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Research paper

Emerging economic geography of urban restaurants as freight generators: Logistics policy implications for managing dark kitchens and food trucks

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ABSTRACT

The rapid rise of app-based food delivery platforms has redefined how restaurants shape urban space. However, little is known about how these evolving restaurant types cluster and interact with urban land use. Using spatial analysis involving Ripley's-*K* and Moran's-*I* and predictive models involving decision trees, random forest, and multinomial logit models, this study attempts to explain the location choices of restaurants based on their relative distance to the city centre, rent, population density, and night-time light (NTL) intensity. Analysis results reveal that dark kitchens exhibit the tightest clustering, often in low-rent, high-density zones, while in-person dining is concentrated in high-rent, high-NTL areas. Among the models tested, random forest outperformed decision trees and multinomial logit models in predicting restaurant types, with night-time light emerging as the strongest spatial predictor. The clustering patterns observed in emerging urban restaurant types differ significantly from traditional brick-and-mortar establishments; study findings highlight the urgent need for adaptive freight planning and zoning policies to address the growing logistical footprint of digitally mediated food establishments. While based in Indian cities, the framework and insights of this study are transferable to other global contexts where on-demand food delivery and mixed-use zoning intersect in urban areas.

1. Introduction

Food industry establishments have undergone significant changes in recent years, with four clearly distinguishable alternatives: (i) "dark kitchens", (ii) in-person dining-only facilities, (iii) "hybrid restaurants", and (iv) "mobile food trucks". Dark kitchens are essentially restaurants, similar to quick commerce, which offer on-demand food deliveries by relying on the tight-knit network of food delivery companies (Bretas & Alon, 2020; Buldeo Rai et al., 2023). "Ghost kitchen", "cloud kitchen", "commissary", or "cyber kitchen" are other terms commonly used to define dark kitchens (Kulshreshtha & Sharma, 2022). Dark kitchens solely partner with online delivery platforms, utilizing an alliance with third-party logistics providers while hiding in obscure urban spaces. In contrast to dark kitchens, in-person dining-only restaurants offer only table service, distinguished from the delivery facilities, but typically involve takeout options (Cheng et al., 2015). Whereas hybrid kitchens are restaurants that incorporate multiple service models, such as table service, take-out service, and independently operated or app-based delivery services. These restaurants are trying to capture varied consumer preferences by combining multiple services (He et al., 2019; Mishra et al., 2025). Lastly, "mobile food trucks" typically do not have seating capacity or lack app-based delivery services, although some have a self-owned delivery system (Kraus et al., 2022).

Despite the rapid proliferation of dark kitchens and food trucks, existing land use ordinances do not account for their presence (Buldeo Rai et al., 2023). Most of the city agencies do not have any specific category for such emerging food establishments, and the licenses are granted by the public health and food safety departments on the same guidelines as traditional in-person dining restaurants (Sharma, 2023). Along with this, managing and controlling the generated freight traffic

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from the restaurants for delivery purposes is another challenge for the planners. According to Wang and He (2021), on-demand food delivery usage in China concentrates on areas with lower food accessibility by walking, a higher mixed land use, and a higher percentage of land used for urban residences and commerce. Similarly, in a recent study, the authors quantified the food industry's emerging freight activity and found that dark kitchens are one of the most prominent short-trip freight generators in the case of food establishments in India (Mishra et al., 2025). However, little is known regarding the economic geography of restaurants – i.e., how the spatial location and distribution of restaurants are influenced by factors such as consumer demand (both in-person dining and on-demand delivery), proximity to other points of interest and central business district, and urban development patterns in various cities, ultimately leading to varying types of clustering in the case of different types of restaurants. Insights into the economic geography of restaurants may not only assist the development of the restaurant industry but also provide valuable information for the evaluation of existing urban policies related to city logistics and the exploration of urban dynamics in an on-demand economy, fulfilling consumers' ever-growing needs for physical goods. This paper addresses above-mentioned critical research gaps and contributes to the literature on key fronts: (1) Examines how and where food industry establishments belonging to different categories cluster in cities using spatial statistical techniques; (2) Quantify strategic locational complementarities between dark kitchens, mobile food trucks, hybrid kitchens, and traditional in-person dining only restaurants; (3) Understand if there are any statistically significant probabilities associated with finding a particular type of restaurant in a particular neighbourhood type and whether it varies depending on the type of the city in terms of mix land-use, and (4) Comparing the accuracy of restaurant type prediction based on land-use parameters using econometric models and machine learning algorithms, in order to guide future research on predicting urban dynamics related to restaurants. The above four contributions are particularly notable in the context of the growing need to regulate the freight activities from various food industry establishments falling under the scope of this study.

To make the above contributions, this study collects data from three cities in India: New Delhi, Gautam Buddha Nagar, and Gurugram, regarding locations of dark kitchens, hybrid restaurants, in-person dining-only facilities, and mobile food trucks. Spatial clustering patterns are examined using Moran's I and Ripley's K function to quantify the degree of spatial autocorrelation between the individual restaurant types and the growing spatial agglomeration of different kinds of restaurants. To classify the land use pattern of different types of restaurants, the study performed two machine learning methods (decision tree and random forest) for predictive analytics and one econometric model (multinomial logit model) to assess probabilistic association within variables by using the publicly available dataset. In doing so, our aim is to support the public sector in better planning for these emerging types of establishments, anticipating their traffic-related impacts, and enacting policies and regulations accordingly. Additionally, this study is expected to help in reducing the freight trip generation by identifying the clusters of high-density food service establishment locations and improving urban logistic planning. Overall, the study provides data-driven insights to develop on-demand food delivery traffic regulations, optimize land use planning, and qualitatively support policies regarding evolving urban dynamics in the restaurant sector.

The rest of the paper is organized as follows. Section 2 provides a brief overview of prior research. The research gap, data requirements, and applied methodology are examined in Section 3, followed by a description of the results in Section 4. Section 5 continues with policy and practice implications, while the final section of the paper concludes.

2. Research background

2.1. Location patterns of restaurants

The location choices of industry type received considerable attention from urban planners, policymakers, and economists. The spatial distribution of these industries has a significant impact on the region's development and economic geography. Location theory provides a framework for understanding the spatial distribution of these industries (North, 1955). It defines the factors influencing the relationship between firm location choice and resulting spatial clustering, often shaped by cost-minimization strategies. In line with the advancement of technology used for on-demand delivery, the term economic geography encompasses both clustering and land use classification. Urban establishments frequently cluster to outline the supply and demand factors. On the supply side, a collaborative business environment within the industry supports the clustering of establishments, whereas on the demand side, the emergence of advanced technology and shifting customer behaviour allows the clustering of establishments (Nilsson et al., 2018).

The spatial distribution and location choice of the commercial establishments are not only shaped by business decisions but also affected by the land use pattern and local land use policies (Li et al., 2020). In the case of restaurants, clustering patterns vary by type; casual restaurants benefit from being clustered, whereas quick-service restaurants exhibit more dispersed patterns (Jung & Jang, 2019). Studies have employed Ripley's k function to investigate the spatial relations among establishments based on restaurant price, distance to CBD, and external variables like theatres, parks, and museums. Additionally, the Tobit model was also followed to define the relationship between agglomeration and pricing segmentation of restaurants. Alghamdi (2023) conducted k-means and an artificial neural network to determine the market segmentation using the social media data, though incorporating land use as a determinant factor is lacking in the study, which has attained limited attention in spatial business analysis.

This spatial concentration of economic activities can interrupt the balance among the five categories of land use, i.e., residential, commercial, recreational, social, and transportation facilities (Lau et al., 2005). Small businesses, including restaurants, support urban vibrancy by integrating with residential neighbourhoods and leading to a more diversified land use mix (Chen et al., 2024). However, the growing reliance on on-demand food delivery presents both economic opportunities and challenges (Dablanc et al., 2017). While these food deliveries enhance economic performance (Seghezzi & Mangiaracina, 2021), they also introduce negative externalities such as noise pollution and freight traffic (Sinha & Pandit, 2021). Existing literature has primarily focused on the logistical challenges raised by the on-demand deliveries (Allen et al., 2021; Paithane et al., 2023; Pani et al., 2024). However, there are limited studies explaining the location of freight trip generators associated with on-demand delivery, highlighting the need for improved urban freight logistics (Mishra et al., 2025). A clustering-based zoning approach could be helpful for freight trip modelling and support urban freight planning (Regal et al., 2023).

2.2. Land use patterns and restaurants as urban freight generators

The growth of food industries and distribution in urban areas is the result of multiple factors, where the rise and fall of restaurants affected the urban growth patterns and their dynamics. These factors include promoting factors like commercial land use and building capacity, hindering factors like restaurant density, and stabilizing factors such as housing prices (Wu et al., 2021). Socioeconomic and spatial determinants, including accessibility (Wang & He, 2021), population and neighbourhood demographics (Moore & Diez Roux, 2006), land use planning (Shoag & Veuger, 2019) and built environmen, have been found to affect the location heterogeneity of restaurants. Moreover, land use attributes aid in defining freight trip zones (Pinheiro et al., 2025). For example, Regal et al. (2023) proposed a zoning procedure for urban logistics planning using spatial, socio-economic, and logistic intensity variables. Similarly, Holguín-Veras et al. (2011); Lawson et al. (2012) proposed a freight trip generation and freight trip attraction model considering land-use classification. Overall, the land use variable contributes to addressing spatial patterns and their impact on urban logistics, which provides insights into planning. Additionally, clustering dynamics are influenced by the agglomeration of economic activity (Samani et al., 2023). Interestingly, research suggests that, in comparison to economic indicators, the distribution of economic activities strongly correlated with the nighttime light (Li et al., 2019).

The spatial organisation of firms is associated with economic decision-making, with external environment factors and agglomeration economies (Håkonsson et al., 2019). While business tendencies exhibit clustering, patterns of dispersion and/or concentration vary across industry types (Albert et al., 2012). However, smaller businesses often face higher spatial constraints than larger businesses due to their higher trade cost (Bartelme et al., 2022). Therefore, location is widely recognized as a key determinant of economic success for restaurants as well (Prayag et al., 2012); and explained by central place theory (Mulligan Gordon, 1984) and spatial interaction theory (Nakaya et al., 2007). However, few studies have underlined the classification of food service establishments beyond basic industry strategy. For instance Canziani et al. (2016), qualitatively classify restaurants into five categories based on the 345 empirical studies based on service type, ownership, and spatial characteristics. This clearly defines the heterogeneity in the food industry with varied locational features. A recent study by Talamini et al. (2022) highlights the regional disparities in the spatial distribution of traditional brick-and-mortar restaurants versus platform-dependent establishments by considering transportation accessibility. However, it is well known that the rise of platform-dependent restaurants negatively impacted transport accessibility.

2.3. Existing city logistics policy assessments focusing on restaurants

Despite growing interest in on-demand delivery and agglomeration patterns of restaurants, limited research has examined land use classification specific to individual restaurant types. Few studies (Canziani et al., 2016; Planinc et al., 2018) attempt the classification of restaurants, but regarding emerging types of commercial establishments, limited efforts have been made to classify food service establishments and understand how their agglomeration patterns influence urban traffic. However, data limitation continues to pose challenges for on-demand freight deliveries.

From an urban planning perspective, managing the on-demand freight deliveries is essential in accordance with the commercial expansion and variation in land use patterns. For instance, McLeod et al. (2019) reviewed the interrelation between proposed freight generation models, strategic land use, and transport planning decisions. The study highlights that demand factors, land use relocation effects, shifting firm strategies, and emerging transport technology are significant in the practice of understanding, managing, modelling, and planning urban freight. Effective land use policies by considering the food establishments as a freight generator, transportation impact assessment, and traffic management strategies are required. Along with regulatory measures for freight trip attraction and production, loading zones have become an important challenge to study with commercial expansion (Bjørgen & Ryghaug, 2022). Furthermore, business charechterstics such as age, size and industry sector has influence on the freight trip production and attraction (Pani et al., 2022).

2.4. Past methodological approaches in firm-level spatial analysis

As well as what was previously mentioned, prior studies are lacking in the explanation of emerging restaurant clustering in the food industry. To study clustering analysis, there are various methods followed in different fields of science, such as crime, accidents, and planning (Jung & Jang, 2019; Prayag et al., 2012; Regal et al., 2023). Notably, Ripley's K function is the most effective and comprehensive method, as it has the ability to study the cluster pattern at various spatial scales (Kan et al., 2022). Similarly, Moran's I is primarily used for spatial autocorrelation statistics, popular because of its sensitivity, easy interpretability, and consistency with other indices. It is the most commonly used method for accident and crime analysis (Chung & Kim, 2019; Gedamu et al., 2024). For the classification of nominal variables, various methods are available, such as decision trees, random forests, K-nearest neighbour analysis, logistic regression, Naïve Bayes, and so on. However, decision tree is a disaggregate analysis method. It uses a non-parametric approach for classification purposes (James et al., 2013). It is used in various fields, including healthcare, environment, and transportation (Pitombo et al., 2017; Ramakrishnan et al., 2023; Zhang et al., 2023). The Random Forest method is a combination of multiple decision trees. It is famous for its enhanced prediction capability, fast computation, and easy interpretability (Biau & Scornet, 2016). Machine learning models learn directly from the data without considering the predefined features and excel in terms of prediction and pattern reorganization. The multinomial logit (MNL) model is an econometric model widely used in choice behaviour studies (Meena et al., 2019). The MNL works on nominal dependent variables when alternatives are non-nested and no alternative-specific independent variables (Thrane, 2015).

3. Data and methodology

The study aims to analyse the location patterns of restaurants and examine if there are any statistically significant probabilities associated with finding a particular type of restaurant in a particular neighbourhood type, and whether it varies depending on the type of city in terms of mixed land-use Ripley's K function and Moran's I are used to identify clusters and analyze the spatial patterns of clusters for different restaurant types. Furthermore, the analysis is performed using the decision tree technique, random forest method, and a multinomial logit model to classify the city into zones containing homogeneous restaurant patterns based on some explanatory variables.

3.1. Data acquisition

3.1.1. Study area

The study area for this research consists of three urban areas: (i) New Delhi (the Capital city of India) and its two neighbouring satellite cities: (ii) Gurugram, and (iii) Gautam Buddha Nagar (GBN). Considering these three cities together is part of the research design to empirically test whether significant differences exist between the economic geography of restaurants depending on city type.

Each of these three study cities has unique characteristics that make it logical to consider them in a single case study. For instance, New Delhi is a megacity with mixed-use land use patterns and a substantially high population density of 11,312 people per square kilometre. On the other hand, Greater Noida (part of GBN) is highly varied, encompassing low-rise planned developments, high-rise residential buildings, and rural villages extensively dispersed throughout the area, comprising of an average population density of 1161 inhabitants per square kilometre. Gurugram, known for its automobile industry and special economic zones, hosts numerous commercial establishments, associated with an average population density of 1241 inhabitants per square kilometre. The visualisation of the study area is presented in Fig. 1.

3.1.2. Data and sampling method

According to the National Restaurant Association of India (Ali, 2024), there are around 66,000 restaurants in New Delhi, 54,000 in Gurugram, and 33,000 in GBN. However, a substantial number of

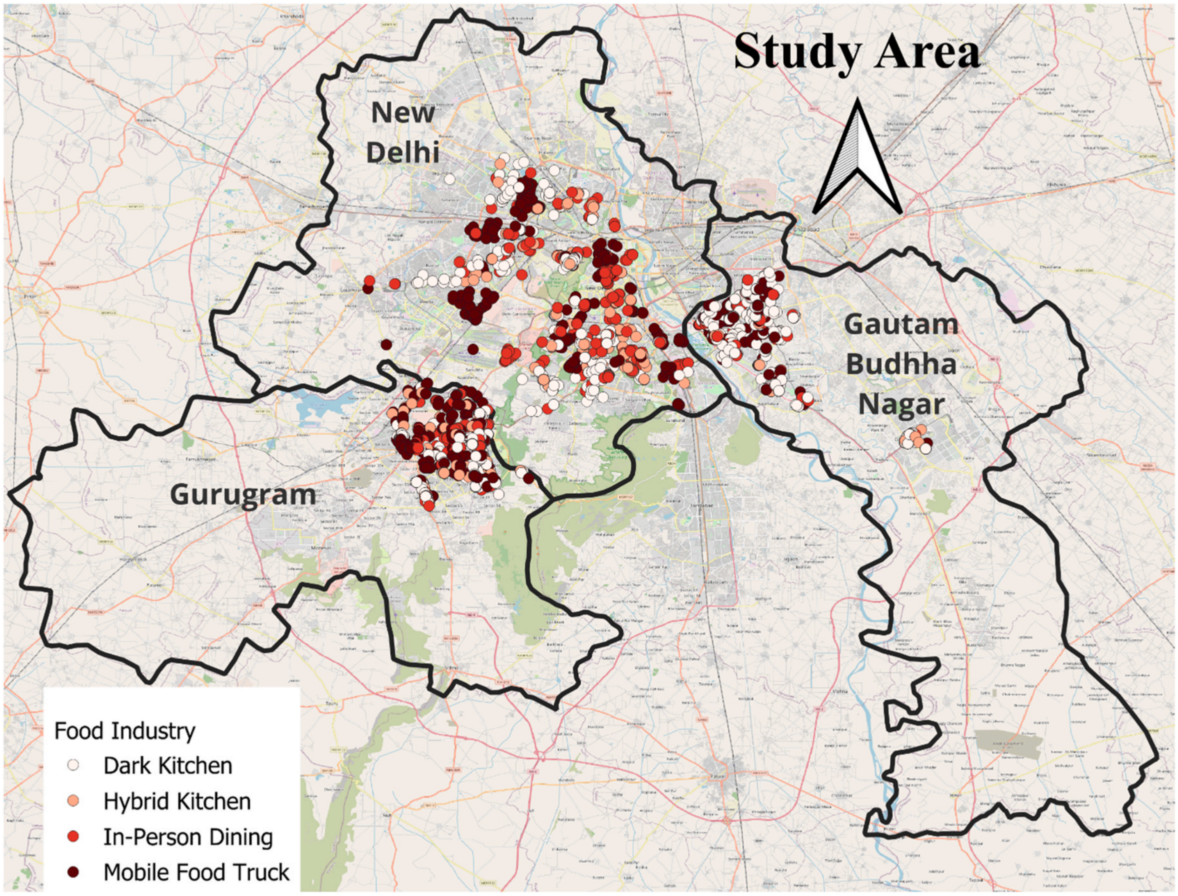


Fig. 1. Study area with restaurant data, consisting of 3 cities: Delhi, Gurugram, and GBN.

restaurants counted in this estimate belong to the informal sector without sufficient information in the public domain. Considering the lack of restaurant-type information in points-of-interest (POI) databases available with OpenStreetMap, data for this study was acquired from the proprietary database of Zomato, a leading app-based restaurant aggregator in India. The primary data set contains information about the 5000 restaurants for all three study areas – i.e., New Delhi, Gurugram, and GBN. After removing some data by checking the originality of the restaurants and eliminating the ones with incomplete information, the final sample size was reduced to 2920. Each restaurant is classified according to two fundamental properties - i.e., whether it has table service and whether it offers delivery. A dark kitchen offers only delivery service, while a traditional in-person restaurant provides only in-person dining service. Hybrid restaurants offer both table service and delivery, and mobile food trucks have neither but feature adaptable space, as presented in Table 1.

Despite the large sample size obtained from a restaurant aggregator, it may be noted that a substantial share of restaurants in the unorganized sector (vendors selling ready-to-eat food on carts, roadside eateries, and street stalls) are not reflected in the database used for this analysis. The scope of our study is limited to restaurants in the organized sector which has formal registration and that adhere to labour and tax laws. It may still be noted that the final sample size used in this study is substantially greater than the datasets reported in past studies, owing to access to the restaurant aggregator database. For example (Vu et al., 2023), consider 20 interviews by using purposive sampling techniques. Buldeo Rai et al. (2023) consider 155 Dar kitchens in New York City and 91 from Paris. Enthoven and Brouwer (2020) considered 591 restaurants to study the spatial concentration of restaurants. In our current study, 1383 restaurants are analysed for New Delhi (2.1 % of the total target population), 813 restaurants in Gurugram (1.5 % of the total target population), and 723 restaurants in GBN (2.2 % of the total target population).

Table 1
Theoretical definition of the classification of restaurants.

Types of Restaurants	Has Table?	Has Delivery?	Final Sample Size		
			New Delhi	Gurugram	GBN
Dark Kitchen	No	Yes	369	266	186
Hybrid Kitchen	Yes	Yes	227	137	162
In-Person Dining	Yes	No	355	51	144
Mobile Food Trucks	No	No	432	359	231
Total Sample Size			1383	813	723

3.1.3. Data description

Only locally accessible data, such as the minimum distance from the Central Business District (CBD), the NASA Nighttime Light, local rent prices, and population density statistics from the 2011 Census, are used to examine diversification. In place of traditional parameters such as land and economic variables, the study considered a unique variable to represent the land use and economic growth together, i.e., Night Time Light (Elvidge et al., 2012). The area is divided into grids of one square kilometre. Data on rent price and population density are collected from a secondary source (Lepetit Quentin, 2023). The restaurant is assigned to a particular grid by using a spatial join. The population density and rent price in that area are determined based on the assigned grid. Connaught Place is identified as Delhi's CBD, and the network distance from each restaurant to this point is calculated using the O-D toolbox in QGIS. For Gurugram and GBN, the maximum NTL grid is used as the CBD reference point to measure distances. Mobile food trucks and dark kitchens share small areas focused on cooking, while hybrid kitchens and in-person dining offer both meal delivery and on-site dining experiences.

3.1.3.1. Night-time light data. The Night Light Index, popularly known as nighttime light (NTL), works as a proxy to study changes in the socio-economic environment. It is a globally available and geographically explicit empirical indicator that reflects human development in the social and demographic domains. It can be used as an indicator of income (Gini index), electrification, human security, human development, and poverty (Elvidge et al., 2012). Collecting data on the NTL is easier compared to other socio-economic data sources. For instance, population censuses provide more detailed information but are conducted only every ten years due to the effort involved. NTL data, however, are both spatially and temporally spread out and are easy to gather. It is publicly accessible on the NASA website and can be downloaded using a supercomputer. In our study, we considered the NTL as a deriving parameter of the classification, of which the unit is nanowatts per square centimetre per steradian (nW/cm^2/sr). Fig. 2 shows the variance in nighttime light in the three cities under consideration.

More intensely developed areas correspond to higher brightness, whereas smaller settlements and less intensively developed areas correspond to lower brightness (Small et al., 2011). On average, New Delhi can be seen to have the highest NTL, followed by Gurugram and GBN. When the highest value of NTL is 183.5 in Delhi, it is 103.67 in Gurugram and 86.92 in GBN. While most of the places in Gurugram and GBN are classified as low NTL, the majority of the areas in Delhi are classified as high NTL. It means that regional variations exist in terms of development, population density, economic prosperity, and the allocation of regions for various uses. With their growing tendency to be located near residential, institutional, and recreational regions, restaurants' spatial organization could be better explained by NTL, as tested in the analysis of this study.

3.1.3.2. Land price real estate data. Land costs and real estate information are key metrics for assessing the economic health of an area. For commercial organizations, land prices play a crucial role in site selection. Urban land use restrictions significantly shape urban development, commercial occupancy, housing and transportation costs, as well as the economic well-being of citizens (Kok et al., 2014). Similarly, topographical and economic factors affect location choices for commercial establishments (Hilber & Robert-Nicoud, 2013; Saiz, 2010). Land prices increased due to the positive amenity effect of land use and regulations (Elliott, 1981), particularly when there are no comparable alternatives in the same metropolitan area (Glaeser & Ward, 2009). The cost of land also varies depending on the land use pattern. To identify locational differences and similarities across categories, we analysed rent prices as a derived variable for classifying and categorizing restaurants.

3.2. Analysis methods

The study followed two methods for clustering analysis, with three methods for the prediction of the land use pattern of four restaurant types across three study areas. The pictorial presentation of the methodological framework is presented in Fig. 3.

3.2.1. Ripley's K function to assess spatial association

Ripley's K-function (Kan et al., 2022) is used to assess the economic activity and land use property of restaurants in relation to their geographical location (Albert et al., 2012). Ripley's K is a function that determines the threshold to quantify cluster, dispersion, and agglomeration over varied distances (Talamini et al., 2022), assuming that restaurants are randomly and independently distributed over the study area. It generates two results: observed K and expected K, based on a distance-based method and the density of restaurants in their service region. For a scattered distribution, the observed K is smaller than expected K, and vice versa for agglomeration. The K-function is mathematically represented by equations (1)–(3).

$$K(r) = \frac{1}{\lambda N} \sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} W_{ij} I(d_{ij}) \tag{1}$$

$$I(d_{ij}) = f(x) = \begin{cases} 1, d_{ij} \leq r \\ 0, d_{ij} > r \end{cases} \tag{2}$$

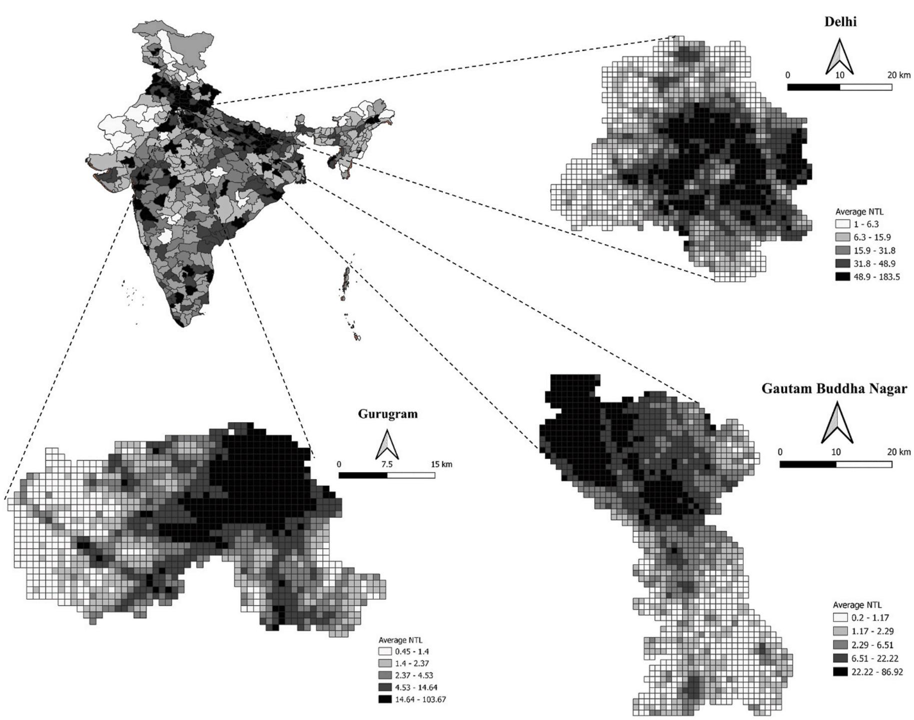


Fig. 2. Night-time light variation in the study cities (size of the grids is 1 km × 1 km).

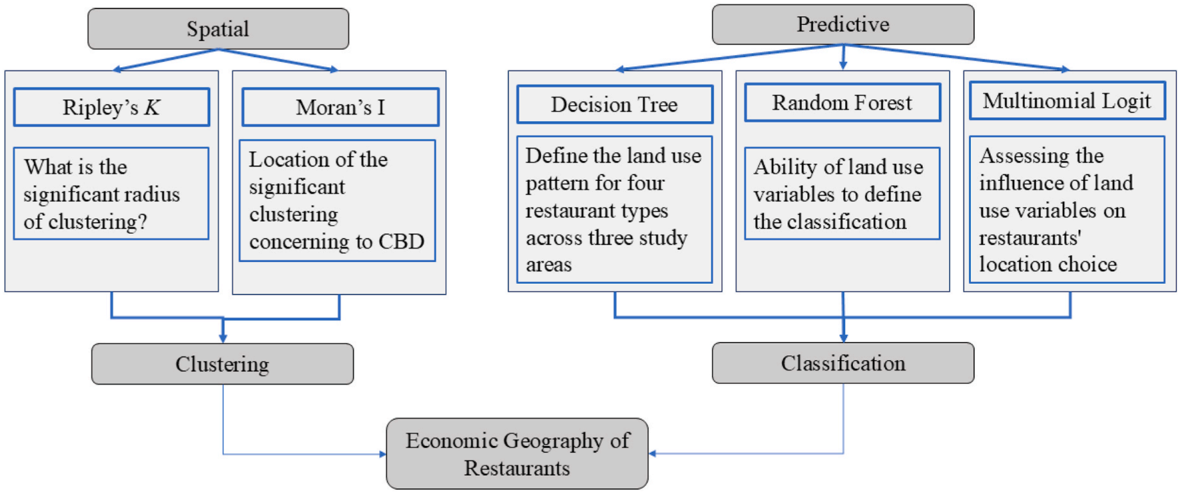


Fig. 3. Methodological framework for the study.

$$\lambda = \frac{A}{N} \tag{3}$$

The characteristics of restaurants are defined by $K(r)$: where r is the radius of the effective area of each element. The total number of restaurants in that radius covered area (A) is represented by N , and the inverse of the density of elements in that area is by λ, i and j represents the indices for different establishments.

Another way to define spatial interrelationships across restaurant classes is the Cross-K Function, which is based on the density of restaurants within respective service regions. It provides insight into the spatial behaviour of one restaurant type in comparison to another (R_Package_spNetwork). The Cross-*K*-Function is mathematically represented as below.

$$K(r) = \frac{1}{n_{ij}n_{ji}} \sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} W_{ij} I(d_{ij}) \tag{4}$$

Where n_{ij} and n_{ji} represent the density of restaurants inThe different establishments.

G-function is another method of finding cluster situations. *K*-functions are used to calculate the *K* and *G* functions using spNetworks in the R-studio. Monte Carlo simulations were used to make the inference. The observed *K* and *G* functions are visually compared to an n-point-generated dataset in which the points are distributed randomly over the road network.

3.2.2. Moran's I function to identify the agglomeration patterns

The spatial autocorrelation coefficient is defined by Moran's *I*. As a defining property of spatial weights (Chen, 2013), it is essentially related to the unpredictability of the spatially dispersed. Moran's *I* function is an indication of dispersion or clustering and behaves as a non-random distribution. Based on the Pearson correlation coefficient, it is described as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \tag{5}$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \tag{6}$$

Where, Z_i or Z_j represent the deviation of an establishment's attributes, i stand for an establishment and j for an establishment in the neighbourhood, W_{ij} is the weight between the establishments based on the feature value, and n is the total number of establishments. Moran's *I* coefficient is presented by *I*.

The Moran's *I* can be estimated as local Moran's *I* and global Moran's *I* (Moran, 1950). Where the global Moran's *I* is the sum of the local Moran's *I*. It statically defined the distribution of spatial data using z-score (Pani et al., 2019). The neighbourhood of the establishments can be decided based on the queen and rook criteria. The spatial weight matrix is decided from the identification of the neighbours and represented by 1 or 0.

3.2.3. Decision trees

In general, a decision tree uses numerical and categorical independent factors to classify the target variable. The nodes are decided based on the residual sum of squares (RSS), and the splitting is done based on recursive binary splitting. It is a non-parametric supervised learning algorithm. The regions selected can be explained as $R_{j1} = \{X|X_j \geq S\}$ and $R_j = \{X|X_j < S\}$. Where the predictor X_j can explain the region from the S disunify point of view for a particular type of variable X (James et al., 2013). Chi-square Automatic Interaction Detection (CHAID) is one of the most popular fast, statistical, multiway growing algorithms used in our study (IBM, 2012).

3.2.4. Random forest algorithms

Random forest is another method of classification. As per Biau and Scornet (2016), "a random forest is a meta estimator that uses averaging to increase prediction accuracy and manage over-fitting after fitting many decision tree classifiers on different subsamples of the data sets". Additionally, the process known as "random features selection" generates the trees by selecting explanatory variables at random to prevent correlations between the base trees (Kulkarni & Lowe, 2016).

3.2.5. Multinomial logit model

Another method for classification is the Multinomial Logit Model (MNL), which can handle more than two categories in both ordinal and nominal variable types. The response variable (Y) is an ordered variable. The assumption is that the error components are identically and independently distributed across alternatives and observations. The distribution followed by the MNL is a gamble distribution, and the distribution of the randomly selected samples follows the same distribution as the dataset, which is not possessed by the normal distribution (Washington et al., 2003).

$$pr\{Y \leq y_i|X\} = F(\alpha_i + \beta' x) \tag{7}$$

The response variable Y categorised as i number of categories where, $y1 < y2 < \ldots < ym$ and the latent variable U can be determined by the explanatory variable vector x represented as $\alpha_i + \beta' x$, where, β is the regression coefficient vector and α_i is the random variable, and F is the logistic distribution function.

3.3. Preliminary analysis

A descriptive analysis of three distinct research areas is presented in Table 2, categorizing areas into 4 zones (0–5 km, 5–10 km, 10–15 km, and beyond 15 km) based on the distance to the central business district (CBD). The table details the statistics of the explanatory variables (average distance between a restaurant and the city centre, the average rent price, the average population density, and the average amount of NTL) for each restaurant type used in the study. From Tables 2 and it is noticed that the number of restaurants increases with distance from the CBD up to 15 km in all three study areas. In the zone, 0–5 km (near CBD), the highest concentration of in-person dining is observed in Delhi, whereas in Gurugram and GBN, dark kitchens and mobile food trucks are more dominant. In Delhi and GBN, the highest number of restaurants is observed in the 10–15 km zone, although in Gurugram, it is in the 5–10 km zone. The distance from CBD to a restaurant represents the average distance of a restaurant type from CBD within a given zone. In Delhi, In-person dining restaurants are concentrated closer to the CBD (average distance of 1.93 km), whereas dark kitchens are farther away (distance of 4. 2 km). However, in Gurugram and GBN most restaurants are located within a distance of 3–4 km from the CBD. In zones away from the CBD, the distance difference between the restaurant types is decreasing for all three cities.

Population density is defined as the average population per square kilometre grid. In Delhi, the dark kitchens in the 0–5 km and 10–15 km zones are concentrated in high-population density areas, whereas in-person dining and hybrid kitchens are more common in low-population-density areas. However, in the 5–10 km zone, the opposite pattern is identified, with dark kitchens found in low-density regions. In Gurugram, dark kitchens are primarily located in low-population areas. As the distance from the CBD increases, the dark kitchen and In-person dining restaurants tend to be found in areas with similar population density. The average rent price is high in the zone 5–10 km for Delhi and Gurugram, whereas in GBN it peaks in the zone 10–15 km. In Delhi, dark kitchens in the 0–5 km zone are located in lower rent-price areas compared to in-person dining restaurants. However, in the 5–10 km zone, the reverse pattern is identified, with dark kitchens located in higher rent areas. In contrast, in Gurugram and GBN, dark kitchens tend to be located in higher-rent-price areas than in-person dining-only restaurants.

In-person dining-only restaurants are located at higher nighttime light (NTL)areas in zone 0–5 km of Delhi. In other zones, the nighttime light pattern is observed to be relatively consistent across restaurant types. In Gurugram, the highest NTL is observed for the 0–5 km zone, whereas in GBN, the highest NTL is observed for the 10–15 km zone. However, in both the cities, NTL across restaurant types is minimal.

4. Results and discussions

4.1. Analysing the spatial organization of restaurants

4.1.1. Ripley's K function

We performed the *K*-function and *G*-function analysis on the spatial pattern of restaurants to examine the geographical distribution of economic activity within cities. The $Y-axis$ plots the variation in the *K*-function and *G*-function, to define the spatial distribution of the set of restaurants whether they are more or less clustered. It counts the average number of neighbouring restaurants for individual restaurants within a given annulus. While the $X-axis$ plots the distance from the restaurants. The blue line in the figure represents the cumulative observed *K*-function of the restaurant network and the grey area represents the expected *K*-function for 50 simulations within a 0.05 confidence interval. It is observed with $50\,m$ steps, the distance ranges *from* 0 *to* 15 *km*. We consider the endpoint to be up to 15 *km* as the maximum delivery distance offered by food delivery apps is 14 *km to* 17 *km*. Similarly, the *G*-function is a representation of the

Table 2
Descriptive statistics of urban restaurants considered in this study across three cities.

Distance from city centre	Restaurant type	Number of restaurants			Distance from CBD towards restaurants(km),			Population Density (population per 1 sq. km area),			Average rent price (INR),			NTL mean (nW/cm2/sr)		
		Delhi	GBN	Gurugram	Delhi	GBN	Gurugram	Delhi	GBN	Gurugram	Delhi	GBN	Gurugram	Delhi	GBN	Gurugram
0 to 5 km	**Dark Kitchen**	36	19	80	4.251	3.374	2.972	27699.57	5603.34	7979.28	18066.31	27367.12	41388.46	46.63	52.83	47.32
	Hybrid Kitchen	46	14	70	2.094	3.363	3.727	13394.26	5572.84	7379.11	58830.29	21392.53	51686.06	76.02	57.00	46.46
	In-Person Dining	111	0	68	1.934	–	3.799	14996.92	–	7346.99	95742.17	–	39626.06	77.23	–	48.49
	Mobile Food Truck	91	40	87	2.549	3.433	3.156	27443.95	5389.07	8323.89	25947.48	23770.61	38780.64	72.32	53.85	46.99
Average					2.707	3.390	3.414	20883.68	5521.75	7757.318	49646.56	24176.75	42870.31	68.05	54.56	47.315
5 km to 10 km	**Dark Kitchen**	92	85	88	8.883	7.776	7.056	17028.51	11302.61	7225.78	206798.91	20900.46	70169.05	54.17	46.40	46.01
	Hybrid Kitchen	71	28	76	8.312	8.062	6991	22383.79	10117.99	6658.06	101585.26	19500.66	47891.35	53.03	45.60	43.68
	In-Person Dining	92	9	70	7.944	7.408	6.904	20723.63	9276.37	7985.95	120101.13	19832.65	33166.84	53.91	49.55	46.03
	Mobile Food Truck	48	106	136	8.358	8.283	7.770	14012.38	10553.80	8352.50	160013.77	20625.84	30595.88	51.37	46.89	42.28
Average					8.374	7.882	7.180	18537.08	10312.69	7555.573	147124.8	20214.9	45455.78	53.12	47.11	44.5
10 km to 15 km	**Dark Kitchen**	189	141	19	12.374	11.217	11.839	27954.21	14847.37	6759.54	34630.74	29030.52	34350.28	55.97	57.34	41.36
	Hybrid Kitchen	96	89	16	11.976	11.211	11.786	25493.41	14774.15	7360.56	50995.94	20395.53	31015.38	52.16	57.09	41.48
	In-Person Dining	127	34	6	12.290	11.069	11.930	24454.03	13439.73	8195.31	60870.99	33752.18	29411.34	52.51	59.85	45.22
	Mobile Food Truck	222	194	8	12.402	11.625	11.499	22914.27	15675.24	5921.48	38769.67	36343.49	37550.74	57.79	57.07	43.24
Average					12.260	11.281	11.763	25203.98	14684.12	7059.223	46316.84	29880.43	33081.94	54.6075	57.83	42.825
More than 15 km	**Dark Kitchen**	52	21	0	16.826	15.344	0.00	20668.76	3112.53	0.00	97174.87	12880.95	0.00	45.77	37.41	0.00
	Hybrid Kitchen	14	6	0	15.753	18.685	0.00	22399.37	2800.45	0.00	7554.61	15583.33	0.00	57.94	41.60	0.00
	In-Person Dining	25	8	0	16.355	18.372	0.00	16270.14	2844.37	0.00	9733.91	18343.75	0.00	60.15	41.59	0.00
	Mobile Food Truck	71	19	0	16.978	16.118	0.00	25372.42	2975.30	0.00	8268.85	16144.74	0.00	52.55	39.90	0.00
Average					16.478	17.129	0	21177.67	2933.163	0.00	30683.06	15738.19	0	54.10	40.12	0

randomness of restaurants within 2*km* annulus from the restaurants up to 15 km. The observed *K*-function is above the grey area up to a certain distance, defining the agglomeration of restaurants, and then it changes to show clear dispersion. The junction points of the observed and predicted represent a transition zone of restaurants within that radius.

In Delhi, the cluster is mostly seen within 1.5 km (Fig. 4). While mobile food trucks have the lower cluster distance, in comparison to dark kitchens, hybrid kitchens, and in-person restaurants have a higher. In Gurugram, the clustering of dark kitchens is noticed within 2 km, and for hybrid kitchens and in-person dining it is within 2.5 km. The mobile food trucks are found to be dispersed in comparison to other restaurant types, but at a higher threshold than in Delhi. In the case of GBN, dark kitchens, hybrid kitchens, and mobile food trucks are found to be clustered within a 2.5 km radius, and the clustering is comparatively lower in the case of in-person dining, i.e., 2 km.

From the G-function, Fig. 5 represents the radius from the restaurants having highly clustered and dispersed characteristics. In Delhi, the peak is for all four types of restaurant class clustering in a compact radius, and the radius is lesser in the case of dark kitchens and mobile food trucks. Whereas in Gurugram and GBN, the clustering radius is larger. Land availability is constrained in Delhi as compared to the other two study areas due to substantially higher population density and land prices. However, Dark kitchens are seen to be concentrated in Delhi within a particular radius with high clustering density. Hybrid kitchens and in-person eating follow the central location theory, but mobile food trucks have a less concentrated space.

4.1.2. *Moran's I function*

Moran's *I* analysis is used to find the spatial correlation among the restaurants. For this, we considered distance from the CBD as a variable of interest for the spatial classification using the Queen argument to define our weight matrix under randomisation. As the data are in point format, we use the knn2nb function to convert a *K*- nearest neighbour object to the neighbour list of class and, by using nb2listw, construct a weight list for the local and global Moran's *I*. The spatial autocorrelation is interpreted in the context of the null hypothesis. The acceptance and rejection of the null hypothesis, i.e., the concentration of restaurants, is decided based on $p < 0.001$. According to the data set, we assume that there is a spatial association between the restaurants within the class.

Local Moran's I: It defines the individual spatial correlation among restaurants. Whether the clustering is high-high or low-low means clustering of similar types of establishments, and Low-high or high-low represents clustering of dissimilar kinds of establishments, considering distance from the CBD. Where $X-axis$ represent the local Moran statistic and $Y-axis$ represents the expectation of the local Moran statistic. The positive and negative values for the $X-axis$ and $Y-axis$ represents the high and low types clustering for each restaurant type respectively.

The result of the local Moran's *I* presented in Fig. 6. It represents the high-low clustering of restaurants in all three cities and for four types of restaurants. It means the observed establishment of local Moran's *I* is significantly higher than expected and indicates significant differences from its neighbourhood.

Global Moran's I: Its value ranges from -1 to $+1$. If the value *I* is near to zero, it indicates no spatial autocorrelation. A value between -1 and 0 shows low-value clusters next to high-value clusters, while a value between 1 and 0 indicates positive autocorrelation, meaning low-value clusters are grouped with low values and high-value clusters with high values. Table 3 indicates the presence of spatial agglomeration of similar establishments in the study areas. Additionally, Moran's *I* value is close to 1, signifying a strong positive spatial correlation. This means that similar types of restaurants are clustering away from the CBD.

The global Moran's *I* with distance class correlation is presented in Fig. 7. It defines the significant clustering points from the CBD. The global spatial autocorrelation and the negative-positive clustering are revealed by the correlogram for 10 sets of different classes.

The plot used the Moran method to represent the vector value for each location with 10 distance class categories. The Euclidean distance class is presented in *X axis* with a degree decimal unit (1-degree decimal is 111.32 km), and in *Y axis* Moran's *I* statistics is given. For supporting parameter testing, we used the logit transformation method. The

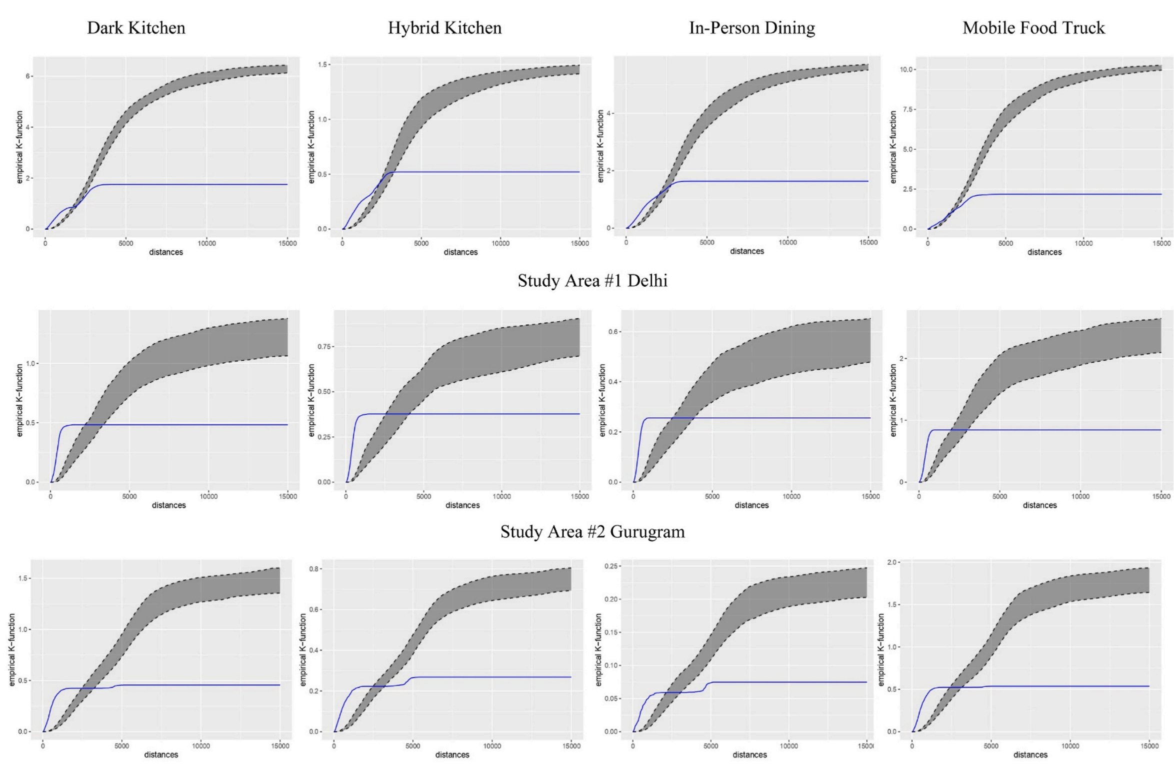


Fig. 4. K-Function analysis for understanding spatial organization of restaurants.

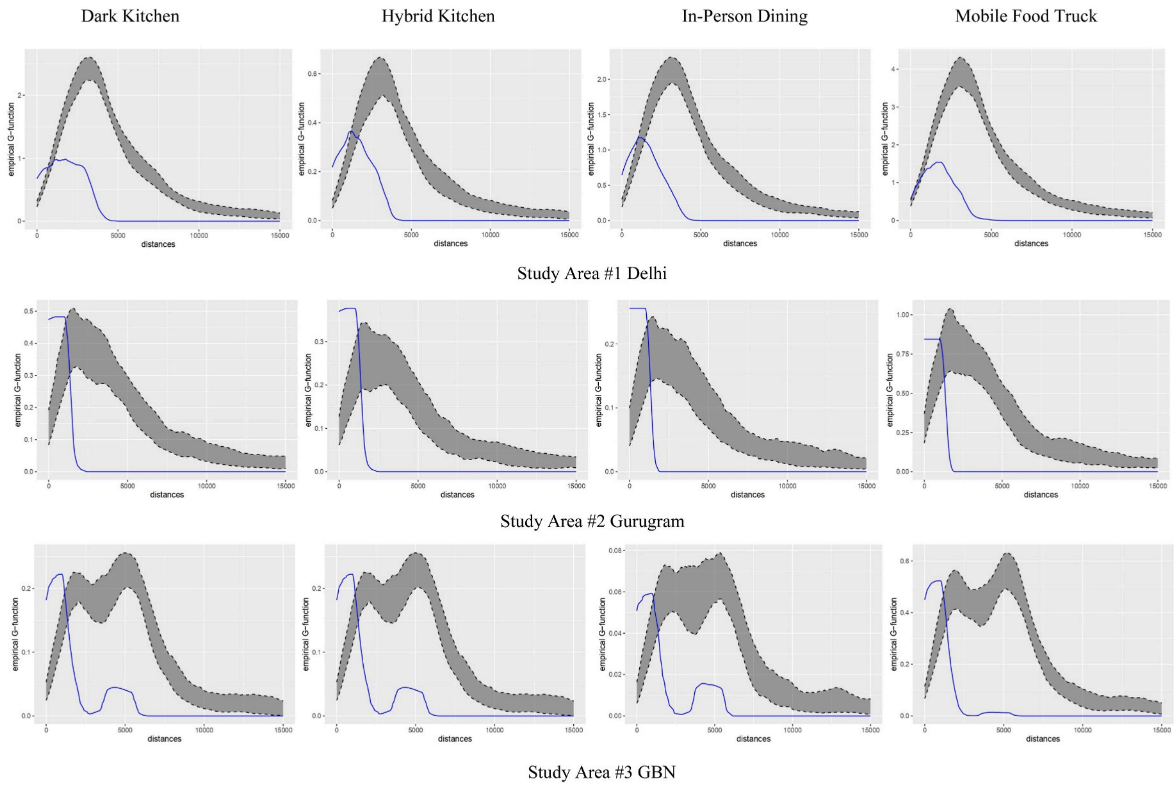


Fig. 5. G-Function analysis for understanding spatial organization of restaurants.

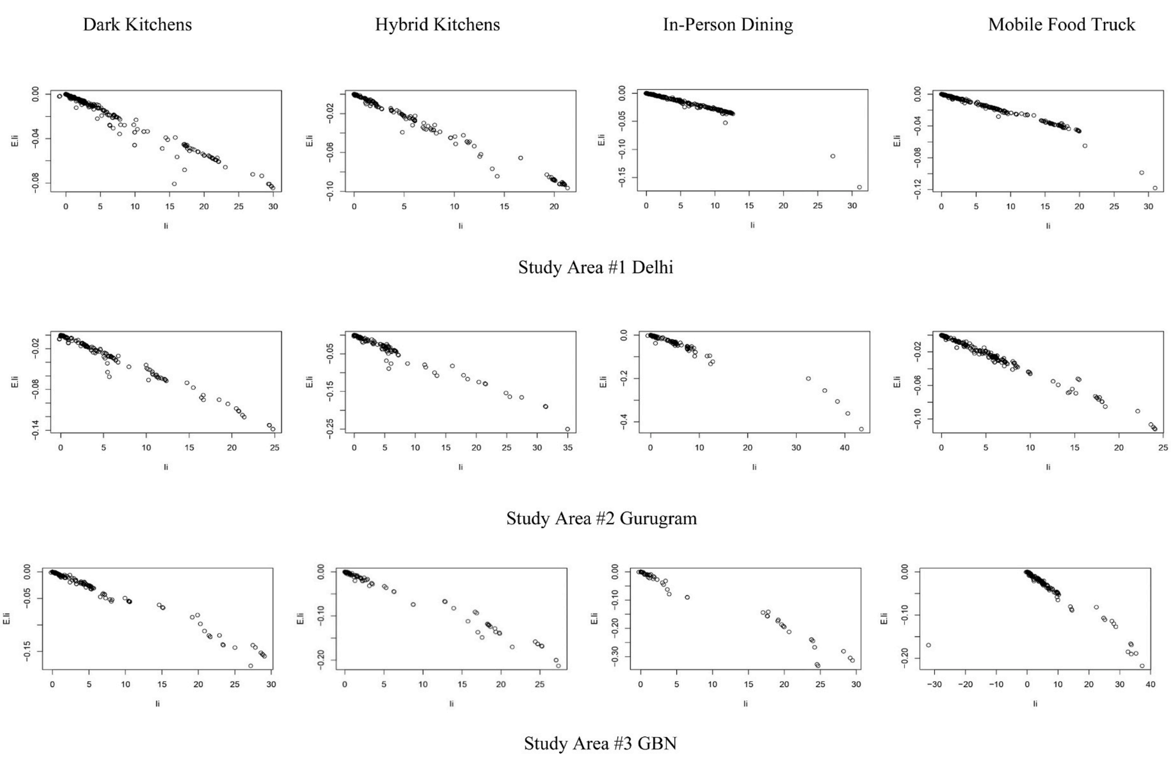


Fig. 6. Local Moran's I function analysis understanding the agglomeration of restaurant establishments.

statistically significant value of having $p < 0.05$ is represented in red colour in the graph. The greatest separation from the restaurants, at which statistically significant clustering is deected, is presented by red spots. It represents the peaks of the spatial concentration.

In the three-study area, the maximum number of clustering are identified for in-person dining and Mobile food trucks. Additionally, it is observed that most restaurants are likely to cluster near the CBD. The spatially significant clustering for restaurants' dark kitchens in Delhi is found within 0.05° decimal (5.56 km). However, in Gurugram and GBN, the first significant cluster is found to be less than 0.01° decimal, and the

Table 3
Summary table of global Moran I.

Types of Kitchens	Moran I statistic	Expectation	Variance	p-value	Z-Score	Moran I statistic standard deviate
Study City #1 - Delhi						
Dark Kitchen	0.944	−0.003	0.001	0	1.035	31.813
Hybrid Kitchen	0.978	−0.004	0.001	0	1.092	25.373
In-Person Dining	0.962	−0.003	0.001	0	1.054	31.234
Mobile food trucks	0.976	−0.002	0.001	0	1.059	35.118
Study City #2 - Gurugram						
Dark Kitchen	0.980	−0.005	0.002	0	1.107	23.437
Hybrid Kitchen	0.929	−0.006	0.002	0	1.065	20.554
In-Person Dining	0.891	−0.007	0.002	0	1.039	19.028
Mobile food trucks	0.985	−0.004	0.001	0	1.097	25.669
Study City #3 – Gautam Budha Nagar						
Dark Kitchen	0.978	−0.005	0.002	0	1.106	23.868
Hybrid Kitchen	0.962	−0.007	0.002	0	1.102	20.430
In-Person Dining	0.939	−0.010	0.003	0	1.117	17.095
Mobile food trucks	0.904	−0.005	0.002	0	1.026	22.512

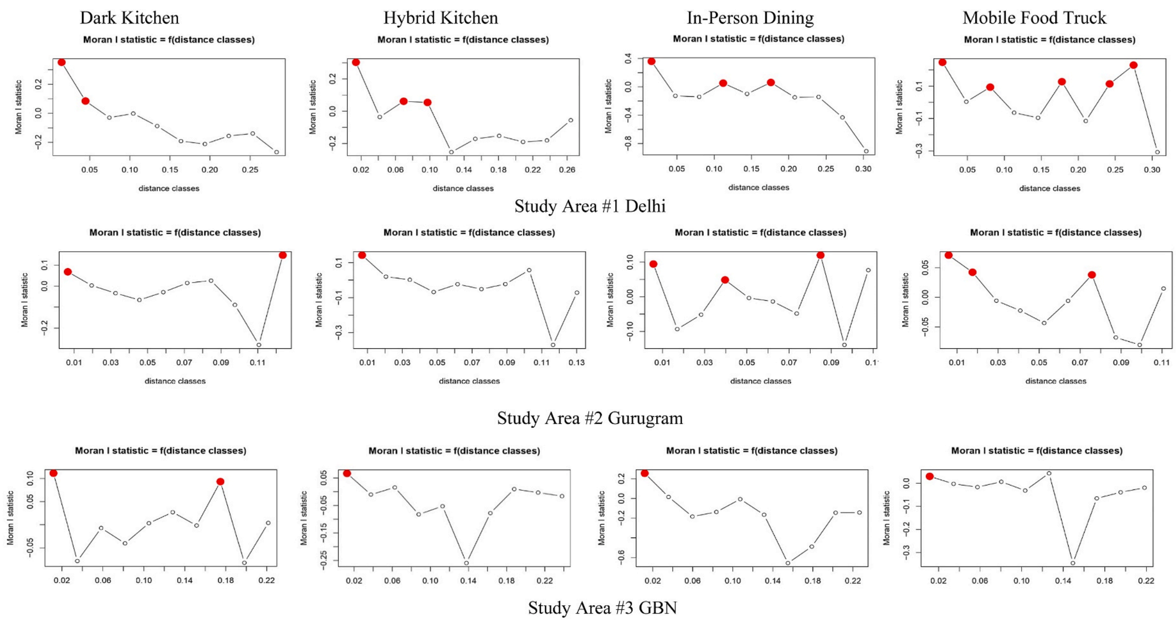


Fig. 7. Measure autocorrelation at differing spatial lags by plotting data in correlogram.

second point is found after 0.11- and 0.14-degrees decimal, respectively. In Delhi, three significant spatial concentration points exist for hybrid kitchens within a radius of 0.1° decimal and one point in the region of 0.01° decimal for Gurugram and GBN. However, in the case of in-person dining only, three significant clustering points exist within 0.2- and 0.09-degrees decimal for study areas Delhi and Gurugram, respectively, while in GBN, there is only one significant clustering point exists within 0.02° decimal. While the number of clusters is similar for Delhi and Gurugram, however, the distance class is different. The cluster locations for Gurugram are near the CBD, followed by GBN and Delhi. Finally, for mobile food trucks, three significant clusters were detected within 0.08 degrees of decimal place in Gurugram, five significant clusters within 0.3° in Delhi (defines a scattered but clustered manner), and one cluster at 0.01 in GBN.

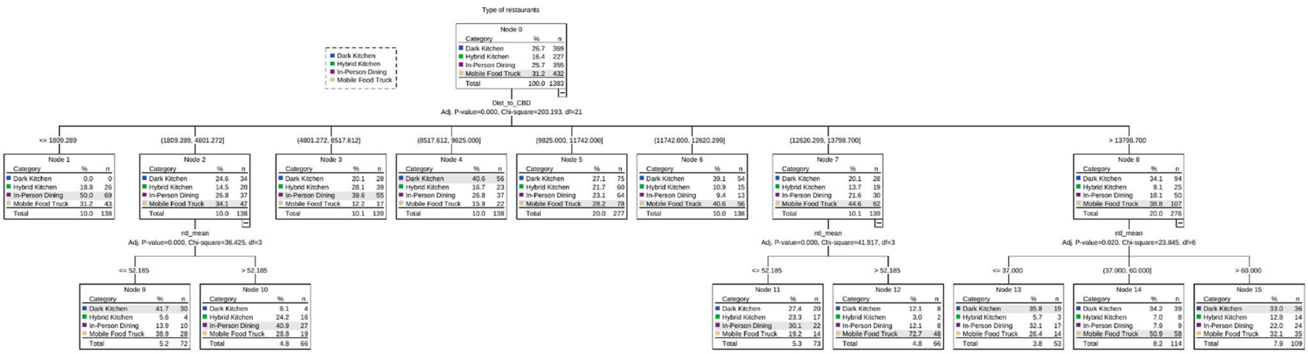
4.2. Predicting restaurant types based on land use parameters

4.2.1. Decision trees

The land use patterns for different restaurant types are analysed using four key parameters, including population density, rent price, distance to CBD, and NTL. The comparative analysis includes results for Delhi and its neighbouring satellite cities (i.e., Gurugram and GBN), with findings presented in Figs. 8–10. The CBDs of study areas are identified as the areas with the highest night-time light. Figs. 8(A), 9(A), and 10(A) represent the decision tree based on the locational attributes, i.e., distance to CBD and nighttime light, while Figs. 8(B), 9(B), and 10 (B) illustrate the decision tree by taking population density and rent price.

As shown in Fig. 8, in Delhi, a majority of dark kitchens are located in low-rent neighbourhoods (7500–8000 INR per month), either situated farther from the city core or within a 1.8–4.8 km radius, where NTL is less than 52.18 nW/cm^2/sr. These restaurants are located with a population density between 11,161–30,874 per square km. Whereas in hybrid kitchens, the rent price ranges from 10,250 to 15,500 INR per month (low to medium). In-person dining establishments are found to be located outside of the city core, typically within an 8.5 km radius in a highly illuminated area. Interestingly, these restaurants are located in areas with higher population density, i.e., more than 15,130 people per square kilometre, or lower population density zones, i.e., 11,152 people per square kilometre, associated with a rental price of more than 40,000 INR per month. Mobile food trucks are located more than 9.8 km from the CBD, although some are within 1.8 km–4.8 km. While these restaurants are found in high NTL regions, i.e., 37–60 nW/cm2/sr. Additionally, mobile food trucks do not have a set price range for where they are located; instead, they may be found subtly paying rent anywhere from 7000 to 18,000 INR around the city. There were no food trucks

(8-A) Urban typology of food delivery establishments in Delhi (Study Area #1) based on night-time light and distance to CBD



(8-B) Urban typology of food delivery establishments in Delhi (Study Area #1) based on population density and average rent per square meter

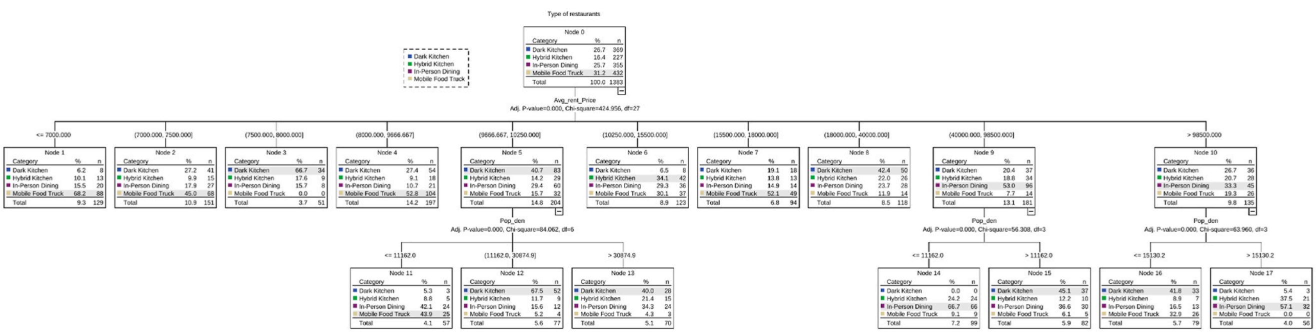
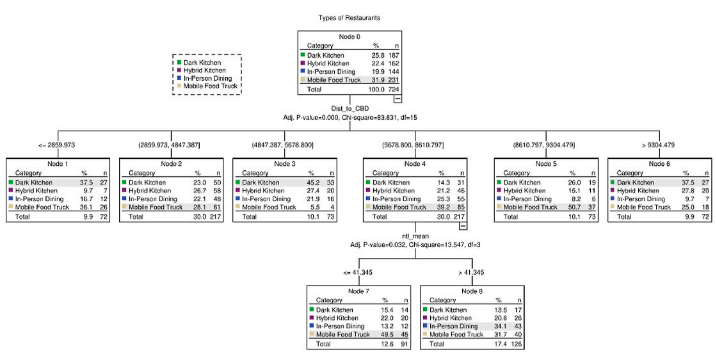


Fig. 8. Decision tree analysis results for Delhi (Study Area#1) based on spatial attributes.

(9-A) Urban typology of food delivery establishments in Gurugram (Study Area #2) based on night-time light and distance to CBD



(9-B) Urban typology of food delivery establishments in Gurugram (Study Area #2) based on population density and average rent per square meter

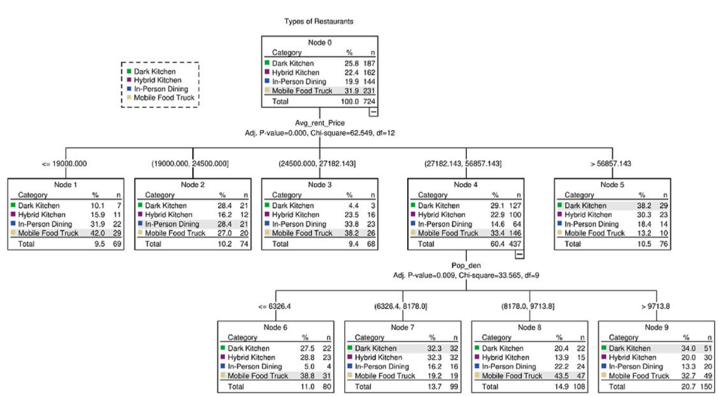
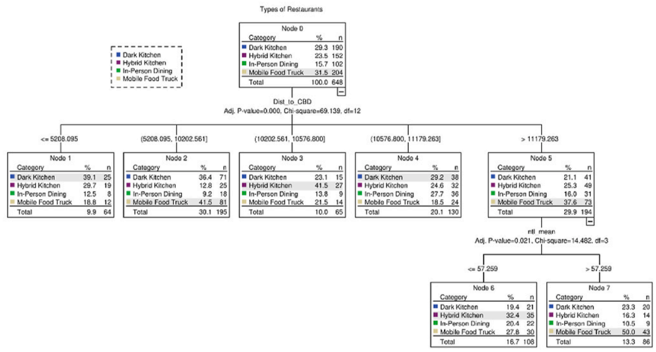


Fig. 9. Decision tree analysis results for Gurugram (Study Area#2) based on spatial attributes.

(10-A) Urban typology of food delivery establishments in GBN (Study Area #3) based on night-time light and distance to CBD



(10-B) Urban typology of food delivery establishments in GBN (Study Area #3) based on population density and average rent per square meter

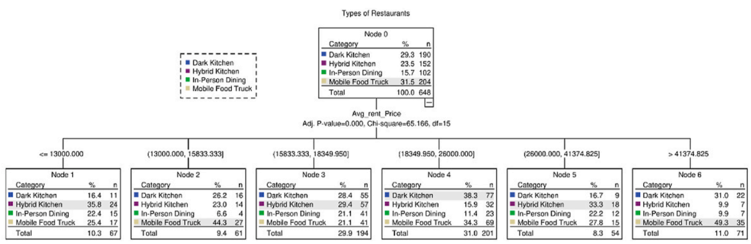


Fig. 10. Decision tree analysis results for Gautam Buddha Nagar (Study Area#3) based on spatial attributes.

with rent prices higher than 18,000.

In Gurugram (study city 2), dark kitchens are located nearer to the CBD (<2.86 km), or in high-rent (>56,857 INR) and high population density (>9713) areas, unlike in Delhi. Some dark kitchens are present in outer territories (>9.3 km), indicating that satellite towns have different patterns of growth and urban morphology, determining the positioning of restaurants. Notably, hybrid kitchens in satellite towns do not follow a distinct spatial pattern, as reflected in the decision tree. In-person dining is found in areas with higher NTL (>41 nW/cm^2/sr), and within 5.6–8.6 km of CBD or in rent zone 19000 to 24500. Mobile food trucks exhibit a scatter distribution independent of rent price, population density, distance to CBD, and NTL. However, within the same radius periphery, mobile food trucks are found in low NTL, whereas in-person dining is found in high NTL.

A similar pattern is observed in GBN as in Gurugram, with variation in values. Dark kitchens in GBN are located within a 5.2 km radius or between a 10.5–11.2 km annulus. Additionally, the rent price variation observed for dark kitchens is between 18349 and 26000 INR per month. Hybrid kitchens are primarily located within a 10–10.5 km radius from the CBD with nighttime light of less than 57 nW/cm^2/sr. However, the rent prices of hybrid kitchen locations vary significantly, with some having high rents and some having low rents. The spatial distribution of in-person dining cannot be explained by our study variables, likely due to the evolving integration of in-person dining with delivery services. Mobile food trucks are located in high NTL when it is away from the CBD (populated area) or within 5 km–10 km of the CBD.

This finding reinforces the stratification of restaurant types within urban areas, suggesting that economic and spatial factors influence the locational preference of different food services. The results suggest that the morphology of satellite towns (i.e., Gurugram and GBN) has a distinct influence on the restaurant spatial distribution, in comparison to megacities like Delhi.

The decision tree result is summarized in Table 4, providing a structured framework to define the spatial pattern of restaurants using the complementarities variables. The classification considers local availability variables: Distance to CBD from the restaurants, population density, and average rent price across the three different study areas. Notably, the definition of high, medium, and low categories varies in each city, reflecting their distinct urban structure.

Table 4
Summary table of decision tree.

Night time light	Distance to CBD	Population density	Average rent price	Types of restaurants
Study area #1 Delhi				
High Low	Far Near	High	Low to Medium	Dark Kitchen
High Low	Near Far	Medium	High	Hybrid Kitchen
High Low	Near Far	Low to Medium	High	In-Person Dining
High	Far	Medium	–	Mobile Food Truck
Study area #2 Gurugram				
High	Near	High	High	Dark Kitchen
High	Near	Medium	High	Hybrid Kitchen
High	Far	Medium	Medium to High	In-Person Dining
Low	Scattered	Medium	–	Mobile Food Truck
Study area #3 GBN				
Low	Near	–	Low to Medium	Dark Kitchen
Low	Far	–	High	Hybrid Kitchen
Low	Far	–	High	In-Person Dining
High	Far	–	–	Mobile Food Truck

For study area #1, Delhi, the threshold high nighttime light level (NTL) is set at more than 52 nW/cm2/sr; while values lower than this are considered as low NTL. Distant to the CBD is categorised as near (less than 10 km) or far (greater than 10 km). Population density is considered low, high, and medium for values less than 11,000, more than 15,000, and between 10,000 to 15,000. In case of rent price, a low rent price is considered as less than 10,000 INR per month, a medium rent price is between 10,000 and 40,000 INR per month, and a high rent price is greater than 40,000.

For study area #2, Gurugram, NTL is classified as low if it is less than 41.34 nW/cm2/sr and otherwise high. The distance to CBD, less than 5.6 km, is considered to be near, and more than that is considered to be remote. Population density is classified as high when it exceeds 9713, low when it is less than 6326, and medium when it is in between. Less than 19,000 INR is considered a low rent price, 19,000 to 27,000 INR is considered a medium rent price, and more than that is considered a high rent price.

*For study area #*3 GBN, a low NTL is defined as less than 57.25 nW/cm2/sr, and a high NTL is greater than that. Less than 10 km is considered close to the CBD, 10 km–11.17 km is considered distant, and more than that is considered far. Less than 15,833 INR is considered cheap rent; 15,833 INR to 26,000 INR is considered medium rent, and more than 26,000 INR is considered expensive rent.

4.2.2. Random forest algorithms

The Random Forest classifiers were used to predict the four restaurant kinds within the food business using land use variables. A total of 1383 restaurants were selected for categorization in Delhi, with 724 in Gurugram and 646 in GBN. The categorization outcomes are presented in Table 5, including the performance indication metrics recall, precision, true positive rate (TPR), and false positive rate (FPR). Recall is the percentage of an actual class relative to the sum of the predicted class, whereas precision is the percentage of a predicted class relative to the total of the actual class. While TPR indicates the proportion of true positive classifications and falsely classified instances among negative cases, termed as FPR.

F-measure is a recall and accuracy combination metric, as given in Eq. (1).

$$f-measure=\left(\frac{Precision^{*}Recall}{Precision+Recall}\right)^{*}2 \tag{8}$$

Study area #1(Delhi); Out of 1383 restaurants, 867 are correctly categorised, yielding an accuracy score of 62.70 overall. Most Dark kitchens, and food trucks are easily recognized since they are situated in low-rent districts and high-density, peripheral areas of the core business centre. Subsequently, a 58 % accurate prediction is made for in-person dining. However, the hybrid kitchen's FPR is high—73 %. Most incorrectly predicted hybrid kitchens are classified as dark kitchens and in-person dining. Hybrid kitchens are observed to have fewer significant features, making it difficult to distinguish them from in-person dining and dark kitchens.

A total of 272, or 37.5 % of the sample space, is properly predicted in the given *study area #2 (Gurugram)*. As well, the percentage of accurate predictions for *study area #3 (GBN)* is 39 %. In Gurugram and GBN, dark kitchens and mobile food trucks can somehow be identified, and the precision for the identification of in-person dining is 43 % for Gurugram. This suggests that Gurugram is still on the cusp of accepting digitization.

Gurugram and GBN have a higher miss-classification rate than Delhi, where all other kitchens, aside from the hybrid kitchen, can be categorised using the research variables. Therefore, additional factors are required to address these diversifications and distinguish the assortment across different places. Neighbourhood features (spatial autocorrelation) may have an impact on diversification as well. Gurugram and GBN-like areas, adjacent to the capital of India, a diversified and populated economic hub, are affected more by neighborhoods with predominant CBD. For example, GBN, like satellite cities, urban development is affected by a metropolis like Delhi.

4.2.3. Multinomial logit model

A multinomial logit (MNL) model is performed to assess the likelihood of different types of restaurants by using the land use parameters, with in-person dining as the reference variable. The model estimates the logarithmic probability of selecting dark kitchen, hybrid kitchens, or mobile food trucks in comparison to in-person dining. After 20 iterations, the final error value is computed as follows: 1803.88 for Delhi, 961.44 for Gurugram, and 851.64 for Gautam Buddha Nagar (GBN). The coefficient of each parameter, with the p-value is explained in Table 6.

For Study Area 1 (Delhi), distance to CBD, population density, and average rent price have a positive impact, while the mean nighttime light has a negative impact on dark kitchens. This suggests that dark kitchens are predominantly located in high-density areas, and farther away from the CBD. In the case of hybrid kitchens, distance to CBD and population density have a positive association, whereas nighttime light and average rent price have a negative impact. It indicates that with an increase in distance from the CBD and population density, the likelihood of a hybrid kitchen increases. However, the confusion matrix of the MNL model indicates a high misclassification rate, suggesting that differentiating them from dark kitchen and in-person dining is difficult. Similarly, for mobile food trucks, all response variable except the average rent price has a positive impact. This implies mobile food trucks are scattered throughout the cities, in high density with respect to other kitchens, potentially contributing to congestion.

For study area 2 (Gurugram), the distance from the CBD is limited in explaining the restaurants' diversification, as it is in proximity to New Delhi. However, nighttime light (NTL) follows a similar pattern as Delhi, where higher NTL decreases the likelihood of dark kitchen and hybrid kitchen. While in mobile food trucks, the trend is reverse; for example, if NTL has a positive impact on mobile food trucks in Delhi but a negative impact on Gurugram, indicating a regional difference. On the other hand, the rent price impact is found to be opposite to population density,

Table 5
confusion matrix table analysed by random forest method.

Actual	Predicted				Precision	Recall	TPR	FPR	F-measure
	Dark Kitchen	Hybrid Kitchen	In-Person Dining	Mobile Food truck					
Study City #1 - Delhi									
Dark Kitchen	*267*	*17*	*26*	*59*	*0.609*	*0.723*	*0.391*	*0.277*	*0.331*
Hybrid Kitchen	*61*	*60*	*79*	*27*	*0.447*	*0.264*	*0.553*	*0.735*	*0.166*
In-Person Dining	*65*	*53*	*185*	*52*	*0.581*	*0.521*	*0.419*	*0.478*	*0.275*
Mobile Food truck	*45*	*4*	*28*	*355*	*0.715*	*0.821*	*0.285*	*0.178*	*0.382*
Study City #2 - Gurugram									
Dark Kitchen	*77*	*44*	*16*	*50*	*0.428*	*0.412*	*0.572*	*0.588*	*0.420*
Hybrid Kitchen	*47*	*26*	*30*	*59*	*0.17*	*0.16*	*0.83*	*0.84*	*0.164*
In-Person Dining	*21*	*28*	*60*	*35*	*0.432*	*0.417*	*0.568*	*0.583*	*0.424*
Mobile Food truck	*35*	*54*	*33*	*109*	*0.431*	*0.472*	*0.569*	*0.528*	*0.450*
Study City #3 – Gautam Budha Nagar									
Dark Kitchen	*97*	*29*	*7*	*57*	*0.364*	*0.511*	*0.636*	*0.489*	*0.425*
Hybrid Kitchen	*48*	*56*	*14*	*34*	*0.378*	*0.368*	*0.622*	*0.632*	*0.186*
In-Person Dining	*43*	*31*	*13*	*15*	*0.309*	*0.127*	*0.691*	*0.873*	*0.180*
Mobile Food truck	*78*	*32*	*8*	*86*	*0.448*	*0.421*	*0.552*	*0.579*	*0.434*

Table 6
Coefficient and standard error table of multinomial logit model (MNL).

Parameter	Study Area	Type of Kitchen	Dark Kitchen	Hybrid Kitchen	Mobile food truck
Intercept	**Delhi**	Coef.	−1.056	−0.296	−1.475
		P-value	0.000	0.000	0.000
	Gurugram	Coef.	0.310	1.221	1.361
		P-value	0.000	0.000	0.000
	GBN	Coef.	3.983	2.354	3.381
		P-value	0.000	0.000	0.000
Distance_to_CBD (in 1000 m)	**Delhi**	Coef.	0.128	0.0166	0.109
		P-value	0.000	0.268	0.000
	Gurugram	Coef.	0.02	0.037	0.035
		P-value	0.566	0.298	0.275
	GBN	Coef.	0.155	−0.053	−0.126
		P-value	0.000	0.149	0.000
ntl_mean (in 10)	**Delhi**	Coef.	−0.016	−0.008	0.008
		P-value	0.000	0.000	0.000
	Gurugram	Coef.	−0.024	−0.036	−0.045
		P-value	0.000	0.000	0
	GBN	Coef.	−0.044	−0.022	−0.049
		P-value	0.000	0.000	0.000
Population density (Per Sq. km)	**Delhi**	Coef.	2.93E-05	9.30E-06	1.16E-05
		P-value	0.000	0.127	0.004
	Gurugram	Coef.	4.03E-05	−2.34E-05	1.09E-04
		P-value	0.184	0.453	0
	GBN	Coef.	3.25E-05	−4.11E-06	7.37E-05
		P-value	0.241	0.882	0.006
Average_rent_price (in 1000 Rs)	**Delhi**	Coef.	8.25E-04	−4.43E-04	−1.27E-03
		P-value	0.039	0.386	0.013
	Gurugram	Coef.	1.49E-02	1.22E-02	2.27E-03
		P-value	6.00E-05	1.19E-03	0.061
	GBN	Coef.	7.80E-03	−6.05E-03	1.09E-02
		P-value	0.125	0.379	0.021

i.e., highly significant and positive.

The distance to the central business district (CBD) in Delhi and Gurugram positively affects all three types of variables; however, *in study area 3 (GBN)*, it positively affects the dark kitchen but negatively affects the hybrid and mobile food trucks. It suggests that the likelihood of having a mobile food truck or hybrid kitchen decreases with increasing distance from the central business district, but the likelihood of having a dark kitchen increases. Thus, it can be concluded that whereas hybrid vehicles and food trucks are more common in commercial regions, dark kitchens are more common in residential neighbourhoods. The same pattern is observed in the case of NTL as observed in Gurgaon. With the increase in nighttime light, the chance of being dark, hybrid, and mobile food trucks is less with respect to in-person dining. Population density, the same pattern observed in the case of Gurugram, but different to Delhi which has a positive impact on dark kitchens and mobile food trucks, but is negative and less significant in the case of hybrid kitchens. In the case of rent price, for dark kitchens same pattern is observed as in Delhi and Gurugram, but for hybrid, it is similar to Delhi, and for mobile food trucks, it is similar to Gurugram. The GBN sector is being more regulated and has expensive business rent. Therefore, hybrids are reducing in-person interactions and digitalizing food to balance space and money.

4.3. Classification accuracy of prediction models

The classification results of the decision trees are compared to the multinomial logit model's and random forests to assess their relative performance. In these models, 80 % sample is taken for training the model, and 20 % of the sample is taken as testing. The kappa index, as shown in the equation below, could be used to compare the confusion matrix produced by the three distinct approaches. The Kappa index is not a tool for measuring accuracy. Better the categorization is indicated by a higher kappa coefficient (Delgado and Tibau, 2019).

$$Kappa\ Coefficient(K_c) = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n} G_i C_i}{N^2 - \sum_{i=1}^{n} G_i C_i} \tag{9}$$

Where *Ci*, *Gi* stand for the total predicted and observed value, respectively, and N for the total number of classified values for i number of classes and mi, i for the number of values belonging to observed class i and predicted class i (diagonal values).

Table 7 represents the comparison between three different methods (Decision tree using CHAID, Random Forest, and Multinomial logit model) used for the classification of restaurants using publicly available datasets for *study area #1*. The comparison was done by using the kappa

Table 7
Confusion matrix of three different methods for Study Area #1 Delhi.

Observed	Predicted				
	Dark Kitchen	Hybrid Kitchen	In-Person Dining	Mobile Food Truck	Percentage Observed (%)
Decision Tree #1					
Dark Kitchen	141	0	52	176	38.2
Hybrid Kitchen	44	0	98	85	0.0
In-Person Dining	88	0	173	94	48.7
Mobile Food Truck	99	0	93	240	55.6
Percentage Predicted (%)	26.9	0.0	30.1	43.0	40.1
Kappa Coefficient: $K_c = 0.16$					
Decision Tree#2					
Dark Kitchen	234	8	3	124	63.4
Hybrid Kitchen	76	42	45	64	18.5
In-Person Dining	115	36	98	106	27.6
Mobile Food Truck	52	37	9	334	77.3
Percentage Predicted (%)	34.5	8.9	11.2	45.4	*51.19*
Kappa Coefficient: $K_c = 0.32$					
Random Forest					
Dark Kitchen	*267*	*17*	*26*	*59*	*72.35*
Hybrid Kitchen	*61*	*60*	*79*	*27*	*26.4*
In-Person Dining	*65*	*53*	*185*	*52*	*52.11*
Mobile Food Truck	*45*	*4*	*28*	*355*	*82.17*
Percentage Predicted (%)	*60.9*	*44.77*	*58.17*	*72.00*	*62.68*
Kappa Coefficient: $K_c = 0.48$					
Multinomial Logistic Regression Model					
Dark Kitchen	*117*	*60*	*99*	*74*	*33.4*
Hybrid Kitchen	*0*	*0*	*0*	*0*	*…*
In-Person Dining	*62*	*67*	*141*	*107*	*37.40*
Mobile Food Truck	*190*	*100*	*115*	*251*	*38.26*
Percentage Predicted (%)	*31.7*	*0*	*39.71*	*58.10*	*36.80*
Kappa Coefficient: $K_c = 0.11$					

index, overall accuracy, and (total observed) sensitivity of individual restaurant types.

The kappa coefficient was employed to determine the most appropriate way of classification (Foody, 2020) for classifying the land use for restaurants. As the following table shows, the random forest model is used to correctly explain the classification, followed by the decision tree and multinomial logit approaches. The agreements between the actual and predicted restaurant types are then represented by the overall accuracy. Among the two decision trees, decision tree 2 (used variable population density and rent price) is predicting more accurately than decision tree 1. Random forest classifies the restaurants with an overall accuracy of 62.68 %. Table 8 shows the comparisons between three distinct approaches for the Gurugram study area. In this instance, random forest outperforms other techniques in precisely explaining the categorization using the study variable. The multinomial logit model has an overall accuracy of 34.94 %, which is less accurate than others. When it comes to decision trees, both decision trees were able to explain the segmentation with an overall accuracy of 36.7 %, which implies that NTL and distance to CBD variables impact classification in the same way as rent price and population density.

A comparison of confusion matrixes is represented in Table 9 for the study area GBN. Similar to other study areas random forest method explained the classification with an overall accuracy of 38.89 %, similar accuracy came from the decision tree 1 (decision tree using distance to CBD and NTL). Decision tree 2 (decision tree using population density and rent price) and multi nominal logit model give an overall accuracy of 36 %.

Among three different classification methods, the random forest has the ability to elucidate the categorization of restaurants considering land use variables accurately, as compared to other methods across all three study areas. Delhi was the research region where our study factors were most accurate in explaining categorization, followed by Gurugram and GBN among all study locations.

Table 8
Confusion matrix of three different methods for Study Area #2 Gurugram.

Observed	Predicted				
	Dark Kitchen	Hybrid Kitchen	In-Person Dining	Mobile Food Truck	Percentage Observed (%)
Decision Tree #1					
Dark Kitchen	112	0	21	54	59.9
Hybrid Kitchen	85	0	12	65	0.0
In-Person Dining	50	0	21	73	14.6
Mobile Food Truck	78	0	20	133	57.6
Percentage Predicted (%)	44.9	0.0	10.2	44.9	36.7
Kappa Coefficient: $K_c = 0.12$					
Decision Tree #2					
Dark Kitchen	112	0	21	54	59.9
Hybrid Kitchen	85	0	12	65	0.0
In-Person Dining	50	0	21	73	14.6
Mobile Food Truck	78	0	20	133	57.6
Percentage Predicted (%)	44.9	0.0	10.2	44.9	36.7
Kappa Coefficient: $K_c = 0.12$					
Random Forest					
Dark Kitchen	*77*	*44*	*16*	*50*	*41.7*
Hybrid Kitchen	*47*	*26*	*30*	*59*	*16.04*
In-Person Dining	*21*	*28*	*60*	*35*	*41.67*
Mobile Food Truck	*35*	*54*	*33*	*109*	*47.18*
Percentage Predicted (%)	*42.78*	*17.10*	*43.16*	*43.08*	*37.56*
Kappa Coefficient: $K_c = 0.15$					
Multinomial Logistic Regression Model					
Dark Kitchen	*37*	*26*	*10*	*23*	*38.54*
Hybrid Kitchen	*18*	*17*	*11*	*20*	*25.75*
In-Person Dining	*24*	*13*	*23*	*12*	*31.94*
Mobile Food Truck	*108*	*106*	*100*	*176*	*35.91*
Percentage Predicted (%)	*369*	*227*	*355*	*432*	*34.94*
Kappa Coefficient: $K_c = 0.083$					

Table 9
Confusion matrix analysed by three different methods for Study Area #3 GBN

Observed	Predicted				
	Dark Kitchen	Hybrid Kitchen	In-Person Dining	Mobile Food Truck	Percentage Observed (%)
Decision Tree #1					
Dark Kitchen	63	36	0	91	33.2
Hybrid Kitchen	51	62	0	39	40.8
In-Person Dining	44	31	0	27	0.0
Mobile Food Truck	36	44	0	124	60.8
Percentage Predicted (%)	29.9	26.7	0.0	43.4	38.4
Kappa Coefficient: $K_c = 0.136$					
Decision Tree#2					
Dark Kitchen	77	75	0	38	40.5 %
Hybrid Kitchen	32	99	0	21	65.1
In-Person Dining	23	68	0	11	0.0
Mobile Food Truck	69	73	0	62	30.4
Percentage Predicted (%)	31.0	48.6	0.0	20.4	36.7
Kappa Coefficient: $K_c = 0.134$					
Random Forest					
Dark Kitchen	*97*	*29*	*7*	*57*	*51.05*
Hybrid Kitchen	*48*	*56*	*14*	*34*	*36.84*
In-Person Dining	*43*	*31*	*13*	*15*	*12.74*
Mobile Food Truck	*78*	*32*	*8*	*86*	*42.15*
Percentage Predicted (%)	*36.46*	*37.83*	*30.95*	*44.79*	*38.89*
Kappa Coefficient: $K_c = 0.154$					
Multinomial Logit Model					
Dark Kitchen	*71*	*43*	*24*	*64*	*35.14*
Hybrid Kitchen	*53*	*61*	*53*	*37*	*30*
In-Person Dining	*1*	*0*	*0*	*0*	*0*
Mobile Food Truck	*65*	*48*	*25*	*103*	*42.74*
Percentage Predicted (%)	*37.36*	*40.13*	*0*	*50.50*	*36.2*
Kappa Coefficient: $K_c = 0.112$					

5. Policy and practice implications

The analysis findings quantified the spatial distribution of restaurants and revealed the strategic locational complementarity in restaurant locations within the food industry across three study cities: Delhi (Metropolitan City), Gurugram (Satellite city), and Gautam Budha Nagar (GBN) (Satellite city). The result shows that the clustering radius is smaller in Delhi (1.5 km) compared to GBN (2.5 km) and Gurugram for all four-restaurant categories. Notably, the clustering radius of dark kitchen is lower than other restaurants clustering radius. A higher number of clusters is observed in Delhi compared to other cities. The number of clusters is particularly high for in-person dining and mobile food trucks, in line with past literature (Jung & Jang, 2019). Most of the significant clusters are concentrated near to the CBD, with Delhi exhibiting an average distance of 0.05 km and GBN and Gurugram both showing an average distance of 0.01 km. A pictorial presentation of the clustering analysis result is presented in Fig. 11. The result is encouraging evidence for the city planners to optimize the zoning regulation by considering high consumer food demand areas for different restaurant types. The varying distribution of in-person dining and dark kitchens suggests a significant difference. It suggests the need for improved logistics and delivery infrastructure in different parts of the city, based on data-driven insights (Dayal et al., 2025). Nighttime light (NTL) is found to be a significant predictor for all restaurant types across all three cities, suggesting a stronger correlation between urban activity level and restaurant distribution (Debnath et al., 2025). The spatial arrangement of these clusters has significant implications for urban traffic congestion, due to freight trip generation (production and attraction), as well as challenges related to parking, loading, and unloading. To mitigate this traffic congestion, it is essential to regulate the restaurant clustering as well as the generated traffic. Defining the permissible clustering radius and implementing policies with restricted licensing could be helpful to curb the proliferation of restaurants and manage the traffic impact. Additionally, the implications of delivery robots in on-demand delivery can be a step towards low-carbon logistics (Pani et al., 2020). Together with accessibility of food in terms of mobility inequalities, the consumer's rising demand needs to be addressed with the autonomous delivery system (Mishra et al., 2023). The varying proportion of restaurants in different city zones and thereby relating to the varying impacts of on-demand food delivery traffic generated in the study cities is presented in Fig. 12. The study divides each study area into four zones based on their distance from the CBD: within a 5 km radius, 5–10 km radius, 10–15 km radius, and beyond 15 km radius, to analyse the spatial distribution. In Delhi, dark kitchens are away from the CBD, whereas in-person dining is clustered closer to the CBD. However, in Gurugram and GBN, the spatial distribution follows the opposite trend, with dark kitchens being more centralized and in-person dining more dispersed.

In terms of broad policy implications, analysis findings highlight that there is a lack of policies addressing the hidden challenges of on-demand food transportation. Dark kitchen tends to be located in high population density areas with low to medium rent prices. Conversely, in-person dining, with a business model that highly prefers to be in locations with high rent prices (Cheng et al., 2015). Therefore, policies should be developed to enhance liveability in residential areas by setting rules and regulations for restaurant openings and clustering (Fitzpatrick Sarah, 2021). Regulations should be tailored to the unique needs of individual cities – as reflected in the above clustering patterns of restaurants – based on the evolving urban dynamics.

6. Conclusions

The COVID-19 pandemic has significantly transformed the spatial and economic dynamics of urban food establishments. This study investigated the emerging geography of restaurants in Delhi, Gurugram, and Gautam Buddha Nagar (GBN), with a focus on four establishment types - dark kitchens, hybrid restaurants, in-person dining, and mobile food trucks – and their implications for urban freight generation and land-use planning. Using Ripley's K and Moran's I statistics, we found distinct clustering radii across restaurant types and cities. Dark kitchens exhibited the most compact clustering: within 1.5 km in Delhi, 2 km in Gurugram, and 2.5 km in GBN. These patterns reflect agglomeration economies, where proximity facilitates knowledge spillovers and shared logistics for dark kitchens, and customer attraction and infrastructure sharing for hybrid and in-person dining establishments. Spatial analysis revealed clear locational tendencies. In Delhi, dark kitchens are predominantly located in low-rent zones (₹7500–8000/month), around

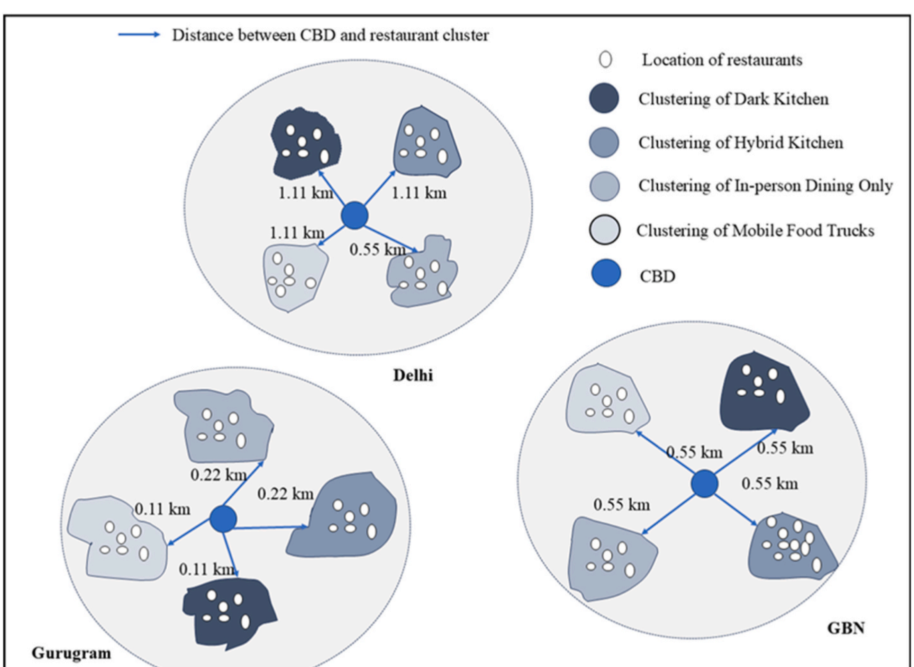


Fig. 11. Clustering patterns of restaurants across three different study area.

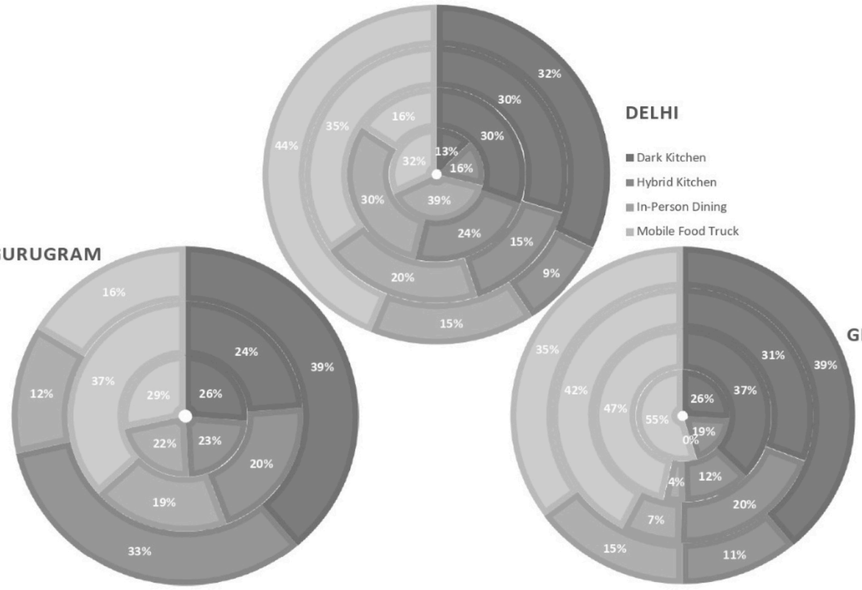


Fig. 12. Varying Proportion of food industry establishments in relation to city centre.

8–9 km from the central business district (CBD), often in areas with moderate population density. In contrast, in-person dining is typically situated in high-rent locations (>₹40,000/month), either in low- or high-density areas, and in regions with high night-time light (NTL) intensity. Gurugram and GBN exhibited contrasting trends, where dark kitchens were more likely to be located near the CBD, indicating differing urban morphologies and development pressures across satellite cities.

Three modelling approaches - decision trees, random forest, and multinomial logit - were used to classify restaurant locations based on spatial variables: distance to CBD, NTL, population density, and rent. Night-time light emerged as the most significant explanatory variable across all cities. Among the models, the random forest approach yielded the highest classification accuracy (62.8 % for Delhi), followed by decision trees and multinomial logit models. Notably, hybrid restaurants exhibited the highest misclassification rates, reflecting their locational ambiguity between delivery- and dine-in-oriented businesses.

While this study is situated in the context of Indian metropolitan and satellite cities, several findings have broader relevance. The clustering behaviour of dark kitchens and food trucks, the predictive strength of night-time light as a spatial proxy, and the misclassification challenges associated with hybrid restaurants are all observable in other rapidly urbanising and platform-driven food economies. Cities across Latin America, Southeast Asia, and parts of North America - where informal retail, app-based deliveries, and zoning gaps coexist - are likely to witness similar spatial dynamics. Thus, the modelling approaches and spatial typologies developed in this study offer transferable insights for urban planners and policymakers in comparable global contexts. These findings have clear policy implications. The agglomeration of food delivery-based restaurants in informal zones and peripheral areas necessitates updating zoning laws, traffic management policies, and loading infrastructure to reflect the freight-intensive nature of dark kitchens and food trucks. Furthermore, the demonstrated effectiveness of NTL and rent data in predicting restaurant typologies offers a scalable, data-driven framework for local governments to anticipate freight trip generation and enable proximity-based land use planning in the platform economy. In sum, this study underscores the need for integrated land use and logistics policies that account for the rise of non-traditional, digitally mediated food businesses - and their spatial footprint in the post-pandemic urban landscape.

As with any research, this study also has some limitations. For instance, it is an open research question how the grid-level freight (trip) generation estimates of different restaurant types aggregate and contrast across the city zones (depending on their location and the nature of land use) and may be correlated to the built environment variables. Such an analysis did not fall under the scope of this study – it would require an integration of multiple data sources, such as street imagery, to make inferences on the built environment and establish linkages with aggregated freight demand. Conducting comparative analyses across cities in Latin America, Southeast Asia, or Africa could reveal how platform-based food establishments cluster and interact with land use under different regulatory, infrastructural, and socioeconomic conditions. In the future, integrating discrete choice experiments or agent-based models could help simulate location choices of restaurants based on rent, demand elasticity, zoning constraints, and delivery platform policies. Additionally, scenario-based simulation tools could be developed further to evaluate how zoning reforms, congestion charges, or dark kitchen bans would impact clustering patterns, delivery volumes, and urban freight flows.

CRediT authorship contribution statement

Suprava Mishra: Writing – review & editing, Visualization, Formal analysis, Writing – original draft, Methodology, Data curation. **Agnivesh Pani:** Writing – review & editing, Supervision, Methodology, Formal analysis, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Ivan Sanchez-Diaz:** Writing – review & editing, Writing – original draft, Visualization. **Heleen Buldeo Rai:** Writing – original draft, Writing – review & editing, Visualization. **Ankit Gupta:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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References

Albert, J. M., Casanova, M. R., & Orts, V. (2012). Spatial location patterns of Spanish manufacturing firms. *Papers in Regional Science, 91*, 107–136. https://doi.org/10.1111/j.1435-5957.2011.00375.x

Alghamdi, A. (2023). A hybrid method for customer segmentation in Saudi Arabia restaurants using clustering, neural networks and optimization learning techniques. *Arab J Sci Eng, 48*, 2021–2039. https://doi.org/10.1007/s13369-022-07091-y

Ali A., 2024. Times of India [WWW Document].

Allen, J., Piecyk, M., Cherrett, T., Juhari, M. N., McLeod, F., Piotrowska, M., Bates, O., Bektas, T., Cheliotis, K., Friday, A., & Wise, S. (2021). Understanding the transport and CO2 impacts of on-demand meal deliveries: A London case study. *Cities, 108*. https://doi.org/10.1016/j.cities.2020.102973

Bartelme, D., Ziv, O., Acosta-Mejia, C., Levchenko, A., Lin, J., Stinson, M., & Zhang, J. (2022). *The internal geography of firms*.

Biau, G., & Scornet, E. (2016). A random forest guided tour. *Test, 25*, 197–227. https://doi.org/10.1007/s11749-016-0481-7

Bjørgen, A., & Ryghaug, M. (2022). Integration of urban freight transport in city planning: Lesson learned. *Transp Res D Transp Environ, 107*. https://doi.org/10.1016/j.trd.2022.103310

Bretas, V. P. G., & Alon, I. (2020). The impact of COVID-19 on franchising in emerging markets: An example from Brazil. *Global Business and Organizational Excellence, 39*, 6–16. https://doi.org/10.1002/joe.22053

Buldeo Rai, H., Mariquivoi, J., Schorung, M., & Dablanc, L. (2023). Dark stores in the city of light: Geographical and transportation impacts of 'quick commerce' in paris. *Research in Transportation Economics, 100*. https://doi.org/10.1016/j.retrec.2023.101333

Canziani, B. F., Almanza, B., Frash, R. E., McKeig, M. J., & Sullivan-Reid, C. (2016). Classifying restaurants to improve usability of restaurant research. *International Journal of Contemporary Hospitality Management, 28*, 1467–1483. https://doi.org/10.1108/IJCHM-12-2014-0618

Chen, Y. (2013). New approaches for calculating moran's index of spatial autocorrelation. *PLoS One, 8*. https://doi.org/10.1371/journal.pone.0068336

Chen, Y., Yin, C., & Sun, B. (2024). Nonlinear associations of built environments around residences and workplaces with commuting satisfaction. *Transp Res D Transp Environ, 133*. https://doi.org/10.1016/j.trd.2024.104315

Cheng, C. C., Tsai, M. C., & Lin, S. P. (2015). Developing strategies for improving the service quality of casual-dining restaurants: New insights from integrating IPGA and QFD analysis. *Total Quality Management and Business Excellence, 26*, 415–429. https://doi.org/10.1080/14783363.2013.839166

Chung, J., & Kim, H. (2019). Crime risk maps: A multivariate spatial analysis of crime data. *Geographical Analysis, 51*, 475–499. https://doi.org/10.1111/gean.12182

Dablanc, L., Morganti, E., Arvidsson, N., Woxenius, J., Browne, M., & Saidi, N. (2017). Supply chain forum. *International Journal*. https://doi.org/10.1080/16258312.2017.1375375ï

Dayal, E., Unnikrishnan, A., Pani, A., & Lakshay. (2025). Optimal location and capacity planning for parcel lockers: A Bi-Level optimization model considering Planners' and Customers' perspectives. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981241311564

Debnath, R., Chandel, T., Han, F., & Bardhan, R. (2025). *Heatwave increases nighttime light intensity in hyperdense cities of the global South: A double machine learning study*.

Elliott, M. (1981). *The Impact of Growth Control Regulations on Housing Prices in California*, 9* pp. 115–133). Real Estate Economics. https://doi.org/10.1111/1540-6229.00235.

Elvidge, C. D., Baugh, K. E., Anderson, S. J., Sutton, P. C., & Ghosh, T. (2012). The Night Light Development Index (NLDI): A spatially explicit measure of human development from satellite data. *Social Geography, 7*, 23–35. https://doi.org/10.5194/sg-7-23-2012

Enthoven, M. P. M., & Brouwer, A. E. (2020). Investigating spatial concentration of sustainable restaurants: It is all about good food. In *Annals of regional science* (pp. 575–594). Springer. https://doi.org/10.1007/s00168-019-00955-6.

Fitzpatrick Sarah. (2021). *Rise of dark kitchen* [WWW Document].

Gedamu, W. T., Plank-Wiedenbeck, U., & Wodajo, B. T. (2024). A spatial autocorrelation analysis of road traffic crash by severity using Moran's I spatial statistics: A comparative study of addis ababa and Berlin cities. *Accident Analysis & Prevention, 200*, Article 107535. https://doi.org/10.1016/j.aap.2024.107535

Glaeser, E. L., & Ward, B. A. (2009). The causes and consequences of land use regulation: Evidence from Greater Boston. *Journal of Urban Economics, 65*, 265–278. https://doi.org/10.1016/j.jue.2008.06.003.

Håkonsson, D., Acosta, C., Håkonsson Lyngemark, D., Baum-Snow, N., Blum, B., Campusano, R., Kalsø Hansen, H., Horstmann, I., Martínez, J., Mulalic, I., Strange, W., & Dohlmann, C. (2019). *The internal Spatial Organization of Firms: Evidence from Denmark the Internal Spatial Organization of Firms: Evidence from Denmark*.

He, Z., Han, G., Cheng, T. C. E., Fan, B., & Dong, J. (2019). Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach. *International Journal of Production Economics, 215*, 61–72. https://doi.org/10.1016/j.ijpe.2018.05.008

Hilber, C. A. L., & Robert-Nicoud, F. (2013). On the origins of land use regulations: Theory and evidence from US metro areas. *Journal of Urban Economics, 75*, 29–43. https://doi.org/10.1016/j.jue.2012.10.002.

Holguín-Veras, J., Jaller, M., Destro, L., Ban, X. J., Lawson, C., & Levinson, H. S. (2011). Freight generation, freight trip generation, and perils of using constant trip rates. *Transportation Research Record*, 68–81. https://doi.org/10.3141/2224-09

IBM. (2012). *IBM SPSS decision trees*.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning, springer texts in statistics*. New York, New York, NY: Springer. https://doi.org/10.1007/978-1-4614-7138-7

Jung, S., & Jang, S. C. (2019). To cluster or not to cluster?: Understanding geographic clustering by restaurant segment. *Int J Hosp Manag, 77*, 448–457. https://doi.org/10.1016/j.ijhm.2018.08.008 (Shawn).

Kan, Z., Kwan, M., & Tang, L. (2022). Ripley's k-function for network-constrained flow data. *Geographical Analysis, 54*, 769–788. https://doi.org/10.1111/gean.12300

Kok, N., Monkkonen, P., & Quigley, J. M. (2014). Land use regulations and the value of land and housing: An intra-metropolitan analysis. *Journal of Urban Economics, 81*, 136–148. https://doi.org/10.1016/j.jue.2014.03.004.

Kraus, S., Sen, S., Savitskie, K., Kumar, S. K., & Brooks, J. (2022). Attracting the millennial customer: The case of food trucks. *British Food Journal, 124*, 165–182. https://doi.org/10.1108/BFJ-09-2021-0996

Kulkarni, A. D., & Lowe, B. (2016). Random Forest algorithm for land cover classification random forest algorithm for land cover classification recommended citation. *Recommended citation International Journal on recent and innovation trends in computing and communication random Forest algorithm for land cover classification*.

Kulshreshtha, K., & Sharma, G. (2022). From restaurant to cloud kitchen: Survival of the fittest during COVID-19 an empirical examination. *Technological Forecasting and Social Change, 179*. https://doi.org/10.1016/j.techfore.2022.121629

Lau, S. S. Y., Giridharan, R., & Ganesan, S. (2005). Multiple and intensive land use: Case studies in Hong Kong. *Habitat International, 29*, 527–546. https://doi.org/10.1016/j.habitatint.2004.04.007

Lawson, C. T., Holguín-Veras, J., Sánchez-Díaz, I., Jaller, M., Campbell, S., & Powers, E. L. (2012). Estimated generation of freight trips based on land use. *Transportation Research Record*, 65–72. https://doi.org/10.3141/2269-08

Lepetit Quentin, V. V. L. C. (2023). Specifications table. https://doi.org/10.5281/zenodo.6821394.

Li, H. min, Li, X. gang, Yang, X. ying, & Zhang, H. (2019). Analyzing the relationship between developed land area and nighttime light emissions of 36 Chinese cities. *Remote Sens (Basel), 11*. https://doi.org/10.3390/rs11010010

Li, G., Sun, W., Yuan, Q., & Liu, S. (2020). Planning versus the market: Logistics establishments and logistics parks in Chongqing, China. *J Transp Geogr, 82*. https://doi.org/10.1016/j.jtrangeo.2019.102599

McLeod, S., Schapper, J. H. M., Curtis, C., & Graham, G. (2019). Conceptualizing freight generation for transport and land use planning: A review and synthesis of the literature. *Transp Policy (Oxf), 74*, 24–34. https://doi.org/10.1016/j.tranpol.2018.11.007

Meena, S., Patil, G. R., & Mondal, A. (2019). Understanding mode choice decisions for shopping mall trips in metro cities of developing countries. *Transp Res Part F Traffic Psychol Behav, 64*, 133–146. https://doi.org/10.1016/j.trf.2019.05.002

Mishra, S., Pani, A., Sanchez-Diaz, I., & Rai, H. B. (2025). Urban freight activity implications from emerging food industry establishments in an on-demand economy: Evidence from India. *Research in Transportation Economics, 110*. https://doi.org/10.1016/j.retrec.2025.101540

Mishra, S., Sharma, I., & Pani, A. (2023). Analyzing autonomous delivery acceptance in food deserts based on shopping travel patterns. *Transportation Research Part A Policy Pract, 169*. https://doi.org/10.1016/j.tra.2023.103589

Moore, L. V., & Diez Roux. (2006). Associations of neighborhood characteristics with the location and type of food stores. *American Journal of Public Health (AJPH), 96*, 325–331. https://doi.org/10.2105/AJPH.2004.058040.

Moran, P. A. P. (1950). *Notes on continuous stochastic phenomena*.

Mulligan Gordon, F. (1984). *Agglomeration and central place theory a review of the literature*.

Nakaya, T., Fotheringham, S. A., Hanaoka, K., Clarke, G., Ballas, D., & Yano, K. (2007). Combining microsimulation and spatial interaction models for retail location analysis. *Journal of Geographical Systems, 9*, 345–369. https://doi.org/10.1007/s10109-007-0052-2.

Nilsson, I., Reid, N., & Lehnert, M. (2018). Geographic patterns of craft breweries at the Intraurban Scale. *The Professional Geographer, 70*, 114–125. https://doi.org/10.1080/00330124.2017.1338590

North, D. C. (1955). Location theory and regional economic growth. *Journal of Political Economy, 63*, 243–258. https://doi.org/10.1086/257668

Paithane, P. M., Jibhau Wagh, S., & Kakarwal, S. N. (2023). Optimization OF route distance using K-nn algorithm for on-demand food delivery. *System Research and Information Technologies*, 85–101. https://doi.org/10.20535/SRIT.2308-8893.2023.1.07, 2023.

Pani, A., Mishra, S., Golias, M., & Figliozzi, M. (2020). Evaluating public acceptance of autonomous delivery robots during COVID-19 pandemic. *Transp Res D Transp Environ, 89*. https://doi.org/10.1016/j.trd.2020.102600

Pani, A., Mishra, S., & Sahu, P. (2022). Developing multi-vehicle freight trip generation models quantifying the relationship between logistics outsourcing and insourcing decisions. *Transportation Research Part E: Logistics and Transportation Review, 159*, 102632.

Pani, A., Sahu, P. K., Chandra, A., & Sarkar, A. K. (2019). Assessing the extent of modifiable areal unit problem in modelling freight (trip) generation: Relationship between zone design and model estimation results. *J Transp Geogr, 80*. https://doi.org/10.1016/j.jtrangeo.2019.102524

Pani, A., Unnikrishnan, A., Sinha, S., & Varghese, V. (2024). Shopping travel behaviour trade-offs between physical stores and online deliveries: post-COVID scenario in new Delhi, India. *Transportation in Developing Economies, 10*, 17. https://doi.org/10.1007/s40890-024-00203-3

Pinheiro, C. D. P., Gonzalez Feliu, J., & Bertoncini, B. V. (2025). A novel comprehensive spatial accessibility indicator to capture the latent nature of accessibility in logistic warehouses. *Research in Transportation Economics, 109*. https://doi.org/10.1016/j.retrec.2024.101517

Pitombo, C. S., de Souza, A. D., & Lindner, A. (2017). Comparing decision tree algorithms to estimate intercity trip distribution. *Transp Res Part C Emerg Technol, 77*, 16–32. https://doi.org/10.1016/j.trc.2017.01.009

Planinc, T., Kukanja, M., & Planinc, S. (2018). Classification and efficiency analysis of Slovenian restaurants SMEs. *Academica Turistica*. https://doi.org/10.26493/2335-4194.11.31-42

Prayag, G., Landré, M., & Ryan, C. (2012). Restaurant location in Hamilton, New Zealand: Clustering patterns from 1996 to 2008. *International Journal of Contemporary Hospitality Management, 24*, 430–450. https://doi.org/10.1108/09596111211217897

Ramakrishnan, J., Liu, T., Zhang, F., Seshadri, K., Yu, R., & Gou, Z. (2023). A decision tree-based modeling approach for evaluating the green performance of airport buildings. *Environmental Impact Assessment Review, 100*, Article 107070. https://doi.org/10.1016/j.eiar.2023.107070

Regal, A., Gonzalez-Feliu, J., & Rodriguez, M. (2023). A spatio-functional logistics profile clustering analysis method for metropolitan areas. *Transp Res E Logist Transp Rev, 179*. https://doi.org/10.1016/j.tre.2023.103312

Saiz, A. (2010). The Geographic Determinants of Housing Supply *. *Quarterly Journal of Economics, 125*, 1253–1296. https://doi.org/10.1162/qjec.2010.125.3.1253.

Samani, A. R., Mishra, S., Golias, M., & Lee, D. J.-H. (2023). What influences the location choice of establishments? An analysis considering establishment types and activities interactions. *J Transp Geogr, 111*, Article 103667. https://doi.org/10.1016/j.jtrangeo.2023.103667

Seghezzi, A., & Mangiaracina, R. (2021). On-demand food delivery: Investigating the economic performances. *International Journal of Retail & Distribution Management, 49*, 531–549. https://doi.org/10.1108/IJRDM-02-2020-0043

Sharma, V. (2023). *Times of India* ([WWW Document]).

Shoag, D., & Veuger, S. (2019). Do land use restrictions increase restaurant quality and diversity? *Journal of Regional Science, 59*, 435–451. https://doi.org/10.1111/jors.12425.

Sinha, D., & Pandit, D. (2021). A simulation-based study to determine the negative externalities of hyper-local food delivery. *Transp Res D Transp Environ, 100*. https://doi.org/10.1016/j.trd.2021.103071

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*. https://doi.org/10.1016/j.cities.2022.103820

Thrane, C. (2015). Examining tourists' long-distance transportation mode choices using a multinomial logit regression model. *Tourism Management Perspectives, 15*, 115–121. https://doi.org/10.1016/j.tmp.2014.10.004

Vu, O. T. K., Duarte Alonso, A., Tran, T. D., & Nicholson, G. J. (2023). Illuminating the dark kitchen business model - A knowledge-based perspective from the supply-side. *Journal of Hospitality and Tourism Management, 55*, 318–331. https://doi.org/10.1016/j.jhtm.2023.04.013

Wang, Z., & He, S. Y. (2021). Impacts of food accessibility and built environment on on-demand food delivery usage. *Transp Res D Transp Environ, 100*. https://doi.org/10.1016/j.trd.2021.103017

Washington, S., Karlaftis, M. G., & Mannering, F. L. (2003). *Statistical and econometric methods for transportation data analysis*. Chapman & Hall/CRC.

Wu, M., Pei, T., Wang, W., Guo, S., Song, C., Chen, J., & Zhou, C. (2021). Roles of locational factors in the rise and fall of restaurants: A case study of beijing with POI data. *Cities, 113*. https://doi.org/10.1016/j.cities.2021.103185

Zhang, M., Chen, Y., & Susilo, W. (2023). Decision tree evaluation on sensitive datasets for secure e-Healthcare systems. *IEEE Transactions on Dependable and Secure Computing, 20*, 3988–4001. https://doi.org/10.1109/TDSC.2022.3219849