



UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL  
INSTITUTO DE BIOCÊNCIAS  
PROGRAMA DE PÓS-GRADUAÇÃO EM ECOLOGIA



Tese de Doutorado

*Estratégias de planejamento da mitigação do atropelamento de  
fauna em rodovias*

Larissa Oliveira Gonçalves

Porto Alegre, junho de 2018

ESTRATÉGIAS DE PLANEJAMENTO DA MITIGAÇÃO DO ATROPELAMENTO  
DE FAUNA EM RODOVIAS

Larissa Oliveira Gonçalves

Tese de Doutorado apresentada ao Programa de Pós-Graduação em Ecologia, do Instituto de Biociências da Universidade Federal do Rio Grande do Sul, como parte dos requisitos para obtenção do título de Doutor em Ciências com ênfase em Ecologia.

Orientador: Prof. Dr. Andreas Kindel

Comissão Examinadora

Prof. Dr. Fernando Gertum Becker

Prof. Dr. Milton Cezar Ribeiro

Prof. Dr. Rafael Antunes Dias

Porto Alegre, junho de 2018

## **Agradecimentos**

Inúmeras são as pessoas que contribuíram para a construção e conclusão desta tese.

Gostaria imensamente de agradecer:

A minha família que SEMPRE esteve ao meu lado, apoiando e ajudando no que eu precisasse. Sorte a minha ter as pessoas mais incríveis que conheço como minha família! Podem ter certeza, Mãe, Pai, Igor, Érika e Manuella, vocês são a base de tudo!

Ao Maurício, a pessoa mais sensacional que eu conheci nesses últimos anos e que com muita paciência e companheirismo me ajudou a chegar nessa etapa final de maneira leve e sensata! Obrigada por me apoiar e estar ao meu lado sempre. Te amo!

Ao Andreas Kindel, que sempre me fez acreditar que fizemos e demos o nosso melhor! Se tu fosses mais organizado, talvez tu não serias tão criativo! Obrigada por aceitar esse doutorado comigo!

À Fernanda Z. Teixeira, minha amiga e parceira de trabalho de todas as horas. Obrigada por sempre estar disposta a me ajudar e discutir, mesmo que seja para discordarmos!

A todos os integrantes e agregados do NERF! Vocês são ótimos e incríveis! Sentirei saudades de incomodá-los. Obrigada por aturarem as minhas chatices diárias!

Aos amigos da melhor turma, que sempre serão os melhores!

Aos tantos melhores amigos que não vou listar aqui, mas que foram muito importantes e guardo no coração o carinho e a ajuda de cada um.

Ao PPG Ecologia, por todo o apoio e ajuda nesse período.

A CAPES, pela bolsa durante todo o doutorado e a bolsa de doutorado Sanduíche.

Ao Rodney van der Ree, que mesmo com dificuldades, me deu a oportunidade de conhecer um excelente grupo de pesquisa na Austrália!

Aos amigos que a Austrália me deu e que fizeram o mundo Aussie mais divertido ainda!

A todos vocês, o meu sincero e carinhoso MUITO OBRIGADA!

## Resumo

Infraestruturas lineares, como as estradas, estão por todos os lugares no mundo e os impactos causados por elas são inúmeros e intensos. Focando no impacto de mortalidade de fauna por colisão com veículos, esta tese teve o objetivo de propor diferentes abordagens para identificar locais para a implementação de medidas de mitigação desse impacto. Além da introdução geral, a tese tem três capítulos que correspondem a três artigos científicos. O primeiro capítulo explorou dados de répteis atropelados em 33 meses de monitoramento mensais em 277 km da BR-101 e avaliou tanto o padrão espacial quanto o padrão temporal de fatalidades além de estimar a magnitude de atropelamentos de répteis na estrada. O segundo e o terceiro capítulo exploram abordagens preditivas de atropelamento de fauna para dois diferentes contextos: uma única estrada e uma rede de estradas. O segundo capítulo teve o objetivo de testar se usando características da paisagem, da rodovia e dos animais, nós podemos prever onde estão os locais com maior chance de um animal ser atropelado. Para isso, também para a BR-101, calculei a probabilidade de travessia através de mapas de conectividade e a probabilidade de colisão através de uma equação que considera o tráfego de veículos, o tamanho dos animais e dos veículos e a velocidade dos animais para duas espécies de mamíferos nativos do Brasil: o furão (*Galictis cuja*) e o zorrilho (*Conepatus chinga*). Para o terceiro capítulo, foi utilizado a rede de estradas do estado de Victoria na Austrália, na qual calculei a probabilidade de travessia e de colisão para o canguru cinza oriental (*Macropus giganteus*), espécie nativa da Austrália. No primeiro capítulo, demonstrei que: 15.377 cágados, lagartos e serpentes são atropelados a cada ano na BR-101 no sul do Brasil; *hot moments* de atropelamentos de répteis ocorreram no verão, especialmente em dezembro para lagartos e serpentes; *hotspots* de atropelamentos foram coincidentes para tartarugas, lagartos e serpentes; existiu um efeito positivo do tráfego e da rizicultura nos

atropelamentos e negativo da silvicultura; medidas de mitigação nos *hotspots* prioritários poderiam evitar 45% das fatalidades de répteis. No segundo capítulo, concluí que a probabilidade de fatalidade através da multiplicação das probabilidades de travessia e colisão não teve um bom poder de predição dos atropelamentos e que a probabilidade de colisão sozinha foi melhor em prever os atropelamentos do que a probabilidade de travessia, entretanto as espécies apresentaram padrões diferentes. No terceiro capítulo, concluí que um modelo aditivo das duas probabilidades foi melhor em prever os atropelamentos de cangurus do que os modelos individuais de probabilidades de travessia e colisão, entretanto o modelo integrado não apresentou a predição esperada. A probabilidade de travessia foi um preditor melhor dos atropelamentos de cangurus que a probabilidade de colisão para a rede de estradas. Portanto, concluo que: 1) os atropelamentos de fauna podem ser bastante acentuados em determinados contextos e que é possível identificar locais de maior agregação que seriam efetivos para mitigação; 2) é possível usar dados de tráfego de veículos e tamanho e velocidade dos animais para prever locais de mais atropelamentos, entretanto deve se ter cuidado pois isso é específico para cada espécie; 3) para o contexto de rede de estradas, é possível prever o atropelamento utilizando a probabilidade de travessia e a probabilidade de colisão em um mesmo modelo. Ainda é necessário explorar outras maneiras de calcular e integrar as probabilidades aqui propostas, mas nesta tese eu demonstrei uma forma possível de prever atropelamentos para um contexto em que não há dados dessa natureza disponíveis, seja para estradas novas ou para uma rede de estradas.

**Palavras-chave:** colisões animais-veículos, *hotspots* de atropelamento, ecologia da paisagem

## **Abstract**

Linear infrastructures, such as roads, are worldwide and impacts caused by them are innumerable and intense. We focused on impact of road-kills due to wildlife-vehicle collisions and aimed to propose different approaches to identify locations to implement mitigation measures for this impact. Besides the general introduction, this thesis has three chapters which correspond to three scientific papers. The first chapter examined reptile road-kill data from monthly road survey during 33 months in a 277 km of BR-101 road. We evaluated spatial and temporal patterns of road-kills and estimated the magnitude of reptile road-kills on that road. The second and third chapters examined predictive approaches of wildlife road-kills for two different contexts: a single road and a road network. The second chapter aimed to test if it is possible to use of landscape, road, animals features to predict locations where there are more road-kills. For the same road (BR-101), I calculated crossing probability using connectivity maps and collision probability using an equation which considers traffic volume, animal and vehicle size, and animal speed for two native mammal species from Brazil: the Lesser Grison (*Galictis cuja*) and the Molina's Hog-nosed Skunk (*Conepatus chinga*). To the third chapter, I used the road network of Victoria state in Australia, which I calculated crossing and collision probabilities for eastern grey kangaroo (*Macropus giganteus*), a native species from Australia. In the first chapter, I demonstrated that: 15,377 freshwater turtles, lizards and snakes are road-kills each year in Br-101 in Southern Brazil; road-kill *hot moments* occur in the summer, specially in December for lizards and snakes; road-kill *hotspots* are coincident among freshwater turtles, lizards and snakes; there is a positive effect of traffic and rice plantation on road-kills and a negative effect of silviculture; mitigation measures of priority *hotspots* could avoid 45% of reptile fatalities. In the second chapter, I concluded that fatality probability through multiplication of crossing and collision

probabilities did not have a good predictive power of road-kills and collision probability alone was better to predict road-kills than crossing probability, however species showed different patterns. In the third chapter, I concluded that an additive model with the two probabilities was better to predict kangaroo road-kills than individual models of crossing and collision probabilities, however the integrated model did not present an expected prediction. Crossing probability was a better predictor of kangaroos road-kills than collision probability for the road network. Therefore, I concluded that: 1) wildlife road-kills can be really high in some contexts and it is possible to identify locations with more road-kill aggregations which would be effective for mitigation; 2) it is possible to use traffic volume, animals size and speed to predict location of road-kills, however it is specific for each species; 3) for road network context, it is possible to predict kangaroo road-kills using crossing and collision probability in the same model. Exploring another ways to calculate and integrate the probabilities used here is necessary, however in this thesis I demonstrated one possible manner to predict road-kills in a context which road-kill are not available, such as new roads or road networks.

**Keywords:** wildlife-vehicle collisions, road-kill hotspots, landscape ecology

## **Sumário**

<b>Resumo</b> .....	4
<b>Abstract</b> .....	6
<b>Introdução Geral</b> .....	9
Capítulo 1 .....	16
<b>Reptile road-kills in Southern Brazil: composition, hot moments and hotspots</b> .....	17
Capítulo 2 .....	47
<b>Do crossing and collision probabilities predict wildlife fatalities on roads?</b> .....	48
Capítulo 3 .....	78
<b>Predicting road fatalities at a road network using crossing and collision probabilities</b> .	79
<b>Considerações finais</b> .....	103
<b>Referências Bibliográficas</b> .....	106



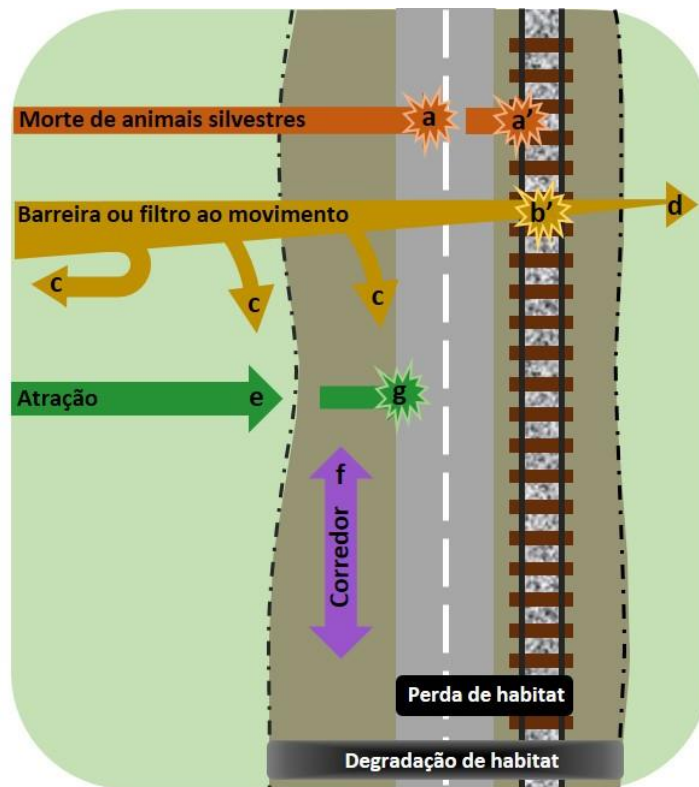
## **Introdução Geral**

### *Rodovias pelo mundo e seus impactos*

Rodovias facilitam o movimento de pessoas, por isso têm um importante papel no desenvolvimento econômico e urbano e, assim, fazem-se presentes onde quer que os humanos se estabeleçam. Contudo, a construção de rodovias de todos os tipos e o consequente tráfego afetam os ecossistemas terrestres e aquáticos, direta e indiretamente, de várias maneiras (Figura 1): a perda de habitat devido à construção da estrada, a mortalidade de fauna por atropelamento, a subdivisão de populações através da fragmentação e a inacessibilidade de recursos através do efeito de barreira (VAN DER REE; SMITH; GRILO, 2015). A mortalidade pode ser considerada um dos principais mecanismos diretos a comprometer o tamanho e persistência das populações silvestres (FAHRIG; RYTWINSKI, 2009; JACKSON; FAHRIG, 2011; JAEGER; FAHRIG, 2004) e a identificação dos fatores e ações para diminuir a mortalidade são fundamentais no contexto da conservação da biodiversidade. Segundo Fahrig & Rytwinski (2009), a mortalidade de fauna por atropelamento pode ter efeitos substanciais na densidade populacional, tendo aparentemente uma maior importância para a persistência das populações do que o isolamento por evitamento da rodovia (JACKSON; FAHRIG, 2011). Os atropelamentos de animais silvestres em rodovias são considerados por alguns autores como a principal causa antrópica direta de mortalidade de fauna, ultrapassando até mesmo a caça (FORMAN; ALEXANDER, 1998). Assim, tem-se despendido um esforço imenso em avaliar a magnitude do impacto de atropelamentos sobre a fauna. A contagem dos animais atropelados pode ser útil para avaliar a magnitude do impacto de rodovias, entretanto essa simples contagem é inadequada para entender as relações entre a rodovia e a fauna silvestre (CLEVINGER; CHRUSZCZ; GUNSON, 2003). Diversos trabalhos

têm demonstrado que os atropelamentos não ocorrem aleatoriamente ao longo das rodovias, mas que são agregados espacialmente (CLEVINGER; CHRUSZCZ; GUNSON, 2003; COELHO; KINDEL; COELHO, 2008). Por isso, alguns estudos têm priorizado as estimativas de pontos de agregação de atropelamentos ao longo da rodovia com o objetivo principal de propor locais e medidas mais adequadas para mitigar esse impacto.

Estratégias e ações visando mitigar os impactos de rodovias sobre a fauna têm sido planejadas e implementadas ao redor do mundo (RYTWINSKI et al., 2016), sendo divididas em dois tipos: aquelas voltadas à mudança de comportamento dos usuários da rodovia, como redutores de velocidade, placas sinalizadoras e sistemas de detecção animal (HUIJSER et al., 2015); e aquelas voltadas ao manejo da fauna, como passagens subterrâneas (BHARDWAJ et al., 2017; CLEVINGER; WALTHO, 2005; JUMEAU; PETROD; HANDRICH, 2017; SMITH; VAN DER REE; ROSELL, 2015) e sobre a rodovia (GOOSEM; WESTON; BUSHNELL, 2005; SOANES et al., 2013; TEIXEIRA et al., 2013), cercas direcionadoras e refletores (BENTEN; ANNIGHÖFER; VOR, 2018; D'ANGELO; VAN DER REE, 2015; GLISTA; DEVAULT; DEWOODY, 2009). Contudo, o sucesso dessas ações depende diretamente da escolha das medidas mais adequadas a cada situação e da correta definição dos locais para sua implementação. Entretanto, definir esses locais não é uma tarefa fácil. Para diferentes contextos haverá diferentes formas que possibilitarão indicar os locais. Na minha tese de doutorado explorei diferentes abordagens para identificar esses lugares dependendo do tipo de dado disponível.



**Figura 1.** Impactos de rodovias e ferrovias na fauna silvestre, perda de habitat causada pela instalação das infraestruturas e degradação do habitat adjacente. Ao tentar cruzar, muitos animais podem morrer por colisões com veículos ou trens (a, a') ou ainda por ficarem presos entre os trilhos (b'). Já o efeito de barreira ou filtro ocorre porque a presença da rodovia e da ferrovia impede que os animais cruzem ou diminuem seu acesso para o outro lado (c) e alguns animais morrem ao tentar cruzar, fazendo com que apenas alguns indivíduos consigam atravessar com sucesso (d). A estrada e suas cercanias também podem ser um atrator (e) para a fauna e a vegetação adjacente ou a própria estrada podem atuar como corredor (f), tanto para espécies nativas como invasoras, eventualmente resultando em um mecanismo adicional de fatalidades (g). Figura retirada de TEIXEIRA et al. (2018) adaptada de VAN DER REE; SMITH; GRILO (2015).

### *Minha tese*

Essa tese nasceu da vontade de pesquisar algo que fosse diretamente aplicado, que pudesse de alguma forma ajudar a orientar estratégias de mitigação dos atropelamentos de fauna em rodovias no Brasil e no mundo.

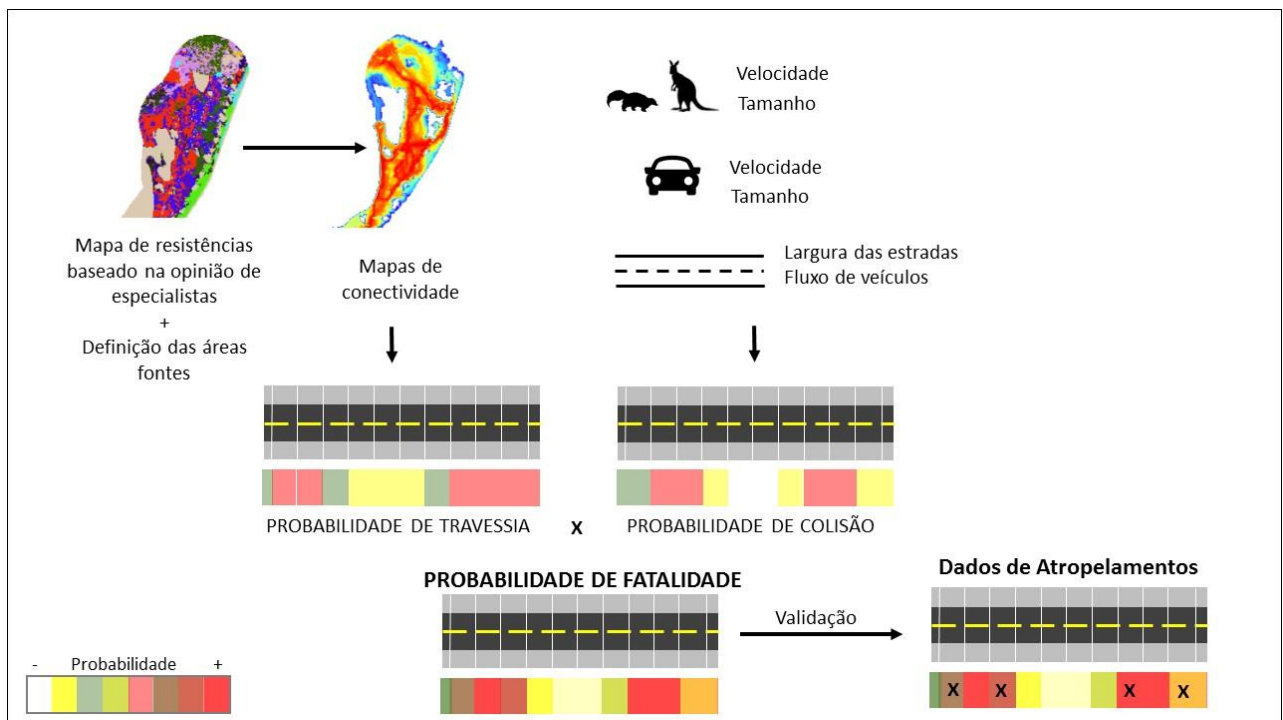
Se houver a possibilidade de monitorar uma estrada e obter dados de fauna atropelada, claramente eu posso usar essa informação para informar os locais onde foram encontrados mais animais atropelados. Dados de monitoramento sistemático (sejam eles semanais,

quinzenais, mensais, trimestrais) podem ser usados para fazer uma análise de agregações de atropelamentos e identificar onde estão os locais em que essa concentração é maior do que o esperado ao acaso, identificando os *hotspots* de atropelamento. Esse foi o enfoque da primeira parte da minha tese (capítulo 1) que explorou padrões de mortalidade de répteis em uma estrada do sul do Brasil. Esse trabalho explorou dados de répteis atropelados em 33 meses de monitoramento mensais em 277 km da BR-101 e avaliou tanto o padrão espacial quanto o padrão temporal de fatalidades, além de estimar a magnitude de atropelamentos de répteis nessa estrada.

A abordagem explorada no capítulo 1 é extremamente útil no contexto de uma estrada construída e já operando, na qual é possível obter dados de atropelamento. Entretanto, o que fazer se eu preciso indicar locais para mitigação em estradas que estão sendo planejadas ou ainda se eu preciso indicar locais prioritários para mitigação em uma rede de estradas, onde o custo para realização de um monitoramento sistemático é altíssimo e as vezes temporalmente inviável. Será que eu consigo indicar locais com maior incidência de atropelamentos sem utilizar os dados de atropelamento para isso? Essa foi a pergunta motivadora dos próximos dois capítulos da tese.

No segundo capítulo, eu testei se usando características da paisagem, da rodovia e dos animais, eu posso prever onde estão os locais com maior chance de um animal ser atropelado. Eu baseei minha ideia no modelo conceitual apresentado na figura 2. A ideia foi reconhecer os dois processos que acontecem sequencialmente para que um animal seja atropelado. Primeiro o animal precisa tentar cruzar uma estrada, depois ele precisa ser atingido por um veículo. Os lugares mais críticos para a ocorrência de fatalidades serão, assim, os locais de maior probabilidade de cruzamento de um animal e onde há maior probabilidade de um veículo colidir com ele. Modelos preditivos foram previamente propostos, mas raramente foram validados. Para calcular a probabilidade de colisão,

HELS & BUCHWALD (2001) propuseram uma equação largamente utilizada (GRILO et al., 2018; JAARSMA et al., 2007; LITVAITIS; TASH, 2008), contudo desconhecemos trabalhos que tenham validado as previsões. Da mesma forma, a probabilidade de cruzar a estrada tem sido avaliada por distintas abordagens (BASTILLE-ROUSSEAU et al., 2018; GIRARDET; FOLTÊTE; CLAUZEL, 2013; GRILO et al., 2011; KANG et al., 2016) e utilizada em modelos preditivos, mas raramente validada (PATRICK et al. 2012).



**Figura 2.** Esquema com as principais etapas e fatores necessários para o desenvolvimento do modelo de probabilidade de fatalidade que baseou o desenvolvimento dos capítulos 2 e 3 desta tese.

O segundo capítulo foi focado em uma única estrada. Eu usei o mesmo trecho da BR-101 usado no primeiro capítulo da tese e construí um modelo de probabilidade de fatalidades para duas espécies de mamíferos nativos: o furão (*Galictis cuja*) e o zorrilho (*Conepatus chinga*). A ideia foi explorar uma abordagem útil para ser usada em estradas a serem construídas ou pavimentadas; nessas últimas espera-se um elevado incremento de velocidade e tráfego de veículos e é bastante difícil obter observações de mortalidade em

número suficiente para fazer uma avaliação como feita no primeiro capítulo. No contexto de uma estrada nova, é possível modelar o tráfego e a velocidade prevista para a futura estrada e já se conhece a paisagem do entorno sabendo o traçado proposto. Assim, seria possível construir os modelos antes da construção ou pavimentação de estradas e propor locais para implementação de mitigação. Eu construí uma série de mapas de conectividade que foram usados para extrair a probabilidade de travessia e usei o tráfego de veículos, o tamanho do carro, do animal, da estrada e a velocidade com que o animal atravessa a estrada para calcular a probabilidade de colisão de cada espécie na estrada. Além disso, eu multipliquei essas probabilidades para obter a probabilidade de fatalidade final. Mas como saber se esses trechos são mesmo os trechos com maior fatalidade e se essa probabilidade integrada final tem um maior poder preditivo do que as probabilidades individuais? Eu validei os modelos e avaliei a capacidade de predição de cada uma dessas probabilidades usando dados de atropelamentos de furão e zorrilho na mesma estrada, para os mesmos trechos, obtidos em um monitoramento sistemático de fauna atropelada.

A partir do segundo capítulo, surgiu a vontade de aplicar o mesmo modelo para uma rede de estradas. A primeira ideia era aplicar para estradas do Rio Grande do Sul, entretanto a dificuldade de acesso aos dados, principalmente de fluxo de veículos nos levou a pensar em alternativas. Ao longo desse percurso, me deparei com um artigo que propôs uma estrutura muito parecida com a minha (Visintin et al. 2016). O trabalho usava a mesma ideia de dois processos hierárquicos para que um animal fosse atropelado: a exposição à estrada e o perigo de atropelamento. A diferença é que neste trabalho, os autores utilizaram a ocorrência da espécie como a probabilidade de travessia e o fluxo e a velocidade dos veículos como a probabilidade de colisão. A partir da oportunidade do Doutorado Sanduíche pela CAPES, resolvi propor os modelos do segundo capítulo para os dados da rede de estradas do estado de Victoria na Austrália e avaliar o poder de

predição dos modelos para um contexto de rede de estradas. Desenvolvi o terceiro capítulo em quatro meses na Austrália junto ao Grupo de Ecologia Quantitativa e Aplicada da Universidade de Melbourne.

No terceiro capítulo, utilizei dados da rede de estradas australianas no estado de Victoria (227.819 km<sup>2</sup>), focando no canguru cinza oriental (*Macropus giganteus*) como espécie-alvo. A partir de mapas de uso e cobertura do solo e da ocorrência da espécie, eu construí mapas de conectividade que foram usados para extrair a probabilidade de travessia. A probabilidade de colisão considerou o fluxo de veículos, a velocidade da espécie e a largura das estradas, pois há dados dessa natureza disponíveis para toda a rede. Utilizei 47.730 trechos de 500 metros e obtive a probabilidade de travessia e a probabilidade de colisão para cada um dos trechos. A validação foi feita com dados de presença de atropelamento em cada trecho baseado em ocorrências reportadas para a Wildlife Victoria (WILDLIFE VICTORIA, 2015), organização que trabalha com bem-estar animal.

Além desta introdução geral, esta tese está estruturada em três capítulos que correspondem a três artigos científicos e uma última seção de considerações finais. Nessa última, fiz um detalhamento das principais conclusões de cada um dos capítulos e de como essa tese pode contribuir para o estudo do impacto de atropelamento de fauna e da proposição de medidas de mitigação.

**Atropelamento de répteis no sul do brasil: composição, hot moments e  
hotspots**

Esse capítulo está publicado na revista Science of the Total Environment e foi feito em colaboração com Diego Janisch Alvares, Fernanda Zimmermann Teixeira, Gabriela Schuck, Igor Pfeifer Coelho, Isadora Beraldi Esperandio, Juan Anza, Júlia Beduschi, Vinicius Augusto Galvão Bastazini. Ele pode ser acessado em <https://doi.org/10.1016/j.scitotenv.2017.09.053>.



1 **Reptile road-kills in Southern Brazil: composition, hot moments and hotspots**

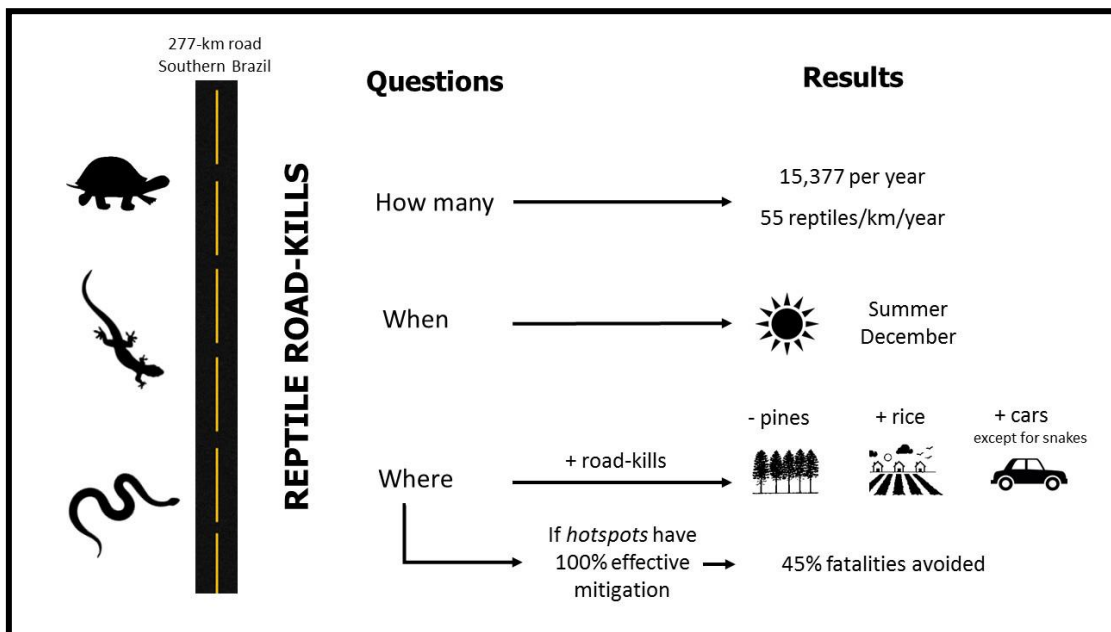
2

3 **HIGHLIGHTS**

- 4 • Estimate of 15,377 freshwater turtles, lizards, and snakes road-killed per year;
- 5 • Road-kill hot moments in summer, especially in December for lizards and snakes;
- 6 • Road-kill hotspots highly coincident among freshwater turtles, lizards, and
- 7 snakes;
- 8 • Positive effects of traffic and rice plantation, and negative of pine plantation;
- 9 • Hotspots (21% of the road extent) included 45% of reptile fatalities.

10

11 **GRAPHICAL ABSTRACT**



12

13

14 **ABSTRACT**

15 Understanding road-kill patterns is the first step to assess the potential effects of road  
16 mortality on wildlife populations, as well as to define the need for mitigation and support  
17 its planning. Reptiles are one of the vertebrate groups most affected by roads through  
18 vehicle collisions, both because they are intentionally killed by drivers, and due to their  
19 biological needs, such as thermoregulation, which make them more prone to collisions.

20 We conducted monthly road surveys (33 months), searching for carcasses of freshwater  
21 turtles, lizards, and snakes on a 277-km stretch of BR-101 road in Southernmost Brazil  
22 to estimate road-kill composition and magnitude and to describe the main periods and  
23 locations of road-kills. We modeled the distribution of road-kills in space according to  
24 land cover classes and local traffic volume. Considering the detection capacity of our  
25 method and carcass persistence probability, we estimated that 15,377 reptiles are road-  
26 killed per year (55 reptiles/km/year). Road-kills, especially lizards and snakes, were  
27 concentrated during summer, probably due to their higher activity in this period. Road-  
28 kill hotspots were coincident among freshwater turtles, lizards, and snakes. Road-kill  
29 distribution was negatively related to pine plantations, and positively related to rice  
30 plantations and traffic volume. A cost-benefit analysis highlighted that if mitigation  
31 measures were installed at road-kill hotspots, which correspond to 21% of the road, they  
32 could have avoided up to 45% of recorded reptile fatalities, assuming a 100% mitigation  
33 effectiveness. Given the congruent patterns found for all three taxa, the same mitigation  
34 measures could be used to minimize the impacts of collision on local herpetofauna.

35

36 **Keywords:** carcass detection, carcass removal, mitigation, road ecology, road-kill  
37 aggregation, wildlife-vehicle collisions

38

## 39 **1. Introduction**

40 Among several road impacts on wildlife, such as habitat loss, degradation, and  
41 fragmentation, fatalities due to vehicle collisions are one of the most concerning impacts  
42 (Forman et al., 2003; van der Ree et al., 2015b). Road mortality can cause faster  
43 population declines compared to other impacts, such as connectivity reduction (Jackson

44 and Fahrig, 2011; Jaeger and Fahrig, 2004). Road-killing can also foster evolutive  
45 changes in populations (Brady and Richardson, 2017). Understanding patterns and  
46 processes related to wildlife-vehicle collisions is fundamental for guiding policies to  
47 minimize their impact.

48 Despite the long interest in understanding the effects of reptile-vehicle collisions  
49 (Fitch, 1949) and the fact that this group seems to be more affected than other vertebrates  
50 (D'Amico et al., 2015; Jochimsen et al., 2014), reptiles are still underrepresented in road  
51 ecology literature (Fahrig and Rytwinski, 2009; Gunson et al., 2011). The lesser interest  
52 on reptile fatalities is probably explained by the importance that other vertebrate groups,  
53 such as medium and large mammals, pose to human safety (Danks and Porter, 2010;  
54 Huijser et al., 2009). However, when mitigations are planned aiming to reduce the  
55 anthropogenic impact on biodiversity, relying on information available for a single  
56 taxonomic group might be ineffective, since road-kill patterns in space (e.g. Teixeira et  
57 al., 2013b) and time can vary among distinct taxonomic or functional groups.

58 Even without knowledge of the demography of local populations, understanding  
59 which species and how many animals die on roads can be the first step to assess the  
60 potential effects of road mortality on wildlife populations, as well as to define the need  
61 for mitigation and support its planning. Road-kill estimates need to incorporate inherent  
62 errors of carcass surveys, such as imperfect detection and carcass persistence (Santos et  
63 al., 2011; Teixeira et al., 2013a). Studies accounting for these errors on reptile road-kill  
64 estimates are rare (but see Gerow et al., 2010 and Teixeira et al., 2013a) and the real  
65 magnitude of reptile mortality is certainly underestimated. Road mortality effects are not  
66 equally distributed in time and space (Beaudry et al., 2010), therefore assessing road-kill

67 hot moments and hotspots, i.e. periods and locations with significantly higher fatalities,  
68 is important to propose periods and locations for mitigation (Gunson and Teixeira, 2015).

69 Both intrinsic and extrinsic factors can affect road-kill distribution. Species have life  
70 traits that make them more vulnerable to vehicle collisions, such as mobility and  
71 behavioral responses to traffic volume (Jacobson et al., 2016; Lima et al., 2014).  
72 Landscape and road characteristics certainly affect road-kill patterns. Variables related to  
73 the presence and distance of water bodies and to traffic volume are recognized as  
74 important factors determining spatial patterns of reptile fatalities on roads (Glista et al.,  
75 2008; Langen et al., 2012, 2009).

76 Knowledge of environmental or road attributes related to higher road-kill probability  
77 can be used to identify priority periods and locations for mitigation on other roads, for  
78 which road-kill data are unavailable (D'Amico et al., 2015; Glista et al., 2008). Although  
79 there is a number of possible mitigation strategies potentially beneficial for reptiles,  
80 passages associated with funneling fencing seem to be the most effective for multispecies  
81 purposes (Jackson et al., 2015). Currently available technologies allow for  
82 implementation of mitigation structures during road operation with relatively little trouble  
83 to traffic, whereas proper design, implementation and maintenance could result on nearly  
84 absolute effectiveness (Aresco, 2005; Van der Ree and Tonjes, 2015).

85 In this study, we described road-kill patterns for freshwater turtles, lizards, and  
86 snakes on BR-101 road, Southernmost Brazil. We evaluated which species are road-  
87 killed, how many reptiles are killed on this road (considering carcass removal and  
88 detection based on experiments), and when and where these road-kills are concentrated.  
89 We also assessed the relationship of reptile fatalities with land cover and local traffic  
90 volume. We expected temporal patterns to show a concentration of fatalities in summer

91 months due to higher reptile activity in this period. We expected distinct spatial  
92 distribution of fatalities for each group, considering they vary in natural history:  
93 freshwater turtles are more associated with aquatic environments, while lizards tend to  
94 occupy open and forested areas. For snakes, we expected the spatial pattern of fatalities  
95 to be less aggregated due to their higher regional species richness. We also expected that  
96 traffic volume would have a stronger association with freshwater turtle fatalities than with  
97 other groups because they are less mobile and present a ‘pauser’ behavior in reaction to  
98 upcoming vehicles (Jacobson et al., 2016).

## 99 **2. Methods**

### 100 **2.1. Study area**

101 We conducted this study on a 277-km stretch of BR-101 road, located at the lowlands  
102 of Rio Grande do Sul state, Brazil (initial coordinates 30°9'1.20"S and 50°30'49.33"W,  
103 and final coordinates 32°0'23.64"S and 52°2'17.73"W; see Fig.2; Appendix A). BR-101  
104 is located in the eastern side of Patos Lagoon, adjacent to the Lagoa do Peixe National  
105 Park, a recognized Ramsar site (Ramsar Convention, 1962). This stretch is a two-lane  
106 paved road with 11 m of width, a speed limit of 80 km/h, and an average daily traffic  
107 (ADT) between 690 and 2,900 vehicles, depending on the locality.

108

### 109 **2.2. Data Collection**

110 We conducted monthly surveys from September 2012 to August 2014, and from  
111 February to October in 2015, totaling 33 surveys. Two observers (including the driver)  
112 conducted surveys by car at 40-50 km/h (speed limit followed minimum allowed speed  
113 according to Brazilian regulation) from dawn to dusk. Detected carcasses were identified

114 to the lowest taxonomic level and their locations were georeferenced with a handheld  
115 GPS.

116 We used vehicle counters (Vehicle Counter Generation III - TRAFx Research Ltd.)  
117 to calculate the average daily traffic (ADT) in three locations linking the main regional  
118 settlements: Capivari do Sul (n=48 days), Mostardas (n=273 days), and São José do Norte  
119 (n=498 days). Since we found a north-to-south decrease in traffic volume, we  
120 extrapolated traffic volume for each 2-km road segment by performing a linear regression  
121 with the recorded ADT in each surveyed location and the distance to the northernmost  
122 city (Capivari do Sul).

123 We used a land cover map from LANDSAT 5 TM images classification for 2009  
124 (UFRGS-IB-Centro de Ecologia, 2016) with eight classes: wetlands, native forest, dry  
125 grassland, water, pine plantation, rice plantation, urban areas and mixed areas (various  
126 crops, annual or perennial, and degraded grasslands). We calculated the area of each of  
127 the eight land cover classes within a 2-km buffer centered on each 2-km road segment.

128

### 129 **2.3. Data Analyses**

130 We assumed that collision risk is related to movement capacity, and grouped reptile  
131 species according to their behavioral responses to traffic volume for subsequent analyses  
132 (Jacobson et al., 2016). Freshwater turtles usually freeze on the road in response to vehicle  
133 presence ('pausers'), lizards usually flee ('speeders') and snakes usually do not respond  
134 to vehicles ('non-responders') or show responses as 'pausers' or 'speeders' (Jacobson et  
135 al., 2016). Therefore, we analyzed freshwater turtles, lizards, and snakes (we included  
136 amphisbaenians in snakes group) as separate groups.

#### 137 *2.3.1. Estimates of road-kill magnitude*

138 We estimated road-kill magnitude for all reptiles, freshwater turtles, lizards, and  
139 snakes through *Nestimate* function based on Korner-Nievergelt et al. (2011) using the  
140 *Carcass* package (Korner-Nievergelt et al., 2015) in R environment (R Core Team, 2016).  
141 This estimate considers the detection capacity of the method, carcass persistence on the  
142 road, number of surveys and survey interval. This method assumes that search intervals  
143 are regular and persistence probability and search efficiency are constant over time.  
144 Carcass persistence was estimated based on the exponential model (Korner-Nievergelt et  
145 al., 2011).

146 To assess carcass detection and persistence we performed experiments by placing 56  
147 carcasses of reptiles (five freshwater turtles and 51 snakes) previously collected on BR-  
148 101 road on a 30-km stretch of the same road. Detection was evaluated for six survey  
149 teams (each of them with two observers following the same method used in regular  
150 surveys) who monitored this 30-km stretch without knowing the location of carcasses.  
151 After all teams had surveyed the road, we checked every carcass placed and found that  
152 ten had been removed. Therefore, we considered 46 carcasses (four freshwater turtles and  
153 42 snakes) for evaluating the probability of detection of the method: 14 carcasses smaller  
154 than 15 cm, 27 from 15 to 35 cm, and five larger than 35 cm. To estimate carcass  
155 persistence, we used the total 56 carcasses, checking their persistence for five consecutive  
156 days. We used *search.efficiency* and *persistence.prob* functions from the *Carcass*  
157 package to calculate carcass detection and persistence separately for freshwater turtles  
158 and snakes. As we did not include lizard carcasses in our experiment, we used detection  
159 and persistence values from snake carcasses. We used carcass detection and persistence  
160 calculated considering all carcasses as values for reptiles.

161 2.3.2. *Road-kill hot moments*

162 We analyzed road-kill hot moments for freshwater turtles, lizards, and snakes using  
163 circular statistics in Oriana 4.02 software (Kovach, 2004) considering only data collected  
164 during the first two continuous years of surveys. Months were converted in angles (30-  
165 degree intervals) and the sum of road-kills in each month was used as a frequency for  
166 each angle. We then obtained the mean angle, which represents the average period with  
167 the highest number of fatalities within the whole period. We assessed the significance of  
168 the average period in relation to an uniform distribution of road-kills through the Rayleigh  
169 test of uniformity, Z (Kovach, 2004). Then, we calculated the intensity of road-kill  
170 concentration through the average period length (r), which varies from 0 (uniform  
171 dispersion) to 1 (road-kill concentration in the same direction).

### 172 2.3.3. *Road-kill hotspots*

173 We evaluated on which scales road-kill hotspots occurred for freshwater turtles,  
174 lizards, and snakes using Ripley's K statistic (Levine, 2000; Ripley, 1981) at a  
175 bidimensional space in Siriema v.2.0 software (Coelho et al., 2014). We used an initial  
176 radius of 300 m, a radius increase of 500 m, and 100 simulations of random distribution  
177 events to evaluate clustering significance (99% confidence interval). After the  
178 identification of the scales with road-kill hotspots, we performed a 2D HotSpot  
179 Identification analysis for recognizing where hotspots were located. We used a 1-km  
180 radius and divided the road into 138 segments of 2 km each. We chose this segment length  
181 because Ripley's K statistic identified the occurrence of clustering on that scale and  
182 because some mitigation measures for reptiles can be easily implemented targeting a 2-  
183 km road segment, as for example, a wildlife passage connected by funnel fencing (Baxter-  
184 Gilbert et al., 2015). We performed 1,000 simulations of random distribution to assess  
185 significance of hotspots locations (95% confidence interval). We considered as hotspots



186 all segments with a road-kill intensity value higher than the upper confidence limit  
187 (Coelho et al., 2014).

188 As many hotspots might be identified on a road and, in most cases, there are budget  
189 restrictions to mitigating all of them, we evaluated the relative contribution of mitigating  
190 hotspots. We calculated the potential reduction in road-kills in the case of mitigating each  
191 of the road segments identified as hotspots for at least one of the three reptile groups  
192 studied. We sorted hotspots by their intensity and we built a cumulative curve of the  
193 number of road-kills recorded at each hotspot location as a proxy of the potential gain  
194 obtained by mitigation.

#### 195 *2.3.4. Road-kill association with land cover and traffic volume*

196 To assess the relationship of road-kills of freshwater turtles, lizards and snakes with  
197 land cover classes and traffic volume, we fit generalized linear models with a Poisson  
198 distribution. We divided the road into 2-km segments, using the same segments from the  
199 2D HotSpot Identification analyses, and the number of road-kills in each segment was  
200 used as response variable. Predictive variables were standardized to have a mean of 0 and  
201 standard deviation equal to 1.

202 We used hierarchical partitioning (Mac Nally, 2002) to assess the influence of each  
203 predictive variable on the number of road-killed freshwater turtles, lizards, and snakes.  
204 Hierarchical partitioning uses models with all combinations of predictive variables to  
205 evaluate the independent (I) and joint (J) effect of each of them on the response variable.  
206 We tested the statistical significance of the contributions of independent variables using  
207 a randomization process (999 randomizations) based on a 95% upper confidence limit (Z-  
208 score > 1.96). This statistical analysis was conducted in R (R Core Team, 2016) with the  
209 *hier.part* package using log-likelihood as the goodness-of-fit measure (Walsh and Mac

210 Nally, 2013). Then, we assessed the explained deviance of each full model (for freshwater  
 211 turtles, lizards, and snakes) calculated as  $1 - (\text{residual deviance} / \text{total deviance})$ .

212

### 213 3. RESULTS

#### 214 3.1.1. Estimates of road-kill magnitude

215 We recorded 1,353 carcasses of reptiles on BR-101 road, 18% of which were  
 216 freshwater turtles belonging to four species, 11% were lizards (Argentine Black and  
 217 White Tegus, *Salvator merianae*), and 70% were snakes belonging to 24 species and one  
 218 amphisbaenian species (*Amphisbaena trachura*) (Table 1; Appendix B). We estimated  
 219 carcass detection as 55% (95% IC [26%, 82%]) for freshwater turtles and 23% (95% IC  
 220 [15%, 34%]) for snakes and lizards. Carcass persistence probability for freshwater turtles  
 221 was 0.85 in one day (95% IC [ 59%, 94%]) with a mean persistence time of six days.  
 222 Carcass persistence probability for snakes was 0.82 in one day (95% IC [76%, 87%]) with  
 223 a mean persistence time of 5.2 days. After correcting for carcass detection and removal,  
 224 we estimated a total of 42,287 road-killed reptiles during 33 months of survey (Table 1),  
 225 which corresponds to 15,377 road-killed reptiles per year (789 freshwater turtles, 1,600  
 226 lizards, and 10,206 snakes).

227

228 **Table 1.** Number of observed carcasses and estimates of road-kill magnitude for  
 229 freshwater turtles, lizards, and snakes during 33 months of surveys on BR-101 road.  
 230 Lower and upper 95% confidence limits are in parentheses.

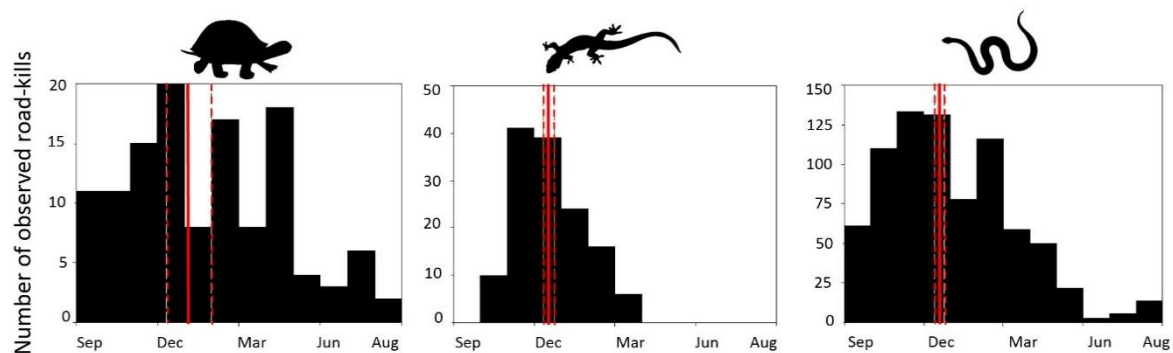
Groups	Observed carcasses	Estimates of road-kill magnitude	Estimates of magnitude per year	Estimates of magnitude per km per year
Freshwater turtles	245	2,170 (550 - 9,206)	789 (200 - 3,347)	2.8 (0.7 - 12.1)
Lizards	151	4,400 (2,545 - 7,671)	1,600 (925 - 2,768)	5.8 (3.3 - 10.8)

Groups	Observed carcasses	Estimates of road-kill magnitude	Estimates of magnitude per year	Estimates of magnitude per km per year
Snakes	957	28,069 (16,654 - 48,631)	10,206 (6,056 - 17,684)	36.9 (21.8 - 63.8)
<b>TOTAL</b>	<b>1,353</b>	<b>42,287</b> <b>(24,080 - 73,890)</b>	<b>15,377</b> <b>(8,756 - 26,869)</b>	<b>55.55</b> <b>(31.6 - 97.1)</b>

231

232 *3.2. Road-kill hot moments*

233 Fatalities of freshwater turtles were concentrated in January, while fatalities of lizards  
 234 and snakes were significantly concentrated in December (Fig.1). Freshwater turtles were  
 235 the group with the lowest road-kill concentration in time ( $r= 0.28$ ;  $Z=9.7$ ;  $p<0.001$ ),  
 236 followed by snakes with intermediate concentration values ( $r=0.47$ ;  $Z=176.7$ ;  $p<0.001$ ),  
 237 and lizards with the highest values ( $r = 0.80$ ;  $Z = 88.2$ ;  $p< 0.001$ ).



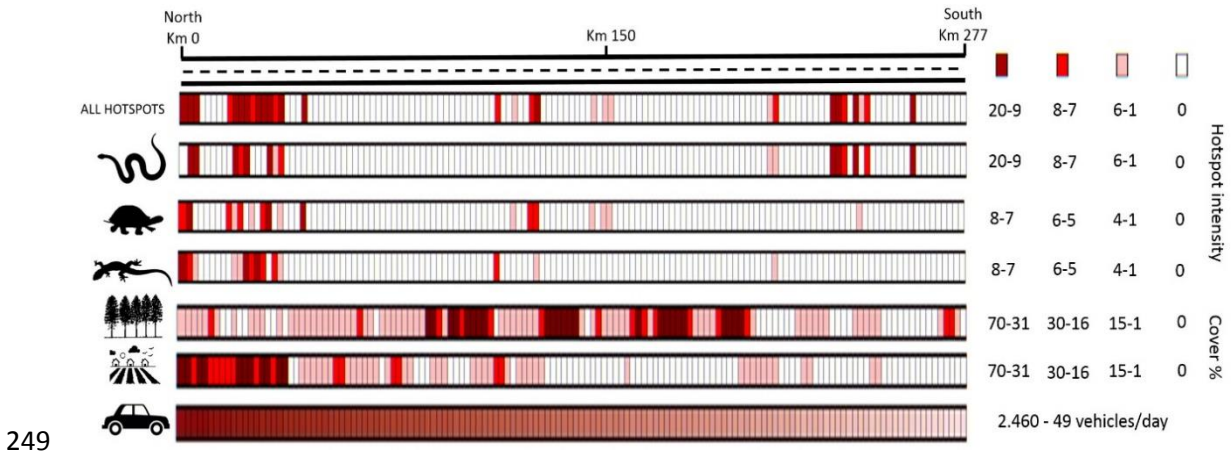
238

239 **Fig. 1.** Road-kill hot moments for freshwater turtles, lizards, and snakes during two years  
 240 of surveys (September 2012 to August 2014). Mean concentration period (full red lines)  
 241 and standard error (dashed red lines).

242 *3.3. Road-kill hotspots*

243 We found road-kill clustering from 300-m to 70-km scales for freshwater turtles,  
 244 from 300-m to 162-km scales for lizards, and from 300-m to 78-km scales for snakes  
 245 (Appendix C). 2D HotSpot Identification analyses indicated that most hotspots were

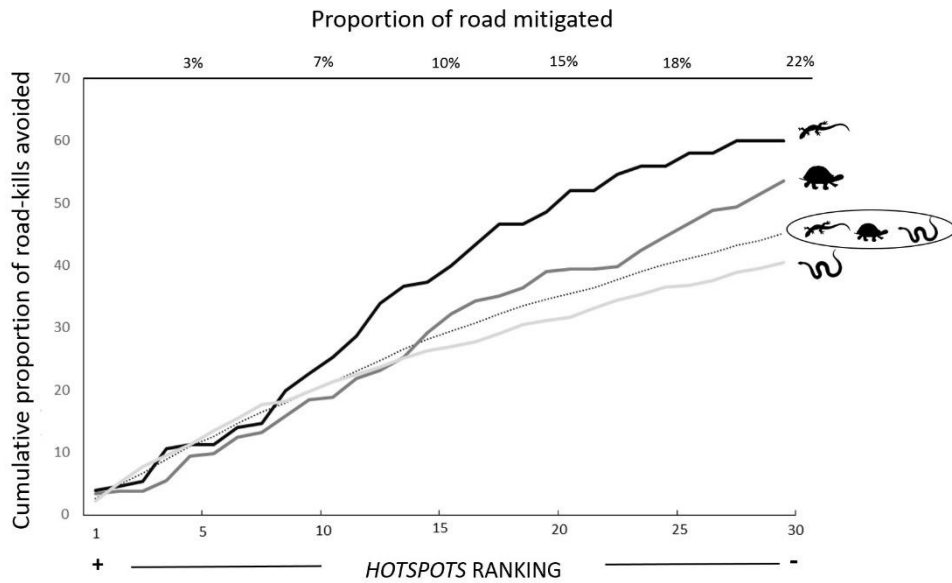
246 concentrated in the Northern portion of the road, the segment with the highest traffic  
 247 volume (Fig.2). For snakes, we also identified some hotspots also in the Southern part of  
 248 the road (Fig.2).



249  
 250 **Fig. 2.** Spatial distribution of hotspots (all reptile hotspots; snakes, freshwater turtles, and  
 251 lizards hotspots separately), percentage of pine plantations, rice plantations, and traffic  
 252 volume (ADT) along BR-101 road. Hotspot values correspond to road-kill intensity  
 253 values from 2D Hotspot Identification analyses. Each segment corresponds to the 2-km  
 254 road stretch used as sampling unit in the models.

255 When assessing road segments that were identified as hotspots for at least one of  
 256 the groups, and assuming the proposed mitigation would be 100% effective, we can infer  
 257 that 45% of reptile deaths could be avoided if 21.7% of the segments of the road (the 30  
 258 hotspot segments) had been mitigated (Fig. 3). That means a twofold efficiency in a cost-  
 259 benefit relationship (km mitigated/road-kills avoided). If we detail this potential reduction  
 260 by group, we would reach a 40% road-kill decrease for snakes, 53% for freshwater turtles  
 261 and 60% for lizards (Fig. 3), a 2-3 cost-benefit rate.

262



263

264 **Fig. 3.** Cumulative proportion of road-kills avoided for lizards, freshwater turtles, reptiles,  
 265 and snakes considering the implementation of 100% effective mitigation measures on  
 266 hotspots locations. Hotspots illustrated correspond to 21.7% of the road (upper x axis).  
 267 Hotspots were ranked in the lower x axis in decreasing order of aggregation intensity.

268

#### 3.4. Road-kill association with land cover and traffic volume

269

The amount of pine and rice plantations were the most important variables for  
 270 determining the fatalities of freshwater turtles, lizards, and snakes (Table 2). Road-kills  
 271 of freshwater turtles showed a significant positive relationship with rice plantations (I%  
 272 = 26.23), urban areas (I% = 11.77), and traffic volume (I% = 8.68), and a significant  
 273 negative relationship with pine plantations (I% = 34.07) and dry grasslands (I% = 8.95).  
 274 For lizards, we found a positive relationship with rice plantations (I% = 33.06) and traffic  
 275 volume (I% = 20.71), and a negative relationship with pine plantations (I% = 22.74).  
 276 Snake fatalities were positively related to rice plantations (I% = 22.7) and mixed areas  
 277 (I% = 8.59), and negatively related to rice plantations (I% = 45.75) and traffic volume  
 278 (I% = 8.59).

279 **Table 2.** Results of variables' associations from the hierarchical partition for each  
 280 group. 'Dev' is the percentage of explained deviance for models including all variables  
 281 in each reptile group. The sign of each variable is obtained from a Poisson regression  
 282 model and shows the relationship between each predictive variable and the response  
 283 variable. 'I' and 'J' are respectively the independent and joint contribution of each  
 284 variable for each reptile group. 'Total' is the sum of 'I' and 'J'. '%I' is the relative  
 285 percentage of independent contribution for each variable. 'Z score' is the randomization  
 286 test of the independent contributions for each predictive variable (\* identifies significant  
 287 variables).

	Freshwater turtles						Lizards						Snakes					
	Dev 39%	I	J	Total	%I	Z.score	Dev 44%	I	J	Total	%I	Z.score	Dev 44%	I	J	Total	%I	Z.score
Traffic volume	+	5.7	7.35	13.1	8.68	2.38*	+	12.9	20.1	33	20.7	6.6*	-	9.84	8.16	1.68	8.95	3.14*
Water	+	0.33	0.31	0.02	0.5	-0.53	-	1	0.62	1.62	1.61	-0.16	-	5.03	2.18	7.21	4.58	1.19
Urban area	+	7.73	5.09	12.8	11.8	3.84*	+	4.07	3.58	7.65	6.53	1.5	-	1.41	1.13	0.28	1.28	-0.16
Wetland	-	0.52	0.45	0.07	0.78	-0.46	-	1.82	3.44	5.26	2.92	0.33	+	1.86	0.75	2.61	1.69	-0.04
Native forest	+	2.52	2.47	0.04	3.83	0.71	-	2.21	4.89	7.1	3.54	0.48	+	4.57	2.39	6.96	4.16	1.04
Dry grassland	-	5.88	2.14	8.01	8.95	2.49*	-	2.59	3.78	6.37	4.16	0.79	+	2.54	0.54	3.08	2.31	0.23
Mixed area	+	3.41	2.38	1.03	5.2	1.28	+	2.95	2.12	0.82	4.73	0.92	+	9.44	2.36	7.08	8.59	2.94*
Rice plantation	+	17.2	14.6	31.8	26.2	8.58*	+	20.6	23	43.6	33.1	11.47*	+	25	6.09	18.9	22.7	9.01*
Pine plantation	-	22.4	10.5	32.9	34.1	11.95*	-	14.2	8.54	22.7	22.7	8.28*	-	50.3	27.2	77.5	45.8	21.12*

288

#### 289 4. DISCUSSION

290 We estimated that 55.55 reptiles are road-killed per kilometer per year (range: 31 -  
 291 97 reptiles/km/year), totaling more than 15 thousand road-killed animals every year on a  
 292 277-km segment of BR-101 road. The estimated road mortality magnitude obtained in  
 293 this study corresponds to 30 times the number of observed carcasses during the road  
 294 surveys, and exceeded the estimates of reptile road-kills on other roads, which did not  
 295 consider carcasses detection and removal (e.g. de Souza et al., 2015; Hartmann et al.,  
 296 2011; Pragatheesh and Rajvanshi, 2013). In a study conducted in the Brazilian Pantanal,  
 297 58 vertebrate road-kills were recorded per kilometer per year (de Souza et al., 2015), in  
 298 which mammals were the most representative group (61%) and reptiles corresponded  
 299 only to 13% of the total. This low reptile representation was also present in other studies

300 (e.g. Bager and Fontoura, 2013). However, it is important to point out that both the  
301 relative frequencies and the road-kill rates are underestimated, since carcass detectability  
302 is associated with body size (Teixeira et al., 2013a) and lower for reptiles when compared  
303 to mammals.

304 A high proportion of the reptile species known for the region is potentially affected  
305 by road-kill. We recorded 72% of the known reptile species pool from the entire coastal  
306 lowlands of Rio Grande do Sul (Borges-Martins et al., 2007) and other seven species that  
307 were not in their inventory (two freshwater turtles and five snakes). The higher number  
308 of snake species recorded as road-kill is in agreement with its higher richness for the  
309 region.

310 The occurrence of a large number of reptile road-kills depends on two factors: (1)  
311 availability (higher exposure) and (2) lethality (higher risk of running over). In the case  
312 of reptiles, higher exposure to roads may be explained by: higher abundance near roads,  
313 necrophagy, and the habit of thermoregulation. The abundance of individuals in habitats  
314 along road verges is the most important factor determining availability, but it is rarely  
315 estimated to allow comparison (Meek, 2015, 2009). Still, several species of lizards and  
316 snakes are active foragers that prefer open environments, increasing the chance of using  
317 roads or open vegetation adjacent to roads for foraging (Brehme et al., 2013; Meek, 2009)  
318 and turtle females may use road edges for nesting (Aresco, 2004; Dorland et al., 2014).  
319 Necrophagy is part of the dietary habit of the only species of lizard recorded (11% of all  
320 records) in our study (Kiefer and Sazima, 2002; Sazima and D'Angelo, 2013), and it has  
321 been documented for our most recorded snake species (*Philodryas patagoniensis*) as well  
322 (Ucha and Santos, 2017). When animals are attracted to roads to feed on road-kills, they  
323 expose themselves to the risk of collisions with vehicles. In addition, reptiles might  
324 increase their exposure when they thermoregulate, as it has been demonstrated that the

325 asphalt temperature is strongly related to the presence of snakes from different species on  
326 roads (Mccardle and Fontenot, 2016).

327 The second factor determining higher road-kill rates is lethality, which is related to  
328 traffic volume and, for the same traffic volume, to drivers' and animals' behaviors, as  
329 well as animal size and mobility. Road-kill rates are usually related to high or medium  
330 traffic volumes (Gunson et al., 2011), especially for species that do not avoid roads.  
331 Several studies demonstrated that drivers' intentional collision with snakes and turtles is  
332 higher than observed for control objects (Ashley et al., 2007; Beckmann and Shine, 2012;  
333 Langley et al., 1989; Secco et al., 2014), and higher for snakes than for freshwater turtles  
334 (Ashley et al., 2007). Crawford & Andrews (2016) demonstrated that drivers would be  
335 less upset (a proxy of intention or care by the authors' point of view) when they run over  
336 a snake than when they run over a turtle or a large mammal. Considering animal size,  
337 Whitaker & Shine (2000) suggested that snakes are a larger target for vehicle collisions  
338 because their body is longer in relation to other animals' when they cross the road  
339 perpendicularly. In relation to animal mobility, Andrews & Gibbons (2005) pointed out  
340 that some snakes and turtles have an immobilization behavior in response to vehicle  
341 approximation ('pausers' category in Jacobson et al., 2016) and could be an additional  
342 explanation for their higher road-kill rate together with their lower crossing speed.

343 Road-kill hot moments were concentrated mostly in summer months. This temporal  
344 pattern has been demonstrated in other studies for reptiles as a whole (Garriga et al.,  
345 2017), for freshwater turtles (Cureton II and Deaton, 2012), and for lizards (Meek, 2014).  
346 Hot moments have been shown to be related to climate variables, such as temperature and  
347 precipitation (Garriga et al., 2017), which influence the breeding season (Cureton II and  
348 Deaton, 2012), foraging (Meek, 2014), and species movement (Andrews and Gibbons,  
349 2005; Shine et al., 2004). Lizard from the only species recorded in our study (*Salvator*



350 *merianae*) are inactive almost half of the year (Borges-Martins et al., 2007), with the  
351 active period in the warm months, when they move to reproduce and to forage, increasing  
352 the probability of using roads. Temporal patterns of fatalities could differ among species  
353 (Mccardle and Fontenot, 2016; Meek, 2014), as well as among sex and age classes  
354 (Jochimsen et al., 2014), thus temporal patterns could be still more restrictive than  
355 observed because it is related to specific behavior characteristics, as thermal biology  
356 (Mccardle and Fontenot, 2016).

357 Road-kill hot moments can be used to plan the implementation of temporary  
358 structures such as directional fences, associated with specific wildlife underpasses for  
359 reptiles (Baxter-Gilbert et al., 2015; Markle et al., 2017). The implementation of temporal  
360 directional fences can be interesting due to their lower costs, even considering the costs  
361 of installation and maintenance. Whenever reptiles are the target group for mitigation, the  
362 existence of road-kill hot moments allows the concentration of field efforts to evaluate  
363 and monitor reptile road-kills during the period with higher fatality frequency. This would  
364 abbreviate decision-making and reduce associated costs.

365 Road-kill hotspots were predominantly coincident between freshwater turtles,  
366 lizards, and snakes, except for some aggregations of snake road-kills that were located in  
367 the southern portion of the road. The coincidence among hotspots for different groups  
368 allows mitigation strategies to be designed for the reptile group as a whole, always  
369 considering that mitigation measures must be effective in their implementation and  
370 operation, since small installation or maintenance failures can have great consequences  
371 on their effectiveness (Baxter-Gilbert et al., 2015). We hereby demonstrated that if  
372 effective mitigation measures were installed on top ranking hotspots, which represent a  
373 relatively small proportion of the road (21%), they could contribute to reduce observed  
374 fatalities in 45%. This twofold cost-benefit ratio was obtained assuming an absolute

375 effectiveness of mitigation that could be attained with well-planned passages associated  
376 to drift fences with recurrent maintenance (Jackson et al., 2015; Van der Ree and Tonjes,  
377 2015).

378 Under some circumstances, such as older roads, the use of hotspots for defining  
379 mitigation locations may not be the most adequate measure, as hotspots can change over  
380 time (as from high-traffic segments to low-traffic segments), as a consequence of  
381 population depletion by road mortality (Teixeira et al., 2017). However, this may not be  
382 the case for the road segment studied here, as its paving started in 1993 for the first 120  
383 km (near Mostardas city) and finished in 2009 for the entire 277-km segment (near São  
384 José do Norte city). Furthermore, we observed a positive relationship between fatalities  
385 and traffic volume (which decreases from north to south), except for snakes, the group  
386 with hotspots both at the northern and at the southern portions of the road.

387 The proportion of pine plantations was the most important land cover variable that  
388 influenced fatalities of freshwater turtles, lizards, and snakes, with a relatively strong  
389 negative effect. This negative relationship has already been highlighted for other wildlife  
390 groups, such as owls (Gomes et al., 2009). Moreover, the impoverishment of habitat and  
391 wildlife caused by exotic pine and/or eucalyptus plantations has been extensively  
392 documented, especially in grassland dominated landscapes (Berthrong et al., 2009;  
393 Brockerhoff et al., 2008; Corley et al., 2006). Even in forest environments, such as in the  
394 northeastern Brazilian Amazon, the richness of both amphibians and lizards was lower in  
395 eucalyptus plantations than in native primary and secondary forests (Gardner et al., 2007;  
396 Saccol et al., 2017). The presence of pine plantations is probably reducing the abundance  
397 and richness of reptiles in the areas surrounding the road, decreasing their availability to  
398 be road-killed.

399 Rice plantations coverage was already recognized as determinant for reptile hotspots  
400 (Grilo et al., 2016; Seo et al., 2015), as these human-modified environments provide  
401 refuge for some wetland species. Water bodies or wetlands at road margins are recognized  
402 as important features for determining road-kill aggregations, both for vertebrates in  
403 general (Freitas and Federal, 2015) and for freshwater turtles (Cureton II and Deaton,  
404 2012; Langen et al., 2012). However, we did not find a relationship between the  
405 percentage of water cover and fatalities, probably because the water category considered  
406 in our mapping represents only large water bodies (lakes and lagoons) and what probably  
407 matters to these animals are the wet areas close to the road, such as puddles and ditches.  
408 Not only the cover percentage, but also the distance to water bodies is important for turtles  
409 and can show a negative relationship with the presence of freshwater turtles hotspots  
410 (Langen et al., 2012). As expected, we found a negative relationship between dry  
411 grassland percentage and freshwater turtle fatalities.

412 For vertebrates in general (Seo et al., 2015), and especially for reptiles, traffic volume  
413 is widely recognized as responsible for fatality locations (see Cureton II & Deaton, 2012,  
414 and Langen et al., 2012 for freshwater turtles). Contrary to this pattern, we found a  
415 negative relationship between traffic volume and road-kill density for snakes. Some  
416 snakes may be avoiding to cross the road in areas where traffic volume is high (Siers et  
417 al., 2016) or some snake populations have already suffered a decline in these areas and  
418 have lower abundance, decreasing their interaction with the road (Teixeira et al., 2017).  
419 In addition, habitat quality in areas with lower traffic may be better (Shepard et al., 2008),  
420 allowing larger populations to thrive.

421 Regardless of the explanations for the occurrence of road-kills (single or multiple  
422 causes or even their interactions), road mortality for the different groups evaluated  
423 showed congruent spatial and temporal patterns. Considering this scenario, the best

424 strategy for an effective multispecific mitigation is to diminish the interaction between  
425 animals and the road or traffic, providing opportunities for safe crossings at each hotspot  
426 segment, associating multiple wildlife passages with directional fences specific for  
427 reptiles (Andrews et al., 2015; Jacobson et al., 2016; Markle et al., 2017). To reduce  
428 deterioration or even theft of fences, they could be installed temporarily only during  
429 summer months, although the cost-benefit of recurrent installation needs to be evaluated  
430 in comparison to permanent fences. Absolute exclusion of animals from the road should  
431 be followed by frequent maintenance inspections. Also, sufficient jump-out opportunities  
432 for animals that get stuck between fences should be provided as a complementary measure  
433 (van der Ree et al., 2015a). By adopting this set of relatively low-cost measures, we expect  
434 a significant reduction of the present-day carnage observed on this road.

435

## 436 **5. CONCLUSION**

437 Reptile fatalities in the Southern portion of BR-101 road were temporally and  
438 spatially aggregated, with hotspots and hot moments overlapping among different reptile  
439 groups. The high number of fatalities may be associated with the recent paving of this  
440 road (ended in 2009), which influenced traffic volume and vehicle speed. Since then,  
441 traffic volume has been rising and is predicted to further increase following higher human  
442 occupation in the region. When sorting hotspots by intensity of road-kill hotspots, we  
443 demonstrated a cost-benefit rate of mitigation (km mitigated/road-kills avoided) of 1:2  
444 for reptiles and even larger for single groups. By showing that areas of pine and rice  
445 plantations and that traffic volume were important for explaining reptile road-kills, we  
446 provided some clues for mitigation planning on roads in similar landscapes where road-  
447 kill data is not available, and indicated important variables for the development of  
448 predictive models.

449 **ACKNOWLEDGEMENTS**

450 We are grateful to Fernando Ascensão, Maria João Ramos Pereira, Murilo Guimarães,  
 451 and Nicole da Rosa for all their comments on the manuscript. To Taís de Fátima  
 452 Guimarães and Bruna Arbo Meneses for helping with land cover data. To all colleagues  
 453 that collaborated during field surveys. LOG would like to thank CAPES for her  
 454 scholarship (process n. 88881.132536/2016-01) FZT received a PNPd/CAPES  
 455 fellowship. VAGB received support from the TULIP Laboratory of Excellence (ANR-  
 456 10-LABX-41 and 394 ANR-11-IDEX-002-02) and from a Region Midi-Pyrenees project  
 457 (CNRS 121090).

458

459 **APPENDIX A.**

460 KML file with road track, hotspots intensity of freshwater turtles, lizards and snakes.

461 **APPENDIX B.**

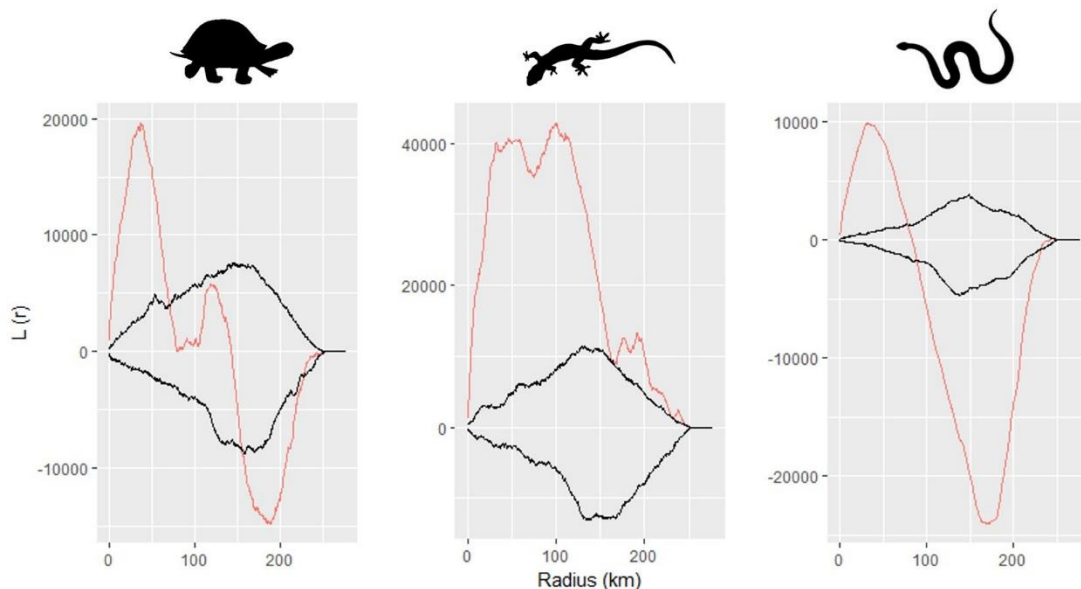
462 Species list (Scientific and common names) and number of observed carcasses during 33  
 463 months of monitoring in the road BR-101.

Scientific Name	Common Name	Observed carcass
<b>Freshwater Turtles</b>		<b>245</b>
<i>Trachemys dorbignii</i>	Black-bellied Slider	130
<i>Acanthochelys spixii</i>	Black Spine-necked Swamp Turtle	72
<i>Phrynops hilarii</i>	Hilaire's Side-necked Turtle	32
<i>Hydromedusa tectifera</i>	South-American Snake-headed Turtle	1
Unidentified freshwater turtles	-	10
<b>Lizards</b>		<b>-</b>
<i>Salvator merianae</i>	Argentine Black and White Tegu	151
<b>Snakes and Amphisbaenians</b>		<b>957</b>
<i>Philodryas patagoniensis</i>	Patagonia Green Racer	163
<i>Erythrolamprus poecilogyrus</i>	Yellow-bellied snake	147
<i>Helicops infrataeniatus</i>	Water snake	141
<i>Erythrolamprus semiaureus</i>	Water snake	114
<i>Thammodonastes hypoconia</i>	-	59
<i>Erythrolamprus jaegeri</i>	Jaeger's Ground Snake	48
<i>Xenodon dorbignyi</i>	South American Hognose Snake	37
<i>Boiruna maculata</i>	Mussurana	34

Cientific Name	Common Name	Observed carcass
<i>Oxyrhopus rhombifer</i>	Amazon False Coral Snake	31
<i>Philodryas aestiva</i>	Brazilian Green Racer	31
<i>Xenodon merremii</i>	Wagler's Snake	30
<i>Lygophis anomalus</i>	-	22
<i>Bothrops alternatus</i>	Urutu	13
<i>Mastigodryas bifossatus</i>	Rio Tropical Racer	12
<i>Philodryas olfersii</i>	Lichtenstein's Green Racer	9
<i>Bothrops pubescens</i>	Pampa's lancehead snake	7
<i>Lygophis flavifrenatus</i>	Fronted Ground Snake	5
<i>Erythrolamprus almadensis</i>	Almaden Ground Snake	4
<i>Sibynomorphus neuwiedi</i>	Neuwied's Tree Snake	4
<i>Atractus reticulatus</i>	Reticulate Ground Snake	2
<i>Phalotris lemniscatus</i>	Dumeril's Diadem Snake	3
<i>Chironius bicarinatus</i>	Two-headed Sipo	1
<i>Psomophis obtusus</i>	Wide Ground Snake	1
<i>Taeniophallus poecilopogon</i>	-	1
<i>Erythrolamprus sp.</i>	-	1
Unidentified snakes	-	24
<i>Amphisbaena sp.</i>	Blinded-snake	10
<i>Amphisbaena trachura</i>	Blinded-snake	2
Unidentified reptile	-	1
<b>TOTAL</b>		<b>1.353</b>

464

465 **APPENDIX C.**



466

467 **FigS1:** L statistic (K observed – K simulated mean; red lines) as a function of scale  
468 distance (radius) and 99% confidence limits (black lines) for the spatial distribution of  
469 road-kills of freshwater turtles, lizards and snakes on BR-101.

470

471 **REFERENCES**

- 472 Andrews, K.M., Gibbons, J.W., 2005. How Do Highways Influence Snake Movement?  
473 Behavioral Responses to Roads and Vehicles. *Copeia* 4, 772–782.  
474 doi:jstor.org/stable/4098651
- 475 Andrews, K.M., Langen, T.A., Struijk, R.P.J.H., 2015. Reptiles: overlooked but often at  
476 risk from roads, in: Van Der Ree, R., Smith, D.J., Grilo, C. (Eds.), *Handbook of*  
477 *Road Ecology*. Wiley-Blackwell, pp. 271–280.
- 478 Aresco, M.J., 2005. Mitigation measures to reduce highway mortality of turtles and  
479 other herpetofauna at a north Florida lake. *J. Wildl. Manage.* 69, 549–560.  
480 doi:https://doi.org/10.2193/0022-541X(2005)069[0549:MMTRHM]2.0.CO;2
- 481 Aresco, M.J., 2004. Reproductive Ecology of *Pseudemys floridana* and *Trachemys*  
482 *scripta* (Testudines: Emydidae) in Northwestern Florida. *J. Herpetol.* 38, 249–256.
- 483 Ashley, P.E., Kosloski, A., Petrie, S.A., 2007. Incidence of Intentional Vehicle–Reptile  
484 Collisions. *Hum. Dimens. Wildl.* 12, 137–143. doi:10.1080/10871200701322423
- 485 Bager, A., Fontoura, V., 2013. Evaluation of the effectiveness of a wildlife roadkill  
486 mitigation system in wetland habitat. *Ecol. Eng.* 53, 31–38.  
487 doi:10.1016/j.ecoleng.2013.01.006
- 488 Baxter-Gilbert, J.H., Riley, J.L., Lesbarrères, D., Litzgus, J.D., 2015. Mitigating Reptile  
489 Road Mortality: Fence Failures Compromise Ecopassage Effectiveness. *PLoS One*  
490 10, e0120537. doi:10.1371/journal.pone.0120537
- 491 Beaudry, F., deMaynadier, P.G., Hunter Jr., M.L., 2010. Identifying Hot Moments in  
492 Road-Mortality Risk for Freshwater Turtles. *J. Wildl. Manage.* 74, 152–159.  
493 doi:10.2193/2008-370
- 494 Beckmann, C., Shine, R., 2012. Do drivers intentionally target wildlife on roads?  
495 *Austral Ecol.* 37, 629–632. doi:10.1111/j.1442-9993.2011.02329.x
- 496 Berthrong, S.T., Schadt, C.W., Piñeiro, G., Jackson, R.B., 2009. Afforestation alters the  
497 composition of functional genes in soil and biogeochemical processes in South  
498 American grasslands. *Appl. Environ. Microbiol.* 75, 6240–6248.  
499 doi:10.1128/AEM.01126-09

- 500 Borges-Martins, M., Baptista, R., Oliveira, D., Anés, C., 2007. Répteis, in: Becker,  
501 F.G., Ramos, R.A., Moura, L. de A. (Eds.), Biodiversidade. Regiões Da Lagoa Do  
502 Casamento E Dos Butiazais de Tapes, Planície Costeira Do Rio Grande Do Sul.  
503 Ministério do Meio Ambiente, Brasília, pp. 293–315.
- 504 Brady, S.P., Richardson, J.L., 2017. Road ecology: shifting gears toward evolutionary  
505 perspectives. *Front. Ecol. Environ.* 15, 91–98. doi:10.1002/fee.1458
- 506 Brehme, C.S., Tracey, J. a, McClenaghan, L.R., Fisher, R.N., 2013. Permeability of  
507 roads to movement of scrubland lizards and small mammals. *Conserv. Biol.* 27,  
508 710–20. doi:10.1111/cobi.12081
- 509 Brockerhoff, E.G., Jactel, H., Parrotta, J.A., Quine, C.P., Sayer, J., 2008. Plantation  
510 forests and biodiversity: Oxymoron or opportunity? *Biodivers. Conserv.* 17, 925–  
511 951. doi:10.1007/s10531-008-9380-x
- 512 Coelho, A.V.P., Coelho, I.P., Teixeira, F.Z., Kindel, A., 2014. Siriema: road mortality  
513 software.
- 514 Corley, J., Sackmann, P., Rusch, V., Bettinelli, J., Paritsis, J., 2006. Effects of pine  
515 silviculture on the ant assemblages (Hymenoptera: Formicidae) of the Patagonian  
516 steppe. *For. Ecol. Manage.* 222, 162–166. doi:10.1016/j.foreco.2005.09.025
- 517 Crawford, B.A., Andrews, K.M., 2016. Drivers ’ attitudes toward wildlife-vehicle  
518 collisions with reptiles and other taxa. *Anim. Conserv.* 19, 444–450.  
519 doi:10.1111/acv.12261
- 520 Cureton II, J.C., Deaton, R., 2012. Hot Moments and Hot Spots: Identifying Factors  
521 Explaining Temporal and Spatial Variation in Turtle Road Mortality. *J. Wildl.*  
522 *Manage.* 76, 1047–1052. doi:10.1002/jwmg.320
- 523 D’Amico, M., Román, J., de los Reyes, L., Revilla, E., 2015. Vertebrate road-kill  
524 patterns in Mediterranean habitats: Who, when and where. *Biol. Conserv.* 191,  
525 234–242. doi:10.1016/j.biocon.2015.06.010
- 526 Danks, Z.D., Porter, W.F., 2010. Temporal, spatial, and landscape habitat characteristics  
527 of moose–vehicle collisions in western Maine. *J. Wildl. Manage.* 74, 1229–1241.  
528 doi:10.2193/2008-358
- 529 de Souza, J.C., da Cunha, V.P., Markwith, S.H., 2015. Spatiotemporal variation in



- 530 human-wildlife conflicts along highway BR-262 in the Brazilian Pantanal. *Wetl.*  
531 *Ecol. Manag.* 23, 227–239. doi:10.1007/s11273-014-9372-4
- 532 Dorland, A., Rytwinski, T., Fahrig, L., 2014. Do Roads Reduce Painted Turtle (*Chrysemys picta*) Populations? *PLoS One* 9, e98414.  
533 doi:10.1371/journal.pone.0098414
- 534
- 535 Fahrig, L., Rytwinski, T., 2009. Effects of Roads on Animal Abundance: an Empirical  
536 Review and Synthesis. *Ecol. Soc.* 14, 21.
- 537 Fitch, H.S., 1949. Road Counts of Snakes in Western Louisiana. *Herpetologica* 5, 87–  
538 90.
- 539 Forman, R.T., Sperling, D., Bissonette, J.A., Clevenger, A.P., Cutshall, C.D., Dale,  
540 V.H., Fahrig, L., France, R., Goldman, C.R., Heanue, K., Jones, J.A., Swanson,  
541 F.J., Turrentine, T., Winter, T.C., 2003. *Road Ecology: Science and Solutions*.  
542 Island Press, Washington DC.
- 543 Freitas, S.R., Federal, U., 2015. How landscape patterns influence road-kill of three  
544 species of mammals in the Brazilian Savanna? *Oecologia Aust.* 18, 35–45.  
545 doi:10.4257/oeco.2014.18.05
- 546 Gardner, T.A., Ribeiro-Júnior, M.A., Barlow, J., Ávila-Pires, T.C.S., Hoogmoed, M.S.,  
547 Peres, C.A., 2007. The value of primary, secondary, and plantation forests for a  
548 neotropical herpetofauna. *Conserv. Biol.* 21, 775–787. doi:10.1111/j.1523-  
549 1739.2007.00659.x
- 550 Garriga, N., Franch, M., Santos, X., Montori, A., Llorente, G.A., 2017. Seasonal  
551 variation in vertebrate traffic casualties and its implications for mitigation  
552 measures. *Landsc. Urban Plan.* 157, 36–44. doi:10.1016/j.landurbplan.2016.05.029
- 553 Gerow, K., Kline, N.C., Swann, D.E., Pokorny, M., 2010. Estimating annual vertebrate  
554 mortality on roads at Saguaro National Park, Arizona. *Human-Wildlife Interact.* 4,  
555 283–292.
- 556 Glista, D.J., DeVault, T.L., DeWoody, J.A., 2008. Vertebrate road mortality  
557 predominately impacts amphibians. *Herpetol. Conserv. Biol.* 3, 77–87.
- 558 Gomes, L., Grilo, C., Silva, C., Mira, A., 2009. Identification methods and deterministic  
559 factors of owl roadkill hotspot locations in Mediterranean landscapes. *Ecol. Res.*

- 560 24, 355–370. doi:10.1007/s11284-008-0515-z
- 561 Grilo, C., Cardoso, T. de R., Solar, R., Bager, A., 2016. Do the size and shape of spatial  
562 units jeopardize the road mortality-risk factors estimates ? *Nat. Conserv.* 14, 8–13.  
563 doi:http://dx.doi.org/10.1016/j.ncon.2016.01.001
- 564 Gunson, K.E., Mountrakis, G., Quackenbush, L.J., 2011. Spatial wildlife-vehicle  
565 collision models: a review of current work and its application to transportation  
566 mitigation projects. *J. Environ. Manage.* 92, 1074–82.  
567 doi:10.1016/j.jenvman.2010.11.027
- 568 Gunson, K.E., Teixeira, F.Z., 2015. Road – Wildlife Mitigation Planning Can Be  
569 Improved By Identifying the Patterns and Processes Associated With Wildlife-  
570 Vehicle Collisions, in: van der Ree, R., Smith, D.J., Grilo, C. (Eds.), *Handbook of*  
571 *Road Ecology*. pp. 101–109. doi:10.1002/9781118568170.ch13
- 572 Hartmann, P.A., Hartmann, M.T., Martins, M., 2011. Snake Road Mortality in a  
573 Protected Area in the Atlantic Forest of Southeastern Brazil. *South Am. J.*  
574 *Herpetol.* 6, 35–42. doi:10.2994/057.006.0105
- 575 Huijser, M.P., Duffield, J.W., Clevenger, A.P., Ament, R.J., McGowen, P.T., 2009.  
576 Cost-benefit analyses of mitigation measures aimed at reducing collisions with  
577 large ungulates in the united states and canada: A decision support tool. *Ecol. Soc.*  
578 14. doi:10.1016/j.contraception.2009.11.002
- 579 Jackson, N.D., Fahrig, L., 2011. Relative effects of road mortality and decreased  
580 connectivity on population genetic diversity. *Biol. Conserv.* 144, 3143–3148.  
581 doi:10.1016/j.biocon.2011.09.010
- 582 Jackson, S.D., Smith, D.J., Gunson, K.E., 2015. Mitigating Road Effects on Small  
583 Animals, in: Andrews, K.M., Nanjappa, P., Riley, S.P.D. (Eds.), *Road and*  
584 *Ecological Infrastructure: Concepts and Applications for Small Animals*. Johns  
585 Hopkins University Press, Baltimore, pp. 177–207.
- 586 Jacobson, S.L., Bliss-ketchum, L.L., Rivera, C.E. De, Smith, W.P., 2016. A behavior-  
587 based framework for assessing barrier effects to wildlife from vehicle traffic  
588 volume. *Ecosphere* 7, 1–15. doi:10.1002/ecs2.1345
- 589 Jaeger, J.A.G., Fahrig, L., 2004. Effects of Road Fencing on Population Persistence.

590 Conserv. Biol. 18, 1651–1657. doi:10.1111/j.1523-1739.2004.00304.x

591 Jochimsen, D.M., Peterson, C.R., Harmon, L.J., 2014. Influence of ecology and  
592 landscape on snake road mortality in a sagebrush-steppe ecosystem. Anim.  
593 Conserv. 17, 583–592. doi:10.1111/acv.12125

594 Kiefer, M.C., Sazima, I., 2002. Diet of juvenile tegu lizard *Tupinambis merianae*  
595 (*Teiidae*) in southeastern Brazil. *Amphibia-Reptilia* 23, 105–108.

596 Korner-Nievergelt, F., Behr, O., Brinkmann, R., Etterson, M.A., Huso, M.M.P.,  
597 Dalthorp, D., Korner-Nievergelt, P., Roth, T., Niermann, I., 2015. Mortality  
598 estimation from carcass searches using the R-package *carcass* — a tutorial.  
599 *Wildlife Biol.* 21, 30–43. doi:10.2981/wlb.00094

600 Korner-Nievergelt, F., Korner-Nievergelt, P., Behr, O., Niermann, I., Brinkmann, R.,  
601 Hellriegel, B., 2011. A new method to determine bird and bat fatality at wind  
602 energy turbines from carcass searches. *Wildlife Biol.* 17, 350–363. doi:10.2981/10-  
603 121

604 Kovach, W.L., 2004. *Oriana for Windows*.

605 Langen, T.A., Gunson, K.E., Scheiner, C. a, Boulerice, J.T., 2012. Road mortality in  
606 freshwater turtles: identifying causes of spatial patterns to optimize road planning  
607 and mitigation. *Biodivers. Conserv.* 21, 3017–3034. doi:10.1007/s10531-012-  
608 0352-9

609 Langen, T.A., Ogden, K.M., Schwarting, L.L., 2009. Predicting hot spots of  
610 herpetofauna road mortality along highway networks. *J. Wildl. Manage.* 73, 104–  
611 114. doi:10.2193/2008-017

612 Langley, W.M., Lipps, H.W., Theis, J.F., 1989. Responses of Kansas Motorists to  
613 Snake Models on a Rural Highway. *Trans. Kansas Acad. Sci.* 92, 43.  
614 doi:10.2307/3628188

615 Levine, N., 2000. *CrimeStat: A Spatial Statistics Program for the Analysis of Crime*  
616 *Incident Locations*.

617 Lima, S.L., Blackwell, B.F., Devault, T.L., Fernández-Juricic, E., 2014. Animal  
618 reactions to oncoming vehicles: a conceptual review. *Biol. Rev. Camb. Philos. Soc.*  
619 90, 60–76. doi:10.1111/brv.12093

620 Mac Nally, R., 2002. Multiple regression and inference in ecology and conservation  
621 biology : further comments on identifying important predictor variables. *Biodivers.*  
622 *Conserv.* 11, 1397–1401. doi:10.1023/A:1016250716679

623 Markle, C.E., Gillingwater, S.D., Levick, R., Chow-Fraser, P., 2017. The True Cost of  
624 Partial Fencing: Evaluating Strategies to Reduce Reptile Road Mortality. *Wildl.*  
625 *Soc. Bull.* 1–9. doi:10.1002/wsb.767

626 Mccardle, L.D., Fontenot, C.L., 2016. The influence of thermal biology on road  
627 mortality risk in snakes. *J. Therm. Biol.* 56, 39–49.  
628 doi:10.1016/j.jtherbio.2015.12.004

629 Meek, R., 2015. Where do snakes cross roads? Habitat associated road crossings and  
630 mortalities in a fragmented landscape in western France. *Herpetol. J.* 25, 15–19.

631 Meek, R., 2014. Temporal distributions, habitat associations and behaviour of the green  
632 lizard (*Lacerta bilineata*) and wall lizard (*Podarcis muralis*) on roads in a  
633 fragmented landscape in Western France. *Acta Herpetol.* 9, 179–186.  
634 doi:10.13128/Acta

635 Meek, R., 2009. Patterns of reptile road-kills in the Vendée region of western France of  
636 western France. *Herpetol. J.* 19, 135–142.

637 Pragatheesh, A., Rajvanshi, A., 2013. Spatial patterns and factors influencing the  
638 mortality of snakes on the national highway-7 along Pench Tiger Reserve, Madhya  
639 Pradesh, India. *Oecologia Aust.* 17, 20–35.

640 R Core Team, 2016. R: A language and environment for statistical computing. R  
641 Foundation for Statistical Computing, Vienna, Austria.

642 Ramsar Convention, 1962. Sites & Countries. <http://www.ramsar.org/sites-countries>  
643 (accessed 20.06.17).

644 Ripley, B.D., 1981. *Spatial Statistics*. John Wiley & Sons, New York.

645 Saccol, S. da S.A., Bolzan, A.M.R., Santos, T.G. dos, 2017. In the Shadow of Trees:  
646 Does Eucalyptus Afforestation Reduce Herpetofaunal Diversity in Southern  
647 Brazil? *South Am. J. Herpetol.* 12, 42–56.

648 Santos, S.M., Carvalho, F., Mira, A., 2011. How long do the dead survive on the road?

- 649 Carcass persistence probability and implications for road-kill monitoring surveys.  
650 PLoS One 6, e25383. doi:10.1371/journal.pone.0025383
- 651 Sazima, I., D'Angelo, G.B., 2013. Range of animal food types recorded for the tegu  
652 lizard (*Salvator merianae*) at an urban park in South-eastern Brazil. *Herpetol.*  
653 *Notes* 6, 427–430.
- 654 Secco, H., Ratton, P., Castro, E., Silva, P., Bager, A., 2014. Intentional snake road-kill :  
655 a case study using fake snakes on a Brazilian road. *Trop. Conserv. Sci.* 7, 561–571.
- 656 Seo, C., Thorne, J.H., Choi, T., Kwon, H., Park, C.-H., 2015. Disentangling roadkill :  
657 the influence of landscape and season on cumulative vertebrate mortality in South  
658 Korea. *Landsc. Ecol. Eng. Engine* 11, 87–99. doi:10.1007/s11355-013-0239-2
- 659 Shepard, D.B., Dreslik, M.J., Jellen, B.C., Christopher, A., 2008. Reptile Road  
660 Mortality around an Oasis in the Illinois Corn Desert with Emphasis on the  
661 Endangered Eastern Massasauga. *Copeia* 2, 350–359. doi:10.1643/CE-06-276
- 662 Shine, R., Lemaster, M., Wall, M., Langkilde, T., Mason, R., 2004. Why Did the Snake  
663 Cross the Road? Effects of Roads on Movement and Location of Mates by Garter  
664 Snakes (*Thamnophis Sirtalis Parietalis*). *Ecol. Soc.* 9, 9.
- 665 Siers, S.R., Reed, R.N., Savidge, J.A., 2016. To cross or not to cross : modeling wildlife  
666 road crossings as a binary response variable with contextual predictors. *Ecosphere*  
667 7, 1–19. doi:10.1002/ecs2.1292
- 668 Teixeira, F.Z., Coelho, A.V.P., Esperandio, I.B., Kindel, A., 2013a. Vertebrate road  
669 mortality estimates: Effects of sampling methods and carcass removal. *Biol.*  
670 *Conserv.* 157, 317–323. doi:10.1016/j.biocon.2012.09.006
- 671 Teixeira, F.Z., Coelho, I.P., Esperandio, I.B., Oliveira, N.R., Porto, F., Dornelles, S.S.,  
672 Delazeri, N.R., Tavares, M., Martins, M.B., Kindel, A., 2013b. Are road-kill  
673 hotspots coincident among different vertebrate groups? *Oecologia Aust.* 17, 36–47.
- 674 Teixeira, F.Z., Kindel, A., Hartz, S.M., Mitchell, S., Fahrig, L., 2017. When road-kill  
675 hotspots do not indicate the best sites for road-kill mitigation. *J. Appl. Ecol.*  
676 doi:10.1111/1365-2664.12870
- 677 Ucha, J., Santos, T.G., 2017. Death and life on the roadway: scavenging behaviour of  
678 the green racer snake *Philodryas patagoniensis* (Girard, 1858) (Dipsadidae).

- 679 Herpetol. Notes 10, 439–441.
- 680 UFRGS-IB-Centro de Ecologia, 2016. Mapeamento da cobertura vegetal do Bioma  
681 Pampa: Ano-base 2009. <https://www.ufrgs.br/labgeo/index.php/dados-espaciais>.
- 682 van der Ree, R., Gagnon, J.W., Smith, D.J., 2015a. Fencing: a valuable tool for  
683 reducing wildlife-vehicle collisions and funneling fauna to crossing structures, in:  
684 van der Ree, R., Smith, D.J., Grilo, C. (Eds.), Handbook of Road Ecology. Wiley-  
685 Blackwell, pp. 159–171.
- 686 van der Ree, R., Smith, D.J., Grilo, C., 2015b. Handbook of Road Ecology. Wiley-  
687 Blackwell.
- 688 Van der Ree, R., Tonjes, S., 2015. How to Maintain Safe and Effective Mitigation  
689 Measures, in: van der Ree, R., Smith, D.J., Grilo, C. (Eds.), Handbook of Road  
690 Ecology. Wiley-Blackwell, pp. 138–142.
- 691 Walsh, A.C., Mac Nally, R., 2013. hier.part: Hierarchical Partitioning. R package  
692 version 1.0-4.
- 693 Whitaker, P.B., Shine, R., 2000. Sources of Mortality of Large Elapid Snakes in an  
694 Agricultural Landscape. *J. Herpetol.* 34, 121. doi:10.2307/1565247

**As probabilidades de travessia e colisão predizem as fatalidades de  
fauna em rodovias?**

Este capítulo será submetido como research paper para a revista Conservation Biology e está formatado conforme as normas da revista. Ele foi feito em colaboração com Bruna Arbo Meneses e Casey Visintin.

1 **Do crossing and collision probabilities predict wildlife fatalities on roads?**

2

3 **Abstract**

4 Predicting road-kills is one of the most urgent task in a context of new roads and road  
5 expansion, when there are no road-kill data. We aimed to test if the integration of two  
6 probabilities (crossing and collision) improves the prediction of wildlife fatality  
7 probability on roads. By using connectivity maps based on resistance surfaces as proxy  
8 of animal crossing probability and multiplying these values with collision probability  
9 based on traffic volume, vehicle and animal speed, vehicle width, and animal body size,  
10 we predicted fatality risk at a single road level for two small carnivore species (Lesser  
11 Grison and Molina's Hog-nosed Skunk). To validate the performance of the models, we  
12 used a road for which we had available road-kill data. Additionally, we compared the  
13 mitigation priority locations from our predictive models with the priority locations  
14 obtained from a road-kill hotspot analysis. We found that multiplicative integration of  
15 probabilities was not good to predict road-kills, and collision probability alone was better  
16 than crossing probability, at least for the Lesser Grison. Although the mitigation outcome  
17 of collision models was lower than hotspots, at least for the Lesser Grison, with a target  
18 of almost 10% of mitigated road, around 70% of road-kills of that species would be  
19 avoided, evidencing that the approach is a good alternative in a decision-making context.

20

21 **Key-words:** Road-kill, Connectivity, Traffic volume, Road mortality, Mitigation

22

23 **Introduction**

24 Reducing the direct impacts of roads on biodiversity is one of the most concerning issues  
25 in conservation biology research (van der Ree et al. 2015c). Among them, mortality by



26 vehicle-animal collisions could have severe outcomes on some animal populations  
27 (Rytwinski & Fahrig 2011; Jackson & Fahrig 2011). Several kinds of mitigation measures  
28 and actions aim to minimise this mortality (Smith et al. 2015; van der Ree et al. 2015a).  
29 Some mitigation measures are focused on changing driver behavior, such as signs or  
30 speed controls (Huijser et al. 2015), whilst others focus on changing animal movement,  
31 e.g. wildlife crossing structures and fencing (Smith et al. 2015; van der Ree et al. 2015a).  
32 In common, the success of all those actions depends directly on choosing suitable  
33 locations to mitigate.

34 Mitigation location planning is a challenging task and most appropriate approaches are  
35 context dependent. Mostly, extensive road networks were implemented before  
36 environmental licensing emerged, so there is an important demand on road retrofitting for  
37 mortality mitigation and defragmentation (van der Grift 2005; Trocmé 2006; Gurrutxaga  
38 & Saura 2013). Further, developing countries are promoting a considerable road network  
39 expansion, with millions of kilometers being built and planned over the next half-century  
40 (Laurance et al. 2015). For retrofitting existing roads, it is possible to plan mitigation  
41 measures based on observational studies of road-kills or connectivity, however, this is  
42 only achievable at a single (or few) road segment level and not at an entire road network  
43 level, as often required. Regarding new roads, observational studies are not feasible at all.  
44 In both contexts the main challenge is to predict wildlife road fatalities without road-kill  
45 data.

46 The risk of a road-kill event can be expressed as the spatial and temporal coincidence of  
47 an animal being on a given road section (exposure risk) and a moving vehicle (hazard)  
48 (Visintin et al. 2016). Exposure risk or hereafter crossing probability is given by the  
49 probability of an animal to cross a road at a specific location, which is related to road and  
50 landscape configuration and to animal occurrence and movement (Lewis et al. 2011; Grilo

51 et al. 2011, 2018; Gurrutxaga & Saura 2013; Thurfjell et al. 2015). Hazard, or collision  
52 probability hereafter, can be dependent on animal attributes (body length and road  
53 crossing speed) and road features including traffic volume, vehicle speed and road width  
54 (Hels & Buchwald 2001; van Langevelde & Jaarsma 2004; Jaarsma et al. 2006).

55 Until recently, few studies addressed the integration of crossing probability and collision  
56 probability to predict fatality risk in a single model (Jaarsma et al., 2007; Patrick et al.,  
57 2012; Visintin et al., 2017, 2016). These studies differed mainly in the ways crossing  
58 probability was assessed: as a result of occurrence likelihood (e.g. Visintin et al. 2016) or  
59 using movement simulations (e.g. Jaarsma et al., 2007). Yet only Visintin et al. (2017,  
60 2016) and Patrick et al. (2012) validated model performances.

61 Our study aimed to evaluate if the integration of these two probabilities (crossing and  
62 collision) allows for the prediction of wildlife fatality probability on roads better than  
63 sub-models of each probability. We first used connectivity maps based on resistance  
64 surfaces as proxy of animal crossing probability and calculated collision probability based  
65 on traffic volume, vehicle and animal speed, vehicle width, and animal body size. Then,  
66 we multiplied crossing and collision probabilities to predict fatality risk at a single road  
67 level for two small carnivore species. We also tested univariate and bivariate models  
68 using both probabilities. To validate the model predictive performance, we used a road as  
69 a model system and two species for which we had available road-kill data. To test our  
70 model when translated into recommendations for mitigation location in a decision-  
71 making context, we used a simple cost-benefit analysis, which cost is represented by the  
72 proportion of the road that is mitigated and benefit corresponds to the proportion of  
73 avoided fatalities, assuming a perfect effectiveness of the hypothetical mitigation.

74 Additionally, we compared the cost-benefit ratio of our predictive model to a  
75 conventional hotspot approach, using the same data set.

76

77 **Methods:**

78 *Target Road and Species*

79 Our study site was a 277-km road (BR-101; initial coordinates 30°9'1.20"S and  
80 50°30'49.33"W, and final coordinates 32°0'23.64"S and 52°2'17.73"W, Appendix A) at  
81 southernmost Brazil. Our target species were Lesser Grison (*Galictis cuja*) and Molina's  
82 Hog-nosed Skunk (*Conepatus chinga*), two small carnivores, and we assumed that these  
83 two species do not avoid crossing the road. The Lesser Grison is a mid-sized mustelid  
84 (1.2–2.5 kg) of southern South America (Yensen & Tarifa 2003) and the Molina's Hog-  
85 nosed Skunk, a 2kg mephitid, is distributed from mid-northern Argentina and Chile to  
86 Bolivia, Paraguay, Uruguay and southern Brazil (Bornholdt et al. 2013). We divided the  
87 road into equally sized segments and obtained the crossing probability and the collision  
88 probability for each road segment for each species. To test for scale (grain size)  
89 dependency this procedure was repeated for multiple segment lengths: 1000 m, 500 m,  
90 and 275 m.

91

92 *Crossing probability*

93 Crossing probability for each road segment was obtained from maps that represent the  
94 expected connectivity between source patches for each species given the assigned  
95 resistance of surrounding land cover classes to their movement. To develop a resistance  
96 surface, we used a land cover map classified from 2009 LANDSAT 5 TM images  
97 (UFRGS-IB-Centro de Ecologia 2016) with 17 land cover/use classes: water, wetland,  
98 native forest (divided in size: < 1 ha, 1-10 ha, 11-100 ha, and > 100 ha), silviculture, rice  
99 monoculture, dry agriculture, outcrop, wet grassland, degraded grassland, dry grassland,  
100 urban area, mining, sand, and mixed areas. Mixed areas included multiple crops, annual

101 or perennial. We queried experts on the natural history/ecology of the target species to  
102 help determine movement resistance values for each land cover class. We used the  
103 Analytic Hierarchy Process (Saaty 1987) by which experts make decisions using a series  
104 of pairwise comparisons among cover classes (see details in Appendix B). We checked  
105 the consistency of each expert's resistance assignment and used only assignments with a  
106 ratio between consistency index and random index lower than 0.1 (Saaty 1987).

107 We used native grassland remnants in a 25-km buffer surrounding the target road as  
108 source patches. This procedure was done in two scenarios: 1) using all grassland remnants  
109 (n=125) and 2) using only patches larger than 1 km<sup>2</sup> (n=74). In the second scenario, we  
110 assumed that areas smaller than 1 km<sup>2</sup> are less important as source patches due to limited  
111 resource quality and/or limited population density. This option is supported by a study in  
112 southern Brazil that estimated the average home-range for 12 Molina's Hog-nosed Skunk  
113 as 1.63 km<sup>2</sup> (Kasper et al. 2012).

114 We used connectivity maps based on circuit-theory and least-cost path to calculate  
115 crossing probability for each species at each road segment. We built the connectivity  
116 maps using circuit-theory in Gflow software (Leonard et al. 2017) and using least-cost  
117 corridor in Linkage Mapper (McRae & Kavanagh 2011). Circuit theory-based  
118 connectivity is modelled by assigning to each pixel in a landscape matrix a resistance  
119 value indicating the degree of landscape permeability for the electrons flow (or animals  
120 by analogy) (Leonard et al. 2017). Landscapes are represented as conductive surfaces,  
121 with low resistances assigned to landscape features that are most permeable to movement,  
122 and high resistances assigned to movement barriers (McRae et al. 2013). In the circuit-  
123 theory approach we used different criteria for the convergence factor, that is, a correlation  
124 factor of the current density between pairs of source patches (it defines the number of  
125 decimal places for the correlation threshold among intermediate connectivity maps; 1N

126 corresponds to 0.9 and 4N correspond to 0.9999), and compared the results. The output  
 127 of each circuit-theory model was a map with cell values that represented the total number  
 128 of potential crossings (in amperes) between all pairwise source patches. We rescaled the  
 129 cell values from 0 to 1 and sampled the mean value of all cells that intersected each road  
 130 segment as the crossing probability.

131 For the second approach, we used normalized least-cost corridor distance which is the  
 132 summation of cost-weighted distance rasters calculated from each pair of connected  
 133 source patches. We rescaled the least-cost corridor distance values from 0 to 1 and  
 134 inverted them as cells with small distances represent high crossing probabilities. For each  
 135 species, we obtained four maps in Gflow software (both source patches scenarios and two  
 136 convergence factors) and two maps in Linkage Mapper (both source patches scenarios).  
 137 The maps were named based on the software used, source patch criteria and convergence  
 138 factor (Gflow only) (Table 1). In the final models, we only used the maps with the best  
 139 road-kill predictive performance for the species (further described in the Validation  
 140 section). We did not use the Gflow connectivity map which considered source patches  
 141 larger than 1 km<sup>2</sup> and a convergence factor of 4N because it was highly correlated with  
 142 the one using a convergence factor of 1N (Pearson correlation of 0.85).

143

144 **Table 1.** Nomination of each crossing model according to adopted connectivity measure  
 145 approach (software) and other criteria.

<b>Model name</b>	<b>Software</b>	<b>Source patch inclusion criteria</b>	<b>Convergence factor</b>
G-All-1	Gflow	all habitat areas (n=125)	1N
G-All-4	Gflow	all habitat areas (n=125)	4N
G-1	Gflow	habitat areas $\geq$ 1km <sup>2</sup>	1N
L-All	Linkage Mapper	all habitat areas (n=125)	Not applicable

146

147 *Collision probability*

148 For the collision probability at each road segment, we used the traffic volume, vehicle  
 149 speed, animal speed, animal length, vehicle width, and road width following Hels &  
 150 Buchwald (2001) and Jaarsma et al. (2006). We used the equation:  $1 - \exp(-N \cdot (a/v))$ , where  
 151 N is traffic volume; “a” is a kill zone (vehicle width + animal length \*2 if a two-lane  
 152 road), and “v” is the animal speed. We used vehicle counters (Vehicle Counter Generation  
 153 III - TRAFx Research Ltd.) to calculate the average daily traffic (ADT) in three locations  
 154 linking the main regional settlements: Capivari do Sul (n=48 days), Mostardas (n=273  
 155 days), and São José do Norte (n=498 days) along BR 101. Since we found a north-to-  
 156 south decrease pattern in traffic volume, we extrapolated traffic volume for each road  
 157 segment by performing a linear regression with the recorded ADT at each surveyed  
 158 location and the distance to the northernmost city (Capivari do Sul). We used a mean  
 159 vehicle width of 1.8 m that represented a small automobile, the most common vehicle on  
 160 this road. For Molina's Hog-nosed Skunk, we used a body length of 0.40 m (Kasper et al.  
 161 2011) and we used half of the fastest recorded speed (116 m/min) for a similarly sized  
 162 and related species (*Mephitis mephitis*) (Hirt et al. 2017). We also tested collision  
 163 probability using 25% of the maximum recorded speed as suggested by Jaarsma et al.  
 164 (2006), however, it was highly correlated to the collision probability using the half speed.  
 165 For Lesser Grison, we used a body length of 0.42 m (Jones et al. 2009) and a recorded  
 166 speed for related species (*Martes foina*) which was 100 m/min (Posillico et al. 1995).

167

168 *Fatality probability and Validation*

169 We multiplied crossing probability and collision probability to obtain a fatality  
170 probability for each road segment. To test the predictive performance of the models, we  
171 used 64 road-kills of Lesser Grison and 159 road-kills of Molina's Hog-nosed Skunk from  
172 a road-kill survey carried out on the same road (Appendix A). The data set was obtained  
173 based on monthly surveys conducted from September 2012 to August 2014, and from  
174 February to October 2015, totaling 33 surveys. Two observers (including the driver)  
175 conducted surveys by car at 40-50 km/h from dawn to dusk. We fitted four Poisson  
176 models to the data using the number of observed road-kills on each segment for each  
177 species: crossing model, collision model, fatality model and crossing and collision in the  
178 same model (bivariate). For the crossing model, we selected one map among the five  
179 connectivity outcomes based on their predictive performance (Table 2).

180 We cross-validated the models by randomly splitting the data into 10 folds (nine subsets  
181 used for training the model and one for testing the model fit). We repeated this procedure  
182 100 times for each model. We obtained the mean absolute error (MAE) to assess the  
183 model predictions (Willmott & Matsuura 2005; Chai & Draxler 2014). MAE varies  
184 between zero and the highest observed number for each sampling unit (Lesser Grison -  
185 six road-kills for 1 km road length and four for 500 m and 275 m lengths; Molina's Hog-  
186 nosed Skunk - six road-kills for 1 km and 500 m road length and four for 275 m). We also  
187 compared the Akaike information criterion (AIC) of each model for each species. We  
188 performed these analyses by using the *train* function in the *caret* package (Kuhn 2008) in  
189 the R environment (R Core Team 2017).

190

#### 191 *Decision support outcome of models*

192 We simulated a mitigation planning scenario and compared the performance of different  
193 models using a cost-benefit approach similar to that previously used by Ascensão et al.

194 (2017) and Gonçalves et al. (2018). For multiple road segment sizes (1000, 500 and 275  
195 meters) and for multiple thresholds of percentage of road mitigated (cost proxy), we  
196 estimated how many fatalities (% of observed carcasses) of each species would be  
197 avoided (benefit proxy). We assumed that mitigation would be 100% effective. For each  
198 segment size, the first cost threshold was defined using the number of segments  
199 prioritized by a hotspot analysis (see below). The following thresholds were arbitrarily  
200 defined as 2 and 3 times the number of segments of the first one. For each model, we  
201 selected the segments with the largest predicted probabilities until the target threshold  
202 cost was achieved.

203 Hotspot number and location was obtained in a two-step analysis. Firstly, we  
204 checked if road-kill aggregation is significant at the selected segment lengths (1000, 500  
205 and 275 m) with Ripley's K statistics (Ripley 1981). We then performed a 2D HotSpot  
206 Identification analyses using half of the segment length as the radius and 1000  
207 simulations. We considered as hotspots all segments with a road-kill intensity value  
208 higher than the upper confidence limit of 95% (Coelho et al., 2014). For both analyses  
209 we used Siriema software (Coelho et al. 2014).

210

## 211 **Results**

212

213 Different crossing models were selected for the two species (Table 2). The circuit-theory  
214 approach using areas larger than 1 km<sup>2</sup> as source patches was the best connectivity map  
215 for the Lesser Grison (Table 2) whereas least-cost corridor using all source patches was  
216 the best for Molina's Hog-nosed Skunk (Table 2). We used these crossing models to build  
217 the final fatality models (Figure 1 and 2).

218



219

220

221

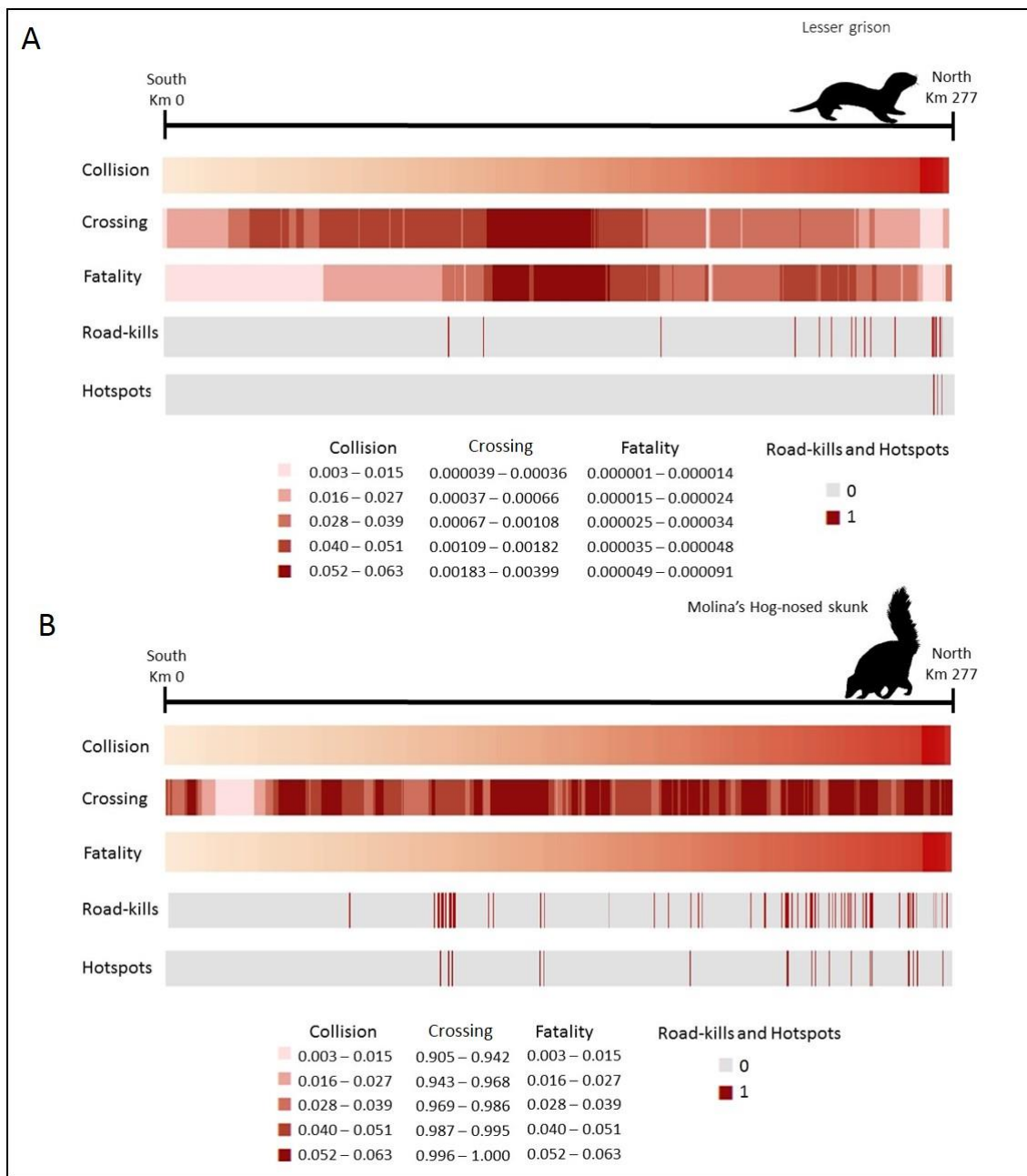
222 **Table 2:** Predictive performance results for each crossing model for each species (Lesser  
 223 Grison - *Galictis cuja* and Molina's Hog-nosed Skunk - *Conepatus chinga*) and segment  
 224 length (1000 m, 500 m, and 275 m). MAE is the mean absolute error, SD is the standard  
 225 deviation of mean absolute error, and AIC is the Akaike Information Criteria.

	Segment length					
	1000 m		500 m		275 m	
	MAE (SD)	AIC	MAE (SD)	AIC	MAE (SD)	AIC
Lesser Grison						
<b>G-1</b>	<b>0.30 (0.11)</b>	<b>255.53 (0.17)</b>	<b>0.17 (0.05)</b>	<b>317.48 (0.10)</b>	<b>0.10 (0.02)</b>	<b>382.85</b>
G-All-4	0.34 (0.11)	281.23 (0.18)	0.18 (0.05)	342.46 (0.11)	0.11 (0.02)	407.5
G-All-1	0.34 (0.11)	285.41 (0.18)	0.18 (0.05)	347.39 (0.11)	0.11 (0.02)	411.74
L-All	0.41 (0.11)	377.54 (0.17)	0.21 (0.05)	438.4 (0.12)	0.12 (0.02)	504.19
L-1	0.41 (0.11)	378.40 (0.17)	0.21 (0.05)	439.04 (0.12)	0.12 (0.02)	504.33
Molina's Hog-nosed Skunk						
<b>L-All</b>	<b>0.69 (0.10)</b>	<b>569.73 (0.44)</b>	<b>0.44 (0.07)</b>	<b>750.32 (0.27)</b>	<b>0.27 (0.03)</b>	<b>900.82</b>
L-1	0.70 (0.10)	575.50 (0.44)	0.44 (0.07)	753.72 (0.27)	0.27 (0.03)	904.34
G-All-4	0.79 (0.08)	630.56 (0.47)	0.47 (0.06)	810.98 (0.28)	0.28 (0.03)	961.24
G-1	0.79 (0.08)	630.83 (0.47)	0.47 (0.07)	811.28 (0.28)	0.28 (0.03)	961.77
G-All-1	0.80 (0.08)	638.82 (0.47)	0.47 (0.07)	819.71 (0.28)	0.28 (0.03)	969.56

226

227 Spatial distribution of collision probabilities showed a similar pattern for both species,  
 228 however crossing and fatality probabilities, road-kills and hotspots were different (Figure  
 229 1 and Appendix C). Predictive performances were also different among species (Figure  
 230 2). For Lesser Grison, for all road lengths, collision models and bivariate models, which  
 231 considered crossing and collision, had the lowest mean absolute errors (Figure 2), but  
 232 collision models presented the lowest AIC (Table 3). Fatality models performed the worst  
 233 at predicting road-kill fatalities on BR-101 road for Lesser Grison (Table 3). Although,  
 234 bivariate model was better than other models to predict road-kills for Molina's Hog-nosed  
 235 Skunk, for all road lengths, (Figure 2 and Table 3), all models were very similar, except  
 236 the crossing model which had the highest mean absolute error (Table 3). Mean absolute

237 errors were lower with decreasing segment size for all models and for both species (Figure  
 238 2).



239

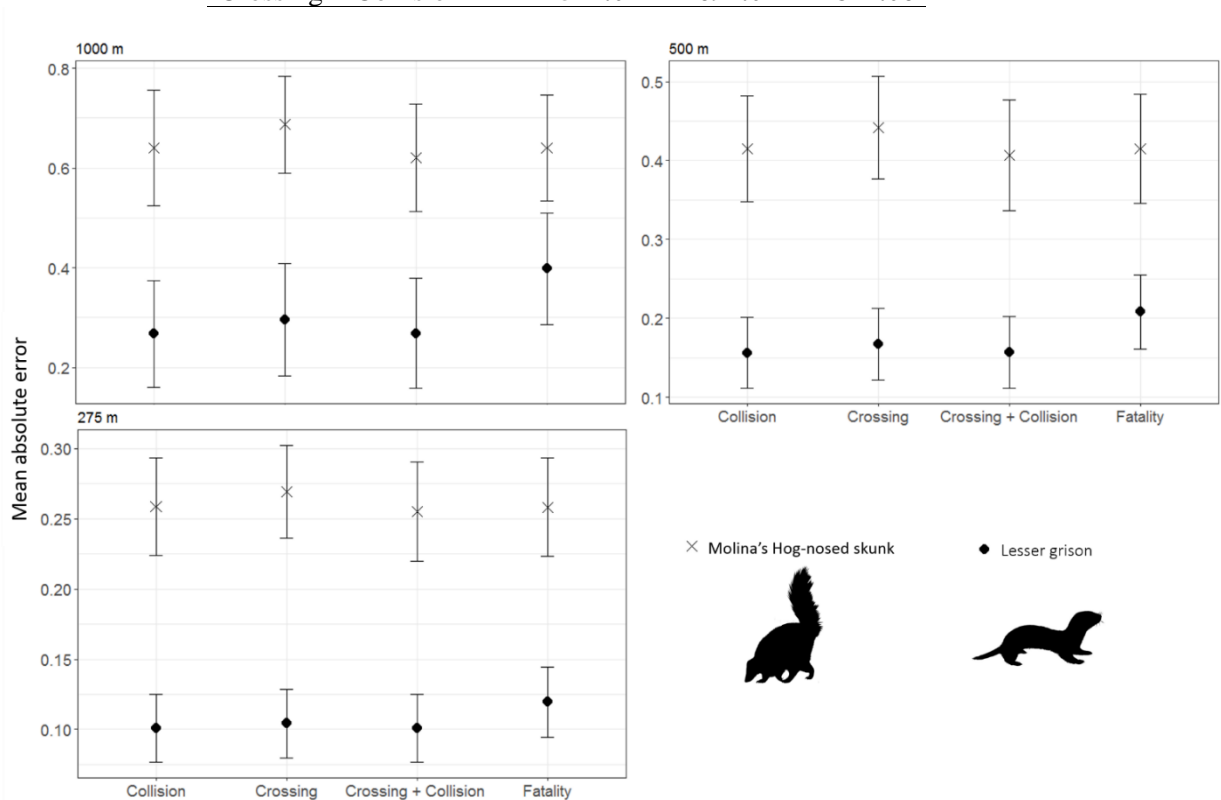
240 **Figure 1:** Collision, Crossing and Fatality probabilities, road-kill records and Hotspots  
 241 for Lesser Grison (A) and Molina's Hog-nosed Skunk (B) for segment length of 275 m  
 242 along BR-101.

243

244

245 **Table 3:** Akaike Information Criteria of the four models (Collision, Crossing, Crossing  
 246 + Collision, and Fatality) for each species (Lesser Grison - *Galictis cuja* - and Molina's  
 247 Hog-nosed Skunk - *Conepatus chinga*) and each segment length (1000 m, 500 m, and  
 248 275 m).

	AIC		
	1000 m	500 m	275 m
<b>Lesser Grison</b>			
Crossing	255.53	317.48	382.85
Collision	<b>232.11</b>	<b>292.54</b>	<b>358</b>
Fatality	346.46	407.38	472.58
Crossing + Collision	233.91	294.4	359.81
<b>Molina's Hog-nosed Skunk</b>			
Crossing	569.73	750.32	900.82
Collision	530.74	711.56	861.51
Fatality	529.95	710.72	860.66
Crossing + Collision	<b>517.07</b>	<b>697.04</b>	<b>847.06</b>



249  
 250 **Figure 2:** Mean absolute error of predictive models for each species: Lesser Grison  
 251 (*Galictis cuja*) and Molina's Hog-nosed Skunk (*Conepatus chinga*). We presented four

252 models (Collision, Crossing, Crossing + Collision, and Fatality) for the three different  
253 segment sizes: 1000 m (left above), 500 m (right above) and 275 m (below).

254

255 Crossing models, even with a good predictive performance, were not good at planning  
256 spatial placements of mitigation structures, especially for the Lesser Grison (Table 4). As  
257 expected, given the predictive performance of collision models, the potential mitigation  
258 outcome for the Molina's Hog-nosed Skunk was smaller than for the Lesser Grison. The  
259 best cost-benefit ratio (% of mitigated road divided by the % of fatalities avoided) resulted  
260 from predictive models for the Molina's Hog-nosed Skunk and was 1:2.6 whereas for the  
261 Lesser Grison the best ratio was 1:14.1 (Table 4).

262 Although the mitigation outcome of collision models was in general lower than the one  
263 resulting from hotspot analyses, at least for the Lesser Grison, with a target of almost 10%  
264 of mitigated road (segment size of 1000 m in Table 4), around 70% of road-kills of that  
265 species would be avoided. Additionally, for this species, the cost-benefit ratio did not  
266 change among road segment sizes (nearly 1:7 with a 5% road mitigation effort; Table 4).

267

268 **Table 4:** Percentage of recorded road-kills that could be avoided if mitigation was  
269 planned considering hotspots analyses, or collision, crossing, and fatality predictive  
270 models for each species (Lesser Grison - *Galictis cuja* and Molina's Hog-nosed Skunk -  
271 *Conepatus chinga*), for multiple segment sizes and multiple thresholds of percentage of  
272 mitigated road. At hotspots column, the first threshold was the number segments which  
273 were identified as hotspots, so there was no percentage of fatalities avoided for the other  
274 two thresholds of number of segments.

275

276

277

278

Segment size	<i>Lesser Grison</i>						<i>Molina's Hog-nosed Skunk</i>					
	number of segments	% road	% of fatalities avoided				number of segments	% road	% of fatalities avoided			
			hotspots	collision	crossing	fatality			hotspots	collision	crossing	fatality
1000 m	13	4.7	62.50	35.94	0	0	19	7	39.62	10.69	13.21	10.69
	26	9.5	-	68.75	0	0	38	14	-	35.85	22.01	35.85
	39	14	-	79.69	0	0	57	20.7	-	49.06	33.96	49.06
500 m	10	1.8	29.69	21.88	0	0	35	6.35	28.93	6.29	6.29	6.29
	20	3.6	-	34.38	0	0	70	12.7	-	31.45	20.75	31.45
	30	5.4	-	35.94	0	0	105	19	-	45.28	25.16	45.28
275 m	10	1	21.88	14.06	0	0	38	3.8	18.87	1.89	5.66	1.89
	20	2	-	26.56	0	0	76	7.6	-	11.32	10.06	11.32
	30	3	-	28.13	0	0	114	11.4	-	23.90	18.24	23.90

279

280 **Discussion**

281

282 Our approach demonstrated that we can predict road-kill risk using traffic volume as a  
 283 main predictor and that connectivity has a potential use for modelling road-kill risk for  
 284 some species. As traffic volume information at a single road could be relatively easily  
 285 measured with traffic counters and/or modelled and is an important determinant of  
 286 wildlife-vehicle collisions (Gunson et al. 2011), we considered the use of our collision  
 287 probability equation as a good alternative for predicting road-kills in the absence of road-  
 288 kill data.

289 Our collision model, however, used the same animal speed and, for a given species, this  
 290 value could change depending on traffic volume (Jacobson et al. 2016). Traffic volume  
 291 was the main predictor because it was the only variable that changed along the road  
 292 segments. Other variables may be incorporated into the equation, such as vehicle speed  
 293 (Jaarsma et al. 2006). Vehicle speed has also been documented as a relevant predictor for  
 294 wildlife collisions (Gunson et al. 2011) however, it is more difficult to obtain or model  
 295 for all road segments. Another potential limitation of the collision probability equation is

296 the exponential relationship between road-kill probability and traffic volume (Litvaitis &  
297 Tash 2008). It has been shown for some species that the highest road-kill risk is observed  
298 with an intermediate traffic volume, since animals are likely to avoid crossing the road  
299 when the traffic is too high (Jacobson et al. 2016). Although our modelled traffic varied  
300 from 140 to 2.500 vehicles/day, the higher level is still within the range of what is  
301 generally recognized as low traffic (van Langevelde & Jaarsma 2004; Sadleir & Linklater  
302 2016), so we assumed that road avoidance not influenced our results.

303 The predictive performance of models using crossing probability based on connectivity  
304 maps was worse than models using the collision probability equation for both species.  
305 The relationship between crossing probability and road-kills for the Lesser Grison was  
306 contrary to expectation; the highest crossing probabilities were at locations with no road-  
307 kills which could result in poor mitigation decisions. This inverse relationship can be  
308 biased by species occurrence since we did not consider this variable to improve the  
309 selection of our source patches and calculate connectivity. Differences in species  
310 occurrence may modify the connectivity pattern.

311 The use of expert opinion as a tool for building resistance maps can have limitations as  
312 an overestimation of the importance of some habitats (Clevenger et al. 2002), however it  
313 can be suitable for species with strong habitat preferences. Further, subjectivity on  
314 resistance assignment could be controlled with the Analytical Hierarchy Process used  
315 (Saaty 1987). It has already been used for predicting wildlife fatalities on roads (Hurley  
316 et al. 2009).

317 To improve the accuracy of connectivity mapping and, consequently, crossing probability  
318 on roads, an alternative is to obtain movement data by telemetry, (Bastille-Rousseau et  
319 al. 2018). Although telemetry is becoming cheaper and more popular, it is still very  
320 difficult to implement for multiple species and study sites. Another possible improvement

321 for crossing probability estimation may be obtained by also incorporating the traffic  
322 volume as another layer in our resistance map (Dutta et al. 2016). Our connectivity  
323 modelling approach is simple and potentially applicable to other roads or at the road  
324 network scale and could possibly be improved if source patches could be modelled from  
325 presence-absence, occurrence or occupancy modelling approach (Mackenzie et al. 2006;  
326 Guillera-Arroita 2017).

327 We proposed the fatality probability (multiplication of crossing probability and collision  
328 probability) based on the logic of collision events – animals and moving vehicles must  
329 coincide in space and time. However, the fatality probability was not good at predicting  
330 road-kills for our target species. Bivariate models (additive) had a better predictive  
331 performance, although not considerably better than the univariate collision model. This  
332 apparently results from the poor performance of crossing models possibly due to low  
333 accuracy of source patch assignment. No other single road study integrated the two sub-  
334 models (crossing and collision) in this manner, therefore comparison with other studies  
335 is difficult due to variation in the use of different statistics to measure predictive  
336 performance. Jaarsma et al. (2007) proposed a very similar idea using an animal  
337 simulation movement approach, but they did not validate their models. Although, new  
338 roads are specially challenging for road-kill mitigation (van der Ree et al. 2015b), and  
339 traffic seems to be a very important variable to predict where road-kill risk is higher, the  
340 approach described here may be applicable for modelling and predicting traffic volume  
341 using variables such as human population density, distance to main cities or main roads,  
342 and road class (Visintin et al. 2016),

343 Our cost-benefit analysis demonstrated that, at least for one of our target species, the  
344 collision model could identify potentially effective mitigation locations with a good  
345 benefit-cost ratio for any evaluated road segment size (scale). Thus, our approach may be

346 useful to apply to roads where road-kill data are not available or on large road networks  
347 as well. Road retrofitting or new road construction are two contexts that demand a move  
348 of road ecology from a tradition of descriptive approaches to the development of  
349 predictive tools able to provide management recommendations with few or no data.

350

### 351 **Acknowledgements**

352 We are grateful to Fernanda Z. Teixeira and Vinicius Bastazini for all their comments on  
353 the manuscript. To Carlos Benhur Kasper, Flávia Tirelli and Felipe Peters for their  
354 opinion about landscape resistance. To all colleagues that collaborated during field  
355 surveys for validation data. LOG would like to thank CAPES for her scholarship (process  
356 n. 88881.132536/2016-01).

357

358

### 359 **References**

- 360 Ascensão F, Desbiez ALJ, Medici EP, Bager A. 2017. Spatial patterns of road mortality  
361 of medium–large mammals in Mato Grosso do Sul, Brazil. *Wildlife Research*  
362 **44**:135. Available from <http://www.publish.csiro.au/?paper=WR16108> (accessed  
363 May 7, 2018).
- 364 Bastille-Rousseau G, Wall J, Douglas-Hamilton I, Wittemyer G. 2018. Optimising the  
365 positioning of wildlife crossing structures using GPS telemetry. *Journal of Applied*  
366 *Ecology*:0–1. Available from <http://doi.wiley.com/10.1111/1365-2664.13117>.
- 367 Bornholdt R, Helgen K, Koepfli K-P, Oliveira L, Lucherini M, Eizirik E. 2013.  
368 Taxonomic revision of the genus *Galictis* (Carnivora: Mustelidae): species  
369 delimitation, morphological diagnosis, and refined mapping of geographical  
370 distribution. *Zoological Journal of the Linnean Society* **167**:449–472. Oxford



371 University Press. Available from [https://academic.oup.com/zoolinnean/article-](https://academic.oup.com/zoolinnean/article-lookup/doi/10.1111/j.1096-3642.2012.00859.x)  
372 [lookup/doi/10.1111/j.1096-3642.2012.00859.x](https://academic.oup.com/zoolinnean/article-lookup/doi/10.1111/j.1096-3642.2012.00859.x) (accessed June 18, 2018).

373 Chai T, Draxler RR. 2014. Root mean square error (RMSE) or mean absolute error  
374 (MAE)? -Arguments against avoiding RMSE in the literature. *Geoscientific Model*  
375 *Development* **7**:1247–1250.

376 Clevenger AP, Wierzchowski J, Chruszcz B, Gunson KE. 2002. GIS-Generated,  
377 Expert-Based Models for Identifying Wildlife Habitat Linkages and Planning  
378 Mitigation Passages. *Conservation Biology* **16**:503–514.

379 Coelho AVP, Coelho IP, Teixeira FZ, Kindel A. 2014. Siriema: road mortality software.  
380 NERF/UFRGS, Porto Alegre, Brasil. Available from [www.ufrgs.br/siriema](http://www.ufrgs.br/siriema).

381 Dutta T, Sharma S, McRae BH, Roy PS, DeFries R. 2016. Connecting the dots:  
382 mapping habitat connectivity for tigers in central India. *Regional Environmental*  
383 *Change* **16**:53–67. Springer Berlin Heidelberg.

384 Gonçalves LO, Alvares DJ, Teixeira FZ, Schuck G, Coelho IP, Esperandio IB, Anza J,  
385 Beduschi J, Bastazini VAG, Kindel A. 2018. Reptile road-kills in Southern Brazil:  
386 Composition, hot moments and hotspots. *Science of The Total Environment*  
387 **615**:1438–1445. Elsevier B.V. Available from  
388 <http://linkinghub.elsevier.com/retrieve/pii/S004896971732394X>.

389 Grilo C, Ascensão F, Santos-Reis M, Bissonette JA. 2011. Do well-connected  
390 landscapes promote road-related mortality? *European Journal of Wildlife Research*  
391 **57**:707–716. Available from <http://link.springer.com/10.1007/s10344-010-0478-6>  
392 (accessed December 12, 2013).

393 Grilo C, Molina-Vacas G, Fernández-Aguilar X, Rodríguez-Ruiz J, Ramiro V, Porto-  
394 Peter F, Ascensão F, Román J, Revilla E. 2018. Species-specific movement traits  
395 and specialization determine the spatial responses of small mammals towards

396 roads. *Landscape and Urban Planning* **169**:199–207. Elsevier. Available from  
397 <http://linkinghub.elsevier.com/retrieve/pii/S0169204617302220>.

398 Guillera-Arroita G. 2017. Modelling of species distributions, range dynamics and  
399 communities under imperfect detection: advances, challenges and opportunities.  
400 *Ecography* **40**:281–295. Wiley/Blackwell (10.1111). Available from  
401 <http://doi.wiley.com/10.1111/ecog.02445> (accessed June 18, 2018).

402 Gunson KE, Mountrakis G, Quackenbush LJ. 2011. Spatial wildlife-vehicle collision  
403 models: a review of current work and its application to transportation mitigation  
404 projects. *Journal of environmental management* **92**:1074–82. Elsevier Ltd.  
405 Available from <http://www.ncbi.nlm.nih.gov/pubmed/21190788> (accessed  
406 December 17, 2013).

407 Gurrutxaga M, Saura S. 2013. Prioritizing highway defragmentation locations for  
408 restoring landscape connectivity. *Environmental Conservation* **41**:1–8. Available  
409 from [http://www.journals.cambridge.org/abstract\\_S0376892913000325](http://www.journals.cambridge.org/abstract_S0376892913000325) (accessed  
410 December 18, 2013).

411 Hels T, Buchwald E. 2001. The effect of road kills on amphibian populations.  
412 *Biological Conservation* **99**:331–340.

413 Huijser MP, Berger CM, Olsson M, Strein M. 2015. Wildlife warning signs and animal  
414 detection systems aimed at reducing wildlife-vehicle collisions. Pages 198–  
415 212 *Handbook of Road Ecology*.

416 Hurley M V., Rapaport EK, Johnson CJ. 2009. Utility of Expert-Based Knowledge for  
417 Predicting Wildlife–Vehicle Collisions. *Journal of Wildlife Management* **73**:278–  
418 286. Available from <http://www.bioone.org/doi/abs/10.2193/2008-136> (accessed  
419 March 24, 2015).

420 Jaarsma CF, van Langevelde F, Botma H. 2006. Flattened fauna and mitigation: Traffic

421 victims related to road, traffic, vehicle, and species characteristics. *Transportation*  
422 *Research Part D: Transport and Environment* **11**:264–276. Available from  
423 <http://linkinghub.elsevier.com/retrieve/pii/S1361920906000289> (accessed  
424 November 9, 2013).

425 Jackson ND, Fahrig L. 2011. Relative effects of road mortality and decreased  
426 connectivity on population genetic diversity. *Biological Conservation* **144**:3143–  
427 3148. Elsevier Ltd. Available from  
428 <http://linkinghub.elsevier.com/retrieve/pii/S0006320711003557> (accessed October  
429 29, 2012).

430 Jacobson SL, Bliss-ketchum LL, Rivera CE De, Smith WP. 2016. A behavior- based  
431 framework for assessing barrier effects to wildlife from vehicle traffic volume.  
432 *Ecosphere* **7**:1–15.

433 Jones KE et al. 2009. PanTHERIA : a species-level database of life history, ecology,  
434 and geography of extant and recently extinct mammals. *Ecology* **90**:2648.

435 Kasper CB, Soares JBG, Freitas TRO. 2012. Differential patterns of home-range, net  
436 displacement and resting sites use of *Conepatus chinga* in southern Brazil.  
437 *Mammalian Biology* **77**:358–362. Elsevier GmbH. Available from  
438 <http://dx.doi.org/10.1016/j.mambio.2012.03.006>.

439 Kuhn M. 2008. Building Predictive Models in R Using the caret Package. *Journal Of*  
440 *Statistical Software* **28**:1–26. Available from <http://www.jstatsoft.org/v28/i05/>.

441 Laurance WF, Peletier-Jellema A, Geenen B, Koster H, Verweij P, Dijck P Van,  
442 Lovejoy TE, Schleicher J, Kuijk M Van. 2015. Reducing the global environmental  
443 impacts of rapid infrastructure expansion. *Current Biology* **25**:1–5.

444 Leonard PB, Duffy EB, Baldwin RF, McRae BH, Shah VB, Mohapatra TK. 2017.  
445 *Gflow: Software for Modelling Circuit Theory-Based Connectivity At Any Scale.*

446       Methods in Ecology and Evolution **8**:519–526.

447   Lewis JS, Rachlow JL, Horne JS, Garton EO, Wakkinen WL, Hayden J, Zager P. 2011.

448       Identifying habitat characteristics to predict highway crossing areas for black bears

449       within a human-modified landscape. *Landscape and Urban Planning* **101**:99–107.

450       Elsevier B.V. Available from

451       <http://linkinghub.elsevier.com/retrieve/pii/S0169204611000375> (accessed August

452       18, 2014).

453   Litvaitis JA, Tash JP. 2008. An approach toward understanding wildlife-vehicle

454       collisions. *Environmental Management* **42**:688–697.

455   Mackenzie DI, Nichols JD, Royle JA, Pollock KH, Bailey LI, Hines JE. 2006.

456       Occupancy Estimation and Modeling - Inferring Patterns and Dynamics of Species

457       Occurrence. Page Igarss 2014. Elsevier.

458   McRae BH, Kavanagh DM. 2011. Linkage Mapper Connectivity Analysis Software.

459       The Nature Conservancy, Seattle WA. The Nature Conservancy, Seattle WA.

460       Available from <http://www.circuitscape.org/linkagemapper>.

461   McRae BH, Shah VB, Mohapatra TK. 2013. Circuitscape 4 User Guide. The Nature

462       Conservancy, Seattle WA. Available from <http://www.circuitscape.org>.

463   Posillico M, Serafini P, Lovari S. 1995. Activity patterns of the stone marten *Martes*

464       *foina* Erxleben, 1777, in relation to some environmental factors. *Hystrix* **7**:79–97.

465       Available from <http://www.italian-journal-of-mammalogy.it/article/view/4056>.

466   R Core Team. 2017. R: A language and environment for statistical computing. R

467       Foundation for Statistical Computing, Vienna, Austria. Available from

468       <https://www.r-project.org/>.

469   Ripley BD. 1981. *Spatial Statistics*. John Wiley & Sons, New York.

470   Rytwinski T, Fahrig L. 2011. Reproductive rate and body size predict road impacts on

471 mammal abundance. *Ecological Applications* **21**:589–600.

472 Saaty TL. 1987. The analytic hierarchy process: what it is and how it is used.

473 *Mathematical Modelling* **9**:161–176.

474 Sadleir RMFS, Linklater WL. 2016. Annual and seasonal patterns in wildlife road-kill

475 and their relationship with traffic density. *New Zealand Journal Of Zoology* **42**:23.

476 Smith DJ, van der Ree R, Rosell C. 2015. Wildlife Crossing Structures: an effective

477 strategy to restore or maintain wildlife connectivity across roads. Pages 172–183 in

478 R. van der Ree, D. J. Smith, and C. Grilo, editors. *Handbook of Road Ecology*.

479 Wiley.

480 Thurfjell H, Spong G, Olsson M, Ericsson G. 2015. Avoidance of high traffic levels

481 results in lower risk of wild boar-vehicle accidents. *Landscape and Urban Planning*

482 **133**:98–104. Elsevier B.V. Available from

483 <http://linkinghub.elsevier.com/retrieve/pii/S0169204614002254> (accessed

484 December 4, 2014).

485 Trocmé M. 2006. The Swiss defragmentation program—reconnecting wildlife corridors

486 between the Alps and Jura: an overview. Pages 144–149 *Proceedings of the 2005*

487 *International Conference on Ecology and Transportation*.

488 UFRGS-IB-Centro de Ecologia. 2016. Mapeamento da cobertura vegetal do Bioma

489 Pampa: Ano-base 2009. <https://www.ufrgs.br/labgeo/index.php/dados-espaciais>.

490 UFRGS-IB-Centro de Ecologia, Porto Alegre, Brasil. Available from

491 [http://www.ecologia.ufrgs.br/labgeo/index.php?option=com\\_content&view=catego](http://www.ecologia.ufrgs.br/labgeo/index.php?option=com_content&view=category&layout=blog&id=18&Itemid=16)

492 [ry&layout=blog&id=18&Itemid=16](http://www.ecologia.ufrgs.br/labgeo/index.php?option=com_content&view=category&layout=blog&id=18&Itemid=16).

493 van der Grift EA. 2005. Defragmentation in the Netherlands : A Success Story ? *Gaia*

494 **14**:144–147.

495 van der Ree R, Gagnon JW, Smith DJ. 2015a. Fencing: a valuable tool for reducing

496 wildlife-vehicle collisions and funneling fauna to crossing structures. Pages 159–  
497 171 in R. van der Ree, D. J. Smith, and C. Grilo, editors. *Handbook of Road  
498 Ecology*. Wiley-Blackwell.

499 van der Ree R, Jaeger JAG, Rytwinski T, van der Grift EA. 2015b. Good Science and  
500 Experimentation are Needed in Road Ecology. Pages 71–81 in R. van der Ree, D. J.  
501 Smith, and C. Grilo, editors. *Handbook of Road Ecology*. Available from  
502 <http://doi.wiley.com/10.1002/9781118568170.ch10>.

503 van der Ree R, Smith DJ, Grilo C. 2015c. *Handbook of Road Ecology*. Wiley-  
504 Blackwell.

505 van Langevelde F, Jaarsma CF. 2004. Using traffic flow theory to model traffic  
506 mortality in mammals. *Landscape Ecology* **19**:895–907.

507 Visintin C, van der Ree R, McCarthy MA. 2017. Consistent patterns of vehicle collision  
508 risk for six mammal species. *Journal of Environmental Management* **201**:397–406.  
509 Elsevier Ltd. Available from <http://dx.doi.org/10.1016/j.jenvman.2017.05.071>.

510 Visintin C, van der Ree R, McCarthy MA. 2016. A simple framework for a complex  
511 problem? Predicting wildlife-vehicle collisions. *Ecology and Evolution*:1–13.

512 Willmott CJ, Matsuura K. 2005. Advantages of the mean absolute error (MAE) over the  
513 root mean square error (RMSE) in assessing average model performance. *Climate  
514 Research* **30**:79–82. Inter-Research Science Center. Available from  
515 <http://www.jstor.org/stable/24869236> (accessed May 7, 2018).

516 Yensen E, Tarifa T. 2003. *Galictis cuja*. *Mammalian Species* **728**:1–8. Available from  
517 <https://academic.oup.com/mspecies/article-lookup/doi/10.1644/728>.  
518  
519  
520

521

522 **Supplementary material**

523

524 **Appendix A.** KML file with road track, road-kill records, road-kill hotspots, crossing  
525 probability, collision probability of Lesser Grison (*Galictis cuja*) and Molina's Hog-nosed  
526 Skunk (*Conepatus chinga*).

527

528 **Appendix B.** Explanation for how we obtained the resistance value based on expert  
529 opinion and Analytic Hierarchy Process.

530

531 We used the Analytic Hierarchy Process to facilitate decision making about resistance  
532 values. Experts determined resistance values by a series of pairwise comparisons based  
533 on Saaty (1987).

534 Experts' responses varied from 1 to 9 and were based on the comparison between land  
535 use classes. The larger the score is, more resistant to kangaroo movement is that class:

---

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two classes contribute equally for the goal
3	Moderate importance of one over another	Experience and judgement slightly favour one class over another
5	Essential or strong importance	Experience and judgement strongly favor one class over another
7	Very strong importance	A class is strongly favoured and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one class over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgements	When compromise is needed

---

536

537 Table below showed the 17 classes of land cover used obtained from UFRGS-IB-Centro  
 538 de Ecologia (2016):

Code	Land cover
A	Water
B	Rock outcrop
C	Sand
D	Wetland
E	Native forest < 1 ha
F	Native forest 1-10 ha
G	Native forest 11 - 100 há
H	Native forest > 100 ha
I	Dry grassland
J	Wet grassland
L	Degraded grassland
M	Silviculture
N	Mixed areas
O	Dry agriculture
P	Rice monoculture
Q	Mining
R	Urban area

539

540 Three experts gave values for each class based on the pairwise comparison (one value per  
 541 class). We present result for one expert in the table below. The value in each cell of the  
 542 table below corresponds to the result of the pairwise comparison. All comparisons were  
 543 always made between rows and columns in this order. For example, class A is five times  
 544 more resistant than class G. Consequently, class G is five times less resistant than class  
 545 A ( $1/5=0.20$ ).

546

Code	A	B	C	D	E	F	G	H	I	J	L	M	N	O	P	Q	R
A	1.00	2.00	2.00	3.00	7.00	7.00	5.00	3.00	9.00	9.00	7.00	7.00	6.00	5.00	7.00	3.00	2.00
B	0.20	1.00	1.00	0.50	1.00	0.50	0.20	0.14	3.00	3.00	1.00	1.00	1.00	0.50	3.00	0.33	0.20
C	0.20	1.00	1.00	1.00	1.00	0.50	0.33	0.14	3.00	3.00	2.00	1.00	1.00	0.50	2.00	0.33	0.20
D	0.33	2.00	1.00	1.00	1.00	0.50	0.33	0.20	3.00	3.00	2.00	1.00	1.00	1.00	2.00	0.33	0.20



E	0.14	1.00	1.00	1.00	1.00	0.50	0.20	0.14	3.00	3.00	1.00	0.50	0.50	0.50	1.00	0.33	0.20
F	0.14	2.00	2.00	2.00	2.00	1.00	0.33	0.17	5.00	5.00	3.00	1.00	1.00	1.00	2.00	1.00	0.33
G	0.20	5.00	5.00	3.00	5.00	3.00	1.00	0.20	5.00	5.00	4.00	2.00	2.00	1.00	5.00	2.00	0.50
H	0.33	7.00	7.00	5.00	7.00	6.00	5.00	1.00	9.00	9.00	7.00	3.00	3.00	2.00	7.00	3.00	1.00
I	0.11	0.33	0.33	0.33	0.33	0.20	0.20	0.11	1.00	1.00	0.50	0.50	0.50	0.33	0.50	0.33	0.14
J	0.11	0.33	0.33	0.33	0.33	0.20	0.20	0.11	1.00	1.00	0.50	0.50	0.50	0.33	0.33	0.33	0.14
L	0.14	1.00	0.50	0.50	1.00	0.33	0.25	0.14	2.00	2.00	1.00	1.00	1.00	0.50	1.00	0.50	0.20
M	0.14	1.00	1.00	1.00	2.00	1.00	0.50	0.33	2.00	2.00	1.00	1.00	1.00	0.50	2.00	0.50	0.20
N	0.17	1.00	1.00	1.00	2.00	1.00	0.50	0.33	2.00	2.00	1.00	1.00	1.00	1.00	2.00	0.50	0.20
O	0.20	2.00	2.00	1.00	2.00	1.00	1.00	0.50	3.00	3.00	2.00	2.00	1.00	1.00	3.00	1.00	0.33
P	0.14	0.33	0.50	0.50	1.00	0.50	0.20	0.14	2.00	3.00	1.00	0.50	0.50	0.33	1.00	0.33	0.20
Q	0.33	3.00	3.00	3.00	3.00	1.00	0.50	0.33	3.00	3.00	2.00	2.00	2.00	1.00	3.00	1.00	0.33
R	0.50	5.00	5.00	5.00	5.00	3.00	2.00	1.00	7.00	7.00	5.00	5.00	5.00	3.00	5.00	3.00	1.00

547

548 On the next step, all cell values were divided by the sum of its specific column resulting in the

549 table below:

550

Code	A	B	C	D	E	F	G	H	I	J	L	M	N	O	P	Q	R
A	0.23	0.06	0.06	0.10	0.17	0.26	0.28	0.38	0.14	0.14	0.17	0.23	0.21	0.26	0.15	0.17	0.27
B	0.05	0.03	0.03	0.02	0.02	0.02	0.01	0.02	0.05	0.05	0.02	0.03	0.04	0.03	0.06	0.02	0.03
C	0.05	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.05	0.05	0.05	0.03	0.04	0.03	0.04	0.02	0.03
D	0.08	0.06	0.03	0.03	0.02	0.02	0.02	0.03	0.05	0.05	0.05	0.03	0.04	0.05	0.04	0.02	0.03
E	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.02	0.05	0.05	0.02	0.02	0.02	0.03	0.02	0.02	0.03
F	0.03	0.06	0.06	0.07	0.05	0.04	0.02	0.02	0.08	0.08	0.07	0.03	0.04	0.05	0.04	0.06	0.05
G	0.05	0.14	0.15	0.10	0.12	0.11	0.06	0.03	0.08	0.08	0.10	0.07	0.07	0.05	0.11	0.11	0.07
H	0.08	0.20	0.21	0.17	0.17	0.22	0.28	0.13	0.14	0.14	0.17	0.10	0.11	0.10	0.15	0.17	0.14
I	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.02
J	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.02
L	0.03	0.03	0.01	0.02	0.02	0.01	0.01	0.02	0.03	0.03	0.02	0.03	0.04	0.03	0.02	0.03	0.03
M	0.03	0.03	0.03	0.03	0.05	0.04	0.03	0.04	0.03	0.03	0.02	0.03	0.04	0.03	0.04	0.03	0.03
N	0.04	0.03	0.03	0.03	0.05	0.04	0.03	0.04	0.03	0.03	0.02	0.03	0.04	0.05	0.04	0.03	0.03
O	0.05	0.06	0.06	0.03	0.05	0.04	0.06	0.06	0.05	0.05	0.05	0.07	0.04	0.05	0.06	0.06	0.05
P	0.03	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.05	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Q	0.08	0.09	0.09	0.10	0.07	0.04	0.03	0.04	0.05	0.05	0.05	0.07	0.07	0.05	0.06	0.06	0.05
R	0.11	0.14	0.15	0.17	0.12	0.11	0.11	0.13	0.11	0.11	0.12	0.17	0.18	0.15	0.11	0.17	0.14

551

552 Finally, we calculated the weight, lambda and relative weight (resistance values) following the

553 equations indicated in the table below:

554

Land Cover Code	Sum of rows	Sum of columns	Weight (sum of rows/number of classes)	$\lambda$ (weight/sum of columns)	Relative Weight (Resistances)
-----------------	-------------	----------------	----------------------------------------	-----------------------------------	-------------------------------

A	3.28	4.40	0.19	0.85	100.00
B	0.52	35.00	0.03	1.06	15.75
C	0.54	33.67	0.03	1.08	16.59
D	0.64	29.17	0.04	1.09	19.39
E	0.44	41.67	0.03	1.08	13.52
F	0.84	27.23	0.05	1.34	25.55
G	1.48	17.75	0.09	1.55	45.26
H	2.67	8.00	0.16	1.26	81.44
I	0.24	63.00	0.01	0.89	7.35
J	0.24	64.00	0.01	0.89	7.24
L	0.42	41.00	0.02	1.01	12.82
M	0.56	30.00	0.03	0.99	17.08
N	0.59	28.00	0.03	0.97	18.03
O	0.86	19.50	0.05	0.99	26.32
P	0.37	46.83	0.02	1.01	11.21
Q	1.03	17.83	0.06	1.08	31.45
R	2.30	7.39	0.14	1.00	70.11

555

556 We checked the consistency between comparisons based on the equation  $CI = (\sum \lambda - n) / (n - 1)$  where  
557 “n” is the number of classes and “λ” is obtained from the table above. Our Consistency Index (CI)  
558 equals 0.071.

559 To evaluate if the consistency is acceptable or not, we also calculated a Consistency Ratio as CR  
560 = CI/RI. The CR is obtained by comparing the CI with an average random consistency index (RI)  
561 (Saaty, 1987). If CR it is not lower than 0.10, experts must revise their judgments related to  
562 pairwise comparisons. The RI for 17 variables is 1.61 (Saaty, 1987). We calculated the CR as  
563 0.044 and, thus, we accepted and used the experts evaluation for each cover class resistance in  
564 the connectivity map.

565 That was one example for one assignment of one expert. Below we present a table with the  
566 consistency index (CI) of the three experts for two target species:

Expert	Lesser Grison	Molina's Hog-nosed Skunk
1	0.044	0.044
2	0.085	0.186
3	0.116	0.379

567

568 For Lesser Grison, two experts were consistent in their evaluation ( $CI < 0.1$ ). Resistance values  
569 provided by these experts were correlated (0.90), so we used the mean of resistance values  
570 between them. For Molina's Hog-nosed Skunk only one expert was consistent, so we used the  
571 resistances gave for this expert.

572

### 573 **References**

574 Saaty T. L. 1987. The analytic hierarchy process: what it is and how it is used. *Mathematical*  
575 *Modelling* **9**:161–176.

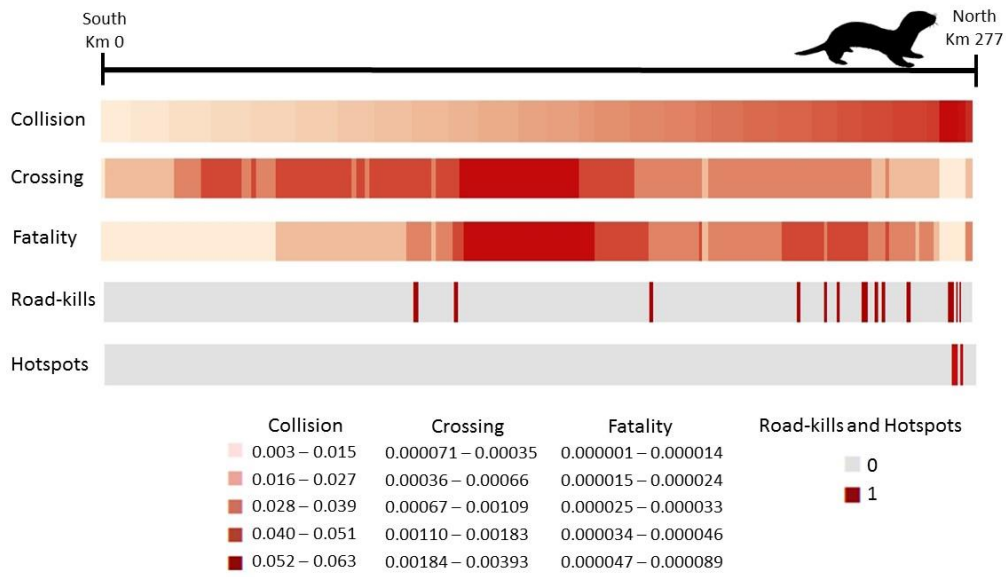
576 UFRGS-IB-Centro de Ecologia. 2016. Mapeamento da cobertura vegetal do Bioma Pampa:  
577 Ano-base 2009. <https://www.ufrgs.br/labgeo/index.php/dados-espaciais>. UFRGS-IB-  
578 Centro de Ecologia, Porto Alegre, Brasil.

579

580 **Appendix C.** Crossing, Collision and Fatality probabilities, Road-kill records and Road-  
581 kill Hotspots for Lesser Grison (*Galictis cuja*) and Molina's Hog-nosed Skunk  
582 (*Conepatus chinga*) along BR-101 for 1000 m and 500 m of segment length.

Segment size = 1000 m

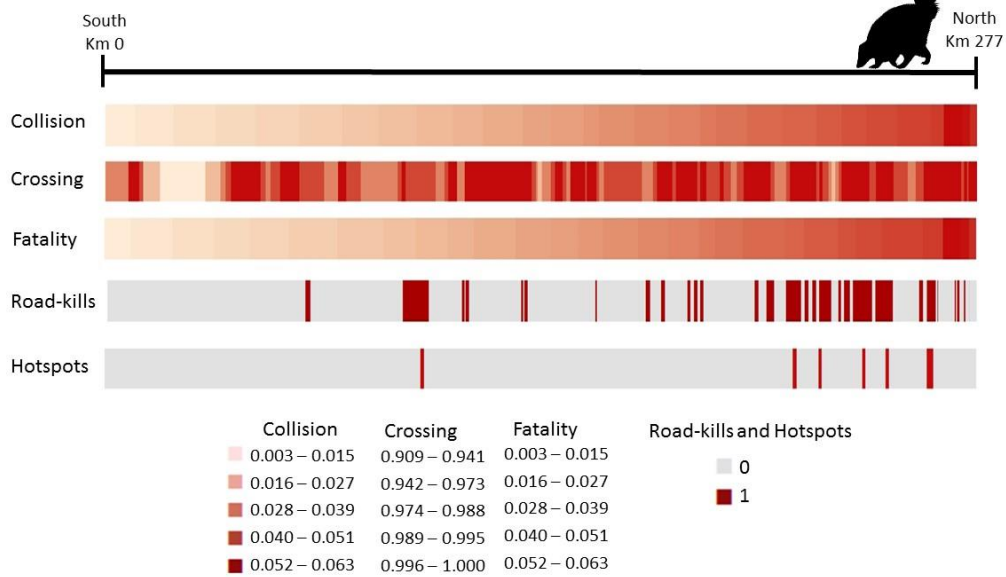
Lesser grison



583

Segment size = 1000 m

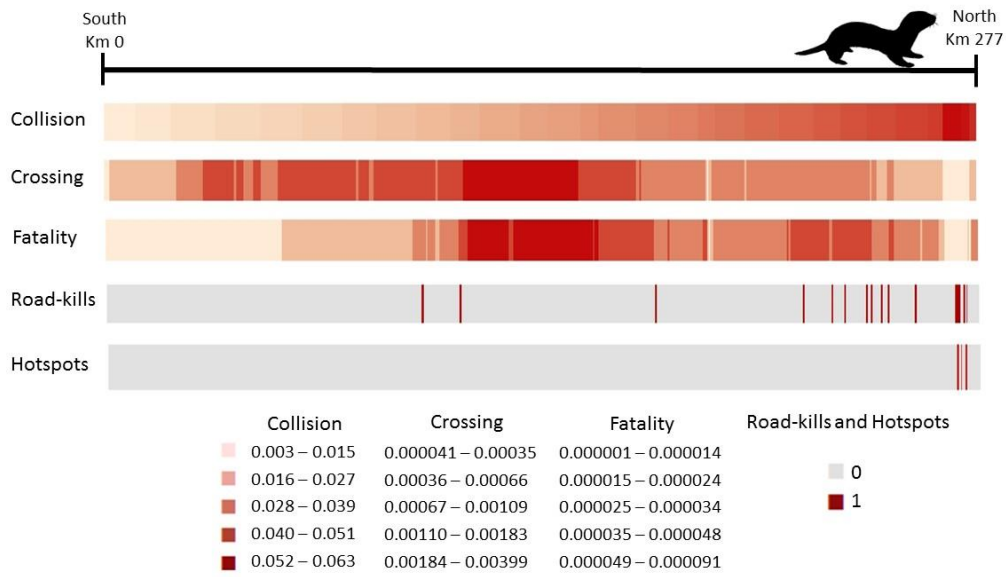
Molina's Hog-nosed skunk



584

Segment size = 500 m

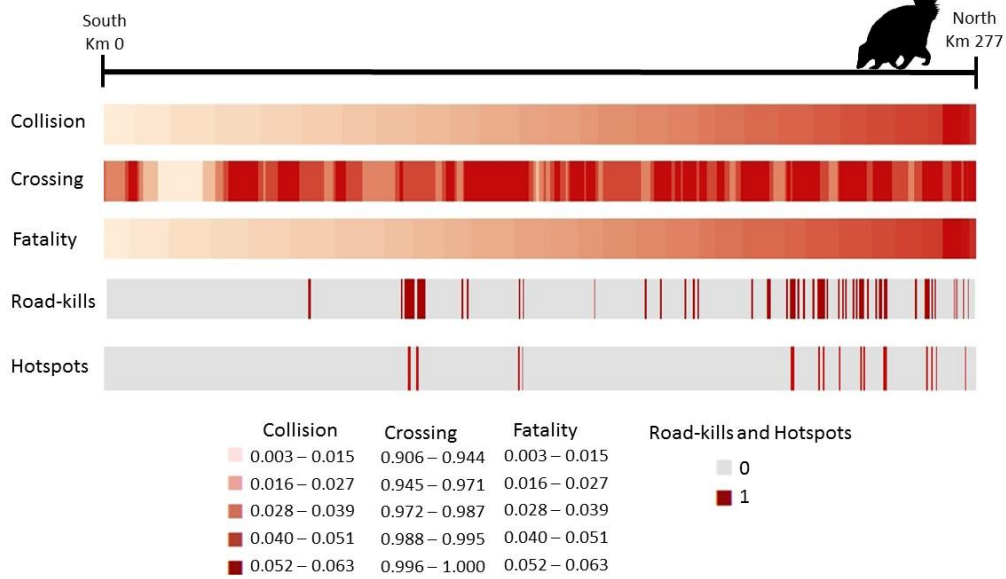
Lesser grison



585

Segment size = 500 m

Molina's Hog-nosed skunk



586

**Predizendo fatalidades em rodovias em uma rede de estradas usando  
as probabilidades de travessia e colisão**

Este capítulo será submetido como research paper para a revista Biodiversity and Conservation e foi feito em colaboração com Casey Visintin e Rodney van der Ree. Ele está formatado conforme as normas dessa revista.

1 **Predicting road fatalities at a road network using crossing and collision probabilities**

2

3 **Abstract**

4 There is an urgent demand to predict wildlife-vehicle collisions at a regional scale due to  
5 the extension and expansion of road networks worldwide. On these networks it is often  
6 unfeasible to obtain road-kill data for mitigation planning. We predicted road-kills of the  
7 eastern grey kangaroo (*Macropus giganteus*) for Victoria roads (South-eastern Australia)  
8 based on the integration of crossing probability (exposure) and collision probability  
9 (hazard). We estimated crossing probability with connectivity maps using occurrence  
10 likelihood of the species as source areas and landscape resistance to movement based on  
11 experts' opinion. We estimated collision probability using models fit to traffic volume,  
12 road width, and animal speed when crossing a road. Both a standard equation and an  
13 alternative equation that included a road avoidance parameter were tested to model  
14 collision probability. Several model variations were validated using spatial locations of  
15 known road-kills through cross-validation. The best model was bivariate which used  
16 crossing and collision sub-models calculated with the avoidance factor. We discuss  
17 possible improvements to the crossing and collision sub-models that may increase the  
18 predictive performance of the integrated model.

19

20

21

22 **Key-words:** connectivity, expert opinion, road-kill, wildlife-vehicle collisions, road  
23 mortality

## 24 **Introduction**

25 There is a massive and dense road and railroad network worldwide (Laurance and  
26 Balmford 2013) and it causes several environmental impacts (van der Ree et al. 2015a)  
27 such as landscape modification, environmental degradation and direct wildlife mortality  
28 (van der Ree et al. 2015b). Road and railroad fatalities may result in negative  
29 consequences for both wildlife population persistence and human safety (van der Ree et  
30 al. 2015b), as they can cause notable economic damage, mainly on roads (Huijser et al.  
31 2009). Therefore, implementing structures and actions for mitigation are necessary to  
32 avoid wildlife-vehicle collisions.

33 Due to the extent of national or regional road networks (CIA 2016) and the potential  
34 cumulative effects of wildlife-vehicle collisions on animal populations (Fahrig and  
35 Rytwinski 2009; Ceia-Hasse et al. 2018), regional scale planning of mitigation is  
36 important. At this scale, observational studies are often unfeasible or extremely costly for  
37 most species, except for those which cause high economic losses or injuries to humans –  
38 connected to road accidents (Danks and Porter 2010; Found and Boyce 2011) – or for  
39 those which are detected and reported by drivers such as open citizen science repositories;  
40 for example, the Taiwan Roadkill Observation Network (<https://roadkill.tw/en>) or  
41 California Roadkill Observational System (<http://www.wildlifecrossing.net/california/>).  
42 On a regional scale, the use of predictive models is almost a commitment.

43 In many scientific areas, statistical models are used mostly for causal explanation, and  
44 models that possess high explanatory power are often assumed to inherently possess  
45 predictive power (Shmueli 2010). However, explanatory and predictive models  
46 investigate different questions in different ways. Explanatory models correspond to the  
47 use of statistical models for testing correlation between variables and predictive modeling  
48 is the process of applying a statistical model for predicting new or future observations



49 (Shmueli 2010). In road ecology, it is not different. There is vast array of explanatory  
50 studies (Gunson et al. 2011), however, few predict to new data and have been developed  
51 to plan mitigation measures for reducing road-kills and/or increase connectivity (Dussault  
52 et al. 2007; Lewis et al. 2011; Nelli et al. 2018). Further, most studies have been  
53 conducted at a local scale or did not validate the predictions (Jaarsma et al. 2007; Patrick  
54 et al. 2012). There is still a need for improving road-kill prediction risk at a regional scale.

55 Visintin et al. (2016) proposed a framework for predictive models for road-kills which  
56 integrated two hierarchically related processes on roads: animal presence on the road  
57 (exposure risk, according to authors' definition), indicated by species occurrence, and  
58 collision probability (hazard according to authors' definition), represented by traffic  
59 volume and vehicle speed. Combining these two processes resulted in a collision risk, or  
60 as we redefine it, 'fatality risk'. Other studies also used these same variable sets (Jaarsma  
61 et al. 2007; Patrick et al. 2012; Girardet et al. 2015), however, Visintin et al. (2016),  
62 formally set up a conceptual framework for predictive road-kill models.

63 In this paper, we adopted a conceptually similar approach to predict road fatality risk on  
64 the Victoria road network (South-eastern Australia) using the Eastern Grey kangaroo  
65 (*Macropus giganteus*) as a case study species. However, we predicted crossing  
66 probability using a connectivity model that considered species occurrence probability and  
67 landscape resistance to movement. The likelihood of crossing a road depends on both the  
68 occurrence of a species at one side of the road and on the connectivity among habitats  
69 across roads. Thus, we expect that a connectivity metric could better predict crossing  
70 probability than species occurrence in the vicinity of the road – as applied by Visintin et  
71 al (2016). To obtain collision probability, we used an equation which considers traffic  
72 volume, a kill zone (road width) and the animal speed when crossing a road (Hels and  
73 Buchwald 2001; Jaarsma et al. 2006; Litvaitis and Tash 2008). We tested two approaches

74 for this later process: the original exponential equation (higher traffic results in higher  
75 collision risk) and an adapted equation which includes an avoidance parameter which  
76 means that from a given traffic volume animals start to avoid crossing the road and  
77 collision risk decreases.

78

## 79 **Methods**

### 80 *Study area and target species*

81 The study area was the 227,819 square kilometer state of Victoria in south-east Australia  
82 and its road network. We considered only freeways, highways, and major arterial roads  
83 based on VicRoads classification (VicRoads 2017a) and divided the road network into  
84 500 m segments (n = 47,730 segments). We used an Australian native species, the Eastern  
85 Grey kangaroo (*Macropus giganteus*), as the target species. Grey kangaroos are large  
86 mammals and road-kills are frequently reported on Victorian roads (Visintin et al. 2016).  
87 Given their large body size, there is a human safety concern (Abu-zidan et al. 2002;  
88 Klöcker et al. 2006).

89

### 90 *Crossing probability*

91 We used a land cover map with a pixel resolution of 100m and nine cover classes: exotic  
92 largely treeless, native woody cover, exotic tree cover (urban trees), exotic plantation  
93 forestry, native grasslands and shrublands, native sparse cover (other native cover and  
94 bare ground), native open, non-woody wetlands and waterbodies, artificial  
95 impoundments, and exotic potential plantation trees (Newell et al. 2006). We elicited two  
96 experts on kangaroo ecology to provide resistance values to kangaroo movement for each  
97 land cover class. We combined their responses using an analytic hierarchy process (Saaty  
98 1987; Hurley et al. 2009) by which experts make decisions using a series of pairwise

99 comparisons among classes (see details in Appendix A). We verified the consistency of  
100 experts' evaluation with a ratio between the Consistency Index and the Random Index of  
101 less than 0.1, which means that values for each class were consistent between experts  
102 (Saaty 1987). We tested three thresholds of relative likelihood of grey kangaroo  
103 occurrence from Visintin et al. (2016) to serve as source areas for the connectivity maps:  
104 only patches with more than 0.5 (n = 373), 0.7 (n = 164) or 0.8 (n = 65) relative likelihood  
105 of occurrence (Appendix B).

106 We developed the connectivity maps using circuit-theory in Gflow software (Leonard et  
107 al. 2017). Circuit theory-based connectivity is modelled by assigning a resistance value –  
108 indicating the degree of permeability – to each pixel in a landscape matrix for electron  
109 flow (or animals by analogy). Landscapes are represented as conductive surfaces, with  
110 low resistances assigned to landscape feature types that are most permeable to movement,  
111 and high resistances assigned to movement barriers (McRae et al. 2013). We used  
112 different criteria for convergence factor (1N and 4N; Leonard et al. 2017), that is, a  
113 correlation factor of the current density between pairs of source areas (it defines the  
114 number of decimal places for the correlation threshold among intermediate connectivity  
115 maps; 1N corresponds to 0.9 and 4N correspond to 0.9999). The output map for each  
116 criterion was a summation of per-cell current density (in amperes) for all source pairwise  
117 nodes. We re-scaled the current density values to be from 0 to 1 and sampled the mean  
118 current density in all intersecting grid cells for each 500 m road segment as the crossing  
119 probability. We obtained six connectivity maps based on the previous criteria (Table 1).  
120 For class 0.5 of species occurrence, we retained only one result, because for convergence  
121 factors 1N and 4N the connectivity maps were highly correlated (> 0.95). In the final risk  
122 models, we only used the map with the best road-kill predictive performance (based on  
123 validation).

124 *Collision probability*

125 To obtain collision probability for each 500m road segment, we used the traffic volume,  
126 animal speed, and road width following Hels and Buchwald (2001) and Jaarsma et al.  
127 (2006) equation:  $1 - \exp(-N \cdot (a/v))$ , where  $N$  is traffic volume; “ $a$ ” is a kill zone (road  
128 width), and “ $v$ ” is animal speed. We refer to this model as collision probability 1 (Co-1).  
129 We adapted the Hels and Buchwald (2001) equation to include an avoidance factor:  $1 -$   
130  $\exp(-N \cdot (a/v)) \cdot \exp(-c \cdot N)$ , where  $N$  is traffic volume; “ $a$ ” is a kill zone (road width), “ $v$ ”  
131 is animal speed, and “ $c$ ” is a parameter related to the traffic threshold of road avoidance.  
132 We selected our parameter “ $c$ ” based on data from Visintin et al. (2017) which found the  
133 peak of collision rate for kangaroo species at 5.000 vehicles/day. We refer to this adapted  
134 model approach as collision probability 2 (Co-2).

135 We modeled traffic volume for each segment using the same approach as Visintin et al.  
136 (2016). Average annual daily traffic (AADT) counts were recorded on, and provided by,  
137 VicRoads for 2333 road segments in the year 2013. We regressed AADT on distance to  
138 developed land use (km), distance to freeways and highways (km), population density  
139 (individuals per km<sup>2</sup>), road class and road density (km per km<sup>2</sup>) using random forests  
140 (Breiman 2001). Using the model fit, we predicted traffic volume to all 47,730 road  
141 segments. Road widths were obtained from VicRoads (2017) and for Eastern Grey  
142 kangaroo road crossing speed, we used half of the fastest recorded speed for the genus  
143 *Macropus* which equals 333 m/min (Hirt et al. 2017).

144

145 *Validation*

146 We used 1,023 kangaroo road-kill recordings from reported incidents to the Wildlife  
147 Victoria organization between 2010 and 2014 (Wildlife Victoria 2015). We then fitted  
148 Binomial models to the data using the presence of observed road-kills on each segment.

149 We fitted three types of models: crossing models, collision models, and crossing and  
150 collision in the same model (bivariate). For the bivariate model, we selected the best  
151 crossing model among the six connectivity outcomes – based on its predictive  
152 performance – and the best collision model.

153 We cross-validated the models by randomly splitting the data into 10 folds (nine of these  
154 subsets for training the model and one for assessing model performance). We repeated  
155 this procedure 100 times for each model. We obtained ROC values to assess the model  
156 predictions. We also compared the Akaike information criterion (AIC) of each model.  
157 We performed these analyses using the *train* function in the *caret* package (Kuhn 2008)  
158 in the R environment (R Core Team 2017).

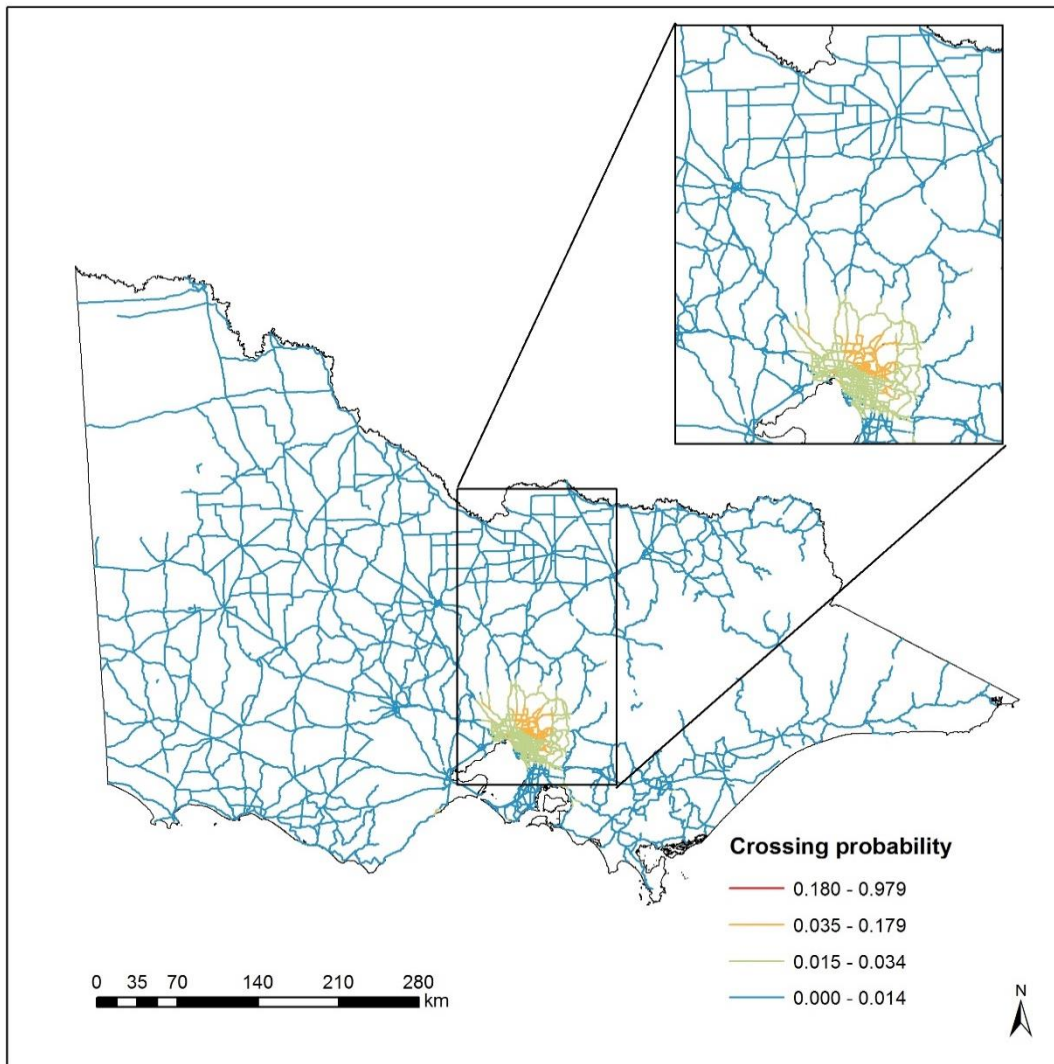
159

## 160 **Results**

161

### 162 *Crossing probability*

163 The Cr-0.7-4 model, which used connectivity maps generated from 0.7 species  
164 occurrence likelihood as source patches and 4N convergence factor (Figure 1), was the  
165 best predictive model for estimating kangaroo crossing probability (Table 1) and was  
166 selected for final modelling.



167

168 **Figure 1:** Eastern grey kangaroo road crossing probability map for the Victoria state road  
 169 network based on a connectivity map generated from 0.7 species occurrence likelihood  
 170 as source patches and 4N convergence factor.

171

172 **Table 1:** Crossing models acronyms, named according to species occurrence  
 173 likelihood and convergence factor, and their predictive performance measured by  
 174 Akaike Information Criteria (AIC) and Receiver Operator Characteristic (ROC).  
 175 Highlighted model (in bold) was selected for the final models.

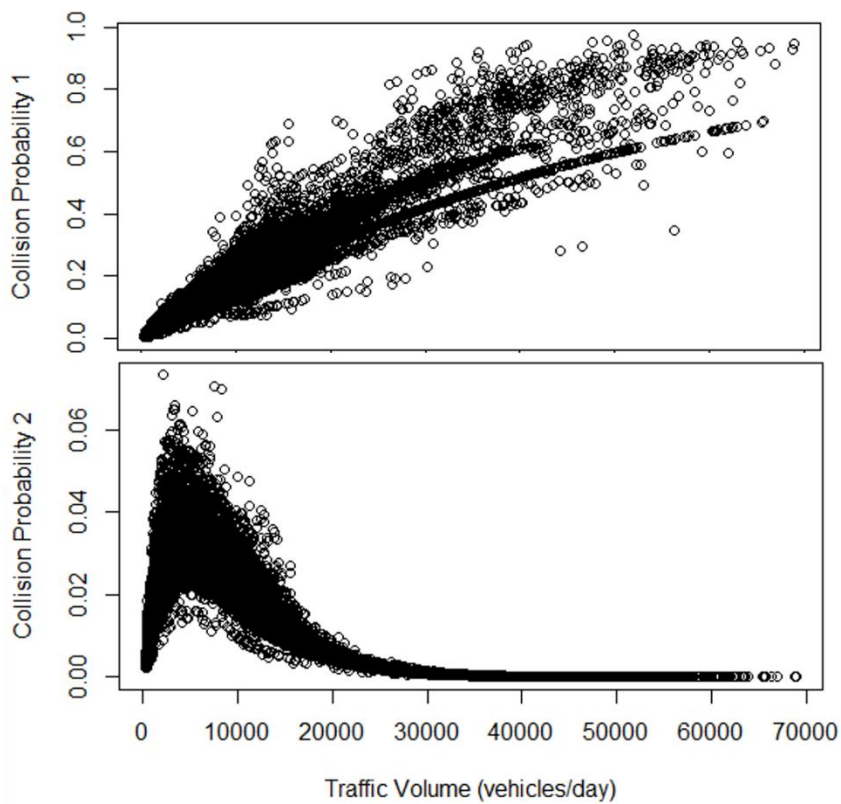
176

Model Acronym	Occurrence Likelihood threshold	Convergence Factor	AIC	ROC
Cr-0.5	0.5	1N/4N	9791	0.663
Cr-0.7-1	0.7	1N	9827	0.423
<b>Cr-0.7-4</b>	<b>0.7</b>	<b>4N</b>	<b>9582</b>	<b>0.692</b>
Cr-0.8-1	0.8	1N	9824	0.611
Cr-0.8-4	0.8	4N	10027	0.326

177

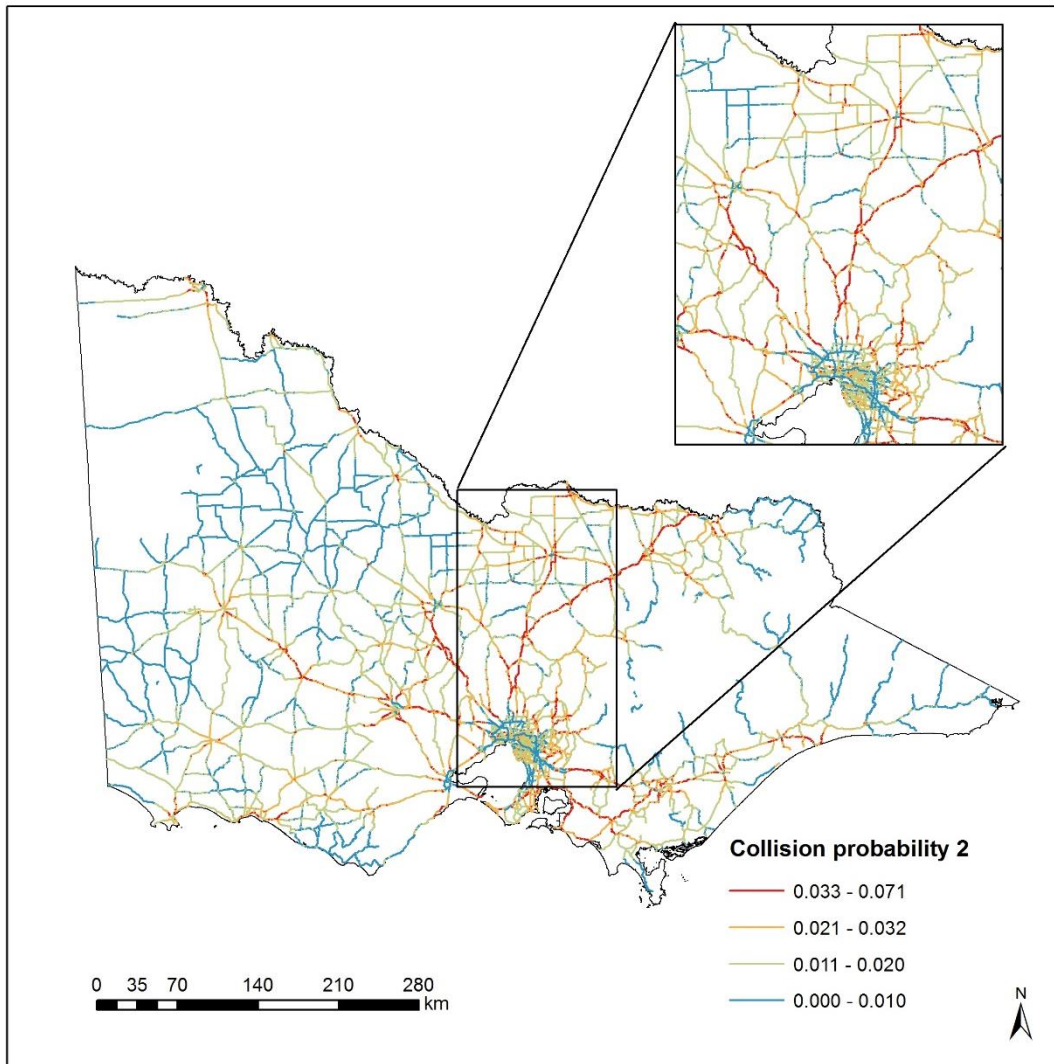
178 *Collision probability*

179 As expected, the Collision Probability 1 (Co-1) and Collision probability 2 (Co-2) models  
 180 differed in their relationship to traffic volume (Figure 2). Collision probability 2 (AIC =  
 181 9632.6; ROC = 0.66; Figure 3) was a better predictor of eastern kangaroo fatalities than  
 182 collision probability 1 (AIC = 9878.3; ROC = 0.65). We used Co-2 for final modelling  
 183 (Figure 3).



184

185 **Figure 2:** Relationship between Collision Probabilities 1 and 2 models and traffic volume  
186 for Eastern Grey kangaroos on each road segment (n = 47,730) of the Victoria state road  
187 network.



188  
189 **Figure 3:** Eastern Grey kangaroo collision probability map based on the Co-2 model for  
190 the Victoria state road network.

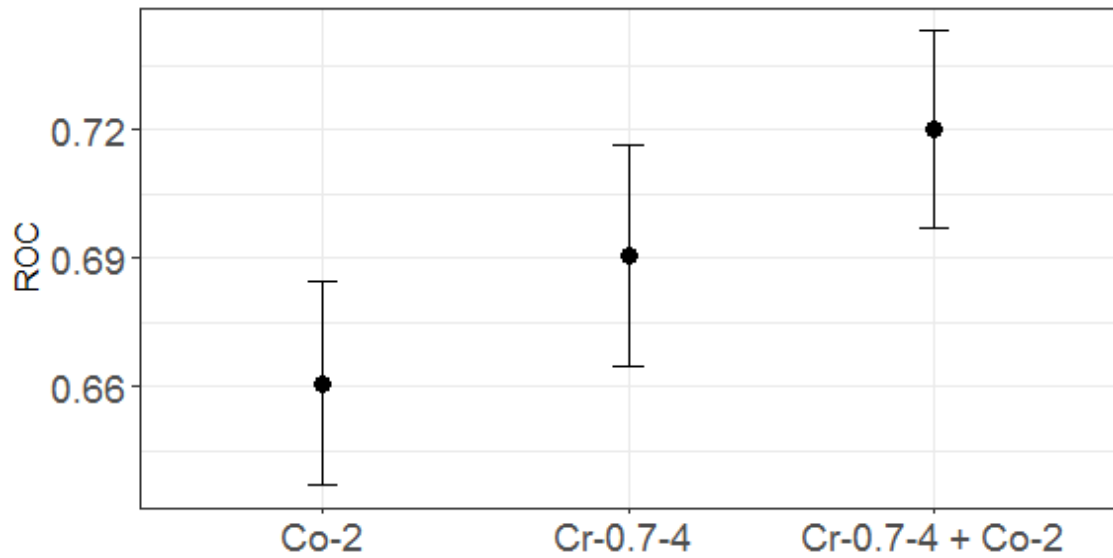
191

192 *Predictive performance*

193 The bivariate Cr-07-4 + Co-2 Model, which considered crossing and collision probability  
194 2, showed the best predictive performance when we compared all final models (Figure

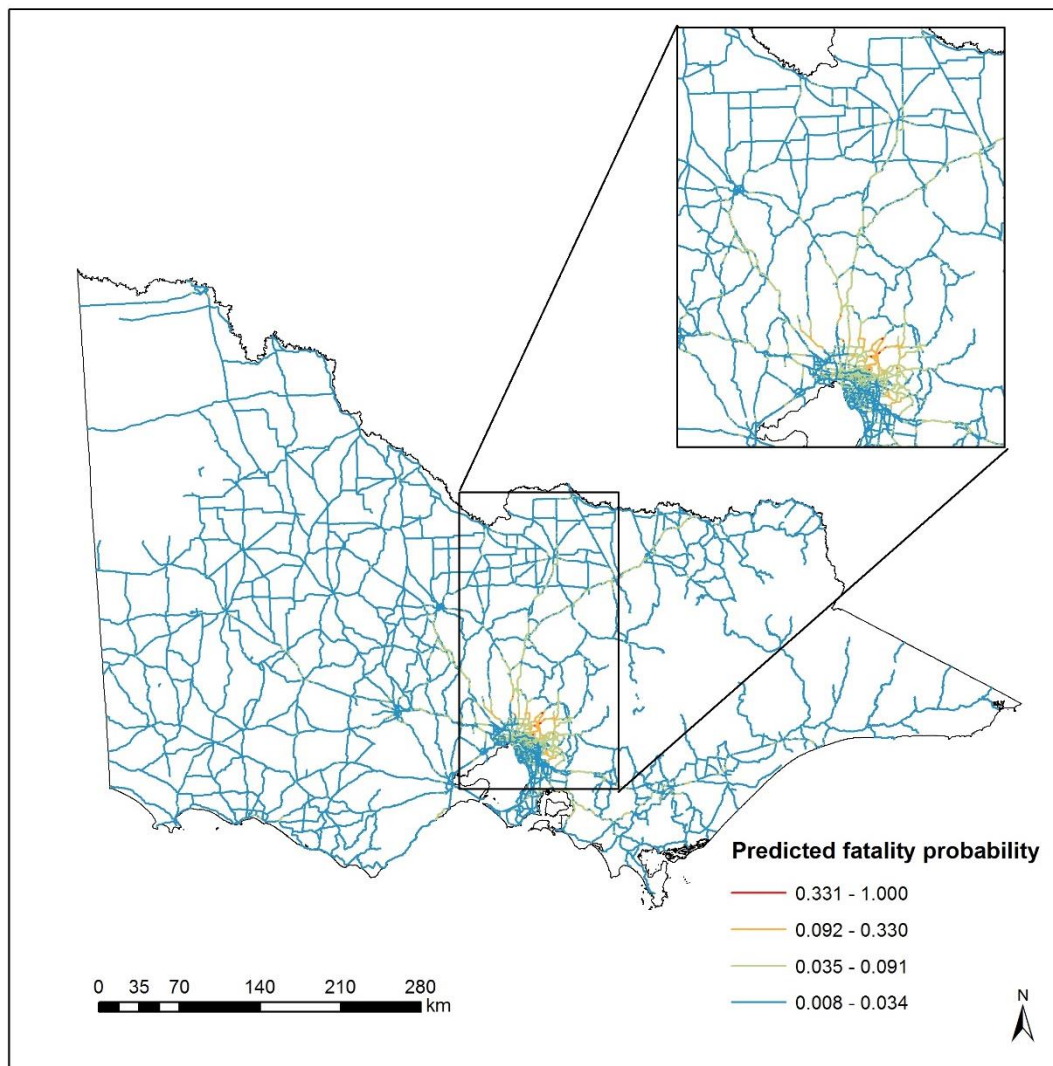


195 4). It also had the lowest AIC (AIC = 9337) when we compared to Cr-07-4 model and  
196 Co-2 model separately. The resulting predicted fatality probability map of this model is  
197 presented on Figure 5.



198  
199 **Figure 4:** Predictive performance based on receiver operator characteristic (ROC) for  
200 Co-2 (Collision probability 2), Cr-0.7-4 (Crossing probability) and Cr-0.7-4+Co-2  
201 (Crossing probability and Collision probability 2). The bars correspond to standard  
202 deviations.

203



204

205 **Figure 5:** Predicted fatality probability of the Eastern Grey kangaroo on all road segments  
 206 in Victoria state from the Cr-0.7-4+Co-2 model, which considered crossing probability  
 207 and collision probability 2 in the same model.

208

209 **Discussion**

210 In this study we demonstrated that taking crossing probability and collision probability  
 211 into account in an integrated model may provide better predictions of kangaroo road-kill  
 212 risk than univariate models. Although we used the same framework as Visintin et al.  
 213 (2016), considering crossing probability (exposure) and collision probability (hazard),  
 214 and the same species and road network, our model had a lower predictive performance

215 (ROC = 0.72 versus ROC = 0.81). Both studies differ on the variables used to build each  
216 sub-model (occurrence likelihood versus connectivity maps to estimate crossing  
217 probability and traffic volume and vehicle speed versus traffic, road width, and animal  
218 speed to estimate collision probability). Apparently, the simpler model of Visintin et al.  
219 (2016) outperformed our model. However, our model may be more appropriate for  
220 researchers that have empirical movement data or good information about species  
221 movements. Furthermore, as road segmentation and road-kill sample for validation also  
222 differed among studies, only comparing models with all the possible combinations of sub-  
223 models building, in the same road system and with the same dataset, will allow us to  
224 select the best approach.

225 One apparent improvement of our approach is the adapted collision equation, which  
226 considered not only the traffic volume but also a species road avoidance parameter,  
227 resulting in a better collision probability model. Some previous studies found that an  
228 exponential distribution was not the best description for collision risk and traffic  
229 association (Gunson et al. 2011). Thurfjell et al. (2015) demonstrated that above a given  
230 traffic volume, animals start to avoid crossing and, thus, they are not hit by vehicles. We  
231 suggest that the use of the collision probability equation, in its original version (Hels and  
232 Buchwald 2001; Jaarsma et al. 2006), should be used with caution on roads or road  
233 networks with high traffic or traffic variation and other alternatives should be tested, with  
234 thresholds modeled that are unique to each species.

235 In our study we used a connectivity map to predict the crossing probability. This option  
236 is supported by Kang et al. (2016) who found that the effect of habitat connectivity on  
237 road-kill abundance was stronger for large mammal species than for small species.  
238 However, the ability of connectivity to explain road-kills is lower than local landscape  
239 variables and road characteristics (Girardet et al. 2015; Kang et al. 2016). Contradicting

240 our initial expectation, the better overall predictive performance of the Visintin et al.  
241 (2016) model may result from their use of occurrence likelihood only, since kangaroo  
242 crossings and consequently road-kills may be more affected by local landscape variables  
243 than connectivity.

244 We have demonstrated an easily implemented landscape resistance assessment by  
245 expert's opinion. Whilst it had been used previously by Hurley et al. (2009) to predict  
246 moose-vehicle collisions, and touted as a valuable tool, some critics have depreciated this  
247 method (Clevenger et al. 2002). Connectivity maps could be improved with the use of  
248 more than one layer to define the landscape resistance values, as in Dutta et al. (2016),  
249 which considered transportation infrastructure. Although rarely available, telemetry data  
250 would strongly improve resistance estimates and connectivity maps (Proctor et al. 2015;  
251 Loraamm and Downs 2016) and movement simulations are another possible approach to  
252 improve these maps (Beier et al. 2008; Semeniuk et al. 2014). In contrast to Gonçalves et  
253 al. (2018), which applied the same general approach to obtain crossing probability for a  
254 single road, the crossing model outperformed the other collision models in our study.  
255 Here, we selected core areas by using species occurrence likelihood data. This performed  
256 better than selecting core areas using habitat preference based on expert opinion as done  
257 by Gonçalves et al (2018).

258 Visintin et al. (2016) propose their framework to be highly flexible and uses several  
259 modelling approaches and input data to build the sub-models. This largely depends on  
260 available information for each study area. Testing multiple approaches in a single study  
261 for multiple species would help compare the performance in each situation. At a network  
262 scale, and even at a road scale, combining solutions for multiple species is a challenge;  
263 however there have already been proposals in that direction (e.g. dispersal guild approach  
264 where species are grouped on similar behavior, see Lechner et al. 2017).

265 Few other studies also showed good performances for predicting road-kills using these  
266 two processes in a single model (Visintin et al. 2017; Nelli et al. 2018). Although we are  
267 not aware of any precedents using this kind of models to plan for mitigation installation,  
268 the accumulating evidence supports their use for this purpose in contexts where  
269 observations are not available or not attainable, like regional road networks.

270

## 271 **Acknowledgements**

272 We are grateful to Graeme Coulson and Jemma Cripps for helping with their opinion  
273 about landscape resistance values. To Michael McCarthy for helping with the avoidance  
274 parameter at the adapted collision probability equation. To VicRoads and Wildlife  
275 Victoria for providing road and road-kill data. LOG would like to thank CAPES for her  
276 scholarship (process n. 88881.132536/2016-01).

277

## 278 **References**

- 279 Abu-zidan FM, Parmar KA, Rao S (2002) Kangaroo-Related Motor Vehicle Collisions.  
280 J Trauma Acute Care Surg 8:360–363
- 281 Beier P, Majka DR, Spencer WD (2008) Forks in the road: choices in procedures for  
282 designing wildland linkages. Conserv Biol 22:836–51. doi: 10.1111/j.1523-  
283 1739.2008.00942.x
- 284 Breiman L (2001) Random Forests. Mach Learn 45:5–32. doi:  
285 10.1023/A:1010933404324
- 286 Ceia-Hasse A, Navarro LM, Borda-De-Água L, Pereira HM (2018) Population  
287 persistence in landscapes fragmented by roads: Disentangling isolation, mortality,  
288 and the effect of dispersal. Ecol Modell 375:45–53. doi:

289 10.1016/j.ecolmodel.2018.01.021

290 CIA (2016) Country comparisons: roadways in: The world factbook.  
291 [https://www.cia.gov/library/publications/the-world-](https://www.cia.gov/library/publications/the-world-factbook/rankorder/2085rank.html)  
292 [factbook/rankorder/2085rank.html](https://www.cia.gov/library/publications/the-world-factbook/rankorder/2085rank.html)

293 Clevenger AP, Wierzchowski J, Chruszcz B, Gunson KE (2002) GIS-Generated,  
294 Expert-Based Models for Identifying Wildlife Habitat Linkages and Planning  
295 Mitigation Passages. *Conserv Biol* 16:503–514

296 Danks ZD, Porter WF (2010) Temporal, spatial, and landscape habitat characteristics of  
297 moose–vehicle collisions in western Maine. *J Wildl Manage* 74:1229–1241. doi:  
298 10.2193/2008-358

299 Dussault C, Ouellet J-P, Laurian C, et al (2007) Moose Movement Rates Along  
300 Highways and Crossing Probability Models. *J Wildl Manage* 71:2338. doi:  
301 10.2193/2006-499

302 Dutta T, Sharma S, McRae BH, et al (2016) Connecting the dots: mapping habitat  
303 connectivity for tigers in central India. *Reg Environ Chang* 16:53–67. doi:  
304 10.1007/s10113-015-0877-z

305 Fahrig L, Rytwinski T (2009) Effects of Roads on Animal Abundance: an Empirical  
306 Review and Synthesis. *Ecol Soc* 14:21

307 Found R, Boyce MS (2011) Predicting deer-vehicle collisions in an urban area. *J*  
308 *Environ Manage* 92:2486–93. doi: 10.1016/j.jenvman.2011.05.010

309 Girardet X, Conruyt-Rogeon G, Foltête JC (2015) Does regional landscape connectivity  
310 influence the location of roe deer roadkill hotspots? *Eur J Wildl Res* 61:731–742.  
311 doi: 10.1007/s10344-015-0950-4

- 312 Gonçalves LO, Meneses BA, Visintin C, Kindel A (2018) Do crossing and collision  
313 probabilities predict wildlife road fatalities? Em prep
- 314 Gunson KE, Mountrakis G, Quackenbush LJ (2011) Spatial wildlife-vehicle collision  
315 models: a review of current work and its application to transportation mitigation  
316 projects. *J Environ Manage* 92:1074–82. doi: 10.1016/j.jenvman.2010.11.027
- 317 Hels T, Buchwald E (2001) The effect of road kills on amphibian populations. *Biol*  
318 *Conserv* 99:331–340
- 319 Hirt MR, Jetz W, Brose U (2017) A general scaling law reveals why the largest animals  
320 are not the fastest. *Nat Ecol Evol* 1:1116–1122. doi: 10.1038/s41559-017-0241-4
- 321 Huijser MP, Duffield JW, Clevenger AP, et al (2009) Cost-benefit analyses of  
322 mitigation measures aimed at reducing collisions with large ungulates in the united  
323 states and canada: A decision support tool. *Ecol Soc* 14:. doi:  
324 10.1016/j.contraception.2009.11.002
- 325 Hurley M V., Rapaport EK, Johnson CJ (2009) Utility of Expert-Based Knowledge for  
326 Predicting Wildlife–Vehicle Collisions. *J Wildl Manage* 73:278–286. doi:  
327 10.2193/2008-136
- 328 Jaarsma CF, van Langevelde F, Baveco JM, et al (2007) Model for rural transportation  
329 planning considering simulating mobility and traffic kills in the badger *Meles*  
330 *meles*. *Ecol Inform* 2:73–82. doi: 10.1016/j.ecoinf.2007.04.004
- 331 Jaarsma CF, van Langevelde F, Botma H (2006) Flattened fauna and mitigation: Traffic  
332 victims related to road, traffic, vehicle, and species characteristics. *Transp Res Part*  
333 *D Transp Environ* 11:264–276. doi: 10.1016/j.trd.2006.05.001
- 334 Kang W, Minor ES, Woo D, Park DLC (2016) Forest mammal roadkills as related to

335 habitat connectivity in protected areas. *Biodivers Conserv*. doi: 10.1007/s10531-  
336 016-1194-7

337 Klöcker U, Croft DB, Ramp D (2006) Frequency and causes of kangaroo-vehicle  
338 collisions on an Australian outback highway. *Wildl Res* 33:5–15. doi:  
339 10.1071/WR04066

340 Kuhn M (2008) Building Predictive Models in R Using the caret Package. *J Stat Softw*  
341 28:1–26. doi: 10.1053/j.sodo.2009.03.002

342 Laurance WF, Balmford A (2013) A global map for road building. *Nature* 495:

343 Lechner AM, Sprod D, Carter O, Lefroy EC (2017) Characterising landscape  
344 connectivity for conservation planning using a dispersal guild approach. *Landsc*  
345 *Ecol* 32:99–113. doi: 10.1007/s10980-016-0431-5

346 Leonard PB, Duffy EB, Baldwin RF, et al (2017) Gflow: Software for Modelling  
347 Circuit Theory-Based Connectivity At Any Scale. *Methods Ecol Evol* 8:519–526.  
348 doi: 10.1111/2041-210X.12689

349 Lewis JS, Rachlow JL, Horne JS, et al (2011) Identifying habitat characteristics to  
350 predict highway crossing areas for black bears within a human-modified landscape.  
351 *Landsc Urban Plan* 101:99–107. doi: 10.1016/j.landurbplan.2011.01.008

352 Litvaitis JA, Tash JP (2008) An approach toward understanding wildlife-vehicle  
353 collisions. *Environ Manage* 42:688–697. doi: 10.1007/s00267-008-9108-4

354 Loraamm RW, Downs J a (2016) A wildlife movement approach to optimally locate  
355 wildlife crossing structures. *Int J Geogr Inf Sci* 30:74–88. doi:  
356 10.1080/13658816.2015.1083995

357 McRae BH, Shah VB, Mohapatra TK (2013) Circuitscape 4 User Guide. *Nat. Conserv.*



358 Nelli L, Langbein J, Watson P, Putman R (2018) Mapping Risk: Quantifying and  
359 Predicting the Risk of Deer-Vehicle Collisions on major roads in England. *Mamm*  
360 *Biol.* doi: 10.1016/j.mambio.2018.03.013

361 Newell GR, White MD, Griffioen P, Conroy M (2006) Vegetation condition mapping at  
362 a landscape-scale across Victoria. *Ecol Manag Restor* 7:2004–2007. doi:  
363 10.1111/j.1442-8903.2006.293\_2.x

364 Patrick DA, Gibbs JP, Popescu VD, Nelson DA (2012) Multi-scale habitat-resistance  
365 models for predicting road mortality “hotspots” for turtles and amphibians.  
366 *Herpetol Conserv Biol* 7:407–426

367 Proctor MF, Nielsen SE, Kasworm WF, et al (2015) Grizzly bear connectivity mapping  
368 in the Canada-United States trans-border region. *J Wildl Manage* 79:544–558. doi:  
369 10.1002/jwmg.862

370 R Core Team (2017) R: A language and environment for statistical computing. R  
371 Foundation for Statistical Computing, Vienna, Austria

372 Saaty TL (1987) The analytic hierarchy process: what it is and how it is used. *Math*  
373 *Model* 9:161–176. doi: 10.1016/0270-0255(87)90473-8

374 Semeniuk CAD, Musiani M, Birkigt DA, et al (2014) Identifying non-independent  
375 anthropogenic risks using a behavioral individual-based model. *Ecol Complex*  
376 17:67–78. doi: 10.1016/j.ecocom.2013.09.004

377 Shmueli G (2010) To Explain or to Predict? *Stat Sci* 25:289–310. doi: 10.1214/10-  
378 STS330

379 Thurfjell H, Spong G, Olsson M, Ericsson G (2015) Avoidance of high traffic levels  
380 results in lower risk of wild boar-vehicle accidents. *Landsc Urban Plan* 133:98–

381 104. doi: 10.1016/j.landurbplan.2014.09.015

382 van der Ree R, Smith DJ, Grilo C (2015a) Handbook of Road Ecology. Wiley-

383 Blackwell

384 van der Ree R, Smith DJ, Grilo C (2015b) The Ecological Effects of Linear

385 Infrastructure and Opportunities of Rapid Global Growth. In: van der Ree R, Smith

386 DJ, Grilo C (eds) Handbook of Road Ecology. Wiley, pp 1–9

387 VicRoads (2017a) VicMap Transport. [https://www.data.vic.gov.au/data/dataset/road-](https://www.data.vic.gov.au/data/dataset/road-network-vicmap-transport)

388 [network-vicmap-transport](https://www.data.vic.gov.au/data/dataset/road-network-vicmap-transport)

389 VicRoads (2017b) VicRoads Open Data: Road Width and Number of Lanes.

390 Visintin C, van der Ree R, McCarthy MA (2017) Consistent patterns of vehicle collision

391 risk for six mammal species. *J Environ Manage* 201:397–406. doi:

392 10.1016/j.jenvman.2017.05.071

393 Visintin C, van der Ree R, McCarthy MA (2016) A simple framework for a complex

394 problem? Predicting wildlife-vehicle collisions. *Ecol Evol* 1–13. doi:

395 10.1002/ece3.2306

396 Wildlife Victoria . (2015) A charity organisation committed to reducing the suffering of

397 wildlife. <https://wildlifevictoria.org.au/>

398

### 399 **Supplementary material**

400 **Appendix A.** Explanation for how we obtained the resistance value based on experts

401 opinion and Analytic Hierarchy Process.

402

403 We used the Analytic Hierarchy Process to facilitate decision making about resistance  
 404 values. Experts determined resistance values by a series of pairwise comparisons based  
 405 on Saaty (1987).

406 Experts' responses varied from 1 to 9 and were based on the comparison between land  
 407 use classes. The larger the score is, more resistant to kangaroo movement is that class:

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two classes contribute equally for the goal
3	Moderate importance of one over another	Experience and judgement slightly favour one class over another
5	Essential or strong importance	Experience and judgement strongly favor one class over another
7	Very strong importance	A class is strongly favoured and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one class over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgements	When compromise is needed

408

409 Table below showed the nine classes of land use of Victoria state used in our land cover  
 410 and use map obtained from Newell et al. (2006):

Cover Class Code	Land Use
A	Exotic - largely treeless (Not native vegetation or tree cover)
B	Native - woody cover (including heaths and woody wetlands)
C	Exotic - tree cover (Urban trees, windbreak trees and other exotic trees)
D	Plantation - tree cover (Plantation forestry (mainly Blue Gums and Pines)
E	Native - grasslands and chenopod shrublands (including some wetlands)
F	Native - sparse cover (Other native cover and bare ground (fires scars, sand dunes, very low cover on floodplains etc.)
G	Native - open, non-woody wetlands and waterbodies (Potential or existing non-woody wetland cover - includes smaller embayments and estuaries)
H	Artificial impoundment (Large artificial freshwater impoundments)
I	Exotic - tree cover (Potential plantation trees)

411

412 Two experts discussed their opinions and gave values for each class based on the pairwise  
 413 comparison (one value per class). The value in each cell of the table below corresponds  
 414 to the result of the pairwise comparison. All comparisons were always made between  
 415 rows and columns in this order. For example, class G is five times more resistant than  
 416 class A. Consequently, class A is five times less resistant than class G ( $1/5=0.20$ ).

Land cover Code	A	B	C	D	E	F	G	H	I
A	1.00	1.00	1.00	0.50	1.00	0.33	0.20	0.14	0.50
B	1.00	1.00	1.00	1.00	1.00	0.50	0.25	0.14	1.00
C	1.00	1.00	1.00	1.00	1.00	0.50	0.25	0.14	1.00
D	2.00	1.00	1.00	1.00	1.00	0.50	0.25	0.14	1.00
E	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.14	1.00
F	3.00	2.00	2.00	2.00	2.00	1.00	1.00	0.14	1.00
G	5.00	4.00	4.00	4.00	2.00	1.00	1.00	0.25	1.00
H	7.00	7.00	7.00	7.00	7.00	7.00	4.00	1.00	1.00
I	2.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

417

418 On the next step, all cell values were divided by the sum of its specific column resulting in the  
 419 table below:

Land cover Code	A	B	C	D	E	F	G	H	I
A	0.0435	0.0526	0.0526	0.0270	0.0588	0.0270	0.0237	0.0459	0.0588
B	0.0435	0.0526	0.0526	0.0541	0.0588	0.0406	0.0296	0.0459	0.1176
C	0.0435	0.0526	0.0526	0.0541	0.0588	0.0406	0.0296	0.0459	0.1176
D	0.0870	0.0526	0.0526	0.0541	0.0588	0.0406	0.0296	0.0459	0.1176
E	0.0435	0.0526	0.0526	0.0541	0.0588	0.0406	0.0592	0.0459	0.1176
F	0.1304	0.1053	0.1053	0.1081	0.1176	0.0811	0.1183	0.0459	0.1176
G	0.2174	0.2105	0.2105	0.2162	0.1176	0.0811	0.1183	0.0804	0.1176
H	0.3043	0.3684	0.3684	0.3784	0.4118	0.5677	0.4734	0.3215	0.1176
I	0.0870	0.0526	0.0526	0.0541	0.0588	0.0811	0.1183	0.3215	0.1176

420

421 Finally, we calculated the weight, lambda and relative weight (which corresponds to the used  
422 resistance value) following the equations indicated in the table below:

Land Cover Code	Sum of rows	Sum of columns	Weight (sum of rows/number of classes)	$\lambda$ (weight/sum of columns)	Relative Weight (Resistances)
A	0.390	23	0.043	0.997	11.78
B	0.495	19	0.055	1.046	14.96
C	0.495	19	0.055	1.046	14.96
D	0.539	18.5	0.060	1.108	16.27
E	0.525	17	0.058	0.992	15.85
F	0.930	12.33	0.103	1.274	28.08
G	1.370	8.45	0.152	1.286	41.36
H	3.312	3.11	0.368	1.143	100
I	0.944	8.5	0.105	0.891	28.50

423

424

425 We checked the consistency between comparisons based on the equation  $CI = (\sum \lambda - n)/(n-1)$  where  
426 “n” is the number of classes and “ $\lambda$ ” is obtained from the table above. Our Consistency Index (CI)  
427 equals 0.0977.

428 To evaluate if the consistency is acceptable or not, we also calculated a Consistency Ratio as CR  
429 = CI/RI. The CR is obtained by comparing the CI with an average random consistency index (RI)  
430 (Saaty, 1987). If CR it is not lower than 0.10, experts must revise their judgments related to  
431 pairwise comparisons. The RI for nine variables is 1.45 (Saaty, 1987). We calculated the CR as  
432 0.067 and, thus, we accepted and used the experts evaluation for each cover class resistance in  
433 the connectivity map.

434

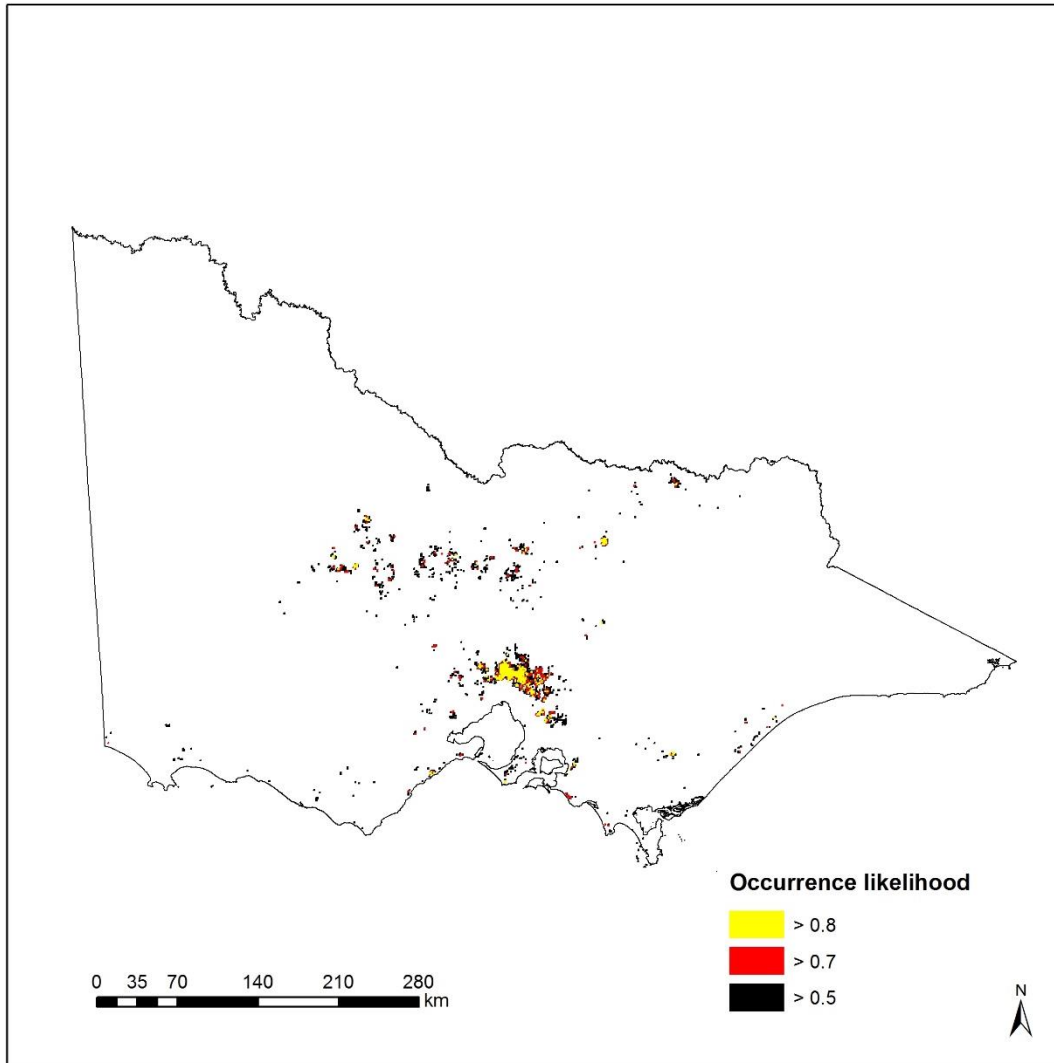
#### 435 **Reference**

436 Saaty T. L. 1987. The analytic hierarchy process: what it is and how it is used. *Mathematical*  
437 *Modelling* **9**:161–176.

438 Newell, G.R., White, M.D., Griffioen, P., Conroy, M., 2006. Vegetation condition  
439 mapping at a landscape-scale across Victoria. *Ecol. Manag. Restor.* **7**, 2004–2007.  
440 doi:10.1111/j.1442-8903.2006.293\_2.x

441

442 **Appendix B.** Source areas based on predicted relative likelihood of grey kangaroo  
443 presence. Black are areas with more than 0.5 of occurrence, red are areas with more than  
444 0.7 of occurrence and yellow are areas with more than 0.8 of kangaroo occurrence. These  
445 data are based on the occurrence likelihood of kangaroo estimated by Visintin et al.  
446 (2016). The larger likelihood thresholds are within the smaller ones.



447

## **Considerações finais**

Nessa tese, explorei diferentes formas de identificar quais são os locais com maior incidência de atropelamentos e poder, com isso, indicar locais prioritários para implementação de medidas de mitigação. Com os resultados do primeiro capítulo, concluí que os atropelamentos de fauna podem ser muito numerosos em determinados contextos, neste caso, para os répteis na BR-101, no qual estimei que mais de 15 mil répteis podem morrer atropelados por ano em 277 km. Além disso, mostrei que é possível identificar locais de maior agregação e que se eles tivessem uma mitigação 100% efetiva poderiam evitar 45% dos atropelamentos encontrados. Nesse capítulo exemplifiquei como é importante levar em consideração os erros de amostragem na estimativa da fatalidade, bem como illustrei como a identificação das zonas de agregação de fatalidades pode otimizar o esforço de mitigação. Além disso, evidenciei a importância do estudo dos atropelamentos em répteis que ainda é um grupo negligenciado em trabalhos de ecologia de estradas e apresentei atributos da paisagem que podem estar associados aos trechos de maior número de fatalidades.

O segundo e terceiro capítulos dessa tese apresentaram uma abordagem preditiva para identificar locais que seriam prioritários para mitigação do impacto de atropelamento de fauna. Explorei nesses modelos os dois processos associados à ocorrência de fatalidades em uma estrada: a probabilidade de travessia do animal e de colisão com um veículo. Com o segundo capítulo, concluí que é possível usar dados de tráfego de veículos e tamanho e velocidade dos animais para prever locais de maior concentração de atropelamentos, entretanto deve se ter cuidado pois a performance dos modelos variou com a espécie. Essa abordagem pode ser utilizada em um contexto de construção de novas estradas ou de pavimentação de estradas existentes, para as quais é possível modelar o futuro tráfego e avaliar a conectividade da paisagem para espécies de especial interesse.

Contudo, ainda são necessárias avaliações multiespecíficas, pois principalmente em países megadiversos, são raras as situações nas quais a proposição de medidas de mitigação é justificável apenas em uma espécie.

Para o contexto de rede de estradas, concluí a partir do capítulo 3 que é possível prever o atropelamento utilizando a probabilidade de travessia e a probabilidade de colisão em um mesmo modelo. Demonstrei ainda que a equação adotada pela maioria dos autores para calcular a probabilidade de colisão precisa ser utilizada com cautela, pois nem sempre a relação entre o risco de atropelamento e o tráfego é exponencial. O modelo proposto no terceiro capítulo da tese é apropriado, por exemplo, para o contexto do Programa de Rodovias Federais Ambientalmente Sustentáveis (Portaria Interministerial nº 288, de 16 de julho de 2013), que prevê que rodovias construídas anteriormente à exigência de licenciamento ambiental passem por um processo de regularização dentro de um período de 06 a 20 anos. Espera-se que o impacto de 55.000 quilômetros de estradas seja avaliado, com a proposição de medidas mitigadoras relacionadas especialmente à diminuição da mortalidade e aumento da permeabilidade da paisagem para a fauna. Desconheço o andamento da implantação do processo de regularização ambiental demandado pela portaria, mas é notório que nessa escala a geração de dados observacionais de fatalidades é extremamente onerosa. Assim, considerando as limitações de recursos para estudos de monitoramento da mortalidade e extrema complexidade de executá-los nessa abrangência, acredito que os modelos propostos no terceiro capítulo podem ser úteis não só para identificar locais prioritários para mitigação, mas também para indicar locais importantes para focar os estudos que queiram avaliar localmente este impacto, explorando efeitos populacionais, por exemplo.

Portanto, concluo que os resultados aqui apresentados podem auxiliar na identificação de locais para possível implementação de medidas de mitigação dos atropelamentos de



fauna. Além de servirem para ajudar na identificação de áreas prioritárias para execução de estudos locais de fatalidade em rodovias. Ainda é necessário explorar outras maneiras de calcular e integrar as probabilidades utilizadas nesta tese, tanto a probabilidade de travessia quanto a de colisão. Entretanto, demonstrei aqui uma forma possível de prever atropelamentos para um contexto em que não há dados dessa natureza disponíveis, seja para estradas novas ou para uma rede de estradas. A utilização de modelos preditivos é uma abordagem ainda pouco usada e aplicada no Brasil, mas muito urgente e necessária para a conservação da natureza de uma forma menos onerosa e mais rápida.

Para além dos artigos que compõem esta tese, queria também utilizar essas considerações finais para dizer o que concluí desses quatro anos e três meses de doutorado no Programa de Pós-Graduação em Ecologia da Universidade Federal do Rio Grande do Sul. Acredito que o período de doutorado pra mim foi muito além destas páginas aqui escritas e que não têm espaço para descrição em nenhuma seção. Além dos artigos aqui apresentados, alcancei objetivos importantes pra minha formação: orientei e participei de outros trabalhos acadêmicos (FREITAS et al., 2017), fiz divulgação científica, que considero uma atividade bastante importante e pouco valorizada (GONÇALVES, 2015; KINDEL et al., 2017a; colunas Fauna e Estradas em [www.faunanews.com.br](http://www.faunanews.com.br)), participei de cursos para capacitação de profissionais na área de Ecologia de Estradas e de atividades diretamente ligadas às políticas públicas para o setor de transportes, as quais também resultaram em trabalhos acadêmicos (KINDEL et al., 2017b). Consegui mesmo com a atual situação do nosso país, ter uma experiência acadêmica fora do país que foi extremamente enriquecedora tanto profissional quanto pessoalmente. Com certeza, todas essas experiências fortaleceram a minha formação como aluna e pesquisadora.

## Referências Bibliográficas

BASTILLE-ROUSSEAU, Guillaume et al. Optimising the positioning of wildlife crossing structures using GPS telemetry. **Journal of Applied Ecology**, p. 0–1, 2018.

Disponível em: <<http://doi.wiley.com/10.1111/1365-2664.13117>>

BENTEN, Anke; ANNIGHÖFER, Peter; VOR, Torsten. Wildlife Warning Reflectors' Potential to Mitigate Wildlife-Vehicle Collisions—A Review on the Evaluation Methods. **Frontiers in Ecology and Evolution**, v. 6, n. April, p. 1–12, 2018.

Disponível em: <<http://journal.frontiersin.org/article/10.3389/fevo.2018.00037/full>>

BHARDWAJ, M. et al. Differential use of highway underpasses by bats. **Biological Conservation**, v. 212, n. May, p. 22–28, 2017.

CLEVINGER, Anthony P.; CHRUSZCZ, Bryan; GUNSON, Kari E. Spatial patterns and factors influencing small vertebrate fauna road-kill aggregations. **Biological Conservation**, v. 109, n. 1, p. 15–26, 2003. Disponível em:

<<http://linkinghub.elsevier.com/retrieve/pii/S0006320702001271>>

CLEVINGER, Anthony P.; WALTHO, Nigel. Performance indices to identify attributes of highway crossing structures facilitating movement of large mammals.

**Biological Conservation**, v. 121, n. 3, p. 453–464, 2005. Disponível em:

<<http://linkinghub.elsevier.com/retrieve/pii/S0006320704002319>>. Acesso em: 8 nov. 2013.

COELHO, Igor Pfeifer; KINDEL, Andreas; COELHO, Artur Vicente Pfeifer. Roadkills of vertebrate species on two highways through the Atlantic Forest Biosphere Reserve, southern Brazil. **European Journal of Wildlife Research**, v. 54, n. 4, p. 689–699, 2008. Disponível em: <<http://link.springer.com/10.1007/s10344-008-0197-4>>. Acesso

em: 17 out. 2016.

D'ANGELO, Gino; VAN DER REE, Rodney. Use of Reflectors and Auditory Deterrents to Prevent Wildlife-Vehicle Collisions. **Handbook of Road Ecology**, p. 213–218, 2015.

FAHRIG, Lenore; RYTWINSKI, Trina. Effects of Roads on Animal Abundance: an Empirical Review and Synthesis. **Ecology and Society**, v. 14, n. 1, p. 21, 2009.

FORMAN, Richard T. T.; ALEXANDER, Lauren E. Roads and Their Major Ecological Effects. **Annual Review of Ecology and Systematics**, v. 29, p. 207–231, 1998.

FREITAS, Karoline Abilhoa et al. Road Effects on Wildlife in Brazilian Environmental Licensing. **Oecologia Australis**, v. 21, n. 3, p. 1–19, 2017.

GIRARDET, Xavier; FOLTÊTE, Jean Christophe; CLAUZEL, Céline. Designing a graph-based approach to landscape ecological assessment of linear infrastructures. **Environmental Impact Assessment Review**, v. 42, p. 10–17, 2013. Disponível em: <<http://dx.doi.org/10.1016/j.eiar.2013.03.004>>

GLISTA, David J.; DEVAULT, Travis L.; DEWOODY, J. Andrew. A review of mitigation measures for reducing wildlife mortality on roadways. **Landscape and Urban Planning**, v. 91, n. 1, p. 1–7, 2009. Disponível em: <<http://linkinghub.elsevier.com/retrieve/pii/S0169204608001886>>. Acesso em: 7 nov. 2012.

GONÇALVES, Larissa Oliveira. Viajar e cuidar da Natureza. **Mundo Jovem**, v. junho, p. 16, 2015.

GOOSEM, Miriam; WESTON, Nigel Graeme; BUSHNELL, Sally. Effectiveness of rope bridge arboreal overpasses and faunal underpasses in providing connectivity for

rainforest fauna. 2005.

GRILO, Clara et al. Do well-connected landscapes promote road-related mortality? **European Journal of Wildlife Research**, v. 57, n. 4, p. 707–716, 2011. Disponível em: <<http://link.springer.com/10.1007/s10344-010-0478-6>>. Acesso em: 12 dez. 2013.

GRILO, Clara et al. Species-specific movement traits and specialization determine the spatial responses of small mammals towards roads. **Landscape and Urban Planning**, v. 169, n. July 2017, p. 199–207, 2018. Disponível em: <<http://linkinghub.elsevier.com/retrieve/pii/S0169204617302220>>

HELS, Tove; BUCHWALD, Erik. The effect of road kills on amphibian populations. **Biological Conservation**, v. 99, p. 331–340, 2001.

HUIJSER, Marcel P. et al. Wildlife warning signs and animal detection systems aimed at reducing wildlife-vehicle collisions. In: VAN DER REE, Rodney; GRILO, Clara; SMITH, Daniel J. (Eds.). **Handbook of Road Ecology**: Wiley-Blackwell, 2015. p. 199–212.

JAARSMA, Catharinus F. et al. Model for rural transportation planning considering simulating mobility and traffic kills in the badger *Meles meles*. **Ecological Informatics**, v. 2, n. 2, p. 73–82, 2007.

JACKSON, Nathan D.; FAHRIG, Lenore. Relative effects of road mortality and decreased connectivity on population genetic diversity. **Biological Conservation**, v. 144, n. 12, p. 3143–3148, 2011. Disponível em: <<http://linkinghub.elsevier.com/retrieve/pii/S0006320711003557>>. Acesso em: 29 out. 2012.

JAEGER, Jochen A. G.; FAHRIG, Lenore. Effects of Road Fencing on Population

Persistence. **Conservation Biology**, v. 18, n. 6, p. 1651–1657, 2004. Disponível em:  
<<http://doi.wiley.com/10.1111/j.1523-1739.2004.00304.x>>

JUMEAU, Jonathan; PETROD, Lana; HANDRICH, Yves. A comparison of camera trap and permanent recording video camera efficiency in wildlife underpasses. **Ecology and Evolution**, n. November 2016, p. 1–9, 2017. Disponível em:  
<<http://doi.wiley.com/10.1002/ece3.3149>>

KANG, Wanmo et al. Forest mammal roadkills as related to habitat connectivity in protected areas. **Biodiversity and Conservation**, 2016.

KINDEL, Andreas et al. Cinco mitos sobre interações entre fauna e rodovias que precisam ser revistos. **Revista Area / Aberta**, v. 1, n. 3, p. 73–79, 2017. a.

KINDEL, Andreas et al. Following the “ Why ? What ? and How ? ” Schema To Improve Road-Kill Evaluation in Environmental Impact Assessments of Southern Brazil. **Oecologia Australis**, v. 21, n. 3, p. 1–18, 2017. b.

LITVAITIS, John A.; TASH, Jeffrey P. An approach toward understanding wildlife-vehicle collisions. **Environmental Management**, v. 42, n. 4, p. 688–697, 2008.

PATRICK, David A. et al. Multi-scale habitat-resistance models for predicting road mortality “hotspots” for turtles and amphibians. **Herpetological Conservation and Biology**, v. 7, n. 3, p. 407–426, 2012.

RYTWINSKI, Trina et al. How Effective Is Road Mitigation at Reducing Road-Kill? A Meta-Analysis. **Plos One**, v. 11, n. 11, p. e0166941, 2016. Disponível em:  
<<http://dx.plos.org/10.1371/journal.pone.0166941>>

SMITH, Daniel J.; VAN DER REE, Rodney; ROSELL, Carme. Wildlife Crossing Structures: an effective strategy to restore or maintain wildlife connectivity across

roads. In: VAN DER REE, Rodney; SMITH, Daniel J.; GRILO, Clara (Eds.).

**Handbook of Road Ecology**: Wiley, 2015. p. 172–183.

SOANES, Kylie et al. Movement re-established but not restored: Inferring the effectiveness of road-crossing mitigation for a gliding mammal by monitoring use.

**Biological Conservation**, v. 159, p. 434–441, 2013. Disponível em:

<<http://linkinghub.elsevier.com/retrieve/pii/S0006320712004363>>. Acesso em: 2 dez.

2014.

TEIXEIRA, Fernanda Zimmermann et al. Canopy bridges as road overpasses for wildlife in urban fragmented landscapes. **Biota Neotropica**, v. 13, n. 1, p. 117–123,

2013.

TEIXEIRA, Fernanda Zimmermann et al. Ferramentas geográficas para análise e mitigação de impactos ambientais causados por infraestruturas viárias de transporte terrestre. In: **Geoprocessamento Aplicado À Análise De Ambiente**: Em prep., 2018.

VAN DER REE, Rodney; SMITH, Daniel J.; GRILO, Clara. The Ecological Effects of Linear Infrastructure and Opportunities of Rapid Global Growth. In: VAN DER REE, Rodney; SMITH, Daniel J.; GRILO, Clara (Eds.). **Handbook of Road Ecology**: Wiley, 2015. p. 1–9.

WILDLIFE VICTORIA, . **A charity organisation committed to reducing the suffering of wildlife**. 2015. Disponível em: <<https://wildlifevictoria.org.au/>>.