

OPTIMIZING SPATIAL PLACEMENT OF EDUCATIONAL INSTITUTIONS USING POI AND GEO-INFORMATION

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Highlights:

- about 30 thousand POIs of educational institutions were crawled;
- urban landscape and road data are derived from the SinoLC-1 dataset;
- whole city realm was divided into 1086 grids and each had an area of 5.29 km²;
- spatial holding capacity was evaluated according to neighboring retails and landscape metrics;
- numbers of college and preschool were higher than needs;
- numbers of public services and schools were insufficient.

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Abstract. The optimization of urban infrastructure (UI) placement relies on the evaluation of the current situation, which refers to neighboring capacities of transport, retail, and landscape. These factors play a critical role in determining the holding capacity of EIs in urban environments and directly influence urban planning and resource allocation. The placement of educational institutions (EI) is critical for the sustainable development of a city because it regulates population movements and attracts services. Points of interest (POI) are novel and flexible instruments for landscape evaluation and optimization based on remote geographical information. Changchun was chosen as the study area, where POIs of EIs were collected through web scraping from five types of educational institutions (EIs): training centers, public services, preschools, schools, and colleges. This method allowed us to gather data on the spatial distribution and characteristics of these institutions systematically. Regional placement of EIs showed agglomerated distributions in six areas of interest (AOIs). Both retail numbers (food, hotel, and market) and road density (classes I–IV) had positive relationships with the number of EIs. Landscape metrics did not have a direct impact on the EI number, but areas of green space and impervious land had contrasting effects on the parameter estimates of the EI number of public services. Both retail numbers and road density also showed positive relationships with the capacity to hold EIs for public services per greenspace area and built-up land area. Compared with the current placement of EIs, the optimization scheme indicated that the number of EI providing public services was far higher than that held by surrounding retailers. In contrast, more schools should be planned in downtown areas because of the large gap in traffic capacity.

Keywords: educational infrastructure, landscape dimension, sustainable urbanization, placement optimization.

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1. Introduction

Urbanization has continuously increased worldwide since the end of the 20th century. It is predicted that by 2050, approximately 68% of the world's population will reside in urban areas (Helbling & Meierrieks, 2023). Against the backdrop of global urbanization, China's urbanization process is particularly noteworthy. Statistical data indicate that China's urbanization rate has increased from approximately 18% in 1978 to approximately 64% in 2021 (Chen et al., 2013), with a rapidly growing population flooding

urbanized areas (Fan et al., 2009). Education plays a significant role in shaping the urban migration patterns. Educational institutions (EIs) attract families and foster human resource development, which in turn influences the urban population distribution and promotes the development of newly urbanized districts. Educational institutions (EIs) are an inevitable type of urban infrastructure that attracts regional populations agglomerated with the demand for education for the next generation (Zhou et al., 2021). Newly built areas of a city are frequently planned with EI placement to induce population movements (Hirono,

2020). Educational resources attract families and individuals to migrate to newly urbanized districts (Zhou et al., 2021), which fosters the cultivation of new urban human resources (Ju et al., 2022). Education-attracted populations further promote sustainable urban economic growth by promoting innovation, enhancing labor productivity (Lutz & Samir, 2011), and the total social capital of the host city (Huang et al., 2009). Therefore, the placement of educational infrastructure is of high importance to urban planners and policymakers.

The geographical position and surrounding urban infrastructure are key factors that influence the holding capacity of educational institutions (EIs) in urban areas (Yoon et al., 2018). These factors, including landscape metrics, transportation networks, and retail densities, directly contribute to the overall capacity of EIs to serve the surrounding population by affecting accessibility, availability of resources, and spatial distribution (Liu et al., 2025b). Therefore, understanding the carrying capacity of education services in new urban areas is a prerequisite for optimizing the location of facilities. The decision to position an EI's location not only determines the regional distribution of educational resources but also affects its accessibility to the public (Köse et al., 2021; Shen et al., 2022). Therefore, the location of an EI matters for the success of its business by efficiently attracting essential customers. It is essential to meticulously consider factors that together enable highly frequent visits by people with educational needs, such as the surrounding retail shops (Vilme et al., 2022), traffic accessibility (Walsh et al., 2015), and carrying capacities of neighboring urban infrastructures (Jamaludin et al., 2014). An adequate number of nearby retailers can meet the living needs of parents and students during their daily visits, which can enhance their attachment to objective EI with terrific experiences to receive educational services (Dong, 2022). Fluent traffic accessibility can result in good connectivity between EI and the public, making it convenient for consumers to visit and commute (Köse et al., 2021). The carrying capacities of neighboring urban infrastructure are limited to the maximum ecosystem and social services, which together determine the number of varied EIs positioned as a part of the neighboring landscape (AlQuhtani, 2023). An overall saturation of EI placement would lead to an excessive demand for landscape services, which further causes dual drawbacks in a low-quality urban ecosystem environment and a poor learning atmosphere (Li et al., 2019). However, the current understanding of the planning of reasonable numbers of EIs in neighboring landscapes is still insufficient. More detailed information is needed for the reasonable planning of EIs' placement in sustainable urban development.

To plan the position of an EI, one should first consider its close geographical relationship with nearby retail formats (Hanning et al., 2019). This is because, during the transaction of educational services, both teachers (providers) and students (customers) have living needs that rely on the surrounding retail. A rich and diverse array of varied living service retailers, rather than a large and

concentrated-sale supermarket, is needed to meet the daily lives of teaching staff and students (McKenzie, 2008; Roggeveen et al., 2020). However, the prosperity of the neighboring retail sector can bring potential customers to EIs and further promote the development of the education and training industries (Kang, 2016; Sazvar & Sepehri, 2020). Scholars have proposed a plan for retail placements in North Carolina, which recommends a buffer range within a 15-minute drive from an objective EI (Vilme et al., 2022). EI managers running businesses in other regions can hardly refer to this type of advice on an occasional region. Therefore, it is essential to explore the relationship between the number of EIs and surrounding retail formats in a given region. Diverse retail shops also generate the capacity to hold resources for adjacent educational services at a reasonable number of positions.

The convenience and accessibility of transportation have a direct impact on the sales of educational services (Kang, 2016). Research indicates that the level of development of the transportation network is closely related to the accessibility of EIs in Miami-Dade County, Florida (Patel et al., 2021). As an important part of the urban road system, the length of the surrounding roads and streets plays a guiding role in the geographical location selection of EIs (Walsh et al., 2015; Agbabiaka et al., 2020). The total cumulative length of a regional road network provides a metre for gauging convenient commuting accessibility for both students and teaching staff (Lee & Kim, 2021). The density of the surrounding road network also determines the buffer radius of the traffic range for visits to EIs (Cui et al., 2022; Liu et al., 2025a). A road with strong connectivity and wide coverage across several blocks can effectively enhance the accessibility of daily visits, even in a broader area (Walsh et al., 2015). The strength of the surrounding road network should be specially considered to meet the traffic needs of EIs' visitors on a large scale (Wang et al., 2025).

Urban landscapes not only constitute the physical surfaces of a city but also affect the quality of local life and behavioral patterns of urban residents (Lin et al., 2016; Li et al., 2019; Ha et al., 2022). Research indicates that the design and layout of urban landscapes have profound impacts on residents' mental health (Wu & Ren, 2021; Zhao & Wang, 2022). Green and blue spaces (GBS) are major ecological infrastructures that provide ecosystem services to neighboring people (Wei et al., 2022; Ayivi et al., 2025). Built-up areas of impervious land and construction account for the baseline geographical extent to which new EIs can be positioned (Neilson & Zimmerman, 2014; Sajady et al., 2020). Studies have shown that school environments with an ample supply of GBS have a positive impact on students' academic performance and learning efficiency (Hodson & Sander, 2017; Zhang et al., 2022). It was also indicated that factors of built environment, types of greenery, and neighboring greenery together made a synthesized contribution to the adaptation of students in non-metropolitan environments with varied sizes and numbers of EIs (Sajady et al., 2020). However, urban GBS

planning must consider carrying capacity to ensure the sustainability of the urban landscape (Zhou et al., 2019). Carrying capacity' refers to the number of educational facilities that can be supported by a unit of space under resource, environmental and functional constraints, which is different from the static spatial capacity of 'holding capacity'. The former is more concerned with the sustained level of the carrying capacity under dynamic regulation. Areas of impervious surfaces and built-up construction together account for the largest number of planned positions for newly introduced EIs (Yang & Chen, 2010; Xu et al., 2018). However, the effect of the number of EIs positioned on the GBS holding capacity remains unclear. The relationship between EI numbers and these neighboring landscape metrics is the key to evaluating the reasonability of the current placement of EIs, but insufficient scientific evidence about this relationship hinders the scientific evaluation of current placement and further suggestions for optimization.

To determine the relationship between EIs and the urban environment in a vast range, scholars have conducted in-depth discussions on their interplays. Studies have focused on the impact of urban landscapes on the health of school-aged youth to provide insights into the positive evidence to assess the holding capacity of urban greening for mentally healthy students (Aradi et al., 2016; Sheng et al., 2023). Studies have emphasized the important impact of surrounding retail formats on EIs according to their magnitude to meet the demands of students with EI (Bader et al., 2013; Scully et al., 2013; Williams et al., 2015). Additionally, studies have assessed road safety issues around EIs and proposed the holding capacity of road networks for the operation of EIs (Amram et al., 2011; Eun, 2023). Although these studies provide valuable perspectives and insights, the accuracy of most research results is still limited by conventional methods of data collection and quantitative analysis. Self-reported data from questionnaire surveys and interviews on holding capacity for EIs have obvious shortcomings due to subjective biases (Aradi et al., 2016). Again, they still have a limited scope, failing to fully capture the broader urban context in which EI operates. Likewise, such manual data collection methods are not only time-consuming, but also unreliable. These methodological limitations may lead to bias in data recording and inaccuracies in the quantified results, which will limit the evaluation and optimization at a larger scale. It is difficult to continuously rely on conventional methodology and data collected from conventional methodologies with low accuracy in further studies with high requirements. To overcome these issues, a novel quantitative indicator methodology is essential to accurately reflect the types and quantities of EI.

Currently, the employment of point-of-interest (POI) data has become key to overcoming the limitations of traditional research and offers new possibilities for analyzing urban information (Liu et al., 2024). The novelty of using POI data is reflected in their ability to scrape extensive data automatically, align and interpret remote sensing landscapes, and quantify various types of surface points

with high precision (Yang & Zhang, 2015; Liu et al., 2020). This approach is particularly effective in drawing comprehensive maps of urban landscapes with accurate objective positions, including the precise location and nature of EIs, retail areas, transportation networks, and other urban features. The integration of POI data with advanced remote sensing technology enables detailed observation and analysis of urban environments at a granular level. This allowed us to systematically capture the multifaceted nature of urban ecosystems, including their spatial distribution and density. Therefore, adopting this methodology is crucial for exploring the feasibility of EI layouts and making informed decisions in the evaluation and optimization of educational resource allocation.

Changchun is an industrial city with a high proportion of well-educated people in Northeast China. Changchun, also called the city of colleges, contains 42 colleges and higher EIs (China Education Examination Office, 2023). Regarding widely distributed eager wishes to receive educational services, reasonable planning of EIs has been listed in the municipal development strategy as a promotion of population regulation towards newly urbanized districts in Changchun. The analysis was conducted using advanced computer-based technologies, including Geographic Information Systems (GIS) for spatial analysis and Python-based web scraping tools for gathering data on educational institutions, retail outlets, and urban infrastructure. The research objectives include: (1) determining the relationship between the POI number of each type of EI and carrying capacities of surrounding retail, road systems, and urban infrastructures; (2) assessing the spatial distribution patterns of the existing EIs; and (3) proposing optimization plans for the layout of EIs in newly urbanized areas. This study proposes a two-path optimization logic: on the demand side, the spatial demand for educational facilities is driven by road class and retail density; on the supply side, the carrying capacity model for regional educational services is constructed using indicators such as green space/impervious surface ratio. Our research findings and conclusions provide theoretical guidance for the layout of the educational industry to decision makers in the urban planning and educational sectors.

2. Data and methodology

This study focuses on Changchun, a city in Northeast China, to investigate the relationship between EIs and urban structure by dividing the city into uniform grids and concentrating on six specific areas. The dependent variable was the number of educational institutions (EIs), and the independent variables included landscape metrics (e.g., green space and impervious surface), retail density, and road network characteristics (Liu et al., 2025b). These were the driving forces influencing the spatial distribution and operational capacity of the EIs. It utilizes a Python-based web scraping program to gather points of interest (POI) from various map platforms, covering EIs and retailers. Urban landscape and road data were derived from the

SinoLC-1 dataset, which was used to analyze the urban landscape features of Changchun. The relationship between the number of EIs and urban environmental factors was assessed using methods such as the Shapiro-Wilk test, Spearman rank correlation analysis, and maximum likelihood estimation. The technical roadmap for this study is shown in Figure 1.

2.1. Study area and sampling plots

Changchun was chosen as the target city for data collection and research. It is a central city in the regions of North-east China, which has been selected as “City of Forests” and “City of Education” according to the “The yearbook of China’s cities” (Chen et al., 2011). EI was classified into five categories based on POIs: college, preschool, public

services, school, and training centers. We also focused on identifying and studying plots in Changchun, where multiple EIs have already been built in the old districts and planned in the new districts. The distribution of the EIs in Changchun is shown in Figure 2. It is evident that EIs are not evenly distributed throughout the city but are mainly concentrated around six areas, radiating towards other regions. These concentrated regions were selected as specific areas of interest (AOI) in this study, where retailers were targeted through their POI information. To facilitate sampling and spatial analysis, the entire municipal realm was divided into 1086 grids, each of which had a side length of 2.3 kilometers. The six AOIs were divided into 184 grids, with each grid containing at least one EI type. In this study, AOIs were targeted as specific areas for evaluation and optimization.

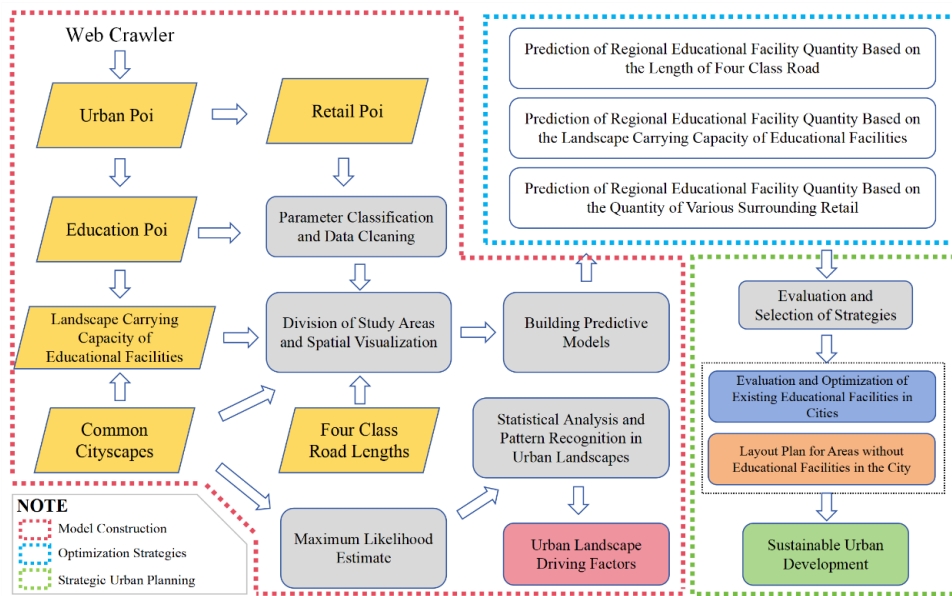


Figure 1. Technical roadmap of the study

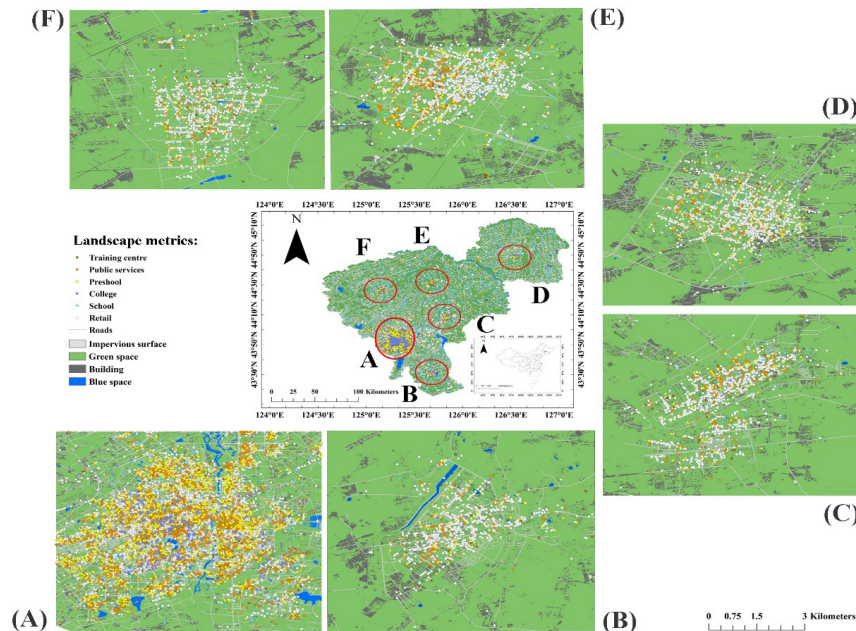


Figure 2. Spatial distribution of EIs and retail in six agglomerations and the entire realm of Changchun, Northeast China

2.2. Crawling POIs for EI and retail shops

Python was used to develop a web scraping program to acquire commercial POI data from the map platforms (Chen et al., 2021). platforms Baidu Map, Amap (Gaode), and Tencent Map were chosen as sources of the POI data (Liu et al., 2025c). Strategies for coping with Application Programming Interface (API) request and access restrictions and obtain data through the API interfaces of map platforms. Additionally, the experiment parsed the HTML content of websites and the JSON from APIs to extract commercial POI information, including their pieces of information about category (type), name, address, and latitude/longitude coordinates of every POI. Given the large volume of POI data, appropriate databases (e.g., SQL and NoSQL) were employed for data storage, and data-processing frameworks (e.g., Pandas) were used for efficient data cleaning and analysis. Throughout the process, the experiment strictly adhered to the terms of the service and data usage policies of relevant websites. Special care was taken regarding the POI data involving personal information to ensure compliance with data privacy and ethical standards. This study utilized a POI spatial dataset from Changchun City, collected in November 2023. The POI data covers a total of 11 categories of infrastructure, including education, healthcare, transportation, finance, commerce, parks, government services, accommodation, food and beverage, culture and other integrated services. From this dataset, we selected data pertaining to EIs and retailers (Figure 3). Based on the secondary classifications within the POI data, the EIs were divided into five categories: college, preschool, public services, school, and training center. Additionally, retail types related to urban life, specifically food, hotels, and markets, were selected because of their close relevance to services provided to EI users (Liu et al., 2025b). The mining of POI was considered for the heterogeneous characteristics of typical urban functional types, thereby providing more refined information on the intricate relationships within urban functional spaces (Chen et al., 2020). The POI data for this study were obtained in November 2023 using the Gaode Map and Baidu

Map APIs, and the API platform was updated approximately once a month. To verify data quality, 120 POIs were randomly selected for field verification.

2.3. Urban landscape and road data

The road data comes from SinoLC-1 v1.0 dataset, which is classified as Class I-IV according to GB/T 917-2017 Classification of Roads Technical Levels. This is the first 1-meter resolution national-scale land-cover map of China (Li et al., 2023). This dataset was created using a deep learning-based framework and open-access data, including global land-cover products, Open Street Map (OSM), and Google Earth imagery, covering the entire land surface of China (approximately 9,600,000 km²) (Li et al., 2022). Data on impervious surfaces, green spaces, blue spaces, buildings, and roads in Changchun were collected. The areas of these four types of urban landscapes were extracted from each grid, as well as the length of each class of road. The advantages of using the SinoLC-1 dataset in this study include its resolution and accuracy, comprehensive coverage, and credibility across China (He et al., 2023). The overall accuracy and kappa coefficient were validated using a visually interpreted validation dataset and a statistical validation dataset, making it a highly reliable source for urban landscape analysis (Cui et al., 2024). Additionally, SinoLC-1's qualitative comparison with other widely used global land-cover products highlights its superior spatial resolution, more accurate land-cover edges, and finer landscape details (Huang et al., 2023). Using this dataset ensures that the urban landscape analysis in this study is based on the most detailed and accurate available land cover data.

2.4. Parameter calculation and statistics

All statistical analyses were performed using SPSS software (IBM Corp., Armonk, NY, USA). In the experimental section of the study, the distribution of data related to retail, EIs, four types of urban landscapes, and the length of four-tier

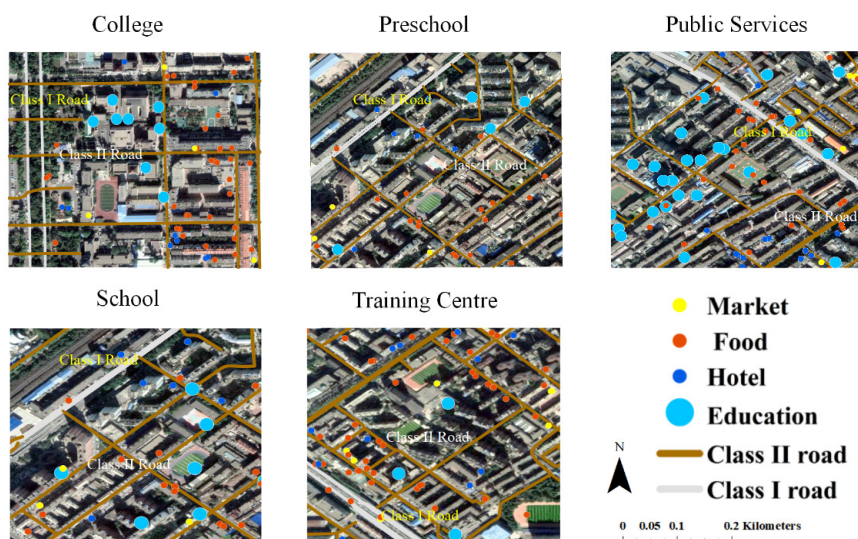


Figure 3. Demonstration of EI placement and neighboring retails and roads for every type of EIs in Changchun

roads were first analyzed for normality. The Shapiro-Wilk test was used for normality testing. This test was chosen because of its effectiveness in assessing the normality of data distribution, especially for small to moderate sample sizes (González-Estrada & Cosmes, 2019). The results revealed that most data did not conform to a normal distribution ($p < 0.05$). Spearman's rank correlation analysis was employed to evaluate the relationship between the number of EIs and urban environmental factors to describe the distribution trends of EIs in the city (Song & Park, 2020). Because the significance between EIs and the four types of urban landscapes was relatively low, this study replaced the landscape type data with the landscape carrying capacity of each type of EI for further correlation analysis. Additionally, the study performed maximum likelihood estimation (MLE) to predict the driving factors of landscape types. This approach was chosen to account for the non-normal distribution of the data and identify the underlying influences on the urban landscape (Moose, 1994). Regression analysis was used to detect causal relationships between the urban environmental factors and the number of EIs. This analysis aimed to reveal the combined effects of EIs and urban environmental factors that collectively shape the current layout of EIs in the city.

3. Results

3.1. Correlations between EIs and retail

Figure 4 demonstrates the correlation between the number of five types of EIs and the number of three types of retailers. Overall, there was a positive linear correlation

between the number of five types of EIs and the number of three types of retailers. The correlations between public services and food ($p < 0.001$, $R^2 = 0.725$) and between the training center and food ($p < 0.001$, $R^2 = 0.740$) showed the highest determination coefficients (R^2). The correlations between college and food ($p < 0.001$, $R^2 = 0.307$) and between college and market ($p < 0.001$, $R^2 = 0.226$) showed relatively lower determination coefficients and slopes. Correlations between the number of EIs and food retail numbers demonstrated higher determination coefficients than relationships with other types of retail. College number showed lower determination coefficients in correlation with all three types of retail. Public services have the highest slopes in correlation with all three types of retail.

3.2. Correlations between EIs and road network

Figure 5 illustrates the correlations between the five types of EIs and the densities of the four classes of roads. The overall relationship between the EIs' number of EIs and road network density presented a multifaceted pattern. Upon analysis of the determination coefficients, preschools ($p < 0.001$, $R^2 = 0.514$), public services ($p < 0.001$, $R^2 = 0.598$), and training centers ($p < 0.001$, $R^2 = 0.486$) exhibited a strong positive linear correlation with Class II Road density. The number of preschools ($p = 0.001$, $R^2 = 0.099$), public services ($p = 0.001$, $R^2 = 0.096$), and schools ($p = 0.002$, $R^2 = 0.073$) showed positive linear correlations with Class III Road density. EIs displayed a nonlinear relationship with the densities of Class I and Class IV roads, where the fit curves for Class I roads showed a peak at a

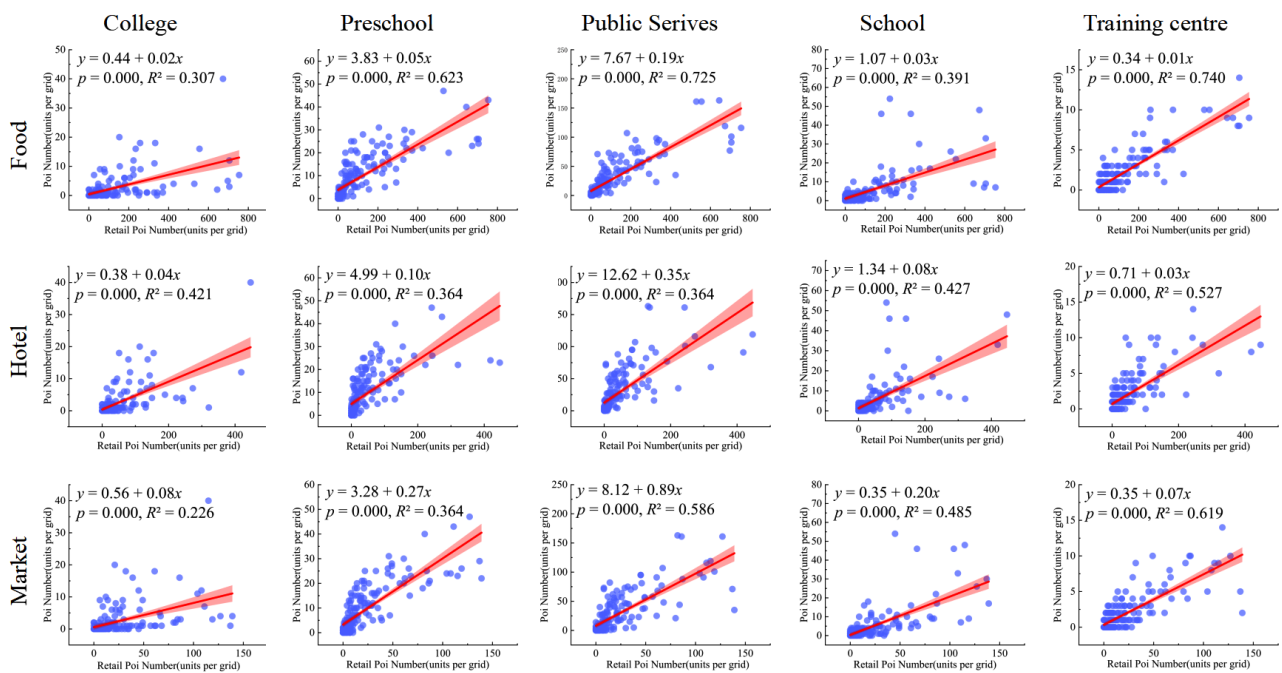


Figure 4. Linear relationships between the numbers of five types of EIs (college, preschool, public services, school, training center) and the number of neighboring retail shops (food, hotel, market). The models of the fit curves are disclosed for each cell of the relationships

certain road density and possessed moderate determination coefficients. The fit curves for the EIs and Class IV road densities tended to plateau after a certain growth period. Correlations between EIs and Class II Road density generally revealed higher determination coefficients, whereas those with Class III roads exhibited lower determination coefficients, suggesting a differential impact of road hierarchy on EI distribution.

3.3. Correlations between urban landscape carrying capacity for EI and retail and roads

Because the number of EIs was not related to the corresponding area of the urban landscape (data not shown), the carrying capacity of the urban landscape for EIs was employed as an independent variable to examine its relationship with retail quantity and road length. The landscape carrying capacity of the EIs exhibited a complex linear relationship with the number of retails, with most showing positive correlations. In Figure 6, it is apparent that the carrying capacity of green space was positively correlated with all three retail categories for the five types of EIs, generally presenting higher determination coefficients, albeit with the smallest slopes. Additionally, the carrying capacity of impervious surfaces for preschool and public services showed a negative correlation with the quantity

of all the three types of retail. Furthermore, the correlation between the carrying capacity of impervious surfaces of EIs and retail quantity was lower, typically exhibiting very low coefficients of determination.

The carrying capacity of the EIs' landscapes exhibited a linear relationship with road length, with most demonstrating a positive correlation. As shown in Figure 7, the landscape carrying capacities of the five types of EIs showed positive correlations with the lengths of the four classes of roads and were associated with higher determination coefficients despite having smaller slopes. Preschools, public services, and schools displayed negative correlations with the carrying capacities of impervious surfaces and road density. Moreover, the correlation between the impervious surface carrying capacity of the EIs and the length of each road class exhibited lower coefficients of determination. In addition, the correlation between the blue space-carrying capacity and road density showed lower determination coefficients.

3.4. Maximum likelihood assessment of urban landscape types

Figure 8 presents the maximum likelihood estimates that assess the impact of urban landscapes on the quantity of various EIs. The green space ratio and imperviousness in

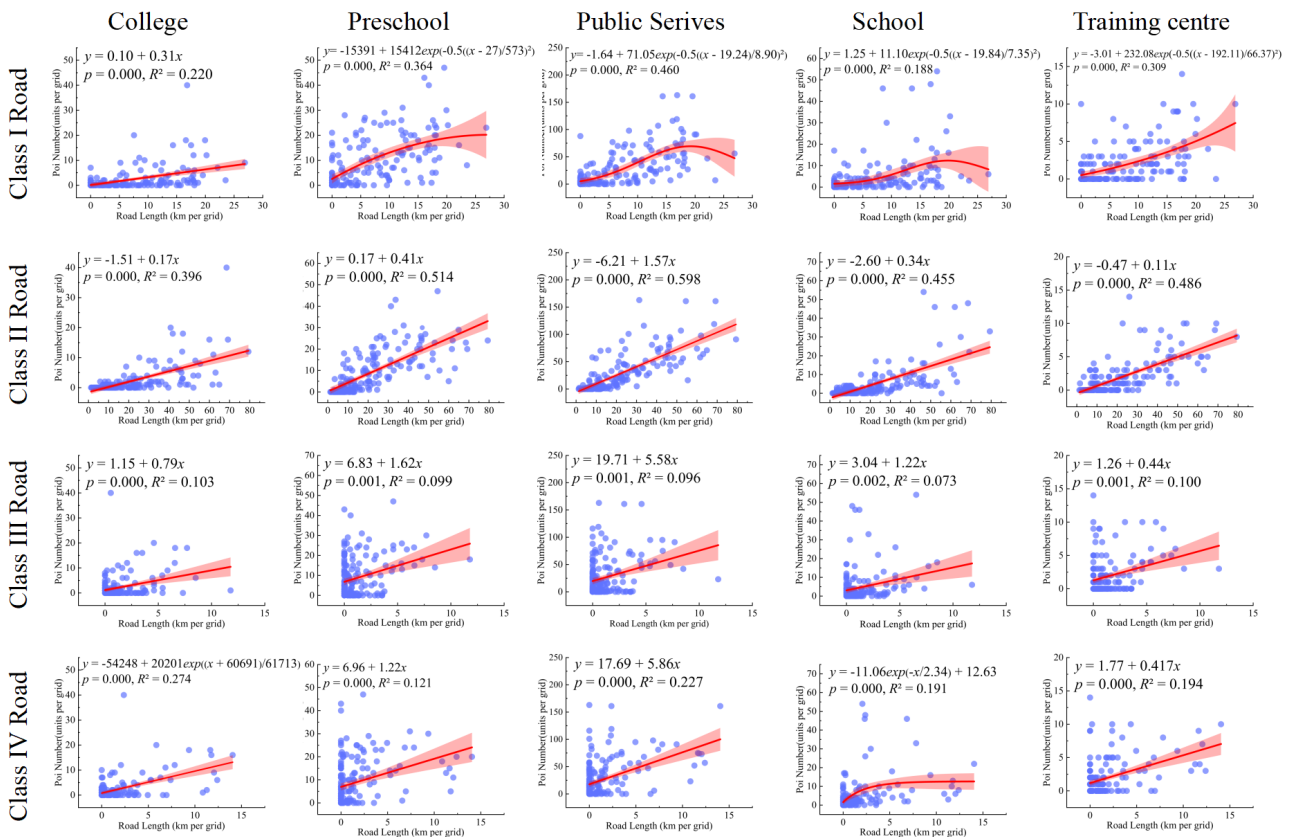
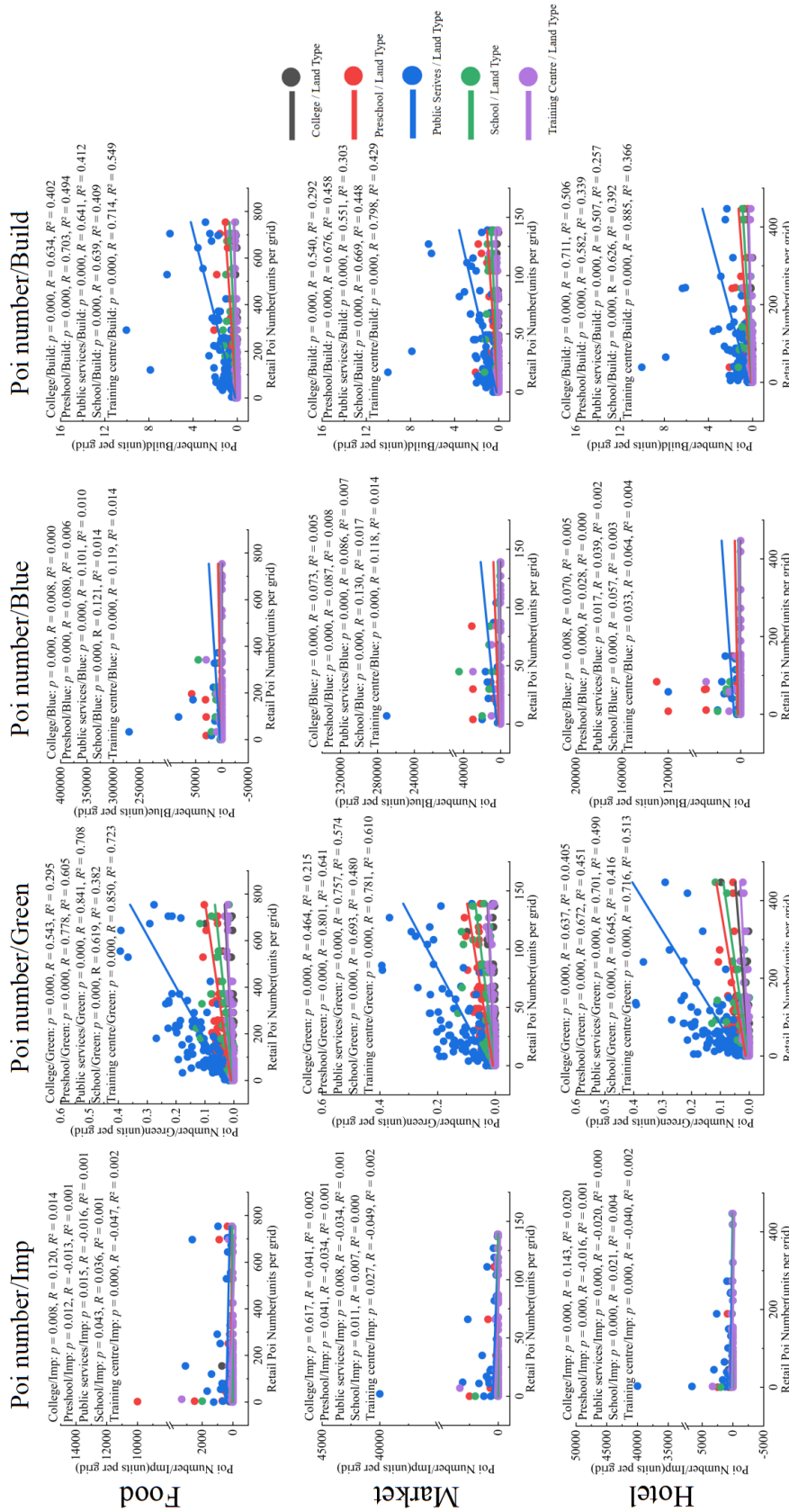
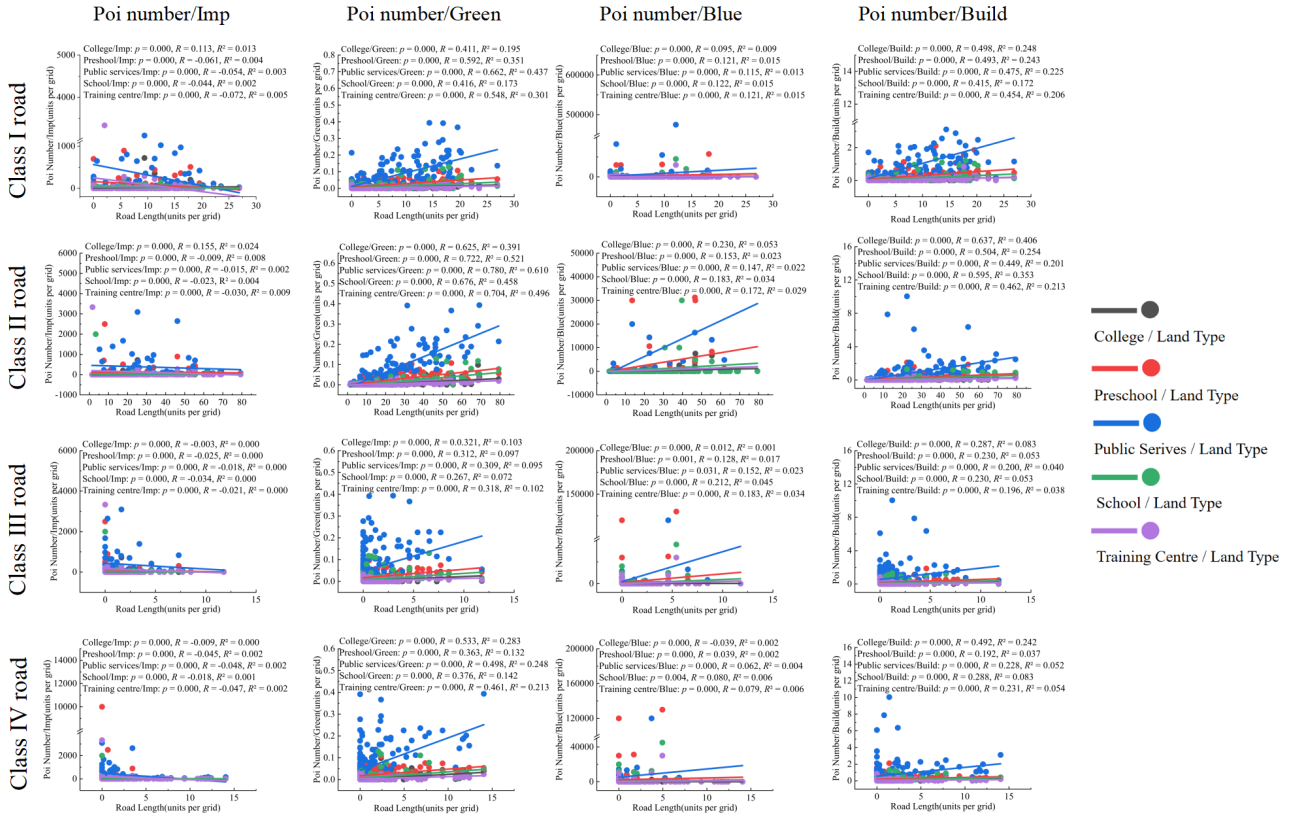


Figure 5. Correlations between the numbers of five types of EIs (college, preschool, public services, school, and training center) and number of neighboring road density (km per grid area) (classes I, II, III, and IV). Models of the fit curves are disclosed in each cell of the relationships



Note: Abbreviations: /Imp – holding capacity of impervious land area; /Green – holding capacity of green space area; /Blue – hold capacity of blue space area; /Build – the holding capacity of built-up land area.

Figure 6. Correlations between the urban landscape-carrying capacity for EI and retail number



Note: Abbreviations: /Imp – holding capacity of impervious land area; /Green – holding capacity of green space area; /Blue – hold capacity of blue space area; /Build – the holding capacity of built-up land area.

Figure 7. Correlations between the urban landscape carrying capacity for EI and roads

Figure 8 were used to set the carrying capacity thresholds in the three optimization scenarios, which were used to limit the upper limit on the number of education facilities. For college, the impervious surface area accounted for the parameter estimate of college number using a nonlinear correlation curve ($p < 0.001, R^2 = 0.136$). The impervious

surface area had a slightly nonlinear correlation with the estimate of preschool number ($p < 0.001, R^2 = 0.149$). The impervious surface area showed an inverse linear relationship with the estimated effect on the number of public services ($p < 0.001, R^2 = 0.058$), which was positively related to the estimated effect of green space area ($p < 0.001,$

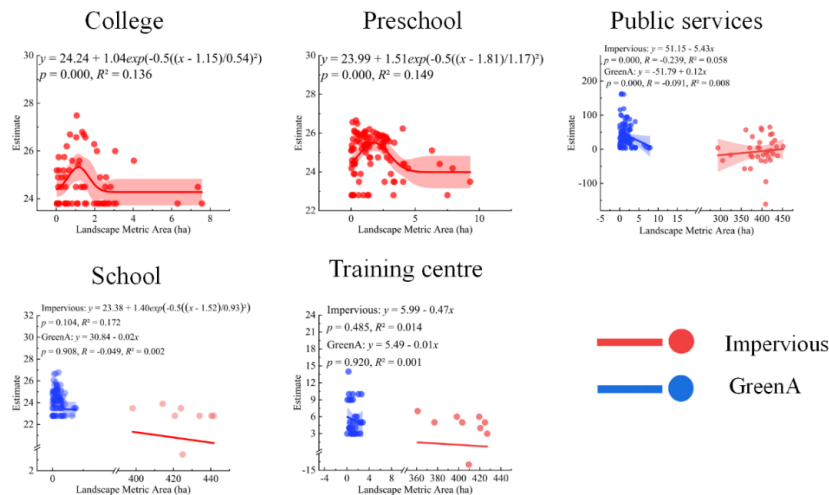


Figure 8. Correlations between landscape metric area (impervious land [impervious] and greenspace area [GreenA]) and parameter estimates analyzed by maximum likelihood models for five types of EIs

$R^2 = 0.008$). The number of schools exhibited negative correlations with estimates for both landscape types. There was no significant relationship between the number of training centers and impervious surfaces ($p = 0.485$, $R^2 = 0.014$) or green spaces ($p = 0.920$, $R^2 = 0.001$).

3.5. Spatial optimization scheme for EIs based on the quantity of retail outlets and road density

We employed the best regression fit function, based on retail quantity and road length, to predict the number of EIs within the six concentrated areas. We then calculated the difference between the predicted and actual values in each grid, categorizing these differences into seven intervals, each represented by a different color, as shown in Figures 9 and 10. Regarding the optimization scheme based on retail quantity, the grid differences for training centers tended to be close to zero (between -10 and 10); this is more consistent with the optimization scheme, suggesting that there may be rarefied space that needs to be optimized. The grid differences for public services showed

a significant number of negative values (between -30 and -11) and some positive values (between 11 and 30), indicating the largest deviation from the optimization scheme for overloaded EI numbers and the required number increment, respectively. The grid differences for the other three types of EIs mostly tended towards zero, with only a few deviating from the optimization scheme. In terms of the optimization scheme based on road density, the grid differences for the training centers tended to be close to zero, aligning more closely with the optimization scheme. The preschool and public services showed a significant number of negative and positive values, respectively, suggesting the largest deviation from the optimization scheme. The other two types of EIs exhibited smaller discrepancies with the optimization scheme. In addition, the addition of new educational facilities in some optimization scenarios may encroach on the existing green space, thus weakening the local cooling capacity. Overall, the optimization scheme based on road length showed a substantial deviation from the existing distribution of EIs in the city, whereas the optimization scheme based on retail quantity was closer to the current distribution of EIs.

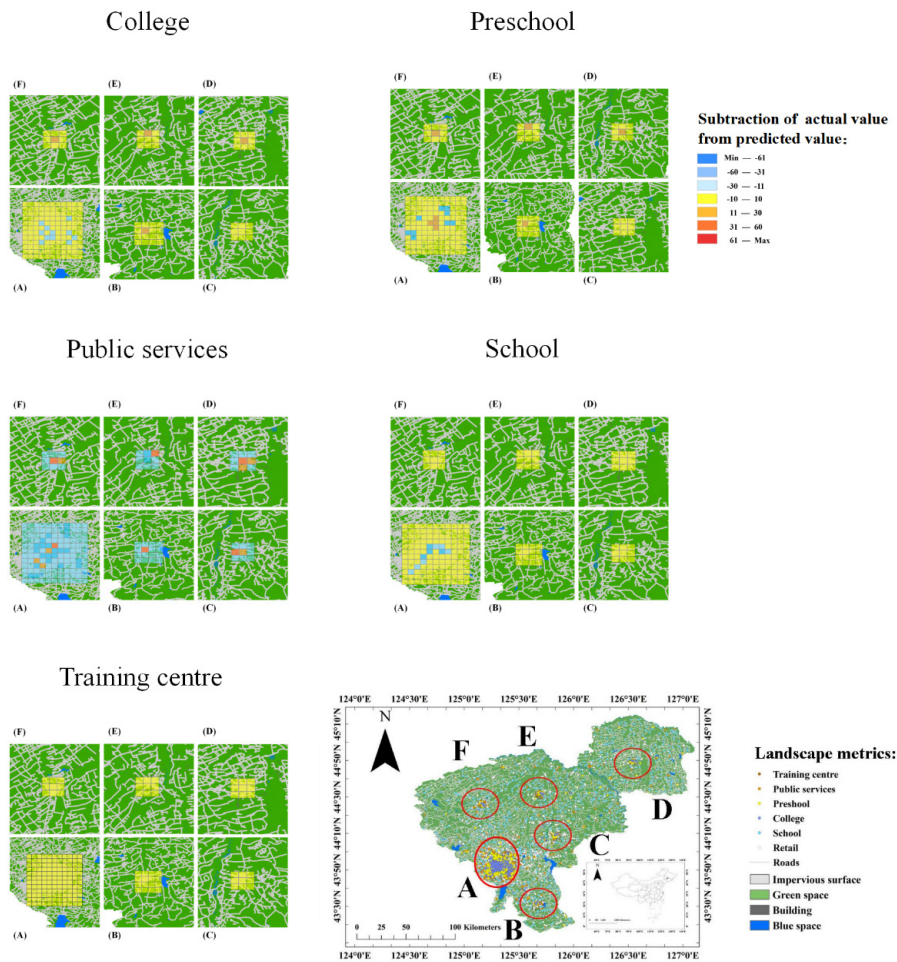


Figure 9. The optimization scheme is based on the retail quantity in the agglomerations of Changchun, Northeast China. This difference represents the difference between the predicted and actual values

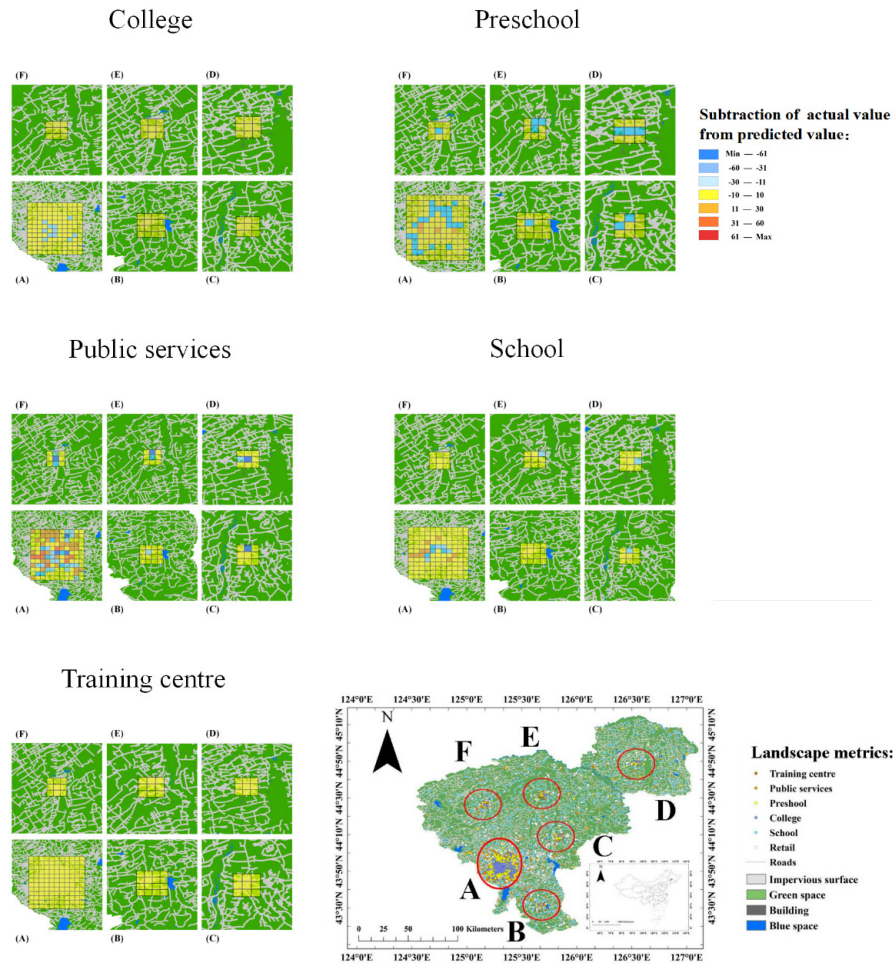


Figure 10. The optimization scheme was based on road densities in the agglomerations of Changchun, Northeast China. Difference represents the difference between predicted and actual values

4. Discussion

4.1. The distributions of retail shops

We assessed how factors, such as retail density and road connectivity, affect the potential number of EIs that can be effectively placed within an area, ensuring optimal accessibility and service to the population. Empirical studies indicated a positive relationship between the number of EIs and retail sales (Bader et al., 2013; Hanning et al., 2019). Concentrated students and faculty at EIs have common demands for goods and living services, which naturally attract and sustain the neighboring placement of various retailers. The microeconomic status and cultural atmosphere formed around EIs may influence the type of established retail (Dong, 2022). Retailers may also provide products and services to tailor customers to specific demographics. This results in different EIs fostering distinct demand-dependent retail ecosystems (Barr, 2005; McKenzie, 2008). In this study, places with a high number of retail shops tended to have more EIs. In our study, colleges were usually positioned at careless locations with rare commercial connections to surrounding retail shops, contrary to previous studies (Bader et al., 2013; Hanning

et al., 2019). Chinese colleges are usually constructed on land with a large area attached to a campus, which has the ability to place retailers that meet the basic needs of local students and faculty. EIs were more likely to be correlated with retail catering, because the operational times of these institutions usually contained times arranged for meals. Our results reveal more nuanced interactions, specifically regarding the relationship between EI and the diversity of surrounding retail establishments. It is not just a simple economic stimulus; instead, it may shape the local retail character.

4.2. Spatial distributions of EIs on different class roads

Road networks play a critical role in determining the accessibility and distribution of educational institutions (EIs). A well-developed road system ensures that EIs are accessible to a larger population, which in turn supports a more efficient and equitable placement of educational resources across urban areas. The connectivity provided by various classes of roads significantly affected the potential catchment area for each EI. A positive correlation was ob-

served between the number of EIs and different classes of roads. This suggests that an increased density of road infrastructure placement can support the proliferation of neighboring EIs. The six AOIs selected for this study were primarily situated in central urban or suburban locations, necessitating robust road connectivity to accommodate the commuting needs of the students and staff. There is a collective demand for students and faculty to be reliable in efficient transportation networks (Kang, 2016; Cui et al., 2022). Previous studies have predominantly confirmed the impact of road accessibility on students and staff within training schools (Lee & Kim, 2021; Patel et al., 2021); however, few have distinguished roads into four functional levels and considered all types of EIs. Our study emphasizes the important role of road infrastructure in supporting the growth in the number of various EIs.

4.3. EIs and urban landscape metrics

The impervious surface area exhibited a nonlinear relationship with its effect on the number of EIs. This was characterized by an initial increase followed by a decrease along with an increase in the impervious surface area. When the area of this urban landscape reached 1.2 hectares, the estimate met its maximum value. Extreme areas of built-up land (either too large or too small) may not be conducive to the growth and development of these two types of EIs. Urbanized areas usually have higher population densities, providing a larger potential student and staff base for EIs. Moreover, the developed transportation networks in urban areas make it easier for students and staff to visit EIs (Kang, 2016; Patel et al., 2021). Green space area showed a negative correlation with the number of public services. This is contrary to many research conclusions that have pointed out the positive role of urban landscapes (Li & Sullivan, 2016; Sajady et al., 2020; Zhao & Wang, 2022). Although greenspace areas may have a positive impact on improving students' learning efficiency and academic performance (Hodson & Sander, 2017; Zhang et al., 2022), their distribution in a city is not sufficient to determine the number of EIs on their own. Furthermore, the establishment of EI is irrelevant to the physical characteristics of urban landscapes. Landscape carrying capacity was positively correlated with road length. A high landscape carrying capacity tends to establish a more comprehensive road network, which is based on the geographic locations of EIs mentioned in the current literature (Kang, 2016; Patel et al., 2021). Previous studies have revealed the positive effects of urban landscapes on the establishment of EI (Wu & Ren, 2021; Wei et al., 2022; Zhao & Wang, 2022). Landscape carrying capacity also showed a positive correlation with the number of retail shops. Retail attracts traffic to potential customers for EIs, while EIs also provide feedback to retail customers and sales (Bader et al., 2013; Scully et al., 2013; Williams et al., 2015). Therefore, the impacts of urban landscape metrics cannot be ignored. In summary, this study reveals that the spatial configuration of educational institutions is shaped by the synergistic interaction be-

tween retail distribution, road hierarchy, and landscape carrying capacity. Specifically, retail density reflects demand clustering, indicating where educational services are most needed; road networks determine accessibility, influencing both service radius and commuting ease; and landscape metrics constrain the spatial supply side, reflecting where additional educational infrastructure can be sustainably accommodated. The proposed composite optimization framework integrates these three dimensions to generate practical siting scenarios.

4.4. Comparison of optimization solutions

For public services, retail optimization suggests that the current distribution of public services is not rational and could benefit from more public services synergizing with the surrounding retail. Public services can benefit from an increased number of services to leverage the advantages of dense road networks. Therefore, the following factors can be considered for increasing public services: the type of EI and its specific needs, demand for transportation and commercial services, and urban sustainability and eco-friendliness. A comprehensive analysis suggests that no single solution meets the needs of any type of EIs. In practical applications, a comprehensive optimization solution should first consider the holding capacities of both road networks and retail numbers. For instance, retail numbers might be more important for institutions reliant on family and student traffic, whereas road density is crucial for those needing good commuting. Additionally, the specific needs and goals of each area should be considered. More optimization solutions are suggested from the lens of sustainability, considering the long-term environmental impacts, traffic congestion, and carbon emissions. Considering the current conditions and allowing room for future changes, this flexible and customized approach is likely the most suitable. Facility layout based on spatial carrying capacity not only prevents resource overload but also enhances the environmental resilience of cities by limiting construction intensity.

4.5. Evaluation and prospects

Previous studies have often relied on data collected using conventional methods, such as surveys and interviews. This study overcomes these limitations by employing POI data in conjunction with advanced GIS technologies. This approach not only utilizes POI data as a static dataset but also as a dynamic tool for urban planning and optimization. This provides a new, objective, and efficient method for analyzing the spatial distribution and optimization needs of EIs. Previous studies have generally lacked a detailed understanding of the capacity of urban infrastructure to support EIs. By integrating POI data with spatial analyses of retail locations, road systems, and urban landscape metrics, this study offers a nuanced understanding of how various urban features affect the placement and success of EIs. Furthermore, earlier studies have typically speculated

on the relationship between environmental factors and the surrounding urban characteristics without strong empirical evidence. This study delivers concrete empirical findings demonstrating the correlation between the presence of EIs and the number of nearby retail outlets, road network density, and urban landscape metrics, filling a critical empirical gap in the literature.

However, this study had some limitations. Although POI data can provide rich information, they may have biases such as being outdated or not comprehensive, which could affect the accuracy of the analysis results. Moreover, the study did not fully consider the impact of socioeconomic factors on the distribution of EIs and optimization schemes.

It is worth noting that socioeconomic variables (e.g., population density, household income level), which may have a significant impact on the distribution of educational facilities, were not included in this study. Future studies may consider introducing such data and constructing multilevel models to further enhance the social responsiveness of site-selection predictions.

Future research could apply this study's framework to a broader urban context in order to enhance its applicability and relevance. Incorporating insights from fields such as environmental science and sociology could enrich future research and offer a more detailed understanding of the interplay between EIs and urban development. For optimization schemes, future research should consider more indicators affecting the distribution of EIs, such as community income levels, population density, and traffic accident data. In addition, developing targeted optimization schemes based on the specific needs of different cities and areas would address diverse urban environments more precisely. Additionally, environmental impact assessments must be integrated into optimization schemes to ensure sustainability and minimize negative environmental impacts. The layout of educational ventures should involve community surveys to collect residents' opinions, ensuring that optimization schemes meet community needs and gain community support. Finally, this study should guide cities in establishing systems that can dynamically adjust based on urban development and population changes, keeping optimization schemes flexible and adaptable.

5. Conclusions

Our study revealed that geographical information can be used to evaluate and optimize the spatial placement of urban infrastructure in terms of commercial-type-specific numbers against landscape holding capacity. An educational institution is a model type of public infrastructure that is limited to the neighboring holding capacities of transport and retail. In this study, we found that the placement of EIs relies heavily on sufficient neighboring retailers and convenient traffic transport. These two facets accounted for the EIs of public services held by neighboring green spaces and built-up areas. These geographical information

results were used for evaluation, which indicated that the current number of EIs providing public services was mostly excessive compared to those that should have been due to an overdraft of local retail supplies. The numbers of colleges and preschools were placed excessively over local road capacities, but the number of EIs providing public services and schools was insufficient compared to the desired numbers supported by road networks. The innovations of this study are mainly reflected in two aspects: firstly, it proposes a composite driving mechanism with "retail aggregation, road access and landscape carrying" as the core to comprehensively quantify the multidimensional logic of the optimal layout of educational facilities; secondly, it constructs a scenario-oriented spatial control path. Overall, more retail should be planned around EIs of public services, and more public services and schools are required.

Data availability statement

All data used in this study are derived from open sources. The POI data used in this study are freely available at <https://github.com/sample-poi-data>; the SinoLC-1 data are available by public request at <http://sinolc1.cn>.

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