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Spatio-temporal patterning of small area low birth weight incidence and its correlates: A latent spatial structure approach

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ABSTRACT

Low birth weight (LBW) defined as infant weight at birth of less than 2500 g is a useful health outcome for exploring spatio-temporal variation and the role of covariates. LBW is a key measure of population health used by local, national and international health organizations. Yet its spatio-temporal patterns and their dependence structures are poorly understood. In this study we examine the use of flexible latent structure models for the analysis of spatio-temporal variation in LBW. Beyond the explanatory capabilities of well-known predictors, we observe spatio-temporal effects, which are not directly observable using conventional modeling approaches. Our analysis shows that for county-level counts of LBW in Georgia and South Carolina the proportion of black population is a positive risk factor while high-income is a negative risk factor. Two dominant residual temporal components are also estimated. Finally our proposed method provides a better goodness-of-fit to these data than the conventional space–time models.

1. Introduction

Descriptive epidemiology is built on the three-cornered stool of person, place and time. Increasingly sophisticated approaches and technologies have been devised in recent years to support risk factor epidemiology, spatial analysis of diseases and health conditions, and time series analysis. Rarely are the three domains of covariates, space and time analyzed within a framework allowing for their simultaneous consideration. Most research examining spatial patterns of disease incidence, for example, examine spatial distributions for a specific time interval, or compare multiple maps over time rather than modeling the temporal component directly.

In this paper we develop and apply an approach to space–time latent component modeling using the outcome of low birth weight (LBW) among resident live births measured at the county level across two US states annually over a decade. Low birth weight, defined as infant birth weight less than 2500 g or 5 lb 8 oz, is one of the principal measures of birth outcomes used at the local, national and international levels (Healthy People 2020, objective MICH-8.1). Birth weight is universally available in the US for a long period of time and the methods of data collection should be standardized across the time and geographical areas in the US. Thus, LBW is a useful health outcome for exploring spatio-temporal variation and the roles of covariates in explaining the spatio-temporal patterns.

Low birth weight is associated with maternal factors and behaviors during pregnancy, socio-cultural factors, as well as demographic characteristics (Adams et al., 2009; Committee to Study the Prevention of Low Birthweight, 1985; Goldenberg and Culhane, 2007). A partial list of

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demographic, reproductive and behavioral factors associated with LBW includes maternal race/ethnicity, age, education, parity, plurality, inadequate prenatal care, marital status, previous preterm birth, smoking, and pre-pregnancy body mass index (Fang et al., 1999; Pearl et al., 2001). More recently, attention has focused on covariates of LBW at the ecological level and in multi-level analyses (Baker and Hellerstedt, 2006; Grady, 2006; Metcalfe et al., 2011; Young et al., 2010). In their recent meta-analysis, Metcalfe et al. (2011) found a modest but statistically significant association between neighborhood income and LBW (pooled Odds Ratio 1.11; 95% CI 1.02–1.20). Other aspects subjected to closer scrutiny have included the role of residential segregation (Baker and Hellerstedt, 2006; Grady, 2006), and race/ethnicity (Fang et al., 1999; Pearl et al., 2001). Low birth weight has also varied over time in the US, rising from approximately 7.0% in 1950 to a peak in the mid-1960s and a nadir in the early-1980s. Since 1985 the incidence of LBW has gradually risen (Brosco et al., 2010). Given its temporal and spatial variation as well as socio-demographic covariates that also provide a spatial context, LBW is an ideal health indicator for the purpose of our methodological evaluation.

In this report, we present a latent spatial structure approach to modeling county-level variation in low birth weight across the states of Georgia and South Carolina during calendar years 1997–2006 inclusive.

2. Data description

2.1. Low birth weight in the Southern US

We obtained county-level low birth weight data set in Georgia and South Carolina for the years 1997–2006 from the state health information systems (Georgia Division of Public Health and South Carolina Department of Health and Environmental Control). There are 205 counties (159 counties for Georgia and 46 counties for South Carolina) and 10 years of data.

Fig. 1 presents the spatial–temporal variation of standardized incidence ratios for low birth weight births, where the standardized incidence ratio is defined as the number of LBW births divided by the number of expected cases calculated by using the internal standardization method (Banerjee et al., 2004) based on the statewide crude population-based rate. In Fig. 1, we can see that

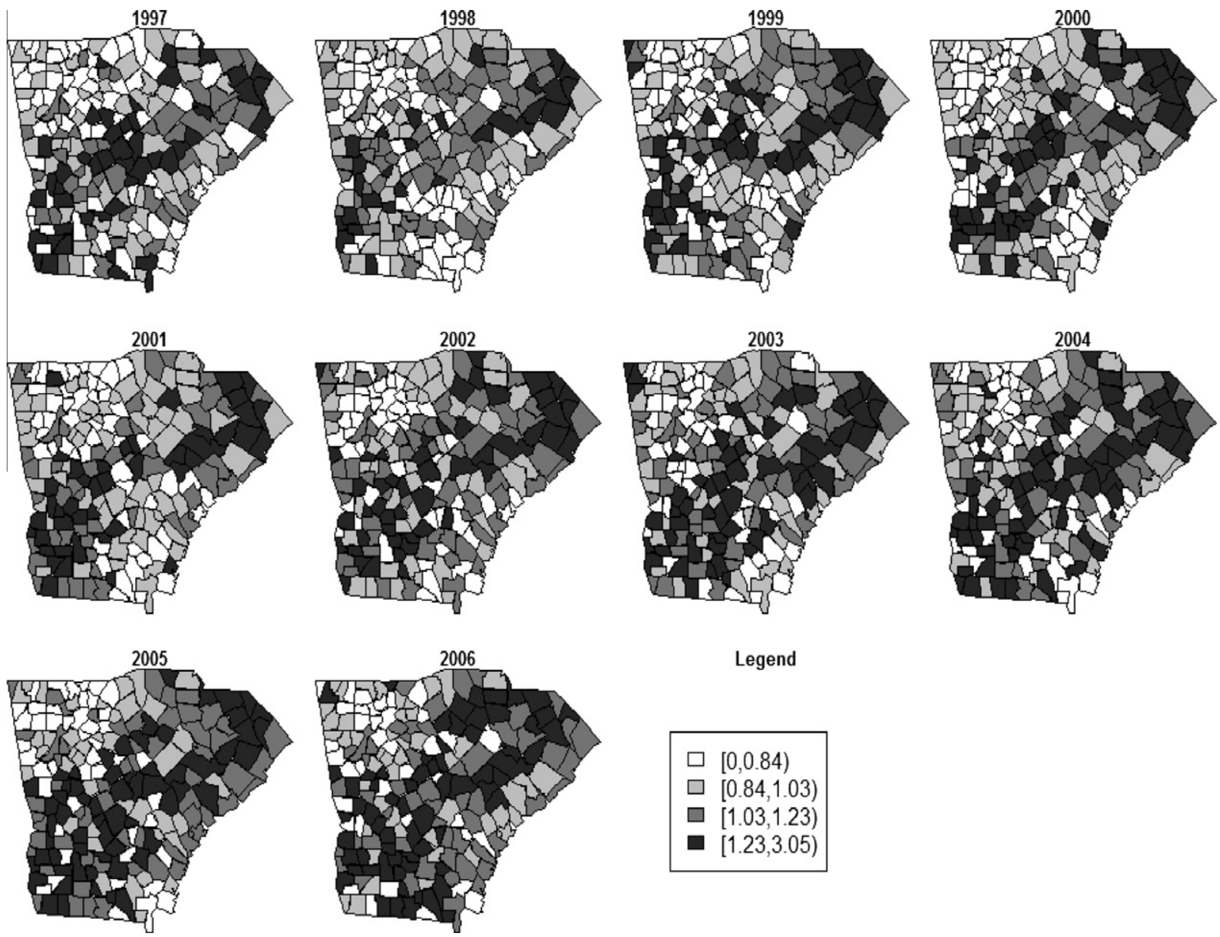

Fig. 1. Standardized incidence maps for county-level low birth weight in Georgia and South Carolina for individual year.

the standardized incidence ratios in south–west areas and north–east areas are higher than other areas over years, while the standardized incidence ratios in north–west areas are lower than other areas.

Fig. 2 shows that two arbitrarily chosen spatial groups have different temporal patterns for log standardized incidence ratio. Overall, east areas of South Carolina (A areas) have higher values of log standardized incidence ratio (SIR) than the Atlanta suburbs (B areas) over years.

2.2. Predictors

Based on prior research and also considering the availability of county-level data, we consider county-level population density, the proportion of black people, median household income, and unemployment rate as socio-economic predictors of low birth weight. Population density is defined as population divided by total land area (square miles). The county proportion of black people is the black or African American population divided by total population. Population and income data sets are obtained from the US census. Unemployment rate data set is obtained from the US Bureau of Labor Statistics. For example, in the Atlanta suburbs, population density and income are high while the proportion of black people is low.

In addition, we considered aggregate data based on birth certificates for the other known socio-demographic and behavioral risk factors for LBW. They are the proportion of mothers with less than 20 years old, and the proportion of mothers over 35 years old, the proportion of mothers with less than 12th grade education, the proportion of mothers smoking during pregnancy, the proportion of mothers with "Inadequate" value from the Kotelchuck Index (= the proportion of mothers with IKI value), and the proportion of mothers with less than five prenatal care visits. Here, the Kotelchuck Index is a measure of adequacy of prenatal care utilization based on the number of prenatal visits, the month prenatal care began, and the gestational age of infant at birth (Kotelchuck, 1994). There are four categories: Adequate Plus, Adequate, Intermediate, and Inadequate. For example, if woman begins prenatal care after the 4th month or receives less than 50% of recommended visits, then she has "Inadequate" value from the Kotelchuck Index. Preliminary analysis showed that the proportions of mothers with less than 20 years old and over 35 years old are highly correlated with income (Pearson's correlation coefficient (r) = −0.71, p-value < 0.001 for young mothers; r = 0.7, p-value < 0.001 for old mothers) and are correlated with each other (r = −0.59, p-value < 0.001). Also, the proportion of mothers with IKI value has a positive correlation with the proportion of mothers with less than five prenatal care visits (r = 0.78, p-value < 0.001).

3. Model approach

In this paper we consider the analysis of LBW counts at county level within the counties of Georgia and South Carolina for the years 1997–2006. The county level counts of LBW consist of 205 units and so have a considerable spatial variation. The temporal period represents a considerable time span which could be considered to yield evidence for spatial–temporal latent structure within the LBW risk. We consider two basic models for this risk in these data. First, we consider a conventional space–time random effect model with separate space–time (ST) components and a ST interaction term (Knorr-Held, 2000). This allows for a parsimonious model representation of space–time variation (Lawson, 2009), and is commonly applied to describe ST variation of disease risk. We call this the SREST model (Standard Random Effect Space–Time model). Let Y_{ij} denote the number of low-birth weight babies for county i (i = 1,…,I) at time point j (j = 1,…,J) and E_{ij} denote the expected count. The count is assumed to follow a standard Poisson distribution as $Y_{ij} \sim \mathrm{Pois}(E_{ij}\vartheta_{ij})$, where ϑ_{ij} is the relative risk.

In the SREST model, the log relative risk can be specified as

$$log(\vartheta_{ij}) = x_{ij}^{T}\beta + u_i + v_i + \eta_j + \gamma_j + \epsilon_{ij} \tag{1}$$

where $X_{ij} = (1, X_{ij1},\ldots, X_{ijp})^T$ is the vector of intercept and p predictors and $\beta = (\beta_0,\beta_1, \ldots, \beta_p)^T$ is the corresponding coefficient vector. The parameters u_i and v_i are the

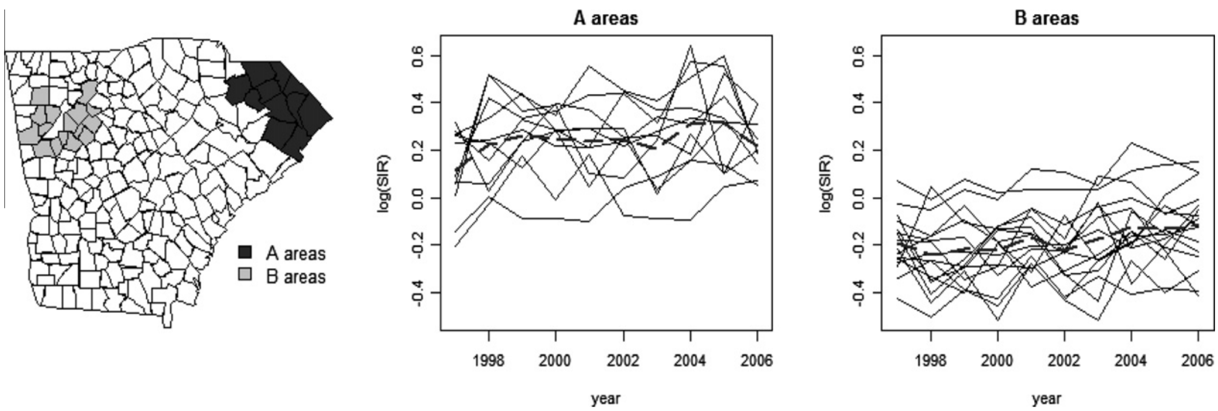

Fig. 2. Map to show the selected areas (Left) and temporal plots of log standardized incidence ratio (SIR) of low birth weights for the period 1997–2006 (Right). The dashed line shows the average of log standardized incidence over the selected areas.

uncorrelated spatial random effect and the correlated spatial random effect, respectively. Similarly, the parameters η_j and γ_j are the uncorrelated temporal random effect and the correlated temporal effect, respectively. The parameter ϵ_{ij} is the space–time interaction term.

The prior distribution of the correlated spatial component v_i is assigned to be a conditional autoregressive (CAR) distribution (Besag et al., 1991),

$$v_i | v_{j \neq i} \sim N\left(\frac{\sum_{j \in \delta_i} v_j}{n_i}, \frac{\sigma_v^2}{n_i}\right) \tag{2}$$

where σ_v^2 is the overall variance parameter, δ_i is the set of labels of the neighbors of county *i*, and n_i is the number of neighbors (adjacent counties) of county *i*. The correlated temporal component γ_j is assigned to be a random walk Gaussian distribution, $\gamma_j \sim N(\gamma_{j-1}, \sigma_\gamma^2)$. The prior distributions of the other random components u_i, η_j, and ϵ_{ij} are specified as $N(0, \sigma_u^2)$, $N(0, \sigma_\eta^2)$, and $N(0, \sigma_\epsilon^2)$, and all the standard deviance parameters in the model are assumed to have a uniform distribution, Uniform(0,5). The coefficient vector β has an independent non-informative Gaussian prior distribution with large variance.

In contrast to this model we also examine the latent structure model of Lawson et al. (2010) which allows there to be a disaggregation of temporal profiles in risk for LBW. The approach is based on the idea that regions have a set of underlying risks that they can support and these risks are temporally varying. The number of these latent risk profiles is usually unknown in advance and must be estimated in the analysis. This model is called the STLS model (Space–Time Latent Structure model) and is given by

$$log(\vartheta_{ij}) = X_{ij}^T \beta + \sum_{l=1}^{L} \psi_l w_{il} \chi_{lj} + \epsilon_{ij} \tag{3}$$

where *L* is the number of components, χ_{lj} is the temporal component that explains the underlying temporal pattern in relative risk, w_{il} is the corresponding weight that depends on space, and ψ_l is the entry parameter that controls the selection of the temporal components. The temporal component χ_{lj} can be assumed to have various temporal dependency structures, and in this paper we assume a random walk Gaussian distribution, $\chi_{lj} \sim N(\chi_{lj-1}, \sigma_\chi^2)$. The weight parameter w_{il} describes the proportion of *l*th temporal component contribution for *i*th county, and it has two conditions: $w_{il} \geqslant 0$ and $\sum_{l=1}^{L} w_{il} = 1$. Thus, the weight w_{il} is modeled as $w_{il} = w_{il}^* / \sum_{l=1}^{L} w_{il}^*$, where $w_{il}^* \geqslant 0$ is the unnormalized weight and is assumed to have a log-normal distribution with the space-dependent mean ζ_{il} and the variance $\sigma_w^2, w_{il}^* \sim LN(\zeta_{il}, \sigma_w^2)$. The mean parameter ζ_{il} has a CAR distribution to take into account the spatial dependency structure of the weights. The number of temporal components (L) is assumed to be a large value apriori in order to find the true temporal components. The entry parameter is used to allow components to enter or be removed from the model during updating. The entry parameter has a value 0 or 1 so the *l*th temporal component is included in the model if $\psi_l = 1$ and is not included if $\psi_l = 0$. We assume that the entry parameter has a Bernoulli prior distribution, $\psi_l \sim \text{Bern}(0.5)$, where 0.5 is a non-informative value. Using entry parameters in the model, it is not necessary to find the number of components in advance and this model can allow for the estimation of the number of components included in the model.

To identify the spatial clusters each of which has a homogeneous temporal trend in relative risk, we consider a post hoc method using the estimated weight values. We define the spatial cluster indicator Z_i(=1,...,L) as

$$Z_i = \text{argmax}_l \{W_{il}\} \tag{4}$$

The indicator Z_i means the index of the temporal component with the largest weight in county *i*, which becomes the primary temporal pattern of the county in relative risk. Using the indicator Z_i, we can allocate a fixed component to a given region.

Since a component identifiability problem can arise in Bayesian STLS modeling due to the invariance of the likelihood with respect to the permutation of the component labels (Stephens, 2000), we make the assumption in the model that the latent components have time-dependent structures while the corresponding weights have only space-dependent structures. Also, in the STLS model, it is possible for components to switch labels during Markov Chain Monte Carlo (MCMC) simulation if multiple chains are used. A single chain run can avoid this problem. Thus, in this paper, we use a single chain and obtain the converged estimates of the parameters from the posterior sampling from the joint models via two packages R (http://www.r-project.org) and WinBUGS (http://www.mrc-bsu.cam.ac.uk/bugs). We use the posterior mean values for estimates of all the parameters except the cluster indicator Z_i and use the posterior mode values for the estimation of Z_i as Z_i is the nominal value.

4. Application

4.1. Model choice

We fit a range of models in our analysis. First, we consider a simple Poisson linear regression model, $\log(\vartheta_{ij}) = x_{ij}^T \beta + \epsilon_{ij}, \epsilon_{ij} \sim N(0, \sigma_e^2)$, which does not include space and time random effects. The second model is the SREST model and the third model is the STLS model with 10(=L) entry parameters. The reason that 10 entry parameters in the STLS model are considered is to make a balance between computing time and model complexity. Also we use a small area data set (205 counties) so L = 10 is large enough to find the true number of components. For each of the models, we include one of two different predictor sets. The first set has 10 predictors: population density, the proportion of black people, income, unemployment rate, the proportion of mothers with less than 12th grade education, smoking during pregnancy, IKI value, less than 5 prenatal care visits, less than 20 years old, and over 35 years old. The second set has 7 predictors, which excludes the proportion of mothers with less than 5 prenatal care visits, less than 20 years old, and over 35 years old. These are excluded because they are highly correlated with the other predictors.

For model selection, the deviance information criterion (DIC) proposed by Spiegelhalter et al. (2002) is considered. The DIC is defined as $\mathrm{DIC} = \bar{D}(\theta) + p_D$, where $\bar{D}(\theta)$ is the posterior mean of the deviance, $D(\theta)$, and represents the model fit, and $p_D = \bar{D}(\theta) - D(\hat{\theta})$ is the difference in the posterior mean of the deviance and the deviance of the posterior means and represents the effective number of parameters. Recently, Celeux et al. (2006) proposed an alternative DIC, DIC_3, which uses a posterior estimate of likelihood, $\hat{p}(y|\theta)$ and is defined as $\mathrm{DIC}_3 = \bar{D}(\theta) + [\bar{D}(\theta) + 2\log\hat{p}(y|\theta)]$. This DIC_3 provides stable and reliable evaluation and performs well for finite mixture models so we use this measure in this study. Lower values of DIC_3 indicate a better fitting model. For the evaluation of prediction performance, we consider the Marginal Predictive likelihood (MPL) using the Conditional Predictive Ordinate (CPO) (Dey et al., 1997), $\mathrm{MPL} = \Sigma_{i,j}\log(\mathrm{CPO}_{ij})$, where CPO_{ij} is the marginal posterior predictive function of Y_{ij} given the data excluding Y_{ij}. We also consider the mean square prediction error (MSPE) given by $\mathrm{MSPE} = \Sigma_{i,j}(Y_{ij} - \hat{Y}_{ij})^2/IJ$, where $\hat{Y}_{ij}$ is a value of Y_{ij} from the posterior predictive distribution. Larger values of MPL and lower values of MSPE indicate a better model in terms of prediction performance.

Table 1
Model comparison statistics for the candidate models (DIC_3, MSPE, and MPL).

Model	The number of predictors	$\hat{L}$	DIC_3	MSPE	MPL
Poisson linear regression model	10 predictors		13793	171	−7118
	7 predictors		13775	171	−7101
SREST model	10 predictors		13627	172	−6850
	7 predictors		13620	171	−6854
STLS model	10 predictors	1	13776	170	−7043
	7 predictors	2	13603	170	−6850

In Table 1, we summarize the DIC_3, MSPE, and MPL measures for the models considered. We also report the estimated number of the latent components included in the STLS model when 10 entry parameters are used. Models having 10 predictors have large DIC_3 values. Particularly, Poisson linear regression models with no space and time random effects have large DIC_3 and small MPL values. So, it suggests that space and time random effects should be considered in this application. The SREST models with different predictors provide similar DIC_3, MPL, and MSPE values. On the other hand, the STLS models estimate different true latent components depending on the number of predictors: 1 component for the 10 predictors and 2 components for the 7 predictors. Thus, they have marginally different DIC_3 and PML values. Here, the STLS model having 7 predictors has the smallest DIC_3 and MSPE values and the largest MPL values and therefore this STLS model is the best fit. In the following section, all the results of parameter estimates and interpretation are based on the STLS model with 7 predictors.

Table 2
Parameter estimates from the posterior distribution in the best-fitted model (Space–Time Latent Structure model with 7 predictors). Posterior mean, SD and 95% credible interval are shown.

Predictors	Mean	SD	2.5%	97.5%
Population density	−0.006	0.008	−0.020	0.013
Proportion of black people	0.140	0.009	0.123	0.159
Household median income	−0.042	0.009	−0.058	−0.025
Unemployment rate	0.002	0.004	−0.007	0.010
Proportion of mothers with <12 grade education level	0.003	0.007	−0.011	0.016
Proportion of mothers smoking during pregnancy	0.010	0.007	−0.003	0.024
Proportion of mothers with IKI value	−0.007	0.006	−0.019	0.004

4.2. Parameter estimates and interpretation

The posterior means and 95% credible intervals for the coefficients in the STLS model with 7 predictors are presented in Table 2. The proportion of black people is a significant positive risk factor of LBW and the household median income is a significant negative risk factor. A higher proportion of black people and lower income are associated with increased risk of LBW. The other predictors are not significant in this model because the latent components in the STLS model capture the locally temporal patterns in risk.

Fig. 3 presents the temporal plots for the selected components in the STLS model. Component 1 has an increasing

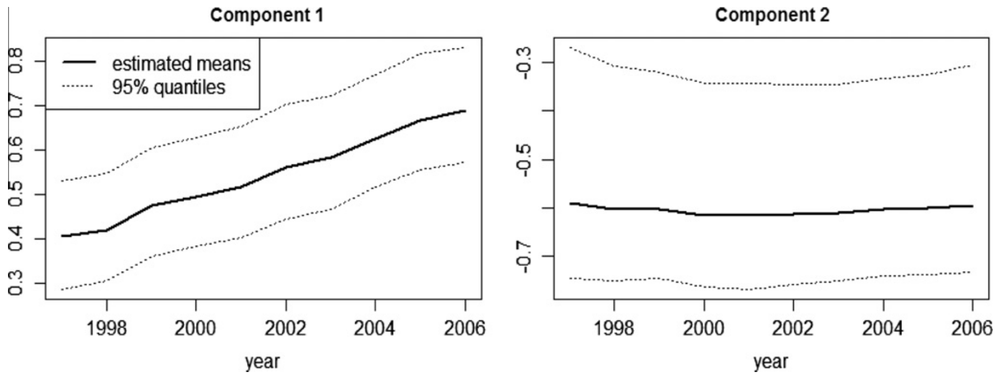

Fig. 3. Temporal plots of the selected components. The solid lines show the posterior mean and the dotted lines show the 95% confidence intervals.

pattern while Component 2 has a quite stable pattern over time. Overall, Component 1 has larger relative risks than Component 2 over time and has smaller credible intervals. In this case, the maps of the weights corresponding to the components are given in the left two maps in Fig. 4. Using the allocation method in Eq. (4), the spatial clusters can be identified and the map of the cluster indicator is presented in the right map in Fig. 4. Overall, many counties (north-east areas) in SC, south-west areas, and the downtown of Atlanta are assigned to Component 1 and the south–east areas and the Atlanta suburbs are assigned to Component 2. Thus, north–east and south–west areas and the Atlanta downtown have an increasing pattern in relative risk over time while the south-eastern areas and the Atlanta suburbs have a stable pattern in risk and smaller relative risk than the other areas, which also takes into account the data well (see Fig. 1).

By contrast, the STLS model with 10 predictors (not shown) estimates 1 component that has an increasing pattern in risk. All the predictors except population density were significant. Lower income, the proportion of mothers with low education level, and IKI values are associated with the increased risk of LBW while lower levels of the other predictors are associated with the decreased risk of LBW. Since the risk effects of the predictors on LBW can vary over states, we also fit the STLS model with 7 predictors and different coefficient vectors depending on the states. This model estimates 3 latent components: an increased pattern over time and two stable patterns (levels of the one component are considerably larger than levels of another component over time). The proportion of black people has a positive association with risk in Georgia (estimate = 0.166; 95% intervals 0.137–0.193) and South Carolina (estimate = 0.098; 95% intervals 0.055–0.145). In addition, in Georgia, income has a negative effect (estimate = −0.034; 95% intervals −0.053 to −0.015) and the proportion of smoking mothers has a positive effect (estimate = 0.015; 95% intervals 0.001–0.030). Thus, in Georgia, high proportions of black people and smoking mothers and lower income are associated with the increased risk of LBW, while in South Carolina, high proportion of black people is only associated with the increased risk of LBW. These different STLS models provide marginally different estimated parameters, but the model comparison measures (DIC_3, PML, and MSPE) suggest that the STLS model with only 7 predictors is the best-fit model.

5. Discussion

It is important to note some implications of this study. First, given the inclusion of conventional LBW predictors (population density, black population proportion, median income etc.), the latent structure model (STLS) still provides a well-defined multi-component risk. This suggests that there is significant unexplained spatio-temporal variation in the LBW risk beyond that explained by predictors. Also, these temporal patterns in risk conditional on the predictors vary locally. We found that there are two temporal components: increasing pattern over time and stable pattern over time. This suggests that future studies should continue to examine the correlates of spatio-temporal patterns even though conventional LBW predictors are considered.

Second, we did not consider here the inclusion of predictors in the latent structure itself, but rather regarded the latent structure as residual effects. This helps to show that there is residual structure in the LBW risk. The extension of these models to include predictors within the components or component weights would be a logical next step and should be a focus in the future development of the methods.

Some additional considerations are the level of resolution of the data (county level) and more general data quality issues. The demographic and behavioral factors considered here were aggregated from individual level data based on birth certificates, which were directly downloaded from public websites. Although these factors are conventional predictors of LBW such as smoking at individual level, they are significant predictors of LBW at county level and these individual level characteristics should be treated as covariates at the individual level. Thus, our choice of county level LBW data would lead to biased results (ecological inference) and so we cannot directly attribute the risk of LBW to a given predictor state at the individual level. To improve this interpretation it would be useful to examine complete birth records for Georgia and South Carolina, and we intend to examine a joint model for county level counts and individual births in the future.

In brief, flexible latent structure models are useful to examine space and time variation in health outcomes. Findings can be used to guide the policy-makers and program planners on where the program efforts should be

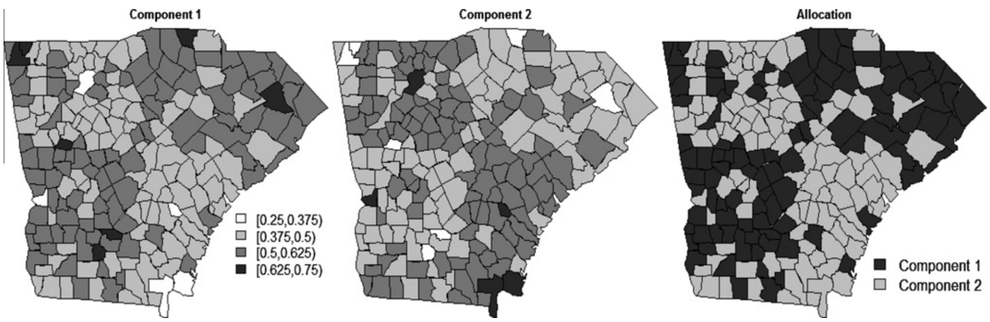

Fig. 4. Maps of the estimated weights corresponding to the selected 2 components (Left and middle) and map of the allocation using the estimated weights values.

strengthened to lower LBW incidence and to reverse the increasing trend of LBW.

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