Examination of infant mortality risk in Turkey with spatio-temporal Bayesian models

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Abstract

The infant mortality rate in Turkey declined from 13.9 deaths per 1,000 live births in 2009 to 9.3 deaths per 1,000 live births in 2017. This study explored the role of spatio-temporal Bayesian models in explaining this decline. Parametric, nonparametric spatio-temporal Bayesian models, and a Bayesian generalized linear model without space, time, and space-time interaction were applied using the Integrated Nested Laplace Approximation (INLA) method. Exceedance probabilities were used for detecting significant risk clusters. The unstructured spatial and structured temporal interaction random effect of the best-fitting spatio-temporal Bayesian model contributed more to explaining variation in the relative risk of infant mortality than the other random effects. From 2009 to 2017, in each year, significant risk clusters were consistently detected in the eastern and south-eastern Anatolia regions. An increase of 1,000 USD in the Gross Domestic Product (GDP) per capita reduced the relative risk of infant mortality by 2.8%. When determining the factors that may affect infant mortality in Turkey, it is also essential to consider the effects of space, time, and space-time interaction. In addition, decision-makers should consider the increase in GDP per capita as a factor in reducing infant mortality in Turkey by focusing on these significant risk clusters in the eastern and south-eastern Anatolia regions.

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Key words: spatio-temporal Bayesian models, infant mortality, relative risk, significant risk clusters, Turkey.

Funding: none.

Conflict of interest: the authors have no conflicts of interest to declare.

Contributions: all authors contributed to the study conception and design. Material preparation and analysis were performed by Sade Kılıç Yıldırım. The first draft of the manuscript was written by Sade Kılıç Yıldırım, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Received: 10 April 2025.
Accepted: 26 September 2025.

Geospatial Health 2025; 20:1396
doi:10.4081/gh.2025.1396

Introduction

Infant mortality is a critical indicator of a country, which reflects the quality of the health care system and societal development. In 2022, almost half (47%) of all deaths in children under 5 years of age were due to deaths occurring in the newborn period (the first 28 days of life) as indicated by the United Nations Children's Fund (UNICEF, 2024) and the World Health Organization (WHO, 2024). Further, the majority of newborn deaths occur in low- and middle-income countries, due to inadequate maternal and newborn care (WHO, 2024).

Government expenditures for public health vary according to the income levels of countries. Higher government expenditures are the major drivers of investment in comprehensive health care, advanced medical technologies, and improved living standards (Ayipe & Tanko, 2023; Jayadevan & Trung Hoang, 2024). Volpe *et al.* (2009) found a negative correlation between public health expenditure as a proportion of Gross Domestic Product (GDP) and the post-neonatal mortality rate. Testoni Costa-Nobre *et al.* (2021) reported a significant correlation between specified cluster areas of high mortality rate due to neonatal asphyxia and low GDP per capita.

The risk factors that influence foetal and newborn development may be related to maternal age. Teenage mothers may have difficulties during the pregnancy period because of poverty, low education, and a lack of family support. These factors increase the risk of birth complications due to inadequate prenatal care, and these mothers are at a higher risk of developing anaemia, preterm birth, and low birth weight. Mothers at advanced maternal age stand a higher risk of medical and obstetric complications (Fretts *et al.*, 2008; Diabelková *et al.*, 2023).Low birth weight is commonly associated with preterm infants, but sometimes, full-term infants are also born underweight because of the mother's chronic health condition or poor nutrition. According to the Eunice

Kennedy Shriver National Institute of Child Health and Human Development (NICHD), it is essential to give adequate prenatal care to ensure that full-term infants are at a healthy weight (NICHD, 2024). Additionally, when available in hospitals, the neonatal intensive care unit provides prompt access to advanced care for newborn babies in need of critical medical attention (Hajdu *et al.*, 2024).

The infant mortality rate in Turkey declined from 13.9 deaths per 1,000 live births in 2009 to 9.3 deaths per 1,000 live births in 2017. If the health outcome shows increasing or decreasing trends over time, then the use of spatio-temporal analysis is significant (Byun *et al.*, 2021). Several studies have explored the spatial clustering of infant mortality (Gupta *et al.*, 2016; Kefale *et al.*, 2023). However, there is a research gap in the spatio-temporal clustering of infant mortality. The significance of our study lies in the detection of significant risk clusters by examining whether this decline occurred for each province over time. The aims of this study were: i) to reveal the spatio-temporal pattern of infant mortality risk in Turkey using different spatio-temporal Bayesian models; ii) to detect significant risk clusters of infant mortality using exceedance probability; and iii) to investigate the factors affecting infant mortality in Turkey by focusing on the percentage of mothers aged <20 years among mothers of live-born infants, the percentage of mothers aged>39 years among mothers of live-born infants, and the GDP per capita.

Identification of significant risk clusters of infant mortality and the correlation between GDP per capita and relative risk of infant mortality may inform policymakers and health consultants about the need for interventions such as promoting economic development of significant risk clusters and conducting poverty alleviation policies in those risk clusters, which allows for a lower infant mortality rate.

Materials and Methods

Data

In this study, GDP per capita, the percentages of mothers aged <20 and >39 years among mothers of live-born infants were examined to determine whether these factors affect infant mortality. Annual data (for T=9, years from 2009 to 2017) on the number of infant deaths and live births, the age of mothers of live-born infants, and GDP per capita (expressed in USD) for 81 provinces of Turkey were obtained from the data portal for statistics of the Turkish Statistical Institute. The percentages of mothers aged <20 and >39 years among mothers of live-born infants and the Standardized Mortality Ratio (SMR) were calculated. As it is known, the infant mortality rate is the number of infant deaths out of every 1,000 live births. However, it was impossible to get aggregated province-level data for Turkey on the socio-economic characteristics of mothers of live-born infants. We intended to overcome this by using the percentages of mothers aged <20 and >39 years among mothers of live-born infants in our analysis. These percentages represent younger and older mothers, respectively.

Statistical analysis

We explored the roles of nonparametric spatio-temporal Bayesian models with different types of spatio-temporal interaction effects and a parametric spatio-temporal Bayesian model in explaining the decline in infant mortality rate. Bayesian approaches have been adopted in spatial and spatio-temporal modelling via Markov Chain Monte Carlo (MCMC) methods. Since the MCMC method is a sampling strategy from the posterior distribution, the convergence of posterior samples should occur. Time and extensive simulations are obligatory for the convergence. During Bayesian inference with MCMC methods, convergence problems and long-term calculations may arise, so the INLA method is used as an alternative to MCMC methods (Martino & Rue, 2010; Blangiardo *et al.*, 2013; Blangiardo & Cameletti, 2015).

In the literature, a Bayesian spatio-temporal analysis without spatio-temporal interaction was implemented to reveal spatial-temporal trends in rural South Africa (Agincourt) from 1992 to 2007 using the MCMC method (Sartorius, 2010). No studies have examined infant mortality in Turkey together with space, time, and different space-time interactions.

Global Moran's I and serial autocorrelation were calculated to examine the global spatial autocorrelation for each year and temporal autocorrelation from 2009 to 2017, respectively. In line with both spatial and temporal dependence, a Bayesian spatio-temporal modelling approach was taken (Lome Hurtado *et al.*, 2021; Chen *et al.*, 2023). We used the variance inflation factor (VIF) to detect multicollinearity among explanatory variables (Kianfar & Saadi Mesgari, 2022).

Disease mapping is generally formed by identifying the relative risk in different geographic regions. The standardized mortality or incidence ratio is a common measure of relative risk. Since direct use of this ratio is not suitable for small regions (Maiti, 1998; Meza, 2003), the relative risk of infant mortality was estimated in this study. It is assumed that the observed number of infant deaths in province i in year t (y_{it}) follows a Poisson distribution, expressed as:

$$y_{it}|\theta_{it} \sim Poisson(E_{it}\theta_{it}) \quad \text{Eq. 1}$$

The expected number of infant deaths in province i in year t can be expressed as follows:

$$E_{it} = R_{it}\frac{\sum_{it} y_{it}}{\sum_{it} R_{it}} \quad \text{Eq. 2}$$

where R_{it} is the number of live births in province i in year t.

The unknown parameter of the Poisson distribution (θ) is the Relative Risk (RR) of infant mortality in this study. The RR of infant mortality in province i in year t is the ratio of the infant mortality rate in province i in year t to the average infant mortality rate of the whole country. We applied parametric, nonparametric spatio-temporal Bayesian models and a Bayesian generalized linear model without space, time and space-time interaction to model the RR of infant mortality in province i (where i = 1,2,….,81) in year t (where t = 1 in 2009, 2 in 2010 etc. up to 9 in 2017) using the INLA package of the R Statistical Programming Language 3.5.1.

The structured and unstructured spatial random effects are defined using the Besag-York-Mollie (BYM) specification in parametric and nonparametric spatio-temporal Bayesian models (Blangiardo & Cameletti, 2015). The structured spatial random effect u_i is modelled using an intrinsic conditional autoregressive structure (*iCAR*) (Rue & Martino, 2007; Rue *et al.*, 2009; Blangiardo *et al.*, 2013; Bakka *et al.*, 2018). The construction of the intrinsic conditional autoregressive structure is based on independent increments. If area i and area j are neighbours, a normal

increment is defined as follows (Rue & Held, 2005):

$$(u_i - u_j) \sim \mathcal{N}(0, \tau_u^{-1}) \quad \text{Eq. 3}$$

The joint distribution is expressed as follows:

$$u|\tau_u \sim \mathcal{N}(0, \frac{1}{\tau_u} R_u^{-1}) \quad \text{Eq. 4}$$

where $u = (u_1, u_2, ..., u_n)$, τ_u is the unknown precision of the structured spatial random effect; and R_u the structure matrix of the structured spatial random effect. If area i and area j are neighbours ($i \sim j$), $(R_u)_{ij}$ is -1. If i is equal to j, $(R_u)_{ij}$ is the number of neighbours to area i, otherwise $(R_u)_{ij}$ is zero (Rue & Held, 2005).

The unstructured spatial random effect reflects heterogeneity between areas (Rue & Martino, 2007; Blangiardo *et al.*, 2013; Bakka *et al.*, 2018). The unstructured spatial random effect v_i is specified by an exchangeable Gaussian prior, which is independent and identically distributed with zero mean and unknown precision of the unstructured spatial random effect (τ_v) (Blangiardo & Cameletti, 2015).

$$v_i \sim \mathcal{N}(0, 1/\tau_v) \quad \text{Eq. 5}$$

Parametric spatio-temporal Bayesian model (model 1)

The parametric model contains an area-wide temporal trend (β) as a linear effect of time and a differential trend (ζ_i) for each area i(i=1,2,…,n) expressed as the difference between an area-wide (β) trend and an area-specific trend. If the differential trend (ζi) is under 0, the area-wide trend is less than the area-specific trend. If the differential trend (ζi) is above 0, the area-wide trend is more than the area-specific trend.

$$log(\theta_{it}) = b_0 + u_i + v_i + (\beta + \zeta_i) * t \quad \text{Eq. 6}$$

Assuming that the differential trend (ζ_i) is specified by a Gaussian prior, distributed with zero mean and unknown precision (τ_ζ) (Blangiardo *et al*., 2013), the prior becomes:

$$\zeta_i \sim \mathcal{N}(0, 1/\tau_\zeta) \quad \text{Eq. 7}$$

Nonparametric spatio-temporal Bayesian model without spatio-temporal interaction random effect (model 2)

The nonparametric spatio-temporal Bayesian model without spatio-temporal interaction random effect contains a structured temporal random effect (γ_t) and an unstructured temporal random effect (ϕ_t).

$$\log(\theta_{it}) = b_0 + u_i + v_i + \gamma_t + \phi_t \quad \text{Eq. 8}$$

The structured temporal random effect is modelled using a random walk. With the assumption of independent increments ($\Delta\gamma_t$), the random walk model of order 1 (RW1) for vector $\gamma = (\gamma_1, ..., \gamma_T)$ is expressed as follows:

$$\Delta\gamma_t = \gamma_t - \gamma_{t-1} \sim \mathcal{N}(0, \tau_\gamma^{-1}) \quad \text{Eq. 9}$$

With the assumption of independent second-order increments, the random walk model of order 2 (RW2) for vector $\gamma = (\gamma_1, ..., \gamma_T)$ is expressed as follows:

$$\Delta\gamma_t^2 = \gamma_t - 2\gamma_{t+1} + \gamma_{t+2} \sim \mathcal{N}(0, \tau_\gamma^{-1}) \quad \text{Eq. 10}$$

The joint distribution for $\gamma = (\gamma_1, ..., \gamma_T)$ is given as follows:

$$\gamma|\tau_\gamma \sim \mathcal{N}(0, \frac{1}{\tau_\gamma} R_\gamma^{-1}) \quad \text{Eq. 11}$$

The unstructured temporal random effect (ϕ_t) is specified by an exchangeable Gaussian prior, which is independent and identically distributed with zero mean and unknown precision (τ_ϕ) (Rue & Held, 2005; Blangiardo & Cameletti, 2015).

$$\phi_t \sim \mathcal{N}(0, 1/\tau_\phi) \quad \text{Eq. 12}$$

Nonparametric spatio-temporal Bayesian models with different spatio-temporal interaction random effects (models 3-6)

The nonparametric spatio-temporal Bayesian model with a spatio-temporal interaction random effect is expressed in Eq. 13. Models 3-6, which are discussed in the following pages, differ in their spatio-temporal interaction random effects (δ_{it}).

$$log(\theta_{it}) = b_0 + u_i + v_i + \gamma_t + \phi_t + \delta_{it} \quad \text{Eq. 13}$$

The joint distribution for $\delta = (\delta_{11}, \delta_{12}, ..., \delta_{nT})$is given as follows:

$$\delta|\tau_\delta \sim N\left(0, \frac{1}{\tau_\delta} R_\delta^{-1}\right) \quad \text{Eq. 14}$$

where τ_δ is the unknown precision for each model. The structure matrices of the structured spatial random effect, the unstructured spatial random effect, the structured temporal random effect and the unstructured temporal random effect are expressed as R_u, R_v, R_γ, and R_ϕ, respectively. The structure matrix of the spatio-temporal interaction random effect R_δ is defined for each model using the Kronecker product ($\otimes$) (Knorr-Held, 2000; Rue & Held, 2005; Blangiardo & Cameletti, 2015). If A is a r×s matrix with $(ij)^{th}$ element a_{ij} for i=1,…,r and j=1,…, s and B any t×v matrix, the Kronecker product combines these two matrices (A$\otimes$B) to form a block matrix by multiplying each a_{ij} element in matrix A by the entire matrix B (Moser, 1996).

Model 3

It is assumed that δ_{it} is the interaction of unstructured spatial random effect and unstructured temporal random effect, with the assumption that all interaction effects are independent without any spatial and temporal structures. The structure matrix of the interaction random effect (R_δ) for model 3 is defined as follows:

$$R_\delta = R_v \otimes R_\phi = I \otimes I = I \quad \text{Eq. 15}$$

where I is the identity matrix (Knorr-Held, 2000; Rue & Held, 2005; Blangiardo & Cameletti, 2015).

Model 4

Assuming that the interaction of unstructured spatial random effect and structured temporal random effect is δ_{it}, each $\delta i=(\delta_{i1},\delta_{i2},....,\delta_{iT})'$ (i =1,…,n) is modelled using a random walk, independent from other areas. Each area has a different temporal trend without any spatial structure. The structure matrix of the interaction random effect (R_δ) for model 4 is defined by the following equation, as given in the same references specified above (Knorr-Held, 2000; Rue & Held, 2005; Blangiardo & Cameletti, 2015):

$$R_\delta = R_v \otimes R_\gamma = I \otimes R_\gamma \quad \text{Eq. 16}$$

Model 5

Assuming that δ_{it} is the interaction of unstructured temporal random effect and structured spatial random effect, each $\delta_t=(\delta_{1t}, \delta_{2t},....,\delta_{nt})'$($t=1,...,.T$) is modelled using an intrinsic autoregressive structure, independent from other time points. Each time point has a different spatial trend without any temporal structure. The structure matrix of the interaction random effect (R_δ) for model 5 is defined according to the same references as above (Knorr-Held, 2000; Rue&Held, 2005; Blangiardo & Cameletti, 2015):

$$R_\delta = R_\emptyset \otimes R_u = I \otimes R_u \quad \text{Eq. 17}$$

Model 6

Assuming that δ_{it} is the interaction of structured spatial effect and structured temporal effect, each area has a temporal trend considering the temporal pattern of neighbouring areas. The temporal trends are likely to be similar for neighbouring areas. The structure matrix of the interaction random effect (R_δ) for model 6 is defined in the same way as given above (Knorr-Held, 2000; Rue & Held, 2005; Blangiardo & Cameletti, 2015):

$$R_\delta = R_u \otimes R_\gamma \quad \text{Eq. 18}$$

We examined the nonparametric spatio-temporal Bayesian models (models 2-6) according to RW1 and RW2. The summarized parametric and nonparametric models are shown in Table 1.

We used default prior distributions in the R-INLA package. For the unknown precisions of the unstructured spatial effect and the structured spatial effect, the minimally informative priors were assigned as log τ_v~ log Gamma (1, 0.0005) and log τ_u~ log Gamma (1, 0.0005). For the unknown precisions of the differential trend, the structured temporal effect (RW1, RW2), the unstructured temporal effect, and the spatio-temporal interaction effect, minimally informative priors were assigned as log τ_ζ~log Gamma (1, 0.00005), log τ_γ ~ log Gamma (1, 0.00005), log τ_ϕ~ log Gamma (1, 0.00005) and log τ_δ~ log Gamma (1,0.00005). For the fixed effects, the Gaussian prior with mean equal to 0 and precision equal to 0.001 was assigned.

Model selection

The Deviance Information Criterion (DIC) is a commonly used measure for the Bayesian model selection procedure. It is expressed as follows:

$$DIC = \bar{D} + p_D \quad \text{Eq. 19}$$

where $\bar{D}$ is the mean of deviance and p_D the effective number of parameters (Blangiardo & Cameletti, 2015). The suitability of using DIC (Blangiardo *et al.*, 2013) as a measure of goodness of fit can only be questioned when mixtures with unknown numbers of components arise (Caroll *et al.*, 2016). As the number of components is fixed in our study, DIC is a valid measure.

Contribution of the random effect

To obtain the contribution of each random effect (structured spatial random effect, unstructured spatial random effect, structured temporal random effect, unstructured temporal random effect and unstructured spatial and structured temporal interaction random effect) of the best fitting spatio-temporal Bayesian model to explaining variation in the RR of infant mortality, samples were drawn from the marginal posterior distribution of the structured spatial random effect for each province (u_i) and from the marginal posterior distributions of $1/\tau_v$, $1/\tau_\phi$, $1/\tau_\gamma$, and $1/\tau_\delta$ (Blangiardo & Cameletti, 2015).

Significant risk clusters

To identify areas where the provinces with RR greater than a certain critical level clustered, the probability of exceeding this critical level in each province and year was calculated from the posterior distribution of RR of infant mortality. Provinces with a substantially high exceedance probability were assessed as being at significant risk. Clusters of these provinces were referred to as significant risk clusters. The critical level was taken as 1 in this study.

Effects of the age of the mother and GDP per capita on the RR of infant mortality

Model 4 (RW1) was extended to include GDP per capita (USD), the percentages of mothers aged <20 years and >39 years.

Table 1. Summary of parametric and nonparametric spatio-temporal Bayesian models.

Parametric model (model 1)		
$log(\theta_{it}) = b_0 + u_i + v_i + (\beta + \zeta_i) * t$		
Nonparametric model (models 2-3-4-5-6)		
without spatio-temporal interaction effect (Model 2)		
$log(\theta_{it}) = b_0 + u_i + v_i + \gamma_t + \phi_t$		
with spatio-temporal interaction effect (Model 3-4-5-6)		
$log(\theta_{it}) = b_0 + u_i + v_i + \gamma_t + \phi_t + \delta_{it}$		
Model 3	$\delta_{it} = v_i and \phi_t interact$	$R_\delta = R_v \otimes R_\phi = I \otimes I$
Model 4	$\delta_{it} = v_i and \gamma_t interact$	$R_\delta = R_v \otimes R_\gamma = I \otimes R_\gamma$
Model 5	$\delta_{it} = \phi_t and u_i interact$	$R_\delta = R_\emptyset \otimes R_u = I \otimes R_u$
Model 6	$\delta_{it} = u_i and \gamma_t interact$	$R_\delta = R_u \otimes R_\gamma$

θ, Relative risk of infant mortality; i, province; t, year; b_0, intercept term; u, structured spatial random effect; v, unstructured spatial random effect; β, linear effect of time; ζ, differential trend; γ, structured temporal random effect; ϕ, unstructured temporal effect; δ, spatio-temporal interaction random effect; R, structure matrix; $\otimes$, Kronecker product; and I, identity matrix.

Model 4 (RW1) with the covariates was referred to as Model 4a (RW1). A Bayesian generalized linear model without space, time, space-time interaction and Model 4a (RW1) were applied. GDP per capita was divided by 1,000 to make the interpretation more understandable.

The Bayesian generalized linear model is given as follows:

$$log(\theta_{it}) = b_0 + b_1(GDPpercapita/1{,}000)_{it} + b_2(\%\ mothersaged < 20\ years)_{it} + b_3(\%\ mothersaged > 39\ years)_{it}$$

Eq.20

and the spatio-temporal Bayesian model (Model 4a (RW1)) as follows:

$$log(\theta_{it}) = b_0 + u_i + v_i + \gamma_t + \phi_t + \delta_{it} + b_1(GDPpercapita/1{,}000)_{it} + b_2(\%\ mothersaged < 20\ years)_{it} + b_3(\%\ mothersaged > 39\ years)_{it}$$

Eq.21

where i=1,2,….,81 and t=1,2,…….,9.

Results

An analysis of the spatial autocorrelation showed that the Global Moran Index of SMR for each year was positive and significant, with a mean value of 0.48 and p<0.0001, clearly indicating spatial dependence. With lag 1 serial autocorrelation evaluated as the correlation between values of SMR one time period apart, and lag 2 serial autocorrelation as the correlation between values two time periods apart, lag 1 serial autocorrelation had a mean of 0.52 and lag 2 a mean of 0.42 across the provinces, which indicates temporal dependence. VIF for the percentage of mothers aged <20 years was 1.55, for mothers aged >39 years1.31, and for GDP per capita 1.86, indicating the absence of multicollinearity.

It can be seen from Table 2 that model 4(RW1), with the lowest DIC, is the best fitting model to reveal the spatio-temporal pattern of infant mortality risk in the study area. A large part of the variation in the RR of infant mortality was explained by the unstructured spatial and structured temporal (RW1) interaction random effect (55.1%) and the structured temporal random effect (RW1) (28%) of this model. Hence, the posterior means of the structured temporal random effect (RW1) and the interaction random effect (RW1) are presented. Figure 1, where it can be seen that the posterior mean of the structured temporal random effect (RW1) decreased from 2009 to 2017, reflects Turkey's overall downward temporal trend (RW1). Furthermore, from 2013 to 2017, the posterior mean of the structured temporal random effect was negative. Figure 2 reflects the temporal trend (RW1) effect of each province from 2009 to 2017 via the posterior mean of the interaction random effect (RW1). It is clear that the number of provinces with a negative posterior mean of the interaction random effect (RW1) increased with the passage of years from 2009 to 2017. This means many provinces had a downward temporal trend (RW1).

The RR of infant mortality was estimated by model 4 (RW1). Posterior means of the RR of infant mortality by province are given by the maps from 2009 to 2017 in Figure 3. From 2009 to 2017, the number of provinces with RR greater than 1 decreased. According to the posterior means, the provinces with the highest risk by year in this regard were Gaziantep in 2009 and 2010; Ağrı in 2011; Şanlıurfa in 2016; and Kilis in 2012, 2013, 2014, and 2017. In 2015, Kilis and Şanlıurfa were at the highest risk.

Posterior probabilities exceeding 1 for the RR of infant mortality for provinces are given by maps from 2009 to 2017 in Figure 4. As the years passed from 2009 to 2017, the number of provinces with exceedance probability between 0.95 and 1 decreased. From 2009 to 2017, in each year, Erzurum, Siirt, Bingöl, Bitlis, Ağrı,

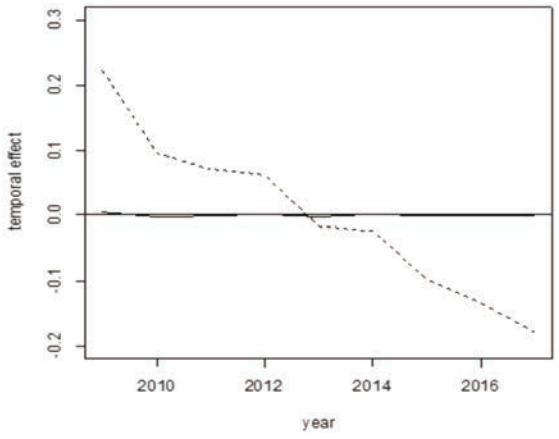

Figure 1. Posterior means of structured temporal random effect (RW1) (γ_t) and unstructured temporal random effect(ϕ_t) between the years 2009 and 2017. Dashed line=structured temporal random effect; solid line = unstructured temporal random effect.

Table 2. Outcome of calculations using parametric and nonparametric models.

Parametric model	DIC	p_D	$\bar{D}$
Model 1	6293.24	131.05	6162.19

Nonparametric models	RW1			RW2		
	DIC	p_D	$\bar{D}$	DIC	p_D	$\bar{D}$
Model 2	6677.33	81.39	6595.93	6677.39	81.27	6596.12
Model 3	5775.11	410.50	5364.60	5775.38	412.57	5362.80
Model 4	5750.91	340.02	5410.89	5852.59	300.59	5552.00
Model 5	5771.31	369.23	5402.08	5771.3	369.22	5402.08
Model 6	5758.35	313.46	5444.88	5833.21	303.39	5529.82

DIC, deviance information criterion;p_D, number of effective parameters; $\bar{D}$, mean of deviance; RW1, random walk model of order 1; RW2, random walk model of order 2.

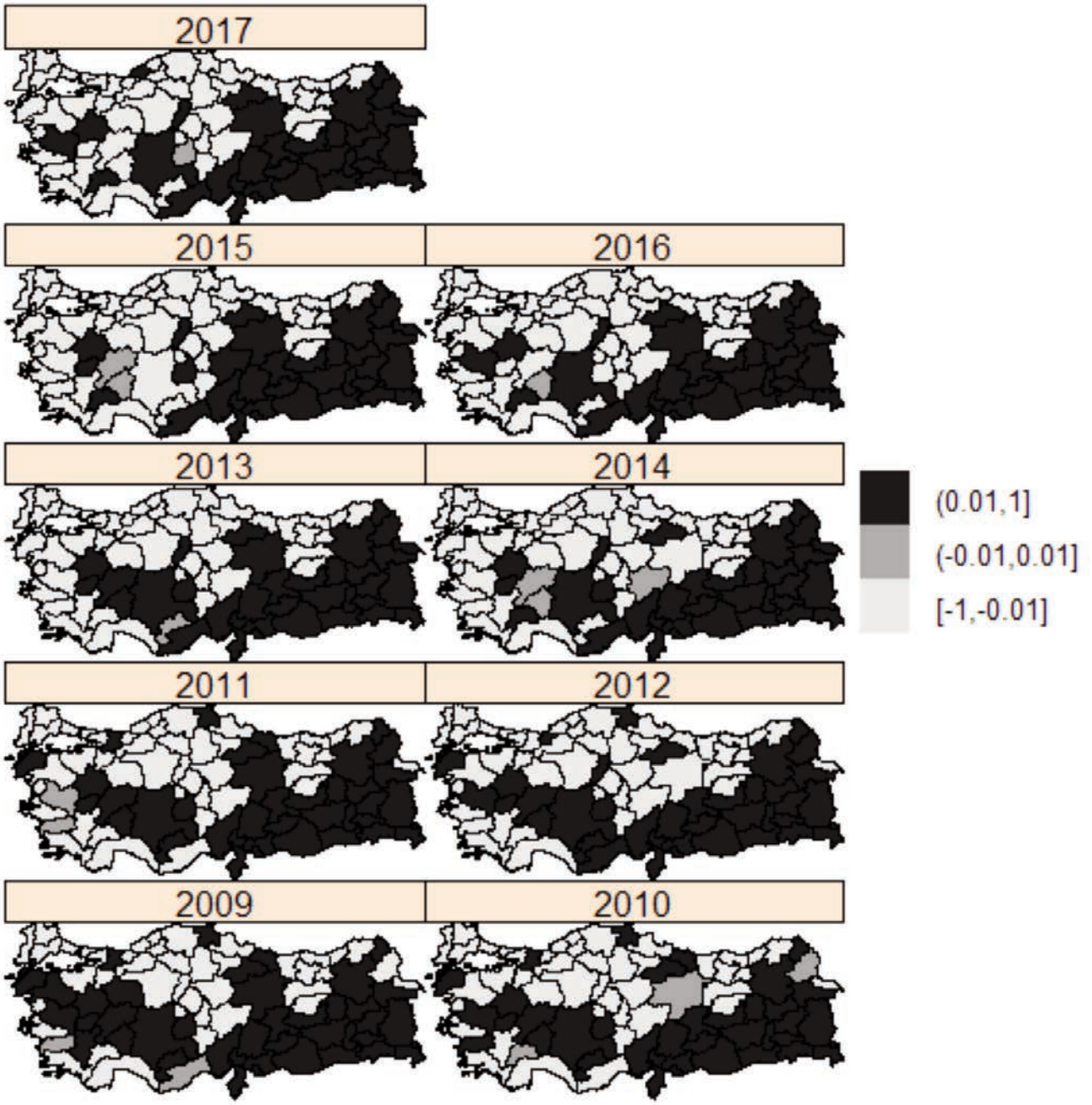

Figure 2. Posterior mean of unstructured spatial and structured temporal (RW1) interaction random effect for each province in Turkey between the years 2009 and 2017.

Table 3. Posterior means of model parameters and effects for infant mortality according to model 4a (RW1).

Subject	Mean	RR	95% CI of RR
Mothers aged<20 years (%)	0.011	1.011	(0.986, 1.037)
Mothers aged >39 years (%)	-0.015	0.985	(0.940, 1.032)
GDP per capita/1,000 (USD)	-0.029	0.972	(0.946, 0.998)

RR, relative risk; CI, credibility interval; GDP, gross domestic product.

Şırnak, Mardin, Kilis, Hakkari, Muş, Gaziantep and Şanlıurfa consistently had exceedance probability between 0.95 and 1. Therefore, from 2009 to 2017, in each year, significant risk clusters were consistently identified in the eastern and south-eastern Anatolia regions. Model 4a (RW1), given by Eq. 21 (DIC=5755.53), had a better fit than the Bayesian generalized linear model, given by Eq. 20 (DIC= 9366.52), to evaluate factors affecting infant mortality. It can be seen from Table 3 that the percentage of mothers aged <20 years (RR=1.011; 95% Cl(0.986, 1.037)) and the percentage of mothers aged >39 years (RR=0.985; 95% Cl(0.940, 1.032)) had no effect on the RR of infant mortality. However, an increase of 1,000 USD in the GDP per capita (RR=0.972; 95% Cl (0.946, 0.998)) reduced the RR of infant mortality by 2.8%.

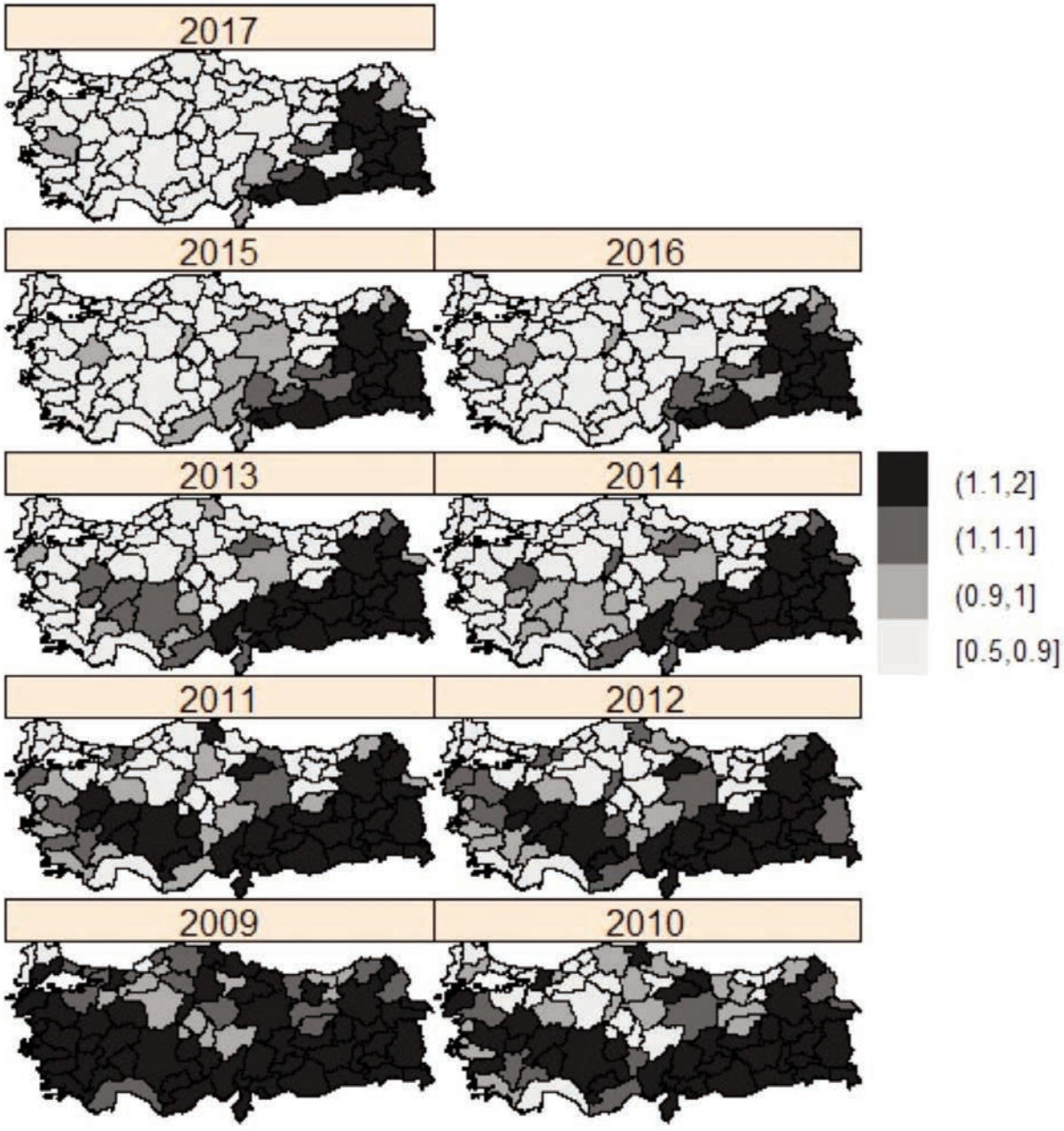

Figure 3. Posterior mean of relative risk of infant mortality for each province in Turkey between the years 2009 and 2017.

Discussion

This work used accessible data about space and time of infant mortality in Turkey to calculate provincial risk assessments based on a set of spatio-temporal models. The assessments were based on the assumption that areas close to each other would have similar risks, and that similarity also occurs for time points close to each other. Mapping was created to reveal spatial and spatio-temporal differences, as described by Blangiardo & Cameletti (2015) and Shaddick & Zidek (2016).

Our study sought answers regarding where and when the significant risk clusters of infant mortality appeared in Turkey. Clusters of asphyxia-associated neonatal mortality in São Paulo State were identified by spatial analysis by Testoni Costa-Nobre *et al.* (2021), who noted a negative correlation between GDP and this mortality. Our finding supports this correlation for infant mortality using spatio-temporal Bayesian analysis, but the effects of the percentages of mothers aged <20 and >39 years on the RR of infant mortality were found to be insignificant. Nonparametric and parametric spatio-temporal Bayesian models were implemented to

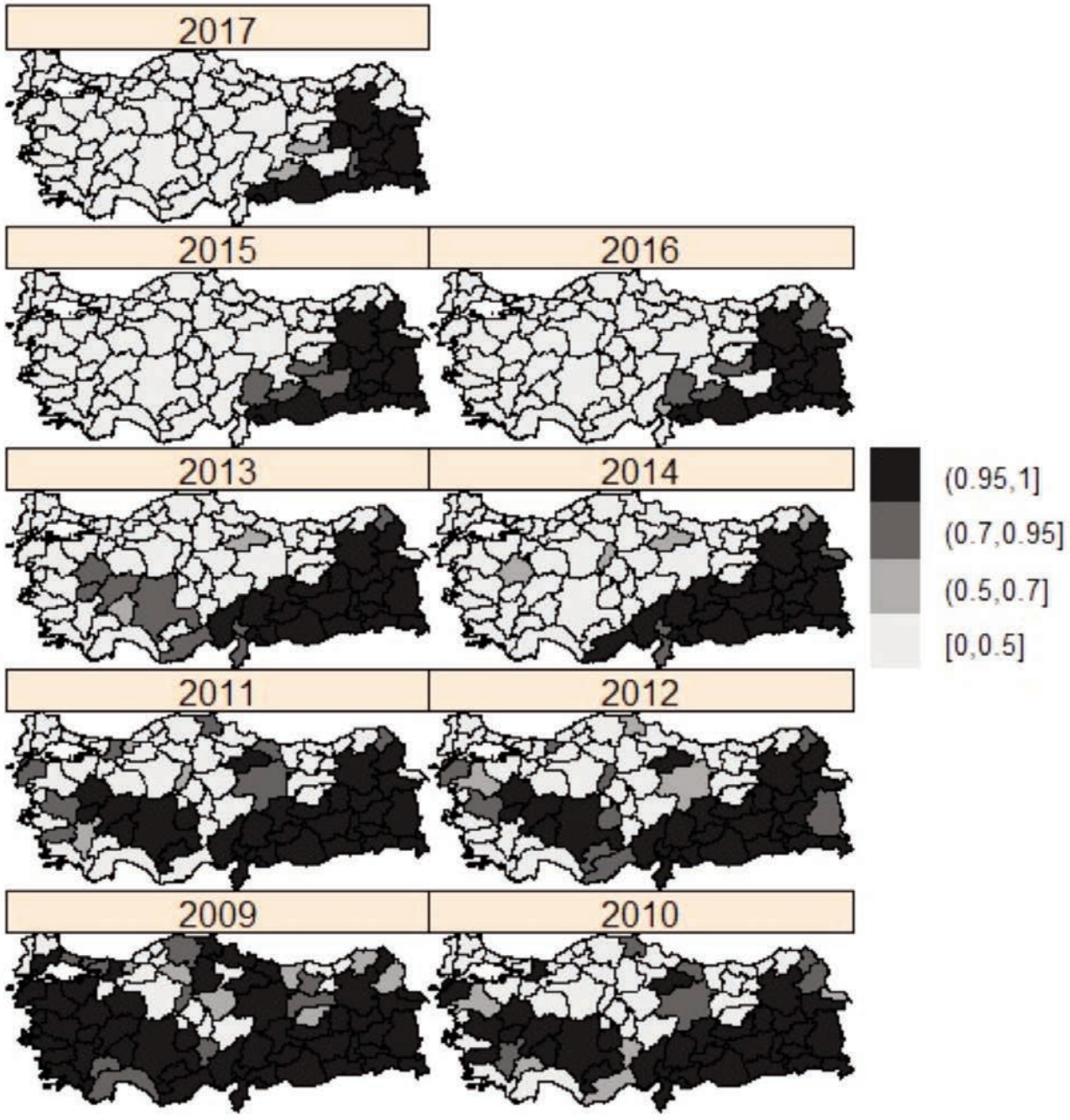

Figure 4. Posterior probability exceeding 1 for the relative risk of infant mortality for each province in Turkey between the years 2009 and 2017.

explore the decline in infant mortality using the INLA method.The results showed that the nonparametric model without a spatio-temporal interaction effect had a lower DIC compared to the parametric model. When different spatio-temporal interaction effects were added to the nonparametric model without a spatio-temporal interaction effect, these interactions were found to reduce the DIC. Indeed, the strongest reduction occurred when adding the unstructured spatial and structured temporal (RW1) interaction random effect.Further, because the unstructured spatial and structured temporal (RW1) interaction random effect and the structured temporal random effect (RW1) of the model with the lowest DIC contributed more to explaining variation in infant mortality risk than the other random effects, we used these effects to explore the decline in infant mortality. According to this interaction random effect (RW1), each province had a temporal trend modelled using RW1, independent from other provinces. From 2009 to 2017, this temporal trend effect followed a downward trend in many provinces. The downward trend was also identified for Turkey's overall temporal trend via the structured temporal random effect (RW1). Because of these downward trends, it is clear that a decrease in RR of infant mortality in many provinces occured between these years.

The spatio-temporal Bayesian analysis assisted the detection of significant risk clusters in Turkey's provinces from 2009 to 2017, and significant risk clusters were consistently found in the eastern and south-eastern Anatolia. It is important to detect significant risk clusters as it helps in assessing the effectiveness of health policies and determining future health policies. Local governments, such as municipalities in these significant risk clusters, can produce policies both on an individual and community basis that reduce infant mortality. Together with public health experts,they should provide adequate nutrition and access to health services through projects aimed at facilitating the birth process of pregnant women with low socio-economic status. Conditions favouring the birth of healthy babies would improve if these municipalities put some of their monetary resources into the health sector.

GDP per capita is a commonly used indicator of national and regional economic development (Li & Wei, 2014). According to the regional inequality index in GDP per capita in large regions, Turkey was placed as the second most unequal country, while the application of the same index in small regions, placed it as the most unequal country (Organization for Economic Co-operation and Development, 2020). Local governments, such as municipalities in significant risk clusters consistently detected in the eastern and south-eastern Anatolia, should collaborate with industry leaders in the private sector to encourage economic development in these areas. This could help to decrease infant mortality in these significant risk clusters by reducing the economic development gap between provinces.

Although it was not possible to obtain aggregated province-level data on the socio-economic characteristics of mothers of live-born infants from the General Directorate of Public Health, our study clearly showed the relation between economy and infant mortality and detected the location of significant risk clusters.

Conclusions

Spatio-temporal models allowed us to investigate the consistency of patterns over time and to identify any unusual patterns over the study period from 2009 to 2017. Significant risk clusters of infant mortality were consistently detected in the eastern and south-eastern Anatolia via substantially high exceedance probabilities. It is essential to produce health policies to reduce infant mortality. The central goal of public health surveillance is to provide information about activities related to existing public health priorities and to set new priorities focusing on significant risk clusters as priority areas. Identifying significant risk clusters plays an essential role in guiding public health planning. In addition, the increase in GDP per capita should be taken into consideration by decision-makers as a factor in reducing infant mortality in Turkey.

References

Ayipe FI, Tanko M, 2023. Public health expenditure and under-five mortality in low-income Sub-Saharan African countries. Soc Sci Humanit Open, 8(1).

Bakka H, Rue H, Fuglstad GA, Riebler, A, Bolin D, Illian J, et al., 2018. Spatial modelling with R-INLA: A review. Cornell University arXiv. https://arxiv.org/pdf/1802.06350.pdf

Blangiardo M, Cameletti M, 2015. Spatial and Spatio-temporal Bayesian Models with R-INLA. John Wiley & Sons, Ltd, United Kingdom.

Blangiardo M, Cameletti M, Baio G, Rue H., 2013. Spatial and spatio-temporal models with R-INLA. Spat Spatiotemporal Epidemiol 7:39-55.

Byun HG, Lee N, Hwang SS, 2021. A systematic review of spatial and spatio-temporal analyses in public health research in Korea. J Prev Med Public Health 54:301-8.

Chen ZY, Deng XY, Zou Y et al., 2023. A Spatio-temporal Bayesian model to estimate risk and influencing factors related to tuberculosis in Chongqing, China, 2014–2020. Arch Public Health 81:42.

Diabelková J, Rimárová K, Dorko E, Urdzík P, Houžvičková A, Argalášová Ľ, 2023. Adolescent Pregnancy Outcomes and Risk Factors. Int J Environ Res Public Health 20:4113.

Fretts RC, Zera C, Heffner LJ, 2008. Maternal Age and Pregnancy. In 'Encyclopedia of Infant and Early Childhood Development', Marshall M. Haith, Janette B. Benson, eds. Elsevier/ Academic Press, p.259-67

Gupta AK, Ladusingh L, Borkotoky K, 2016. Spatial clustering and risk factors of infant mortality: district-level assessment of high-focus states in India. Genus 72;2.

Hajdu T, Kertesi G, Kézdi G, Szabó-Morvai Á, 2024. The effects of neonatal intensive care on infant mortality and long-term health impairments. Am J Health Econ 10:1-29.

Jayadevan CM, Trung Hoang N, 2024. Healthcare spending in high-income and upper-middle-income countries: a cross-country analysis. Discov Health Systems 3:37.

Kefale BA, Woya AA, Tekile AK et al., 2023. Geographical disparities and determinants of infant mortality in Ethiopia: mapping and spatial analysis using EDHS data. BMC Pediatr 23:221.

Kianfar N, Saadi Mesgari M, 2022. GIS-based spatio-temporal analysis and modelling of COVID-19 incidence rates in Europe, Spat spatiotemporal Epidemiol 41:100498.

Knorr-Held L, 2000. Bayesian modelling of inseparable space-time variation in disease risk. Stat Med 19:2555-67.

Li Y, Wei YD, 2014. Multidimensional inequalities in health care distribution in provincial China: A case study of henan province. Tijdschr Econ Soc Ge 105:91-106.

Lome Hurtado A, Guangquan L, Touza-Monter J, White PCL, 2021. Patterns of low birth weight in Greater Mexico City: a

Bayesian spatio-temporal analysis. Appl Geogr 134:102521.
Maiti T, 1998. Hierarchical Bayes estimation of mortality rates for disease mapping. J Stat Plan Inference 69:339-48.
Martino S, Rue H, 2010. Case studies in Bayesian computation using INLA. In: Mantovan P, Secchi P, editors. Complex Data Modeling and Computationally Intensive Statistical Methods. Contributions to Statistics. Springer, p.99-114
Meza JL, 2003. Empirical Bayes estimation smoothing of relative risks in disease mapping. J Stat Plan Inference 112:43-62.
Moser BK, 1996.Linear Models:A Mean Model Approach.Academic Press, Inc, USA.
NICHD, Eunice Kennedy Shriver National Institute of Child Health and Human Development, 2024. Are there ways to reduce the risk of infant mortality? Available from: https://www.nichd.nih.gov/health/topics/infant-mortality/topicinfo/reduce-risk
Organization for Economic Co-operation and Development (OECD), 2020. OECD Regions and Cities at a Glance 2020. https://www.oecd.org/en/publications/oecd-regions-and-cities-at-a-glance-2020_959d5ba0-en.html
Rue H, Held L, 2005. Gaussian Markov Random Fields Theory and Applications. Boca Raton, FL: Chapman &Hall/CRC, Taylor and Francis Group, USA
Rue H, Martino S, 2007. Approximate Bayesian inference for hierarchical Gaussian Markov random fields Models. J Stat Plan Inference 137:3177-92.
Rue H, Martino S, Chopin N, 2009. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. JR Stat Soc Ser B Stat Method 71:319-92.
Sartorius BK, Kahn K, Vounatsou P, Collinson MA, Tollman SM, 2010. Young and vulnerable: Spatial-temporal trends and risk factors for infant mortality in rural South Africa (Agincourt), 1992-2007. BMC Public Health 10:645.
Shaddick G, Zidek JV, 2016. Spatio-Temporal Methods in Environmental Epidemiology. Boca Raton, FL: CRC Press Taylor & Francis Group, USA.
Testoni Costa-Nobre D, Kawakami MD, Areco KCN, Sanudo A, Balda RCX, Marinonio ASS, Miyoshi MH, Konstantyner T, Bandiera-Paiva P, Freitas RMV, Morais LCC, Teixeira MP, Waldvogel B, Almeida MFB, Guinsburg R, Kiffer CRV, 2021. Clusters of cause specific neonatal mortality and its association with per capita gross domestic product: A structured spatial analytical approach. PLoS One 16:e0255882.
Turkish Statistical Institute. Data portal for statistics of Turkish Statistical Institute. https://data.tuik.gov.tr/
United Nations Children's Fund (UNICEF), 2024. Newborn care. Available from: https://data.unicef.org/topic/maternal-health/newborn-care/
Volpe FM, Abrantes MM, Capanema FD, Chaves JG, 2009. The impact of changing health indicators on infant mortality rates in Brazil, 2000 and 2005. Rev Panam Salud Publica 26:478-84.
World Health Organization (WHO), 2024. Newborn mortality. Avaiable from: lhttps://www.who.int/news-room/fact-sheets/detail/newborn-mortality