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# Predicting deer–vehicle collision risk across Victoria, Australia

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**Abstract.** The risk of deer–vehicle collisions (DVCs) is increasing in south-east Australia as populations of introduced deer expand rapidly. There are no investigations of the spatial and temporal patterns of DVC or predictions of where such collisions are most likely to occur. Here, we use an analytical framework to model deer distribution and vehicle movements in order to predict DVC risk across the State of Victoria. We modelled the occurrence of deer using existing occurrence records and geographic climatic variables. We estimated patterns of vehicular movements from records of average annual daily traffic and speeds. Given the low number of DVCs reported in Victoria, we used a generalised linear regression model fitted to DVCs in California, USA. The fitted model coefficients suggested high collision risk on road segments with high predicted deer occurrence, moderate traffic volume and high traffic speed. We used the California deer model to predict collision risk on Victorian roads and validated the predictions with two independent datasets of DVC records from Victoria. The California deer model performed well when comparing predictions of collision risk to the independent DVC datasets and generated plausible DVC risk predictions across the State of Victoria.

**Additional keywords:** Cervidae, introduced species, invasive species, modelling, wildlife management.

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## Introduction

Globally, wildlife–vehicle collisions (WVCs) cause significant social, economic and ecological impacts (van der Ree *et al.* 2011). Each year, WVCs are responsible for several human deaths and serious injuries as well as millions of dollars' worth of damage to vehicles and road infrastructure (Huijser *et al.* 2007). Additionally, billions of vertebrate animals are thought to be killed each year on global transportation networks; however, accurate estimates of wildlife deaths are difficult to ascertain (Seiler and Helldin 2006). This can cause substantial negative ecological impacts, particularly where native or rare and endangered species are affected (Clements *et al.* 2014). In Australia, WVCs are common and involve a range of native and introduced animals.

Each year thousands of vehicle collisions involving wildlife are reported in Australia (Rowden *et al.* 2008). The five native mammal species most commonly killed on Australian road networks are: eastern grey kangaroo (*Macropus giganteus*), common wombat (*Vombatus ursinus*), black wallaby (*Wallabia bicolor*), koala (*Phascolarctos cinereus*) and brushtail possum (*Trichosurus vulpecula*) (Dique *et al.* 2003; Visintin *et al.* 2017). Collisions can significantly impact native animal populations and may also result in costly insurance claims, medical expenses and in some cases the loss of human life (Huijser *et al.* 2007). A recent study in Victoria demonstrated that in the last decade 152 major traumatic injuries resulted from vehicle collisions with animals; and collision rates are likely to increase in coming years (Ang *et al.* 2019).

In the United States and Europe, deer are involved in the majority of WVCs and present the greatest risk to motorists due to their large body size and crepuscular activity patterns (Conover 1995; Huijser *et al.* 2007; Hothorn *et al.* 2012). The latter often coincide with periods of commuter traffic, especially during winter (Kämmerle *et al.* 2017). Many studies clearly relate areas of high deer density with the greatest risks of collision (Joyce and Mahoney 2001; Langbein *et al.* 2011). Where deer are commonly involved in collisions several mitigation strategies can be put in place. Commonly applied strategies to mitigate the risk of deer–vehicle collisions (DVCs) include the construction of exclusion fencing (Bissonette and Rosa 2012), reduction of speed limits (Romin 1996) and the erection of warning signs (Huijser *et al.* 2007).

Populations of the four wild deer species present in Victoria have undergone rapid increases in the last decade (Moloney and Turnbull 2017) and recognition that they present a substantial risk to motorists, especially in periurban areas, is growing (Parliament of Victoria 2017; DEDJTR 2018). Individuals of Victoria's largest and most abundant deer species, sambar deer (*Rusa unicolor*), can weigh up to 300 kg. Such a large-bodied animal has the potential to cause catastrophic damage during a high-speed collision. While DVCs have been reported in Australia

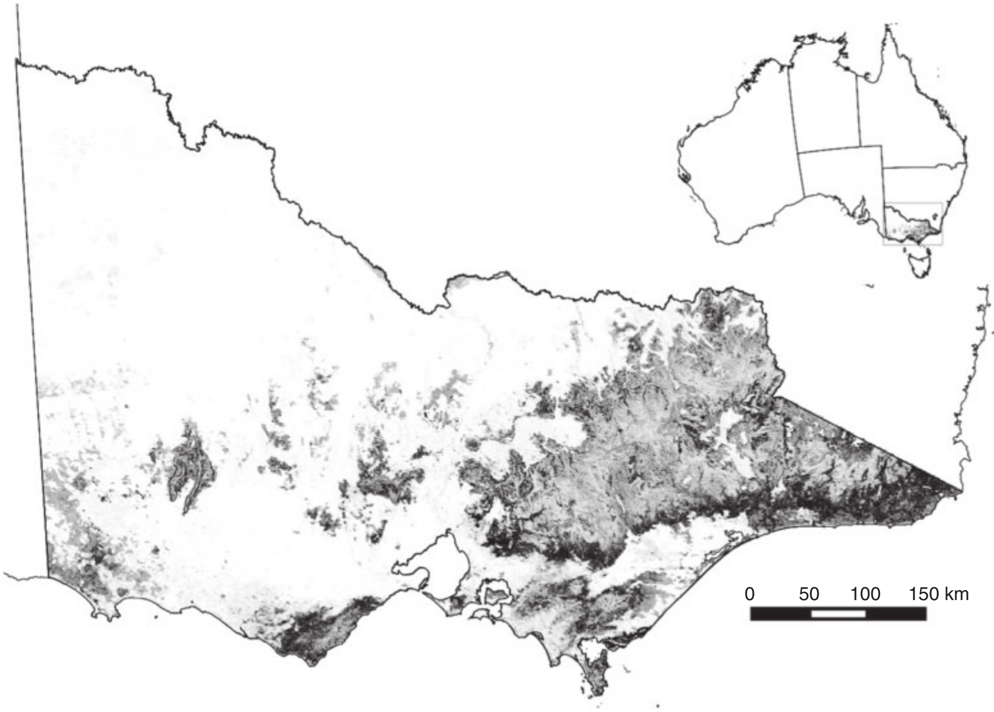


**Fig. 1.** Predicted relative likelihood of deer occurrence (all species) in Victoria. Darker shading indicates higher relative likelihood of deer occurrence. The location of the study area, the State of Victoria, in south-east Australia, is shown top right.

(Ramp *et al.* 2006), few studies have investigated the spatial and temporal patterns of DVCs or attempted to identify DVC risk across the Victorian road network. The Royal Automobile Club of Victoria (RACV) identifies deer as the fourth most common animal involved in insurance claims – after kangaroos, wombats and dogs – and reports 89 insurance claims for DVCs in Victoria during 2014–15 and 76 in 2015–16 (Keogh 2016).

The current draft deer management strategy for Victoria calls for an improvement of deer management in periurban areas, including identifying hot spots and trialling mitigation strategies for DVCs (DEDJTR 2018). However, the literature regarding DVCs in Victoria is severely under-represented, thus constraining management decisions. Modelling DVCs in Australia is important to clearly identify high-risk areas and to help optimise mitigation strategies. Once areas of high risk have been identified, mitigation strategies to reduce the risk of DVCs can be assessed and implemented. High-risk areas can be targeted for deer eradication programs, the construction of fencing, and signage or speed limit reductions.

Statistical modelling has been used to effectively quantify the risk of WVCs in Australia and elsewhere (Visintin *et al.* 2016; Yang *et al.* 2019). Models incorporating Poisson (Ye *et al.* 2018), negative binomial (Zou *et al.* 2015), Poisson–lognormal (Murphy and Xia 2016) and Gamma regression (Oh *et al.* 2006) have been used by researchers to investigate spatial and temporal trends in vehicle-collision data. Australian studies involving native species including wombats, kangaroos and wallabies have been undertaken (Ramp *et al.* 2005) but there is little research about the risks associated with collisions involving wild deer. Despite increases in deer abundance and distribution no previous studies have predicted spatial and temporal patterns of DVCs in Victoria.

The source of data for WVC studies can influence the accuracy of results and identification of collision hotspots (Yang *et al.* 2019). Several studies have used carcass records of individual species as data for collision modelling (Knapp *et al.* 2007; Stevens and Dennis 2013; Santos *et al.* 2018). Carcass records can be under-reported as carcasses may be difficult to detect and may not be reported to management agencies (Santos *et al.* 2016). Collision data can also be collected directly from motorists during insurance claims, accident investigations and self-reporting databases (Visintin *et al.* 2017). Collision data directly from motorists is also commonly under-reported as collisions are reported only if damage is over a certain threshold (Yang *et al.* 2019).

This study employs an existing conceptual risk model to predict where in Victoria DVCs are likely to take place. Predictions are tested by comparing predicted DVC risk with patterns of actual DVC events. Determining priority areas where accidents are most likely to occur will help support decision making to reduce the risks and identify where control mechanisms can be implemented.

## Materials and methods

### *Study area*

The entire State of Victoria (227 819 $km^2$: Australian Bureau of Statistics 2018), located in south-east Australia was used as our study area (Fig. 1). Our study analysed deer collision risk

**Table 1. Predictor variables used in the deer occurrence model**
The spatial variables X and Y were set to zero when predicting from the species occurrence model

| Variable | Description and justification for inclusion | Units | Mean | Range |
|---|---|---|---|---|
| ELEV | Elevation of terrain in metres above sea level. Elevation has been shown to be influential for the occurrence of many deer species, including sambar (Forsyth *et al.* 2009) and red deer (Debeljak *et al.* 2001). | m | 248.16 | 0.00–949.63 |
| GREEN | Remote-sensed mean seasonal change in greenness (2003–13) in vegetation. This variable has been shown to be influential for predicting the occurrence of mule deer in California (Visintin 2017). | – | 0.22 | 0.62–0.63 |
| LIGHT | Remote-sensed relative artificial light intensity. Artificial light has been negatively correlated with the probability of occurrence of roe deer (*Capreolus capreolus*) in urban landscapes (Ciach and Fröhlich 2019). | – | 0.19 | 0.00–54.69 |
| SLOPE | Slope of terrain in decimal percent rise. Slope was found to be the most influential non-spatial predictor for mule deer occurrence in California (Visintin 2017). | % | 2.13 | 0.00–28.48 |
| TREE DENSITY | Tree canopy coverage in decimal percentage. Deer in Victoria, especially sambar deer, are thought to prefer areas with high levels of vegetation coverage as protection from predators, hunters and adverse weather conditions (Moore 1994). | Decimal % | 23.81 | 0.00–81.01 |
| X | X spatial coordinate of intersecting 500-m$^2$ grid centroid, in metres. | m | – | |
| Y | Y spatial coordinate of intersecting 500-m$^2$ grid centroid, in metres. | m | – | |

across ~147 970 km of sealed roads. The roads were divided into segments of 500 m and less, which were used as the modelling units for collision risk. We overlaid a spatial grid of 500 m × 500 m (25 ha) cells on the study area and used each grid cell as a modelling unit for deer occurrence.

### *Study species*

Four species of introduced deer have established wild populations in Victoria: sambar deer (*Rusa unicolor*), fallow deer (*Dama dama*), red deer (*Cervus elaphus*) and hog deer (*Axis porcinus*). Wild deer are distributed widely across Victoria and have varied habitat preferences. Harvest rates from recreational hunters suggest that deer numbers are increasing (Moloney and Turnbull 2017), leading to concern regarding ecological impacts and risks posed to motorists. We obtained occurrence records for all deer species from the Victorian Biodiversity Atlas (DELWP 2018), and collision records from Vicroads and Wildlife Victoria. Deer collision records were not species specific and, therefore, represented collisions involving either sambar, fallow, red or hog deer.

### *Model framework*

We used a quantitative risk model framework (Visintin *et al.* 2016) to predict DVC risk on the Victorian road network based on traffic volume, traffic speed and modelled occurrence of deer. The model framework predicts collision risk by modelling hazard (presence and movement of vehicles) and exposure (the occurrence of animals) across geographical space. We developed a species distribution model (SDM) (pooling presence records for all Victorian deer species: fallow, red, hog and sambar) to predict the occurrence of deer across the study area. Traffic volume and traffic speed for all road segments were predicted from a model that regressed annual average daily traffic counts and speed limit data on anthropogenic variables – detailed methods are provided in Visintin *et al.* (2016). All statistical analyses were conducted using the open-source software package R 3.4.1 (R Core Team 2016).

### *Deer occurrence modelling*

We obtained deer observation records made between the years 2000 and 2018, inclusive, from the Victorian Biodiversity Atlas. Only occurrences with spatial uncertainty equal to or below 500 m were considered. Presence of deer across the study area was determined by selecting all grid cells that contained at least one occurrence record; grid cells with multiple occurrences were treated as single records. As deer absence data were not available, we randomly selected 10 000 grid cells as background data. Our choice of 10 000 grid cells is based on a common practice in SDM work; however, we acknowledge that in some cases more background cells may improve model performance (Warton and Shepherd 2010). In our case, this choice balanced adequately capturing environmental variation – given the scale of our landscape – with computational efficiency.

We selected environmental variables that the published literature suggested were influential on the ecology of deer species (Table 1). Each predictor variable was represented as a 500 m × 500 m (25 ha) raster grid to match the grid cells used to model deer occurrence. Because environmental variables exhibit spatial gradients, and species surveying is subject to spatial biases, we included grid cell coordinates – X (Easting) and Y (Northing) – as predictor variables in the species occurrence model to reduce the effects of spatial autocorrelation and survey bias. All variables used in the species occurrence model exhibited variable inflation factors between 1 and 6, indicating low effects of multicollinearity (James *et al.* 2013). However, our chosen modelling method is less influenced by these effects than generalised linear regression models (Dormann *et al.* 2013). We fitted Boosted Regression Tree (BRT) models to deer presence/background data. This is a machine learning method that uses classification to produce a null model of binary splits based on the predictor variables and then iteratively regresses the residuals of each fit on the predictor variables using internal cross-validation to prevent overfitting (Elith *et al.* 2008). A tree complexity of 5, a learning rate of 0.005 and bag fraction of 0.5 were used in our BRT model.

### Collision model and validation

GPS coordinates of spatially unique deer collision/carcass records ($n = 9$) involving all deer species were provided by the Victorian State Government's road management agency, VicRoads. All road segments that intersected with a reported collision/carcass were coded '1' and the remaining road segments were coded '0', to represent background data. For each road segment, we sampled species occurrence predictions based on the values in grid cells that intersected with the road segment. For cases where road segments were contained entirely within grid cells, the segments were assigned the cell values of deer occurrence. Otherwise, road segments spanning multiple grid cells were allocated weighted averages of deer occurrence based on the proportions of segment length intersecting each grid cell. Traffic volume and speed data for each road segment were provided from previous modelling (Visintin *et al.* 2016).

Due to the low number of deer collision/carcass records we were unable to properly train a collision model for Victoria. Instead, we predicted collision risk for all road segments within our study area using our predictor variables (deer occurrence, traffic volume and traffic speed) and the coefficients of an existing model developed by C. Visintin, F. Shilling, R. van der Ree and M. McCarthy (unpubl. data) for mule deer (*Odocoileus hemionus*) in a 146 478-km$^2$ section of central California. The latter model regressed reported collisions on variables of deer occurrence, traffic volume and traffic speed using a complementary log–log (cloglog) link. An offset term was included to account for variation in road lengths. The model, with fitted coefficients, is expressed as:

$$\mathrm{cloglog}(p_i) = -55.43 + 0.83 * \log(O_i) + 4.68 * \log(V_i) - 0.26 * (\log(V_i))^2 + 7.52 * \log(S_i) + \log(\mathrm{L_i})$$

where $p_i$ (=Pr($\mathrm{Y}_i = 1$)) is the relative likelihood of a collision occurring on a road segment $i$, $O_i$ is species occurrence, $V_i$ is traffic volume, $S_i$ is traffic speed, and $\mathrm{L_i}$ is an offset for road segment length.

We validated the collision model predictions using the dataset of deer collision/carcass records obtained from VicRoads. We tested the calibration strength and discrimination ability of the model predictions with the collision/carcass data. To assess calibration strength, we regressed the collision/carcass observations on predictions made using the collision/carcass observations in the trained California model expressed as:

$$\mathrm{cloglog}(\mathrm{p_i}) = \beta_0 + \beta_1 \mathrm{P_i}$$

where $p_i$ (= Pr($\mathrm{Y}_i = 1$)) is the relative likelihood of a collision occurring on a road segment $i$, and $\mathrm{P_i}$ is the predicted relative collision rate for each segment on the link scale (complementary log–log). An intercept coefficient of 0 and slope coefficient of 1.0 indicates a perfectly calibrated model (Miller *et al.* 1991). To measure the ability of the model to discriminate between true positive and false positive predictions we used a receiver operating characteristic (ROC) score – a score of 1.0 indicating perfect discrimination ability and 0.5 suggesting a performance no better than random (Metz 1978).

Given the small sample size of the data from VicRoads, we performed sensitivity analysis on the validation outputs to determine whether our results were from a collision risk signal produced by the model or by random chance. For each of 1000 iterations, we randomly shuffled the locations of the nine recorded collisions on the road network, made new predictions, and then compared the observations with the predictions to calculate a slope coefficient and ROC score.

We also validated collision model predictions using a second dataset obtained from the Wildlife Victoria database, comprising reported DVCs between the years of 2010 and 2018, inclusive ($n = 254$). Because the spatial accuracy of these records was resolved only to town level, we could not use the same validation methods as for the VicRoads collision/carcass data. We therefore summed collision records by town and calculated the expected number of collisions within each town boundary based on the predicted values of collision risk for all road segments within the boundary. To assess calibration strength, we regressed the total reported collisions on the expected total collisions based on the predictions made from the trained California model. Due to the response data being positive integers, we used the Poisson link:

$$\log(\mathrm{C_j}) = \beta_0 + \beta_1 \log(\mathrm{E_j})$$

where $\mathrm{C_j}$ is the count of reported collisions, $\mathrm{E_j}$ is the expected count of collisions, in a town j. Once again, an intercept coefficient of 0 and slope coefficient of 1.0 indicates a perfectly calibrated model.

## Results

### Deer occurrence modelling

The deer occurrence model produced plausible predictions of deer occurrence across Victoria (Fig. 1). The deviance reduced by the model was 35.1% and the mean cross-validated ROC score was 0.93.

### Collision model performance

The collision model performed well when validated with independent data. Using VicRoads data, the model was able to discriminate between true positives and false positives (ROC value of 0.91). Regressing the VicRoads collision observations on the predictions made by the collision model resulted in a slope coefficient of 0.63 while regressing the Wildlife Victoria observations on the predictions resulted in a slope coefficient of 0.83. All regression coefficients were highly significant ($P < 0.001$).

Although the VicRoads data contained few observations, they were useful for validation. Both the slope coefficient (0.63) and ROC value (0.91) were outside the ranges of values obtained through simulating variations in the collision observations: slope coefficient (–0.68–0.49), ROC (0.50–0.85).

### Effect of predictor variables

DVC risk increased with the likelihood of deer occurrence (Fig. 2*a*) and with higher traffic speeds (Fig. 2*b*). We observed a quadratic shape in the response to traffic volume (Fig. 2*c*), indicating a possible threshold effect, where deer may avoid areas of high traffic volume due to the disturbance of traffic noise (Forman and Alexander 1998).

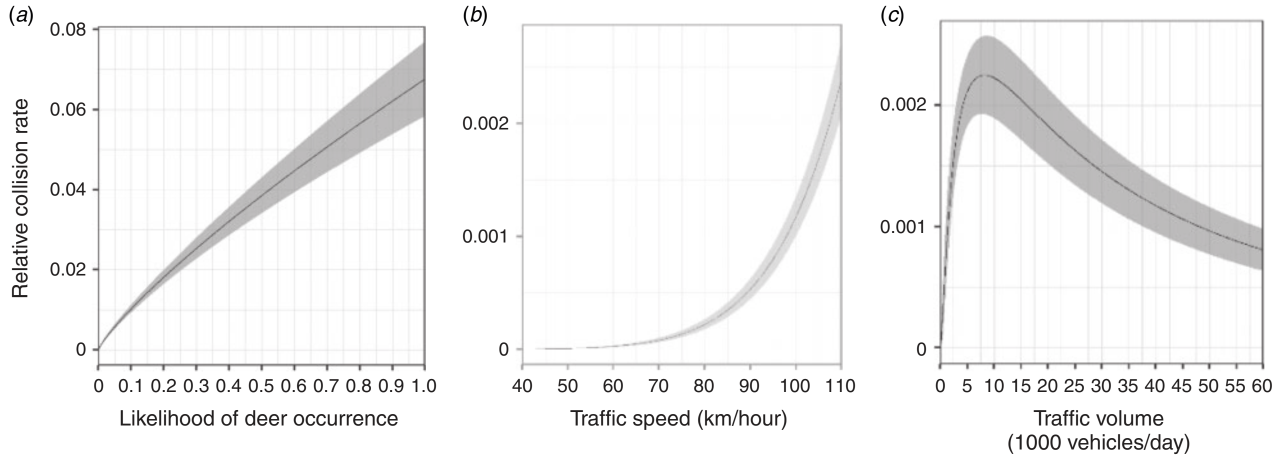


**Fig. 2.** Effects of predictor variables on relative likelihood of collision. Note that shapes are based on the fitted model coefficients for California mule deer. (*a*) Relative likelihood of deer occurrence, (*b*) traffic speed and (*c*) traffic volume. Shaded regions indicate error bounds (95% confidence) on coefficient estimates.

### *Model predictions*

The map of predicted DVC risk identifies road segments where DVCs are most likely to occur in Victoria. Visual inspection of predicted collision risk across the Victorian road network indicated three regions with increased DVC risk (Fig. 3). Roads with high speed limits and high traffic volumes that border forested areas appear to exhibit the highest overall collision risk. In particular, three main areas of Victoria had increased DVC risk. The first location was an area of the Western Freeway near Gordon (Fig. 3*a*). This is one of the few areas of the Western Highway between Ballarat and Melbourne that has remnant vegetation close to the highway. The second (Fig. 3*b*) occurs to the east of Melbourne, including Wellington Road near Lysterfield Park and roads surrounding Emerald and Gembrook, including the Gembrook–Launching Place Road. The third location of predicted increased DVC risk is an area incorporating many of the roads in West Gippsland (Fig. 3*c*), including segments of the Strzelecki Highway between Mirboo North and Driffield and roads north of Moe including the Moe–Rawson Road and Tyers–Walhalla Road.

## Discussion

Our study successfully applied a collision-risk framework in south-eastern Australia and made plausible predictions of DVC risk across the entire Victorian road network. We highlight three regions of heightened DVC risk in Victoria. This is the first study to specifically model DVC risk in Victoria and was performed at a large spatial scale. Other studies have used similar modelling approaches to assess wildlife collision risk in Australia but have focused on native species, including kangaroos, common wombats, koalas and wallabies (Dique *et al.* 2003; Klöcker *et al.* 2006; Ramp and Ben-Ami 2006).

Monitoring changes in the distribution of wild deer in Victoria was established as a research priority by the comprehensive review of deer impacts and management conducted by Davis *et al.* (2016). While the focus of this paper is to help establish DVC risk in Victoria, it also provides useful information on the current modelled distribution of deer in Victoria. Our results show that wild deer are likely to occur within most forested areas across the State and confirm anecdotal reports of deer in the Great Otway and Grampians National Parks (Fig. 1). This is concerning as without proper management deer can cause significant ecological damage to these important and biodiverse protected areas. As deer numbers increase across Victoria so will the risk they pose to motorists.

Our results suggest that DVC risk is greatest in three main regions in Victoria (Fig. 3): the first on the Western Freeway near Ballarat, the second to the east of Melbourne near Lysterfield and the third in West Gippsland. All these regions are known to be occupied by wild deer, particularly sambar and fallow deer (Forsyth *et al.* 2015, 2016). Despite many anecdotal reports of DVCs between Orbost and the New South Wales border on the Princes Freeway in eastern Victoria (C. Davies, pers. obs.), road sectors in this area did not show high predicted risk of DVC. This section of the Princes Freeway has a speed limit of 110 km $h^{-1}$ and is located in known deer habitat (Gormley *et al.* 2011). The low risk of DVC predicted in eastern Victoria may have been influenced by relatively low daily traffic volumes. The three main areas that had higher DVC risk could be considered as collision hotspots, a term commonly used in road ecology. However, collision hotspots are commonly identified using Kernel Density Estimation (Ramp *et al.* 2005; Snow *et al.* 2014), a method that was not applied during this study.

This study was constrained by a lack of accurate DVC data from Victoria to train models; we therefore used a model trained for mule deer in California as a surrogate to make predictions. Our results assume that the four deer species in Victoria share similar ecological and behavioural traits to mule deer. This assumption is supported by ecological data: mule deer and the deer species present in Victoria are all medium-to-large ungulate herbivores and are likely to share similar ecological requirements (Keegan *et al.* 2011; Leslie 2011; Forsyth *et al.* 2015). Deer often display overlap in dietary preferences in areas where multiple species coexist, as observed with white-tailed deer and mule deer (Berry *et al.* 2019) and white-tailed deer and sika deer (Kalb *et al.* 2018) in the USA. It is likely that if mule deer were introduced to Victoria their dietary preferences would be similar

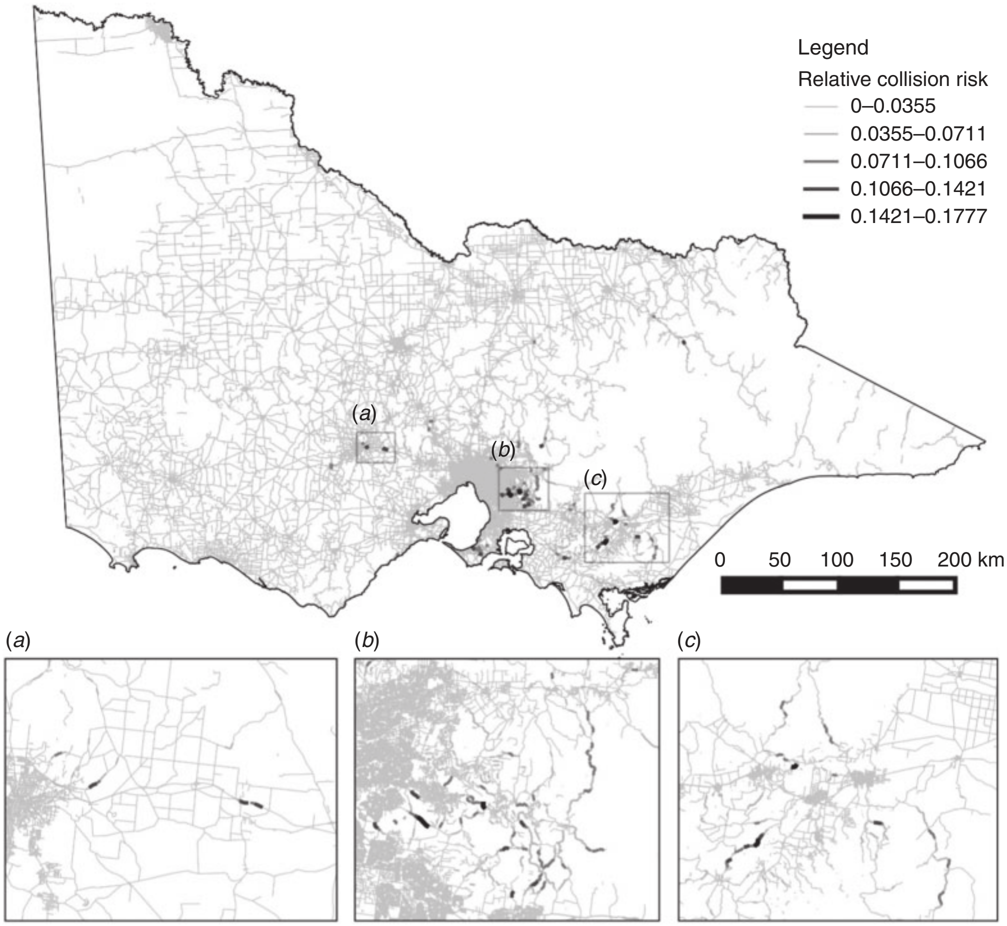


**Fig. 3.** Map of deer collision risk per road segment. Darker line segments indicate higher relative risk of deer–vehicle collisions. Visual inspection of predicted collision risk across the Victorian road network indicated three regions with increased deer–vehicle collision risk: Gordon, Lysterfield and West Gippsland (labelled on map by *a*, *b* and *c*).

to the deer species already established. Previous modelling has also shown similarities between the habitat preferences of mule deer and deer species present in Victoria. Russell *et al.* (2015) showed that elevation, vegetation cover and distance to roads are important in determining habitat selection for mule deer during winter and summer in the USA. Forest cover was also found to be an important determinant of mule deer habitat use in Oregon, USA (Coe *et al.* 2018). Similarly, sambar deer prefer dense cover (Moore 1994) and have demonstrated seasonal altitudinal movements in their native range in Taiwan (Yen *et al.* 2019).

Our model also assumes that Victorian roads have similar characteristics to roads in California. With the exception of a few $>$12-lane freeway segments in the central California study region, the characteristics of the road network were similar to those in Victoria. Both used classification systems that categorised roads into local, collector, subarterial, arterial, highway, and freeway/interstate types with similar implications for traffic planning. The traffic models – parameterised and fitted using the same covariates – were used to predict traffic volume and speed for Victoria and central California, respectively. In Victoria, predicted traffic volumes were between 195 and 130 000 vehicles per day whereas the central California traffic volumes were between 765 and 189 000 vehicles per day. Traffic speeds were predicted to be between 42 and 101 km $h^{-1}$ in Victoria and between 36 and 112 km $h^{-1}$ in central California. We visually inspected the distributions of traffic volume and speed between the two areas and discovered similar patterns; however, we acknowledge that the two road networks have notable differences. Despite these assumptions and limitations, the predictions made by the model may be useful to authorities with responsibility for road safety to target areas for further investigation and greater data collection.

There are potential reporting biases involving DVCs because deer are an introduced species in Victoria and not a priority for wildlife rescues or reporting. As such, accurate records describing vehicle collisions involving deer were difficult to obtain. In accordance with recommendations from the Victorian Draft Deer Management Strategy (DEDJTR 2018), we advocate that a database registry for vehicle collisions involving deer be initiated. This concept is considered a priority to improve the extent and accuracy of DVC data, increase the statistical power of modelling studies such as this one, and provide better information to management authorities.

Many collision records did not identify deer to the species level so it was not possible to separately model the collision risks posed by each of the four species of deer found in Victoria.

The database registry suggested above should make use of improved techniques for recording data relating to DVCs, including the time and date of the accident as well as information regarding the species of deer involved. Accurate and more extensive collision data for each individual deer species (sambar, red, fallow and hog) will allow the risk of collisions to be estimated for each species. This is important due to differences (such as the behaviour and size of the animal) that could influence the likelihood or severity of a collision.

Temporal variation in animal activity can be a useful predictor of collision risk. Deer often display crepuscular activity patterns and are therefore more likely to be involved in collisions with transport during the early morning and evening (Steiner *et al.* 2014). The inclusion of temporal data would help identify high-risk times of day. Additionally, deer may display migratory patterns such as moving from higher elevations to lower elevations during winter. Collision risk may therefore be increased on roads at higher elevations during early winter. If DVC risk is found to be higher during particular times of the day and the year, warning signs or a reduction in speed limits during high-risk times could be used to help reduce DVC risk.

Several mitigation strategies could be applied in high-risk areas. Fencing to prevent deer from accessing road networks was proved effective for mule deer in the USA (Bissonette and Rosa 2012). The removal of roadside vegetation may also reduce collision risk in some areas, especially where such vegetation is known to attract ungulates (Rea 2003). Furthermore, signage could be improved in high-risk areas to make motorists aware of DVC risk, particularly during high-risk times of day. However, there is little evidence that warning signs as a primary mitigation strategy actually reduce the rate of wildlife collisions (Bond and Jones 2013). Culling deer through ground and aerial shooting is the primary control method used to reduce the negative impacts associated with deer in Australia (Pople *et al.* 2017; DEDJTR 2018). As shown by DeNicola and Williams (2008), targeted culling of deer populations in high-risk areas can reduce the risk of DVC. Currently in Victoria, deer culling programs aim to improve ecological outcomes rather than reduce the risk of DVC. As such, future culling operations could be coordinated to achieve dual outcomes: reduction of DVC risk as well as favourable ecological outcomes. However, deer control operations that incorporate shooting are not feasible in periurban areas. As such, other mitigation strategies such as fencing along high-risk roads should be prioritised in these areas.

In conclusion, we have used a modelling approach to identify road sectors within Victoria's road network that are likely to be of increased risk for DVCs. As more DVC data are collected, the modelling and analyses can be updated and improved.

Recommendations from this study include:

(1) The development of a DVC register to provide more detailed data for further investigation, including subsequent modelling and analysis.
(2) Future modelling to further delineate areas of Victoria's road network with high risk of DVC.
(3) Applying mitigation strategies to high-risk areas.

## Conflicts of interest

The authors declare no conflicts of interest.

## Acknowledgments

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