

Food service spatial pattern after the emergence of online retail

Chairul Maulidi^{1,2,*}, Adenantera Dwicaksono³, Adiwan Fahlan Aritenang³, Haryo Winarso³

¹ Doctoral Program at Department of Urban and Regional Planning, School of Architecture, Planning and Policy Development, Bandung Institute of Technology, Bandung 40132, Indonesia

² Urban and Regional Planning Department, Engineering Faculty, Brawijaya University, Malang 65145, Indonesia

³ Department of Urban and Regional Planning, School of Architecture, Planning and Policy Development, Bandung Institute of Technology, Bandung 40132, Indonesia

* **Corresponding author:** Chairul Maulidi, c.maulidi@gmail.com

CITATION

Maulidi C, Dwicaksono A, Aritenang AF, Winarso H. (2024). Food service spatial pattern after the emergence of online retail. *Journal of Infrastructure, Policy and Development*. 8(4): 3005. <https://doi.org/10.24294/jipd.v8i4.3005>

ARTICLE INFO

Received: 10 October 2023

Accepted: 29 November 2023

Available online: 9 April 2024

COPYRIGHT



Copyright © 2024 by author(s).

Journal of Infrastructure, Policy and Development is published by EnPress Publisher, LLC. This work is licensed under the Creative Commons Attribution (CC BY) license.

<https://creativecommons.org/licenses/by/4.0/>

Abstract: Online shopping has eliminated the need to visit physical commercial centres. As a result, trips to these centres have shifted from primarily shopping-motives to leisure, companionship, and dining. The shifting in consumer behaviour is implicated in the growing spatial agglomeration of restaurants/cafes within commercial centres in European cities. Conversely, in southern cities, various casual restaurants/cafes also serve as leisure and companionship hubs. However, their spatial patterns are less explained. This article aims to elucidate the spatial pattern of these diverse restaurants/cafes in a typical southern city, Surabaya City. In this study, we employ the term ‘food services’ to encompass the various types of restaurants/cafes found in southern cities. We gather Points of Interest (POIs) data about food services via web scraping on Google Maps, then map out their spatial distribution across 116 spatial units of Surabaya City. Utilising k-means cluster analysis, we classify these 116 spatial units into six distinct clusters based on the composition of food service variants. Our findings show that City Centres and Sub-City Centres are locations for different types of restaurants/cafes. The City Centre is typically a location for fine dining restaurants and cafes, whereas Sub-City Centres are locations for fast casual dining and fast food restaurants. Cafes and fast food restaurants are centralised throughout downtown areas. Casual food service restaurants, such as casual style dining, coffee shops, and food stalls, are dispersed along business, residential zones, and periphery areas without intense domination of any specific variant.

Keywords: online shopping; restaurants; cafes; food services; spatial patterns

1. Introduction

The urban spatial structure is a crucial reference for resource and infrastructure allocation within the urban planning and development. This structure entails the spatial organisation of diverse activities, encompassing physical and social dimensions (Krehl et al., 2016). Its primary purpose is to establish a harmonious distribution of activities, foster an integrated transportation network system, promote inclusive economic development, and, in a broader context, serve as a guiding instrument for urban development. Studying an urban’s spatial structure finds its place within various scientific disciplines, including economics, sociology, and geography. In the economic context, the spatial structure represents a pattern of economic activity within the urban landscape, often manifesting as the arrangement of several retail centres hierarchically (Anas et al., 1998; Zhong et al., 2017).

The hierarchical structure of the retail landscape undergoes continuous transformation, primarily propelled by advancements in mobility technology.

Notably, in the 20th century, the proliferation of private car ownership and the construction of highways generated a phenomenon known as suburbanisation. This shift engendered a decentralised spatial structure for retail, marked by the proliferation of suburban commercial centres (Rodrigue, 2020). The advancement of the Internet of Things (IoT) in the 21st century has integrated the transportation and transaction of goods into the platform ecosystem. Online retail, facilitated through marketplace platforms, empowers consumers to shop virtually from anywhere, eliminating the necessity to visit physical stores (Beckers et al., 2021). The advancement of online retail has caused a decrease in traditional shopping trips, resulting in store closures within commercial centres. Several cities in Britain, Belgium, France, Japan, and North America have observed a phenomenon referred to as ‘demalling,’ signifying a decline in the vitality of commercial centres (Coutinho Guimarães, 2019; Delage et al., 2020; Hallsworth & Coca-Stefaniak, 2018; Lee et al., 2017). In response to this shift, commercial property owners in Europe have adapted by incorporating more restaurants and cafes into their establishments, aligning with the changing landscape following the emergence of online retail (Ceylan et al., 2020; Das et al., 2018; Gavilan et al., 2021; Tran, 2021). This adaptation has led to a notable shifting in the functionality of commercial centres, from traditional retail shopping centres into restaurant and café hubs (Che et al., 2023; Jones, 2021).

As restaurants and cafes occupy more retail floor space, the need for a comprehensive understanding of their spatial distribution becomes pivotal. In European cities, several studies have begun to recognise formal restaurants and cafes as parameters for commercial centre hierarchy (Dolega et al., 2021; Jones, 2021; Jones & Livingstone, 2018). In contrast, the urban areas in the Global South boast an array of dining establishments, including diverse formal and informal restaurants, cafes, and various providers like neighbourhood food stalls, roadside vendors, crossroad coffee shops, and hawkers (Henderson, 2016). Considering the unique context of informality that characterises the urban south, this study seeks to unveil the spatial patterns of restaurants, cafes, and like activities following the advent of online retail. Diverging from previous research focusing primarily on restaurants and cafes (Dolega et al., 2021; Jones, 2021), this study employs a broader conceptual term, ‘food service’. Food service encompasses the business of serving food and beverages that are purchased outside the home but can be consumed either on-site or off-site (Edwards & Overstreet, 2009). The study’s location focus is Surabaya, Indonesia’s second-largest city. Surabaya, in particular, had the highest e-commerce penetration rate in the country in 2017 (Cahyani, 2017).

The following sections provide a structured overview of this study. The second section reviews the urban retail spatial structure theory and the evolving pivotal function of restaurants and cafes for commercial centres. The third section details the data collection method and the application of the K-means cluster analysis to uncover the spatial patterns of food service across city spaces. The Fourth section presents the analysis results of food service spatial patterns. In section five, we examine the research findings in the previous studies. The last section summarises the study’s findings and suggests further investigation.

2. Review of literature

The proliferation of internet technologies and digital platforms has accelerated online retail penetration into everyday life. Digital platforms serve as hubs for various entities to exchange information, showcase and provide goods and services, conduct transactions, and coordinate service deliveries (Hein et al., 2020). Marketplaces based on digital platforms empower consumers to engage in online retail, offering the convenience of shopping from the comfort of their homes (Beckers et al., 2021; Etmnani-Ghasrodashti & Hamidi, 2020; Shao et al., 2022). Furthermore, the platform system is further enhanced by integrating blockchain and geolocation technology, enabling real-time monitoring of online payment transactions and logistics (Allahviranloo & Baghestani, 2019; Kasali, 2018). Collectively, these developments have given rise to a new style of shopping where consumers can make purchases without physically visiting commercial areas (Beckers et al., 2021). Due to the growing popularity of digital platforms, the number of daily travels to commercial centres has decreased (Aldo et al., 2023; Bjerkan et al., 2020; Bjørgen et al., 2021; Nahiduzzaman et al., 2019). In response to evolving consumer buying behaviours, retailers strategically relocate their stores closer to residential areas (Jones & Livingstone, 2018). This relocation strategy enhances their appeal by reducing consumer delivery costs (Cárdenas et al., 2017; Nahiduzzaman et al., 2019).

As shopping centres experience decreased foot traffic, consumer preferences have shifted noticeably. Restaurants and cafes have become more appealing leisure trip destination than traditional retail shops. (Dolega et al., 2021; Ecker & Strüver, 2022; Hood et al., 2020; etc.). In response to this evolving trend, malls have redefined their strategies, significantly increasing the provision of restaurants and cafes within their commercial properties. In European cities, the pivotal role and contribution of culinary establishments to sustaining the vibrancy of existing commercial centres have been well-acknowledged by recent studies (Ceylan et al., 2020; Das et al., 2018; Gavilan et al., 2021; etc.). Those studies argue that restaurants and cafes tend to agglomerate around the city centre and sub-city centres, further reinforcing their significance (Che et al., 2023; Jones, 2021). This pattern follows the pattern of restaurant/café establishments that existed prior to online retail. Restaurant and café locations tend to congregate, reinforcing the location's attraction and making it easy for consumers to select food varieties and flavours in adjacent places (Sevtsuk, 2014). High-end restaurants usually prioritise the prestige of the place to be located, both from the quality of the neighbourhood infrastructure and the surrounding social character (Hanaysha, 2016; Parsa et al., 2005; Thornton et al., 2016). More casual restaurants are clustered in accessible places to consumers (Hwang & Ok, 2013). However, the agglomeration of café-restaurants in commercial centres is one view of the location pattern of café/restaurants after the emergence of online retail. On the other hand, there is an argument that the restaurant/café service system has also developed online food ordering, and it impacts the location of restaurants/cafes, which is also more dispersed. Some empirical studies suggest restaurants are growing in the suburbs (Zhang et al., 2022). Restaurants grow near residential neighbourhoods outside commercial centres (Talamini et al., 2022;

Widaningrum et al., 2020).

A critique levelled at the preceding studies is that the subject of investigation is confined. They look at high-end and casual restaurants separately. In contrast, and as a novelty, this study will examine the location patterns of several types of restaurants/cafés in one city in depth. This study contends that leisure and companionship destinations in the urban south extend beyond formal restaurants and cafes. In the urban south, various food services are provided to varied preferences, encompassing fine dining, fast-casual dining, fast food, casual-style dining, cafes, coffee shops, and stalls. Fine dining restaurants are distinguished by their bespoke culinary menus, luxurious ambience, and personalised service experiences provided by skilled chefs (Hwang & Ok, 2013). Fast casual dining refers to chain restaurants offering a streamlined menu selection and efficient service facilitated by waitstaff (Line & Hanks, 2020). Fast food restaurants, known for their specific menus and speedy service, typically offer limited menus (Thornton et al., 2016). Casual style dining restaurants provide a selection of speciality cuisine in generous portions (Hwang & Ok, 2013). Cafes offer a sophisticated setting for coffee consumption, characterised by the carefully curated interior ambience. On the other hand, coffee shops are simple establishments where individuals can enjoy coffee, often featuring compact booth seating. Food stalls, whether pushcarts or non-permanent tents. However, food stall presence in zones with limited road capacity can lead to traffic congestion and disrupt public spaces (Henderson, 2016; Recio & Gomez, 2013). Given the informal nature of food service in the urban south, it is imperative to comprehend the spatial patterns of all food service variants in the wake of the rising food service industry following the emergence of online retail. The term 'food service,' introduced in this article as a novel perspective, represents a departure from previous studies that predominantly focused on formal restaurants and cafes.

3. Methodology

3.1. Study area

Surabaya is the second largest metropolitan city in Indonesia. Surabaya has a rich history dating back to the 13th century (Ricklefs et al., 2013). It initially served as a vital hub for commercial activities and was strategically located in what is now the Tanjung Perak district. Over time, Tanjung Perak witnessed significant development, evolving into a bustling retail centre featuring modern markets such as Pasar Turi and Pasar Atom and regional commercial centres like International Trade Centre (ITC) Mega Shopping Mall and Jembatan Merah Plaza. By the 18th century, Surabaya's growth extended southward, leading to the establishment of the Tunjungan district (Handinoto, 2010). This expansion created commercial landmarks such as Tunjungan Plaza, Pasar Blauran, Bubutan Golden (BG) Junction, and World Trade Centre (WTC) Mall. Further development in the 19th century saw the emergence of a residential district for the Dutch in what is now known as the Wonokromo district (Handinoto, 2010). Recent ritel developments point to prime shopping spots such as the Modern Market Wonokromo, Royal Plaza, Marvel City Mall, and Ciputra World. Throughout the 20th century, Surabaya experienced significant urban expansion in its western and eastern regions. This expansion was

facilitated by constructing the eastern ring road and a toll road in the western part of the city (Silas, 2002). In 1991, a notable retail centre emerged in the eastern part of Surabaya, specifically in the Kertajaya district. This retail complex, known as Galaxy Mall, strategically positioned itself near two prominent universities and some private campuses. Expanding commercial centres continued, encompassing establishments such as Plaza Marina and Pakuwon City Mall. In 2005, a new commercial complex emerged in the western part of Surabaya, specifically situated on the border of Dukuh Pakis and Wiyung district. This development included the Pakuwon Mall and Lenmarc Mall. The City of Tomorrow Mall shopping centre has also been established in the Ahmad Yani district at the city's southern end. The existing land use of Surabaya is shown in **Figure 1**.

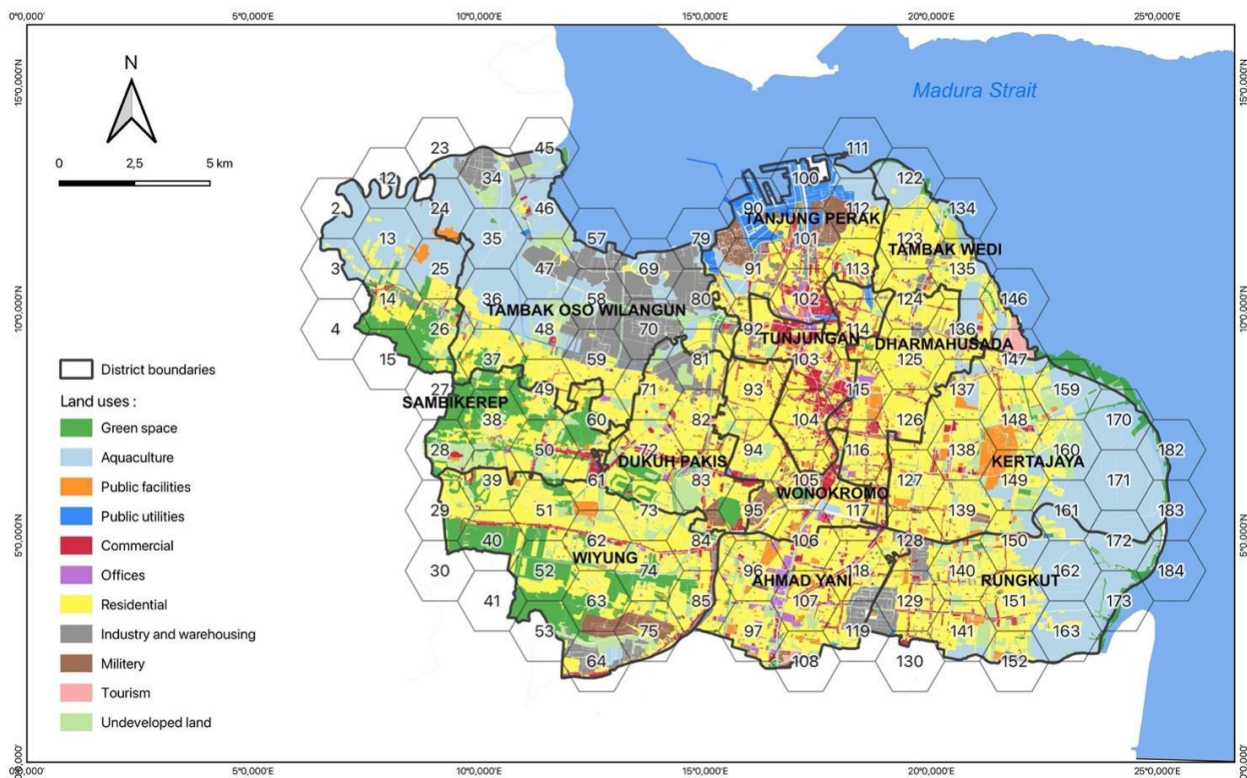


Figure 1. Surabaya’s existing land use.

The increase in online retail emergence in Surabaya and other Indonesian cities has been noticeable since 2015. This growth can be attributed to the widespread use of digital platform applications in e-commerce, which has dramatically accelerated the adoption of online retail. This shift is primarily facilitated by utilising marketplace and mobility platforms accessible on smartphones. In Indonesia, platform mobility falls under network accumulation operation (Stehlin et al., 2020). Initially, these platforms address mobility needs in areas lacking public transportation by reorganising informal modes of transportation. In urban areas with lenient regulations, digital platforms have diversified their services by expanding into additional sectors (Pelzer et al., 2019; Yuana et al., 2019), such as last-mile delivery services, food ordering, and electronic financing. In 2020, the central government regulated pricing standards for online transportation services.

Transportation costs are calculated in rupiah per kilometre. We adopted this price unit as a reference for determining the range of spatial units. Surabaya City is divided into multiple spatial units with a 1-kilometer radius. The threshold between the circles results in 116 hexagon-shaped spatial units, as shown in **Figure 1**.

Following the proliferation of online retail platforms, there has been a discernible decline in the occupancy rates of shopping centres in Surabaya. Between 2018 and 2019, the occupancy rate dipped, reaching 77% and 75%, respectively. During the Covid-19 pandemic, the rate experienced a further drop, hitting 71.5% (Gobiz, 2020; Rahman, 2022). In contrast, Surabaya's restaurant and café industry witnessed significant growth during the same period. In the fiscal year 2018–2019, the restaurant sector recorded a remarkable growth rate of 20%, while the café segment saw growth ranging from 15% to 20% (Gobiz, 2020). These statistics indicate the growing trend of food service establishments becoming critical determinants for the viability of the local economy in Surabaya.

3.2. POI food service data collection

Obtaining comprehensive spatial data on the diverse food service activities within Surabaya City poses a significant challenge. The city's statistics office provides data on the number of food services per administrative unit but lacks the crucial spatial attributes. Meanwhile, the trade office offers formal data on food services, complete with unit addresses. However, the conversion of address data into spatial coordinates is a time-consuming and labour-intensive task. Nevertheless, the Google Maps website is an alternative data source, providing spatial data on formal and informal food services. Individual business units often add their data location to Google Maps to enhance visibility and seamless integration with service-oriented digital platforms. Notably, the business unit data on Google Maps remains consistently maintained and updated. This dataset enables real-time analysis of urban life, introduces innovative approaches to urban governance, and forms the basis for envisioning and implementing cities that are more efficient, productive, open, and transparent (Kitchin, 2014). Therefore, this study leverages the micro-data Points of Interest (POIs) on food service units listed on the Google Maps website. The steps of collecting and preparing the POIs dataset are outlined as follows:

1) POIs food service data collection

We collect POI data for food service business units using web scraping techniques on the Google Maps website. This process involves utilising the Instant Data Scraper tool, an add-ons compatible with the Google Chrome browser. We employ keywords such as 'restoran,' 'cafe,' and 'warung kopi' on the searching bar. The resulting data from web scraping is organised in a tabular format, including location coordinates, name, address, type, and operational hours attribute.

2) Classifying food service types

This step involves categorising food service data into distinct variants, including fine dining (FD), fast casual dining (FCD), fast food (FF), casual style dining (CSD), café (C), coffee shop (CS), and stall (S). We employ four methods for this classification process. The first method categorises data based on the information in the 'type attribute' obtained from web scraping. The second method

involves assigning types to units with unspecified 'type attributes' by referencing the terms attached to their names. For example, 'warung,' 'depot,' and 'rumah makan' are classified as CSD, while 'warkop' is categorised as CS. The third method focuses on identifying names that explicitly denote franchise restaurant chains. FF categories include well-known establishments such as McDonald's, Kentucky Fried Chicken, and Pizza Hut. The fourth method assesses the 'type attribute' based on criteria similarity. These criteria were formulated through supervised learning by selecting specific examples. Our sample selection was guided by including widely recognised entities that unmistakably represent each category. We then analysed attribute similarities within each respective category. The results of our analysis indicate a similarity in operational hours for each food service variant, as follows:

- FD: open at midday (11.00 am or 12.00 pm)
- FCD: open at 10.00 am
- FF: open at 10.00 am
- CSD: open at 8:00 am or 9:00 am
- C: open at 09.00 am
- CS: open 24 hours
- S: open half day, morning to noon or afternoon to evening.

FCD and FF share similar operational hours, as do CSD and C. In cases where distinguishing between these options posed challenges for specific business units, we clarify these by accessing their official websites. This clarification method was exclusively utilised for a few business units that yielded inconclusive results when applying the earlier four methods.

3.3. K-means clustering analysis

The spatial pattern of food services is operationalised as a distinct composition of food service variants throughout the 116 spatial units of Surabaya City. The spatial units are categorised into clusters based on the similarities of food service combinations. The clusterisation employed the non-hierarchical k-means cluster analysis. The K-means clustering technique is utilised to partition data elements into 'k' clusters to maximise the similarity within each cluster while minimising the similarity between different clusters (Telgarsky & Vattani, 2010). The K-Means method is the most regularly employed and straightforward clustering technique. The K-Means algorithm is frequently employed due to its capacity to cluster substantial datasets, enabling rapid computation efficiently. It facilitates data distribution analysis by initialising centroids and determining the extent of data inside each cluster (Alizadeh et al., 2017; Kassambra & Mundt, 2020). The K-means algorithm is a clustering algorithm that relies on distance measurements to assign data to clusters. Consequently, the variance in this approach is computed by considering the distances between data points. It is essential to acknowledge that in K-means clustering analysis, the term "distance" does not pertain to the physical distance between two observations or samples. This algorithm aims to quantify the degree of similarity between two observations or samples. This study chose the Euclidean distance metric for the K-means algorithm. The function can be expressed as follows (MacQueen, 1967; Hartigan and Wong, 1979):

$$J = \sum_{i=1}^k \sum_{j \in C_i}^{n_i} \|\chi_j - \mu_i\|^2 \quad (1)$$

In this context, J denotes the objective function, C_i represent the i^{th} cluster, n_i denote the number of samples in i^{th} cluster, and the distance function $d_{ji} = \|\chi_j - \mu_i\|^2$ represents the calculation of the distance between each sample point χ_j and centroid μ_i in the i^{th} cluster. The centroid μ_i can be determined through the following function:

$$\mu_i = \frac{1}{|C_i|} \sum_{j \in C_i} \chi_j \quad (2)$$

The cluster analysis involves several key steps (Zagouras et al., 2013). Firstly, initialising the cluster centroid $\mu_1, \mu_2, \dots, \mu_k$ randomly. Secondly is performing the calculation of the distance function d_{ji} between each sample point χ_j and centroid μ_i in the i^{th} cluster. The distance function is denoted as d_{ji} utilised the Euclidean distance as its basis. Thirdly, moving each sample point χ_j to the cluster that contains its nearest centroid $\mu_{nearest}$. The cluster centroids are also updated to account for any sample points that have been moved or reassigned. Fourthly, the objective function J is computed, as presented in Equation (1). If function J converges, the centroids do not change from the previous iteration, and the K-means clustering algorithm generates the final centroids of the cluster. Furthermore, steps 2 and 3 are iteratively performed until the objective function J converges. After calculating the centroids, the subsequent step is to describe the characteristics of each cluster. This step involves analysing the attributes or features of the data points within each cluster and identifying the common patterns or traits that define each cluster. This study runs those analysis steps in the open-source statistic software Jamovi. Finally, once the characteristics of each cluster have been identified, it is essential to label the clusters accordingly. Labelling involves assigning labels to each cluster based on their distinguishing characteristics associated with external factors. These labels can provide valuable insights and facilitate the interpretation and understanding of the cluster analysis results. The analysis's final phase involves cartographically representing each cluster category's spatial distribution on the Surabaya map.

Other parameters that need to be considered in cluster analysis are the data preparation, assumption test, and the decision of optimal cluster number. Firstly, data preparation is crucial in addressing potential issues arising from variables with varying values and units. Significant disparities among variables can introduce bias into the calculation of Euclidean distances. Hence, standardisation becomes imperative. This study uses a z-score for standardising the calculated data, which has a variety of maximum values.

Secondly, assessing assumptions regarding data quality. According to Hair et al. (2010), cluster analysis has two data requirements: the number of representative samples and multicollinearity among variables. The representative sample size is tested using Kaiser Mayer Olin (KMO). If the KMO value is >0.5 , then the data is representative. The multicollinearity test ensures that there is no close relationship

between variables. The test uses Pearson correlation if the data is distributed normally and Spearman rank if not.

Thirdly, the optimal number of clusters is determined. The number of clusters is built on pre-existing knowledge and can be aided by statistical methods. This study utilises the Silhouette technique. The tool can generate concise visual representations that effectively illustrate classification accuracy. Additionally, it provides silhouette values that can be used to interpret and confirm the coherence of clusters within the samples. The silhouette values can be utilised to quantify the degree of similarity between an observation and its corresponding cluster.

4. Results

4.1. Spatial distribution of Surabaya food service

The dataset was scraped in January 2022, eight years after online retail emergence in Surabaya. The collected POI data retrieved a total of 51,176 food service units. **Figure 2a** is heatmaps, represents the density of all food service variants. **Figure 2b–h** shows the density of seven food service variants, sequentially: fine dining restaurants (46 units), fast casual dining restaurants (70 units), fast food restaurants (179 units), casual style dining restaurants (15,785 units), coffee shops (3692 units), and food stalls (25,588 units). Notably, the most significant concentration of food services can be observed in two areas: Unit 49 Tambak Oso Wilangun, housing 540 food service units, and Unit 123 Tambak Wedi, accommodating 541 food service units. These establishments primarily comprise coffee shops and casual-style dining restaurants.

The heatmaps (**Figure 2**) also reveals two distinct spatial patterns, i.e., dispersed and clustered patterns. The Dispersed Pattern is characterised by a wide distribution across the city, including casual style dining (**Figure 2e**), coffee shops (**Figure 2g**), and food stalls (**Figure 2h**). Notable concentrations, such as Unit 49 on the boundary of Tambak Oso Wilangun and Sambikerep districts, renowned for its casual-style dining, can be observed. Unit 93 in Wonokromo stands out for its abundance of coffee shops, while Unit 91 in Tanjung Perak boasts the highest number of stalls. The Clustered Patterns are when businesses typically gather in multiple locations, including fine dining (**Figure 2b**), fast casual dining (**Figure 2c**), fast food (**Figure 2d**), and café (**Figure 2f**). The concentration of fine dining establishments is observed in nearby areas of Unit 83 Dukuh Pakis and Unit 105 Wonokromo. The concentration of fast food can be observed in three specific locations: Unit 103 Tunjungan, Unit 61 Dukuh Pakis-Wiyung border, and Unit 138 Kertajaya. Cafes are tend to concentrated on the city centre, Unit 103 Tunjungan and Unit 105 Tunjungan—Wonokromo border.

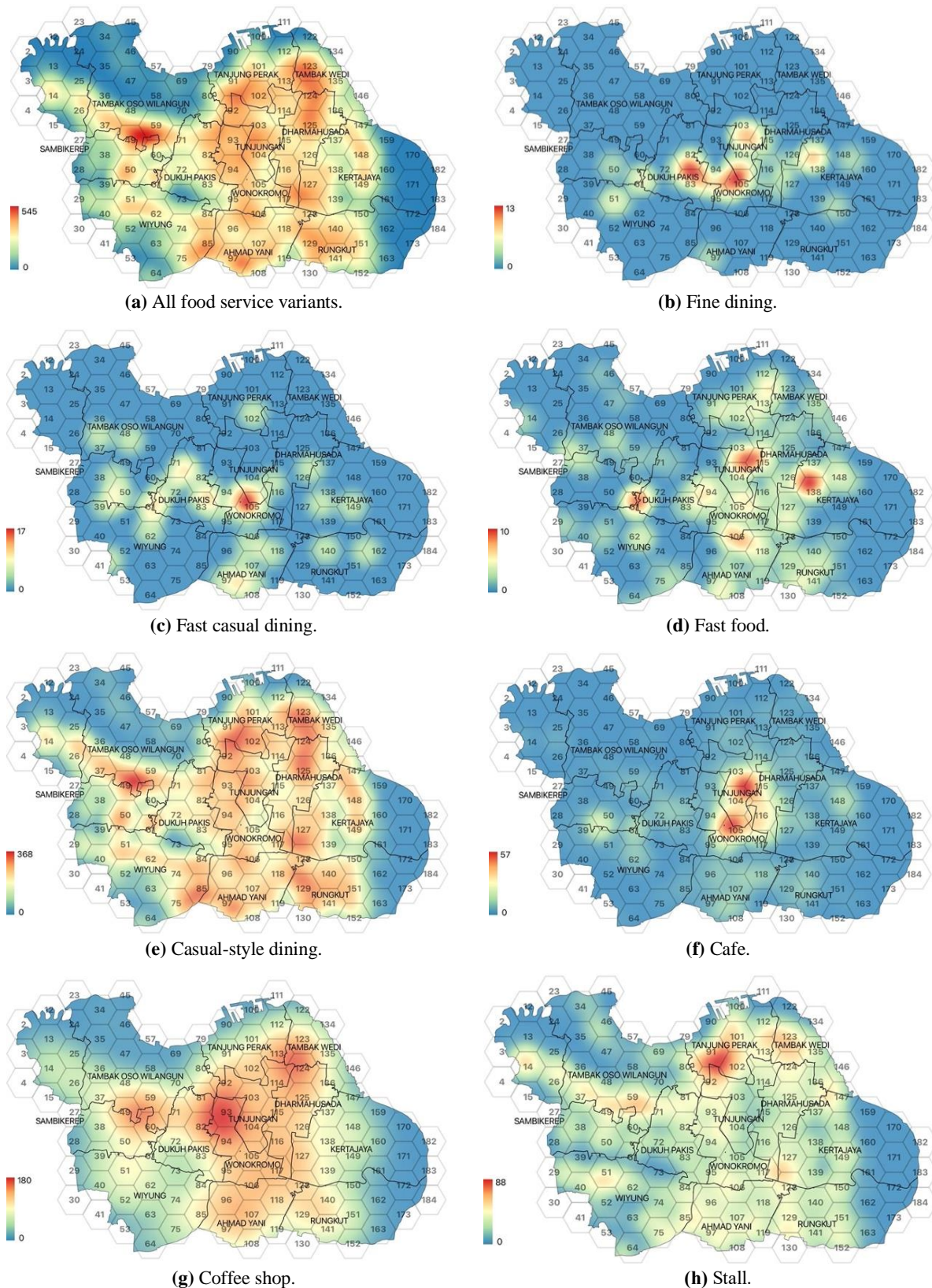


Figure 2. Heatmap of food services distribution on Surabaya.

4.2. Basic data and assumption test

Table 1 presents an overview of the standardised basic information about 116 spatial units within Surabaya City. A notable disparity exists in the range of values

between fine dining, fast casual, fast food, and cafe establishments. The observed differences demonstrate significant variability across all 116 spatial units. In addition to their similarity in median value, it is noteworthy that the median values of both variables are closely aligned with their respective minimum values. The observed similarities suggest that the data is distributed in a severe positive model. This data distribution model is substantiated by a Skewness value >2 . In contrast, coffee shops and stalls, which fall under casual style dining, exhibit a wider range of maximum and minimum values. Additionally, the median value in these establishments typically falls towards the centre of this range. The data exhibits a more evenly dispersed pattern than the four previously described alternatives. Nevertheless, the Shapiro-Wilk test yielded a p -value < 0.005 , indicating that the entire dataset does not exhibit a normal distribution. Data normalisation was not performed at the data processing stage since sample or object cluster analysis does not necessitate data normalisation (Hair et al., 2010; Supranto, 2010). Nevertheless, identifying non-normal data is a basis for employing a non-parametric methodology in the subsequent analysis.

Table 1. Descriptives standardised statistical parameters for six food service variants in Surabaya.

	FD	FCD	FF	CSD	C	CS	S
N	116	116	116	116	116	116	116
Missing	0	0	0	0	0	0	0
Mean	8.62×10^{-5}	2.24×10^{-4}	1.47×10^{-4}	-1.72×10^{-5}	-1.29×10^{-4}	-1.72×10^{-5}	6.90×10^{-5}
Median	-0.268	-0.265	-0.239	0.0355	-0.381	-0.178	0.00700
Standard deviation	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minimum	-0.268	-0.265	-0.680	-1.22	-0.506	-1.08	-1.26
Maximum	8.52	7.21	3.73	2.08	6.63	2.67	2.23
Skewness	6.24	6.20	2.05	0.198	3.98	0.563	0.295
Std. error skewness	0.225	0.225	0.225	0.225	0.225	0.225	0.225
Shapiro-Wilk W	0.292	0.266	0.702	0.902	0.527	0.894	0.930
Shapiro-Wilk p	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

The results of assessing the adequacy of sample size and the presence of variable multicollinearity are presented in **Tables 2** and **3**. The Kaiser Meyer Olkin (KMO) is applied for measuring sampling adequacy (MSA). MSA test value > 0.5 suggests that the available samples and variables are sufficient for cluster analysis. The multicollinearity test employs the non-parametric Spearman’s rank correlation test. The test results reveal a statistically significant association among the food service variations: fine dining, fast casual dining, fast food, and café (p -value < 0.01). However, this relationship is not considered strong, as indicated by Spearman’s rho coefficient < 0.75 . The informal food services such as casual style dinner restaurants, coffee shops and stalls show a notable correlation. Despite multicollinearity among certain factors, the cluster analysis used the available variables. However, it should be noted that casual style dining, coffee shops, and food stalls can not serve as singular determinators for their clusters.

Table 2. Keiser Mayer Olkin (KMO) measure of sampling adequacy.

	MSA
Overall	0.745
FD	0.712
FCD	0.635
FF	0.807
C	0.659
CSD	0.792
CS	0.794
S	0.739

Table 3. Correlation matrix of non-paramteric Spearman’s rho.

		FD	FCD	FF	C	CSD	CS	S
FD	Spearman’s rho	-						
	<i>p</i> -value	-						
FCD	Spearman’s rho	0.404	-					
	<i>p</i> -value	<0.001	-					
FF	Spearman’s rho	0.461	0.452	-				
	<i>p</i> -value	<0.001	<0.001	-				
C	Spearman’s rho	0.532	0.519	0.720	-			
	<i>p</i> -value	<0.001	<0.001	<0.001	-			
CSD	Spearman’s rho	0.347	0.340	0.652	0.770	-		
	<i>p</i> -value	<0.001	<0.001	<0.001	<0.001	-		
CS	Spearman’s rho	0.342	0.309	0.643	0.788	0.908	-	
	<i>p</i> -value	<0.001	<0.001	<0.001	<0.001	<0.001	-	
S	Spearman’s rho	0.196	0.178	0.585	0.610	0.873	0.869	-
	<i>p</i> -value	0.035	0.055	<0.001	<0.001	<0.001	<0.001	-

4.2. Food service spatial pattern

K-mean cluster analysis was applied to all seven variables. Before carrying out cluster analysis, the appropriate cluster number was determined based on the average silhouette method, as shown in **Figure 3**. The silhouette value suggests that 8 clusters are the most appropriate classifications. However, three adjacent cluster numbers were run considering the potential instability of specific criteria, the relatively similar silhouette value and possible outliers. K-means cluster analysis runs in Jamovi software using MacQueen’s ‘snowCluster’ package algorithm (Seol, 2023). The algorithm produces a maximum of 7 cluster centres. Therefore, we took 6 and 7 clusters to compare their scatter plot, as shown in **Figure 4**. The comparison shows that the scatter plot of 6 clusters is more clearly delineated and less overlapping than 7 clusters. Thus, 6 clusters were selected as the cluster number for describing the spatial pattern of food services.

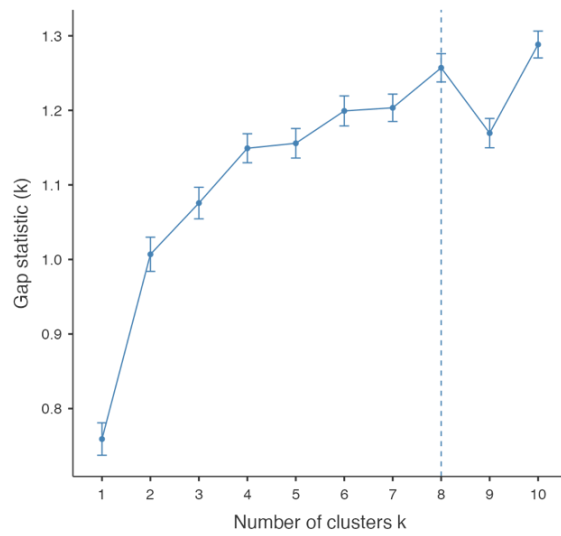


Figure 3. Result of silhouette value under different cluster number.

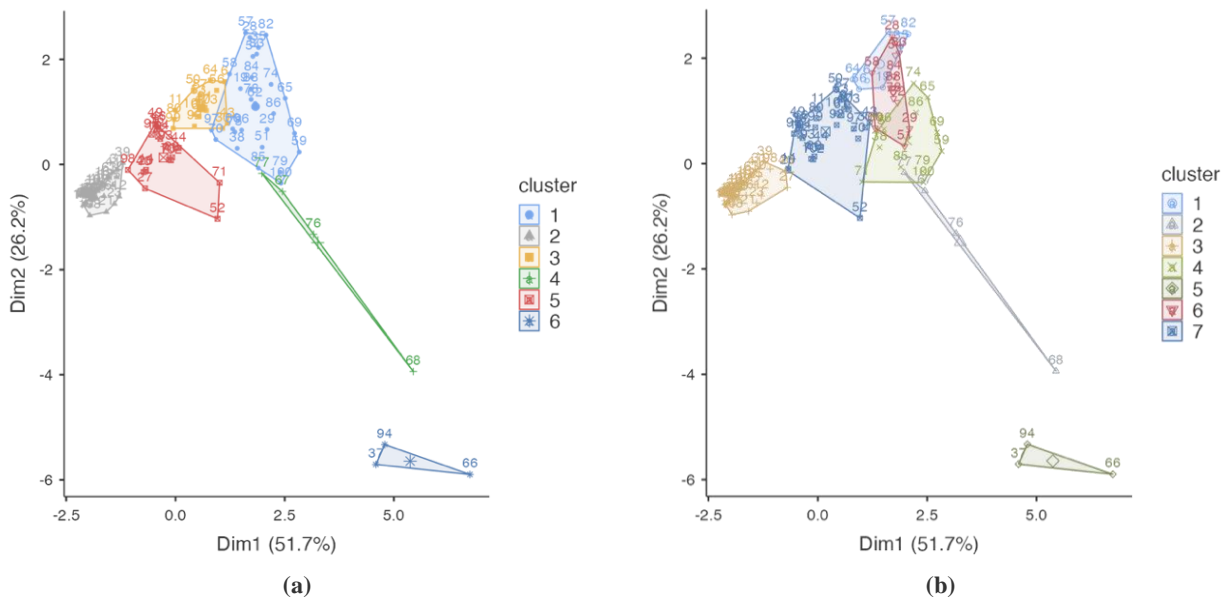


Figure 4. Comparing scatter plots for 6 clusters (a) and 7 clusters (b).

Table 4. The sum of squares and clustering count.

	Value	Count
Cluster 1	0.747	2
Cluster 2	45.686	25
Cluster 3	13.779	49
Cluster 4	35.314	30
Cluster 5	29.481	8
Cluster 6	21.143	2
Between clusters	665.793	
Total	811.942	

Table 5. Centroids of clusters.

Cluster No	FD	FCD	FF	CSD	C	CS	S
1.00	2.436	6.991	3.728	0.613	0.808	0.092	-0.113
2.00	-0.025	-0.124	0.131	1.201	0.140	1.284	1.284
3.00	-0.268	-0.229	-0.590	-1.029	-0.465	-0.951	-0.983
4.00	-0.178	-0.133	-0.078	0.347	-0.197	0.145	0.419
5.00	0.239	0.009	1.910	0.905	1.778	1.045	0.340
6.00	6.155	2.154	2.627	0.760	4.687	0.796	0.504

As presented in **Tables 4** and **5** and **Figure 5**, the Means values demonstrate six distinct clusters based on food service combinations. Cluster 1 exhibits the highest provision of fast casual dining and cafés than the remaining clusters. Cluster 2 exhibits a moderate level of food services on average. The high mean values are observed in the casual-style dining, coffee shops and stalls. Cluster 3 lacks a distinct character due to its comparatively low number of food services compared to other clusters. Cluster 4 has a similar food service combination with Cluster 2 but in lower means values. Cluster 5 tends to have medium mean values compared to all clusters, but fast food and café provisions are relatively higher than other food service variants. Cluster 6 exhibits a higher prevalence of fine dining establishments and cafés than the other clusters.

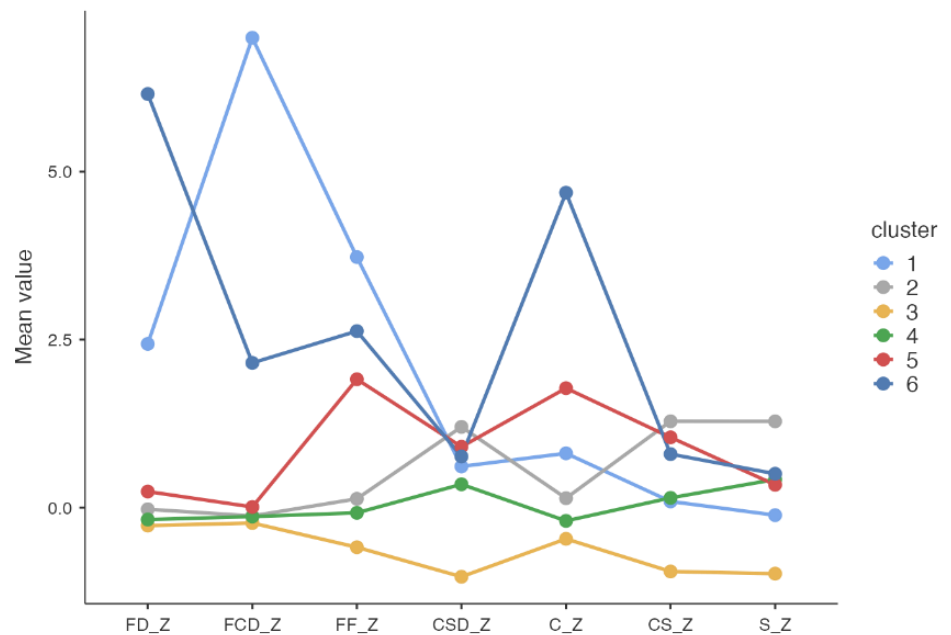


Figure 5. Means plot of 7 food service variants in each cluster.

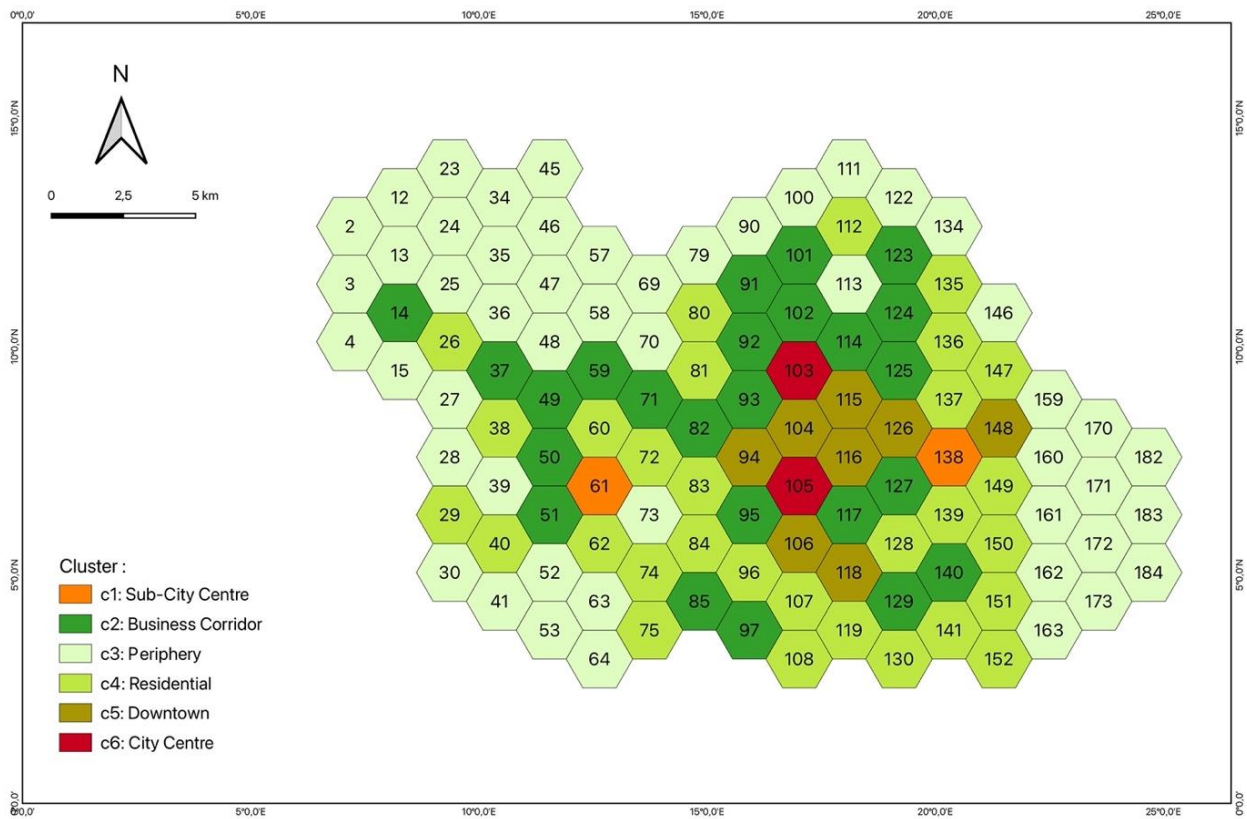


Figure 6. Surabaya’s spatial partition based on the composition of food service variants.

Figure 6 illustrates the spatial arrangement of the six clusters within Surabaya. Upon overlaying **Figure 6** onto **Figure 1**, it becomes apparent that an association exists between the food service spatial pattern and the predominant land use. The association between them is used as a reference for assigning labels to each cluster. Cluster 1 comprises spatial units 61 and 138. Unit 61 denotes the economic hub’s geographical position in the city’s western region, featuring the prominent Pakuwon Mall. Unit 138 is the primary business hub in the city’s eastern region, containing the prominent Galaxy Mall. Both sub-centres are delineated in Surabaya’s spatial structure plan. Cluster 1 is designated a Sub-City Centre cluster, distinguished by the concentration of fast casual dining and fast food restaurants. Cluster 2 encompasses an area distinguished by trade and office land uses along the streets. Cluster 2 is designated as a Business Corridor cluster with a notable presence of casual dining restaurants, coffee shops, and food stalls. Cluster 3 is spatially dispersed across the city’s peripheral areas, therefore earning the designation of the Periphery cluster. This particular cluster exhibits fewer food services than the remaining clusters. Within this particular group are several formal restaurants, such as fine dining restaurants, fast casual dining restaurants, and a small selection of cafés. Residential land use is closely linked to Cluster 4. The designated classification for this particular cluster is a Residential cluster, characterised by a comparatively limited number of food service establishments. Cluster 5 is geographically dispersed around the city core, specifically in the city’s eastern region. This site is affiliated with the campus district and is near the youth lifestyles. This cluster’s designation as a Downtown cluster is primarily due to its large young population, particularly college

students. A notable abundance of fast food establishments and cafes characterises this cluster. Cluster 6 is within units 103 and 105, which are situated in the City Centre. Unit 103 serves as the primary commercial hub in the city centre, the location for the most prominent mall, Tunjungan Plaza. Additionally, unit 105 accommodates many smaller shopping centres, like Marvell Plaza, Transmart, and Royal Plaza. The cluster in question is designated the City Centre cluster, distinguished by its notable copiousness of fine dining restaurants and cafes.

In addition, overlaying **Figure 6** and **Figure 3** exhibits two anomalies: a peripheral cluster located in the city core and a retail centre area classified as a Business Corridor. The First anomaly is observed in the spatial distribution of units 113 and 73, which are situated in the City Centre but have a similar food services composition as the Peripheral cluster. The anticipated outcome can be attributed to the distinctive land utilisation of unit 113, characterised by a concentrated human habitation amidst two large public cemetery sites. Also, a portion of the area encompasses the Sidotopo station, serving as a warehouse for used locomotive and train pieces. This particular unit has characteristics that deviate significantly from the other units. Unit 73, similarly characterised by an upper-class residential area, remains incompletely built, with a substantial amount of unoccupied land yet to be utilised. A component of this property encompasses a golf course that features cafeterias and clubhouses. The second anomaly is spatial unit 102, which is situated in the northern part of the city. The predominant land uses within this unit consist of commercial facilities such as offices and shopping complexes, including Jembatan Merah Plaza, Bubutan Golden Junction, and International Trade Centre Mega Grosir. Unit 102 is classified as a business corridor cluster. This mall site is distinguished from other places commonly categorised as City Centre and Sub-City Centre clusters. Gaining a comprehensive understanding of this anomaly necessitates conducting further investigation.

5. Discussion

The trend of online retail operations through digital platforms has been prevalent for about a decade. Dolega (2021) asserted that the advent of online retail has significantly influenced the decrease in the frequency of shopping trips. Coutinho (2019) highlighted that the decrease in commercial activities within shopping malls led to demalling in several global urban areas. In order to sustain their vibrancy, shopping malls often strive to increase the number of restaurants and cafes they feature. To date, no empirical evidence indicates a reduction in the frequency of shopping trips within Surabaya. Nevertheless, Surabaya had a decrease in the vibrancy of shopping centres and a simultaneous rise in the presence of café restaurants after the surge in online retail in 2015. Between 2017 and 2019, there was a significant decline of 71.5% in the occupancy rates of retail shopping establishments located within commercial centres. During the same time frame, there was a notable rise of 20% in cafes and restaurants (Gobiz, 2020; Rahman, 2022). In response to the need for resilience in shopping malls, retail stores have relocated from these establishments, subsequently supplanted by the emergence of restaurants and cafes. The case study conducted in the UK reveals that both the City Centre and

Sub-City Centres are predominantly occupied by restaurants and cafes (Dolega et al., 2021; Jones, 2021). In more comprehension, this research findings elucidate that various categories of café-restaurants do not uniformly agglomerate around the existing commercial centre. This study discloses six distinct clusters characterised by varying compositions of food service variants within them. They include the city centre, sub-city centres, business corridor, downtown, residential and peripheral clusters.

City Centres and Downtown clusters typically contain high-end restaurants and cafes. The Downtown clusters currently utilise the space between the units 103-Tunjungan and 105-Wonokromo, located at the mid-town. The present mid-town was established during Dutch colonialism in the 19th century, serving numerous structures of urban heritage. Fine dining and cafés are typically located close to commercial hubs and hotels (Chen et al., 2021; Constantin & Reveiu, 2018), creating an atmosphere of prestige and exclusivity (Abuthahir & Krishnapillai, 2018). This findings inline with Singleton et al. (2016) statement, wherein the city centre can sustain its vibrancy as a hub for leisure trips due to the potential distinctive ambience of the old town.

Fast casual dining clusters characterise Cub-City Centres. Two shopping malls exhibit this clustering pattern. The first one is located in Unit 61 Wiyung, where Pakuwon Mall is situated. The second one is on Unit 138 Kertajaya, where Galaxy Mall is located. Pakuwon Mall, situated in the western part of the city, is a prominent shopping complex created in a mixed-use format. It is strategically located amidst a lavish residential community, offering a combination of retail spaces and apartments. The Galaxy Mall is situated in the city's eastern part, surrounded by middle-class residential areas and in proximity to several prominent campuses that cater to the youth lifestyle. Both of these sub-city centres share the characteristic of being situated near residential compared to the city centre.

Fast food restaurants are often popular places for family leisure activities. Fast food is effectively situated in accessible places to residential areas (Widaningrum et al., 2020), specifically on the outer tier of the shopping mall (Zhou et al., 2022). However, a different pattern can be observed in the context of Surabaya. Indicators suggest a correlation between the number of fast food restaurants and the characteristics of the respective neighbourhoods. The number of fast food around the Western Sub-City Centre is comparatively lower than in the Eastern Sub-City Centre. The different scales of fast food restaurant clusters around the two sub-city's central areas might indicate the social dynamics prevalent within their surrounding community, as Cachinho (2014) and Thornton (2016) posited. The lifestyles of the middle class and young individuals exhibit a greater exposure to fast food restaurants than those of higher economic classes.

The area along the main road tends to be a location for the concentration of fast casual style dining restaurants, coffee shops and food stalls. Casual style dining establishments were primarily characterised by their utilitarian nature. Taste and accessible location are the determining factors for casual restaurants (Hwang & Ok, 2013). The observed pattern aligns with the findings in China, where casual restaurants tend to disperse spatially (Talamini et al., 2022). In comparison, the periphery areas are characterised by the lowest prevalence of food service. However,

formal restaurants are more plentiful than informal food services, although they are available in relatively minor numbers, are exclusive, and are in clubhouse formats. This pattern is similar but not as massive as in the UK, where many restaurants and cafes flourish in the urban periphery (Zhang et al., 2022).

6. Conclusion

A significant increase in the number of food service units has emerged as a new strategy to respond to the decline in the vitality of retail stores following the emergence of online retail. Food services attract people to urban business districts, and the availability of food services plays an important role for shopping centres vitality. Prior European research reveals a noteworthy trend of restaurants and cafés clustering within existing commercial centres, both in the city and sub-city centres. This article offers a comprehensive analysis of the spatial distribution of restaurants, cafés, and other variants of food service establishments. The analysis results show that the location pattern of restaurants/cafes after the emergence of online retail continues the pattern that existed before. The growth of restaurants/cafés in commercial centres reinforces a location pattern that has existed since before the rise of online retail. Formal establishments (fine dining, fast-casual dining, fast food, and cafes) tend to cluster in established commercial hubs within the City Centre, Sub-City Centre, and Downtown area. The City Centre notably features fine dining restaurants and cafes, while fast-casual dining and fast food are prevalent in the Sub-City Centre. Conversely, the downtown area stands out for its many cafes and fast-food restaurants. On the other hand, informal food service variations like casual style dining restaurants, coffee shops, and food stalls are dispersed across both business corridors and residential areas. The informal variants exhibit consistent characteristics, with none exerting singular dominance in the landscape.

In addition, this article finds that not all existing commercial centres show a concentration of restaurants and cafes. Specifically, the commercial sector in Unit 102 of the Tanjung Perak district does not attain an equivalent level of prominence compared to the two prominent commercial centres, namely Pakuwon Mall in the western region and Galaxy Mall in the eastern part of the city. Therefore this study underscores the importance of further research to investigate specific commercial centres that have successfully and unsuccessfully accommodated the growth of restaurants and cafes. Further investigations are expected to offer a holistic comprehension of the factors that impact the endurance and adaptability of Surabaya's commercial centres amidst the era of online retail.

Author contributions: Conceptualization, CM and HW; methodology, CM and AD; software, CM and AD; validation, AD, AFA and HW; formal analysis, CM; investigation, CM; resources, CM; data curation, CM; writing—original draft preparation, CM; writing—review and editing, AD, AFA and HW; visualization, CM; supervision, AD, AFA and HW; project administration, CM; funding acquisition, CM. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: This research was funded by the Indonesian Endowment Fund for Education/ Lembaga Pengelola Dana Pendidikan (LPDP), grant number 201906211014601.

Conflict of interest: The authors declare no conflict of interest.

References

- AbuThahir, S. B. S., & Krishnapillai, G. (2018). How does the Ambience of Cafe Affect the Revisit Intention Among its Patrons? A S on the Cafes in Ipoh, Perak. *MATEC Web of Conferences*, 150, 05074. <https://doi.org/10.1051/mateconf/201815005074>
- Aldo, A. L., Andreas, B., & Martin, L. (2023). Exploring the associations between E-shopping and the share of shopping trip frequency and travelled time over total daily travel demand. *Travel Behaviour and Society*, 31, 202–208. <https://doi.org/10.1016/j.tbs.2022.11.007>
- Alizadeh, M. J., Shahheydari, H., Kavianpour, M. R., et al. (2017). Prediction of longitudinal dispersion coefficient in natural rivers using a cluster-based Bayesian network. *Environmental Earth Sciences*, 76(2). <https://doi.org/10.1007/s12665-016-6379-6>
- Allahviranloo, M., & Baghestani, A. (2019). A dynamic crowdshipping model and daily travel behavior. *Transportation Research Part E: Logistics and Transportation Review*, 128, 175–190. <https://doi.org/10.1016/j.tre.2019.06.002>
- Anas, A., Arnott, R., & Small, K. (1998). Urban Spatial Structure. *Journal of Economic Literature*, 36, 1426–1464.
- Beckers, J., Weekx, S., Beutels, P., & Verhetsel, A. (2021). COVID-19 and retail: The catalyst for e-commerce in Belgium? *Journal of Retailing and Consumer Services*, 62, 102645. <https://doi.org/10.1016/j.jretconser.2021.102645>
- Bjerkan, K. Y., Bjørgen, A., & Hjelkrem, O. A. (2020). E-commerce and prevalence of last mile practices. *Transportation Research Procedia*, 46, 293–300. <https://doi.org/10.1016/j.trpro.2020.03.193>
- Bjørgen, A., Bjerkan, K. Y., & Hjelkrem, O. A. (2021). E-groceries: Sustainable last mile distribution in city planning. *Research in Transportation Economics*, 87, 100805. <https://doi.org/10.1016/j.retrec.2019.100805>
- Cachinho, H. (2014). Consumerscapes and the resilience assessment of urban retail systems. *Cities*, 36, 131–144. <https://doi.org/10.1016/j.cities.2012.10.005>
- Cahyani D. R. (2017). Riset Google: Warga Surabaya Paling Banyak Belanja Online. *Tempo.Co*.
- Cárdenas, I., Beckers, J., & Vanelslander, T. (2017). E-commerce last-mile in Belgium: Developing an external cost delivery index. *Research in Transportation Business & Management*, 24, 123–129. <https://doi.org/10.1016/j.rtbm.2017.07.006>
- Ceylan, R. F., Ozkan, B., & Mulazimogullari, E. (2020). Historical evidence for economic effects of COVID-19. *The European Journal of Health Economics*, 21(6), 817–823. <https://doi.org/10.1007/s10198-020-01206-8>
- Che, J., Lee, J. S., & Kim, S. (2023). How has COVID-19 impacted the economic resilience of retail clusters?: Examining the difference between neighborhood-level and district-level retail clusters. *Cities*, 140, 104457. <https://doi.org/10.1016/j.cities.2023.104457>
- Chen, Q., Guan, X., & Huan, T. C. (2021). The spatial agglomeration productivity premium of hotel and catering enterprises. *Cities*, 112, 103113. <https://doi.org/10.1016/j.cities.2021.103113>
- Constantin, D. L., & Reveiu, A. (2018). A Spatial Analysis of Tourism Infrastructure in Romania: Spotlight on Accommodation and Food Service Companies. *REGION*, 5(1), 1–16. <https://doi.org/10.18335/region.v5i1.111>
- Coutinho Guimarães, P. P. (2019). Shopping centres in decline: analysis of demalling in Lisbon. *Cities*, 87, 21–29. <https://doi.org/10.1016/j.cities.2018.12.021>
- Das, K., Tamhane, T., Vetterrot, B., et al. (2018). The digital archipelago: How online commerce is driving Indonesia's economic development.
- Delage, M., Baudet-Michel, S., Fol, S., et al. (2020). Retail decline in France's small and medium-sized cities over four decades. Evidences from a multi-level analysis. *Cities*, 104, 102790. <https://doi.org/10.1016/j.cities.2020.102790>
- Dolega, L., Reynolds, J., Singleton, A., et al. (2019). Beyond retail: New ways of classifying UK shopping and consumption spaces. *Environment and Planning B: Urban Analytics and City Science*, 48(1), 132–150. <https://doi.org/10.1177/2399808319840666>

- Ecker, Y., & Strüver, A. (2022). Towards alternative platform futures in post-pandemic cities? A case study on platformization and changing socio-spatial relations in on-demand food delivery. *Digital Geography and Society*, 3, 100032. <https://doi.org/10.1016/j.diggeo.2022.100032>
- Edwards, J. S. A., & Causa, H. (2009). What is food service? *Journal of Foodservice*, 20(1), 1–3. Portico. <https://doi.org/10.1111/j.1748-0159.2008.00122.x>
- Etmnani-Ghasrodashti, R., & Hamidi, S. (2020). Online shopping as a substitute or complement to in-store shopping trips in Iran? *Cities*, 103, 102768. <https://doi.org/10.1016/j.cities.2020.102768>
- Gavilan, D., Balderas-Cejudo, A., Fernández-Lores, S., et al. (2021). Innovation in online food delivery: Learnings from COVID-19. *International Journal of Gastronomy and Food Science*, 24, 100330. <https://doi.org/10.1016/j.ijgfs.2021.100330>
- Gobiz. (2020). Growing 20%, Here are the Culinary Business Trends in Surabaya (Indonesian). Gobiz.Co.Id.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis*, 7th ed. Prentice Hall.
- Hallsworth, A. G., & Coca-Stefaniak, J. A. (2018). National high street retail and town centre policy at a cross roads in England and Wales. *Cities*, 79, 134–140. <https://doi.org/10.1016/j.cities.2018.03.002>
- Hanaysha, J. (2016). Restaurant Location and Price Fairness as Key Determinants of Brand Equity: A Study on Fast Food Restaurant Industry. *Business and Economic Research*, 6(1), 310. <https://doi.org/10.5296/ber.v6i1.9352>
- Handinoto. (2010). *Architecture and Cities in Colonial Java (Indonesian)*. Graha Ilmu.
- Hein, A., Schreieck, M., Riasanow, T., et al. (2019). Digital platform ecosystems. *Electronic Markets*, 30(1), 87–98. <https://doi.org/10.1007/s12525-019-00377-4>
- Henderson, J. C. (2016). Foodservice in Singapore: Retaining a place for hawkers? *Journal of Foodservice Business Research*, 19(3), 272–286. <https://doi.org/10.1080/15378020.2016.1175900>
- Hood, N., Urquhart, R., Newing, A., & Heppenstall, A. (2020). Sociodemographic and spatial disaggregation of e-commerce channel use in the grocery market in Great Britain. *Journal of Retailing and Consumer Services*, 55, 102076. <https://doi.org/10.1016/j.jretconser.2020.102076>
- Hwang, J., & Ok, C. (2013). The antecedents and consequence of consumer attitudes toward restaurant brands: A comparative study between casual and fine dining restaurants. *International Journal of Hospitality Management*, 32, 121–131. <https://doi.org/10.1016/j.ijhm.2012.05.002>
- Jones, C. (2021). Reframing the intra-urban retail hierarchy. *Cities*, 109, 103037. <https://doi.org/10.1016/j.cities.2020.103037>
- Jones, C., & Livingstone, N. (2017). The ‘online high street’ or the high street online? The implications for the urban retail hierarchy. *The International Review of Retail, Distribution and Consumer Research*, 28(1), 47–63. <https://doi.org/10.1080/09593969.2017.1393441>
- Kasali, R. (2018). *The Great Shifting*.
- Kassambra, A., & Mundt, F. (2020). Factoextra: Extract and Visualise the Results of Multivariate Data Analyses. Available online: <https://CRAN.R-project.org/package=factoextra> (accessed on 9 January 2023).
- Kitchin, R. (2013). The real-time city? Big data and smart urbanism. *GeoJournal*, 79(1), 1–14. <https://doi.org/10.1007/s10708-013-9516-8>
- Krehl, A., Siedentop, S., Taubenböck, H., et al. (2016). A Comprehensive View on Urban Spatial Structure: Urban Density Patterns of German City Regions. *ISPRS International Journal of Geo-Information*, 5(6), 76. <https://doi.org/10.3390/ijgi5060076>
- Le, H. T. K., Carrel, A. L., & Shah, H. (2021). Impacts of online shopping on travel demand: a systematic review. *Transport Reviews*, 42(3), 273–295. <https://doi.org/10.1080/01441647.2021.1961917>
- Lee, R. J., Sener, I. N., Mokhtarian, P. L., et al. (2017). Relationships between the online and in-store shopping frequency of Davis, California residents. *Transportation Research Part A: Policy and Practice*, 100, 40–52. <https://doi.org/10.1016/j.tra.2017.03.001>
- Line, N. D., & Hanks, L. (2020). A holistic model of the servicescape in fast casual dining. *International Journal of Contemporary Hospitality Management*, 32(1), 288–306. <https://doi.org/10.1108/ijchm-04-2019-0360>
- Nahiduzzaman, K. M., Aldosary, A. S., & Mohammed, I. (2019). Framework Analysis of E-Commerce Induced Shift in the Spatial Structure of a City. *Journal of Urban Planning and Development*, 145(3). [https://doi.org/10.1061/\(asce\)up.1943-5444.0000512](https://doi.org/10.1061/(asce)up.1943-5444.0000512)
- Parsa, H. G., Self, J. T., Njite, D., et al. (2005). Why Restaurants Fail. *Cornell Hotel and Restaurant Administration Quarterly*, 46(3), 304–322. <https://doi.org/10.1177/0010880405275598>

- Pelzer, P., Frenken, K., & Boon, W. (2019). Institutional entrepreneurship in the platform economy: How Uber tried (and failed) to change the Dutch taxi law. *Environmental Innovation and Societal Transitions*, 33, 1–12. <https://doi.org/10.1016/j.eist.2019.02.003>
- Rahman, D. F. (2022). Mall Kiosk Tenants in Surabaya Predicted to Increase in 2022 (Indonesian). Databoks. Katadata. Co. Id.
- Recio, R. B., & Gomez, J. E. A. (2013). Street Vendors, their Contested Spaces, and the Policy Environment: A View from Caloocan, Metro Manila. *Environment and Urbanization ASIA*, 4(1), 173–190. <https://doi.org/10.1177/0975425313477760>
- Ricklefs, M. C., Lockhart, B., Lau, A., et al. (2013). History of Southeast Asia from Prehistory to Contemporary Times (Indonesian). Komunitas Bambu.
- Rodrigue, J. P. (2020). *The Geography of Transport Systems*. Routledge. <https://doi.org/10.4324/9780429346323>
- Seol, H. (2023). SnowCluster: Multivariate Analysis (Version 7.1.7). jamovi module.
- Sevtsuk, A. (2014). Location and Agglomeration. *Journal of Planning Education and Research*, 34(4), 374–393. <https://doi.org/10.1177/0739456x14550401>
- Shao, R., Derudder, B., & Witlox, F. (2022). The geography of e-shopping in China: On the role of physical and virtual accessibility. *Journal of Retailing and Consumer Services*, 64, 102753. <https://doi.org/10.1016/j.jretconser.2021.102753>
- Silas, J. (2002). Toll roads and the development of new settlements; The case of Surabaya compared to Jakarta. *Bijdragen Tot de Taal-, Land- En Volkenkunde / Journal of the Humanities and Social Sciences of Southeast Asia*, 158(4), 677–689. <https://doi.org/10.1163/22134379-90003761>
- Singleton, A. D., Dolega, L., Riddlesden, D., et al. (2016). Measuring the spatial vulnerability of retail centres to online consumption through a framework of e-resilience. *Geoforum*, 69, 5–18. <https://doi.org/10.1016/j.geoforum.2015.11.013>
- Stehlin, J., Hodson, M., & McMeekin, A. (2020). Platform mobilities and the production of urban space: Toward a typology of platformization trajectories. *Environment and Planning A: Economy and Space*, 52(7), 1250–1268. <https://doi.org/10.1177/0308518x19896801>
- Supranto, J. (2010). *Multivariat Analysis, Meaning and Interpretation* (Indonesian). Penerbit Rineka Cipta.
- Talamini, G., Li, W., & Li, X. (2022). From brick-and-mortar to location-less restaurant: The spatial fixing of on-demand food delivery platformization. *Cities*, 128, 103820. <https://doi.org/10.1016/j.cities.2022.103820>
- Telgarsky, M., & Vattani, A. (2010). Hartigan's Method: K-means Clustering without Voronoi. In: *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. pp. 820–827.
- Thornton, L. E., Lamb, K. E., & Ball, K. (2016). Fast food restaurant locations according to socioeconomic disadvantage, urban-regional locality, and schools within Victoria, Australia. *SSM - Population Health*, 2, 1–9. <https://doi.org/10.1016/j.ssmph.2015.12.001>
- Tran, L. T. T. (2021). Managing the effectiveness of e-commerce platforms in a pandemic. *Journal of Retailing and Consumer Services*, 58, 102287. <https://doi.org/10.1016/j.jretconser.2020.102287>
- Widaningrum, D. L., Surjandari, I., & Sudiana, D. (2020). Discovering spatial patterns of fast-food restaurants in Jakarta, Indonesia. *Journal of Industrial and Production Engineering*, 37(8), 403–421. <https://doi.org/10.1080/21681015.2020.1823495>
- Yuana, S. L., Sengers, F., Boon, W., et al. (2019). Framing the sharing economy: A media analysis of ridesharing platforms in Indonesia and the Philippines. *Journal of Cleaner Production*, 212, 1154–1165. <https://doi.org/10.1016/j.jclepro.2018.12.073>
- Zhang, Y., Li, X., Jiang, Q., et al. (2022). Quantify the Spatial Association between the Distribution of Catering Business and Urban Spaces in London Using Catering POI Data and Image Segmentation. *Atmosphere*, 13(12), 2128. <https://doi.org/10.3390/atmos13122128>
- Zhong, C., Schläpfer, M., Müller Arisona, S., et al. (2016). Revealing centrality in the spatial structure of cities from human activity patterns. *Urban Studies*, 54(2), 437–455. <https://doi.org/10.1177/0042098015601599>
- Zhou, Y., Shen, X., Wang, C., et al. (2022). Mining the Spatial Distribution Pattern of the Typical Fast-Food Industry Based on Point-of-Interest Data: The Case Study of Hangzhou, China. *ISPRS International Journal of Geo-Information*, 11(11), 559. <https://doi.org/10.3390/ijgi11110559>