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# Modelling the Spatial Variation of Road Safety in Greece

Eleonora Papadimitriou, Ph.D.
National Technical University of Athens, School of Civil Engineering,
Department of Transportation Planning and Engineering
5 Iroon Polytechniou str., GR-15773 Athens, Greece
Tel: +30 210 7721380
Fax: +30 210 7721454
E-mail: nopapadi@central.ntua.gr

Vojtech Eksler, Ph.D.
European Transport Safety Council (ETSC)
Avenue des Celtes 20, B-1040 Brussels, Belgium
Tel: +32 (0) 22 30 41 06
Fax: +32 (0) 22 30 42 15
E-mail: vojtech.eksler@etsc.eu

George Yannis, Associate Professor - corresponding author
National Technical University of Athens, School of Civil Engineering,
Department of Transportation Planning and Engineering
5 Iroon Polytechniou str., GR-15773 Athens, Greece
Tel: +30 210 7721326
Fax: +30 210 7721454
E-mail: geyannis@central.ntua.gr

Sylvain Lassarre, Ph.D.
INRETS - French National Institute for Transport and Safety Research
Tel: +331 45925764
E-mail: lassarre@inrets.fr

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**Abstract**

The analysis of spatial dependences among road safety outcomes (road accidents and fatalities) has received increased attention in recent research with interesting findings at national or European level. The objective of this research is the modelling of the spatial variation of road accidents and fatalities in Greece. Greece is selected as a country for which spatial effects have not been previously explored, and also as a country presenting some spatial particularity (i.e. loose spatial structure with many clusters of islands), making such an analysis interesting. For that purpose, NUTS-3 road accident and fatalities risk rates are used for the development of CAR and CAR-convolution spatial models. Moreover, two types of neighbourhood structures of the regional road safety data are tested: a basic structure defined according to the road connections between counties and an extended structure defined on the basis of both road and ferry connections between counties. The results suggest that the basic spatial structure accounts for an important part of the variation in road accident rates in the Greek counties, revealing a pattern of risk increase from northern to southern Greece. Spatial effects are also identifiable when considering the extended spatial structure, however without explaining a larger part of the overall variation compared to the basic structure. Finally, it is shown that the effect of a key explanatory variable of road safety in Greece, namely alcohol enforcement, would have been quite overestimated if spatial effects were not taken into account in the models.

**Key-words:** road accidents; fatalities; spatial analysis.

## 1. Background and objective

Spatial analysis includes a broad range of techniques, which may be applied in different fields, in order to study entities or observations in relation to their topological, geometric or geographical properties. The basic idea around which these techniques have been developed, is that part of the properties of an entity are due to the properties of the nearby entities. Spatial dependence is therefore a covariation of the properties of a set of entities within a geographical space. This dependence, if not accounted for, leads to a violation of the 'independence among observations' assumption, used by most standard statistical analysis methods. For that purpose, different techniques have been developed in order to capture the spatial dependence among observations.

In road safety research, spatial dependences may be involved in different cases. For example, when comparing European countries in terms of road safety performance, the geographical relationship between countries needs to be accounted for, in order to test whether neighbour countries are similar in terms of road safety. Moreover, the spatial dependences within each country (e.g. spatial dependences among regions within the country) may affect each country's overall road safety. For instance, it is likely that the poor road safety performance of a country is due to the disappointing performance of particular areas within that country.

Road safety analyses often aim to identify parameters that may explain the variation of road accident risk. Such explanatory effects are typically tested through the incorporation of (often numerous) variables in the statistical models of road accident risk. In the recent years, there was an increasing interest in identifying and modelling the spatial dependence among road safety outcomes (Amoros et al. 2003; Noland and Quddus, 2004; Aguero-Valverde and Jovanis 2006; Yannis et al. 2007). These studies often revealed important spatial effects on road accident risk. Moreover, once these spatial ('endogenous') effects were accounted for, a more accurate estimation and interpretation of the other ('exogenous') explanatory effects was achieved (Eksler and Lassarre, 2008).

In most of these studies, the spatial dependence is defined by means of a 'neighbourhood structure' of the spatial units considered. These spatial units may concern regions, counties, municipalities etc., and their 'neighbourhood structure' is based on the physical borders between them. From a transportation / road safety viewpoint, neighbouring regions may share common infrastructure (e.g. road or railway connections) and present similar demographic and economic characteristics, resulting in similar road and traffic environments and similar road users' behaviour, and eventually in similar road safety levels.

Within this context, the objective of this research is to analyse the spatial variation of road accident and fatality risk. Standard spatial analysis techniques are used for that purpose, namely the CAR and CAR convolution models. Data from Greece are used to demonstrate the usefulness of such analyses. Greece is a country for which spatial effects have not been previously explored.

Moreover, a large part of Greece lies on the Aegean and Ionian Seas, and includes several clusters of small or quite big islands. Therefore, many neighbouring counties may not share a physical border, but only a sea border. A spatial analysis on such a country may be particularly interesting.

Four types of models are presented in this research, as shown in Figure 1:

- Models without spatial effects, i.e. standard Poisson models for accident risk rates
- Models with spatial effects on accident rates, in which the spatial structure is defined, as in most studies, on the basis of the physical borders between counties. More specifically, counties connected through a road connection are considered to be neighbouring counties.
- Models with spatial effects on accident rates, in which the spatial structure is defined on the basis of either physical or sea borders between counties. More specifically, counties connected through either a road or a ferry connection are considered to be neighbouring counties.
- Models with spatial effects on accident rates, as well as other explanatory variables.

***Figure 1 to be inserted here***

The third model tests whether spatial effects on road safety may rise not only from similar infrastructure and socio-economic features, but also from similar users' behaviour (e.g. the fact that two counties are connected by ferry may also imply an exchange of local road safety behaviours and attitudes). The fourth model serves as a typical example of the consequences of ignoring possible spatial effects, on the estimated effects of other explanatory variables. Through these models for Greece, the advantages of spatial analyses in road safety research are discussed and the usefulness of applying such methods at European level is demonstrated.

## 2. Methods and data

### 2.1. Spatial modelling

The basic idea behind spatial modelling techniques is the decomposition of the random variation of road accident outcomes into two distinct components: a "structured" component, which is assumed to represent random variation due to the spatial structure of the road safety outcomes, and an "unstructured" component, which is assumed to represent the remaining random variation. The road safety outcome $Y_i$ of county (i) is considered to be the sum of systematic variables effects $\beta_i x_i$, and random variation $\varepsilon_i$, which is further decomposed into "structured" variation $u_i$ and unstructured variation $v_i$. A Poisson distribution with parameter $\lambda_i$ is typically assumed for road safety outcomes, which are considered to be conditional on random effects.

Therefore,the dependent variable of the model is taken as the logarithm of the road safety outcome examined (e.g. accidents, fatalities). Moreover, an offset term is incorporated in the model, usually corresponding to an exposure estimate (e.g. the population $N_i$), in order to model road accident risk ($Y_i/N_i$)(e.g. accidents per population) in county (i) rather than accident counts ($Y_i$).

Such a model, incorporating a random effect within $\lambda_i$ and combining thus fixed and random effects is sometimes called a mixture model. The Bayesian modelling (see next section 2.2) may be implemented in this case, whereas the model formulation is written as follows:

$Y_i / \varepsilon \sim \text{Poisson}(\lambda_i N_i)$

where $\lambda_i$ is the Poisson parameter, so that:

$$\log(\lambda_i^{\varepsilon})=\log(N_i)+ \beta_i x_i + \varepsilon_i \qquad (1)$$

With $\varepsilon_i = u_i + v_i$

In particular, the random effect $\varepsilon_i$ captures all the uncertainty regarding the accident risk in each geographical unit, which may be due to reporting error, missing covariates, overdispersion in accidents counts or even genuine underlying differences in accident risk. The exponential of random effect $\exp(\varepsilon_i)$ represents the local area accident risk, adjusted for population (also called Bayes relative risk).

For example, the number of fatalities in a region (dependent variable $Y_i$) per population of that region (offset term $N_i$) may be the sum of the effects $\beta_i$ of the number of vehicles per 1,000 inhabitants and the number of speed violations per 1,000 inhabitants (independent / explanatory variables $x_i$), random variation due to the fatality risk of the neighbouring countries (structured variation $u_i$) and random variation due to unobserved parameters or other types of error (unstructured variation $\varepsilon_i$).

There are alternative ways to estimate the structured component of the random variation in statistical modelling, however all of these fall within the family of hierarchical (multilevel) models (Goldstein, 2003). The most common models used in spatial analysis are the CAR model (Conditional Auto-Regressive model) and the CAR convolution model (Besag, 1974; Aguero-Valverde & Jovanis, 2006). A detailed presentation of the formulation and statistical properties of these models is beyond the scope of this paper, and only a summary of basic assumptions is presented here. For a complete presentation, the reader is also referred to Eksler & Lassarre (2008).

Spatial models are based on a "neighbourhood matrix", in which a spatial structure is defined through the identification of neighbouring regions. Obviously, the neighbourhood matrix needs to be symmetrical (i.e. if region *i* is indicated as a neighbour of region *j*, then region *j* should also be indicated as a neighbour of region *i*). The way this neighbourhood matrix is used differs between different methods.

In the CAR model regions are not considered to be separate entities (Browne, 2004) and a conditional auto-regressive distribution is assumed for the structured component $u_i$ of the random variation. In particular, the CAR model assumes one (global) random neighbourhood effect for each region. Consequently, in the CAR model, the set of neighbours of each region is examined as a whole. Moreover, only the structured part of the random variation can be estimated in the CAR model.

The incorporation of an unstructured random effect results in the CAR convolution model, in which both the structured and the unstructured components are estimated, by means of a mixture of an exchangeable normal and a conditional autoregressive distribution. Moreover, in the CAR convolution model, the neighbours of each county are considered to be separate entities.

Regardless of the method used, the estimated unstructured and spatial (structured) variations are not directly comparable, given that different statistical distributions are considered for each component. However, the relative contribution of the structured variation versus the unstructured variation can be used instead. The estimation of the relative importance of each component of the total random variation can be done through a ratio called spatial fraction (k), which stands for the fraction of total variation in log-relative risks due to spatial effects.

$$\kappa = \sigma^2(u_i)/[\sigma^2(u_i) + \sigma^2(v_i)] \qquad (2)$$

A value of the spatial fraction close to 1 indicates the domination of spatial variation over the unstructured variation, while a value close to 0 indicates the domination of unstructured variation.

## 2.2. Bayesian modelling

The above models are estimated by means of Bayesian multilevel modelling (Dupont and Martensen, 2007). In particular, unlike most conventional estimation methods, which produce point estimates of the model parameters, Bayesian modelling produces interval estimates. This is achieved after a large number of successive simulated random draws from an initially assumed "prior" distribution of a model parameter, allowing eventually for an estimate of the "posterior distribution" of the model parameter. Given that this could not be done analytically for the examined spatial models, a simulation-based estimation method is applied.

The motivation for Bayesian statistics (Barnett, 1999; Casella & George, 1992) and simulation-based model estimation comes from the need to obtain accurate statistics of model parameters with small samples. The idea is to draw a sample from the full posterior distribution and make inferences using the sample. For example, instead of computing the mean and variance of a parameter, the sample mean and sample variance of the parameter is calculated from the sample. A posterior distribution of a parameter can be obtained by an empirical density function of the distribution of the parameter in the sample. Particularly in the context of Bayesian statistics, the simple Bayes rule dictates that the posterior is equal to the prior times the likelihood of available data.

More specifically, in a Bayesian formulation of the model presented in (1), prior information about the fixed and random parameters, $\beta$, $u_i$ and $v_i$ are combined with the data. All these parameters are regarded as random variables described by probability distributions, and the prior information for a parameter is incorporated into the model via a prior distribution (a uniform distribution is typically considered). A large number of simulated random draws from the joint posterior distribution of all the parameters is made. Thesethese random draws are used to form a summary of the underlying distribution. After fitting the model, a posterior distribution is produced for the above parameters, which combines the prior information with the data.

Unlike many numerical algorithms, this simulation-based estimation is not guaranteed to converge around the correct solution. Hence, in addition to models fit and diagnostics, it is necessary to carry out convergence diagnostics as well. In this analysis, the estimation method is ran for 20,000 iterations, from which the first 15,000 are considered as "burn-in" and are therefore discarded. The presented values are the averages of the results produced from 15,000 to 20,000 iterations. A Bayesian Deviance Information Criterion (DIC) is used to assess the models fit. A reduced DIC indicates an improved model.

### 2.3. Data

A NUTS-3 spatial classification is opted for the Greek road safety data (accidents, fatalities, and population) of year 2002. NUTS stands for 'Nomenclature of Units for Territorial Statistics' and is a geocode standard developed and regulated by the European Union for referencing the subdivisions of countries for statistical purposes. A hierarchy of three NUTS levels is established by Eurostat; however, the subdivisions in some levels do not necessarily correspond to administrative divisions within the country. According to the NUTS-3 classification for Greece, 51 counties are considered, and their neighbourhood structure is defined in two ways: first, according to the road connections between counties and second, according to the road and/or ferry connections between counties. The variables and values used in the analysis are summarized in Table 1.

***Table 1 to be inserted here***

In particular, the dataset includes road accident and road fatality data for year 2002 by county, collected from the National Statistical Service of Greece (NSSG) and having as source the national road accident data collection forms filled by the Police at the scene of all road accidents with casualties in Greece. The population by county is also obtained from the NSSG. These are the necessary data for examining spatial effects on accident and fatality risk in Greece. It is noted that fatalities in Greece conform to the common European definition of persons killed within 30 days from the accident.

Moreover, the number of alcohol controls is selected as a key explanatory variable of road safety in Greece for several reasons. First, an important decrease of road accidents and fatalities was observed during the period 1998-2003 in Greece, and was mainly attributed to an important intensification of speeding and alcohol enforcement during that period (Yannis et al. 2008). Moreover, a spatial variation of the effect of alcohol enforcement on road safety in Greece has been identified in previous research (Yannis et al. 2007); therefore, alcohol enforcement may be a particularly relevant variable in the context of the present analysis. The number of alcohol controls by county is regularly published by the Greek Police.

## 3. Results

### 3.1. Models without spatial effects

The first step of the analysis concerns the basic "empty" models, in which no spatial dependence is considered and only a constant term is included. Both log-accidents and log-fatalities are examined, together with the log-population used as an offset term. In these models, presented in Table 2, the constant term corresponds to the mean accident and fatality rates of all counties of Greece.

***Table 2 to be inserted here***

### 3.2. Models with spatial effects based on road connections

The first type of spatial dependence to be examined is the one resulting from neighbourhood effects of counties connected by roads. In this case, a neighbourhood matrix indicating the presence of road connections between counties was created; the minimum number of neighbours for one county is zero (corresponding to island counties) and the maximum number of neighbours for one county is 7.

***Table 3 to be inserted here***

The models are presented in Table 3. An initial remark concerns the impressive reduction of the DIC in both models, compared to the "empty" models especially in the accidents model, indicating that the random effects incorporated in these models (structured and unstructured components), account for a very important part of the variation of accident and fatality rates of the Greek counties.

According to both the CAR and CAR convolution methods, a significant part of the variation in accident and fatality rates is attributable to the spatial structure of the examined counties. It is noted that spatial effects are non significant in the CAR convolution model for accidents, most likely due to the fact that the overdispersion of road accident counts is controlled for in the model (i.e. a dominant part of random variation corresponds to overdispersion). However, the spatial fraction is significant, indicating that the spatial effect is important when compared to the remaining random variation. On the contrary, fatality rates are less subject to overdispersion, due to the lower number of fatalities per county.

The CAR method results may serve as a useful demonstration of the role of the spatial structure of road safety outcomes in Greece. Although the CAR and CAR convolution models are considered equivalent in this case, given that the DIC reduction is similar, the results suggest that the CAR convolution model is far more appropriate, given that overdispersion is present in the data. These results allowed for the estimation of the spatial fraction, which was found equal to 0.62 for accident rates and 0.12 for fatality rates. It is deduced that only a small part of the variation of fatality rates is attributed to the spatial structure, whereas a non negligible part of the variation in accident rates is due to the spatial structure among Greek counties. In other words, neighbouring counties are quite likely to present similar accident rates, but rather unlikely to present similar fatality rates. It is thereby indicated that common underlying factors are affecting the occurrence of road accidents in neighbouring counties, but not their severity.

As an example, the structured and unstructured components of the variation in fatality rates in Greece are demonstrated in Figure 2. It can be seen that the structured component (left panel of Figure 2) shows a relatively smooth evolution of fatality rates among neighbouring counties. More specifically, increased fatality rates are observed in central Greece, mainly on counties including or surrounding large urban areas. On the other hand, the unstructured component (right panel of Figure 2) shows no clear pattern, indicating that this part of the variation is random indeed.

***Figure 2 to be inserted here***

Finally, the Bayes relative risk rates for fatalities and accidents on the basis of the CAR models results are presented in Figure 3. Two remarks can be made on this Figure:

- First, the fatality rates (left panel of Figure 3) are very similar to those represented in the unstructured component of fatality rates (right panel of Figure 2). This confirms that the unstructured component is predominant in the variation of fatality rates and the structured component is not significant.
- On the other hand, the accident rates (right panel of Figure 3) present a clear north / south spatial pattern. This spatial effect is quite evident and confirms the predominance of the structured component over the unstructured component of accident risk.

***Figure 3 to be inserted here***

### 3.3. Models with spatial effects based on road and ferry connections

Given the above encouraging results as per the role of the neighbourhood structure of the Greek counties in their accident rates, the next step is to examine whether this spatial structure goes beyond the presence of road connections to the existence of other type of connections e.g. ferry connections. The general idea is that neighbourhood may be not only a matter of proximity but also a matter of connectivity.

Therefore, an extended neighbourhood matrix of Greece was created, on the basis of not only road but also ferry connections between counties. In this case, the minimum number of neighbours for one county is one (corresponding to island counties having a single ferry connection to a mainland county) and the maximum number of neighbours for one county is 14 (corresponding to the Athens area which has ferry connections with a high number of islands).

Due to the fact that the structured component for fatalitiy rates was non significant in the previous example (section 3.2), in the present example only accidents are examined. The modelling results are presented in Table 4.

***Table 4 to be inserted here***

The structured component based on road and ferry connections in the CAR model is significant, suggesting that the spatial structure of underlying risk factors represented by road and ferry connections accounts for important part of the variation of accident rates in Greece.

In the CAR convolution model, however, the random parameters (structured and unstructured) become non significant, possibly due to the fact that oversidpersion in the accident counts is possibly the main source of random variation. However, a significant spatial fraction was estimated equal to 0.54, indicating a non negligible contribution of the structured component to the variation of accident rates in Greece.

It is noted though that the fraction of this spatial structure (road and ferry connections) is slightly reduced in relation to the initial one presented in Table 3 (road connections). On the other hand, the DIC of both the CAR and CAR convolution models is reduced in relation to those of Table 3. It appears that the extended neighbourhood structure accounts for a larger part of the total variation, but not in favour of the structured component. In other words, the incorporation of ferry connections between counties in Greece appears to add to the randomness in accident rates, and does not reveal additional spatial effects.

It is noted that road and ferry connections were assigned equal weights in the neighbourhood structure. An alternative consideration might involve assigning higher weights to road connections in relation to ferry connections. However, such a consideration goes beyond the standard estimation methods for these models and is therefore considered to be beyond the scope of this paper.

### 3.4. Models with spatial effects and explanatory variables

In this section, the effects of the spatial structure of Greece on road accident rates are examined jointly with exogenous factors, namely alcohol enforcement. It will be also shown here how the magnitude and significance of explanatory variables can be modified once spatial effects are considered in a road accident rates model. A comparison of a simple Poisson model with explanatory variables, to the related CAR convolution model is carried out for that purpose.

The neighbourhood structure based on road connections between counties is considered. The number of alcohol controls per population is used as an explanatory variable; as mentioned above, according to previous research (Yannis et al. 2007) the intensification of police enforcement is a key explanatory factor of road safety development in Greece from year 1998 onwards.

***Table 5 to be inserted here***

As shown in the top part Table 5 Poissonl model), the number of alcohol controls per population by county has a negative effect on accident rates by county i.e. an increase of alcohol controls per population leads to a decrease in accident rates, which is intuitive. Moreover, it can be seen that, once the spatial structure component is introduced resulting in the CAR convolution model (bottom part of Table 5), the effect of alcohol controls per population is somewhat reduced. This suggests that, if the effect of the spatial structure of Greece is not explicitly accounted for, the effect of alcohol controls is overestimated. In other words, the estimated effect of alcohol controls in the Poisson model also included part of the spatial structure effect.

In the CAR convolution model of Table 5, a spatial fraction of around 0.65 is obtained, indicating a predominance of the structured component over the unstructured component. When comparing this spatial model with the CAR convolution model of Table 3, it can be seen that the introduction of the explanatory variable leads to a small increase of the spatial fraction, as well as a decrease in the DIC. Consequently, the CAR convolution model with a neighbourhood structure based on road connections and the specific explanatory variable is the best model for explaining the variation of accident rates by county in Greece.

These results suggest that the accident rates of Greek counties are very much dependent on the intensity of alcohol enforcement in each county. Moreover, the accident rates of each county are significantly affected by underlying factors that are due to similarities with the neighbouring counties. These factors may include similar road user attitudes and behaviours, similar road infrastructure due to similar landscape (e.g. the mountainous mainland of the northern and western part of the country) etc.

## 4. Conclusions

Several applications of spatial analysis techniques in road safety have been published in the recent years with interesting findings, which highlight the consequences of ignoring the spatial dependence between regional road safety data. In the present research, an additional example was provided, concerning road accidents and fatalities in Greece.

Previous research (Yannis et al. 2007) had suggested that random variation due to spatial effects is important for explaining local accident risk rates in Greece. In that research, however, a global random variation of accident risk between Greek counties had been estimated, but no detailed neighbourhood effects between individual counties had been examined. The present application of spatial analysis techniques for the analysis of the road accident and fatality risk rates in Greece examined such detailed neighbourhood effects and provided some interesting results.

First of all, spatial effects on road accident and fatality rates were found to be significant, even though Greece has a relatively loose spatial structure compared to other countries, due to the existence of many islands. This suggests that spatial dependences may need to be examined also in such spatial structures. Two types of neighbourhood structure were examined, one based on road connections between counties and one based on road or ferry connections between counties. The results showed that only neighbourhood effects based on road connections between counties were significant. The consideration of neighbourhood effects based on both road and ferry connections were not found to add explanatory power to the models.

Moreover, it was found that there exist common unobserved factors affecting the occurrence of road accidents in neighbouring counties, but not their severity. In particular, the fatality rates per country are not significantly affected by spatial effects. On the contrary, road accident rates appear to be strongly dependent on spatial effects.

In the present analysis, other explanatory effects were not a priority, as the emphasis was given on the identification of spatial variation in road safety outcomes by county. However, testing a key explanatory variable in the spatial models, namely the alcohol enforcement by county revealed that, if the spatial structure among counties was not accounted for, the effect of alcohol enforcement would be quite overestimated.

## 5. Discussion

In recent research, there was particular interest in analysing road safety outcomes at a more disaggregate level than the global country level. It is argued that the overall road safety performance of a country may be better understood and improved by such a disaggregate analysis, which may not only reveal the highest risk areas but also provide a comprehensive picture of the evolution of risk in space. Spatial analysis allows for such questions to be investigated, by explicitly taking into account the spatial structure of road safety outcomes, as well as the various exogenous effects.

The added value of using such an approach, either within a country or across Europe was also demonstrated in recent research (Eksler, 2008), where a number of interesting examples highlight the importance of investigating the spatial structure of road safety outcomes. For example, at European level, a series of neighbouring and spatially dependent regions was identified, stretching from north-west Spain to north-east Poland, with increased fatality risk. This set of regions appears to be homogenous and not affected by the presence of national borders. In particular, this set of regions appeared to correspond to areas of international transit corridors for heavy goods vehicles.

Moreover, a clear east-west spatial pattern was identified in Germany, accounting for part of the random variation in fatality risk. In particular, the eastern regions of Germany present increased fatality risk compared to the western ones, and this pattern can only be identified once the spatial dependence among regions is examined separately. Accordingly, a distinct south-north pattern is observed in Belgium, where the spatial analysis revealed increased fatality risk in the southern region of Wallonia.

From the results of the present research, it is confirmed that it is important to explicitly model the spatial dependence among observations, when working with regional road safety data. Road safety data are available at more disaggregate level than the national level. For example, the CARE road accidents and fatalities data are available and may be obtained according to the European NUTS territorial classification. Moreover, in most European countries, several other road safety related data may be available at NUTS level (e.g. demographic and economic data, traffic data, police enforcement data etc.). Consequently, the necessary data for the analysis of spatial effects in road safety are largely available. Once the spatial effects are taken into account in road safety analyses, the (often more interesting) explanatory effects can be estimated more accurately.

## Aknowledgment

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**Figure 1**. Methodology flowchart

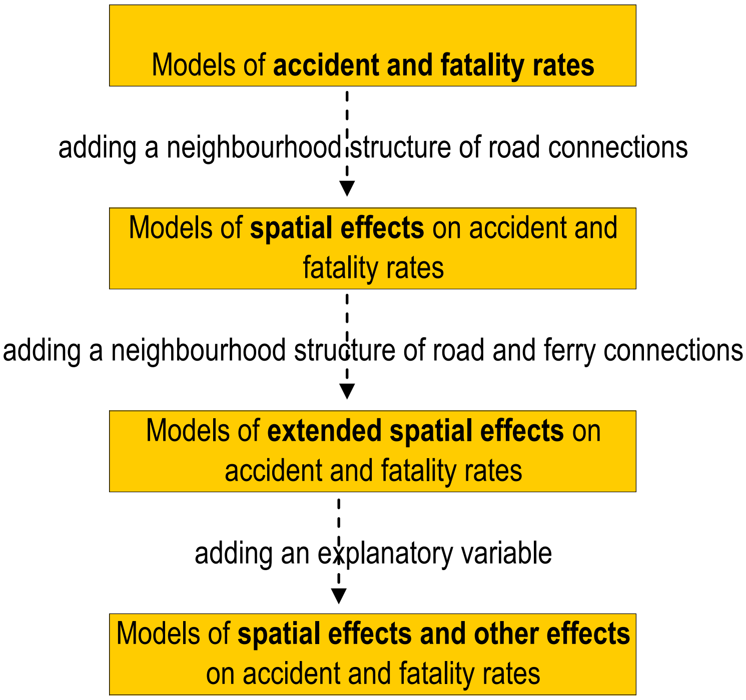

**Figure 2.** Structured (left panel) and unstructured (right panel) component of Bayes relative risk for fatalities per population (exp(U), exp(V))

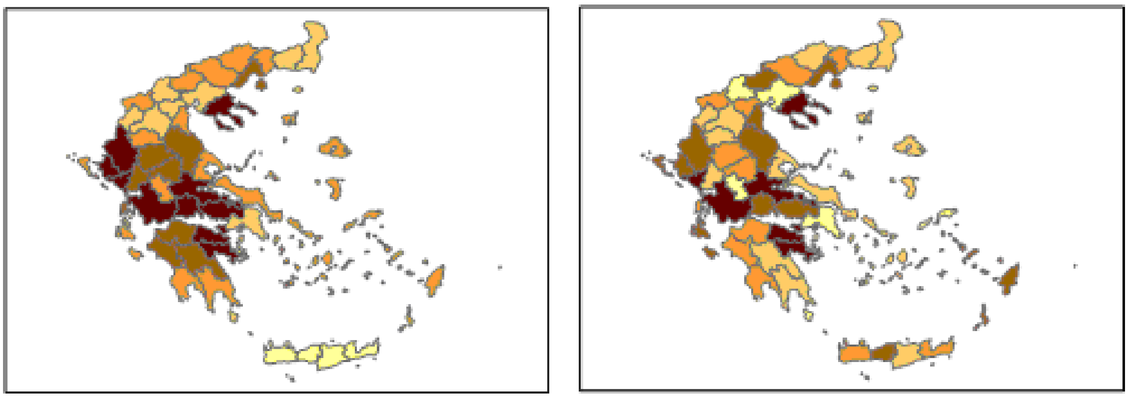

**Figure 3.** Bayes relative risk rates for fatalities (left panel) and accidents (right panel) per population

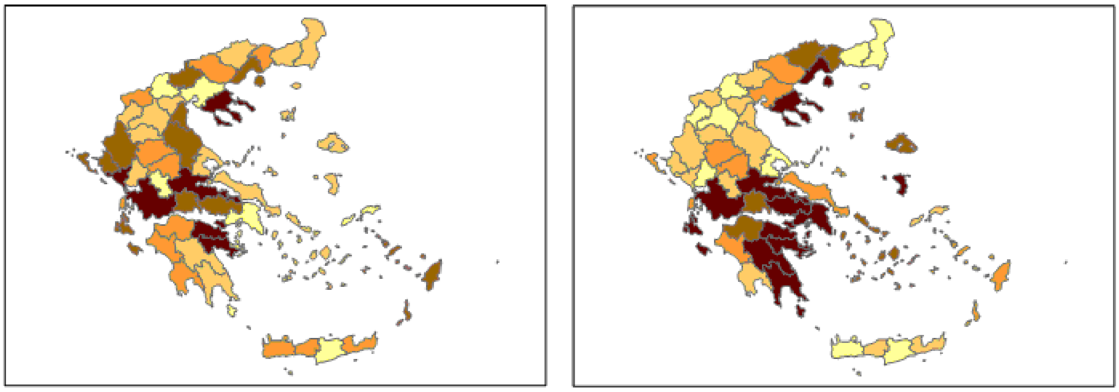

**Table 1.** Variables and values used in the analysis

| | |
|---|---|
| County | The 1-51 counties of Greece |
| Accidents | The number of accidents of each county on year 2002 |
| Fatalities | The number of accident fatalities of each county on year 2002 |
| lnpop (offset) | The natural logarithm of the population of each county on year 2002 |
| Cons | The constant term |
| Lnalcpop | The natural logarithm of the number of alcohol controls per population |

**Table 2.** Single level Poisson model (15,000-20,000 iterations)

| | Fatalities | | Accidents | |
|---|---|---|---|---|
| Parameter | Estimate | Sd | Estimate | Sd |
| Constant | -8.812 | 0.025 | -6.518 | 0.008 |
| DIC | 658.41 | | 2939.88 | |

**Table 3.** Spatial models based on road connections (15,000-20,000 iterations)

| | | Fatalities | | Accidents | |
|---|---|---|---|---|---|
| **CAR model** | Parameter | Estimate | Sd | estimate | Sd |
| | Constant | -8.615 | 0.048 | -6.839 | 0.057 |
| Spatial structure | $\sigma^2(u)$ | 0.775 | 0.028 | 0.540 | 0.021 |
| DIC | | 349 | | 525 | |
| **CAR convolution model** | | | | | |
| | Constant | -8.629 | 0.067 | -6.827 | 0.120 |
| Unstructured | $\sigma^2(v)$ | 0.088 | 0.028 | 0.108 | 0.197 |
| Spatial structure | $\sigma^2(u)$ | 0.001 | 0.000 | 0.280 | 0.520 |
| Spatial fraction | $\kappa$ | 0.116 | 0.170 | 0.623 | 0.091 |
| DIC | | 341 | | 489 | |

**Table 4.** Spatial models based on road and ferry connections (15,000-20,000 iterations)

| | | Accidents | |
|---|---|---|---|
| **CAR model** | Parameter | Estimate | Sd |
| | Constant | -6.817 | 0.018 |
| Spatial structure | $\sigma^2(u)$ | 0.699 | 0.190 |
| DIC | | 453 | |
| **CAR convolution model** | | | |
| | Constant | -6.821 | 0.066 |
| Unstructured | $\sigma^2(v)$ | 0.061 | 0.096 |
| Spatial structure | $\sigma^2(u)$ | 0.142 | 0.190 |
| Fraction | $\kappa$ | 0.540 | 0.184 |
| DIC | | 467 | |

**Table 5.** Models with explanatory variables (15,000-20,000 iterations)

| | | Accidents | |
|---|---|---|---|
| **Single level model** | Parameter | Estimate | sd |
| | Constant | -7.014 | 0.044 |
| Alcohol controls / population | Beta | -0.193 | 0.017 |
| DIC | | 2767 | |
| **CAR convolution model** | | | |
| | Constant | -7.175 | 0.177 |
| Alcohol controls / population | Beta | -0.155 | 0.070 |
| Spatial structure | $\sigma^2(u)$ | 0.213 | 0.489 |
| Unstructured | $\sigma^2(v)$ | 0.091 | 0.188 |
| Fraction | $\kappa$ | 0.646 | 0.092 |
| DIC | | 480 | |