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Bayesian spatial models of the association between interpersonal violence, animal abuse and social vulnerability in São Paulo, Brazil

Oswaldo Santos Baquero[a,*], Fernando Ferreira[a], Marcelo Robis[b], José Soares Ferreira Neto[a], Jason Ardila Onell[a]

[a] Department of Preventive Veterinary Medicine and Animal Health, School of Veterinary Medicine, University of São Paulo, São Paulo, Brazil
[b] Militar Police of the State of São Paulo, São Paulo, Brazil

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ABSTRACT

Animal abuse adversely affects animal health and welfare and has been associated with interpersonal violence in studies of individuals. However, if that association also depends on sociocultural contexts and can be detected on a geographic scale, a wider source of data can be used to identify risk areas to support the surveillance of both types of violence. In this study, we evaluated the association between interpersonal violence notifications, animal abuse notifications and an index of social vulnerability in São Paulo City, on a geographic scale, using Bayesian spatial models. The social vulnerability index was a risk factor for the number of interpersonal violence notifications and presented a dose-response pattern. The number of animal abuse notifications was also a risk factor for the number of interpersonal violence notifications, even after controlling for the social vulnerability index. The incorporation of spatial effects produced marked improvements in model performance metrics and allowed the identification of excess risk clusters. Geographical data on notifications on either animal abuse or interpersonal violence should be considered incitement for investigations and interventions of both types of violence. We suggest that notifications of animal abuse be based on an explicit definition and classification, as well as on objective measurements that allow a better understanding of the species and type of abuse involved, the animal health consequences, and the context in which they occurred.

1. Introduction

Animal abuse is a determinant of animal health and its association with interpersonal violence has lead to a causal progression hypothesis: those who abuse animals tend to become violent against people in the future (Beirne, 2004; Flynn, 2011). However, causality might occur in the reverse direction (interpersonal violence predispose to animal abuse (Ascione, 1993; Dadds et al., 2002; Flynn, 1999)) or even in both directions. Moreover, if the relationship is the product of confounding factors, both types of violence would be manifestations of a generalized behavioral deviance (Arluke et al., 1999; Flynn, 2011), or institutionalized social practices (Beirne, 2004) where these types of violence are accepted. Nonetheless, the relevance of the relationship does not lie just in the causal nature, for if the co-occurrence of animal abuse and interpersonal violence is greater than expected, the identification of one type of violence would be a red flag to trigger investigation of both types.

Research into the relationship between animal abuse and interpersonal violence often involves the study of individuals from a psychopathological perspective (Flynn, 2001). However, besides psychopathology, sociocultural factors might be involved, creating contextual determinants spatially segregated. Thus, if the relationship is also detectable at scales above the individual, as is the case of the geographic scale, other sources of data can be used to predict risk maps to build or improve risk-based surveillance.

Inference about geographic processes are often based on hierarchical Bayesian models, which can be fitted using the Integrated Nested Lapplace Approximation (INLA) (Blangiardo and Cameletti, 2015). Under this computationally efficient approach, inference about the risk of violence notifications would be based on a joint probability distribution composed by a conditional independent likelihood of the notifications (first level); a latent Gaussian field with spatial and covariate parameters (second level); and prior distribution for theses parameters (third level). Prior distributions represent the current knowledge about model parameters and the joint probability distribution results in a posterior probability distribution representing the knowledge updated by observed data. Prior distributions can be informative, vague to represent little knowledge, or penalize model

* Corresponding author.
E-mail address: baquero@usp.br (O.S. Baquero).

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complexity in order to follow the Occam's razor and other convenient principles (Simpson et al., 2017).

São Paulo is the largest Brazilian city, with an estimated human population of 12,106.920 inhabitants in 2017 (IBGE, 2017). It is located in Southwestern region of the country, which in 2013 had an estimate of 42.4% and 13.5% households with dogs and cats respectively (IBGE, 2013). As in many other Brazilian cities, there are economic and social disparities that increases the vulnerability of some of its inhabitants (Rolnik, 2001) and violence and crime are spatially segregated (Departamento de Estatística e Produção de Informação, 2008).

In this ecological study we used Bayesian models to identify excess risk geographic clusters and predict the effects of social vulnerability and animal abuse notifications on interpersonal violence notifications in São Paulo City.

2. Methods

This section is divided in six subsections. The first describes the data and their sources, the second presents the conceptual framework of our hypothesis, and the third explains the statistical models that represented the conceptual framework. The fourth describes the model's priors, while the last two subsections present the model diagnostic procedures and used software, respectively.

2.1. Data

All analysis were based on secondary data. The Environmental Militar Police of São Paulo City provided us with notifications of animal abuse and interpersonal violence, while the Statistical Bureau of the State of São Paulo (Fundação Sistema Estadual de Análise de Dados do Governo do Estado de São Paulo) provided the social vulnerability index (IPVS).

In 2012 and 2013, the Environmental Militar Police received 2110 notifications of animal abuse and 64,151 of interpersonal violence. They were classified according to the subjective interpretation of the notification details, which were not recorded. We geocoded the addresses of those notifications and calculated how many came from each of the 96 São Paulo's districts. We discarded 370 notifications of animal abuse and 3093 of interpersonal violence due to address inconsistencies.

Demographic and socioeconomic census data of 2010 were used to build the IPVS, for which conceptual and methodological details have already been described (Fundação Sistema Estadual de Análise de Dados, 2013). However, as this description is in Portuguese, we briefly describe it again here. The IPVS was built using factor and cluster analysis. The factor analysis found two factors (socioeconomic and demographic) that explained 73% of the total variability of nine variables. The socioeconomic variables were household per capita income, percentage of household with a household per capita income of up to 0.5 the minimum wage, percentage of household with a household per capita income of up to 0.25 the minimum wage, income of women heads of households, percentage of households by income level, and percentage of alphabetized heads of households. The demographic variables were percentage of heads of households aged 10–29 years, percentage of women heads of households aged 10–29 years, mean age of heads of households, and percentage of children with 0–5 years. The cluster analysis was based on the factor scores and classified the socioeconomic factor in three categories (low, mid, high) and the demographic factor in two categories (adult/elderly families, young families). The combination of these categories with another set of categories that classified census tracts by type (urban, rural) and situation (normal, slum), resulted in seven categories of the IPVS: 1 (lowest vulnerability) to 7 (highest vulnerability). Because our unit of analysis was the district, we aggregated the IPVS using the rounded mean value of each census tract, weighted by the human population. This aggregation removed the categories 5, 6 and 7. The reason of aggregation was that 17,410 (92%) census tracts did not have animal abuse notifications.

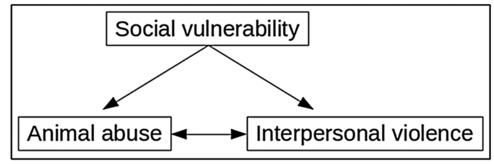

Fig. 1. Conceptual framework of the relationship between social vulnerability, animal abuse and interpersonal violence.

Table 1
Description of fitted models. See the text for notation details.

Model	Log Relative Risk
M1n	$log(\theta_i) = b_0$
M1s	$log(\theta_i) = b_0 + \frac{1}{\sqrt{\tau}}(\sqrt{(1-\Phi)}v_i + \sqrt{\Phi}u_i)$
M2n	$log(\theta_i) = b_0 + b_1x_1$
M2s	$log(\theta_i) = b_0 + b_1x_1 + \frac{1}{\sqrt{\tau}}(\sqrt{(1-\Phi)}v_i + \sqrt{\Phi}u_i)$
M3n	$log(\theta_i) = b_0 + b_1x_1 + b_2x_2$
M3s	$log(\theta_i) = b_0 + b_1x_1 + b_2x_2 + \frac{1}{\sqrt{\tau}}(\sqrt{(1-\Phi)}v_i + \sqrt{\Phi}u_i)$

2.2. Conceptual framework

The hypothesis was that social vulnerability is determinant of violence in general, whether the victims are humans or animals. Social vulnerability explains part of the association among the different types of violence and should be considered as a confounding factor, when the association between animal abuse and interpersonal violence is evaluated (Fig. 1). Furthermore, social vulnerability is spatially segregated, and this is reflected in the spatial patterns of violence occurrence. Operationally, our hypothesis is translated as the association between the number of interpersonal violence notifications, the number of animal abuse notifications and the IPVS in São Paulo's districts, taking into account the spatial structure of data.

2.3. Statistical models

We made exploratory analysis before fitting three sets of Bayesian models of interpersonal violence notifications. The first set of models included only the intercept, the second included the intercept and IPVS, and the third included the intercept, IPVS and number of animal abuse notifications. Each set was composed of two models, one of them with spatial dependency. The first set predicted background risks and was the reference to compare the performance of the remaining models. The second set predicted the effect of the IPVS, while the third predicted the effect of the number of animal abuse notifications, after controlling for the effect of the IPVS.

Given the i ($i = 1, \ldots, 96$) districts, let y_i be the number of interpersonal violence notifications in district i, P_i be the human population at risk in district i, and E_i be the expected number of interpersonal violence notifications in district i, calculated by indirect standardization:

$$E_i = P_i \frac{\sum_i y_i}{\sum_i P_i}$$

We assumed that

$$y_i|\theta_i \sim Poisson(E_i\theta_i),$$

and θ_i is the district-specific relative risk (RR) (Bernardinelli et al., 1995). Hereafter we refer to the set of models as M1, M2 and M3, and