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Research Article

Mapping Respiratory Disease Mortality in Turkey by Using Bayesian Conditional Autoregressive Model

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Abstract

Spatial analysis plays a prominent role in revealing and characterizing the spatial patterns over a geographical region by considering both the attributes of objects in a data set and their locations. The response variable can display spatial autocorrelation. The objects close together tend to produce more similar observations than objects further apart. Despite covariates in the model, we cannot capture spatial autocorrelation explicitly. It remains in the model residuals. Then, the independence assumption is violated by the residuals. We apply conditional autoregressive (CAR) model to prevent the residual spatial autocorrelation. In this study, we consider the problem of identifying the provinces at high risk to respiratory diseases mortality in Turkey. The number of deaths from respiratory diseases in 81 provinces of Turkey is modelled by using Leroux Model. We assume that the observed number of deaths have a Poisson distribution. Disease mapping is performed over calculated risk values. The results show that an increase in the household consumption of alcoholic beverages, cigarettes and tobacco and, also in the rate of people aged over 65 years in a province trigger a significant increase in respiratory disease mortality. Furthermore, Kastamonu has the highest mortality risk from respiratory diseases.

Keywords: spatial autocorrelation, CAR models, MCMC, respiratory disease, mortality risk.

Introduction

The response variable of spatial data obtained from each areal unit displays spatial dependence. The reason of this dependence is the neighbourhood or grouping effects since the areal units close together tend to produce more similar observations than the areal units further apart. Thus, the assumption of independence of errors is violated because of spatial dependency. For this situation, random effect part is included in the model in order to get rid of residual spatial autocorrelation. In such cases, Spatial Generalized Linear Mixed Models (SGLMM) are used and spatial correlation can be modelled by CAR prior distributions in the R packages.

There are several packages such as hSDM, spatcounts, spdep and INLA implemented in R for the analysis of CAR models. Although these models have some restrictions or weakness, CARBayes have some advantages over other packages for fitting CAR models (Lee, 2013). It gives an opportunity to identify the neighbourhood matrix in order to explain the spatial adjacency and this matrix can be implemented easily by a single function. Moreover, response variable can follow Gaussian, Binomial or Poisson distributions. In this package, regression parameters and random effects are updated using Metropolis and block Metropolis-Hastings algorithms, respectively. Besides, Gibbs sampling is used for the sample of variance parameters (Lee, 2011).

There are various models for CAR prior distribution as well. For instance, intrinsic autoregressive model is the simplest CAR prior and convolution model is the combination of intrinsic model and a set of independent random effects. Both models are proposed by Besag et al. (1991). Later, Cressie (1993) and Leroux et al. (2000) developed their models. Lee (2011) compares the performance of four different models and concludes that the Leroux model is the best model after simulation and real life example. Therefore, in this study, Leroux model is preferred to model the random effects rather than others.

The aim of this study is to get the spatial distribution of respiratory disease mortality in Turkey and make an inference about provinces with elevated levels of respiratory disease mortality risk. Thus, for this study, 81 provinces of Turkey were chosen as areal units and the numbers of deaths from respiratory diseases in each province were used as the response variable. The presence of spatial autocorrelation was tested by Moran's I statistics over standardized mortality ratio (SMR) values. Then, using the CARBayes package, Leroux model was applied to the data set for estimating and mapping the mortality risk of the respiratory disease in Turkey. Hereby, this study is the first application of CAR models to Turkish disease data via the CARBayes package in R.

The methodology of the study including disease mapping and Leroux model is explained and it is

mentioned how the neighbourhood matrix is defined. Then, the Bayesian mapping respiratory disease mortality after the SGLMM in Turkey is presented and the detailed information about features of spatial data is given. The last section summaries the main part of our study and gives a conclusion.

Methodology

When modelling data, we actually attempt to represent the data as the sum of two parts: 'fit' and 'error'. 'fit' is the variation in the data explained by the model; however, 'error' is the remaining variation in the data unexplained by the model. There is a core assumption behind the modelling process. It is that errors are assumed to be independent of each other. When modelling spatial data, the response variable typically exhibits spatial autocorrelation because of neighbourhood and grouping effects of features. Neighbourhood effect defines the tendency of feature's behaviour, which is influenced by that of neighbouring features. Each feature also chooses to be close to features with similar characteristics, which is known as grouping effect. On the other hand, an important spatially correlated covariate can be either unmeasured or unknown in the modelling process. As a natural result of these factors, spatial autocorrelation cannot be captured explicitly and remains in the residuals part of the model and thus the residual spatial autocorrelation violates the assumption of independence.

As the solution, we use Spatial Generalized Linear Mixed Models to avoid from the spatial autocorrelation remaining in the residuals. The linear predictor includes the random effects for modelling any spatial correlation and over-dispersion in the data, which has not been accounted for by the available covariate information. These random effects are assigned a CAR prior distribution. A number of CAR models have been developed within this general class of CAR priors to deal with the random effects which exhibit a single global level of autocorrelation (Besag et al., 1991; Leroux et al., 2000) and a localized spatial autocorrelation (Lee and Mitchell, 2012; Lee and Sarran, 2015). Lee (2011) has compared the performance of commonly used CAR models and showed that the CAR model proposed by Leroux et al. (2000) is the best overall. Based on Lee (2011), we used Leroux model for estimating and then mapping the risk of the respiratory disease mortality in Turkey. The remaining part of this section interprets the disease mapping and then the Leroux model.

Disease Mapping

Spatial statistics have been widely applied in disease mapping for providing a representation of the spatial distribution of the disease risk over a defined geographical region and detecting "*which areas exhibit elevated levels of disease risk*". The disease risk reflects the mortality or the morbidity of a disease within a period of time for the population at risk. In this study, we focus on the mortality risk of the respiratory diseases in Turkey and therefore we address the disease mapping through the mortality risk (Doğru et al., 2017; Ülker et al., 2018; Badur et al., 2021).

In disease mapping studies, the geographical region is generally partitioned into K nonoverlapping small areal units. The observed number of deaths in each area are collectively denoted by $\boldsymbol{Y} = (Y_1, \dots, Y_k)$, where Y_k $(k = 1, \dots, K)$ denotes the number of deaths in area k. The observed number of deaths alone gives no information about the mortality risk. To fairly determine and appraise the areas with elevated risk levels, the expected number of deaths for each area is calculated. The expected number of deaths for area k is calculated as $E_k = P_k r_+$ where, P_k is the population at risk in area k and, r_+ is the overall deaths ratio. r_+ equals to (Y_+/P_+) where, Y_+ is the total number of deaths and P_+ is the total population at risk. Bivand et al. (2013) state that the population at risk can be the number of children born during the period of study or the reduced subset of the total population.

The observed number of deaths in area k is assumed to follow a Poisson distribution with mean $\mu_k = \theta_k E_k$ where, θ_k is the true mortality risk in area k. The true mortality risk is simply estimated by the standardized mortality ratio (SMR). SMR for area k is calculated as $SMR_k = (Y_k/E_k)$. If $SMR_k > 1$, the mortality risk for area k is worse than expected in the population at risk and thus area k represents an elevated risk. On the contrary, if $SMR_k < 1$, the mortality risk for area k is better than expected in the population at risk and thus area k indicates comparatively a healthier area.

The raw definition of SMR is deficient for some reasons. First, when the underlying disease is rare or the population at risk is small, E_k will be small and thus elevated risks are likely to happen by chance. Second, the raw SMR does not borrow strength from values in neighbouring areas, which can also lead the mortality risk to increase by chance. Last, the raw SMR does not include the effects of covariates on the mortality risk. As a result of these deficiencies, SMRs can badly misrepresent the spatial distribution of the mortality risk. They may be the extremes of the map in some areas and hence these extremes disrupt the patterns of the map. To overcome these problems, Spatial Generalized Linear Mixed Models is used for disease mapping. The class of these models can be found in Bivand et al. (2013), Lawson (2008) and Banerjee et al. (2014). The general form of these models is given by

$$\begin{aligned} Y_k|\mu_k &\sim Poisson(\mu_k), k = 1,2, \dots, K \\ ln(\mu_k) &= ln(E_k)\,\boldsymbol{X}_k^T\boldsymbol{\beta} + \phi_{\boldsymbol{k}} \\ \boldsymbol{\beta} &\sim N(\boldsymbol{\mu_\beta}, \boldsymbol{\Sigma_\beta}) \end{aligned} \qquad (1)$$

where, $ln(E_k)$ is the known offset term, $\boldsymbol{X}_k^T = (1, x_{k1}, x_{k2}, , \dots x_{kp})$ is the vector of p covariates for area k (including the intercept term), $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots \beta_p)$ is the vector of regression parameters, $\phi_{\boldsymbol{k}}$ is the random effect for area k, $\boldsymbol{\mu_\beta}$ and $\boldsymbol{\Sigma_\beta}$ are the $1 \times p$ mean vector and the $p \times p$ diagonal variance matrix for β, respectively. The inference for this type of model is based on Markov

chain Monte Carlo (MCMC) simulations, using a combination of Gibbs sampling and Metropolis Hastings algorithms.

Leroux Model

The random effects in Equation 1 comprise the spatial structure component $\boldsymbol{\phi} = (\phi_1, \phi_2, \dots, \phi_K)$. This component plays an important role in the spatial modelling process. Random effects are expected to model both over dispersion and spatial correlation which remains in the response data after covariate effects have been accounted for. The spatial closeness among the areas influence the spatial correlation between the random effects. The spatial closeness is identified by a neighbourhood matrix $\boldsymbol{W}$, which defines how K area are spatially located with respect to each other. $\boldsymbol{W} = [w_{kj}]_{K\times K}$ is a symmetric and non-negative $K \times K$ matrix. The $k\,j$-th element w_{kj} is the spatial weight for areas k and j. The most commonly used specification of W is the binary specification given by

$$w_{kj} = \begin{cases} 1, if\ (k,j)\ share\ a\ common\ border\ (k \sim j) \\ 0, otherwise \end{cases}$$

This specification means that the random effects related to adjacent areas are correlated while those related to non-adjacent areas are conditionally independent, given the remaining random effects.

The random effects are modelled by different types of CAR prior distribution. CAR priors are commonly specified by a set of K univariate full conditional distributions $f(\phi_k|\phi_{-k}), \quad k = 1,2, \dots, K$ where, $\phi_{-k} = (\phi_1, \phi_2, \dots, \phi_{k-1}, \phi_k, \dots, \phi_K)$. Many CAR models have been developed with different specifications of CAR priors. Leroux et al. (2000) have proposed a CAR prior distribution for modelling varying strengths of spatial dependence. The proposed prior distribution includes separate parameters for over dispersion and the strength of spatial dependence between the random effects. The univariate full conditional distributions for the random effects are given by

$$\begin{gathered} \phi_k|\phi_{-k}, \boldsymbol{W}, \tau^2, \rho \sim N\left(\frac{\rho\sum_{j=1}^{K} w_{kj}\phi_j}{\rho\sum_{j=1}^{K} w_{kj} + 1 - \rho}, \frac{\tau^2}{\rho\sum_{j=1}^{K} w_{kj} + 1 - \rho}\right) \\ \tau^2 \sim Inverse - Gamma(a,b) \\ \rho \sim Uniform(0,1) \end{gathered} \quad (2)$$

where, τ^2 is the variance parameter to control the amount of the variation between the random effects, ρ is the spatial autocorrelation parameter for controlling the strength of the spatial autocorrelation. $\rho = 1$ indicates that there is a strong positive spatial correlation between random effects and hence perfect clustering of similar areas. If $\rho = 0$, the random effects are independent, which shows that similar areas are neither close nor distant from each other.

Mapping Respiratory Disease Mortality in Turkey

In our study, we analyse the number of deaths from respiratory diseases in 81 provinces of Turkey in 2015. Figure 1 shows the observed number of deaths in each province. The highest number of deaths occurred in İstanbul, İzmir, Ankara, Bursa and Konya, respectively. Hakkâri, Tunceli, Kilis, Bayburt and Bingöl are, respectively, in the first five provinces with the least deaths. These observed numbers of deaths alone are not sufficient to determine the provinces with elevated risk levels and therefore we estimate the risk by combining covariate information with neighbouring and grouping information of provinces.

Fig. 1. Number of Deaths from Respiratory Diseases in 81 Provinces of Turkey in 2015.

The data for this study were obtained from the databases of Republic of Turkey Ministry of Environment and Urbanization (2017), Republic of Turkey General Directorate of Forestry (2014), The Union of Chambers and Commodity Exchanges of Turkey (2014) and Turkish Statistical Institute (2017). All the variables used for mapping respiratory disease mortality in Turkey are given below.

(1) Y: Number of deaths from respiratory diseases by provinces of Turkey in 2015
(2) Number of births in each province in 2015
(3) PM10: Average of PM10 values (mcg/m^3) in each province within the period of 2011-2014
(4) HCE: The percentage of the household consumption expenditures for alcoholic beverages, cigarette and tobacco by statistical regions in 2014
(5) FA: The percentage of forest area per km^2 in each province in 2014

(6) PD: Population density (number of people per km^2) by province in 2014
(7) NI: Provincial rate of net migration (‰)
(8) AGR: Annual growth rate of population (‰) in each province for 2014-2015
(9) PR014: Population ratio for 14 years and under aged group by province in 2014
(10) PR65: Population ratio for 65 years and over aged group by province in 2014

Y is taken as the response variable. The second one is the population at risk for calculating the overall deaths ratio (r_+) and the expected number of deaths E_k ($k = 1, \dots, 81$) for each province. The remaining variables are the covariates.

To assess whether or not there is a spatial correlation in the response variable, we realized a permutation test (at the 5% level) of Moran's I statistic for SMR values. P-value turns out to be 0.000002, which is much less than 0.05. Moran's I statistic for SMR values is equal to 0.61404, which indicates the presence of a high degree of positive spatial autocorrelation.

The respiratory data set is explained by the CAR model given in Equations 1 and 2. Bayesian inference was based on 2000000 MCMC samples. The initial 1000000 samples were discarded for burn-in. Every fifteenth iteration values are kept after burn-in. Table 1 shows the modelling results.

All Geweke's Z scores fall within the 95% confidence interval and thus each chain has converged to its target posterior distribution. Posterior medians are Bayesian estimates for model parameters. HCE, PD, AGR, PR014 and PR65 are found as the statistically significant covariates at the 5% level because their related 95% credible intervals do not contain zero value. 96% percent of the total variation has been explained by the model. Deviance information criteria (DIC) is equal to 793.7394 and the log-likelihood value is −313.19216.

The residuals were controlled for the presence of spatial autocorrelation by using a permutation test (at the 5% level) of Moran's I statistic. P-value was 0.7638, which is greater than 0.05. Therefore, residuals do not contain any spatial autocorrelation.

Table 1. Modelling Results for Leroux Model.

Parameters	Posterior Median	95% Credible Interval 2.5% Bound	97.5% Bound	Geweke Diagnostic Z-Scores
Intercept	0.1802	-0.698	1.1187	-1.9
PM10	0.0027	-0.0003	0.0056	0.3
HCE	0.1*	0.0245	0.178	0.9
FA	-0.0004	-0.0032	0.0026	-0.7
PD	0.0003*	0.0001	0.0004	-0.7
NI	0.013	-0.0032	0.0281	1.8
AGR	-0.0149*	-0.0267	-0.0022	-1.5
PR014	-0.054*	-0.0781	-0.0284	1.8
PR65	0.085*	0.0468	0.1194	1.6
τ^2	0.0707	0.0375	0.1244	-1.4
ρ	0.4807	0.1377	0.8802	0.5

$*$ *Significant Parameters*

Table 2. Effects of Covariates.

Covariates	Estimated Relative Risks	95% Credible Interval 2.5% Bound	97.5% Bound	Interpretation
PM10	1.00270	0.99970	1.00562	2.7‰ increased risk
HCE	1.10517*	1.02480	1.19483	10.5% increased risk
FA	0.99960	0.99681	1.00260	0.4‰ reduced risk
PD	1.00030*	1.00030	1.00040	0.3‰ increased risk
NI	1.01308	0.99681	1.02850	1.3% increased risk
AGR	0.98521*	0.97365	0.99780	1.5% reduced risk
PR014	0.94743*	0.92487	0.97200	5.3% reduced risk
PR65	1.08872*	1.04791	1.12682	8.9% increased risk

$*$ *Significant Relative Risks*

Table 2 presents the estimated relative risks and their 95% credible intervals. The estimated relative risks indicate the effects of covariates on disease risk for respiratory morality at a one-unit increase in each covariate.

According to Table 2, the estimated relative risks related to significant covariates are interpreted as the following:

- 1% increase in HCE and PR65 result in 10.5% and 8.9% increased risk in respiratory mortality, respectively.
- One person increase per km^2 causes a very low level of risk increase for respiratory mortality.
- One unit increase in AGR leads to 1.5% reduced risk in respiratory mortality.

- 1% increase in PR014 results in 5.3% reduced risk in respiratory mortality.

Figure 2 displays the map of the estimated relative risks for respiratory disease mortality. They range from 0.214 to 3.843. The riskiest province in Turkey is Kastamonu with the value of 3.843. Then, the second risky provinces are Bartın and Çankırı, which are neighbours of Kastamonu. In the third riskiest groups, Edirne, Sinop, Zonguldak, Giresun and Kütahya are placed, respectively. The comparatively least risky provinces are, respectively, Şırnak, Şanlıurfa, Diyarbakır and Batman.

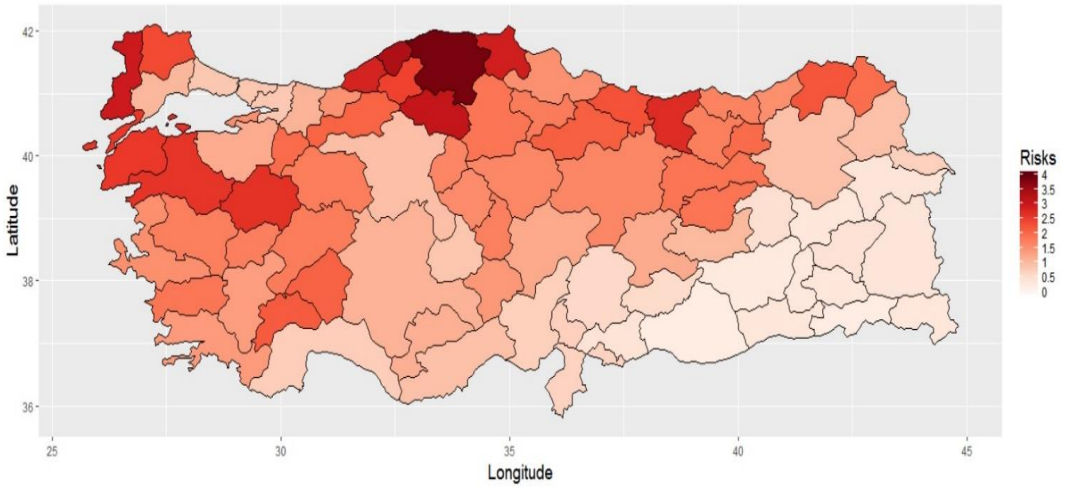

Fig. 2. Estimated Relative Risks for Respiratory Disease Mortality.

In order to determine whether the mortality risks for areas are significantly elevated or not, we computed the 95% credible intervals of the true mortality risks for 81 provinces in Turkey. Figure 3 summarizes these credible intervals. The dot in each interval represents the estimated mortality risk for the underlying area. There is a statistically significant elevated mortality risk for areas whose credible intervals are above the value of one, i.e., $H_0: \theta_k = 1$ versus $H_1: \theta_k > 1$. Kastamonu has the highest credible interval among 81 provinces and therefore carries the highest risk for respiratory disease mortality. After Kastamonu, the riskiest provinces are Bartın, Çankırı, Edirne, Zonguldak and Sinop, respectively. Their lower bound is above the level of 2.5. On the other hand, Konya, Malatya, Bursa and Kayseri are significantly the least risky provinces, respectively. Their lower bound is above one but below 1.15.

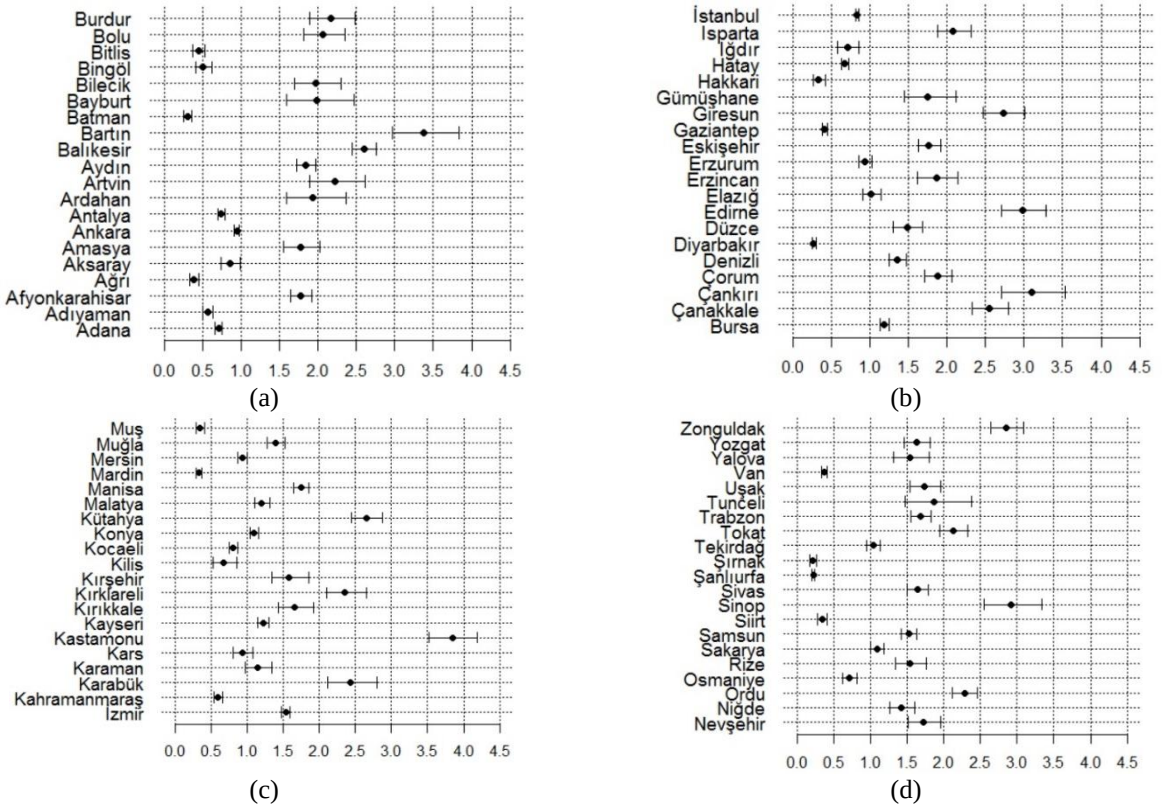

Fig. 3. 95% Credible Intervals of the True Mortality Risks for 81 Provinces in Turkey

We calculated the posterior probabilities that the risks are greater than 1 and 2 for all provinces in Turkey. Figure 4 and Figure 5 show the maps of these posterior probabilities, respectively. Light-coloured provinces carry less risk of respiratory diseases deaths, compared to dark-coloured provinces in both maps.

According to Figure 4, the risk is definitely not expected to be greater than 1 in all provinces in the South-eastern Anatolia Region; İstanbul and Kocaeli in the Marmara Region; Adana, Antalya, Hatay, Osmaniye and Kahramanmaraş in the Mediterranean Region; Van, Muş, Hakkari, Bitlis, Bingöl, Ağrı and Iğdır in the Eastern Anatolia Region. Additionally, Ankara and Aksaray have posterior probabilities less than 1% for the risk to be greater than 1.

In Figure 5, the risk for respiratory diseases deaths is definitely to be higher than two in Kastamonu, Sinop, Ordu, Giresun, Bartın, Zonguldak, Karabük, Çankırı, Kırklareli, Edirne, Çanakkale, Balıkesir and Kütahya. Artvin and Tokat have also posterior probabilities that are slightly higher than 90% for the risk to be greater than 2.

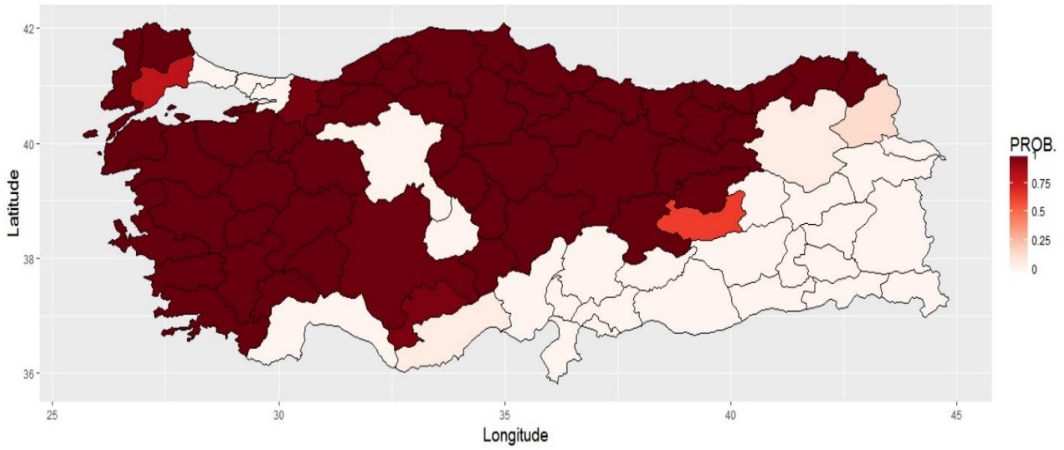

Fig. 4. Posterior Probabilities that Mortality Risks are Greater than 1

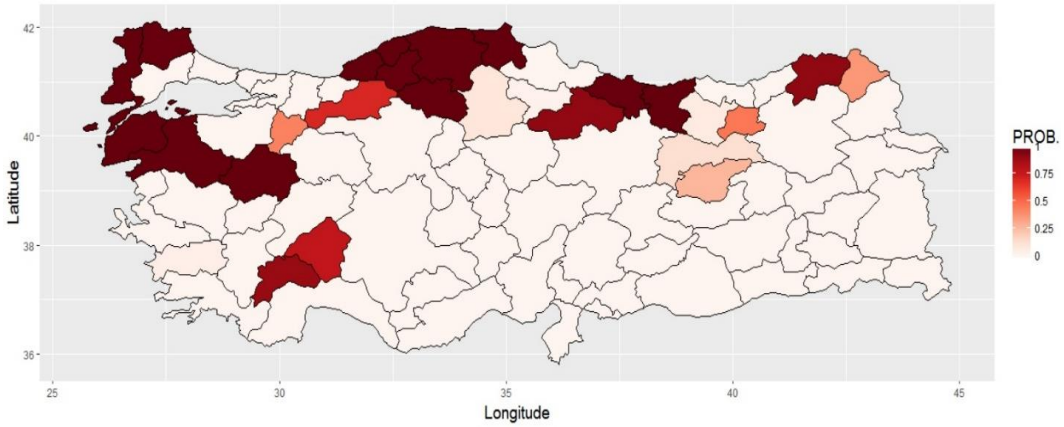

Fig. 5. Posterior Probabilities that Mortality Risks are Greater than 2

Conclusion

In this study, we used Leroux model for modelling the counts of deaths from respiratory diseases in 81 provinces of Turkey.

As known that cigarette and alcohol consumption play a significant role in the increase of the respiratory diseases. The respiratory disease mortality increases 10.5% for one percent increase in covariate HCE which is related to cigarette and alcohol consumption in the population. HCE is the most effective covariate among other covariates. As for the riskiest province for deaths from respiratory diseases, Kastamonu, household consumption for cigarette and alcohol in that province is higher than most of the other provinces of Turkey.

The other significant covariates are respectively PR65, which is the rate of people aged over 65 years in the population, PR014, which is the rate of people aged under 14 years in the population, and AGR, which is the annual growth rate of the population. As known that various anatomical, physiological and immunological changes occur in the respiratory system with aging. Due to the effects of aging on respiratory system, older people are more prone to have severe respiratory diseases. As a result of this fact, the rate of people aged over 65 years leads to a significant increase in respiratory disease mortality. Conversely, the rate of young people in population leads to a

significant decrease in respiratory disease mortality. One percent increases in the PR65 increases the mortality from respiratory diseases by 8.9%. Contrary to PR65, one percent increase in the PR014 result in 5.3% reduced risk in the mortality from respiratory diseases and also 1‰ increase in the AGR results in 1.5% reduced risk in mortality from respiratory diseases. As the riskiest province, Kastamonu is the second province with the highest population ratio for 65 years and over aged group. Also, the population ratio for 14 years and under aged groups in Kastamonu is lower than most of the other provinces in Turkey. The annual growth rate of population in Kastamonu is neither too high nor to low compared to other provinces of Turkey.

The least effective covariate is PD, which is the number of people per km^2 in a province. One person increase in the PD results in 0.3‰ increased risk in the mortality from respiratory diseases. This indicates that the mortality from respiratory diseases in a province rises as the population density of a province increases.
PM10 concentration of the air in a province shows the degree of air pollution in that province. As known that air pollution causes severe respiratory diseases, the covariate PM10 should have been a significant covariate in this study. However, based on the modelling results, it is not a significant covariate. PM10 concentration of the air varies depending on meteorological conditions, natural and anthropogenic factors. Therefore, during the time period when data are collected, anthropogenic factors and meteorological conditions may not significantly affect the amount of PM10 in the air in terms of increasing deaths from respiratory diseases. In that case, the spatial-temporal data models can be used for representing the temporal evolution of the objects over time.

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