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Infant mortality and death clustering at the district level in India: A Bayesian approach

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ABSTRACT

This study assessed the clustering of and spatial variations in infant mortality between districts in selected states of India using a Bayesian geoadditive model. The study utilized 10 years of retrospective birth history of women from the fourth round of NFHS-4 (2015–16). Findings suggest, except Kerala, there was a significant amount of clustering of infant deaths in families in the selected Indian states. The maximum impact of clustering was observed in Assam, followed by Madhya Pradesh, Bihar, Uttarakhand, and Uttar Pradesh. The estimated residual spatial effect was statistically significant in all the states, with the maximum effect being in Assam and Chhattisgarh. The risk of infant death in Assam was higher in the north-eastern districts and lower in the southern districts of the state. Mother's age at child birth had a nonlinear effect on infant death in all the states, although significant effects were observed only in Bihar and Assam. In both of these states, mother's age at child birth had a "U-shape," showing that the risk of infant death was higher at both earlier and later ages of mother's reproductive period. With the exception of Kerala, all the other selected states in the study had an "elongated L shaped" pattern, showing that in the early ages of the reproductive period, the risk of infant death was very high and that it gradually decreased with age and remained constant thereafter. In Kerala, mother's age at child birth was a straight line, implying that the risk of infant death was constant across the reproductive age of women. In order to keep infant mortality at a low level and to achieve better maternal and child health outcomes, the government needs to target families experiencing multiple infant deaths. In addition, programs must take into consideration the prevailing state-specific spatial heterogeneity in infant deaths and factors like mother's age at child birth.

1. Introduction

Infant mortality rate (IMR) is considered an important indicator of human development, and it reflects the state of health of any community, region, or nation. In spite of advancements in technology and medical sciences, IMR remains a matter of grave concern around the globe, including India. India joined the United Nations in its effort to achieve eight Millennium Development Goals (MDGs) that were established around the premise of creating a life of dignity for all. Lowering child mortality is at the forefront of the MDGs, and India is making steady progress towards its achievement. However, there is still much work to be done as the IMR revolves around an unacceptably high figure of 32 per 1000 live births (ORG, 2018).

The state-level disparities in IMR that prevail in the country need to be studied so that the states performing below expectations can learn from the experience of the better-performing ones in how to address the structural causes of infant mortality and make improvements year by year. The modelling of infant deaths has effectively examined the structural causes of IMR, and socioeconomic and biological factors are seen to play a crucial role in the modelling (Baird, Friedman, and Schady, 2011; Claeson, Bos, Mawji, and Pathmanathan, 2000; Geruso & Spears, 2018; Ghosh, 2012; Guo, 1993; Palloni, 1987; Zenger, 1993; Ronsmans, 1995; Das Gupta, 1997; Majumder, May et al., 1997; Sastry, 1997; Madise, Matthews et al., 2003; Omariba, Beaujot and Rajulton, 2007; Arulampalam and Bhalotra, 2006; Arulampalam and Bhalotra, 2008; Saha and van Soest, 2011; Ranjan, Dwivedi and Mishra, 2018; Dwivedi and Ranjan, 2018). Nevertheless, there is a need to more accurately model infant deaths with their correlates and spatial dimensions to derive meaningful policy insights. In recent years, the modelling of infant deaths has become more advanced. The models are

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no longer limited only to socioeconomic and biological factors but have become more flexible and take into account nonlinear covariates, time-varying covariates, and spatial patterns as well, along with unobserved factors, using individual-level response variable (Adebayo, Fahrmeir and Klasen, 2004; Adebayo and Fahrmeir, 2005; Kazembe and Mpeketula, 2010; Ghilagaber, Antai and Kandala, 2014; Ayele, Zewotir and Mwambi, 2015; Dedefo, Oljira and Assefa, 2016; Gayawan, Adarabioyo, Okewole, Fashoto and Ukaegbu, 2016; Wang and Wu, 2020). The Bayesian geoadditive discrete-time survival model is one of the recently developed techniques which helps in drawing meaningful conclusions about the spatial pattern of clustered infant deaths. The model contains the well-established framework of generalized linear models and generalized additive models as a special case and, in addition, allows for the measurement of the effects of geographical location or spatio-temporal effects. The model has been used by various studies done in the African countries, where the level of infant mortality is relatively very high, for example in Nigeria (Adebayo, Fahrmeir and Klasen, 2004; Adebayo & Fahrmeir, 2005; Ghilagaber, Antai and Kandala, 2014), Malawi (Kazembe and Mpeketula, 2010), Ethiopia (Dedefo, Oljira and Assefa, 2016) and countries of West Africa (Gayawan, Adarabioyo, Okewole, Fashoto and Ukaegbu, 2016). Ours is perhaps the first study to use the model in the Indian context and utilize individual-level data from the National Family Health Survey (NFHS-4) to examine the effects of factors like spatial and nonlinear covariates, including survival status of older siblings during infancy, (captures the clustering of infant deaths) on the probability of infant death of the index child. There have been studies that have assessed the spatial clustering and risk factors of infant mortality in India before but they ignored the individual-level variability present in the data set (Singh, Pathak, Chauhan and Pan, 2011; Ladusingh, Gupta and Yadav, 2016; Gupta, Ladusingh and Borkotoky, 2016). It is well documented in literature that aggregate level of mortality analysis in many developing countries masks spatial variations (Jain, 1985; Pandey, Choe, Luther, and Sahu, 1998; Ranjan, Dwivedi, and Mishra, 2016; Sahu, Nair, Singh, Gulati, and Pandey, 2015; Saikia et. al., 2009; Bhatia, Ranjan, Dixit and Dwivedi, 2018) .

The models used in earlier studies considered the effects visible in a district to be independent of the neighboring districts, leading to a certain underestimation of the standard errors for district-level factors (Goldstein, 2011; Rabe-Hesketh and Everitt, 2003). However, the geoadditive models regard spatial heterogeneity as an outcome by taking the effects between neighboring districts to be correlated. In India, where there are states that are bigger than some of the countries of the world and makes them quite unsuitable for planning purposes. There is a need to decentralize the entire planning process to get into micro-level understanding of the problem for better and more efficient ways of targeting resources. District-level planning is fairly suitable for India as different districts are quite heterogenous in terms of the nature of problems, solutions, and functioning. The level of development across the districts varies a lot, and districts are viewed as an important geographical unit to study the risk factors of childhood morbidity and mortality. A few recent studies done in Africa have also highlighted the importance of the geographical location in which a child resides for studying the risk factors of childhood morbidity (Kandala et al. 2007, 2009; Gayawan et al., 2014).

In the present paper, a Bayesian geoadditive model was applied to unravel the significant temporal, regional, and spatial variations in infant mortality at the district level. The uniqueness of the present study lies in utilizing individual-level information to model infant deaths with their important predictors after adjusting for the nonlinear and spatial effects. Smoothness priors for spatial and nonlinear effects were introduced, and the recently-developed Markov Chain Monte Carlo (MCMC) simulation techniques were employed in the computation of the spatial effects.

The inclusion of previous infant deaths (a measure of clustering of infant deaths in families) as a predictor in the model emphasizes that there are certain families where there is a concentration of infant deaths, leading to an uneven distribution of infant deaths in the families (Das Gupta, 1997; Sastry 1997a, 1997b; Pradhan and Arokiasamy, 2005; Arulampalam & Bhalotra, 2006, 2008; Ranjan, Dwivedi and Mishra, 2018; Dwivedi & Ranjan, 2018). Several studies have included previous infant deaths at the family (or mother) level and considered it an independent factor affecting the survival status of index child in the model (Arulampalam and Bhalotra, 2006, Arulampalam and Bhalotra, 2008, Saha and van Soest, 2011, Ranjan and Dwivedi, Mishra, 2018; Dwivedi and Ranjan, 2018). The present study too incorporated previous infant deaths in the model as an independent factor.

The present research utilized data from the fourth round of the National Family Health Survey, conducted in the year 2015-16, with the aim to provide the effects of clustering of infant deaths (measured through the coefficient of previous death covariate) on the death of the index child during infancy and also to study the pattern of presence of residual spatial heterogeneity, along with how nonlinear covariates like age of mother plays a role in explaining infant deaths in the different selected states of India.

2. Data source

The present study utilized individual-level data from the fourth round of the National Family Health Survey (NFHS) conducted in the year 2015-16. NFHS is conducted under the stewardship of the Ministry of Health and Family Welfare (MoHFW), Government of India. MoHFW has designated the International Institute for Population Sciences (IIPS), Mumbai, as the nodal agency for the survey. Funding for NFHS-4 was provided by the United States Agency for International Development (USAID), the United Kingdom Department for International Development (DFID), the Bill and Melinda Gates Foundation (BMGF), UNICEF, UNFPA, the MacArthur Foundation, and the Government of India. Technical assistance for NFHS-4 was provided by ICF, Maryland, USA. Data collection was conducted in two phases (from 20 January 2015 to 4 December 2016) by 789 field teams. Each trained team consisted of one field supervisor, three female interviewers, one male interviewer, two health investigators, and a driver. The NFHS-4 sample was designed to provide estimates of all key indicators at the national and state levels, as well as estimates of most key indicators at the district level (for all 640 districts in India, as of the 2011 Census). The total sample size of approximately 572,000 households was based on the size needed to produce reliable estimates for each district and for the urban and rural areas in the districts in which the urban population accounted for 30-70% of the total district population. The rural sample was selected through a two-stage sample design, with the selection of villages as the Primary Sampling Units (PSUs) at the first stage (selected with probability proportional to size), followed by a random selection of 22 households in each PSU at the second stage. In urban areas too, there was a two-stage sample design, with the selection of Census Enumeration Blocks (CEB) at the first stage and a random selection of 22 households in each CEB at the second stage. At the second stage, in both urban and rural areas, households were selected after conducting a complete mapping and household listing operation in the selected first-stage units.

NFHS-4 was the fourth in the NFHS series (the Indian version of the Demographic and Health Survey), which provided information on population, health, and nutrition for India and each state/union territory. NFHS-4 gathered information from 601,509 households, 699,686 women, and 103,525 men, and, for the first time, provided district-level estimates for important indicators.

NFHS interviewed eligible women of reproductive age (15-49 years) and recorded the complete retrospective birth history of each child born. NFHS-4 has information on 131,5617 births, nested within 699,686 mothers, ages 15 to 49 years, from 1970 to 2016.

In the complete retrospective birth history, siblings are easily identified from mother's identification information common between them. Siblings born to a mother have almost similar characteristics, and if the mother has experienced any child death, the age at death is reported in the data.

The present study utilized information on 462,507 children born during ten years prior to the survey, including each child's date of birth, survivorship status, and current age or age at death, corresponding to each mother. The survey contains other information like year of birth, birth order, and sex of child, providing an opportunity to examine family-level death clustering. The present study was carried out on a few selected Indian states, namely Madhya Pradesh, Assam, Odisha, Uttar Pradesh, Rajasthan, Chhattisgarh, Bihar, Uttarakhand, Jharkhand, Kerala, Maharashtra, and West Bengal. As per the SRS-2018 report, infant mortality is above the national level in the first six states and below, or equal to, the national level in the remaining six.

3. Methodology

The present study used a Bayesian geoadditive discrete-time survival model, which is a flexible framework with many advantages like the ability to control for nonlinear covariates and to adjust for time-varying covariates. It also allows for bringing the nonlinear spatial component into the same model (Kandala, Ghilagaber, 2006). This model contains the framework of other well-established models like generalized linear models and generalized additive models as special cases and allows for specification of complex and realistic models. The entire analysis for this study was performed in R (version 3.5.0). Given below is a description of the model.

3.1. Geoadditive Bayesian discrete-time survival model

Let T denote a discrete survival time, where t $\in\{1, \ldots, q+1\}$ represents the t^{th} month after birth, and let $x_t^* = (x_1, \ldots, x_t)$ denote the history of a covariate up to month t .

The discrete-time conditional probability of death at month t is then given by:

$$\lambda(t, xt^*) = \mathrm{pr}\left(T = t \middle| T \geq t, x_t^*\right), \quad t = 1, \ldots, q \tag{1}$$

Survival information is recorded by (t_i, δ_i), $i \in \{1, \ldots, N\}$, where $t_i \in \{1, \ldots, 12\}$ denotes a child's observed survival time in months, and δi is a censoring indicator with value 1 if child i died, and 0 if it is still alive.

We assume non-informative censoring Lagakos (1979) so that the risk set R_t includes all individuals who are censored (or the child survives) in the interval ending in t.

Thus, the binary event indicator is as follows:

$$y_{it}\{i \in R\_t, t = 1, \ldots, t_i\}$$

$$y_{it} = \begin{cases} 1 & \textit{if} \quad t = t_i \quad \textit{and} \quad \delta_i = 1 \\ 0 & \textit{Otherwise} \end{cases} \tag{2}$$

The death process of individual i is a binary sequence of "outcomes," that is, died at age t (y_{it}=1) or survived beyond age t (y_{it}=0), and it yields a sequence of 0s and 1s, indicating the survival history of each child at various points of time.

3.2. Incorporating fixed, time-varying and spatial effects

In parallel with the sequence of 0s and 1s, we have records of values of relevant explanatory variables $x_{it}^* = (x_{i1}, \ldots, x_{it})$, i =1, 2, ... These variables may be fixed over time – such as sex and place of residence – or may vary over time, such as breastfeeding of a child at time t, (although in our case, we did not adjust this time-varying covariate since the information was available only for the most recent birth. Had information been available for all children, it could have been included in the present model). The indicator $y_{i\ t}$ can be linked to the covariates x_{it}^* by an appropriate link function, for a binary response model, such as probit, logit or complementary log-log function link function, and a predictor $\eta_{it}(x_{it})$. Assuming that y_{it} has a normal distribution, and using a probit link function for $i \in R_t$, the probability of death of a child i is given by:

$$\varphi(\eta_{it}) = \mathrm{pr}(y_{it} = 1 | x_{it}*) \tag{3}$$

The usual form of the predictor is:

$$\eta_{it} = f_0(t) + x_{it}*\beta \tag{4}$$

where the baseline effect $f_0(t)$, t =1, 2, . . . is an unknown, usually nonlinear, function of t to be estimated from the data, while β is the vector of the fixed covariate effects. In a parametric framework, the baseline hazard is often modelled by a few dummy variables dividing the time-axis into a number of relatively small segments or by some low-order polynomial. In practice, however, it is difficult to correctly specify such parametric functional forms for the baseline effects in advance. Nonparametric modelling, based on some qualitative smoothness restrictions, offers a more flexible framework to explore unknown patterns of the baseline. Restrictions to fixed effects alone may not be adequate because, in most cases, we have covariates whose values may vary over time. The predictor in (4) is, therefore, extended to a more flexible semiparametric model that can accommodate time-varying effects. If we include another term representing the spatial effects, this semiparametric predictor is given by:

$$\eta_{it} = f_0(t) + f_1(X) + f(t)X_{it} + f_{spat}(si) + X_{it}*\beta \tag{5}$$

Here, $f_0(t)$ is the baseline function of time, and f_1 is a nonlinear effect of the metrical covariate X. The effects, f (t), of the covariates in X_{it} are time-varying, while X_{it}* comprises fixed covariates whose effect is represented by the parameter vector β. The spatial effects $f_{spat}(si)$ may be further split into spatially correlated (structured) and uncorrelated (unstructured) effects of the form $f_{str}(si)+f_{unstr}(si)$. The rationale behind doing so is that a spatial effect is a surrogate of many unobserved influential factors, some of which may obey a strong spatial structure, while others may only be present locally. Eqs. (4) and (5) are the basis of our analysis and will be referred to, henceforth, as constant fixed-effects model and geo-additive model, respectively.

3.3. The estimation process

Second-order random walk priors are used to smooth the functions f_0, f_1, and f using the MCMC techniques implemented in BayesX (Fahrmeir and Lang, 2001a, b; Lang and Brezger, 2000).

Let f = {f (1) . . . f (m), m≤n} be a vector of corresponding function evaluations at the observed values of x. Then, the general form of the prior for f is:

$$f|\tau 2 \propto \exp\left(-1/2\tau^2 * f\text{`}Kf\right) \tag{6}$$

Where K is a penalty matrix that penalizes too many abrupt jumps between neighboring parameters. In most cases, K is rank deficient and, hence, the prior for f is improper.

In traditional approaches, the smoothing parameter is equivalent to the variance parameter τ^2, which controls the trade-off between flexibility and smoothness. A highly dispersed but proper hyperprior is assigned to τ^2 in order to estimate the smoothness parameter simultaneously with f. A proper prior for τ^2 is required in order to obtain a proper posterior for f (Hobart and Casella, 1996). If we choose an inverse gamma distribution with hyper parameters a and b (τ^2~ IG(a, b)), then a first- and second-order random walk priors for f are defined by:

$$f(t) = f(t-1) + u(t), \text{and } f(t) = 2f(t-1) - f(t-2) + u(t) \tag{7}$$

respectively, with Gaussian errors u(t)~N(0; τ^2) and diffuse priors f (1)∝ constant, or f (1) and f (2)∝, constant as initial values. A first-order random walk penalizes abrupt jumps f (t) − f (t − 1) between successive states, whereas a second-order random walk penalizes deviations from the linear trend 2f (t −1)-f (t −2). The trade-off between flexibility and smoothness of f is controlled by the variance parameter τ^2. The goal in our approach was to estimate the variance parameter and the smoothing function simultaneously. This was achieved by introducing an additional hyperprior for τ^2 at a further stage of the hierarchy. We chose a highly dispersed but proper inverse gamma prior, $p(\tau^2) \sim IG(a; b)$, with a=1 and b=0.005. In analogy, we also defined for the overall variance σ^2 a highly dispersed inverse gamma prior.

A fully Bayesian inference is based on the posterior distribution of model parameters whose form is not known. Therefore, MCMC sampling from full conditionals, for nonlinear, spatial and fixed effects and for smoothing parameters, was used for the posterior analysis. For the nonlinear and spatial effects, we applied the sampling scheme of Iterative Weighted Least Squares (IWLS) in BayesX (Lang& Brezger, 2000). This is an alternative to the general Metropolis–Hastings algorithm based on conditional prior proposals that was first suggested by Knorr-Held (1999) in the context of state space models as an extension to Gamerman (1997). A more detailed, related work is also given in Knorr-Held and Rue (2002).

An essential task in the model-building process is comparing a set of plausible models – for example rating the impact of covariates and assessing if their effects are time-varying or not – or comparing geo-additive models with simpler parametric alternatives. We adopted the measure of complexity and fit suggested by Spiegelhalter et al. (2002) for comparison and selected the model that took all relevant structures into account while remaining parsimonious. The Deviance Information Criterion (DIC), which may be used for model comparison, is defined as:

$$DIC\ (M) = \overline{D(M)} + pD \tag{8}$$

Thus, the posterior mean of the deviance is penalized by the effective number of model parameters pD. Models can be validated by analyzing the DIC, which is smaller in models with covariates of high explanatory value.

3.4. Empirical model

Our response variable was:

$$y_{it} = \begin{cases} 1 & \text{if child } i \text{ died in month } t \\ 0 & \text{if child } i \text{ survived beyond time } t \end{cases} \tag{9}$$

Based on the previous literature and the association of the independent covariates with the outcome, an array of covariates that affect infant deaths was selected and included in the model. Most of the covariates selected for the analysis have been found to be associated with infant deaths in past studies on childhood mortality and clustering of infant deaths in India and other developing countries (Arulampalam and Bhalotra, 2006, 2008; Omariba, Rajulton, Beaujot, 2008; and Dwivedi and Ranjan, 2018). Mother's age at child birth was taken as the nonlinear covariate, while district where a child resided was taken as the spatial covariate.

The categorical covariates taken were: Previous infant death in family (yes "1" or no "0"); place of residence (rural "1" or urban "0"); religion (other "1" or Hindu "0"); caste (non-SC/ST "1" or SC/ST "0"); sex of child (female "1" or male "0"); wealth index (poorest "1", poorer "2", middle "3", richer "4," or richest "5"); and mother's education (illiterate "1", primary "2", secondary "3," or higher "4"). The last level of each covariate was selected as the baseline (reference) level.

4. Results

4.1. Fixed effects

Table 1 shows the estimates of posterior means of the fixed effects by selected variables, along with their standard errors and quantiles. Except Kerala, for all the other selected states, the estimates of posterior mean of previous infant deaths, at quantiles 2.5% and 97.5%, were positive. It suggests that even after adjusting for nonlinear and spatial covariates effect, the posterior mean of previous deaths was positive and statistically significant in all the major selected states of India. The risk of infant death was higher in families that had experienced prior infant deaths in comparison to those that had not. The maximum impact was seen in Assam, followed by Madhya Pradesh, Bihar, Uttarakhand, and Uttar Pradesh. The impact was minimum in the state of Maharashtra. As compared to the urban areas, the risk of infant death was lower in the rural areas of Chhattisgarh and Jharkhand and was not significant (estimates at quantile 2.5% were positive, while those at 97.5% were negative). The risk of infant death was insignificant in non-Hindu families in most of the states except Assam and Jharkhand. In comparison to SC/ST caste groups, the risk of infant death was significantly lower in non-SC/ST caste groups in the states of Kerala and Madhya Pradesh. Wealth index had a differential impact on the risk of infant death in the states of Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh, and Uttarakhand. The posterior mean effect shows that female children were at a higher risk of death in comparison to male children in the states of Assam, Bihar, Chhattisgarh, Maharashtra, Madhya Pradesh, and Odisha. Children of illiterate women were at a higher risk of death in comparison to those born to educated women in Bihar, Uttar Pradesh, Chhattisgarh, and Uttarakhand.

4.1.1. Nonlinear effect

Fig. 1 shows the effect of mother's age at child birth on the survival chance of the infant, which is assumed to have a possibly nonlinear effect on the response and is modelled through P-splines in some selected states of India. Mother's age at child birth was found to be significant in all the selected states of the country. The result shows that in the state of Bihar, the nonlinear effect of mother's age at child birth on the risk of infant death followed a standard "U" shape. This implies that children who were born to younger mothers (15 to 28 years) and those who were born to mothers 37 years or older had a higher risk of infant death. The risk of infant death decreased consistently as mother's age at the time of child birth increased from 15 to 28 years but remain constant where mother's age was between 30 and 37 years. In Uttar Pradesh, the nonlinear effect of mother's age on the risk of infant death had an "L" shape, which was different from Bihar, indicating that the risk decreased constantly for mothers in the age group 15 to 25 years and remained at that level for mothers who gave birth after 25 years of age. In Kerala, children born to mothers aged 40 years or less at the time of child birth had almost no or little risk of infant death, but for those born to mothers 40 years or older, the risk increased. In Assam, for children born to younger mothers (15 to 23 years), the nonlinear effect of mother's age at child birth was positive and declining, indicating that the risk of infant death decreased with increase in mother's age. Mother's age at child birth in the age group 24 to 45 years had a negative and constant effect on infant death but the risk increased thereafter. In the states of Jharkhand, Maharashtra, and Rajasthan, the survival risk of infant death decreased sharply between 15 and 23 years, then remained constant for mothers in middle age groups till the age of 45 years and decreased thereafter. In Madhya Pradesh, the risk of infant death was almost negligible in the case of mothers who gave birth after 22 years of age. For ages between 15 and 21 years, the nonlinear age effect was positive and decreased constantly with age. Mothers who gave birth after 27 years of age in Odisha and after 23 years of age in West Bengal had an almost negligible risk of infant deaths. In Uttarakhand, the nonlinear effect of mother's age at child birth on the risk of infant death decreased till 22 years. The risk was negligible till the age of 35 years. Thereafter, it increased for mothers aged 35 to 40 years and afterwards, it decreased. In Chhattisgarh, there was a sharp decline in the risk of infant deaths for mothers aged between 15 and 32 years of age. For women between 32 and 49 years of age, the risk increased.

4.1.2. Spatial effects

The posterior means of the estimated residual spatial effects in the selected states of India are shown in Fig. 2. The estimated residual spatial effect was statistically significant in all the states since the

Table 1
Estimates of posterior means of the fixed-effect parameters on the survival of infant in the model for selected states of India, 2015-16.

Covariates	Bihar				Uttar Pradesh				Kerala			
	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%
Constant	0.039	0.009	0.022	0.056	0.043	0.004	0.034	0.051	0.016	0.005	0.007	0.027
Previous Death												
No (ref.)												
Yes	0.082	0.006	0.070	0.094	0.074	0.005	0.065	0.083	0.036	0.002	-0.003	0.073
Residence												
Urban (ref.)												
Rural	0.002	0.004	-0.005	0.009	-0.003	0.002	-0.007	0.002	-0.001	0.003	-0.006	0.004
Religion												
Hindu (ref.)												
Others	-0.003	0.003	-0.008	0.003	-0.004	0.002	-0.008	0.001	0.001	0.003	-0.004	0.006
Caste												
SC/ST (ref.)												
Others	-0.005	0.002	-0.001	0.000	-0.002	0.002	-0.006	0.002	-0.010	0.004	-0.018	-0.001
Wealth Index												
Richest (ref.)												
Poorest	0.010	0.008	-0.007	0.027	0.018	0.004	0.010	0.025	-0.023	0.016	-0.057	0.011
Poorer	0.008	0.008	-0.009	0.024	0.013	0.004	0.006	0.021	0.017	0.008	0.000	0.033
Middle	0.002	0.008	-0.014	0.019	0.013	0.004	0.007	0.021	0.006	0.004	-0.001	0.014
Richer	0.000	0.008	-0.016	0.016	0.009	0.004	0.002	0.016	-0.001	0.003	-0.007	0.004
Sex of the Child												
Male (ref.)												
Female	-0.012	0.002	-0.015	-0.008	-0.003	0.002	-0.007	0.000	-0.003	0.002	-0.008	0.002
Mother's Education												
Higher (ref.)												
Illiterate	0.013	0.006	0.000	0.025	0.020	0.004	0.012	0.028	0.014	0.016	-0.016	0.046
Primary	0.014	0.007	0.001	0.026	0.015	0.004	0.007	0.024	0.030	0.009	0.012	0.047
Secondary	0.005	0.006	-0.008	0.017	0.011	0.004	0.004	0.018	0.001	0.003	-0.004	0.007
Covariates	Assam				Chhattisgarh				Jharkhand			
	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%
Constant	0.034	0.011	0.011	0.058	0.049	0.009	0.031	0.067	0.027	0.008	0.011	0.042
Previous death												
No (ref.)												
Yes	0.093	0.009	0.075	0.110	0.056	0.010	0.037	0.075	0.053	0.008	0.038	0.069
Residence												
Urban (ref.)												
Rural	0.006	0.006	-0.005	0.017	-0.014	0.005	-0.024	-0.004	-0.011	0.004	-0.020	-0.004
Religion												
Hindu (ref.)												
Others	-0.009	0.003	-0.016	-0.003	-0.001	0.009	-0.018	0.015	-0.007	0.003	-0.013	-0.002
Caste												
SC/ST (ref.)												
Others	0.007	0.004	0.000	0.014	-0.001	0.004	-0.009	0.008	-0.003	0.003	-0.008	0.002
Wealth Index												
Richest (ref.)												
Poorest	0.021	0.010	0.000	0.041	0.023	0.009	0.006	0.040	0.029	0.008	0.014	0.043
Poorer	0.010	0.010	-0.011	0.029	0.014	0.008	-0.002	0.032	0.020	0.008	0.005	0.035
Middle	0.006	0.010	-0.014	0.025	0.006	0.008	-0.010	0.021	0.016	0.008	0.001	0.031
Richer	-0.005	0.010	-0.025	0.014	0.001	0.008	-0.015	0.017	0.011	0.008	-0.004	0.026
Sex of the Child												
Male (ref.)												
Female	-0.013	0.003	-0.019	-0.007	-0.011	0.004	-0.018	-0.004	-0.005	0.003	-0.010	0.000
Mother's Education												
Higher (ref.)												
Illiterate	0.011	0.010	-0.010	0.029	0.023	0.010	0.003	0.042	0.014	0.007	0.000	0.028
Primary	0.010	0.010	-0.010	0.029	0.014	0.010	-0.006	0.033	0.014	0.008	-0.002	0.029
Secondary	0.001	0.009	-0.017	0.019	0.009	0.009	-0.009	0.026	0.007	0.007	-0.005	0.022
Covariates	Maharashtra				Madhya Pradesh				Odisha			
	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%
Constant	0.032	0.006	0.020	0.044	0.036	0.006	0.025	0.048	0.031	0.009	0.013	0.050
Previous Death												
No (ref.)												
Yes	0.027	0.009	0.009	0.045	0.091	0.006	0.079	0.103	0.055	0.009	0.037	0.073
Residence												
Urban (ref.)												
Rural	-0.005	0.003	-0.011	0.001	-0.004	0.003	-0.010	0.003	0.004	0.005	-0.005	0.014
Religion												
Hindu (ref.)												
Others	-0.001	0.003	-0.006	0.005	0.000	0.004	-0.008	0.009	-0.008	0.006	-0.019	0.004
Caste												
SC/ST (ref.)												
Others	-0.003	0.003	-0.009	0.002	-0.007	0.002	-0.012	-0.003	-0.004	0.003	-0.011	0.003

(*continued on next page*)

Table 1 (*continued*)

Covariates	Maharashtra				Madhya Pradesh				Odisha			
	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%
Wealth Index												
Richest (ref.)												
Poorest	0.007	0.006	-0.005	0.017	0.025	0.005	0.014	0.035	0.024	0.009	0.008	0.041
Poorer	0.011	0.005	0.002	0.020	0.028	0.005	0.017	0.038	0.016	0.008	-0.001	0.032
Middle	0.007	0.004	-0.001	0.015	0.017	0.005	0.008	0.027	0.012	0.008	-0.006	0.028
Richer	0.002	0.004	-0.006	0.010	0.015	0.005	0.006	0.024	0.007	0.009	-0.010	0.024
Sex of the Child												
Male (ref.)												
Female	-0.009	0.002	-0.014	-0.005	-0.007	0.002	-0.011	-0.003	-0.008	0.003	-0.014	-0.003
Mother's Education												
Higher (ref.)												
Illiterate	-0.001	0.006	-0.012	0.011	0.008	0.006	-0.004	0.020	0.012	0.009	-0.007	0.031
Primary	0.003	0.006	-0.008	0.014	0.011	0.006	-0.001	0.022	0.001	0.010	-0.017	0.020
Secondary	0.001	0.005	-0.008	0.010	0.008	0.006	-0.004	0.018	-0.005	0.009	-0.021	0.013

Covariates	Rajasthan				Uttarakhand				West Bengal			
	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%	Mean	S. E.	2.50%	97.50%
Constant	0.031	0.006	0.019	0.041	0.019	0.008	0.002	0.034	0.031	0.006	0.019	0.042
Previous Death												
No (ref.)												
Yes	0.058	0.007	0.045	0.072	0.075	0.012	0.051	0.098	0.058	0.007	0.046	0.071
Residence												
Urban (ref.)												
Rural	0.003	0.003	-0.003	0.009	0.001	0.005	-0.009	0.011	0.003	0.003	-0.003	0.009
Religion												
Hindu (ref.)												
Others	0.001	0.004	-0.006	0.008	0.005	0.006	-0.006	0.016	0.001	0.004	-0.006	0.007
Caste												
SC/ST (ref.)												
Others	-0.003	0.003	-0.007	0.002	0.004	0.005	-0.005	0.013	-0.003	0.003	-0.008	0.002
Wealth Index												
Richest (ref.)												
Poorest	0.007	0.005	-0.003	0.017	0.042	0.010	0.021	0.061	0.007	0.005	-0.003	0.016
Poorer	0.009	0.005	0.000	0.019	0.021	0.008	0.007	0.036	0.010	0.005	0.000	0.018
Middle	0.010	0.004	0.001	0.018	0.006	0.007	-0.007	0.019	0.010	0.004	0.002	0.019
Richer	0.003	0.004	-0.005	0.011	0.011	0.006	0.000	0.024	0.003	0.004	-0.005	0.012
Sex of the Child												
Male (ref.)												
Female	-0.004	0.002	-0.009	0.000	-0.004	0.004	-0.011	0.004	-0.004	0.002	-0.008	0.000
Mother's Education												
Higher (ref.)												
Illiterate	0.008	0.005	-0.002	0.018	0.026	0.008	0.011	0.041	0.008	0.005	-0.003	0.019
Primary	0.007	0.006	-0.004	0.018	0.004	0.008	-0.013	0.021	0.007	0.006	-0.004	0.018
Secondary	0.000	0.005	-0.010	0.010	0.006	0.006	-0.007	0.019	0.000	0.005	-0.011	0.011

Note: (ref.) refers to Reference Category

estimates at the 2.5% and 97.5% quantiles had the same sign. The maps show a strong spatial pattern, with the dark shade of purple indicating regions with high risk of mortality, the paler shade of purple showing a moderate risk of mortality, and the blueish color showing regions with a low risk of mortality. The maps for different states show an interesting spatial pattern and confirm our hypothesis about the spatial dependence between districts in the selected states of India. Districts in the north-western parts of Bihar – like Pashchim Chamaparan, Purba Champaran, Gopalganj, Sitamarhi, and Muzzfarpur – had a lower chance of infant survival than districts in the eastern and southern parts of the state. In Uttar Pradesh, all of the districts fell in the middle range of spatial effect showing very little variation in terms of survival chances of children, implying that children in all the districts of the state were at an equal risk of infant death. In Kerala, the southern districts, including the capital city of Thiruvananthapuram and the districts of Kollam, Pathamthitta, and Idukki, were better off in terms of survival chances of infants than the northern districts of the state. In Assam, the risk of infant death was higher in the north-eastern districts of Dhemaji, Lakhimpur, and Jorhat. In the state of Jharkhand, the estimated residual spatial effect showed that the risk of infant death was higher in the districts of East Singhbhum and West Singhbhum and in the districts near the state of West Bengal – like Dhanbad, Dumka, and Pakur. On the other hand, infants in the urban centers and in the capital city of Ranchi were at a lower risk of death. In Maharashtra, districts in the eastern parts of the state – like Gadhchiroli, Gondia, Chandrapur, and Bhandara – had a relatively higher risk of infant death than the other districts of the state. Districts located mainly in the southern part of Madhya Pradesh, like Balaghat, Seoni, Chhindawara, Betul, and Burhanpur, had a higher risk of infant deaths. The districts of Odisha located in the south-western part of the state – like Malkangiri, Koraput, Nabarangapur, Naupada, Kalahandi, and Rayagada – experienced a higher risk of infant mortality than the other regions of the state. Districts in the southern part of Rajasthan, namely Banswara, Dungarpur, Udaipur, and Jhalawar, had a higher risk of infant death as compared to the other parts of the state. In the state of West Bengal – the North 24 Parganas and South Parganas districts of the sunderban delta, together with the districts of Nadia, Birbhum, and Uttar Dinajpur – had low child survival. In Chhattisgarh, all the districts were at an equal risk of experiencing infant deaths just like Uttar Pradesh and Uttarakhand.

5. Discussion & conclusions

The main aim of the present paper was to model infant deaths with their correlates after taking into account the nonlinear effects of mother's age at the time of child birth and the residual spatial effects of districts. The study was done on individual-level data using a flexible

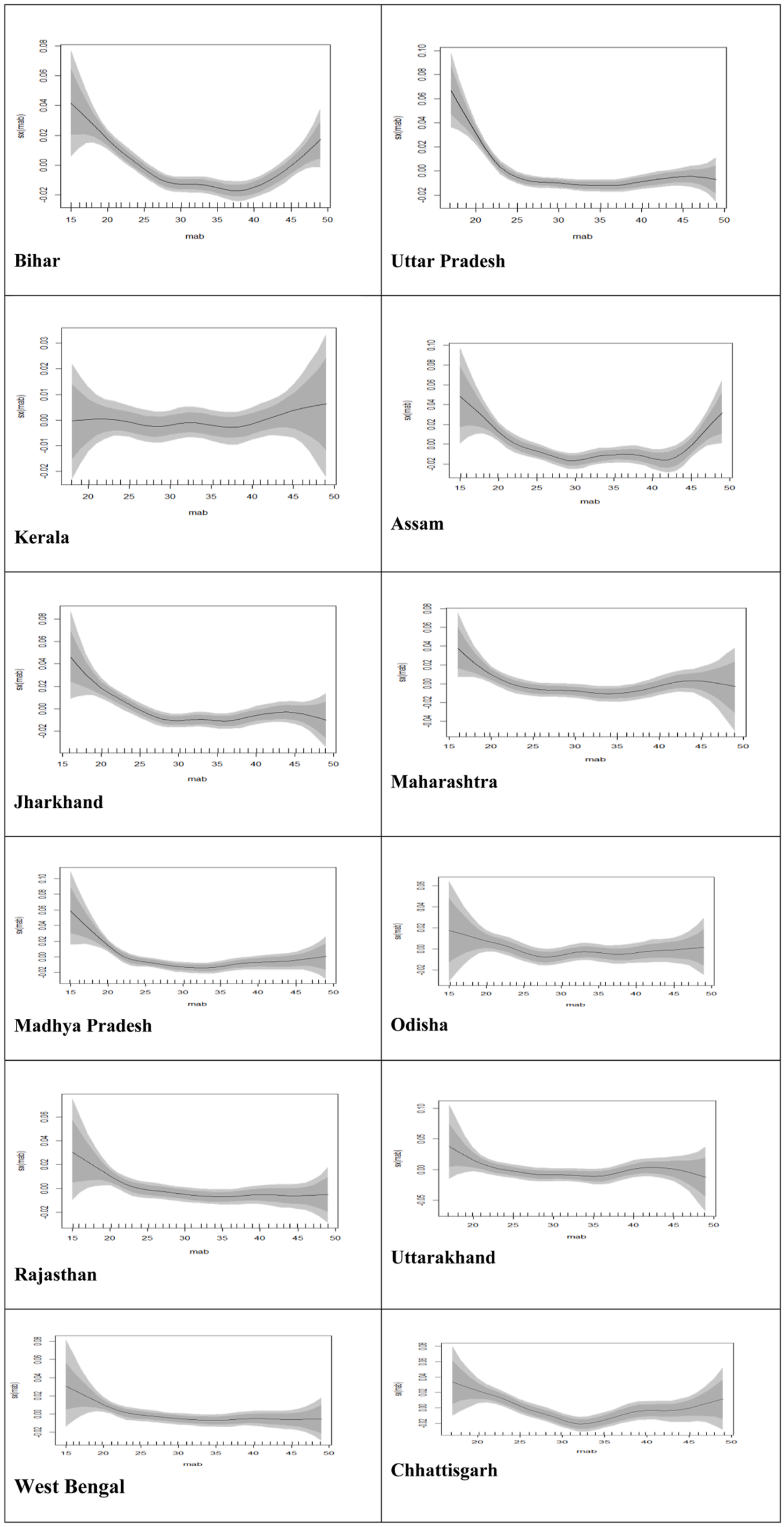

Fig. 1. Estimated non-parametric effect of mother's age at child birth on the survival of infant in selected sates of India with posterior mean with 80% and 95% credible intervals, 2015-16.

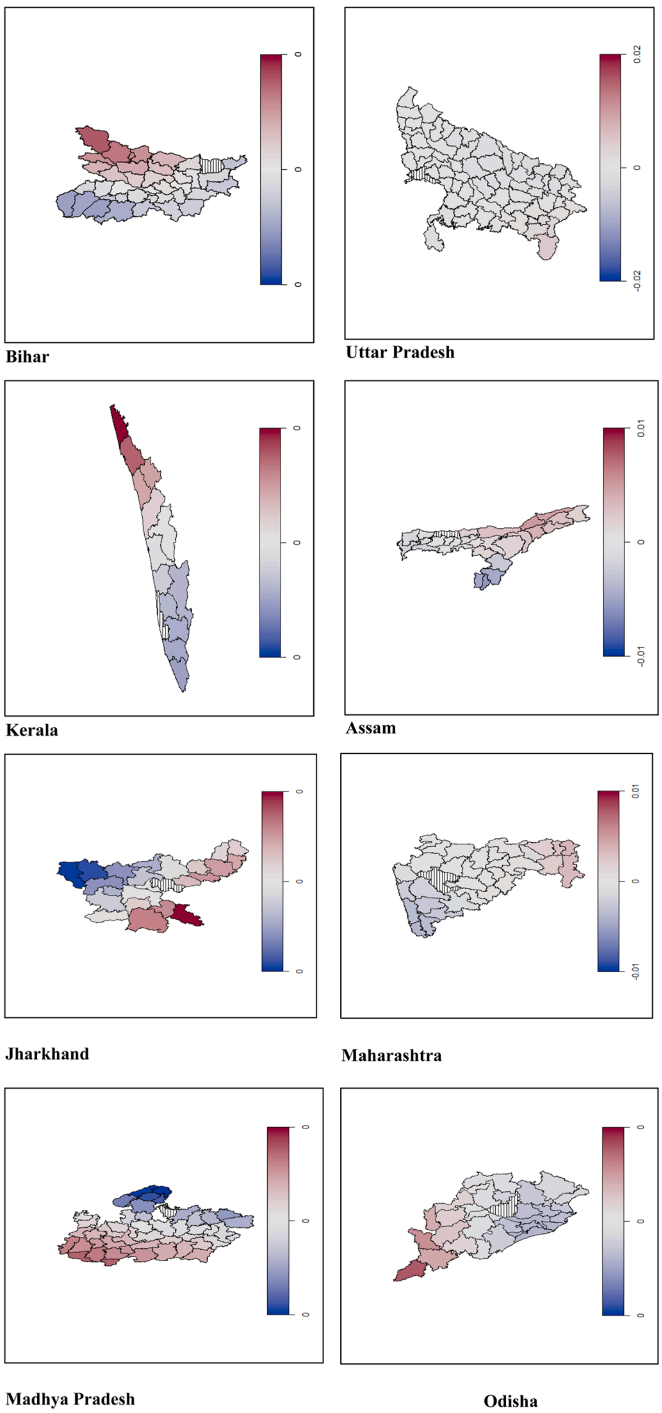

Figure 2. Posterior means of the estimated residual spatial effects on the survival of infant for selected states of India, 2015-16

geoadditive modelling based on the Bayesian approach, which has features of both generalized linear models and generalized additive models. The estimation process was mainly based on the MCMC technique and was found to be a better model in comparison to other models based on the DIC criterion. The inference was fully Bayesian as it used posterior distribution of model parameters whose form is not known.

Our study found that in all the selected states, except Kerala, previous infant death/s in families had a significant positive effect on the survival chance of the index infant child. This implies that even after controlling for the nonlinear effects of mother's age and the effects of spatial dependence of the various districts of a state, there was a significant amount of clustering of infant deaths in families in all of those states, which increased the risk of death of the subsequent child. The impact of the clustering of infant deaths on the infant death of the index child was most prominent in Assam, followed by Madhya Pradesh, Bihar, Uttarakhand, and Uttar Pradesh. These states are a part of a group categorized as high-focus states by the Government of India (MoHFW, 2005) as they experience higher mortality compared to the other states of India. In order to lower infant mortality and improve child health and wellbeing in these states, the Government of India needs to target families experiencing multiple deaths.

In most of the selected states, factors like sex of child, wealth index, and mother's education significantly affected infant deaths. Wealth index was found to be significantly associated with infant deaths in the states of Uttar Pradesh, Jharkhand, and Madhya Pradesh, whereas mother's education significantly affected infant deaths in the states of Bihar and Uttar Pradesh. A significant proportion of population in these states is poor, and they have inadequate resources to improve child health. Some recent studies have found that not only is mortality high in these states, but there is also a relatively high level of inequality between the poorest and the richest groups (Bhatia et al., 2018). A recent article cited mother's education and household wealth as the deciding factors for the survival of infants in India Salve (2018). Factors like place of residence, religion, and caste were found to be insignificant in our model.

The study highlights that different districts in each of the selected states showed a significant geographical variability in the risk of infant deaths as measured by the residual spatial heterogeneity. The government can plan different types of intervention strategies for different districts based on the level of risk in order to tackle infant mortality. The posterior mean of the spatial effect (that is, the heterogeneity) captured by the model was positive, and it was the highest in Assam (0.0032), followed by Chhattisgarh (0.0011). The risk of infant deaths was higher in the districts in the north-eastern region of Assam, such as Upper Assam Brahmaputra valley, while the chances of infant survival were higher in the districts located in southern Assam, mainly in the Cachar Plain like Silchar, Hailakandi, and Karimganj (districts near the Bangladesh border). The residual spatial heterogeneity map of different districts of Chhattisgarh shows that almost all of its districts had a moderate risk of infant deaths. The plotting of the risk of infant deaths in different districts of the different states gives policy makers and other stakeholders a close-up view of the situation on the ground so that they can identify the regions that need to be targeted for the allocation of health resources and plan effectively.

After adjusting the covariates in the model, the districts of almost all the selected states showed a clear high-low risk zone in terms of infant deaths, except in the states of Uttar Pradesh and Chhattisgarh. These two states had an almost similar color pattern on the spatial plot, indicating a moderate risk of infant death. This brings out an important finding that after adjusting for the spatial effect, the nonlinear effect of age and other factors in the model, the situation in the different districts of Uttar Pradesh does not vary much. The heterogeneity between the districts in the state has also been shown by a previous study (Gupta, Ladusingh and Borkotoky, 2016). This implies that there is a possibility that some important geographical covariates like rainfall, humidity, and temperature may be playing a considerable role, which if controlled in the model, might more accurately bring out the actual picture of spatial heterogeneity in infant mortality in Uttar Pradesh and Chhattisgarh.

Mother's age at child birth, a nonlinear age effect, was found to have a significant nonlinear effect on infant death in the districts of each of the selected states. The effect of mother's age at child birth on the risk of infant deaths followed quite different patterns in different states. In Bihar and Assam, it was noticed that the risk of infant death was higher in the earlier ages as well as in the older ages, with a typical "U-shaped pattern," while in Chhattisgarh, the effect of mother's age on the risk of infant deaths had an almost "V-shaped" pattern. Except Kerala, all the other states had an "elongated L shaped" pattern, indicating that the risk of infant death decreased with increase in age of mother till the age of 25 years and remained constant at that level. Kerala, by contrast, showed a straight line, which suggests that the risk of infant death did not vary with mother's age. An understanding of the state differentials in the risk of infant death at various ages of mothers will allow policy makers identify the factors that raise the risk of infant deaths in a particular state and pay special attention to women who need it.

Overall, our study, based on the realistic Bayesian modelling, clearly highlights that Assam is the most vulnerable state in terms of child health and infant mortality and requires urgent attention. The state has high infant mortality, a high level of clustering of infant deaths in families, and the highest spatial disparity in infant mortality. Mothers, in Assam, at both earlier and later ages of the reproductive period are prone to experiencing a high number of infant deaths. The states of Madhya Pradesh, Bihar, and Uttar Pradesh have an almost similarly high burden of clustering of infant deaths. As health is a state subject in India, both state and central governments have to synergistically bring intervention policies for tackling infant mortality and clustering of infant deaths. The health infrastructure in the states too needs to be strengthened across the districts. At the village level, Accredited Social Health Activists (ASHA) and Auxiliary Nurse Midwives (ANMs) need to be appropriately trained to provide mothers timely and proper ANC check-ups and assistance for institutional delivery. Various ongoing governmental programs related with mother & child health care – like Janani Shishu Suraksha Karyakram (JSSK), Janani Suraksha Yojana (JSY), and Reproductive, Maternal, Newborn, Child Plus Adolescent Health (RMNCH+A) – need to be strengthened. The 2030 Agenda for Sustainable Development provides a blueprint for peace and prosperity of people and the planet, now and in the future. Strategies to improve health and wellbeing are at the core of the 17 Sustainable Development Goals (SDGs), which are an urgent call for action by all countries, including India. The SDGs can be achieved if the Government of India makes policies and allocates resources based on research findings. In order to keep infant mortality at a low level and to achieve better health, previous infant deaths in families, spatial heterogeneity, and other factors like mother's age at child birth need to be included in intervention policies.

Declaration of Competing Interest

None of the authors have any conflict of interest on the content of this manuscript.

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