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Research Article

Local Spatial Analysis of the Crash Frequency of Food Delivery Motorcyclists vs. Nondelivery Motorcyclists in relation to Points of Interest

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The COVID-19 pandemic has increased the demand for online food delivery services (OFDS), leading to an increase in related crashes over the last few years. While recent studies have focused on nonmotorised vehicles (such as bicycles or e-bikes), few researchers have examined the role of motorcycles and the possible spatial relationships with various points of interest (POIs). In addition, most crash and POIs studies have utilized typical restaurant datasets instead of specific restaurants partnered with OFDS, which might bias the impact of traffic safety estimation. To address these gaps, a geographically weighted negative binomial model (GWNBR) was used to determine the factors contributing to OFDS-related motorcycle accidents and account for spatial heterogeneity. The results indicated that areas with more restaurants, intersections, and shopping malls (only significant on weekends) tended to have more OFDS motorcycle crashes. The results should inspire more effective policies for delivery drivers, given the increasing popularity of OFDS.

1. Introduction

Anyone can order food from a variety of restaurants by using simple online apps. The order is picked up from the restaurant by a courier and delivered to nearby customers. This industry has grown exponentially worldwide [1, 2]. For instance, in Australia, nearly four million people used online food delivery services (OFDS) in 2020, a number that has grown by 81.1% since 2015 [3]. Mexico also experienced an upswing of more than 70% in visits to OFDS websites [4]. It must be noted that the popularity of this service was further increased by the COVID-19 quarantines, during which many restaurants partnered with these companies to stay in business [5].

The surging demand has led to intense competition among delivery service companies that are vying to offer speedier and more cost-effective options [6]. Motorcycles are the favored vehicle due to their capacity to circumnavigate through congested roads, which is crucial for maintaining fast delivery times. This ability is particularly relevant in Asia, where dense road networks and narrow alleys are common. Hence, motorcycles, known for their wide availability, popularity, and low cost, emerged as the primary choice of delivery companies. Notably, in Taiwan alone, these companies hired approximately 88,000 OFDS workers in 2020, which underscores this sector's substantial impact on employment rates [7]. However, the proliferation of OFDS startups has brought about a noticeable increase in motorcycle-related crashes in recent times. A study conducted by Chen [8] clarified this pattern, illustrating that the proportion of motorcycle riders deemed at fault rose from 31.0% in 2017 to 61.1% in 2020 in the context of all traffic accidents involving OFDS motorcycle riders in Taiwan. Strikingly, the numbers of Korean hospital patients revealed that the percentage of severe crash injuries among these individuals was much higher compared to nondelivery motorcyclists from 2014 to 2018 [9]. A similar pattern manifested in South Korea, where the fatality rate attributed to delivery-related crashes constituted roughly 12% of all fatal traffic accidents, a stark contrast to the 5% attributable to nondelivery crashes [1]. This concerning trend may be rooted in the demanding environment of delivery drivers, characterized by substantial workloads and stringent time constraints for each order. In their pursuit of maximizing earnings and averting customer complaints, delivery personnel resort to reckless driving, including speeding, weaving through traffic, texting while driving, and ignoring traffic signals [10, 11], practices which differ significantly from nondelivery motorcyclists who tend to prioritize safety over speed.

Over the past several years, researchers have compared the driving behaviors of nondelivery and delivery motorcyclists as well as other crash-related factors, particularly those linked to traffic violations and driver characteristics [1, 12]. For example, Wang et al. [13] conducted an extensive observational study involving 600 delivery drivers, in which 480 participants were interviewed to assess their driving behaviors and identify factors that may contribute to injury crashes in China. The findings revealed that 91.3% of the respondents frequently exceeded speed limits, ran red lights, and disregarded traffic signals, which led to 76.5% of the interviewees being involved in at least one traffic accident. Li et al. [14] conducted a similar analysis which revealed that delivery-related vehicles in Shanghai, China, were 5.4% more likely to be involved in red-light running incidents compared to personal vehicles.

Surprisingly, there are few motorcycle traffic studies in which the built environmental factors are considered (e.g., points of interest). According to Qin et al. [15], OFDS motorcycle riders may resort to riskier driving behaviors and travel routes compared to nondelivery motorcyclists who are typically commuters. Furthermore, the partners of the OFDS are no longer limited to well-known restaurants; they also include local eateries, convenience stores, and supermarkets that deliver to hotels, schools, and residential areas. This expansion may raise the crash risk for OFDS drivers [16, 17]. In other words, these types of points of interest (POIs) may increase the use of OFDS, contributing to higher collision rates.

The present study focuses on specifying and comparing the POIs associated with OFDS and nondelivery motorcycle crashes. Specifically, OFDS-related crashes, defined as motorcycle crashes in this context, involve drivers employed by OFDS platforms to deliver food to customers. In contrast, nondelivery motorcycle crashes encompass accidents where motorcycles are not involved in food delivery activities. In order to establish a more robust relationship with the exposure specific to OFDS, various risk factors were considered including partnerships with restaurants affiliated with OFDS platforms (Uber Eats and Food Panda), traffic conditions, road geometry, and population density. To enhance the methodological approach, this study used the geographically weighted negative binomial regression (GWNBR) model, which is unique and ideal for the analysis of OFDS motorcycle crashes, as it effectively addresses the spatial heterogeneity and the overdispersion issues commonly observed in crash data [18, 19]. This approach serves to provide a local-level analysis of the factors influencing crash patterns in the context of OFDS motorcycles and nondelivery motorcycles.

2. Literature Review

2.1. Factors Associated with OFDS Motorcycle Crashes. During peak hours, online food orders, particularly takeout, prompt concentrated order aggregations in densely populated zones such as residential, commercial, and urban centers [20]. This scenario necessitates that OFDS, often on motorcycles, navigate through the bustling streets and intersections of Asian cities, where they share the road with a diverse mix of vehicles, pedestrians, and cyclists [13]. Consequently, a notable correlation was frequently observed between vehicle density and OFDS motorcycle-related crashes [21]. The increased width of these intersections is often accompanied by longer traffic signal intervals ranging from 60 to 120 seconds [15]. In addition, main roads are frequently divided by physical barriers such as fences and green belts, forcing traffic to move to the nearest front or rear intersection to execute U-turns [22]. Given this chaotic environment, instances of traffic violations among delivery couriers are prevalent, with intersections serving as hotspots for such behaviors [15, 23].

The popularity of these services continues to grow. Han et al. [24] and Li and Zhang [25] showed that in China, students and white-collar workers use OFDS because they are fast, convenient, and do not require leaving the workplace or school. Similarly, 15 Italian cities saw an increase of 137% in the use of OFDS by office employees at lunchtime [26]. In other words, office and school areas become the main destination for OFDS which might increase the crash likelihood. This platform is also frequently used by tourists who have meals delivered to their hotels [27] in order to have more time for sightseeing. Most are unfamiliar with the area and others wish to avoid long lines at famous restaurants. Thus, in this study, universities, schools, offices, and hotels were treated as POIs (destinations with a concentration of customers) that are associated with a high number of OFDS motorcycle crashes.

2.2. Factors Associated with Nondelivery Motorcycle Crashes. Several studies of nondelivery motorcycle crashes have shown that POIs, such as commercial centers, schools, and public transportation stops, attract many pedestrians, which subjects these areas to heavy traffic, conflicts, and collisions [28–32]. Ivan et al. [29] found that primary schools are a hotspot for pedestrian-motorcycle crashes due to unsafe crossing conditions. Increased pedestrian activity also occurs near commercial areas, shopping centers, bus stops, and subway stations. Thus, there is an increase in traffic accidents at these locations [33, 34].

Chen et al. [28] found that few motorcycle crashes occur in touristy areas with many hotels because visitors are more likely to travel by tour bus and public transit than by motorcycle, so traffic patterns in these areas are relatively simple. Similarly, open spaces, such as parks and green spaces, are not as populated as other POIs, so there is less traffic and fewer collisions [35]. Areas with many POIs, pedestrians, and heavy traffic tend to experience high rates of motorcycle accidents [30, 36, 37].

2.3. Crash Prediction Models. Several models have been used in existing crash studies to define the spatial dependency and heterogeneity of crash frequency and predictor factors [38].

In order to address the spatial heterogeneity of the crash data, researchers such as Flask et al. [39], Jia et al. [30], and Truong et al. [40] mainly focused on spatial global regression; however, the parameter estimates remained constant across the study area, so it was impossible to accurately determine the relationship between environmental conditions and crash frequency. For example, Cheng et al. [41] successfully applied spatial modeling to predict crash frequency in traffic analysis zones (TAZs) in California; however, their model only accounted for spatial dependence and disregarded spatial heterogeneity. GWR-based models were utilized in several later studies to allow the coefficients to change throughout the study area in order to more accurately predict crash frequency [42]. For example, Hezaveh et al. [43] and Bao et al. [44] used a geographically weighted Poisson regression (GWPR) at various spatial units, which performs better than the traditional global Poisson model because it accounts for spatial heterogeneity. However, it must be noted that GWPR has a limited ability to predict high variability in crash data, as typically there are a higher number of crashes in urban than in rural areas, so GWPR might be not suitable for use in large study areas (whether urban or rural) or study units that include a variety of land uses. When DaSilva and Rodrigues [45], Amoh-Gyimah et al. [46], Gomes et al. [18], Obelheiro et al. [47], and Mathew et al. [48] used a geographically weighted negative binomial regression model (GWNBR) for crash frequency prediction; they found it to be more accurate than the GWPR and traditional global modeling, possibly because it addresses spatial heterogeneity and the overdispersion problem simultaneously, thus avoiding the underestimation of standard errors and misleading inferences regarding coefficients. Yet, despite its potential use in practical implications for local OFDS policy regulation and road safety improvement, it has not been utilized to assess the association between OFDS motorcycle crashes and POIs.

The present study, therefore, specified the POIs that may be associated with OFDS motorcycle crashes, through the novel approach of examining the restaurants that partnered with OFDS (such as Uber Eats and Food Panda). Furthermore, in order to explain this relationship more accurately and provide new evidence that OFDS workers are in more danger than nondelivery motorcyclists, several risk factors were considered, such as traffic conditions, road geometry, and population. Unlike any previously published study, the GWNBR model was utilized in this study because, as previously stated, it accounts for the spatial heterogeneity and overdispersion found within the crash data [19].

3. Data and Methodology

3.1. Data. This study utilized the 2020 motorcycle crash reports from the Taipei Department of Transportation. Taipei City was selected as the study site because after 2019, the crash dataset was separated into OFDS-related accidents (platform partner restaurants are on-demand food applications) and nondelivery accidents. The study area encompasses both the urban region in the central-western part of the city and the suburbs, located on the periphery of the downtown area, including the districts of Beitou, Shilin, Neihu, Wenshan, and Nangang (refer to Figure 1 for an illustration of the study area).

The crash dataset is accessible to the public through the government website (https://data.gov.tw), which provides free and open access to the data. The statistics show that out of the 64,795 total number of motorcycle crashes in 2020, 2,314 involved OFDS drivers. The crash dataset for this study includes location data (latitude and longitude) and other nonspatial information, such as crash ID codes, causal factors, collision type, severity, number of fatalities and injuries, road surface, weather, lighting conditions, crash date, vehicle type maneuvers, and directions. Other unrelated variables are not included due to space constraints.

Four explanatory variables are used: POIs, traffic conditions (number of bus stops and vehicle density in each village), road geometry, and population in Taipei City. The general POIs data (excluding restaurants) were downloaded from OpenStreetMap, including the number of supermarkets, shopping malls, schools, universities, hotels, and hospitals within the study area.

Unlike previous literature, this study utilized restaurants that partnered with OFDS such as Uber Eats and Food Panda. These OFDS are commonly used by citizens and have many partner restaurants. For restaurant data (limited to those partnered with OFDS), the Python "Selenium" library and "BeautifulSoup" library were used to collect information on the restaurants partnered with OFDS in the study area. Because the current open datasets are not limited to online options, the Selenium web driver was used to mimic how the user would search for this information, while BeautifulSoup was used to filter the webpage content and scrape the data into csv files. These tools can open the browser automatically and access OFDS websites in just a few steps, as shown in Figure 2. The procedure begins with accessing OFDS websites (Food Panda and Uber Eats in this case). Selenium was used to simulate how a customer would enter a pseudogeolocation (based on WGS84) into the search bar and how this program would scan the websites for restaurants closely associated with OFDS. The URLs of nearby restaurants were recorded based on query outcomes within the pseudolocation. This process was iterated across various locations until it covered the entire study area. Next, pertinent elements such as each restaurant's name, address, and coordinates were collected from the URLs and individually extracted using the Python "BeautifulSoup" library. This study also utilized this library to create a restaurant database in the csv format. Subsequently, duplicate entries (sharing identical names, coordinates, addresses, and floors) were

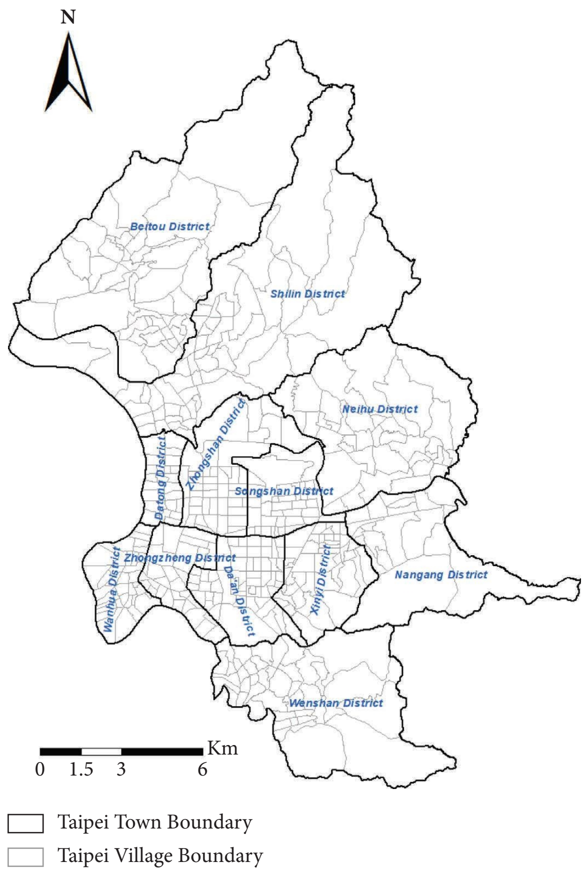


Figure 1: Illustration of the study area.

removed. For more in-depth information on Python-based web browsing with Selenium, please see references from Raghavendra [50] and Yudin [51].

The other explanatory variable is traffic flow, which is automatically generated by using traffic flow data from vehicle detectors on main streets in Taipei City. Road geometry data were collected using ArcGIS to calculate the key characteristics for the road network, including the number of intersections and total road length for each village. This study employed 456 villages as the study unit (Figure 1), as they constitute the smallest administrative entity and align with the practical implementation scale for local governments.

3.2. Methodology

3.2.1. Negative Binomial (NB) Model. As described in previous studies, crash frequency is assumed to be Poisson-distributed where the mean is assumed to be gamma-distributed [52, 53]. This gives rise to the Poisson-gamma or negative binomial (NB) distribution. The NB (gamma Poison) distribution is particularly well-suited for count data when there is evidence of overdispersion, which occurs when the variance of the data is higher than what would be expected under a binomial distribution [52]. In this case, the occurrence of motorcycle crashes may exhibit varying levels of dispersion due to factors such as a variety of road conditions, traffic density, and weather conditions. In addition, the NB model was used in this study because of the general relationship between each prediction variable and crash frequency [19, 54, 55] and shows the effects of not accounting for spatial heterogeneity. The relationship is shown as follows:

$$y_i \sim \mathrm{NB}\left[\exp\left(\sum_k \beta_k x_{ik}\right), \alpha\right], \tag{1}$$

where NB stands for the negative binomial distribution, y_i is the number of motorcycle crashes in the i^{th} $(i = 1, \ldots, n)$ spatial unit, x_{ik} represents the k^{th} explanatory variable for a spatial unit i, β_k $(k = 0, 1, \ldots, p)$ are the coefficients for variable k, which is the offset variable, and α is the overdispersion parameter.

3.2.2. Geographically Weighted Negative Binomial Model. A geographically weighted-based model is used to determine a nonstationary relationship between crash frequency and related factors. This model allows its parameters to vary over space, in order to determine the spatial heterogeneity between the dependent variable (motorcycle crash frequency) and independent variables. Most traffic crash prediction studies show that the GWR-based model performs better than other conventional nonspatial methods [56].

GWR is derived from the first law of geography, which states that occurrences near location i have a greater influence on the estimation of β_k (u_i, v_i) than those farther away. A kernel function, such as the Bisquare, represents the magnitude of this influence which is illustrated as follows:

$$w_{ij} = \begin{cases} \left(1 - \left(\dfrac{d_{ij}}{b_{i(k)}}\right)\right)^2, & \text{if } d_{ij} < b_{i(k)}, \\ 0, & \text{otherwise}, \end{cases} \tag{2}$$

where d_{ij} is the distance between spatial units i and j and $b_{i(k)}$ represents the adaptive bandwidth. GWNBR is the most commonly used model for crash frequency prediction.

In an early study, Nakaya et al. [57] developed a GWPR to construct a Poisson regression model with various explanatory variables. The Poisson model cannot be used for analyzing crash data since the mean is assumed to be the same for similar characteristics, other than the spatial components, which is not true [19]. Later, Xu and Huang [58] used the GWNBR, which accounts for overdispersed count data. This model can address the problems of spatial heterogeneity and overdispersion, as shown in the following equation:

$$y_i \sim \mathrm{NB}\left[\exp\left(\sum_k \beta_k (u_i, v_i) x_{\mathrm{ik}}\right), \alpha (u_i, v_i)\right], \tag{3}$$

where β_k (u_i, v_i) is the coefficient for the explanatory variable x_k in location (u_i, v_i), $k = 1, \ldots, n$, y_i is the number of crashes in the i^{th} spatial unit, and α is the overdispersion parameter. Therefore, this study assessed the performance of the

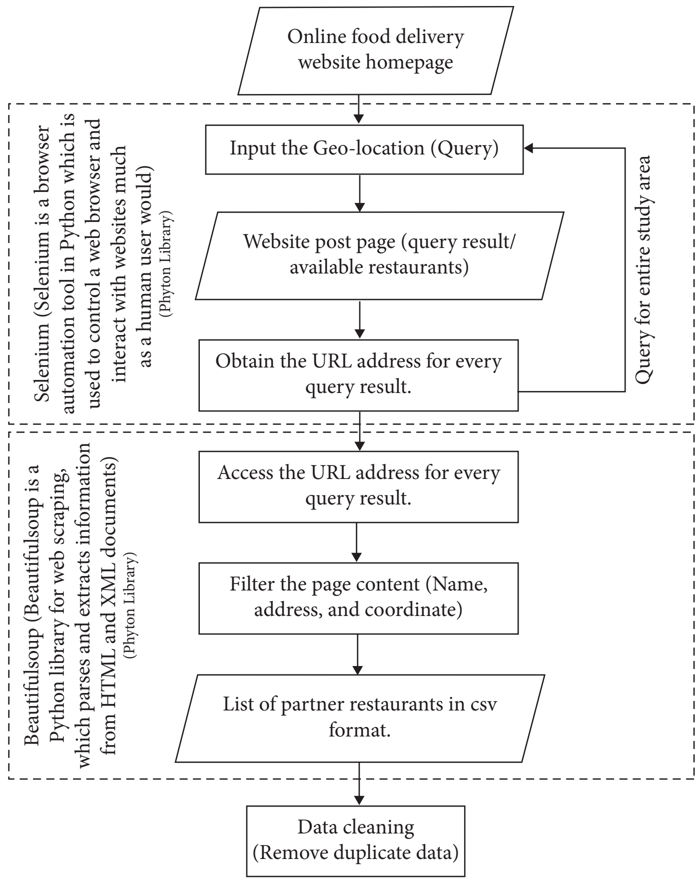


Figure 2: Web scrapping (web scraping is a data collection technique that involves extracting information from websites [49]) partnered restaurant with OFDS (Selenium is a browser automation tool in Python which is used to control a web browser and interact with websites much as a human user would).

GWNBR, which was used as a local crash prediction model; by comparing the results (in terms of AIC, log-likelihood, and R-square), it yielded to those of commonly used models such as NB and GWR.

4. Results

4.1. Descriptive Statistics. The descriptive statistics and expected association for these candidate variables are shown in Table 1 based on an analysis of the literature [30, 59, 60]. The results of web scraping revealed that 13,318 restaurants partnered with online OFDS. Supermarkets and shopping malls totaled 233 and 54, respectively. The numbers of notable customer-centric locations such as schools, universities, hotels, and hospitals were 276, 26, 20, and 32, respectively.

Furthermore, the expected association is that all POIs would have a positive relationship with traffic crashes [15–17]. For example, supermarkets, universities, and hospitals would have a positive association with traffic crashes, meaning that the areas with a high density of these POIs would tend to have a higher crash frequency. However, the association of schools and restaurants with traffic crashes is inconsistent across studies [59, 61], which requires further exploration.

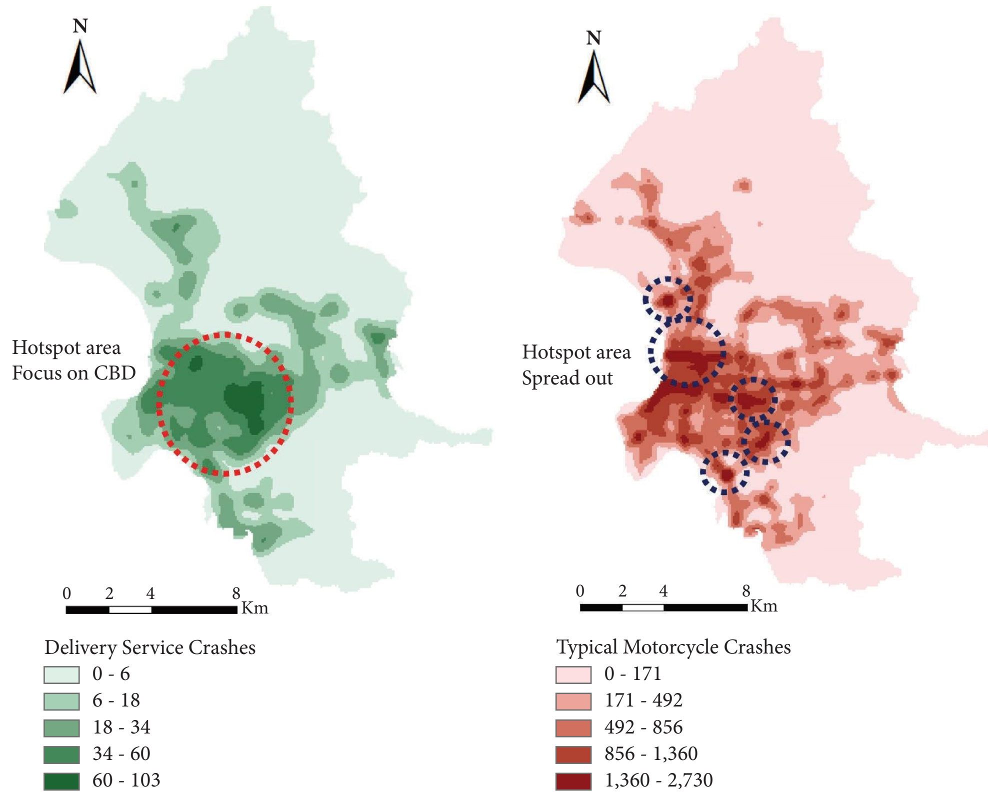
This study also uses visual results to confirm this spatial relationship among related factors and crashes. To establish an initial correlation between crash frequency and the number of POIs, the present study used the kernel density estimation method to better understand and visualize the relationship between crashes and POI hotspots. A predefined search bandwidth and cell size (100 meters and 20 meters) were selected based on Silverman's rule of thumb in order to better separate the hotspots (smaller bandwidth) and the smoothness of the figure (smaller cell size) [62, 63]. The red circle in Figure 3(a) shows that crash hotspots for OFDS personnel are concentrated in the central business district (CBD) of Taipei City, which is an area with many restaurants, supermarkets, shopping malls, and hospitals (Figure 4). This area also has a high population density and a large commercial zone (purple areas in Figure 5(b)). The nondelivery crash hotspots (black circles in Figure 3(b)) are dispersed throughout the central, western, and southern regions of Taipei City in the commercial and school zones.

Figure 6 illustrates the temporal trends in OFDS and nondelivery motorcycle crashes. Both types of crashes exhibit bimodal distributions with two peak crash frequencies. However, the peak crash frequency for OFDS motorcycles is observed during lunch and dinner hours, specifically at 12 PM and 6 PM. In contrast, nondelivery motorcycle crashes

Table 1: Summary of statistics for variables for each village.

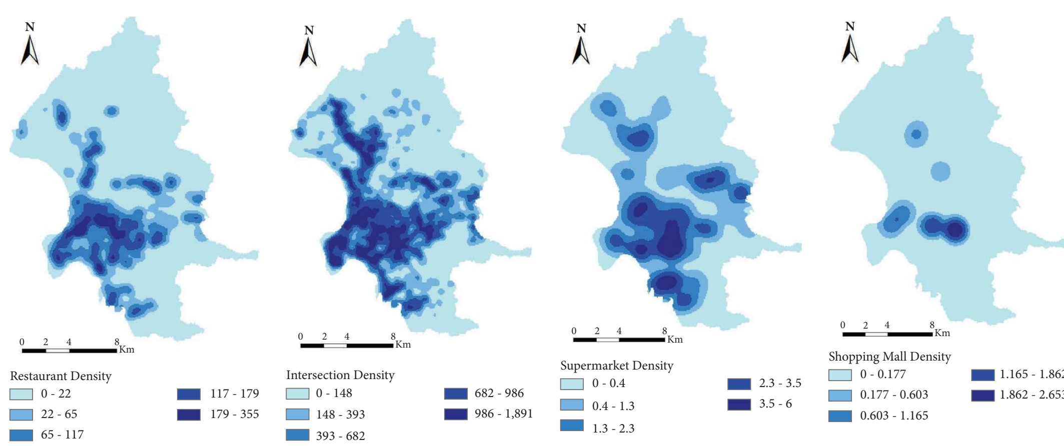
Variables			Expected association with traffic crashes	Mean	Min	Median	Max	Std dev	Total
Dependent variables		OFDS crash frequency on weekdays	n/a	3.662	0	3	26	3.680	1670
		OFDS crash frequency on weekends	n/a	1.412	0	1	13	1.706	644
		Nondelivery crash frequency on weekdays	n/a	112.41	2	89.5	840	91.452	51263
		Nondelivery crash frequency on weekends	n/a	29.675	0	25	156	22.523	13532
Independent variables	Points of interest	Restaurants (count)	+	29.206	0	21	387	31.042	13318
		Supermarkets (count)	+	0.511	0	0	5	0.725	233
		Schools (count)	+	0.605	0	0	6	0.812	276
		Universities (count)	+	0.057	0	0	2	0.250	26
		Shopping malls (count)	+	0.066	0	0	2	0.273	54
		Hotels (count)	–	0.044	0	0	5	0.321	20
		Hospitals (count)	+	0.070	0	0	3	0.288	32
		Bus stops (count)	+	0.375	0	0	12	0.977	171
	Traffic conditions	Log vehicle density per day (1000 vehicles/day)	–	2.119	2.042	2.111	2.354	0.437	966.299
	Road geometry	Log count of intersections	+	2.106	0.792	2.115	3.631	0.549	1028.19
		Log road lengths (1000 m)	+	2.188	1.878	2.184	2.411	0.073	997.954
	Census data	Log population density	+	1.672	1.192	1.732	1.950	0.328	740.281

n/a: not applicable. OFDS: online food delivery service. Std dev: standard deviation.



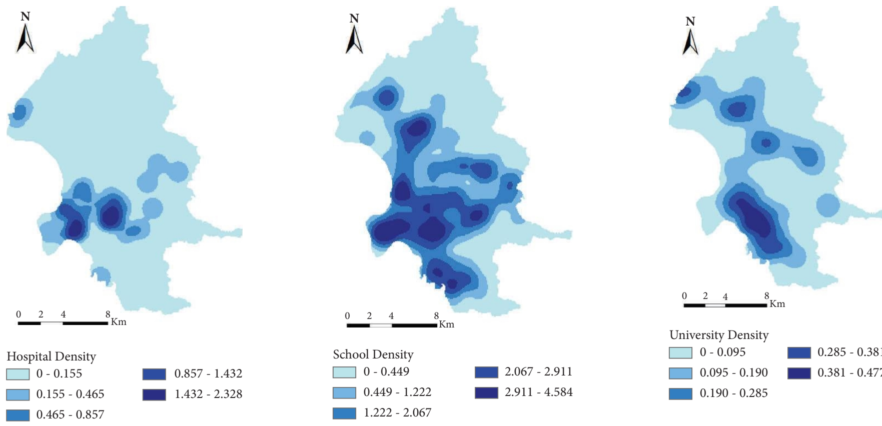
(a) (b)

Figure 3: (a) OFDS-related and (b) nondelivery motorcycle crash hotspots.



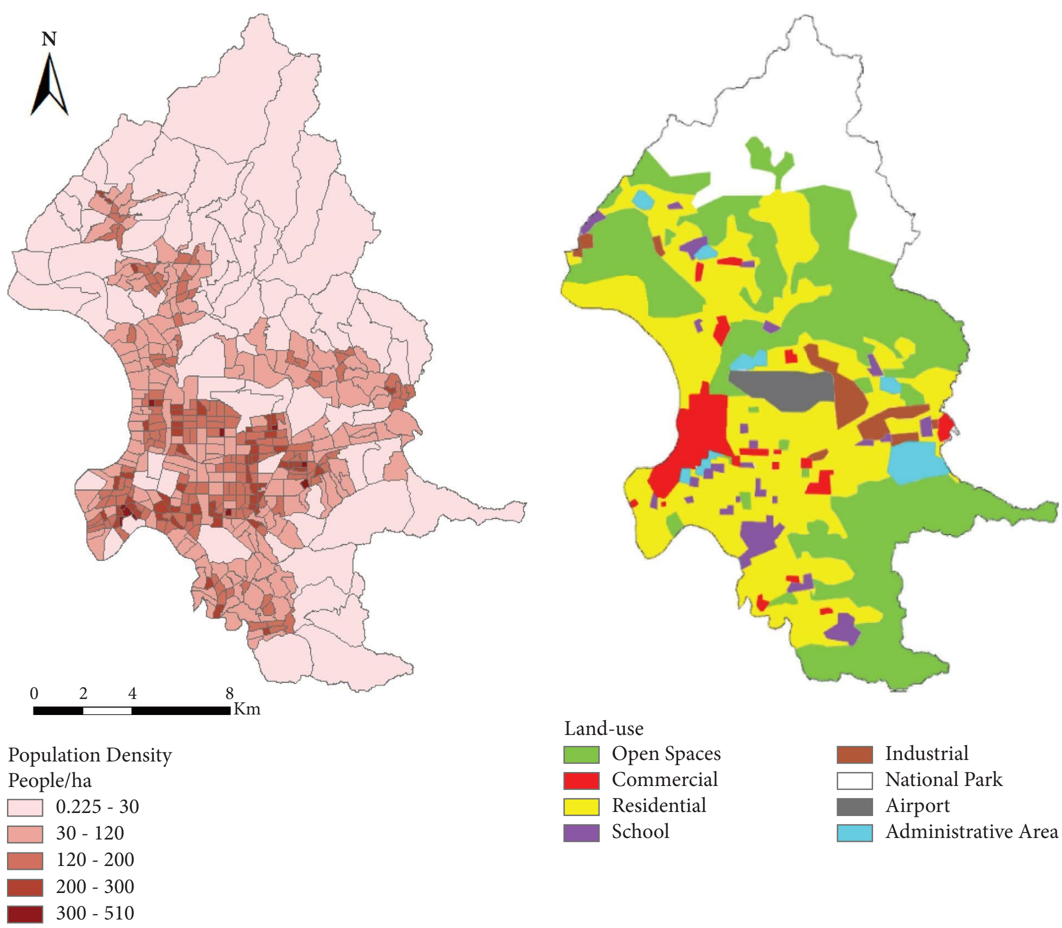
(a) (b) (c) (d)

Figure 4: Continued.



(e) (f) (g)

FIGURE 4: Kernel density for each POI. (a) Restaurants. (b) Intersections. (c) Supermarkets. (d) Shopping malls. (e) Hospitals. (f) Schools. (g) University.



(a) (b)

FIGURE 5: (a) Population density distribution and (b) land use in Taipei City.

peak during commuting hours, at the start and end of the workday, which are 8 AM and 6 PM. These findings indicate a distinct temporal pattern for OFDS motorcycle crashes compared to nondelivery motorcycle crashes.

4.2. Model Comparison. A nonspatial global model (NB) and spatial local model (GWNBR) were developed to determine the effect of overdispersion on crash analyses and spatial heterogeneity, using the methodology that is described.

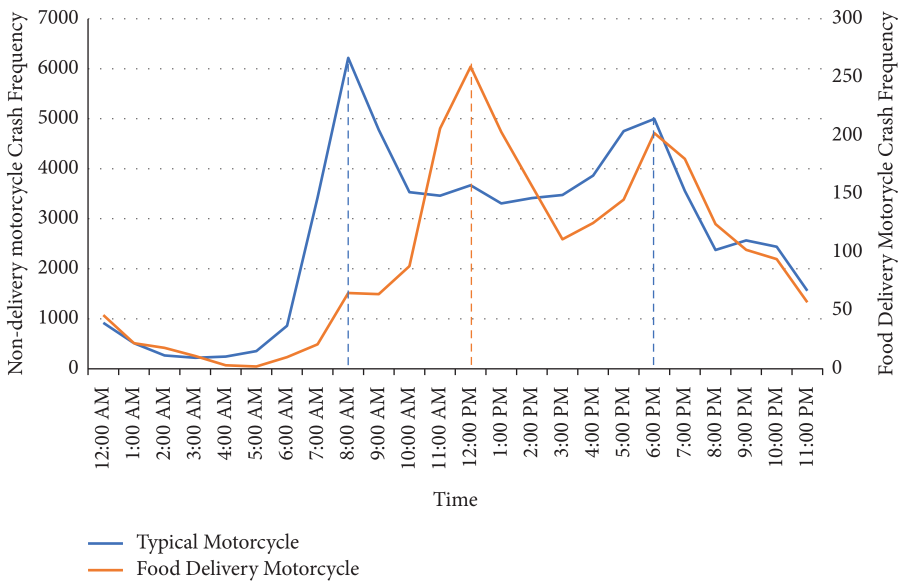


Figure 6: Temporal variation of OFDS and nondelivery motorcycle crashes.

These NB-based models were used because the dependent variable, which is the frequency of crashes, has a skewed distribution. The results for the coefficient are presented in Tables 2–5. The nonspatial model (NB) only estimates a single coefficient, so the parameters of the NB model are constant over the entire study area. However, the coefficients for the spatial models (GWNBR) are spatially varied, so they are described using the average, minimum, median, and maximum values for the coefficients. The variables and-coefficients highlighted in bold within the GWNBR model indicate that their coefficient values demonstrate statistical significance at a 5% level in over 50% of the total study units. Please refer to the percentage of significant coefficients column for the specific proportion of study units with-significance levels of 5% for each variable.

Four criteria were used to determine the performance of the models; recall that models were estimated for four dependent variables, as described in Table 1. In order to show the model complexity and model fitting, the Akaike information criterion (AIC) is used to assess the model performance. The model with the lowest AIC value has a better fit with the observed crash data. The model with the highest R-square and log-likelihood values and the lowest RMSE value also indicates a better model fit with higher likelihood and lower prediction errors. The model-fitting results for OFDS-related crashes and nondelivery crashes are shown in Tables 2–5. The GWNBR model performed better than the NB model, as expected. The results show that the spatial models outperform the nonspatial model because the local model incorporates more spatial heterogeneity than the NB, for which coefficients can vary spatially across observations.

There is no residual clustering within the GWNBR models because its p value for Moran's I is higher than 0.05. Otherwise, for the NB model residuals, the Moran's I value is positive with a p value lower than 0.05. In other words, the residual clustering becomes insignificant when the local model and overdispersion in the data are incorporated. Therefore, the spatial autocorrelation between the model residuals (spatial heterogeneity) and the overdispersion of crash frequency is explained by the GWNBR model.

Furthermore, the variance inflation factor (VIF) was used as a metric to evaluate multicollinearity. VIF gauges the degree to which multicollinearity contributes to an increase in the variance of estimated regression coefficients. A VIF value exceeding 1 indicates the presence of multicollinearity, with higher values denoting more pronounced multicollinearity [64, 65]. Typically, VIF values surpassing 5 or 10 are deemed indicative of substantial multicollinearity, as suggested by Akinwande et al. [66] and Tsagris and Pandis [67], although specific thresholds may vary depending on the specific context. However, it is noteworthy that all independent variables in the model yielded VIF values below 5, signifying the absence of multicollinearity issues in the crash risk model.

5. Discussion

The results of this study show that the GWNBR model performs better because it can account for spatial heterogeneity. The results show that areas with more restaurants, major intersections, and shopping malls (only on weekends) tend to experience more crashes involving OFDS drivers. The nondelivery crash model uses the same predictor variables but schools are added. Each POI has a different spatial coefficient distribution in relation to OFDS-related crashes on weekends and weekdays. The distributions for local coefficient estimations and their significance are plotted in Figures 7 and 8. Areas with a significance level of more than 50% were included in the parameter analysis [47].

5.1. The Association of POI, Traffic Conditions, and Road Geometry. The results reveal a significant and positive correlation between the presence of restaurants as POIs and

Table 2: Comparison of the results for OFDS-related crashes on weekdays for different models.

Variables	NB	GWNBR					VIF
		Mean	Min	Median	Max	Percentage of sig. coef. (%)	
Intercept	−13.869	−19.100	27.228	−20.570	−12.683	52.19	
Restaurants	**0.011* (0.001)**	0.009	0.007	0.009	0.014	**90.57**	2.081
Supermarkets	0.051	0.051	0.019	0.051	0.090	11.62	1.848
Shopping malls	0.234	0.217	0.089	0.223	0.326	48.25	1.791
Schools	0.119	0.103	0.077	0.098	0.139	20.18	1.308
Universities	0.204	0.199	−0.781	0.186	0.534	47.81	1.441
Hotels	0.208	0.180	0.132	0.181	0.229	3.29	1.798
Hospitals	0.270	0.197	−0.054	0.146	0.515	25.22	1.239
Bus stops	0.071	0.073	−0.044	0.022	0.350	4.82	1.624
Vehicle density	0.312	0.290	0.664	0.423	−3.105	10.31	1.219
Intersections	**0.400* (0.007)**	0.438	0.312	0.453	0.548	**91.01**	3.846
Road lengths	4.368	3.957	5.229	3.970	2.878	19.30	3.608
Population	0.988	0.663	0.002	0.771	5.302	22.37	1.707
Overdispersion	2.549	—					
Model performance							
AIC	1344.033	1251.147					
R2	0.284	0.482					
Log-likelihood	−658.688	−623.89					
RMSE	1.663	1.1019					
Global Moran's I (*P*-value)	**0.218* (0.0001)**	0.042 (0.259)					

*Significance levels of 5%. The variables and coefficients highlighted in bold within the GWNBR model indicate that their coefficient values demonstrate statistical significance at a 5% level in over 50% of the total study units. Please refer to the percentage of significant coefficients column for the specific proportion of study units with significance levels of 5% for each variable.

Table 3: Comparison of results for OFDS-related crashes on weekends for different models.

Variable	NB	GWNBR					VIF
		Mean	Min	Median	Max	Percentage of sig. coef. (%)	
Intercepts	−15.429	−18.210	−43.538	−16.813	−1.700	47.37	
Restaurants	**0.009* (0.004)**	0.008	0.002	0.008	0.015	**81.58**	1.894
Supermarkets	0.126	0.089	−0.087	0.079	0.273	10.96	1.663
Shopping malls	**0.335* (0.038)**	0.270	0.033	0.350	0.478	**67.54**	1.612
Schools	0.081	0.078	0.005	0.081	0.114	3.07	1.216
Universities	0.064	0.110	−1.083	0.119	0.847	7.89	1.369
Hotels	0.236	0.176	0.009	0.166	0.524	18.20	1.618
Hospitals	0.385	0.307	0.048	0.258	0.874	12.72	1.127
Bus stops	0.127	0.104	−0.050	0.084	0.281	14.47	1.494
Vehicle density	0.819	1.433	−1.740	0.737	7.001	9.21	1.109
Intersections	**0.328* (0.009)**	0.380	0.218	0.391	0.502	**83.99**	3.577
Road length	4.366	0.273	−0.928	0.246	1.392	18.20	3.392
Population	1.674	1.274	−0.419	1.256	4.186	20.83	1.622
Overdispersion	3.354	—					
Model performance							
AIC	1334.151	1223.345					
R2	0.283	0.479					
Log-likelihood	−653.845	−619.312					
RMSE	1.651	1.292					
Global Moran's I (*P* value)	**0.181* (0.0001)**	0.110 (0.213)					

*Significance levels of 5%. The variables and coefficients highlighted in bold within the GWNBR model indicate that their coefficient values demonstrate statistical significance at a 5% level in over 50% of the total study units. Please refer to the percentage of significant coefficients column for the specific proportion of study units with significance levels of 5% for each variable.

both types of motorcycle crashes in 69.30%–90.57% of the study area, as illustrated in Tables 2–5. This finding implies that areas with a higher density of restaurants tend to experience increased crash rates for both OFDS and nondelivery motorcycles. This result is consistent with that of Lin et al. [17], which shows that more crashes involved OFDS drivers (mean coefficient value of 0.009 on weekdays and 0.008 on weekends) in areas with a higher number of

Table 4: Comparison of results for nondelivery motorcycle crashes on weekdays for different models.

Variables	NB	GWNBR					VIF
		Mean	Min	Median	Max	Percentage of sig. coef. (%)	
Intercepts	−13.534	−13.676	−15.616	−13.742	−9.513	92.32	
Restaurants	**0.008* (0.002)**	0.007	0.003	0.007	0.012	**74.56**	1.500
Supermarkets	−0.007	−0.019	−0.121	−0.011	0.308	19.52	1.805
Shopping malls	0.052	0.010	−0.136	0.013	0.085	15.79	1.308
Schools	**0.093* (0.021)**	0.075	0.039	0.067	0.135	**62.94**	1.443
Universities	0.164	0.136	−0.744	0.134	0.917	47.59	1.629
Hotels	0.059	0.192	0.669	0.149	−0.113	25.88	1.814
Hospitals	0.178	0.122	−0.082	0.096	0.392	36.62	1.526
Bus stops	0.040	0.069	−0.127	0.011	0.390	1.97	2.034
Vehicle density	1.713	1.199	−0.385	2.527	7.603	5.70	1.210
Intersections	**0.229* (0.006)**	0.314	0.191	0.337	0.390	**76.97**	2.894
Road lengths	4.960	1.209	−6.820	0.837	1.147	31.14	2.874
Population	1.053	1.404	2.457	1.404	0.527	44.30	1.857
Overdispersion	3.727	—					
Model performance							
AIC	4672.406	4563.509					
R2	0.458	0.759					
Log-likelihood	−2322.875	−2254.414					
RMSE	74.411	69.799					
Global Moran's I (P value)	**0.331*(0.0001)**	0.093 (0.176)					

*Significance levels of 5%. The variables and coefficients highlighted in bold within the GWNBR model indicate that their coefficient values demonstrate statistical significance at a 5% level in over 50% of the total study units. Please refer to the percentage of significant coefficients column for the specific proportion of study units with significance levels of 5% for each variable.

Table 5: Comparison of results for nondelivery motorcycle crashes on weekends for different models.

Variables	NB	GWNBR					VIF
		Mean	Min	Median	Max	Percentage of sig. coef. (%)	
Intercepts	−10.971	−11.314	−12.999	−11.296	−8.160	78.29	
Restaurants	**0.006* (0.019)**	0.005	0.003	0.006	0.009	**69.30**	1.389
Supermarkets	−0.033	−0.027	−0.050	−0.032	0.046	8.33	1.835
Shopping malls	0.060	0.015	−0.093	0.020	0.089	32.24	1.113
Schools	0.088	0.069	0.043	0.061	0.111	17.76	1.265
Universities	0.088	1.007	4.744	1.139	2.355	30.04	1.091
Hotels	0.039	0.087	−0.061	0.005	0.082	41.89	1.233
Hospitals	0.130	0.042	−0.186	0.032	0.337	41.23	1.202
Bus stops	0.017	0.012	−0.047	0.035	0.088	18.42	1.237
Vehicle density	1.637	0.327	0.342	1.719	7.152	28.95	1.499
Intersections	**0.234* (0.007)**	0.258	0.086	0.25	0.461	**69.96**	3.475
Road lengths	3.378	4.380	2.612	4.763	7.234	38.16	3.182
Population	0.702	0.697	0.307	0.631	0.944	42.54	1.979
Overdispersion	3.951	—					
Model performance							
AIC	3529.252	3432.069					
R2	0.413	0.744					
2 × Log-likelihood	−1751.335	−1715.761					
RMSE	17.743	16.710					
Global Moran's I (P value)	**0.322*(0.0001)**	0.019 (0.626)					

*Significance levels of 5%. The variables and coefficients highlighted in bold within the GWNBR model indicate that their coefficient values demonstrate statistical significance at a 5% level in over 50% of the total study units. Please refer to the percentage of significant coefficients column for the specific proportion of study units with significance levels of 5% for each variable.

restaurants than nondelivery crashes (mean coefficient value of 0.007 on weekdays and 0.005 on weekends). This outcome is expected, given the simplicity of the majority of OFDS routes from the restaurant to the customer, while routes for nondelivery motorcyclists vary widely. Regarding nondelivery crashes, studies underscore that patrons often park near restaurants, disrupting traffic flow and increasing the likelihood of accidents [68–70].

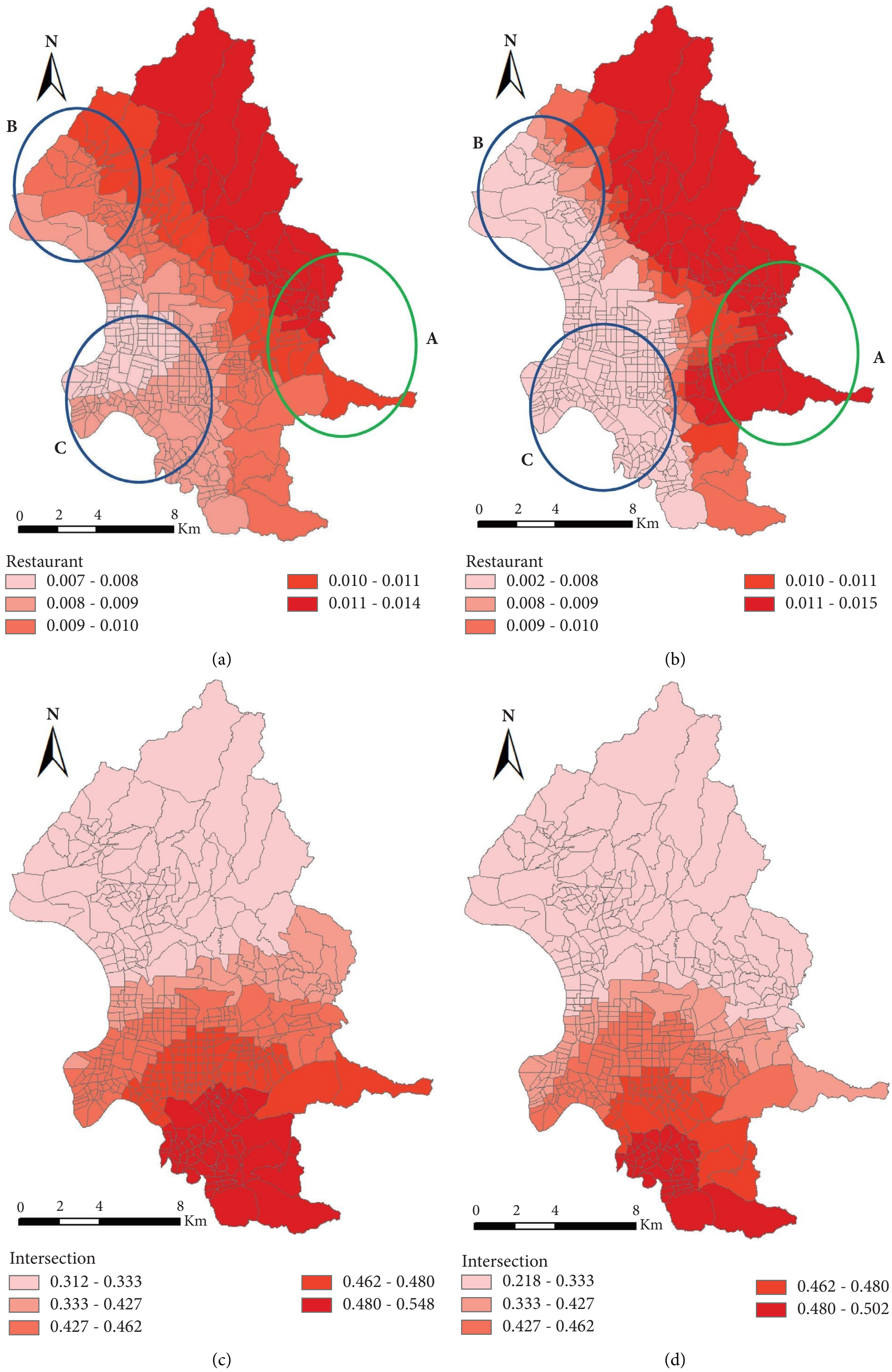
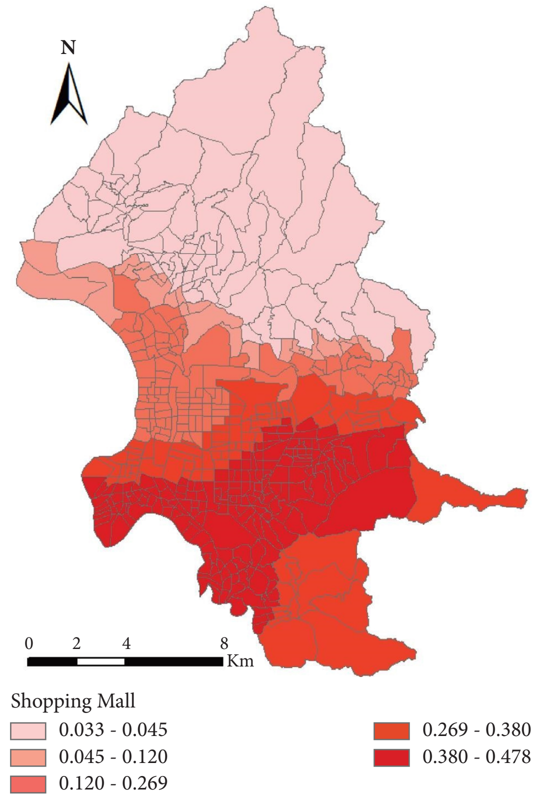
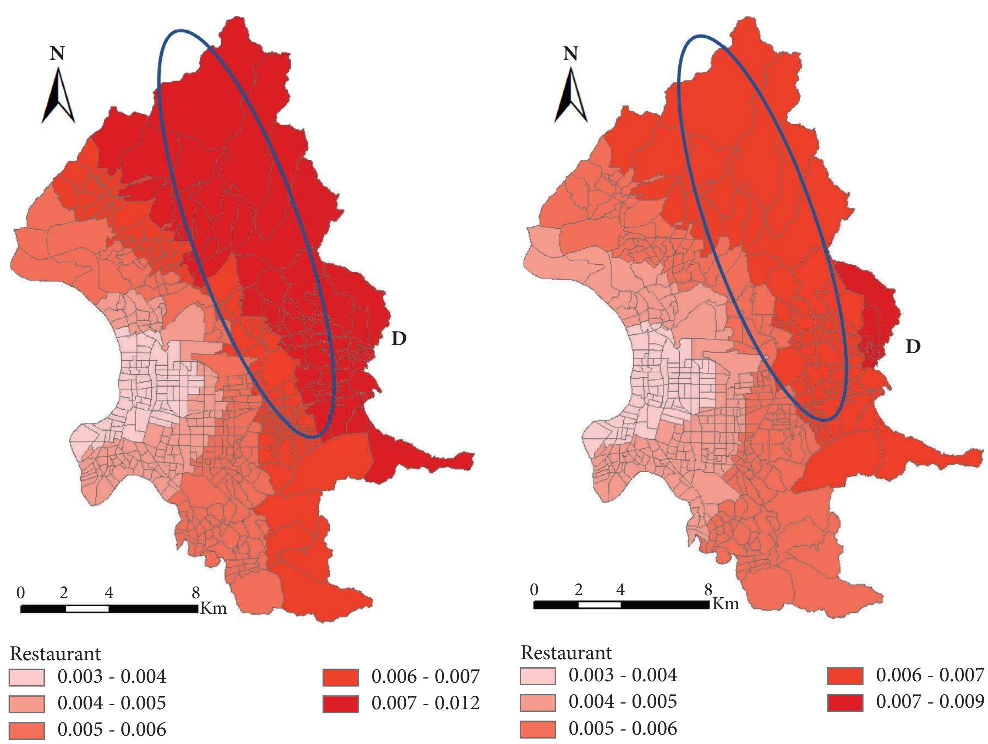


Figure 7: Continued.



(e)

Figure 7: The spatial distribution for parameter estimation for OFDS motorcycle crashes. (a) Restaurants on weekdays. (b) Restaurants on weekends. (c) Intersections on weekdays. (d) Intersections on weekends. (e) Shopping malls on weekends.



(a) (b)

Figure 8: Continued.

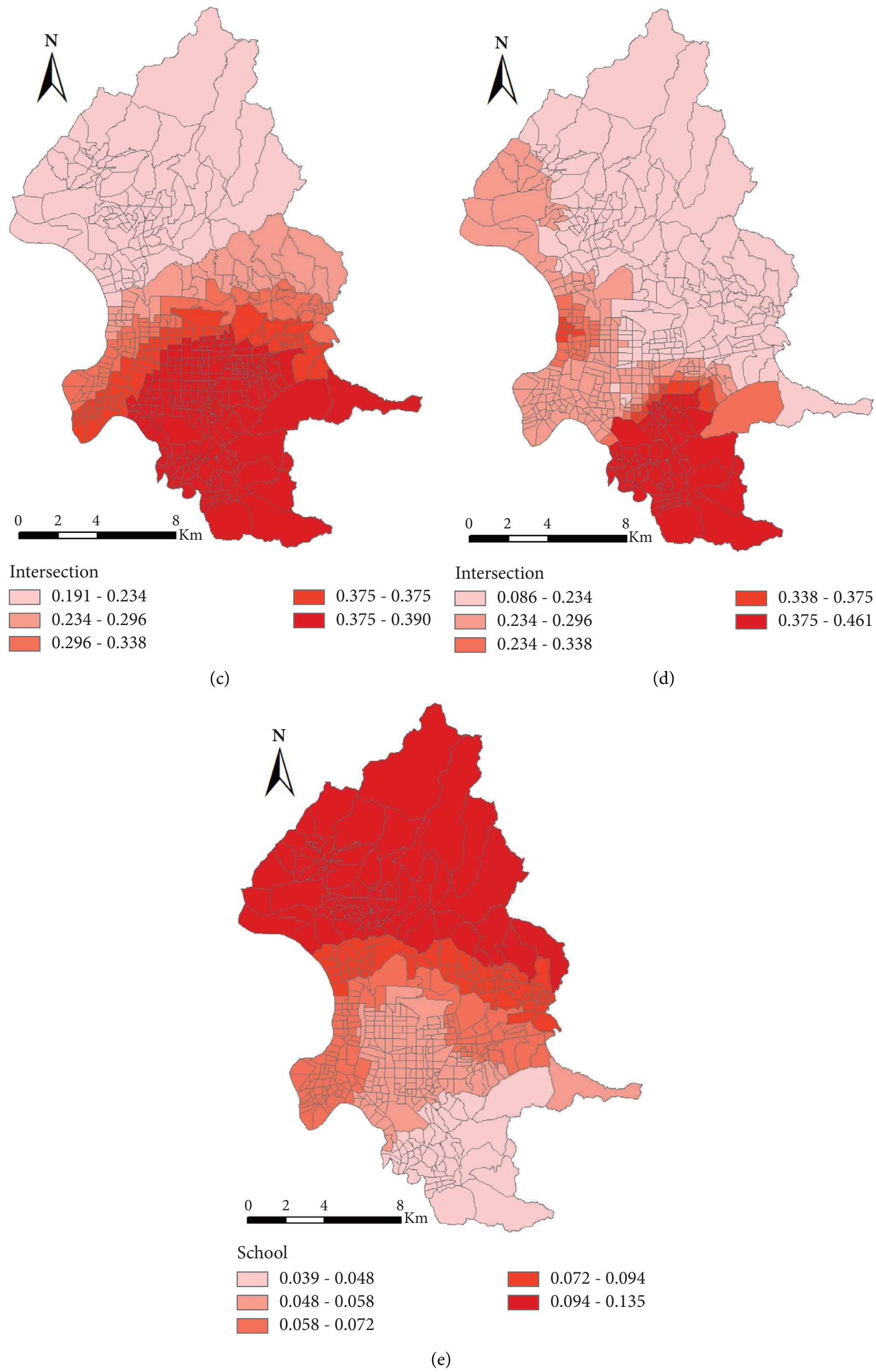


Figure 8: The spatial distribution for parameter estimation for nondelivery motorcycle crashes. (a) Restaurants on weekdays. (b) Restaurants on weekends. (c) Intersections on weekdays. (d) Intersections on weekends. (e) Schools on weekdays.

Furthermore, the results of this study show that commercial districts (shopping malls) have a significant positive relationship with crashes involving OFDS drivers in 67.54% of the study area (Table 3). This result aligns with previous studies [71, 72], highlighting the finding that food courts in shopping malls which are associated with OFDS contribute to an increased probability of crashes in the vicinity of these commercial centers. Such zones, which are characterized by high pedestrian and vehicle density, often witness frequent traffic accidents [73, 74].

The other POI in this study is schools, which show a significant positive association with nondelivery crashes in 62.94% of the study area (Table 4). This result is consistent with that of prior studies, such as the study by Ivan et al. [29], which identified several vehicle crash hotspots near schools. Most motorcycle-pedestrian crashes occur when the driver does not give pedestrians enough time to cross the street, so intersections are prime areas for traffic accidents [75]. Interestingly, this study reveals that schools and universities are not significantly correlated with OFDS motorcycle crashes, a finding that diverges from a study by Li et al. [26], which stated that OFDS are commonly used by high school and university students. One possible reason is that the majority of schools in Taiwan offer students several canteens and lunch box options, which reduces the likelihood that they will order food from an outside source, which also may be too expensive.

In terms of traffic conditions, the number of intersections is significantly and positively associated with an increase in both types of motorcycle crashes in 69.96%–91.01% of the study area (Tables 2–5). This result is consistent with that of earlier studies citing high incidence rates of drivers running red lights at intersections [1, 12]. However, the coefficient value shows that this behavior has more of an effect on OFDS drivers than on other motorcyclists (0.438 and 0.314, respectively). Li et al. [26] discovered that these two groups have different reasons and temporal patterns for running red lights, indicating that OFDS couriers are more likely to violate traffic signals during lunch and dinner hours due to time pressures, whereas other motorcyclists are more likely to commit traffic violations during the morning rush hour (8-9 AM). This temporal distinction results in an increased occurrence of right-angle collisions during the morning rush hour, leading to more severe injuries and fatalities, particularly for those involved in collisions with other vehicles.

5.2. Spatial Distribution Trend for the Estimated Parameter. The GWNBR analysis revealed a notable spatial distribution trend for the estimated parameters, particularly concerning the restaurant variable. The coefficient values exhibited an increasing trend from urban to rural areas, spanning from west-central to the northeast, for both OFDS and nondelivery motorcycle crashes (refer to Figures 7(a), 7(b), 8(a), and 8(b)). This pattern aligns with expectations, as rural areas with national parks, such as northern Taipei, tend to have fewer restaurants. Thus, the addition of one restaurant in such an area increases the demand for OFDS, consequently elevating the likelihood of accidents involving delivery drivers. This observation is consistent with findings from Vahedi and Effati [74] that commercial POIs, such as restaurants, are the key factors in crashes in rural areas.

However, it is crucial to note that each POI exhibited different spatial coefficient distributions with regard to OFDS-related activities depending on whether it is a weekday or a weekend (represented by coefficients "*a*" and "*b*"). On weekdays, the coefficient values were higher in the northern, western, and south-western regions of Taipei (indicated by the blue circles B and C in Figure 7(a)), whereas in the east, they were lower (illustrated by the green circle A in Figure 7(b)) compared to weekends.

The higher coefficients on weekdays can be attributed to a higher number of deliveries to commercial districts, schools or universities, offices, and industrial complexes situated in the central-western and eastern parts of Taipei City. This aligns with the findings of Li et al. [26], indicating that OFDS are particularly popular among white-collar workers. This finding explains the higher coefficient values for restaurants near these areas during the week. On weekends, the delivery focus shifts to residential areas mainly in the northern and southern regions of Taipei (represented by the green circle). However, a reduction in the coefficient distribution of nondelivery crashes occurred in most areas, except in western Taipei (indicated by the blue circle D in Figure 8(b)).

Figures 7(c), 7(d), 8(c), and 8(d) illustrate that the coefficient values for the intersection variable in urban areas were higher than in suburban locals (central to southern) for both nondelivery and OFDS crashes. While the trend for coefficient distribution remained similar, the overall value decreased on weekends, potentially due to reduced demand for OFDS and less traffic. Consequently, the probability of motorcycle crashes decreased throughout Taipei City. It is essential to note that the magnitude of the coefficients for two different models (weekdays and weekends) cannot be used to determine the effect of the same variable because the datasets are different and weekends are much shorter than weekdays.

Regarding other POIs, shopping malls were found to be significantly associated with OFDS crashes only on weekends (refer to Figure 7(e)). Shopping malls have a similar coefficient distribution to other variables in that the coefficient value increases from urban to suburban and rural areas (central to north and south). A high number of shopping malls in rural areas heighten the probability of OFDS crashes as malls contribute to increased traffic, particularly on weekends [48, 76].

Furthermore, the presence of schools had a significant positive association with nondelivery crashes on weekdays, with the coefficient value increasing from urban to rural areas of Taipei (see Figure 8(e)). This result is expected because, on weekdays, traffic density increases significantly when students are walking to school and parents are dropping their kids off or picking them up. In addition, during school hours, there is less OFDS motorcycle traffic because most people are working.

6. Conclusions

This study has documented the development of several statistical models to define the association between built environmental (e.g., POIs) factors and OFDS motorcycle crashes. In addition, this study also investigated the difference in the significant variable related to OFDS and nondelivery motorcycle crashes. The traditional NB model and GWR local models (GWNBR) were estimated. The GWNBR outperforms the traditional model for all dependent variables because it captured spatial heterogeneity. Thus, the results suggest the use of the local model for better estimating crash frequency. Despite its better performance, the optimum bandwidth for the GWNBR model is large (84% of the study area), which indicated that a small spatial dependence between the frequency of OFDS and nondelivery crashes exists in the study area.

The local model results are mostly nonstationary, but some built environmental variables have a more homogenous relationship with OFDS and nondelivery crashes. The results of the study by Obelheiro et al. [47] show that a built environmental variable can significantly affect crashes if it has a homogenous direction (either positive or negative) and the significant coefficient is high (at least 50%). The results show that the restaurant and intersection variables have a more stable and strong relationship with OFDS and nondelivery crashes during the weekends and weekdays. However, restaurants have a greater effect on food delivery-related crashes because they have a higher coefficient value.

In terms of other POIs, shopping malls have a significant effect on OFDS-related crashes only on weekends. The school variable only has a significant effect on nondelivery crashes on weekdays.

In terms of policy implications, the results highlight the need for effective strategies to reduce OFDS-related crashes, with a specific focus on areas with a high density of restaurants, schools, shopping malls, and numerous intersections. For instance, restaurants and local authorities could collaborate to establish dedicated drive-through or pick-up lanes exclusively for OFDS drivers. This could help streamline the process, reduce time spent in congested areas, and minimize interaction between OFDS motorcycles and pedestrians or other road users. In addition, for particularly popular drop-off locations, such as shopping malls and schools, deploying additional police officers to direct traffic during peak hours in city centers (areas with higher coefficients) could prove effective for reducing traffic violations and the overall number of crashes involving delivery drivers [77]. The higher crash rates at intersections are a major area of concern. To address this issue, retrofitting these intersections with variable message signs (VMS) could influence delivery drivers to choose routes [78] that would help them avoid traffic congestion and reduce delays. This would lower the risk associated with weaving through heavy traffic and enhance the safety of all road users. Lastly, collaborative efforts between local authorities and OFDS platforms to launch public awareness campaigns are suggested to educate both delivery drivers and pedestrians about safe driving and the importance of obeying traffic laws.

To the best of our knowledge, this study is one of the first to define the relationship between POI and OFDS motorcycle crashes that utilized the GWNBR model to analyze their association at a zonal level. According to our findings, using the GWNBR model is an approach that could yield valuable results, which contribute to the expanding literature on the impacts of built environmental factors on traffic safety. Another contribution of this study shows that restaurants with OFDS have distinct relationships between POIs and OFDS motorcycle crashes.

However, this study contains some limitations. First, this study is not able to consider the size or area of the POIs due to the dearth of comprehensive data. This is especially notable for restaurants, hotels, and supermarkets. Furthermore, there is a lack of information about small restaurants, which are not involved with OFDS. Future studies should consider this information to better illustrate the difference between the impact of larger and smaller POIs in the regions under study. Second, future studies might use the number of students as a prediction variable which could better describe the impact on OFDS motorcycle crashes. Lastly, this study recommends that future investigations encompass extended periods of time to enable temporal analysis of OFDS motorcycle crashes, particularly during mealtimes [20, 79]. In addition, consideration of the operational hours of each POI category could enhance the temporal diversity of the data, consequently improving the model's performance when assessing temporal patterns. As a possible avenue for improvement, adopting alternative models such as geographical and temporal weighted regression (GTWR) might be beneficial. If spatial and temporal heterogeneity were included, this model could provide a more comprehensive framework for analyzing the complex dynamics of OFDS crash data.

Data Availability

The data that support the findings of this study are available in the Ministry of Digital Affairs at https://data.gov.tw.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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