Supplementary Material

Data and methods: To obtain the year-wise number of CS deliveries, we used the information available on year of birth for each birth in the last five yr. For the trend analysis from 2001 to 2019, we used linear trend interpolation to estimate the rate of CS from 2006 to 2010. For spatial autocorrelation, estimation of RR, and spatio-temporal modelling using MCMC, we used data on the number of CS deliveries from 2011 to 2019.

Risk of CS in the area k with time t is denoted by,

$$\ln(\theta_{kt}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

where, y_{kt} is the number of CS in local authority area k during year t, θ_{kt} is the RR of CS in local authority area k during year t and E_{kt} is the expected count. In addition, x_1, x_2, x_3, x_4 denote the proportion of mothers with higher education, with age 30-49 yr, with obesity, and with richest wealth quintile, respectively.

Moran's I: Moran's I provide a value in the range -1 to 1 for the entire dataset, indicating whether the spatial distribution pattern of CS is dispersed (-1), random (0), or clustered (+1). The statistical significance of clustering is determined by the Z-score and its P-value for each district. We also computed the Local Indicator of Spatial Autocorrelation (LISA) for each year from 2011 to 2019. The LISA measures the statistical correlation between the CS rates in an area with respect to its neighbouring values, defining neighbours as districts sharing a common border.

The standardized incidence ratio (SIR): SIR is widely used to compare the observed number of occurrences of an event in a population relative to what might be the expected number of occurrences, assuming the population had the same experience as the north-eastern States' population (15-49-year women) designated as normal or average or reference or standard population. For calculating the SIR of CS, we used data on CS occurrences and reference incidence rates for comparison (expected CS cases). Statistical inference for the SIR is usually based on the assumption that the denominator is fixed, and the numerator follows a Poisson distribution. SIRs may be misleading and insufficiently reliable when regions have small populations. It is often preferred to estimate disease risk by using models that are unable to borrow information from neighbouring areas and incorporate covariates information resulting in the smoothing or shrinkage of extreme values based on small sample sizes.

We introduced the above-mentioned predictors in the model based on previous research article where these predictors had shown significant association with CS. The RR θ_{kt} quantifies whether area k has a higher $(\theta_{kt} > 1)$ or lower $(\theta_{kt} < 1)$ risk than the average risk in the standard population (or regional population of northeastern States). This Poisson log-linear model (1) is fitted in a Bayesian setting with MCMC simulation using the function S.glm(). Before including spatio-temporally autocorrelated random effects in the model, it's important to verify that the existing covariates account for all spatio-temporal autocorrelation present in the disease data. Therefore, a straightforward initial model is a Poisson log-linear model is used.

Bayesian spatio-temporal modelling using Markov Chain Monte Carlo (MCMC) simulation: This study utilized the conditional autoregressive model to represent the spatially correlated variation in CS risk and used CAR as a prior distribution for a set of spatially structured random effects. Several authors have proposed CAR models as spatio-temporal extensions. This model assumes that risk varies smoothly in space and time, and thus accounts for the inherent spatio-temporal autocorrelation typically observed amongst the CS data. A Bayesian approach to inference is typically adopted, using either MCMC simulation

The model can then be fitted using MCMC simulation through the ST.CARar() function to the ordered data. The CARBayesST package requires the data to be ordered so that the first K data points relate to all the spatial units for time-period 1, the next K data points relate to all the spatial units for time-period 2, and so on. We have run the model three times to generate MCMC samples from three independent Markov chains. We received 6,000 samples for inference overall, with 2,000 samples obtained from each Markov chain.