# Title: Bayesian Hierarchical Modelling for Spatial Mapping of Sterilization among Females in India Using R-INLA

## Introduction:

Family planning has profound health, economic, and social benefits for families and communities, including protecting the health of women by preventing high-risk pregnancies, protecting the health of children by allowing sufficient time between pregnancies, reducing abortions, supporting women's rights and opportunities for education, employment, and full participation in society, and protecting the environment by stabilizing population growth. (Heil, et al., 2012). The use of contraception is the major component of family planning programs. Improved access to contraception methods has the potential to reduce poverty and hunger, avert maternal and childhood deaths, contribute substantially to women's empowerment and thus contributed significantly to addressing the 3.7 and 5.6 target of Sustainable Development Goals which supports universal access to sexual and reproductive health care services, including family planning and universal access to sexual and reproductive rights, respectively (United Nation, 2015). Contraceptives are mainly used by the majority of married or in-union women throughout the world. In 2015, 64 percent of married or in-union women of reproductive age (15-49 years) worldwide were using some form of contraception. According to global analysis, the proportion of reproductive-age married women who use a modern or traditional contraceptive method rose from 55% to 63% between 1990 and 2010 (Joshi et al., 2015). Most of the increment was due to a 10 percentage-point rise in contraceptive prevalence in the developing world, contraceptive use also increased in developed countries (Doskoch, 2013). The increase in contraceptive prevalence in India has been paralleled by declining fertility, with the total fertility rate declining from 5.7 in 1970 to 2.2 in 2016 (NFHS-4, 2016). Much of this fertility decline has been achieved through increases in the adoption of female sterilization (Pathak et al., 1998).

Globally, female sterilization is used by 19% of women aged 15–49 years who are married or in the union (United Nation, 2015), more than two-thirds of all sterilization procedures worldwide are performed for contraceptive purposes (Melville & Bigrigg, 2008). Female sterilization is one of the most common methods of contraception in the developing world. According to United Nations estimates, about 1 out of 5 women worldwide are sterilized, with a large portion in Asia – 28.7% of women in China and close to 36% in India (United Nations, 2018). The reliance on female sterilization in India has its roots in the National Family Planning Programme of the 1970s, which promoted a permanent method of contraception, i.e. sterilization as an effective mechanism for fertility reduction (Saavala, 1999). According to the fourth round of National Family Health Survey (NFHS-4) carried out during 2015-16, about 36 % of currently married women were female sterilization adopters compared to 37% in 2005-06, 34% in 1998-99 and 27% in 1992-93 (6). Thus, the percentage of women adopting sterilization in India is not varying significantly since 1998 (NFHS-2), and it still remains the most popular modern contraceptive method.

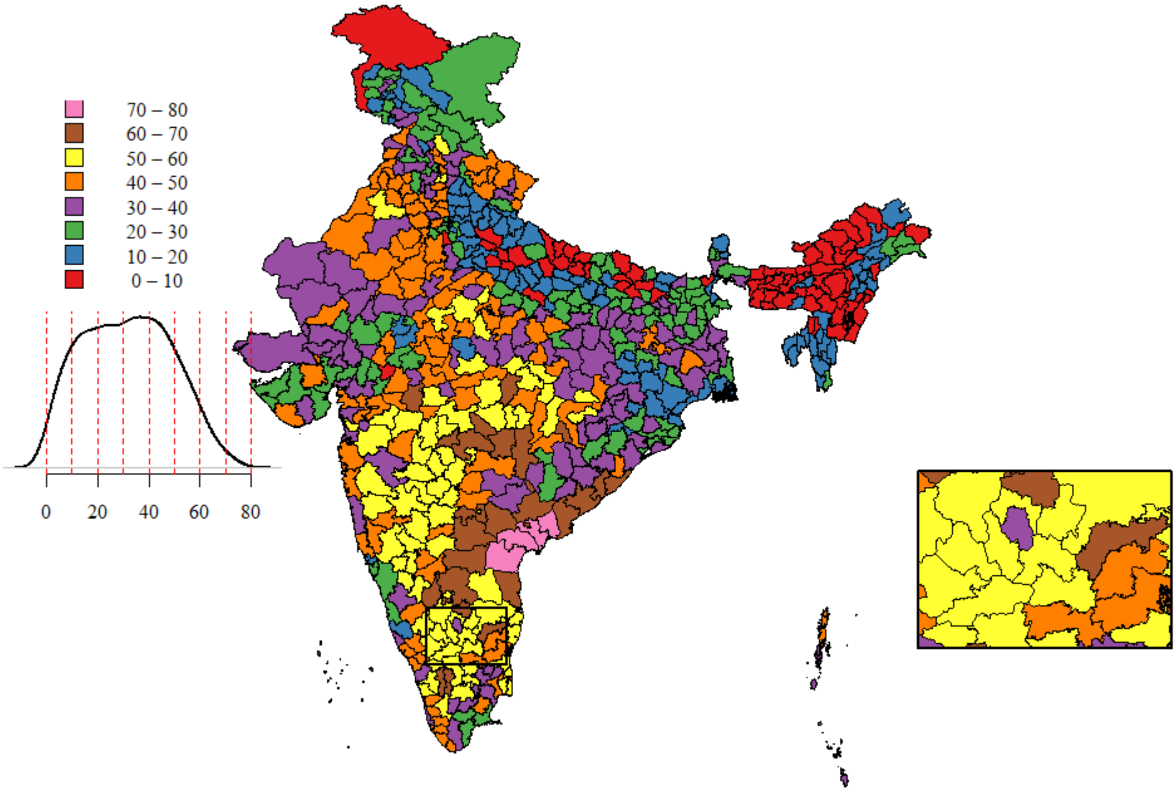
In India, the high proportion of women using female sterilization continues to be a concern, because of the potential for sterilization regret particularly among women who are young, have lost a child or have had only female children (Bertrand et al., 2014). It has been compounded by the fact that out of the total women, who have undergone sterilization, before the acceptance of sterilization the majority were neither informed about other methods of contraception nor were they informed about the possible post-sterilization health problems by the providers, leaving a question mark on the intentions of the providers (Pradhan & Ram, 2009). The decision to adopt sterilization was also driven by a woman's age, parity, education, caste, place of residence (Stephension, 2006). The use of financial incentives to promote family planning is an innovative approach; sterilization has also been a target of incentives (Heil et al., 2012). Female sterilization is performed at the cesarean section for medical reasons, and when further pregnancies are deemed inadvisable and hazardous, also, tubal sterilization during C-section is cost-effective (Celik et al., 2018). Tubal sterilization is a method which is conducted during birth with C-section and has an important role in the prevention of unplanned pregnancy and reduction of maternal mortality.  A district-level study on sterilization shows the regional variation that the southern region dominates sterilization choices whereas modern temporary method choices are popular in the northern and western regions. About one-half of the women in the northeast region choose traditional methods which in contrast is less than one-tenth in the southern (Stephension, 2006).

A review of sterilization related literature in India reveals that the spatial perspective of the prevalence of sterilization and factors associated is not explored yet. Most of the research is focused on an individual level, but spatial variations across the regions, i.e. state and district are undermined. The present study attempts to address these research gaps, as it is vital to consider spatial variations for a geographically diverse country like India. Spatial variations at district and state level will give a true picture of factors prompting sterilization at the macro level. In this paper we focus on female sterilization mapping, the aim of which is to map the spatial pattern in sterilization over the districts of India. In disease mapping studies, the region of interest is split into n contiguous small-areas, for our study it is 640 districts, and the aim of the study is to detect which districts of India exhibit an elevated level of sterilization. Bayesian hierarchical models are typically used in such analyses, where any spatial correlation in the data is modelled at the second level of the hierarchy by a set of random effects, in addition to potentially available covariate information. (Marta Blangiardo R-INLA). The associations between female sterilization data and socio-demographic and other risk factors can locally vary due to various facts such as averaging effects of aggregated sterilization data, measurement units of risk factors, spatially changing socio-economic and individual characteristics of the understudied population.

## Data Source:

This study used data from the fourth round of National Family Health Survey (NFHS-4), which is a national level household survey conducted in 2015-2016 under the stewardship of the Ministry of Health and Family Welfare (MOHFW). It provides information on population health and nutrition at national and subnational levels. The current study used survey data of sample size 533,429 out of the total sample of 699,686 eligible women age 15-49 years, who were interviewed at the time of the survey regarding sterilization. The women questionnaire collected information on family planning: knowledge and use of contraception, sources of contraceptive methods, information on contacts with community health workers and respondent's health check-ups.The unit of analysis in the current study is states (level 1) and districts (level 2). India is a federal union comprising twenty-nine states and seven union territories, for a total of thirty-six entities. The states and union territories are further divided into 640 districts which are the unit of analysis.

**Graph 1: Prevalence of Sterilization among Females in India- District Level**




**Outcome Measurement:**

Females were directly asked whether "Have you ever used anything or tried in any way to delay or avoid getting pregnant?" and further "What have you used or done?". The self-reported percentage of women age 15-49 years, having used sterilization as one of the contraception methods was used as the outcome variable. The individual-level data was constructed in percentage form for analysis at the district and state level. The density curve of the prevalence of sterilization is Normally distributed throughout the districts. The prevalence graph shows, sterilization among females is higher in Southern parts of the country followed by central and western India. Prevalence is low in east and north-east regions of India. Whereas, some parts of northern India also have a low prevalence of female sterilization.

**Covariates:**

Factors like last birth cesarean, no knowledge about other methods, no information about side-effects of sterilization, compensation received and have insurance were recorded. The main exposure variable investigated was the respondent's geographic location, i.e., the districts and the states. Other socio-demographic covariates were the education level of the respondent (Illiterate vs. Literate), household socioeconomic status (low and middle-income vs. high-income households), Place of residence, caste and Religion.

## Statistical Analysis:

Bayesian Hierarchical Model

The popularity of Bayesian methods has constantly increased with the time and is now at its peaks, Bayesian models are used in virtually every research area, from social science to public health, from health economics to econometrics (Blangiardo & Cameletti, 2015). The basic idea behind the Bayesian approach is that effectively only one form of uncertainty exists, which is described by suitable probability distributions (Blangiardo et al., 2013). The objectives of the Bayesian computation are the marginal posterior distributions for each of the elements of the parameters vector, in addition, within the Bayesian approach, it is easy to incorporate a hierarchical structure on the data. Bayesian hierarchical models are typically used in the context of disease mapping, which represents the risk surface using a combination of available variables in the data and a set of spatial random effects (Lee, 2011), it further considers a spatially structured latent random effect to account for spatial correlation (Bivand et al., 2014). Disease mapping is the area of epidemiology that estimates the spatial pattern in disease risk over an extended geographical region (Lee, 2011), it is commonly used with areal data to assess the spatial pattern of a particular disease and to identify areas characterized by unusually low or elevated risk levels (Lawson, 2013). Disease data often shows spatial patterns, and spatial econometrics models aim at including this spatial dependence so that the value of an observation depends on the observed values of its neighbors (Bivand et al., 2014). Health and morbidity data are commonly collected at different geographical space and at different spatial aggregation levels.

Integrated Nested Laplace Approximation (INLA)

Bayesian Hierarchical model is typically used in such analyses, where any spatial correlation in the disease data is modelled at the second level of the hierarchy by a set of random effects. These effects are most commonly represented by a conditional autoregressive (CAR) prior distribution, which is a type of Markov random field (Lee, 2011). In general, the interest in spatial econometrics is on modelling especially the spatial correlation in an autoregressive technique, so that the observation at a given area, depends on a weighted sum of the values of the variable at its neighbours plus some other (fixed) effects and some random noise (Bivand et al., 2014). An approximate method is developed for Bayesian inference based on the marginals of the parameters of the models; this is an alternative approach to the simulation-based Monte Carlo integration an analytic approximation with the Laplace method (Rue et al., 2009: Lindgren, et al., 2011). They consider the class of Latent Gaussian Markov Random Fields, which are flexible enough to be used in many different types of applications (Bivand et al., 2014). Integrated Nested Laplace Approximation (INLA) approach is developed as a computationally efficient method alternative to MCMC, and the availability of an R package (R-INLA) allows researchers to apply this method easily. One of the fundamental differences between MCMC and INLA methods is that the former provides (asymptotically) exact inference, while the latter gives, by definition, an approximation to the relevant posterior distributions (Blangiardo et al., 2013).

The first step in defining a latent Gaussian model within the Bayesian framework is to identify a distribution for the observed data y= ($y_1, \ldots\ldots, y_n$). A very A very general approach consists in specifying a distribution for $y_i$ characterized by a parameter $\phi_i$ (usually the mean $E(y_i)$) defined as a function of a structured additive predictor $\eta_i$ through a link function $g(\cdot)$, such that $g(\phi_i) = \eta_i$. The additive linear predictor $\eta_i$ is defined as follows:

$$\boldsymbol{\eta i} = \boldsymbol{\beta_0} \sum_{m=1}^{M} \boldsymbol{\beta_m x_{mi}} + \sum_{l=1}^{L} \boldsymbol{f}(\boldsymbol{z_{li}}) \ldots\ldots\ldots\ldots \boldsymbol{eqn}(\mathbf{1})$$

Here $\beta_0$ is a scalar representing the intercept; the coefficients $\boldsymbol{\beta} = \{\beta_1, \ldots., \beta_M\}$ quantify the (linear) effect of some covariates $x = (x1, \ldots, x_M)$ *on* the response; and $f = \{f_1(\cdot), \ldots, f_L(\cdot)\}$ is a collection of functions defined in terms of a set of covariates $z = (z_1, \ldots, z_L)$.

We collect all the latent components of interest for the inference in a set of parameters named $\boldsymbol{\theta}$ defined as $\boldsymbol{\theta} = \{\beta 0, \boldsymbol{\beta}, f\}$. Moreover, we denote with $\boldsymbol{\psi} = \{\psi_1, \ldots, \psi_K\}$ the vector of the K hyperparameters. By assuming conditional independence, the distribution of the n observations (all coming from the same distribution family) is given by the likelihood

$$\boldsymbol{p(y|\theta,\psi)} = \prod_{i=1}^{n} p(y_i|\boldsymbol{\theta}_i, \boldsymbol{\psi}), \ldots\ldots\ldots\ldots \boldsymbol{eqn}(\mathbf{2})$$

where each data point $y_i$ is connected to only one element $\theta_i$ in the latent field $\boldsymbol{\theta}$.

We assume a multivariate Normal prior on $\boldsymbol{\theta}$ with mean $\mathbf{0}$ and precision matrix $Q(\boldsymbol{\psi})$, i.e., $\boldsymbol{\theta}$ ~ Normal $(\mathbf{0}, \mathbf{Q{-}1}(\boldsymbol{\psi}))$ with density function given by

$$p(\theta|\psi) = 2\pi^{-\frac{n}{2}} \, |Q(\boldsymbol{\psi})|^{\frac{1}{2}} \mathbf{exp}\left(-\frac{1}{2}\, \boldsymbol{\theta}' Q(\boldsymbol{\psi})\boldsymbol{\theta}\right), \ldots\ldots\ldots\ldots \text{eqn}(3)$$

where $|\cdot|$ denotes the matrix determinant and $'$ is used for the transpose operation. The components of the latent Gaussian field $\boldsymbol{\theta}$ are supposed to be conditionally independent with the consequence that Q($\boldsymbol{\psi}$) is a sparse precision matrix. This specification is known as Gausa sian Markov random field (GMRF), (Rue & Held, 2005). The joint posterior distribution of $\boldsymbol{\theta}$ and$\boldsymbol{\psi}$ is given by the product of the likelihood of the GMRF density and of the hyperparameter prior, distribution, i.e. produ,ct of equation 2 and 3. To approximate Bayesian inference with INLA we need to perform following tasks: (i) compute $p(\boldsymbol{\psi}|y)$, from which also all the relevant marginals $p(\psi_k|y)$ can be obtained; (ii) compute p $(\theta_i|\boldsymbol{\psi}, y)$, which is needed to compute the parameter marginal posteriors $p(\theta_i|y)$ (Blangiardo & Cameletti, 2015).

Besag, York and Mollie's Model (BYM)

The primary aim of the BYM model is to lead to the improved parameter control as the hyperparameters can be seen independently from each other. Furthermore, the need for a scaled spatial component is also discussed in details, which facilitates assignment of interpretable hyperpriors and make these transferable between spatial applications with different graph structures (Riebler et al., 2016). Besag proposed an intrinsic autoregressive model, often referred to as the Conditional Auto-regressive prior or Besag model, where the spatial effect of a particular geographical region depends upon the effects of all neighbouring regions (Besag, 1991). The available BYM model, where an additional unstructured spatial random effect is included to account for independent region-specific noise was also proposed by them. The primary goal of BYM is not to optimize model choice criteria, such as deviance criterion values, but to provide a sensible model formulation where all parameters have a clear meaning (Riebler et al., 2016). The Besag model only assumes a spatially structured component and cannot take the limiting form that allows for no spatially structured variability. Hence, unstructured random error or pure overdispersion within area i, will be modelled as a spatial correlation, giving misleading parameter estimates (Breslow et al., 1998). To address this issue, the (BYM) model decomposes the regional spatial effect b into a sum of a structured spatial component and an unstructured, so that b = v + u. Here, v ∼ N(0, τ−1 v I) accounts for pure overdispersion, while u ∼ N(0, τ−1 u Q−) is the Besag model, whereby Q denotes the generalized inverse of Q.

**R-INLA Package:**

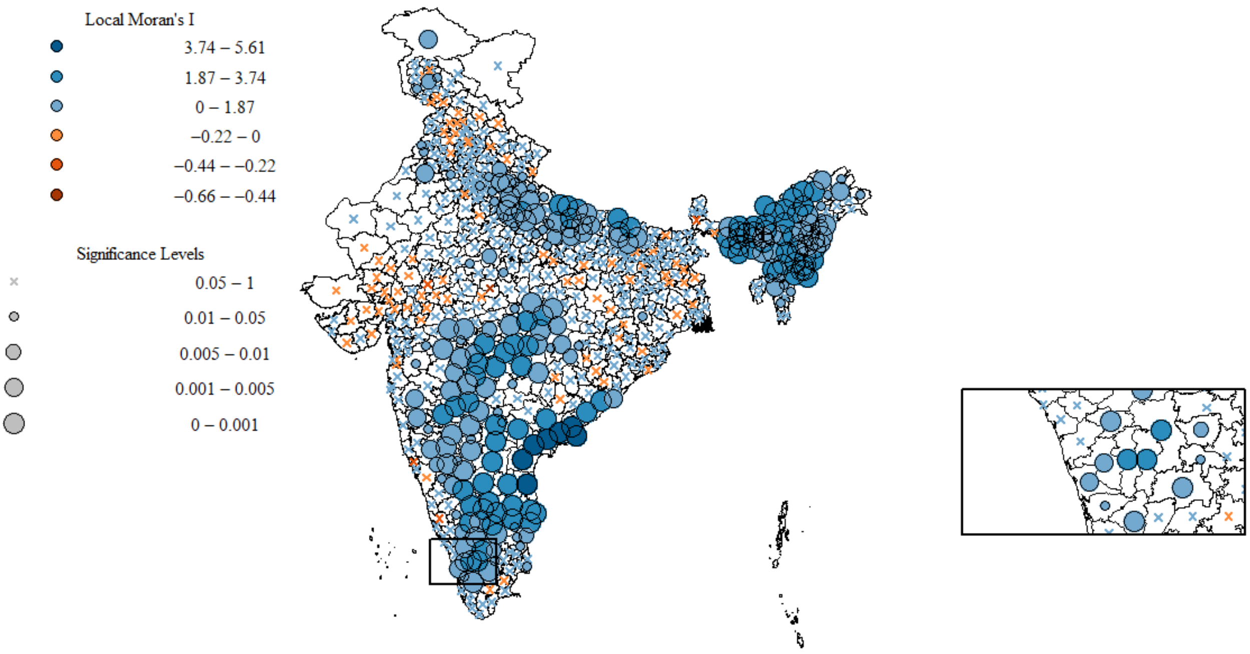
Two models were created for the Bayesian Hierarchical spatial analysis. First one is for factors, i.e., factors affecting female sterilization and the second model comprised of socio-demographic variables. The data and the shapefile were merged, and the multilevel data was created using a unique ID. Further using the "poly2nb" and "nb2listw" of "spdep" package and "nb2INLA" of "INLA" package neighbours weight matrix was created. Using "moran.test" Moran values were obtained for sterilization among females in India at the district level. Using the multilevel dataset, the formula for the analysis was formulated and then using "inla" from INLA package results were obtained. The model used for the analysis is BYM which was mentioned in the "model." The "control.family" function was used to mention the prior, which is Gaussian in nature N~ (0, 1). Further the "control.predictor" was set to be true and "control.compute" was equal to "die" Deviance Information Criterion. The analysis was done separately for the factors, and Socio-demographic variables are affecting sterilization, and two models were fitted. Post analysis, a summary of the posterior mean and spatial random effects of both the models were plotted using the India shapefile. The "inla.tmarginal" function was used to transform precision and further the variance and density were plotted for the models.

## Results:

| Table 1: Moran's I for Female Sterilization | | |
|---|---|---|
| **District** | **Expectation** | **Variance** |
| 0.805 | -0.002 | 0.001 |
| **State** | **Expectation** | **Variance** |
| 0.351 | -0.03030303 | 0.01542595 |
| **Random Effect (Factors)** | **Expectation** | **Variance** |
| 0.893 | -0.001574803 | 0.00061032 |
| **Random Effect (Socio-demographic)** | **Expectation** | **Variance** |
| 0.907 | -0.001574803 | 0.00061028 |

Table 1 shows the Moran's I statistic for the district, state and spatial random effect for the factor and socio-demographic variables . Moran's I statistic for the district level is 0.805 showing a positive and high spatial autocorrelation, whereas for the state level the statistic is positive but quite low 0.351. The Moran's I statistic for both the model is too high and statistically significant. The value for the spatial random effect for factor model is 0.893 and for the socio-demographic variable is 0.907.

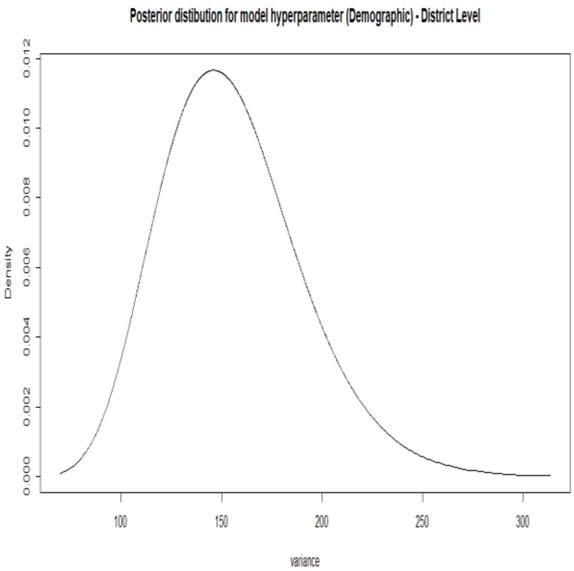
**Graph 2: Univariate LISA Map for Female Sterilization in India at District Level**

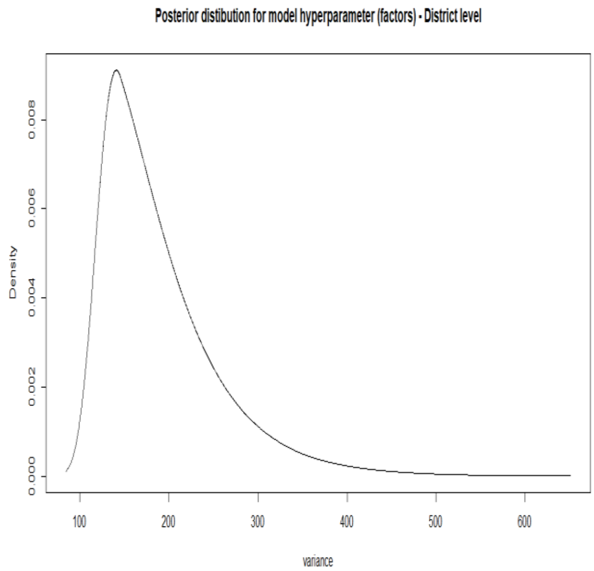


Graph 2, presents the univariate LISA for female sterilization at the district level, the size of the bubbles shows the level of significance in that district. The colour of the bubble shows the values of the Moran's I in that particular space. From the graph, it is clear that in the southern and north-east parts of the country there is a high level of spatial clustering. The bubbles are overlapped in the above-mentioned regions which shows a positive and statistically significant spatial autocorrelation among the districts of India and females opting for sterilization.

**Graph 3: Posterior Marginal Distribution between Districts variance.**

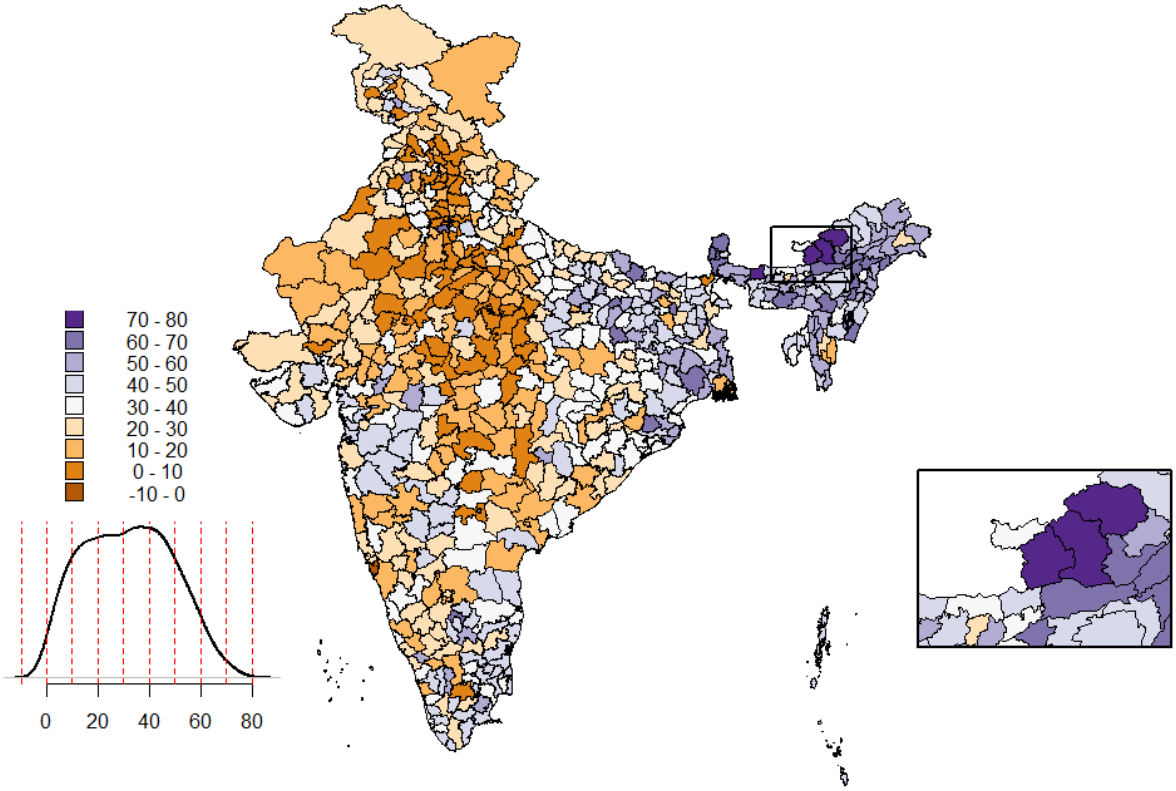
The graph shows the marginal posterior distribution between district variance .From the nature of the curve, it is clear that the distribution of variance at the district level for the socio-demographic variables is normally distributed throughout the space. For the factor variables, the graph of posterior marginal distribution between district variance is not normally distributed; it is skewed towards the right. The below graph depicts that variance does exist at the district level.



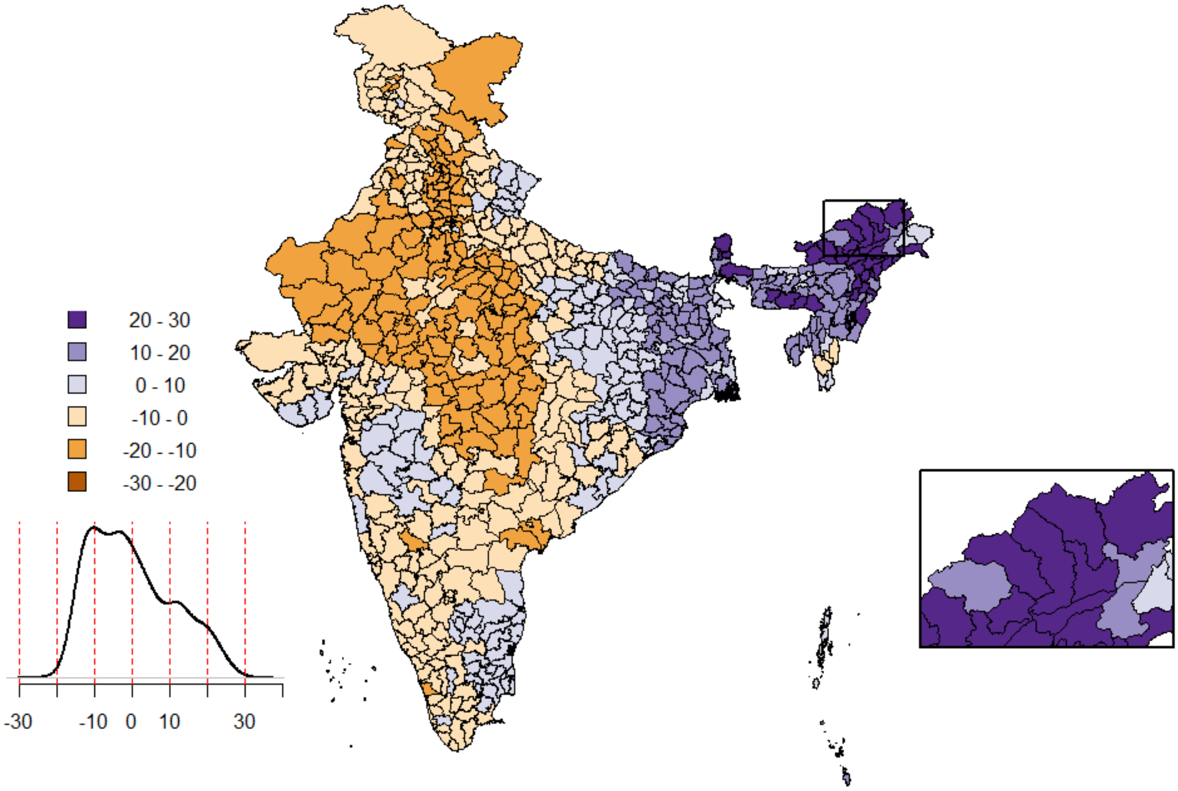

**Graph4: Posterior Mean Distribution for Socio-demographic Variables**

The socio-demographic factors like females with high household income, belonging to Schedule caste and other backward class, females who are literate and residing in rural areas were considered for the model. The posterior mean distribution curve for the model is normally distributed. Kurung Kumey, Lower Subhansiri, and East Kameng districts of Arunachal Pradesh and the border sharing neighbour districts, Lakhimpur, Dhemaji and Sonitpur districts of Assam show a high level of posterior mean. Similarly, Districts of West Bengal sharing a border with districts of Jharkhand state have cluster formation; such clusters are also formed between the districts of Jharkhand and the neighbouring districts of Bihar. States with a high level of schedule caste population such as Punjab and Maharashtra have also cluster formation for female sterilization. The southern parts of India also show cluster in the states of Karnataka, Andhra Pradesh, Telangana, and Tamil Nadu.



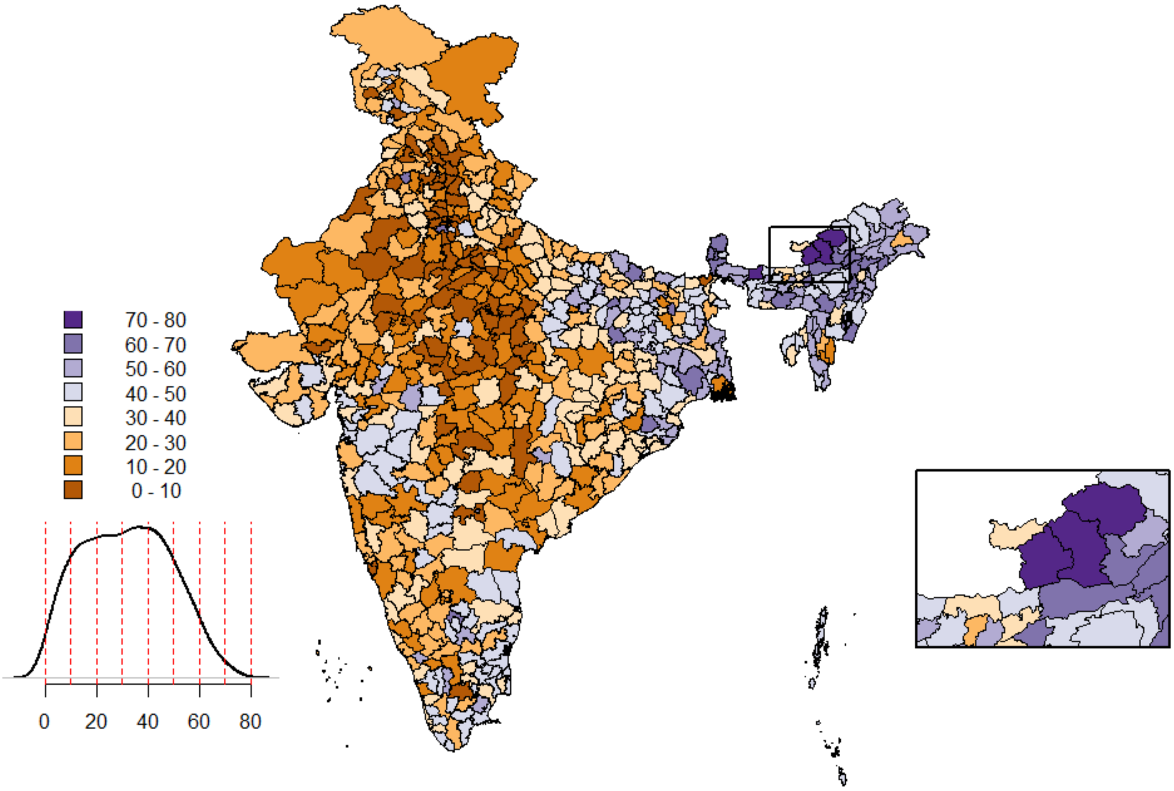

**Graph5: Posterior Distribution of Spatial Random Effect (Structured) for Socio-demographic Variables**

The BYM model decomposes the regional spatial effect into a sum of an unstructured and a structured spatial component, the map presented above is the structured posterior spatial random effects. The Neighbouring districts of Arunachal Pradesh and Assam have a high level of spatial random effects, for example, Upper Siang, East Siang, and Lower Dibang Valley are neighbouring to Dhemaji, Dibrugarh and Tinsukia and have high spatial random effects for the socio-demographic model. A similar pattern can be seen between the districts of Assam and neighbouring districts of Nagaland with a high level of Spatial random Effects. As discussed above for the Posterior means, similar results were found for the spatial random effects in the Eastern region of the country, West Bengal, Jharkhand, and Bihar have spatial random effect in their neighbours or the districts sharing the same boundaries. Low level of Spatial random effects, still positive in nature, were found in the southern parts of the country. Districts of Maharashtra sharing boundaries with Karnataka have spatial random effects. In the similar pattern, Andhra Pradesh the and Telangana also have spatial effects. Negative spatial values were found in the most of the northern regions, which shows there are no spatial effects for the socio-demographic model.




**Graph 6: Posterior Mean Distribution for Factors Affecting Sterilization**

The Bayesian posterior mean distribution curve in the graph using Besag, York and Mollie's model for factors shows that it's normally distributed. The high level of clusters is found in the southern and north-east part of the country. In the north-east region, Arunachal Pradesh has districts with high values of posterior mean followed by Nagaland, Mizoram and other states. In the east region states like West Bengal, Jharkhand and Bihar's border districts neighbouring the north-east region are showing high posterior means. The Northern and the and central India have low values of posterior means. When compared to the Local Moran's I map the cluster formation is similar in the pattern for this region and rest of the country. The factors model depicts that with last birth cesarean, females receiving compensation for sterilization and having insurance contributes to female sterilization in the above-discussed states and districts.




**Graph 7: Posterior Distribution of Spatial Random Effect (Structured) for Factors Affecting Sterilization**

The structured spatial random effect distribution among the districts of India was calculated using the BYM model explains that the districts in the north-east regions have high spatial random effects, Districts from the Arunachal Pradesh, i.e. Upper Siang, West Siang, etc. and few districts from Assam like Dibrugarh, Lakhimpur are having high level of spatial random effects. States Like Meghalaya and Nagaland are also having a high level of spatial cluster formation. In the east region, districts of West Bengal, Jharkhand and Bihar (neighbouring to West Bengal and Jharkhand) too have high values of spatial random effects followed by the southern region. In the southern region districts from the Andhra Pradesh, Karnataka and Tamil Nadu have spatial random effects. Whereas, when compared to the prevalence of sterilization these states have a high prevalence of female sterilization. In the West region, districts of Maharashtra neighbouring to southern states like Karnataka have high adherence to female sterilization.

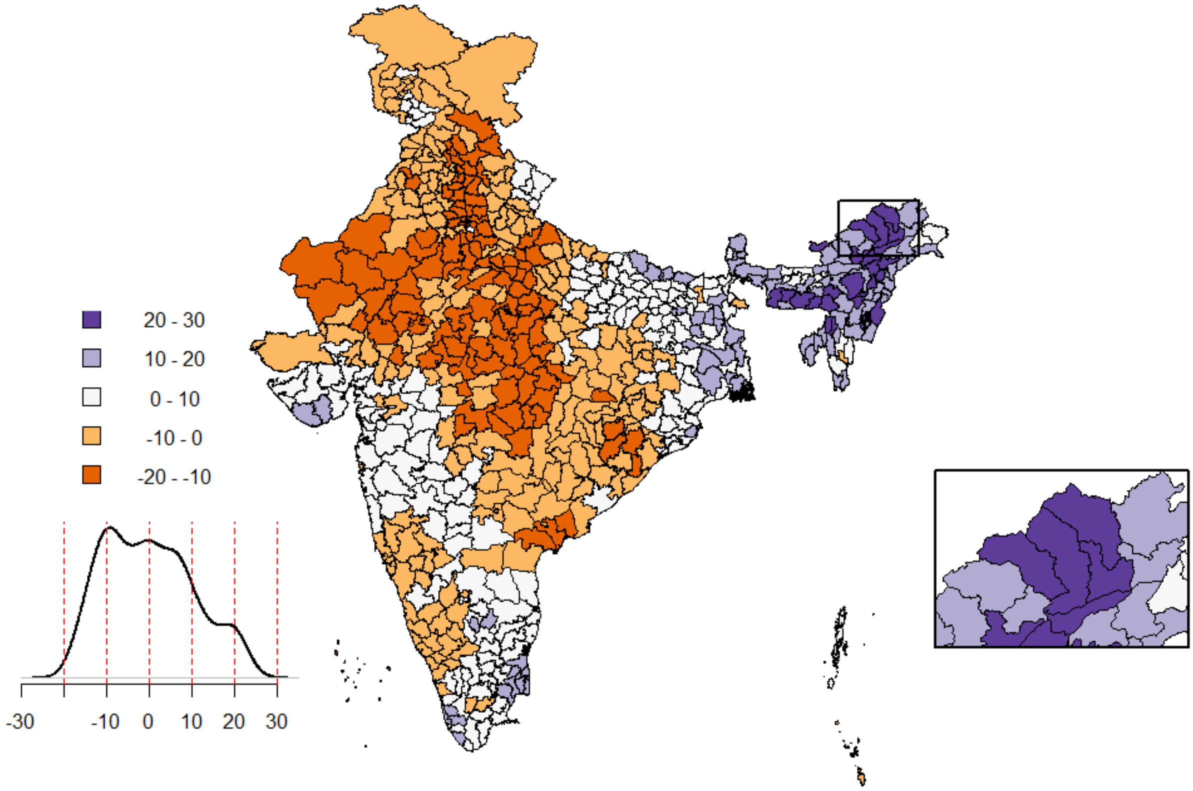



Table 2 presents the Bayesian hierarchical spatial model for the socio-demographic variables affecting sterilization among females in India. The fixed effect of the model shows that females residing in rural parts of the country are 18 % more likely to go for sterilization and among the castes Schedule caste females are 19% more likely whereas the Other backward class females are 13 % more likely to go for sterilization, which is less in comparison to the Schedule caste females. Literate females are only 4% likely to go for sterilization whereas for illiterate females the coefficient was found to be statistically insignificant. Sterilization is found to be high among females with high household income. Random effects of the model show that the precision at the state level is 1.64 whereas the precision at the identically and independently distributed district level is 0.01. the precision of the spatial component at the district level comes out to be 0.01 which shows a high level of variation for sterilization at the district level. The deviance information criterion for this model fit is lowest at 2462, and the marginal log-likelihood for this model is -2414, the values for deviance information criterion and marginal log-likelihood explain the model to be the best fit.

| Table 2: Model for Socio-demographic variables affecting Sterilization | | | | | |
|---|---|---|---|---|---|
| **Fixed Effects** | | | | | |
| | **Mean** | **SD** | **0.025quant** | **0.5quant** | **0.975quant** |
| **(Intercept)** | -1.95 | 3.97 | -9.75 | -1.95 | 5.85 |
| **Rural** | 0.18 | 0.03 | 0.11 | 0.18 | 0.24 |
| **SC&ST** | 0.19 | 0.05 | 0.08 | 0.19 | 0.29 |
| **OBC** | 0.13 | 0.03 | 0.08 | 0.13 | 0.18 |
| **literate** | 0.04 | 0.04 | -0.04 | 0.04 | 0.13 |
| **Rich** | 0.24 | 0.04 | 0.16 | 0.24 | 0.33 |
| **Random Effects** | | | | | |
| **Model** | **Besag, York and Mollie Model** | | | | |
| **Model hyperparameters** | **Mean** | **SD** | **0.025quant** | **0.5quant** | **0.975quant** |
| **Precision for the State observations** | 1.64 | 2.20 | 0.15 | 0.98 | 7.20 |
| **Precision for District (iid component)** | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 |
| **Precision for District (spatial component)** | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 |
| **Deviance Information Criterion** | 2462.30 | | | | |
| **Deviance Information Criterion (saturated)** | 1238.99 | | | | |
| **The effective number of parameters** | 613.58 | | | | |
| **Marginal log-Likelihood** | -2414.86 | | | | |

Table 3 presents the Bayesian spatial model for factors affecting sterilization using BYM function. The fixed effect of the Bayesian model shows that compensation received is positively associated with sterilization, females receiving compensation are 24% more likely to go for sterilization. Females who are having health insurance are 13% more likely to go for sterilization. Whereas females who did not have information about other methods are 7% less likely to go for sterilization, similarly, women who delivered their last baby through cesarean are 23 % more likely to go for sterilization. The credible interval for each of the variable considered in the study was found to be statistically significant. Random effects of the model describe that the precision for the state level is too high which shows a low level of variation at the state level. Whereas, the precision of the independent and identically distributed model for the random effect is low 0.01 and so as for the spatial component is 0.01, showing a large variation for the posterior distribution. The deviance Information criterion is 2471 which is low in comparison to another model fit. Thus this model fit is found to be the best to explain the dependent variable under question. The marginal likelihood is found to be negative with value -2407 which is lowest in comparison to another fitted model with a combination of variables.

| Table 3: Model for factors affecting Sterilization | | | | | |
|---|---|---|---|---|---|
| **Fixed effects:** | | | | | |
| | **Mean** | **SD** | **0.025quant** | **0.5quant** | **0.975quant** |
| **(Intercept)** | 14.20 | 3.00 | 8.31 | 14.20 | 20.09 |
| **Compensation** | 0.24 | 0.03 | 0.17 | 0.24 | 0.30 |
| **Insurance** | 0.13 | 0.03 | 0.07 | 0.13 | 0.19 |
| **Method** | -0.07 | 0.03 | -0.13 | -0.07 | -0.005 |
| **Caesarean** | 0.23 | 0.05 | 0.14 | 0.23 | 0.32 |
| **Random Effects** | Districts | | | | |
| **Model** | **Besag, York and Mollie Model** | | | | |
| **Model hyperparameters**: | **Mean** | **SD** | **0.025quant** | **0.5quant** | **0.975quant** |
| **Precision for the State observations** | 1.61 | 2.06 | 0.14 | 1.00 | 6.90 |
| **Precision for District (iid component)** | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 |
| **Precision for District (spatial component)** | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 |
| **Deviance Information Criterion (DIC)** | 2471.72 | | | | |
| **Deviance Information Criterion (saturated)** | 1292.37 | | | | |
| **The effective number of parameters** | 639.67 | | | | |
| **Marginal log-Likelihood** | -2407.10 | | | | |

## Discussion:

The variables representing demographic and socio-economic characteristics and factors like insurance, knowledge about other methods, last birth cesarean, side effects of sterilization, marital duration at the time of sterilization and compensation received were considered in this study. The models included only those variables which were found to be credible to achieve the best model fit according to the deviance information criterion and marginal log-likelihood. The posterior distribution summarizes our understanding of the parameters given observed data and plays a fundamental role in Bayesian modelling (Lawson, 2013). The high use of sterilization found in rural areas over urban areas is consistent with the findings of this study. (Stephenson, 2006). The probable reason can be that temporary methods of contraception are largely unavailable in rural areas. Sterilization choice is common for poor women with those belonging to socially disadvantaged ethnic groups such as schedule tribe, Schedule caste, and other backward communities. (De Oliveira et al., 2014). Our analysis also shows that women's ethnic status had a positive influence on sterilization use. The map of the posterior mean and structured spatial random effects from the Bayesian hierarchical model corroborates the above-discussed facts, and it can be concluded that regions with a higher percentage of schedule caste, schedule tribe, and other backward caste have greater adherence to female sterilization.

(Census, 2011). Informed consent of female before opting sterilization is mandatory despite the fact that they are literate or not (Pandey, 2014), mostly females who adopt sterilization are found to be literate in this study. The Bayesian posterior structured spatial effects using the BYM model too show a high level of sterilization in north-eastern and southern regions where the literacy rate among females is higher in comparison to the national average (Census, 2011). Most of the studies show that female from poor economic background go for sterilization (De Oliveira et al., 2014). This study in contradiction depicts that females who are from the well-off economic background are more inclined to adopt sterilization. The possible reason for such difference may be the high prevalence of sterilization in the developed regions with high level of Human Development Index.

The concept of providing incentives to males and females going for sterilization is not new (Heil et al., 2012), the government has been providing incentives to females going for sterilization, it plays a crucial role in curbing population and promoting sterilization through the incentives. This study finds out that females who have received compensation are more into sterilization (Sharma, 2014). Many women find lucrative to undergo sterilization for government incentives and benefits. The prevalence of insurance provided by central and state government covers large population in some states of India especially southern part of the country (NFHS-4, 2016), our findings are in line with this fact; the spatial clusters formed in southern part of the country show increased level of female sterilization. Females having no knowledge of other methods are left with no option other than going for sterilization. Especially in case of female residing in rural areas as they are rarely counseled on the full spectrum of contraceptive choices available. In north-eastern states, where the status of women is expected to be high (owing to the matriarchal system and also higher female literacy), women probably are at an advantageous position where they can make a decision to choose the method of their choice (Pradhan & Ram, 2009). The exceptionally high use of sterilization in the southern region could be correlated with high demand for limiting fertility and a better network of family planning services. Although the use of modern temporary method has increased recently, the results from this study clearly demonstrate evidence of continuing sterilization dominance in the Indian family planning program (Srinivasan, 2006). This study adds the structured spatial effect of female sterilization to all the existing literature, North-east and Eastern part of India's districts neighbouring to North-east were found to be more inclined towards sterilization. Similarly, Southern India and Western part of the country's districts neighbouring to south India shows a similar pattern. A gender trans-formative health strategy is required. Thus, strengthening National Policy for Women 2016, which aims at recognizing women's reproductive rights by shifting focus towards male sterilization.

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