



## Research article

# Predicting spatiotemporal patterns of road mortality for medium-large mammals

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## ABSTRACT

We modelled the spatiotemporal patterns of road mortality for seven medium-large mammals, using a roadkill dataset from Mato Grosso do Sul, Brazil (800 km of roads surveyed every two weeks, for two years). We related roadkill presence-absence along the road sections (1000 m) and across the survey dates with a collection of environmental variables, including land cover, forest cover, distance to rivers, temperature, precipitation and vegetation productivity. We further included two variables aiming to reflect the intrinsic spatial and temporal roadkill risk. Environmental variables were obtained through remote sensing and weather stations, allowing the estimate of the roadkill risk for the entire surveyed roads and survey periods. Overall, the models could explain a small fraction of the spatiotemporal patterns of roadkills ( $< 0.23$ ), probably due to species being habitat generalists, but still had reasonable discrimination power (AUC averaging  $0.70 \pm 0.07$ ). The intrinsic spatial and temporal roadkill risk were the most important variables, followed by land cover, climate and NDVI. We show that identifying spatiotemporal roadkill patterns may provide valuable information to define specific management actions focused on road sections and time periods, in complement to permanent road mitigation measures. Our approach thus offers a new insight into the understanding of road effects and how to plan and strategize monitoring and mitigation.

## 1. Introduction

Transportation infrastructures, particularly roads, are the most common human-made features in the globe, spreading across nearly its entire surface (Ibsch et al., 2016). Despite their value to human living and development, they may be responsible for significant and deleterious impacts on biodiversity, of which roadkill is amongst the most visible and significant ones (Bennett, 2017; Forman and Alexander, 1998; Van der Ree et al., 2015). When roadkill rates are not offset by an increase in per-capita recruitment, the growth rate of populations can be seriously affected, ultimately leading to local extinctions or to a strong population depletion in the surrounding areas (Borda-de-Água

et al., 2014, 2011; Silva et al., 2010). For this reason, strategies to reduce wildlife road mortality are becoming a significant component of many wildlife conservation efforts (e.g. [www.giantanteater.org](http://www.giantanteater.org) and [www.tapirconservation.org.br](http://www.tapirconservation.org.br)).

The success of conservation and mitigation management strategies may greatly depend on the knowledge of the temporal and spatial patterns of roadkill risk, and its relation with key environmental drivers, in order to place or perform mitigation actions where and when they are most required (Lesbarrères and Fahrig, 2012). Whilst most research studies on roadkill effects have addressed separately the spatial and the temporal patterns of mortality (Crawford et al., 2014; Cureton and Deaton, 2012; Garrah et al., 2015; Santos et al., 2017), we

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claim that focusing simultaneously on spatial and temporal patterns may provide important and complementary information for management and mitigation of the transportation infrastructures (e.g. Santos et al., 2018). For example, most of the reported roadkill of turtle species occurred in specific road sections and during the breeding season (Beaudry et al., 2009; Crawford et al., 2014; Cureton and Deaton, 2012). Hence, it may be more cost-effective to apply specific actions in such well-defined road segments with higher mortality and during those periods of higher likelihood of collision, i.e. when animals tend to move more and/or longer distances.

In this study, we aimed to assess how the locations and occasions of collisions relate to a collection of environmental variables in order to model the spatiotemporal patterns of roadkill risk. We were particularly interested in freely available environmental variables that could be easily obtained and used on the broader landscape scale to assess and predict the roadkill risk along different roads, and therefore to better assist in road and landscape planning and management actions. These variables included habitat information from remote sensing observations and climatic information from weather stations. The use of these environmental variables was meant to explain the variation in spatiotemporal patterns of roadkills, assuming that the number of casualties along the road and year have a direct relation with species' occupancy and movement activity in neighboring areas (Barrientos and Bolonio, 2009; D'Amico et al., 2015).

Road mortality in Brazil is known to be a major concern for numerous species (Ascensão et al., 2017; Cunha et al., 2010; González-Suárez et al., 2018). Medium-large mammals are particularly relevant as some species are highly vulnerable to roadkill given their general low reproductive rates and low densities, associated with large area requirements that often lead to higher road crossing rates and eventually higher collision rates (Rytwinski and Fahrig, 2012). On the other hand, given their high body-mass, they represent a serious threat when involved in animal-vehicle collisions, potentially resulting in significant costs and human fatalities (Huijser et al., 2013). Here, we modelled the spatiotemporal patterns of roadkill of medium-large mammals across the state of Mato Grosso do Sul, Brazil. We expected favorable habitat areas to be related to higher density of individuals and therefore to higher concentration of casualties; and time periods of longer and more frequent displacements (e.g. mating, dispersal) to be related to temporal peaks of mortality (D'Amico et al., 2015; Grilo et al., 2009). The combination of both habitat and climate data should therefore allow to model and predict the spatiotemporal patterns of road mortality. We further expected those species having a more generalist niche breadth to show a less defined and more variable spatiotemporal roadkill patterns, when compared to more specialized species.

## 2. Materials and methods

### 2.1. Study area and data collection

We used the roadkill datasets collected within the research projects "Anteaters and Highways" ([www.giantanteater.org](http://www.giantanteater.org)) and "Lowland Tapir Conservation Initiative" ([www.tapirconservation.org.br](http://www.tapirconservation.org.br)) in the state of Mato Grosso do Sul (MS), Brazil. Therein, researchers conducted two distinct year-round roadkill surveys, on a regular basis, with intervals of 11–17 days (mean 14 days), comprising 37 and 38 surveys in the two years, respectively. The surveys spanned from April 2013 to March 2014, and February 2017 to January 2018. In both survey periods, three transects were performed: the first comprised the BR-262 between the bridge over the Paraguay River to Campo Grande (CG\_PRP; 339 km); a second transect, also in BR-262, from Campo Grande to Três Lagoas (CG\_TL; 307 km); and the third transect along the highways BR-163 and BR-267, from Campo Grande to Nova Casa Verde (BR163; 225 km) (Fig. 1).

The land cover bordering these transects is dominated by savanna and grassland, but in its western section, the CG\_PRP transect runs

through part of the Pantanal biome and has more native vegetation in its surroundings when compared to the rest of the transects, mostly running across the Cerrado biome (Fig. 1). Urban areas have relatively low representation. The roads are paved and have two lanes on most of their extension. There is no detailed information of traffic volumes, but according to official traffic counts, the daily traffic volumes on BR-262 near the city Três Lagoas (Fig. 1) was  $3358 \pm 410$  (mean  $\pm$  SD) in 2011 (counts in May, September, and November) and  $3417 \pm 286$  in November 2016. Other point count near Miranda (west of Campo Grande) reported a traffic volume of  $1318 \pm 133$  in July 2016 (<http://servicos.dnit.gov.br/dadospntc>; counts performed in 7-consecutive counting days). Thus, apparently, traffic volumes are similar over time, but CG\_PRP seems to have lower traffic than CG\_TL (this is also supported by personal observations).

Roadkill surveys were performed by car driving at ca. 40–60 km/h, searching for road-killed animals ( $> 1$  kg) on both lanes and shoulders. Each observation was classified to the species level (when possible) and its location recorded with a hand-held GPS unit before carcasses were removed from the road. Overall, the dataset currently comprises 3396 records, of which 64% were recorded in CG\_PRP, 23% in CG\_TL, and 13% in BR-163. Due to logistical constraints, researchers were not able to assess the carcass persistence time or observer efficiency in detecting roadkills (Santos et al., 2016). Likewise, there was no data regarding the abundance of scavengers and their carcass removal rates. Hence, the roadkill numbers may be underestimated and potentially biased. However, the researchers were highly experienced in roadkill surveys, and given the focus on large-bodied animals, with lower carcass removal rates and higher detectability (Santos et al., 2016, 2011), these biases should not have caused major distortions in the observed patterns.

### 2.2. Focal species

We focused on the seven top-killed medium-sized mammals observed in the pool of the two year-round surveys on both transects: yellow armadillo (*Euphractus sexcinctus*,  $n = 585$ ), crab-eating fox (*Cerdocyon thous*,  $n = 563$ ), nine-banded armadillo (*Dasypus novemcinctus*,  $n = 253$ ), capybara (*Hydrochoerus hydrochaeris*,  $n = 247$ ), southern tamandua (*Tamandua tetradactyla*,  $n = 246$ ), giant anteater (*Myrmecophaga tridactyla*,  $n = 238$ ), and lowland tapir (*Tapirus terrestris*,  $n = 82$ ), which together assemble ca. 65% of all records. These species are widespread throughout Brazil, having different habitat requirements and tolerance to human presence. In Supplementary material S1 we provide a brief description of each species. Both tapir and giant anteater are classified by the IUCN as Vulnerable, threatened by human activities, namely habitat loss and fragmentation, and poaching. All seven species weight 5–250 kg (Table S1.1) and can cause serious injuries in humans when involved in animal-vehicle collisions, particularly the lowland tapir, capybara and giant anteater.

## 3. Environmental data

### 3.1. Spatial information

Land cover was obtained from remote sensing via the MODIS MCD12Q1 product (Friedl and Sulla-Menashe, 2015). This product provides global land cover types at yearly intervals (2001–2017), with 500 m resolution, derived from six different classification schemes, from which we used the *Annual International Geosphere-Biosphere Programme* (IGBP) classification (Friedl and Sulla-Menashe, 2015). The land cover classes are derived using supervised classifications of MODIS Terra and Aqua reflectance data, which undergo additional post-processing that incorporate prior knowledge and ancillary information to further refine specific classes. The majority ( $> 98\%$ ) of the land cover classes were either 'Savanna' (tree cover 10–30%; canopy  $> 2$  m), or 'Grassland' (dominated by herbaceous annuals;  $< 2$  m). We

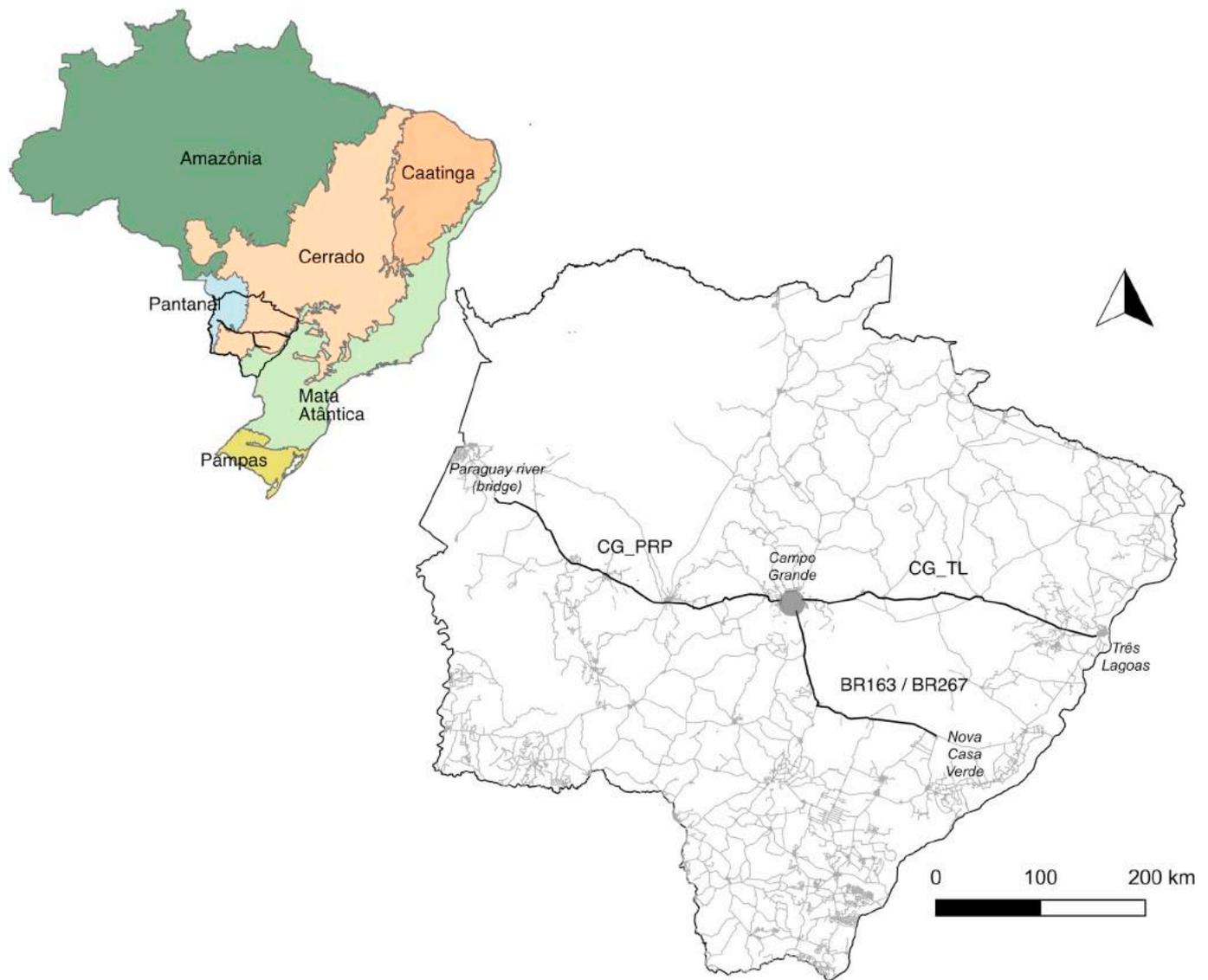


Fig. 1. Location of surveyed roads (black lines) in Mato Grosso do Sul state, Brazil. The main five biome are presented in the Brazilian map. Grey lines represent the main roads in Mato Grosso state. Localities of starting/ending transects are also presented.

complemented this information with data on forest cover, using the dataset by Hansen et al. (2013; updated to 2017).

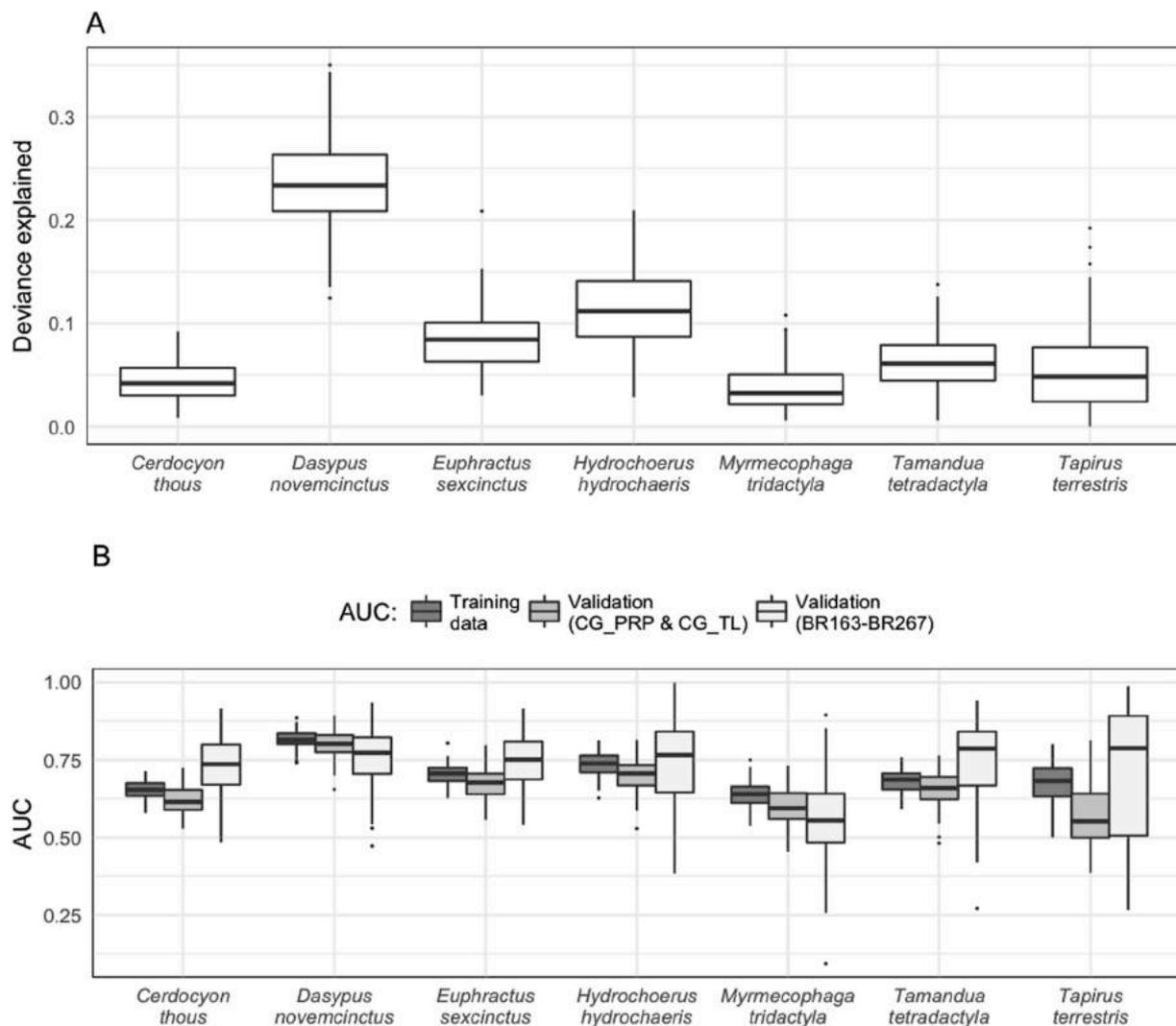
As the vegetation can be highly dynamic within each land cover class, across space and time, we also collected an indicator of vegetation productivity from remote sensing observations, the Normalized Difference Vegetation Index (NDVI), to describe the variation of greenness of the vegetation (Huete et al., 2002; Pettorelli et al., 2005). The NDVI has a direct relation with aboveground net primary productivity, and has been used as a successful predictor of biological patterns of vertebrates, including species richness, abundance and distribution, and landscape connectivity (Hurlbert and Haskell, 2003; Planillo and Malo, 2017; Root-Bernstein and Svenning, 2017; Seto et al., 2004). The NDVI data was obtained using the MODIS-Terra MOD13Q1, with 250 m resolution (Didan, 2015).

The land cover, forest cover and NDVI were retrieved through Google Earth Engine (Gorelick et al., 2017) using a customized script. For this, the surveyed roads were first sectioned in 1000 m segments, and the center point of each section was retained. A buffer with radius of 500 m was defined around each center point and for each buffer and dataset (2013/14 and 2017/18) we retrieved the dominant land cover class (modal value) and forest cover (mean value). For each buffer and roadkill survey date we retrieved the median of the NDVI. For

prediction purposes (see below), we further collected the NDVI information for the complete year-round dates (i.e. for all dates within the datasets 2013/14 and 2017/18). To obtain the information regarding water availability, we calculated the distance to streams and rivers, using the spatial layer 'inland water' of the Digital Chart of the World through the DIVA-GIS web site (<http://www.diva-gis.org/gdata>).

### 3.2. Temporal information

The temperature and precipitation information were obtained from the weather database CEMTEC/MS-Semagro (available at URL: <http://www.cemtec.ms.gov.br>), containing information from 28 stations scattered throughout MS state. In order to obtain more accurate temperature and precipitation estimates for each road section and survey date, we performed daily interpolations from the 28 stations to all MS state through Inverse Distance Weighting Interpolation, using the function *idw* from the R package 'gstat' (Pebesma and Heuvelink, 2016). Because surveys were performed every ca. two weeks and we had no information on the specific date of collisions, for each survey date we aggregated the temperature (mean) and precipitation (sum) from the previous 15 days and assign for each road section and survey date the respective values of both interpolations (temperature and



**Fig. 2.** Evaluation, discrimination performance and validation of GLMs relating roadkill occurrence with environmental variables. Panel A – deviance explained across the GLM replicates for each focal species. Panel B - Area Under the Curve (AUC) of the receiver operating characteristic plot, per species, considering the training data, testing data and independent data from BR163/BR267.

precipitation).

#### 4. Data analysis

##### 4.1. Model building, performance and validation

For each of the seven focal species we performed binomial logistic regressions (GLM) relating the roadkill presence-absence in the road sections (1000 m) across the survey dates, with the collection of environmental variables (land cover classes, forest cover, distance to rivers, temperature, precipitation, and NDVI). We further included two additional variables aiming to reflect the intrinsic roadkill risk, by using the total number of roadkills (per dataset) at each date and road section, excluding the records of modelled species (Ascensão et al., 2017; Santos et al., 2013), hereafter referred as temporal and spatial trends of overall roadkill. The variables forest cover, distance to rivers, temperature, precipitation and NDVI were scaled and centered, and therefore their estimates are comparable. The temporal and spatial trends of overall roadkill were log-transformed.

We used the data from CG\_PRP and CG\_TL for model building (training data) and the data from BR-163 as an independent dataset for model validation. Given the disproportionate number of presences (roadkills) versus absences (per road section and date), we repeatedly

partitioned both datasets into matrices of spatiotemporal blocks (road sections by survey days) and fitted independent regression models in each subset matrix of training data from which we extracted the estimates of the environmental variables. For each GLM, we randomly sampled two-thirds of presences (of a given focal species) and the same number of absences. This subset was further refined to remove duplicated road sections (i.e. two records in the same road) to avoid pseudo-replication issues, while keeping the ratio presences:absences. The other one-third of the occurrences was grouped with an equivalent number of absences for model validation procedures (again, removing duplicated road sections). The full GLMs, were then simplified through backward variable selection procedures, using the *step* function in R.

This partitioning procedure was repeated 100 times to assess the consistency of variables selected in the final models, its estimates, as well for model evaluation and validation. We considered that if a given variable was repeatedly selected in the final models and the distribution of its coefficients did not overlap zero, it would indicate a significant effect of the predictor on the spatiotemporal mortality patterns. Model evaluation and discrimination performance were assessed using the adjusted proportion of deviance explained and the Area Under the Curve (AUC) of the receiver operating characteristic plot, using the functions *Dsquared* and *AUC*, respectively, from the R package ‘ModEva’ (Barbosa et al., 2016).

Model validation was performed also using the AUC metric, this fold using for each replicate the subset of one-third of occurrences and the same number of absences from CG\_PRP and CG\_TL, and also using the independent data from the transect BR163.

#### 4.2. Predicting the spatiotemporal roadkill probability

We estimated the spatiotemporal roadkill probability for the two roadkill transects (CG\_PRP and CG\_TL) for the full periods within surveys (per yearly survey) using the predictions of the GLMs (100 replicates). As different models have different power in discriminating the 'presences' and 'absences', we averaged the predictions across replicates using the weighted mean, where the weights were the amount of deviance explained by each GLM. Hence, models with higher deviance explained had higher weight in averaged prediction computation.

### 5. Results

Higher values of variance explained were found for *Dasyopus novemcinctus* ( $0.23 \pm 0.05$ ), followed by *Hydrochoerus hydrochaeris* ( $0.12 \pm 0.04$ ), *Euphractus sexcinctus* ( $0.08 \pm 0.03$ ), *Tamandua tetradactyla* ( $0.05 \pm 0.03$ ), *Tapirus terrestris* ( $0.05 \pm 0.04$ ), *Cerdocyon thous* ( $0.04 \pm 0.02$ ) and *Myrmecophaga tridactyla* ( $0.03 \pm 0.02$ ) (Fig. 2, panel A). The models had a reasonable discrimination power, with the AUC for the training data averaging  $0.70 \pm 0.07$  across species and replicates; and the AUC for validation averaging  $0.66 \pm 0.09$  for the CG\_PRP and CG\_TL data, and  $0.72 \pm 0.14$  for the BR163 data (Fig. 2, panel B). Overall, the models could explain a small fraction of the spatiotemporal patterns of roadkills but had a reasonable prediction power, particularly for the independent dataset.

The different explanatory variables had different effects and importance in explaining the mortality patterns across species (Fig. 3). The roadkill temporal trend was the most important predictor for *C. thous*, *D. novemcinctus*, *E. sexcinctus*, *H. hydrochaeris* and *T. tetradactyla*, being selected in 76–100% of all replicates. Likewise, the roadkill spatial trend seemed to be highly important for *T. tetradactyla*, followed by *D. novemcinctus*, *T. terrestris* and *C. thous*. The collisions of *M. tridactyla*, *E. sexcinctus* and *C. thous* seemed to be more likely in areas dominated by grassland, while for *H. hydrochaeris* the collisions seemed to occur more in savanna. The distance to rivers had always a negative effect and was more important for *T. tetradactyla*, *H. hydrochaeris* and *M. tridactyla*. As for the climatic variables, temperature had a high importance for *C. thous*, *D. novemcinctus*, *E. sexcinctus*, with a negative effect in the former and a positive effect for the latter two. Precipitation had a lower importance, being its effect positive for *H. hydrochaeris* and *E. sexcinctus* and negative for *T. terrestris*. Finally, the NDVI seemed to have a higher importance for *D. novemcinctus* and *H. hydrochaeris*.

The predictions of the spatiotemporal roadkill risk allowed to highlight road sections and time periods where collisions are more likely to occur, although for some species as the *M. tridactyla* the patterns of high/low roadkill risk are less obvious (Fig. 4). Yet, the overlay of observed roadkills with the predictions have a general concordance, supporting the modeling approach and its usefulness (Fig. 4).

### 6. Discussion

In this study, we modelled and predicted the spatiotemporal patterns of road mortality for seven medium-large mammals, all of which have different habitat and food specializations, suggesting that our approach can be generalized to other vertebrates. In general, higher roadkill risk aggregations spanned for some kilometers and days, suggesting that tailored mitigation measures focusing simultaneously on certain road sections and periods could be beneficial. Importantly, the modeling procedure was able to capture the distinct differences in roadkill rates across the two datasets, probably due to changes in climatic conditions and/or the habitat surrounding the road that may lead

to variations in population abundance near roads (D'Amico et al., 2015; Eberhardt et al., 2013). Hence, predicting where and when these dynamic roadkill aggregations are likely to emerge within the spatio-temporal dimensions is a challenge that, if properly understood, could greatly improve the effectiveness of road management and mitigation actions.

Here, we related the spatiotemporal patterns with different environmental variables and two predictors related to intrinsic roadkill risk. The amount of variance explained for some species was low, as for *M. tridactyla* precluding a strong inference of the models. Yet, such low values probably stem from the fact that the species can occupy such a wide range of habitats and are active year-round, and therefore their movements and consequent crossing rates and road mortality are relatively similar across time. Nevertheless, the models had reasonable discrimination power, allowing to obtain spatiotemporal patterns of mortality risk that reflected the distribution of observed casualties in space and time. The traffic volumes were apparently similar between the two years of survey, and thus should not be the main driver of the increased mortality recorded in 2017/18 relatively to 2013/14.

The most important predictors across species were the two variables aimed to reflect the intrinsic temporal and spatial roadkill risk. This result has been reported elsewhere (Santos et al., 2013) and supports previous findings in our study area (Ascensão et al., 2017) suggesting that despite being wide range species, particularly *T. tetradactyla*, *D. novemcinctus*, *T. terrestris* and *C. thous*, they tend to be more road-killed in road sections having higher number of collisions involving other species. However, we show for the first time that this pattern also appears at the temporal dimension, as detected for *C. thous*, *D. novemcinctus*, *E. sexcinctus*, *H. hydrochaeris* and *T. tetradactyla*. This suggests that mitigation measures can be planned, at least as an initial step and for some species, by targeting where and when the majority of roadkills are detected.

We expected the roadkill events to be broadly related to periods of higher movement activity, as the mating or dispersal periods (D'Amico et al., 2015; Grilo et al., 2009). However, our focal species generally mate year-round (see Table S1.1), which precluded evaluating this expectation appropriately. Yet, we found some agreement between the peak of the mating period of *C. thous* and its peak of mortality (November/December). Likewise, *H. hydrochaeris* has a mating period peaking at May/June, which coincided with a peak of mortality. To our knowledge there is no information on dispersal periods for our focal species. Yet, the relation of the different climatic variables, temperature and precipitation, with the temporal pattern of mortality, probably reflects the seasonality of movements of these species, namely regarding the dispersal periods. This is more evident for both armadillos relatively to other larger species (Fig. 4), probably due to their smaller home range and also because their physiological constraints and limited thermoregulatory capabilities restrict longer movements during colder periods (Maccarini et al., 2015).

On the other hand, despite most species being habitat generalists, we found some concordance between their habitat preferences and the patterns of mortality. For example, *M. tridactyla* is known to forage in grasslands and treeless areas (Medri and Mourão, 2005; Mourão and Medri, 2007), where most roadkills of this species occurred. In fact, previous research in the neighboring Pantanal detected higher densities of this species in open habitats (open grasslands, scrub grasslands and forest edge) rather than in forested ones (Desbiez and Medri, 2010). Also, *T. tetradactyla* is known to favor areas near streams and rivers, as well forest areas, where most collisions were recorded. Importantly, all species' mortality patterns, but particularly those of *T. tetradactyla*, *H. hydrochaeris* and *M. tridactyla*, were related with the proximity of rivers, highlighting the importance of these vegetation strips for wildlife connectivity (Lees and Peres, 2008; Zimbres et al., 2017). Concerning vegetation productivity, we found some evidence of positive correspondence for *D. novemcinctus*, *H. hydrochaeris*, *M. tridactyla* and *T. terrestris*, suggesting that primary productivity influences these species'

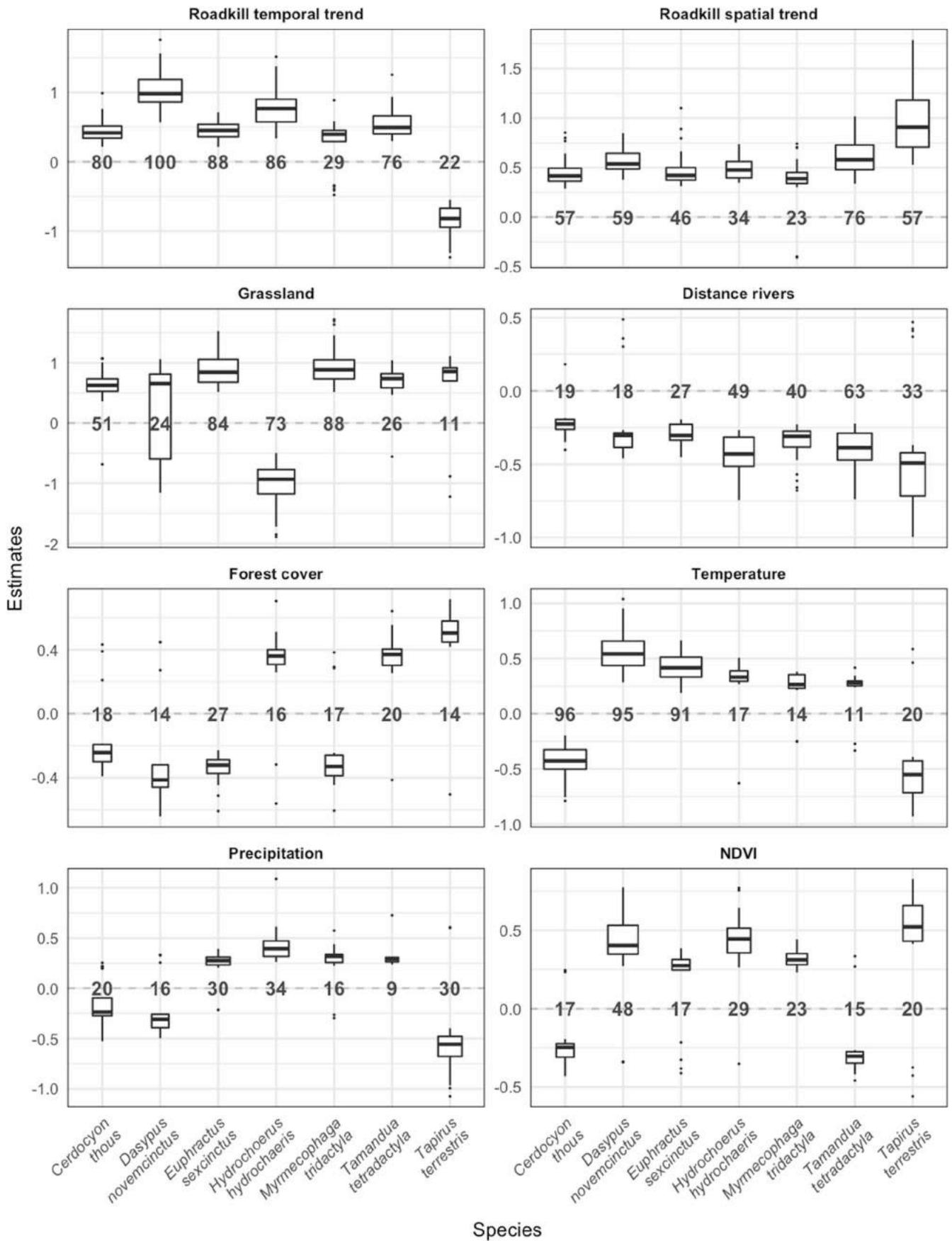


Fig. 3. Boxplots of coefficients for the environmental variables used to model the spatiotemporal patterns of roadkill, per focal species ('savanna' is the reference level for the 'grassland' categorical variable). In each boxplot, the box encompasses the interquartile range, the line is the median, whiskers extend to the upper and lower quartiles ( $\pm 1.5$  times the interquartile range), and outliers are shown outside the whiskers as dots. Boxplot widths is proportional to the square-roots of the number of observations in the groups. The proportion of replicates that the predictor was selected for the final model is presented in each species column at  $y = 0$ .

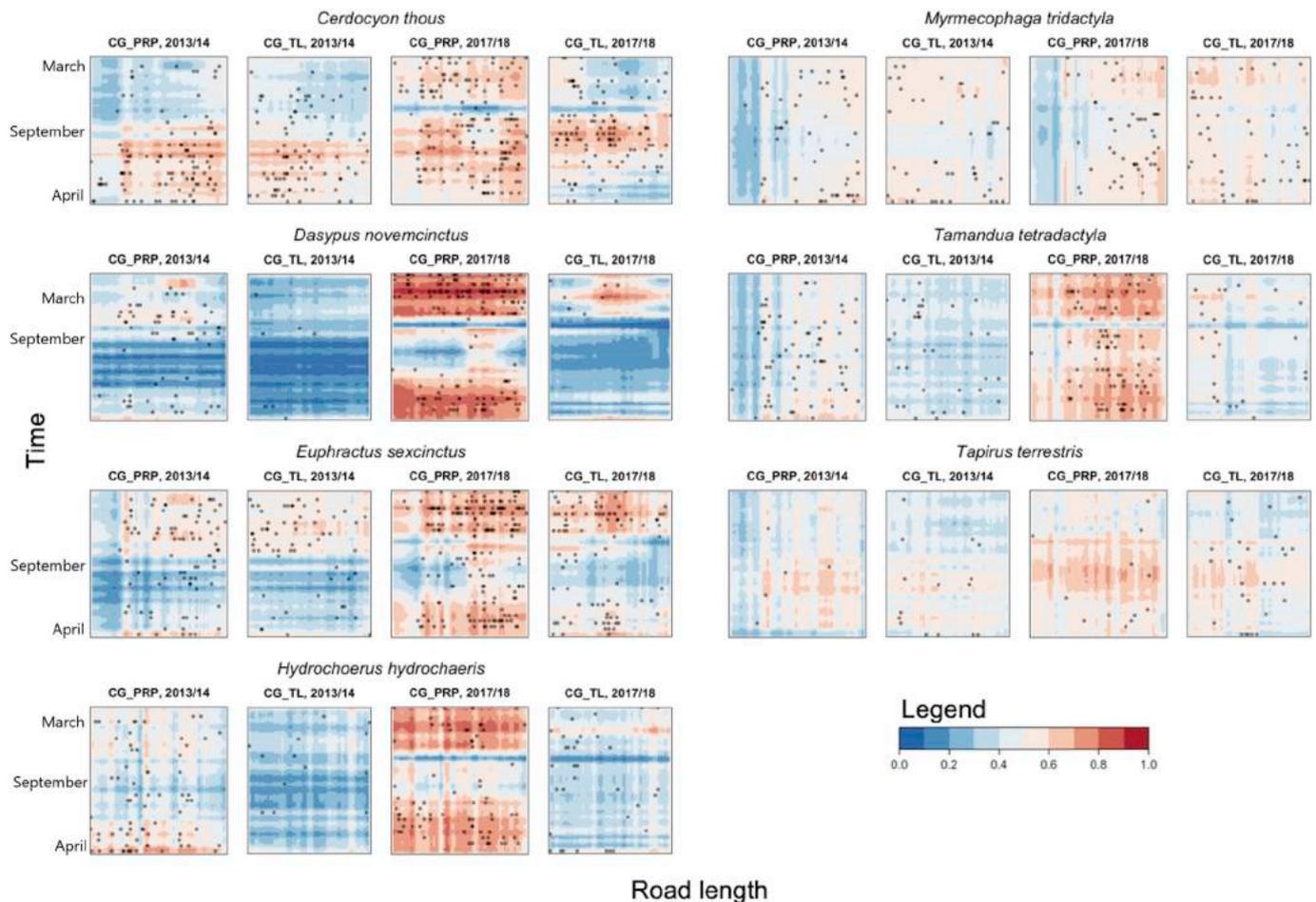


Fig. 4. Spatiotemporal predictions of roadkill risk for each focal species, transect (CG\_PRP and CG\_TL) and survey period (years 2013/14 and 2017/18). In each box, the xx-axis represent the road and yy-axis the days of the year. Dots represent the observations. For each species the four boxes represent the predictions for i) CG\_PRP in 2013/14, ii) CG\_TL in 2013/14, iii) CG\_PRP in 2017/18, and iv) CG\_TL in 2017/18. See text for details of surveyed roads.

daily or seasonal movements, and thus where and when animals will try to cross the roads and eventually be hit. For example, the capybara prefers to move through humid areas and with higher vegetation productivity (Corriale and Herrera, 2014).

The lack of estimates on carcass persistence across the different habitats may have partially biased the results. However, the landscape across the study area is dominated by grasslands with scattered patches of savanna-like forests (Cerrado), and therefore the abundance and composition of the community of scavengers is likely to be similar across the region. Moreover, as we replicated the modeling procedure 100 times for each species, with a different set of locations in each replicate, the effect of false negatives was diluted. Nevertheless, future research should strive to correct for these bias, in order to provide more accurate estimates of roadkill (Santos et al., 2016).

Overall, we show that identifying spatiotemporal roadkill patterns may provide valuable information to define specific management actions focused on specific road sections and time periods, in complement to permanent road mitigation measures, as road passages. For example, one may reduce the impact of a road on a given species or community, by reducing the traffic volume and/or speed in certain road sections during specific periods of higher collision probability. Likewise, one can set temporary fences to prevent animals from crossing the road and guiding them to safe passages (Cunnington et al., 2014), thus avoiding the potential barrier effect caused by permanent fencing along the entire road length (Ascensão et al., 2013). Our approach offers a new insight into the understanding of road effects and how to plan and strategize monitoring and mitigation. Notably, we used a set of freely

available environmental variables that can be easily obtained, namely remote sensing information and climate data from weather stations, to assess and predict the roadkill risk. These information sources allow the modeling and predictions of spatiotemporal patterns over large extents, potentially at the global scale. In fact, our goal is to improve the modeling framework, expanding the coupling of remote sensing information, climate data, traffic volume and biodiversity metrics, to be able to provide more accurate roadkill risk predictions, eventually in near real time, for any part of the globe.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2019.109320>.

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