$$BuLE_{it} = \sum_{j=1995}^{2020} \beta_j \left(Develop_i * Year_j\right) + \gamma N_{it} + \sum_{j=1995}^{2020} \phi G_i * Year_j + \sum_{j=1995}^{2020} \varphi P_i * Year_j + u_i + \lambda_t + \varepsilon_{it} \quad (5)$$

$$BuLE_{it} = \sum_{j=1995}^{2020} \beta_j \left(Intensity_i * Year_j\right) + \gamma N_{it} + \sum_{j=1995}^{2020} \phi G_i * Year_j + \sum_{j=1995}^{2020} \varphi P_i * Year_j + u_i + \lambda_t + \varepsilon_{it} \quad (6)$$

The binary ($Develop_i$) and continuous ($Intensity_i$) planning variables were used to obtain a robust estimation. β_j represents the causal effect of built-up land zoning on built-up land expansion in the years 1995, 2000, 2005, 2013, 2015, 2018, and 2020. I 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).

(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 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 and those located outside the development-permitted zones. Before estimating the DID model, the PSM was used to overcome the above two challenges.

The propensity scores of the village being assigned, in the planning process, to the development-permitted zones were estimated by the following logistic regression model:

$$ps = Prob(Develop_i = 1|X_i) = \beta_0 + \beta_i X_i + \varepsilon_{it} \quad (7)$$

where ps represents the propensity score and $Develop_i$ is the binary planning variable. X_i are the confounding variables, which include the area of built-up land in the neighboring villages of village i in 2010 ($Nei\_Built.up_{i,2010}$), built-up land expansion of village i in 2010 ($BuLE_{i,2010}$), distance to waterbodies ($Dis2water_i$), distance to coastlines ($Dis2coastline_i$), elevation ($Elevation_i$), proximity to urban centers ($Dis2city_i$ and $Dis2county_i$), and proximity to roads ($Dis2road_i$). Based on the estimated coefficients β_i, the propensity score was calculated for each village. I 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. I set up matching without replacement, which can obtain precise estimates in a relatively large dataset (Butsic et al., 2011). I 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).

(4) Robustness test

Event study, balance check, and placebo test were used to check whether the causal effect estimated by the PSM-DID was robust (Annex A.4). An event study was used to check whether the parallel trend assumption was satisfied. The model for the event study is the same as model $BuLE_{it} = \sum_{j=1995}^{2020} \beta_j \, (Develop_i * Year_j) + \gamma N_{it} + \sum_{j=1995}^{2020} \phi G_i * Year_j + \sum_{j=1995}^{2020} \varphi P_i * Year_j + u_i + \lambda_t + \varepsilon_{it}$ (5), which is commonly used to test the parallel trend assumption (Jacobson et al., 1993). β_j should be non-significant for the pre-implementation years (i.e., 1995, 2000, and 2005) if the parallel trend assumption was satisfied. The results of the event study show in Annex A.5.1.

The standard mean difference (model 2) was used to check the extent to which PSM reduced the selection bias (Austin, 2011). A higher standard mean difference indicates a larger difference in the confounding variables. The value 0.1 is considered a reasonable threshold for ignoring this difference (Austin, 2011; Stuart et al., 2013). The results of standard mean difference show in Annex A.5.2.

I conducted a placebo test using model (3). All variables are the same except for $Time_t$. Here, I 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. The results of the placebo test show in Annex A.5.3.

2.2.3 Conformance-based evaluation

Conformance-based evaluation was carried out in Fujian Province, because it does not consider selection bias. In the conformance-based evaluation, the effect of the MFOZ was estimated by comparing the difference in the mean built-up land expansion between 386 towns of the development-prioritized zone and 568 towns of the development-restricted zone in 2013–2015, 2013–2018 and 2013–2020. The t-test was used to assess the statistical significance.

The conformance-based evaluation was also used to evaluate the extent to which built-up land zoning contained built-up land expansion in Zhangzhou City between 2010 and 2020. First, I built a layer of actual built-up land expansion between 2010 and 2020, using an Erase tool in ArcGIS 10.6. The years 2010 and 2020 were selected because the land use plan in Zhangzhou City was approved in 2010 and came to an end in 2020. I then intersected actual built-up land expansion with built-up land zoning, using an Intersect tool in ArcGIS 10.6, to identify built-up land expansion that occurred outside the development-permitted zones (i.e., non-conforming built-up land expansion).

Next, I analyzed land use changes in the regions where the non-conforming built-up land occurred. I intersected the non-conforming layer with the land use layer in 2010 to calculate how much arable land, forest, grassland, water, and bare land was converted to the three non-conforming built-up land uses, i.e., urban built-up land, rural settlements, and industrial/mining/transportation land.

Lastly, I identified three expansion types of the non-conforming built-up land, i.e., infill, edge, and outlying. I sed the ratio (R) of the length of the common boundary shared by a non-conforming built-up land developed between 2010 and 2020 and the existing built-up land in 2010 (L_c) to the perimeter of the non-conforming built-up land (L) to identify expansion types (Sun et al., 2013; Wilson et al., 2003; C. Xu et al., 2007). The ratio was formulated as follows:

$$R = {}^{L_c}/_{L} \qquad (8)$$

where the value of R ranged from 0 to 1. Infill expansion had an R value ≥ 0.5, indicating that the non-conforming built-up land was surrounded by at least 50% existing built-up land (Figure 7.a). Edge expansion has $0 < R < 0.5$, indicating that the non-conforming built-up land is surrounded by ≤ 50% existing built-up land (Figure 7.b). With outlying expansion R = 0, i.e., the non-conforming built-up land is isolated from the existing built-up land (Figure 7.c).

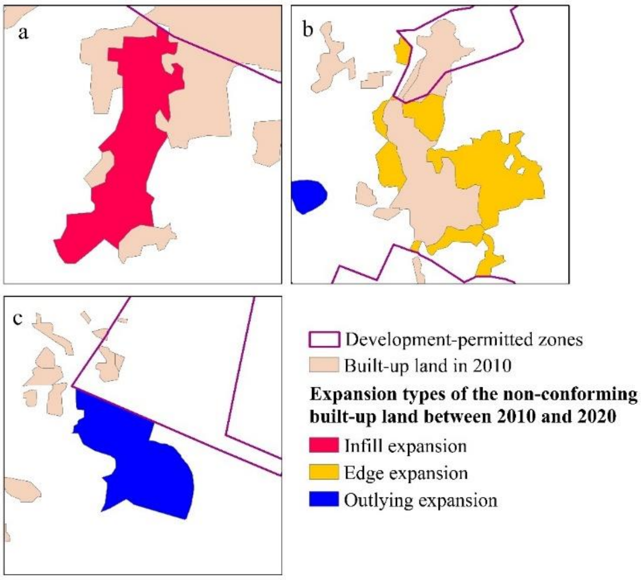

Figure 7. Examples of infill, edge, and outlying expansion of non-conforming built-up land

2.2.4 The SAR

The SAR models were built to estimate the peer effects on non-conforming built-up land expansion among 307 villages (LeSage & Pace, 2009). The SAR model was specified as:

$$NC\_Builtup_i = \alpha + \rho W * NC\_Builtup_j + \beta X_i + \varepsilon_i \qquad (9)$$

where the dependent variable ($NC\_Builtup_i$) is the non-conforming built-up land developed between 2010 and 2020, expressed as a percentage of the total land area in the village i. $W * NC\_Builtup_j$ is the spatially lagged dependent variable. W is a spatial weight matrix. It has zero diagonal elements (w_{ii}) and off-diagonal elements (w_{ij}). w_{ij} represents the peer relationship between village i and village j.

This dissertation defined the five peer relationships: (1) W^{Geo} represented the geographical peer relationship, where w_{ij}^{Geo} equaled 1 if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0 (Figure 3a); (2) W^{Poli} represented the political peer relationship, where w_{ij}^{Poli} equaled 1 if villages i and j were located in the same county, otherwise 0 (Figure 3b); (3) W^{Econ} represented the economic peer relationship, with $w_{ij}^{Econ} = 1/(|PGDP_i - PGDP_j| + 1)$, where $PGDP$ was the GDP per capita in 2010 (Figure 3c); (4) W^{GEcon} represented the geographical-economic peer relationship combining W^{Geo} and W^{Econ}, where $w_{ij}^{GEcon} = 1/(|PGDP_i - PGDP_j| + 1)$ if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0 (Figure 3d); (5) W^{PEcon} represented the political-economic peer relationship combining W^{Poli} and W^{Econ}, where $w_{ij}^{PEcon} = 1/(|PGDP_i - PGDP_j| + 1)$ if villages i and j were located in the same county, otherwise 0 (Figure 3e). All spatial weight matrices were row normalized to make each row sum to one. ρ was the spatial autoregressive coefficient of interest; it represented the effect of the different peer relationships on the village's non-conforming expansion of built-up land. α was the intercept, X_i were control variables, β was the influence of the control variables on non-conforming expansion of built-up land, and ε_i was the disturbance term. To overcome heteroskedasticity, I used a generalized spatial two-stage least squares estimator to estimate the SAR model (Drukker et al., 2013).

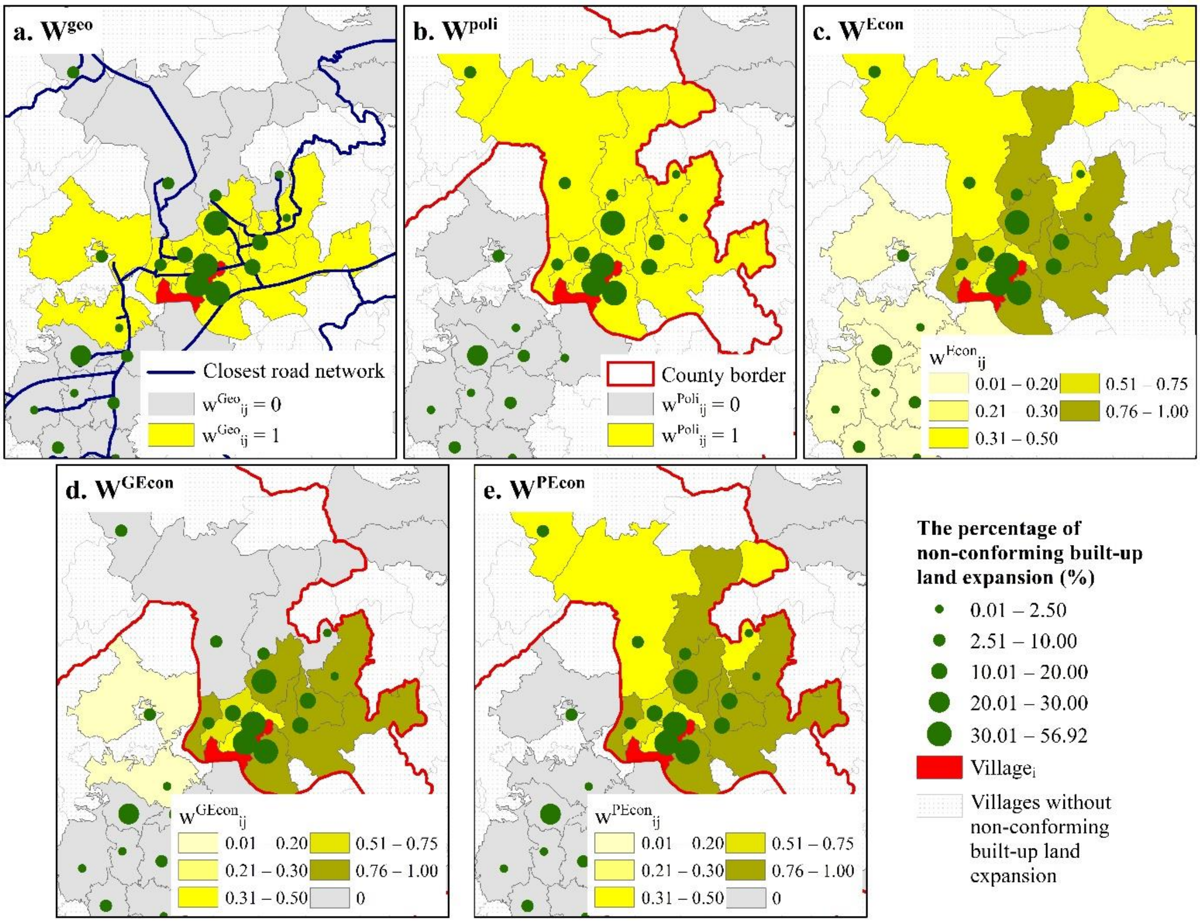

Figure 8. Illustrations of the considered peer relationships: (a) geographical, (b) political, (c) economic, (d) geographical-economic, and (e) political-economic.

While research on the causes why built-up land often did not conform to zoning is scarce, the extensive literature on spatial patterns and drivers of built-up land development helped us to specify our models. Furthermore, our models helped us to gain insight on whether the same factors driving built-up land expansion also contributed to non-conforming expansion of built-up land. The following control variables were included in the SAR model: (1) Built-up land is significantly affected by rivers and coastlines (le Berre et al., 2016; G. Tian & Wu, 2015). I measured the Euclidean distance from village i to the nearest river ($Dis2water_i$) and to the nearest coastline ($Dis2coast_i$). (2) Urban accessibility drives built-up land expansion (Kasraian et al., 2019; Yin et al., 2018). I used the closest road network distance from village i to the city center ($Dis2city_i$) and to its county center ($Dis2county_i$). (3) Mountainous and hilly terrain increases construction costs and restricts built-up land expansion (Onsted &

Chowdhury, 2014; Zhong et al., 2011). I measured the average elevation and relief in village i ($Elevation_i$ and $Relief_i$). (4) Built-up land tends to stretch along roads (Poelmans & van Rompaey, 2010; G. Tian & Wu, 2015). I measured the Euclidean distance from village i to the nearest road ($Dis2road_i$), considering expressways, national highways, and provincial roads. (5) Natural land is a main source of built-up land expansion (Abrantes et al., 2016; Lichtenberg & Ding, 2008). Meanwhile, considering the constraints of mountainous and hilly terrain, I measured the percentage of arable land, forest, grassland (slope < 5 degree) out of the total land area in village i in 2010 ($Arable10_i, Forest10_i$, and $Grass10_i$). (6) Built-up land development is influenced by the previous tendency, i.e., path dependence (Colsaet et al., 2018). I measured the percentage of built-up land out of the total land area in village i in 2010 ($Builtup10_i$). (7) Economic development promotes the need for built-up land (Park et al., 2018; Y. Zhou et al., 2017). I used GDP per capita in 2010 to represent economic development in village i ($PGDP10_i$). Because census data on GDP per capita at the village level are inaccessible in China, I used raster data to extract GDP and total population at the village level. (8) Abundant development-permitted zones can restrict non-conforming expansion of built-up land (Gennaio et al., 2009). I measured the percentage of land located inside the development-permitted zones out of the total land area in village i (DPZ_i).

2.3 Data sources

Table 1. Overview of the variables in the PSM, PSM-DID, and SAR

Variables	Descriptions	Unit	Data sources
Outcome variables in PSM			
-	Changes in the amount of built-up land in the town between 2013 and 2015	km^2	RESDC
-	Changes in the amount of built-up land in the town between 2013 and 2018	km^2	RESDC
-	Changes in the amount of built-up land in the town between 2013 and 2020	km^2	RESDC
Planning variable in PSM			
Plan	1 was assigned to towns located in the development-prioritized zones and the value 0 for towns within the development-restricted zones.	-	Local government
Confounding variables in PSM			

Dis2water	Euclidean distance from the town to the nearest waterbody	km	RESDC
Slope	Average slope within the town	Degree	Local government
GDP	Average GDP in 2010 within the town	million RMB	RESDC
Pop	Average population in 2010 within the town	no. of persons	China Science Data
Road	The length of road within the town in 2010	km	NavInfo Company
Dis2city	Euclidean distance from the town to the nearest prefectural city center	km	Local government
Nei_Arable	Area of arable land in neighboring towns in 2010	km^2	RESDC
Nei_Forest	Area of forest land in neighboring towns in 2010	km^2	RESDC
Nei_Builtup	Area of built-up land in neighboring towns in 2010	km^2	RESDC
Dependent variables in PSM-DID			
BuLE	Percentage of built-up land out of the total land area in the village	%	RESDC
Planning variables in PSM-DID			
Develop	1 means the villages that were partially or entirely located inside the development-permitted zones, and 0 means the villages that were entirely located outside the develop-permitted zones	-	Local government
Intensity	The percentage of land assigned to the development-permitted zones in the village	%	Local government
Control variables in PSM-DID			
Dis2water	Euclidean distance from the village to the nearest waterbody	km	RESDC
Dis2coastline	Euclidean distance from the village to the nearest coastline	km	RESDC
Elevation	Average elevation within the village	km	Local government
Dis2city	Euclidean distance from the village to the city center	km	Local government
Dis2county	Euclidean distance from the village to the nearest county center	km	Local government
Dis2road	Euclidean distance from the village to the nearest road	km	NavInfo Company

Nei_Built.up	Area of built-up land in neighboring villages	km^2	RESDC
Dependent variables in SAR			
NC_Builtup	Percentage of non-conforming built-up land developed between 2010 and 2020 out of the total land area in the village	%	RESDC
Spatial weight matrix in SAR			
W^{Geo}	1 if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0	-	Author's own calculations
W^{Poli}	1 if villages i and j were located in the same town, otherwise 0	-	Author's own calculations
W^{Econ}	$w_{ij}^{Econ} = 1/(\lvert PGDP_i - PGDP_j \rvert + 1)$, where $PGDP$ was the GDP per capita in 2010	-	Author's own calculations
W^{GEcon}	$w_{ij}^{GEcon} = 1/(\lvert PGDP_i - PGDP_j \rvert + 1)$ if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0	-	Author's own calculations
W^{PEcon}	$w_{ij}^{PEcon} = 1/(\lvert PGDP_i - PGDP_j \rvert + 1)$ if villages i and j were located in the same county, otherwise 0	-	Author's own calculations
Control variables in SAR			
Dis2water	Euclidean distance from the village to the nearest waterbody	km	RESDC
Dis2coast	Euclidean distance from the village to the nearest coastline	km	RESDC
Dis2city	Euclidean distance from the village to the city center	km	Local government
Dis2county	Euclidean distance from the village to the nearest county center	km	Local government
Elevation	Average elevation within the village	km	Local government
Relief	Average relief within the village	/	Author's own calculations
Dis2road	Euclidean distance from the village to the nearest road	km	NavInfo Company
Arable10	Percentage of arable land (slope < 5 degree) out of the total land area in 2010	%	RESDC
Forest10	Percentage of forest (slope < 5 degree) out of the total land area in 2010	%	RESDC

Grass10	Percentage of grassland (slope < 5 degree) out of the total land area in 2010	%	RESDC
Builtup10	Percentage of built-up land out of the total land area in 2010	%	RESDC
PGDP10	GDP per capita in the village in 2010	10, 000 RMB/person	China Science Data
DPZ	Percentage of land located inside the development-permitted zones out of the total land area in the village	%	Local government

3. Results

3.1 Causal effect of spatial planning on built-up land expansion

The results from the PSM-based evaluation shows that the MFOZ was effective in containing built-up land expansion in Fujian Province between 2013 and 2018 and between 2013 and 2020 (Table 2). The mean difference in evaluation interval of 2013-2020 is 0.77 km^2. It indicates that each of the 103 matched towns assigned within the development-restricted zone would have additionally expanded by 0.77 km^2 of built-up land if there would have been no the MFOZ. In aggregate, a total of 79.31 km^2 of built-up land was prevented within the development-restricted zone in Fujian Province between 2013 and 2020.

Table 2. Results concerning the area of built-up land expansion in the development-prioritized zones and development-restricted zones estimated from the conformance-based and PSM-based evaluation in Fujian Province in 2013-2015, 2013-2018, and 2013-2020

Evaluation methods	Evaluation interval	Development -prioritized zones (km^2)	Development -restricted zone (km^2)	Mean difference (km^2)	Evaluation results
PSM-based	2013-2015	0.44	0.37	0.07	Ineffective
evaluation	2013-2018	1.01	0.60	0.41*	Effective
	2013-2020	1.43	0.66	0.77***	Effective
No. of towns		103	103	-	-
Conformanc	2013-2015	0.61	0.20	0.41***	Effective
e-based	2013-2018	0.97	0.34	0.63***	Effective
evaluation	2013-2020	1.57	0.46	1.11***	Effective
No. of towns		386	568	-	-

Note: "", "**", and "***" represent the mean difference of built-up land expansion area between the towns in the development- prioritized zones and the development- restricted zone are significant at the 10%, 5%, and 1% level, respectively.*

The results based on the PSM-DID suggest that built-up land 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 at the absence of built-up land zoning (Table 3). To interpret the practical meaning of the coefficient, I assumed that every matched village had the identical total land area (5.74 km^2), 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^2 of built-up land if there were no built-up land zoning. In aggregate, a total of 27.02 km^2 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 development-permitted zones between 2010 and 2020 was 83.23 km^2, with zoning preventing an additional 32.46% of built-up land expansion outside the development-permitted zones. I 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%.

Table 3. Average effect of built-up land zoning on built-up land expansion in Zhangzhou City between 2010 and 2020

	Model 3	Model 4
$Develop_i * Time_t$	1.21* (0.67)	
$Intensity_i * Time_t$		0.06** (0.03)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	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 *A2 in the Annex A.3.*

3.2 The discrepancy between causal effect and plan effect evaluated by conformance-based evaluation

The conformance-based evaluation shows contrasting effect of spatial planning in built-up land expansion. The conformance-based evaluation estimated a larger effect of the MFOZ than the PSM-based evaluation in Fujian Province. For example, the conformance-based evaluation shows that the towns in the development-restricted zone experienced lower built-up land expansion (on average 1.11 km^2 less built-up land expansion) than the towns in the development-prioritized zone between 2013 and 2020 (Table 2). However, the mean difference is much lower when using the PSM-based evaluation (0.77 km^2).

The conformance-based evaluation shows that the newly developed built-up land area between 2010 and 2020 is 144.75 km^2 in Zhangzhou City, of which the non-conforming built-up land expansion accounted for 67.61% (97.87 km^2). This finding indicates that large amount of the built-up land occurred outside the development-permitted zones, despite the fact that built-up land zoning played a causal role in containing built-up land expansion via PSM-DID.

3.3 Temporal variation in causal effect of spatial planning

The results suggest a time-lag effect existed in the initial period of plan implementation. The PSM-based evaluation shows that the t-test was insignificant in 2013-2015 (Table 2). It indicates that the MFOZ was ineffective in restricting built-up land expansion in the development-restricted zone at the start of its implementation (i.e., 2013-2015) in Fujian Province. In the intervals 2013-2018 and 2013-2020, the t-test became significant. This suggests that the causal effect of the MFOZ varied, from ineffective at the start of its implementation to effective later in its implementation period.

Likewise, built-up land zoning did not play a causal role in containing built-up land expansion at the start of its implementation in Zhangzhou City, because the coefficients of $Develop_i * Year_{2013}$ (-0.02, p=0.50) and $Intensity_i * Year_{2013}$ (0.0003, p=0.60) were close to zero and non-significant (Figure 9). However, the coefficients of $Develop_i * Year_{2015}$ (0.97, p=0.06), $Intensity_i * Year_{2015}$ (0.04, p=0.02), and $Intensity_i * Year_{2018}$ (0.06, p=0.05) were positive and significant at the 10% level. These results indicate that built-up land zoning started to play a causal role in containing built-up land expansion after 2013.

Besides the time-lag effect, built-up land zoning became ineffective in containing built-up land expansion as time elapsed (Figure 9). 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 non-significant. This means that built-up land zoning was ineffective in containing built-up land expansion in 2018 and 2020. When I controlled for the continuous planning variable, the coefficient of $Intensity_i * Year_{2020}$ (0.05, p=0.10) also decreased and became non-significant.

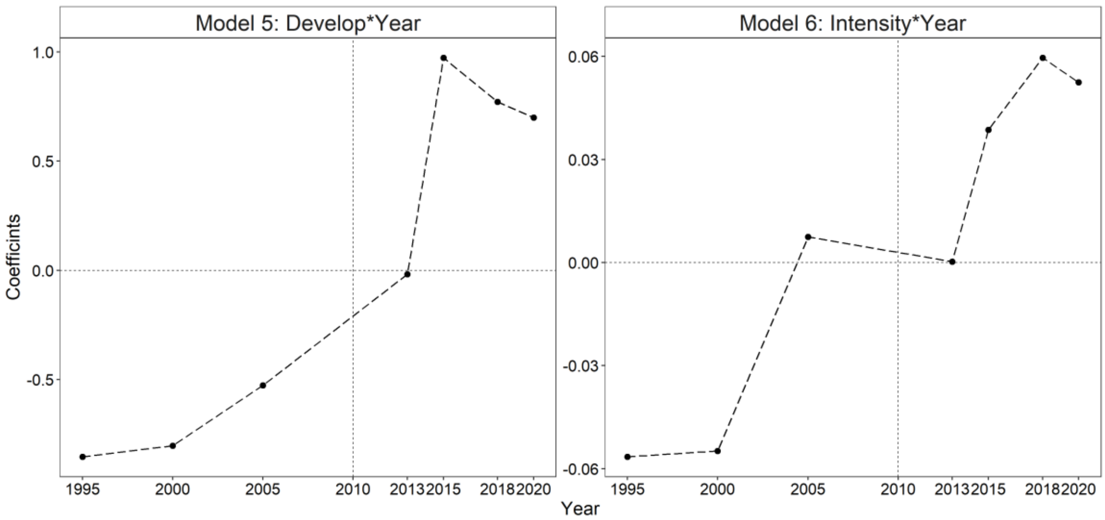

Figure 9. The coefficients of $Develop_i * Year_j$ in model 5 and $Intensity_i * Year_j$ in model 6; the other coefficients are listed *in Table A3 in* the Annex A.4

3.4 Characteristics of non-conforming built-up land expansion in Zhangzhou City

In Zhangzhou City, the newly developed built-up land area between 2010 and 2020 covered 144.75 km^2, with non-conforming built-up land expansion accounted for 67.61% (97.87 km^2). There was 376.21 km^2 of non-built-up land inside the development-permitted zones in 2020. Thus, the development-permitted zones would have been sufficient to contain the entire expansion of built-up land between 2010 and 2020. Arable land and forest were the main sources of non-conforming built-up land expansion (Figure 10). They contributed 53.61 km^2 and 21.67 km^2 of non-conforming built-up land expansion, respectively. The non-conforming built-up land was mainly used as industrial/mining/transportation land (71.27km^2) and rural settlements (16.91 km^2).

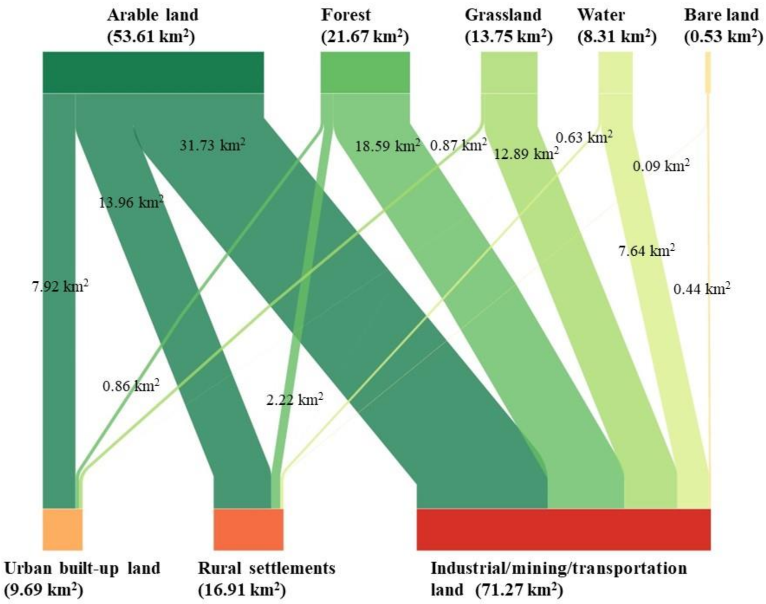

Figure 10. Land use changes from arable land, forest, grassland, water, and bare land to non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land in Zhangzhou City between 2010 and 2020

Edge expansion was the dominant type of non-conforming built-up land expansion (Figure 11). It accounted for 94.23% (9.14 km^2), 89.83% (15.19 km^2), and 77.32% (55.1 km^2) of the non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land expansion, respectively. The non-conforming industrial/mining/transportation land had more outlying expansion than the other two non-conforming built-up land uses. Only a small percentage of the non-conforming built-up land expansion was infill expansion.

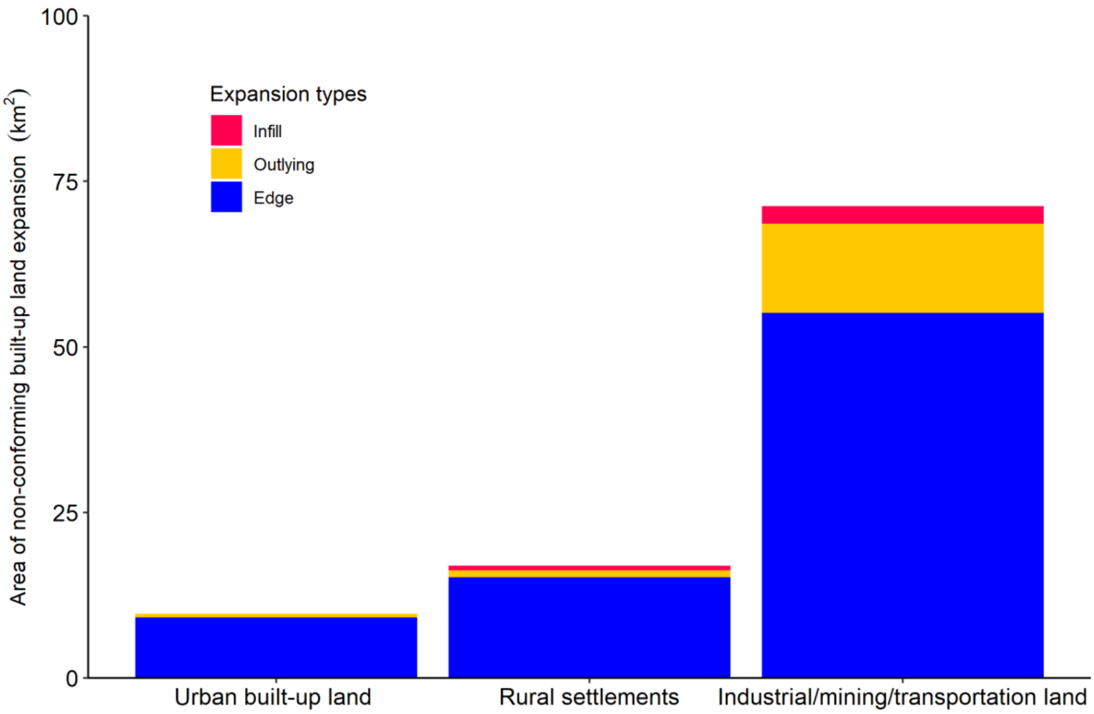

Figure 11. Areas of the infill, edge, and outlying expansion types in the non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land in Zhangzhou City between 2010 and 2020

3.5 Peer effects of non-conforming built-up land expansion in Zhangzhou City

3.5.1 Performance of the SAR

Pseudo R^2 values ranged from 0.160 to 0.194 (Table 4). Large unexplained variation in the villages' non-conforming expansion of built-up land was expected, as non-conforming built-up land expansion can be sensitive to local-scale land-use activities and the sudden appearance of land development opportunities (Padeiro, 2016). The high degree of randomness and uncertainty might be explained by omitted variables I could not include in the models, such as villagers' livelihoods or their attitudes toward zoning regulations.

3.5.2 Peer effects on villages' non-conforming built-up land expansion

ρ values were significant at the 10% level for all five peer relationships, meaning that the peer effects were indispensable in explaining non-conforming expansion of built-up land at the village level (Table 4). The ρ values indicated that a given village's non-conforming built-up land area increased by 3.9%, 6.2%, and 22.5% if its geographical peers, political peers, and economic peers increased in non-conforming built-up land area by 10%. Regarding combined peer relationships, economic competition enhanced the geographical and political peer effects. The ρ value of the geographical-economic (0.47) and the political-economic peer relationships (0.71) were higher than those of the geographical (0.39) and political peer relationships (0.62).

3.5.3 Other drivers of villages' non-conforming built-up land expansion

While the statistical significances of some control variables varied in our models, positiveness and negative of their coefficients were relatively stable. I presented the empirical meaning of the control variables whose statistical significances all were significant at the 10% level in the five SAR models. $Dis2county$ had positive coefficients, indicating that the non-conformance was less likely to occur in the villages that are closer to the county centers. One reason for this finding could be that development pressure is concentrated around the city center, rather than the county centers in Zhangzhou City. The coefficients of $Elevation$ were negative, indicating that the villages at lower elevations had more non-conforming expansion of built-up land. The positive coefficients of $Arable10_i$ and $Grass10_i$ suggest that the villages with more available arable land and grassland in 2010 had more non-conforming built-up land expansion between 2010 and 2020. DPZ had negative coefficients, indicating that the villages with less land allocated to the development-permitted zones developed more non-conforming built-up land.

Table 4. Results of the SAR

Peer relationships	Geographical	Political	Economic	Geographical-economic	Political-economic
ρ	0.39**	0.62***	2.25*	0.47**	0.71***
	(0.17)	(0.18)	(1.34)	(0.16)	(0.20)
$Dis2water$	0.083	0.14*	0.065	0.092	0.15*
	(0.075)	(0.081)	(0.084)	(0.076)	(0.079)
$Dis2coast$	0.041	0.045	0.042	0.041	0.049
	(0.039)	(0.041)	(0.042)	(0.039)	(0.042)

$Dis2city$	-0.023	-0.023	-0.036**	-0.018	-0.019
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
$Dis2county$	0.14***	0.15***	0.19***	0.12**	0.13**
	(0.053)	(0.054)	(0.058)	(0.053)	(0.053)
$Elevation$	-16.0***	-21.9***	-21.7***	-13.6**	-20.2***
	(5.97)	(6.13)	(5.76)	(6.12)	(6.00)
$Relief$	0.18	0.24	0.26*	0.15	0.24
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
$Dis2road$	2.36**	2.21*	1.98	2.26*	2.20*
	(1.18)	(1.23)	(1.27)	(1.19)	(1.24)
$Arable10$	0.14***	0.14***	0.15***	0.14***	0.15***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)
$Forest10$	0.074	0.081*	0.090*	0.075	0.082*
	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)
$Grass10$	0.36**	0.35**	0.37**	0.37**	0.36**
	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)
$Builtup10$	0.086	0.083	0.087*	0.083	0.087
	(0.053)	(0.052)	(0.052)	(0.052)	(0.054)
$PGDP10$	-0.21*	-0.21*	-0.066	-0.15	-0.15
	(0.12)	(0.12)	(0.15)	(0.12)	(0.11)
DPZ	-0.061***	-0.057**	-0.055**	-0.064***	-0.061***
	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)
Pseudo R^2	0.194	0.177	0.177	0.190	0.160
Obs.	307	307	307	307	307

Note: Standard errors are given in parentheses; p-values of the LM tests are given in brackets;

** p<0.10, ** p<0.05, *** p<0.01*

4. Discussion

4.1 Do we get closer to causality?

While the ineffectiveness of spatial planning on containing built-up land expansion is common around the world (Abrantes et al., 2016; Alfasi et al., 2012; Guo et al., 2020; Kleemann et al., 2017; Sharifi et al., 2014; L.-G. Wang et al., 2014), most previous research did not answer the question of how built-up land expansion would have differed in the absence of spatial planning. The findings from the PSM and PSM-DID show that built-up land would have expanded by an additional 27.02 km^2 and 79.31 km^2 if there were no built-up land zoning in Zhangzhou City (2010-2020) and the MFOZ in Fujian Province (2013-2018). The 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 and 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 conventional conformance-based evaluation led to inaccurate evaluations resulting from selection bias. Within the conformance-based evaluation, the changes in built-up land may be a result of the confounding variables and less so of spatial planning, since the confounding variables affected both the assignment to a planning status and the changes in built-up land. For example, *Dis2city* had not only a negative impact on the probability of a town being assigned to the development-prioritized zone during the making of the MFOZ, but also had a negative impact on built-up land expansion. The conformance-based evaluation attributed the effect of *Dis2city* on built-up land expansion to the effect of the MFOZ. It exaggerates the effect of the MFOZ on built-up land expansion. Whereas, the PSM-based evaluation eliminated the effect of *Dis2city* on built-up land expansion, thereby identifying solely the effect of the MFOZ on built-up land expansion. That is, the causal effect of spatial planning on built-up land expansion should be conceptualized as the built-up land expansion that is solely attributable to spatial planning.

The discrepancy between the findings from the PSM and PSM-DID 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. This is also the principle of the conformance-based evaluation. The conformance-based evaluation considers the effect of spatial planning on land use change as the combined effect brought about by spatial planning in combination with other forces, e.g., geographical, socio-economic or proximity factors (Wong & Watkins, 2009). However, the combined effects of spatial planning and other forces lead to inaccurate results. This dissertation defines the causal effect 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). The results from the PSM and PSM-DID provide compelling causal evidence for the effectiveness of spatial planning in containing built-up land expansion. The question of how to define the effect is still controversial in plan evaluation (E. 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.

4.2 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. The findings from the PSM and PSM-DID show that the time-lag effect existed in the initial implementation period of built-up land zoning and the MFOZ. 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 the findings, it is reasonable to observe that built-up land zoning started to play a causal role in containing built-up land expansion after 2013. The MFOZ, which was only developed at the national and provincial levels, lacks local administrative measures and implementation regulations. Thus, it is inevitable that the implementation of the MFOZ is immensely costly in terms of time. For example, the smallest unit of the Fujian's MFOZ is a town, which means every town only has one major function-oriented zone. Such coarse zoning results in town-level governments spending considerable amounts of time coordinating with the superior government to develop their local corresponding spatial regulations.

Time makes the effect of spatial planning on land use change more difficult to evaluate, as the effect is delayed. 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.

4.3 Concerns about non-conforming built-up land expansion

The large amount of non-conforming built-up land expansion in 307 of the 1,662 villages of Zhangzhou City between 2010 and 2020 raises serious concerns. The percentage (67.61%) of newly developed built-up land outside the development-permitted zones was higher than in most previous studies. For example, < 30% of the total developed land was found to occur outside building zones in Switzerland (Gennaio et al., 2009). In studies in developing countries (e.g., China, Brazil, Pakistan, Ethiopia), non-conformance rates of 50–60% were often reported (Bulti & Sori, 2017; Hussain & Nadeem, 2021; Liu et al., 2020; Menzori et al., 2021; L. Tian & Shen, 2011; L.-G. Wang et al., 2014). These findings suggest that the non-conformance of built-up land expansion to zoning regulations increases with greater development pressure, as discussed by Brody & Highfield (2005) and Loh (2011). The concentration of all non-conforming built-up land expansion in 307 of the 1,662 villages means that only a few villages were affected, but often to a high degree. One reason for this pattern could be that the planning authority in Zhangzhou City underestimated the development pressure in these villages.

The non-conforming built-up land expanded at the expense of arable land and forest in Zhangzhou City. This finding is consistent with previous research in Israel, Spain, and China (Alfasi et al., 2012; Padeiro, 2016; Shen et al., 2019). This pattern may threaten food security, biodiversity, and landscape quality. Industrial/mining/transportation land accounted for 72.82% of the newly developed non-conforming built-up land. Likewise, Shen et al. (2019) found that manufacturing land accounted for 48% of the non-conforming urban land in Baiyun County in southwestern China. In contrast, residential land development was found to be the main type of non-conforming built-up land expansion in Ethiopia and Brazil (Bulti & Sori, 2017; Menzori et al., 2021). The prominence of non-conforming industry/mining/transportation development is closely associated with the land supply strategies of local governments in China. That is, under a government-led land market, local governments supply a limited amount of residential and commercial land to developers, in order to increase land-leasing fees, but lease out abundant industrial land at low prices to attract manufacturing investment (M. Cai, 2017; Z. Huang & Du, 2017; Shen et al., 2019). While the extensive non-conforming development of industry/mining/transportation land promotes local economic growth in the short term, it may lead to an overheated economy, excess production capacity, and inefficient land use.

Edge expansion was the dominant type of non-conforming built-up land expansion is inconsistent with some previous research suggesting that non-conforming built-up land expansion occurs in a fragmented way (Abrantes et al., 2016; Guo et al., 2020; Yue et al., 2013). The results of this dissertation suggest that, while non-conforming built-up land does continue to spread outward, it mostly contributes to reducing landscape fragmentation and improving urban agglomeration.

4.4 Varying peer effects on villages' non-conforming built-up land expansion

While a disparity between established zoning regulations and built-up land expansion is common around the world, the drivers of such non-conforming built-up land expansion have only been empirically investigated in a few studies (Alterman & Hill, 1978; Brody et al., 2006; Padeiro, 2016). Furthermore, few attempts have been made to analyze the spatial interdependencies of local governments' land use behaviors of violating established zoning regulations. So far, research has only confirmed that geographical contiguity matters in non-conforming built-up land expansion among 262 of the prefecture-level cities in China (J. Wang et al., 2020). In this dissertation, I found five positive peer effects driving villages to violate zoning regulations in Zhangzhou City between 2010 and 2020. That is, a given village's non-conforming built-up land area increased to varying degrees as their geographical peers, political peers, economic peers, geographical-economic peers, and political-economic peers expanded their non-conforming built-up land area.

An interesting finding is that the economic peer effect enhanced the geographical and political peer effects, as the geographical-economic and the political-economic peer effect were higher than the geographical and political peer effect, respectively. This finding indicates that the primary motivation for villages to violate zoning regulations is to compete more effectively for economic growth. This fits with the common view that China's local governments, which compete fiercely for economic growth, loosen established regulatory rules (e.g., lower environmental standards, lenient land development permissions, lower industrial land prices) to attract investment, essentially leading a "race to the bottom" (Z. Huang & Du, 2017; Peng, 2020; B. Wang et al., 2020). This finding is original since little attention is given to the village-level governmental (the lowest level in China's top-down administrative hierarchy) race to the bottom in zoning regulation.

Institutional background determines the village-level governmental race to the bottom in zoning regulation. While the village committees can be considered a superior governmental agent, their authority relies considerably on the support of local villagers. The villagers' support often depends heavily on how many development opportunities the village committee can secure for the village (X. Zhou, 2009). In this case, villagers and villager committees make comparisons between geographical, political, and economic peer. And economic performance become a vital benchmark when comparing. This argument is reinforced by the fact that most non-conforming built-up land in Zhangzhou City has been converted to industrial/mining/transportation land, which is highly profitable and allows local governments to increase their revenues and employment and thus boost their economy (C. He et al., 2014).

4.5 Policy implications

Spatial planning 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 a concerning degree of non-conformance between spatial planning and the actual built-up land expansion have been reported in many cities (Guo et al., 2020; T. Liu et al., 2020; Shao et al., 2018; Shen et al., 2021), and the credibility of spatial planning is therefore declining. The findings of this dissertation suggest, however, that a lack of conformance alone does not mean that causality does not exist. Indeed, the findings suggest that spatial planning played a causal role in containing built-up land expansion in southeastern China. The causal evidence from the PSM and PSM-DID can enhance the credibility of spatial 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 et al., 2009), green belts (Macdonald et al., 2020; Siedentop et al., 2016), and land use zoning (Alfasi et al., 2012; Sharifi et al., 2014). This dissertation 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.

Non-conforming built-up land expansion is the main contributor to rapid built-up land expansion worldwide, which leads to a series of environmental issues. Moreover, non-conforming built-up land expansion is often associated with land-related crimes (e.g., corruption and illegal land transactions), not only undermining the credibility of spatial planning but also triggering social conflicts. The findings of this dissertation provided some suggestions for policies to effectively restrict non-conforming built-up land expansion in China. First, industrial/mining/transportation land was the main form of non-conforming built-up land expansion in Zhangzhou City. The government's supply of industrial/mining/transportation land therefore should be strictly controlled. Simultaneously, the permission process for developing industrial/mining/transportation land should be strengthened by conducting comprehensive feasibility evaluations and strict environmental assessments. In addition, local governments in China should be required to optimize their industrial structure, including moving from extensive to intensive industrial activities and converting underused industrial land into residential land, commercial land, and green spaces.

Non-conforming built-up land expansion cannot be restricted by local governments in China because local governments do not make land use decisions in isolation. Intervention from the central government and cooperation between local governments are indispensable to restrict peer effects on a local government's non-conforming built-up land expansion. One the one hand, the central government should continue its reform of the evaluation indices used in local officials' promotions, for example by highlighting the costs of non-conforming built-up land expansion and incentivizing local governments to provide more public services and protect the environment (Zuo, 2015). Tang et al. (2021) found that this type of reform can significantly restrict the land violations of local governments. On the other hand, local governments should strengthen cooperation to develop regional resolutions. Within regions, local governments can, for example, specialize in different functions and trade built-up land quotas with their peers.

The planning system in China should be improved in several respects. (1) Currently, planning authorities in this country have a high degree of discretionary power. For example, they can legally authorize non-conforming activities on the grounds of public interest, and they often do so, so that the political leaders can pursue specific political (and private) interests rather than serving the common good (Shen et al., 2019). The position of the planning authorities should be strengthened to emphasize technical, rational aspects, whereas the use of discretionary power should be minimized. (2) Low levels of transparency are common, for example due to the absence of public participation in the plan-making process and a lack of disclosure of information in the plan-implementation process (Zhu & Tang, 2018). The planning system should be improved by guaranteeing public participation both in the plan-making and in the plan-implementation process. Public participation is an effective tool to minimize power inequalities between local people and governments and to obtain more consensus (Hartmann, 2012). It enables and motivates local people to supervise plan implementation. (3) The planning authorities need to develop a real-time and highly accurate monitoring system to track land use change and plan-implementation. As part of this, the Land Supervision System that is responsible for investigating, auditing, and correcting land violations should be strictly implemented. When a local government's non-conforming built-up land expansion is punished promptly, its peers will most likely restrict their non-conforming built-up land expansion immediately. Some studies have indicated that the Land Supervision System significantly suppresses illegal land use (S. Chen et al., 2021; Z. Chen et al., 2015).

5. Conclusions and outlooks

This dissertation evaluated the causal effect of spatial planning in containing built-up land expansion and investigated the characteristics and peer effects on non-conforming built-up land expansion in rapid urbanization context of southeastern China. The two quasi-experimental methods (PSM and PSM-DID) were applied to evaluate the causal effect of built-up land zoning in Zhangzhou City (2010-2020) and of the MFOZ in Fujian Province (2013-2020) on built-up land expansion. The conformance-based evaluation was used as s a reference for the PSM and PSM-DID evaluation, to demonstrate the problem of selection bias. The characteristics and the peer effects on the non-conforming built-up land expansion were analyzed in Zhangzhou City between 2010 and 2020 via the conformance-based evaluation and SAR. Key findings of this dissertation are as follows:

- Built-up land zoning and the MFOZ played a causal role in containing built-up land expansion. Built-up land would have expanded by an additional 27.02 km^2 and 79.31 km^2 if there were no built-up land zoning in Zhangzhou City (2010-2020) and the MFOZ in Fujian Province (2013-2018).
- The time-lag effect existed in the initial implementation period of built-up land zoning and the MFOZ. Built-up land zoning started to play a causal role in containing built-up land expansion after 2013, and so did the MFOZ after 2015.
- The large amount of non-conforming built-up land expansion in Zhangzhou City between 2010 and 2020 raises serious concerns. e.g., arable land and forest loss, inefficient land use, overheated economy, excess production capacity
- The geographical, political, economic, geographical-economic, and political-economic peer effects significantly increased the area of non-conforming built-up land expansion at the village level in Zhangzhou City

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. This dissertation recommends a wider application of the quasi-experimental approach in the evaluation of spatial planning. This would not only promote a better understanding of the causes of land use change, but also increases the likelihood of spatial planning resulting in its expected outcomes by providing better causal evidence in the decision-making process.

Non-conforming built-up land expansion is often associate with illegal land grabs, informal settlements, and land use zoning amendments. These processes remain largely unexplored but have profound impacts on sustainable development. Future research should focus on how the disparity between spatial planning and actual land use changes shapes landscapes. This will require close interdisciplinary collaborations between spatial planning and land-system science, as well as spatially explicit models that can address non-conforming land use behaviors.

Acknowledgements

It was a time fraught with frustrations. I am still fortunate to have great helps from many people. I am genuinely grateful to my supervisors Christine Fürst and Anna M. Hersperger for their brilliant and generous supervision. When I was desperate and lost my way three years ago, Christine encouraged me that '*if you think there is no way, a light will come and show you where to go*.' She supported me to follow my research interests and to resume the research at WSL in Switzerland. Without her support, I would have never persevered.

Studying at WSL is an important turning point in my academic career. Anna M. Hersperger provides an expert and unselfish supervision. I appreciate the monthly meetings and the detailed comments from Anna. Although the meetings often made me worried, and the comments made the pages wholly red, they are the invaluable fortune for developing my critical thinking and academic writings.

I also appreciate the colleagues at MLU (Marcin Spyra, Janina Kleemann, and Hongmi Koo) and WSL (Ana Beatriz Pierri-Daunt, Chunhong Zhao, Darío Domingo, Franziska Schmid, Simona Bacau). They significantly contributed to the work of this dissertation and helped me a lot in my PhD life.

Without the love and support from my family, this adventure would not have been possible. I appreciate my parents, my wife and daughter. Finally, I would like to express the gratitude to the China Scholarship Council for supporting my PhD study.

Eidesstattliche Erklärung / Declaration under Oath

Ich erkläre an Eides statt, dass ich die Arbeit selbstständig und ohne fremde Hilfe verfasst, keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.
I declare under penalty of perjury that this thesis is my own work entirely and has been written without any help from other people. I used only the sources mentioned and included all the citations correctly both in word or content.

Datum / Date

Unterschrift des Antragstellers / *Signature of the applicant*

References for the dissertation

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies*, *72*(1), 1–19. https://doi.org/10.1111/0034-6527.00321

Abrantes, P., Fontes, I., Gomes, E., & Rocha, J. (2016). Compliance of land cover changes with municipal land use planning: Evidence from the Lisbon metropolitan region (1990–2007). *Land Use Policy*, *51*, 120–134. https://doi.org/10.1016/j.landusepol.2015.10.023

Acuto, M., Parnell, S., & Seto, K. C. (2018). Building a global urban science. *Nature Sustainability*, *1*(1), 2–4. https://doi.org/10.1038/s41893-017-0013-9

Akın, A., Clarke, K. C., & Berberoglu, S. (2014). The impact of historical exclusion on the calibration of the SLEUTH urban growth model. *International Journal of Applied Earth Observation and Geoinformation*, *27*, 156–168. https://doi.org/10.1016/j.jag.2013.10.002

Albrechts, L. (2010). More of the same is not enough! How could strategic spatial planning be instrumental in dealing with the challenges ahead? *Environment and Planning B: Planning and Design*, *37*(6), 1115–1127. https://doi.org/10.1068/b36068

Albrechts, L., Healey, P., & Kunzmann, K. R. (2003). Strategic spatial planning and regional governance in Europe. *Journal of the American Planning Association*, *69*(2), 113–129. https://doi.org/10.1080/01944360308976301

Alexander, E. (2009). Dilemmas in evaluating planning, or back to basics: What is planning for? *Planning Theory and Practice*, *10*(2), 233–244. https://doi.org/10.1080/14649350902884177

Alexander, E. R., & Faludi, A. (1989). Planning and plan implementation: Notes on evaluation criteria. *Environment & Planning B: Planning & Design*, *16*(2), 127–140. https://doi.org/10.1068/b160127

Alexander, P., Prestele, R., Verburg, P. H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., Doelman, J. C., Dunford, R., Engström, K., Eitelberg, D., Fujimori, S., Harrison, P. A., Hasegawa, T., Havlik, P., Holzhauer, S., … Rounsevell, M. D. A. (2017). Assessing uncertainties in land cover projections. *Global Change Biology*, *23*(2), 767–781. https://doi.org/10.1111/gcb.13447

Alfasi, N., Almagor, J., & Benenson, I. (2012). The actual impact of comprehensive land use plans: Insights from high resolution observations. *Land Use Policy*, *29*(4), 862–877. https://doi.org/10.1016/j.landusepol.2012.01.003

Alterman, R., & Hill, M. (1978). Implementation of urban land use plans. *Journal of the American Institute of Planners*, *44*(3), 274–285. https://doi.org/10.1080/01944367808976905

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(42), 16089–16094. https://doi.org/10.1073/pnas.0800437105

Anthony, J. (2004). Do state growth management regulations reduce sprawl? *Urban Affairs Review*, *39*(3), 376–397. https://doi.org/10.1177/1078087403257798

Atella, V., Belotti, F., Depalo, D., & Piano Mortari, A. (2014). Measuring spatial effects in the presence of institutional constraints: The case of Italian Local Health Authority expenditure. *Regional Science and Urban Economics*, *49*, 232–241. https://doi.org/10.1016/j.regsciurbeco.2014.07.007

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, *46*(3), 399–424. https://doi.org/10.1080/00273171.2011.568786

Baer, W. C. (1997). General plan evaluation criteria: An approach to making better plans. *Journal of the American Planning Association*, *63*(3), 329–344. https://doi.org/10.1080/01944369708975926

Barber, C. P., Cochrane, M. A., Souza, C., & Veríssimo, A. (2012). Dynamic performance assessment of protected areas. *Biological Conservation*, *149*(1), 6–14. https://doi.org/10.1016/j.biocon.2011.08.024

Barredo, J. I., Demicheli, L., Lavalle, C., Kasanko, M., & McCormick, N. (2004). Modelling Future Urban Scenarios in Developing Countries: An Application Case Study in Lagos, Nigeria. *Environment and Planning B: Planning and Design*, *31*(1), 65–84. https://doi.org/10.1068/b29103

Bieling, C., Plieninger, T., & Schaich, H. (2013). Patterns and causes of land change: Empirical results and conceptual considerations derived from a case study in the Swabian Alb, Germany. *Land Use Policy*, *35*, 192–203. https://doi.org/10.1016/j.landusepol.2013.05.012

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics*, *34*, 1–16. https://doi.org/10.1016/j.forpol.2013.04.006

Braimoh, A. K., & Onishi, T. (2007). Spatial determinants of urban land use change in Lagos, Nigeria. *Land Use Policy*, *24*(2), 502–515. https://doi.org/10.1016/j.landusepol.2006.09.001

Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., Haberl, H., Creutzig, F., & Seto, K. C. (2017). Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(34), 8939–8944. https://doi.org/10.1073/pnas.1606036114

Bressers, N., van Twist, M., & ten Heuvelhof, E. (2013). Exploring the temporal dimension in policy evaluation studies. *Policy Sciences*, *46*(1), 23–37. https://doi.org/10.1007/s11077-012-9169-3

Briassoulis, H. (2008). Land use policy and planning, theorizing, and modeling: Lost in translation, found in complexity? *Environment and Planning B: Planning and Design*, *35*(1), 16–33. https://doi.org/10.1068/b32166

Brody, S. D., & Highfield, W. E. (2005). Does planning work?: Testing the implementation of local environmental planning in Florida. *Journal of the American Planning Association*, *71*(2), 159–175. https://doi.org/10.1080/01944360508976690

Brody, S. D., Highfield, W. E., & Thornton, S. (2006). Planning at the urban fringe: An examination of the factors influencing nonconforming development patterns in southern Florida. *Environment and Planning B: Planning and Design*, *33*(1), 75–96. https://doi.org/10.1068/b31093

Brown, D. G., Verburg, P. H., Pontius, R. G., & Lange, M. D. (2013). Opportunities to improve impact, integration, and evaluation of land change models. *Current Opinion in Environmental Sustainability*, *5*(5), 452–457.

https://doi.org/10.1016/j.cosust.2013.07.012

Bruggeman, D., Meyfroidt, P., & Lambin, E. F. (2015). Production forests as a conservation tool: Effectiveness of Cameroon's land use zoning policy. *Land Use Policy*, *42*, 151–164. https://doi.org/10.1016/j.landusepol.2014.07.012

Bulti, D. T., & Sori, N. D. (2017). Evaluating land use plan using conformance-based approach in Adama city, Ethiopia. *Spatial Information Research*, *25*(4), 605–613. https://doi.org/10.1007/s41324-017-0125-3

Bürgi, M., Celio, E., Diogo, V., Hersperger, A. M., Kizos, T., Lieskovsky, J., Pazur, R., Plieninger, T., Prishchepov, A. v., & Verburg, P. H. (2022). Advancing the study of driving forces of landscape change. *Journal of Land Use Science*, 1–16. https://doi.org/10.1080/1747423x.2022.2029599

Bürgi, M., Hersperger, A. M., & Schneeberger, N. (2004). Driving forces of landscape change - current and new directions. *Landscape Ecology*, *19*(8), 857–868. https://doi.org/10.1007/s10980-005-0245-3

Bürgi, M., Salzmann, D., & Gimmi, U. (2015). 264 years of change and persistence in an agrarian landscape: A case study from the Swiss lowlands. *Landscape Ecology*, *30*(7), 1321–1333. https://doi.org/10.1007/s10980-015-0189-1

Butsic, V., Lewis, D. J., & Ludwig, L. (2011). An econometric analysis of land development with endogenous zoning. *Land Economics*, *87*(3), 412–432. https://doi.org/10.3368/le.87.3.412

Cai, H., Henderson, J. V., & Zhang, Q. (2013). China's land market auctions: Evidence of corruption? *RAND Journal of Economics*, *44*(3), 488–521. https://doi.org/10.1111/1756-2171.12028

Cai, M. (2017). Revenue, time horizon, and land allocation in China. *Land Use Policy*, *62*, 101–112. https://doi.org/10.1016/j.landusepol.2016.12.020

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Calkins, H. W. (1979). The planning monitor: An accountability theory of plan evaluation.

Environment and Planning A: Economy and Space, *11*(7), 745–758. https://doi.org/10.1068/a110745

Cao, Y., Zhang, X., Fu, Y., Lu, Z., & Shen, X. (2020). Urban spatial growth modeling using logistic regression and cellular automata: A case study of Hangzhou. *Ecological Indicators*, *113*. https://doi.org/10.1016/j.ecolind.2020.106200

Cassette, A., Di Porto, E., & Foremny, D. (2012). Strategic fiscal interaction across borders: Evidence from French and German local governments along the Rhine Valley. *Journal of Urban Economics*, *72*(1), 17–30. https://doi.org/10.1016/j.jue.2011.12.003

Chadwick, G. (1978). A systems view of planning: Towards a theory of the urban and regional planning process. In *Pergamon Press*.

Chai, S.-L., Tanner, E., & McLaren, K. (2009). High rates of forest clearance and fragmentation pre- and post-National Park establishment: The case of a Jamaican montane rainforest. *Biological Conservation*, *142*(11), 2484–2492. https://doi.org/10.1016/j.biocon.2009.05.020

Chapin, T. S., Deyle, R. E., & Baker, E. J. (2008). A parcel-based GIS method for evaluating conformance of local land use planning with a state mandate to reduce exposure to hurricane flooding. *Environment and Planning B: Planning and Design*, *35*(2), 261–279. https://doi.org/10.1068/b32114

Chen, H., Tang, L., Qiu, Q., Hou, L., & Wang, B. (2020). Construction and case analysis of an index for the sustainability of ecosystem services. *Ecological Indicators*, *115*, 106370. https://doi.org/10.1016/j.ecolind.2020.106370

Chen, S., Chen, Z., & Shen, Y. (2021). Can improving law enforcement effectively curb illegal land use in China? *PLOS ONE*, *16*(2), e0246347. https://doi.org/10.1371/journal.pone.0246347

Chen, Z., Tang, J., Wan, J., & Chen, Y. (2017). Promotion incentives for local officials and the expansion of urban construction land in China: Using the Yangtze River Delta as a case study. *Land Use Policy*, *63*, 214–225. https://doi.org/10.1016/j.landusepol.2017.01.034

Chen, Z., Wang, Q., Chen, Y., & Huang, X. (2015). Is illegal farmland conversion ineffective in China? Study on the impact of illegal farmland conversion on economic growth.

Habitat International, *49*, 294–302. https://doi.org/10.1016/j.habitatint.2015.05.036

Chetan, A., Glen M., G., J. Morgan, G., Tom P., E., & Charles M., S. (2002). *A review and assessment of land use change models: Dynamics of space, time, and human choice (UFS Technical Report NE-297)*.

Chiputwa, B., Spielman, D. J., & Qaim, M. (2015). Food standards, certification, and poverty among coffee farmers in Uganda. *World Development*, *66*, 400–412. https://doi.org/10.1016/j.worlddev.2014.09.006

Cho, S. H., Poudyal, N., & Lambert, D. M. (2008). Estimating spatially varying effects of urban growth boundaries on land development and land value. *Land Use Policy*, *25*(3), 320–329. https://doi.org/10.1016/j.landusepol.2007.08.004

Christafore, D., & Leguizamon, S. (2015). Spatial spillovers of land use regulation in the United States. *Housing Studies*, *30*(3), 491–503. https://doi.org/10.1080/02673037.2014.927054

Colantoni, A., Grigoriadis, E., Sateriano, A., Venanzoni, G., & Salvati, L. (2016). Cities as selective land predators? A lesson on urban growth, deregulated planning and sprawl containment. *Science of The Total Environment*, *545–546*, 329–339. https://doi.org/10.1016/j.scitotenv.2015.11.170

Colsaet, A., Laurans, Y., & Levrel, H. (2018). What drives land take and urban land expansion? A systematic review. *Land Use Policy*, *79*, 339–349. https://doi.org/10.1016/j.landusepol.2018.08.017

Davidoff, P., & Reiner, T. A. (1962). A choice theory of planning. *Journal of the American Planning Association*, *28*(2), 103–115. https://doi.org/10.1080/01944366208979427

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, *84*(1), 151–161. https://doi.org/10.1162/003465302317331982

Dempsey, J. A., & Plantinga, A. J. (2013). How well do urban growth boundaries contain development? Results for Oregon using a difference-in-difference estimator. *Regional Science and Urban Economics*, *43*(6), 996–1007. https://doi.org/10.1016/j.regsciurbeco.2013.10.002

Domingo, D., Palka, G., & Hersperger, A. M. (2021). Effect of zoning plans on urban land use change: A multi-scenario simulation for supporting sustainable urban growth. *Sustainable Cities and Society*, *69*, 102833. https://doi.org/10.1016/j.scs.2021.102833

Driessen, P. (1997). Performance and implementing institutions in rural land development. *Environment and Planning B: Planning and Design*, *24*(6), 859–869. https://doi.org/10.1068/b240859

Drukker, D. M., Prucha, I. R., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*, *13*(2), 221–241. https://doi.org/10.1177/1536867x1301300201

Ellis, E. A., & Porter-bolland, L. (2008). Is community-based forest management more effective than protected areas? A comparison of land use/land cover change in two neighboring study areas of the Central Yucatan Peninsula, Mexico. *Forest Ecology and Management*, *256*, 1971–1983. https://doi.org/10.1016/j.foreco.2008.07.036

European Commission. (1999). *European Spatial Towards Balanced and Sustainable of the European Union*.

Faludi, A. (2000). The performance of spatial planning. *Planning Practice and Research*, *15*(4), 299–318. https://doi.org/10.1080/713691907

Fan, J., Sun, W., Zhou, K., & Chen, D. (2012). Major Function Oriented Zone: New method of spatial regulation for reshaping regional development pattern in China. *Chinese Geographical Science*, *22*(2), 196–209. https://doi.org/10.1007/s11769-012-0528-y

Fan, P., Yue, W., Zhang, J., Huang, H., Messina, J., Verburg, P. H., Qi, J., Moore, N., & Ge, J. (2020). The spatial restructuring and determinants of industrial landscape in a mega city under rapid urbanization. *Habitat International*, *95*. https://doi.org/10.1016/j.habitatint.2019.102099

Fang, L., & Tian, C. (2020). Construction land quotas as a tool for managing urban expansion. *Landscape and Urban Planning*, *195*, 103727. https://doi.org/10.1016/j.landurbplan.2019.103727

Feitelson, E., Felsenstein, D., Razin, E., & Stern, E. (2017). Assessing land use plan implementation: Bridging the performance-conformance divide. *Land Use Policy*, *61*, 251–264. https://doi.org/10.1016/j.landusepol.2016.11.017

Feng, J., Lichtenberg, E., & Ding, C. (2015). Balancing act: Economic incentives, administrative restrictions, and urban land expansion in China. *China Economic Review*, *36*, 184–197. https://doi.org/10.1016/j.chieco.2015.09.004

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005). Global consequences of land use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Fox, J., Vogler, J. B., Sen, O. L., Giambelluca, T. W., & Ziegler, A. D. (2012). Simulating land-cover change in Montane mainland southeast Asia. *Environmental Management*, *49*(5), 968–979. https://doi.org/10.1007/s00267-012-9828-3

Gao, J., & O'Neill, B. C. (2020). Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways. *Nature Communications*, *11*(1), 1–12. https://doi.org/10.1038/s41467-020-15788-7

Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience*, *52*(2), 143–150. https://doi.org/https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Gennaio, M. P., Hersperger, A. M., & Bürgi, M. (2009). Containing urban sprawl—Evaluating effectiveness of urban growth boundaries set by the Swiss Land Use Plan. *Land Use Policy*, *26*(2), 224–232. https://doi.org/10.1016/j.landusepol.2008.02.010

Gómez-Antonio, M., Hortas-Rico, M., & Li, L. (2016). The causes of urban sprawl in Spanish urban areas: A spatial approach. *Spatial Economic Analysis*, *11*(2), 219–247. https://doi.org/10.1080/17421772.2016.1126674

Guo, Z., Hu, Y., & Zheng, X. (2020). Evaluating the effectiveness of land use master plans in built-up land management: A case study of the Jinan Municipality, eastern China. *Land Use Policy*, *91*, 104369. https://doi.org/10.1016/j.landusepol.2019.104369

Guyadeen, D., & Seasons, M. (2016). Plan evaluation: Challenges and directions for future research. *Planning Practice & Research*, *31*(2), 215–228. https://doi.org/10.1080/02697459.2015.1081335

Guyadeen, D., & Seasons, M. (2018). Evaluation theory and practice: Comparing program evaluation and evaluation in planning. *Journal of Planning Education and Research*, *38*(1), 98–110. https://doi.org/10.1177/0739456X16675930

Han, Y., & Jia, H. (2017). Simulating the spatial dynamics of urban growth with an integrated modeling approach: A case study of Foshan, China. *Ecological Modelling*, *353*, 107–116. https://doi.org/10.1016/j.ecolmodel.2016.04.005

Hanlon, B., Howland, M., & McGuire, M. P. (2012). Hotspots for growth: Does Maryland's priority funding area program reduce sprawl? *Journal of the American Planning Association*, *78*(3), 256–268. https://doi.org/10.1080/01944363.2012.715501

Hansen, H. S. (2010). Modelling the future coastal zone urban development as implied by the IPCC SRES and assessing the impact from sea level rise. *Landscape and Urban Planning*, *98*(3–4), 141–149. https://doi.org/10.1016/j.landurbplan.2010.08.018

Hartmann, T. (2012). Wicked problems and clumsy solutions: Planning as expectation management. *Planning Theory*, *11*(3), 242–256. https://doi.org/10.1177/1473095212440427

He, C., Huang, Z., & Wang, R. (2014). Land use change and economic growth in urban China: A structural equation analysis. *Urban Studies*, *51*(13), 2880–2898. https://doi.org/10.1177/0042098013513649

He, C., Liu, Z., Tian, J., & Ma, Q. (2014). Urban expansion dynamics and natural habitat loss in China: A multiscale landscape perspective. *Global Change Biology*, *20*(9), 2886–2902. https://doi.org/10.1111/gcb.12553

He, J., Liu, Y., Yu, Y., Tang, W., Xiang, W., & Liu, D. (2013). A counterfactual scenario simulation approach for assessing the impact of farmland preservation policies on urban sprawl and food security in a major grain-producing area of China. *Applied Geography*, *37*, 127–138. https://doi.org/10.1016/j.apgeog.2012.11.005

He, Z., Ling, Y., Fürst, C., & Hersperger, A. M. (2022). Does zoning contain built-up land expansion? Causal evidence from Zhangzhou City, China. *Landscape and Urban*

Planning, *220*, 104339. https://doi.org/10.1016/j.landurbplan.2021.104339

He, Z., Zhao, C., Fürst, C., & Hersperger, A. M. (2021). Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China? *Land Use Policy*, *108*, 105562. https://doi.org/10.1016/j.landusepol.2021.105562

Henríquez-Dole, L., Usón, T. J., Vicuña, S., Henríquez, C., Gironás, J., & Meza, F. (2018). Integrating strategic land use planning in the construction of future land use scenarios and its performance: The Maipo River Basin, Chile. *Land Use Policy*, *78*, 353–366. https://doi.org/10.1016/j.landusepol.2018.06.045

Hermelin, B. (2009). Spatial strategic planning in the Stockholm Region—Discourses on the space-economy and growth factors. *European Planning Studies*, *17*(1), 131–148. https://doi.org/10.1080/09654310802514029

Hersperger, A. M., & Bürgi, M. (2010). How do policies shape landscapes? Landscape change and its political driving forces in the Limmat Valley, Switzerland 1930-2000. *Landscape Research*, *35*(3), 259–279. https://doi.org/10.1080/01426391003743561

Hersperger, A. M., & Fertner, C. (2021). Digital plans and plan data in planning support science. *Environment and Planning B: Urban Analytics and City Science*, *48*(2), 212–215. https://doi.org/10.1177/2399808320983002

Hersperger, A. M., Grădinaru, S., Oliveira, E., Pagliarin, S., & Palka, G. (2019). Understanding strategic spatial planning to effectively guide development of urban regions. *Cities*, *94*, 96–105. https://doi.org/10.1016/j.cities.2019.05.032

Hersperger, A. M., Oliveira, E., Pagliarin, S., Palka, G., Verburg, P., Bolliger, J., & Grădinaru, S. (2018). Urban land use change: The role of strategic spatial planning. *Global Environmental Change*, *51*, 32–42. https://doi.org/10.1016/j.gloenvcha.2018.05.001

Huang, D., Huang, J., & Liu, T. (2019). Delimiting urban growth boundaries using the CLUE-S model with village administrative boundaries. *Land Use Policy*, *82*, 422–435. https://doi.org/10.1016/j.landusepol.2018.12.028

Huang, J., Huang, Y., Pontius, R. G., & Zhang, Z. (2015). Geographically weighted regression to measure spatial variations in correlations between water pollution versus land use in a coastal watershed. *Ocean and Coastal Management*, *103*, 14–24.

https://doi.org/10.1016/j.ocecoaman.2014.10.007

Huang, J., Pontius, R. G., Li, Q., & Zhang, Y. (2012). Use of intensity analysis to link patterns with processes of land change from 1986 to 2007 in a coastal watershed of southeast China. *Applied Geography*, *34*, 371–384. https://doi.org/10.1016/j.apgeog.2012.01.001

Huang, Z., & Du, X. (2017). Strategic interaction in local governments' industrial land supply: Evidence from China. *Urban Studies*, *54*(6), 1328–1346. https://doi.org/10.1177/0042098016664691

Hussain, Z., & Nadeem, O. (2021). The nexus between growth strategies of master plans and spatial dynamics of a metropolitan city: The case of Lahore, Pakistan. *Land Use Policy*, *109*, 105609. https://doi.org/10.1016/j.landusepol.2021.105609

Ibisch, P. L., Hoffmann, M. T., Kreft, S., Pe'er, G., Kati, V., Biber-Freudenberger, L., DellaSala, D. A., Vale, M. M., Hobson, P. R., & Selva, N. (2016). A global map of roadless areas and their conservation status. *Science*, *354*(6318), 1423–1427. https://doi.org/10.1126/science.aaf7166

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference for statistics, social, and biomedical sciences: An introduction*. Cambridge University Press.

Irwin, E. G., & Bockstael, N. E. (2004). Land use externalities, open space preservation, and urban sprawl. *Regional Science and Urban Economics*, *34*(6), 705–725. https://doi.org/10.1016/j.regsciurbeco.2004.03.002

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, *83*(4), 685–709. https://doi.org/https://www.jstor.org/stable/2117574

Jantz, C. A., Goetz, S. J., & Shelley, M. K. (2004). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington Metropolitan Area. *Environment and Planning B: Planning and Design*, *31*(2), 251–271. https://doi.org/10.1068/b2983

Jiang, Y., Sun, S., & Zheng, S. (2019). Exploring urban expansion and socioeconomic vitality using NPP-VIIRS data in Xia-Zhang-Quan, China. *Sustainability*, *11*(6), 1739. https://doi.org/10.3390/su11061739

Jones, B. D. (1999). Bounded rationality. *Annual Review of Political Science*, *2*(1), 297–321. https://doi.org/10.1146/annurev.polisci.2.1.297

Kasraian, D., Maat, K., & Van, W. B. (2019). The impact of urban proximity, transport accessibility and policy on urban growth: A longitudinal analysis over five decades. *Environment and Planning B: Urban Analytics and City Science*, *46*(6), 1000–1017. https://doi.org/10.1177/2399808317740355

Khakee, A. (1998). Evaluation and planning: Inseparable concepts. *Source: The Town Planning Review*, *69*(4), 359–374. https://www.jstor.org/stable/40113511

Kim, Y., Newman, G., & Güneralp, B. (2020). A review of driving factors, scenarios, and topics in urban land change models. *Land*, *9*(8), 246. https://doi.org/10.3390/land9080246

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S., & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and Urban Planning*, *165*, 280–294. https://doi.org/10.1016/j.landurbplan.2017.02.004

Kline, J. D., Thiers, P., Ozawa, C. P., Alan Yeakley, J., & Gordon, S. N. (2014). How well has land use planning worked under different governance regimes? A case study in the Portland, OR-Vancouver, WA metropolitan area, USA. *Landscape and Urban Planning*, *131*, 51–63. https://doi.org/10.1016/j.landurbplan.2014.07.013

Kong, L., Tian, G., Ma, B., & Liu, X. (2017). Embedding ecological sensitivity analysis and new satellite town construction in an agent-based model to simulate urban expansion in the Beijing metropolitan region, China. *Ecological Indicators*, *82*, 233–249. https://doi.org/10.1016/j.ecolind.2017.07.009

Lambin, E. F., Meyfroidt, P., Rueda, X., Blackman, A., Börner, J., Cerutti, P. O., Dietsch, T., Jungmann, L., Lamarque, P., Lister, J., Walker, N. F., & Wunder, S. (2014). Effectiveness and synergies of policy instruments for land use governance in tropical regions. *Global Environmental Change*, *28*(1), 129–140. https://doi.org/10.1016/j.gloenvcha.2014.06.007

Landis, J. D. (2021). Fifty years of local growth management in America. *Progress in Planning*, *145*. https://doi.org/10.1016/j.progress.2019.100435

Lauf, S., Haase, D., Hostert, P., Lakes, T., & Kleinschmit, B. (2012). Uncovering land use dynamics driven by human decision-making - A combined model approach using cellular automata and system dynamics. *Environmental Modelling and Software*, *27–28*, 71–82. https://doi.org/10.1016/j.envsoft.2011.09.005

Laurian, L., Day, M., Berke, P., Ericksen, N., Backhurst, M., Crawford, J., & Dixon, J. (2004). Evaluating plan implementation: A conformance-based methodology. *Journal of the American Planning Association*, *70*(4), 471–480. https://doi.org/10.1080/01944360408976395

Le Berre, I., Maulpoix, A., Thériault, M., & Gourmelon, F. (2016). A probabilistic model of residential urban development along the French Atlantic coast between 1968 and 2008. *Land Use Policy*, *50*, 461–478. https://doi.org/10.1016/j.landusepol.2015.09.007

LeSage, J., & Pace, R. K. (2009). Introduction to spatial econometrics. In *Introduction to Spatial Econometrics*. Chapman and Hall/CRC.

Lewis, D. (1973). Causation. *The Journal of Philosophy*, *70*(17), 556–567. https://doi.org/10.2307/2025310

Li, F., Li, Z., Chen, H., Chen, Z., & Li, M. (2020). An agent-based learning-embedded model (ABM-learning) for urban land use planning: A case study of residential land growth simulation in Shenzhen, China. *Land Use Policy*, *95*. https://doi.org/10.1016/j.landusepol.2020.104620

Li, M., Verburg, P. H., & van Vliet, J. (2022). Global trends and local variations in land take per person. *Landscape and Urban Planning*, *218*, 104308. https://doi.org/10.1016/j.landurbplan.2021.104308

Li, X., Chen, Y., Liu, X., Xu, X., & Chen, G. (2017). Experiences and issues of using cellular automata for assisting urban and regional planning in China. *International Journal of Geographical Information Science*, *31*(8), 1606–1629. https://doi.org/10.1080/13658816.2017.1301457

Li, X., Zhou, W., & Ouyang, Z. (2013). Forty years of urban expansion in Beijing: What is the relative importance of physical, socioeconomic, and neighborhood factors? *Applied Geography*, *38*, 1–10. https://doi.org/10.1016/j.apgeog.2012.11.004

Liao, J., Shao, G., Wang, C., Tang, L., Huang, Q., & Qiu, Q. (2019). Urban sprawl scenario simulations based on cellular automata and ordered weighted averaging ecological constraints. *Ecological Indicators*, *107*, 105572. https://doi.org/10.1016/j.ecolind.2019.105572

Lichtenberg, E., & Ding, C. (2008). Assessing farmland protection policy in China. *Land Use Policy*, *25*(1), 59–68. https://doi.org/10.1016/j.landusepol.2006.01.005

Liu, T., Huang, D., Tan, X., & Kong, F. (2020). Planning consistency and implementation in urbanizing China: Comparing urban and land use plans in suburban Beijing. *Land Use Policy*, *94*, 104498. https://doi.org/10.1016/j.landusepol.2020.104498

Liu, X., Hu, G., Ai, B., Li, X., Tian, G., Chen, Y., & Li, S. (2018). Simulating urban dynamics in China using a gradient cellular automata model based on S-shaped curve evolution characteristics. *International Journal of Geographical Information Science*, *32*(1), 73–101. https://doi.org/10.1080/13658816.2017.1376065

Liu, X., & Lynch, L. (2011). Do agricultural land preservation programs reduce farmland loss? Evidence from a propensity score matching estimator. *Land Economics*, *87*(2), 183–201. https://doi.org/10.3368/le.87.2.183

Liu, Y., Fu, B., Zhao, W., Wang, S., & Deng, Y. (2018). A solution to the conflicts of multiple planning boundaries: Landscape functional zoning in a resource-based city in China. *Habitat International*, *77*(19), 43–55. https://doi.org/10.1016/j.habitatint.2018.01.004

Loh, C. G. (2011). Assessing and interpreting non-conformance in land use planning implementation. *Planning Practice and Research*, *26*(3), 271–287. https://doi.org/10.1080/02697459.2011.580111

Loh, C. G. (2019). Placemaking and implementation: Revisiting the performance principle. *Land Use Policy*, *81*, 68–75. https://doi.org/10.1016/j.landusepol.2018.10.024

Long, Y., Gu, Y., & Han, H. (2012). Spatiotemporal heterogeneity of urban planning implementation effectiveness: Evidence from five urban master plans of Beijing. *Landscape and Urban Planning*, *108*(2–4), 103–111. https://doi.org/10.1016/j.landurbplan.2012.08.005

Long, Y., Han, H., Lai, S., & Mao, Q. (2013). Urban growth boundaries of the Beijing Metropolitan Area: Comparison of simulation and artwork. *Cities*, *31*, 337–348.

https://doi.org/10.1016/j.cities.2012.10.013

Long, Y., Shen, Z., Machi, K., & Mao, Q. (2012). Retrieving spatial policy parameters from an alternative plan using constrained cellular automata and regionalized sensitivity analysis. *Environment and Planning B: Planning and Design*, *39*, 586–605. https://doi.org/10.1068/b37122

Macdonald, S., Monstadt, J., & Friendly, A. (2020). From the Frankfurt greenbelt to the Regionalpark RheinMain: An institutional perspective on regional greenbelt governance. *European Planning Studies*, *4313*. https://doi.org/10.1080/09654313.2020.1724268

Malek, Ž., & Verburg, P. H. (2020). Mapping global patterns of land use decision-making. *Global Environmental Change*, *65*. https://doi.org/10.1016/j.gloenvcha.2020.102170

Martellozzo, F., Amato, F., Murgante, B., & Clarke, K. C. (2018). Modelling the impact of urban growth on agriculture and natural land in Italy to 2030. *Applied Geography*, *91*, 156–167. https://doi.org/10.1016/j.apgeog.2017.12.004

Mastop, H., & Faludi, A. (1997). Evaluation of strategic plans: The performance principle. *Environment and Planning B: Planning and Design*, *24*(6), 815–832. https://doi.org/10.1068/b240815

Menzori, I. D., Sousa, I. C. N. de, & Gonçalves, L. M. (2021). Urban growth management and territorial governance approaches: A master plans conformance analysis. *Land Use Policy*, *105*, 105436. https://doi.org/10.1016/j.landusepol.2021.105436

Meyfroidt, P. (2016). Approaches and terminology for causal analysis in land systems science. *Journal of Land Use Science*, *11*(5), 501–522. https://doi.org/10.1080/1747423X.2015.1117530

Müller, D., & Zeller, M. (2002). Land use dynamics in the central highlands of Vietnam: A spatial model combining village survey data with satellite imagery interpretation. *Agricultural Economics*, *27*, 333–354.

Nagendra, H., Bai, X., Brondizio, E. S., & Lwasa, S. (2018). The urban south and the predicament of global sustainability. *Nature Sustainability*, *1*(7), 341–349. https://doi.org/10.1038/s41893-018-0101-5

Nordjo, R. E., & Adjasi, C. K. D. (2019). The impact of credit on productivity of smallholder farmers in Ghana. *Agricultural Finance Review*, *80*(1), 91–109. https://doi.org/10.1108/AFR-10-2018-0096

Nunn, N., & Qian, N. (2011). The potato's contribution to population and urbanization: Evidence from a historical experiment. *The Quarterly Journal of Economics*, *126*(2), 593–650. https://doi.org/10.1093/qje/qjr009

Oliveira, V., & Pinho, P. (2010). Evaluation in urban planning: Advances and prospects. *Journal of Planning Literature*, *24*(4), 343–361. https://doi.org/10.1177/0885412210364589

Onsted, J. A., & Chowdhury, R. R. (2014). Does zoning matter? A comparative analysis of landscape change in Redland, Florida using cellular automata. *Landscape and Urban Planning*, *121*, 1–18. https://doi.org/10.1016/j.landurbplan.2013.09.007

Padeiro, M. (2016). Conformance in land use planning: The determinants of decision, conversion and transgression. *Land Use Policy*, *55*, 285–299. https://doi.org/10.1016/j.landusepol.2016.04.014

Palka, G., Grădinaru, S. R., Jørgensen, G., & Hersperger, A. M. (2018). Visualizing planning intentions: From heterogeneous information to maps. *Journal of Geovisualization and Spatial Analysis*, *2*(2), 16. https://doi.org/10.1007/s41651-018-0023-9

Park, S., Hyun, J., & Clarke, K. C. (2018). Capturing the heterogeneity of urban growth in South Korea using a latent class regression model. *Transactions in GIS*, *22*(3), 789–805. https://doi.org/10.1111/tgis.12451

Paul R. Rosenbaum. (2002). *Observational Studies*. Springer.

Paulsen, K. (2014). Geography, policy or market? New evidence on the measurement and causes of sprawl (and infill) in US metropolitan regions. *Urban Studies*, *51*(12), 2629–2645. https://doi.org/10.1177/0042098013512874

Pearman, A. D. (1985). Uncertainty in planning: Characterisation, evaluation, and feedback. *Environment and Planning B: Planning and Design*, *12*(3), 313–320. https://doi.org/10.1068/b120313

Pendall, R. (1999). Do land use controls cause sprawl? *Environment and Planning B: Planning and Design*, *26*(4), 555–571. https://doi.org/10.1068/b260555

Peng, X. (2020). Strategic interaction of environmental regulation and green productivity growth in China: Green innovation or pollution refuge? *Science of The Total Environment*, *732*, 139200. https://doi.org/10.1016/j.scitotenv.2020.139200

Perrin, C., Clément, C., Melot, R., & Nougarèdes, B. (2020). Preserving farmland on the urban fringe: A literature review on land policies in developed countries. *Land*, *9*(7), 223. https://doi.org/10.3390/land9070223

Plieninger, T., Draux, H., Fagerholm, N., Bieling, C., Bürgi, M., Kizos, T., Kuemmerle, T., Primdahl, J., & Verburg, P. H. (2016). The driving forces of landscape change in Europe: A systematic review of the evidence. *Land Use Policy*, *57*, 204–214. https://doi.org/10.1016/j.landusepol.2016.04.040

Poelmans, L., & Van Rompaey, A. (2010). Complexity and performance of urban expansion models. *Computers, Environment and Urban Systems*, *34*(1), 17–27. https://doi.org/10.1016/j.compenvurbsys.2009.06.001

Prestele, R., Alexander, P., Rounsevell, M. D. A., Arneth, A., Calvin, K., Doelman, J., Eitelberg, D. A., Engström, K., Fujimori, S., Hasegawa, T., Havlik, P., Humpenöder, F., Jain, A. K., Krisztin, T., Kyle, P., Meiyappan, P., Popp, A., Sands, R. D., Schaldach, R., … Verburg, P. H. (2016). Hotspots of uncertainty in land use and land-cover change projections: A global-scale model comparison. *Global Change Biology*, *22*(12), 3967–3983. https://doi.org/10.1111/gcb.13337

Putraditama, A., Kim, Y.-S., & Sánchez Meador, A. J. (2019). Community forest management and forest cover change in Lampung, Indonesia. *Forest Policy and Economics*, *106*, 101976. https://doi.org/10.1016/j.forpol.2019.101976

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1017/CBO9780511810725.016

Rounsevell, M. D. A., Pedroli, B., Erb, K.-H., Gramberger, M., Busck, A. G., Haberl, H., Kristensen, S., Kuemmerle, T., Lavorel, S., Lindner, M., Lotze-Campen, H., Metzger, M. J., Murray-Rust, D., Popp, A., Pérez-Soba, M., Reenberg, A., Vadineanu, A., Verburg, P. H., & Wolfslehner, B. (2012). Challenges for land system science. *Land Use Policy*, *29*(4), 899–910. https://doi.org/10.1016/j.landusepol.2012.01.007

Sanglestsawai, S., Rejesus, R. M., & Yorobe, J. M. (2015). Economic impacts of integrated pest management (IPM) farmer field schools (FFS): Evidence from onion farmers in the Philippines. *Agricultural Economics*, *46*(2), 149–162. https://doi.org/10.1111/agec.12147

Santana-Cordero, A. M., Bürgi, M., Hersperger, A. M., Hernández-Calvento, L., & Monteiro-Quintana, M. L. (2017). A century of change in coastal sedimentary landscapes in the Canary Islands (Spain) — Change, processes, and driving forces. *Land Use Policy*, *68*, 107–116. https://doi.org/10.1016/j.landusepol.2017.07.028

Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, *96*(2), 108–122. https://doi.org/10.1016/j.landurbplan.2010.03.001

Schneeberger, N., Bürgi, M., Hersperger, A. M., Ewald, K. C., Bu, M., Hersperger, A. M., & Ewald, K. C. (2007). Driving forces and rates of landscape change as a promising combination for landscape change research — An application on the northern fringe of the Swiss Alps. *Land Use Policy*, *24*(2), 349–361. https://doi.org/10.1016/j.landusepol.2006.04.003

Schone, K., Koch, W., & Baumont, C. (2013). Modeling local growth control decisions in a multi-city case: Do spatial interactions and lobbying efforts matter? *Public Choice*, *154*(1), 95–117. https://doi.org/10.1007/s11127-011-9811-1

Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A Meta-Analysis of Global Urban Land Expansion. *PLoS ONE*, *6*(8), e23777. https://doi.org/10.1371/journal.pone.0023777

Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Shao, Z., Spit, T., Jin, Z., Bakker, M., & Wu, Q. (2018). Can the land use master plan control urban expansion and protect farmland in China? A case study of Nanjing. *Growth and Change*, *49*(3), 512–531. https://doi.org/10.1111/grow.12240

Sharifi, A., Chiba, Y., Okamoto, K., Yokoyama, S., & Murayama, A. (2014). Can master planning control and regulate urban growth in Vientiane, Laos? *Landscape and Urban Planning*, *131*, 1–13. https://doi.org/10.1016/j.landurbplan.2014.07.014

Shen, X., Wang, L., Wang, X., Zhang, Z., & Lu, Z. (2019). Interpreting non-conforming urban expansion from the perspective of stakeholders' decision-making behavior. *Habitat International*, *89*, 102007. https://doi.org/10.1016/j.habitatint.2019.102007

Shen, X., Wang, X., Zhang, Z., & Fei, L. (2021). Does non-conforming urban development mean the failure of zoning? A framework for conformance-based evaluation. *Environment and Planning B: Urban Analytics and City Science*, *48*(5), 1279–1295. https://doi.org/10.1177/2399808320926179

Shu, B., Zhang, H., Li, Y., Qu, Y., & Chen, L. (2014). Spatiotemporal variation analysis of driving forces of urban land spatial expansion using logistic regression: A case study of port towns in Taicang City, China. *Habitat International*, *43*, 181–190. https://doi.org/10.1016/j.habitatint.2014.02.004

Siedentop, S., Fina, S., & Krehl, A. (2016). Greenbelts in Germany's regional plans—An effective growth management policy? *Landscape and Urban Planning*, *145*, 71–82. https://doi.org/10.1016/j.landurbplan.2015.09.002

Sobhani, P., Esmaeilzadeh, H., & Mostafavi, H. (2021). Simulation and impact assessment of future land use and land cover changes in two protected areas in Tehran, Iran. *Sustainable Cities and Society*, *75*, 103296. https://doi.org/10.1016/j.scs.2021.103296

Sohl, T. L., & Claggett, P. R. (2013). Clarity versus complexity: Land use modeling as a practical tool for decision-makers. *Journal of Environmental Management*, *129*, 235–243. https://doi.org/10.1016/j.jenvman.2013.07.027

Stock, J. H., & Watson, M. W. (2019). *Introduction to Econometrics* (New York: Pearson, Vol. 4). www.pearson.com/mylab/economics

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*(1), 1–21. https://doi.org/10.1214/09-STS313

Stuart, E. A., Lee, B. K., & Leacy, F. P. (2013). Prognostic score–based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research.

Journal of Clinical Epidemiology, *66*(8), S84-S90.e1. https://doi.org/10.1016/j.jclinepi.2013.01.013

Sun, C., Wu, Z. F., Lv, Z. Q., Yao, N., & Wei, J. B. (2013). Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *21*(1), 409–417. https://doi.org/10.1016/j.jag.2011.12.012

Sundaresan, J. (2019). Urban planning in vernacular governance: Land use planning and violations in Bangalore, India. *Progress in Planning*, *127*, 1–23. https://doi.org/10.1016/j.progress.2017.10.001

Tan, R., Liu, Y., Liu, Y., He, Q., & Ming, L. (2014). Urban growth and its determinants across the Wuhan urban agglomeration, central China. *Habitat International*, *44*, 268–281. https://doi.org/10.1016/j.habitatint.2014.07.005

Tang, P., Feng, Y., Li, M., & Zhang, Y. (2021). Can the performance evaluation change from central government suppress illegal land use in local governments? A new interpretation of Chinese decentralisation. *Land Use Policy*, *108*, 105578. https://doi.org/10.1016/j.landusepol.2021.105578

Tellman, B., Eakin, H., Janssen, M. A., de Alba, F., & Turner II, B. L. (2021). The role of institutional entrepreneurs and informal land transactions in Mexico City's urban expansion. *World Development*, *140*, 105374. https://doi.org/10.1016/j.worlddev.2020.105374

Tellman, B., Magliocca, N. R., Turner, B. L., & Verburg, P. H. (2020). Understanding the role of illicit transactions in land-change dynamics. *Nature Sustainability*, *3*(3), 175–181. https://doi.org/10.1038/s41893-019-0457-1

Thapa, G. B., & Rasul, G. (2006). Implications of changing national policies on land use in the Chittagong Hill Tracts of Bangladesh. *Journal of Environmental Management*, *81*(4), 441–453. https://doi.org/10.1016/j.jenvman.2005.12.002

Tian, G., & Wu, J. (2015). Comparing urbanization patterns in Guangzhou of China and Phoenix of the USA: The influences of roads and rivers. *Ecological Indicators*, *52*, 23–30. https://doi.org/10.1016/j.ecolind.2014.11.024

Tian, L. (2015). Land use dynamics driven by rural industrialization and land finance in the peri-urban areas of China: “The examples of Jiangyin and Shunde.” *Land Use Policy*, *45*, 117–127. https://doi.org/10.1016/j.landusepol.2015.01.006

Tian, L., & Shen, T. (2011). Evaluation of plan implementation in the transitional China: A case of Guangzhou city master plan. *Cities*, *28*, 11–27. https://doi.org/10.1016/j.cities.2010.07.002

Tong, X., & Feng, Y. (2019). How current and future urban patterns respond to urban planning? An integrated cellular automata modeling approach. *Cities*, *92*, 247–260. https://doi.org/10.1016/j.cities.2019.04.004

Towe, C. A., Nickerson, C. J., & Bockstael, N. (2008). An empirical examination of the timing of land conversions in the presence of farmland preservation programs. *American Journal of Agricultural Economics*, *90*(3), 613–626. https://doi.org/10.1111/j.1467-8276.2007.01131.x

Triantakonstantis, D., & Mountrakis, G. (2012). Urban growth prediction: A review of computational models and human perceptions. *Journal of Geographic Information System*, *04*(06), 555–587. https://doi.org/10.4236/jgis.2012.46060

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

Turner, B. L., Meyfroidt, P., Kuemmerle, T., Müller, D., & Roy Chowdhury, R. (2020). Framing the search for a theory of land use. *Journal of Land Use Science*, *15*(4), 489–508. https://doi.org/10.1080/1747423X.2020.1811792

van Vliet, J. (2019). Direct and indirect loss of natural area from urban expansion. *Nature Sustainability*, *2*(8), 755–763. https://doi.org/10.1038/s41893-019-0340-0

van Vliet, J., Eitelberg, D. A., & Verburg, P. H. (2017). A global analysis of land take in cropland areas and production displacement from urbanization. *Global Environmental Change*, *43*, 107–115. https://doi.org/10.1016/j.gloenvcha.2017.02.001

van Vliet, J., Naus, N., van Lammeren, R. J. A., Bregt, A. K., Hurkens, J., & van Delden, H.

(2013). Measuring the neighbourhood effect to calibrate land use models. *Computers, Environment and Urban Systems*, *41*, 55–64. https://doi.org/10.1016/j.compenvurbsys.2013.03.006

Verburg, P. H., de Nijs, T. C. M., van Eck, J. R., Visser, H., & de Jong, K. (2004). A method to analyse neighbourhood characteristics of land use patterns. *Computers, Environment and Urban Systems*, *28*(6), 667–690. https://doi.org/10.1016/j.compenvurbsys.2003.07.001

Verburg, P. H., Tabeau, A., & Hatna, E. (2013). Assessing spatial uncertainties of land allocation using a scenario approach and sensitivity analysis: A study for land use in Europe. *Journal of Environmental Management*, *127*. https://doi.org/10.1016/j.jenvman.2012.08.038

Verburg, P. H., van Eck, J. R. R., de Nijs, T. C. M., Dijst, M. J., & Schot, P. (2004). Determinants of land use change patterns in the Netherlands. *Environment and Planning B: Planning and Design*, *31*(1), 125–150. https://doi.org/10.1068/b307

Vliet, J. van, Bregt, A. K., Brown, D. G., Delden, H. van, Heckbert, S., Verburg, P. H., van Vliet, J., Bregt, A. K., Brown, D. G., van Delden, H., Heckbert, S., Verburg, P. H., Vliet, J. van, Bregt, A. K., Brown, D. G., Delden, H. van, Heckbert, S., Verburg, P. H., van Vliet, J., … Verburg, P. H. (2016). A review of current calibration and validation practices in land-change modeling. *Environmental Modelling & Software*, *82*, 174–182. https://doi.org/10.1016/j.envsoft.2016.04.017

Vorovencii, I. (2018). Quantification of forest fragmentation in pre- and post-establishment periods, inside and around Apuseni Natural Park, Romania. *Environmental Monitoring and Assessment*, *190*(6), 367. https://doi.org/10.1007/s10661-018-6741-0

Walsh, C. (2012). Spatial planning and territorial governance: Managing urban development in a rapid growth context. *Urban Research and Practice*, *5*(1), 44–61. https://doi.org/10.1080/17535069.2012.656451

Wang, B., Zhang, Y., Zhan, C., & Yang, X. (2020). Strategic interaction of industrial land conveyance behaviors in China: Based on an asymmetric two-regime Spatial Durbin Model. *Journal of Cleaner Production*, *270*, 122598. https://doi.org/10.1016/j.jclepro.2020.122598

Wang, J., Wu, Q., Yan, S., Guo, G., & Peng, S. (2020). China's local governments breaking the land use planning quota: A strategic interaction perspective. *Land Use Policy*, *92*(1), 104434. https://doi.org/10.1016/j.landusepol.2019.104434

Wang, L., Pijanowski, B., Yang, W., Zhai, R., Omrani, H., & Li, K. (2018). Predicting multiple land use transitions under rapid urbanization and implications for land management and urban planning: The case of Zhanggong District in central China. *Habitat International*, *82*, 48–61. https://doi.org/10.1016/j.habitatint.2018.08.007

Wang, L.-G., Han, H., & Lai, S.-K. (2014). Do plans contain urban sprawl? A comparison of Beijing and Taipei. *Habitat International*, *42*, 121–130. https://doi.org/10.1016/j.habitatint.2013.11.001

Wang, M., Krstikj, A., & Koura, H. (2017). Effects of urban planning on urban expansion control in Yinchuan City, Western China. *Habitat International*, *64*, 85–97. https://doi.org/10.1016/j.habitatint.2017.04.008

Weilenmann, B., Seidl, I., & Schulz, T. (2017). The socio-economic determinants of urban sprawl between 1980 and 2010 in Switzerland. *Landscape and Urban Planning*, *157*, 468–482. https://doi.org/10.1016/j.landurbplan.2016.08.002

Wildavsky, A. (1973). If planning is everything, maybe it's nothing. *Policy Sciences*, *4*, 127–153.

Williams, D. R., Clark, M., Buchanan, G. M., Ficetola, G. F., Rondinini, C., & Tilman, D. (2021). Proactive conservation to prevent habitat losses to agricultural expansion. *Nature Sustainability*, *4*(4), 314–322. https://doi.org/10.1038/s41893-020-00656-5

Wilms, R., Mäthner, E., Winnen, L., & Lanwehr, R. (2021). Omitted variable bias: A threat to estimating causal relationships. *Methods in Psychology*, *5*, 100075. https://doi.org/10.1016/j.metip.2021.100075

Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, M. P., & Arnold, C. (2003). Development of a geospatial model to quantify, describe and map urban growth. *Remote Sensing of Environment*, *86*(3), 275–285. https://doi.org/10.1016/S0034-4257(03)00074-9

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: Best practices for public health policy research. *Annual Review of Public Health*, *39*(1), 453–469. https://doi.org/10.1146/annurev-publhealth-040617-013507

Wolff, S., Schrammeijer, E. A., Schulp, C. J. E., & Verburg, P. H. (2018). Meeting global land restoration and protection targets: What would the world look like in 2050? *Global Environmental Change*, *52*, 259–272. https://doi.org/10.1016/j.gloenvcha.2018.08.002

Wong, C., & Watkins, C. (2009). Conceptualising spatial planning outcomes: Towards an integrative measurement framework. *Town Planning Review*, *80*(4–5), 481–516. https://doi.org/10.3828/tpr.2009.8

Wu, J. J., & Cho, S. H. (2007). The effect of local land use regulations on urban development in the Western United States. *Regional Science and Urban Economics*, *37*(1), 69–86. https://doi.org/10.1016/j.regsciurbeco.2006.06.008

Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, C., Liang, Y., & Huang, Z. (2006). Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. *Landscape and Urban Planning*, *75*(1–2), 69–80. https://doi.org/10.1016/j.landurbplan.2004.12.005

Xiong, C., & Tan, R. (2018). Will the land supply structure affect the urban expansion form? *Habitat International*, *75*, 25–37. https://doi.org/10.1016/j.habitatint.2018.04.003

Xu, C., Liu, M., Zhang, C., An, S., Yu, W., & Chen, J. M. (2007). The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. *Landscape Ecology*, *22*(6), 925–937. https://doi.org/10.1007/s10980-007-9079-5

Xu, G., Huang, X., Zhong, T., Chen, Y., Wu, C., & Jin, Y. (2015). Assessment on the effect of city arable land protection under the implementation of China's National General Land Use Plan (2006-2020). *Habitat International*, *49*, 466–473. https://doi.org/10.1016/j.habitatint.2015.06.017

Xu, Q., Zheng, X., & Zheng, M. (2019). Do urban planning policies meet sustainable urbanization goals? A scenario-based study in Beijing, China. *Science of the Total Environment*, *670*, 498–507. https://doi.org/10.1016/j.scitotenv.2019.03.128

Yin, H., Kong, F., Yang, X., James, P., & Dronova, I. (2018). Exploring zoning scenario impacts upon urban growth simulations using a dynamic spatial model. *Cities*, *81*, 214–229. https://doi.org/10.1016/j.cities.2018.04.010

Yu, J., Zhou, L. A., & Zhu, G. (2016). Strategic interaction in political competition: Evidence from spatial effects across Chinese cities. *Regional Science and Urban Economics*, *57*, 23–37. https://doi.org/10.1016/j.regsciurbeco.2015.12.003

Yue, W., Liu, Y., & Fan, P. (2013). Measuring urban sprawl and its drivers in large Chinese cities: The case of Hangzhou. *Land Use Policy*, *31*, 358–370. https://doi.org/10.1016/j.landusepol.2012.07.018

Zengjian Guan, & Konrad Herrmann. (2019). *Kao Gong Ji: The World's Oldest Encyclopaedia of Technologies*. Boston: Brill.

Zhang, Z., Kim, H. J., Lonjon, G., & Zhu, Y. (2019). Balance diagnostics after propensity score matching. *Annals of Translational Medicine*, *7*(1), 16–16. https://doi.org/10.21037/atm.2018.12.10

Zhong, T., Huang, X., Zhang, X., & Wang, K. (2011). Temporal and spatial variability of agricultural land loss in relation to policy and accessibility in a low hilly region of southeast China. *Land Use Policy*, *28*(4), 762–769. https://doi.org/10.1016/j.landusepol.2011.01.004

Zhong, T., Mitchell, B., & Huang, X. (2014). Success or failure: Evaluating the implementation of China's National General Land Use Plan (1997–2010). *Habitat International*, *44*, 93–101. https://doi.org/10.1016/j.habitatint.2014.05.003

Zhong, T., Qian, Z., Huang, X., Zhao, Y., Zhou, Y., & Zhao, Z. (2018). Impact of the top-down quota-oriented farmland preservation planning on the change of urban land use intensity in China. *Habitat International*, *77*(February), 71–79. https://doi.org/10.1016/j.habitatint.2017.12.013

Zhou, W., Yu, W., Qian, Y., Han, L., Pickett, S. T. A., Wang, J., Li, W., & Ouyang, Z. (2022). Beyond city expansion: multi-scale environmental impacts of urban megaregion formation in China. *National Science Review*, *9*(1), nwab107. https://doi.org/10.1093/nsr/nwab107

Zhou, Y., Huang, X., Chen, Y., Zhong, T., Xu, G., He, J., Xu, Y., & Meng, H. (2017). The effect of land use planning (2006–2020) on construction land growth in China. *Cities*, *68*, 37–47. https://doi.org/10.1016/j.cities.2017.04.014

Zhu, J., & Tang, W. (2018). Conflict and compromise in planning decision-making: How does a Chinese local government negotiate its construction land quota with higher-level governments? *Environment and Urbanization*, *30*(1), 155–174. https://doi.org/10.1177/0956247817753524

Zuo, C. (2015). Promoting city leaders: The structure of political incentives in China. *The China Quarterly*, *224*, 955–984. https://doi.org/10.1017/S0305741015001289

Annex A: Supplementary to dissertation

Annex A.1 Balance indicator after PSM

After the PSM, the balance of the matched data was checked, that is, how similar the confounding variables of the matched towns in the development-prioritized and the development-restricted zone are (Figure A1). All confounding variables have the standard mean differences below 0.1 after matching. Moreover, the standard mean difference of the propensity scores dramatically decreased from 2.62 to 0.01. This indicates that PSM removed the overt selection biases relatively well. The remaining difference in built-up land expansion can be attributed solely to the difference in a planning status of the MFOZ.

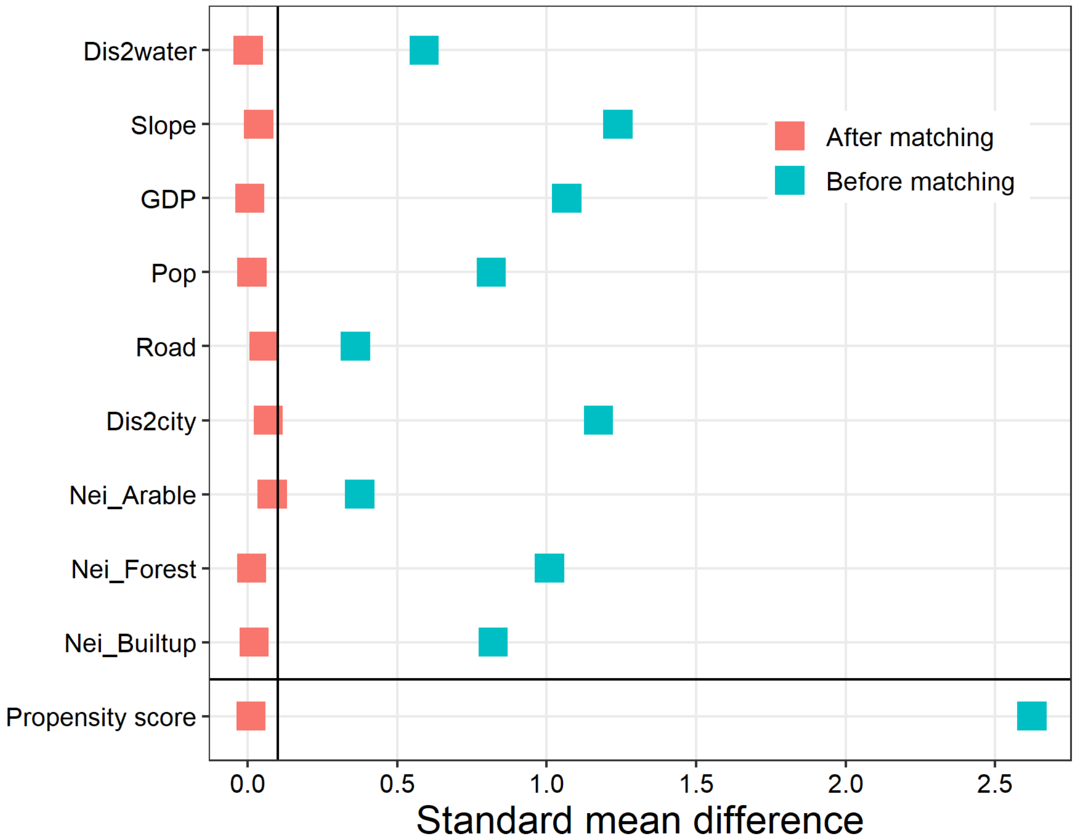

Figure A1. Standard mean difference of the confounding variables and the propensity score between the towns of the development-prioritized and development-restricted zones before and after matching

Annex A.2 Results of Robustness test of PSM

Annex A.2.1 Rosenbaum bounds sensitivity test of PSM

The PSM is an effective evaluation method for controlling selection bias from the observed confounding variables. When planning process and built-up land expansion are systematically determined only by the selected confounding variables, the causal effect of the MFOZ on built-up land expansion from the PSM-based evaluation will be unbiased. However, spatial planning is decision-making processes based on bounded rationality (Chadwick, 1978; Oliveira & Pinho, 2010). In addition to the selected confounding variables, the unobserved factors (e.g., leaders' judgements, negotiations among interest groups) are also the vital confounding variables influencing the allocation of the major function-oriented zones and built-up land expansion. A regular planning process is not only determined by spatial analysis of land suitability, but more or less determined by political negotiations or the leaders' subjective choice which are unobserved. These unobserved confounding variables may bias the results of the PSM.

The Rosenbaum bounds was used to test the sensitivity of the results to the unobserved confounding variables (Paul R. Rosenbaum, 2002). The probability of the town i being assigned to the development-prioritized zone was denoted as π_i, and transformed the probability into the odds ($\frac{\pi_i}{1-\pi_i}$). The log odds ratio of the town i can be written as:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = f(x_i) + \gamma\mu_i \qquad \text{(A.1)}$$

where $f(x_i)$ is an unknown function based on a set of the observed confounding variables x_i. $0 \leq \mu_i \leq 1$ and $\gamma \geq 0$. $\gamma\mu_i$ can be understood as the influence of the unobserved confounding variables on the probability of the town i being assigned to the development-prioritized zone. The town j was assumed as a matched counterfactual for the town i, and got a new formula:

$$\frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)} = \exp\{\gamma(\mu_i - \mu_j)\} \qquad \text{(A.2)}$$

where $f(\cdot)$ was eliminated because $x_i = x_j$. $\frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)}$ was denoted as the Rosenbaum bound (Γ). If μ does not exist, $\Gamma = 1$. Conversely, as the influence of μ increases ($\mu_i - \mu_j$

increases), Γ increases. A level of Γ, when its p-value is greater than 0.05, measures how big the difference in the unobserved confounding variables between the town i and j is, in order to invalidate the results from the PSM-based evaluation.

Table A1 shows the sensitivity degrees of the PSM's results to the unobserved confounding variables. Because the PSM-based evaluation results are significant in the evaluation interval 2013–2018 and 2013–2020, this dissertation only used Rosenbaum bounds to test the robustness of the results in these two intervals. The results from the Rosenbaum bounds suggest that in order to invalidate the estimated effectiveness of the MFOZ on built-up land expansion, the unobserved confounding variables would have to increase the ratio of the odds by less than 20% ($\Gamma = 1.20$) in 2013-2015 and by more than 50% ($\Gamma = 1.60$) in 2013-2020. In social science, researchers consider $\Gamma > 1.50$ and p-value < 0.05 to be not sensitive to the unobserved confounding variables (Chiputwa et al., 2015; Nordjo & Adjasi, 2019; Sanglestsawai et al., 2015). Thus, the PSM-based evaluation result between 2013 and 2020 is robust to the unobserved confounding variables. But the results of Rosenbaum bounds cannot conclude that the PSM-based evaluation result between 2013 and 2018 is robust to the unobserved confounding variables.

Table A1. Rosenbaum upper bound on p-value at given levels of Γ

	Built-up land expansion between 2013 and 2018	Built-up land expansion between 2013 and 2020
1	0.012	0.000
1.1	0.032	0.001
1.2	0.070	0.004
1.3	0.129	0.011
1.4	0.208	0.024
1.5	0.302	0.045
1.6	0.404	0.077
1.7	0.506	0.120
1.8	0.602	0.174
1.9	0.687	0.236
2	0.760	0.305

Annex A.2.2 Robustness of matching algorithms of PSM

There is not a universal strategy for choosing optimal matching algorithm (Caliendo & Kopeinig, 2008). This dissertation used a 1:1 nearest neighbour matching with a calliper of 0.01 and with no-replacement as the primary matching algorithm. To ensure that the results are not sensitive to the choice of matching algorithms, I applied the different matching algorithms. For the following matching algorithms, a common support condition was imposed.

(1) Calliper. Imposing a calliper is to avoid poor matches if the closest neighbour is far away. However, a reasonable calliper is difficult to predict (Caliendo & Kopeinig, 2008). Here, I used the four callipers (0.01, 0.05, 0.1, and 0.25) in 1:1 nearest neighbour matching with no-replacement. Figure A2 indicates that the standard mean differences of most confounding variables and propensity score increased as the callipers increased. When the callipers of 0.05, 0.1, 0.25 were used. *Nei_Arable* had standard mean differences of greater than 0.1 which is often considered as the imbalance.

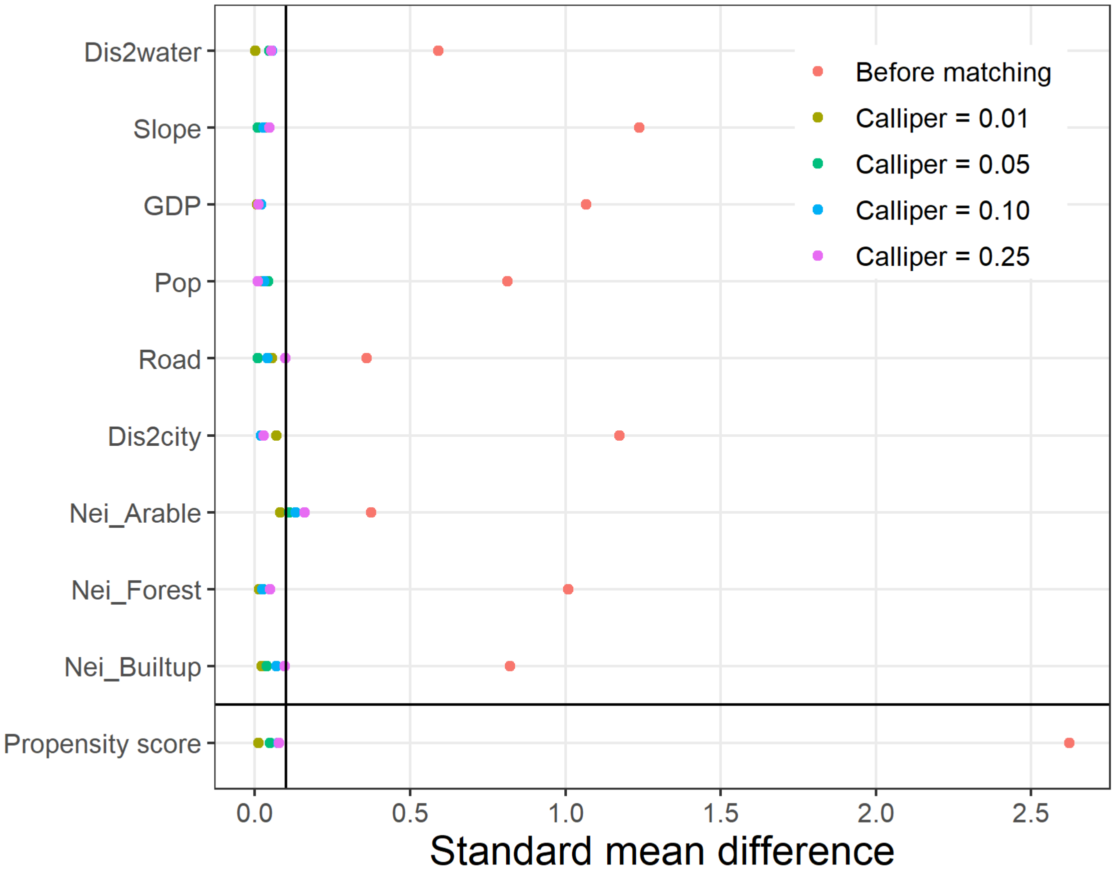

Figure A2. Standard mean difference from 1:1 nearest neighbour matching with no-replacement and with the four callipers (0.01, 0.05, 0.1, and 0.25)

(2) Replacement or no-replacement. Matching with replacement or no-replacement may influence the balance of the matched data. Matching with replacement can often decrease selection bias, especially when control units are fewer than treated units (Stuart, 2010). For a relatively large dataset, matching with no-replacement may yield a more precise estimation than matching with replacement (Butsic et al., 2011). Here, I used 1:1 nearest neighbour matching with replacement and with a calliper of 0.01. Figure A3 indicates that the standard mean differences of most confounding variables and propensity score increased as I changed no-replacement to replacement. I got an imbalanced matched data in terms of *Dis2city* (standard mean difference = 0.354) and *Nei_Forest* (standard mean difference = 0.122), when I used 1:1 nearest neighbour matching with replacement and with a calliper of 0.01.

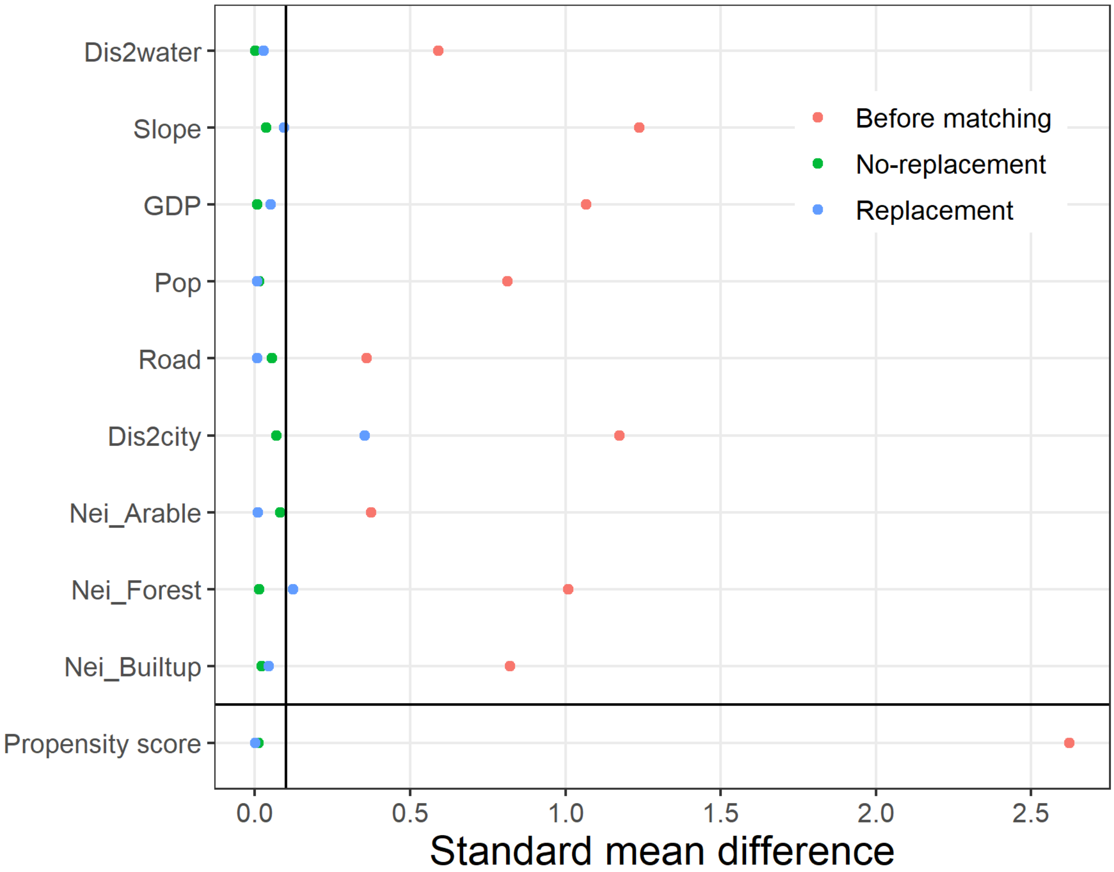

Figure A3. Standard mean difference from 1:1 nearest neighbour matching with replacement and no-replacement

(3) 1:1 to 1:N nearest neighbour matching. Selecting several control units for each treated unit will increase selection bias, however, decrease sample variance due to a lager matched data (Stuart, 2010). Fujian Province contains 386 treated units (towns were fully located within the development-prioritized zone) and 568 control units (towns were fully located within the development-restricted zone). Thus, I used 1:1, 1:2, 1:3, 1:4 nearest neighbour matching with replacement and with a calliper of 0.01. Figure A4 indicates the imbalance matched data, when 1:N nearest neighbour matching were used.

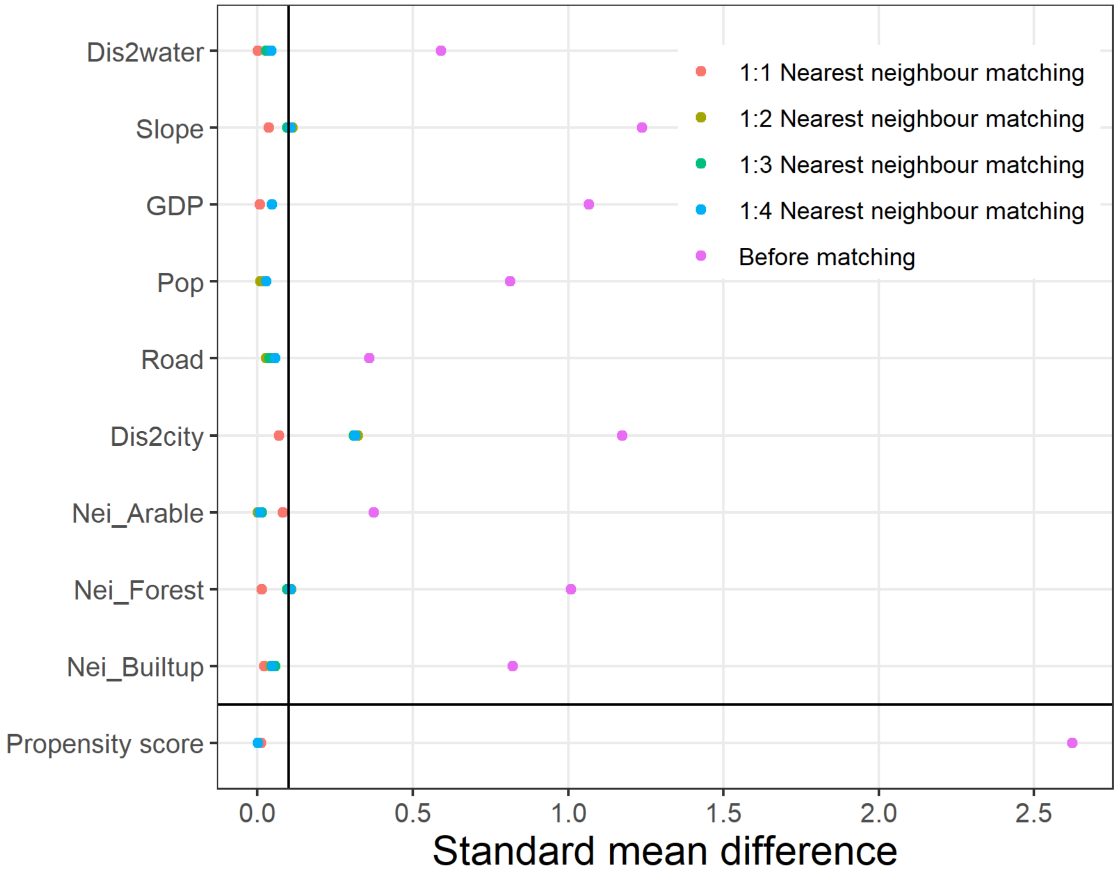

Figure A4. Standard mean difference from 1:1, 1:2, 1:3, 1:4 nearest neighbour matching with the calliper =0.01 and with replacement

(4) Radius matching. Radius matching considers all of the control units within the calliper. Compared that nearest neighbour matching only considers one or several nearest control units, radius matching allows for usage of extra (fewer) units when good matches are (not) available (Dehejia & Wahba, 2002). I used radius matching with the four callipers (0.01, 0.05, 0.1, and 0.25). Figure A5 indicates that radius matching was unable to remove selection biases. The standard mean differences of *Dis2city* are greater than 0.01, when radius matching with the four callipers were used.

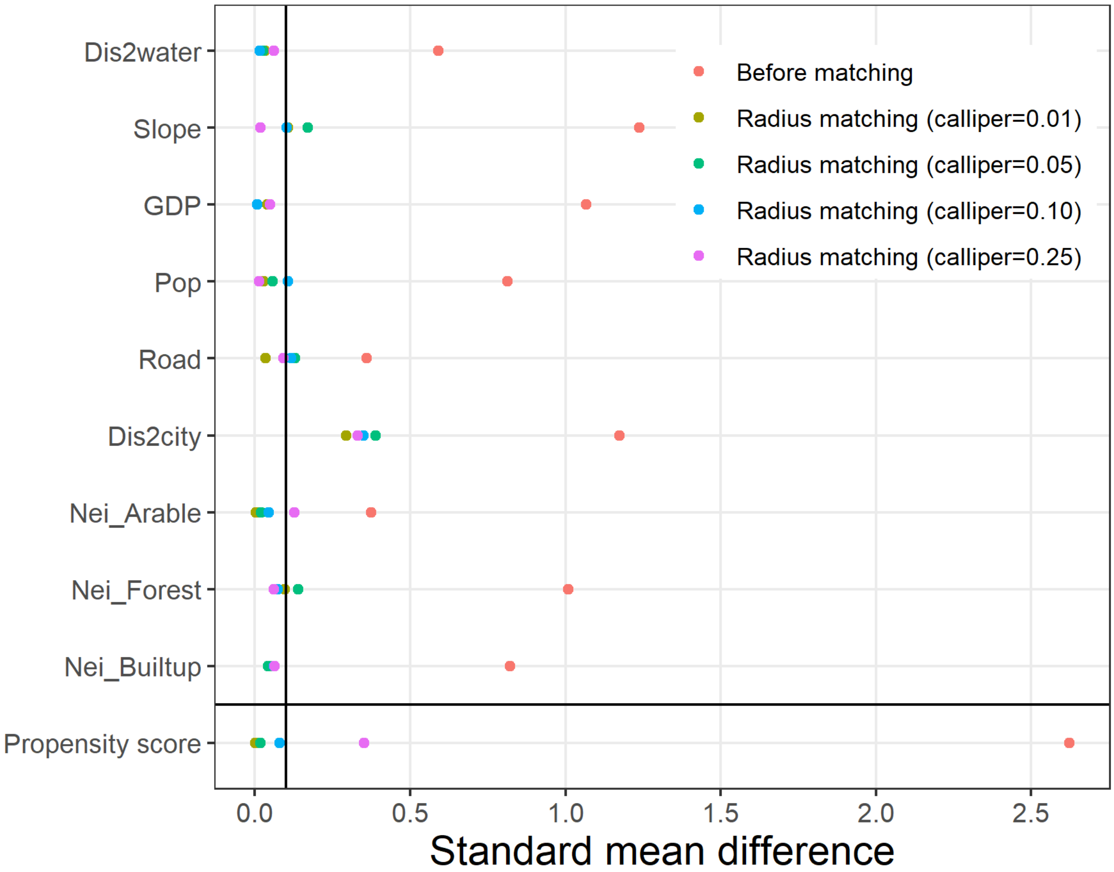

Figure A5. Standard mean difference from radius matching with the calliper =0.01, 0.05, 0.1, and 0.25

(5) Kernel matching. Kernel matching uses weighed averages of all control units to construct the counterfactuals. Figure A6 indicates that kernel matching was unable to remove selection biases. I obtained the imbalanced matched data concerning *Slope*, *Dis2city*, and *Nei_Forest.*

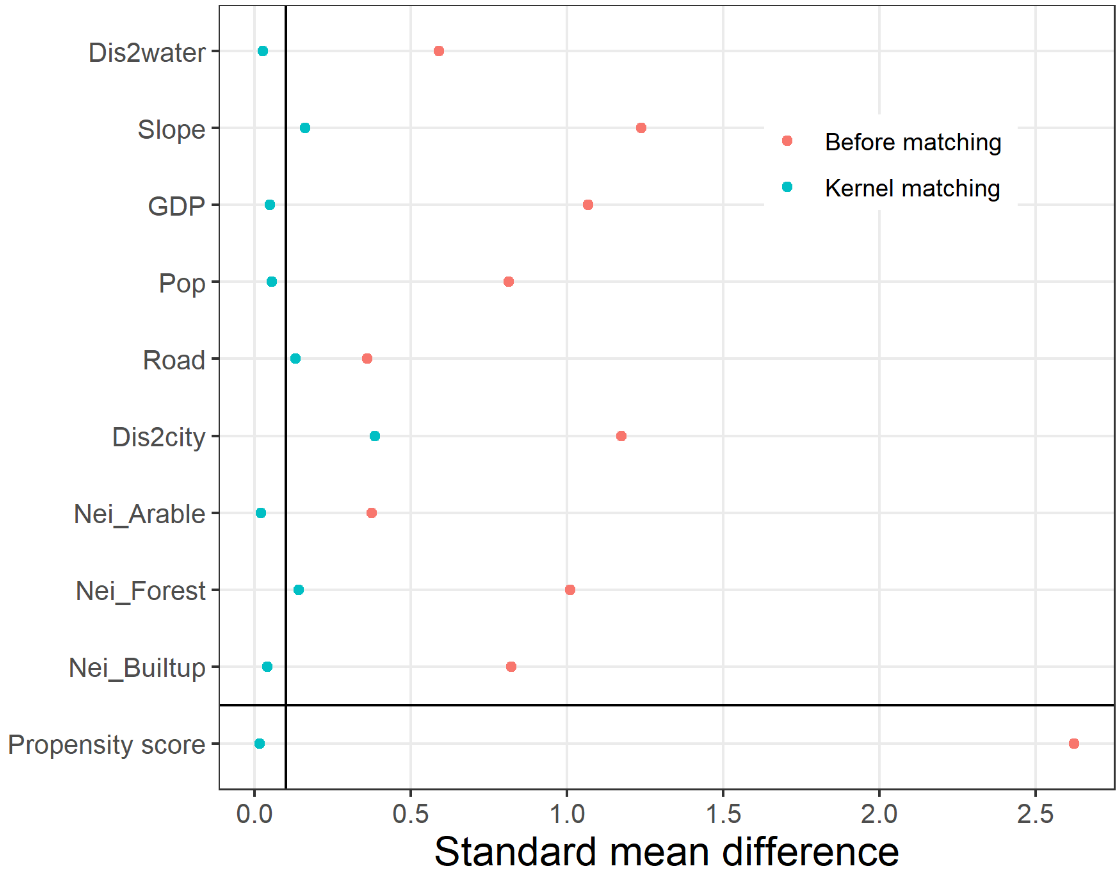

Figure A6. Standard mean difference from kernel matching

In conclusion, 1:1 nearest neighbour matching with a calliper of 0.01 and with no-replacement is the better match algorithm than the other match algorithms, because it can obtain a balance matched data.

Annex A.3 Average effect estimated by PSM-DID

Table A2. Average effect of built-up land zoning on built-up land expansion in Zhangzhou City between 2010 and 2020

Variables	Model 3	Model 4
$Develop_i * Time_t$	1.21* (0.67)	
$Intensity_i * Time_t$		0.06** (0.03)
$Nei\_Built.up_{it}$	2.27*** (0.26)	2.27*** (0.25)
$Dis2city_i * Year_{2000}$	-0.004* (0.002)	-0.004* (0.0023)
$Dis2city_i * Year_{2005}$	-0.04*** (0.01)	-0.04*** (0.012)
$Dis2city_i * Year_{2010}$	-0.02* (0.01)	-0.02 (0.01)
$Dis2city_i * Year_{2013}$	-0.02* (0.01)	-0.02 (0.01)

$Dis2city_i * Year_{2015}$	-0.01 (0.01)	-0.001 (0.01)
$Dis2city_i * Year_{2018}$	-0.02 (0.01)	-0.02 (0.01)
$Dis2city_i * Year_{2020}$	-0.04** (0.02)	-0.03** (0.01)
$Dis2county_i * Year_{2000}$	0.03* (0.02)	0.03* (0.02)
$Dis2county_i * Year_{2005}$	-0.02 (0.04)	-0.02 (0.04)
$Dis2county_i * Year_{2010}$	-0.13** (0.05)	-0.12** (0.05)
$Dis2county_i * Year_{2013}$	-0.13** (0.05)	-0.12** (0.05)
$Dis2county_i * Year_{2015}$	-0.08 (0.05)	-0.07 (0.05)
$Dis2county_i * Year_{2018}$	-0.13** (0.06)	-0.11** (0.06)
$Dis2county_i * Year_{2020}$	-0.13** (0.06)	-0.12* (0.06)
$Dis2water_i * Year_{2000}$	0.01 (0.03)	0.01 (0.03)
$Dis2water_i * Year_{2005}$	0.03 (0.17)	0.03 (0.17)
$Dis2water_i * Year_{2010}$	0.41* (0.22)	0.4* (0.21)
$Dis2water_i * Year_{2013}$	0.4* (0.22)	0.39* (0.21)
$Dis2water_i * Year_{2015}$	0.7*** (0.25)	0.69*** (0.25)
$Dis2water_i * Year_{2018}$	0.55* (0.31)	0.54* (0.31)
$Dis2water_i * Year_{2020}$	0.67** (0.33)	0.66** (0.33)
$Dis2coastline_i * Year_{2000}$	-0.005 (0.003)	-0.005 (0.003)
$Dis2coastline_i * Year_{2005}$	0.01 (0.02)	0.01 (0.02)
$Dis2coastline_i * Year_{2010}$	0.02 (0.02)	0.03 (0.02)
$Dis2coastline_i * Year_{2013}$	0.02 (0.02)	0.03 (0.02)
$Dis2coastline_i * Year_{2015}$	0.01 (0.02)	0.01 (0.02)
$Dis2coastline_i * Year_{2018}$	0.02 (0.03)	0.02 (0.03)
$Dis2coastline_i * Year_{2020}$	0.03 (0.03)	0.03 (0.03)
$Elevation_i * Year_{2000}$	-0.51 (0.45)	-0.52 (0.45)
$Elevation_i * Year_{2005}$	-10.19*** (2.91)	-10.18*** (2.9)
$Elevation_i * Year_{2010}$	-12.69*** (3.53)	-10.9*** (3.45)
$Elevation_i * Year_{2013}$	-12.64*** (3.54)	-10.85*** (3.46)
$Elevation_i * Year_{2015}$	-19.1*** (4.03)	-17.3*** (3.93)
$Elevation_i * Year_{2018}$	-18.97*** (4.31)	-17.17*** (4.2)
$Elevation_i * Year_{2020}$	-19.35*** (4.36)	-17.57*** (4.26)
$Dis2road_i * Year_{2000}$	-0.04 (0.02)	-0.04 (0.02)
$Dis2road_i * Year_{2005}$	0.01 (0.08)	0.01 (0.08)
$Dis2road_i * Year_{2010}$	-0.03 (0.11)	-0.05 (0.11)
$Dis2road_i * Year_{2013}$	-0.03 (0.11)	-0.05 (0.11)
$Dis2road_i * Year_{2015}$	0.3* (0.17)	0.27 (0.17)
$Dis2road_i * Year_{2018}$	0.14 (0.16)	0.12 (0.16)
$Dis2road_i * Year_{2020}$	-0.1 (0.17)	-0.13 (0.18)
Village Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
R^2	0.19	0.19
Hausman test	98.60 ***	103.50***
No. of villages ($Develop_i = 1$)	386	386
No. of villages ($Develop_i = 0$)	386	386

No. of year	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.*

Annex A.4 Annual effect estimated by PSM-DID

Table A3. Annual effect of built-up land zoning on built-up land expansion in Zhangzhou City between 2010 and 2020

Variables	Model 5	Model 6
$Develop_i * Year_{1995}$	-0.85 (0.81)	
$Develop_i * Year_{2000}$	-0.8 (0.81)	
$Develop_i * Year_{2005}$	-0.53 (0.47)	
$Develop_i * Year_{2013}$	-0.02 (0.03)	
$Develop_i * Year_{2015}$	0.97* (0.51)	
$Develop_i * Year_{2018}$	0.77 (0.51)	
$Develop_i * Year_{2020}$	0.7 (0.55)	
$Intensity_i * Year_{1995}$		-0.06 (0.04)
$Intensity_i * Year_{2000}$		-0.05 (0.04)
$Intensity_i * Year_{2005}$		0.01 (0.02)
$Intensity_i * Year_{2013}$		0.0003 (0.001)
$Intensity_i * Year_{2015}$		0.04** (0.02)
$Intensity_i * Year_{2018}$		0.06** (0.03)
$Intensity_i * Year_{2020}$		0.05 (0.03)
$Nei\_Built.up_{it}$	2.27*** (0.26)	2.26*** (0.25)
$Dis2city_i * Year_{1995}$	0.02* (0.01)	0.02 (0.01)
$Dis2city_i * Year_{2000}$	0.02 (0.01)	0.01 (0.01)
$Dis2city_i * Year_{2005}$	-0.01* (0.01)	-0.01* (0.01)
$Dis2city_i * Year_{2013}$	-0.001 (0.001)	-0.0005 (0.0005)
$Dis2city_i * Year_{2015}$	0.02 (0.01)	0.02* (0.01)
$Dis2city_i * Year_{2018}$	-0.001 (0.01)	0.004 (0.01)
$Dis2city_i * Year_{2020}$	-0.01 (0.01)	-0.01 (0.01)
$Dis2county_i * Year_{1995}$	0.13** (0.05)	0.12** (0.05)
$Dis2county_i * Year_{2000}$	0.16*** (0.05)	0.15*** (0.05)
$Dis2county_i * Year_{2005}$	0.11*** (0.04)	0.11*** (0.04)
$Dis2county_i * Year_{2013}$	0.001 (0.003)	0.001 (0.003)
$Dis2county_i * Year_{2015}$	0.05 (0.04)	0.06 (0.04)
$Dis2county_i * Year_{2018}$	0.004 (0.03)	0.01 (0.03)
$Dis2county_i * Year_{2020}$	-0.003 (0.04)	0.01 (0.04)
$Dis2water_i * Year_{1995}$	-0.41* (0.22)	-0.4* (0.21)
$Dis2water_i * Year_{2000}$	-0.4* (0.21)	-0.39* (0.21)

$Dis2water_i * Year_{2005}$	-0.37*** (0.11)	-0.37*** (0.11)
$Dis2water_i * Year_{2013}$	-0.01 (0.01)	-0.01 (0.01)
$Dis2water_i * Year_{2015}$	0.3* (0.15)	0.29* (0.15)
$Dis2water_i * Year_{2018}$	0.14 (0.22)	0.14 (0.21)
$Dis2water_i * Year_{2020}$	0.27 (0.23)	0.26 (0.23)
$Dis2coastline_i * Year_{1995}$	-0.02 (0.02)	-0.03 (0.02)
$Dis2coastline_i * Year_{2000}$	-0.03 (0.02)	-0.03 (0.02)
$Dis2coastline_i * Year_{2005}$	-0.01 (0.01)	-0.01 (0.01)
$Dis2coastline_i * Year_{2013}$	-0.0005 (0.001)	-0.0004 (0.001)
$Dis2coastline_i * Year_{2015}$	-0.01 (0.01)	-0.01 (0.01)
$Dis2coastline_i * Year_{2018}$	-0.005 (0.01)	-0.002 (0.01)
$Dis2coastline_i * Year_{2020}$	0.01 (0.01)	0.01 (0.01)
$Elevation_i * Year_{1995}$	12.69*** (3.53)	11.09*** (3.46)
$Elevation_i * Year_{2000}$	12.18*** (3.51)	10.62*** (3.43)
$Elevation_i * Year_{2005}$	2.51 (1.86)	2.73 (1.9)
$Elevation_i * Year_{2013}$	0.05 (0.12)	0.06 (0.12)
$Elevation_i * Year_{2015}$	-6.39*** (2.03)	-5.33** (2.08)
$Elevation_i * Year_{2018}$	-6.26*** (2.09)	-4.62** (2.11)
$Elevation_i * Year_{2020}$	-6.65*** (2.38)	-5.24** (2.34)
$Dis2road_i * Year_{1995}$	0.03 (0.11)	0.05 (0.11)
$Dis2road_i * Year_{2000}$	-0.01 (0.1)	0.01 (0.11)
$Dis2road_i * Year_{2005}$	0.03 (0.07)	0.03 (0.07)
$Dis2road_i * Year_{2013}$	0.001 (0.01)	0.0004 (0.01)
$Dis2road_i * Year_{2015}$	0.32** (0.14)	0.31** (0.13)
$Dis2road_i * Year_{2018}$	0.17 (0.12)	0.14 (0.12)
$Dis2road_i * Year_{2020}$	-0.08 (0.14)	-0.1 (0.14)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	0.19	0.2
Hausman test	138.15 ***	199.79 ***
No. of villages ($Develop_i = 1$)	386	386
No. of 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.*

Annex A.5 Results of Robustness test of the PSM-DID

Annex A.5.1 Parallel trend test

An event study was conducted to validate the parallel trend assumption using the unmatched and matched data (Table A4). Before applying the PSM, the coefficients of $Develop_i * Year_{1995}$, $Develop_i * Year_{2000}$, 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 (Figure A7). After implementing the 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 (Figure A7). 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 to evaluate the causal effect of built-up land zoning using a DID method.

Table A4. Event study on parallel trend assumption before and after matching

Variables	Model 5 (before matching)	Model 5 (after matching)
$Develop_i * Year_{1995}$	-6.03*** (0.7)	-0.85 (0.81)
$Develop_i * Year_{2000}$	-5.51*** (0.68)	-0.8 (0.81)
$Develop_i * Year_{2005}$	-1.53*** (0.37)	-0.53 (0.47)
$Develop_i * Year_{2013}$	0.04* (0.02)	-0.02 (0.03)
$Develop_i * Year_{2015}$	0.46 (0.42)	0.97* (0.51)
$Develop_i * Year_{2018}$	0.13 (0.41)	0.77 (0.51)
$Develop_i * Year_{2020}$	-0.17 (0.44)	0.7 (0.55)
$Nei\_Built.up_{it}$	2.59*** (0.18)	2.27*** (0.26)
$Dis2city_i * Year_{1995}$	0.05*** (0.01)	0.02* (0.01)
$Dis2city_i * Year_{2000}$	0.04*** (0.01)	0.02 (0.01)
$Dis2city_i * Year_{2005}$	-0.02*** (0.01)	-0.01* (0.01)
$Dis2city_i * Year_{2013}$	0.0002 (0.0004)	-0.001 (0.001)
$Dis2city_i * Year_{2015}$	0.02** (0.01)	0.02 (0.01)
$Dis2city_i * Year_{2018}$	0.02*** (0.01)	-0.001 (0.01)
$Dis2city_i * Year_{2020}$	0.01 (0.01)	-0.01 (0.01)
$Dis2county_i * Year_{1995}$	0.12*** (0.04)	0.13** (0.05)
$Dis2county_i * Year_{2000}$	0.13*** (0.03)	0.16*** (0.05)
$Dis2county_i * Year_{2005}$	0.06*** (0.02)	0.11*** (0.04)
$Dis2county_i * Year_{2013}$	-0.001 (0.001)	0.001 (0.003)
$Dis2county_i * Year_{2015}$	0.04** (0.02)	0.05 (0.04)
$Dis2county_i * Year_{2018}$	-0.001 (0.02)	0.004 (0.03)

$Dis2county_i * Year_{2020}$	0.004 (0.02)	-0.003 (0.04)
$Dis2water_i * Year_{1995}$	-0.41*** (0.1)	-0.41* (0.22)
$Dis2water_i * Year_{2000}$	-0.38*** (0.1)	-0.4* (0.21)
$Dis2water_i * Year_{2005}$	-0.17*** (0.04)	-0.37*** (0.11)
$Dis2water_i * Year_{2013}$	0.001 (0.003)	-0.01 (0.01)
$Dis2water_i * Year_{2015}$	0.12** (0.05)	0.3* (0.15)
$Dis2water_i * Year_{2018}$	0.1 (0.07)	0.14 (0.22)
$Dis2water_i * Year_{2020}$	0.11 (0.07)	0.27 (0.23)
$Dis2coastline_i * Year_{1995}$	-0.05*** (0.02)	-0.02 (0.02)
$Dis2coastline_i * Year_{2000}$	-0.05*** (0.02)	-0.03 (0.02)
$Dis2coastline_i * Year_{2005}$	-0.01* (0.01)	-0.01 (0.01)
$Dis2coastline_i * Year_{2013}$	-0.001* (0.0004)	-0.0005 (0.001)
$Dis2coastline_i * Year_{2015}$	-0.01 (0.01)	-0.01 (0.01)
$Dis2coastline_i * Year_{2018}$	0.004 (0.01)	-0.005 (0.01)
$Dis2coastline_i * Year_{2020}$	0.01 (0.01)	0.01 (0.01)
$Elevation_i * Year_{1995}$	8.97*** (1.8)	12.69*** (3.53)
$Elevation_i * Year_{2000}$	8.37*** (1.76)	12.18*** (3.51)
$Elevation_i * Year_{2005}$	1.76** (0.74)	2.51 (1.86)
$Elevation_i * Year_{2013}$	0.03 (0.05)	0.05 (0.12)
$Elevation_i * Year_{2015}$	-2.99*** (0.88)	-6.39*** (2.03)
$Elevation_i * Year_{2018}$	-2.74*** (0.88)	-6.26*** (2.09)
$Elevation_i * Year_{2020}$	-2.93*** (1)	-6.65*** (2.38)
$Dis2road_i * Year_{1995}$	0.11* (0.06)	0.03 (0.11)
$Dis2road_i * Year_{2000}$	0.08 (0.06)	-0.01 (0.1)
$Dis2road_i * Year_{2005}$	0.03 (0.03)	0.03 (0.07)
$Dis2road_i * Year_{2013}$	0.003 (0.004)	0.001 (0.01)
$Dis2road_i * Year_{2015}$	0.16*** (0.06)	0.32** (0.14)
$Dis2road_i * Year_{2018}$	0.08 (0.06)	0.17 (0.12)
$Dis2road_i * Year_{2020}$	-0.04 (0.06)	-0.08 (0.14)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	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	13296	6176

Note: *The clustered standard errors of the coefficients are given in parentheses; *, **, and *** denote a significance level of 10%, 5%, and 1%, respectively.*

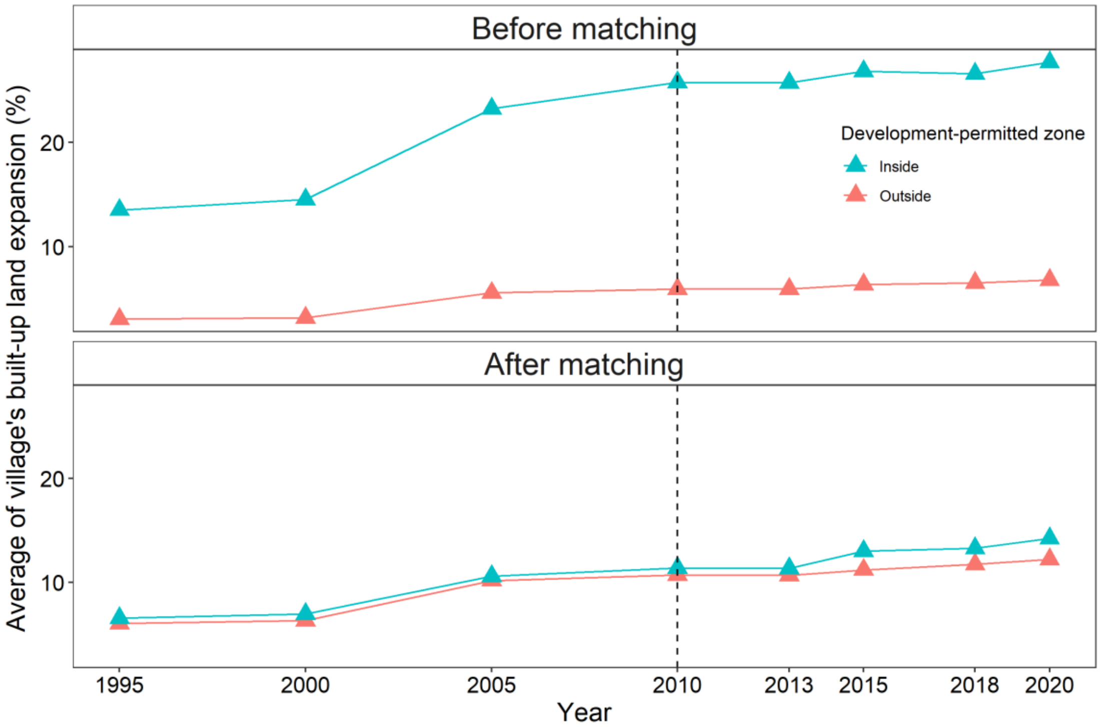

Figure A7. Trends of built-up land expansion in Zhangzhou City from 1995 to 2020

Annex A.5.2 Balance check

After implementing the PSM, the balance of the matched data was checked. All eight confounding variables had a standard mean difference < 0.1 after matching (Figure A8). Moreover, the standard mean difference 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 built-up land expansion between the villages located inside the development-permitted zones and the matched villages located outside the development-permitted zones could be attributed solely to the difference in planning status.

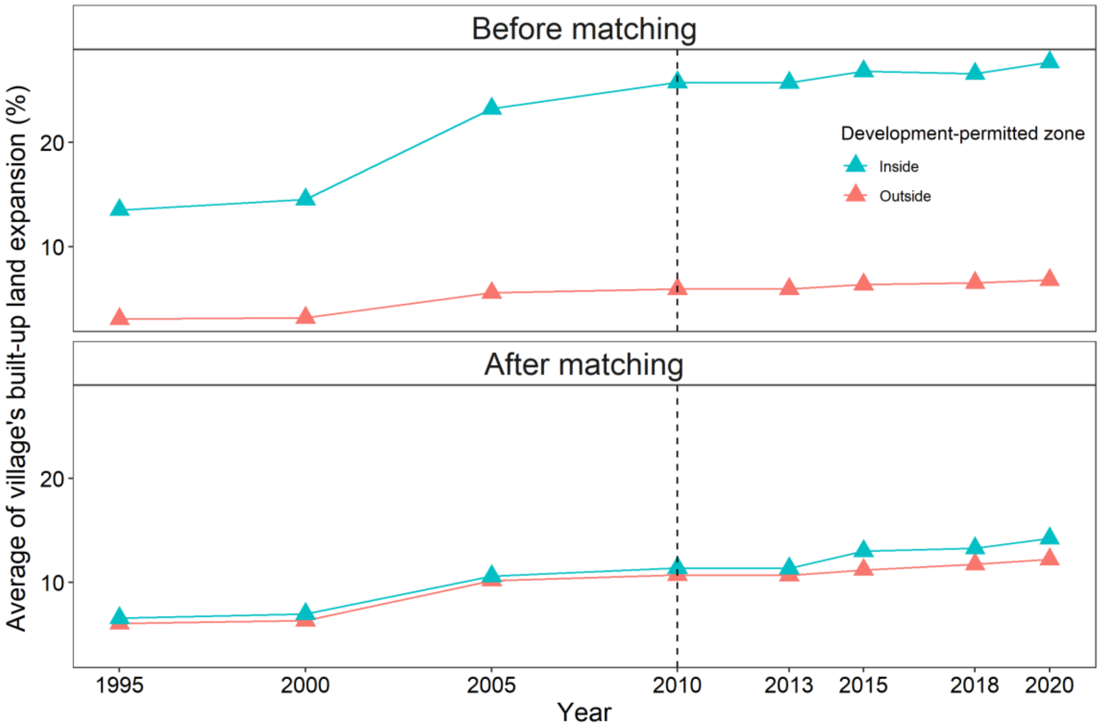

Figure A8. Standard mean difference of the confounding variables and the propensity score between the villages of the development-permitted and development-restricted zones before and after matching

Annex A.5.3 Placebo test

In the placebo test, the coefficient of $Develop_i * Time_t$ was non-significant (1.15, p=0.13, Table A5), 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 the findings. In addition, there was an anticipation effect.

Table A5. Results of placebo test

Variables	Model 3 (placebo test)
$Develop_i * Time_t$	1.15 (0.76)
$Nei\_Built.up_{it}$	2.28*** (0.26)
$Dis2city_i * Year_{2000}$	-0.004* (0.002)
$Dis2city_i * Year_{2005}$	-0.03*** (0.01)
$Dis2city_i * Year_{2010}$	-0.02* (0.01)
$Dis2city_i * Year_{2013}$	-0.02* (0.01)
$Dis2city_i * Year_{2015}$	-0.01 (0.01)
$Dis2city_i * Year_{2018}$	-0.02 (0.01)

$Dis2city_i * Year_{2020}$	-0.04** (0.02)
$Dis2county_i * Year_{2000}$	0.03* (0.02)
$Dis2county_i * Year_{2005}$	-0.02 (0.04)
$Dis2county_i * Year_{2010}$	-0.13** (0.05)
$Dis2county_i * Year_{2013}$	-0.13** (0.05)
$Dis2county_i * Year_{2015}$	-0.08 (0.05)
$Dis2county_i * Year_{2018}$	-0.13** (0.06)
$Dis2county_i * Year_{2020}$	-0.13** (0.06)
$Dis2water_i * Year_{2000}$	0.01 (0.03)
$Dis2water_i * Year_{2005}$	0.04 (0.17)
$Dis2water_i * Year_{2010}$	0.41* (0.22)
$Dis2water_i * Year_{2013}$	0.4* (0.22)
$Dis2water_i * Year_{2015}$	0.7*** (0.25)
$Dis2water_i * Year_{2018}$	0.54* (0.31)
$Dis2water_i * Year_{2020}$	0.67** (0.33)
$Dis2coastline_i * Year_{2000}$	-0.005 (0.003)
$Dis2coastline_i * Year_{2005}$	0.01 (0.02)
$Dis2coastline_i * Year_{2010}$	0.02 (0.02)
$Dis2coastline_i * Year_{2013}$	0.02 (0.02)
$Dis2coastline_i * Year_{2015}$	0.01 (0.02)
$Dis2coastline_i * Year_{2018}$	0.02 (0.03)
$Dis2coastline_i * Year_{2020}$	0.03 (0.03)
$Elevation_i * Year_{2000}$	-0.51 (0.45)
$Elevation_i * Year_{2005}$	-10.17*** (2.91)
$Elevation_i * Year_{2010}$	-12.69*** (3.53)
$Elevation_i * Year_{2013}$	-12.65*** (3.54)
$Elevation_i * Year_{2015}$	-19.1*** (4.04)
$Elevation_i * Year_{2018}$	-18.97*** (4.31)
$Elevation_i * Year_{2020}$	-19.35*** (4.36)
$Dis2road_i * Year_{2000}$	-0.04 (0.02)
$Dis2road_i * Year_{2005}$	0.002 (0.09)
$Dis2road_i * Year_{2010}$	-0.03 (0.11)
$Dis2road_i * Year_{2013}$	-0.03 (0.11)
$Dis2road_i * Year_{2015}$	0.3* (0.17)
$Dis2road_i * Year_{2018}$	0.15 (0.16)
$Dis2road_i * Year_{2020}$	-0.1 (0.17)
Village Fixed effect	Yes
Year Fixed effect	Yes
R^2	0.19
Hausman test	74.25***
No. of villages ($Develop_i = 1$)	386
No. of villages ($Develop_i = 0$)	386
No. of year	8
No. of observations	6176

Note: *The clustered standard errors of the coefficients are given in parentheses; *, **, and *** denote a significance level of 10%, 5%, and 1%, respectively.*

Annex B: Publications

- **He, Zhichao**, Chunhong Zhao, Christine Fürst, and Anna M. Hersperger. "Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China?." Land Use Policy 108 (2021): 105562.
- **He, Zhichao**, Yuheng Ling, Christine Fürst, and Anna M. Hersperger. "Does zoning contain built-up land expansion? Causal evidence from Zhangzhou City, China." Landscape and Urban Planning 220 (2022): 104339.
- **He, Zhichao**, Zhaowu Yu, Christine Fürst, and Anna M. Hersperger. "Peer effects drive non-conformance between built-up land expansion and zoning: Evidence from Zhangzhou City, China." Applied Geography 152 (2023), 102875.

Land Use Policy 108 (2021) 105562

Contents lists available at ScienceDirect

Land Use Policy

journal homepage: www.elsevier.com/locate/landusepol

Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China?

Zhichao He [a,b,*], Chunhong Zhao [b,c], Christine Fürst [a], Anna M. Hersperger [b]

[a] Department of Sustainable Landscape Development, Institute for Geosciences and Geography, Martin-Luther-University Halle-Wittenberg, Halle (Saale), Germany
[b] Land Change Science Research Unit, Swiss Federal Research Institute WSL, Birmensdorf, Switzerland
[c] School of Geographical Sciences, Northeast Normal University, Changchun, China

ARTICLE INFO

Keywords:
Built-up land change
Causality
Selection bias
Propensity score matching
The Major Function oriented Zone
Fujian Province

ABSTRACT

Spatial planning has been globally developed as a policy tool to govern built-up land expansion. However, causal evidence of the effect of spatial planning on built-up land expansion is limited, which raises doubts on the credibility of spatial planning and hinders theoretical developments in land-system science. We evaluated the effect of the Major Function Oriented Zone (MFOZ), the first strategic spatial plan in China, on built-up land expansion in Fujian Province over three time intervals (2013–2015, 2013–2018 and 2013–2020). Propensity score matching (PSM) was applied to overcome selection bias and obtain causal evidence. We implemented a conventional conformance evaluation as a reference for the PSM-based conformance evaluation, to demonstrate the problem of selection bias. The conventional conformance evaluation showed that the MFOZ effectively governed built-up land expansion in the three time intervals. The PSM-based conformance evaluation showed the smaller effect of the MFOZ and the effect was significant only in the time period 2013–2018 and 2013–2020. That is, the conventional conformance evaluation results in an initially ineffective effect of the MFOZ being estimated as effective in 2013–2015 and exaggerates the effect of the MFOZ on built-up land expansion in 2013–2018 and 2013–2020. In aggregate, Fujian's MFOZ prevented a total of 79.31 km^2 of built-up land within the development-restricted zone between 2013 and 2020. To conclude, we recommend a wider application of the PSM-based conformance evaluation in evaluating the effect of spatial planning on land-use change, since this method accounts for selection bias and provides more accurate results regarding causality than conventional conformance evaluations.

1. Introduction

Spatial planning has been globally developed as a form of policy tool to govern built-up land expansion. Built-up land is one of the most human-dominated land-use types and has become the hotspot of the human-environment relationship. The development of built-up land drives a series of environment changes from directly encroaching on cropland and natural land (Bren d'Amour et al., 2017; van Vliet, 2019) to indirectly causing biodiversity degradation (Seto et al., 2012). In contrast, its expansion is strongly correlated to economic development and dramatically promotes human's material living standards (Acuto et al., 2018; He et al., 2014). These opposing effects reveal the need for governing the development of built-up land. In response, governments around the world have deployed a range of policy measures, such as urban growth boundary policies (Gennaio et al., 2009; Long et al., 2013), greenbelt planning (Macdonald et al., 2020; Siedentop et al., 2016), urban planning (Sharifi et al., 2014; Wang et al., 2017), and land-use planning (Alfasi et al., 2012; Zhong et al., 2014).

While various plans have been put into practice, causal evidence of the effect of spatial planning on land-use change is limited (Hersperger et al., 2018). Land-system science considers spatial planning as one of the drivers of land-use change (Bürgi et al., 2004; Geist and Lambin, 2002). Literature reviews have shown that political drivers (e.g., spatial development policies, nature conservation policies and land-use planning) were more frequently mentioned than economic, technological, cultural, and natural drivers, when explaining urban sprawl (Colsaet et al., 2018; Plieninger et al., 2016). However, land-system science still calls for more robust approaches to evaluate the causal effect of spatial

* Corresponding author at: Department of Sustainable Landscape Development, Institute for Geosciences and Geography, Martin-Luther-University Halle-Wittenberg, Halle (Saale), Germany

E-mail addresses: zhichao.he@student.uni-halle.de, zhichao.he@wsl.ch (Z. He).

https://doi.org/10.1016/j.landusepol.2021.105562
Received 4 November 2020; Received in revised form 19 April 2021; Accepted 21 May 2021
Available online 1 June 2021
0264-8377/

planning on land-use change, in particular because driving force frameworks consider spatial planning as a process exogenous to land-use system, thus neglecting the potential of selection bias (Meyfroidt, 2016). Furthermore, there is disagreement amongst scholars on conceptualizing the effect of spatial planning. Some scholars suggested that the effect of spatial planning should be understood as the influence of spatial plans on the actors in a policy network, via guidelines for their execution of policy in the plan implementation process (Driessen, 1997; Faludi, 2000; Mastop and Faludi, 1997). This would indicate that a direct relationship between planned and actual land-use change is not necessarily expected. Other scholars proposed that the relationship between planned and actual land-use change was the "gold standard" to evaluate the effect of spatial planning (Chapin et al., 2008; Laurian et al., 2004). Such disagreement erodes public confidence in spatial planning. Consequently, an evaluation of the causal effect of spatial planning on land-use change is necessary to ensure an efficient use of the financial, human and political resources dedicated to spatial planning (Blackman, 2013). Such an evaluation would also consolidate the theoretical foundations of the causes of land-use change (Meyfroidt et al., 2018; Turner et al., 2007) and enhance the credibility of spatial planning (Oliveira and Pinho, 2010).

The conventional conformance evaluation is a straightforward comparison of a region's built-up land expansions before and after spatial planning or of the different regions with and without spatial planning. Many researchers found a lack of conformance by overlaying planned land-use with actual built-up land expansion, and concluded that there was a failure of spatial planning (Abrantes et al., 2016; Alfasi et al., 2012; Guo et al., 2020; Kleemann et al., 2017; Sharifi et al., 2014; Wang et al., 2014). Other research using a similar overlay method suggested the success of spatial planning in containing built-up land expansion (Gennaio et al., 2009; Siedentop et al., 2016). However, these conventional types of conformance evaluation can biasedly estimate the effect of spatial planning on land use change due to selection bias (Andam et al., 2008; Blackman, 2013; Butsic et al., 2011).

Selection bias is a central problem in the evaluation of the causal effect of spatial planning on land-use change. However, this problem has not been fully acknowledged to date (Blackman, 2013). We will briefly illustrate the problem of selection bias with a thought experiment: $Y_i(1)$ and $Y_i(0)$ denote two changes in built-up land area for the same area *i* in the same period, where 1 indicates that the area *i* is assigned inside the urban growth boundaries and 0 indicates that the area *i* is assigned outside the urban growth boundaries. The difference between $Y_i(1)$ and $Y_i(0)$ in this example can only result from a difference in the planned status (inside or outside the urban growth boundaries), as the area *i* is unchanged. In this case, the effect of the urban growth boundaries on built-up land expansion could be computed as $Y_i(1) - Y_i(0)$ and could be considered as a causal effect. However in reality, we cannot simultaneously observe $Y_i(1)$ and $Y_i(0)$. If we assume that the area *i* was assigned inside the urban growth boundaries, we are able to observe $Y_i(1)$, whereas the potential $Y_i(0)$ is missing and can be considered as a counterfactual for $Y_i(1)$. In most circumstances, researchers presume that the area *j*, outside the urban growth boundaries, is a counterfactual for the area *i*, and consider their difference $(Y_i(1) - Y_j(0))$ as an effect of the urban growth boundaries on built-up land expansion. However, this is arbitrary due to selection bias inherent in plan-making, in which the most suitable areas are assigned for particular uses. The areas with higher suitability for built-up land are more likely to be assigned inside the urban growth boundaries. These areas are more likely to experience built-up land expansion due to their suitability for built-up land use, rather than due to the urban growth boundaries.

To overcome the evaluation problems associated with selection bias, a PSM-based approach was developed (Imbens and Rubin, 2015; Rosenbaum and Rubin, 1983). It follows counterfactual thinking and is thus an effective statistical tool for evaluating the causal effect. In this approach the causal effect is regarded as the difference in the outcome when the characteristics of the evaluated units are identical in all aspects except in the variable of interest (Imbens and Rubin, 2015). Recent studies applied PSM-based approaches to evaluate the effect of protected areas or forest conservation policies on forest change (Andam et al., 2008; Bruggeman et al., 2015; Putraditama et al., 2019) or the effect of agricultural land preservation programs on farmland loss (Liu and Lynch, 2011). The main principle of the PSM-based approach is to find counterfactual units which are close to evaluated units in terms of confounding variables. Confounding variables such as elevation, distance to the nearest urban centre, etc. are crucial, as they impact both the planned status (plan-making) and land-use change. However, they are often neglected in evaluations of the effect of spatial planning on land-use change. By incorporating confounding variables into evaluations, the PSM-based approach enables us to untangle the interplay of spatial planning and confounding variables and to identify land-use changes which are solely attributable to spatial planning. The PSM-based approach is promising because, aside from handling selection bias, it relies on observational data (such as land-use data from remote sensing, socioeconomic data from censuses and big data from social sensing). Additionally, it is less restrictive to model assumption and model specification, as it is based on non-parametric estimations. Despite the above-mentioned strengths of the PSM, it still suffers from the weakness of hidden biases caused by the unobserved confounding variables (Rosenbaum, 2002). For example, leaders' judgements often influence the probability of the area to be assigned into a specific zone during the plan-making and the probability of this area to be developed in the actual development. The subjective judgements are the unobserved confounding variable which is out of control of the PSM.

In this study we selected the MFOZ, which is the first strategic spatial plan in China, to evaluate its causal effect in terms of built-up land expansion in Fujian Province, China. To handle selection bias, we used the PSM to compare the changes in the amount of built-up land in the towns of the development-prioritised zone with the matched towns of the development-restricted zone. Additionally, we used three evaluation intervals (2013–2015, 2013–2018 and 2013–2020) to evaluate temporal variation in the causal effect of the MFOZ on built-up land expansion. This study adds valuable new knowledge to literature on the causal relationship between spatial planning and land-use change, using a method capable of handling selection bias.

2. The MFOZ and study area

2.1. The MFOZ

In 2010 the Chinese central government released the MFOZ (2010–2020) to achieve a coordinated regional development, through spatial regulation and zoning of development (Fan et al., 2012). The provincial governments then developed the zoning schemes of the MFOZ covering their full provincial territory. The MFOZ divided land into four major function-oriented zones with different planning intentions on built-up land expansion:

(a) The development-optimized zone is characterized by a high level of urbanisation and industrialisation, here land-use needs to be optimized due to inefficient uses of built-up land and a decreasing quality of farmland. As a result, built-up land expansion is required to slow down in the development-optimized zone.
(b) The development-prioritised zone intends to promote the future regional development through large-scale urbanisation and industrialisation. Thus, in this zone the demand for built-up land expansion should be accommodated.
(c) The development-restricted zone restricts large-scale urbanisation and industrialisation. It is divided into two types of zones: an agricultural production zone and an ecological security zone. The former is important for food security, the latter aims to restore ecosystems and to protect ecological security. Hence, only small

amounts of built-up land expansion are permitted within the development-restricted zone.

(d) The development-prohibited zone can be regarded as a natural and cultural heritage protection region, in which built-up land expansion is strictly prohibited.

In order to delineate the different zones, the government developed an indicator framework. The framework assessed suitability with 10 indicators addressing such as environmental capacity, ecological vulnerability, ecological importance, natural hazards, population density, economic development, and strategic selection (Liu et al., 2018). Each indicator is comprised of several factors. For example, the indicator of ecological vulnerability included desertification, soil erosion, and stone desertification (Fan et al., 2012). The final zoning scheme of the MFOZ was selected based on the suitability evaluation.

The MFOZ was developed at the national and provincial administrative levels. The national MFOZ is diagrammatic and lacks an accurate cartographic delineation of the major function-oriented zones (Fan et al., 2012). In contrast the provincial MFOZ contains maps with high geographical accuracy and clear boundaries. We only consider the provincial MFOZ. Moreover, we do not deal with the development-prohibited zone, since this zone is not present in the study area. The MFOZ for Fujian was published in 2012 and comes to an end in 2020. While there are other plans or policies which may influence our results, including these plans or polices into our study is huge data-demanding due to the unavailability in plan data. Furthermore, the research on how plans or policies relate and work as a network for land-use change is still missing (Bacău et al., 2020).

2.2. Study area

Fujian Province was chosen as a study area because of its problems of built-up land expansion and farmland and forest land conservation. Fujian Province, located in southeast China, has nine prefectural cities which are further divided into 84 counties (Fig. 1.a). The topography of Fujian Province is dominated by mountains and hills (Fig. 1.b). Western mountainous and hilly areas are mostly forested and provide a wide range of ecosystem benefits (Fig. 1.c). Fertile plains are concentrated in the narrow eastern coastal areas which have been highly industrialised and urbanised. A local saying—eighty percent is mountains and hills, ten percent is water and ten percent is arable land—vividly stresses the shortage of areas for farmland and built-up land-use. Moreover, the

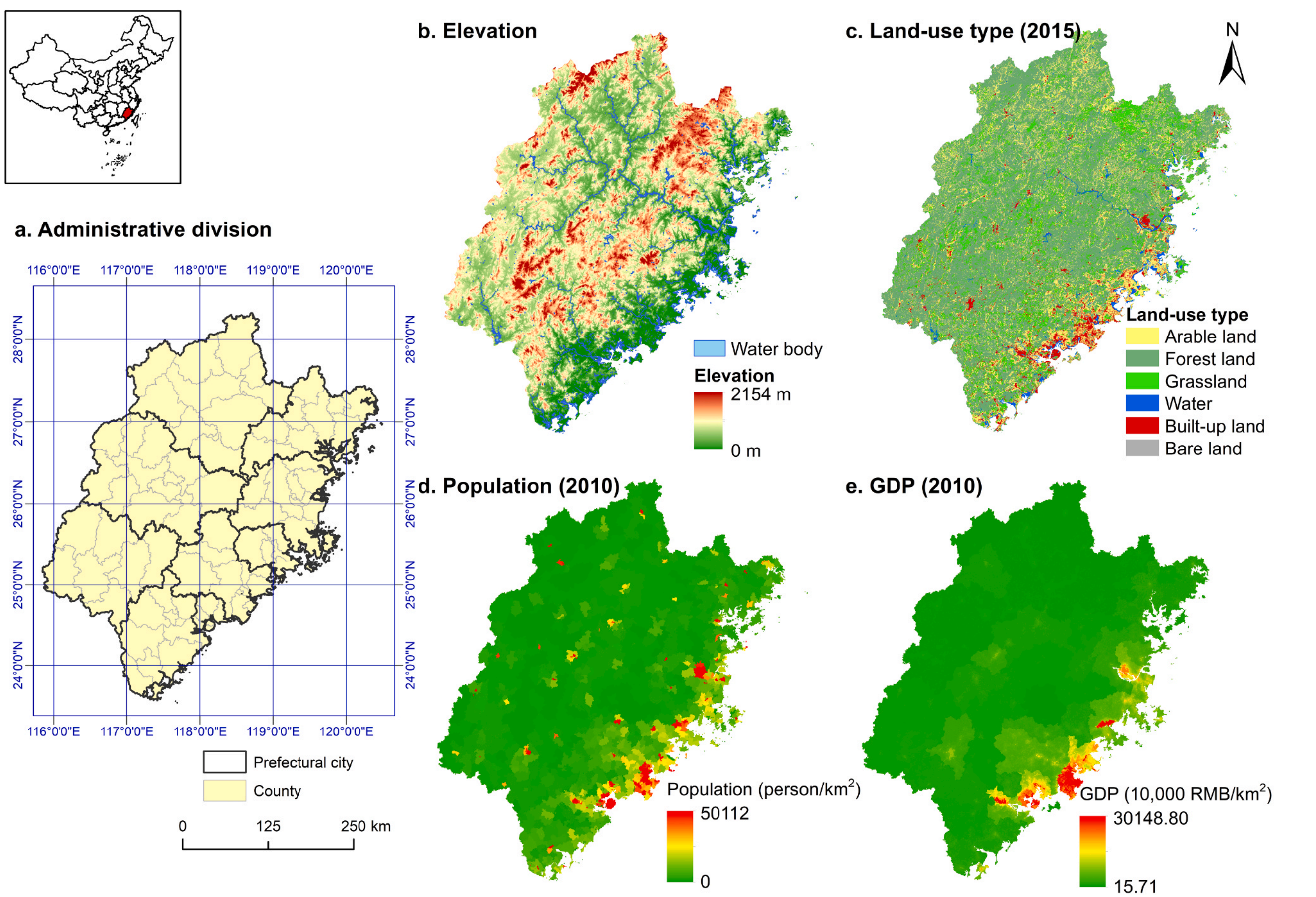

Fig. 1. The study area. 1a. Fujian Province, its location within China and division into nine prefectural cities; 1b. The topography of the study area; 1c. The different land-use types in the study area in 2015; 1d and e. The population and GDP density in 2010 within the study area.

conflicts concerning built-up land and farmland are intensifying as rapid urbanisation and economic development. Since China's Reform and Opening-up Policy in 1978, the urban population in Fujian Province has risen from 13.70% in 1978 to 65.80% in 2018, which exceeded the national average urban population of 59.58% (Fujian Bureau Statistics, 2019). Furthermore, Fujian Province has experienced rapid economic growth, with its gross domestic product (GDP) increasing from 6637 million RMB in 1978 to 3580,404 million RMB in 2018 (FSB, 2019). Such developments were mainly concentrated in the eastern coastal areas (Fig. 1.d and e) where built-up land is consuming the limited fertile plains. Thus, governing built-up land expansion to align demands for economic development with farmland conservation and ecosystem protection is a challenging task for the local government in this area.

954 of the 974 town-level administrative units in Fujian Province serve as evaluation units, because the delineation of the MFOZ follows the town boundaries (Fig. 3.a). These town units approximate the actual unit of plan-making and plan-implementation of the MFOZ. Of the 954 towns, 386 towns are fully located within the development-prioritised zone and 568 within the development-restricted zone. The 20 towns that are located within the development-optimized zone were excluded from the analysis, because it was not possible to find enough suitable matching pairs from the development-prioritised and development-restricted zones.

3. Methods

3.1. PSM-based conformance evaluation

Our PSM-based conformance evaluation consisted of four steps (Fig. 2): (1) select confounding variables and estimate propensity scores, (2) execute matching and check balance, (3) evaluate the causal effect, and (4) conduct robustness tests.

3.1.1. Select confounding variables and estimate propensity score

The confounding variables that determine which the major function-oriented zone a town is assigned to may also affect built-up land change. We selected the following confounding variables:

- *Distance to water (Dis2water)*: Fujian Province is topographically dominated by mountains and hills, as a result, settlements have a distinctive distribution pattern in areas close to water. This variable was measured as the Euclidean distance from the town to the nearest waterbody, via a Near tool in ArcGIS 10.6.
- *Slope (Slope)*: Steep slopes increase the cost of construction and pose a higher risk of erosion and landslides than flatter areas (Onsted and Chowdhury, 2014). This variable was measured as the average slope within the town, via a Zonal Statistics tool in ArcGIS 10.6.
- *Economic development (GDP)*: Built-up land expansion is strongly positively correlated to economic development (Acuto et al., 2018; He et al., 2014). This variable was measured as the average GDP in 2010 within the town, via a Zonal Statistics tool in ArcGIS 10.6.
- *Population growth (Pop)*: Population growth increases the demand for built-up land (van Vliet et al., 2017). This variable was measured as the average population in 2010 within the town, via a Zonal Statistics tool in ArcGIS 10.6.
- *Road length (Road)*: Transport is usually considered as a determining factor influencing land-use change (Kasraian et al., 2019; Li et al., 2017). This variable was measured as the length of road within each town in 2010, via a Intersect tool in ArcGIS 10.6.
- *Distance to city centre (Dis2city)*: Proximity to urban centres is an important driver for built-up land expansion (Kasraian et al., 2019; Yin et al., 2018). This variable was measured as the Euclidean distance from the town to the nearest prefectural city centre, via a Near tool in ArcGIS 10.6.
- *Neighbourhood effect*: The neighbourhood effect is an indispensable driver of land-use change (van Vliet et al., 2013; Verburg et al.,

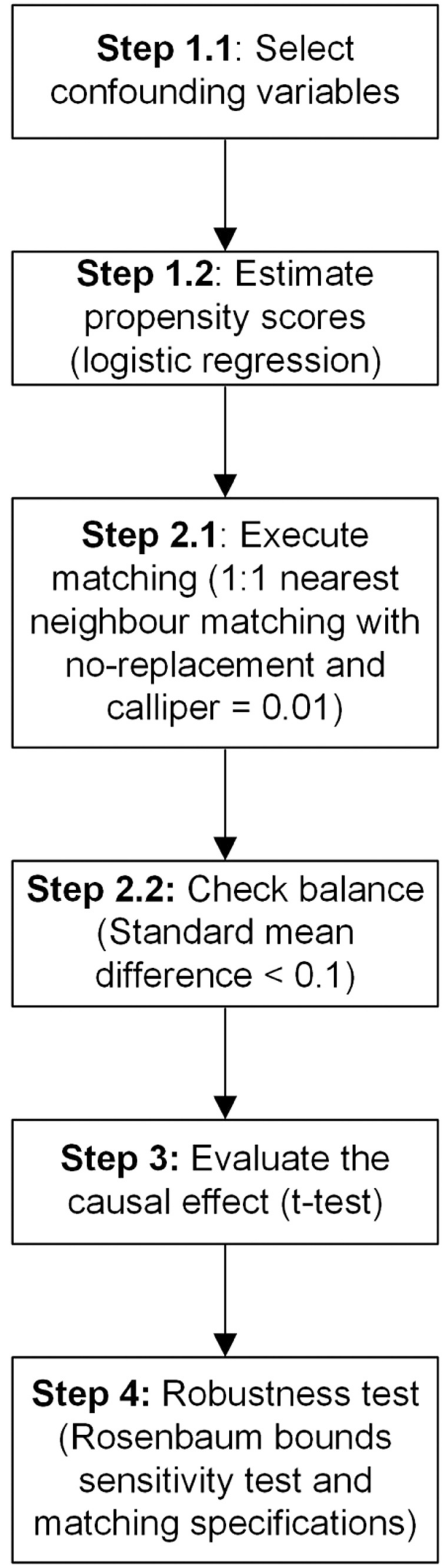

Fig. 2. Steps for the PSM-based conformance evaluation.

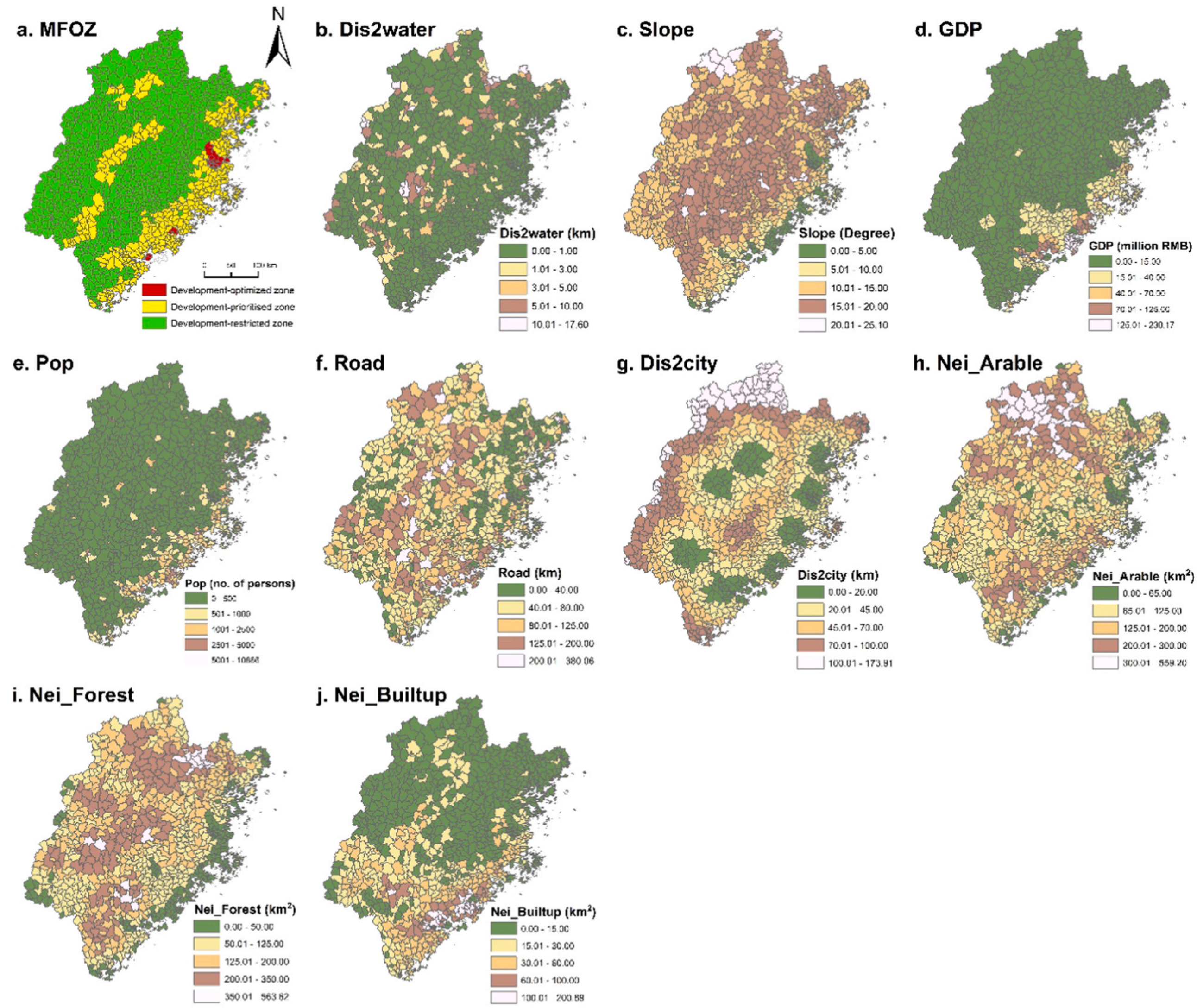

Fig. 3. An overview of the planning variable and confounding variables at the town level.

2004). In general, planners prefer compact strategies for built-up land expansion, in order to avoid the negative impacts of built-up sprawl. We measured three types of neighbourhood effect, the area of: arable land (*Nei_Arable*); forest land (*Nei_Forest*) and built-up land (*Nei_Builtup*) neighbouring town *i* in 2010, using a Polygon Neighbour tool in ArcGIS 10.6. A first-order contiguity was used to define the neighbourhood relationship, that is, the towns that share an edge or a corner will be considered as the neighbouring towns.

We used logistic regression to calculate the propensity scores via incorporating the confounding variables as independent variables and the planning variable as a dependent variable. The planning variable is a binary variable, where the value 1 was assigned to towns located in the development-prioritised zone and the value 0 for towns within the development-restricted zone. The propensity score provides a univariate standard to identify the counterfactual (Rosenbaum and Rubin, 1983). The propensity score in our study refers to the probability of the town *i* being assigned, in the planning process, to the development-prioritised zone, given confounding variables we selected.

3.1.2. Execute matching and check balance

We carried out 1:1 nearest neighbour matching. A town from the development-restricted zone was chosen as a matching counterfactual when it was closest to the town of the development-prioritised zone in terms of propensity score. We also set up matching without replacement, as it can yield the most precise estimates in a relatively large dataset (Butsic et al., 2011). Nearest neighbour matching risks poor matches if the closest neighbour is far away (Caliendo and Kopeinig, 2008). To avoid this, we imposed a tolerance level of 0.01 on the maximum propensity score difference (calliper). We imposed a common support by dropping the towns of the development-prioritised zone whose propensity score was higher than the maximum or less than the minimum propensity score of the towns of the development-restricted zone.

After PSM, we obtained 103 matched pairs (Fig. 4.d) and checked the balance, that is, the confounding variables between 103 matched towns of the development-prioritised zone and 103 matched towns of the development-restricted zone should be similar (Rosenbaum and Rubin, 1983). Standard mean difference can be used as a balance indicator and is defined as (Austin, 2011):

$$SMD = \frac{|\overline{x}_1 - \overline{x}_0|}{\sqrt{\frac{s_1^2 + s_0^2}{2}}}$$

In which $\overline{x}_1$ and $\overline{x}_0$ are the means of the confounding variables of the towns in the development-prioritised zone and development-restricted zone respectively. s_1^2 and s_0^2 denote the sample variances. Standard mean difference is not influenced by sample size and is independent of the unit of measurement, which enables to compare the relative balance

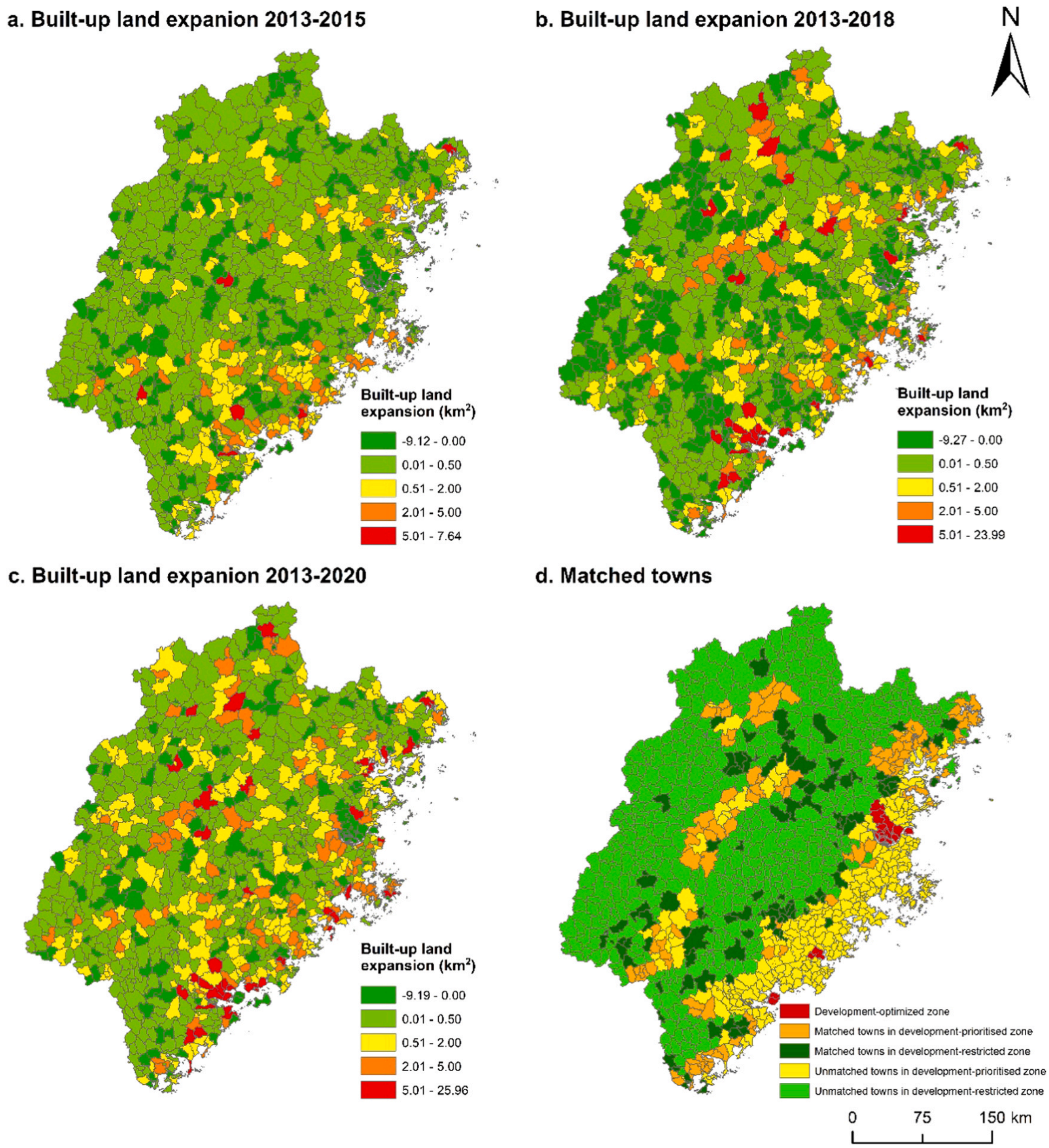

Fig. 4. Built-up land expansion and the matched towns.

among the different confounding variables (Zhang et al., 2019). A higher standard mean difference indicates a higher dissimilarity in the confounding variables. The value 0.1 is considered as a reasonable threshold for ignoring dissimilarity (Austin, 2011; Stuart et al., 2013).

3.1.3. Evaluate the causal effect

We estimated the causal effect of the MFOZ on built-up land expansion, by comparing the difference in the mean built-up land expansion between 103 matched towns of the development-prioritised zone and 103 matched towns of the development-restricted zone. To reflect temporal changes in the causal effect of the MFOZ on built-up land expansion, we used three time intervals: 2013–2015, 2013–2018 and 2013–2020 (Fig. 4.a–c). We used a *t*-test to assess the statistical significance of the causal effect, which enabled us to be less restrictive with model specifications and to directly compare the results with the conventional conformance evaluation.

3.1.4. Robustness test

We tested the robustness of our results in two ways. First, we used the Rosenbaum bounds sensitivity test to check whether our results were robust to potential hidden bias from unobserved confounding variables (Appendix A). Second, we tested the robustness of our matching algorithms by applying the different matching specifications, which included nearest neighbour matching with multiple callipers, radius matching with multiple callipers, and kernel matching (Appendix B).

3.2. Conventional conformance evaluation

As a reference for the PSM-based conformance evaluation, a conventional conformance evaluation was carried out, because it does not consider selection bias. We compared the difference in the mean built-up land expansion between 386 towns of the development-prioritised zone and 568 towns of the development-restricted zone in 2013–2015, 2013–2018 and 2013–2020. We also used a *t*-test to assess the statistical significance.

3.3. Data sources

The land-use dataset (from the years: 2010, 2013, 2015, 2018, and 2020) was provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn) and is a vector format. Land use data in 2010 was interpreted based on Landsat TM images (resolution 30 × 30 m). Land use data in 2013, 2015, 2018, and 2020 were interpreted based on Landsat 8 images (resolution 30 ×30 m). The MFOZ, the boundary of the town-level administrative unit, and the digital elevation model (DEM) (resolution 30×30 m) were provided by the local government. A data with slope information was calculated based on the DEM data using a Surface tool in ArcGIS 10.6. Road network data for 2010 were obtained from NavInfo company (http://www.navinfo.com/en/index.aspx), which is the largest digital map provider in China. The raster data for GDP in 2010 (resolution 1 ×1 km) was provided by RESDC. The raster data for township-level population in 2010 (resolution 1 ×1 km) was provided by China Science Data (http://csdata.org/en/p/420/).

4. Results

4.1. Overt selection biases

There were overt selection biases in the confounding variables between the towns in the development-prioritised zone and the towns in the development-restricted zone (Table 1). The second and third column of Table 1 display the mean values of the confounding variables. The towns located in the development-restricted zone were generally further away from waterbodies and city centres and had steeper slopes, lower populations and GDP, less road length, more neighbouring arable and forest land, and less neighbouring built-up land areas than those in the development-prioritised zone. The fourth column of Table 1 shows estimation results from a logistic regression and indicates that the confounding variables indeed influenced the probability that towns would be assigned to the development-prioritised zone. We also carried out an Ordinary Least Square (OLS) regression on changes in the amount of built-up land between 2013 and 2020. The results in the fifth column indicate that the confounding variables also had significant impacts on built-up land expansion. Thus, in terms of the confounding variables we selected, the overt selection biases existed in our study because these confounding variables influenced the assignment of the MFOZ (proved by logistic regression) and built-up land expansion (proved by OLS regression).

Based on the estimated coefficients from the logistic regression, we calculated the propensity score of assignment to the development-prioritised zone for each town. Fig. 5 presents the distribution of the propensity scores, which are separated into the development-prioritised and the development-restricted zone. Both histograms show long-tailed distributions, indicating that the majority of the towns of the development-prioritised zone have high propensity scores and the towns of the development-restricted zone tend to have low propensity scores. In other words, whether a town would be assigned to the development-prioritised zone is not random.

Table 1
Selection biases of the confounding variables prior to matching.

Confounding variables	Mean: Development-prioritized zone	Mean: Development-restricted zone	Coefficients of logistic regression (Y=1, development-prioritised zone, otherwise 0)	Coefficients of OLS (Y=Change of built-up land area 2013–2020)
Intercept	–	–	2.3508* (1.3072)	2.2042*** (0.4428)
Dis2water	0.22	1.39	-0.2157* (0.1238)	-0.0084 (0.0199)
Slope	10.11	15.45	-0.1229* (0.0638)	-0.1115*** (0.0258)
GDP	37.61	4.79	0.1538*** (0.0514)	-0.008 (0.0049)
Pop	1113	181	0.0006** (0.0003)	0.00004 (0.0001)
Road	81.04	62.47	0.0087* (0.0044)	0.0135*** (0.0028)
Dis2city	30.38	61.96	-0.0483*** (0.0106)	-0.0079*** (0.0029)
Nei_Arable	111.57	139.88	0.0077 (0.005)	0.0017 (0.0014)
Nei_Forest	70.9	147.96	-0.0164*** (0.004)	-0.0022** (0.0009)
Nei_Builtup	36.57	14.09	-0.0013 (0.012)	-0.0095** (0.0046)
LR statistic	–	–	-259.74	–
Pseudo R^2	–	–	0.59	–

Note: The standard errors in parentheses are clustered by county; "*", "**", and "***" represent rejection of the null hypothesis at the 10%, 5%, and 1% significance level, respectively.

4.2. Balance indicator

After matching, we checked the balance of the matched data, that is, how similar the confounding variables of the matched towns in the development-prioritised and the development-restricted zone are (Fig. 6). All confounding variables have the standard mean differences below 0.1 after matching. Moreover, the standard mean difference of the propensity scores dramatically decreased from 2.62 to 0.01. This indicates that PSM removed the overt selection biases relatively well. The remaining difference in built-up land expansion can be attributed solely to the difference in a planning status.

4.3. Effect of the MFOZ

The conventional conformance and PSM-based conformance evaluation show contrasting results regarding the effect of the MFOZ on built-up land expansion (Table 2). In the conventional conformance evaluation, the towns in the development-prioritised zone experienced higher built-up land expansion than those in the development-restricted zone in each of the three evaluation intervals. The difference in the mean built-up land expansion between the two zones increased from 0.41 km^2 in the interval 2013–2015 to 1.11 km^2 in the interval 2013–2020. Moreover, the *t*-test on the mean difference was significantly positive in the three evaluation intervals, suggesting that the MFOZ was effective in governing built-up land expansion in Fujian Province. However, the PSM-based conformance evaluation shows the opposite. The *t*-test was

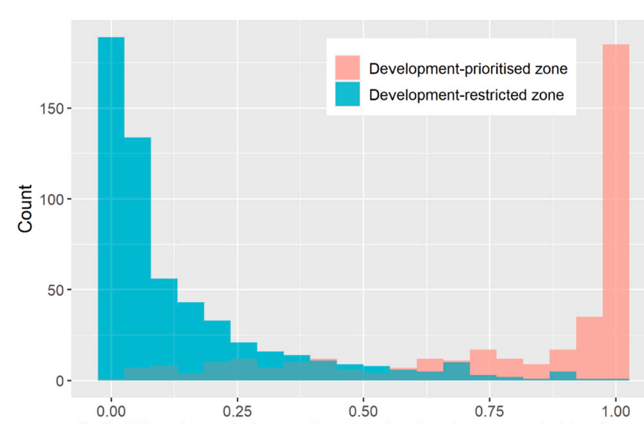

Fig. 5. Distribution of the propensity scores of the towns in the development-prioritised and development-restricted zone.

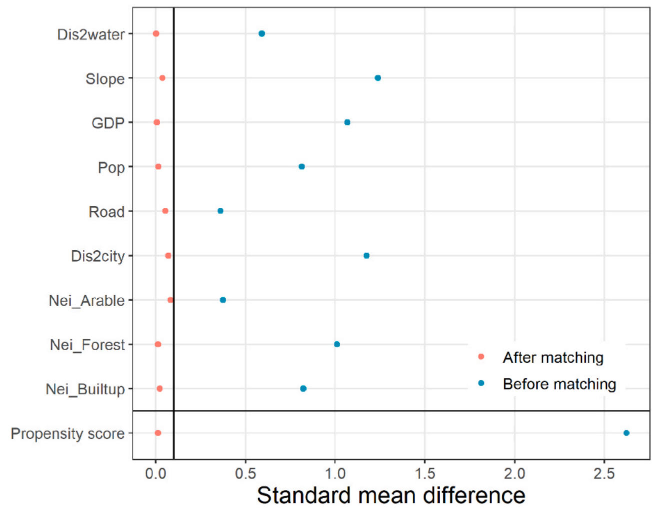

Fig. 6. Standard mean difference of the confounding variables and the propensity score between the towns of the development-prioritised and development-restricted zone before and after matching.

insignificant in 2013–2015. It indicates that the MFOZ was ineffective in restricting built-up land expansion in the development-restricted zone at the start of its implementation. In the intervals 2013–2020 and 2013–2020, the *t*-test became significant. This suggests that the effect of the MFOZ varied, from ineffective at the start of its implementation to effective later in its implementation period. Finally, it is worth noting that the PSM-based conformance evaluation estimated a smaller effect of the MFOZ. For example, the conventional conformance evaluation shows that the towns in the development-restricted zone experienced lower built-up land expansion (on average 1.11 km^2 less built-up land expansion) than the towns in the development-prioritised zone from 2013 to 2020. However, the mean difference is much lower when using the PSM-based conformance evaluation (0.77 km^2). The coefficient (0.77 km^2) indicates that each of the matched towns assigned within the development-restricted zone would have additionally expanded by 0.77 km^2 of built-up land if there would have been no the MFOZ. In aggregate, a total of 79.31 km^2 of built-up land was prevented within the development-restricted zone between 2013 and 2020, considering that there were 103 matched towns in the development-restricted zone.

5. Discussion

5.1. Reflection on selection bias

Evaluating causal evidence for the effect of spatial planning on land-use change may suffer from selection bias. The conventional conformance evaluation considers the effect of spatial planning on land-use change as the combined effect brought about by spatial planning in combination with other forces (e.g., geographical, socio-economic or proximity factors) (Wong and Watkins, 2009). In our study, the conventional conformance evaluation showed that the MFOZ could effectively govern built-up land expansion during the three evaluation intervals. Another conventional conformance evaluation at the national scale also found that the development-restricted zone had a lower annual increase in built-up land area than the development-prioritised zone between 2010 and 2013 (Liu et al., 2017). However, the combined effects of spatial planning and other forces may be exaggerated or even result in ineffective outcomes being falsely estimated as effective. The PSM-based conformance evaluation showed that the MFOZ was ineffective in governing built-up land expansion between 2013 and 2015, and that the effect of the MFOZ on built-up land expansion were lower than the effect from the conventional conformance evaluation in 2013–2018 and 2013–2020. The difference between the results of the conventional conformance and PSM-based conformance evaluation is a result of selection bias. Within the conventional conformance evaluation, the changes in built-up land may be a result of the confounding variables and less so of the MFOZ, since the confounding variables affected both the town's assignment to a planning status and the town's changes in built-up land. For example, as a logistic and an OLS regression found in our study, *Dis2city* had not only a negative impact on the probability of a town being assigned to the development-prioritised zone (coefficient=−0.0483, $p < 0.01$), but also had a negative impact on built-up land expansion (coefficient=−0.0079, $p < 0.01$). The conventional conformance evaluation attributed the effect of *Dis2city* on built-up land expansion to the effect of the MFOZ. Whereas, the PSM-based conformance evaluation eliminated the effect of *Dis2city* on built-up land expansion, thereby identifying solely the effect of the MFOZ on built-up land expansion. Our finding is essential for future studies on plan evaluations, which should take selection bias into account in order to avoid inaccurate evaluations.

5.2. Temporal variation in the causal effect of the MFOZ

Prior work has highlighted the influence of time in the occurrence and evaluation of plan success or failure (Baer, 1997; Bressers et al., 2013; Loh, 2011). However, these studies rarely showed empirical evidence for whether and how the effect of spatial planning varied across time. In our study, the causal effect of the MFOZ on built-up land expansion varied over the duration of its implementation. In the first few years of implementation (2013–2015) there was not significant difference in built-up land expansion between the two zones, which is inconsistent with planning intentions. Later on, the development-restricted zone significantly had lower rates of built-up land expansion than the development-prioritised zone, which is consistent with planning intentions. These results indicate a certain time lag in plan implementation (Loh, 2011). Time lags make the effect of spatial planning on land-use change more difficult to evaluate, as the effect is delayed. Plan implementation is an ongoing process with discrete steps, which include the enforcement of regulations, the delivery of programme services and coordination among stakeholders (Lyles et al., 2016). In China, local governments are de facto owners and administrators of land (Li et al., 2015) and are responsible for implementing spatial plan (Shen et al., 2019). The MFOZ, which was only developed at the national and provincial levels, lacks local administrative measures and implementation regulations. Thus, it is inevitable that

Table 2
Results concerning the area of built-up land expansion from the conventional conformance and PSM-based conformance evaluation.

Conformance evaluation	Evaluation interval	Development- prioritised zone (km^2)	Development- restricted zone (km^2)	Mean difference (km^2)	*t*-test	Evaluation results
PSM-based evaluation	2013–2015	0.44	0.37	0.07	0.56	Ineffective
	2013–2018	1.01	0.6	0.41	1.32*	Effective
	2013–2020	1.43	0.66	0.77	2.38***	Effective
Conventional evaluation	2013–2015	0.61	0.2	0.41	5.97***	Effective
	2013–2018	0.97	0.34	0.63	5.27***	Effective
	2013–2020	1.57	0.46	1.11	8.51***	Effective

Note: "*", "**", and "***" represent rejection of the null hypothesis at the 10%, 5%, and 1% significance level, respectively.

the implementation of the MFOZ is immensely costly in terms of time. For example, the smallest unit of the Fujian MFOZ is a town, which means every town only has one major function-oriented zone. Such coarse zoning results in town-level governments spending considerable amounts of time coordinating with the superior government to develop their local corresponding spatial regulations. Furthermore, in our study, 2020 is the final year of implementation of the MFOZ. Our results confirm that evaluation of the entire planning duration is necessary for a rigorous causal evaluation of spatial planning and land-use change.

5.3. Do we get closer to causality?

Although the PSM-based conformance evaluation is effective for causal evaluation, its wider application in evaluation of spatial planning needs support from spatial planning theory. Spatial planning is embedded in socio-political and institutional complexity and is highly context-dependent, which makes it difficult to grasp from a theoretical perspective (Hersperger et al., 2019). For example, the propensity score is the basis for identifying counterfactuals. However, what are the underlying variables which may influence the probability of the allocation of zones of the MFOZ? In addition to the confounding variables we selected, the unobserved factors (e.g., leaders' judgements, negotiations among interest groups) are also the vital confounding variables influencing the allocation of the major function-oriented zones and built-up land expansion. A regular planning process is not only determined by spatial analysis of land suitability, but more or less determined by political negotiations or the leaders' subjective choice which are unobserved. These unobserved confounding variables may bias our results, even that we get a well balance matched data. It is difficult to improve the predictive ability of propensity scores considering such unobserved confounding variables, particularly in the absence of a fully elaborated theory. For future studies, an empirically-based analytical framework which illustrates the key components and interrelationships necessary for making and implementing spatial plan, such as the SPlaMI framework based on 21 European urban regions (see Hersperger et al., 2019), might be useful for conceptualizing and operationalizing the relevant features of the planning process. Another obstacle limiting the PSM-based conformance evaluation in its application of plan evaluation is related to the fact that the land system is a complex human-environmental system with chains of causality (Bürgi et al., 2004). Consequently, the PSM-based conformance evaluation which focuses on the effect of a certain cause may be unsuitable for identifying complex chains of causality (Meyfroidt, 2016). The PSM-based conformance evaluation may have to test for causal effects piecemeal to explain fragmentary causal effect within a highly context-specific causal mechanism.

The PMS-based evaluation is a preferred method for our study, compared with the other causality approaches, i.e. difference in difference, synthetic control, instrumental variable, regression discontinuity, and Granger causality regression. First, difference in difference and synthetic control rely on longitudinal information prior to the intervention to construct the counterfactuals (Bouttell et al., 2018; Nunn and Qian, 2011). In our study, we only have longitudinal information after the implementation of the MFOZ. Second, a suitable instrumental variable, which impacts the assignment of zones of the MFOZ and has no effect on built-up land expansion, is difficult to find in our study. Third, regression discontinuity needs a cut-off point to distinguish the treatment and control group (Lee and Lemieux, 2010; Turner et al., 2014). In our study, the assignment of zones of the MFOZ was not based on a cut-off point of a specific variable. Last, Granger causality regression uses a relatively long time series of variables to incorporate lagged variables in regression models. In our study, the four years' data is unable to satisfy the data requirement of Granger causality regression. Furthermore, Granger causality regression is useful to examine the causality between the variables changing over time, such as GDP growth and NDVI change (He et al., 2020). Thus, Granger causality regression is an inappropriate choice for the time-invariant planning variable. In conclusion, most of causality approaches may be too data-demanding for our research question, because the enough longitudinal information is necessary for demonstrating causal effect. Nevertheless, we are looking forward to the wider application of the other causality approaches in the future evaluation of spatial planning.

6. Conclusion

Spatial planning to govern built-up land expansion is now commonplace among most governments. Evaluating causality from spatial planning to land-use change is crucial to ensure efficient uses of resources designated to spatial planning and to improve the likelihood of spatial planning resulting in its expected outcome. We used the MFOZ, the first strategic spatial plan in China, as an example to evaluate whether spatial planning played a causal role in built-up land change in Fujian Province, considering the three time intervals (2013–2015, 2013–2018 and 2013–2020). The conventional conformance evaluation showed that the development-restricted zone significantly had lower built-up land expansion than the development-prioritised zone in the three intervals. Whereas, the PSM-based conformance evaluation showed that the development-restricted zone significantly had lower built-up land expansion than the development-prioritised zone only in the interval 2013–2018 and 2013–2020. Furthermore, the effect estimated by the PSM-based conformance evaluation was smaller than that estimated by the conventional conformance evaluation. This suggests that the conventional conformance evaluation may produce false or exaggerated estimates compared to the PSM-based conformance evaluation, due to selection biases. Furthermore, we note that the causal effect of the MFOZ on built-up land expansion varied over its implementation time, suggesting a time lag in plan implementation.

The PSM-based conformance evaluation is effective for evaluating the effect of spatial planning on land-use change and achieves results more accurate in terms of causality than conventional conformance evaluations. We recommend a wider application of the PSM-based approach in the evaluation of spatial planning. This would not only promote a better understanding of the causes of land-use change, but also increases the likelihood of spatial planning resulting in its expected outcomes by providing better causal evidence in the decision-making process. Finally, although our analysis method is more accurate in terms of causality than a conventional conformance evaluation it can still be further refined. Further research could build on and refine our method, for example by including additional potential confounding variables or identifying the effect of multiple plans.

CRediT authorship contribution statement

Zhichao He: Conceptualization, Methodology, Software, Writing - Original Draft. **Chunhong Zhao:** Conceptualization, Writing - review & editing. **Christine Fürst:** Supervision, Writing - review & editing. **Anna M. Hersperger:** Supervision, Writing - review & editing, Funding acquisition.

Declarations of interest

None.

Acknowledgements

This research was funded by the Swiss National Science Foundation through the CONCUR project - From plans to land change: how strategic spatial planning contributes to the development of urban regions (ERC TBS Consolidator Grant number BSCGIO 157789). The first author would like to express his gratitude to the China Scholarship Council for supporting his PhD.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2021.105562.

References

Abrantes, P., Fontes, I., Gomes, E., Rocha, J., 2016. Compliance of land cover changes with municipal land use planning: evidence from the Lisbon metropolitan region (1990–2007). Land Use Policy 51, 120–134. https://doi.org/10.1016/j.landusepol.2015.10.023.

Acuto, M., Parnell, S., Seto, K.C., 2018. Building a global urban science. Nat. Sustain. 1, 2–4. https://doi.org/10.1038/s41893-017-0013-9.

Alfasi, N., Almagor, J., Benenson, I., 2012. The actual impact of comprehensive land-use plans: insights from high resolution observations. Land Use Policy 29, 862–877. https://doi.org/10.1016/j.landusepol.2012.01.003.

Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105, 16089–16094. https://doi.org/10.1073/pnas.0800437105.

Austin, P.C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar. Behav. Res. 46, 399–424. https://doi.org/10.1080/00273171.2011.568786.

Bacău, S., Grădinaru, S.R., Hersperger, A.M., 2020. Spatial plans as relational data: using social network analysis to assess consistency among Bucharest's planning instruments. Land Use Policy 92, 104484. https://doi.org/10.1016/j.landusepol.2020.104484.

Baer, W.C., 1997. General plan evaluation criteria: an approach to making better plans. J. Am. Plan. Assoc. 63, 329–344. https://doi.org/10.1080/01944369708975926.

Blackman, A., 2013. Evaluating forest conservation policies in developing countries using remote sensing data: an introduction and practical guide. For. Policy Econ. 34, 1–16. https://doi.org/10.1016/j.forpol.2013.04.006.

Bouttell, J., Craig, P., Lewsey, J., Robinson, M., Popham, F., 2018. Synthetic control methodology as a tool for evaluating population-level health interventions. J. Epidemiol. Community Health 72, 673–678. https://doi.org/10.1136/jech-2017-210106.

Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., Haberl, H., Creutzig, F., Seto, K.C., 2017. Future urban land expansion and implications for global croplands. Proc. Natl. Acad. Sci. 114, 8939–8944. https://doi.org/10.1073/pnas.1606036114.

Bressers, N., van Twist, M., ten Heuvelhof, E., 2013. Exploring the temporal dimension in policy evaluation studies. Policy Sci. 46, 23–37. https://doi.org/10.1007/s11077-012-9169-3.

Bruggeman, D., Meyfroidt, P., Lambin, E.F., 2015. Production forests as a conservation tool: effectiveness of Cameroon's land use zoning policy. Land Use Policy 42, 151–164. https://doi.org/10.1016/j.landusepol.2014.07.012.

Bürgi, M., Hersperger, A.M., Schneeberger, N., 2004. Driving forces of landscape change - current and new directions. Landsc. Ecol. 19, 857–868. https://doi.org/10.1007/s10980-005-0245-3.

Butsic, V., Lewis, D.J., Ludwig, L., 2011. An econometric analysis of land development with endogenous zoning. Land Econ. 87, 412–432. https://doi.org/10.3368/le.87.3.412.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. J. Econ. Surv. 22, 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x.

Chapin, T.S., Deyle, R.E., Baker, E.J., 2008. A parcel-based GIS method for evaluating conformance of local land-use planning with a state mandate to reduce exposure to hurricane flooding. Environ. Plan. B Plan. Des. 35, 261–279. https://doi.org/10.1068/b32114.

Colsaet, A., Laurans, Y., Levrel, H., 2018. What drives land take and urban land expansion? A systematic review. Land Use Policy 79, 339–349. https://doi.org/10.1016/j.landusepol.2018.08.017.

Driessen, P., 1997. Performance and implementing institutions in rural land development. Environ. Plan. B Plan. Des. 24, 859–869. https://doi.org/10.1068/b240859.

Faludi, A., 2000. The performance of spatial planning. Plan. Pract. Res. 15, 299–318. https://doi.org/10.1080/713691907.

Fan, J., Sun, W., Zhou, K., Chen, D., 2012. Major Function Oriented Zone: new method of spatial regulation for reshaping regional development pattern in China. Chin. Geogr. Sci. 22, 196–209. https://doi.org/10.1007/s11769-012-0528-y.

Fujian Bureau Statistics, 2019. Statistical Yearbook of Fujian Province in 2019. China Statistics Press, Beijing.

Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience 52, 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2.

Gennaio, M.P., Hersperger, A.M., Bürgi, M., 2009. Containing urban sprawl—evaluating effectiveness of urban growth boundaries set by the Swiss Land Use Plan. Land Use Policy 26, 224–232. https://doi.org/10.1016/j.landusepol.2008.02.010.

Guo, Z., Hu, Y., Zheng, X., 2020. Evaluating the effectiveness of land use master plans in built-up land management: a case study of the Jinan Municipality, eastern China. Land Use Policy 91, 104369. https://doi.org/10.1016/j.landusepol.2019.104369.

He, C., Huang, Z., Wang, R., 2014. Land use change and economic growth in urban China: a structural equation analysis. Urban Stud. 51, 2880–2898. https://doi.org/10.1177/0042098013513649.

He, Z., Xiao, L., Guo, Q., Liu, Y., Mao, Q., Kareiva, P., 2020. Evidence of causality between economic growth and vegetation dynamics and implications for sustainability policy in Chinese cities. J. Clean. Prod. 251, 119550 https://doi.org/10.1016/j.jclepro.2019.119550.

Hersperger, A.M., Oliveira, E., Pagliarin, S., Palka, G., Verburg, P., Bolliger, J., Grădinaru, S., 2018. Urban land-use change: the role of strategic spatial planning. Glob. Environ. Chang. 51, 32–42. https://doi.org/10.1016/j.gloenvcha.2018.05.001.

Hersperger, A.M., Grădinaru, S., Oliveira, E., Pagliarin, S., Palka, G., 2019. Understanding strategic spatial planning to effectively guide development of urban regions. Cities 94, 96–105. https://doi.org/10.1016/j.cities.2019.05.032.

Imbens, G.W., Rubin, D.B., 2015. Causal Inference for Statistics, Social, and Biomedical Sciences: An introduction. Cambridge University Press, New York.

Kasraian, D., Maat, K., Van, W.B., 2019. The impact of urban proximity, transport accessibility and policy on urban growth: a longitudinal analysis over five decades. Environ. Plan. B Urban Anal. City Sci. 46, 1000–1017. https://doi.org/10.1177/2399808317740355.

Kleemann, J., Inkoom, J.N., Thiel, M., Shankar, S., Lautenbach, S., Fürst, C., 2017. Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. Landsc. Urban Plan. 165, 280–294. https://doi.org/10.1016/j.landurbplan.2017.02.004.

Laurian, L., Day, M., Berke, P., Ericksen, N., Backhurst, M., Crawford, J., Dixon, J., 2004. Evaluating plan implementation: a conformance-based methodology. J. Am. Plan. Assoc. 70, 471–480. https://doi.org/10.1080/01944360408976395.

Lee, D.S., Lemieux, T., 2010. Regression discontinuity designs in economics. J. Econ. Lit. 48, 281–355. https://doi.org/10.1257/jel.48.2.281.

Li, H., Wei, Y.D., Liao, F.H., Huang, Z., 2015. Administrative hierarchy and urban land expansion in transitional China. Appl. Geogr. 56, 177–186. https://doi.org/10.1016/j.apgeog.2014.11.029.

Li, X., Chen, Y., Liu, X., Xu, X., Chen, G., 2017. Experiences and issues of using cellular automata for assisting urban and regional planning in China. Int. J. Geogr. Inf. Sci. 31, 1606–1629. https://doi.org/10.1080/13658816.2017.1301457.

Liu, W., Liu, J., Kuang, W., Ning, J., 2017. Examining the influence of the implementation of Major Function-oriented Zones on built-up area expansion in China. J. Geogr. Sci. 27, 643–660. https://doi.org/10.1007/s11442-017-1398-0.

Liu, X., Lynch, L., 2011. Do agricultural land preservation programs reduce farmland loss? Evidence from a propensity score matching estimator. Land Econ. 87, 183–201. https://doi.org/10.3368/le.87.2.183.

Liu, Y., Fu, B., Zhao, W., Wang, S., Deng, Y., 2018. A solution to the conflicts of multiple planning boundaries: landscape functional zoning in a resource-based city in China. Habitat Int. 77, 43–55. https://doi.org/10.1016/j.habitatint.2018.01.004.

Loh, C.G., 2011. Assessing and interpreting non-conformance in land-use planning implementation. Plan. Pract. Res. 26, 271–287. https://doi.org/10.1080/02697459.2011.580111.

Long, Y., Han, H., Lai, S., Mao, Q., 2013. Urban growth boundaries of the Beijing Metropolitan Area: comparison of simulation and artwork. Cities 31, 337–348. https://doi.org/10.1016/j.cities.2012.10.013.

Lyles, W., Berke, P., Smith, G., 2016. Local plan implementation: assessing conformance and influence of local plans in the United States. Environ. Plan. B Plan. Des. 43, 381–400. https://doi.org/10.1177/0265813515604071.

Macdonald, S., Monstadt, J., Friendly, A., 2020. From the Frankfurt greenbelt to the Regionalpark RheinMain: an institutional perspective on regional greenbelt governance. Eur. Plan. Stud. 4313. https://doi.org/10.1080/09654313.2020.1724268.

Mastop, H., Faludi, A., 1997. Evaluation of strategic plans: the performance principle. Environ. Plan. B Plan. Des. 24, 815–832. https://doi.org/10.1068/b240815.

Meyfroidt, P., 2016. Approaches and terminology for causal analysis in land systems science. J. Land Use Sci. 11, 501–522. https://doi.org/10.1080/1747423X.2015.1117530.

Meyfroidt, P., Roy Chowdhury, R., de Bremond, A., Ellis, E.C., Erb, K.H., Filatova, T., Garrett, R.D., Grove, J.M., Heinimann, A., Kuemmerle, T., Kull, C.A., Lambin, E.F., Landon, Y., le Polain de Waroux, Y., Messerli, P., Müller, D., Nielsen, J., Peterson, G. D., Rodriguez García, V., Schlüter, M., Turner, B.L., Verburg, P.H., 2018. Middle-range theories of land system change. Glob. Environ. Chang 52–67. https://doi.org/10.1016/j.gloenvcha.2018.08.006.

Nunn, N., Qian, N., 2011. The potato's contribution to population and urbanization: evidence from a historical experiment. Q. J. Econ. 126, 593–650. https://doi.org/10.1093/qje/qjr009.

Oliveira, V., Pinho, P., 2010. Evaluation in urban planning: advances and prospects. J. Plan. Lit. 24, 343–361. https://doi.org/10.1177/0885412210364589.

Onsted, J.A., Chowdhury, R.R., 2014. Does zoning matter? A comparative analysis of landscape change in Redland, Florida using cellular automata. Landsc. Urban Plan. 121, 1–18. https://doi.org/10.1016/j.landurbplan.2013.09.007.

Plieninger, T., Draux, H., Fagerholm, N., Bieling, C., Bürgi, M., Kizos, T., Kuemmerle, T., Primdahl, J., Verburg, P.H., 2016. The driving forces of landscape change in Europe: A systematic review of the evidence. Land Use Policy 57, 204–214. https://doi.org/10.1016/j.landusepol.2016.04.040.

Putraditama, A., Kim, Y.-S., Sánchez Meador, A.J., 2019. Community forest management and forest cover change in Lampung, Indonesia. For. Policy Econ. 106, 101976 https://doi.org/10.1016/j.forpol.2019.101976.

Rosenbaum, P.R., 2002. Observational Studies. Springer.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55. https://doi.org/10.1017/CBO9780511810725.016.

Seto, K.C., Guneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. 109, 16083–16088. https://doi.org/10.1073/pnas.1211658109.
Sharifi, A., Chiba, Y., Okamoto, K., Yokoyama, S., Murayama, A., 2014. Can master planning control and regulate urban growth in Vientiane, Laos? Landsc. Urban Plan. 131, 1–13. https://doi.org/10.1016/j.landurbplan.2014.07.014.
Shen, X., Wang, L., Wang, X., Zhang, Z., Lu, Z., 2019. Interpreting non-conforming urban expansion from the perspective of stakeholders' decision-making behavior. Habitat Int. 89, 102007 https://doi.org/10.1016/j.habitatint.2019.102007.
Siedentop, S., Fina, S., Krehl, A., 2016. Greenbelts in Germany's regional plans—an effective growth management policy? Landsc. Urban Plan. 145, 71–82. https://doi.org/10.1016/j.landurbplan.2015.09.002.
Stuart, E.A., Lee, B.K., Leacy, F.P., 2013. Prognostic score–based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research. J. Clin. Epidemiol. 66, S84–S90. https://doi.org/10.1016/j.jclinepi.2013.01.013.
Turner, B.L., Lambin, E.F., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. Proc. Natl. Acad. Sci. 104, 20666–20671. https://doi.org/10.1073/pnas.0704119104.
Turner, M.A., Haughwout, A., Klaauw, W. van der, 2014. Land use regulation and welfare. Econometrica 82, 1341–1403. https://doi.org/10.3982/ECTA9823.
van Vliet, J., 2019. Direct and indirect loss of natural area from urban expansion. Nat. Sustain. 2, 755–763. https://doi.org/10.1038/s41893-019-0340-0.
van Vliet, J., Naus, N., van Lammeren, R.J.A., Bregt, A.K., Hurkens, J., van Delden, H., 2013. Measuring the neighbourhood effect to calibrate land use models. Comput. Environ. Urban Syst. 41, 55–64. https://doi.org/10.1016/j.compenvurbsys.2013.03.006.
van Vliet, J., Eitelberg, D.A., Verburg, P.H., 2017. A global analysis of land take in cropland areas and production displacement from urbanization. Glob. Environ. Chang. 43, 107–115. https://doi.org/10.1016/j.gloenvcha.2017.02.001.
Verburg, P.H., de Nijs, T.C.M., van Eck, J.R., Visser, H., de Jong, K., 2004. A method to analyse neighbourhood characteristics of land use patterns. Comput. Environ. Urban Syst. 28, 667–690. https://doi.org/10.1016/j.compenvurbsys.2003.07.001.
Wang, L.-G., Han, H., Lai, S.-K., 2014. Do plans contain urban sprawl? A comparison of Beijing and Taipei. Habitat Int. 42, 121–130. https://doi.org/10.1016/j.habitatint.2013.11.001.
Wang, M., Krstikj, A., Koura, H., 2017. Effects of urban planning on urban expansion control in Yinchuan City, Western China. Habitat Int 64, 85–97. https://doi.org/10.1016/j.habitatint.2017.04.008.
Wong, C., Watkins, C., 2009. Conceptualising spatial planning outcomes: towards an integrative measurement framework. Town Plan. Rev. 80, 481–516. https://doi.org/10.3828/tpr.2009.8.
Yin, H., Kong, F., Yang, X., James, P., Dronova, I., 2018. Exploring zoning scenario impacts upon urban growth simulations using a dynamic spatial model. Cities 81, 214–229. https://doi.org/10.1016/j.cities.2018.04.010.
Zhang, Z., Kim, H.J., Lonjon, G., Zhu, Y., 2019. Balance diagnostics after propensity score matching. Ann. Transl. Med. 7, 16. https://doi.org/10.21037/atm.2018.12.10.
Zhong, T., Mitchell, B., Huang, X., 2014. Success or failure: evaluating the implementation of China's National General Land Use Plan (1997–2010). Habitat Int. 44, 93–101. https://doi.org/10.1016/j.habitatint.2014.05.003.

Landscape and Urban Planning 220 (2022) 104339

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

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

Zhichao He [a,b,*], Yuheng Ling [c], Christine Fürst [a], Anna M. Hersperger [b]

[a] Department of Sustainable Landscape Development, Institute for Geosciences and Geography, Martin-Luther-University Halle-Wittenberg, Halle (Saale), Germany
[b] Land Change Science Research Unit, Swiss Federal Research Institute WSL, Birmensdorf, Switzerland
[c] Business School, Yangzhou University, Yangzhou City, Zhejiang Province, China

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-in-difference 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^2 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).

https://doi.org/10.1016/j.landurbplan.2021.104339
Received 8 March 2021; Received in revised form 16 December 2021; Accepted 18 December 2021

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 built-up 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 land-use 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 land-use 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, difference-in-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 development-permitted 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 time-invariant 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 land-use 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 × 10 m to 1 × 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 socio-economic 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-

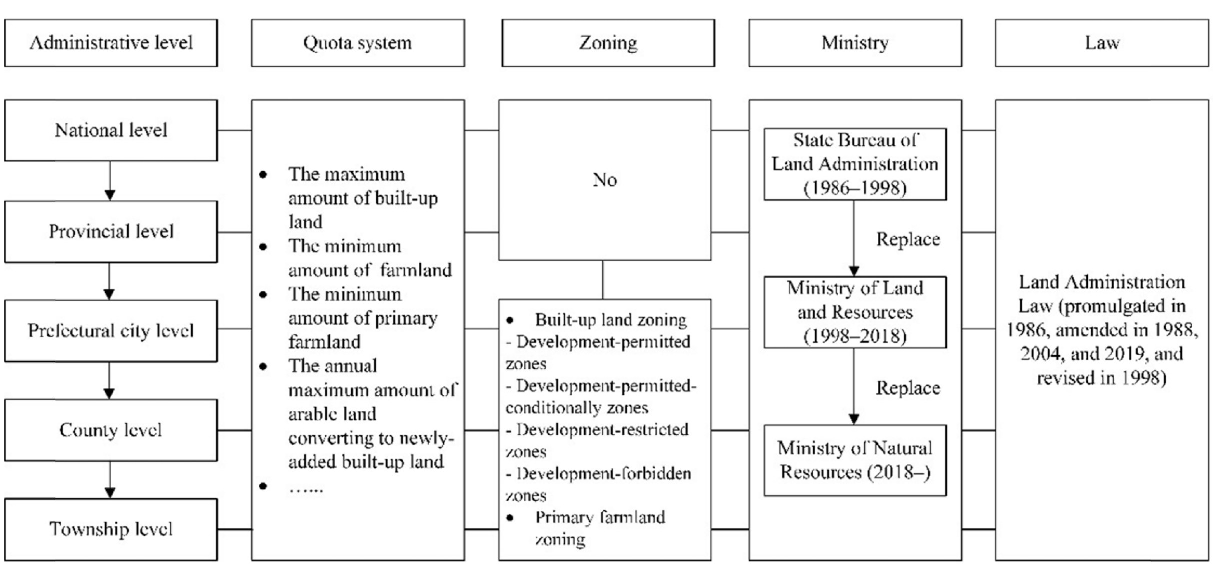

Fig. 1. Land-use planning system in China.

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 land-use 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-restricted zones are faced with more stringent regulations that require them to reduce built-up land expansion. Thus, we

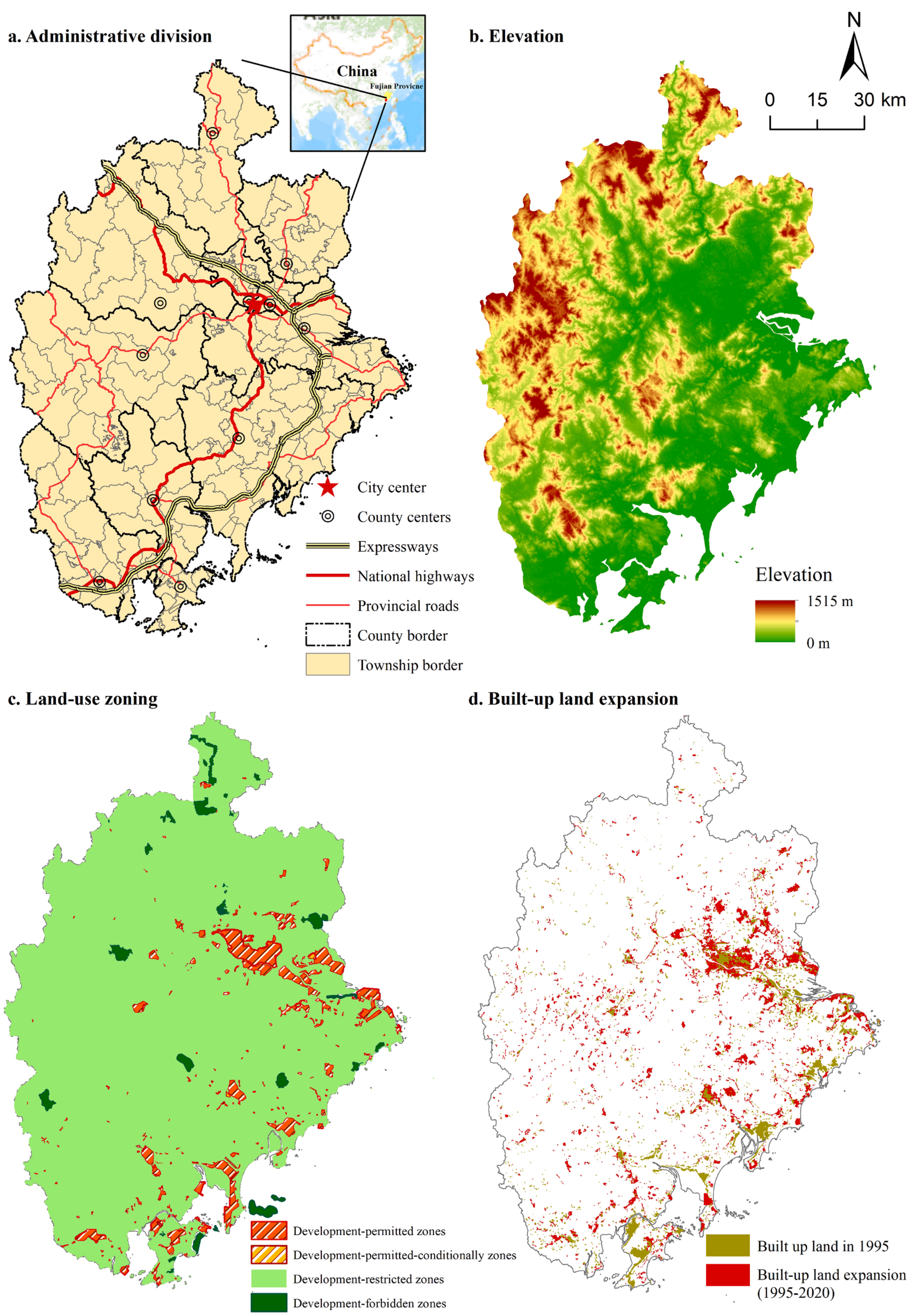

Fig. 2. Study area.

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^2 in 1995 to 1000.84 km^2 in 2020 (Fig. 2.d). Correspondingly, arable land decreased from 2883.50 km^2 to 2548.08 km^2 and forest land decreased from 6802.45 km^2 to 6492.81 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-permitted-conditionally zones, development-restricted zones, and development-forbidden zones (Fig. 2.c). Built-up land development is allowed only inside the development-permitted and development-permitted-conditionally 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 ($Intensity_i$) by calculating the percentage of land that was assigned to the development-permitted 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 ($Nei\_Built.up_{it}$) 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 ($Dis2water_i$) and to coastlines ($Dis2coastline_i$) 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 ($Elevation_i$) 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.

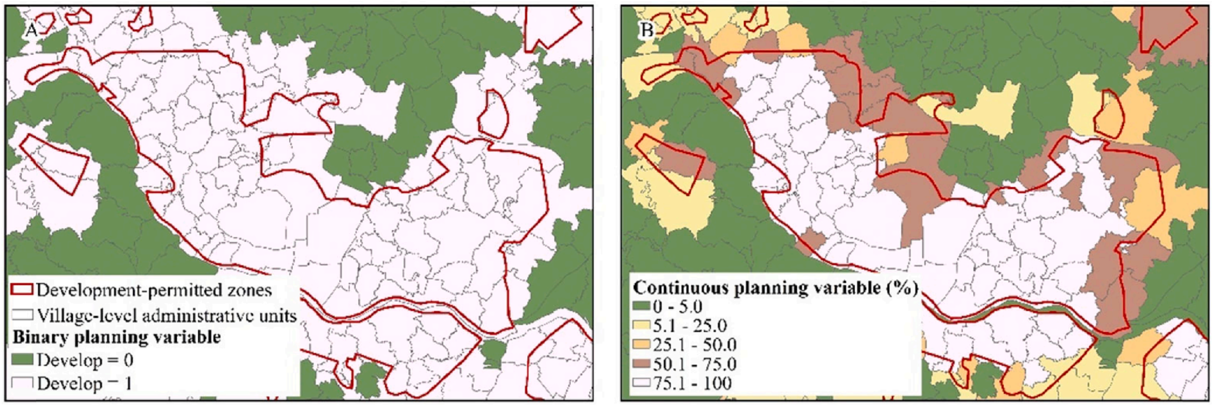

Fig. 3. Illustration of planning variables.

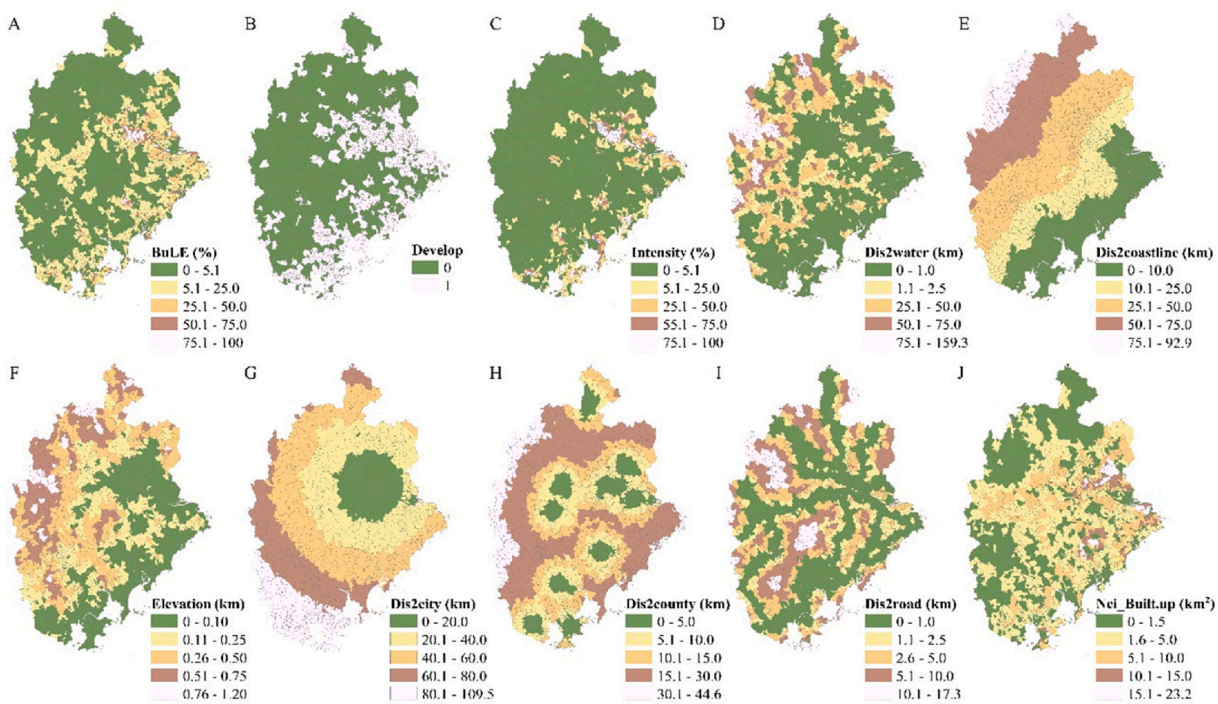

Fig. 4. Variables in the DID model: (A) The percentage of built-up land out of the total land area for each village in 2020; (B) binary planning variable; (C) continuous planning variable; (D) Euclidean distance to the nearest waterbody; (E) Euclidean distance to the nearest coastline; (F) elevation; (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:

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

where $BuLE_{it}$ is the dependent variable, representing built-up land expansion in village i in year t . $Develop_i$ is a binary planning variable. $Develop_i = 0$ if the village was assigned as being entirely outside the development-permitted zones, otherwise $Develop_i = 1$. $Time_t$ 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 (β) 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 $\sum_{t=2000}^{2020} \varphi P_i * Year_t$). The dummy variable $Year_j = 1$ if $j \in T = [2000, 2005, 2010, 2013, 2015, 2018, 2020]$, otherwise $Year_j = 0$. 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	–	0.42	0	1	0.49	Local government
Intensity	%	13.50	0.00	100.00	27.35	Local government
Control variables						
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	km	2.55	0.00	17.30	3.51	NavInfo company
Nei_Built.up	km^2	2.67	0.00	23.21	2.72	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences

model, where u_i and λ_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. ε_{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:

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

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:

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

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

We used the binary ($Develop_i$) and continuous ($Intensity_i$) planning variables to obtain a robust estimation. β_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 and those located outside 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:

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

where ps represents the propensity score and $Develop_i$ 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 ($Nei\_Built.up_{i,2010}$) , built-up land expansion in 2010 ($BuLE_{i,2010}$), distance to waterbodies ($Dis2water_i$), distance to coastlines ($Dis2coastline_i$), elevation ($Elevation_i$), proximity to urban centers ($Dis2city_i$ and $Dis2county_i$), and proximity to roads ($Dis2road_i$). Based on the estimated coefficients β_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). β_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., selection 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):

$$SMD = \frac{|\bar{x}_1 - \bar{x}_0|}{\sqrt{\frac{s_1^2+s_0^2}{2}}} \quad \text{(VI)}$$

where $\bar{x}_1$ and $\bar{x}_0$ are the means of the confounding variables of the villages when their $Develop_i$ 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^2), 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^2 of built-up land if there were no zoning. In aggregate, a total of 27.02 km^2 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 development-permitted zones between 2010 and 2020 was 83.23 km^2, 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^2 in 2010 to 353.19 km^2 in 2020 inside the development-permitted zones. Meanwhile, built-up land area increased from 562.26 km^2 to 645.49 km^2 outside the development-permitted zones. That is, the amount of built-up land expansion outside the development-permitted zones (83.23 km^2) was three times higher than the amount inside the development-permitted zones (27.71 km^2). 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.

Table 2
Average effect of zoning on built-up land expansion

	Model I	Model II
$Develop_i{*}Time_t$	1.21* (0.67)	
$Intensity_i{*}Time_t$		0.06** (0.03)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	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.

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 $Develop_i{*}Year_{2013}$ (−0.02, p = 0.50) and $Intensity_i{*}Year_{2013}$ (0.0003, p = 0.60) were close to zero and non-significant (Fig. 5 and Table A.2). However, the coefficients of $Develop_i{*}Year_{2015}$ (0.97, p = 0.06), $Intensity_i{*}Year_{2015}$ (0.04, p = 0.02), and $Intensity_i{*}Year_{2018}$ (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 non-significant. 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 $Develop_i{*}Year_{1995}$, $Develop_i{*}$

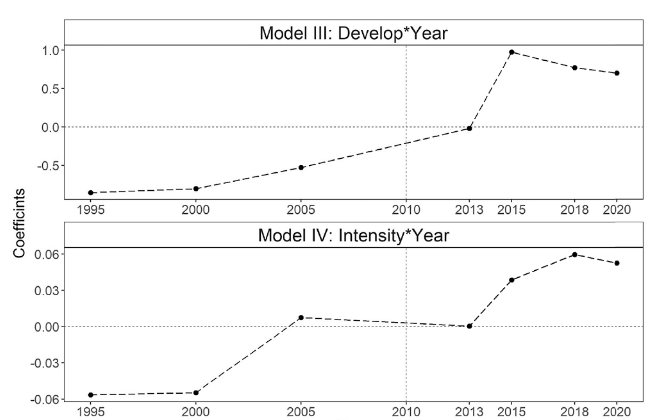

Fig. 5. The coefficients of $Develop_i{*}Year_j$ in model III and $Intensity_i{*}Year_j$ in model IV; the other coefficients are listed in Table A.2 in the Appendix A.

Table 3
Event study on the parallel trend assumption before and after matching

Variable	Before matching	After matching
$Develop_i*Year_{1995}$	−6.03*** (0.7)	−0.85 (0.81)
$Develop_i*Year_{2000}$	−5.51*** (0.68)	−0.8 (0.81)
$Develop_i*Year_{2005}$	−1.53*** (0.37)	−0.53 (0.47)
$Develop_i*Year_{2013}$	0.04* (0.02)	−0.02 (0.03)
$Develop_i*Year_{2015}$	0.46 (0.42)	0.97* (0.51)
$Develop_i*Year_{2018}$	0.13 (0.41)	0.77 (0.51)
$Develop_i*Year_{2020}$	−0.17 (0.44)	0.7 (0.55)
Village fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	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 built-up land expansion between the villages located inside the development-permitted zones and the matched villages located outside the development-permitted zones could be attributed solely to the difference in planning status.

4.3.3. Placebo test

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

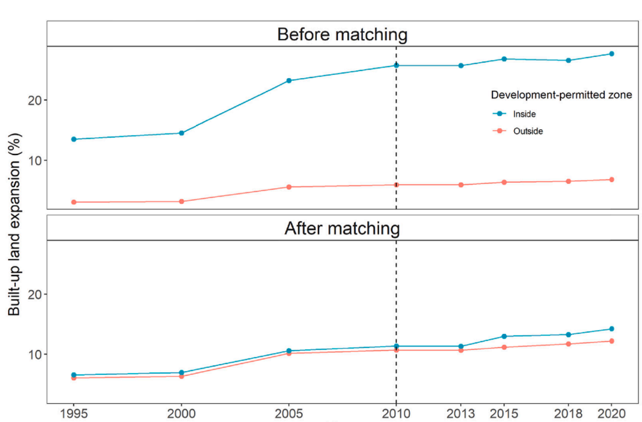

Fig. 6. Trends of built-up land expansion from 1995 to 2020.

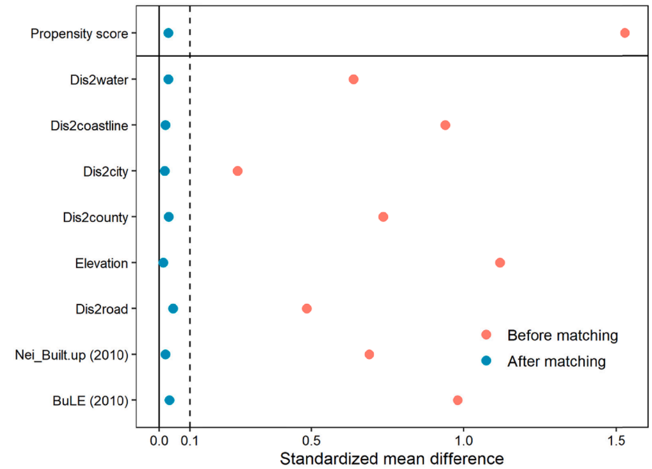

Fig. 7. Standardized mean difference of the confounding variables and the propensity score before and after matching.

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^2) was three times as large as the amount inside the development-permitted zones (27.71 km^2) 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^2 of built-up land expansion outside the development-permitted 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 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 non-conforming built-up land expansion need to be explored in future research.

Acknowledgements

This research was funded by the Swiss National Science Foundation through the CONCUR project - From plans to land change: how strategic spatial planning contributes to the development of urban regions (ERC TBS Consolidator Grant number BSCGIO 157789). The first author would like to express his gratitude to the China Scholarship Council for supporting his PhD.

Appendix A. Supplementary data

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

References:

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies, 72*(1), 1–19. https://doi.org/10.1111/0034-6527.00321

Abrantes, P., Fontes, I., Gomes, E., & Rocha, J. (2016). Compliance of land cover changes with municipal land use planning: Evidence from the Lisbon metropolitan region (1990–2007). *Land Use Policy, 51*, 120–134. https://doi.org/10.1016/j.landusepol.2015.10.023

Acuto, M., Parnell, S., & Seto, K. C. (2018). Building a global urban science. *Nature Sustainability, 1*(1), 2–4. https://doi.org/10.1038/s41893-017-0013-9

Alexander, E. (2009). Dilemmas in evaluating planning, or back to basics: What is planning for? *Planning Theory and Practice, 10*(2), 233–244. https://doi.org/10.1080/14649350902884177

Alfasi, N., Almagor, J., & Benenson, I. (2012). The actual impact of comprehensive land-use plans: Insights from high resolution observations. *Land Use Policy, 29*(4), 862–877. https://doi.org/10.1016/j.landusepol.2012.01.003

Alterman, R., & Hill, M. (1978). Implementation of urban land use plans. *Journal of the American Institute of Planners, 44*(3), 274–285. https://doi.org/10.1080/01944367808976905

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences of the United States of America, 105*(42), 16089–16094. https://doi.org/10.1073/pnas.0800437105

Anthony, J. (2004). Do state growth management regulations reduce sprawl? *Urban Affairs Review, 39*(3), 376–397. https://doi.org/10.1177/1078087403257798

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399–424. https://doi.org/10.1080/00273171.2011.568786

Baer, W. C. (1997). General plan evaluation criteria: An approach to making better plans. *Journal of the American Planning Association, 63*(3), 329–344. https://doi.org/10.1080/01944369708975926

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics, 34*, 1–16. https://doi.org/10.1016/j.forpol.2013.04.006

Braimoh, A. K., & Onishi, T. (2007). Spatial determinants of urban land use change in Lagos, Nigeria. *Land Use Policy, 24*(2), 502–515. https://doi.org/10.1016/j.landusepol.2006.09.001

Bressers, N., van Twist, M., & ten Heuvelhof, E. (2013). Exploring the temporal dimension in policy evaluation studies. *Policy Sciences, 46*(1), 23–37. https://doi.org/10.1007/s11077-012-9169-3

Butsic, V., Lewis, D. J., & Ludwig, L. (2011). An econometric analysis of land development with endogenous zoning. *Land Economics, 87*(3), 412–432. https://doi.org/10.3368/le.87.3.412

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Chen, H., Tang, L., Qiu, Q., Hou, L., & Wang, B. (2020). Construction and case analysis of an index for the sustainability of ecosystem services. *Ecological Indicators, 115*, 106370. https://doi.org/10.1016/j.ecolind.2020.106370

Cheng, J., & Masser, I. (2003). Urban growth pattern modeling: A case study of Wuhan city, PR China. *Landscape and Urban Planning, 62*(4), 199–217. https://doi.org/10.1016/S0169-2046(02)00150-0

Colantoni, A., Grigoriadis, E., Sateriano, A., Venanzoni, G., & Salvati, L. (2016). Cities as selective land predators? A lesson on urban growth, deregulated planning and sprawl containment. *Science of The Total Environment, 545–546*, 329–339. https://doi.org/10.1016/j.scitotenv.2015.11.170

Dempsey, J. A., & Plantinga, A. J. (2013). How well do urban growth boundaries contain development? Results for Oregon using a difference-in-difference estimator. *Regional Science and Urban Economics, 43*(6), 996–1007. https://doi.org/10.1016/j.regsciurbeco.2013.10.002

Fang, L.i., & Tian, C. (2020). Construction land quotas as a tool for managing urban expansion. *Landscape and Urban Planning, 195*, 103727. https://doi.org/10.1016/j.landurbplan.2019.103727

Feitelson, E., Felsenstein, D., Razin, E., & Stern, E. (2017). Assessing land use plan implementation: Bridging the performance-conformance divide. *Land Use Policy, 61*, 251–264. https://doi.org/10.1016/j.landusepol.2016.11.017

Gao, J., & O'Neill, B. C. (2020). Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways. *Nature Communications, 11*(1), 1–12. https://doi.org/10.1038/s41467-020-15788-7

Gennaio, M. P., Hersperger, A. M., & Bürgi, M. (2009). Containing urban sprawl—Evaluating effectiveness of urban growth boundaries set by the Swiss Land Use Plan. *Land Use Policy, 26*(2), 224–232. https://doi.org/10.1016/j.landusepol.2008.02.010

Guo, Z., Hu, Y., & Zheng, X. (2020). Evaluating the effectiveness of land use master plans in built-up land management: A case study of the Jinan Municipality, eastern China. *Land Use Policy, 91*, 104369. https://doi.org/10.1016/j.landusepol.2019.104369

He, Z., Zhao, C., Fürst, C., & Hersperger, A. M. (2021). Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China? *Land Use Policy, 108*, Article 105562. https://doi.org/10.1016/j.landusepol.2021.105562

Hersperger, A. M., & Fertner, C. (2021). Digital plans and plan data in planning support science. *Environment and Planning B: Urban Analytics and City Science, 48*(2), 212–215. https://doi.org/10.1177/2399808320983002

Hersperger, A. M., Grădinaru, S., Oliveira, E., Pagliarin, S., & Palka, G. (2019). Understanding strategic spatial planning to effectively guide development of urban regions. *Cities, 94*, 96–105. https://doi.org/10.1016/j.cities.2019.05.032

Huang, D., Huang, J., & Liu, T. (2019). Delimiting urban growth boundaries using the CLUE-S model with village administrative boundaries. *Land Use Policy, 82*, 422–435. https://doi.org/10.1016/j.landusepol.2018.12.028

Huang, J., Huang, Y., Pontius, R. G., & Zhang, Z. (2015). Geographically weighted regression to measure spatial variations in correlations between water pollution versus land use in a coastal watershed. *Ocean and Coastal Management, 103*, 14–24. https://doi.org/10.1016/j.ocecoaman.2014.10.007

Huang, J., Pontius, R. G., Li, Q., & Zhang, Y. (2012). Use of intensity analysis to link patterns with processes of land change from 1986 to 2007 in a coastal watershed of southeast China. *Applied Geography, 34*, 371–384. https://doi.org/10.1016/j.apgeog.2012.01.001

Huang, B., Zhang, L., & Wu, B. (2009). Spatiotemporal analysis of rural–urban land conversion. *International Journal of Geographical Information Science, 23*(3), 379–398. https://doi.org/10.1080/13658810802119685

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review, 83*(4), 685–709. https://www.jstor.org/stable/2117574.

Jiang, Y., Sun, S., & Zheng, S. (2019). Exploring urban expansion and socioeconomic vitality using NPP-VIIRS data in Xia-Zhang-Quan, China. *Sustainability, 11*(6), 1739. https://doi.org/10.3390/su11061739

Kasraian, D., Maat, K., & Van, W. B. (2019). The impact of urban proximity, transport accessibility and policy on urban growth: A longitudinal analysis over five decades. *Environment and Planning B: Urban Analytics and City Science, 46*(6), 1000–1017. https://doi.org/10.1177/2399808317740355

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S., & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and Urban Planning, 165*, 280–294. https://doi.org/10.1016/j.landurbplan.2017.02.004

Kline, J. D., Thiers, P., Ozawa, C. P., Alan Yeakley, J., & Gordon, S. N. (2014). How well has land-use planning worked under different governance regimes? A case study in the Portland, OR-Vancouver, WA metropolitan area, USA. *Landscape and Urban Planning, 131*, 51–63. https://doi.org/10.1016/j.landurbplan.2014.07.013

le Berre, I., Maulpoix, A., Thériault, M., & Gourmelon, F. (2016). A probabilistic model of residential urban development along the French Atlantic coast between 1968 and 2008. *Land Use Policy, 50*, 461–478. https://doi.org/10.1016/j.landusepol.2015.09.007

Lewis, D. (1973). Causation. *The Journal of Philosophy, 70*(17), 556–567. https://doi.org/10.2307/2025310

Li, Y., Fan, P., & Liu, Y. (2019). What makes better village development in traditional agricultural areas of China? Evidence from long-term observation of typical villages.

Habitat International, 83, 111–124. https://doi.org/10.1016/j.habitatint.2018.11.006

Liu, T., Huang, D., Tan, X., & Kong, F. (2020). Planning consistency and implementation in urbanizing China: Comparing urban and land use plans in suburban Beijing. *Land Use Policy, 94*, 104498. https://doi.org/10.1016/j.landusepol.2020.104498

Loh, C. G. (2011). Assessing and interpreting non-conformance in land-use planning implementation. *Planning Practice and Research, 26*(3), 271–287. https://doi.org/10.1080/02697459.2011.580111

Macdonald, S., Monstadt, J., & Friendly, A. (2020). From the Frankfurt greenbelt to the Regionalpark RheinMain: An institutional perspective on regional greenbelt governance. *European Planning Studies, 4313*. https://doi.org/10.1080/09654313.2020.1724268

Meyfroidt, P., Roy Chowdhury, R., de Bremond, A., Ellis, E. C., Erb, K.-H., Filatova, T., … Verburg, P. H. (2018). Middle-range theories of land system change. *Global Environmental Change, 53*, 52–67. https://doi.org/10.1016/j.gloenvcha.2018.08.006

Nunn, N., & Qian, N. (2011). The potato's contribution to population and urbanization: Evidence from a historical experiment. *The Quarterly Journal of Economics, 126*(2), 593–650. https://doi.org/10.1093/qje/qjr009

Oliveira, V., & Pinho, P. (2010). Evaluation in urban planning: Advances and prospects. *Journal of Planning Literature, 24*(4), 343–361. https://doi.org/10.1177/0885412210364589

Onsted, J. A., & Chowdhury, R. R. (2014). Does zoning matter? A comparative analysis of landscape change in Redland, Florida using cellular automata. *Landscape and Urban Planning, 121*, 1–18. https://doi.org/10.1016/j.landurbplan.2013.09.007

Padeiro, M. (2016). Conformance in land-use planning: The determinants of decision, conversion and transgression. *Land Use Policy, 55*, 285–299. https://doi.org/10.1016/j.landusepol.2016.04.014

Poelmans, L., & van Rompaey, A. (2010). Complexity and performance of urban expansion models. *Computers, Environment and Urban Systems, 34*(1), 17–27. https://doi.org/10.1016/j.compenvurbsys.2009.06.001

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55. https://doi.org/10.1017/CBO9780511810725.016

Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America, 109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Shao, Z., Spit, T., Jin, Z., Bakker, M., & Wu, Q. (2018). Can the land use master plan control urban expansion and protect farmland in China? A case study of Nanjing. *Growth and Change, 49*(3), 512–531. https://doi.org/10.1111/grow.2018.49.issue-310.1111/grow.12240

Sharifi, A., Chiba, Y., Okamoto, K., Yokoyama, S., & Murayama, A. (2014). Can master planning control and regulate urban growth in Vientiane, Laos? *Landscape and Urban Planning, 131*, 1–13. https://doi.org/10.1016/j.landurbplan.2014.07.014

Shen, X., Wang, X., Zhang, Z., & Fei, L. (2021). Does non-conforming urban development mean the failure of zoning? A framework for conformance-based evaluation. *Environment and Planning B: Urban Analytics and City Science, 48*(5), 1279–1295. https://doi.org/10.1177/2399808320926179

Shu, B., Zhu, S., Qu, Y.i., Zhang, H., Li, X., & Carsjens, G. J. (2020). Modelling multi-regional urban growth with multilevel logistic cellular automata. *Computers, Environment and Urban Systems, 80*, 101457. https://doi.org/10.1016/j.compenvurbsys.2019.101457

Siedentop, S., Fina, S., & Krehl, A. (2016). Greenbelts in Germany's regional plans—An effective growth management policy? *Landscape and Urban Planning, 145*, 71–82. https://doi.org/10.1016/j.landurbplan.2015.09.002

Stock, J. H., & Watson, M. W. (2019). *Introduction to Econometrics* (New York: Pearson, Vol. 4). www.pearson.com/mylab/economics.

Stuart, E. A., Lee, B. K., & Leacy, F. P. (2013). Prognostic score–based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research. *Journal of Clinical Epidemiology, 66*(8), S84–S90.e1. https://doi.org/10.1016/j.jclinepi.2013.01.013

Tian, G., & Wu, J. (2015). Comparing urbanization patterns in Guangzhou of China and Phoenix of the USA: The influences of roads and rivers. *Ecological Indicators, 52*, 23–30. https://doi.org/10.1016/j.ecolind.2014.11.024

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America, 104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

van Vliet, J., Naus, N., van Lammeren, R. J. A., Bregt, A. K., Hurkens, J., & van Delden, H. (2013). Measuring the neighbourhood effect to calibrate land use models. *Computers, Environment and Urban Systems, 41*, 55–64. https://doi.org/10.1016/j.compenvurbsys.2013.03.006

Verburg, P. H., de Nijs, T. C. M., van Eck, J. R., Visser, H., & de Jong, K. (2004). A method to analyse neighbourhood characteristics of land use patterns. *Computers, Environment and Urban Systems, 28*(6), 667–690. https://doi.org/10.1016/j.compenvurbsys.2003.07.001

Wang, L.-G., Han, H., & Lai, S.-K. (2014). Do plans contain urban sprawl? A comparison of Beijing and Taipei. *Habitat International, 42*, 121–130. https://doi.org/10.1016/j.habitatint.2013.11.001

Wilms, R., Mäthner, E., Winnen, L., & Lanwehr, R. (2021). Omitted variable bias: A threat to estimating causal relationships. *Methods in Psychology, 5*, 100075. https://doi.org/10.1016/j.metip.2021.100075

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: Best practices for public health policy research. *Annual Review of Public Health, 39*(1), 453–469. https://doi.org/10.1146/annurev-publhealth-040617-013507

Wong, C., & Watkins, C. (2009). Conceptualising spatial planning outcomes: Towards an integrative measurement framework. *Town Planning Review, 80*(4–5), 481–516. https://doi.org/10.3828/tpr.2009.8

Yin, H., Kong, F., Yang, X., James, P., & Dronova, I. (2018). Exploring zoning scenario impacts upon urban growth simulations using a dynamic spatial model. *Cities, 81*, 214–229. https://doi.org/10.1016/j.cities.2018.04.010

Zhong, T., Huang, X., Zhang, X., & Wang, K. (2011). Temporal and spatial variability of agricultural land loss in relation to policy and accessibility in a low hilly region of southeast China. *Land Use Policy, 28*(4), 762–769. https://doi.org/10.1016/j.landusepol.2011.01.004

Zhou, Y., Huang, X., Chen, Y., Zhong, T., Xu, G., He, J., Xu, Y., & Meng, H. (2017). The effect of land use planning (2006–2020) on construction land growth in China. *Cities, 68*, 37–47. https://doi.org/10.1016/j.cities.2017.04.014

Peer effects drive non-conformance between built-up land expansion and zoning: Evidence from Zhangzhou City, China

Zhichao He[a,b,d], Zhaowu Yu[a]*, Christine Fürst[b,c], Anna M. Hersperger[d]

a. Department of Environmental Science and Engineering, Fudan University, Shanghai 200438, China
b. Department of Sustainable Landscape Development, Institute for Geosciences and Geography, Martin-Luther-University Halle-Wittenberg, Halle (Saale), Germany
c. German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Leipzig, Germany
d. Land Change Science Research Unit, Swiss Federal Research Institute WSL, Birmensdorf, Switzerland

Abstract: Rapid expansion of built-up land is widespread and often does not follow established zoning regulations. This non-conforming expansion of built-up land may exacerbate social and environmental problems and has emerged as an important sustainability concern. In this study, we first evaluated the non-conforming expansion of built-up land to zoning in Zhangzhou City, China from 2010 to 2020. Non-conforming expansion of built-up land accounted for 67.61% of the newly developed built-up land area. These non-conformances mainly were edge expansion, via conversions from arable land and forest to industrial/mining/transportation land. We then used spatial autoregressive models to estimate five types of peer effects on non-conforming built-up land expansion among local governments. The geographical, political, economic, geographical-economic, and political-economic peer effects significantly increased the expansion area of non-conforming built-up land at the village level. Our findings improve our understanding, from the perspective of inter-governmental interactions, of why the extent of built-up land often was beyond the permitted limits of zoning regulations. Our research also has policy

implications and suggests constraining the peer effects of local government land-use behaviors that violate zoning regulations. We recommend the establishment of closer interdisciplinary collaborations between spatial planning and land-system science to address non-conforming land-use changes.

Keywords:

Built-up land zoning; conformance-based evaluation; interdependence; land-use change; spatial autoregressive model

1. Introduction

Built-up land is one of the most human-dominated land-use types and has strong sustainability implications (Acuto et al., 2018; Foley et al., 2005; Nagendra et al., 2018; Xiao et al., 2022; W. Zhou et al., 2022). Global built-up land has expanded dramatically over recent decades (Li et al., 2022; Seto et al., 2011). This trend is projected to continue (Gao & O'Neill, 2020). The fast rate of this expansion is often associated with large amounts of built-up land expansion that does not conform to zoning regulations. While the non-conforming expansion of built-up land is prevalent across countries (Abrantes et al., 2016; Alfasi et al., 2012; Hussain & Nadeem, 2021; Kleemann et al., 2017; Long et al., 2020; Sharifi et al., 2014), an understanding of why this non-conformance happens, persists, and spreads is still lacking yet urgently needed. On the one hand, researchers in land-system science often fail to distinguish between conforming and non-conforming built-up land when developing land-change theories and models, due to a paucity of planning data (Tellman et al., 2020, 2021). On the other hand, although spatial planning is struggling to govern built-up land expansion in an sustainable way (Hersperger et al., 2019; Wende et al., 2020), studies on plan evaluation have frequently indicated that a large proportion of built-up land growth was non-conforming and suggested that it is a main cause of plan ineffectiveness (Abrantes et al., 2016; Alfasi et al., 2012; Liu et al., 2020; Sharifi et al., 2014; Sobhani et al., 2021). Thus, analysis of non-conformance between built-up land expansion and zoning regulations can help land-system researchers better understand the causes of land use changes and assist spatial planners in improving plan effects in containing built-up land expansion.

China has implemented a strict land-use planning system since 1986 to restrict rapid built-up land growth. Built-up land zoning (subsequently called zoning) is the core tool of land-use planning. Zoning allocates planning intentions for built-up land into four zone types, i.e., development-permitted zones, development-permitted-conditionally zones, development-restricted zones, and development-forbidden zones. Built-up land is only permitted to develop within the first two zone types (subsequently referred to collectively as development-permitted zones). In this study, non-conforming built-up land expansion refers to the expansion of built-up land outside the development-permitted zones (Figure 1). Land-use plans are legally validated once approved, based on the Land Administrative Law in China. In this respect, non-conforming built-up land can be regarded as illegal land use. However, the extent of built-up land occurring outside the development-permitted zones often exceeds the area of expansion inside the development-permitted zones (Liu et al., 2020; Shao et al., 2018; Shen et al., 2019; L.-G. Wang et al., 2014; Zhong et al., 2014). The ineffectiveness of zoning in containing non-conforming built-up land expansion seems to be rooted, at least partly, in competition among local governments.

Local governments are commonly regarded as playing a formal role in land-use changes (Bürgi et al., 2022). However, one interesting phenomenon is that local governments, originally in charge of making spatial plans and implementing them, frequently contribute to non-conforming expansion of built-up land (Alfasi et al., 2012; Menzori et al., 2021; Sharifi et al., 2014; Sundaresan, 2019; Tellman et al., 2021). Research from China has shown that local governments use permission for non-conforming built-up land expansion as an effective tool to foster the local economy and increase municipal revenue, which in turn can positively affect the political career of local officers (Cai et al., 2013; Z. Chen et al., 2015; Feng et al., 2015; Z. Huang & Du, 2017; Shen et al., 2019; Tang et al., 2021). Further, the behavior of local governments in developing the non-conformance may depend on the behavior of other local governments (J. Wang et al., 2020). Such interdependencies create peer effects, i.e., local governments might consider other local governments' non-conforming built-up land expansion in their own land-use activities. Different inter-governmental relationships may lead to different peer effects facilitating non-conforming expansion of built-up land in China.

(I) Geographical peer effect: a local government's behavior of developing non-conforming built-up land is influenced by the behavior of geographically adjacent local governments. Numerous studies have demonstrated that geographical proximity has an influence on a local government's land-use decisions and behaviors (Christafore & Leguizamon, 2015; Gómez-Antonio et al., 2016; Z. Huang & Du, 2017; Schone et al., 2013; J. Wang et al., 2020). On the one hand, local governments can easily observe what happens in geographically adjacent governments (Schone et al., 2013). On the other hand, the development conditions of geographically adjacent local governments are relatively similar. Consequently, geographically adjacent local

governments often adopt similar land-use decisions and behaviors.

(II) Political peer effect: a local government's behavior of developing non-conforming built-up land is influenced by the behavior of other local governments within the same political jurisdiction. Confinement within a political jurisdiction is a vital channel for influencing a local government's decisions and behaviors (Atella et al., 2014; Cassette et al., 2012; Yu et al., 2016). In China, superior governments have exclusive control over a local government official's promotion, and over the funds and political support that are crucial to local developments (Z. Huang & Du, 2017). Specifically, to outperform other local governments within the same political jurisdiction, local governments may be more sensitive to non-conforming built-up land expansion of their political peers and less sensitive to the behaviors of local governments in different political jurisdictions.

(III) Economic peer effect: a local government's behavior of developing non-conforming built-up land is influenced by the behavior of other local governments with similar levels of economic development. In China, economic competition among local governments is fierce, and local governments with similar economic levels are close rivals (Yu et al., 2016). Because non-conforming built-up land expansion can generate a greater marginal economic return compared with conforming expansion (Z. Chen et al., 2015), local governments are interested in whether and how their economic peers employ non-conforming built-up land expansion to advance economic development, even when they are not geographically adjacent and/or in different political jurisdictions.

(IV) Geographical-economic peer effect and (V) political-economic peer effect: a local government's behavior of developing non-conforming built-up land is more likely to be influenced by geographical peers with similar economic levels and by

political peers with similar economic levels. Considering the intense economic competition among local governments in China, we expected that economic competition would enhance geographical and political peer effects. That is, the geographical-economic and political-economic peer effects in promoting non-conforming built-up land expansion would be greater than the geographical and political peer effects, respectively.

The first objective of this study is to answer what are the characteristics of non-conforming built-up land expansion. To this aim, we used three analytical phases: (1) we performed a conformance-based evaluation to calculate the amount of built-up land occurring inside and outside the development-permitted zones in Zhangzhou City from 2010 to 2020; (2) we analyzed land-use changes in the regions where the non-conforming built-up land occurred; (3) we identified three expansion types of the non-conforming built-up land, i.e., infill, edge, and outlying. The second objective is to answer do peer effects among local governments facilitate non-conforming expansion of built-up land. We employed a spatial autoregressive model to estimate the effects of five types of peer relationships (i.e., the geographical, political, economic, geographical-economic, and political-economic peer effects) on non-conforming expansion of built-up land expansion.

2. Study area and data sources

2.1 Study area

We selected Zhangzhou City as our study area because it has already been established that large amounts of newly developed built-up land were located outside the development-permitted zones from 2010 to 2020 (Z. He et al., 2022). Zhangzhou City is a prefecture-level city in Fujian Province in southeastern China (Figure 1). It includes 11 counties. These counties are further divided into 161 townships and finally into 1,662 village-level administrative units (subsequently called villages). We chose the villages as research units. As the lowest unit in China's top-down administrative hierarchy (nation – province – prefectural city – county – township – village), villages are legalized grassroots self-governance units that elect a village committee as their leader in China. The Article 8 in the Organic Law of the Village Committees of the People's Republic of China states that village committees shall, in accordance with the law, manage collective land and other collective property. In practice, the township level governments ultimately must depend on the village committees to implement most governance tasks, such as land expropriation, building demolition, and farmland protection (D. Huang et al., 2019). The villages serve as nerve endings of China's administrative hierarchy, reflecting the most realistic effectiveness of spatial planning in land use changes.

The growth of the city's economy was exponential in recent decades, with gross domestic product (GDP) increased from 1.17 billion in 1980 to 454.56 billion RMB in 2020. Such economic development resulted in a significant expansion of built-up land into arable land and forest. The area of built-up land expanded from 442.39 km^2 to 1000.84 km^2 from 1995 to 2020. Meanwhile, arable land decreased from 2883.50 km^2 to 2548.08 km^2 and forest decreased from 6802.45 km^2 to 6492.81 km^2 (Z. He et al., 2022). The significant land-use changes from arable land and forest to built-up land were associated with environmental problems, such as water pollution and degraded ecosystem services (H. Chen et al., 2020; J. Huang et al., 2015). To mitigate the negative impacts of rapid built-up land expansion, local governments have implemented the land-use plan (2010–2020). However, a plan evaluation shows that most of newly developed built-up land happened outside the development-permitted zones from 2010 to 2020 (Z. He et al., 2022). Thus, we considered that Zhangzhou City is excellent study area to investigate our research questions.

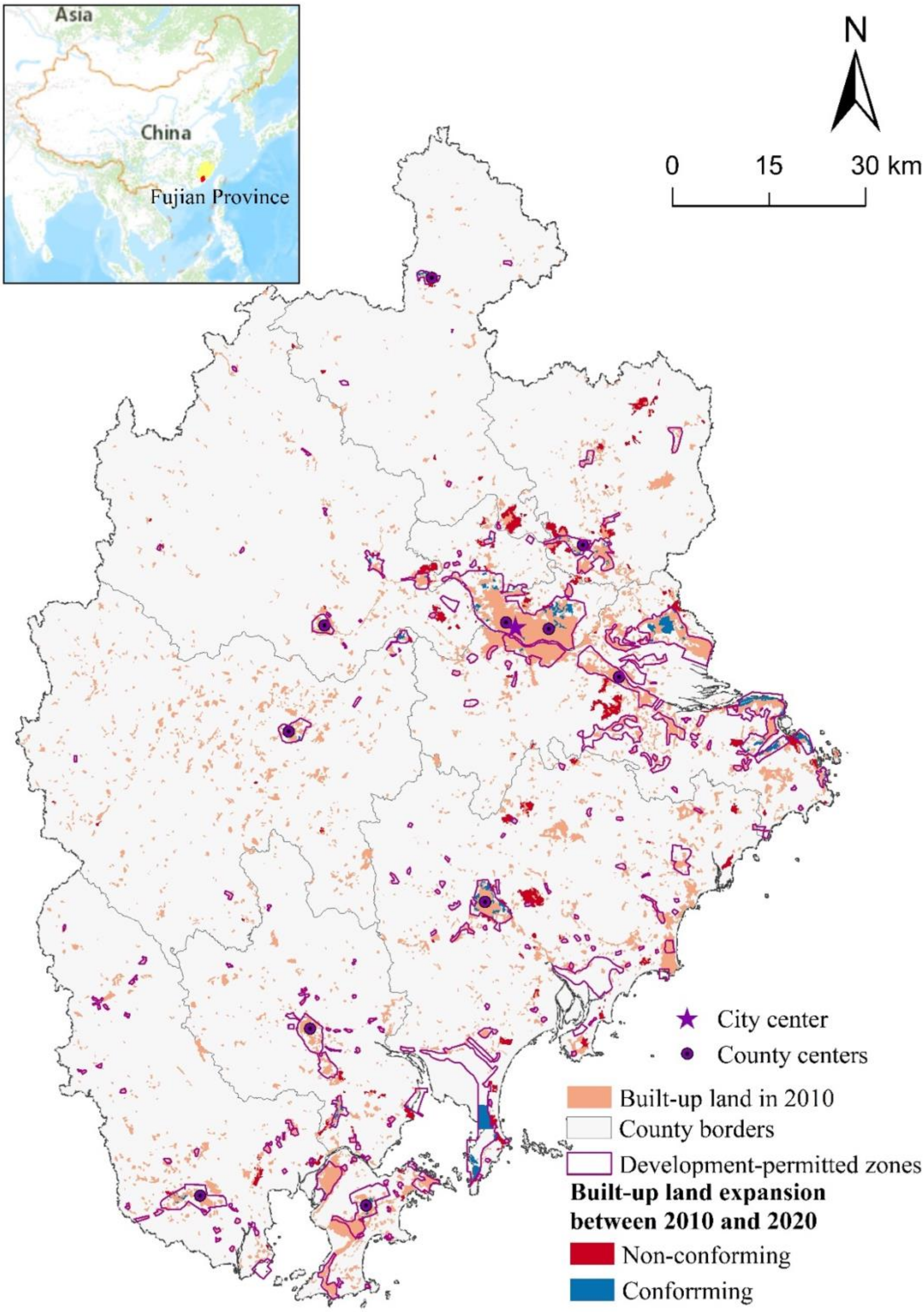

Figure 1. Map of the Zhangzhou City study area showing conforming and non-conforming expansion of built-up land between 2010 and 2020

2.2 Data sources

We obtained the land-use plan (2010–2020), the administrative borders of villages, and the raster data of elevation (resolution 30 × 30 m) from the planning authority in Zhangzhou City. We collected vector data on rivers, city center, county centers and road networks from National Catalogue Service for Geographical Information (https://www.webmap.cn/commres.do?method=result25W). The land-use data (2010 and 2020) and the raster data for GDP in 2010 (resolution 1 × 1 km) were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn). The land-use data had a vector format and were manually interpreted from Landsat TM and 8 images with six land-use types: arable land, forest, grassland, water, built-up land, and bare land. Furthermore, built-up land was divided into urban built-up land, rural settlements, and industrial/mining/transportation land (L. Wang et al., 2018). Urban built-up land mainly referred to urban land for residence, commerce, public infrastructure, storage in the centers of cities, counties, and townships. Rural settlements referred to stand-alone land for housing, living needs, and other necessary infrastructures in rural areas. Industrial/mining/transportation land referred to factories, mines, large industrial areas, transportation land, oil fields, saltworks, quarries. The raster data for the population in 2010 (resolution 1 × 1 km) were provided by China Science Data (http://csdata.org/en/p/420/).

3. Methods

3.1 Conformance-based evaluation

We used a conformance-based evaluation to investigate the extent to which zoning contained built-up land expansion in Zhangzhou City between 2010 and 2020.

First, we built a layer of newly developed built-up land between 2010 and 2020, using an Erase tool in ArcGIS 10.6. We chose the years 2010 and 2020 because the land-use plan in Zhangzhou City was approved in 2010 and came to an end in 2020. We then intersected the newly developed built-up land layer with zoning, using an Intersect tool in ArcGIS 10.6, to identify built-up land expansion that did not conform to the development-permitted zones (i.e., non-conforming built-up land expansion).

Next, we analyzed land-use changes in the regions where the non-conforming built-up land occurred. We intersected the non-conforming layer with the land-use layer in 2010 to calculate how much arable land, forest, grassland, water, and bare land was converted to the three non-conforming built-up land-uses, i.e., urban built-up land, rural settlements, and industrial/mining/transportation land.

Lastly, we identified three expansion types of the non-conforming built-up land, i.e., infill, edge, and outlying. We used the ratio (R) of the length of the common boundary shared by a non-conforming built-up land developed between 2010 and 2020 and the existing built-up land in 2010 (L_c) to the perimeter of the non-conforming built-up land (L) to identify expansion types (Sun et al., 2013; Wilson et al., 2003; Xu et al., 2007). The ratio was formulated as follows:

$$R = {}^{L_c}\!/_{L} \tag{1}$$

where the value of R ranged from 0 to 1. Infill expansion had an R value ≥ 0.5, indicating that the non-conforming built-up land was surrounded by at least 50% existing built-up land (Figure 2a). Edge expansion has $0 < R < 0.5$, indicating that the non-conforming built-up land is surrounded by $\leq$ 50% existing built-up land (Figure 2b). With outlying expansion R = 0, i.e., the non-conforming built-up land is isolated from the existing built-up land (Figure 2c).

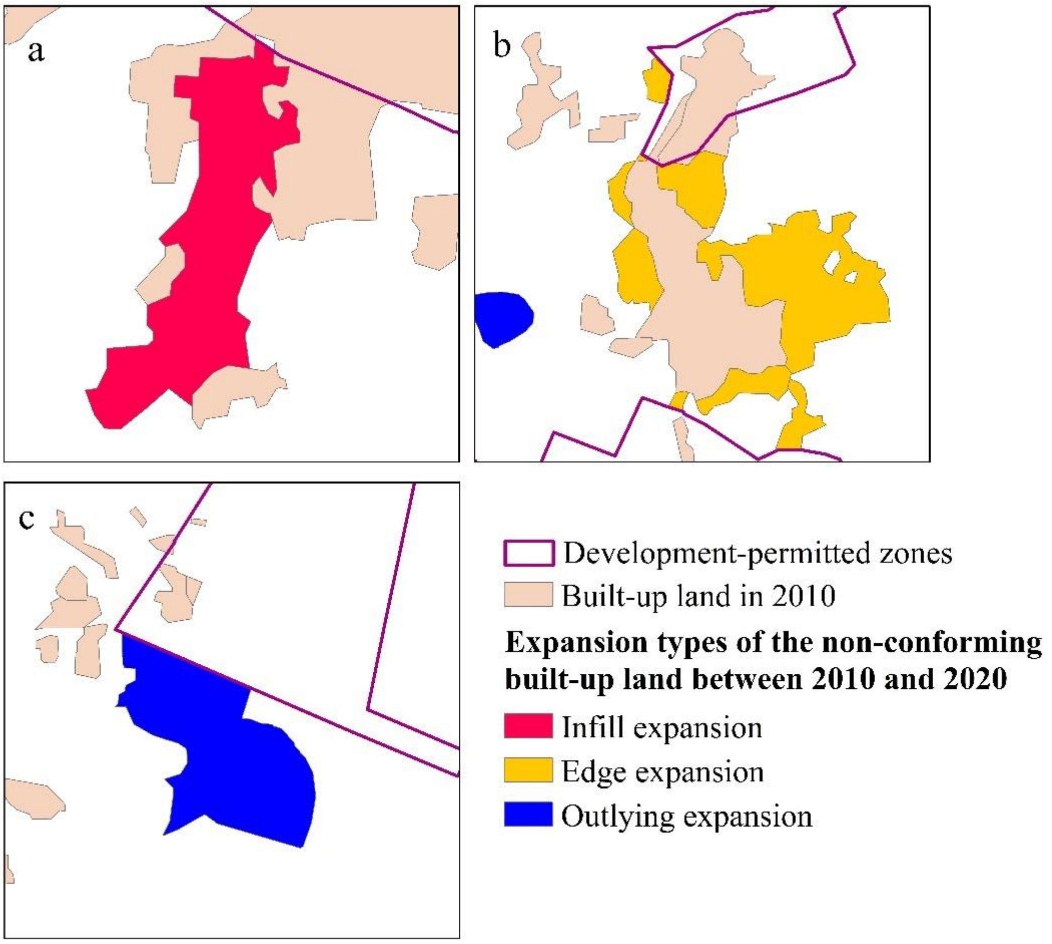

Figure 2. Examples of infill, edge, and outlying expansion of non-conforming built-up land

3.2 Spatial autoregressive models to investigate peer effects

We built a spatial autoregressive (SAR) model that included a spatially lagged dependent variable to estimate the peer effects on non-conforming built-up land expansion among 1,662 villages (LeSage & Pace, 2009). The SAR model was specified as:

$$NC\_Builtup_i = \alpha + \rho W * NC\_Builtup_j + \beta X_i + \varepsilon_i \tag{2}$$

where the dependent variable ($NC\_Builtup_i$) is the non-conforming built-up land developed between 2010 and 2020, expressed as a percentage of the total land area in the village i. $W * NC\_Builtup_j$ is the spatially lagged dependent variable. W is a spatial weight matrix. It has zero diagonal elements (w_{ii}) and off-diagonal elements (w_{ij}). w_{ij} represents the peer relationship between village i and village j.

We defined the five peer relationships: (1) W^{Geo} represented the geographical peer relationship, where w_{ij}^{Geo} equaled 1 if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0 (Figure 3a); (2) W^{Poli} represented the political peer relationship, where w_{ij}^{Poli} equaled 1 if villages i and j were located in the same county, otherwise 0 (Figure 3b); (3) W^{Econ} represented the economic peer relationship, with $w_{ij}^{Econ} = 1/(|PGDP_i - PGDP_j| + 1)$, where $PGDP$ was the GDP per capita in 2010 (Figure 3c); (4) W^{GEcon} represented the geographical-economic peer relationship combining W^{Geo} and W^{Econ}, where $w_{ij}^{GEcon} = 1/(|PGDP_i - PGDP_j| + 1)$ if village j was one of the 10-nearest neighbors of village i based on actual road network distance, otherwise 0 (Figure 3d); (5) W^{PEcon} represented the political-economic peer relationship combining W^{Poli} and W^{Econ}, where $w_{ij}^{PEcon} = 1/(|PGDP_i - PGDP_j| + 1)$ if villages i and j were located in the same county, otherwise 0 (Figure 3e). All spatial weight matrices were row normalized to make each row sum to one. ρ was the spatial autoregressive coefficient of interest; it represented the effect of the different peer relationships on the village's non-conforming expansion of built-up land. α was the intercept, X_i were control variables, β was the influence of the control variables on non-conforming expansion of built-up land, and ε_i was the disturbance term. To overcome heteroskedasticity, we used a generalized spatial two-stage least squares estimator to estimate the SAR model (Drukker et al., 2013).

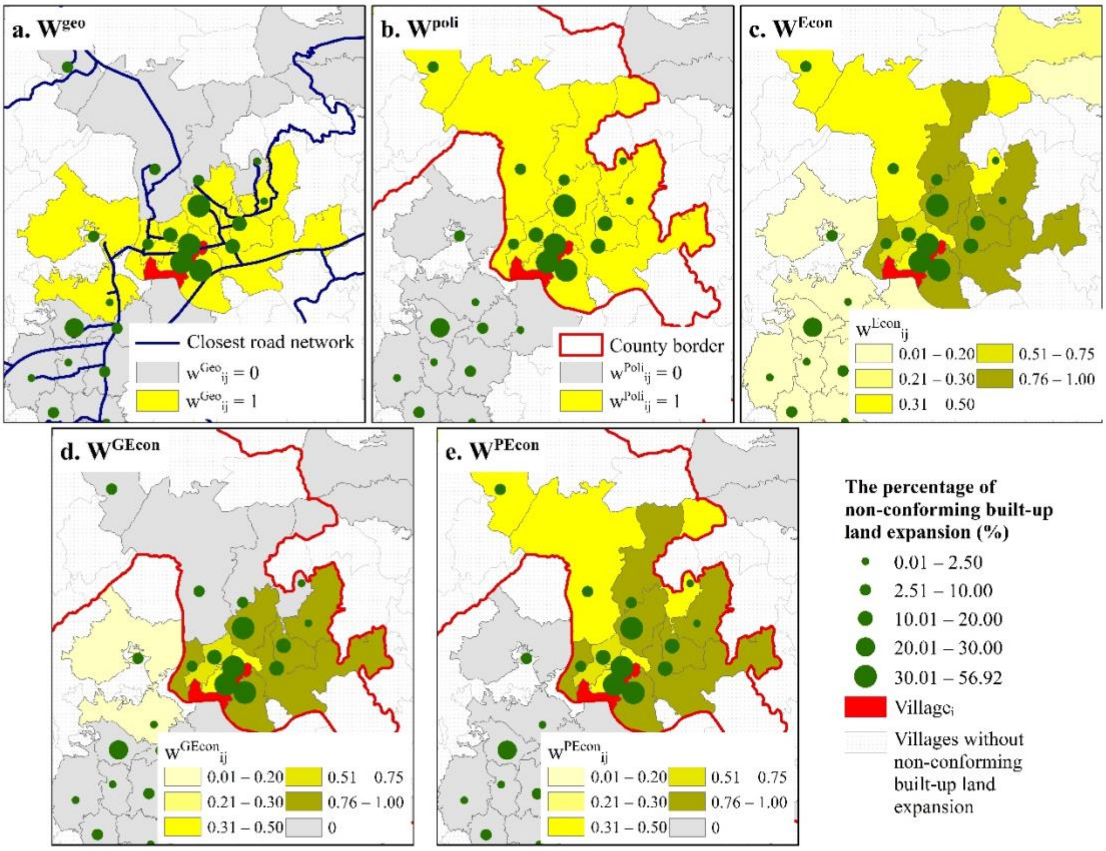

Figure 3. Illustrations of the considered peer relationships: (a) geographical, (b) political, (c) economic, (d) geographical-economic, and (e) political-economic.

While research on the causes why built-up land often did not conform to zoning is scarce, the extensive literature on spatial patterns and drivers of built-up land development helped us to specify our models. Furthermore, our models helped us to gain insight on whether the same factors driving built-up land expansion also contributed to non-conforming expansion of built-up land. The following control variables were included in the SAR model: (1) Built-up land is significantly affected by rivers and coastlines (le Berre et al., 2016; G. Tian & Wu, 2015). We measured the Euclidean distance from village i to the nearest river ($Dis2water_i$) and to the nearest coastline ($Dis2coast_i$). (2) Urban accessibility drives built-up land expansion

(Kasraian et al., 2019; Yin et al., 2018). We used the closest road network distance from village i to the city center ($Dis2city_i$) and to its county center ($Dis2county_i$). (3) Mountainous and hilly terrain increases construction costs and restricts built-up land expansion (Onsted & Chowdhury, 2014; Zhong et al., 2011). We measured the average elevation and relief in village i ($Elevation_i$ and $Relief_i$). (4) Built-up land tends to stretch along roads (Poelmans & van Rompaey, 2010; G. Tian & Wu, 2015). We measured the Euclidean distance from village i to the nearest road ($Dis2road_i$), considering expressways, national highways, and provincial roads. (5) Natural land is a main source of built-up land expansion (Abrantes et al., 2016; Lichtenberg & Ding, 2008). Meanwhile, considering the constraints of mountainous and hilly terrain, we measured the percentage of arable land, forest, grassland (slope < 5 degree) out of the total land area in village i in 2010 ($Arable10_i$, $Forest10_i$, and $Grass10_i$). (6) Built-up land development is influenced by the previous tendency, i.e., path dependence (Colsaet et al., 2018). We measured the percentage of built-up land out of the total land area in village i in 2010 ($Builtup10_i$). (7) Economic development promotes the need for built-up land (Park et al., 2018; Y. Zhou et al., 2017). We used GDP per capita in 2010 to represent economic development in village i ($PGDP10_i$). Because census data on GDP per capita at the village level are inaccessible in China, we used raster data to extract GDP and total population at the village level. (8) Abundant development-permitted zones can restrict non-conforming expansion of built-up land (Gennaio et al., 2009). We measured the percentage of land located inside the development-permitted zones out of the total land area in village i (DPZ_i). We summarize these statistical descriptions in Table 1.

Table 1. Statistical descriptions of the variables used in the spatial autoregressive models

Variables	Descriptions	Obs.	Unit	Mean	Min	Max	S.D.
Dependent variable							
NC_Builtup	Percentage of non-conforming built-up land developed between 2010 and 2020 out of the total land area	307	%	6.08	0.01	56.92	9.82
Control variables							
Dis2water	Euclidean distance from village to the nearest river	307	km	9.08	0.12	35.75	8.08
Dis2coast	Euclidean distance from village to the nearest coastline	307	km	18.40	0.22	84.99	18.77
Dis2city	Closest road network distance from village to the city center	307	km	59.09	2.77	144.79	38.72
Dis2county	Closest road network distance from village to its county center	307	km	20.97	1.09	69.2	14.25
Elevation	Average elevation in village	307	km	0.08	0	0.72	0.13
Relief	Average relief in village	307	/	8.73	0.86	30.66	6.56
Dis2road	Euclidean distance from village to the nearest road	307	km	0.27	0	3.21	0.29
Arable10	Percentage of arable land (slope < 5 degree) out of the total land area in 2010	307	%	26.75	0	95.81	21.54
Forest10	Percentage of forest (slope < 5 degree) out of the total land area in 2010	307	%	12.59	0	88.89	14.95
Grass10	Percentage of grassland (slope < 5 degree) out of the total land area in 2010	307	%	3.37	0	37.22	5.29
Builtup10	Percentage of built-up land out of the total land area in 2010	307	%	15.24	0	74.04	15.53

PGDP10	GDP per capita in 2010	307	10, 000 RMB/person	3.89	0.23	26.72	3.88
DPZ	Percentage of land located inside the development-permitted zones out of the total land area	307	%	13.49	0	94.82	21.72

4. Results

4.1 Characteristics of non-conforming built-up land expansion

4.1.1 Sources and uses of non-conforming built-up land expansion

In Zhangzhou City, the newly developed built-up land area between 2010 and 2020 covered 144.75 km^2, with non-conforming expansion of built-up land accounted for 67.61% (97.87 km^2). There was 376.21 km^2 of non-built-up land inside the development-permitted zones in 2020. Thus, the development-permitted zones would have been sufficient to contain the entire expansion of built-up land between 2010 and 2020. Figure 4 shows how much non-built-up land was converted into non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land during the studied period. Arable land and forest were the main sources of non-conforming built-up land expansion. They contributed 53.61 km^2 and 21.67 km^2 of non-conforming expansion of built-up land, respectively. The non-conforming built-up land was mainly used as industrial/mining/transportation land (71.27km^2) and rural settlements (16.91 km^2).

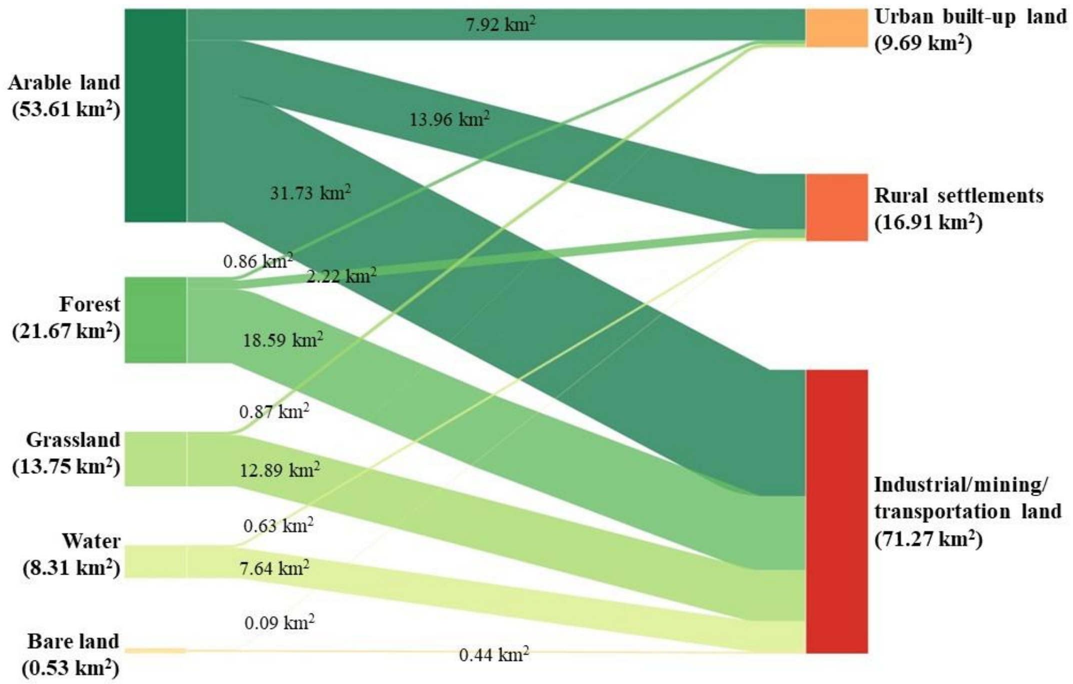

Figure 4. Land-use changes from arable land, forest, grassland, water, and bare land to non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land in Zhangzhou City between 2010 and 2020

4.1.2 Expansion types of the non-conforming built-up land

Edge expansion was the dominant type of non-conforming built-up land expansion (Figure 5). It accounted for 94.23% (9.14 km^2), 89.83% (15.19 km^2), and 77.32% (55.1 km^2) of the non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land expansion, respectively. The non-conforming industrial/mining/transportation land had more outlying expansion than the other two non-conforming built-up land uses. Only a small percentage of the non-conforming expansion was infill expansion.

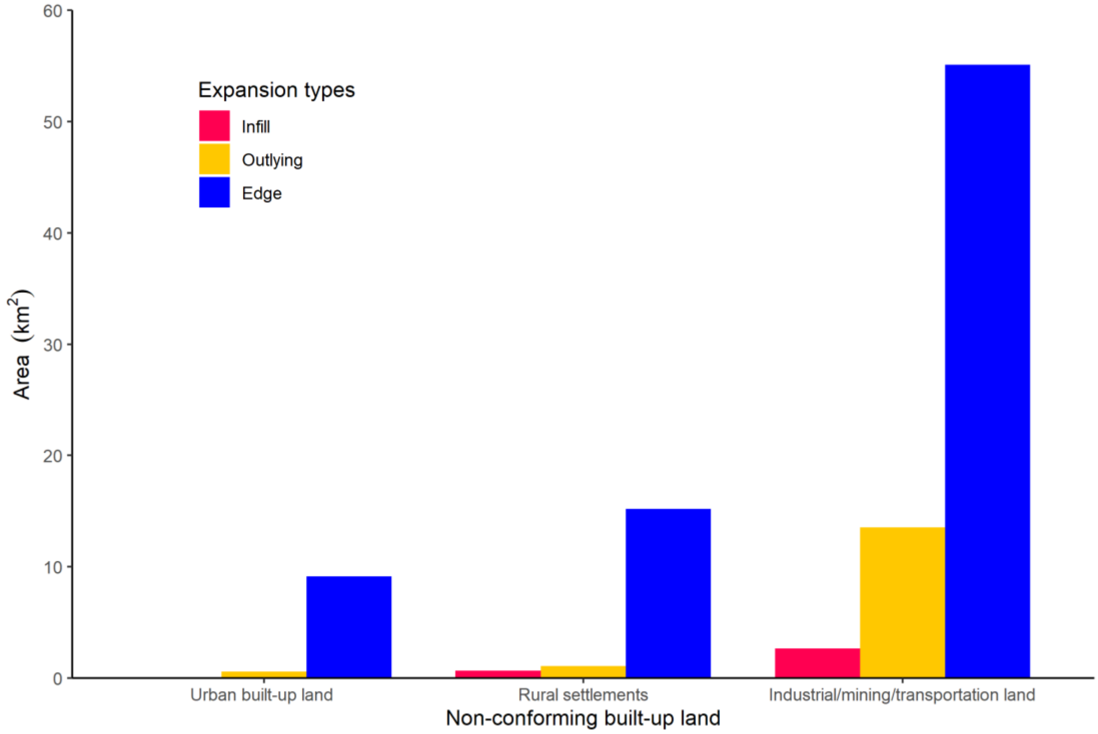

Figure 5. Areas of the infill, edge, and outlying expansion types in the non-conforming urban built-up land, rural settlements, and industrial/mining/transportation land in Zhangzhou City between 2010 and 2020

4.1.3 Spatial patterns of villages' non-conforming built-up land expansion

The spatial distribution of the villages' non-conforming built-up land expansion followed some obvious patterns (Figure 6). First, the non-conforming built-up land mainly occurred in the villages at the periphery of the city center, where development pressure is high and the development-permitted zones are finitely allocated. Second, although the area of the newly developed non-conforming built-up land accounted for 67.61% of the total built-up land expansion, it was concentrated in only 307 villages out of 1,662. Third, the 307 villages were not isolated from each other spatially. We used Moran's index to examine whether the percentages of non-conforming built-up land expansion were spatially dependent at the village level. Moran's index was 0.27 and significant at the 1% level, indicating that non-conforming built-up land expansion was spatially autocorrelated among the 307 villages.

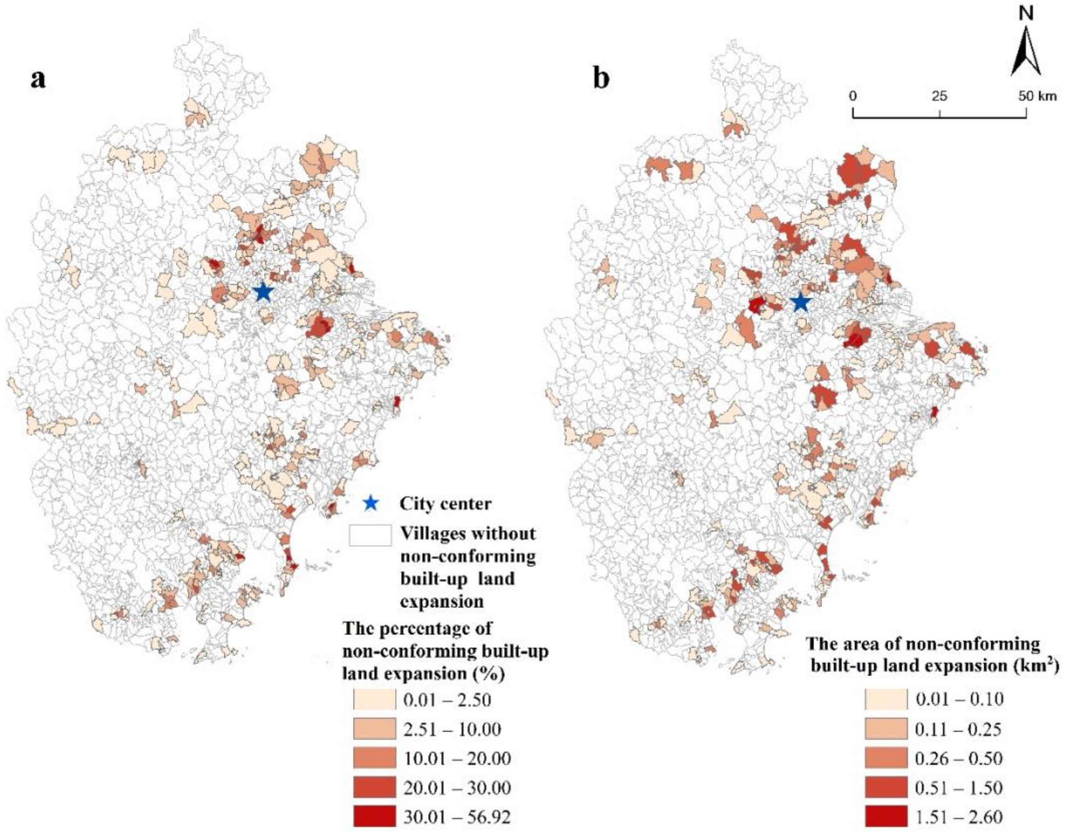

Figure 6. The percentage (a) and area (b) of non-conforming built-up land expansion in 307 villages in Zhangzhou City between 2010 and 2020

4.2 Results of the SAR

4.2.1 Performance of the models

Pseudo R^2 values ranged from 0.160 to 0.194 (Table 2). Large unexplained variation in the villages' non-conforming expansion of built-up land was expected, as non-conforming built-up land expansion can be sensitive to local-scale land-use activities and the sudden appearance of land development opportunities (Padeiro, 2016). The high degree of randomness and uncertainty might be explained by omitted variables we could not include in our models, such as villagers' livelihoods or their attitudes toward zoning regulations. Despite these limitations, we were able to estimate peer effects and other factors facilitating non-conforming expansion of built-up land at the village level.

4.2.2 Peer effects on villages' non-conforming built-up land expansion

ρ values were significant at the 10% level for all five peer relationships, meaning that the peer effects were indispensable in explaining non-conforming expansion of built-up land at the village level. The ρ values indicated that a given village's non-conforming built-up land area increased by 3.9%, 6.2%, and 22.5% if its geographical peers, political peers, and economic peers increased in non-conforming built-up land area by 10%. Regarding combined peer relationships, we found that economic competition enhanced the geographical and political peer effects. The ρ value of the geographical-economic (0.47) and the political-economic peer relationships (0.71) were higher than those of the geographical (0.39) and political peer relationships (0.62).

4.2.3 Other drivers of villages' non-conforming built-up land expansion

While the statistical significances of some control variables varied in our models, positiveness and negative of their coefficients were relatively stable. We presented the empirical meaning of the control variables whose statistical significances all were significant at the 10% level in the five SAR models. $Dis2county$ had positive coefficients, indicating that the non-conformance was less likely to occur in the villages that are closer to the county centers. One reason for this finding could be that development pressure is concentrated around the city center, rather than the county centers in Zhangzhou City. The coefficients of $Elevation$ were negative, indicating that the villages at lower elevations had more non-conforming expansion of built-up land. The positive coefficients of $Arable10_i$ and $Grass10_i$ suggest that the villages with more available arable land and grassland in 2010 had more non-conforming built-up land expansion between 2010 and 2020. *DPZ* had negative coefficients, indicating that the villages with less land allocated to the development-permitted zones developed more non-conforming built-up land.

Table 2. Results of the spatial autoregressive models

	Geographical	Political	Economic	Geographical economic	Political economic
ρ	0.39** (0.17)	0.62*** (0.18)	2.25* (1.34)	0.47** (0.16)	0.71*** (0.20)
Dis2water	0.083 (0.075)	0.14* (0.081)	0.065 (0.084)	0.092 (0.076)	0.15* (0.079)
Dis2coast	0.041 (0.039)	0.045 (0.041)	0.042 (0.042)	0.041 (0.039)	0.049 (0.042)
Dis2city	-0.023 (0.017)	-0.023 (0.016)	-0.036** (0.017)	-0.018 (0.016)	-0.019 (0.017)
Dis2county	0.14*** (0.053)	0.15*** (0.054)	0.19*** (0.058)	0.12** (0.053)	0.13** (0.053)
Elevation	-16.0*** (5.97)	-21.9*** (6.13)	-21.7*** (5.76)	-13.6** (6.12)	-20.2*** (6.00)
Relief	0.18 (0.15)	0.24 (0.15)	0.26* (0.15)	0.15 (0.15)	0.24 (0.15)
Dis2road	2.36** (1.18)	2.21* (1.23)	1.98 (1.27)	2.26* (1.19)	2.20* (1.24)
Arable10	0.14*** (0.044)	0.14*** (0.044)	0.15*** (0.043)	0.14*** (0.044)	0.15*** (0.044)
Forest10	0.074 (0.048)	0.081* (0.048)	0.090* (0.049)	0.075 (0.049)	0.082* (0.049)
Grass10	0.36** (0.16)	0.35** (0.16)	0.37** (0.16)	0.37** (0.15)	0.36** (0.16)
Builtup10	0.086 (0.053)	0.083 (0.052)	0.087* (0.052)	0.083 (0.052)	0.087 (0.054)
PGDP10	-0.21* (0.12)	-0.21* (0.12)	-0.066 (0.15)	-0.15 (0.12)	-0.15 (0.11)
DPZ	-0.061*** (0.023)	-0.057** (0.023)	-0.055** (0.023)	-0.064*** (0.024)	-0.061*** (0.023)
Pseudo R^2	0.194	0.177	0.177	0.190	0.160
Obs.	307	307	307	307	307

*Note: Standard errors are given in parentheses; * p<0.10, ** p<0.05, *** p<0.01*

5. Discussion

5.1 Concerns about non-conforming built-up land expansion

The large amount of non-conforming built-up land expansion in 307 of the 1,662 villages of Zhangzhou City between 2010 and 2020 raises serious concerns. The percentage (67.61%) of newly developed built-up land that did not conform to zoning was higher than in most previous studies. For example, < 30% of the total developed land was found to occur outside building zones in Switzerland (Gennaio et al., 2009). In studies in developing countries (e.g., China, Brazil, Pakistan, Ethiopia), non-conformance rates of 50–60% were often reported (Bulti & Sori, 2017; Hussain & Nadeem, 2021; Liu et al., 2020; Menzori et al., 2021; L. Tian & Shen, 2011; L.-G. Wang et al., 2014). These findings suggest that the non-conformance of built-up land expansion to zoning regulations increases with greater development pressure, as discussed by Brody & Highfield (2005) and Loh (2011). In our study, the concentration of all non-conformance in 307 of the 1,662 villages means that only a few villages were affected, but often to a high degree. One reason for this pattern could be that the planning authority in Zhangzhou City underestimated the development pressure in these villages.

The non-conforming built-up land expanded at the expense of arable land and forest in Zhangzhou City. This finding is in line with previous studies in Israel, Spain, and China (Alfasi et al., 2012; Padeiro, 2016; Shen et al., 2019). This pattern may threaten food security, biodiversity, and landscape quality. Industrial/mining/transportation land accounted for 72.82% of the newly developed non-conforming built-up land. Likewise, Shen et al. (2019) found that manufacturing land accounted for 48% of the non-conforming urban land in Baiyun County in southwestern China. In contrast, residential land development was found to be the main type of non-conforming built-up land expansion in Ethiopia and Brazil (Bulti & Sori, 2017; Menzori et al., 2021). The prominence of non-conforming industry/mining/transportation development is closely associated with the land supply strategies of local governments in China. That is, under a government-led land market, local governments supply a limited amount of residential and commercial land to developers, in order to increase land-leasing fees, but lease out abundant industrial land at low prices to attract manufacturing investment (Shen et al., 2019; W. Wang et al., 2018; Xiong & Tan, 2018). The imbalance land supply strategies are enhanced at the village level, because land-leasing fees are monopolized by local governments of the township and above. The villages are more likely to use the non-conforming built-up land to develop township and village enterprises in Zhangzhou City (Q. Guo et al., 2022). The township and village enterprises are small-size manufacturers which mainly are owned by village collectives or individual villager. It is main form of rural industrialization and significantly contributes to economic growth in rural China (Fu & Balasubramanyam, 2003). However, the extensive non-conforming development of industry/mining/transportation land may lead to an overheated economy, excess production capacity, and inefficient land use.

Our finding that edge expansion was the dominant type of non-conforming built-up land expansion is inconsistent with some previous research suggesting that non-conforming expansion of built-up land occurs in a fragmented way (Abrantes et al., 2016; Yue et al., 2013). Our results suggest that, while non-conforming built-up land does continue to spread outward, it mostly contributes to reducing landscape fragmentation and improving urban agglomeration.

5.2 Positive peer effects on villages' non-conforming built-up land expansion

A disparity between established zoning regulations and built-up land expansion is prevalent across countries, however, the drivers of such non-conformance have only been empirically investigated in a few studies (Alterman & Hill, 1978; Brody et al., 2006; Padeiro, 2016). Furthermore, few attempts have been made to analyze the spatial interdependencies of local governments' land-use behaviors of violating established zoning regulations. So far, research has only confirmed that geographical contiguity matters in non-conforming expansion of built-up land among 262 of the prefecture-level cities in China (J. Wang et al., 2020). In our study, we found five positive peer effects driving villages to violate zoning regulations in Zhangzhou City between 2010 and 2020. That is, a given village's non-conforming built-up land area increased to varying degrees as their geographical peers, political peers, economic peers, geographical-economic peers, and political-economic peers expanded their non-conforming built-up land area.

An interesting finding is that the economic peer effect enhanced the geographical and political peer effects, as the geographical-economic and the political-economic peer effect were higher than the geographical and political peer effect, respectively. This finding indicates that the primary motivation for villages to violate zoning regulations is to compete more effectively for economic growth. This fits with the common view that China's local governments, which compete fiercely for economic growth, loosen established regulatory rules (e.g., lower environmental standards, lenient land development permissions, lower industrial land prices) to attract investment, essentially leading a "race to the bottom" (Z. Huang & Du, 2017; Peng, 2020; B. Wang et al., 2020). This finding is original since little attention is given to the village-level governmental (the lowest level in China's top-down administrative hierarchy) race to the bottom in zoning regulation.

Institutional background determines the village-level governmental race to the bottom in zoning regulation. While the village committees can be considered a superior governmental agent, their authority relies considerably on the support of local villagers. The villagers' support often depends heavily on how many development opportunities the village committee can secure for the village (X. Zhou, 2009). In this case, villagers and villager committees make comparisons between geographical, political, and economic peer. And economic performance become a vital benchmark when comparing. This argument is reinforced by the fact that most non-conforming built-up land in Zhangzhou City has been converted to industrial/mining/transportation land, which is highly profitable and allows local governments to increase their revenues and employment and thus boost their economy (C. He et al., 2014).

5.3 Policy Implications

Non-conforming expansion of built-up land is the main contributor to rapid built-up land expansion worldwide, which leads to a series of environmental issues. Moreover, non-conformance is often associated with land-related crimes (e.g., corruption and illegal land transactions), not only undermining the credibility of spatial planning but also triggering social conflicts. Based on our findings, we have developed some suggestions for policies to effectively restrict non-conforming expansion of built-up land in China. First, industrial/mining/transportation land was the main form of non-conforming built-up land expansion in Zhangzhou City. The government's supply of industrial/mining/transportation land therefore should be strictly controlled. Simultaneously, the permission process for developing industrial/mining/transportation land should be strengthened by conducting comprehensive feasibility evaluations and strict environmental assessments. In addition, local governments in China should be required to optimize their industrial structure, including moving from extensive to intensive industrial activities and converting underused industrial land into residential land, commercial land, and green spaces.

Non-conforming built-up land expansion cannot be restricted by local governments in China because local governments do not make land-use decisions in isolation. Intervention from the central government and cooperation between local governments are indispensable to restrict peer effects on a local government's non-conforming built-up land expansion. One the one hand, the central government should continue its reform of the evaluation indices used in local officials' promotions, for example by highlighting the costs of non-conformance and incentivizing local governments to provide more public services and protect the environment (Zuo, 2015). Tang et al. (2021) found that this type of reform can significantly restrict the land violations of local governments. On the other hand, local governments should strengthen cooperation to develop regional resolutions. Within regions, local governments can, for example, specialize in different functions and trade built-up land quotas with their peers.

The planning system in China should be improved in several respects. (1) Currently, planning authorities in this country have a high degree of discretionary power. For example, they can legally authorize non-conforming activities on the grounds of public interest, and they often do so, so that the political leaders can pursue specific political (and private) interests rather than serving the common good (Shen et al., 2019; M. Wang et al., 2017). The position of the planning authorities should be strengthened to emphasize technical, rational aspects, whereas the use of discretionary power should be minimized. (2) Low levels of transparency are common, for example due to the absence of public participation in the plan-making process and a lack of disclosure of information in the plan-implementation process (Zhu & Tang, 2018). The planning system should be improved by guaranteeing public participation both in the plan-making and in the plan-implementation process. Public participation is an effective tool to minimize power inequalities between local people and governments and to obtain more consensus (Hartmann, 2012). It enables and motivates local people to supervise plan implementation. (3) The planning authorities need to develop a real-time and highly accurate monitoring system to track land-use change and plan-implementation. As part of this, the Land Supervision System that is responsible for investigating, auditing, and correcting land violations should be strictly implemented. When a local government's non-conforming built-up land expansion is punished promptly, its peers will most likely restrict their non-conforming built-up land expansion immediately. Some studies have indicated that the Land Supervision System significantly suppresses illegal land use (S. Chen et al., 2021; Z. Chen et al., 2015).

6. Conclusions

Spatial planning is an essential policy tool for controlling built-up land expansion. However, non-conforming expansion of built-up land often exceeds conforming expansion, especially in developing countries. In this study, we evaluated the non-conformance of newly developed built-up land with zoning in Zhangzhou City, China, between 2010 and 2020 and estimated the peer effects on the non-conforming built-up land expansion of 1,662 villages. We found more non-conforming newly developed built-up land (67.61%) than conforming developments (32.39%). The spatial autoregressive models showed that the peer effects (geographical, political, economic, geographical-economic, and political-economic) were significant factors facilitating the non-conforming expansion of built-up land at the village level.

This study has several limitations. First, the low explanatory power of our spatial autoregressive models can partly be explained by the degree of uncertainty and randomness of built-up land expansion that we were not able to include in the model. The inclusion of additional variables, such as villagers' land-use decision-making characteristics, might improve the model performance. Second, we estimated peer effects with a statistical model. The mechanisms by which peer effects influence local governments' behaviors of developing non-conforming built-up land were not explored in this study. Future research should aim to uncover these mechanisms with village-level data on the contextual interactions behind the peer effects. Third, peer effects may play different roles in the different types of non-conforming built-up land expansion, considering the different costs and benefits from the different types of non-conforming built-up land expansion. Further research could build on and refine our method, for example by dividing the non-conforming built-up land into residential and industrial land uses.

Non-conforming built-up land expansion is often associate with illegal land grabs, informal settlements, and land-use zoning amendments. These processes remain largely unexplored but have profound impacts on sustainable development. In future, we need to further investigate how the disparity between spatial planning and actual land-use changes shapes landscapes. This will require close interdisciplinary collaborations between spatial planning and land-system science, as well as spatially explicit models that can address non-conforming land-use behaviors.

References:

Abrantes, P., Fontes, I., Gomes, E., & Rocha, J. (2016). Compliance of land cover changes with municipal land use planning: Evidence from the Lisbon metropolitan region (1990–2007). *Land Use Policy*, *51*, 120–134. https://doi.org/10.1016/j.landusepol.2015.10.023

Acuto, M., Parnell, S., & Seto, K. C. (2018). Building a global urban science. *Nature Sustainability*, *1*(1), 2–4. https://doi.org/10.1038/s41893-017-0013-9

Alfasi, N., Almagor, J., & Benenson, I. (2012). The actual impact of comprehensive land-use plans: Insights from high resolution observations. *Land Use Policy*, *29*(4), 862–877. https://doi.org/10.1016/j.landusepol.2012.01.003

Alterman, R., & Hill, M. (1978). Implementation of urban land use plans. *Journal of the American Institute of Planners*, *44*(3), 274–285. https://doi.org/10.1080/01944367808976905

Atella, V., Belotti, F., Depalo, D., & Piano Mortari, A. (2014). Measuring spatial effects in the presence of institutional constraints: The case of Italian Local Health Authority expenditure. *Regional Science and Urban Economics*, *49*, 232–241. https://doi.org/10.1016/j.regsciurbeco.2014.07.007

Brody, S. D., & Highfield, W. E. (2005). Does planning work?: Testing the implementation of local environmental planning in Florida. *Journal of the American Planning Association*, *71*(2), 159–175. https://doi.org/10.1080/01944360508976690

Brody, S. D., Highfield, W. E., & Thornton, S. (2006). Planning at the urban fringe: An examination of the factors influencing nonconforming development patterns in southern Florida. *Environment and Planning B: Planning and Design*, *33*(1), 75–96. https://doi.org/10.1068/b31093

Bulti, D. T., & Sori, N. D. (2017). Evaluating land-use plan using conformance-based approach in Adama city, Ethiopia. *Spatial Information Research*, *25*(4), 605–613. https://doi.org/10.1007/s41324-017-0125-3

Bürgi, M., Celio, E., Diogo, V., Hersperger, A. M., Kizos, T., Lieskovsky, J., Pazur, R., Plieninger, T., Prishchepov, A. v., & Verburg, P. H. (2022). Advancing the study of driving forces of landscape change. *Journal of Land Use Science*, 1–16. https://doi.org/10.1080/1747423x.2022.2029599

Cai, H., Henderson, J. V., & Zhang, Q. (2013). China's land market auctions: Evidence of corruption? *RAND Journal of Economics*, *44*(3), 488–521. https://doi.org/10.1111/1756-2171.12028

Cassette, A., di Porto, E., & Foremny, D. (2012). Strategic fiscal interaction across borders: Evidence from French and German local governments along the Rhine Valley. *Journal of Urban Economics*, *72*(1), 17–30. https://doi.org/10.1016/j.jue.2011.12.003

Chen, H., Tang, L., Qiu, Q., Hou, L., & Wang, B. (2020). Construction and case analysis of an index for the sustainability of ecosystem services. *Ecological Indicators*, *115*, 106370. https://doi.org/10.1016/j.ecolind.2020.106370

Chen, S., Chen, Z., & Shen, Y. (2021). Can improving law enforcement effectively curb illegal land use in China? *PLOS ONE*, *16*(2), e0246347. https://doi.org/10.1371/journal.pone.0246347

Chen, Z., Wang, Q., Chen, Y., & Huang, X. (2015). Is illegal farmland conversion ineffective in China? Study on the impact of illegal farmland conversion on economic growth. *Habitat International*, *49*, 294–302. https://doi.org/10.1016/j.habitatint.2015.05.036

Christafore, D., & Leguizamon, S. (2015). Spatial spillovers of land use regulation in the United States. *Housing Studies*, *30*(3), 491–503. https://doi.org/10.1080/02673037.2014.927054

Colsaet, A., Laurans, Y., & Levrel, H. (2018). What drives land take and urban land expansion? A systematic review. *Land Use Policy*, *79*, 339–349. https://doi.org/10.1016/j.landusepol.2018.08.017

Drukker, D. M., Prucha, I. R., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*, *13*(2), 221–241. https://doi.org/10.1177/1536867x1301300201

Feng, J., Lichtenberg, E., & Ding, C. (2015). Balancing act: Economic incentives, administrative restrictions, and urban land expansion in China. *China Economic Review*, *36*, 184–197. https://doi.org/10.1016/j.chieco.2015.09.004

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005). Global consequences of land use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Gao, J., & O'Neill, B. C. (2020). Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways. *Nature Communications*, *11*(1), 1–12. https://doi.org/10.1038/s41467-020-15788-7

Gennaio, M. P., Hersperger, A. M., & Bürgi, M. (2009). Containing urban sprawl—Evaluating effectiveness of urban growth boundaries set by the Swiss Land Use Plan. *Land Use Policy*, *26*(2), 224–232. https://doi.org/10.1016/j.landusepol.2008.02.010

Gómez-Antonio, M., Hortas-Rico, M., & Li, L. (2016). The causes of urban sprawl in

Spanish urban areas: A spatial approach. *Spatial Economic Analysis*, *11*(2), 219–247. https://doi.org/10.1080/17421772.2016.1126674

Hartmann, T. (2012). Wicked problems and clumsy solutions: Planning as expectation management. *Planning Theory*, *11*(3), 242–256. https://doi.org/10.1177/1473095212440427

He, C., Huang, Z., & Wang, R. (2014). Land use change and economic growth in urban China: A structural equation analysis. *Urban Studies*, *51*(13), 2880–2898. https://doi.org/10.1177/0042098013513649

He, Z., Ling, Y., Fürst, C., & Hersperger, A. M. (2022). Does zoning contain built-up land expansion? Causal evidence from Zhangzhou City, China. *Landscape and Urban Planning*, *220*, 104339. https://doi.org/10.1016/j.landurbplan.2021.104339

Hersperger, A. M., Grădinaru, S., Oliveira, E., Pagliarin, S., & Palka, G. (2019). Understanding strategic spatial planning to effectively guide development of urban regions. *Cities*, *94*, 96–105. https://doi.org/10.1016/j.cities.2019.05.032

Huang, J., Huang, Y., Pontius, R. G., & Zhang, Z. (2015). Geographically weighted regression to measure spatial variations in correlations between water pollution versus land use in a coastal watershed. *Ocean and Coastal Management*, *103*, 14–24. https://doi.org/10.1016/j.ocecoaman.2014.10.007

Huang, Z., & Du, X. (2017). Strategic interaction in local governments' industrial land supply: Evidence from China. *Urban Studies*, *54*(6), 1328–1346. https://doi.org/10.1177/0042098016664691

Hussain, Z., & Nadeem, O. (2021). The nexus between growth strategies of master plans and spatial dynamics of a metropolitan city: The case of Lahore, Pakistan. *Land Use Policy*, *109*, 105609. https://doi.org/10.1016/j.landusepol.2021.105609

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S., & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and Urban Planning*, *165*, 280–294. https://doi.org/10.1016/j.landurbplan.2017.02.004

le Berre, I., Maulpoix, A., Thériault, M., & Gourmelon, F. (2016). A probabilistic model of residential urban development along the French Atlantic coast between 1968 and 2008. *Land Use Policy*, *50*, 461–478. https://doi.org/10.1016/j.landusepol.2015.09.007

LeSage, J., & Pace, R. K. (2009). Introduction to spatial econometrics. In *Introduction to Spatial Econometrics*. Chapman and Hall/CRC.

Li, M., Verburg, P. H., & van Vliet, J. (2022). Global trends and local variations in land take per person. *Landscape and Urban Planning*, *218*, 104308. https://doi.org/10.1016/j.landurbplan.2021.104308

Lichtenberg, E., & Ding, C. (2008). Assessing farmland protection policy in China. *Land Use Policy*, *25*(1), 59–68. https://doi.org/10.1016/j.landusepol.2006.01.005

Liu, T., Huang, D., Tan, X., & Kong, F. (2020). Planning consistency and implementation in urbanizing China: Comparing urban and land use plans in suburban Beijing. *Land Use Policy*, *94*, 104498. https://doi.org/10.1016/j.landusepol.2020.104498

Loh, C. G. (2011). Assessing and interpreting non-conformance in land-use planning implementation. *Planning Practice and Research*, *26*(3), 271–287. https://doi.org/10.1080/02697459.2011.580111

Long, Y., Han, H., Lai, S.-K., Jia, Z., Li, W., & Hsu, W. (2020). Evaluation of urban planning implementation from spatial dimension: An analytical framework for Chinese cities and case study of Beijing. *Habitat International*, *101*, 102197.

https://doi.org/10.1016/j.habitatint.2020.102197

Menzori, I. D., Sousa, I. C. N. de, & Gonçalves, L. M. (2021). Urban growth management and territorial governance approaches: A master plans conformance analysis. *Land Use Policy*, *105*, 105436. https://doi.org/10.1016/j.landusepol.2021.105436

Nagendra, H., Bai, X., Brondizio, E. S., & Lwasa, S. (2018). The urban south and the predicament of global sustainability. *Nature Sustainability*, *1*(7), 341–349. https://doi.org/10.1038/s41893-018-0101-5

Onsted, J. A., & Chowdhury, R. R. (2014). Does zoning matter? A comparative analysis of landscape change in Redland, Florida using cellular automata. *Landscape and Urban Planning*, *121*, 1–18. https://doi.org/10.1016/j.landurbplan.2013.09.007

Padeiro, M. (2016). Conformance in land-use planning: The determinants of decision, conversion and transgression. *Land Use Policy*, *55*, 285–299. https://doi.org/10.1016/j.landusepol.2016.04.014

Park, S., Hyun, J., & Clarke, K. C. (2018). Capturing the heterogeneity of urban growth in South Korea using a latent class regression model. *Transactions in GIS*, *22*(3), 789–805. https://doi.org/10.1111/tgis.12451

Peng, X. (2020). Strategic interaction of environmental regulation and green productivity growth in China: Green innovation or pollution refuge? *Science of The Total Environment*, *732*, 139200. https://doi.org/10.1016/j.scitotenv.2020.139200

Poelmans, L., & van Rompaey, A. (2010). Complexity and performance of urban expansion models. *Computers, Environment and Urban Systems*, *34*(1), 17–27. https://doi.org/10.1016/j.compenvurbsys.2009.06.001

Schone, K., Koch, W., & Baumont, C. (2013). Modeling local growth control decisions in a multi-city case: Do spatial interactions and lobbying efforts matter? *Public Choice*, *154*(1), 95–117. https://doi.org/10.1007/s11127-011-9811-1

Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A Meta-Analysis of Global Urban Land Expansion. *PLoS ONE*, *6*(8), e23777. https://doi.org/10.1371/journal.pone.0023777

Shao, Z., Spit, T., Jin, Z., Bakker, M., & Wu, Q. (2018). Can the land use master plan control urban expansion and protect farmland in China? A case study of Nanjing. *Growth and Change*, *49*(3), 512–531. https://doi.org/10.1111/grow.12240

Sharifi, A., Chiba, Y., Okamoto, K., Yokoyama, S., & Murayama, A. (2014). Can master planning control and regulate urban growth in Vientiane, Laos? *Landscape and Urban Planning*, *131*, 1–13. https://doi.org/10.1016/j.landurbplan.2014.07.014

Shen, X., Wang, L., Wang, X., Zhang, Z., & Lu, Z. (2019). Interpreting non-conforming urban expansion from the perspective of stakeholders’ decision-making behavior. *Habitat International*, *89*, 102007. https://doi.org/10.1016/j.habitatint.2019.102007

Sobhani, P., Esmaeilzadeh, H., & Mostafavi, H. (2021). Simulation and impact assessment of future land use and land cover changes in two protected areas in Tehran, Iran. *Sustainable Cities and Society*, *75*, 103296. https://doi.org/10.1016/j.scs.2021.103296

Sun, C., Wu, Z. F., Lv, Z. Q., Yao, N., & Wei, J. B. (2013). Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *21*(1), 409–417. https://doi.org/10.1016/j.jag.2011.12.012

Sundaresan, J. (2019). Urban planning in vernacular governance: Land use planning and violations in Bangalore, India. *Progress in Planning*, *127*, 1–23. https://doi.org/10.1016/j.progress.2017.10.001

Tang, P., Feng, Y., Li, M., & Zhang, Y. (2021). Can the performance evaluation change from central government suppress illegal land use in local governments? A new interpretation of Chinese decentralisation. *Land Use Policy*, *108*, 105578. https://doi.org/10.1016/j.landusepol.2021.105578

Tellman, B., Eakin, H., Janssen, M. A., de Alba, F., & Turner II, B. L. (2021). The role of institutional entrepreneurs and informal land transactions in Mexico City's urban expansion. *World Development*, *140*, 105374. https://doi.org/10.1016/j.worlddev.2020.105374

Tellman, B., Magliocca, N. R., Turner, B. L., & Verburg, P. H. (2020). Understanding the role of illicit transactions in land-change dynamics. *Nature Sustainability*, *3*(3), 175–181. https://doi.org/10.1038/s41893-019-0457-1

Tian, G., & Wu, J. (2015). Comparing urbanization patterns in Guangzhou of China and Phoenix of the USA: The influences of roads and rivers. *Ecological Indicators*, *52*, 23–30. https://doi.org/10.1016/j.ecolind.2014.11.024

Tian, L., & Shen, T. (2011). Evaluation of plan implementation in the transitional China: A case of Guangzhou city master plan. *Cities*, *28*, 11–27. https://doi.org/10.1016/j.cities.2010.07.002

Wang, B., Zhang, Y., Zhan, C., & Yang, X. (2020). Strategic interaction of industrial land conveyance behaviors in China: Based on an asymmetric two-regime Spatial Durbin Model. *Journal of Cleaner Production*, *270*, 122598. https://doi.org/10.1016/j.jclepro.2020.122598

Wang, J., Wu, Q., Yan, S., Guo, G., & Peng, S. (2020). China's local governments breaking the land use planning quota: A strategic interaction perspective. *Land Use Policy*, *92*(1), 104434. https://doi.org/10.1016/j.landusepol.2019.104434

Wang, L., Pijanowski, B., Yang, W., Zhai, R., Omrani, H., & Li, K. (2018). Predicting multiple land use transitions under rapid urbanization and implications for land management and urban planning: The case of Zhanggong District in central China. *Habitat International*, *82*, 48–61. https://doi.org/10.1016/j.habitatint.2018.08.007

Wang, L.-G., Han, H., & Lai, S.-K. (2014). Do plans contain urban sprawl? A comparison of Beijing and Taipei. *Habitat International*, *42*, 121–130. https://doi.org/10.1016/j.habitatint.2013.11.001

Wang, M., Krstikj, A., & Koura, H. (2017). Effects of urban planning on urban expansion control in Yinchuan City, Western China. *Habitat International*, *64*, 85–97. https://doi.org/10.1016/j.habitatint.2017.04.008

Wang, W., Wu, Y., & Sloan, M. (2018). A framework & dynamic model for reform of residential land supply policy in urban China. *Habitat International*, *82*, 28–37. https://doi.org/10.1016/j.habitatint.2018.10.006

Wende, W., Walz, U., & Stein, C. (2020). Evaluating municipal landscape plans and their influence on selected aspects of landscape development – An empirical study from Germany. *Land Use Policy*, *99*. https://doi.org/10.1016/j.landusepol.2020.104855

Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, M. P., & Arnold, C. (2003). Development of a geospatial model to quantify, describe and map urban growth. *Remote Sensing of Environment*, *86*(3), 275–285. https://doi.org/10.1016/S0034-4257(03)00074-9

Xiao, S., Fügener, T., Wende, W., Yan, W., Chen, H., Syrbe, R., & Xue, B. (2022). The dynamics of vegetation and implications for ecosystem services in the context of urbanisation: An example from Huangyan-Taizhou, China. *Ecological Engineering*, *179*. https://doi.org/10.1016/j.ecoleng.2022.106614

Xiong, C., & Tan, R. (2018). Will the land supply structure affect the urban expansion form? *Habitat International*, *75*, 25–37. https://doi.org/10.1016/j.habitatint.2018.04.003

Xu, C., Liu, M., Zhang, C., An, S., Yu, W., & Chen, J. M. (2007). The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. *Landscape Ecology*, *22*(6), 925–937. https://doi.org/10.1007/s10980-007-9079-5

Yu, J., Zhou, L. A., & Zhu, G. (2016). Strategic interaction in political competition: Evidence from spatial effects across Chinese cities. *Regional Science and Urban Economics*, *57*, 23–37. https://doi.org/10.1016/j.regsciurbeco.2015.12.003

Yue, W., Liu, Y., & Fan, P. (2013). Measuring urban sprawl and its drivers in large Chinese cities: The case of Hangzhou. *Land Use Policy*, *31*, 358–370. https://doi.org/10.1016/j.landusepol.2012.07.018

Zhong, T., Huang, X., Zhang, X., & Wang, K. (2011). Temporal and spatial variability of agricultural land loss in relation to policy and accessibility in a low hilly region of southeast China. *Land Use Policy*, *28*(4), 762–769. https://doi.org/10.1016/j.landusepol.2011.01.004

Zhong, T., Mitchell, B., & Huang, X. (2014). Success or failure: Evaluating the implementation of China's National General Land Use Plan (1997–2010). *Habitat International*, *44*, 93–101. https://doi.org/10.1016/j.habitatint.2014.05.003

Zhou, W., Yu, W., Qian, Y., Han, L., Pickett, S. T. A., Wang, J., Li, W., & Ouyang, Z. (2022). Beyond city expansion: multi-scale environmental impacts of urban megaregion formation in China. *National Science Review*, *9*(1), nwab107. https://doi.org/10.1093/nsr/nwab107

Zhou, Y., Huang, X., Chen, Y., Zhong, T., Xu, G., He, J., Xu, Y., & Meng, H. (2017). The effect of land use planning (2006–2020) on construction land growth in China. *Cities*, *68*, 37–47. https://doi.org/10.1016/j.cities.2017.04.014

Zhu, J., & Tang, W. (2018). Conflict and compromise in planning decision-making: How does a Chinese local government negotiate its construction land quota with higher-level governments? *Environment and Urbanization*, *30*(1), 155–174. https://doi.org/10.1177/0956247817753524

Zuo, C. (2015). Promoting city leaders: The structure of political incentives in China. *The China Quarterly*, *224*, 955–984. https://doi.org/10.1017/S0305741015001289