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Variability and stability in child maltreatment risk across time and space and its association with neighborhood social & housing vulnerability in New Mexico: A bayesian space-time model

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ABSTRACT

Background: Modeling the spatio-temporal characteristics of substantiated child maltreatment risk has significant implications for child welfare policy.
Objective: This study quantifies the spatiotemporal risk of child abuse and neglect in New Mexico at the census tract level over 9 years, identifies areas of increased risk, and evaluates the role of multiple measures of social and housing insecurity on substantiated child maltreatment referrals.
Participants and Setting: Child maltreatment substantiation data across 499 census tracts from 2007 to 2015 were obtained from the New Mexico Department of Public Health.
Methods: Substantiated referral counts were analyzed within census tracts with Bayesian hierarchical space-time models using Laplace approximation. Standardized incidence ratios, spatial risk, and probability exceedances were calculated and mapped.
Results: Multiple neighborhood structural factors were associated with an increased risk of substantiated child maltreatment, including the eviction rate (Incidence Density Ratio [IDR] = 1.09 [95 % CrI = 1.01–1.12]), rent burden (IDR = 1.11 [95 % CrI = 1.01–1.13]), urban tracts (IDR = 1.36 [95 % CrI = 1.05–1.77]), food desert tracts (IDR = 1.21 [95 % CrI = 1.04–1.41]), low income tracts (IDR = 1.27 [95 % CrI = 1.09–1.49]), percent of households with no vehicle access ([IDR] = 1.27 [95 % CrI = .247–6.47]), and percent of persons with a disability (IDR = 1.05 [95 % CrI = 1.03–1.06]). The racial/ethnic diversity ratio, however, was associated with lower incidence of child maltreatment allegation risk (IDR = .988 [95 % CrI = .982–.995]).
Conclusions: Population-based child abuse and neglect prevention and intervention efforts should be aided by the characteristics of neighborhoods that demonstrate strong spatial patterns of household and housing vulnerability, particularly in low income, racially segregated neighborhoods.

1. Introduction

In New Mexico, where the present study was conducted, child maltreatment is a significant public health issue affecting thousands of children annually (NM-IBIS, 2017). A recent report conducted by Child Trends found that the state of New Mexico has the highest percentage of youth who experience multiple adversities in early childhood (Child Trends, 2015), including child abuse and neglect, placing them in a category of particularly high risk. In New Mexico, child welfare referrals and substantiation rates are higher than the national average. In 2015, about 18 per 1000 children under 18 were substantiated for abuse and neglect, compared to 9.4 substantiations per 1000 children nationally (Child Trends, 2015). Due to limited resources, despite the relatively higher share of

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youth who are involved with Child Protective Services (CPS) in New Mexico, only 40 % percent of victims received post-response services in 2015 – 24 percentage points lower than the US average (Child Trends, 2015).

Public health policy and research acknowledges the importance of safe and affordable housing for child development (Anderson et al., 2002), particularly for children who are born to extremely poor mothers (Culhane & Elo, 2001). The most extreme form of housing insecurity, homelessness, has been linked to greater risk for childhood illness, injury, malnourishment, and maltreatment. High rates of substantiated maltreatment coupled with low response rates makes the spatial variations and neighborhood level risk factors within the state of New Mexico important to understand for its own sake. However, a better understanding of the spatio-temporal child maltreatment risk in a state where a large percentage of children experience early childhood adversity will also yield important information about the risk factors associated with child maltreatment in similar areas and/or with similar needs. In 2016, New Mexico ranked 49th on indicators of economic, family and community well-being (Annie E. Casey Foundation 2020): 32 % of children lived in households with a high housing cost burden, 36 % of children had parents who lacked secure employment and 24 % of children lived in high-poverty areas. A recent study conducted by Pew Charitable Trusts (2018) reported that rent burdened households in the United States increased by 19% from 2001 to 2015, concluding that the growing number of rent-burdened households is becoming an increasing threat to the economic mobility and financial resiliency of American families. Efforts to describe the temporal progression of geographic patterns of substantiated child maltreatment rates across census tracts in New Mexico, and to link neighborhood characteristics and processes to multiple indicators of housing and household insecurity will help target interventions to areas of high housing need. Accordingly, this paper aims to: (1) examine *small area* spatio-temporal trends in child maltreatment substantiation risk over a 9-year period; (2) evaluate the role of multiple measures of neighborhood social, housing and household vulnerability on relative risk of substantiated maltreatment controlling for spatial and temporal heterogeneity; and (3) demonstrate the utility of region-specific surveillance for child welfare response in the state of New Mexico.

2. Socio-economic status and child maltreatment

Decades of research has shown that children living in families with limited economic resources have a higher risk of child welfare involvement than children from higher socioeconomic strata (Cancian, Slack, & Yang, 2010). Past research has uncovered a linear relationship between child maltreatment and neighborhood affluence whereby rates of child maltreatment referrals and substantiated allegations are higher in the most vulnerable areas compared to areas of medium-vulnerability, which in turn are higher than in low-vulnerability areas (Barboza, 2019a; Drake & Pandey, 1996). Higher substantiated maltreatment rates are generally associated with socio-economic vulnerability which encompasses “quality of life” variables such as poverty and economic hardship (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Freisthler, Lery, Gruenewald, & Chow, 2006; Heller, Larrieu, D’Imperio, & Boris, 1999), unemployment, family income, parental education level, and single parenthood (Deccio, Horner, & Wilson, 1994; Merritt, 2009).

Many studies have sought to explain the association between poverty and child maltreatment (Berger, 2007; Drake & Pandey, 1996; Jonson-Reid, Drake, & Kohl, 2009). One explanation common to many studies has focused on the role of economic stress in undermining a parent’s ability to provide for a child’s basic needs due to inadequate resources. Alternative explanations suggest that economic strain may lead to changes in parental mental health, caregiving behaviors, or family dynamics that interfere with parental functioning and pose a threat to child safety and well-being (Cancian, et al., 2010). Economic hardship is also related to less access to resources such as early childhood programming that may be a protective mechanism against maltreatment (Garbarino & Crouter, 1978). As well, studies have shown that perceptions of neighborhood disorder vary depending on socioeconomic status which is, in turn, associated with different views about how best to respond to and prevent child abuse and neglect (Garcia & Herrero, 2006; Coulton et al., 2007).

3. Housing insecurity, food access and child maltreatment

Neglect is defined as the inability among parents and guardians to support the basic needs of their children including the provision of food, clothing and shelter. Since housing and food insecurity is more characteristic of families struggling with poverty, parents deemed neglectful are more likely to be low income and/or reside in low income neighborhoods. The underlying mechanisms put forth to explain the relationship between housing insecurity and child maltreatment include parents’ experiences of chronic stress over rental payments, eviction notices, and/or the threat of being homeless. Moreover, families who are financially burdened by high rents have less money for food and medical care. These families are more susceptible to diseases and illnesses associated with improper nutrition and inadequate health care (Freeman, 2002). Further, substandard housing is a barrier to both child protection and the solidarity of the family unit (Cunningham & Pergamit, 2015). On the other hand, the provision of stable housing promotes child well-being. Research has shown that homeless families, or families with the imminent threat of being homeless, who are provided with housing, plus critical services, are less likely to have children who are removed from the home or who are involved with child welfare services (Cunningham & Pergamit, 2015). Despite clear linkages between neglect and housing insecurity across different spatial regimes (Barboza, 2019b), there is a dearth of research investigating multiple measures of neighborhood-level housing insecurity and child welfare outcomes.

4. Race, ethnicity and child maltreatment

Previous research has shown that residents of racially diverse neighborhoods may face stigma due to stereotypes or cultural differences that influence how events in those neighborhoods are perceived (Sampson & Raudenbush, 2004). Similarly, in the case of child welfare, stereotypes about potential abusers and victims, operating through community characteristics, may influence how abuse and/or neglect is identified, and subsequently reported, to officials. Previous research has shown disproportionate contact between youth of color and child protective service agencies, suggesting that some professional sources of referrals are more likely to report children of color. For example, studies have shown that black children are between 2 & 5 times more likely than white children to receive an investigation for maltreatment (Bowman, Hofer, O'Rourke, & Read, 2009; Crampton & Coulton, 2008; Drake, Lee, & Jonson-Reid, 2009; Rolock & Testa, 2005). Some research suggests that while African Americans are more likely to live in disadvantaged neighborhoods, neighborhood disadvantage may have a weaker effect on maltreatment rates in communities of color compared to predominately White communities (Korbin, Coulton, Chard, Platt–Houston, & Su, 1998). Other studies have confirmed that the magnitude of racial disparities in child maltreatment substantiations are unique to the geographic area under consideration (Nilsen, 2007), prompting scholars to consider the interaction between race and place. Accordingly, Drake et al. (2009) found that Black children living in high poverty areas were less likely to be reported to child welfare services compared to White children living in high poverty areas. Klein and Merritt (2014) found evidence for a 'differential sensitivity' effect whereby maltreatment referral rates were higher for Hispanic and White children living in impoverished areas but not black children. A Bayesian spatio-temporal analysis conducted by Barboza (2019a) found that racial homogeneity offers a degree of protection against risk of substantiated child maltreatment in high vulnerability neighborhoods in California; however, no such protective effect was observed in low vulnerability neighborhoods. Explanations for the increased risk of child welfare involvement in communities of color has focused on increased visibility and scrutiny to potential maltreatment reporters, multiple risk factors that increase the likelihood that Black parents will maltreat their children (Cappelleri, Eckenrode, & Powers, 1993), and institutional racism whereby black children who live in poor minority neighborhoods are treated differently at various stages of the decision-making process (Hill, 2004).

5. The utility of bayesian hierarchical space-time modeling in child maltreatment studies

A growing number of scholars have adopted an ecological approach that considers the multiple contextual overlapping contributions of community-related factors, including structural inequality, to understand child maltreatment risk. These studies have adopted the National Research Council's (1993) suggestion that research on maltreatment should employ an ecological perspective that views the etiology of maltreatment as transactions of risk and protective factors at multiple levels of ecology (Cicchetti & Lynch, 1993; National Research Council, 1993). Using a conditionally autoregressive Bayesian model, Freisthler and her colleagues found that counties with similar rates of referrals are clustered near each other and experience similar changes in referral rates over time (Freisthler & Weiss, 2008; Freisthler, Kepple, & Holmes, 2012). Similarly, Gracia, López-Quílez, Marco, and Lila (2017) showed chronic spatial patterns of high risk of substantiated child maltreatment in the city of Valencia, Spain where some areas demonstrated risks that were much higher, and some much lower, than the city average. In both cases, however, the risks remained stable over the entire 12-year time frame under investigation. In a study of maltreatment substantiation rates in Los Angeles County, California, Barboza (2019b) found a residual space time interaction effect identifying census tracts with elevated risks of child maltreatment representing sporadic outbreaks similar to short-term clusters (DiMaggio, 2015). Finally, autoregressive models were used to examine the temporal pattern of child maltreatment risk between 2008–2016 across zip codes in Davidson County, Tennessee (Morris et al., 2019). The authors found important differences in temporal patterns between maltreatment subtypes. Specifically, they found that the risk of child sexual and physical abuse decreased from 2008 to 2016 whereas the risk of child neglect increased from 2011 to 2014, followed by a rapid decrease in risk. These studies have shown important spatial inequalities in substantiated child maltreatment risk across distinct time periods and geographical locations which have been linked to different neighborhood structural factors including socio-economic vulnerability, crime and disorder, immigrant concertation and poverty. Therefore, these studies not only highlight the utility of spatiotemporal modeling, they reinforce the importance of region-specific surveillance across space and time for understanding child maltreatment prevention.

6. Methodology

6.1. Data

Dependent variable. Counts of child maltreatment substantiations for each year based on data from the Protective Services Division of New Mexico's Department of Child Youth & Families (CYFD) were acquired from the New Mexico Department of Public Health (New Mexico Department of Public Health and 2019).[1] The counts were aggregated by census tracts and ordered both spatially and temporally. Population estimates were based on American Community Survey data for the years 2006–2010 and 2011–2015.

Independent variables. Several indicators of social vulnerability were downloaded from the Social Vulnerability Index (SVI) website at the Centers for Disease control (Centers for Disease Control, 2016). The Social Vulnerability Index (SVI) was constructed using census data at the tract level to identify communities that need extra support when faced with external pressures, such as a natural disaster (Centers for Disease Control, 2016). The following data was extracted from the SVI: (1) the percentage of persons living in group quarters; (2) the percentage of persons with no vehicle access; (3) the percentage of persons with a disability; (4) the percentage of persons with no high school diploma; (5) the percentage of unemployed persons; and (6) the percentage of single parents.

[1] The data are available at the following website: https://www.arcgis.com/home/webmap/viewer.html?useExisting=1&layers=a5c50c2894bf431aaf1007c5dc024a62

Using the SVI, population density was calculated to reflect the number of persons per square mile (i.e. population per square mile) and a burden ratio of individuals over 64 to individuals under 18 was calculated to measure household burden.

Two dichotomous variables from the United States Department of Agriculture's (USDA) Food Access Research Atlas (Economic Research Service, 2019) identified low income census tracts (= 1 if low income, 0 = not low income) and census tracts with limited access to food (= 1 if a food desert; 0 = not a food desert). According to the USDA, low income census tracts have: (1) a poverty rate that is at least 20 percent; and (2) a median family income that is less than or equal to 80 percent of the greater of either the metropolitan statistical area (MSA) median family income or the median family income of the state if the tract falls outside of an MSA (Economic Research Service, 2019). To determine whether a tract is low food access, the number and share of people more than 1 mile (for urban areas) from the nearest food store or 10 miles (for rural areas) was totaled. If at least 500 people or 33 percent of the tract population was more than 1 mile (in urban areas) or more than 10 miles (in rural areas) from a food store, the tract was deemed a low food access tract (for more information about the atlas see https://www.ers.usda.gov/data-products/food-access-research-atlas/about-the-atlas).

The Diversity Index is a measure developed by the Environmental Science Research Institute (ESRI) that summarizes racial and ethnic diversity in an area (ESRI, 2012 Enviornmental Science Research Institute 2012). The Diversity Index measures the likelihood that two persons chosen at random from the same census tract belong to different races or ethnic groups (the index ranges from 0 (no diversity) to 100 (complete diversity). Of note is that ESRI's definition of diversity is two-dimensional and combines racial diversity with ethnic diversity. Finally, data on housing insecurity was downloaded from the Eviction Lab at Princeton University. The Eviction Lab has collected, cleaned and geocoded a data set consisting of over 82,000,000 court records related to evictions in the United States from 2010 to 2016 (Desmond et al., 2018a, 2018b). The dataset has been merged with data from the American Community Survey (2011–2016) and in addition to the census tract eviction rate includes a number of other characteristics that measure housing insecurity including rent burden, median gross rent, median property value, median family income and the percent of renter occupied households in a census tract. Rent burden is defined as spending 35 % or more of one's income on rent. For more information on this dataset see http://www.evictionlab.org.

6.2. Statistical approach

The models used in this research are based on a class of models known as Generalized Linear Mixed Models (GLMMs) that are formulated within a hierarchical Bayesian framework. First, child maltreatment substantiation data for each of the 499 census tracts was indexed $i = 1 \ldots 499$ across the 9 time periods, indexed $t = 1, \ldots 9$. Some census tracts contain a larger at-risk population than others; therefore, standardized incidence ratios (SIRs) were first calculated to control for demographic differences. SIRs are defined as the expected number of substantiated maltreatment cases, e_{it}, in census tract i at time t. Conditional on the relative risk, r_{it} the observed number of child maltreatment substantiations was assumed to follow a Poisson distribution, $y_{it} \sim Pois(\lambda_{it} = e_{it} r_{it})$, where y_{it} is the observed count of substantiated maltreatment in census tract i at time t and the mean is given by $\lambda_{it} = e_{it} r_{it}$. The relative risk quantifies whether a census tract has higher ($r_{it} > 1$) or lower ($r_{it} < 1$) risk than the average risk in New Mexico state (Moraga, 2019). The corresponding relative risk of substantiated maltreatment was modeled using a number of different approaches as follows.

First, the relative risk of child maltreatment substantiations was modeled as a function of time (in years) in order to assess temporal trends in substantiated maltreatment across the state. Both linear and non-linear time trends were compared to determine the temporal structure that best fit the data. Next a simple random effects model (also called a frailty model) was fit to the data as a baseline model ($y_i = \beta_0 + u_i$),where β_0 is the intercept and the u_i' s represent the unstructured spatial random effects that are assumed to be independent and identically distributed in the absence of spatial autocorrelation (Duncan, White, & Mengersen, 2017). In this model, rates are nested within census tracts and a separate random intercept term for each tract is estimated. The unstructured spatial random effect captures the heterogeneity, or spatial distribution, in the maltreatment rate for each census tract.

In spatio-temporal settings where counts are observed over time, spatio-temporal models that account not only for spatial structure but also for temporal correlations and spatio-temporal interactions are frequently used (Moraga, 2019). To account for spatial dependence, a convolution model, known as the Besag-York-Mollié (BYM) model (Besag, York, & Mollié, 1991) was next estimated. The BYM model adds a spatially structured conditional autoregression term (CAR) to the spatially unstructured random effect term so that the mean of the structured effect depends on the structured effects of each neighboring region. This accounts for the possibility that neighboring areas have similar substantiated child maltreatment risks than areas farther away. The BYM model requires inclusion of a neighbor-adjacency matrix graph used to connect areas of close proximity and define the neighborhood structure across census tracts. The neighborhood adjacency matrix used to define neighborhood structure was created using the poly2nb function in the spdep package (Bivand et al., 2005) in R (R Core Team, 2013). The structure gives more weight to census tracts that are closer in proximity to an arbitrarily defined tract than to those that are farther away. In the BYM specification, a linear time trend can be included in the model to capture temporal trends. A logarithmic transformation allows a linear, additive model of regression terms so that the risk associated with a given census tract is the sum of the structured and unstructured spatial effects. The model is specified as follows:

$$y_{it} \sim Pois(\lambda_{it} = e_{it} r_{it}),$$

$$\log(\lambda_{it}) = \log(e_{it}) + \log(r_{it}),$$

$$\eta_{it} = log(r_{it}) = \beta_0 + u_i + v_i, + (\beta_1 + \delta_i) \times t_j$$

Table 1

Descriptive statistics for study variables. All data from data sources listed in the table are publicly available. Notes: CDC SVI = Centers for Disease Control Social Vulnerability Index; USDA = United States Department of Agriculture; ERSI = Environmental Research Science Institute.

Child maltreatment	Mean	Std. Dev.	Data Source
Substantiation rates of child physical abuse and neglect (per 1000 children)	23.34	16.46	New Mexico Department of Public Health
Population Density			
Total child population	1023.8	609.4	CDC SVI
Population/square Mile	1983.3	2299.8	CDC SVI
Neighborhood Social Vulnerability			
Socioeconomic vulnerability			
Percent individuals below poverty	20.8	12.1	CDC SVI
Percent civilian unemployed	9.8	5.6	CDC SVI
Per capita Income	24,386.0	11,223.5	CDC SVI
Percent persons with no high school diploma	16.5	11.8	CDC SVI
Food Deserts	61.8	48.3	USDA Food Atlas
Low Income Tracts	49.5	50.0	USDA Food Atlas
Percent households receiving SNAP	14.8	9.73	
Household Composition Vulnerability			
Percent persons 65 years of age or older	15.0	5.8	CDC SVI
Percent persons 17 years of age of younger	23.5	6.8	CDC SVI
Burden Ratio (65 and over to 17 and younger)	3.03	8.95	CDC SVI
Percent persons more than 5 years old with a disability	14.7	5.8	CDC SVI
Percent male or female householder, no spouse present, with children under 18	11.0	6.0	CDC SVI
Racial/Ethnic Vulnerability			
Percent minority	58.9	22.3	CDC SVI
Diversity Index	63.4	13.6	ERSI Diversity Index
Housing/Transportation Composition Vulnerability			
Eviction Rate	3.03	2.84	Princeton Eviction Lab
Rent Burden	39.42	15.65	Princeton Eviction Lab
Percent multi-unit structure	6.1	11.3	CDC SVI
Percent mobile homes	17.4	18.4	CDC SVI
Percent Crowding	3.9	4.7	CDC SVI
Percent No vehicle available	6.0	5.3	CDC SVI
Percent of persons in group quarters	2.3	7.1	CDC SVI

$$u \sim \Phi(0,\ \tau_v),$$

$$v \sim \Phi\left(\bar{v}_\delta,\ \frac{\tau_v}{\eta_\delta}\right),$$

Here, β_0 is the intercept, $u_i + v_i$, is an area level random effect, β_1 is the global linear trend effect, and δ_i is the differential time trend (i.e. the difference between the global trend β_1 and the area specific trend). In this model, u_i and δi are modeled with a CAR distribution, and the $v_i's$ are independent and identically distributed normal variables. Each census tract has its own time trend with spatial intercept ($\alpha + u_i + v_i$)and slope ($\beta + \delta_i$). The effect δ_i is called differential trend of the ith area, and denotes the amount by which the time trend of area $i$differs from the overall linear time trend, β_1. To account for nonlinearity, the above model was extended to include a temporal random effect common to all areas as well as a space-time interaction allowing for a specific temporal evolution to emerge in each census tract. The temporal random effect was modeled as a first order random walk to account for dependence between the previous time period. The space time interaction accounts for the behavior of a census tract for each year above and beyond the common spatial and temporal terms. In addition to modeling the region and temporal periods, multiple covariates, *C,* were incorporated into the modeling scheme (see Table 1). In all models, expected counts were included as an offset variable. On this basis, the intercept is interpreted as the average state level per-population risk on the log scale of substantiated child maltreatment adjusted for random effects, spatial and temporal structure and covariates.

In order to examine clustering of the relative risk, spatial exceedance probabilities were calculated and mapped. Spatial exceedance probabilities were defined as the probability that the relative risk of substantiated maltreatment in each census tract is at least twice the state average, given by:

$$P([(r = \exp(\beta_0 + \beta_1 * x_i + \geq u_i) > 2)]$$

The Deviance Information, Criterion (DIC) (posterior mean of the deviance plus the number of effective parameters) (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002), the Watanabe-Akaike Information Criterion (WAIC) score, and the Brier score (the mean square difference between the predicted probability and the observed count of child maltreatment substantiations in each census tract) were calculated to determine model fit. Plots of the structured and unstructured random effects were used to explore

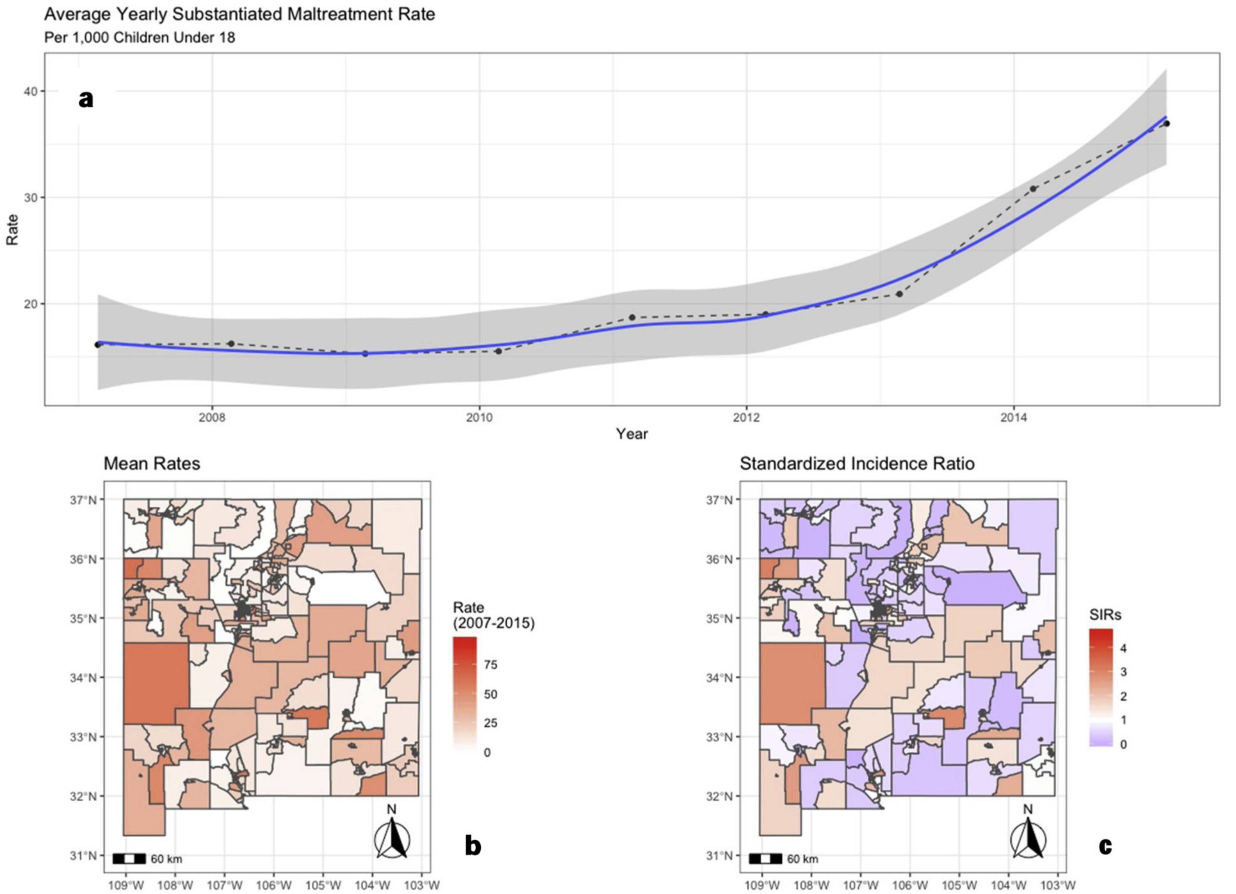

Fig. 1. (a). Average Yearly Rate of Child Abuse or Neglect Substantiations in New Mexico State 2007 – 2015 per 1000 Children. The estimates for each year are based on the previous year's population estimates for the state; Fig. 1 **(b).** Average yearly child maltreatment substantiation rates per 1000 children; Fig. 1 **(c).** Standardized Incidence Ratios (SIRs) of child maltreatment rates. SIRs are observed counts divided by expected counts. Expected counts represent the total number of cases that are expected in each census tract if the census tract "behaved" like the state. In the figure, the areas shaded white represent census tracts with SIRs that have expected counts similar to the state, whereas areas shaded red and blue represent census tracts with expected counts that are higher (SIR > 1) and lower (SIR < 1) than the state, respectively.

deviations from normality and several predictive measures were used to validate and compare models and to identify possible outliers. These measures include identifying unusually large or small cross-validated log score values of conditional predictive ordinates (CPO) and assessing whether the probability of integral transform (PIT) values follow a uniform distribution. The assumption of uniformity was tested using the goftest package in the R programming environment. A Gaussian prior with mean 0 and variance 1000 was used as the hyperparameter for the fixed effects and an inverse gamma prior with shape 1 and inverse scale $5 \times 10 - 5$ was used for the variance components. The Bayesian spatiotemporal analysis was conducted using the INLA (Integrated Nestes Laplace Approximation) package (DiMaggio, 2015; Rue, Martino, & Chopin, 2009; Ruiz-Cárdenas, Krainski, & Rue, 2012), also available in R. The replication code and data are provided in the Data in Brief that accompanies this manuscript.

7. Results

Total child maltreatment substantiations. A total of 97,250 children were substantiated for maltreatment in New Mexico between 2007–2015, an average rate of 23.34 substantiations per 1000 children 0–17 per year (see Table 1). Table 1 lists the descriptive statistics for the variables considered in this study along with the source of the data. Fig. 1a shows the smoothed trend in the average yearly substantiated maltreatment rate per 1000 children under 18. As shown by the figure, the average yearly substantiation rate was fairly stable between 2007 and 2010 but increased substantially between 2010 – 2015. Over the study period, the rate of substantiated child maltreatment increased by 128.83 %, from 16.14 per 1,000 in 2007 to 36.94 per 1,000 in 2015. Fig. 1b shows the spatial distribution of substantiated child maltreatment rates by census tract and Fig. 1c shows the smoothed standardized incidence ratios. The maps reveal that substantiated maltreatment rates and SIRs are highest in the central and western parts of the state. In Fig. 1c, the areas shaded white represent census tracts with SIRs that have expected counts similar to the state, whereas areas shaded red and blue represent census tracts with expected counts that are higher (SIR > 1) and lower (SIR < 1) than the state, respectively.

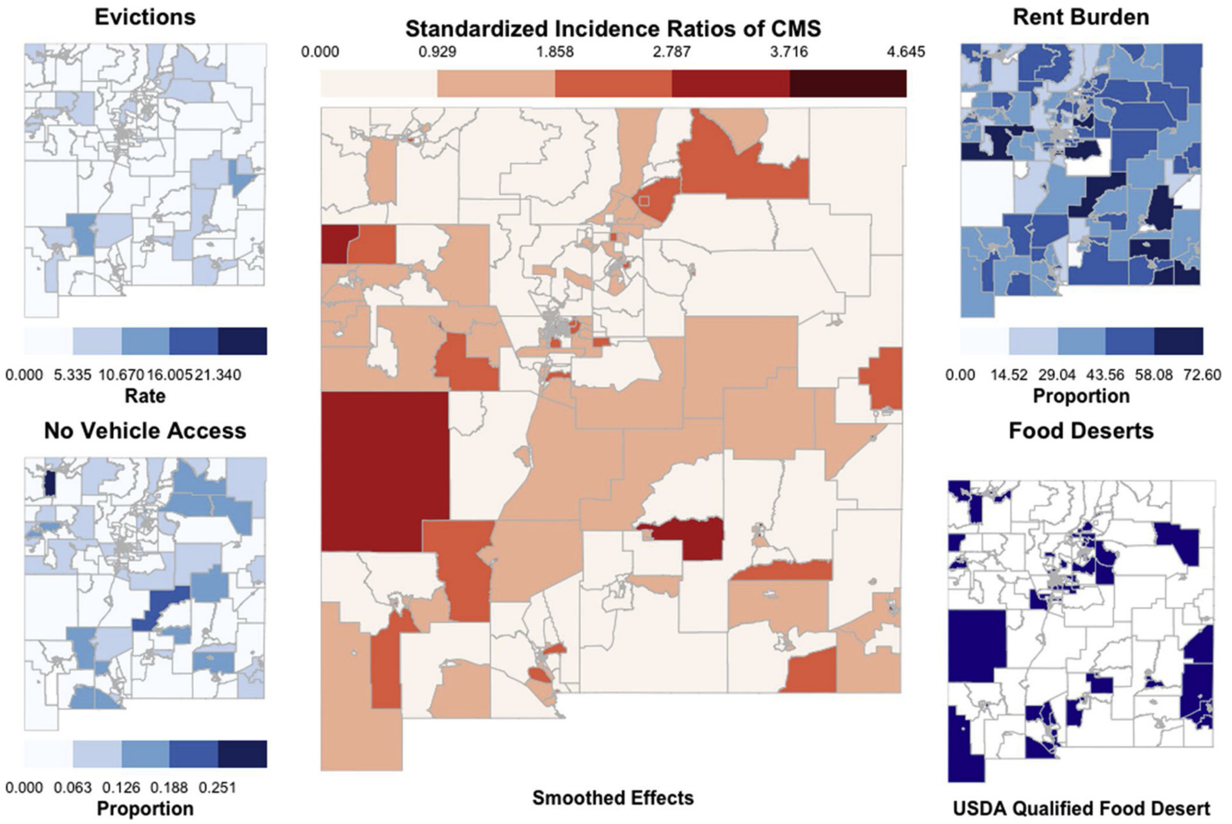

Fig. 2. Map of Housing Insecurity along with Standardized Incidence Ratios of Substantiated Child Maltreatment in New Mexico. Note: CMS = Child Maltreatment Substantiations.

An analysis of the distribution of SIRs revealed a shift in the distribution over time whereby several census tracts with SIRs < 1 in 2007 had SIRs > 1 by 2015. More specifically, a count of census tracts revealed that between 2007 and 2015 the number of census tracts with SIRs > = 1 increased by 10 (from 192 to 202) and the number of census tracts with SIRs > = 2 increased by 11 (from 62 to 73). However, no more than 25 census tracts had SIRs > = 3 at any time period under consideration. Fig. 2 shows the spatial distribution of key variables (i.e. the eviction rate, percent no vehicle access, rent burden and food deserts) in conjunction with the spatial distribution of SIRs of child maltreatment over the period. The map demonstrates substantial overlap between areas of housing, household and food insecurity and substantiated maltreatment risk.

Spatially Unstructured Effects. A simple random effects model (i.e. frailty model) was computed in order to assess the individual area level of risk and to have a baseline to compare with other models (DiMaggio, 2015). The spatially unstructured random effect term captures the random variation around the intercept (DiMaggio, 2015). In this model, the fixed effect, or intercept, revealed an exponentiated mean of 0.692 with a standard deviation of 1.05 (95 % CrI 0.643, .755). This translates into an average increase in child maltreatment of approximately 31 % for each census tract over the study period, or a yearly increase of 3.85 %. Moran's I was used to test for spatial autocorrelation in the data and to identify census tracts with high or low values of substantiated child maltreatment rates. Moran's I indicated the presence of significant residual spatial autocorrelation and clustering (I = .481, < .001). Therefore, subsequent models included a conditionally autoregressive (CAR) term to account for the spatial correlation in the data.

Spatially Structured Effects. The convolution model adds a spatially structured conditional autoregressive term to the baseline frailty model. Table 2, which presents the model fit statistics, shows the improvement in fit of the convolution model over the baseline model once the spatial structure is accounted for (DIC = 4284.01; WAIC = 4181.92; Log Score = 5.21). The spatially structured conditional autoregression term explained 56.7 % of the total heterogeneity in child maltreatment substantiations.

Five additional spatio-temporal models were assessed to explore improvements in model fit through the addition of temporal and spatio-temporal correlations as well as the covariates listed in Table 1. As shown by Table 2, the convolution model with a first-order random walk correlated time variable, an uncorrelated time variable, and a space-time interaction term was the best fitting model. The variables listed in Table 1 were incorporated into the modeling scheme in a stepwise fashion. The final model included variables measuring the eviction rate, rent burden, low income tract, median family income, food desert, diversity index, urbanicity, percent disability status, percent no vehicle access and percent receiving SNAP benefits.

Fixed Effects. With the inclusion of covariates and the space-time interaction, the intercept is interpreted as the average census tract relative risk on the log scale adjusted for covariates, random and spatiotemporal effects (DiMaggio, 2015). The exponentiated coefficients for the explanatory covariates are interpreted as incidence density ratios. The results showed that holding all other

Table 2
. Model Selection Criteria Statistics.

	Model	DIC	WAIC	Log score	Brier score	PIT p-value
Space	Frailty	4307.45	4211.10	5.313881	71803.11	< .001
	Convolution	4284.01	4181.91	5.210539	71803.14	< .001
Space-Time	Convolution + uncorrelated time	46566.77	49764.77	5.553029	1112.501	< .001
	Convolution + First order random walk	46562.89	49760.16	5.552743	1112.494	< .001
	Convolution + First order random walk + iid time	46565.28	49774.18	5.554333	1112.494	< .001
Space-Time Interaction	convolution +1 st order random walk correlated time (time RW1) + space-time interaction term (Type I)	26571.65	26122.58	3.712874	1098.014	< .001
	convolution +1 st order random walk correlated time (time RW1) + space-time interaction term (Type I) + uncorrelated time	26569.73	26110.83	3.708329	1097.994	< .001
	convolution +1 st order random walk correlated time (time RW1) + space-time interaction term (Type I) + uncorrelated time + COVARIATES	26562.90	26102.05	3.708849	1178.362	.01

Notes: DIC = Deviance Information Criterion; WAIC = Watanabe-Akaike Information Criterion; PIT = probability of integral transform. In all cases lower numbers represent a better fit to the data.

covariates to zero and adjusting for both random and spatial variation and the interaction between space and time, every one unit increase in the eviction rate increased the risk of child abuse and neglect by 8.7 % (Incidence Density Ratio [IDR] = 1.088 [95 % CrI = 1.01–1.112] and a one standard deviation increase in the eviction rate (see Table 1) increased the relative risk of maltreatment by 27.2 %. The relative risk of maltreatment in urban tracts was 36.3 % higher compared to rural tracts ([IDR] = 1.363 [95 % CrI = 1.051–1.766]). As well, substantiated maltreatment risk was 27.4 % and 21.1 % higher in low income tracts ([IDR] = 1.274 [95 % CrI = 1.090–1.488]) and tracts designated as food deserts ([IDR] = 1.211 [95 % CrI = 1.039–1.410]). As the percentage of households with no vehicle access ([IDR] = 1.27 [95 % CrI = .247–6.47]) and persons with a disability in each tract increased ([IDR] = 1.046 [95 % CrI = 1.031–1.061]) so too did the relative risk of child maltreatment. On the other hand, every standard deviation increase in the diversity index was associated with a 22.4 % decrease in child maltreatment allegation risk (([IDR] = .988 [95 % CrI = .982–.995])). Fig. 3 shows the posterior distributions of the covariate coefficients. In Fig. 3, the red lines represent the benchmark whereby the variables are unrelated. Estimates of the posterior distributions were created by spline smoothing the marginal distributions of the coefficient using the function inla.smarginal which were then plotted in R (Wickham & Chang, 2016). After controlling for space, time and the covariates, 49 tracts had a relative risk greater than 2 with posterior probability > = .90, a 65.5 % decrease from the frailty model.

Space-Time Trends. Fig. 4 maps the posterior estimates of the census tract area relative risk of substantiated child maltreatment from the "winning" model for years 2007, 2010 and 2015. These maps reflect the temporal increase in risk over time; and, by comparing the maps it is evident that the relative risk increased substantially in the central portions of the state. Fig. 5a shows the

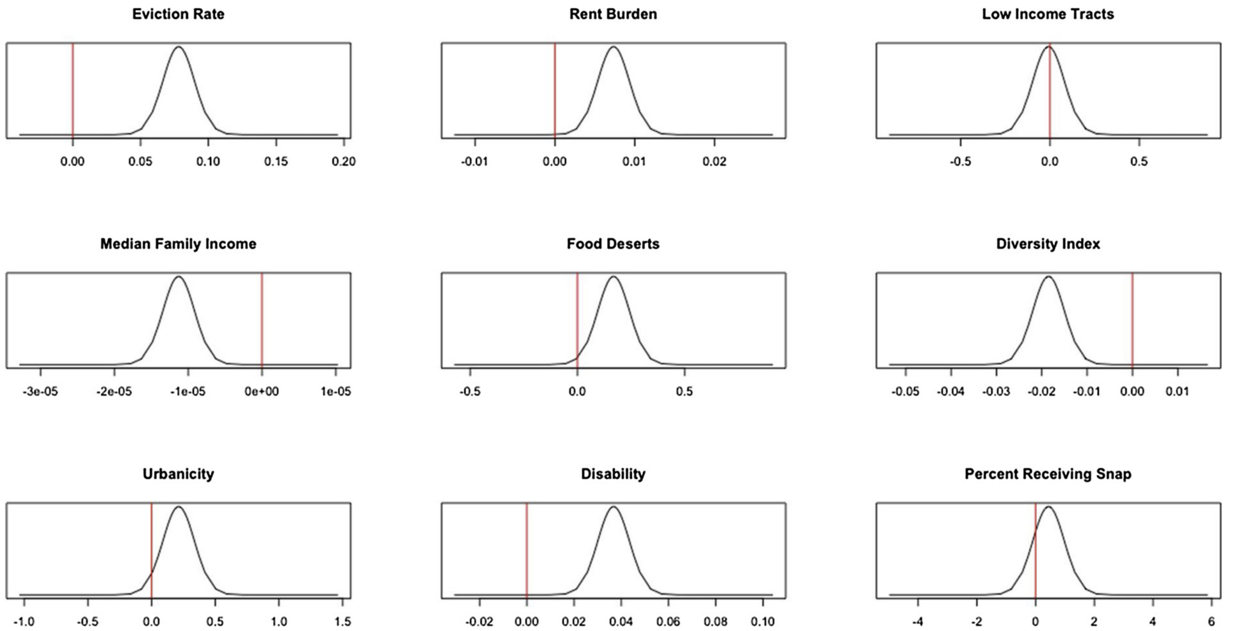

Fig. 3. Posterior distributions of the fixed effects from the convolution model plus structured (i.e. a first order random walk) and unstructured (i.e. time *i.i.d.*) time. Red lines at zero suggest no association between substantiated child maltreatment risk and covariate.

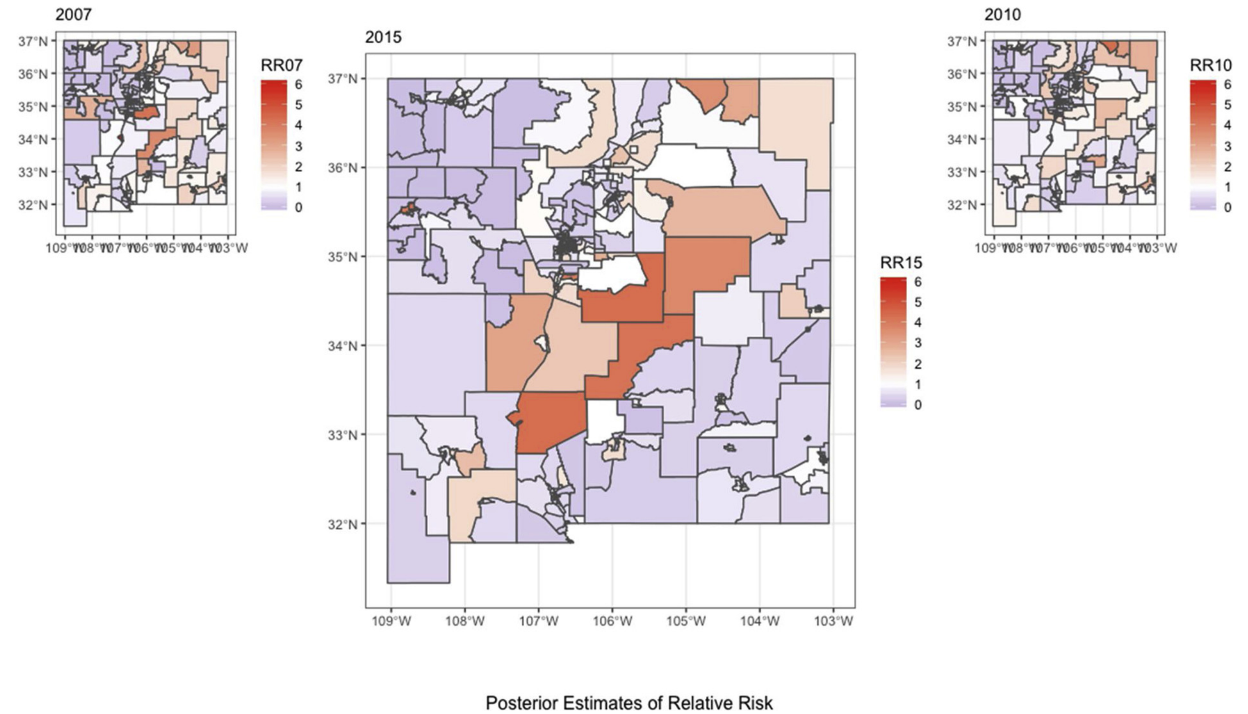

Fig. 4. Posterior Estimates of the census tract specific relative risk (RR) for 2007 (left), 2010 (right) and 2015 (center) controlling for spatiotemporal effects and covariates.

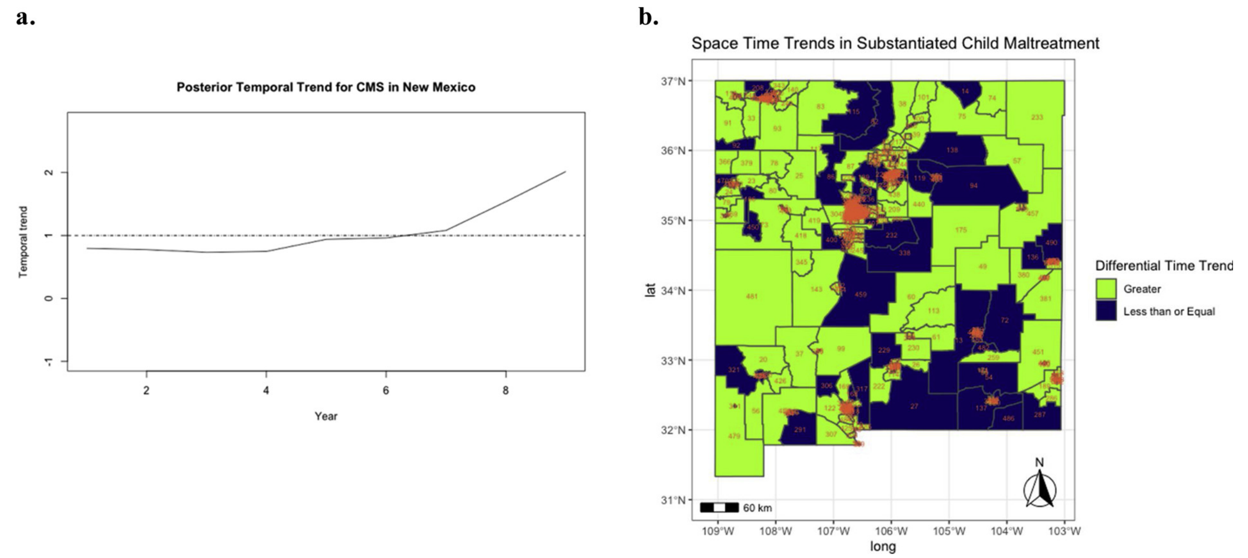

Fig. 5. (a) Posterior temporal trend for substantiated maltreatment risk for the 9 years (1 (= 2007) to 9 (= 2015) on the x-axis). **(b)** Census tracts with positive and negative differential time trends with slopes more, or less, steep than the global time trend β.

posterior temporal trend of child maltreatment substantiations in New Mexico. The structured temporal effect (rw1) demonstrates an increasing trend across the time period whereas the unstructured temporal effect hovered near 1. Since the two are additive, this suggests that the structured time component contributes more to the risk estimate. Fig. 5b displays the temporal evolution of the posterior mean of the interaction between space and time mapped to each census tract. As shown by the figure, some census tracts exhibit differential trends characterized by slopes that are more, or less, steep (or no different) from the state's average trend, respectively. A mean difference test was used to compare census tracts with decreasing/no trends and increasing trends. The result showed that census tracts with a positive (increasing) differential time trend were more likely to be urban (d = .340, p < .036), designated as a food desert (d = .213, p = .004) and have higher eviction rates (d = 1.89, p < .001).

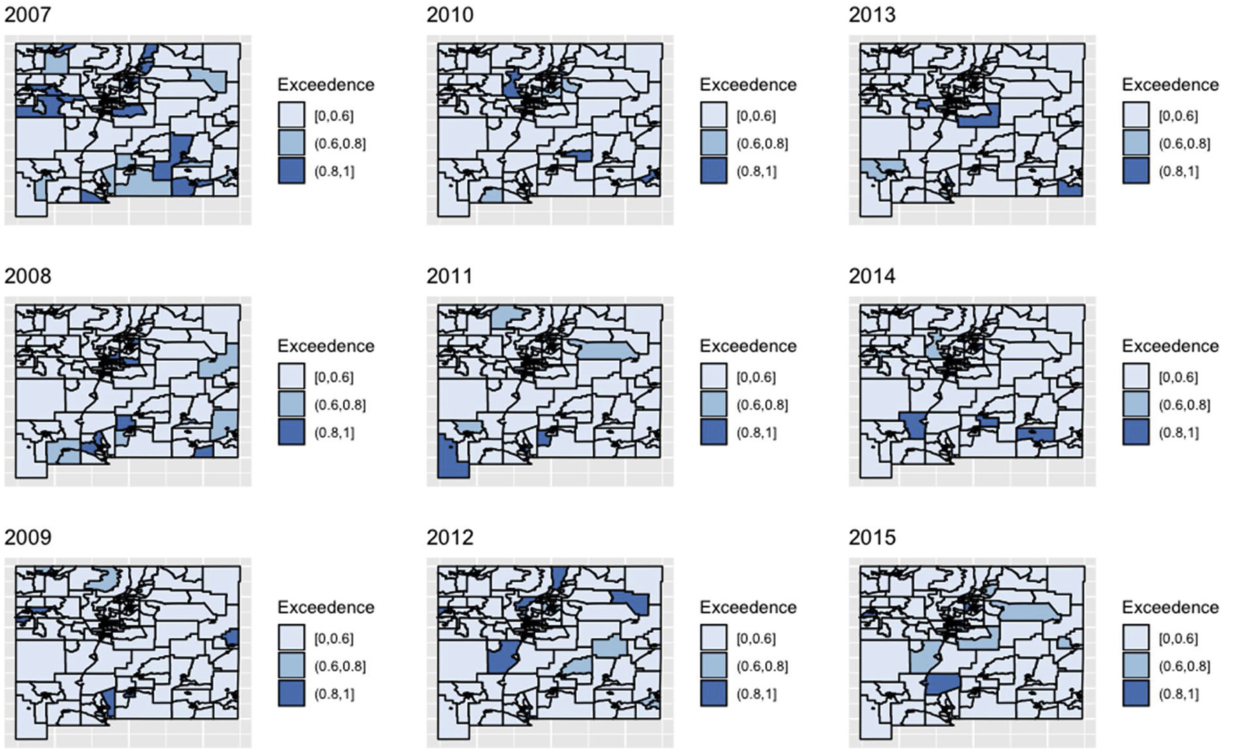

Fig. 6. Space-time interaction effect of child maltreatment relative risk for census tract and year $exp(\delta_{it})$ controlling for space, time and covariate effects.

The space-time interaction is a random effects term added to the linear model and is interpreted as the residual effect after the unstructured, spatially structured and time effects are controlled. The map of exceedances probabilities for the space–time interaction term is presented in Fig. 6 for each year. As shown by the figure, a small number of areas characterized by a high probability (> 0.8) of having a relative risk that is about twice that of the state of New Mexico are apparent even after controlling for multiple covariates, the unstructured, spatially structured effects, and the structured and unstructured time trend. These areas represent sporadic, short-term clusters of substantiated child maltreatment in the state of New Mexico across the period.

8. Discussion

This study contributes to the small but growing literature that uses spatiotemporal models to explore the small area relative risk of child maltreatment (Morris et al., 2019) in New Mexico where the rate of child abuse and neglect is twice the national average. Previous studies using Bayesian space-time models have found that areas with similar risks of substantiated maltreatment are clustered near each other and are associated with poverty, crime and social disorder, unemployment rates and immigration (Gracia et al., 2017; Morris et al., 2019). The present study makes two major contributions to the present literature. First, using a novel data set that merged multiple indicators of social and housing disadvantage, this study showed that housing and food insecurity is associated with distinct cross-sectional and longitudinal patterns of child maltreatment risk. Second, this paper demonstrates the utility of using a spatiotemporal analysis for identifying areas of high-risk at a finer level of geographic detail than previous studies that aggregate counts over larger geographic units (e.g. counties or zip codes). The identification of risk can help public health initiatives implement more focused and targeted interventions.

The analysis showed that child maltreatment substantiation rates increased significantly from 2010 to 2015. The average yearly rate of substantiated maltreatment was 23.34 per 1000 children during the period spanning 2007 – 2015. Throughout the period, the rate of maltreatment increased by almost 129 %, from 16.4 per 1000 children in 2007 to 36.94 per 1000 children in 2015. Each census tract had a 31 % increase in substantiated child maltreatment risk across the 9-year period, on average, a yearly rate of increase of 3.85 %. This increase may be attributed to changes in requirements made during the period which facilitated the reporting and identification of suspected child abuse and/or neglect. According to a recent report issued by the New Mexico Children, Youth and Families Department (New Mexico Department of Children et al., 2015), between 2009–2015, the number of referrals made for suspected child maltreatment did increase by 23 %, from 31,243 to 38,624. This increase, however, does not fully explain the magnitude of the change from 2010 to 2015 that was observed in the present study. Moreover, the ratio of cases that were screened-in compared to the ratio of cases that were screened-out showed little fluctuation over the period (47.4 % were screened in in 2009 compared to 52.3 % in 2015; NMCYFD, 2015). Whereas observed increases in abuse and neglect may be partly attributed to factors making reporting easier, the data strongly suggests that other factors are also at play. It is more likely that the global increase is due to state-wide policies that were (or were not) in effect during this time period.

Although the global temporal trend demonstrated that substantiated maltreatment increased significantly across the state, some areas demonstrated slopes that were steeper than the global trend. Mean differences suggested that census tracts with slopes that were steeper than the global trend were more likely to be characterized as urban, as a food deserts, and had higher eviction rates compared to census tracts characterized by time trends that were less steep. The association with urbanicity, low food access and housing insecurity signifies the importance of these factors for explaining the increasing trend in child maltreatment in some areas over time. The observed relationships between urbanicity, food deserts, eviction rates and child maltreatment suggests that programs that focuses narrowly on the role of neighborhood poverty as an explanation for child maltreatment may overlook more important modifiable risk factors necessary for prevention (Barboza, 2019b). Instead, public health initiatives should focus on addressing the symptoms of poverty that place children at risk, such as housing and food insecurity, rather than poverty per se, in order to reduce the risk of child maltreatment.

As with other studies before this one, the present study found that as median family income increases, risk of child maltreatment decreases (Coulton, Korbin, & Su, 1999; Coulton, Korbin, Su, & Chow, 1995; Deccio et al., 1994; Garbarino & Crouter, 1978; Korbin et al., 1998), suggesting that income continues to be an important risk factor for child maltreatment above and beyond housing and food insecurity. However, multiple measures of housing insecurity contributed uniquely to maltreatment risk over and above measures of poverty and income. Census tracts with higher levels of food and housing insecurity, including the percent of rent burdened households, the eviction rate and whether the census tract was identified by the USDA as a food desert, were associated with a higher risk for child maltreatment. Noteworthy is the fact that the term ‘physical neglect’ in New Mexico, as elsewhere, is defined as the failure of a parent to provide adequate food and shelter for their child, meaning that families who are food and housing insecure are, by definition, neglectful. According to official records, almost 3 in 4 substantiated reports of maltreatment in New Mexico are attributed to “physical neglect” in New Mexico (New Mexico Department of Children, Youth and Families, 2019). Not surprisingly, 72 % of mothers and 47 % of fathers who were investigated for abuse in 2015 were either homeless or inadequately housed (New Mexico Appleseed, 2018). One explanation for the disproportionate involvement of housing insecure families in child protective services focuses on poor families’ increased visibility among service providers due to their involvement with housing programs or homeless shelters (Park, Metraux, Culhane, & Mandell, 2012).

Housing and food insecurity may also be indirectly associated with child maltreatment by increasing parents’ stress and depleting their emotional and/or financial resources. For example, families who are evicted tend to be struggling financially and families who are rent burdened, regardless of income, have little income left for food costs, medical care and transportation needs. This is consistent with a study conducted by Warren and Font (2015), who found that lack of affordable housing and housing instability, defined as frequent moves, evictions and homelessness, were both indirectly liked to child abuse risk through maternal stress. However, they further found evidence of housing insecurity’s potential role as an indicator of other material hardships. As well, studies have shown that drug users are disproportionately represented among the unstably housed and that residential evictions can impact mental and physical health outcomes in ways distinguishable from housing instability (Collins et al., 2018). According to federal data, 63 % of abuse and neglect victims have a caregiver with a substance abuse issue, 43 % points higher than the national average. Finally, previous research has shown that housing/transportation vulnerability increases the likelihood of child maltreatment through the unequitable distribution of community-based resources. The benefits associated with targeting resources to areas defined as child maltreatment hotspots is reinforced by Shenoi et al. (2013), who found that while the distribution of community health centers (including community clinics, WIC and Head Start centers) were concentrated in low-income neighborhoods, only 11 % were located in the 12 high-risk hot spot areas for fatal child maltreatment and some hot spot areas had no community health centers located within their block group.

Funds from existing federal programs could help alleviate the multiple public health problems associated with child maltreatment in New Mexico and states with similar housing issues. One existing program that would target resources to areas in need is the Capital Magnet Fund (CMF) Project. The CMF project offers federal grants to finance affordable housing solutions and community revitalization efforts that benefit low income families spending over half of their paychecks on rent (Capital Magnet Fund, 2020). According to the Community Development Financial Institutions (CDFI) fund, a division of the US Department of the Treasury which administers the CMF, applicants are scored more favorably if they are located in a census tract defined by high housing need, meaning it meets one of the following criteria: 1) at least 20 percent of households are ‘very low-income’ renters paying more than half their income for rent; 2) greater than 20 percent of households have incomes below the poverty rate with a rental vacancy rate of at least 10 percent; or 3) it qualifies as an underserved rural area. Table 3 shows the top 10 census tracts with the highest substantiated maltreatment rates, along with data on whether the census tract is CMF eligible and whether the census tract qualifies as a food desert. As shown by the table, all 10 census tracts with the highest levels of substantiated child maltreatment qualify as either a CMF ‘high housing needs’ area or as a USDA food desert. Notably, not one CMF project has been funded in the state of New Mexico (PolicyMap, 2020). The results of this study suggest that the CMF programs and others like it will greatly alleviate housing and food insecurity in areas with the greatest risk of child maltreatment.

The present study’s results showed that child maltreatment risk decreases with increasing levels of racial/ethnic diversity indicating as well that substantiated child maltreatment risk is higher in racially segregated areas. Similarly, in a study using Bayesian spatio-temporal models of child maltreatment risk, Barboza (2019a) found that child maltreatment risk was greater in highly segregated neighborhoods. However, this study further found that racial homogeneity offered a degree of protection against risk of substantiated maltreatment in areas characterized by socioeconomic vulnerability. According to Barboza (2019a), the moderating role of racial heterogeneity found in high-vulnerability areas may be due to different forms of informal social control that are

Table 3

Census tracts with the highest rates of substantiated child maltreatment, Capital Magnet Fund qualified tracts and tracts designated a food deserts.

Census Tract	County	Child Maltreatment Rate	Metropolitan Status	At least 20 % of households are 'very Low-Income renters' are paying more than half their income for rent	More than 20 % of households have incomes below the poverty rate and is there a rental vacancy rate of at least 10 %	Tract is in an Underserved Rural Areas	The Census Tract a CMF Area of High Housing Need?	Is the Census Tract a HUD food desert?
35037958602	Quay	95.87021	Non-metro	No	Yes	Yes	Yes	Yes
35061970901	Valencia	95.87021	Metro	No	No	No	No	Yes
35007950600	Colfax	86.89249	Non-metro	No	No	Yes	Yes	No
35009000400	Curry	81.68220	Non-metro	No	Yes	Yes	Yes	Yes
35047957300	San Miguel	72.59097	Non-metro	No	No	Yes	Yes	Yes
35061970800	Valencia	72.31600	Metro	No	Yes	No	Yes	Yes
35037958601	Quay	72.29463	Non-metro	No	No	Yes	Yes	Yes
35007950500	Colfax	70.35702	Non-metro	No	Yes	Yes	Yes	Yes
35001000903	Bernalillo	64.36042	Metro	Yes	Yes	No	Yes	Yes
35013000600	Dona Ana	63.17044	Metro	Yes	No	No	Yes	Yes

Source: Child Maltreatment rates were provided by the New Mexico Department of Public Health. Metropolitan status and housing needs data were provided by the Community Development Financial Institutions (CDFI) Fund, US Department of the Treasury (https://www.cdfifund.gov/programs-training/Programs/cmf/Pages/apply-step.aspx). These data are available for download at http://www.policymap.com. Food Desert data was provided by the U.S. Department of Agriculture and is available for download at http://www.usda.gov.

conditioned by race. In other words, in highly vulnerable neighborhoods, consensus around shared norms of child rearing practices may be conditioned by race to a greater degree than they are in less socially vulnerable neighborhoods. The present research did not explore a possible interaction between race and socioeconomic status in New Mexico, so this important question is left as a direction of future research.

Despite the novelty of this study, it is not without limitations. The reliance on administrative data might lead to biased estimates since child welfare involvement has been shown to be higher in neighborhoods with higher poverty rates (Coulton et al., 2007). As well, this was an ecological study and as such it was not possible to evaluate the role of individual- or family- level factors which are critical for understanding child abuse and neglect in context. These factors should be incorporated into future studies and include such things as parental socioeconomic status, family structure and race and age of the child. In addition, census tracts, while considered a good proxy for neighborhood boundaries, may be imperfect definitions of neighborhoods. A number of studies suggest important differences exist according to the type of child maltreatment, however the present study was unable to disaggregate child maltreatment risk accordingly. Finally, although this was a longitudinal study, no claims of causation are possible and the results are generalizable only to the state of New Mexico and similar states.

Despite its limitations, this study is an important part of a growing body of research examining multiple indicators of neighborhood structural vulnerability and its relationship to child welfare. Serious efforts to prevent child abuse and neglect should consider the multiple overlapping social-structural inequities that produce the observable spatial heterogeneity (i.e. the unequal distribution over space) in child maltreatment risk. The present study points to the importance of acknowledging the multiple interacting *neighborhood* (as opposed to individual) factors that interfere with a parent's ability to ensure the welfare of their children and suggests that positive outcomes for children are conditional on the structural determinants of neighborhoods that shape parenting choices, particularly in low-income, racially homogenous communities characterized by housing and food insecurity. Future research should continue to examine the important role that housing and food insecurity particularly in light of determinations of how physical neglect is defined in low income, racially segregated, communities.

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