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The Analysis of Spatial Distribution of Tourist Accommodation in Chiang Mai City

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ABSTRACT

This study examines the spatial distribution patterns and factors influencing the density of three tourist accommodation types in Chiang Mai City: hotels, non-hotels (e.g., small accommodations such as hostels and guesthouses), and Airbnb rentals. Spatial distribution patterns were analyzed using Moran's I index, while factors influencing accommodation density were evaluated through spatial regression analysis. The findings indicated significant clustering and overlap among all types of tourist accommodations within the city center, with hotels and non-hotels exhibiting particularly high concentrations. Airbnb rentals were more geographically dispersed across the city than hotels and non-hotels but still showed a notable concentration within the city center. Key factors influencing hotel density included proximity to popular tourist attractions and location within the old city area. In contrast, the density of Airbnb accommodation was more strongly associated with the presence of tourism-related services and facilities, such as shopping malls and cafes. These findings underscore the importance of integrating the distinct spatial patterns of various accommodation types into future planning and zoning policies. Such an approach is crucial for effectively regulating urban tourism expansion, mitigating the adverse impacts of overtourism, and preserving the local community's well-being and quality of life.

Keywords: Spatial analysis, tourism, tourist accommodation, Chiang Mai City, Airbnb

Introduction

Tourism has increasingly driven economic growth in cities worldwide, catalyzing urban development and altering land-use patterns. As a consumption-based activity with a complex supply chain—including food, lodging, transportation, and retail—tourism significantly impacts local economies and spatial dynamics (Gotham, 2005). Rapid tourism growth can transform urban physical, economic, and social landscapes, affecting local residents in areas where tourism overlaps with residential zones.

Accommodations play a crucial role in shaping urban tourism (Arbel & Pizam, 1977; Shabrina, Buyuklieva, & Ng, 2021) and have expanded rapidly, particularly in the era of the platform economy (Cerezo-Medina et al., 2022). Platforms such as Airbnb and Booking facilitate the conversion of residential properties into short-term rentals, creating new revenue streams but often operating outside formal regulatory frameworks (Guttentag & Smith, 2017), unlike hotels that are under regulations. Platform-based rentals tend to increase the overlap between residential and tourist spaces, which can impact housing markets, neighborhood dynamics, and resident-tourist relations. (Almeida, Oliveira, & Silva, 2021). In response, several major tourist destinations worldwide, such as Barcelona, Berlin, New York, Paris, and

London, have implemented regulatory frameworks to manage the expansion and impacts of Airbnb (Nieuwland & van Melik, 2020).

Thailand has long been renowned for its tourism, with major cities such as Bangkok, Phuket, and Chiang Mai recognized as global tourist destinations. In recent years, the short-term rental market has grown rapidly in Thailand, and cities such as Bangkok and Chiang Mai demonstrate significant potential for expansion in this market (AirDNA, 2024b). However, this expansion has increasingly contributed to displacement pressures, particularly in areas with high tourism intensity. Despite these challenges, tourist cities in Thailand lack comprehensive legislation to govern short-term rental activities effectively.

A notable gap exists in the literature regarding the spatial effects of tourist accommodations in Thai urban contexts, as existing studies predominantly focus on the location of traditional accommodations (Nathiwutthikun, 2018; Sangkaew & Phucharoen, 2018). The spatial effects of short-term rental expansion remain underexplored, particularly in Chiang Mai, a major tourist destination experiencing significant growth in Airbnb rentals and an influx of Chinese tourists over the past decade.

Therefore, this study aims to 1) analyze the spatial distribution patterns of three types of tourist accommodation in Chiang Mai City—namely hotels, non-hotels (small accommodations such as hostels and guesthouses), and Airbnb rentals; and 2) examine the spatial factors influencing the distribution of these accommodations. Findings from this study will contribute to urban planning and land-use management, offering insights to better address the impacts of tourism industry growth and mitigate adverse effects on the quality of life for local residents.

Literature review

The literature review was divided into two main sections: 1) spatial patterns of tourist accommodation and 2) factors influencing the density of tourist accommodation.

Spatial patterns of tourist accommodation

Location is a critical factor in analyzing urban economic phenomena (Bárcena-Ruiz et al., 2020). Tobler's First Law of Geography stated that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Spatial effects can be categorized as follows: 1) spatial heterogeneity, which refers to structural variations across different areas such as urban-rural, or urban hierarchy; and 2) spatial dependence, which refer to systematic variation that results in observable clusters or a systematic spatial pattern, as observed in housing markets where properties nearby tend to exhibit similar prices or characteristics (Florax & Nijkamp, 2005). The accommodation sector is crucial to the tourism industry (Arbel & Pizam, 1977; Shabrina et al., 2021) and includes a range of accommodation types, from formal options such as hotels and hostels to informal types, such as accommodations via platform. The spatial distribution and density of these accommodations can significantly affect urban land use patterns.

Hotels, as formal accommodations, have tended to locate strategically, often forming spatial clusters (Fang, Xie, Yao, & Liu, 2020; Shoval, McKercher, Ng, & Birenboim, 2011; Valenzuela-Ortiz, Chica-Olmo, & Castañeda, 2022) that benefit from agglomeration effects, which improve productivity and market demand through shared market space (Canina, Enz, & Harrison, 2005; Chung & Kalnins, 2001; Cró & Martins, 2018). These clusters allow diverse hotels with unique features to attract a broader clientele (Urtasun & Gutiérrez, 2006). Consequently, hotels are typically situated in high-demand areas, such as central business districts or tourist centers, which offer diverse amenities, accessibility, and convenience for visitors (Li, Fang, Huang, & Goha, 2014). Furthermore, tourists are often willing to pay a premium for centrally located hotels, which offer easy access to city attractions and reduce uncertainties related to navigation (Shoval, 2006). Location thus plays a vital role in the profitability of hotels (Lado-Sestayo, Vivel-Búa, & Otero-González, 2020).

In the era of the digital economy, accommodations are no longer limited to formal establishments. Digital platforms, such as Airbnb, have facilitated and transformed residential properties into short-term rentals, creating new rent gaps through the utilization of technological and cultural mechanisms (Wachsmuth & Weisler, 2018). This process involves the reallocation of long-term housing units to serve as tourist accommodations, driven by property owners' pursuit of greater flexibility and profit margins through short-term rental arrangements (Cocola-Gant & Gago, 2021). This trend has led to an uneven distribution of short-term rentals across cities (Franco & Santos, 2021; Grisdale, 2021; A. Gutiérrez & Domènech, 2020) and has widened tourist behavior and reach to less-visited urban and rural areas (Tussyadiah & Pesonen, 2016), expanding the tourism boundary and potentially transforming neighborhoods (Ioannides, Röslmaier, & van der Zee, 2019).

Existing studies on the spatial patterns of tourist accommodations focus on cities in Western contexts and China. In the Thai context, research exploring the spatial effects of tourist accommodations remains limited. The majority of existing studies have centered on the location of traditional accommodations (Nathiwutthikun, 2018; Sangkaew & Phucharoen, 2018). However, the spatial effects of platform-based accommodations, such as Airbnb, remain significantly underexplored. The research in this issue primarily examined the characteristics and situation of Airbnb accommodations (Khotcharee & Fukushima, 2022). This indicates a significant research gap in understanding the spatial effects of platform-based accommodations within the Thai context.

Factors influencing the density of tourist accommodation

The location also affects the success of tourist accommodation businesses (Yang & Mao, 2020), with different areas offering varying location advantages that influence tourists' accommodation choices (Caldeira & Kastenholz, 2017). Earlier studies found several factors influencing accommodation density in urban tourism.

Accessibility to attractions is a significant factor, as most tourist accommodations are located in areas with easy access to main city attractions. Hotels are usually near major roads and landmarks (Yang & Mao, 2020; Yang, Wong, & Wang, 2012), while platform-based accommodations may cluster around neighborhood-level attractions such as museums, theaters, parks, and universities (Xu, Hu, La, Wang, & Huang, 2020; Yang & Mao, 2019). Previous studies indicated that short-term rentals tend to cluster in city centers and near tourist amenities, with density decreasing with distance (Ioannides et al., 2019; Lagonigro, Martori, & Apparicio, 2020). Furthermore, these rentals are often found in areas with convenient transportation access (Xu et al., 2020).

The neighborhood environment also influences accommodation distribution, especially platform-based rentals such as Airbnb. For example, in the case of Barcelona, Lagonigro et al. (2020) indicated that neighborhood income, education levels, and household sizes are primary determinants of Airbnb density, with varying effects across different communities. Additionally, factors such as coastal proximity and hotel room availability have positive associations with Airbnb density (Adamiak, Szyda, Dubownik, & Álvarez, 2019), while higher tourist numbers, local hotel rates, self-employment rates, and housing costs encourage Airbnb listings. Conversely, larger average household sizes reduce Airbnb supply (Yang & Mao, 2020).

Other factors, such as market conditions and competition, also affect accommodation density. High clustering may foster productivity and demand through positive externalities, but it may also increase competition (Yang & Mao, 2020). Regulations likewise impact accommodation density (Cró & Martins, 2018). Hotels, for instance, are often subject to strict zoning regulations, clustering in commercial districts under top-down urban planning, while short-term rentals expand more flexibly by repurposing existing residential properties (Wen et al., 2023; Zervas, Proserpio, & Byers, 2017).

This review highlights how both formal and informal accommodation types contribute to urban spatial transformations, revealing multifaceted interactions between location, accessibility, neighborhood traits, and regulatory contexts.

Research method

Step 1: Research framework

1.1 Unit and framework of analysis

The unit of analysis in this study is tourist accommodation, divided into three types: *1) Hotels* are formal, commercial establishments that provide temporary lodging to travelers for a fee, regulated by hospitality industry standards; *2) Non-hotel accommodations* include small, licensed properties such as hostels and guesthouses, limited to 8 rooms or a maximum capacity of 30 guests, offering basic lodging with fewer services; and *3) Platform-based rentals* are unregistered short-term accommodations, typically residential properties repurposed for tourists via digital platforms. This study focuses specifically on Airbnb listings, standing for informal market impacts on urban housing and tourism. These categories reflect the varied accommodation landscape, which is critical to understanding their spatial effects and urban impacts within the tourism sector.

This analysis aims to examine the distribution patterns and density determinants of three types of tourist accommodations—hotels, non-hotels, and Airbnb. The analysis is structured in two parts: 1) spatial autocorrelation analysis to identify distribution patterns of each accommodation type, and 2) spatial regression analysis to determine spatial factors influencing the distribution of each accommodation type. The analytical framework is illustrated in Figure. 1

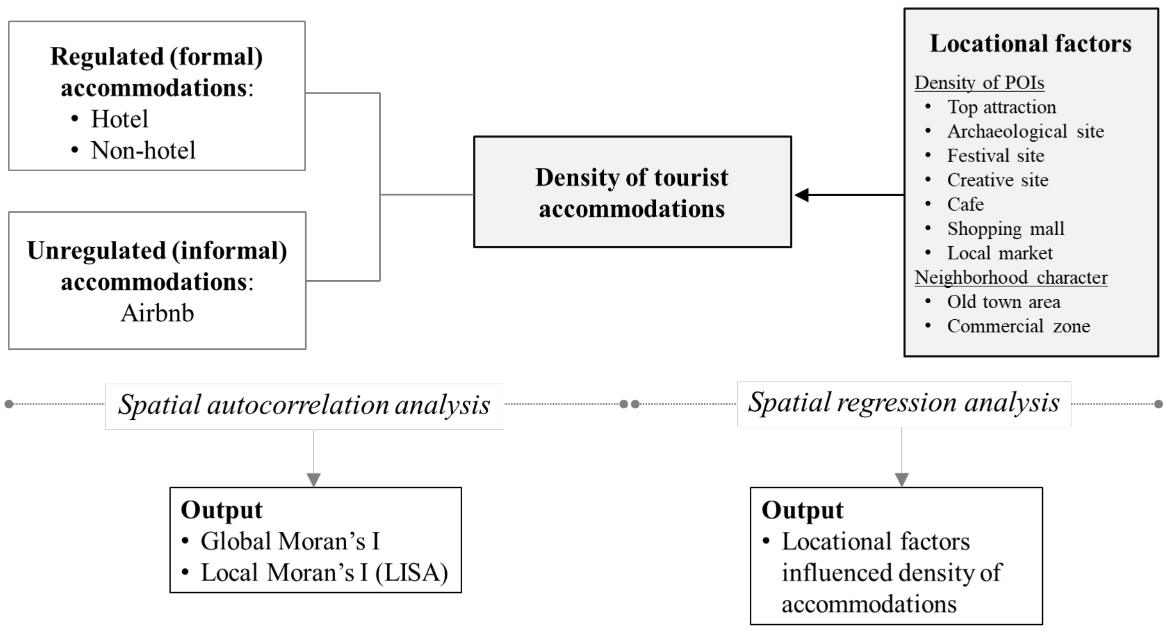


Figure. 1 Analytical framework

1.2 Study area

The study area is Chiang Mai City, a globally recognized tourism destination known for its cultural heritage, with the historic old town at its core. This area is surrounded by key economic districts and tourist attractions. Chiang Mai City spans 154.95 km² across 16 sub-districts, with a population of approximately 223,000 people (see Figure. 2 for the study area boundary).

In the past decade, Chinese tourists have significantly affected both the local tourism industry and urban land use. While Thai tourists are still predominant, the rapid increase in Chinese visitors has shifted demand patterns, elevating the proportion of international tourists. Chinese tourists are concentrated in the old town and modern areas such as Nimmanhaemin, Maya Mall, and Chiang Mai University (Pongpatcharatrontep, 2019). This growth has also attracted Chinese investment in local tourism-related businesses, including accommodations, restaurants, and retail, driving further urban transformation.

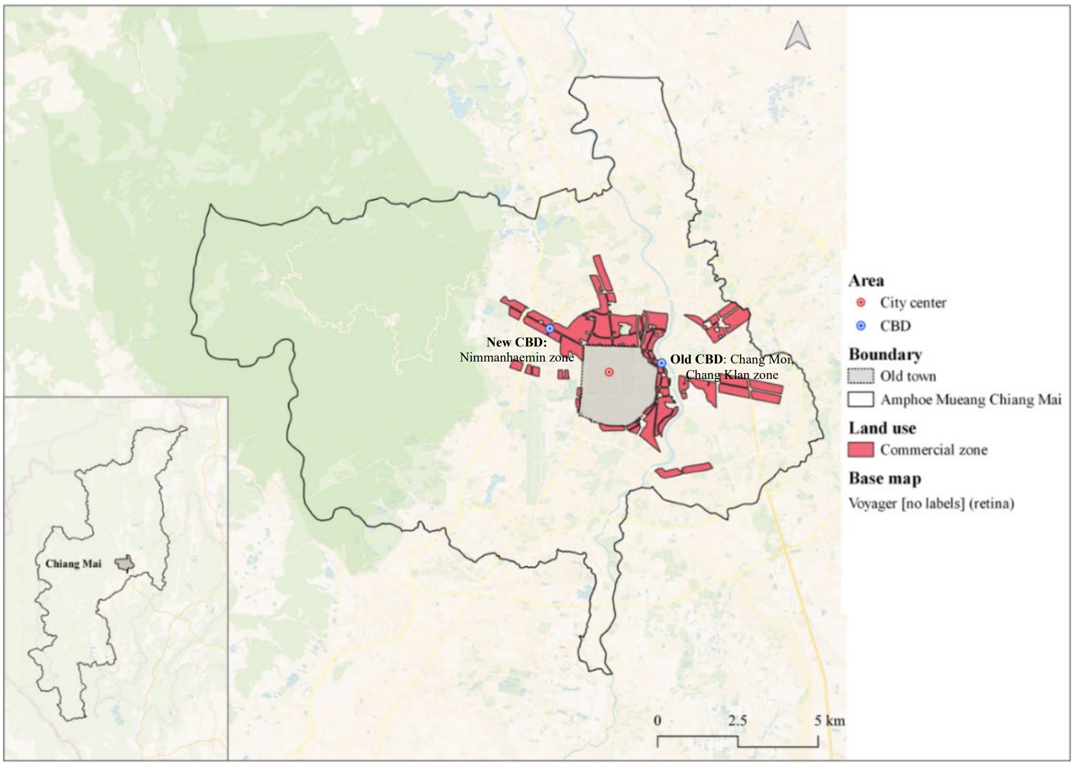


Figure. 2 Study area

Step 2 Data collection and descriptive statistics

2.1 Tourist accommodations

This study collected data on tourist accommodations from two sources. Official accommodation data, including hotels and non-hotel establishments, were obtained from the Department of Provincial Administration (DOPA), Ministry of the Interior. Informal accommodation data, specifically reflecting Airbnb listings, were sourced from AirDNA, which provided detailed information on Airbnb properties, including their locations within the Mueang Chiang Mai district (Table 1).

Table 1 Number of place and bedroom for tourist accommodation

Accommodation type	Place	Bedroom	Data source
Hotel	657	32,033	DOPA (2024a)
Non-hotel	451	1,640	DOPA (2024b)
Airbnb listing	6,002	9,668	AirDNA (2024a)

The study area was divided into 500m-by-500m grids to analyze the distribution and density of tourist accommodations. The grid size, determined based on an acceptable walking distance, was adopted following the methodology of Sun, Wang, and Hu (2022) for analyzing Airbnb distribution in Suzhou, China. This approach was considered suitable for the present study, given the comparable characteristics of Chiang Mai, which, similar to Suzhou, is characterized as an old town city and a walkable urban layout. A total of 818 grids were created within Mueang Chiang Mai district. However, areas within the Doi Suthep-Pui National Park in the Suthep, Chang Phueak, and Mae Hia sub-districts were excluded. This results in 560 grids for the analysis of urban land use and accommodation patterns, as shown in Figure. 3. Based on the analysis approach outlined above, the descriptive data of each accommodation type is presented in Table 2.

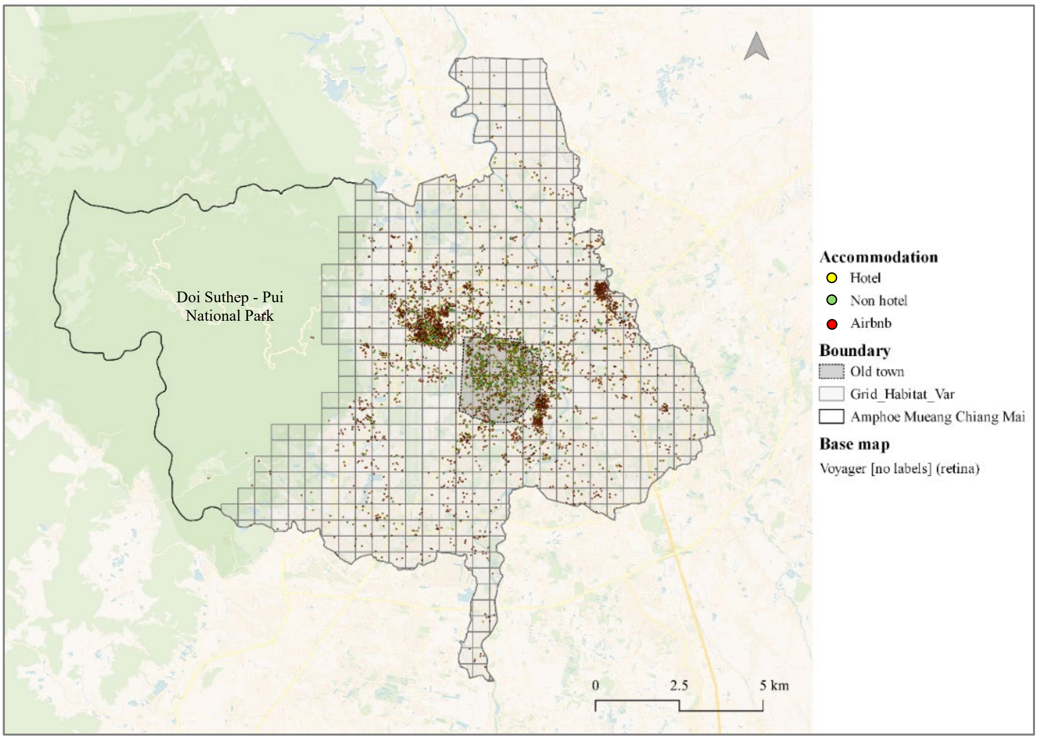


Figure. 3 Study area divided by grid size 500m by 500m

Table 2 Descriptive statistics of tourist accommodations

Grid	Hotel		Non-hotel		Airbnb	
	Place	Bedroom	Place	Bedroom	Listing	Bedroom
Number of grids	560	560	560	560	560	560
Minimum in grid	0	0	0	0	0	0
Maximum in grid	31	1,610	26	102	442	576
Mean	1.17	57.15	0.80	2.93	10.70	17.24
Standard Deviation (SD)	3.32	169.31	2.95	11.04	36.42	51.08
Coefficient of variation (CV)	277.25	296.26	368.22	376.89	340.30	296.24
Sum	656	32,003	451	1,640	5,994	9,656

Figure. 4 illustrates the density of accommodation by room count. Hotels are most concentrated in the old city and central business district (CBD), particularly along Nimmanhaemin and Chang Klan roads, with grids having over 200 rooms. Non-hotels are concentrated in the old city but with lower densities and more limited spread. Airbnb properties show high density along Nimmanhaemin Road, but are dispersed across the city, often overlapping with traditional accommodations. Despite an average of 17 rooms per grid, Airbnb's presence reflects a shift towards short-term rentals in residential areas, particularly as long-term housing is converted for tourist use.

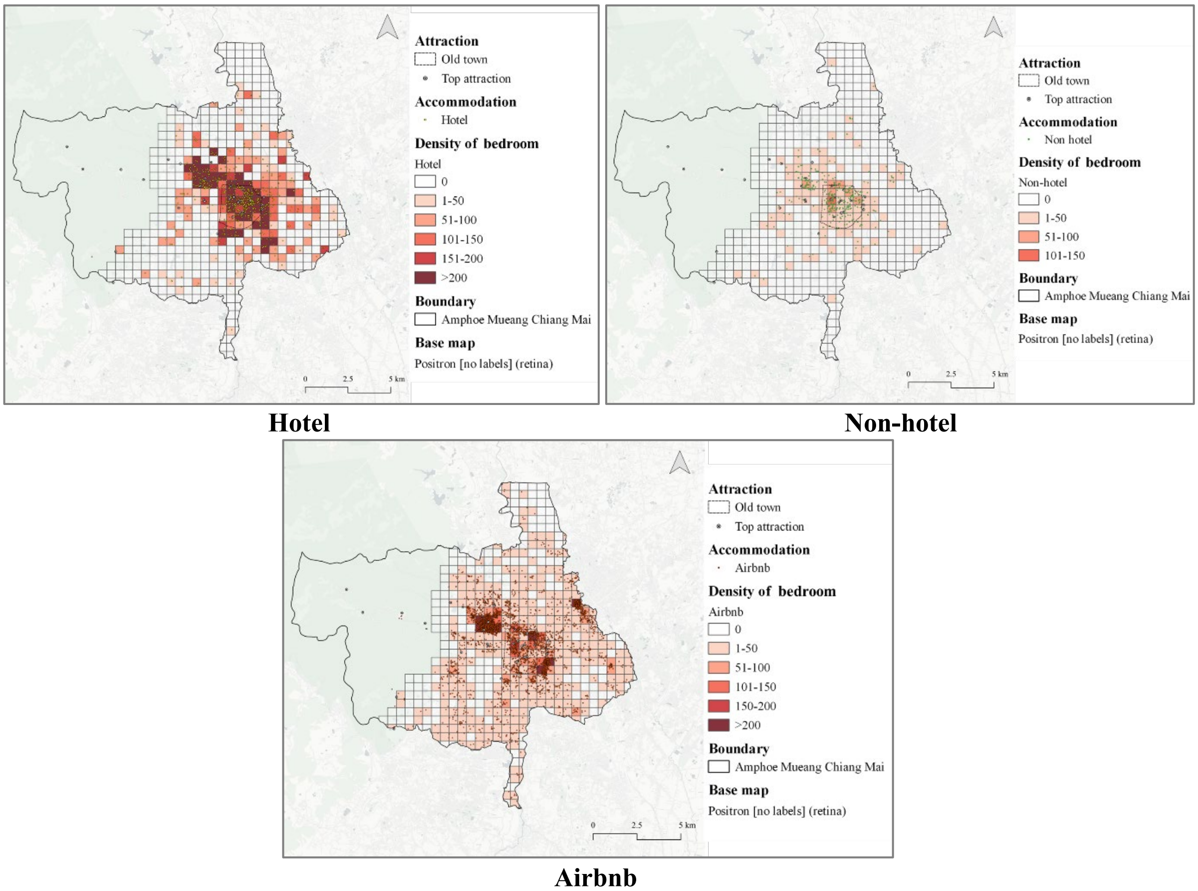


Figure. 4 Distribution of location and density of rooms of tourist accommodation

2.2 Tourism points of interest

In this study, tourism points of interest (POIs) were categorized into top attractions, archaeological sites, annual festivals, cafes, creative areas, local markets, and shopping malls. This POIs adapted from earlier studies (Sun et al., 2022; Xu et al., 2020) and available data. The descriptive data for these POIs are presented in Table 3.

Table 3 Descriptive statistics of tourism POIs in the grid

POI	Data source	Sum	Mean	SD
Top attraction	Tripadvisor, Mafengwo* and Tourism Authority of Thailand (TAT)	23	0.04	0.23
Archaeological site	Urban Design and Development Center (UddC)	71	0.13	0.57
Festival	TAT	43	0.08	0.52
Cafe	UddC	854	1.53	4.07
Creative area	UddC	72	0.13	0.54
Local market	UddC	29	0.05	0.27

POI	Data source	Sum	Mean	SD
Shopping mall	Tripadvisor	17	0.03	0.23

*Mafengwo, known as the "travel guide" for China's new generation of online users, provides extensive resources for long-term travel planning. Founded in 2006, it has evolved into one of the leading social media platforms for travel in China. Accessed http://www.mafengwo.cn/travel-scenic-spot/mafengwo/15284.html

POIs are concentrated in the old city and its surrounding CBD, including both the old and new CBDs, as shown in Figure. 5. These zones are critical for analyzing the relationship between tourism, commerce, and tourist accommodation in the city.

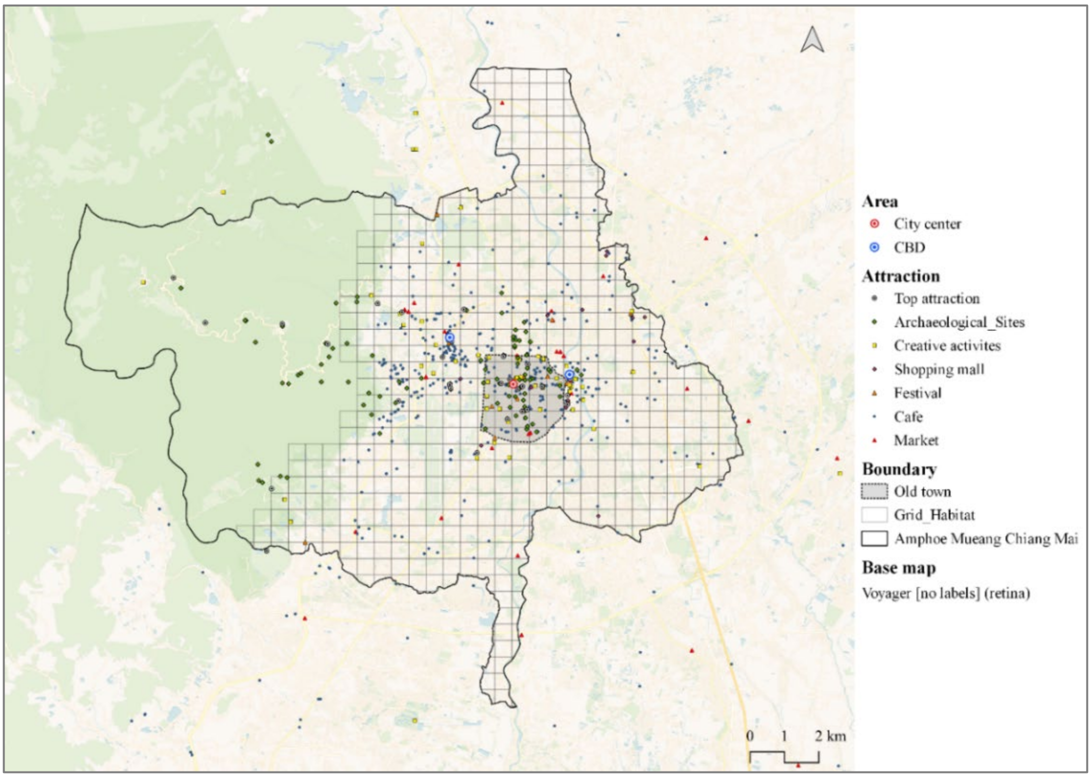


Figure. 5 Distribution of tourism points of interest in Chiang Mai city

Step 3 Analysis

3.1 Spatial autocorrelation (Moran's I)

Spatial autocorrelation, or spatial dependence, refers to the tendency for similar values to cluster in proximate areas, creating systematic spatial patterns. Moran's I index was used to quantify these spatial effects and clustering patterns of tourist accommodations. The analysis consisted of two components:

3.1.1 Univariate Moran's I was used to identify the location and extent of spatial clusters of types of accommodation. To evaluate overall spatial autocorrelation across accommodation types (hotels, non-hotel accommodations, and Airbnb), Global Moran's I was employed. This index ranges from -1 to 1, where values near to 1 indicate clustering or positive spatial autocorrelation, values near -1 indicate dispersion or negative spatial autocorrelation, and values equal to 0 indicate randomness or no spatial autocorrelation. Additionally, Anselin Local Moran's I (LISA) was used to detect local clusters within defined grids, categorizing spatial patterns into High-High clusters (high values surrounded by high values), Low-Low clusters (low values surrounded by low values), High-Low (high values surrounded by low values) or Low-High (low values surrounded by high values) (Anselin, 1995).

3.1.2 Bivariate Moran's I was used to analyze spatial autocorrelation between different accommodation types. Global Bivariate Moran's I was used to examine the spatial relationship between different accommodation types (e.g., Airbnb vs. hotels) to determine clustering, dispersion or randomness. Furthermore, Bivariate Local Moran's I was used to analyze local spatial clustering between accommodation types, categorizing patterns as high-high, low-low, high-low, and low-high.

Spatial contiguity weight using the Queen contiguity matrix was applied, considering neighboring grids with shared boundaries. All analyses were conducted using GeoDa software.

3.2 Spatial regression

Spatial regression analysis accounts for spatial dependence and the potential influence of neighboring units on the variable of interest, in addition to the factors included in a standard Ordinary Least Squares (OLS) regression model. By incorporating spatial weights, it captures the spatial relationships within the data and quantifies the influence of neighboring observations on the target variable. This enables a more precise and robust analysis of phenomena characterized by spatial correlation.

In this study, independent variables were chosen to examine their relationship with the density of each accommodation type within the grid, as shown in Table 4. Influential factors on accommodation density were divided into two main categories: 1) density of tourism POIs and 2) neighborhood character.

Table 4 Variables used in the spatial regression model

Variables	Description
Dependent variables	
Airbnb	The number of Airbnb listings within the grid
Hotel	The number of hotels within the grid
Non-hotel	The number of non-hotel accommodations within the grid
Independent variables	
Density of tourism POIs	
Top attraction	Number of popular tourist attractions within the grid
Archaeological site	Number of archaeological sites within the grid
Festival	Number of locations hosting traditional/ annual festivals within the grid
Cafe	Number of cafes within the grid
Creative area	Number of creative activity spaces within the grid
Local market	Number of markets within the grid
Shopping mall	Number of popular shopping malls within the grid
Neighborhood character	
Old town area	Dummy variable indicating whether the grid is within the old town conservation zone (0 = outside the old town zone, 1 = within the old town zone)
Commercial zone	Dummy variable indicating whether the grid is in a high-density residential and commercial area as per Chiang Mai's urban plan (0 = outside the commercial zone, 1 = within the commercial zone)

This spatial regression analysis used two models:

Spatial lag model is applied when spatial autocorrelation exists in the dependent variable. This model accounts for spatial effects by including a spatially lagged dependent variable as an additional predictor. The equation is:

$$y = \rho W y + X\beta + \varepsilon \tag{1}$$

Where y is the dependent variable, X is the independent variable, β is the regression coefficient, ε is the error term, Wy is the spatially lagged dependent variable for spatial weight matrix W, and ρ is the spatial autoregressive coefficient. If there is no spatial dependence and y does not depend on neighboring y values, $\rho = 0$.

Spatial error model is applied when spatial autocorrelation is present in the residuals. This model addresses spatial effects through the error term. A coefficient for spatially correlated errors (λ) is included as an additional parameter in the spatial error model. The equation is:

$$y = X\beta + \varepsilon \tag{2}$$

$$\varepsilon = \lambda W\varepsilon + \xi \tag{3}$$

Where y is the dependent variable, X is the independent variable, β is the regression coefficient, ε is the error term, $W\varepsilon$ is the spatially lagged error term for spatial weight matrix W, ξ is the uncorrelated (random) error term, and λ is the spatial error coefficient. If there is no spatial correlation between the errors, $\lambda = 0$.

The spatial regression analysis procedure follows these steps:

1) OLS Model: Initial analysis using the OLS model to estimate the coefficients of independent variables.

2) Spatial autocorrelation test: Moran's I statistic is used to assess spatial autocorrelation. If the statistics are significant, it indicates spatial dependence. Further, Lagrange Multiplier (LM) tests are conducted for a missing spatially lagged dependent variable (LM-Lag) and for error dependence (LM-Error).

3) Model selection: If both LM-Lag and LM-Error are significant, robust LM diagnostics are used to determine the most suitable spatial regression model. The robust LM diagnostics help choose between the spatial error model and the spatial lag model by evaluating the significance of robust LM-Error and robust LM-Lag. The preferred model is the model with the larger value of the robust LM statistics.

Results

Spatial distribution of tourist accommodation

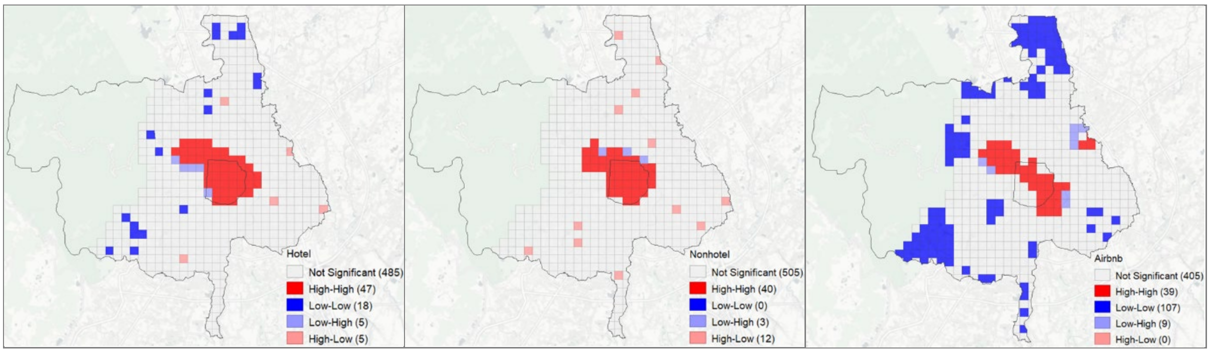
Univariate Moran's I result

Global Moran's I analysis indicated significant spatial autocorrelation across all accommodation types, with a clustered pattern (Table 5). Hotels exhibited the highest Moran's I values, followed by non-hotels and Airbnb. This suggested a more pronounced clustering for formal accommodations (hotels and non-hotels) compared to Airbnb.

Table 5 Results of global Moran's I (univariate) analysis

Accommodation	Global Moran's I	Z-score	*p*-value
Hotel	0.606	27.295	0.000
Non-hotel	0.520	23.537	0.000
Airbnb	0.366	17.087	0.000

LISA analysis revealed high-high clusters (red) of tourist accommodations primarily in the old city center, with hotels and non-hotel accommodations forming extensive clusters. However, Airbnb showed more localized high-high clusters within the CBD, including both the old (Chang Klan) and new (Nimmanhaemin) CBDs (Figure. 6). Furthermore, Airbnb showed a clear low-low clustering pattern (blue), indicative of a centre-periphery spatial pattern, with clusters of high concentration in the center, and lower density in the suburbs. In contrast, non-hotel accommodations showed less low-low clustering, suggesting limited spread outside the city center. Notably, non-hotel accommodation also exhibited high-low outliers, where peripheral grids with high accommodation density were surrounded by grids with low density.



Hotel **Non-hotel** **Airbnb**

Note: Significant at the 0.05 confidence level

Figure. 6 Results of local Moran's I (univariate) analysis

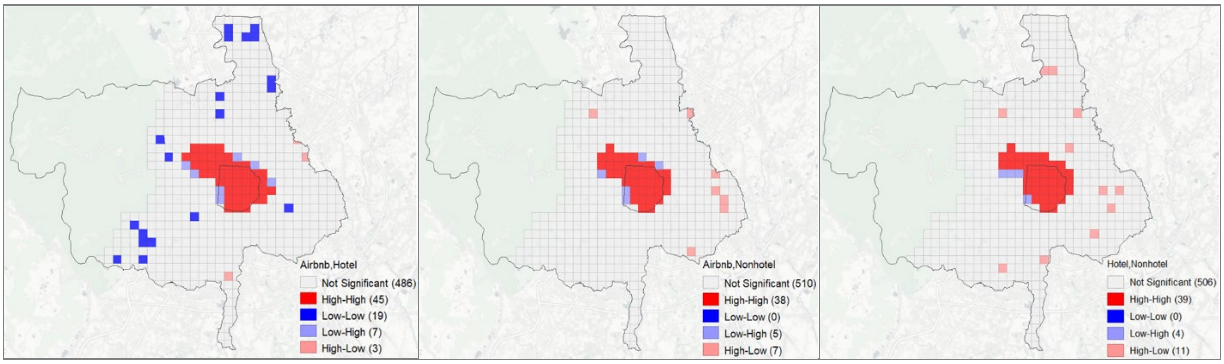
Bivariate Moran's I result

Bivariate Moran's I test was used to examine the spatial relationship between different types of accommodation in neighboring areas. An analysis revealed significant spatial autocorrelation with clustered patterns (Table 6). This indicated that accommodation tended to be located in areas with high spatial continuity, particularly between hotels and non-hotels. In grids with high hotel density, neighboring grids also showed high density for non-hotels. This showed that both formal accommodations were strongly correlated.

Table 6 Results of global Moran’s I (bivariate) analysis

Accommodation	Global Moran’s I	Z-score	*p*-value
Airbnb - Hotel	0.334	18.539	0.000
Airbnb - Non-hotel	0.285	15.919	0.000
Hotel - Non-hotel	0.542	26.659	0.000

LISA analysis (Figure. 7) revealed a clear clustering pattern of accommodation types, with high-density grids in the old city center of Chiang Mai, extending into the new CBD (Nimmanhaemin Road). Specifically, high-density grids of Airbnb accommodation were surrounded by high-density hotels and non-hotel accommodations. This indicated a strong spatial overlap of different accommodation types, particularly in the old city center. The findings suggest that the growth of accommodation in these areas are concentrated, intensifying tourism pressures, especially in the historical area. Consequently, further development in these areas will worsen overtourism.



Airbnb: Hotel **Airbnb: Non-hotel** **Hotel: Non-hotel**

Note: Significant at the 0.05 confidence level.

Figure. 7 Results of local Moran's I (bivariate) analysis

Pearson Correlation Results

Bivariate Moran's I analysis has limitations, as it only examines the spatial relationship between accommodation types in neighboring grids. To address this, Pearson correlation was used to analyze in-place correlations within the same grid (Gyódi, 2024). The results (Table 7) showed a strong positive correlation between the density of hotels and non-hotel accommodations within the same grid (r = 0.803). Similarly, Airbnb accommodations also exhibited a positive correlation with other types of accommodations. These findings suggested that all types of accommodations tended to cluster within the same areas, particularly hotels and non-hotel accommodations. However, Airbnb accommodations demonstrated broader spatial dispersion, with higher densities in grids that did not necessarily coincide with those of hotels and non-hotel accommodations.

Table 7 Results of Pearson correlation analysis

Accommodation	Correlation (r)	*p*-value
Airbnb - Hotel	0.482	0.000
Airbnb - Non-hotel	0.470	0.000
Hotel - Non-hotel	0.803	0.000

Locational factors affecting the density of tourist accommodation

Spatial diagnostics, including Moran's I, revealed significant spatial autocorrelation in all three models, indicating the need for spatial awareness models rather than OLS regression. The Lagrange Multiplier (LM) test confirmed the presence of spatial dependence, with the highest statistical significance observed in the spatial lag model, which was subsequently selected for further analysis (Table 8).

The spatial lag model results indicated that the density of hotels was positively correlated with the density of popular tourist attractions in Chiang Mai city, highlighting that hotels tended to cluster near popular tourist sites. However, the density of non-hotel accommodation and Airbnb properties did not show a significant correlation with popular tourist attractions. Additionally, both hotels and non-hotel accommodations exhibited a positive relationship with the density of creative spaces and cafes, while a negative relationship was found with the density of annual festivals and local markets.

The old city area had a significant positive effect on the density of both hotels and non-hotel accommodations, suggesting that these accommodation types were more likely to cluster in this historic area. In contrast, Airbnb accommodation was positively correlated with the density of cafes and shopping centers, as well as with the presence of modern commercial zones, indicating that Airbnb properties were concentrated in areas with a lifestyle-oriented, modern infrastructure conducive to tourism.

The R-squared values showed that the model explains 74% of the variation in hotel density, 61% in non-hotel accommodation density, and 40% in Airbnb density. These model results suggested that tourism POIs in this study have a greater impact on the location of hotels and non-hotel accommodations, which were primarily intended for short-term stays. In contrast, Airbnb properties, which often repurpose residential spaces such as houses and apartments, are less influenced by tourism POIs due to their more diverse and long-term residential purposes.

Table 8. Results of spatial regression analysis of tourist accommodation

Variables	Hotel			Non-hotel			Airbnb		
	OLS	Spatial lag	Spatial error	OLS	Spatial lag	Spatial error	OLS	Spatial lag	Spatial error
Constant	0.149 *	-0.054	0.727	-0.037	-0.091	0.030	2.361	-0.115	5.459 *
POIs									
Top attraction	1.709 ***	1.628 ***	1.776 ***	0.582	0.465	0.659	1.405	0.471	-0.979
Archaeological site	0.439 **	0.083	-0.074	0.491 ***	0.111	0.261	-3.705	-2.943	-1.261
Festival site	-0.700 ***	-0.790 ***	-0.960 ***	-0.612 ***	-0.671 ***	-0.748 ***	1.617	0.486	-0.839
Creative site	0.900 ***	0.341 *	0.229	0.671 ***	0.322 *	0.576 ***	1.245	-0.195	0.953
Cafe	0.344 ***	0.281 ***	0.278 ***	0.280 ***	0.251 ***	0.278 ***	3.243 ***	2.406 ***	2.415 ***
Shopping mall	0.900 **	0.834 **	0.783 **	0.356	0.402	0.495	14.014 **	10.732 *	8.925
Local market	-0.376	-0.569 **	-0.569 **	-0.243	-0.230	-0.139	-6.021	-4.985	-3.377
Neighborhood									
Old town area	6.503 ***	2.859 ***	1.713 **	6.327 ***	4.041 ***	6.111 ***	18.819 **	3.654	-2.018
Commercial zone	0.318	-0.390	-0.544 **	0.275	-0.154	0.121	24.631 ***	12.591 ***	13.439 ***
λ			0.813 ***			0.228 ***			0.575 ***
ρ		0.564 ***			0.417 ***			0.539 ***	
R-squared	0.664	0.741	0.739	0.566	0.610	0.572	0.265	0.398	0.375
Adjusted *R*-squared	0.660			0.559			0.253		
N	560	560	560	560	560	560	560	560	560
Spatial diagnostics									
Moran's I test	**5.381** ***			**1.671** *			**7.033** ***		
Spatial lag:									
Lagrange multiplier	96.652 ***			36.355 ***			88.874 ***		
Robust Lagrange multiplier	78.290 ***			64.815 ***			57.350 ***		
Spatial error:									
Lagrange multiplier	26.281 ***			2.129 ***			45.700 **		
Robust Lagrange multiplier	7.919 ***			30.589 ***			14.176 ***		

Notes: t-statistics in parentheses ***, **, and * indicate coefficient estimates that are statistically significant at 0.01, 0.05, and 0.1 confidence levels, respectively.

Discussion and conclusion

This study revealed that tourist accommodation in Chiang Mai city, including hotels, non-hotels, and Airbnb, exhibited a clear clustering pattern, particularly in the old city center. This finding confirms the spatial patterns of tourist accommodation as consistent with Tobler's First Law of Geography. Moran's I analysis confirms spatial autocorrelation, indicating that accommodations are concentrated in specific areas rather than being evenly distributed (Shoval et al., 2011; Valenzuela-Ortiz et al., 2022). Hotels and non-hotel accommodations are densest in the city center, a trend typical in tourist cities. This clustering reflects the tendency of hotels to be located in high-demand areas, such as business districts or tourist hubs (Ashworth, 1989; J. C. Gutiérrez, Palomares, Romanillos, & Salas-Olmedo, 2017; Li et al., 2014; Nathiwutthikun, 2018). In addition, the clustering pattern of hotels and non-hotel accommodations in Chiang Mai City reflects a monocentric structure.

Airbnb properties also followed a clustering pattern, particularly in the city center, but with a broader distribution across the city compared to hotels and non-hotels. This creates a centre-periphery pattern, where central areas have higher densities and peripheral areas are less concentrated. This aligns with trends seen in other tourist cities such as Barcelona (J. C. Gutiérrez et al., 2017; Gyódi, 2024) London (La, Xu, Hu, & Xiao, 2021), and Berlin (Gyódi, 2024). However, the concentration of Airbnb properties in the city center was narrower than hotels. This pattern contrasts with the case of Barcelona, where hotels were concentrated in a relatively narrower area in the city center than Airbnb. (Gyódi, 2024). This suggests that Airbnb tends to be concentrated in specific locations, particularly in commercial districts within the central area of Chiang Mai City.

The overlap between high-density areas of hotels, non-hotel accommodations, and Airbnb properties was most prominent in the old city, particularly within the ancient city walls, which still houses the local community and preserves the cultural heritage of Chiang Mai. This overlap suggests that the increasing presence of Airbnb in residential and cultural areas could contribute to the pressures of overtourism, potentially displacing local residents and altering the housing market in the old city.

Spatial regression analysis highlighted distinct locational factors for different accommodation types. Hotel density was notably correlated with proximity to prominent tourist attractions, indicating a clustering of hotels in high-demand, visitor-heavy areas. This pattern aligns with research linking hotels to densely populated, commercially vibrant zones (Yang et al., 2012). In contrast, Airbnb density was less associated with traditional tourist sites and more influenced by lifestyle amenities, such as cafes, shopping malls, and modern commercial areas. This finding suggests that Airbnb expansion does not merely alleviate demand in heavily visited areas but rather shifts accommodation availability to emerging areas, potentially redistributing tourism flow to less conventional destinations (Guttentag, 2015).

However, this study also revealed that despite Airbnb's expanding presence, its distribution is still heavily concentrated in areas with strong tourism infrastructure (Davidson & Infranca, 2016; Sun, Zhang, & Wang, 2021; Xie, Kwok, & Heo, 2020), such as modern commercial zones or old city center. The clustering of Airbnb properties in areas with tourism infrastructure may also compensate for perceived shortcomings, such as safety concerns (Birinci, Berezina, & Cobanoglu, 2018), offering a competitive edge over traditional hotels.

In conclusion, the spatial distribution of tourist accommodations in Chiang Mai City exhibited clear clustering patterns, with hotels and non-hotel accommodations concentrated in the city center, particularly around popular tourist attractions. Airbnb properties, while spreading more widely across the city, still showed a strong concentration in central areas and regions with supporting tourism infrastructure.

The expansion of tourism in Chiang Mai City, driven by the platform economy, has accelerated the shift from long-term residential use to short-term rentals, particularly of houses and apartments. While these rentals generate income for property owners, their proliferation intensifies tourism-related pressures in high-density areas, particularly the old city. Furthermore, platform-based accommodations frequently emerge in unplanned residential zones, contributing to displacement, community fragmentation, and overtourism. Notably, Thailand lacks comprehensive regulatory frameworks to govern short-term rentals, including measures to control expansion, establish quality and safety standards, and implement taxation mechanisms. This regulatory gap risks exacerbating negative externalities and potentially triggering displacement and gentrification.

Implication and recommendation

Implications

The findings of this study contribute to urban planning and tourism geography literature by emphasizing the role of spatial agglomeration in shaping the distribution of tourist accommodation. The concentration of both formal and informal accommodation establishments in city center reflects broader theoretical perspectives on urban tourism and spatial clustering. This pattern aligns with agglomeration economics, wherein businesses within the same sector tend to cluster due to shared infrastructure, labor markets, and consumer demand. Furthermore, the study supports the concept of touristification, which suggest that tourism-driven urban transformation can lead to the reconfiguration of central urban spaces into predominantly tourist-oriented environments. This phenomenon raises concerns about over-tourism and its potential socio-spatial consequences, particularly in historic city centers where local communities still reside. The displacement pressures on long-term residents, coupled with changes in land use patterns and housing markets, underscore the tension between tourism-driven economic benefits and the need for sustainable urban development.

Policy recommendations

The expansion of tourist accommodation significantly affects urban change. Formal accommodations, such as hotels, are typically regulated by urban planning policies and concentrated in commercial zones. In contrast, informal accommodations such as Airbnb are more flexible and can utilize existing residential spaces, facilitating broader supply expansion. While hotels and non-hotel accommodations support Chiang Mai’s traditional tourist infrastructure by clustering near prominent attractions, Airbnb contributes to a more dispersed tourism landscape. This pattern underscores the need for urban planning strategies that balance accommodation distribution with local quality of life, particularly in historic or residential areas. Future planning and zoning policies could benefit from considering the distinct locational dynamics of each accommodation type to better manage growth, prevent overtourism, and preserve local quality of life.

In Chiang Mai, the proliferation of Airbnb in the old city may intensify existing tourism-related pressures. As a high-density accommodation area and a residential hub for locals, limiting growth in this area could reduce negative impacts on the local community such as limiting the amount of Airbnb accommodations, the amount of allowed visitors, or days rented. Conversely, allowing more flexibility in less saturated areas could encourage the distribution of tourism outside the city center. Additionally, policies promoting equitable development of tourist infrastructure across broader urban areas may help alleviate pressures in high-density zones, fostering sustainable tourism in Chiang Mai City. Furthermore, the government should establish clear standards for safety, waste management, and taxation for Airbnb to ensure fair competition with other accommodation types.

Limitations and suggestions for future research

This study primarily analyzes the spatial distribution of tourist accommodations, which may limit the understanding of their functional impacts on different user groups. The focus on spatial positioning captures geographic concentration but does not account for variations in accommodation size, type, and usage patterns, which influence the intensity of space utilization. As a result, the study may not fully capture the diverse socio-spatial dynamics associated with different accommodation models. Future research should incorporate an analysis of the intensity of tourist accommodation concentration to better understand both the physical and social impacts on urban spaces. Additionally, socioeconomic factors, such as household income, education level, residential size, and number of tourists, influence accommodation density, especially for Airbnb accommodation. Integrating these variables into models may improve their capacity to explain variations in Airbnb density. Due to data limitations, these factors were not included in this study. Future research should incorporate these variables to deepen understanding of their effects on accommodation distribution and urban change.

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