Child Indicators Research (2024) 17:2099–2121
https://doi.org/10.1007/s12187-024-10161-2

Correlations between Hotspots of Child Maltreatment and Neighborhood-Level Interventions

Seonga Cho[1] · Sewon Kim[2] · Bong Joo Lee[3]

Accepted: 28 July 2024 / Published online: 7 August 2024

Abstract

Child maltreatment, which seriously impacts children's well-being, is influenced by characteristics of neighborhood. Notably, previous studies have neglected the role of neighborhood spatial features in child maltreatment. Hence, we aimed to determine the distribution of child maltreatment occurrence by city, county, and district in South Korea; whether high child maltreatment incidence rates are clustered spatially; and the neighborhood factors that affect child maltreatment incidence. We analyzed 26,354 child maltreatment cases from 225 regions for 2020 using data from the National Child Abuse Database System. Data analysis procedures followed a three-tiered approach: ordinary least squares regression, Jarque–Bera and Breusch–Pagan tests, and geographically weighted regression. We identified concentrated hotspots and found that child maltreatment incidences were spatially autocorrelated. Key neighborhood characteristics that increased child maltreatment were the number of child community centers, the number of vacant houses, the number of multicultural households, and the number of single-parent households. Financial independence of local governments, the size of the older-adult population, and population density are the key neighborhood characteristics that decrease child maltreatment. Our findings reveal that prioritizing socioeconomically vulnerable regions is critical to alleviating child maltreatment. This study provides a valuable reference for identifying areas at high risk of child maltreatment and for implementing cost-effective, neighborhood-level interventions to reduce child maltreatment.

Keywords Child maltreatment · South Korea · Hotspot · Local characteristics · Neighborhood

✉ Sewon Kim
kimsw@cku.ac.kr

1 Department of Geography, University of California, Santa Barbara, CA, USA

2 Department of Social Welfare, Catholic Kwandong University, Beomil-ro 579beon-gil, Gangneung-si, Gangwon-do, South Korea

3 Department of Social Welfare, Seoul National University, Seoul, South Korea

1 Introduction

Child maltreatment results in severely adverse effects on children, continuously impacting their childhood and even adulthood. Maltreated children experience numerous difficulties, such as physical health problems, anxiety, interpersonal difficulties, psychotic disorders, post-traumatic stress disorder, drug abuse, and poor educational performance (Cicchetti, 2016). In addition, abuse/maltreatment can trigger high social costs (e.g., intergenerational transmission of violence, crime, and health issues) as well as place a burden on society (Fang et al., 2012).

Many studies have examined the related risk factors to prevent child maltreatment or its recurrence. Studies on child maltreatment have generally focused on individual or family risk factors, such as a child's physical or mental disability, child's age (Jaudes & Mackey-Bilaver, 2008), number of children at home (Schick et al., 2015), parental mental illness (Ajdukovic et al., 2018), parental marital discord (Zhao et al., 2018), economic hardship (Ajdukovic et al., 2018; Bartlett et al., 2014; Horikawa et al., 2016), social isolation (Bartlett et al., 2014), and offender's history of maltreatment during childhood (Horikawa et al., 2016). However, it is important to understand the concept of "place" to comprehend the rate of child maltreatment occurrence and the differences in incidence between neighborhoods (Gracia et al., 2017; Freisthler et al., 2006). For instance, child maltreatment incidences are influenced by such factors as neighborhood poverty, unemployment, race, female-headed households, vacant housing, residential instability, murder, assault, domestic violence, social support, and neighborhood type (Coulton et al., 2007; Freisthler et al., 2006; Garbarino & Sherman, 1980; Jung, 2023; Kim et al., 2018; Oh, 2003; Weissman et al., 2003).

Child maltreatment cases per region are not evenly distributed at a spatial level. According to Korea's Ministry of Health and Welfare (2018), the number of child maltreatment reports in the country varies by city, county, and district. In 2018, 30,923 child maltreatment cases were reported to specialized child protection institutions. Among these, 584 cases (2.4%) were from the Seo-gu district in the city of Incheon, 494 (1.6%) from the city of Mokpo in South Jeolla Province, and 471 (1.5%) from the Dalseo-gu district in the city of Daegu. On the contrary, Goseong-gun county in Gangwon Province and Hapcheon-gun county in Gyeongsangnam-do reported three cases each, and Ganghwa-gun county in the city of Incheon and Hamyang-gun county in South Gyeongsang Province reported four cases each. According to the most recent 2020 Child Maltreatment Report, among a total of 42,251 child maltreatment reports, Gyeonggi Province had 9,192 cases (23.6%), and the capital Seoul had 4,167 cases (10.7%), whereas the city of Sejong had 371 cases (1.0%) and Jeju Island had 859 cases (2.2%) (Ministry of Health and Welfare, 2021). These results are similar to those of studies conducted abroad. In San Diego County, the rate of child maltreatment was found to be 68.8 per 1,000 children. McBrayer and Mostofi (2015) found that 26 zip codes had higher child maltreatment rates compared to the overall county average. Barboza-Salerno (2019) showed that the incidence of child maltreatment in the 628 census tracts varied by region. These geographic differences suggest that the mechanisms underlying child maltreatment exhibit spatial heterogeneity across the county.

Even though there are regional differences in the incidence of child maltreatment and several studies have explained how risk factors in a neighborhood affect or are correlated with the incidence (e.g. Barboza-Salerno, 2019; Coulton et al., 2007; Freisthler et al., 2006; Freisthler & Wolf, 2016; Jung, 2023; Kim et al., 2018; Weissman et al., 2003), many studies describing the effects on neighborhood have failed to consider the meaning of the spatial dimension of neighborhood (e.g., Coulton et al., 2007; Freisthler et al., 2006; Jung, 2023; Kim et al., 2018). Neighborhoods in close proximity to each other are more likely to have similarities than those that are farther apart from each other as well as more interactions between each other. Although the spatial features of a neighborhood may also influence the incidence of child maltreatment, numerous studies on the relationship between child maltreatment and neighborhood have not sufficiently considered these features (Freisthler et al., 2006; Klein, 2011). Few studies have used spatial analysis techniques and disease mapping methods to analyze geographic patterns of risk factors for child maltreatment to explain whether these patterns are related to neighborhood-level variables (Gracia et al., 2017). It is necessary to analyze the geographic patterns of risk factors for child maltreatment to elucidate the effects of neighborhood features on maltreatment, and to utilize spatial analytical techniques to clarify whether these patterns are related to neighborhood-level variables.

1.1 The Meaning of Neighborhood as an Analysis Unit

There is widespread recognition that neighborhoods play an important role in parenting behavior and influence the likelihood of a child experiencing abuse and neglect (Coulton et al., 2007). Bronfenbrenner's (1979) ecological model can be employed to understand the relationship between child maltreatment and neighborhood. The ecological model is instrumental in understanding children's and adolescents' exposure to violence. Recognizing the importance of evaluating risk and protective factors across various contexts, researchers emphasize the need to understand broader influences, including family, peers, community behavior, and cultural characteristics. The ecological model assesses exposure to violence within four nested systems: micro (e.g., home), meso (e.g., school), exo (e.g., community), and macro (e.g., cultural values). This model guides the development of prevention and intervention programs at both individual and environmental levels, highlighting the need for comprehensive, multi-system approaches (Krug et al., 2002).

In particular, regarding child maltreatment, Garbarino (1977) described a human ecological model with four factors: (1) understanding how humans adapt to their environments; (2) research on how different systems affect individuals; (3) examining the social "habitability" in an environment; and (4) political, economic, and demographic conditions that influence maltreatment. This model is useful for explaining the impact of communities and families interacting with each other on child maltreatment. This model has significantly influenced contemporary research and policy approaches by addressing the multi-level factors impacting child maltreatment (Maguire-Jack & Katz, 2022). Using an ecological perspective, a growing body of research has shown that child maltreatment, poverty, violence, and rates of juvenile delinquency in neighborhoods are highly correlated with socio-economic indicators (Freisthier et al., 2004; Garbarino & Sherman, 1980; McDonell & Skosireva, 2009).

Freisthler et al. (2006) explained why neighborhoods are important units of analysis to understand child maltreatment. First, a neighborhood can influence the social conditions of individuals within neighborhoods. Levels of poverty or available resources have significant differences between neighborhoods, and a number of social issues can be identified along with social and economic inequality in neighborhoods. Every neighborhood has its own social issues that are related to the social and structural features within the neighborhood. Second, neighborhood-based interventions are linked to preventive behavior. Practitioners or policymakers attempt to identify children and family members who are at the highest risk of maltreatment and to change the behavior of parents or the risk factors for abuse within families in order to prevent the recurrence of child maltreatment. However, even if an individual's behavioral changes are successful, the individual may return to their family of origin and face the same situations leading to the recurrence of child maltreatment. Interventions at the neighborhood level can enhance safety in neighborhood environments where there is a high risk of maltreatment and neglect. Such efforts could prevent children and family members within neighborhoods from becoming exposed to maltreatment.

Another advantage of such interventions is more cost-effectiveness in preventive behavior at the neighborhood level compared to other approaches. Gelles and Perlman (2012) estimated the socioeconomic costs of child maltreatment in the US to be $80,260,411,087 per year. In South Korea, Kim and Chung (2016) estimated a minimum of KRW 389.9 billion (0.03% of gross domestic product [GDP]) and a maximum of KRW 7.6 trillion (5.1% of GDP). The socioeconomic cost of child maltreatment is substantial, and neighborhood-level interventions can be effective in preventing child maltreatment at a lower cost. This allows for targeted interventions in high-risk areas, making these interventions more efficient than person-centered approaches, as they address the broader context affecting families (Díez-Roux & Mair, 2010; Freisthler et al., 2006).

Many studies on the relationships between child maltreatment and features of neighborhoods have employed ordinary least squares (OLS) regression, a traditional method of analysis. Studies on geographic locations can produce biased results if they neglect the fact that neighborhoods share similar characteristics (Bailey & Gatrell, 1995). Freisthler et al. (2006) employed OLS regression and generalized linear squares spatial regression to explain the links between the features of neighborhood and child maltreatment, and compared the results. They found that although the immigrant population and childcare burden had a negative effect on the incidence of child maltreatment in the OLS analysis, there was no significant impact in the spatial regression model. Another problem is that as neighborhoods share boundaries that are permeable, the following fact is not considered: the characteristics of social and physical environments within a region (e.g., the availability of social services) can influence matters in other regions (Freisthler et al., 2006). Independent or dependent variables in the crime phenomenon exist in space, are related to each other, and influence each other (Yeom, 2018). In other words, everything is related to everything, but these connections are stronger between neighboring things than between distant things (Tobler, 1970). The effect of spatial autocorrelation on the dependent variable is greater than the effect of other independent variables, and models that do not account for this introduce errors that erode accuracy by statistical inference (Morenoff et al., 2001). Thus, it is necessary to consider spatial features and employ appropriate analytical techniques to analyze collected data at the neighborhood level.

1.2 Child Maltreatment and Neighborhood Factors

Several studies indicate that diverse features of neighborhoods are connected to child maltreatment. McGuigan et al. (2003) and Morris et al. (2019a, b, c) showed that indicators of violence within a neighborhood (e.g., the number of murders, assaults, rapes, and arrests made for domestic violence) affect child maltreatment. Neighborhood violence exerts a negative impact on children's healthy growth and development, is associated with violence in the family, and increases child maltreatment (Lynch & Cicchetti, 1998). Weissman et al. (2003) identified an association between child maltreatment and neighborhood characteristics, such as population density, the size of the older-adult population, the unemployment rate, the median family income, the number of children under the age of six in low-income families, the divorce rate, the percentage of families with children under the age of eighteen, the percentage of single-parent households, the average family size, the teen birth rate, the substantiated child maltreatment rate, and the elder abuse rate. Coulton et al. (1995) found neighborhood features (e.g., economic and family resources, housing instability, household and age structure, and poverty concentration) to be correlated with child maltreatment incidence. Drake et al. (2002) found that neighborhood-level poverty affected the recurrence of all types of child maltreatment. Ben-Arieh (2010) found a relationship between locality hardship and high rates of child maltreatment. The study also demonstrated a clear correlation between the availability of social services and reported rates of child maltreatment. Maguire-Jack and Negash (2016) examined the buffering effects of neighborhood service availability and accessibility on the relationship between parenting stress and child maltreatment in a sample of parents. They found that service availability potentially protected against physical abuse and neglect, and service accessibility had an additional protective effect beyond service availability on child neglect.

Molnar et al. (2003) described the impacts of neighborhood factors on child maltreatment through a multilevel study. They used indicators such as poverty, the share of immigrants, and housing instability as neighborhood features, and found that the percentage of immigrants within a neighborhood was related to child abuse when controlling for family and individual influences. In addition, the risk of child maltreatment occurrence was higher in a neighborhood with a large number of residents living for less than a year, a high number of vacant homes, and a low percentage of owner-occupation (Ernst, 2001). Regions with more drug and alcohol availability have higher rates of maltreatment, whereas regions with more bars and greater rates of drug possession incidents per capita are tied to higher rates of abuse and neglect (Freisthler, 2004).

A small number of studies have examined the relationship between child maltreatment and neighborhood characteristics in South Korea. The findings of these studies indicate that the features of a neighborhood—such as the financial independence of local governments (Jung, 2020), areas of poverty (Oh, 2003), the take-up rate for the basic livelihood benefit, property and land taxes per capita (Lee & Kim, 2005), and divorce rates (Jung, 2020; Lee & Kim, 2005)—are related to the incidence of child abuse. These findings are consistent with studies in other countries that have analyzed neighborhood factors influencing the incidence of child maltreatment (e.g. Lynch & Cicchetti, 1998; McGuigan et al., 2003; Molnar et al., 2003; Weissman et al., 2003). However, these studies have limitations in examining the spatial distribution features of child maltreatment, as they have measured child maltreatment incidence as subjectively recognized by children, rather than having officially confirmed child maltreatment cases or the incidence within a broader range like a city or province in terms of geographic units.

Even if the impact of neighborhood factors on the incidence of child maltreatment is similar to other countries, South Korea's neighborhood environment may differ from other countries. For example, according to the Organisation for Economic Co-operation and Development's (OECD's) analysis of 'urban areas', South Korea's population is concentrated in 22 urban areas, while major European countries, such as the United Kingdom (96), Italy (84) and Spain (81), have populations spread across four times as many urban areas as South Korea (OECD, 2020). OECD countries had an average old-age support ratio of 29.8% in 2019 and Japan had the highest ratio at 54.0%. South Korea's old-age dependency ratio was 21.6%, lower than the OECD average. In 2019, Greece, Australia, Canada, France, and the United Kingdom were among the OECD countries with the highest regional disparities in old-age support, while South Korea had a regional disparity of 21.5%, lower than the OECD average of 23.7% (OECD, 2020). Crime rates also vary between countries. While different definitions and methods of counting crimes make it difficult to compare crime rates between countries, homicide is defined in the same way in most countries and can be compared using the homicide rate. South Korea's homicide rate was 0.5 per 100,000 people in 2021, which is low by international standards, but more than double Japan's rate of 0.2 (Statistics Korea, 2023). Although South Korea's crime rate is lower than that of other countries, there are differences in the incidence of crime between municipalities and counties (Yeom & Choi, 2022). Therefore, it is important to examine the role of the neighborhood environment in explaining the incidence of child maltreatment in South Korea.

Several neighborhood characteristics have been inconsistently associated with child maltreatment. For instance, Coulton et al. (1995) estimated the childcare burden with factor scores including the ratio of children to adults, the percentage of residents aged 65 or older, and the ratio of adult males to females in a neighborhood; an area with a high childcare burden displayed greater rates of child maltreatment occurrence. Ernst (2000) measured the childcare burden through the percentage of working women and found a negative correlation between the share of working women and child maltreatment. Young and Gately (1988) found that unemployment rates in a neighborhood were a significant predictor of child maltreatment committed by men, but not by women. Freisthler et al. (2006) could not identify the relationship between unemployment rates and child maltreatment occurrence.

Many prior studies have limitations in that they used a traditional method of analysis to identify the relationship between child maltreatment and neighborhood features. Some studies that employed spatial analyses indicate that local economic and educational levels, policy activities, and immigration rates are linked to child maltreatment (Gracia et al., 2017). Morris et al. (2019a, b, c) pointed out the correlations linking neglect to the number of households in poverty and the unemployment rate, in addition to the connections between crime rates and physical and sexual abuse. Concentrated disadvantages, housing stress, and the percentage of poverty within neighboring regions have positive impacts on child maltreatment occurrence (Freisthler et al., 2006).

1.3 Study Purpose

As described earlier, previous studies have shown some variations in neighborhood features with an influence on the incidence of child maltreatment, implying that more research should aim to understand how neighborhood features influence maltreatment. As neighborhood risk factors associated with child maltreatment are often clustered in space, it would be appropriate to apply spatial analysis to examine the effects of neighborhood risk factors in relation to spatial differences in child maltreatment. In other words, it is necessary to spatially investigate the distribution of child maltreatment occurrence and to explain spatial differences with risk factors in a neighborhood.

Therefore, we targeted the city, county, and district levels in South Korea, and examined the distributions of substantiated child maltreatment cases that were reported to professional child protection institutions. In addition, we attempted to verify spatial features in a region with a high rate of child maltreatment occurrence. Simultaneously, we tried to explain regional features that influence child maltreatment occurrence through spatial metric analysis. We aimed to provide both the appropriateness of estimating the demand for child protection services in light of regional features and instructions on reasonable criteria for estimating the scale of institutions that provide appropriate services. Our findings can offer policy implications to prevent child maltreatment and its recurrence. To this end, we clarified the following research questions.

(1) What is the distribution of child maltreatment occurrence by city, county, and district in South Korea?
(2) Are areas with high child maltreatment incidence rates clustered spatially?
(3) What neighborhood factors affect the incidence of child maltreatment?

2 Materials and Research Methodology

2.1 Research Data

This study examined the distribution patterns of child maltreatment and associated factors within South Korea. Initially, we utilized data from the National Child Abuse Database System, which compiles reported cases of child maltreatment along with information on the residence of the targeted children at the city, county, and district levels. The National Child Abuse Database System in South Korea is a comprehensive information management system established to efficiently manage and prevent child maltreatment cases. This system aims to ensure a swift and effective response to child maltreatment by integrating all processes, including reporting, investigation, protection, and follow-up care. It operates based on the Child Welfare Act of Korea, which aims to protect children's rights and promote their well-being, providing various institutional measures for the prevention and response to child maltreatment.

Our analysis focused on cases with clear evidence of maltreatment reported for children under the age of 18 years during 2020, specifically on cases reported and substantiated as child maltreatment in the National Child Abuse Database System. This study includes all types of child abuse and neglect. Local administrative units (LAUs), referred to *as si*, *gun*, or *gu* in Korean, were used as the units for aggregating the data on maltreatment reports. Out of 229 LAUs, our study included 225 regions where at least one incidence of child maltreatment occurred. Employing LAUs allowed for precise data access while maintaining privacy by anonymizing the specific locations of the abused children. We calculated the incidence rate of child maltreatment based on the number of cases per 100,000 children under 18 years within each LAU. In total, we identified 26,354 child maltreatment cases with traceable locations for the year 2020. The 2020 data are the most recent available for researchers.

When using an ecological model to explain the influence of neighborhood variables on child maltreatment, various factors can be selected. Such factors as the socioeconomic characteristics of the neighborhood, the availability and accessibility of social support services, and neighborhood stability indicators, like crime rates and residential stability, have been shown to impact child maltreatment (Garbarino, 1977; Bronfenbrenner, 1979). Therefore, this study aims to examine the relationship between neighborhood variables and child maltreatment by considering these ecological models and findings from previous research. To reveal the patterns of child maltreatment in South Korea, we included eight variables related to social and environmental factors that significantly influence the dynamics behind child maltreatment incidence. These variables were broadly categorized into two groups. The first encompasses social-environmental factors that reflect the surrounding environment's influence on abused children. While these factors might not be directly tied to human social interactions, they are deeply connected to the economic and social forces that shape child maltreatment scenarios (Freisthler, 2004). Although not directly related to human social dynamics, these factors are intricately linked to the economic and social forces that shape child maltreatment. The second group of variables includes (1) the financial independence of LAUs, reflecting their capacity to invest in social infrastructure; (2) the prevalence of child community centers, which provide protection and education to children under the age of 12 years who live in poverty as well as services linking the children's parents and their neighborhood; (3) a vacant house, which can generate urban blight; and (4) violent crime, which reveals the safety of the region.

On the regional scale, the financial independence of LAUs and the prevalence of child community centers are two significant components of the built environment. When the local government is financially able to support childcare, child maltreatment is controlled to a certain extent. Furthermore, child community centers help children from low-income families grow up in decent conditions by providing appropriate protection and education. Although the built environment has a significant influence, housing conditions and the safety of social communities emerge as pivotal factors, revealing the complex underpinnings of child maltreatment dynamics. The presence of vacant homes has engendered social issues within South Korea, as such properties have transformed promising neighborhoods into areas of urban blight (Wassmer, 2008). The ensuing decay often gives rise to substandard living conditions and heightened crime rates (Ellen & O'Regan, 2010). Thus, the rates of vacant homes and violent crime are intimately tied to the quality of life within a region. This recognition has led us to identify four pivotal social-environmental factors that are crucial for comprehending the nuanced distribution of child maltreatment within cities (Fesselmeyer & Seah, 2022).

The second group of variables that fosters understanding of child maltreatment dynamics pertains to human factors. Household composition profoundly influences cultural and societal dynamics, with socially interconnected households playing a vital role in early child maltreatment detection (Morris et al., 2019a, b, c; Barboza et al., 2021). The share of the older-adult population, the number of multicultural households, and the number of single-parent homes serve as indicative variables highlighting the distinctive characteristics of a given region's broader population. These can be social connectivity and the neighborhood index for the region. Additionally, each of these factors exhibits intricate links with child maltreatment occurrence (Weissman et al., 2003; Morris et al., 2019a, b, c). Notably, high population density characterizes urban areas, thereby suggesting a plausible connection between population density and child maltreatment incidence. We collected data to determine the impact of explanatory variables on child maltreatment cases. These variables were calculated using multiple datasets from the Korean Statistical Information Service, the official governmental statistics portal. The variables are outlined in Table 1. The next subsection delves into the nuanced relationships between these variables and the patterns of child maltreatment.

2.2 Analysis Approaches

Understanding the causal and interrelated dynamics underpinning child maltreatment requires the appropriate use of robust analytical tools. To enhance explanatory power, we conducted a comparative analysis of two distinctive methods: the spatial and non-spatial approaches. The spatial analysis employed in our study is based on spatial autocorrelation—a concept originating from Tobler's first law of geography (Tobler,

Table 1 Explanatory variables

Category	Variable	Explanation
Social-environmental factors	Financial independence of local governments	The extent to which local governments self-fund their financial activities
	The number of child community centers	The number of child community centers per 100,000 children in a neighborhood
	The number of vacant homes	The ratio of vacant homes to the total number of homes in a neighborhood
	The number of violent crimes	The number of violent crimes per 100,000 people
Human factors	The size of the older-adult population	The ratio of people aged 65 years and older to the total number of people in a neighborhood
	The number of multicultural households	The ratio of multicultural households to the total number of households in a neighborhood
	The number of single-parent households	The ratio of single-parent households to the total number of households in a neighborhood
	Population density	The number of people per km^2 in a neighborhood

1970; Miller, 2004; Walker, 2022). When spatial phenomena contain spatial autocorrelations, the application of conventional statistical techniques without incorporating spatial context can violate key assumptions underlying statistical analyses (Koenig, 1999). Consequently, we advocated for a three-tiered approach to comprehensively scrutinize and elucidate the intricate dynamics of child maltreatment.

We initiated our analysis using OLS regression, a fundamental method in linear regression analysis. OLS works by minimizing the sum of the squared differences between observed child maltreatment occurrences per 100,000 children and the predicted values based on independent variables. This method helps predict a model that best fits the patterns of child maltreatment. The implementation of OLS allowed us to delineate the influence of each variable, solidifying the foundation for our findings, as shown in Eq. (1). The critical aspect of this equation is the residual term, ϵ, indicating that the strength of our regression model depends on the assumption of independently and identically distributed (i.i.d.) residuals. Any deviation from this assumption could undermine the model's explanatory power. To verify the i.i.d. assumption, we conducted rigorous stationarity assessments on both the child maltreatment cases and the residuals.

$$\begin{aligned} &\text{Child abuse cases per 100,000 children} = \\ &\beta_0 + \beta_{finance} x_{finance} + \beta_{center} x_{center} + \beta_{house} x_{house} + \\ &\beta_{crime} x_{crime} + \beta_{elderly} x_{elderly} + \beta_{multi} x_{multi} + \\ &\beta_{single} x_{single} + \beta_{density} x_{density} + \epsilon(0, \sigma) \end{aligned} \tag{1}$$

Proceeding to the second phase, we rigorously assessed the presence of spatial effects in the realm of child maltreatment phenomena. The recognition of spatial effects is imperative as it disregard renders the assumptions underpinning OLS infeasible. In particular, the presumption of i.i.d. residuals crumbles in the face of spatially correlated data, and heteroskedasticity can be established. To ascertain the relationships and statistical attributes of the variables, we used the Jarque–Bera and Breusch–Pagan tests. Scrutinizing residuals enables the mitigation of spatial non-stationarity within the regression framework.

In the final stage, we harnessed the power of geographically weighted regression (GWR) to probe the nuanced interplay between child maltreatment patterns and multiple variables. The advent of GWR was spearheaded by Brunsdon et al. (1996), offering a paradigm that harnesses proximate information for each observation. GWR's adaptive coefficient variation for each observation facilitates the exploration of spatially non-stationary relationships. GWR's versatility has led to its widespread application across diverse research domains; GWR has been subject to iterative enhancements by scholars (Fotheringham et al., 2003; Fotheringham & Oshan, 2016). Equation (2) illustrates the GWR model applied to our regions, which incorporates an adaptively defined neighborhood distance determined via cross-validation techniques:

$$\mathrm{y}\left(\mathrm{s}\right) = \beta_1\left(s\right) x_1\left(s\right) + \cdots + \beta_p\left(s\right) x_p\left(s\right) + \epsilon\left(\mathrm{s}\right) \tag{2}$$

To adequately address the spatial complexities inherent in our study, it was essential to utilize GWR. As previously noted, our model integrates a comprehensive set of eight variables, resulting in the GWR formulation shown in Eq. (3). This model assigns unique coefficients to each spatial unit, thereby predicting an optimal model using an adaptive bandwidth kernel. This approach ensures consideration of spatial autocorrelation between child maltreatment incidents and corresponding explanatory variables, thereby encapsulating the spatial relationships effectively. The analytical approaches and visualization methods of our study was supported technically by R 4.3.1 and QGIS 3.22:

$$\begin{aligned}
&\text{Child maltreatment cases per 100,000 children at unit s} = \\
&\beta_0 + \beta_{finance}\left(s\right) x_{finance}\left(s\right) + \beta_{center}\left(s\right) x_{center}\left(s\right) + \\
&\beta_{house}\left(s\right) x_{house}\left(s\right) + \beta_{crime}\left(s\right) x_{crime}\left(s\right) + \beta_{elderly}\left(s\right) x_{elderly}\left(s\right) + \\
&\beta_{multi}\left(s\right) x_{multi}\left(s\right) + \beta_{single}\left(s\right) x_{single}\left(s\right) + \beta_{density}\left(s\right) x_{density}\left(s\right) + \epsilon(0, \sigma)
\end{aligned} \tag{3}$$

3 Results

3.1 Spatial Non-stationarity

We analyzed the relationship between child maltreatment patterns and eight explanatory variables. OLS assumes the stationarity of each observation. Linear regression with multiple variables can be utilized to define the model if the assumption meets the observation. The conceptualized equation was generally formulated as in Eq. (1) in the precious section. By using the same coefficient for each region, the model assumes the stationary characteristics of each region. If the stationarity assumption is not satisfied, simple multiple linear regression cannot guarantee the outcome. Additionally, the second significant point of Eq. (1) is the residual term, ϵ. If the derived regression model cannot ensure the i.i.d. assumption, the model loses the power of explanation. Hence, we tested the stationarity of child maltreatment cases and the residual characteristics.

We utilized the Jarque–Bera test—a well-established method for testing the normality of sample data. First introduced by Jarque and Bera (1980), this test has found broad applicability in testing normality assumptions (Thadewald & Buning, 2007; Gel & Gastwirth, 2008). For the number of child maltreatment cases per 100,000 children across administrative units, the Jarque–Bera test yielded an χ^2 value of 75.23 with two degrees of freedom, accompanied by a p-value below 0.001. Evidently, the observed data—reflecting the number of child maltreatment cases per 100,000 children across administrative units—deviate from the normality assumption.

Turning our focus to the characteristics of the residual term, we employed the Breusch–Pagan test, introduced by Breusch and Pagan in 1979. Underpinning this test is its potential to uncover heteroskedasticity within residuals—an imperfection that undermines the ideal conditions of the OLS assumptions (Halunga et al., 2017). Application of the Breusch–Pagan test to our linear multiple regression model revealed significant heteroskedasticity, supported by a p-value below 0.001 and a Breusch–Pagan score of 30.854 across eight degrees of freedom. The convergence of outcomes from both the Jarque–Bera and Breusch–Pagan tests underscores the limited explanatory potency of the multiple linear regression model in capturing the intricate dynamics of child maltreatment phenomena.

In response to these limitations, we applied spatial methods to further our comprehension of child maltreatment occurrence and its underlying variables. Visual representation, as portrayed in Fig. 1 through choropleth mapping, provides supporting insight. Notably, the majority of child maltreatment cases are concentrated in metropolitan areas, such as Seoul (indicated by the red circle) and Busan (indicated

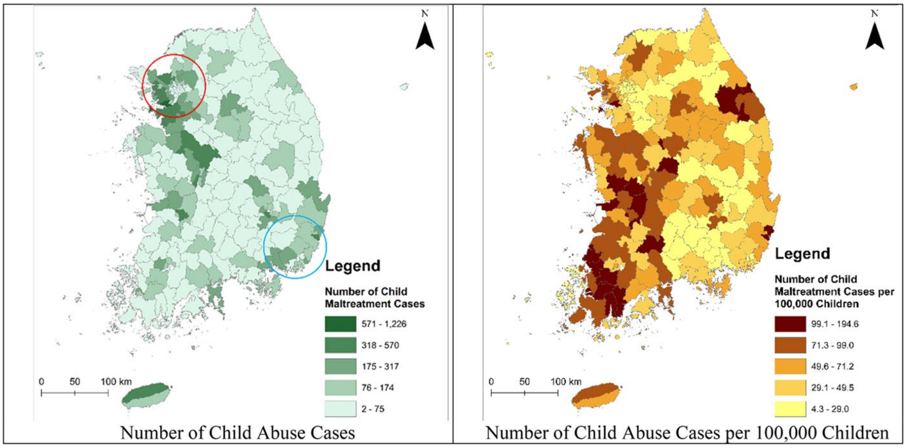

Fig. 1 Child maltreatment case distribution maps

by the blue circle). However, after normalizing the data for the number of children within each administrative unit, the choropleth map shows a shift, revealing more pronounced patterns of child maltreatment in rural settings. Our focus on spatial autocorrelation of child maltreatment acts as a precursor to exploring an appropriate model, as explained in the next subsection.

3.2 Spatial Autocorrelation Analysis

For this section, we analyzed the problem considering the non-stationarity of child maltreatment patterns, shedding light on the role of spatial effects. At its core, our analysis started with the application of Moran's I index—a well-established measure for gauging spatial autocorrelation across two spatial dimensions (Moran, 1950). The index is formulated as shown in Eq. (4), where N denotes the count of observations, W signifies the cumulative spatial weights, and w_{ij} encapsulates the spatial weight linking observation i with observation j. The Moran's I index for attribute x can have values between −1 and 1, with positive values indicative of positive spatial autocorrelation.

$$\mathrm{I} = \frac{N}{W}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{4}$$

Specifically, the spatial autocorrelation computation for child maltreatment cases per 100,000 children yielded a coefficient of 0.458, complemented by a statistically significant p-value of 0.00. This outcome attests to the presence of strong positive spatial autocorrelation within child maltreatment phenomena. An improved analytical approach to the spatial heterogeneity of this phenomenon is accomplished by using local indicators of spatial autocorrelation (LISA), a method first proposed by Anselin (1995). This technique discerns localized hotspots and cold spots within spatial phenomena and identifies spatial heterogeneity (Anselin, 1999).

As Fig. 2 depicts, our LISA analysis result suggests intriguing dynamics. Notably, Seoul's metropolitan area and selected rural zones emerge as cold spots—clusters characterized by lower child maltreatment incidences than their counterparts. Conversely, regions like Jeolla Province (the most southwestern province in South Korea) emerge as hotspots, signifying heightened instances of child maltreatment. These distinctive clusters substantiate the presence of a clustered pattern, effectively underscoring the pervasive spatial effect at play. In light of these findings, it is crucial to adopt methods that accommodate spatial heterogeneity and clustering effects.

3.3 Geographically Weighted Regression

The specific outcomes are detailed in Table 2. Through the prism of OLS regression, just four variables emerged as statistically significant: (1) the number of child community centers; (2) the size of the older-adult population; (3) the number of multicultural households; and (4) population density. Notably, the R^2 value of the OLS linear regression model is 0.3778, which implies a moderate explanatory capacity.

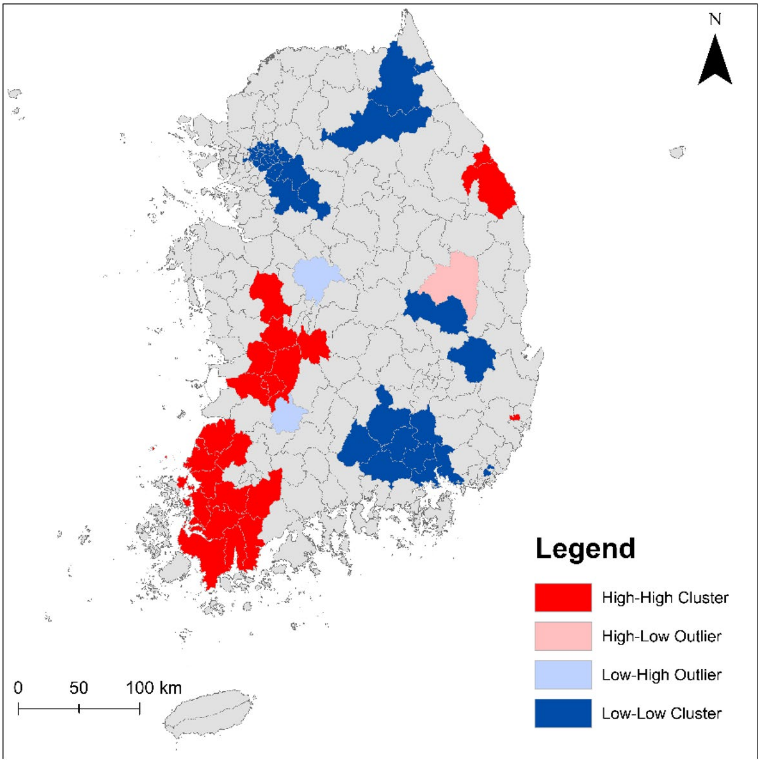

Fig. 2 LISA map of child abuse cases

Although statistical significance within the OLS framework may inherently contain problems, the associations between the variables and child maltreatment cases remain intriguing.

The presence of child community centers demonstrates a positive correlation with child maltreatment cases, as the centers provide services to children from low-income families. Multicultural households, characterized by lower incomes and less stable family dynamics, exhibit an increased propensity for child maltreatment. This suggests the necessity for connected neighborhood-based vigilance in such settings. Conversely, variables showing a negative correlation with child maltreatment cases—namely, a larger older-adult population and higher population density—signify the potential of strong social connectivity to deter child Maltreatment. However, statistical validation of these relationships is still necessary.

To bridge the gap left by the OLS regression, we used GWR coupled with an adaptive bandwidth kernel derived through cross-validation. Using the method outlined by Leung et al. (2000), we tested the statistical significance of each variable through p-values. In comparison to OLS regression, GWR formulated a more robust model, presenting an augmented explanatory power of 0.6552 and displaying statistical significance across most variables (except for the number of violent crimes). This compelling enhancement underscores the utility of GWR in capturing the nuanced spatial dynamics at play (Brunsdon et al., 2002; Crespo et al., 2007).

Table 2 OLS and GWR results: a comparison

		Child maltreatment cases per 100,000 children	
		OLS	GWR
		β	β
Independent variables	Constant	42.72	– 4.08***
	Financial independence of local governments	– 0.62	– 0.49*
	Number of child community centers	0.24***	0.18*
	Number of vacant homes	1.31	1.47***
	Number of violent crimes	– 0.01	– 0.005
	Size of the older-adult population	– 2.67***	– 1.91***
	Number of multicultural households	14.11***	13.22***
	Number of single-parent households	3.52	4.44***
	Population density	– 0.001**	– 0.001***
Explanatory power	R^2/Quasi-global R^2	37.78%	65.52%
F-test	F	17.99***	0.79***

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 2 shows that variables associated with social vulnerability have positive coefficients correlating with the number of child maltreatment cases. For instance, an increase in vacant homes contributes to urban blight, while a rise in single-parent households indicates a greater number of children in potentially precarious financial and parenting situations. Conversely, higher financial independence among LAUs is linked to fewer instances of child maltreatment, underscoring the effectiveness of administrative interventions. The interconnected impact of these social vulnerabilities suggests that employing a spatially oriented approach, such as GWR, could provide deeper insights into these variables' effects.

The GWR findings are explicitly depicted in Fig. 3, which embodies local explanatory power (R^2) and predicted cases per 100,000 children. Notably, local R^2 values surpass those of OLS regression, even in regions characterized by lower appropriateness, as indicated by the blue-shaded areas. Most notably, the model demonstrates exceptionally outstanding explanatory capacity within close proximity to the Seoul metropolitan area. Employing the GWR model, we successfully predicted the number of child maltreatment cases, as highlighted in the right panel of Fig. 3. These predictive insights have the potential to inform child maltreatment prevention strategies, thereby enhancing the efficacy of decision-making processes in this critical domain.

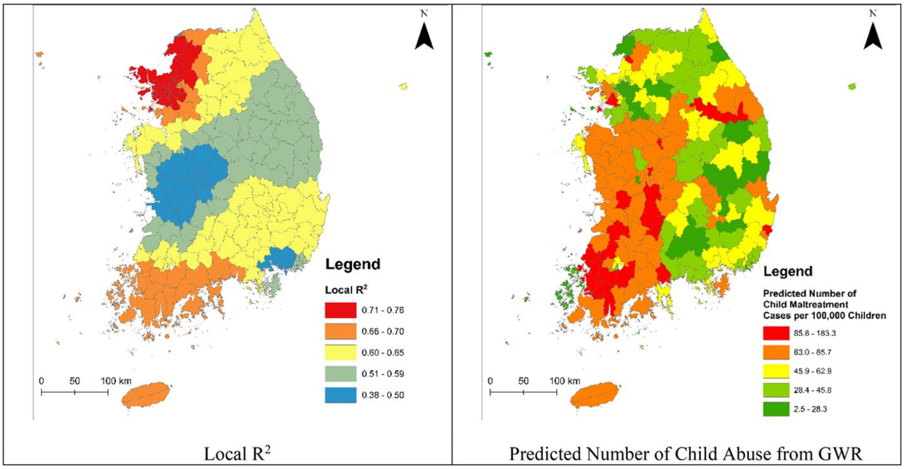

Fig. 3 The explanatory power of GWR and predictive maps

4 Discussion and Conclusion

This study explains the impacts of the characteristics of a neighborhood on child maltreatment. First, we applied hotspot analysis to identify which areas in South Korea have concentrated instances of child maltreatment. To describe regional features with an influence on child maltreatment occurrence, we used OLS regression to construct a model. However, if we were to analyze spatially correlated data using OLS, the assumption of independence of residuals—which is the basic premise of the analysis—could not have been satisfied. Considering such a limitation, we performed GWR to appropriately analyze the spatial data.

Moran's I was statistically significant at 0.458 ($p<0.01$), which implies that the incidence of child maltreatment has a positive spatial autocorrelation. By analyzing hotspots and cold spots using LISA, we identified metropolitan areas and several rural zones as cold spots where child maltreatment occurrence is relatively low. Contrarily, Jeolla Province (in the southwestern part of South Korea) is a hotspot with high rates of child maltreatment in corresponding and neighboring areas. In this study, we identified hotspots primarily in counties with low population density; these areas have fewer services and resources compared to large cities. In large cities, it is relatively easy for people to use public transit to access services and resources even though people reside in different areas; however, this is not the case in (rural) counties. Research findings on the relationship between neighborhood population density and child maltreatment are mixed. Some studies indicate higher rates of child maltreatment in densely populated urban areas (Barboza-Salerno, 2019) whereas other studies find higher rates of child maltreatment in rural areas (Maguire-Jack & Kim, 2021). This inconsistency suggests that various factors, such as socio-economic conditions, social support systems, and community resources, may influence the prevalence of child maltreatment in different settings.

Thus, it is necessary to use models that consider regional variations and take into account the characteristics of hotspots of child maltreatment. The collected data at a local level have high correlations in spatial proximity. If data with spatial dependence and heterogeneity are estimated by OLS regression, errors occur and spatial variations cannot be considered (Park et al., 2016). Hence, it is desirable to estimate a model by using GWR in light of spatial correlations, rather than general regression analysis. Like Coulton et al. (2007), many studies have failed to explain spatial processes when clarifying the relationship between neighborhood and child maltreatment. Our findings are significant as we attempted to elucidate the size of the impact of neighborhood on child maltreatment. In other words, we empirically demonstrated the impact of neighborhood features on child maltreatment incidence as well as regional variations in child maltreatment occurrence by using GWR.

The GWR showed that greater child maltreatment occurrence is linked to a higher number of child community centers, a larger number of single-parent households, a higher number of multicultural households, and a greater number of vacant homes within the neighborhood. Child community centers in Korea provide services primarily to children from low-income families. Therefore, a high number of child community centers in a neighborhood indicates economic vulnerability in that area. In particular, although the number of multicultural households has continuously risen since 2000 in South Korea, discrimination and prejudice against such families are high. A lack of acceptance of multicultural households can lead to neighborhood conflicts and a lower sense of neighborhood, which can increase the likelihood of child maltreatment. In South Korea, some areas with a high concentration of multicultural families are characterized by poor housing conditions or relatively low rental costs. Additionally, these regions may exhibit closed community dynamics owing to conflicts with native residents (Kong, 2013). These neighborhood characteristics, such as economic vulnerability and low social cohesion, may have influenced the incidence of child maltreatment. Vacant homes can increase the risk of child maltreatment by becoming sites where sexual abuse takes place; they can also indirectly increase the chance for criminal behavior to occur (Brantingham & Brantingham, 2013). In other words, socioeconomic features in the neighborhood affect child maltreatment occurrence. Children in economically disadvantaged neighborhoods are at a higher risk of various forms of abuse and neglect owing to such factors as financial stress, lack of resources, and limited access to supportive services. Previous studies have also pointed toward significant links between neighborhood factors (e.g., the socioeconomic characteristics of the neighborhood and the percentage of immigrants) and child maltreatment incidence (Ernst, 2000; Freisthler et al., 2006; Gracia et al., 2017; Lynch & Cicchetti, 1998; McGuigan et al., 2003; Morris et al., 2019a, b, c; Weissman et al., 2003). These findings can help to identify vulnerable communities and provide information that should be initially considered for resource allocation in order to prevent child maltreatment.

The size of the older-adult population, the financial independence of neighborhoods, and population density have a negative effect on child maltreatment occurrence. Regions with few older-adult residents have a higher risk of child maltreatment (Coulton et al., 1995). Older neighbors can exert a positive impact on children's well-being by providing support for parents and children and contributing to neighborhood safety and housing stability (Jespersen et al., 2021). According to Jung (2020), the greater the financial independence of LAUs, the higher the social service budget, which leads to more services for mental health, alcohol and drug abuse, domestic violence, housing, childcare, medical care, and parenting, and consequently lower risks of child maltreatment. Areas with higher population density are more likely to be urban; in cities, compared to rural areas, there are diverse cultural facilities and amenities, such as public transit, hospitals, parks, and libraries. Such conditions can lower the risk of child maltreatment. Sedlak et al. (2010) found that rural areas with fewer amenities have higher rates of maltreatment than urban areas with more resources. Diverse cultural resources and infrastructure in neighborhoods can mitigate stress factors that may lead to child maltreatment by providing healthcare, social services, and recreational opportunities for children and families. Our findings show that child maltreatment occurs differently across neighborhoods; this study underscores the perspective that the concept of place is related to child maltreatment incidence.

The results of research that explains differences between neighborhoods in relation to child maltreatment risk can provide useful information for child maltreatment prevention and intervention. First, it is possible to identify areas at high risk of child maltreatment and to subsequently implement preventive interventions while targeting children and families in such areas. Unlike individual-level approaches, neighborhood-level interventions can target more families and employ more cost-effective strategies (Gracia et al., 2017).

As such, the finding that child maltreatment is spatially autocorrelated and related to regional characteristics has important policy implications. The prevention of child maltreatment recurrence and interventions for prevention are generally conducted for children and families, and geographic location is not generally considered (Freisthler et al., 2006). However, our findings indicate that it is necessary to prioritize socioeconomically vulnerable regions to solve and prevent child maltreatment. In other words, researchers and practitioners can increase access to and availability of services by identifying where services are most needed and can be highly utilized.

Though neighborhood factors (e.g., the number of single-parent households, the number of multicultural households, and the financial independence of LAUs) are considerably difficult to change directly, there are neighborhood-level interventions that can indirectly address these factors (Gracia et al., 2017). For instance, urban planning (e.g., the redevelopment of regions, the development of services and programs, and better access to resources) and environmental methods can increase residents' quality of life; such approaches are effective at reducing crime and violence in the vulnerable neighborhood (Kelaher et al., 2010).

This study has certain limitations. First, we obtained and utilized data on child maltreatment incidence at the city, county, and district levels. Compared to districts in metropolitan areas, cities and counties cover a larger area, and there may be differences in economic characteristics as well as crime rates within the same city, county, or district. However, it was impossible for us to identify the extent of child maltreatment incidence in smaller neighborhoods owing to privacy issues. Future studies should target smaller-scale spaces and examine relationships between child maltreatment occurrence and regional features. Second, we calculated the rate of child maltreatment occurrence based on officially reported and substantiated cases. The detection rate of child maltreatment in South Korea is 5.02‰, which is considerably lower than the US rate of 8.4‰ (Ministry of Health and Welfare, 2020). We were unable to cover cases that were not officially reported or substantiated, even though maltreatment actually occurred. Moreover, the impact of COVID-19 during the study period remains a variable that could have significantly influenced both the incidence and detection of child maltreatment. The full extent of COVID-19's effects on these dynamics remains to be explored and can only be fully understood through subsequent analysis. Third, features such as social networks, a sense of neighborhood, and social norms within a neighborhood can affect child maltreatment occurrence (Fujiwara et al., 2016; Kim, 2018; Maguire-Jack & Showalter, 2016). However, as there is no information about social networks or a sense of neighborhood within the neighborhood—which are measured at the city, county, and district levels—we did not include these factors in the analysis. Future studies should target smaller communities as analysis units and include awareness/perceptions of neighborhood members and cultural factors. Fourth, Morris et al. (2019a, b, c) considered the changing rates of child maltreatment over time to explain neighborhood effects. However, their study was able to use only cases of child maltreatment reported and substantiated in 2020 from the National Child Abuse Database System. Therefore, future research should longitudinally explain the characteristics between child maltreatment rates and neighborhood variables.

Author Contributions All authors contributed to the study conception and design. Data collection was performed by Seonga Cho, Sewon Kim, and Bong Joo Lee, and data analysis was done by Seonga Cho. The first draft of the manuscript was written by Seonga Cho, Sewon Kim, and Bong Joo Lee and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea(NRF-2022S1A5A2A01050217).

Data Availability Data derived from the National Child Maltreatment Database System is not not publicly available and can not be used by anyone other than the authors with permissions. Data collected by the Office for National Statistics is available.

Declarations

Ethical Approval Not applicable.

Informed Consent Not applicable.

Research Involving Human Participants and/or Animals Not applicable.

Competing Interests Not applicable.

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