Toward the integration of uncertainty and probabilities in spatial multi-criteria risk analysis: An application to tanker oil spills

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ABSTRACT: Quantitative risk assessment supports decision-making processes in an increasing variety of contexts. Within the domain of environmental decision-making, the spatial distribution of impacts, vulnerabilities and consequences associated to different risk-mitigation alternatives calls for a different framework, i.e. spatial multi-criteria risk analysis. In this paper, we propose the combined use of a hierarchical Bayesian modelling approach and Geographic Information Systems to integrate uncertainty and model probabilities into an overall risk map. The research aims at testing the operability of the integration between Bayesian modelling and spatial analysis in the context of spatial risk processes for resource allocation. To this end, we applied the model on a case study dealing with tanker oil spill risk in the Mediterranean Sea. The innovative contribution of the study stems from both the context of application point of view and the use of Bayesian modelling to calculate not only probabilities but an overall spatial risk measure.

1 INTRODUCTION

A rapidly emerging field of research within both the discipline of quantitative risk analysis (e.g. Fischhoff, 2015) and the now broad and consolidated literature on spatial decision support systems (e.g. Malczewski and Rinner, 2015) is spatial risk analysis, as demonstrated by the recent special issue on the topic in the Risk Analysis Journal (http://www.sra.org/sites/default/files/pdf/SpecialissueproposalforRiskAnalysis_Jun20.pdf). This growing interest may be explained by the following factors: (i) impacts of both positive and adverse events have heterogeneous spatial distributions across the territory, (ii) land vulnerability is characterized by spatial heterogeneity, (iii) risk-mitigation alternatives also lead to different spatial consequences, and (iv) recent advances in both decision modelling and Geographic Information Systems (GIS) technologies make it possible to bring the two fields together towards the formalization of an analytical framework for spatial risk analysis (e.g. Ferretti and Montibeller, 2017).

Despite several applications conducted in different domains (e.g. natural hazards management, health issues, etc.), the criteria they employ are often risk factors with deterministic preference modelling replacing probabilistic information. Furthermore, evaluations of spatial risks have often neglected the multi-dimensional nature of spatial impacts, such as infrastructure damage, lost lives,

lost crops, etc., which typically occur in such decision problems (e.g. Ferretti and Montibeller, 2017).

There are several reasons that can explain the above weaknesses. First, the lack of publicly accessible spatial data about vulnerability and probability of occurrence spatial distributions; second, the need to involve risk analysts to facilitate probability elicitation using appropriate protocols (e.g. structured expert judgment elicitation protocols, Dias et al. (2018)); third, the need to allocate enough time to the necessary preliminary phase of expert training in probabilities elicitation (e.g. Keeney and Winterfeldt, 1991).

However, preliminary ideas and suggestions on how to formalize a framework for spatial risk analysis and how to spatially elicit preference information have recently been proposed (e.g. Keller and Simon, 2017, Ferretti and Montibeller, 2017).

In this paper, we propose the combined use of a hierarchical Bayesian modelling approach (e.g. Kalinina et al., 2016, Spada et al., 2014) and GIS to update prior probability maps and obtain an overall risk map. The research aims at testing the feasibility and operability of the integration between hierarchical Bayesian modelling and spatial analysis in the context of spatial risk processes for resource allocation. To this end, we applied the model on a case study dealing with tanker oil spill risk in the Mediterranean Sea. The main reasons for the selection of this context of application can be summarized as follows: (i) international

relevance of the phenomenon, (ii) availability of historical data collected in the PSI's Energy-related Severe Accident Database (ENSAD), and (iii) the strong spatial dimension of the phenomenon (e.g. the geographical heterogeneity of both vulnerabilities and impacts in the areas affected by oil spills).

The innovative contribution of the present study stems from two aspects. First, the context of application, i.e. tanker oil spill risk distribution, is an innovative one for the use of a Bayesian modelling approach. Indeed, Bayesian modelling in the spatial domain has been mostly used for ecological studies (e.g. He et al., 2006, Tucker et al., 1997), health concerns (e.g. Saravana Kumar et al., 2017), archeological analysis (e.g. Ford et al., 2009), and natural hazards (e.g. Liu et al., 2017) to name the most recurrent ones. In the area of maritime transportation, few applications of the Bayesian approach do exist, but they are mainly non-spatial (e.g. Goerlandt and Montewka, 2015, Bouejla et al., 2014). The second reason why this study is innovative is linked to the Bayesian modelling approach. Indeed, while many applications use a Bayesian network approach (e.g. Landuyt et al., 2015), we test a hierarchical Bayesian model not only to update an initial estimate of the probability of occurrence of tanker oil spills (e.g. Burgherr et al., 2015), using information concerning the distribution of past accidents in the geographical region under analysis, but also to generate an overall risk map.

The reminder of the paper is organized as follows. Section 2 provides an overview of the proposed methodological approach. Section 3 explains how the method has been applied to model tanker oil spill risk in the geographical region under analysis and, finally, section 4 discusses conclusions and future developments arising from this study.

2 METHOD

This study is part of a larger research project funded by the Swiss National Science Foundation aiming at the development of a methodology able to integrate Bayesian modelling, Geographic Information Systems (GIS), multi criteria decision analysis and structured expert judgement elicitation protocols to comprehensively assess spatial risks associated to adverse events. This paper focuses on the integration between the Bayesian inference and GIS and represents a preliminary test of the operability of the proposed approach.

Bayesian inference is an alternative to the classical statistical inference. In the latter, also known as frequentist inference, only repeatable events have probabilities, while in Bayesian inference probability describes both epistemic and aleatory uncertainty (e.g. O'Hagan, 2003). Indeed, Bayesian analysis combines data representing the entire like-

lihood function with prior knowledge about the parameters, which may come from other data sets or the modeler's experience and physical intuition (e.g. Reis Jr and Stedinger, 2005). The *a priori* distribution describes what is known before observing any data, while the likelihood reflects the information about the parameters contained in the data. Parameters estimation is made through the posterior distribution, which is computed using Bayes' Theorem (e.g. O'Hagan, 2003):

$$p(y|\theta) \propto L(y; \theta)p(\theta) \quad (1)$$

where $p(y | \theta)$ is the posterior distribution for the parameter θ given the observed data y , $L(y; \theta)$ is the likelihood function, and $p(\theta)$ is the *a priori* distribution of parameter θ . The proportionality ($\propto$) refers to the direct sample of the parameter values from the posterior distribution, which is commonly assessed using a Markov Chain Monte Carlo (MCMC) method (e.g. Andrieu et al., 2003).

To combine the Bayesian inference and GIS, different issues could arise due to the spatial dimension of the problem: (i) lack of local data (i.e. spatial heterogeneity in the distribution and density of the data), and (ii) potential spatial correlation among locations, to name the two most relevant ones. To cope with these challenges, a spatial hierarchical Bayesian model is employed in this framework as will be explained in the following paragraphs (e.g. Cooley et al., 2007, DiMaggio, 2012, Eastwood et al., 2014, Juan et al., 2016).

A spatial Bayesian hierarchical method produces parameter (θ) estimates for each individual analysis unit (e.g. location) by borrowing information from all analysis units (e.g. Eckle and Burgherr, 2013). This procedure is known as Bayesian "borrow of strength" effect (e.g. Zhu et al., 2006). In this way, the approach compensates lack of data for individual analysis units (e.g. Kalinina et al., 2016).

Based on this premise, equation (1) could be rewritten as follows:

$$p(y|\theta) \propto L(y; \theta)p(\theta|\phi)p(\phi) \quad (2)$$

An extra level is added to the standard Bayesian theorem for the hierarchical Bayesian approach. In this level, the parameter (θ) can be described with a distribution, which is conditional on the hyperparameter (ϕ). The distribution of this hyperparameter ($p(\phi)$) is a hyperprior distribution. Therefore, when estimating the posterior for the parameter (θ), information from the hyperprior is used in addition to the information from the prior and likelihood.

Finally, to overcome the spatial heterogeneity in the distribution and density of the data and the potential spatial correlation among locations, in the spatial Bayesian hierarchical model they are

included as prior knowledge about the parameter (θ). This is possible, since they are commonly seen as “unexplained variance” in a model (e.g. DiMaggio, 2012, Eastwood et al., 2014). Based on this premise, by considering a set of i locations, the parameter for each location of interest (θ_i) is transformed into a log scale (making relationships additive rather than multiplicative) and is set equal to an intercept term (a_i) and two random effects, one non-spatial, i.e. the spatially unstructured latent covariates, (p_i) and the other spatial (λ_i), i.e. spatially correlated latent covariates in the model (e.g. Rodrigues and Assunção, 2012):

$$\log \theta_i = a_i + p_i + \lambda_i \quad (3)$$

The spatially structured component is described as a conditional autoregressive (CAR) Gaussian process ($\lambda \sim \text{CAR.normal}(W, \tau_\lambda)$) where the conditional distribution of each λ_i , given all the other λ_j ’s, is normal with μ = the average λ of its neighbors and a precision (τ_λ) proportional to the number of neighbors. W represents the matrix of neighbors that defines the neighborhood structure. The non-spatial component of the model (p_i) is defined as normally distributed with $\mu = 0$ and precision (τ_p). The model is completed by assigning additional (hyperprior) distributions to the precision terms τ_λ and τ_p (e.g. Clements et al., 2006, Cooley et al., 2007). More details about each step are going to be discussed in the case study section.

3 CASE STUDY

The proposed methodology has been applied to tanker oil spills due to the strong spatial nature of the phenomenon (e.g. Veites et al., 2004, Burgherr, 2007).

Crude oil and its refined products are a driving factor of many economic activities. Furthermore, the oil demand is expected to increase worldwide in the coming decades and it will continue to have the highest share in the global primary energy mix (e.g. International Energy Agency (IEA), 2015). However, oil spills are one of the major causes of ocean pollution, producing ecological disasters of wide public concern. Furthermore, linked to the damage caused to the environment are the high costs to fisheries, related industries, and tourism in the affected areas. This is especially true along the major oil tanker transport routes (e.g. Burgherr, 2007, Psarros et al., 2011).

In this study, only accidental spills from tankers were taken into account, whereas spills from acts of war and operational spillages allowed by international or national regulations, such as the International Convention for the Prevention of Pollution (MARPOL) were excluded (e.g. Burgherr, 2007).

The geographical region under analysis is the Mediterranean Sea including the Bosphorus strait. This area has been selected since (i) it is still the shortest route from Asia to Europe; (ii) about 16% of the global maritime traffic and 33% of the global seaborne oil (almost 8 million oil barrels per day) is carried through the Mediterranean Sea, which represents only 0.8% of the ocean surface; (iii) is one of the most affected areas with a major number of spill events (REMPEC, 2011).

3.1 Data

The data used for the case study analysis come from ENSAD, which is the most authoritative database for energy-related accidents worldwide (e.g. Burgherr et al., 2017). ENSAD comprehensively collects information about accidents in the energy sector and assigns them to energy chains and activities within those chains. Accident data go back to 1970 and cover fossil, nuclear, hydropower and new renewables technologies. In contrast to databases that rely on a single or few information sources, the multitude of sources considered by ENSAD is thoroughly verified, harmonized, and merged to ensure (1) a worldwide coverage, (2) consistently high data quality across regions and over time, and (3) a high degree of completeness. ENSAD focuses on severe accidents, which are distinguished from small accidents based on seven criteria, i.e. ≥ 5 fatalities, ≥ 10 injured persons, or $\geq 10,000$ metric tons (t) of hydrocarbons released, etc. (e.g. Burgherr et al., 2017).

With reference to oil spills in the Mediterranean Sea including the Bosphorus strait, the ENSAD database registered 106 events, including small accidents (e.g. $<10,000$ t spilled oil), in the period 1970–2012. In this study, we updated the information about oil spills in the Mediterranean Sea until the end of 2016 by using the following sources:

- Analysis, Research and Information on Accidents (ARIA) database
- Failure and Accidents Technical information System (FACTS)
- Hazards Intelligence (HINT)
- Centre of Documentation, Research and Experimentation on Accidental Water Pollution (Cedre)
- European Maritime Safety Agency (EMSA)
- Regional Marine Pollution Emergency Response Centre for the Mediterranean Sea (REMPEC)
- Center for Tankship Excellence (CTX)
- Igamma by Swiss Re
- Other sources, such as newspaper, national and local publications, technical reports, etc.

In addition to severe accidents, also accidents with smaller consequences ($<10,000$ t and ≥ 0.1 t) have been included. All the accidents collected from the aforementioned sources were homogenized

prior to analysis, in order to avoid possible double counting. The final dataset comprises a total of 271 fully geo-referenced tanker oil spill accidents in the Mediterranean Sea including the Bosphorus straight for the period 1970–2016.

3.2 Overview of tanker oil spills in the Mediterranean Sea

Figure 1 displays maritime accidental tanker spills by year and severity for the period 1970–2016. Most of the accidents (161) result in a release <7 t, followed by 59 and 57 accidents with a release between 7–700 t and >700 t, respectively. According to the severe accident definition in ENSAD (section 3.1), only 16 accidents out of 271 could be considered as severe with 3 out of them even extreme since they account for a release bigger than 100,000 t. Although the annual maxima of historically observed spills exhibit some variability, the data suggest a decreasing trend until 2000 followed by a generally constant spill rate in the period 2000–2016, which is also confirmed by decadal averages and in accordance with previous studies (e.g. Psarros et al., 2011, Burgherr, 2007). Furthermore, the relatively constant numbers of annual spills in the period 2000–2016 could be explained by the introduction of the regulation 13 F of Annex 1 of MARPOL (The Marine Environment Protection Committee (MEPC), 2003), which effectively mandated double hulls for new built oil tankers of 5000 dead weight tonnage and above starting from year 2000. However, the general trend in Figure 1 should not be taken as

evidence that a catastrophic spill accident (e.g. 100.000 t or greater) can be excluded in the future, but the frequency of such an event may be expected at a lower frequency (e.g. Burgherr et al., 2012).

Figure 2 depicts the spatial distribution of the oil spills in the Mediterranean Sea including the Bosphorus strait for the period 1970–2016. Historical observations show different “hot spots”, such as the Gibraltar and Bosphorus straights, the Peloponnese, the North Tyrrhenian Sea, the Malta and Lebanon areas. This is not always correlated with the average number of tankers per year (in 2012, <http://medgismar.rempec.org/>) navigating in a location shown as a 0.5° × 0.5° grid. Indeed, the Gibraltar and Bosphorus strait as well as the Malta and Peloponnese areas show rather large average numbers of tankers per year, while the corresponding numbers are relatively low for the Northern Tyrrhenian Sea and Lebanon. The “hot spots” in the latter cases could be explained by the fact that most of the accidents happened in ports.

The final updated dataset is subdivided into two periods: 1970–2011 and 2012–2016. This has been done in order to use the former as input for the model presented in section 3.3 and the latter as a validation of the model.

3.3 Model setup

Risk is the potential for realization of unwanted, negative consequences of an event. In other words, risk can be defined as the product of probability/frequency and magnitude/severity of consequences (e.g. Committee on Foundations of Risk Analysis, 2015).

Figure 1. Distribution of tanker oil spills by year and severity in the Mediterranean Sea including the Bosphorus strait. The bold black line indicates decadal averages. The colors indicates the number of accidents with the same spill size (t) in the same year.

Figure 2. Spatial distribution of tanker oil spills by severity in the Mediterranean Sea including the Bosphorus strait in the period 1970–2016. The average number of tankers per year (2012) navigating in the area is shown in a $0.5^\circ \times 0.5^\circ$ grid size (modified from AIS data from REMPEC (<http://medgismar.rempec.org/>)). White cells indicate areas where no tanker per year data are available.

In this study, the number of accidents per year gives the frequency, while severity measures the extent of the consequences of each accident. Furthermore, the frequency of accidents was normalized by the unit of tanker-year to allow for comparative evaluation of the modeled parameters among different areas in terms of accidents per tanker (e.g. Burgherr, 2007). It is also important to note that at a first approximation, the frequency of spills is not considered as a function of the number of tankers.

Essentially, accidents can be considered rare, independent events so that the frequency can be modeled as a Poisson distribution (e.g. Spada et al., 2014). Therefore, the frequency is modeled applying the Bayesian procedure described in section 2. In equation (2), the likelihood is described by the Poisson model. In a standard Poisson model, the variance is required to be equal to the mean. However, when dealing with spatial statistics, the Poisson models have more variances, and these are called over-dispersed Poisson models (e.g. DiMaggio, 2012). These variances are identified as either spatially-correlated effects or heterogeneity effects (section 2). The essential idea is that the probability of values estimated at any given location (e.g. the frequency at one area) are conditional on the level of neighboring values (frequencies on the neighboring areas).

Based on these premises, the parameter of interest, the frequency rate λ , is modeled as the combination of a normal distribution and the spatial random effects (section 2). For each area, the normal distribution is described by a mean and a standard deviation. This is the step where information between areas is exchanged in the hierarchical model. Both parameters of the hyper distribution are modelled with non-informative priors, so that they have no influence before the data is introduced.

The parameters are modelled with normal and gamma distributions (e.g. Eckle and Burgherr, 2013), respectively.

The spatial random effects are modeled using a combination of the intrinsic conditional autoregressive (CAR) prior, which is smoothed based on the weight related to the number of the neighboring areas and their tanker-year normalization values, and a standard normal prior as described in section 2.

Once the posterior distribution for the mean frequency in each area is estimated, it is normalized by the corresponding tanker-year resulting in the expected accidents per tanker.

The severity is modeled as absolute numbers of oil spilled (tons) per accident. The expected oil spill in each area is modeled using a Lognormal (LOGNO) distribution (e.g. Burgherr et al., 2015). In this case, at a first approximation, the spill is considered independent from the area; therefore, no spatial random effects are included. The LOGNO distribution is commonly described by two parameters, namely the scale σ_i and location μ_i , which are used to define the mean value and variance of the distribution (e.g. Spada et al., 2014). In this study, the LOGNO distribution employed for the Bayesian Hierarchical modeling is described by mean and precision parameters, where the latter is the inverse of the variance. Hierarchical models are defined for the mean and standard deviation of the posterior and are modeled using a normal and gamma distributions, respectively. All the hyperparameters of both the mean and standard deviation are thus modeled with non-informative distributions.

The MCMC algorithm is run for 30,000 iterations, following a burn-in of 3,000 updates, which is also used to train the model, for both frequency

and severity cases. According to the Gelman-Rubin diagnostic (e.g. Gelman and Rubin, 1992), the simulated chains converged adequately in the MCMC practice implemented in this study for both cases. Furthermore, the models for both frequency and severity distributions have been validated using the Deviance Information Criterion (DIC), which tests how good the proposed model predicts a replicate dataset which has the same structure as the observed one, e.g. the historical observations (e.g. Gelman, 2003).

Finally, the risk in each area is estimated as the product of the expected accidents per tanker and the expected amount of oil spilled, giving the expected spilled oil in tons/tanker for each of the area in Figure 3.

3.4 Results and discussion

Figure 3 shows the risk of tanker oil spills in terms of expected tons of spilled oil per tanker. Areas of relatively high risk ($1\text{E}-8$ – $1\text{E}-9$ tons/tanker) could be identified in the Tyrrhenian, Adriatic and Ionic Sea, in the north and west side of Sardinia, in the area of Mallorca, in the northern part of Libya and in north and east sides of Cyprus. In most of the cases, these results are driven by the comparatively large historical spills in areas with relatively low tanker traffic expressed in tanker-year (Figure 2).

Areas with a high spill risk ($>1\text{E}-8$ tons/tanker) could be identified in the Bosphorus strait and different port areas along the Mediterranean coasts, such as in the Northern Tyrrhenian Sea, in Southern France, in the northern coast of Algeria, in the eastern side of the Peloponnese area and in Crete. This reflects the risk during port operations like loading and unloading of the tanker in ports and potential accidents due to grounding or collisions.

Relatively low risk areas ($<1\text{E}-10$ tons/tanker) could be found in the southern part of Spain, in the northern part of Algeria, in the Sicilian Sea, around Malta and in the Peloponnese region excluding its eastern side. These results are driven by generally low (or even absent) accidents recorded in the area combined with relatively high tanker-year (Figure 2). This result could be explained by the fact that these are open sea areas, and thus areas with limited possibilities of, for example groundings and collisions. Furthermore, in the relatively low risk areas, the result should not be taken as evidence that a spill accident can be excluded in the future, but that a spill event may be less expected than in areas of higher risk (e.g. the one with $>1\text{E}-8$ tons/tanker).

Finally, the remaining areas in the Mediterranean Sea show a risk level of the same order of magnitude ($1\text{E}-10$ – $1\text{E}-9$ tons/tanker).

To validate our model, the oil spill accidents in the period 2012–2016 have been considered. In this period, a total number of 19 oil spills have been recorded in the Mediterranean Sea. Most of them in the Greek area and in particular in the Peloponnese and on the eastern Greek coasts.

Largest spills (>700 t) happened in areas of relatively extreme risk in the model (Figure 3), while smaller spills (<7 t) in areas of average risk in the sea, i.e. $1\text{E}-10$ – $1\text{E}-9$ tons/tanker, with the exception of an event in Cyprus (1 t released), which falls into the relative high-risk category ($1\text{E}-9$ – $1\text{E}-8$ tons/tanker). Furthermore, one spill accident of 15 t in the Peloponnese area falls into the relative low risk category ($<1\text{E}-10$ tons/tanker).

In general, historical observations in the period 2012–2016 are generally in good agreement with the model in terms of spill sizes/tanker, thus validating the proposed approach.

Figure 3. Spatial distribution of the Expected oil spill (t)/tanker in the Mediterranean Sea including the Bosphorus strait. The oil spills (t) recorded in the period 2012–2016 used to validate the model are also shown.

4 CONCLUSIONS

In this study, we tested the operability of a spatial hierarchical Bayesian model by applying it to study the oil spill risk of tankers in the Mediterranean Sea.

A comprehensive and up to date database of oil spill accidents was used both as input to the model and for validation purposes. In particular, the results of the validation step confirm that the proposed methodological approach represents a promising tool for dealing with quantitative spatial risk assessments. Indeed, the proper consideration of the spatial component inherent in accidents that can have consequences spread over a geographic region, plays a vital role in supporting spatial monitoring procedures and risk mitigation measures.

The main benefits associated with the proposed methodological approach can be summarised as follows: (i) ability to deliver quantitative results at high spatial resolution, for example in comparison to previous studies (e.g. Burgherr et al., 2015), (ii) possibility to combine expert knowledge with empirical data (e.g. Choy et al., 2009), (iii) accountability for uncertainties and lack of data, and (iv) possibility of integrating sensitivity analysis to improve the interpretability of the parameters (e.g. Roos et al., 2015).

On the other hand, the following limitations should be acknowledged. First, we are using a simplified approach, which does not model the causality between influencing parameters (e.g. size of the tanker, marine currents, wind, spill cause, type of location such as ports, open sea, narrow strait, etc.). Second, the model is assessing an average number of accidents per year, rather than taking into account the actual yearly trend (i.e. traffic patterns).

Finally, we envisage several future developments of this research. The first one refers to the study of how structured expert judgement elicitation protocols could be included in the development of the spatial Bayesian model. Indeed, the facilitation of the quantitative expression of subjective judgement plays a crucial role in the context of probability and risk assessments. However, the presence of the spatial dimension, where basically every pixel of the map becomes an alternative to be assessed, makes this task a particularly challenging one (e.g. Ferretti and Montibeller, 2016), thus opening interesting avenues for future research. The second direction for future developments concerns the combination of the present methodological approach with multi criteria decision analysis to account for multiple impacts associated with the adverse event (e.g. Ferretti and Montibeller, 2017). The third direction of further research concerns the inclusion modelling of data about spatial vulnerabilities within the spatial multi impact Bayesian approach.

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