A Spatio-Temporal Auto-regressive Model for Generating Savings Calls to a Health Line

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Abstract. Urgency admission is one of the most important factors regarding hospital costs, which can possibly be mitigated by the use of national health lines such as the Portuguese Saúde24 line (S24). Aiming future development of decision support indicators in a hospital savings context, based on the economic impact of the use of S24 rather than hospital urgency services, this study investigates spatio-temporal dependencies of the number of S24 calls generating savings in each Portuguese municipality, over the period 2010–2016, under an autoregressive approach. An econometric analysis of the savings obtained by the use of S24 is also carried out considering a savings index.

Combining insights from classical spatial econometrics and from the analysis of spatio-temporal data, novel Bayesian Poisson spatio-temporal lag models are presented and applied in this paper. This extends to time the ideas of a Bayesian Poisson spatial lag model, considering both a parametric and a non-parametic structure for time and space-time effects.

The results obtained for the savings index reveal that, over the last seven years, there has been a more comprehensive spatial effectiveness of the S24 line in solving the non-urgent emergency situations, that could be handled by primary health care services or in a self care basis.

Keywords: Bayesian analysis · Spatial econometrics · Autoregressive models · Space-time correlation · Poisson

Supported by national funds through FCT - Foundation for Science and Technology - under the projects UID/MAT/00297/2019 and UID/MAT/00006/2013.

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S. Misra et al. (Eds.): ICCSA 2019, LNCS 11621, pp. 81–96, 2019.
https://doi.org/10.1007/978-3-030-24302-9_7

1 Introduction

The use of national health lines can possibly mitigate the effects of one of the most important factors responsible for a considerable part of hospital costs, urgency admissions [1]. It is possible that a considerable part of the admissions corresponds to non-urgent cases that could be handled by primary health care services. This helps to understand why, in Portugal, hospital urgency service has become one of the most important worries of the Health Ministry over the last years.

Within this context in April 2007 a Portuguese National Health Line, Saúde24 line (S24), was created in order to improve accessibility to health care and to racionalize the use of existing resources [2]. The S24 service directs users to the most appropriate institutions of the public health service or offers counsels on self-care measures.

The S24 offers various services, including Triage, Couseling and Routing (TCR) in disease situations, which represents approximately 90% of the calls to the health line. This study focuses on these calls at a municipality level, in Continental Portugal, annually over the period 2010–2016. In order to evaluate the economic impact of the use of S24 rather than hospital urgency services, in terms of the reached savings by avoiding unnecessary urgent care in hospitals, the main interest is on the TCR calls whose initial intention of the user was to go to hospital urgency but, after using the health line the final disposal is a non-emergent situation, that does not require hospital emergency care. Taking into account that the savings achieved with S24 are proportional to the number of savings calls, considering the price of a simple medical appointment in the urgency, these are the calls analysed in this study, described as S24 savings calls.

Spatio-temporal dependencies might be expected on the number of S24 savings calls in each Portuguese municipality, during the study period, and should be accounted for in the modelling process [3], since observations from geographically close spatial units and temporally close time periods tend to have more similar values. This requires the selection of a neighbourhood structure that specifies the relations between regions to identify spatial association among them [4].

An autoregressive spatio-temporal Bayesian econometric approach for processing count data [5] can be implemented allowing, for example, to describe and evaluate in which municipalities the use of S24 must be potentiated and highlight those regions that most contribute to the economic success of the use of the health line. This resorts to Integrated Nested Laplace Approximation (INLA) methodology [6,7] for implementing the Bayesian paradigm.

The spatio-temporal modelling formulation proposed here extends the spatial autoregressive approach for count data in [5], allowing for temporal and spatio-temporal components. The essence of this methodology was driven based on the main idea that is plausible to consider that the risk of what is being counted in one area is related to the risk of what is being counted in the areas of its neighbourhoods. Within a Poisson response setting, a spatial lag term is included on the log relative risks accommodating the magnitude of the spatial influences

while preserving other important factors. Additionally, temporal and spatio-temporal effects are allowed, considering both a parametric and a nonparametric structure for these components. When the purpose of the analysis is to estimate which areas are exhibiting linear trends in the response over time a parametric structure is considered with the model proposed by Bernardelli *et al.* [8]; however if time trends and spatial patterns are to be estimated considering interaction, a dynamic nonparametric formulation is more adequate and the propose of Knorr-Held is considered [9]. The lag model with temporal and space-temporal effects is now implemented for the first time in a Poisson response Bayesian setting. This contribution may also be important for other spatio-temporal econometric practitioners.

An econometric analysis of the savings obtained by the use of S24 is carried out considering a savings index, in order to reach a more detailed health econometric analysis, developing an economic understanding of the advantages for the health system. The main reason for the support of public health research is the common understanding that new knowledge leads to more effective health care, expecting that the upper mentioned econometrics analysis contributes, in general, to an improvement by helping to reduce the per capita costs of the health care, through management policies [10].

This work organises as follows: first, Sect. 2 presents an overview of the considered approaches and describes the new proposals of spatio-temporal autoregressive models for Poisson count data; then Sect. 3 describes and details the application of the econometric analysis of S24 calls to assess hospital savings; finally Sect. 4 discusses some of the main conclusions as well as some possibilities for future work.

2 Modelling Spatial and Temporal Variability on Count Data

Traditional spatial econometric models, such as the spatial autoregressive model (slm) and the spatial error model (sem), rely on the Gaussian assumption of the response variable [11], which does not hold for count data in areas or spatial units - *lattice data* [4,12]. Consequently their usage for count data, such as the number of calls, demands data transformation to meet the assumptions of the models. In order to avoid that, this work investigates new possible spatio-temporal modelling strategies for handling count data following a Poisson distribution.

In the scope of these spatial autoregressive models there are alternatives for modelling counts that we have explored in a previous work [5]. More specifically, considering a standard spatial lag model developed within a new class of latent models defined in Integrated Nested Laplace Approximations (INLA) [13], by Gómez-Rubio, Bivand and Rue in 2015 [6]; considering a spatial autoregressive lag model of counts developed by Lambert, Brown and Florax in 2010 [14], under a classical perspective; a spatial lag autoregressive component was incorporated in the model for counts, under a Bayesian paradigm and using INLA methodology. This resulted in a spatial lag Poisson model for count data.

In this paper, this alternative is further elaborated into a more complex spatio-temporal autoregressive model where time and spatio-time effects are incorporated, eventually capturing dynamic evolutions [3,7]. The Bayesian estimation can be considered under INLA methodology, being implemented with R-INLA. The lag model with temporal and spatio-temporal interaction effects has not yet been implemented in a Poisson response Bayesian setting.

This section describes and explains different Bayesian spatio-temporal models for Poisson count data, that resort to random effects to account for spatial and temporal correlation. For spatial correlation, the models presented here take an autoregressive approach in space [15]. They further consider time effects modelled simply through a parametric linear trend model [8] or through a nonparametric dynamic trend model [9], implemented, respectively, within a Bayesian Poisson spatio-temporal lag linear model and a Bayesian Poisson spatio-temporal lag dynamic model.

2.1 General Log-Poisson Regression Model

Considering the study region divided into a set of n spatial units let $y_t = (y_{1t}, \ldots, y_{nt})$ and $e_t = (e_{1t}, \ldots, e_{nt})$ represent, respectively, the number of observed and expected cases of what is being measured in each spatial unit $i = 1, \ldots, n$ and recorded for $t = 1, \ldots, T$ consecutive time periods. The counts y_{it} are assumed to be Poisson distributed with expected value $E(y_{it}) = \mu_{it} = e_{it}\theta_{it}$, where θ_{it} is the relative risk in area i and time t.

The general log-Poisson regression model is defined as:

$$y_{it}|\eta_{it} \sim \text{Poisson}\ (e_{it}\theta_{it}), \tag{1}$$

where $\eta_{it} = \log(\theta_{it})$, $i = 1, \ldots, n$, $t = 1, \ldots, T$, are the log relative risks. Note that $\log(e_{it})$ enter as known offsets in the model.

The log relative risks are decomposed into the effects of covariates $\mathbf{X}_{it}^T = (X_{it1}, \ldots, X_{itk})$ measured for spatial unit i and time period t, corresponding X_{it1} to the intercept term and being $\beta = (\beta_1, \ldots, \beta_k)$ the associated regression parameters, plus some random effects that are able to account for possible overdispersion:

$$\eta_{it} = \log(\theta_{it}) = \mathbf{X}_{it}^T\beta + u_{it}. \tag{2}$$

The u_{it} term is a latent component for spatial unit i and time period t which may capture remaining space, time and spatio-temporal effects or trends in the data, after accounting for the covariates. Different configurations of u_{it} correspond to different models.

For the regression coefficients β_j weak informative Normal$(0, 1000)$ prior distributions are considered.

2.2 Spatio-Temporal Bayesian Autoregressive Log-Poisson Models

This subsection details spatio-temporal Bayesian autoregressive log-Poisson models as members of the general log-Poisson regression model.

Spatial Component. Under formulation (2), we get an autoregressive lag Poisson model if u_{it} includes a spatial lag term ε_{it} on the log relative risks.

In the formulation of the Bayesian Poisson spatial lag model [5], spatial dependencies are accounted in the observed responses through a spatial lag term ε_{it} on the log relative risks, to be included in u_{it} and given by:

$$\varepsilon_{it} = \rho \sum_{j \neq i} w_{ij} \eta_{jt}, \tag{3}$$

where η_{jt} is the log relative risk for unit area j and time t, w_{ij} are the elements of an adjacency matrix W defined by a contiguity criterion between areas [4], for establishing the neighbouring structure, and ρ is the spatial autoregressive parameter. For the logit transformation of parameter ρ, $logit(\rho)$, a Normal(0,10) weak informative prior distribution is considered. The log-risks η_{jt} are modelled also with temporal and spatio-temporal effects, justifying the dependency of the quantities ε_{it} on time.

Temporal and Spatio-Temporal Components. Temporal effects may also be added into the u_{it} component. These effects are going to be considered in two different ways, under a simplicity argument. Firstly we adopt a parametric trend for the temporal component as proposed by Bernardelli *et al.* [8], that includes in u_{it} a separate linear trend for each area. Secondly we consider a nonparametric dynamic trend as proposed by Knorr-Held [9] for the temporal component, that includes in u_{it} a temporally structured temporal effect and an unstructured space-time interaction effect.

Linear Trend Model. This model incorporates the spatio-temporal variation additively in u_{it} in (2) as a separate linear trend in time for each area:

$$(\alpha + \delta_i) t^*, \tag{4}$$

where t^* corresponds to the time normalized to belong to an unit interval. The spatial unit i has then its own linear time trend with a spatially varying intercept $(\beta_1 + \varepsilon_{it})$ and a spatially varying slope $(\alpha + \delta_i)$. The differential trend δ_i represents the difference between the global trend α and the spatial unit specific trend. If $\delta_i > 0$ the trend for the corresponding spatial unit is steeper than the mean trend while it $\delta_i < 0$ is the other way around.

This specification is similar to the spatially varying linear time trend model proposed by Bernardinelli *et al.* [8] for spatio-temporal hierarchical models. It considers spatio-temporal interactions δ_i differentiated for each spatial unit.

It is assumed for each element of $\delta = (\delta_1, \ldots, \delta_n)$ and for the overall slope parameter α independent Gaussian prior distributions,

$$\begin{aligned} \delta_i &\sim \text{Normal}\ (0, \sigma^2_{slo}) \\ \alpha &\sim \text{Normal}\ (\mu_\alpha, \sigma^2_\alpha) \end{aligned} \tag{5}$$

For σ^2_{slo} an inverse-gamma prior distribution is considered [7]. The corresponding hyperparameters $(a, b, \mu_\alpha, \sigma^2_\alpha)$ are chosen in this work such that the resulting

prior distributions are weakly informative. It is assumed that $a = 1, b = 0.01$, $\mu_\alpha = 0$ and $\sigma_\alpha^2 = 1000$.

The assumption of linearity of the δ_i component can be relaxed, using instead a dynamic nonparametric formulation of the temporal component as follows.

Dynamic Trend Model. This model is similar to the simplest form of the one proposed by Knorr-Held [9] for spatio-temporal hierarchical models, although there are other more complex alternatives that could also have been explored. It incorporates additively in u_{it} in (2), specific year spatial effects ε_{it}, an overall temporal trend common to all spatial units δ_t as well as space-time interactions γ_{it}:

$$\varepsilon_{it} + \delta_t + \gamma_{it}, \tag{6}$$

where δ_t are modelled dynamically by a random walk of order 1 and unstructured space-time random effect are considered [7]. Denoting $\delta = (\delta_1, \ldots, \delta_t)$ the set of temporal random effects, they are modelled through a random walk of order 1:

$$\delta_t - \delta_{t+1} \sim \text{Normal}\left(0, \sigma_T^2\right) \tag{7}$$

For the independent space-time interactions $\gamma = (\gamma_{11}, \ldots, \gamma_{nT})$ Gaussian prior distributions are specified,

$$\gamma_{it} \sim \text{Normal}\left(0, \sigma_I^2\right) \tag{8}$$

For σ_I^2 a weak informative inverse-gamma prior distribution is considered ($a = 1, b = 0.01$) and for $\log(\sigma_T^{-2})$ a weak informative log-gamma prior distribution is considered ($a = 1, b = 0.00005$).

The Bayesian Poisson spatial lag model [5] is now extended to allow the inclusion of a temporal and spatio-temporal components in u_{it} in (2) through (4) or (6).

Analogously to [5], and given the exposed in Sect. 2.1, we are able to write the predictor η_{it} of the autoregressive in space log-Poisson model as:

$$\eta_{it} = \log(\theta_{it}) = \mathbf{X}_{it}^T\beta + \rho\textstyle\sum_{j\neq i} w_{ij}\eta_{jt} + \delta_t + \gamma_{it}, \tag{9}$$

considering, without loss of generality, that δ_t represents a temporal effect and γ_{it} a space-time interaction effect. For each time t this can be expressed in matrix notation as:

$$\eta_t = \mathbf{X}_t^T\beta + \rho W\eta_t + \delta_t 1_{n\times 1} + \gamma_t, \tag{10}$$

where η_t denotes the log-risks η_{it} for year t, $\mathbf{X}_t^T$ represents the observed covariates in year t (including a first column of 1's for the intercept), $1_{n\times 1}$ is a column of n 1's and γ_t denotes the space-time interaction effects γ_{it} for year t.

Equivalently this can be expressed as:

$$\begin{aligned} &\eta_t = (I_n - \rho W)^{-1}\mathbf{X}_t^T\beta + (I_n - \rho W)^{-1}\delta_t 1_{n\times 1} + (I_n - \rho W)^{-1}\gamma_t \quad \Leftrightarrow \\ &\eta_t = (I_n - \rho W)^{-1}\mathbf{X}_t^T\beta + \delta_t^* + \gamma_t^*, \end{aligned} \tag{11}$$

where

$$\delta_t^* = (I_n - \rho W)^{-1}\delta_t 1_{n\times 1} \quad \Leftrightarrow \delta_t 1_{n\times 1} = (I_n - \rho W)\delta_t^* \tag{12}$$

and

$$\gamma_t^* = (I_n - \rho W)^{-1}\gamma_t \quad \Leftrightarrow \gamma_t = (I_n - \rho W)\gamma_t^* \tag{13}$$

Expression for η_t in (11) is then given as a sum of three random effects, $x_1 = (I_n - \rho W)^{-1}\mathbf{X}_t^T\beta$, $x_2 = \delta_t^*$, and $x_3 = \gamma_t^*$, allowing its estimation through INLA methodology, which requires models to be written under such a formulation [5]. Temporal and spatio-temporal effects are considered in this transformed version (δ_t^* and γ_{it}^*), being related to the untransformed effects δ_t and γ_{it}, respectively, by a factor of $(1 - \rho)$. This relation can be used to recover the original effects.

When it is chosen a linear trend temporal component (4) the resulting model is the Bayesian Poisson spatio-temporal lag linear model (ST.splm.linear). A simple dynamic nonparametric formulation (6) corresponds to the Bayesian Poisson spatio-temporal lag dynamic model (ST.splm.dynamic).

3 Spatio-Temporal Modelling of S24 Data

The data considered in this study were provided by the Support Unit of the Call Center of the National Health Service of the Portuguese Directorate-General of Health. It is a comprehensive data set of the calls recorded by the S24 health line, over the period 2010–2016, and includes information such as user's gender, residence, age, call's day of the week and the health problem specification.

The S24 has two call centers and offers various services, such as Triage, Counseling and Routing in disease situations (TCR); Therapeutic counseling to clarify issues relating to medication; Assistance in Public Health in specific topics as flu, heat, poisoning, etc.; General Health Information such as the location of public health units, pharmacies, among others. The S24 service is provided by qualified nurses, trained to give the best advice or, when appropriate, to assist citizens in solving the situation by themselves, being available to the beneficiaries of all different kinds of health sub-systems.

The majority of the calls answered by S24, approximately 92%, are catalogued as TCR. For those, the description of the health problem and the original intention of the user about how to solve it (go to an urgency room, for example) are recorded, and then a decision algorithm follows. The final disposition is given by this algorithm jointly with the evaluation of the nurse.

3.1 Econometric Analysis of S24 Calls to Assess Hospital Savings

This work focuses on the number of TCR calls to S24 at a municipality level in Continental Portugal annually over the period 2010–2016. The interest is evaluating the economic impact of the use of this health line concerning the reached savings by avoid unnecessary urgent care in hospitals. For that what is relevant are the TCR calls whose initial intention of the user was to go to hospital urgency but, according with the final health line disposition, that is

not necessary. These are the calls analyzed in this work, described as TCR savings calls.

Taking into account that the savings achieved with S24 are proportional to the number of savings calls, this work investigates and models spatial and temporal dependencies of the number of TCR savings calls in the Portuguese municipalities and for the time period from 2010 to 2016. Given this, the data considered in this study are the number of S24 savings calls that were registered in each of the 278 municipalities of Continental Portugal from 2010 to 2016 inclusive.

Within this context, the expected savings can be given by the following simple measure:

$$S_t = \sum_{i=1}^{278} y_{it} p_t - C_t,$$

where y_{it} are the number of savings calls in each municipality $i = 1, \ldots, 278$ and year $t = 1, \ldots, 7$; p_t corresponds to the price of a simple medical appointment in the urgency, which is set every year in a decree-law by the Ministry of Health; and C_t are costs associated with annual health line maintenance, provided by Portuguese Directorate-General of Health.

It should be emphasized that this is a simplistic measure which does not consider collateral costs as, for example, those caused by unnecessary increased contagion risk or those caused by increasing the number of patients in the urgency, requiring more human and financial resources.

The results of this study will contribute to understand one of the major factors regarding hospital costs of the Portuguese health care system, the non-urgent emergency situations, responsible for the decrease of hospital system efficiency. At the same time it will help to realize if this phenomenon has been mitigated through the creation, promotion and use of Saude24, with the perception that presently there are still about 15% of non-urgent cases per year in Portuguese Hospital Care System.

3.2 Preliminary S24 Data Analysis

The number of TCR savings calls are registered in each of the 278 municipalities of Continental Portugal from 2010 to 2016 inclusive. Naturally these numbers depend on the size and demographic structure of the population, in terms of age and gender characteristics of the underlying population, which requires adjustment in terms of (indirect) standardization. The observed (y_{it}) and the resulting expected number (e_{it}) of savings calls in each municipality $i = 1, \ldots, 278$, and year $t = 1, .., 7$, can then be used to roughly estimate the relative call risk, θ_{it}, through the Standard Call Rate (SCR) in municipality i and year t, $\text{SCR}_{it} = \frac{y_{it}}{e_{it}}$, mapped in Fig. 1. Several demographic, socio-economic, development and health indicators were investigated as possible covariates for modelling the TCR savings calls counts using a simple log-Poisson model.

Taking into account that the covariates are related in the model to the natural log of SCR, the relationships between the selected variables for all years

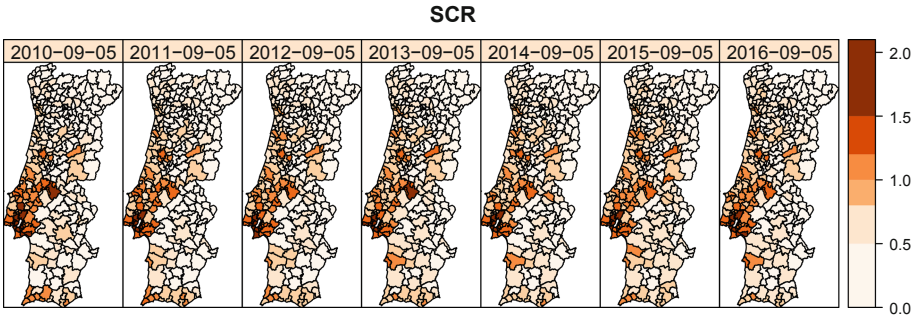

Fig. 1. SCR-2010 to 2016.

under analysis and the natural log of SCR were analysed. A positive relationship between the log of SCR and the average number of years of schooling was evident, suggesting that increased levels of schooling are connected to an increased risk of savings calls. It was also noted a slightly negative relationship between the log of SCR and the number of hospitals, suggesting that an increase in the number of hospitals have a decreasing impact on the savings calls risk.

The expected number of savings calls is included in the model as an offset. Bayesian covariable selection using indicator auxiliary variables under different scenarios [16] was performed. The most significant set of explanatory variables turned out to be the *average number of years of schooling* (x_1), the *proportion of active population* (x_2), the *rurality index* (x_3), the *number of hospitals* (x_4) and the *number of health centers per 1000 inhabitants* in each municipality (x_5). This was implemented in R-package `"R2WinBUGS"` [17] that run WinBugs [18].

It was further fitted a log-Poisson model with the covariates and unstructured random effects to account for possible over-dispersion, that is expected in these Poisson data. This confirmed the significance of some of the previous set of covariates, but two, the *number of hospitals* and the *number of health centers* revealed not to be significant. Nevertheless these covariates were kept in the model for their intrinsic econometric interest.

3.3 Spatial and Temporal Correlation

Preliminary analyses of these data included using Moran's I statistics [19] to look for spatial dependence of the number of TCR savings calls to S24 per 1000 inhabitants, by municipality and by year, and in the residuals of the log-Poisson model with covariates and unstructured random effects fitted before for each year, using a contiguity neighbourhood spatial structure (results were obtained with R-project package `spdep`). These resulted in clear rejection of the spatial independence hypothesis in both cases suggesting that there is positive spatial correlation among of the number of TCR savings calls, from 2010 to 2016, and also a strong evidence of unexplained spatial correlation in each year, after accounting for the covariate effects.

The residual temporal correlation could be assessed similarly considering a temporal neighbourhood structure but with only 7 time periods the resulting estimates would not be reliable [19,21].

3.4 Spatio-Temporal Bayesian Econometric Modelling of S24

The number of TCR savings calls in each municipality for the period 2010–2016 is analysed here through the Bayesian Poisson spatial lag model with temporal effects. The first model considered incorporates a spatial autocorrelation lag component in the econometric model of counts and a parametric trend for the temporal component (ST.splm.linear model). Then a nonparametric dynamic space-time model is also implemented within the spatial lag Bayesian Poisson model with temporally structured effects and allowing an unstructured interaction between space and time (ST.splm.dynamic model).

The estimates were obtained in R-INLA, using `slpmINLA` function, adapted for the spatio-temporal linear and dynamic cases. Main results are displayed in Table 1 and correspond to formulation (11). The estimated temporal and spatio-temporal effects of the original formulation were retrieved in an ad hoc manner by the existing relation between parameters δ_t and δ_t^*, γ_{ti} and γ_{ti}^*, being quite similar to each other.

Table 1. Parameter estimates (mean and 95% credible intervals) for the ST.splm.linear model and for ST.splm.dynamic model, for the S24 2010-2016 data. σ^2 is the estimated variance of the spatial effects for the autoregressive model.

Variable	Id	ST.splm.linear Model	ST.splm.dynamic Model
		Mean (CI)	Mean (CI)
Average number of years of **schooling**	x_1	0.41 (0.14; 0.62)	0.14 (0.10; 0.19)
Proportion of **active population**	x_2	−3.89 (−7.66; −0.02)	−0.11 (−0.88; 0.63)
Rurality index	x_3	0.17 (−0.53; 0.84)	0.11 (−0.05, 0.26)
Number of **hospitals**	x_4	0.18 (−4.01; 4.33)	0.54 (−0.42; 1.49)
Number of **health centers**	x_5	0.61 (−2.31; 1.00)	−0.17 (−0.55, 0.21)
Intercept		−1.11 (−3.95; 1.68)	−1.00 (−1.61, −0.39)
α^*/σ_T^2		0.06 (0.05; 0.09)	1.17e−04 (3.9e−05; 5.74e−04)
ρ		0.56 (0.55; 0.56)	0.56 (0.55; 0.57)
σ^2		0.08 (0.07; 0.10)	0.08 (0.07; 0.09)
$\sigma_{slo}^2/\sigma_I^2$		0.04 (0.03; 0.05)	0.005 (0.004; 0.006)

In relation to the ST.splm.linear model only two of the initial covariates revealed to be significant, the average number of years of schooling and proportion of active population residents. This model has an estimated value of the spatial dependence parameter ρ of 0.56. The main linear trend α, which represents the global time effect, is estimated as 0.06, being significant, and the estimated value of σ^2_{slo} is 0.04.

For the ST.splm.dynamic formulation only the average number of years of schooling is significant and the estimated values of σ^2_I and σ^2_T are 0.005 and 1.17e−04, respectively. It has an estimated value of the spatial dependence parameter ρ of 0.56, similar to the value obtained for the linear case.

In order to compare models, the chosen measures were the WAIC (Watanabe-Akaike information criteria) and the DIC (Deviance information criteria), as DIC is the predictive measure most used in Bayesian applications [22] and WAIC revealed to be more stable and particularly helpful with mixture structures [23]. In terms of the different temporal structures, DIC and WAIC were concordant and smaller for the dynamic parametrization - see Table 2. In what concerns each of the different temporal structures considered, one can say that within the parametric trend formulation, similar estimates were obtained for the spatial effects; the main linear trend was significant and displays an estimated value of 0.06, although the significance of the initial set of covariates differed from the simple log-Poisson regression model.

Table 2. DIC and WAIC measured for the case of a linear and a dynamic trend.

Model	DIC	pD	WAIC	pW
ST.splm.linear	16997	463	17474	773
ST.splm.dynamic	16387	1007.9	16370	760

The dynamic parametrization improved the model fit (smaller DIC and WAIC) suggesting that this parametrization for time is more appropriate to S24 data. Under this formulation, only one of the initial set of covariates revealed to be significant, the average number of years of schooling.

The estimated posterior means of the spatial main effect, $\zeta_i = \exp(\varepsilon_i)$, and the estimated posterior temporal trend $\xi_t = \exp(\delta^*_t)$, for the ST.splm.dynamic formulation are depicted in Fig. 2, suggesting a soft increase in the time effect and mild spatial effect around the metropolitan area of Lisbon.

The estimated posterior mean for the space-time interaction for the ST.splm.dynamic model, for the years 2010, 2012, 2014 and 2016, are displayed in Fig. 3. The considered space-time interaction effects did not seem to be of added value in explaining the TCR savings calls risk.

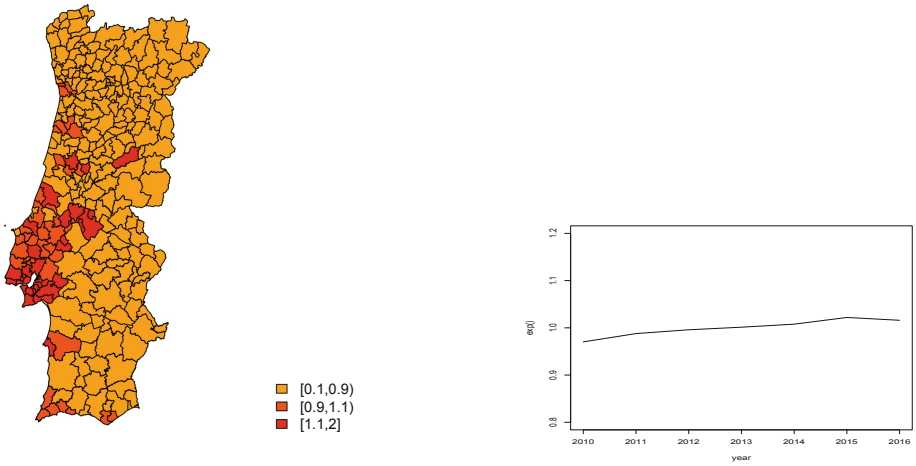

Fig. 2. Estimated spatial and temporal effects for the chosen model.

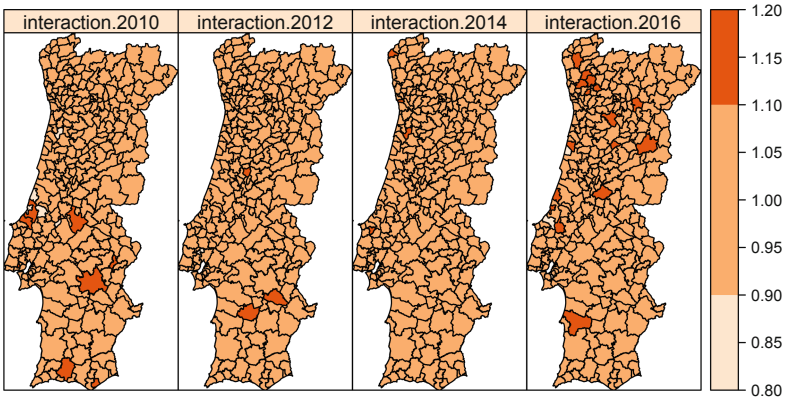

Fig. 3. Estimated spatio-temporal interaction effects for years of 2010, 2012, 2014 and 2016 for the chosen model.

3.5 The Savings Index

The S24 data analysis can be extended, exploring the econometric analysis of a Savings Index, obtained for each municipality $i = 1, \ldots, 278$ and year $t = 1, \ldots, 7$ as:

$$IS_{it} = \frac{(y_{it}p_t - C_{it})}{U_{it}}$$

where y_{it} is the number of savings calls, p_t corresponds to the price of a simple medical appointment in the urgency, C_{it} are costs associated with annual health line maintenance attributable to municipality i and is U_{it} are the total number of calls whose initial intention is urgency. It is mapped in Fig. 4.

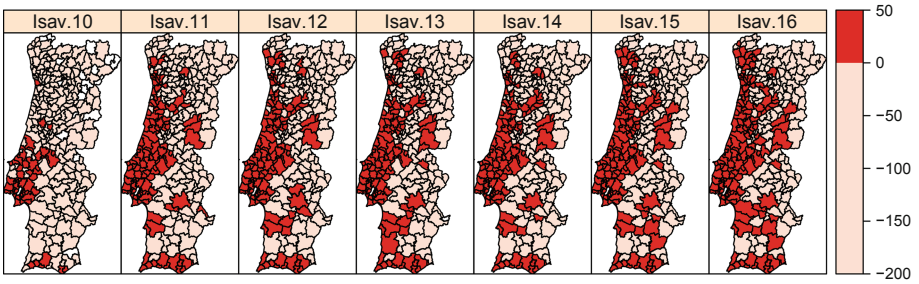

Fig. 4. The Savings Index from 2010 to 2016.

The municipalities of metropolitan area of Lisbon stand out as the ones corresponding to higher savings. On the other hand municipalities of northern interior should be considered for having implemented management policies in order to improve the impact of S24 in solving their non-urgent emerging situations.

4 Discussion

Induced by the application of modelling the number of savings calls to a national health line S24, this work proposes a Bayesian Poisson spatio-temporal lag approach for modelling lattice data. It comprehends different spatio-temporal models for Poisson count data which resorts to autocorrelated random effects to account for spatial and temporal correlation, here under Bayesian paradigm, extending a spatial autoregressive model for count data. Within this novel spatio-temporal modelling formulation, spatial dependencies are accounted in the observed responses. Including a spatial lag term on the log relative risks allows to accommodate the magnitude of the spatial influences while preserving other important factors, corresponding to the autoregressive lag Poisson model. The lag model with temporal effects had not yet been implemented in a Poisson response Bayesian setting.

The benefits of the autoregressive approach over other classical approaches for count data, as hierarchical models, are mainly concerned with econometric interpretation, since the response variable in a given area constitutes a good predictor of the response variable in its neighbourhood areas.

The models derived for count data were accommodated in the mathematical framework given by

$$\begin{gathered} y_{it}|\eta_{it} \sim \text{Poisson } (e_{it}\theta_{it})), \\ \eta_{it} = \log(\theta_{it}) = \mathbf{X}_{it}^T\beta + u_{it}, \;\; i = 1, \ldots, n, \;\; t = 1, \ldots, T \end{gathered} \tag{14}$$

with different representations of u_{it} corresponding to different model specifications. Within this common frame other possibilities can also be investigated for spatio-temporal modelling. For example, time effects can be further explored

resorting to other possibilities, as for example considering temporal effects a priori distributed according to the time analogous of Leroux et al. [20] conditional autoregressive (CAR) distribution [21]. Other ways of modeling the space-time component can be also investigated according to the ones proposes by Knorr-Held [9].

For the S24 savings calls data, a spatial structure was evident from the analysis as well as a slight temporal trend. The considered space-time interaction effects did not seem to be of added value. The temporal correlation could not be assessed as well as the spatial correlation, due to the short time series of seven time periods, although we consider that is was important to include the temporal component and allowing an interaction term between time and space. The small number of time periods was also the reason for not considering more complex structures for space-time interaction effects. An alternative would have been considering a different distribution [20] for the spatial effects for each year, resulting in differentiated autocorrelation parameter for each year, and evaluating afterwards the time evolution of these estimates [21].

In terms of the savings index, one can say that over the last seven years, there has been a more comprehensive effectiveness of the S24 line over space in solving the non-urgent emergency situations, that could be handled by primary health care services or in a self care basis. The savings index detected the municipalities of the metropolitan area of Lisbon as those that most contribute to the economic success of the S24 line. At the same time it identified the northern interior municipalities as those in which the use of the health line should be encouraged. This suggests that the S24 line is not equally well disseminated over the whole territory and, moreover, that this is not even associated with the available health services offer. Consequently, regional directed campaigns of the S24 line use should be considered as a priority.

The results of this study contribute to understand one of the major factors regarding hospital costs of Portuguese health care system, the non-urgent emergency situations, responsible for major efficacy losses of the hospital systems, and at the same time helps to realize if this phenomenon have been mitigated through the creation, promotion and use of S24, knowing that presently there are still about 15% of non-urgent cases per year in Portuguese Hospital Care System.

This study could now be extended in order to reach a more detailed health econometric analysis of the savings obtained by the use of S24, developing an economic understanding of the advantages for the health system and learning about the political and economic factors that influence health policies at a global, national, regional and local levels. The main reason for the support of public health research is the common understanding that new knowledge leads to more effective health care, expecting that the upper mentioned econometrics analysis contributes, in general, to an improvement by helping to reduce the per capita costs of the health care, through management policies [10].

Acknowledgements. This work is financed by national funds through FCT - Foundation for Science and Technology - under the projects UID/MAT/00297/2019 and UID/MAT/00006/2013.

References

1. Hughes, D., McGuire, A.: Stochastic demand, production responses and hospital costs. J. Health Econ. **22**, 999–1010 (2003)
2. Portal of the National Portuguese Health Service. https://www.dgs.pt/paginas-de-sistema/saude-de-a-a-z/saude-24.aspx. Accessed 3 Sept 2015
3. Cressie, N., Wikle, C.: Statistics for Spatio-Temporal Data. Wiley, Hoboken (2011)
4. Cressie, N.: Statistics for Spatial Data. Wiley, Hoboken (1993)
5. Simões, P., Carvalho, M.L., Aleixo, S., Gomes, S., Natário, I.: A spatial econometric analysis of the calls to the portuguese national health line. Econometrics **5**(24), 24 (2017). MDPI Journals
6. Goméz-Rubio, V., Bivand, R., Rue, H.: A new latent class to fit spatial econometrics models with integrated nested laplace approximations. Spat. Stat.: Emerg. Patterns-Part 2 **27**, 116–118 (2015). Details of the implementation in http://www.math.ntnu.no/inla/r-inla.org/doc/latent/slm.pdf, downloaded in September of 2016
7. Blangiardo, M., Cameletti, M.: Spatial and Spatio-temporal Bayesian Models with R-INLA. Wiley, Hoboken (2015)
8. Bernardinelli, L., et al.: Bayesian analysis of space-time variation in disease risk. Stat. Med. **14**(21–22), 2433–2443 (1995)
9. Knorr-Held, L.: Bayesian modelling of inseparable space-time variation in disease risk. Stat. Med. **19**, 2555–2567 (2000)
10. Sobolev, B., Levy, A. (eds.): Comparative Effectiveness Research in Health Services. Springer, Boston (2016). https://doi.org/10.1007/978-1-4899-7600-0
11. Lesage, J., Pace, R.: Introduction to Spatial Econometrics. CRC Press, Boca Raton (2009)
12. Besag, J.: Spatial interaction and the statistical analysis of lattice systems (with discussion). J. R. Stat. Soc. B **36**, 192–236 (1974)
13. Rue, H., Martino, S., Chopin, N.: Approximate Bayesian inference for lattent Gaussian models by using integreted nested Laplace approximations. J. Roy Stat. Soc. B **71**(Part 2), 319–392 (2009)
14. Lambert, D., Brown, J., Florax, R.: A two-step estimator for a spatial lag model of counts: theory, small sample performance and an application. Reg. Sci. Urban Econ. **40**, 241–252 (2010)
15. Bivand, R., Goméz-Rubio, V., Rue, H.: Approximate Bayesian inference for spatial econometrics models. Spat. Stat. **9**, 146–165 (2014)
16. George, E., McCulloch, R.: Approaches for Bayesian variable selection. Stat. Sin. **7**, 339–373 (1997)
17. Gelman, A., Sturtz, S., Ligges, U., Gorjan, G., Kerman, J.: Package `R2WinBUGS` (2015)
18. Lunn, D., Spiegelhalter, D., Thomas, A., Best, N.: The BUGS project: evolution, critique and future directions. Stat. Med. **28**, 3049–3067 (2009)
19. Anselin, L., Bera, A.K.: Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Statistics Textbooks and Monographs, vol. 155, pp. 237–290 (1998)

20. Leroux, B.G., Lei, X., Breslow, N.: Estimation of disease rates in small areas: a new mixed model for spatial dependence. In: Halloran, M.E., Berry, D. (eds.) Statistical Models in Epidemiology, the Environment, and Clinical Trials. IMA, vol. 116, pp. 179–191. Springer, New York (2000). https://doi.org/10.1007/978-1-4612-1284-3_4
21. Lee, D., Rushworth A., and Napier G.: CARBayesST: an R package for spatio-temporal areal unit modelling with conditional autoregressive priors. R Package Version 2.2 (2015). https://cran.r-project.org/web/packages/CARBayesST/. Accessed 25 Feb 2016
22. Spiegelhalter, D., Best, N., Carlin, B., Van der Linde, A.: Bayesian measures of model complexity and fit. J. R. Stat. Soc. B **64**(4), 583–639 (2002)
23. Gelman, A., Hwang, J., Vehtari, A.: Understanding predictive information criteria for Bayesian models. J. Stat Comput **24**, 997–1016 (2014)