# Examining Extreme Weather Effects on Birth Weight From the Individual Effect to Spatiotemporal Aggregation Effects

Ge LIN and Tonglin ZHANG

Extreme weather events are related to low birth weight. Monitoring this relationship in the context of climate change has a wide range of public health implications, as birth weight is a key indicator of many life course health outcomes, and climate change increases both frequency and intensity of extreme weather events. However, most birth weight data are not available with sufficient spatial and temporal resolution. The current study examined the relationship between birth weight and weather variables in a series of aggregations, from individual birth outcomes to month-county, season-county, and county-only mean birth weights. Data were based on a 20 % sample of White mothers aged 19 to 38 from the United States Natality Data Files, and the baseline model was for the 1974–1978 and 1984–1988 periods with 2,269,009 and 2,652,552 individual birth records, respectively. The evaluation was based on multiple regression for aggregation effects, and conditional autoregressive and spatial association models for spatial clustering effects. The results show that the number of extreme cold and hot days during the birth month is inversely associated with birth weight, and that temporal aggregation by month-county or season-county was likely to preserve the relationship between birth weight and extreme weather from the individual model. While both conditional autoregressive and spatial association models can remove some spatial autocorrelation, the spatial association approach may not work effectively without further modifying the existing method.

**Key Words:** Ambient temperature; Birth weight; Extreme temperature days; Moran's $I$; Spatial clusters; Weather.

## 1. INTRODUCTION

Data for individual health outcomes are increasingly restricted due to confidentiality concerns. If aggregated data could be used without going through requesting, collecting,

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*Journal of Agricultural, Biological, and Environmental Statistics, Volume 17, Number 3, Pages 490–507*
*DOI: 10.1007/s13253-012-0102-1*

and processing individual data, the efficiency of disease surveillance and the availability of published data for research would be enhanced significantly (diez Roux 2004). Birth weight is a key indicator for health outcome surveillance, and aggregated birth weight data are widely available in the United States, but individual birth weight data that cover large geographic areas are available for only a small number of metropolitan counties. For the current study, we obtained early years of individual birth weight data coded at the county level for the continental United States. We examined the influence of data aggregation on estimates of trends for climate variables and associated birth weight variables. Ultimately, we hope to assess how aggregated data might be used for monitoring the effect of climate change on human health outcomes, but here, we restricted the outcome variable to birth weight.

The influence of ambient temperature on birth weight has been extensively studied. Ambient temperature extremes can cause biological and physiological stresses for pregnant women, and inhibit fatal growth and gestation (Behrman and Butler 2007; Flouris et al. 2009; Wells and Cole 2002). In a recent review, Strand, Barnett, and Tong (2011) listed four potential reasons for why low-birth weight and preterm births are like to be associated with changes in temperature. Supporting evidence was found in many places worldwide (Flouris et al. 2009; Murray et al. 2000; Strand, Barnett, and Tong 2012; Yackerson, Piura, and Sheiner 2008), but most notably in Japan, where preterm births peaked both in summer and winter with the winter peak dominant in the north, and the summer peak in the South (Matsuda and Kahyo 1990). In addition, many other related diseases, such as sudden infant death syndrome (Campbell 1994), cardiovascular disease (Barnett et al. 2005), and infection disease (Fisman 2007), are all associated with geographic regions, and changes in ambient temperature, suggesting that weather affects people through different biological mechanisms in different regions and different seasons.

Since climate change will increase the intensity and frequency of extreme weather (Alley et al. 2003; Meehl et al. 2000), it is likely to adversely affect birth outcomes. Monitoring the effects of temperature or weather extremes on health is critical for public health preparedness for climate change. However, due to confidentiality concerns, individual data are unlikely to be released at the county level in the foreseeable future. Therefore, it is necessary to assess whether aggregated data can be used effectively to monitor health outcomes.

Furthermore, even when individual data are available, data processing time and computational resource needs often limit their use for timely health outcome surveillance. For example, hourly weather data are widely available, but processing hourly weather data for more than 3000 counties in the United States is daunting. These limitations are especially true for health studies related to climate change, because climate variations must be observed over a long period of time and across a wide geographic area. Spatial statisticians interested in climate change and human health want to know whether existing aggregated data analysis of health outcomes produces results that are consistent with individual data analysis. In the current study, we compared the relationship between date- and county-specific individual birth and extreme weather to the relationship between aggregated (1) month-county data, (2) season-county data, and (3) county-only data and climate variations. A previous study used daily temperature data (Deschénes, Greenston, and

Guryan 2009), and found that extreme hot weather negatively affected birth weight, and the authors attributed the effect to *in utero* exposure primarily during the third trimester. Based on this finding, Lin and Feng (2011) found that aggregated monthly temperature and extreme weather frequency data are sufficient to capture the essential finding of Deschénes, Greenston, and Guryan (2009). Therefore, for the current study, we used individual birth data and monthly weather data.

Previous studies have examined data aggregation effects. Econometricians and epidemiologists have assessed individual data aggregation effects in terms of data smoothing and loss in efficiency (Lang and Gottschalk 1996). They suggest that ecological covariates often play important roles in various grouping effects. Theoretically, results from a linear regression model based on individual data can be captured at an aggregated level if all ecological covariates can sufficiently explain individual variation at the given aggregation level. In contrast to the individual aggregation problem, spatial aggregation studied by geographers often ranges from small area units, such as census tracts, to large area units, such as county or city, resulting in the so-called multiple area unit problem or MAUP (Fotheringham and Wong 1991). The MAUP suggests that results from one level of aggregation often cannot be replicated at another level, perhaps due to lack of corresponding covariates. In the current study, we extend these previous studies by examining both individual-to-spatial temporal aggregation and spatial temporal-to-pure spatial unit aggregation.

When data are aggregated from individual to some area units, the association between the original relationship and the aggregated relationship may have an inconsistent directional effect. This phenomenon is labeled ecological fallacy in epidemiology due to Robinson (1950), which is also known as the Simpson Paradox (Simpson 1951). This effect comes from the disparate relationship between an individual and an aggregated correlation. Individual association is from each individual outcome, while aggregated association is from mean or other aggregated outcomes. In the case of birth weight and weather, the individual relationship is between individual birth weight and extreme weather; the aggregated relationship (e.g., from individual to small area units) is between the overall mean effects of areal unit birth weight and a mean extreme weather measure.

Our task is to identify an aggregation point at which we can reasonably preserve individual effects while using aggregated data. We investigate the relationship between birth weight and extreme weather using multivariate analysis for individuals, and using ecological analysis for a group of individuals. In addition, we also used spatial cluster modeling as an additional method to capture spatial variation that cannot be explained by an ecological model. The rest of this article is organized as follows. In Section 2, we introduce data, data processing procedures, and statistical models. In Section 3, we present the results. In Section 4, we discuss findings and provide the conclusion.

# 2. METHOD

## 2.1. Data and Data Processing

*Birth Data* We obtained Natality Data Files (NDFs) for 1969 to 1988 from the U.S. Centers for Disease Control and Prevention (CDC). This data set has wide geographical coverage and relatively rich information about women who gave birth. The U.S. NDFs were formally launched in 1968. States were required to submit individual birth certificate data to the CDC. The CDC made the data for 1968 to 1988 publicly available, with geographic resolution at the county level. We processed annual birth data for each year for 50 states and the District of Columbia and combined the data into a single file with 56.5 million birth records. The CDC also released individual birth records after 1988, but only those counties with a population greater than 100,000 can be identified.

From 1969 to 1973, states submitted different sample sizes to the NDFs, with little consistency. Therefore, we compared data from 1974 to 1978 to data from 1984 to 1988. We used the early period to capture extreme weather effects at a time when most people had relatively few mitigation options, and the later period to capture extreme weather effects at a time when central air conditioners had become more widely available (Lin et al. 2007).

We restricted our samples to 48 continental states and the District of Columbia in United States, and created a 20 % random sample file. We also restricted the sample to White or Caucasian mothers to eliminate race as a potential confounder. We also excluded women younger than 19 years or older than 38 years, so that the sample follows a nice normal distribution without having to control age groups in aggregation. In the preliminary analysis, we attempted to exclude twins or multiple births. However, we eventually decided to include all births because (1) not all states in the early period had a singleton birth indicator, and (2) among 2 % multiple births in the 1984–1988 period, 50 % of them had low birth weight (or <2500 g) which were distributed almost evenly across states and geographic regions. We opted to provide some evidence in the result section to show the consistency.

*Weather Data* We used the National Climatic Data Center Summary of the Day Data (File TD-3200) and associated the population center point for each county with weather variables at each county location. Since most station data for those years did not include humidity, we used various combinations of temperature variables. First, we created all the variables used in (Deschénes, Greenston, and Guryan 2009) which included county's daily averages temperature in the following bins: <25 °F, 25–45 °F, 45–65 °F, 65–85 °F, or >85 °F. We then added additional extreme weather variables, such as daily maximum >90 °F, >95 °F or a daily minimum <20 °F (see Lin et al. 2007 for some justifications of temperature variables). In order to control for acclimation effects (becoming accustomed to a warm or cold climate), we also included the average annual temperature from 1960 to 1969 in each county. Figure 1 shows numbers of days with minimum temperature <20 °F (Figure 1a) and maximum temperature >90 °F (Figure 1b). In a preliminary analysis, we used previous month as exposure, and the results were not as strong as the current months in terms of the goodness of fit statistics.

*Other County Level Data* We attempted to control some of the known factors. Since the birth certificates did not include data on birth mother or family income, we used county per capita income in each year from the U.S. census as a control variable. We also included the average elevation of a county as it showed a negative effect on birth weight (Jensen and Moore 1997). In particular, we created two variables: one was an indicator variable contrasting the average elevation either above or below 1500 meters, and the other was

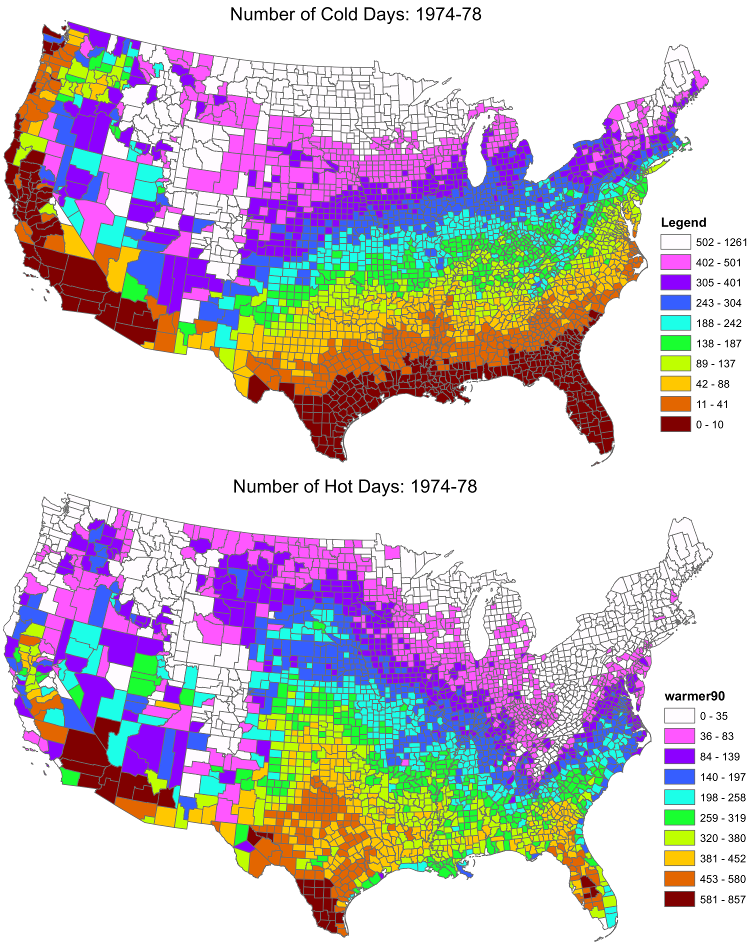


Figure 1. Extreme cold (<20 °F) or hot (>90 °F) days: 1974–1978.

simply the average elevation. Both variables were derived from the National Elevation Data in grid from the U.S. Geological Survey (Lin et al. 2007).

After linking birth data to county-level weather data, we found that Key West, Florida, had few weather records, and we subsequently excluded this county. We also excluded some independent cities in Virginia that were either split or combined during the 1970s, because of lack of corresponding county socioeconomic data. After completely linking weather data and county income data with individual birth records, we had 2,260,009 and 2,652,552 records in 1974–1978 and 1984–1988, respectively. Since all the data were obtained from our previous studies, we intend to make them available upon the publication of this paper.

## 2.2. Study Design

Due to the emphasis on evaluating aggregation effects, we attempted to use as parsimonious as possible for the baseline relationship between extreme weather and birth weight.

We replicated the previous study (Deschénes, Greenston, and Guryan 2009) by using the same regression framework. We found that the number of days with extreme weather, measured as either >85 °F average or >90 °F daily maximum were significantly related to lower birth weight, with the latter being more significant. For this reason, we used daily maximum and daily minimum temperature measures. Since income data had only 3100 data points each year, we decided to fit a random effect multilevel model.

Let $Y_i$ be $i$th individual birth weight, $k(i)$ be its county index, $L_i$ be the number of days in the birth month with a minimum temperature less than 20 °F, $H_i$ be the number of days in the birth month with a maximum temperature higher than 90 °F, $T_{k(i)}$ be the county-level annual average temperature in the birth year, $E_{k(i)}$ be the indicator of county-level average elevation greater than 1500 meters, and $P_{k(i)}$ be the county-level per capita income in the birth year. Then, we can fit a multilevel model as:

$$Y_i = \beta_0 + \beta_1 L_i + \beta_2 H_i + \beta_3 T_{k(i)} + \beta_4 E_{k(i)} + \beta_5 P_{k(i)} + V_{k(i)} + \epsilon_i, \tag{2.1}$$

where $V_{k(i)}$ is the county-level unstructured random effect and $\epsilon_i$ is the individual-level random error. We assume $V_{k(i)} \sim^{\text{i.i.d.}} N(0, \sigma_V^2)$ and $\epsilon_i \sim^{\text{i.i.d.}} N(0, \sigma^2)$. This design is analogous to a recent time-stratified case-crossover study (Basu, Malig, and Ostro 2010). In the following, we design to examine aggregated effects between birth weight and extreme weather in an ordinary linear regression that had an identical number of independent variables, and county units.

Model (2.2) is month-county specific. It aggregates model (2.1) from a 60-month individual level to a 12-month county level:

$$\bar{Y}_{m,jk} = \beta_0 + \beta_1 L_{jk} + \beta_2 H_{jk} + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k + \epsilon_{jk}, \quad j = 1, \dots, 12, \tag{2.2}$$

where $\bar{Y}_{m,jk}$ is the $j$th month-specific average birth weight for the $k$th county in the study period, $L_{jk}$ is the number of days with a minimum temperature less than 20 °F in the given month and county, $H_{jk}$ is the number of days with a maximum temperature higher than 90 °F in the given month and county, $T_k$ is the county-level average annual temperature, $E_k$ is the indicator of county-level average elevation greater than 1500 meters, $P_k$ is the county-level per capita income for the $k$th county, and the error term $\epsilon_{jk}$ is i.i.d. $N(0, \sigma^2)$.

Likewise, Model (2.2) can be specified by aggregating 12 months to 4 seasons (Winter (1)—December to February, Spring (2)—March to May, Summer (3)—June to August, and Fall (4)—September to November) and generating season-specific average weather variables at the county level:

$$\bar{Y}_{s,jk} = \beta_0 + \beta_1 L_{jk} + \beta_2 H_{jk} + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k + \epsilon_{jk}, \quad j = 1, 2, 3, 4, \tag{2.3}$$

where $\bar{Y}_{s,jk}$ is the $j$th season specific average birth weight for the $k$th county in the study period. The remaining variables are defined in the same way as in Model (2.2), and the error term $\epsilon_{jk}$ is also i.i.d. $N(0, \sigma^2)$.

Finally, Model (2.4) can be specified by dropping the month-specific average in weather variables in Model (2.2) and aggregating all individuals to their counties of residence:

$$\bar{Y}_k = \beta_0 + \beta_1 L_k + \beta_2 H_k + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k + \epsilon_k, \ \epsilon_k \sim^{\text{i.i.d.}} N\big(0, \sigma^2\big), \tag{2.4}$$

where $\bar{Y}_k$ is the county-level average birth weight in the study period and the remaining variables are defined in the same way as in Model (2.2). Model (2.4) is the most parsimonious model that combines 60 month-specific weather information into a single number. As we will see later, doing so may not capture extreme weather patterns.

Since counties in the three aggregated models above may exhibit correlation, it is necessary to test for model residuals at the county level for spatial autocorrelation. If the test is significant, spatial autocorrelation can be removed in two ways. One common way is to use an autoregressive term (Anselin 1988), but it only mechanically removes spatial clustering without providing information about local clusters. The other way is to make use of spatial association terms to identify local clusters, which can then be used to remove its contribution to autocorrelation in a multiple regression framework (Zhang and Lin 2009). We used both methods in our assessments.

### 2.3. Spatial Autoregressive Model

The conditional autoregressive (CAR) model can incorporate spatial dependence by specifying a set of spatial adjacent weights (Besag 1974; Haining 1990; Ord 1975). Here we used the rook weight rule as

$$w_{ij} = \begin{cases} 1 & \text{if counties } i \text{ and } j \text{ share a common boundary,} \\ 0 & \text{otherwise.} \end{cases} \tag{2.5}$$

In a CAR model, the conditional expected value of the response variable is its mean value plus a weighted sum of the mean-centered values. We specify a random effect $\gamma_k$ for county $k$ with a CAR model in Models (2.2) and (2.3) such that Model (2.2) is modified as

$$\bar{Y}_{m,jk} = \beta_0 + \beta_1 L_{jk} + \beta_2 H_{jk} + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k + \gamma_k + \epsilon_{jk}, \quad j = 1, \ldots, 12 \tag{2.6}$$

and Model (2.3) is modified as

$$\bar{Y}_{s,jk} = \beta_0 + \beta_1 L_{jk} + \beta_2 H_{jk} + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k + \gamma_k + \epsilon_{jk}, \quad j = 1, 2, 3, 4, \tag{2.7}$$

where $\epsilon_{jk}$ are i.i.d. $N(0, \sigma^2)$. In Models (2.6) and (2.7), respectively, $\gamma_k$ is a CAR random effect modeled as

$$\gamma_k | \text{all } \gamma_{l \neq k} = \rho \sum_{l \neq k} w_{kl} \gamma_l + \omega_k, \quad \omega_k \sim^{\text{i.i.d.}} N\left(0, \tau^2\right)$$

where $\rho$ and $\tau^2$ are parameters.

Likewise, Model (2.4) is modified as

$$\bar{Y}_k | \text{all } \bar{Y}_{l \neq k} = \mu_k + \rho \sum_{l \neq k} w_{kl} (\bar{Y}_l - \mu_l) + \epsilon_k, \quad \epsilon_k \sim^{\text{i.i.d.}} N\left(0, \sigma^2\right), \tag{2.8}$$

where

$$\mu_k = \beta_0 + \beta_1 L_k + \beta_2 H_k + \beta_3 T_k + \beta_4 E_k + \beta_5 P_k.$$

The parameter $\rho$ describes the spatial dependence between counties, in which $\rho = 0$ indicates spatial independence and the spatial dependence becomes stronger when $|\rho|$ becomes large. We considered both $\rho < 0$ and $\rho > 0$ cases and use the maximum likelihood method to estimate model parameters in all of Models (2.6), (2.7), and (2.8).

### 2.4. SPATIAL ASSOCIATION MODEL

The spatial association model is based on the residual test of Moran's $I$ in a linear regression. For a study area with $m$ units, let $z_i$ be the value associated with the $i$th unit. Moran's $I$ (Moran 1948) is expressed as:

$$I = \frac{1}{b_2 S_0} \sum_{i=1}^{m} \sum_{j=1}^{m} w_{ij}(z_i - \bar{z})(z_j - \bar{z}) \tag{2.9}$$

where $\bar{z} = \sum_{i=1}^{m} z_i/m$, $S_0 = \sum_{i=1}^{m} \sum_{j \neq i} w_{ij}$, $b_k = \sum_{i=1}^{m} (z_i - \bar{z})^k/m$, and $w_{ij}$ is the spatial weight between units $i$ and $j$, defined by (2.5).

The $p$-value of Moran's $I$ is calculated under the random permutation test scheme if $m$ is large (Cliff and Ord 1981). Let $E_R(\cdot)$ and $V_R(\cdot)$ be the expected value and variance under a random permutation, respectively. Then, Moran's $I$ is approximately normally distributed (Sen 1976):

$$I_{\text{std}} = \frac{I - E_R(1)}{\sqrt{V_R(I)}} \sim^{\text{approx}} N(0, 1).$$

Therefore, the $p$-value of Moran's $I$ is calculated according to a two-sided $z$-test given by $2[1 - \Phi(I_{\text{std}})]$. A significant and positive value of Moran's $I$ (i.e., $I_{\text{std}} > z_{\alpha/2}$) indicates a positive autocorrelation, while a significant and negative value of Moran's $I$ indicates a negative autocorrelation.

It is pointed out that Moran's $I$ can be alternatively tested by treating $z_i$ as the $i$th unit residual of a linear regression, and be used to remove local clusters by first identifying the locations and the number of local clusters, and then adding them as indicator variables in the regression model (Zhang and Lin 2009). To briefly describe the local association method, we assume that $S$ is the only spatial cluster in the study area, where a spatial cluster is defined as a set of spatially connected units with values significantly higher or lower than the expected. Let $e_i$ be the predicted value of the response $Y_i$ at the $i$th unit. Then, the simplest way to define the cluster $S$ is to assume $E(Y_i) = e_i + \delta_S$ if $i \in S$ and $E(Y_i) = e_i$ if $i \notin S$ so that a spatial cluster model can be formulated as

$$E(Y_i) = e_i + \delta_S I_{i \in S}, \tag{2.10}$$

with $\delta_S I_{i \in S}$ being the spatial associate term. $S$ is a hot spot (denoted by $H$) when $\delta > 0$, and it is a cool spot (denoted by $C$) when $\delta < 0$. However, $S$ is unknown, and one can search from a collection of spatial candidates $\mathcal{S}$ (Kulldorff 1997), so that the spatial cluster $S$ can be identified by maximizing the standard $t$-value from Model (2.10), i.e.,

$$S = \arg\max_{S' \in \mathcal{S}} \left| \frac{\hat{\delta}_{S'}}{\hat{\sigma}_{\hat{\delta}_{S'}}} \right|,$$

where $\hat{\delta}_{S'}$ is the point estimate and $\hat{\sigma}_{\hat{\delta}_{S'}}$ is the standard error of the point estimate of $\delta_{S'}$ conditional on a given $S' \in \mathcal{S}$.

With regard to the low birth weight model in (2.2), the local association term $\delta_S I_{i \in S}$ can be added as

$$Y_i = X_i'\beta + \delta_S I_{i \in S} + \epsilon_i, \qquad \epsilon_i \sim^{\text{i.i.d.}} N(0, \sigma^2), \tag{2.11}$$

where $\beta$ is the vector of unknown slopes and $\delta_S$ is the strength of the cluster. The cluster detection problem under Model (2.11) can be understood by the hypothesis testing problem as

$$H_0\colon\ \delta_S = 0 \quad \text{against} \quad H_1\colon\ \delta_S \neq 0. \tag{2.12}$$

If $H_0$ is accepted, then there is no spatial cluster. If $H_0$ is rejected, it is necessary to search for clusters.

The search process starts with the test of significance of Moran's $I$ without the local association term in Model (2.11). If $I$ is not significant, then it is not necessary to search for any clusters, and the algorithm stops. If $I$ is significant, then a stepwise procedure is invoked by fitting the model with the local association term $\delta_S I_{i\in S}$. Let the first identified cluster be $S_1$, and suppose there are no greater than $J$ potential local clusters.

Then, after identifying the $J-1$ local association terms $\delta_{S_1} I_{i\in S_1}, \ldots, \delta_{S_{J-1}} I_{i\in S_{J-1}}$, the stepwise procedure stops searching when Moran's $I$ test for an additional cluster $S_J$ is not significant. Model (2.11) can then expressly include spatial association terms

$$Y_i = X_i'\beta + \delta_{S_1} I_{i\in S_1} + \cdots + \delta_{S_J} I_{i\in S_J} + \epsilon_i, \qquad \epsilon \sim^{\text{i.i.d.}} N\bigl(0, \sigma^2\bigr), \tag{2.13}$$

where $S_1, \ldots, S_J$ are the identified local clusters.

Note that Model (2.13) has three components—ecological covariates, local association terms and residuals, and the latter two terms can be used iteratively. The local association term indicates the significance of a potential cluster. The residuals can be used to check residual clustering effect. In our current evaluation, we restricted the number of identified clusters to less than seven, because human brain can generally process only five to seven groups on a map (Slocum et al. 2009). Therefore, in Model (2.13) either the residual Moran's $I$ test is not significant or $J = 6$.

## 3. RESULTS

We established a baseline relationship by using 20 % random samples with 2,269,009 and 2,652,552 observations from 1974–1978 and 1984–1988, respectively. Table 1 provides the results from Model (2.1), which is a multilevel model with the random effect being at the county level. As expected, county per capita income was significantly positively related to birth weight. County elevation was also significant. In contrast to counties with an average elevation below 1500 meters, counties above this level were associated with lower birth weight. Average temperature was also negatively associated with birth weight: the warmer the average temperature of a county, the lower the birth weight. After controlling for these effects, we confirmed that birth weight was negatively related to both extremely cold and extremely hot temperatures.

As mentioned earlier, we estimated data from two periods with an intention to assess if there was a mitigation effect 10 years later. Our results were mixed. One the one hand, the number of hot days had a reduced effect, suggesting a mitigation effect. One the other hand, the effect for the number of cold days was strengthened, suggesting less effective coping strategies for cold weather. Since these relationships have not been investigated

Table 1. Baseline birth weight and extreme weather: Model (2.1), where (∗) indicates county level effect.

| | 1974–1978 | | 1984–1988 | |
|---|---|---|---|---|
| Term | Est. | Std. err. | Est. | Std. err. |
| Intercept | 3383.82 | 6.395 | 3469.1 | 5.090 |
| No. of days <20 °F | −0.0761 | 0.0734 | −0.4749 | 0.0739 |
| No. of days >90 °F | −0.7449 | 0.0802 | −0.2927 | 0.06147 |
| Mean temperature (*) | −1.1409 | 0.3683 | −4.7054 | 0.2594 |
| Elevation >1500 M | −182.39 | 9.2263 | −162.88 | 6.3766 |
| Per capita income (*) | −0.0068 | 0.0005 | 0.0013 | 0.0002 |
| $\sigma_v$ | 159.40 | | 80.12 | |
| $\sigma$ | 404.99 | | 324.64 | |
| Total obs. | 2,269,009 | | 2,652,552 | |

empirically in other studies, we present our findings empirically and will not describe them comparatively below.

It is also necessary to point out that in the 1984–1988 random sample, there were 57,268 plural births, and excluding them had little effect on those reported from Table 2. The parameter estimates for the numbers of cold days and hot days were −0.462 (Std. err. = 0.07207) and −0.2973 (Std. err. = 0.05997), respectively. In addition, all other independent variables had almost identified parameter estimates: average temperature −4.7039 (Std. err. = 0.2586), elevation −165.03 (Std. err. = 6.3584), and per capita income 1.631 (Std. err. = 0.227). Given that all the results were consistent with findings from the previous literature, we next examined to what extent the above relationships can be preserved by using different aggregations through time.

Table 2 lists results for the pure ecological models based on month-county specific, season-county specific and county-only aggregate data. Since the results from both 1974–78 and 1984–88 were similar, we describe only the results from 1974 to 1988. The upper panel of the table shows that month-county specific aggregated data could preserve essential temperature effects exhibited in the individual model. In addition, all the control variables were consistent with parameter estimates from Model (2.1). In particular, the average temperature and per capita income were inversely related to mean birth weight. High elevation was related to low mean birth weight. Month-specific extreme weather (hot or cold days) was inversely related to birth weight. The middle panel of the table shows that the seasonal model preserved most relationships established in Model (2.1), especially those related to climate, suggesting that season-county specific aggregation might be feasible for studying extreme weather effects. However, there is a caveat, as the effect for the income variable was reversed, and this result was also not consistent with most empirical studies of income and birth weight relationship at the individual. Finally, the lower panel of the table shows the number of extremely hot days (>90 °F) was no longer significant in the county only aggregation model. Since preserving the established weather relationship is essential, county-level only aggregation is not effective.

Note that in Table 2, the residual test for all three models showed strong spatial autocorrelation. We therefore used both the CAR and spatial association models to assess their

Table 2. Birth weight and extreme weather: aggregated ecological models, where all the $p$-values of Moran's $I$ are less than 0.0001.

| Model | Term | 1974–1978 Est. | 1974–1978 Std. err. | 1984–1988 Est. | 1984–1988 Std. err. |
|---|---|---|---|---|---|
| Month-county | Intercept | 3459 | 7.394 | 3456 | 6.704 |
| (Model (2.2)) | No. of days <20 °F | −0.0874 | 0.0317 | −0.128 | 0.0343 |
| | No. of days >90 °F | −0.0681 | 0.0346 | −0.0745 | 0.0334 |
| | Mean temperature | −4.739 | −0.2781 | −4.859 | 0.271 |
| | Elevation >1500 M | −177.2 | 5.935 | −177.2 | 5.907 |
| | Per capita income | 0.0051 | 0.0011 | 0.0022 | 0.0004 |
| | $\sigma$ | 186.3 | | 184.7 | |
| | Total obs. | 36,131 | | 36,143 | |
| | Moran's $I$ | 0.1903 | 0.0047 | 0.1896 | 0.0047 |
| | $I_{std}$ | 40.42 | | 40.27 | |
| Season-county | Intercept | 3455 | 8.319 | 3.453 | 7.240 |
| (Model (2.3)) | No. of days <20 °F | −0.0298 | 0.0129 | −0.0509 | 0.0135 |
| | No. of days >90 °F | −0.0592 | 0.0141 | −0.0322 | 0.0127 |
| | Mean temperature | −3.024 | 0.3172 | −4.876 | 0.2946 |
| | Elevation >1500 M | −199.4 | 6.579 | −175.3 | 6.290 |
| | Per capita income | −0.0031 | 0.0009 | 0.0025 | 0.0004 |
| | $\sigma$ | 120.9 | | 116.0 | |
| | Total obs. | 12,179 | | 12,176 | |
| | Moran's $I$ | 0.2223 | 0.0048 | 0.1883 | 0.0047 |
| | $I_{std}$ | 46.24 | | 39.99 | |
| County-only | Intercept | 3542 | 15.99 | 3535 | 14.36 |
| (Model (2.4)) | No. of days <20 °F | −0.1003 | 0.0151 | −0.1073 | 0.0154 |
| | No. of days >90 °F | 0.0524 | 0.0129 | 0.0596 | 0.0138 |
| | Mean temperature | −9.978 | 0.9073 | −10.22 | 0.7543 |
| | Elevation >1500 M | −159.5 | 8.067 | −155.8 | 8.144 |
| | Per capita income | 0.0038 | 0.0011 | 0.0023 | 0.0005 |
| | $\sigma$ | 70.48 | | 70.23 | |
| | Total obs. | 3048 | | 3049 | |
| | Moran's $I$ | 0.1943 | 0.0047 | 0.1920 | 0.0047 |
| | $I_{std}$ | 41.27 | | 40.78 | |

impacts on model correction and model consistency. The directional effects for all independent variables in Table 2 were preserved in the CAR and spatial association models.

All the values of $\rho$ in CAR models (2.6), (2.7), and (2.8) show positive effects (Table 3), suggesting that they could absorb significant spatially structured autocorrelations from the three aggregated models in Table 2. While all spatial association models were able to identify spatial clusters, they had modest effects on reducing spatial autocorrelations from Table 2. To save space here, we present only the month-county specific aggregation or Model (2.2). The standard Moran's $I$ were 40.57 and 40.71 for 1974–1978 and 1984–1988, respectively. Again, due to similar results for the two periods, here we briefly describe them for only 1984–1988 (Table 4).

Table 3. Birth weight and extreme weather: aggregated CAR models.

| Model | Term | 1974–1978 Est. | 1974–1978 Std. err. | 1984–1988 Std. | 1984–1988 Std. err. |
|---|---|---|---|---|---|
| Month-county (Model (2.6)) | Intercept | 3437 | 19.07 | 3425 | 20.45 |
| | No. of days <20 °F | −0.0737 | 0.0497 | −0.0591 | 0.0545 |
| | No. of days >90 °F | −0.1626 | 0.0562 | −0.962 | 0.0518 |
| | Mean temperature | −3.0846 | 0.8818 | −3.3103 | 1.0357 |
| | Elevation >1500 M | −125.3 | 16.13 | −107.5 | 19.00 |
| | Per capita income | 0.0051 | 0.0026 | 0.0026 | 0.0009 |
| | $\sigma$ | 181.8 | | 179.5 | |
| | $\tau$ | 39.76 | | 52.05 | |
| | $\rho$ | 0.1085 | | 0.1050 | |
| Season-county (Model (2.7)) | Intercept | 3438 | 12.81 | 3430 | 13.11 |
| | No. of days <20 °F | −0.0167 | 0.0119 | −0.0336 | 0.0126 |
| | No. of DAYS >90 °F | −0.0760 | 0.0133 | −0.0451 | 0.0120 |
| | Mean temperature | −2.2813 | 0.5643 | −3.5413 | 0.6998 |
| | Elevation >1500 M | −140.7 | 10.68 | −94.28 | 11.09 |
| | Per capita income | −0.0024 | 0.0014 | 0.0027 | 0.0006 |
| | $\sigma$ | 109.1 | | 106.2 | |
| | $\tau$ | 39.04 | | 28.90 | |
| | $\rho$ | 0.1081 | | 0.1357 | |
| County-only (Model (2.8)) | Intercept | 3510 | 19.46 | 3500 | 17.79 |
| | No. of days <20 °F | −0.0743 | 0.0190 | −0.0732 | 0.0194 |
| | No. of days >90 °F | 0.0394 | 0.0181 | 0.0513 | 0.0188 |
| | Mean temperature | −8.0875 | 1.0112 | −8.2734 | 0.9633 |
| | Elevation >1500 M | −121.4 | 10.81 | −122.3 | 10.77 |
| | Per capita income | 0.0039 | 0.0013 | 0.0024 | 0.0006 |
| | $\sigma$ | 64.21 | | 64.12 | |
| | $\rho$ | 0.0954 | | 0.0944 | |

First, the process of searching for spatial associations identified six clusters, and the inclusion of these association terms did not affect significant and directional effects of the ecological covariates. This result suggests that ecological covariates and spatial autocorrelation captured different spatial effects, and spatial association terms were not correlated with temperature or other effects. Second, among the six clusters, three were spatially connected albeit not overlapping. It suggests that (1) the circular cluster shape may not be sufficient for cluster detection in a large area with thousands of area units, and (2) non-overlapping spatial association terms may not be sufficient, as overlapping units can capture different geometric shapes and cluster slope (Lin 2003). Third, after the sixth spatial association term was entered, the residual spatial autocorrelation was still very strong with the $p$-value for Moran's $I$ being less than 0.0001. It suggests that even though the search algorithm can go on with additional spatial association terms, processing a large number of clusters may not be useful in practice. Finally, for the six identified clusters, four were cool spots, and two were hot spots, which reveal additional information.

Table 4. Month-county specific spatial association models, where all the $p$-values of Moran's $I$ are less than 0.0001.

| | 1974–1978 | | 1984–1988 | |
|---|---|---|---|---|
| Term | Est. | Std. | Est. | Std. |
| Intercept | 3430 | 7.941 | 3415 | 7.489 |
| No. of days <20 °F | −0.0750 | 0.0315 | −0.1090 | 0.0341 |
| No. of days >90 °F | −0.0878 | 0.0347 | −0.0783 | 0.0333 |
| Mean temperature | −2.937 | 0.3156 | −1.846 | 0.3178 |
| Elevation >1500 M | −109.9 | 6.437 | −105.7 | 6.517 |
| Per capita income | 0.0058 | 0.0011 | 0.0023 | 0.0004 |
| $\delta_1$ | −83.48 | 4.345 | −83.87 | 4.233 |
| $\delta_2$ | 59.40 | 3.856 | 62.70 | 3.889 |
| $\delta_3$ | −55.45 | 5.179 | 57.94 | 7.063 |
| $\delta_4$ | −29.15 | 3.505 | −53.19 | 6.112 |
| $\delta_5$ | 54.79 | 7.106 | −32.34 | 3.457 |
| $\delta_6$ | 37.33 | 5.082 | −60.69 | 7.268 |
| $\sigma$ | 183.8 | | 183.8 | |
| Moran's $I$ | 0.0591 | 0.0047 | 0.0620 | 0.0047 |
| $I_{\text{std}}$ | 12.50 | | 13.12 | |

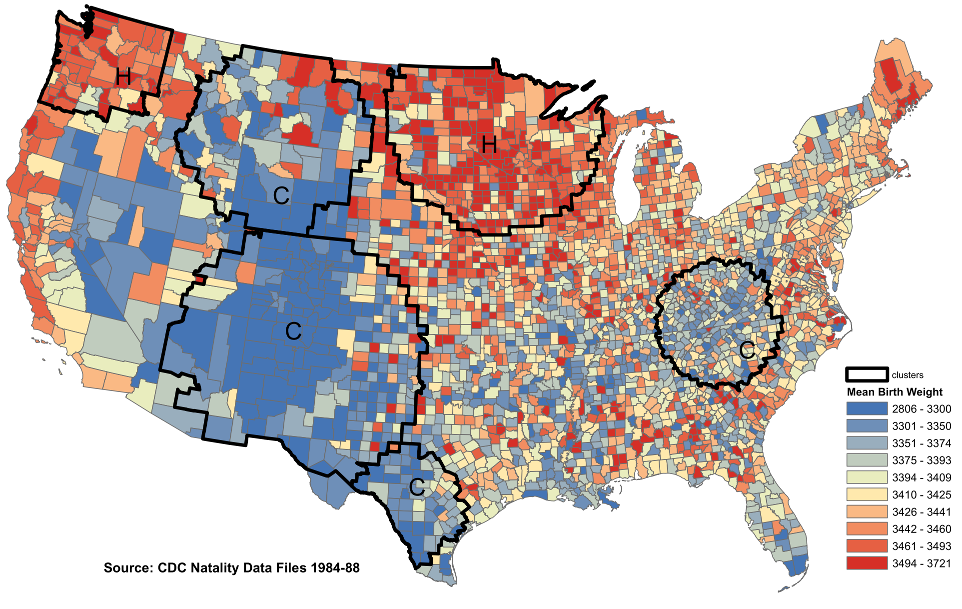


Figure 2. Spatial associations of cool (C) and hot (H) spots for Model (2.2) (1984–1988).

Figure 2 displays the six spatial cool and hot spots in mean birth weight data by county for 1984–1988. The figure shows a general geographic tendency toward a low mean birth weight from north to south, with some regional patterns. Minnesota, Wisconsin, and Iowa had severe winter storms during this period, but the storms tended to be associated with high birth weight. This general or average effect was captured by the hot spot spatial association in the upper Midwest. A swath of the Mountain region, however, had a relatively low mean birth weight. The main reason for this regional effect was elevation, as the region sits on the mountainous areas in the Mountain region, where weather is likely to be more volatile. Findings for this region and the Southwest region (e.g., Oklahoma, Arkansas, and Texas) suggest both relative hot temperatures and more extreme weather events. While these effects were partially captured by the elevation term used in the model, the month-county specific model cannot fully account for these effects. As a result, residual clusters from the whole Mountain region were captured by three cool spot clusters. Finally, there were two separated clusters, a hot spot in Washington State, and a cool spot in West Virginia extending to Virginia, where the low mean birth weight could be sufficiently explained by extreme weather and low per capita income.

## 4. DISCUSSION

Since Robinson's seminal work on ecological fallacy in the 1950s, epidemiological studies have gradually shifted toward using individual survey and experimental data. Using individual data with an experimental design or case matching is now considered the gold standard. However, most public health data are still released at an aggregated level, such as county, census tract, or ZIP Code. In order to meet the needs of climate change and human health data requirements, we have provided a series of aggregation analysis of birth weight and its relationship with two extreme weather measures ($<20$ °F or $>90$ °F) controlling for average county temperature, per capita income, and high elevation counties. To provide meaningful aggregation, we restricted the sample to White birth mothers aged 19 to 38 years. At the individual level, extreme temperatures were negatively associated with birth weight: the more hot days and cold days, the lower the birth weight. These results are consistent with results from a previous study using the same data set [5], which also reinforced findings from other studies.

Our empirical regression assessments showed a range of results according to the study design. On the one hand, aggregating individuals into month-county specific groups tended to preserve the established relationship at the individual level. In most cases, spatial autocorrelation exists, but accounting for spatial association terms would not change the directional effects of ecological covariates. On the other hand, county-only aggregation destroyed the established weather-birth weight relationship, and the result became inconsistent with the one from individual model. Between the two, the season-county specific model worked fine in weather-related relationships, but showed some inconsistency in the income relationship. While income was used as a control variable, its effects become reversed during the aggregation process, suggesting the existence of the Simpson paradox for the income variable. We speculate that the birth rate of high income families is usually much lower than that of low income families, and the aggregation ignores difference in the spatial distribution of high or low income families. After aggregation, the contribution by difference birth rates among different counties weighted equally, which in turn, might cause the reversed income effect, or the ecological fallacy.

Our evaluations of the CAR model and the spatial association model had mixed results. While both models had little effect on climate variables, they provided different interpretations. All CAR models suggest a strong spatial-random effect of clustering, while all spatial association models can identify specific clusters that may worth looking into later on. In contrast to removing an overall autocorrelation effect of $|\rho|$ in the CAR model, each association term in the spatial association model had only an incremental effect on removing spatial autocorrelation. There could be several reasons for this result. First, the circular cluster shape may not be sufficient for cluster detection in a large area with thousands of area units, as it may force many candidates into the cluster that should not be included. Second, the assumption and design of non-overlapping spatial association terms may not be sufficient. For example, if two cool spots are overlapping, the overlapping area is even more negative to the main effect. Third, for ease of cluster interpretation or etiological discovery, we stopped after detecting the sixth cluster. Additional iterations may or may not explain the residual patterns that were captured by spatial autocorrelation. While any of the reasons above could lead to a separate study, together, they also suggest the limitation of a spatial association model for modeling a large number of spatial units.

In addition to the above limitation of the spatial association modeling approach, this study has several other limitations. First, hourly humidity measures are not available for most counties. We therefore could not generate the heat index, which combines temperature and humidity. Like most studies, our exposure variables were based on birth month, which may not be as good as 6 days prior to birth shown in Basu, Malig, and Ostro (2010). However, it has its advantage of avoiding costly daily temperature data collection and compilation. Second, we did not have enough geographical or ecological variables. Key air pollutants, such as PM2.5, were related to low birth weight (Bell, Ebisu, and Belanger 2007), but data on PM2.5 at the county level only became available after 1998. Spatial associations may capture some effects from missing ecological covariates, but other relationships between weather and birth weight could not be recovered without additional ecological covariates. Third, for regions with distinct weather and socioeconomic patterns, separate analyses are warranted. For instance, the low-birth weight region that covers Wyoming, Colorado, and New Mexico seems relate to a set of factors that include elevation, maintain weather and access to care. One approach that might be fruitful is spatially weighted regression that provides local parameter estimates. Fourth, there might be state-level effects due to different regulations, which we did not include in our spatial multilevel regression, but which might be the reason why Washington State is a hot spot cluster. Finally, we did not experiment with spatial aggregation. For some counties with small population sizes, aggregating a number of adjacent counties with similar climate and weather variables may still preserve the essential relationship. Again, some of these limitations point to future research directions.

Although our primary interest was assessing aggregation effect, the substantive results are worth noting. Early studies about birth weight and temperature or seasonality tended to be based on a single location. Preterm births and perinatal deaths were found to be higher in July and August in Minnesota. Babies born in the summer had the lowest birth weights in New York State (Selvin and Janerich 1971), and preterm labors were higher in winter and summer in New York City (Lajinian et al. 1997). Our results were based on data from across the continental U.S. in different time periods, and it added credence to other studies. We used temperature as a control variable, but the result showed a gradient of birth weight from cold to warm temperature zone; the warmer the temperature, the lower the birth weight. This result is consistent with the finding from a multi-county meta-data analysis that showed a north-to-south gradient of heavier to lower birth weights (Wells and Cole 2002). Early studies tended to imply extreme weather effect through seasonality. Our study explicitly use extreme weather indicators, and showed that controlling for temperature, the number of cold or hot days in the birth month was negatively associated with birth weight, which can be captured at the individual and aggregated (e.g., month-year or season-year) level. In addition, we also found that elevation can significantly modify birth weight. Controlling for area income, those living in relatively high altitude tend to have lower birth weights, a result consistent with previous studies in Colorado, U.S. and Bolivia (Jensen and Moore 1997; Giussani et al. 2001). Our study provided supporting and generalizable evidence to other single site studies.

In conclusion, temporal aggregation by month-county or season-county is likely to preserve the relationship between birth weight and extreme weather in the individual model. If health outcome measures cannot be released at the individual level, they should be released at the month-county specific level for weather-related public health research. The spatial association approach for removing spatial autocorrelation may not work without further modifying the existing method.

## ACKNOWLEDGEMENTS

We appreciate the helpful comments from the anonymous referees and the editor of the special issue, which significantly improve the quality of the paper. This research was funded by U.S. National Science Foundation Grants SES-07-52657 (Zhang) and SES-07-52019 (Lin).

*[Published Online August 2012.]*

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