Patterns of low birth weight in Greater Mexico City: a Bayesian spatio-temporal analysis.

Abstract

There is strong evidence that low birth weight (LBW) has a negative impact on infants' health. Children with LBW are more vulnerable to having disabilities. There are many studies on LBW, but only a small proportion has examined local geographical patterns in LBW and its determinants. LBW is a particular health concern in Mexico. The study aims to: (i) model the change in the LBW risk at the municipality level in Greater Mexico City, identifying municipalities with highest and lowest LBW risk; and (ii) explore the role of some socioeconomic and demographic risk factors in explaining LBW variations. We propose a Bayesian spatio-temporal analysis to control for space-time patterning of the data and for maternal age and prenatal care, both found to be important LBW determinants. Most of the high-risk municipalities are in the south-west and west of Greater Mexico City; and although for many of these municipalities the trend is stable, some present an increasing LBW risk over time. The results also identify those with medium-risk and with an increasing trend. These findings can support decision-makers in geographical targeting efforts to address spatial health inequalities, they may also facilitate a more proactive and cost-efficient approach to reduce LBW risk.

Keywords: Child health; term low birth weight; Bayesian spatio-temporal modelling; space-time variation; spatial random effects.

1. Introduction

There is an increasing policy interest in improving children's health, reflecting the United Nations' third Sustainable Development Goal (SDG 3) on good health and wellbeing, and particularly the SDG 3 target to reduce neonatal mortality to at least as low as 12 per 1,000 live births by 2030 (UN, n.d.). There are also two World Health Organization (WHO) programmes, 'Maternal, new-born, child and adolescent health (WHO, n.d. a)' and 'Global Strategy for Women's, Children's and Adolescent's Health 2016-2030' (WHO, n.d. b), which are focused specifically on improving the health of mothers and new-born children. Low Birth Weight (LBW), when new-born infants weigh less than 2 500g at birth (Abrevaya & Dahl, 2008), is one of the principal causes of neonatal mortality in many low- and middle-income countries. LBW is one of the risk factors associated with early childhood deaths and is linked with various metabolic disorders (Valsamakis et al., 2006; McGovern & Miletin, 2018). Children with LBW are more likely to suffer

from hypertension, coronary heart disease, type II diabetes and blood coagulation when they become adults (Osmond & Barker, 2000; Morley, 2006). These health impacts can have adverse effects on lifespan and quality of life for individuals, as well as having economic implications for society. LBW is a major public concern in Mexico (Ministry of Health in Mexico, 2002). Here, 9.15% of children are born with LBW, which is the highest rate in North America, and one of the highest throughout the Americas. Similar, figures can be found in Greater Mexico City, which includes Mexico City, where the LBW rate was 9.63% (Buekens et al., 2013). Given the policy interest and the SDG 3 target, there is a need to understand the factors behind LBW, so that policies can be developed to reduce both the mentioned long-lasting health implications and new-born deaths. This paper focuses on understanding the spatial distribution and temporal evolution of LBW in the largest urban area in Mexico, Greater Mexico City, from 2008 to 2015.

The neonatal mortality rate (number of infant deaths in the first 28 days of life per 1 000 live births) has been decreasing in Mexico from 11.52% in 1990 to 8% in 2012, but these values are still considered high (Ministry of Health in Mexico, 2002; Ministry of Health in Mexico, 2014). In 2001, there were 110 daily deaths of infants under 1 year old (Ministry of Health in Mexico, 2002). According to the Ministry of Health in Mexico (2008), 60% of infant deaths (44 000) occur in the neonatal period, and around 45% of these neonatal deaths could be avoided with proper medical interventions. The Ministry of Health in Mexico has therefore created a number of public programmes to decrease the neonatal mortality risk. These include ‘Programa de Acción: Arranque Parejo en la Vida, 2002’, ‘Programa de Acción Específico 2007-2012, 2008’ and Programa de Acción Específico Salud Maternal y Perinatal, 2013-2018’ (Ministry of Health in Mexico, 2014).

In addition to individual-based maternal risk factors, other risk factors associated with high neonatal mortality and, by inference, LBW include neighbourhood-level factors such as marginal and deprived economic conditions (Ministry of Health in Mexico, 2002). Understanding these neighbourhood-level risk factors can therefore make a significant contribution to reducing LBW and can serve as important evidence for policy makers. Specifically, understanding the geographical variation in overall LBW risk, and the individual risk factors underlying this, could provide information for the development of geographically targeted programmes that mitigate such risk in the most efficient way.

Previous studies on the spatial pattern of LBW have used spatial heterogeneity measures such as the Moran Index and local indicators of spatial association (LISA) to identify areas with high or low LBW (Francis et al., 2012; Tu et al., 2012; Tian et al., 2013). Studies such as Tu et al. (2012) and Tian et al. (2013), which analysed patterns of LBW in the state of Georgia, USA, focus on spatial analysis in a given year or within a specific period of time. Analyses that combine space and time can provide greater insights into public health issues because of the combined spatial and temporal structure of much disease data (Shin et al., 2012; Blangiardo et al., 2013; Lawson, 2013; Papoila et al., 2014), and the ability to link these patterns to underlying spatio-temporal variation in socio-economic conditions and other risk factors. Examples of research which has taken this type of approach include studies using conditional autoregressive spatio-temporal Bayesian models for the mapping and analysis of mortality risk from brain cancer (Ugarte et al., 2015) and gastric cancer (Aragonés et al., 2013).

There are several studies (Pearl et al., 2001; Baker & Hellerstedt, 2006; Young et al., 2010) that have explored the relation between LBW and demographic or socioeconomic determinants. For example, lack of prenatal care and older maternal age are both associated with a higher probability of having a child with LBW (Torres-Arreola et al., 2005; Insaf & Talbot, 2016). In contrast, being married and having no more than two children are associated with a lower risk of LBW (Pearl et al., 2001; Frank et al., 2004). However, few studies have accounted for the spatial (Insaf & Talbot, 2016) or spatial-temporal structure (Kirby et al., 2011) of the data, either in relation to health outcomes or their determinants. Knorr-Held and Besag (1998) acknowledge that communities are often clustered with respect to their socioeconomic background. Hence, it is likely that people with better socioeconomic conditions live close to each other, supported by good services in terms of schools and housing, whereas people with lower socioeconomic status are clustered in other places with poorer services. Socioeconomic status may also vary across time for both individuals and neighbourhoods, with important influences on health risk (Knorr-Held & Besag, 1998). Therefore, the association between LBW and socioeconomic risk factors may vary over space and time, and these types of spatio-temporal variation in risk have been observed for stomach cancers (Papoila et al. (2014) as well as air pollution ($PM_{2.5}$) and asthma (Lawson, 2013). Moreover, the health status of certain portions of the population may vary over space and time due to changes in health-related behaviours such as physical activity, smoking and diet (Shin et al., 2012).

There are also statistical and policy-related reasons for accounting for the spatio-temporal structure of health problems. Not accounting properly for space and time structure in the data can lead to errors with spatial autocorrelation and serial correlation respectively. In these cases, assumptions regarding the independence and identical distribution of the residuals would not be met, with a consequence that estimators of effect size may be biased or incorrect (Harvey, 1990; Anselin, 2002; Dormann et al., 2007). Even when these components are taken into account, endogeneity may still exist due to omitted risk factors that may have an impact on LBW when space and time are considered simultaneously. An example of one such spatio-temporally related risk factor that affects LBW is smoking during pregnancy (Baker & Hellerstedt, 2006). Most previous studies of LBW have not controlled for this spatial-time effect which may bias estimators upwards, although Kirby et al. (2011) is one exception, which accounts for this spatial-temporal variation with Bayesian latent structures models.

The aim of the study was therefore twofold. Firstly, we aimed to model the change in LBW risk across time for each municipality in Greater Mexico City. We did so by characterising the evolution of high, medium and low risk municipalities (model 1). Locations with high LBW risk should be a priority for policy attention, so this analysis provide important baseline information for decision-makers. Secondly, we considered the extent to which LBW risks could be explained by various socioeconomic risk factors at municipality level, controlling for spatio-temporal variability in these factors (model 2). Where known socioeconomic risk factors contribute significantly to overall LBW risk, the level of residual risk is lowered, reducing uncertainty around potential policy interventions. However, where known socioeconomic risk factors do not contribute to the overall LBW risk, a high level of residual risk remains unaccounted for, and more investigation would be needed to obtain evidence to support specific policy interventions. We applied a Bayesian modelling approach (Bernardinelli et al., 1995), since this provides a flexible framework to model space, time and space-time structure of the LBW data through random effects which can capture the unobserved heterogeneity. While the Bayesian analysis of space-time variability, using a two-stage classification method, has been applied in the area of criminology (Li et al., 2014), to our knowledge, this is the first time that this methodology has been used to account for the space-time structure of LBW risk.

2. Data and Methods

2.1 Area of study

Greater Mexico City is the third most populated metropolitan area in OECD countries (OECD, 2015). It comprises 59 municipalities which belong to the State of Mexico[1] and 16 municipalities within Mexico City (Appendix Figure A1). Greater Mexico City is the most important metropolitan area economically in Mexico, producing 23% of gross domestic product in the country in 2010 (OECD, 2015). Socioeconomic and educational conditions vary across Greater Mexico City (Appendix Figure A2), with the north, west, and east areas of the city being characterized by relatively lower socioeconomic and education levels with respect to the average (e.g. the municipalities of Hueypoxtla and Villa del Carbón), while the areas in the south-west (those that belong to Mexico City) have the best economic and educational conditions (e.g. Cuauhtémoc and Miguel Hidalgo).

The population of Mexico increased from 117,274,155 in 2012 to 124,777,324 in 2017; among these, 51.1% were men and 48.9% were women in 2017 (The World Bank, n.d.). There was a slight decreasing trend in births during the study period; there were 319,002 births in 2012 and 29,356 in 2017, respectively (own elaboration based on the information from Ministry of Health[2]). The distribution of births across Mexico City between 2012 and 2017 is shown in Appendix Figure A2. There was a higher number of births over the study period in the centre and centre-west of Greater Mexico City (e.g. the municipalities of Ecatepec de Morelos, Naucalpan de Juárez, Gustavo A. Madero and Iztapalapa). Conversely, the north and east areas had lower number of births over this period (e.g. Atlautla, Hueypoxtla and Otumba).

2.2 Data

Birth weight data were obtained from the Ministry of Health[2] for all registered births in the 75 municipalities of Greater Mexico City from January 2012 to December 2017. The analysis was focused on those babies with a birth weight <2,500g during the normal period of gestation from 37 to 42 weeks, known in the specialised literature as term low birth weight, and reflecting restricted fetal growth (Falcão et al., 2020). This resulted in a

[1]There is one more municipality which belongs to the State of Hidalgo but it is excluded from this analysis.

[2] https://www.gob.mx/salud/acciones-y-programas/menu-informacion-en-salud-dgis

dataset of 1,846,535 records of full-term live birth, amongst which 135,685 babies were considered to be in the LBW category. We define the rate or probability of LBW as the number of LBW births relative to the total number of births. The aims of this study are: (a) to reveal the spatial-temporal variation in LBW risk, providing an understanding of how the LBW risk varies across municipalities over the 6 years from 2012 to 2017; and (b) to investigate how socioeconomic and demographic risk factors can be used to explain such spatial-temporal variation in overall LBW risk. In order to achieve both goals, the individual birth records were aggregated annually at the municipality level. Modelling the aggregated municipality-annual data, instead of the individual-level data, offers a side benefit of easing the computational demands.

To determine the extent to which the spatial-temporal variability of overall LBW risk in Greater Mexico City could be explained by observable socioeconomic risk factors, we followed previous studies by including a set of demographic and socioeconomic covariates, attending also to data availability. Not having prenatal care and being an older mother (>30 years of age) are both significant risk factors associated with LBW (Torres-Arreola et al., 2005; Insaf & Talbot, 2016). The marital status of the mothers and their parity have also been identified as risk factors associated with LBW (Pearl et al., 2001; Frank et al., 2004). Socioeconomic variables, at the municipality level, have been used in previous studies as important covariates associated with LBW (Kirby et al., 2011; Insaf & Talbot, 2016). Here, we linked the residential addresses of the mothers to the INEGI intercensus data in 2015 that provides information on (all expressed as percentages): households with a medical service, either public or private (social variables), households with a TV, households with a car, households with a computer, households with a land line, households with a mobile phone and households with internet. Using a principal component analysis, we derived an economic index which represents purchasing power at the municipality level. This economic index was transformed into a categorical variable with three categories: low, mid-income, and high.

2.3 Statistical analysis

As an initial explanatory analysis, we calculated the global Moran Index (Anselin et al., 1996) and the serial autocorrelation respectively to investigate the spatial and temporal autocorrelation structure of the LBW data. The results, as we shall discuss in Section 3.2,

indicated the presence of spatial clustering in LBW risk across the municipalities and temporal dependency in the annual LBW risk over the study period. Guided by these data features, a Bayesian spatial-temporal modelling approach was taken. Specifically, y_{it}, the number of LBW babies in municipality i ($i = 1, \dots, N$ with $N = 75$) during year t ($t = 1, \dots, T$ with $T = 6$) is modelled using a binomial distribution where $y_{it} \sim Binomial\ (n_{it}, \mu_{it})$ with n_{it} representing the corresponding number of full-term birth records. The interest, therefore, lies in the modelling of μ_{it}, the LBW risk in municipality i in year t. Note that we used the binomial distribution to model the count of LBW babies because the data pair, y_{it} and n_{it}, forms the classic situation of modelling number of "successes" out of n trials where each trial returns two possible outcomes (McCullagh & Nelder, 1989), i.e. a newborn baby with low birth weight or otherwise.

Following Law et al. (2014) and Li et al. (2014), the risk of LBW on the logit scale (to ensure μ_{it} lies between 0 and 1) is modelled via Eq. (1), which is referred to as Model 1 hereafter.

$$\text{logit}(\mu_{it}) = \alpha + (s_i + u_i) + (\gamma_0 t^* + v_t) + \gamma_{1i} t^* + \varepsilon_{it} \qquad (1)$$

The purpose of Model 1 is to (a) reveal the overall spatial pattern and the overall temporal pattern of the LBW risk and (b) identify municipalities showing unusual space-time behaviours where the overall LBW risk considerably high, the local time trend deviates from the overall time trend pattern or a combination of both. Therefore, under this model, the space-time variability of LBW risk is formulated as a combination of the following components: α, the overall intercept; $(s_i + u_i)$, a spatial component that captures the spatial variation of the municipality i; $(\gamma_0 t^* + v_t)$, a temporal component describing the overall temporal pattern; $\gamma_{1i} t^*$, a space-time component quantifying a linear departure of a municipality's time trend from the overall time trend and ε_{it}, a second space-time component to deal with any observed space-time variability unexplained by all other components in the model.

To fully specify Model 1, prior models are to be assigned to each component. For the overall spatial component $(s_i + u_i)$, we used the Besag, York and Mollié (BYM) model (Besag et al., 1991). The BYM model consists of two sets of municipality-specific random effects. The set of random effects, $s_1, \dots, s_N$, is modelled using the intrinsic conditional autoregressive (ICAR) model so that they are spatially structured and thus

capturing the spatial autocorrelation structure evident in the data. The spatial structure on $s_1, \dots, s_N$ is imposed via the spatial weights matrix, W, in the ICAR model. Here, W, an $N \times N$ symmetric matrix, is defined based on the rook's move contiguity such that w_{ij}, an off-diagonal value in W, is 1 if municipalities i and j ($i \neq j$) share a common boundary, otherwise $w_{ij} = 0$. This choice of W corresponds to a modelling assumption that municipalities that are close together in space tend to experience similar levels of LBW risk. This assumption is fully justifiable based on the positive global Moran's Index as well as the smooth-looking maps in the observed LBW risk (Figure A3 in the appendix). Defining W using the queen's move contiguity, for example, will have little impact on the modelling results as the two weights matrices tend to differ only slightly for a map with a large number of areas irregular in shape and both definitions reflect the same underlying (prior) assumption. The second set of random effects, $u_1, \dots, u_N$, in the BYM model are spatially unstructured so they capture the part of the overall spatial variability that does not display a spatial pattern. Each random effect term u_i follows a common Normal distribution with mean 0 and variance σ_u^2, i.e. $u_i \sim N(0, \sigma_u^2)$. The variance σ_u^2 is to be estimated using the data. Here, we did not include any fixed effects (e.g. some functional form of longitude and or latitude) in the overall spatial component since there is no obvious spatial trend (e.g. gradual change in LBW risk from north to south) in the data. The BYM model, on the other hand, offers the flexibility to describe the overall spatially pattern well.

The overall temporal component contains two terms, $\gamma_0 t^*$ and v_t, where $t^* = 4$, around the mid-point of the 6-years interval. The first term, $\gamma_0 t^*$, describes a linear pattern in the overall time trend whilst the second term, which is modelled as Gaussian noise via $v_t \sim N(0, \sigma_v^2)$, allows for nonlinearity. The reason for estimating the overall linear pattern, in particular the estimation of the overall slope γ_0, is that it allows us to compare the time trend of LBW risk in each municipality to the overall linear pattern This, as we shall describe, allows us to classify municipalities according to their temporal behaviours.

The local-overall trend comparison is carried out via the space-time component $\gamma_{1i} t^*$ in Eq. (1). The municipality-specific slope, γ_{1i}, in particular, quantifies a linear departure of the time trend of a municipality from the overall time trend. More specifically, if γ_{1i} is estimated to be close to 0, then the time trend of municipality i is considered to be similar

to the overall time trend for Greater Mexico City. If, however, γ_{1i} is estimated to be different from 0, the time trend of LBW risk for municipality i is shown to be different from that of the whole of Greater Mexico City. The sign of the γ_{1i} estimate will inform the type of departure, which we shall return to in the Results section.

The municipality-level slopes, $\gamma_{11}, \dots, \gamma_{1N}$, are modelled using the BYM prior model. This prior specification assumes that whilst each municipality can have different time trends, the slopes of two nearby municipalities tend to be more similar to each other compared to a situation where these two municipalities are far apart. The term $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is the component for the variability that is not explained by all the other terms in the model. Such variability may arise due to overdispersion which indicates a higher variation of the observed LBW data compared with its mean. Finally, the random effect standard deviations such as σ_u, σ_v and σ_ε have a positive half Gaussian prior $N_{+\infty}(0,10)$ following the recommendation from Gelman (2006). The prior distribution for the intercept, α, is the improper uniform distribution defined on the whole real line (p. 246-247 Haining & Li, 2020) and the vague prior of $N(0,10000)$ is assigned to the overall slope γ_0.

Using the results from Model 1 together with the two-stage classification method proposed by Li et al. (2014) and followed by other studies (Lome-Hurtado et al., 2021), we can classify municipalities based on their overall level of LBW risk (through the use of the overall spatial component $s_i + u_i$) and their temporal behaviour (through the municipality-level slope γ_{1i}). At the first stage, to identify municipalities of high, medium and low overall LBW risk, we obtained the posterior probability of the spatial component $p(\exp(u_i + s_i) > 1|data)$. The exponentiated spatial term, $\exp(u_i + s_i)$, gives the odds ratio so $\exp(u_i + s_i) > 1$ implies that the overall LBW risk of municipality i within the study period is higher than that for the whole of Greater Mexico City. Therefore, $p(\exp(u_i + s_i) > 1|data)$ tells us the posterior probability of municipality i having a higher overall LBW risk. Following the criterion used in previous studies (Richardson et al., 2004; Li et al., 2014), we classified those municipalities with $p(\exp(u_i + s_i) > 1|data) > 0.8$ as high risk, and those with $p(\exp(u_i + s_i) > 1|data) < 0.2$ as low risk (i.e. municipalities with overall risks lower than that of the whole Greater Mexico City). Those municipalities with $p(\exp(u_i + s_i) > 1|data)$ between 0.2 and 0.8, were

classified as medium risk and their overall risk levels are considered to be similar to the overall risk of the whole City. Following Li et al. (2014), we label each municipality via f_i which takes the value of 1, 2 or 3 if that municipality is classified as high, low, or medium risk, respectively.

At the second stage, to explore how LBW risk associated with each municipality changed across time, we further classified the time trend of each municipality as increasing, decreasing or stable based on the posterior probability of the local slope, i.e., $p(\gamma_{1i} > 0|f_i, data)$. Recall that the local slope γ_{1i} measures the difference in slope between the trend of that municipality and the overall trend. Therefore, if the posterior probability $p(\gamma_{1i} > 0|f_i, data)$ is greater than 0.8, then this particular municipality presents an increasing trend relative to the overall trend. On the other hand, if the posterior probability is less than 0.2 then the associated municipality has a decreasing trend compared to the overall trend. If the posterior probability $p(\gamma_{1i} > 0|f_i, data)$ is estimated to be between 0.2 and 0.8, then the time trend of that municipality is shown to be similar to the overall trend, meaning the municipality presents a stable trend.

We extend Model 1 to include a set of demographic and socioeconomic covariates described in the data section as individual risk factors potentially contributing to the spatial-temporal distribution of overall LBW risk. Model 1 with the covariates, referred to as Model 2, is given as follows:

$$\text{logit}(\mu_{it}) = \alpha + (\textstyle\sum_{k=1}^{K} \beta_k X_{itk}) + \beta_{K+1} EconIndex_i + (s_i + u_i) + (\gamma_0 t^* + v_t) + \gamma_{1i} t^* + \varepsilon_{it} \qquad (2)$$

where, X_{itk} represents the kth covariate ($k = 1, \dots, K$ with $K = 6$) whose values vary over both space and time. These space-time covariates are marital status (mothers who are married or in a free union), low education level (those without education or who did not finish primary school), those with a high education (Bachelor's degree level), mothers aged over 35 years old, parity (mothers who have no more than 2 children), prenatal care (mothers who received prenatal attention), mothers who had access to medical services (either public or private). The regression coefficient β_k quantifies the effect of the kth covariate on the municipality-level annual risk of LBW. The covariate $EconIndex_i$

represents the 2015 municipality-level economic index. Whilst this index varies across municipalities, due to data availability, we assumed it remained the same throughout the study period. The coefficient β_{K+1} measures the association between the economic index and LBW risk. To complete the model specification, we assigned the following noninformative prior, $N(0, 1000)$, a normal distribution with mean zero and a large variance (1000), to each of the regression coefficients, $\beta_1, \ldots, \beta_{K+1}$, to reflect the absence of genuine prior information on the covariate effects.

Parameter estimation was carried out using WinBUGS (Spiegelhalter et al., 1999), a widely applied software for fitting Bayesian models via Markov chain Monte Carlo (MCMC) methods. To facilitate the preparation of data and for producing maps of results, we used the R package R2WinBUGS (Sturtz et al. 2005). Specifically, we prepared data in R (version 4.0.3), then used the bugs function in the R2WinBUGS package to fit a model in WinBUGS. The results from the WinBUGS fit were then gathered and imported back to R, via the use of the coda package (Plummer et al. 2015), for summary and for mapping. The specific detail on running both models in WinBUGS is given as follows.
For Model 1, we ran two MCMC chains with different initial values over 115000 iterations for each chain. Convergence was achieved after running both chains for 60000 iterations. Here, convergence was examined by visual inspection of the history plots and through the Gelman-Rubin diagnostic. The value from the Gelman-Rubin diagnostic remained lower than 1.04 for every single parameter, showing that both chains have achieved convergence after the period of 60000 iterations (Gelman & Rubin, 1992). Thus, the first 6000 iterations from each chain were discarded as burn-in, leaving a total of 110,000 iterations from both chains for posterior inference. A similar setting was used for fitting Model 2. Two MCMC chains with different initial values were run, each with 250,000 iterations. 50,000 iterations were discarded as burn-in and a total of 200,000 iterations from both chains were used for posterior inference. Again, history plots and the Gelman-Rubin diagnostic were used to check for convergence.

3. Results

3.1 Descriptive analysis

Table 1 presents an overview of the descriptive statistics of the observed LBW and potential associated risk factors, from 2012 to 2017, in Greater Mexico City. Overall,

there is a slight decrease in the annual average number of LBW births during the period of study. Likewise, there is a decrease in the overall number of births. However, there is a slight increase of the observed LBW risk which is consistent with the trend shown in Figure 1b. In general, there were also declines over time in the numbers of mothers who were married or in a free union, the number with no or low level of education only, the number of mothers who received prenatal attention, mothers who have no more than two children, and mothers over 35 years of age . In contrast, the number of mothers with access to medical services increased from the beginning until the middle of the time period of study, although it has decreased since. Finally, more than half of the municipalities (59%) are in the category of low income.

INSERT TABLE 1

3.2 Local geographical evolution of LBW risk

An analysis of the spatial and serial autocorrelation showed that the Global Moran Index of LBW for each year was positive and significant with a mean value of 0.36 and a *p* value<0.0001, illustrating positive spatial autocorrelation in the LBW data. This implies that there is some clustering of LBW risk in Greater Mexico City. Across the municipalities, the lag 1 serial autocorrelation had a mean of -0.3 with a standard deviation of 0.36. This shows evidence of certain level of association of the observed LBW data over time.

Figure 1 highlights some key results from Model 1. Figure 1a shows the posterior means of $\exp(s_i + u_i)$ across the municipalities. Here, $\exp(s_i + u_i)$ represents the odds ratio comparing the overall LBW risk of municipality i against the overall LBW risk of Greater Mexico City over the study period. An estimated odds ratio above (below) 1 suggests a higher (lower) risk for this municipality compared to the Greater Mexico City average across the 6 years. Results illustrate that areas in the south west (orange and red areas) are characterized by having higher risks of LBW, whilst areas in the east, in the north and some in the south-east have lower risks of LBW. This result is congruent with the observed data: Figure A3 in the appendix shows that the observed higher LBW risk municipalities are in the west and south-west of Greater Mexico City. Figure 1b shows the posterior estimates of the temporal odds (i.e. $\exp(\gamma_0 t^* + v_t)$ in Model 1). The

posterior mean of the overall slope γ_0 is 0.013 with a 95% credible interval of (-0.039, 0.064), suggesting the overall LBW risk remained stable between 2012 and 2017.

INSERT FIGURES 1a, 1b and 1c

The posterior means of the local slope, $\gamma_0 + \gamma_{1i}$ including the overall slope (γ_0) and the local departure (γ_{1i}), are displayed in Figure 1c. Those municipalities with negative values present a reduction in LBW risk over the 6 years. Conversely, municipalities with positive values show increasing risks in LBW over the study period. Overall, trends in LBW at municipality level vary spatially with a large number of municipalities showing an increasing pattern. These municipality slopes also appear to be spatially-autocorrelated – the slopes of nearby municipalities tend to be more similar compared to those from municipalities that are far apart.

As described in the Statistical Analysis section, each municipality is classified into the high, medium or low risk category via the posterior estimate of its spatial odds ratio $\exp(s_i + u_i)$. Figures 2a, 2b and 2c respectively show the municipalities in the high-, medium- and low-risk categories. High-risk municipalities are located in the south-west and west of the metropolitan area with a few high-risk municipalities located relatively in the north (Figure 2a). In contrast, most of the low-risk municipalities (Figure 2c) are located in the north and north-west, few of them in the centre. Medium-risk municipalities (Figure 2b) are mostly in the east and relatively few in the north.

INSERT FIGURE 2a

Using the posterior estimates of the local slope departures (γ_{1i}), we further classified each municipality into one of the three categories according to the temporal risk pattern of that municipality. The three trend categories are: stable, decreasing and increasing[3]. The inserted graphs in Figures 2a, 2b and 2c show the different trends for the observed LBW risk, the estimated LBW risk and the estimated common trend. Figure 2a shows that most of the high-risk municipalities (67%) had a stable time trend, whereas four of those high-risk municipalities (19%) had an increasing trend pattern in LBW risk. Figure 2b shows

[3] Note that 37 of these classified municipalities were significant at the 95% CI, and the rest were at the 90% CI.

the medium-risk municipalities, of which 14% showed an increasing trend in risk but a high proportion of these medium-risk municipalities, 72%, presented a stable trend.

INSERT FIGURE 2b

Finally, Figure 2c illustrates that only a small number of the low-risk municipalities (18%) showed an increase in LBW risk over time. Meanwhile, 63% of these low-risk municipalities presented a stable trend.

INSERT FIGURE 2c

3.3 Role of socioeconomic factors in explaining LBW risk

The posterior means of the odds ratios associated with the risk factors together with the 95% credible intervals are presented in the Table 2 (model 2); women with bachelor's degrees were excluded due to the high correlation of this variable with the other covariates (Pearson correlation r>0.55 with a *p* value<0.001). Results in this table illustrate that mothers over 35 years old is an important risk factor contributing to overall LBW risk: for mothers of this age, one year increase in their age is associated with a 0.6% increase in LBW risk (with 95% CI of 0.1% - 0.24%). Likewise, prenatal care is also a significant determinant associated with overall LBW risk: access to prenatal care is associated with a 0.8% reduction in LBW risk (with 95% CI of 0.2% - 2.8%). The rest of the individual risk factors are not significant as their 95% CIs all cover 1. However, other factors such as marital status, parity (mothers with not more than two children), medical services and the economic index were significant at the 90% level.

INSERT TABLE 2

The addition of socioeconomic covariates explained partially the risk for the 21 high risk municipalities, moving some of them into a low risk category in terms of residual risk.

We analyzed the observed, estimated and residuals of model 1 and 2 to measure the goodness of fit of such models. Figure A4 shows the observed (the black solid dots) and the estimated (open circles and dashed line) LBW risk values for Greater Mexico City as a whole, for model 1 and 2. Such values are very similar implying a good fit of both models. In addition, Table A1 illustrates the values of the residuals (difference between the observed and estimated values) for Greater Mexico City in each year, such values are close to cero and consistent with the results of Figure A4.

4. Discussion

This study has examined the temporal dynamics of overall LBW risk across municipalities in Greater Mexico City and investigated some potential socioeconomic and demographic risk factors to explain differences in these LBW risks between municipalities. To the best of our knowledge this is the first work in this area which has accounted for space, time and space-time patterns by applying a two-stage classification method incorporating random effects using a Bayesian approach (Li et al., 2014).

A number of municipalities have been identified as high risk for LBW, with a large cluster located in the south-west and a few high-risk municipalities scattered in the north of Greater Mexico City. Some of these high-risk municipalities are in Mexico City, which is consistent with a previous study that found that Mexico City has a higher rate of LBW than any other State in Mexico (Buekens et al., 2013). The presence of Miguel Hidalgo municipality in Mexico City in the high-risk category may appear unexpected, since it has good medical facilities, and high levels of income and education. However, it also has a high population density of women, and a high number of jobs compared with other municipalities explored in this study, and it is one of the most dynamic municipalities in terms of transport mobility (DENUE, 2009) which leads to a high level of exposure of its inhabitants to air pollution. Mexico City and the area covered by the south-west high risk cluster are both characterized by having high levels of pollution; ozone reached higher concentrations, between 65 to 70 parts per billion (the mean was 56.8 parts per billion) in 2015 (Lome-Hurtado et al., 2019). Air pollution has previously been considered as increasing LBW risk factor (Coker et al., 2015), but lack of reliable information at the municipal level prevented us from exploring its importance at the local level in this study. Two municipalities in the west of Greater Mexico, Naucalpán de Juárez and Cuatitlán Izcalli, were also characterized as high-risk municipalities. Naucalpán de Juárez was one

of the municipalities with the highest number of mothers over 35 years old from 2012 to 2017; 1641 mothers over 35 years old compared with the average number in Greater Mexico of 454. Meanwhile, the municipality of Cuatitlán Izcalli is one of the municipalities with more limited access to prenatal care compared with the rest of the municipalities; only 6152 mothers in the municipality had access to prenatal care, compared with a mean of 23,545 across Greater Mexico.

A large number of medium-risk municipalities were located in the east of Greater Mexico. Six of them (Chalco, Chiconcuac, Nopaltepec, Tlalnepantla de Baz, San Martín de las Pirámides and Tepetlaoxtoc) showed a tendency for increasing risk over time. Finally, a cluster of low-risk municipalities was located relatively in the north. The LBW risk showed a smooth increasing trend over the 6-year period of study. This slight increase in the LBW risk may have been partly due to the results of different health programmes (Ministry of Health in Mexico, 2002; Ministry of Health in Mexico, 2014). Such programmes aimed to give universal access to good quality medical services to women in pregestational, pregnancy, childbirth, puerperium and neonatal stages, in order to reduce maternal morbidity and mortality in groups of women who were at greatest risk. The percentage of attended pregnant women (in medical services such as public clinics and health centers) in their first trimester increased slightly; it was 41.4% in 2013 and 42.3% in 2014. Furthermore, the maternal mortality ratio decreased slightly from 41.2% to 39.5% in 2014 (Ministry of Health in Mexico, 2014).

Our analysis highlighted mothers over 35 years old is a risk factor which increase LBW risk. In contrast, having access to prenatal care may reduce such LBW risk. Our results are similar to findings from previous studies (Abrevaya and Dahl, 2008; Young et al., 2010; Abrevaya, 2002). For instance, Abrevaya and Dahl (2008) found a stronger positive relation between mother age and at the lower quantiles of birth weight (when compared with higher quantiles of the birth weight sample) for mothers living on Washington and Arizona, US. Abrevaya (2002), also in the United States, found that mothers with access to prenatal care are more likely to have babies with normal weight. With respect to economic status, our income index (proxy variable of income) was not a significant risk factor for LBW. This finding is similar to another study (Cubbin et al., 2008) where income was found not to be a significant risk factor for LBW in Washington, USA. However, other studies (Masi et al., 2007; Kirby et al., 2011) have found income to be

negatively associated with LBW. Kirby et al. (2011) concluded that household median income may reduce the LBW risk, across the states of Georgia and South Carolina. These results may differ because of differences in methodology, such as the use of different types of regression model, different geographical units of analysis and variations in local context.

These results should be interpreted with caution due to some methodological and data limitations. This is particularly true for analysis of covariates of LBW. We used covariates at the municipality level, but this potentially masks important variations within municipalities, and to obtain more reliable results on the role of covariates as individual risk factors for overall LBW risk, it would be better to analyze birth records at the individual level; this would be a priority for future work. In addition, there may other potential risk factors such as smoking habits, and air pollution (Coker et al., 2015, Kirby et al., 2011) not included in this study, but their potential variation may be captured for the spatial or/and spatial-temporal components. Very low maternal age (18 or lower) has been found in other studies to be a significant predictor of LBW (Insaf and Talbot, 2016), but we could not address this in this study, since the proportion of teenage pregnancy is lower than 0.1 in our data. Finally, we have assumed that there is no mobility of women. This assumption may not apply in a dynamic area as Greater Mexico City. It is not easy to account the mobility of people which would require more precise data; therefore, we did not measure it as other studies (Havard et al., 2009; Fecht et al., 2015). Nevertheless, key strengths of this study include the specific inclusions of time, space and space-time structures, which are important to take into account due to the nature of the data. Because the analysis controls for any unobserved heterogeneity, it is possible to derive more robust estimators.

5. Conclusion

The findings of this study, showing the spatial evolution of patterns of LBW risk and the associated individual risk factors, may provide an important input to decisions on policy to reduce LBW. Spatial and temporal trends may provide useful information for policy makers in designing programmes to tackle health inequalities. Therefore, the identification of municipalities at highest risk of LBW would permit the geographical targeting of policy efforts to reduce the risk of LBW, which could offer significant

benefits in terms of developing cost-effective policy, given the overall scarcity of healthcare resources in Mexico. Such high-risk municipalities were located in the south-west and a few scattered in the north of Greater Mexico City. On the other side, the identification of current medium-risk municipalities (in the east of Greater Mexico) which show how an increasing risk over time could be important in developing more proactive geographically-targeted policy initiatives.

Geographical targeting of policy may also bring benefits in enhancing the confidence and capacity of the local participation. The results of the analysis of contributing socioeconomic and demographic risk factors also provide some potential levers for policy-makers to address as a means of influencing rates of LBW. The results of this study suggest that decision-makers should focus on reducing broader social determinants of LBW through social programmes, such as access to prenatal care and better communication around the links between maternal age and LBW, since these would be likely to bring benefits in reducing the rate of LBW.

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Declaration of interest

Conflicts of interest: none

6. References

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Figure 1a, 1b and 1c. Spatial risk, overall trend and local trends (including the overall trend) of each municipality in Greater Mexico City.

Figure 1a **Figure 1b** **Figure 1c**

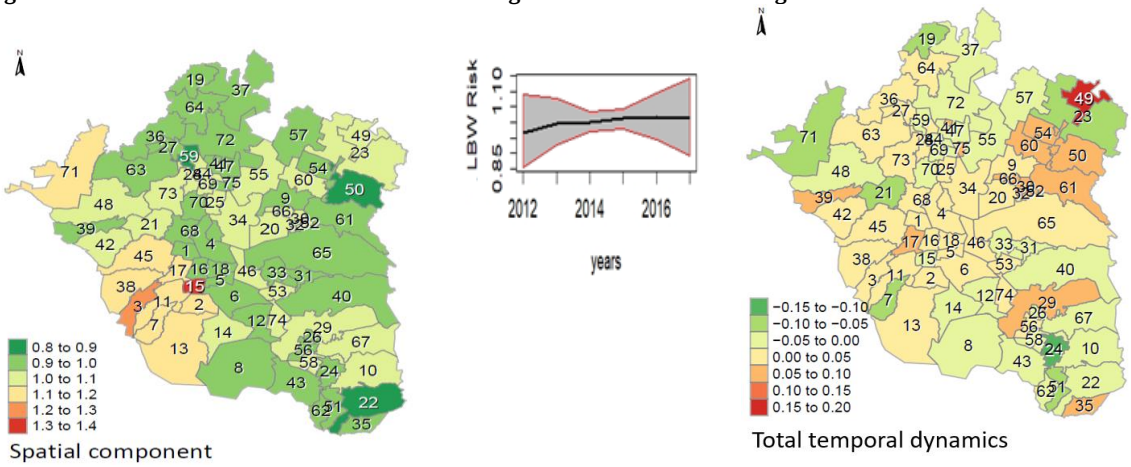


Figure 1a shows the overall spatial component (the posterior means of the odds ratios, $\exp(s_i + u_i)$ with $i = 1, \ldots, 75$) during the studied period. Those areas with an odds ratio greater than (less than) 1 have a higher (lower) LBW risk compared to the average risk of Greater Mexico City over the study period. Figure 1b displays the overall time trend compared to the Greater Mexico City average with 95% credible interval. Figure 1c shows the local trends of each municipality respect to the overall trend; a positive (negative) value corresponds to an increase (a decrease) pattern in LBW risk over time.

Figure 2a. Temporal trends in LBW risk for high-risk municipalities

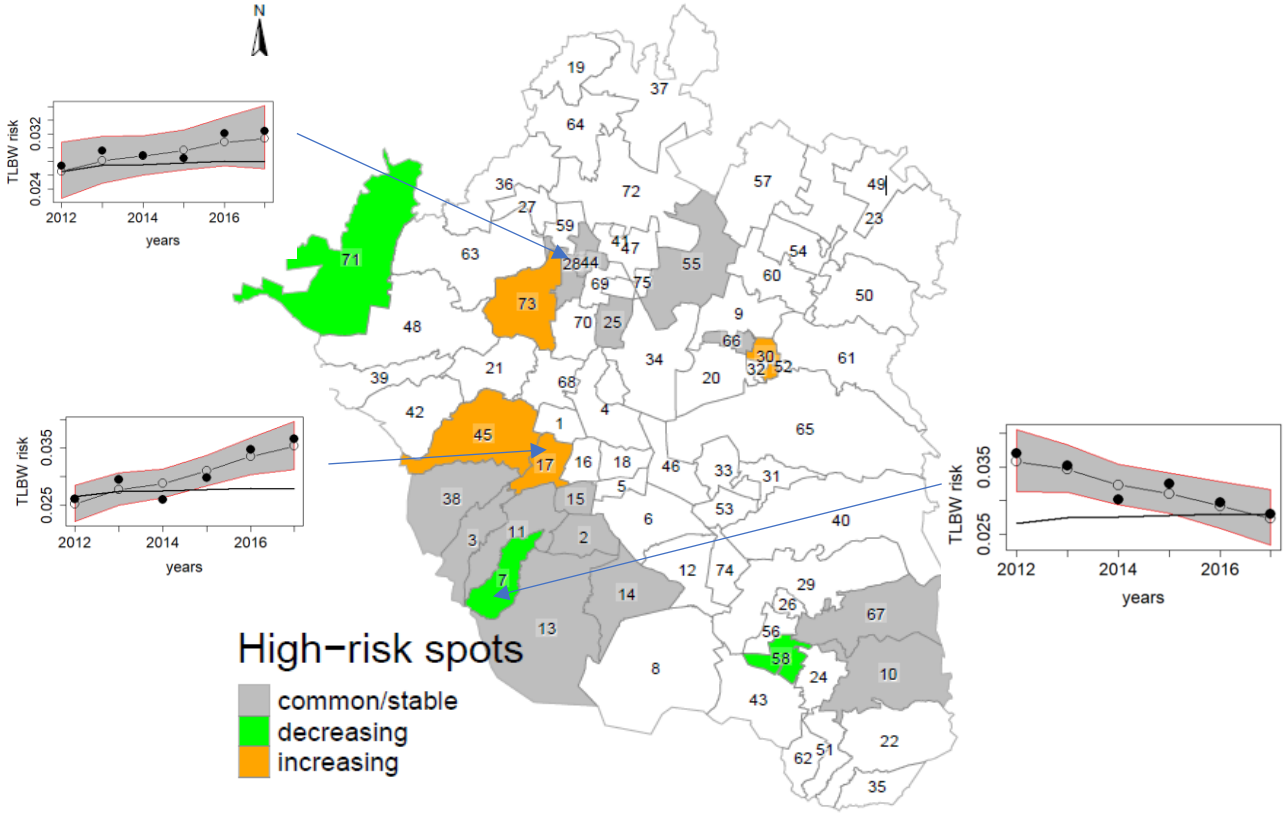


Figure 2a shows the temporal dynamics of LBW risk for high-risk municipalities in greater Mexico City, which are classified into 3 categories: stable, decreasing and increasing risk. The inserted figures show the observed LBW risk (the black solid dots), the estimated LBW risk – the posterior means of the risks over time, i.e. μ_{it} in Model 1 - (open circles and dashed line) with 95% CI (grey region) and the estimated common trend (black line) over time.

Figure 2b. Temporal trends in LBW risk for medium-risk municipalities

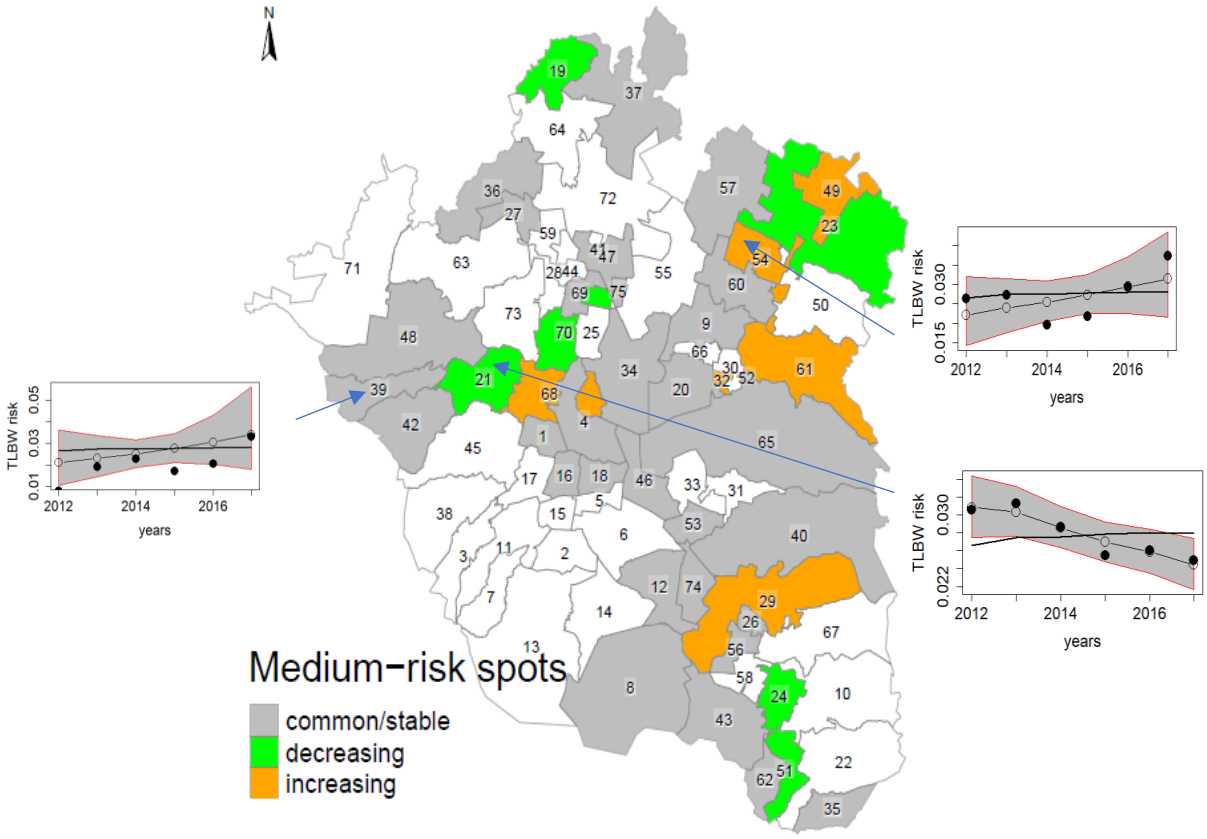


Figure 2b displays the temporal dynamics of LBW risk for medium-risk municipalities in greater Mexico City, which are classified into 3 categories: stable, decreasing or increasing risk. The inserted figures show the observed LBW risk (the black solid dots), the estimated LBW risk (open circles and dashed line) with 95% CI (grey region) and the estimated common trend (black line) over time.

Figure 2c. Temporal trends in LBW risk for low-risk municipalities

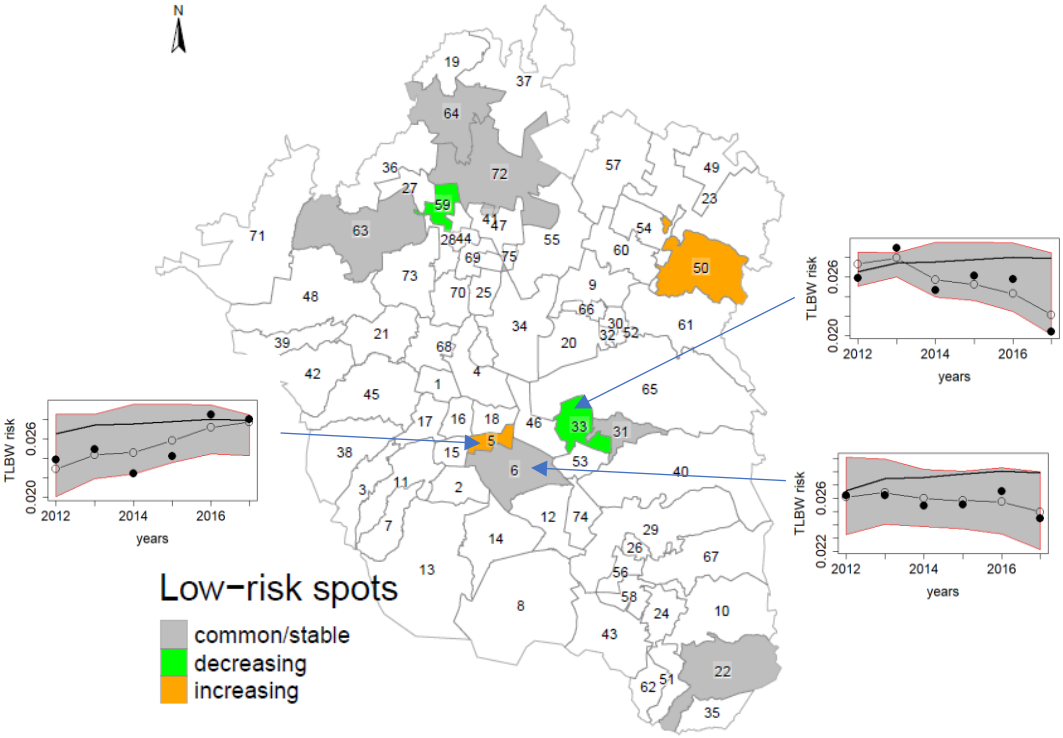


Figure 2c displays the temporal dynamics of LBW risk for low-risk municipalities in Mexico City, which are classified into 3 categories: stable, decreasing or increasing risk. The inserted figures show the observed LBW risk (the black solid dots), the estimated LBW risks (open circles and dashed line) with 95% CI (grey region) and the estimated common trend (black line) over time.

Table 1. Descriptive statistics of the LBW and associated risk factors across the 75 municipalities and its municipality-level potential determinants in Greater Mexico City.

Name	**2012** **Mean; sd** **(min; max)**	**2013** **Mean, sd** **(min, max)**	**2014** **Mean, sd** **(min, max)**	**2015** **Mean, sd** **(min, max)**	**2016** **Mean, sd** **(min, max)**	**2017** **Mean, sd** **(min, max)**
Number of LBW births	111.8;146.4 (1;732)	114.2;150.4 (1;706)	113.5;153.5 (0;757)	109.8;146 (1;692)	107.2;142.7 (1;738)	103.3;132 (0;665)
Total number of births	4253.4;5762 (81;27948)	4180.4;5693.8 (79;28668)	4128.6;5628.4 (46;28716)	3964.7;5392.2 (46;26807)	3833.4;5145 (58;25925)	3721.1;4899.6 (74;24613)
Observed LBW risk	0.0262; 0.0068 (0.0056; 0.0510)	0.0267; 0.0061 (0.0127; 0.0414)	0.0267; 0.0082 (0;0.0652)	0.0270; 0.0052 (0.0145; 0.0393)	0.0289; 0.0118 (0.0076; 0.1034)	0.0275;0.0069 (0;0.0506)
Risk factors						
Marital Status	3709.6;4992.7 (73;24143)	3640.8;4922 (71;24685)	3599;4870.9 (41;24698)	3459.3;4671.3 (39;23407)	3356.6;4473.8 (53;22460)	3262.9;4274.8 (64;21615)
Not/low education	159.3;239.2 (2;1147)	162.9;303.6 (1;1992)	139;242.5 (2;1406)	147.6;332.1 (0;2511)	124.1;288.8 (0;2204)	105.6;202 (0;1057)
Mother age over 35	465.7;639.8 (6;3065)	457.5;625.8 (4;3036)	466.7;626.3 (5;2932)	454.7;611.8 (6;2858)	448.5;604.4 (4;2862)	447.8;586.3 (7;2764)
Prenatal care	4163.9;5618.9 (79;27272)	4087.5;5540 (76;27971)	4026.7;5467.7 (46;28045)	3869.4;5246.1 (45;26199)	3755.6;5021.1 (58;25395)	3642.1;4778.8 (73;24089)
Parity	3255.1;4378.5 (63;21117)	3226.5;4372.6 (63;22066)	3217.1;4364.2 (33;22367)	3110.3;4202.5 (39;20882)	3014.5;4026.4 (44;20374)	2924.2;3813.3 (65;19209)
Medical service	2775.5;3715.4 (32;19573)	2838;3955 (39;20596)	2874.3;3984.3 (20;21281)	2849.6;3912.8 (25;20342)	2862.1;3872.7 (30;19583)	2787.1;3696.3 (44;18880)
	Low, 2015	***Medium, 2015***	***High, 2015***			
Economic index[a]	44	*26*	*5*			

The numbers without brackets are the mean and standard deviation, those in brackets are the minimum and maximum values respectively (except for the economic index). Each variable refers, from the 3rd row onwards, the number of mothers with the mentioned characteristic. For example, the number 3710 (2012 year) for marital status displays the mean, 3710, of mothers with marital status in Greater Mexico City.

[a]The numbers in the economic index, represent how many municipalities belong to each category.

[b]It is obtained as the total number of LBW divided by number of births.

TABLE 2. Posterior means of odds relating to different potential risk factors affecting LBW, with 95% credible intervals displayed in the brackets.

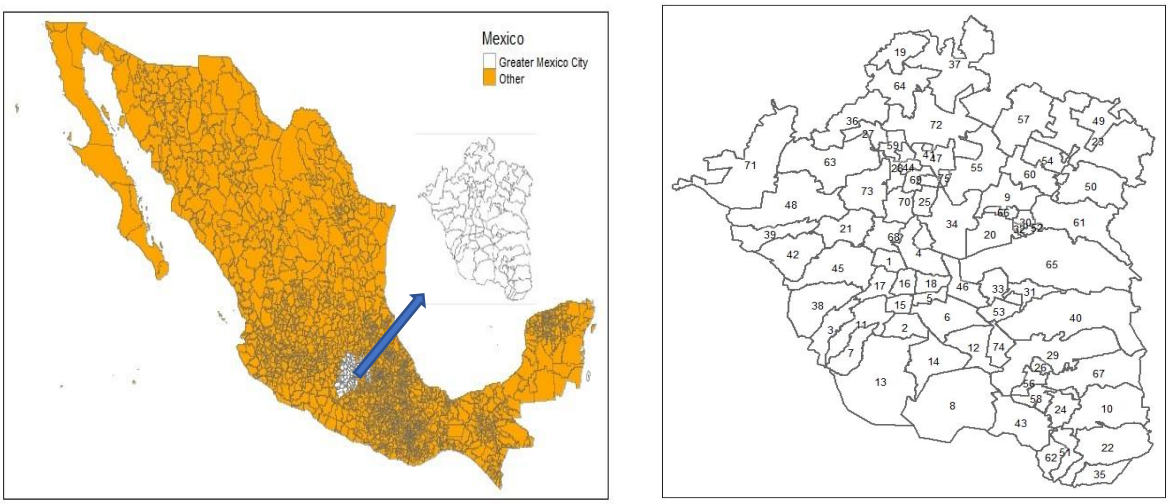
Variable	Posterior estimates
Marital Status	1.009 (0.997, 1.02)
Not/low education	1.00 (0.99, 1.007)
Mother age over 35	1.006 (1.001, 1.024)
Prenatal care	0.992 (0.972, 0.998)
Parity	0.998 (0.987, 1.009)
Medical service	1.001 (0.997, 1.003)
Economic index [1] (middle)	1.047 (0.972, 1.132)
Economic index [1] (high)	1.134 (0.970, 1.313)

[1]The economic index variable is categorical (poor, middle and high), the poor is the reference and equal to 1 on the odds ratio scale.

The figures between the brackets indicate the 95% credible interval. A 95% credible interval covers the value of 1 indicates a change to that covariate has little effect on the LBW risk. In other words, that covariate is not an important factor for explaining the LBW risk.

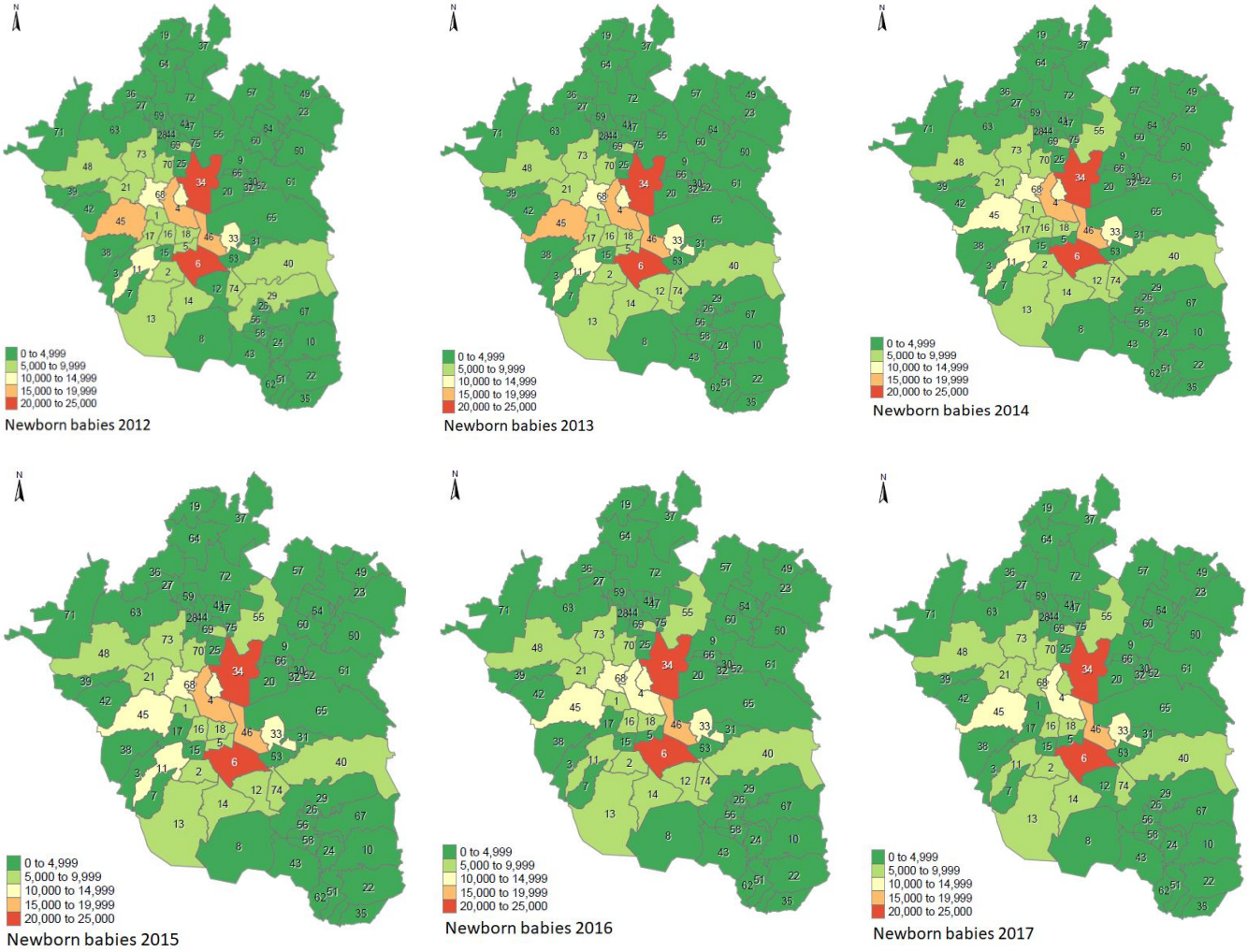
Appendix

Figure A1. Mexico and Greater Mexico City.



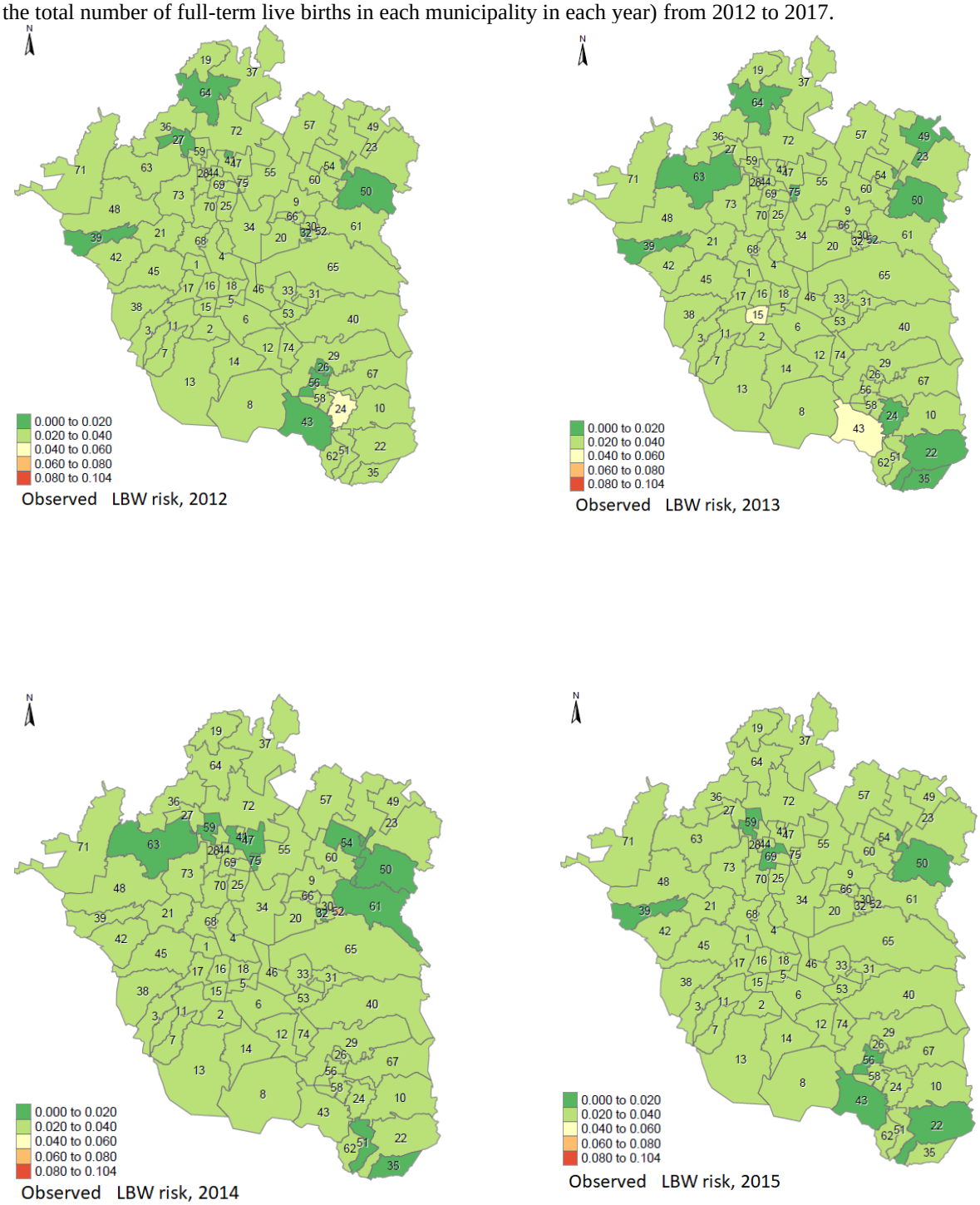
Municipalities of Greater Mexico City: 1) Azcapotzalco, 2) Coyoacán, 3) Cuajimalpa de Morelos, 4) Gustavo A. Madero, 5) Iztacalco, 6) Iztapalapa, 7) La Magdalena Contreras, 8) Milpa Alta, 9) Acolmán, 10) Amecameca, 11) Alvaro Obregón, 12) Tláhuac, 13) Tlalpan, 14) Xochimilco, 15) Benito Juárez, 16) Cuauhtémoc, 17) Miguel Hidalgo, 18) Venustiano Carranza, 19) Apaxco, 20) Atenco, 21) Atizapán de Zaragoza, 22) Atlautla, 23) Axapusco, 24) Ayapango, 25) Coacalco de Berriozábal, 26) Cocotitlán, 27) Coyotepec, 28) Cuautitlán, 29) Chalco, 30) Chiautla, 31) Chicoloapan, 32)Chiconcuac,33) Chimalhuacán,34) Ecatepec de Morelos, 35) Ecatzingo, 36) Huehuetoca, 37) Hueypoxtla, 38) Huixquilucan, 39) Isidro Fabela, 40) Ixtapaluca, 41) Jaltenco, 42) Jilotzingo, 43) Juchitepec, 44) Melchor Ocampo, 45) Naucalpan de Juárez, 46) Nezahualcóyotl, 47) Nextlalpan, 48) Nicolas Romero, 49) Nopaltepec, 50) Otumba, 51) Ozumba, 52) Papalotla, 53) La Paz, 54) San Martín de las Pirámides, 55) Tecámac, 56) Temamatla, 57) Temascalapa, 58) Tenango del valle, 59) Teoloyucan, 60) Teotihuacan, 61) Tepetlaoxtoc, 62) Tepetlixpa, 63) Tepotzotlán, 64) Tequixquiac, 65) Texcoco, 66) Tezoyuca, 67) Tlalmanalco, 68) Tlalnepantla de Baz, 69) Tultepec, 70) Tultitlan, 71) Villa del Carbón, 72) Zumpango, 73) Cuautitlán Izcalli, 74) Valle de Chalco Solidaridad and 75) Tonanitla. Source: Lome-Hurtado et al. 2021

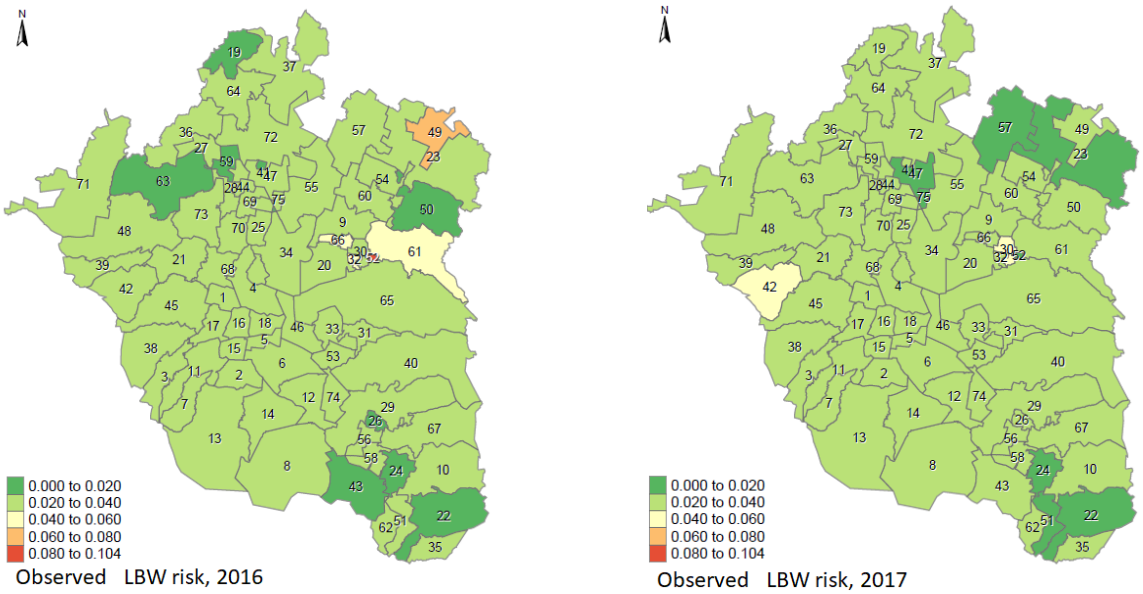
Figure A2. Spatial distribution of newborn babies with the normal period of gestation from 37 to 42 weeks from 2012 to 2017.



Source: Own elaboration using data from Ministry of Health.

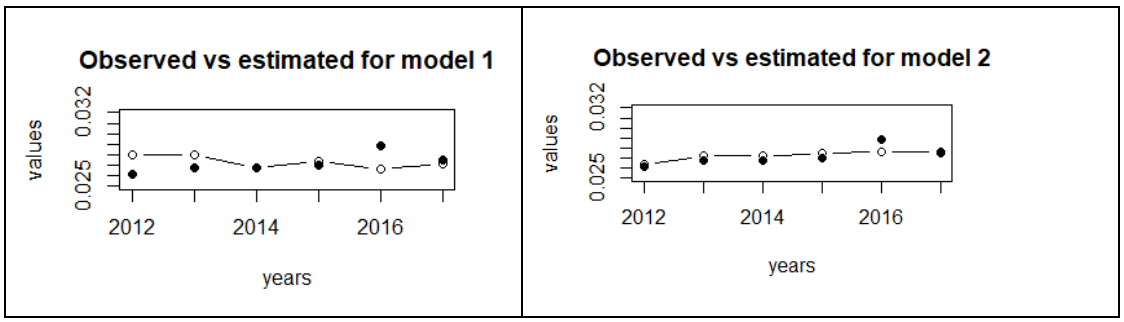
Figure A3. Spatial distribution of the observed LBW risk (defined as number of LBW babies divided by the total number of full-term live births in each municipality in each year) from 2012 to 2017.





Source: Own elaboration using data from Ministry of Health.

Figure A4. Observed vs estimated LBW risk values, in Greater Mexico City, for model 1 and 2.



Note: The graphs illustrate the observed (the black solid dots) and the estimated (open circles and dashed line) values for Greater Mexico City as a whole, for model 1 and 2. We do not present graphs for each municipality due to the space, in total it would be 150 graphs. Source: Own elaboration.

Table A1. Mean of the residuals for model 1 and model 2 in Greater Mexico City.

Year	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Model 1	0.001824644	0.001255827	-0.00000012178	0.000387882	-0.002274906	-0.000324434
Model 2	0.00022	0.00050	0.00055	0.00046	-0.00121	0.00011

Note: The residuals are for Greater Mexico City as a whole, for model 1 and 2. We do not present the residual for each municipality due to the space, in total it would be 150 cells. Source: Own elaboration.