On Dashboard and Frequency Model Development for Terrorism in Southern Philippines

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Abbreviated abstract: The Philippines ranked 12th globally in terms of terrorism's impact due to an increase in the number of fatalities in 2017. Hence, terrorism caused widespread and extraordinary fear and panic. Consequently, it is considered as major threat to security. However, modeling on terrorism activities is unlikely or nonexistent in Philippine context. Thus, results on dashboard development supports in-depth understanding in coming up with a Bayesian hierarchical frequency model which shows that expected number of attacks can be achieved with the combination of space, ethnicity and religion. Overall, the model provides satisfactory performance verified by existing Bayesian criteria.

Related publications:

– A. Python *et al.*, arXiv, pp.1-20 (2016)

4th Conference on
Statistics and Data Science
Salvador, Brazil (online)
December 1-3, 2022

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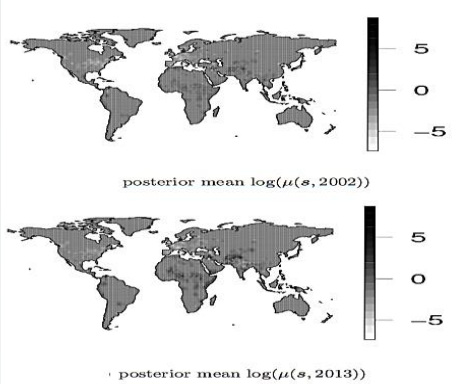
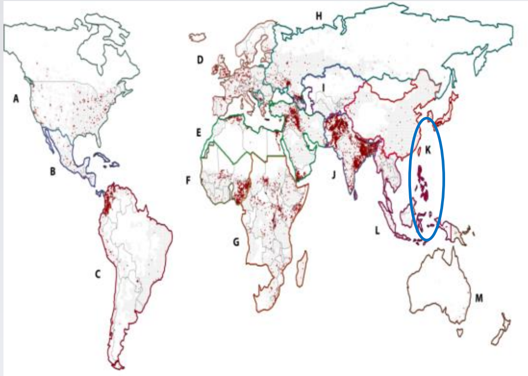
Previous work and challenge



Poisson model of the frequency of lethal terrorist attacks with posterior mean of the frequency of lethal attacks (Python et al.)



Location of terrorist events (2002–2016) and spatial domain (grid cells) worldwide.

Existing studies

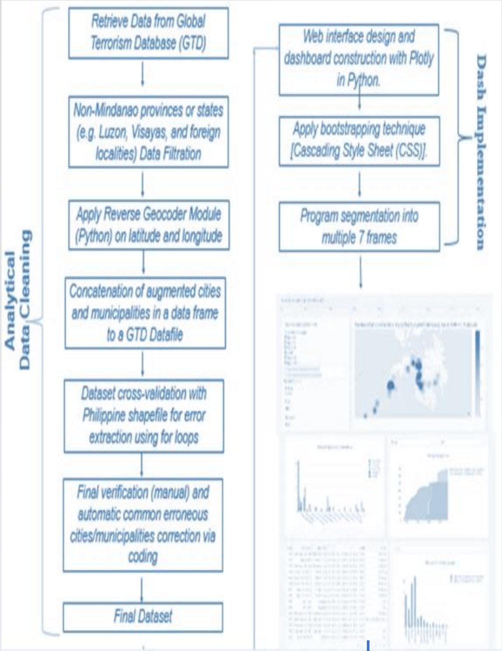
Issues

1. Most of the terrorism studies are on a national scale.
2. No visualization tools that can attribute for prior knowledge in the context of Bayesian modelling and activity monitoring purposes.
3. Modelling studies are almost nonexistent (i.e., specific places in the Philippines, say Southern Philippines/Mindanao)

Solution

Clever application of visualization tools and Bayesian modelling incorporating high accuracy on uncertainty levels

Methods



Dashboard Development Phase

Hierarchical Modelling Phase

1st Stage (Likelihood function construction)

- $L(s)|\Psi_F,\theta_F \sim \prod_{i\in\mathcal{J}} \pi[\,l(s_i)|\,\eta_i,\theta_F\,] = \pi[\,l(s)|\,\Psi_F,\theta_F\,]$ where θ_F denotes the hyperparameters for both models and Ψ_F denotes the latent field which estimates all the set of parameters present the predictor η over indices $\mathcal{J}$ containing the realizations.

2nd Stage (Latent field construction)

$$\psi = \psi_F\,|\theta_F \sim N(0,\Sigma\,),$$

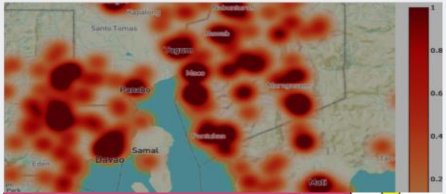
where the latent field for each model is conditioned on the hyperparameters and drawn from the multivariate Gaussian or Normal distribution. The notation Σ signifies the covariance matrix of the model

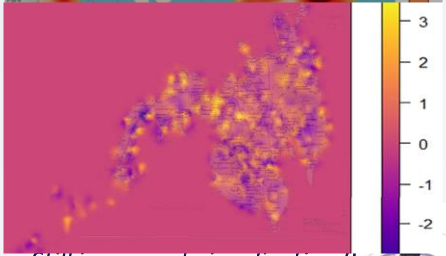
3rd Stage (Parameter specification)

$$\theta_F \sim \pi(\theta)\,,$$

where $\theta = \{\beta,\sigma^2,\tau,\kappa,r\}$. In this paper, default option for the stationary models in R –INLA as priors are utilized which consists of independent and identically distributed (iid) zero-mean normal distribution with precision equal to 0.001 for fixed effects .

Qualitative Covariates in the paper:





Still images of visualization & prediction

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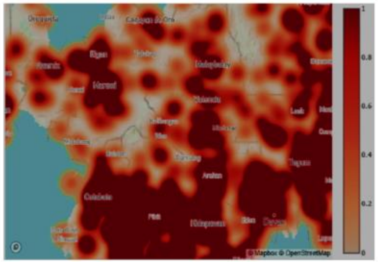
Results and Conclusions

Frequency model summary

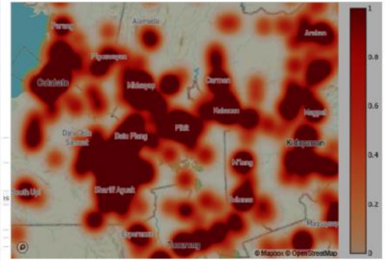
Covariate coefficient	Mean	SD	95% CI
$\beta_1(Religion)$	-	-	-
$XCov1(Others)$	-0.556	0.6	$(-0.578,-0.534)$
$XCov2(Islam)$	-0.799	0.4	$(-0.813,-0.785)$
$XCov3(RomanCatholic)$	-0.686	0.4	$(-0.700,-0.672)$
$\beta_2(Ethnicity)$	-	-	-
$XCov5(Badjao)$	-5.693	1.2	$(-6.120,-5.270)$
$XCov6(Bagobo)$	0.339	0.4	$(0.325,0.353)$
$XCov9(Cebuano)$	1.462	0.7	$(1.437,1.487)$
$XCov22(Maguindanao)$	1.297	0.5	$(1.278,1.316)$
$XCov26(Maranao)$	-1.125	0.6	$(-1.145,-1.105)$
$XCov31(Surigaonon)$	1.772	0.5	$(1.756,1.788)$
$XCov36(Tausug)$	0.592	0.4	$(0.577,0.607)$
$XCov39(Zamboangueno-Chavacano)$			
GMRF parameter	**Mean**	**SD**	**95% CI**
$\log(\sigma)$	0.882	0.2	$(0.874, 0.891)$
$\log(\kappa)$	-2.995	0.3	$(-3.006,-2.984)$

Note: Posterior mean, standard deviation and 95% CI of the intercepts, coefficients of primary covariates and GMRF for spatial field

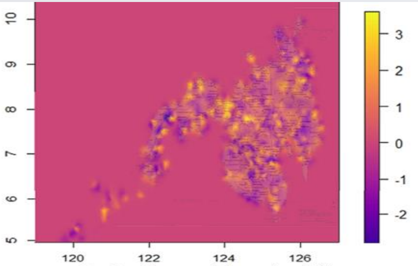
Frequency of attacks is less likely on areas with religion as main driving factor since $CI_{95\%}\beta_1(Religion) < 0$ overall. Now, religious belief or concept is a mixture of latent variables, and the result cannot be just attributed to one factor, making it multidimensional. However, analytics presented in previous section reveals that though religious belief is part of terrorist's action plan towards spreading terroristic event, such motive is only secondary. On the other hand, ethnicity as second variable show otherwise since $CI_{95\%}\beta_2(Ethnicity) > 0$. This is in consistent with Basuchhoudry and Shughart that expected attacks are more likely to be lethal in ethnically diverse locations, perhaps due to strong tensions between groups.



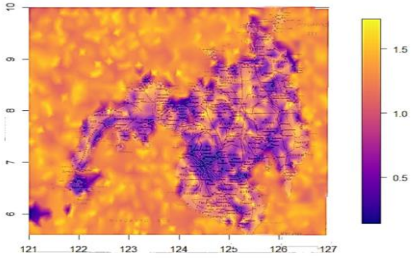
(a)



(b)



(a) Spatial mean of the random field



(b) Standard deviation of the random field

The plot for spatial field as to quantifying the uncertainty in the spatial dynamics of frequency of attacks in Southern Philippines, the posterior mean and standard deviation of the random field are visualized in the rightmost part of the figure. According to Python et al., high values of standard deviation imply high uncertainty levels on the prediction of terrorism. From the figure, it can be observed that areas such as Maguindanao, Sulu, Davao region, Zamboanga provinces and Basilan yields the lowest standard deviation for the resulting model. These areas are assaulted frequently, which supports the visualization in the right side. As conclusion, the modelling adopted in this study along with chosen explanatory variables concisely explained the mechanism of terrorism incidents in Southern Philippines. Local governments may focus on these aforementioned areas.

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