UNRAVELING THE DYNAMICS OF URBAN CATERING

Analysing the Factors in Shaping Neighbourhood Restaurants Sceneries

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Abstract. This research explores the dynamics of neighbourhood restaurants distribution in Tianjin, China, against the backdrop of rapid urbanization and evolving consumer preferences. Analysing key factors such as consumer demand, transportation, location, built environment, and competition, the study utilizes count regression models to assess occurrence frequency. The investigation reveals a significant surge in community restaurants from 2018 to 2021, influencing spatial patterns. Population density, housing prices, transportation infrastructure, and built environment emerge as pivotal factors impacting neighbourhood restaurants dynamics. The Hurdle-NB model, considering both count and zero parts, demonstrates the best fit. This study contributes nuanced insights for policymakers and industry stakeholders, aiding in enhancing accessibility, sustainability, and competitiveness of neighbourhood restaurants in urban areas amidst changing urban dynamics and consumer trends.

Keywords. Urban Catering, Culinary Geography, Urban Dynamics Community Catering.

1. Introduction

The catering industry, a vital component of urban consumption economy, plays a crucial role in promoting consumption upgrades and economic growth. Rising national income levels in China elevate consumer demands for catering quality and personalized choices. The development of information network technology introduces new modes of catering establishments such as e-commerce and food delivery, while policies like the "15-minute convenient living circle" expand new dimensions for catering consumption services. (Wu et al., 2021). Traditional restaurants face both opportunities and challenges.

Scholars have explored changes in catering consumption under new environments. In the era of information technology, spatial aggregation and diffusion

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occur simultaneously in the catering industry (W.D Liu and Z. Feng, 2004, Graham, S, 1998). Scholars emphasize the strengthening concentration of catering enterprises in urban core areas and the formation of new clusters in peripheral areas due to online buying（Ren，F.，and M. P. Kwan.,2009; Shi et al., 2021）. While various studies delve into the spatial layout and trends of emerging catering models like food delivery, neighbourhood restaurants, a category closely related to consumers' daily lives with substantial potential, has received less attention. However, it has rapidly developed as a new growth hotspot, catering to the preferences and needs of community residents.

Neighbourhood catering establishments, primarily located in residential areas, have smaller consumption radii and are less impacted by new catering models like e-commerce and food delivery (Xv et al. 2019, Wu et al., 2021,). They exhibit significant commercial and social value, particularly in diverse and digitized consumer environments. Additionally, neighbourhood restaurants, with lower operating costs and flexible business models, demonstrated relative resilience during the pandemic, presenting growth opportunities (Liu et al, 2023). Existing research often integrates neighbourhood restaurants into overall community business studies (Liu T and Chai Y, 2015). Few studies specifically focus on the spatial distribution and influencing factors of neighbourhood restaurants outlets. Moreover, current research tends to involve qualitative analysis of macro factors, lacking sufficient quantitative analysis and dynamic analysis of neighbourhood restaurants development.

In recent years, Chinese governments have actively promoted the construction of convenient living circles, providing favourable opportunities and support for the deep integration of the catering industry into communities (Li M. 2017, Chai L, Li C., 2019). This study, using geospatial and quantitative data analysis, explores the distribution and changes of neighbourhood restaurants in Tianjin from 2019 to 2021. It investigates factors influencing the growth or decline of neighbourhood restaurants during this period. This research contributes to understanding the trends and influencing factors of neighbourhood restaurants, offering development strategies for urban policymakers, assisting restaurant operators in location decisions, and promoting the healthy development of neighbourhood restaurants.

2. Materials and Methods

2.1. STUDY AREA

Tianjin is one of China's most important economic hubs, which currently consists of 16 municipal districts, including 6 downtown districts. This paper focuses on the downtown area of Tianjin (as shown in Figure 1), which includes Heping District, Hexi District, Nankai District, Hedong District, Hebei District, and Hongqiao District, covering a total area of 301.9 square kilometres. The downtown area has a well-developed catering industry, with diverse food categories, service methods, and business formats. This has been instrumental in attracting tourists, driving the economy, and improving the city's overall image. Additionally, the area has a highly developed residential area and covers most of the population in Tianjin.

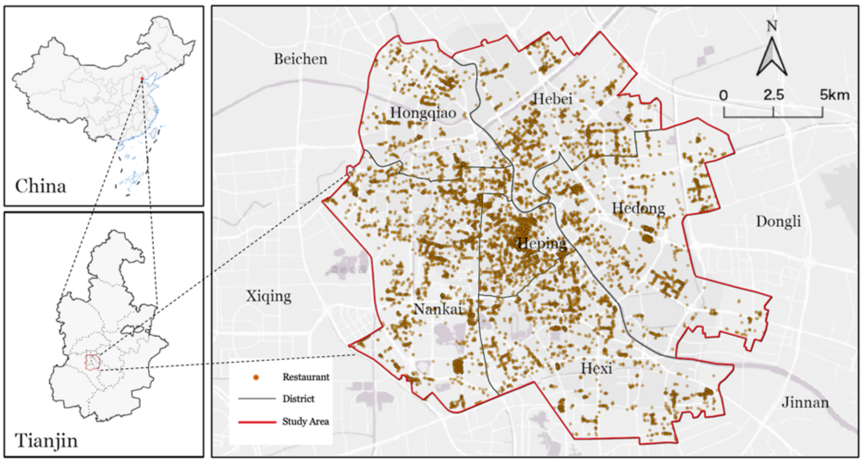

Figure 1. Study Area

2.2. DATA SOURCES

The research utilized road network, POI, and Dianping data. Road network data were sourced from the National Geographic Information Public Service Platform. POI data, extracted from Baidu Map and Amap, included information on community entrances, bus and subway stations, and commercial facilities. Dianping data for 2018 and 2021 from six Tianjin districts comprised 21,465 and 26,297 entries, respectively, encompassing review numbers(x1), per capita consumption(x2), taste(x3) , environment scores(x4) service ratings(x5),and distance to the nearest mall(x6). To highlight neighbourhood restaurants' proximity, outlets within 500m of community entrances were selected, resulting in 21,465 (2018) and 26,297 (2021) entries. Standardizing data and employing K-means clustering produced 10,357 (2018) and 12,252 (2021) items, revealing two neighbourhood restaurant types significantly closer to large malls than other clusters.

Table 1. Neighbourhood restaurants Clustering Results

Cluster	Year	Group Size	x1	x2	x3	x4	x5	x6
1	2018	1445	336.2	43.6	8.2	8.2	8.2	71.2
	2021	1666	392.3	47.4	9.1	9.1	9.1	107.6
2	2018	1730	80.5	33.5	7.2	7.2	7.2	120.3
	2021	2056	128.2	33.9	7.6	7.5	7.5	146.5
3	2018	1361	1795.4	89.3	8.8	8.8	8.8	130.4
	2021	1452	2569.1	102.9	9.5	9.5	9.5	167.3
4	2018	1290	306.2	49.0	7.6	7.5	7.5	312.7
	2021	1778	407.8	51.5	8.4	8.1	8.2	366.3
5	2018	1515	467.4	65.2	8.5	8.5	8.5	782.1
	2021	1729	544.2	71.2	9.2	9.1	9.1	804.7

6	2018	3016	93.1	30.6	7.4	7.3	7.3	818.7
	2021	3571	124.9	37.0	7.6	7.5	7.5	834.8

Identifying five pivotal factors—consumer demand, transportation, location, built environment, and competition—that influence the distribution of neighbourhood restaurants in Tianjin, this study employs population density and housing prices to assess consumer demand, aligning with the consumption saturation index theory. Enhancing public transportation improves convenience, positively impacting neighbourhood restaurants (Lin et al., 2018). In the analysis of transportation, three variables—subway stations, bus stations, and road network density—were selected. The distribution of surrounding facilities (public, leisure, entertainment, and cultural) significantly influences the agglomeration of the catering industry. Considering the built environment, the study evaluates building capacity (floor space index and floor area ratio) and road form, measured by proximity and linear centrality indicators. The degree of restaurant competition is assessed by including the base of neighbourhood restaurants in the regression analysis of new and decreased establishments (Olvera & Sutton, 2020). Additionally, the study explores the impact of the business district on neighbourhood restaurants by calculating the distance between plot centers and surrounding large shopping malls.

To establish a comprehensive analysis, this study employs a 300m side-length square grid covering the entire study area as a statistical unit. This grid serves for computing the density of the catering industry and other relevant indicators. The analysis includes calculations of the increase or decrease in catering establishments for each grid, streamlining data processing and variable summarization. This approach enhances the ability to capture the heterogeneity of neighbourhood restaurants distribution within each locality.

3. Methods

Count regression models are crucial for analysing factors influencing occurrence frequency over a specific period or area. Given the non-negative integer nature of neighbourhood restaurants data, this study employs four count regression models: Poisson, Negative Binomial (NB), Zero-Inflated Negative Binomial (ZINB), and Generalized Poisson Hurdle.

The Poisson model is fitting for situations with equal mean and variance, described by a probability mass function:

$$P(Y = y; \lambda) = \exp(-\lambda) * (\lambda^{\wedge}y) / y! \quad (1).$$

However, real-world data often exhibit over-dispersion, leading to the application of the Negative Binomial model, addressing this issue with a shape parameter

$$\lambda = \exp(\beta_0 + \beta^T x) \ (2)$$

To handle excess zeros, Zero-Inflated Negative Binomial and Generalized Poisson

Hurdle models were employed. The Hurdle model combines a zero-truncated NB component for positive counts and a logit barrier for zero counts:

$$P(Y = y; \mu, \theta) = (\Gamma(y + \theta) / (\Gamma(\theta) * y!)) * ((\mu / (\mu + \theta))^y) * ((\theta / (\mu + \theta))^\theta) \quad (3).$$

Moreover, for insights into restaurant changes, an offset term was included in the regression model's intensity parameter:

$$P(X = k) = (1 - \pi) * \delta(k, 0) + \pi * (1 - \theta) * (\theta^k * \exp(-\theta)) / (1 - \exp(-\theta))^2 \quad (4).$$

This allows modeling the increase/decrease ratio as the exponential function of a linear combination of factors:

$$P(Y = y; \alpha, \beta, \gamma) = \{ (1 - \pi) * f(y; \alpha, \beta), \text{ if } y > 0\ \pi * g(0; \alpha, \gamma), \text{ if } y = 0 \} \quad (5).$$

4. Evaluation and Results

4.1. NEIGHBORHOOD RESTAURANTS SPACE DISTRIBUTION PATTERN

Over the study period (2018 to 2021), the number of community restaurants in Tianjin surged from 10,932 to 15,396, marking a notable 40.8% increase (figure 2). This growth aligns with the upward trajectory observed in the number of designated-size catering seats, which rose by 51% from 2018 to 2021, as reported in the Tianjin Statistical Yearbook. This expansion occurred alongside a stable resident population of 13.83 million in 2018 and 13.73 million in 2021, contributing to enhanced dining convenience for residents.

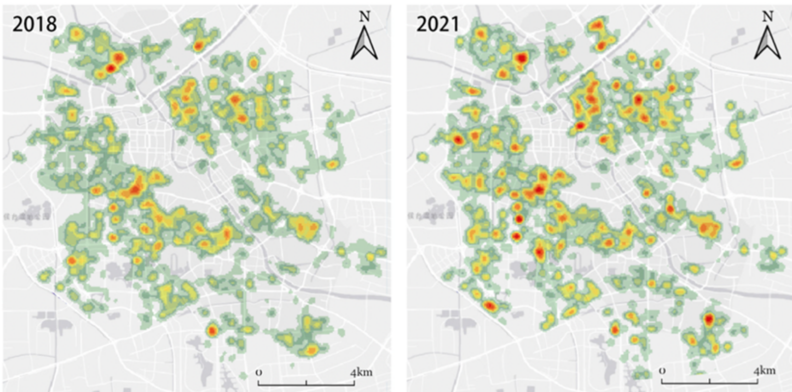

Figure 2. Neighbourhood Restaurant Kernel Desntity between 2018-2021

The spatial distribution pattern of neighbourhood restaurants remained consistent between 2018 and 2021, with a noteworthy increase in high-value areas for neighbourhood restaurants in 2021. Particularly, more high-value areas emerged in communities near the city's periphery. In 2018, high-value neighbourhood restaurants areas were concentrated in mature, large-scale residential zones like Zhongshanmen, Wangchuanchang, Dingzigu, and Wanxing neighborhoods, displaying a patchy distribution. In 2021, these mature communities sustained high-density neighbourhood restaurants, while newer residential areas, such as Chentangzhuang, Tiedong Road, and Huayuan, also exhibited robust development, unveiling numerous new hot spots. Consequently, the overall density of neighbourhood restaurants significantly increased across most neighbourhoods in the city.

4.2. DYNACMICS OF NEIGHBORHOOD RESTAURANTS DISTRIBUTION

Analysing grid statistics reveals notable shifts in neighbourhood restaurants across central Tianjin. The data indicates a substantial increase in neighbourhood restaurants across 966 grids, outnumbering the 488 grids where a decrease is observed, with 178 grids showing no change. While the spatial distribution of increased and decreased community restaurants doesn't perfectly align, the increasing trend generally corresponds with high-value areas, particularly evident along Hongqi South Road near the city's edge (Figure 3A).

Despite this overall competitive landscape, variations in the increase or decrease of neighbourhood restaurants are considerable among different communities. The proportions of increases and decreases, along with spatial autocorrelation results, exhibit a more regular distribution than mere quantity. Grids with higher growth rates in neighbourhood restaurants are primarily located at the city's periphery, notably in the west and south, including areas like Wangdingdi, Huayuan, Meijiang, and high-rise residential areas such as Fuxingmen(Figure 3B).

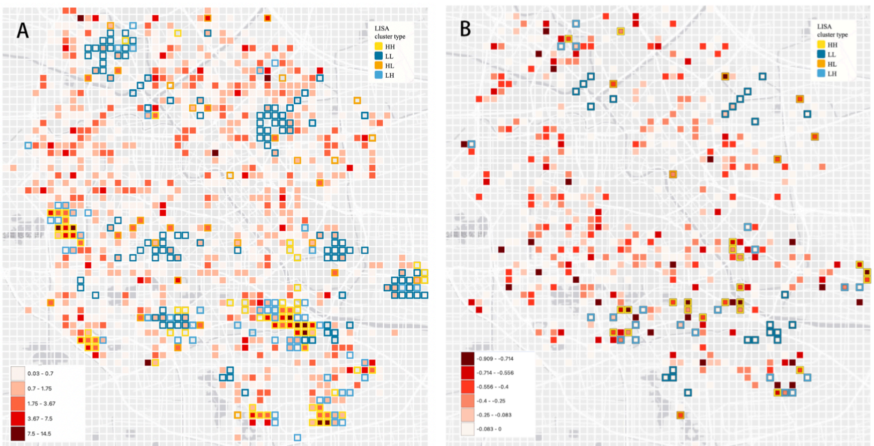

Figure 3. Growth Rate & Decrease Rate of Neighbourhood Restaurants between 2018-2021

Conversely, mature communities with a dense distribution of neighbourhood restaurants, such as Zhongshanmen, Wangchuanchang, Dingzigu, and Wanxing, experience smaller growth rates, indicating market saturation. Areas with decreasing amplitude display a more dispersed pattern than increasing amplitude, suggesting lower aggregation characteristics. High- and low-value agglomeration areas with reduction rates are concentrated in urban fringe areas, while neighbourhood restaurants within urban areas remains relatively stable.

It's noteworthy that most low-value agglomeration areas experiencing a decline in neighbourhood restaurants have a historically low number of community establishments. For example, in areas like Beiyunhe River and Lushan Road, neighbourhood restaurants remain consistently at a low level. The spatial differentiation in the distribution and fluctuations of neighbourhood restaurants underscores significant spatial layout differences. A comprehensive analysis beyond quantity and spatial description necessitates the establishment of an indicator system for influencing factors to further understand the influencing mechanism of spatial distribution and fluctuations in neighbourhood restaurants within central urban areas in Tianjin.

5. Analysis of Influence Factors

5.1. FACTORS INFLUENCING NEIGHBORHOOD RESTAURANTS DISTRIBUTION

The pseudo R-squares for the Poisson, Negative Binomial (NB), Zero-Inflated Negative Binomial (ZINB), and Hurdle Negative Binomial (Hurdle-NB) models all exceed 0.6, indicating a robust model fit. Notably, the Hurdle-NB model, considering both count and zero parts, achieves the lowest AIC value, demonstrating the best overall fit.

The regression outcomes reveal key factors impacting neighbourhood restaurants distribution. Across all models, population density consistently exerts a positive influence, while housing prices exhibit a negative impact, likely due to increased commercial costs in high-priced areas. Transportation emerges as a crucial factor, with bus stops and road network density showing positive associations, suggesting that convenient transportation attracts patrons, fostering demand for neighbourhood restaurants. Educational and public cultural facilities positively contribute to neighbourhood restaurants density, whereas business office facilities have a negative impact. Higher building coverage and floor area ratio positively correlate with the number of community restaurants, while local road characteristics significantly impact density.

Interestingly, the establishment year of a community demonstrates a negative correlation with restaurant numbers, suggesting that older communities with stable ecosystems tend to accumulate more dining facilities. These findings provide valuable insights into the determinants of neighbourhood restaurants distribution, enhancing our understanding of these patterns.

Table 2. Regression Results For Distribution of Neighbourhood Restaurants Establishments in 2018

Variable properties	Poisson	NB	ZINB	Hurdle-NB
(intercept)	1.7886***	1.7473***	1.7607***	1.6995***
Population density	0.1126***	0.1504***	0.1672***	0.1662***
House Price	-0.025*	-0.087*	-0.094*	-0.083*
Subway station	0.0056	0.0463+	0.0368	0.0493
Bus Station	0.1302***	0.1382***	0.1349***	0.119***
Road Density	0.1859***	0.1746***	0.1721***	0.1851***
Educational Facility	0.1503***	0.1615***	0.1621***	0.1644***
Medical Facilities	0.018**	0.0158	0.0112	0.008
Cultural Facilities	0.3015***	0.3699***	0.3735***	0.3841***
Office Buildings	-0.184***	-0.154***	-0.131***	-0.144***
FAR	0.191***	0.2708***	0.3041***	0.2908***
FSI	0.2083***	0.1764***	0.1487***	0.1852***
Malls	-0.002	-0.022	-0.032	-0.038
Built Year	-0.133***	-0.143***	-0.127***	-0.118**
AIC	14761	9099.4	9056.8	9095.3
PseudoR2	0.387	0.3641	0.4156	0.3788
LogLik	-7363	-4532	-4493	-4513
Only counting part are shown above				

5.2. FACTORS INFLUENCING THE INCREASE OF NEIGHBORHOOD RESTAURANTS

The regression analysis results provide insights into the predictive performance of different models for neighbourhood restaurants growth proportion. Notably, the Hurdle-NB model outperforms others, displaying the lowest AIC value and the highest pseudo-R square. This indicates that the model achieves optimal fitting and possesses substantial explanatory power.

Across all models, population density emerges as a significant driver with a positive impact on neighbourhood restaurants growth. Higher population density correlates with a swifter expansion of the neighbourhood restaurants industry, likely due to increased demand that attracts more restaurants.

Building coverage also plays a crucial role, positively influencing neighbourhood restaurants growth. Increased building coverage translates to more commercial space, presenting catering companies with additional opportunities to establish a presence within the community and expand their business scale. Interestingly, the impact of floor area ratio on neighbourhood restaurants growth is not statistically significant, possibly because community restaurants, predominantly situated on the ground floor, are more closely associated with building coverage.

Despite neighbourhood restaurants establishments not being in business districts, proximity to such districts positively influences the growth of neighbourhood restaurants. Communities near commercial centres or prosperous areas are more likely to attract customers and business opportunities, fostering the expansion of the neighbourhood restaurants industry. The year a community was built also exhibits a positive correlation with the growth of neighbourhood restaurants. Newer communities are inclined to offer more business opportunities, thereby stimulating the development of the neighbourhood restaurants sector. The significant positive correlation between the neighbourhood restaurants base and neighbourhood restaurants growth highlights the aggregative characteristics of neighbourhood restaurants expansion.

6. Results

In conclusion, this study sheds light on the intricate dynamics of neighbourhood restaurants distribution in Tianjin, emphasizing the pivotal role played by various factors. The comprehensive analysis encompassed consumer demand, transportation, location, built environment, and competition, providing a holistic understanding of the forces shaping the neighbourhood restaurants landscape.

The spatial distribution pattern of neighbourhood restaurants remained consistent between 2018 and 2021, with a notable surge in high-value areas in 2021, particularly in communities near the city's periphery. The study highlighted the impact of population density, housing prices, transportation infrastructure, and the built environment on neighbourhood restaurants dynamics. Notably, the findings indicated that older communities with stable ecosystems tend to accumulate more dining facilities.

The application of count regression models, including Poisson, Negative Binomial, Zero-Inflated Negative Binomial, and Generalized Poisson Hurdle, provided a robust framework for analysing factors influencing neighbourhood restaurants occurrence frequency. The Hurdle-NB model exhibited the best overall fit, indicating its effectiveness in capturing the complexities of the data.

Evaluation and results revealed that population density consistently exerted a positive influence on neighbourhood restaurants distribution, while housing prices had a negative impact. Transportation, educational and public cultural facilities, and the built environment were also identified as crucial factors. Moreover, the study delved into the factors influencing the increase of neighbourhood restaurants, with population density, building coverage, proximity to business districts, and the establishment year of a community emerging as significant drivers.

In essence, this research contributes valuable insights into the determinants of neighbourhood restaurants distribution and growth, offering a nuanced understanding of the spatial layout differences and influencing mechanisms within central urban areas in Tianjin. Policymakers, urban planners, and industry stakeholders can leverage these findings to make informed decisions that enhance the accessibility, sustainability, and competitiveness of neighbourhood restaurants in the region.

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