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# An examination of the effect of area-level characteristics on juvenile justice and child welfare referrals using multivariate Bayesian spatial modeling

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ABSTRACT

*Background:* Neighborhood disadvantage is linked to a higher risk of referrals to child welfare and juvenile justice systems. While past research has explored these associations independently, no study has concurrently examined the spatial overlap of child maltreatment and juvenile justice involvement.
*Objective:* We examine the spatial overlap of involvement in juvenile justice and child welfare systems to identify areas of shared risk.
*Participants and setting:* Youth who received either a juvenile justice or child welfare referral in New Mexico between 2008 and 2015 aggregated to census tracts.
*Methods:* We examined the spatial overlap of child welfare and juvenile justice involvement using multivariate Bayesian spatial modeling.
*Results:* Results show a significant positive association between juvenile justice and child maltreatment referrals across neighborhoods. After adjusting for residential instability, immigrant concentration, and residential racial segregation, children in the least deprived 20 % of neighborhoods were 95.2 % and 55.5 % less likely to be referred to child welfare or justice systems, respectively, compared to those in the most deprived 20 %.
*Conclusions:* Our findings highlight the value of geospatial analyses to guide public health interventions by targeting the shared overlapping risk factors associated with neighborhoods with high risk for both child welfare and juvenile justice system involvement.

## 1. Introduction

Annually in the United States, juvenile justice and child welfare systems grapple with a staggering number of new cases, including fifty-nine referrals out of every 1000 children under eighteen and a weekly influx of 84,600 referrals to Child Protective Services (CPS), on average (Puzzanchera et al., 2022). Studies indicate that between 9 and 47 % of maltreated youth engage in delinquent behavior (Barboza, 2020; Bender, 2010; Bolton et al., 1977; Ryan & Testa, 2005), and between 45 and 70 % of justice-involved youth have

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maltreatment histories (Kelley & Haskins, 2021). Youth who are involved in the child welfare and juvenile justice systems are considered high-risk populations with complex and overlapping needs. Child welfare and juvenile justice-involved youth have similar trauma histories, family circumstances, and limited neighborhood economic resources, which contribute to their increased likelihood of involvement in both systems (Goodkind et al., 2013; Kim & Kim, 2008; Modrowski et al., 2023; Onifade et al., 2011). In addition, system-involved youth have similar long-term maladaptive outcomes such as engagement in adult violence (Barboza & Siller, 2021), teenage pregnancy (Cioffi et al., 2022), substance use (Schaeffer et al., 2010), poor academic performance (Yoon et al., 2021), and mental health problems (McNally et al., 2015).

Above and beyond the persistent link between maltreatment and delinquency found in individual-level studies (Mersky et al., 2012; Mersky & Reynolds, 2007; Smith & Thornberry, 1995), ecological studies analyzing child welfare and juvenile justice involvement independently have demonstrated heterogeneity across space and time (Huang & Ryan, 2014; Klein & Merritt, 2014). Nevertheless, despite the interdependency between systems and the role that both systems play in perpetuating inequitable outcomes, no study to date has concurrently examined the spatial overlap of both child welfare and juvenile justice involvement (Ransome et al., 2020). Accordingly, this study assesses the spatial overlap of child welfare and juvenile justice involvement in New Mexico using joint (multivariate) Bayesian conditional autoregressive models that control for multidimensional measures of area-level effects and spatiotemporal heterogeneity and dependence. The current study aims to guide policy and practice by targeting structural forces associated with child welfare and juvenile justice system involvement in high-risk areas marked by severe social and economic inequality.

### 1.1. *Child welfare and juvenile justice systems overlap*

Various definitions describe youth with child welfare and juvenile justice system involvement. "Crossover youth" describes individuals who have experienced child maltreatment and who have engaged in delinquent behavior, irrespective of their official involvement in either system (Herz et al., 2012). Conversely, "dually involved youth" are those concurrently engaged with both systems in one way or another, be it through formal involvement or participation in preventive services (Herz et al., 2012). Both child welfare and juvenile justice systems process, supervise and often care for a subset of 'dually involved youth,' also known as 'dually adjudicated youth' (Herz et al., 2012). Rather than focusing on the specific status of dual involvement or adjudication, the present study focuses on the neighborhood-level risk factors contributing to heightened engagement in both systems. As such, for the purpose of our study, "*dual systems involvement potential*" (Marçal & Maguire-Jack, 2021) refers to youth who have a higher risk of involvement in both the child welfare and juvenile justice system whereas "*dual systems involvement*" refers to youth with actual connection to both systems.

Past studies concentrate on dual systems involvement, often focusing on individual factors (e.g., chronic absenteeism) or family-level factors (e.g., housing insecurity). These studies fail to consider the legal determinants that create pathways from one system to another, mandating similar and often duplicated services. In other words, legal mandates result in the integration and overlap between the juvenile justice and child welfare systems resulting in dual systems involvement above individual or family characteristics (Wiig et al., 2013). By mandating similar services across different settings, the law implicitly acknowledges that the environment—such as the availability of foster homes or child welfare facilities—plays a crucial role in the outcomes for these youth. For instance, the New Mexico legislature mandates that a child adjudicated as 'delinquent' may be placed or detained, pending a court hearing, in various settings, including licensed foster homes, child welfare facilities, shelter-care facilities, certified detention facilities, or any other suitable place *authorized by law* (NM Stat § 32A-2-12 (1)). By allowing for multiple types of placements, communities with more such facilities will see more children in the system, leading to spatial overlap in higher-density areas and geographic heterogeneity. Furthermore, the law permits discretion in deciding whether to place a maltreated youth under the supervision of the juvenile courts, and youth found 'delinquent' often come under the protection of child welfare. As a result, areas with more placement options are likely to see greater overlap in system involvement, which may vary by geographic region. This flexibility also means that depending on local resources, a child's experience within these systems - and their long-term outcomes - can differ significantly.

If the pathways created by law and policy, rather than individual actions, contribute to the increased risk of dual systems involvement, these risks should be observable across administrative units. For example, risk factors vary based on geographical context, resulting in different child welfare outcomes for families with similar risks but different county-level vulnerabilities (Barboza-Salerno et al., 2024). Furthermore, it is worth emphasizing that the child welfare and juvenile justice systems do not operate in isolation. Instead, they collaborate with community members, such as schools and healthcare providers, to exercise authority over children and adolescents (Stewart, 2022). As a result, the heterogeneity of risk for child maltreatment due to structural considerations has resulted in the placement of social services agencies in areas associated with the highest endogenous risk (i.e., referring a child to community-based services, child welfare, or juvenile court or to 'stabilize' the case by closing it altogether).

### 1.2. *Neighborhood characteristics and systems involvement*

To date, a large body of research establishes the broader ecological and community systems (Drake & Pandey, 1996) that structure the dynamic interactions and social processes (Molnar et al., 2016) associated directly or indirectly with child welfare and juvenile justice systems involvement. Rooted in social disorganization theory, research on the contextual effects of child welfare and juvenile justice involvement has examined how specific circumstances and policy impacts shape the spatial interactions between individuals and their environments. Ecological studies analyzing child maltreatment and juvenile justice involvement independently argue that both are manifestations of etiological processes that are rooted in neighborhood structural vulnerability and deprivation (Barboza-

Salerno, 2023; Ryan & Testa, 2005).

According to social organization theory, social and economic "disorder" results in low levels of collective efficacy and community cohesion, which hinders the ability of community members to "know and care about each other, work together, and remember past outcomes from efforts to influence other community problems (Mustaine et al., 2014, p. 174)." Typical indicators measuring the lack of social organization across neighborhoods hypothesized to increase child maltreatment risk include residential instability, family disruption, ethnic heterogeneity, and concentrated disadvantage. For example, using social disorganization theory as a guiding framework, Schuck and Widom (2005) found that neighborhood disadvantage (i.e., the percentage of families in poverty, families receiving public assistance, residents unemployed, female-headed households, and Black residents) and residential stability (i.e., the percentage of owner-occupied and non-movers in the past 5 years) moderated the relationship between early child maltreatment and subsequent youth offending (Schuck & Widom, 2005). Moreover, researchers have increasingly emphasized the importance of applying an inequities framework to examine the relationship between poverty and child welfare to identify the social determinants of systems contact (Keddell et al., 2019; Keddell & Davie, 2018). An inequalities framework requires a distinct theoretical orientation that emphasizes neighborhood-level material hardship, assessed through area-level deprivation, above and beyond the typical indicators of social disorganization (Barboza-Salerno, 2024; Bellair et al., 2019, 2021; Xu et al., 2021).

Neighborhood-level research on juvenile justice involvement demonstrates the role of socioeconomic status (Fountain & Mahmoudi, 2021), accessibility to resources (i.e., lack of adequate public or private transportation) (Fountain & Mahmoudi, 2021; NeMoyer et al., 2014), and racial and ethnic heterogeneity (Nadel et al., 2021) in increasing the risk of juvenile arrest and confinement rates. Individuals from areas with higher neighborhood socioeconomic disadvantages are more likely to receive a prison sentence (Wooldredge, 2007). For example, one study found that as the number of impoverished families who live in a specific county increases, so does the rate of violent crime in that county (Gunuboh, 2023). Another study observed that neighborhood disadvantage influenced youth offending behaviors through the impact of neighborhood context on hostile peer relations (Chung & Steinberg, 2006). Similarly, gang involvement has been linked to community violence exposure, residing in public housing, and other markers of poverty (Voisin et al., 2017). There is also an evident gap in resources available for youth who engage in rule-breaking or criminal behaviors, such as a lack of general mental healthcare (Golzari et al., 2006) or school-based mental health services (Bruns et al., 2005) and limited school involvement (Malmgren & Meisel, 2002). Gaps in school support are compounded by racial segregation in school districts that result in institutional racial biases in school assessments and policies and the heightened criminalization of behaviors (Krishna, 2014).

Child welfare research has similarly focused on highlighting the relationship between specific contexts, such as alcohol outlet zoning and density (Freisthler, 2004; Freisthler et al., 2007), racial/ethnic heterogeneity (Freisthler & Kranich, 2020; Klein & Merritt, 2014; Thurston et al., 2022), and housing policy (Barboza, 2020). Similar to the involvement in the juvenile justice system, youth in child welfare services are more likely to live in an impoverished neighborhood with higher rates of crime as compared to youth who are not involved in child welfare services (Howes et al., 2000; McDaniel & Slack, 2005). Furthermore, youth in child welfare services often lack health insurance, supportive school and community resources, and mental healthcare broadly (United States General Accounting Office, 2003). These services are especially important following the closure of a child maltreatment case and for preventing future maltreatment by changing the child's environment and by leveraging rehabilitative, ancillary services in other systems (Jonson-Reid, 2004). Service use for these children is further complicated by racial biases embedded in the systems allocating services (Miller et al., 2013; Wright & Thomas Jr., 2003). Increasing evidence further suggests that numerous community-level characteristics may be shared risk factors for systems involvement, such as poverty, limited occupation and educational opportunities, frequent housing relocation, unstable employment, and neighborhood violence (Maschi et al., 2008; Voisin et al., 2017). Therefore, it is crucial to conduct further research to comprehend better the simultaneous vulnerabilities associated with the potential for dual-systems involvement and to optimize protective resources for these families.

### *1.3. Hypotheses*

In previous studies, child maltreatment and juvenile justice referrals have been modeled independently using Bayesian spatial analyses (Barboza, 2019; Fountain & Mahmoudi, 2021; Mennis et al., 2011; Mennis & Harris, 2011; Oldakowski et al., 2022; Thurston et al., 2022). However, these studies have yet to consider the correlation between both outcomes at the neighborhood level. This is a significant omission because ecological models can only sometimes disentangle two highly related phenomena, as in the present case (Ransome et al., 2020). For example, research has shown that as much as 50 % of dually-involved youth have non-concurrent systems contact, which means that a juvenile justice assessment will not necessarily collect information about child welfare involvement unless specifically asked and vice versa (Dual system youth, 2020). Multivariate methods make it possible to quantify and account for the spatial dependence and cross-correlation of juvenile justice and child welfare referrals within the same area during a given period. Bayesian joint modeling has been used to analyze the standard spatial distribution of child maltreatment and intimate partner violence (Gracia et al., 2018) and the geographical overlap between substantiated and unsubstantiated child maltreatment referrals (Marco et al., 2020). In this paper, we use the multivariate conditional autoregressive (CAR) model to spatially analyze the joint distribution of juvenile justice and child welfare referrals across levels of area deprivation in the state of New Mexico. Since juvenile justice and child protective services referrals are heavily conditioned by "delinquency" and child "maltreatment," respectively, our study provides valuable information about the geographic patterns of child maltreatment and delinquent juvenile behavior in addition to dual systems involvement potential (Martinez-Beneito et al.; Botella-Rocamora, Paloma). Specifically, the present study examined 1) the spatial overlap between child welfare and juvenile justice system referrals and 2) the association between structural neighborhood characteristics and dual systems involvement. We expect that child welfare and juvenile justice system referrals will demonstrate significant spatial overlap. We further expect neighborhood disadvantage to be associated with a higher likelihood of dual involvement in child welfare and juvenile justice systems.

## 2. Methods

### 2.1. Data

The New Mexico Children, Youth, and Families Department (NM CYFD) collected the data used in the current study. Both juvenile justice and child welfare referral data for 2008–2015 were made available to the New Mexico Community Data Collaborative, a data analytic organization under the New Mexico Department of Health umbrella, and are available online (New Mexico Data Collaborative, n.d.). In this study, a welfare referral is a referral to the Child, Youth, and Families Department for alleged child maltreatment (i.e., physical or sexual abuse, physical neglect, medical neglect), and a juvenile justice referral is a referral for any offense including felony, misdemeanor or status offenses. Additionally, we used five-year estimates of the number of youths living in each census tract from the American Community Survey's 5-year estimates for each year under investigation from 2008 to 2015.

### 2.2. Dependent variables

The count of youths under 18 referred to the juvenile justice or child welfare system between 2008 and 2015 served as the dependent variable. The counts were derived by aggregating the location for each incident to census tracts (i.e., neighborhoods) and summing the number of referrals within each census tract for each year from 2008 to 2015 separately for both referral types.

### 2.3. Independent variables

The Area Level Deprivation Index (ADI), which captures a neighborhood's socioeconomic position (Kurani, 2020; Messer et al., 2006; Purcell et al., 2021), was used to measure material deprivation. The ADI has been repeatedly shown to be a robust measure of a

**Table 1**
Median, IQR and factor loadings for ADI indicators in New Mexico.

| | Least deprived 20 % of neighborhoods (Q1) | | Most deprived 20 % of neighborhoods (Q5) | | Factor loading |
|---|---|---|---|---|---|
| | Median | IQR | Median | IQR | |
| Area deprivation indicator | | | | | |
| Median Family Income | 93,203 | 30,644 | 30,147 | 11,464 | −0.865 |
| Median Mortgage | 1617 | 492.0 | 825.0 | 266.0 | −0.739 |
| Median Rent | 1188 | 447.0 | 625.0 | 172.0 | −0.693 |
| Median House Value | 255,500 | 130,300 | 79,400 | 45,600 | −0.679 |
| % Families In Poverty | 0.023 | 0.061 | 0.362 | 0.178 | 0.784 |
| % Owner-Occupied Housing | 0.850 | 0.161 | 0.559 | 0.321 | −0.442 |
| Ratio of Income Under $10K to Over 50K | 1.677 | 0.979 | 4.548 | 1.148 | 0.789 |
| % People Living Below 150 % FPL | 0.102 | 0.099 | 0.587 | 0.146 | 0.875 |
| % Single Parent HHs w/Children | 0.223 | 0.244 | 0.593 | 0.304 | 0.483 |
| % HH with no vehicle | 0.009 | 0.025 | 0.125 | 0.130 | 0.542 |
| % Individuals w/White Collar Jobs | 0.553 | 0.191 | 0.177 | 0.146 | −0.720 |
| % Unemployment | 0.037 | 0.049 | 0.122 | 0.133 | 0.469 |
| % At least HS education | 0.967 | 0.047 | 0.696 | 0.167 | −0.732 |
| % Less than 9th grade education | 0.006 | 0.021 | 0.130 | 0.133 | 0.606 |
| % HHs with >1 person/room | 0.000 | 0.009 | 0.078 | 0.124 | 0.530 |
| Immigrant Concentration | | | | | |
| Foreign Born | 0.061 | 0.044 | 0.101 | 0.179 | 0.852 |
| English Language Proficiency less than 'very well' | 0.033 | 0.027 | 0.146 | 0.143 | 0.867 |
| Not at All | 0.000 | 0.004 | 0.021 | 0.042 | 0.896 |
| Residential Instability | | | | | |
| Vacant Housing | 0.072 | 0.077 | 0.167 | 0.125 | 0.301 |
| Times Moved | 0.244 | 0.114 | 0.275 | 0.199 | 0.997 |
| Renter-to-Owner occupied households | 0.184 | 0.146 | 0.365 | 0.298 | 0.835 |
| Hirschman-Herfindahl Index Variables | | | | | 0.465[a] |
| Non-Hispanic White | 0.649 | 0.218 | 0.166 | 0.231 | – |
| Non-Hispanic Black | 0.013 | 0.016 | 0.008 | 0.026 | – |
| Non-Hispanic Asian | 0.018 | 0.020 | 0.003 | 0.006 | – |
| Non-Hispanic Other | 0.032 | 0.019 | 0.049 | 0.822 | – |
| Hispanic/Latine | 0.270 | 0.201 | 0.598 | 0.634 | – |

*Notes*. Least deprived neighborhoods are defined as the 20th percentile on the Area Deprivation Index (ADI), and most deprived neighborhoods are defined as the 100th percentile. Median = 50th percentile. IQR = the interquartile range or the 75th minus the 25th percentile. The factor loadings of the ADI are provided by the *sociome* package in R and are based on principal components.

[a] The factor loading for the Hirschman-Herfindahl Index is the mean of the summary measure, i.e., the average probability that two individuals randomly selected from the same census tract belong to the same racial or ethnic group is 0.465.

neighborhood's socioeconomic position that better elucidates the socioeconomic gradients of health and well-being (Berg et al., 2021; Wiemken et al., 2020). Researchers have refined, adapted, and validated the ADI to the census tract level or neighborhood, using variables of theoretical importance and findings from previous empirical research. A principal components analysis showed that one factor, representing 'deprivation,' significantly loaded fifteen indicators. These indicators were used to construct the ADI (see Table 1). Our final measure consists of fifteen factors designed to measure multiple domains of income, education, employment, transportation, and housing quality. We grouped the ADI rankings into quintiles, with the highest quintile (Q1) representing the most deprived 20 % of neighborhoods and the lowest quintile (Q5) representing the least deprived 20 % of neighborhoods, as has been previously validated (Johnson et al., 2021; Shih et al., 2024). We chose this coding scheme for both substantive and methodological reasons. First, categorizing the ADI into quintiles simplifies our data, making group comparisons more transparent and straightforward. This approach enables us to effectively compare the most deprived areas with the least deprived areas. Additionally, using quintiles helps identify and target interventions specifically for highly deprived areas (i.e., the most deprived 20 %). Finally, the quintile approach helps address potential non-linear relationships between area deprivation and referral outcomes, which are more challenging to model with continuous variables. We utilized the R function *get_adi* from the *sociome* package (Krieger et al., 2023) to download the Area Deprivation Index (ADI) at the census tract level, employing five-year American Community Survey (ACS) estimates for the period from 2011 to 2015. To control for neighborhood social "disorganization," we included well-established measures (Sampson et al., 2002; Lyons et al., 2013; Legewie & Schaeffer, 2016) such as residential instability and immigrant concentration derived from the 2011–2015 ACS five-year estimates. Following the approach outlined by Legewie (2016, 2018), we employed exploratory maximum likelihood factor analysis to obtain predicted factor scores for each control variable. Residential instability was constructed using three items from the ACS data: vacant housing, defined as the number of vacant housing units divided by the total number of housing units in each census tract; times moved, which represents the number of primary householders moved within census years; and occupancy rates, calculated by dividing the percentage of renter-occupied households and owner-occupied households. Immigrant concentration was based on three variables: the share of foreign-born residents, the proportion of residents who speak English less than "very well" or "not at all," and the share of residents who speak Spanish. In this context, higher values of these constructed variables indicate greater residential instability and higher immigrant concentrations. To account for racial and ethnic diversity within each census tract, we applied a Hirschman-Herfindahl index fractionalization index (HHI), which ranges from 0 (maximum homogeneity) to 1 (maximum heterogeneity). The HHI is computed as $Frac_i = 1 - \sum_{i-1}^{N} s_{ij}^2$, where $s_{ij}^2$ represents the proportion of racial or ethnic group $i$ in census tract $j$ (Legewie, 2018). The HHI quantifies the likelihood that two individuals randomly selected from the same census tract belong to the same racial or ethnic group.

Table 1 shows the median and interquartile range of area-level deprivation, residential instability, immigrant concentration, and the HHI in the least and most deprived 20 % of neighborhoods in New Mexico, along with the factor loadings for each indicator. The table shows stark differences in social and economic deprivation in the state. The median percentage of individuals in the most deprived 20 % of neighborhoods living 150 % under the federal poverty line was 58.7 % compared to 10.2 % in the least deprived 20 % of neighborhoods. Similarly, >12 % of occupied housing units in the most deprived 20 % of neighborhoods lacked a motor vehicle. The unemployment rate was almost four times higher in the most deprived 20 % of neighborhoods compared to the least deprived 20 %. Almost 8 % of households in the most deprived 20 % of neighborhoods had more than one person per room. Similarly, the median home value in the most deprived 20 % of neighborhoods was lower than in the least deprived 20 % ($79,400 vs $255,500). The overall median ADI (IQR) for the state was 99.241 (IQR = 26.70) but was significantly higher within the most deprived 20 % of neighborhoods (median = 127.07; IQR = 12.111) and significantly lower in the least deprived 20 % of neighborhoods (median = 75.54; IQR = 11.11) (result not shown). The factor loadings suggest that all indicators fall along one dimension.

Regarding residential instability, the percentage of vacant housing is significantly higher in the most deprived neighborhoods (0.167) compared to the least deprived neighborhoods (0.072). Also, the renter-to-owner occupancy ratio shows that the ratio of the renter-to-owner occupied households is much lower in the least deprived neighborhoods (0.184 v. 0.365). The index of Immigrant Concentration shows higher levels of foreign-born residents in the most deprived neighborhoods (0.101) compared to the least deprived (0.061) and a higher proportion of residents with limited English proficiency (0.033 v. 0.146). The least deprived neighborhoods also have a higher proportion of non-Hispanic whites (0.649) compared to the most deprived neighborhoods (0.166). Conversely, the percentage of Hispanic/Latina individuals is much higher in the most deprived neighborhoods (0.598) versus the least deprived (0.270), suggesting a more heterogeneous population in areas of more significant economic hardship. The HHI reflects substantial diversity across the state such the probability that two individuals randomly selected from the same census tract belong to the same racial or ethnic group is 0.465, on average.

### 2.4. *Statistical approach*

To understand the patterns of juvenile justice and child welfare referrals in different census tracts or neighborhoods, we first calculated the Smoothed Standardized Incidence Density Ratios (SIRs), which help to summarize the relative likelihood of each type of referral in a given census tract. The SIR represents the ratio between the actual number of referrals and the number we would expect based on the population of youth under 18. To calculate the SIRs for any given census tract, we let $Y_{ij}$ and $e_{ji}$ denote the observed and expected referral counts in census tract $i$ for $j = 1$ (i.e., child welfare) or $j = 2$ (juvenile justice), respectively. Then, the SIR is computed as $\frac{\sum Y_{ji}}{\sum n_{ji} e_{ji}}$. Since we have two outcomes capturing systems-level involvement, we estimated a multivariate CAR model where the observed numbers of child maltreatment ($j = 1$) or juvenile justice ($j = 2$) counts ($Y_{ji}$) in census tract $i$, is assumed to follow a Poisson distribution:

$$Y_{ji} \mid \lambda_{ji} \sim Poisson(\lambda_{ji}), i = 1, \ldots, 499, j = 1, 2.$$

We assumed a generalized linear relationship between the expected number of referrals ($e_{ji}$), the ADI, residential instability, immigrant concentration, and the HHI, as follows:

$$ln(\lambda_{ji}) = lne_{ji} + \beta_j ADI_{ji} + \beta_j \boldsymbol{X}'_{ji} + \theta_{ji} + \phi_{ji},$$

where the $\beta_j^{\prime}s$ represent the regression coefficients corresponding to the risk factors for the ADI and the $\boldsymbol{X}'_{ji}$ term captures the risk factors for the three social 'disorganization' indicators. The residual terms $\theta_{ji}$ and $\phi_{ji}$ are vectors of the unstructured heterogeneous and spatially structured effects for the expected counts within each census tract. To account for spatial dependence, we used a spatial weights matrix to capture possible correlations between juvenile justice and child welfare involvement across adjacent neighborhoods. We specified the matrix as $\omega_{i,j} = 1$ if two census tracts share a boundary and zero otherwise. Given the first-order neighborhood structure is used, the bivariate CAR prior is given by (Wen et al., 2018):

$$\boldsymbol{\Phi_i} \sim N_2\left(\overline{\boldsymbol{\Phi}}_1, \frac{\boldsymbol{\Omega}}{n_i}\right), \boldsymbol{\Phi_i} = \begin{pmatrix} \phi_{1i.} \\ \phi_{2i} \end{pmatrix}, \overline{\boldsymbol{\Phi}}_i = \begin{pmatrix} \overline{\phi}_{1i.} \\ \overline{\phi}_{2i} \end{pmatrix}, \boldsymbol{\Omega} = \begin{pmatrix} \sigma_{1,1}^{bs} & \sigma_{1,2}^{bs} \\ \sigma_{2,1}^{bs} & \sigma_{2,2}^{bs} \end{pmatrix},$$

where $n_i = \sum_{i \neq j} \omega_{i,j}$ is the number of census tracts that are adjacent to census tract $i$ and $\overline{\phi}_{ji} = \sum_{i \neq j} \frac{\phi_{kj}\omega_{i,j}}{n_i}$.The variance-covariance matrix for spatial correlation, $\boldsymbol{\Omega}$, contains estimates for the spatial variances of child welfare $\sigma_{1,1}^{bs}$ and juvenile justice counts $\sigma_{2,2}^{bs}$ as well as the covariance between heterogeneous effects, $\sigma_{2,1}^{bs} = \sigma_{1,2}^{bs}$ while the correlation between spatial effects is given by $\rho_s = \frac{\sigma_{1,2}^{bs}}{\sqrt{\sigma_{1,1}^{bs}\sigma_{2,2}^{bs}}}$ (Wen et al., 2018). The term, $\phi$, induces spatial dependence in the estimates of the SIRs while the variance-covariance matrix, $\boldsymbol{\Omega}$, induces multivariate dependence between outcomes by incorporating dependence. Finally, the posterior proportion of variation explained by the spatial correlation for each referral type is defined by (Aguero-Valverde, 2013; Wen et al., 2018) as $n_j = \frac{sd(\phi_j)}{sd(\theta_j) + sd(\phi_j)}, i = 1, 2.$

Research has demonstrated that modeling spatial and multivariate dependence within a Bayesian estimation context can overcome the small area estimation problem and enhance risk estimates (Bell & Broemeling, 2000; Earnest et al., 2010). We conducted our analysis using Markov chain Monte Carlo (MCMC) simulation methods, implemented through the software WinBUGS (version 1.4.3) from within the R Statistical Programming Environment (R Core Team, 2023). The *pbugs* package (Martínez-Beneito & Vergara-

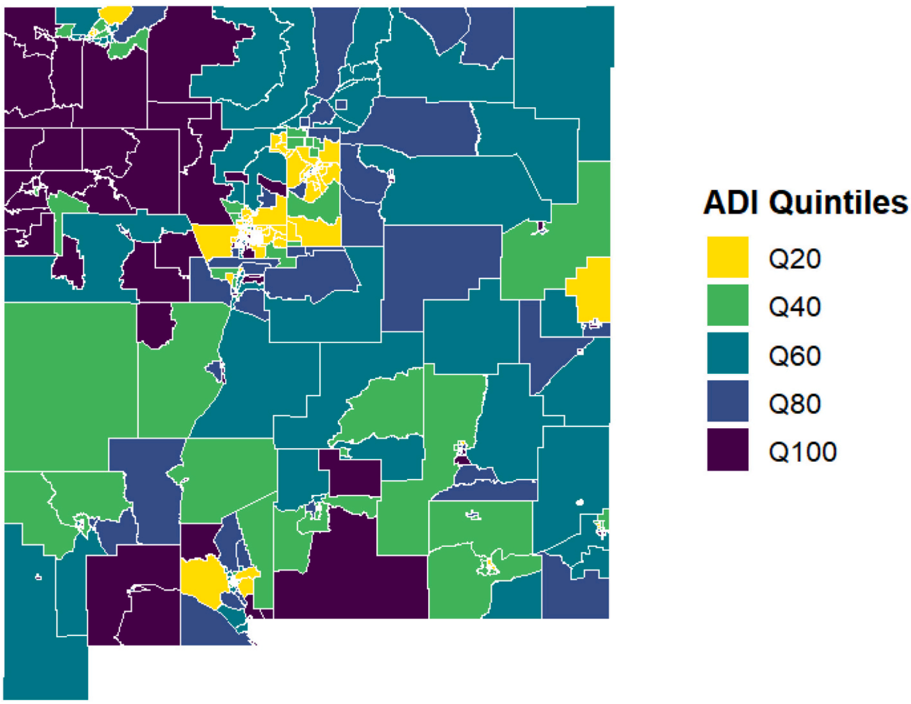


**Fig. 1.** Area Deprivation Index (ADI) for different regions, organized by quintiles. Each color represents a quintile of deprivation from least (Q20 = yellow) to most (Q100 = Purple) deprived. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Hernández, 2023) in R was used for running the MCMC chains for each run. Five thousand MCMC draws were simulated as burn-in, followed by 20,000 additional draws per chain. We employed the Deviance Information Criterion (DIC) to select the model that best fits the data. Our final model was selected based on the lowest DIC as the preferred model, indicating the best balance of goodness-of-fit and parsimony.

Initially, we estimated independent Besag York Mollie (BYM; Besag & Newell, 1991) models of child welfare and juvenile justice referrals without incorporating spatial dependence between the respective geographic patterns. Then, we incorporated a multivariate conditional autoregressive (MCAR) spatial term into the model, preserving the spatial independence between outcomes to reproduce completely random heterogeneity. The third model was similar, but we assumed the precision matrix between outcomes followed a Wishart distribution. Lastly, we incorporated a correlated multivariate normal distribution for the heterogeneous term to assess spatial dependence between outcomes into a multivariate BYM model. This model also used a Wishart prior distribution for the precision matrices of spatial and heterogeneous terms (see Martínez-Beneito & Botella-Rocamora, 2019 for more information about these models). We used a noninformative (vague) prior distribution for the hyperparameters and assessed model convergence using the R-hat Brooks–Gelman–Rubin statistic (R-hat <1.1) and the effective sample sizes (>100) for all identifiable parameters in each chain. Finally, we visually inspected MCMC trace plots representing the model parameters to determine model convergence further.

## 3. Results

We mapped the Area Deprivation Index (ADI) across the state, organized by quintiles (Fig. 1). Geographically, the least deprived 20 % of neighborhoods (shaded in yellow) show a distinct clustering pattern, predominantly located in the central part of the state. Similarly, the most deprived 20 % of areas are highly clustered in the northwest. This distribution highlights regional socioeconomic disparities, with areas of higher deprivation spread throughout the state.

Fig. 2 shows the bivariate relationships between both juvenile justice and child welfare referrals (observed cases and standardized incidence ratio quartiles) and the area deprivation index (shown by ADI quartile). Two observations are noteworthy. First, the aspatial correlation between child maltreatment and juvenile justice cases (top row, column two) is high 0.701 ($p < .001$). Additionally, the strength and direction of the relationship between referral types holds across all ADI quintiles but is strongest in the most deprived 20 % of neighborhoods ($r = 0.737$, $p < .001$). The chart also shows that the relationship between juvenile justice and child maltreatment referrals and the ADI is positive and statistically significant ($r = 0.363$, $p < .001$; $r = 0.442$, $p < .001$). As expected, the relationship between area deprivation and both juvenile justice referrals and child maltreatment referrals is stronger in areas of least deprivation.

To identify areas with high relative risk, we began by mapping the Standardized Incidence Ratios (SIRs) for child welfare referrals (Fig. 3A) and juvenile justice referrals (Fig. 3B). These maps display referral rates, with primary roads overlaid in yellow for geographic context. In the juvenile justice referral map (A), dark blue areas representing the highest referral rates are scattered but more concentrated around central urban regions, including Taos, Albuquerque, Carlsbad, and Santa Fe. This distribution suggests higher juvenile justice referral rates are clustered in urbanized, densely populated cities. In contrast, the map of child maltreatment referrals (B) shows more extensive dark blue regions, particularly throughout the central parts of the state, indicating relatively broader geographic coverage of high child welfare referral rates.

With the lowest DIC score, the multivariate BYM model that incorporated a correlated multivariate normal distribution for the heterogeneous term and Wishart prior to the precision matrices of the spatial and heterogeneous terms provided the best fit to the data ($\text{DIC} = 8092.461$, $pD = 939.387$). Therefore, the remainder of this paper focuses on Model 2. Table 2 shows the combined spatial patterns and outcome-specific spatial effects from the model. To ease interpretation, we transformed the coefficients to represent percent increases/decreases using $\left(exp^{\beta_i} - 1\right) \times 100$. Results demonstrate that the relative risk of joint child maltreatment and juvenile justice referral is highest in the most deprived 20 % of neighborhoods. The outcome-specific intercepts were negative and significantly different from zero. The pattern of coefficients on the ADI quintiles shows a graded relationship between both the ADI and the risk of referral. The coefficient measuring the effect of residing in the least deprived 20 % of neighborhoods (i.e., ADI 20) indicates that the relative risk of child maltreatment ($\beta = -3.046$, $crI = [-3.706, -2.615]$) and juvenile justice referrals ($\beta = -0.809$, $crI = [-1.044, -0.619]$) is decreased by 95.25 % and 55.47 %, respectively, compared to residing in the most deprived 20 % of neighborhoods (ADI 100; reference) holding immigrant concentration, residential instability, and racial/ethnic diversity terms constant. Turning to the effect of these specific indicators of social 'disorganization' on the relative risk of referrals, Table 2 also shows that the HHI was significantly and positively associated with greater risk for child welfare ($\beta = 2.52, crI = [1.766, 3.217]$) and juvenile delinquency ($\beta = 1.101, crI = [0.701, 1.490]$) referrals. As well, residential instability was significantly positively associated with child maltreatment referral risk: every one unit increase in residential instability increased the risk of a child maltreatment referral by 0.089 ($\beta = 0.089, crI = [0.005, 0.170]$).

Table 3 shows the hyperparameters and posterior means of the covariance and correlation matrices between outcomes for the spatial term. The parameters capture the spatial variance (variability; $\sigma_{11}^{bs}, \sigma_{22}^{bs}$) and covariance (association; $\sigma_{12}^{bs}, \sigma_{21}^{bs}$) of the random effects across areas, focusing specifically on how juvenile delinquency and child welfare co-vary. These spatial effects highlight shared local variations (e.g., specific neighborhood effects). Notably, $\sigma_{22}^{bs}$ (Mean = 0.09) has a lower mean and wider range, indicating more uncertainty and weaker spatial effects on child welfare than juvenile delinquency. This confirms the results of the exploratory analysis shown in Fig. 3. $\rho$ and $\rho_s$ represents the correlation independent of spatial factors and spatial correlation between juvenile delinquency and child welfare, respectively. The correlation coefficients for spatial dependence ($\rho_s = 0.24$) and non-spatial dependence ($\rho = 0.41$) between juvenile justice and child welfare suggest a moderate but significant spatial relationship and overlapping spatial risks. The estimates corresponding to $\eta_1$ and $\eta_2$ reflect the relative strength of the spatial influence of child welfare involvement and juvenile

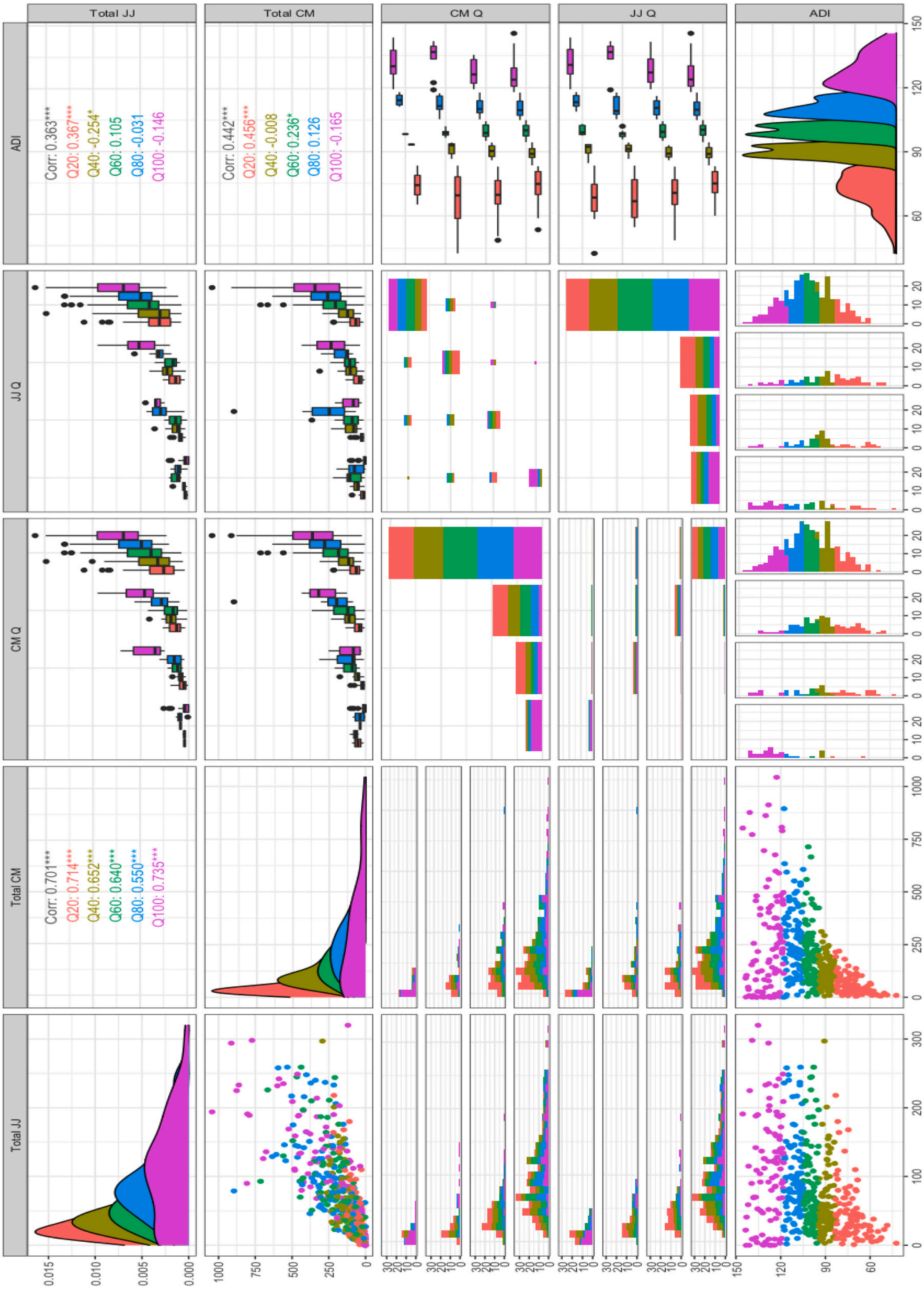


**Fig. 2.** Bivariate associations between child maltreatment (CM) and juvenile justice (JJ) referral counts and the area deprivation index (ADI). The figure shows the correlation between the total number of referrals for juvenile justice (Total JJ), the total number of referrals for child maltreatment

(Total CM), SIR quintiles for both JJ and CM and the ADI as both continuous measures (shown in grey) and by quintiles (color-coded; Q1 = red; Q2 = olive; Q3 = green; Q4 = blue; Q5 = pink). For example, the correlation between JJ and CM counts is 0.701 ($p < .001$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

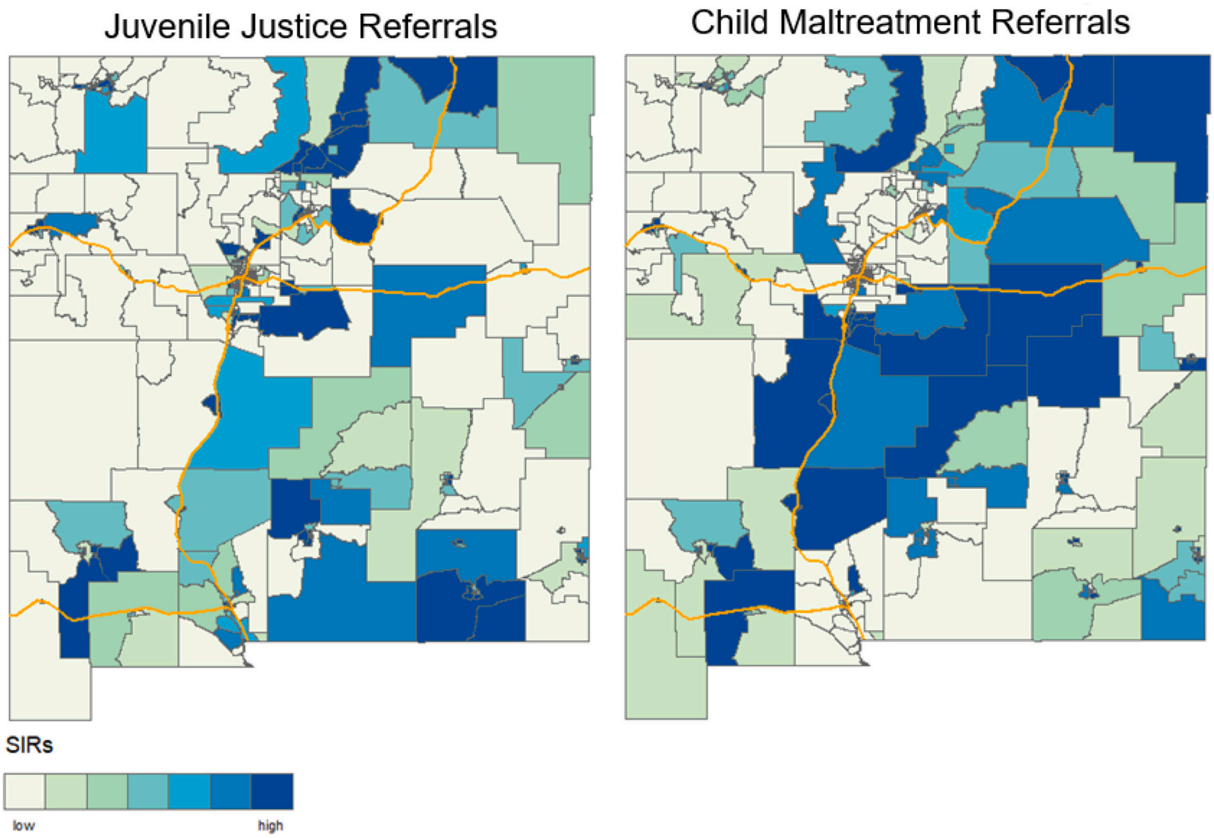


**Fig. 3.** Standardized Incidence Ratios (SIRs) for (A) juvenile justice referrals and (B) child maltreatment referrals across the state of New Mexico. Each map uses color shading to illustrate variation in referral rates. Areas with higher-than-expected referral rates are shaded in dark blue, while areas with lower-than-expected rates are shaded in lighter colors. The yellow lines indicate primary roads, providing context for how major transportation routes intersect with the geographic distribution of referrals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 2**
Parameter estimates in the bivariate CAR model of juvenile delinquency and child welfare involvement.

| | Child maltreatment referral | | | Juvenile justice referral | | |
|---|---|---|---|---|---|---|
| | Mean | 95 % CrI | Geweke.diag | Median | 95 % CrI | Geweke.diag |
| Intercept | −0.38 | −0.43, −0.34 | 1.01 | −0.24 | −0.30, −0.16 | 1.00 |
| Area deprivation | | | | | | |
| ADI 100 (omitted) | | | | | | |
| ADI 20 | −3.046 | −3.706, −2.615 | −0.2 | −0.809 | −1.044, −0.619 | 1.6 |
| ADI 40 | −1.160 | −1.527, −0.888 | −0.1 | −0.441 | −0.678, −0.279 | 0.5 |
| ADI 60 | −0.622 | −0.870, −0.341 | −1.1 | −0.177 | −0.381, −0.040 | −1.1 |
| ADI 80 | −0.212 | −0.428, −0.037 | 1.2 | −0.148 | −0.319, −0.010 | 1.0 |
| Social disorganization | | | | | | |
| Racial Segregation | 2.520 | 1.766, 3.217 | −1.0 | 1.101 | 0.701, 1.490 | −2.0 |
| Residential instability | 0.089 | 0.005, 0.170 | −0.8 | 0.006 | −0.044, 0.057 | −3.4 |
| Immigrant concentration | 0.346 | −1.299, 1.894 | 0.7 | 0.7022 | −0.429, 1.592 | 1.2 |

*Notes.* ADI = Area Deprivation Index; ADI 20 = ADI for least deprived 20 % of neighborhoods. 95 % crI = credible interval.

**Table 3**
Hyperparameter estimates in the bivariate CAR model of juvenile delinquency and child welfare involvement.

| | Mean | SD | 95 % CrI | Rhat |
|---|---|---|---|---|
| $\sigma_{11}^{b}$ | 0.92 | 0.10 | 0.72, 1.11 | 1.06 |
| $\sigma_{12}^{b} = \sigma_{21}^{b}$ | 0.56 | 0.07 | 0.43, 0.69 | 1.02 |
| $\sigma_{22}^{b}$ | 0.97 | 0.07 | 0.84, 1.11 | 1.01 |
| $\sigma_{11}^{bs}$ | 0.66 | 0.24 | 0.25, 1.20 | 1.11 |
| $\sigma_{12}^{bs} = \sigma_{21}^{bs}$ | 0.21 | 0.13 | 0.03, 0.51 | 1.14 |
| $\sigma_{22}^{bs}$ | 0.09 | 0.08 | 0.00, 0.29 | 1.21 |
| $\rho$ | 0.41 | | | |
| $\rho_s$ | 0.24 | | | |
| $\eta_1$ | 0.87 | | | |
| $\eta_2$ | 0.53 | | | |

*Notes.* Covariances, Correlations and spatial correlation between juvenile justice and child welfare referrals.

justice, respectively, with child welfare (86.8 %) more strongly affected by spatial patterns than juvenile justice (53.3 %), also confirmed in Fig. 3.

The maps in Fig. 4 illustrate the spatial dependence indicative of significant spatial heterogeneity and overlap in both child maltreatment and juvenile justice referrals. These results demonstrate the importance of considering spatial correlation in modeling the risk of systems involvement for youth.

## 4. Discussion

While past studies have used Bayesian modeling to explore the spatial features of child welfare involvement and juvenile justice involvement independently, no study to date has utilized multivariate Bayesian methods to examine the spatial overlap of dual systems involvement potential and its association with area-level deprivation and social 'disorganization.' In this study, we used multivariate spatial models to estimate the effect of ADI quintiles while controlling for key indicators of social factors and spatial dependence. We found a strong spatial association between child maltreatment and juvenile justice referrals, demonstrating the presence of shared, underlying spatial risks associated with both referral types. Further, we identified significant spatial heterogeneity, dependence, and shared, overlapping risks associated with both referral outcomes. Specifically, we found that the relative risk for both child welfare and juvenile justice referrals was highest in the most deprived 20 % of neighborhoods, controlling for racial segregation, residential instability, and immigrant concentration (characteristics not accounted for by the ADI). Evidence showed a strong socioeconomic gradient in dual systems involvement when measured by area-level deprivation. In addition, we found that even after we controlled for indicators of social disorganization, children who lived in neighborhoods with the lowest deprivation scores had 95.2 % and 55.5 % lower chances of substantiation for child maltreatment and receiving a juvenile justice system referral, respectively, compared to those who lived in neighborhoods with the highest levels of deprivation.

Research shows that understanding the overlap between the child welfare system and the juvenile justice system is critical to deciphering the limits and contributions of these systems in relation to neighborhood-level risk factors. Although these two systems have different roles, their goal is often comparable when attempting to decrease the involvement of juveniles within them. New Mexico has adopted a positive youth development approach to juvenile justice (Office of Juvenile Justice and Delinquency Prevention, 2019). However, the Office of Juvenile Justice and Delinquency Prevention published a report stating that New Mexico detained 44 % of youth for a technical violation of probation or parole or a violation of a valid court order, ranking second highest among all fifty states (Puzzanchera et al., 2022). Most studies focus on individual-level characteristics of probation violations rather than the macro contexts associated with recidivism. Nevertheless, research has found that individuals who return to disadvantaged neighborhoods recidivate more. In comparison, those who return to resource-rich or affluent communities recidivate less, controlling for individual-level factors (Kubrin & Stewart, 2006). As we have shown here, areas of deprivation are plagued with chronic and problematic issues, that both affect youth developmental outcomes, such as housing and transportation vulnerability and poor educational achievement, and make technical violations more likely (Colon, 2022). Systems-level coordination and collaboration are critical to addressing these modifiable risk factors to ensure youth access the necessary services. Unfortunately, these two systems have limited collaboration abilities and communication even in the best situations. This limitation results in either duplication of services for the involved individuals and families or, conversely, the systems misidentify a child to fit the system that contains the service best suited to the child's needs. Making it a priority to integrate these two systems effectively will enhance services, reduce replication, and produce successful outcomes for those involved with both overlapping systems.

Previous research has demonstrated the importance of family dynamics, social isolation, mental health problems, and school performance as explanations for dual systems involvement (Fountain & Mahmoudi, 2021). As Fountain and Mahmoudi (2021) noted, however, individual-level explanations ignore the multiple structural barriers that explain disparities in systems involvement that may be outside an individual's control. In that regard, our study is most consistent with previous research showing that justice-involved youth and their families face multiple structural and spatial barriers, including living in areas with extremely low levels of vehicle access and where the median household income is 25 % below the city median (Fountain & Mahmoudi, 2021). While a few studies have found that proximity to social services is associated with lower levels of child maltreatment (Freisthler, 2013; Maguire-Jack & Klein, 2015; Maguire-Jack & Negash, 2016), proximity to some types of services was associated with higher risk of recidivism for

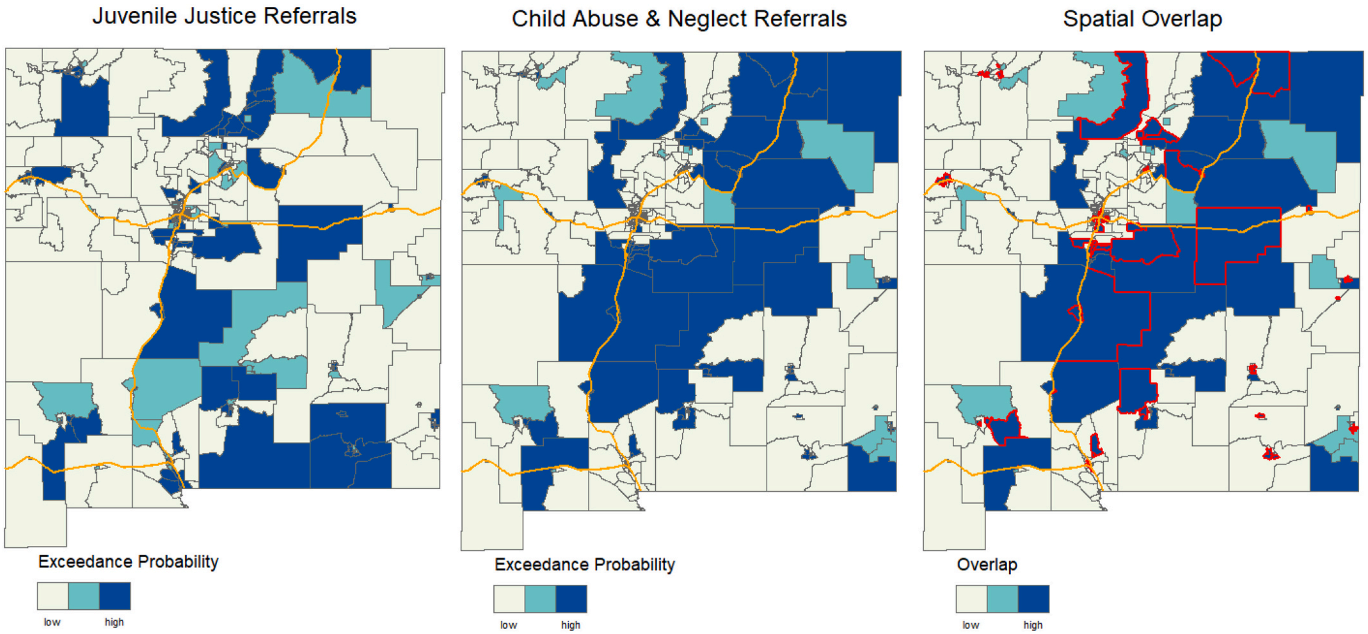


**Fig. 4.** Exceedance probabilities for (A) juvenile justice referrals, (B) child welfare referrals, and (C) spatial overlap of dual-systems involvement. The Exceedance probability indicates how likely it is that the risk of both referral types will be at least double the state average. It is categorized as 1) low (0.20 or less), 2) moderate (>0.2 and <0.9), and 3) high (above 0.90). The red borders outlining the census tracts illustrate the areas where the spatial overlap in both juvenile justice and child maltreatment referrals exceeds 2 times the state average with probability >0.90. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

juvenile justice-involved youth (Abrams & Freisthler, 2010; Thompson-Dyck, 2022), with one study finding that accessibility to services for youth were hampered by spatial barriers such as a lack of transportation (Fountain & Mahmoudi, 2021; Fareed et al., 2020; Garland et al., 2005). These studies highlight the importance of distinguishing the availability of services from accessibility and utilization.

### 4.1. Implications for policy and practice

One important policy implication from our study pertains to the provision of services to cross-over youth, particularly given the multiple overlapping risks found in the most deprived neighborhoods and that racially heterogeneous neighborhoods have a higher risk of dual-system involvement potential. Youth involved in service sectors, such as child welfare and juvenile justice, exhibit high rates of substance use disorders (Aarons et al., 2001), attention-deficit/hyperactivity disorder (ADHD), and disruptive behavior disorder (Garland et al., 2001). Minoritized youth have more unmet needs and are overrepresented in these systems (Garland et al., 2005). In this regard, an important implication of our study pertains to the necessity of establishing stronger or more formal partnerships with healthcare providers for the provision of health-related care and mental health-related services and community advocacy groups to promote regular, non-overlapping and consistent access to resources that build on individual assets in areas of high deprivation.

Establishing neighborhood deprivation as a modifiable risk exposure to economic inequality, unemployment, low levels of educational attainment, rental and mortgage burden, and lack of transportation has crucial institutional and policy implications that play a key role in minimizing the cumulative and excess burden of systems involvement in the most vulnerable areas of New Mexico. In these areas, providing resources that facilitate long-term, low-cost housing options and employment opportunities is critical to minimize the significantly higher risk of justice and child welfare involvement. In this regard, our findings regarding the importance of residential instability, as well as the finding regarding the greater risk that living in the most deprived 20 % of neighborhoods characterized by extreme housing insecurity, suggests that service provision must remain stable even if a client moves, particularly for child welfare families. Housing instability is typical in child welfare families and results in poorer outcomes for those families (Fowler et al., 2013; Fowler & Farrell, 2017). Transferring services to the “nearest provider” every time a family moves can result in families falling through the cracks due to a lack of engagement or bureaucratic diffusion of responsibility.

Whereas this study importantly implies the distribution of resources among these two systems, we do not provide any information on how the education system might contribute to the overlap in system involvement. For example, how students are disciplined within their schools has a significant impact on their involvement with the juvenile justice system, with suspension highly correlated with future juvenile justice involvement (Nicholson-Crotty et al., 2009), a phenomenon referred to as the school-to-juvenile justice pipeline. A recent investigation by ProPublica uncovered harsh discipline of Native American youth in the Gallup-McKinely School District, leading to an investigation by the Attorney General (Furlow, 2023). Child welfare, too, provides a pathway to the juvenile justice system, especially for older youth living in low-income areas (Vidal et al., 2017). Students of color and those with various educational disabilities are more likely to be suspended/expelled due to disciplinary reasons, increasing the likelihood of being involved with the juvenile justice system and child welfare system (Fabelo et al., 2011). Stewart (2022) describes the interconnectedness of these three systems—all of which manifest systemic racism as evidenced by the disproportionate representation of non-White children—as synergistically exacerbating the harm to children, especially Black children (Stewart, 2022). The legal apparatus’s involvement raises the harm to a civil rights crisis.

While the education system is entangled in these systems, it also presents the most likely entry point for effective interventions to reduce child welfare and juvenile justice outcomes. Adopting suspension alternatives can reduce subsequent juvenile justice involvement (Hughes et al., 2020). However, there are other potential points of impact schools can have in improving the lives of students and the community. At the individual/family level, who decides which resources are best for every child involved with these two systems? School psychologists, social workers, nurses, and other support staff can help ensure educational continuity for students involved in these service sectors once they have been identified by or have had formal involvement with these systems of care. School administrators should partner with systems and community professionals to coordinate services, offer programming to prevent systems involvement, and provide critical academic and related psychosocial resources (Atkins et al., 2010), and there should be no break in these services should a child transfer schools for any reason (such as housing, or educational program availability). Such a child and family-centered approach would streamline services and guarantee continuity of care regardless of housing instability or other neighborhood-related deprivation factors. However, expecting individual schools or districts to bear the burden of such coordination is untenable. Instead, local and state governments that are willing to work toward social justice should transform schools into “integrated hubs” of services, also known as “community hubs,” which could be tailored to the specific areal needs to provide an array of health, human, and social services to address the holistic needs of both the students and their caregivers (Haig, 2014). Schools benefit from this concept with increased attendance, improved test scores, and reduced disciplinary actions (Horn et al., 2015), and communities benefit from streamlined coordinated services that increase opportunities for residents, thus reducing overall poverty (Haig, 2014). Families in these hubs are given opportunities to build relationships with individuals and agencies, increasing individual and communal social capital (Teo et al., 2022). Community hubs embody social justice by “…breaking the bonds of the dispositional spheres of power and sharing and distributing that power with the self-determination and actualization of possibility” (Williams-Boyd, 2010, p. 20).

### 4.2. Limitations and directions for future research

Despite the present analysis's novelty, this study has limitations. This study was completed in New Mexico, which consistently ranked lowest of all states on multiple child development indicators (Barboza-Salerno, 2020). Although this study aims to discover how the spatial distributions and areas of deprivation contribute to high child maltreatment and juvenile justice involvement, the results may not be generalizable to other states. There is a multitude of other factors to consider when understanding child maltreatment and the juvenile justice system, such as laws and policies within these two systems, specifically with New Mexico, that may differ from other states. It is critical to distinguish law and policy between states, as this may impact how these two systems interact with other important dynamics, such as the education system, and how these systems respond to the needs of individuals and communities. Importantly, however, we did not examine the spatial distribution of resources in the most deprived areas, such as the distribution of schools and behavioral health care services. Future research should incorporate data on school discipline and proximity to behavioral health care institutions to contextualize further the factors contributing to dual systems involvement. This is particularly important to examine over time, which we did not do in this study. Our data is also ten years old, and more recent data may show changes over time. Finally, we used aggregate social disorganization and area deprivation measures to reveal how multiple overlapping risk factors exacerbate dual-systems involvement. Our interest was primarily in the spatial overlap of these two service sectors. Future research would benefit from exploring the individual indicators we used to create the indices to detect the most effective intervention point.

## 5. Conclusion

Advancements in geospatial analyses provide the ability to identify the social and spatial components of areas of extreme vulnerability precisely and clearly for youth. While singular interventions may provide some relief for some children and families, they are subject to marginalization-related diminished returns (MDR), wherein society limits the efficacy of interventions for marginalized people (Assari & Zare, 2022). Various interventions can and do impact individuals but rarely move the needle on the area deprivation score. Further, social justice for our youth requires more than diverting youth from negative proximal (school disciplines, child maltreatment) and distal (juvenile justice involvement) outcomes; we must also provide the resources so that they have educational and economic opportunities (Ginwright & James, 2002) to thrive. Public policy that promotes and provides for holistic sustained commitments to area deprivation improvements, such as establishing school-based community hubs and other efforts that might build collective efficacy and sustained social capital, is a step in the right direction.

## CRediT authorship contribution statement

**Gia E. Barboza-Salerno:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Holly Thurston:** Writing – review & editing, Writing – original draft, Conceptualization. **Yujeong Chang:** Writing – review & editing, Writing – original draft, Conceptualization. **Charis Stanek:** Writing – review & editing, Writing – original draft, Conceptualization.

## Data availability

Data will be made available on request.

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