

# Incorporating habitat use in models of fauna fatalities on roads

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## ABSTRACT

**Aim** To highlight the benefit of using habitat use to improve the accuracy of predictive road fatality models.

**Location** The Snowy Mountains Highway in southern New South Wales, Australia.

**Methods** A binary logistic regression model was constructed using wombat fatality presences and randomly generated absences. Species-specific habitat variables were included as predictors in the model selection process as well as two spatially explicit measures of wombat habitat use. Generalized additive models (GAMs) were constructed for each possible combination of predictors in R. The final model was selected by comparing all models subsets for the eight predictors and employing the one standard error rule to select the best model set.

**Results** The final predictive model had high discriminatory power and incorporated both measures of species habitat use, greatly exceeding the variation explained by a previously published model for the same species and road.

**Main Conclusions** Our findings highlight the importance of incorporating variables that describe habitat use by fauna for predictive modelling of animal-vehicle crashes. Reliance upon models that ignore landscape patterns are limited in their capacity to identify hotspots and inform managers of locations to engage in mitigation.

## Keywords

Common wombats, Getis–Ord clustering, habitat use, predictive modelling, road-kill, spatial analysis, *Vombatus ursinus*.

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## INTRODUCTION

The adverse impacts of roads on wildlife are well documented (see reviews by Forman *et al.*, 2003; Seiler, 2003; Coffin, 2007). Although population effects on fauna extend well beyond the boundary of the road (Reijnen *et al.*, 1997; Gaines *et al.*, 2005; Jaarsma *et al.*, 2006; Ramp & Ben-Ami, 2006), fatalities of fauna killed in collisions with vehicles on the road itself are of major concern to conservationists and road managers (Forman & Alexander, 1998; Trombulak & Frissell, 2000). Recently, many quantitative models of animal–vehicle collisions have been developed (Malo *et al.*, 2004; Saeki & Macdonald, 2004; Gaines *et al.*, 2005; Jaeger *et al.*, 2005; Ramp *et al.*, 2005; Orlowski & Nowak, 2006), with the goal of providing effective mitigation techniques for management (Jaarsma *et al.*, 2007). These probabilistic approaches to predicting locations of animal–vehicle collisions are conducted for two primary purposes: (1) to infer those factors contributing to collisions, and (2) to identify hotspots for targeted mitigation.

Driven by the need to develop feasible models, modelling approaches for predicting fatality locations have typically relied on variables that characterize the road environment; such as road sinuosity, road-verge attributes and spatial and temporal traffic variation (Finder *et al.*, 1999; Taylor & Goldingay, 2004; Clevenger & Waltho, 2005). Often missing, or at best generic in nature, are species-specific variables that describe how the animals in question utilize the landscape. When included, species-specific variables are often restricted to vague characterizations of landscape utilization (Jaeger *et al.*, 2005), and often multiple species are modelled simultaneously using the same suite of generic variables (Clevenger *et al.*, 2003; Taylor & Goldingay, 2004; Ramp *et al.*, 2005). The biological link between these habitat variables and the fauna that are involved in collisions is never explicitly described. This oversight has significant ramifications, as the importance of understanding species-specific distributions in ecological studies in road environments has been shown for a wide range of species (Forman *et al.*, 2002; Alexander *et al.*, 2005; Lesbarreres *et al.*,

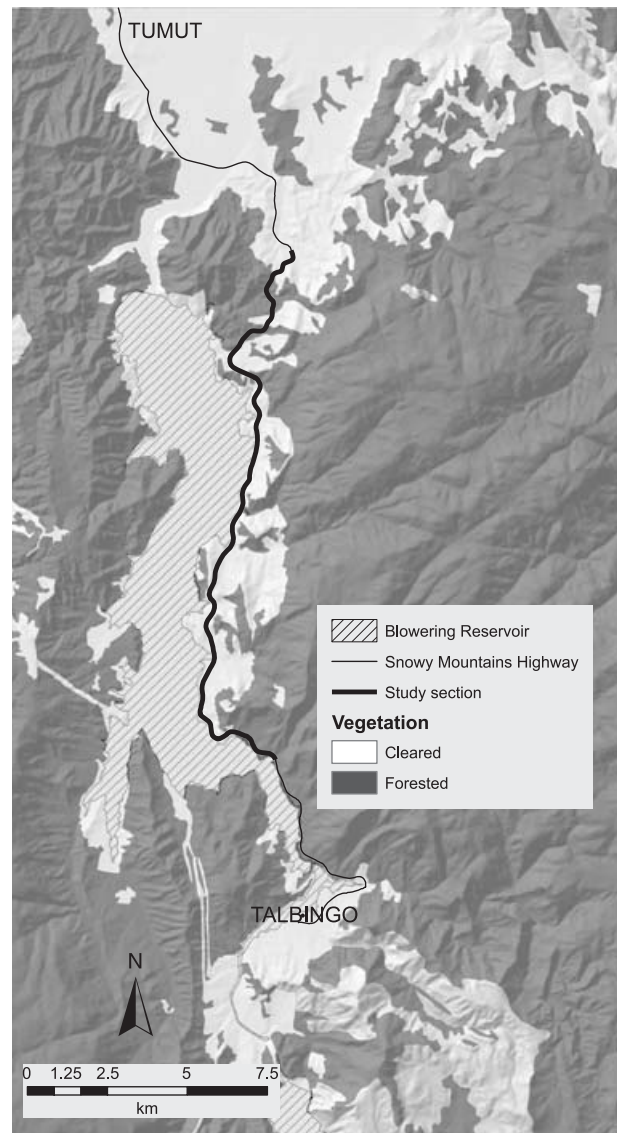
2006; Barnum *et al.*, 2007; Eigenbrod *et al.*, 2008). Although often due to the absence of relevant data, the adoption of species-specific habitat variables within predictive fatality modelling has been slow, despite many models suffering from poor explanatory power.

To highlight the benefit of including species habitat use information in fatality models we chose to model fatalities of common wombats *Vombatus ursinus* using spatially explicit information on habitat use. As burrow-dwelling animals, wombats emerge from their burrow at dusk and re-enter at dawn. They generally have at least four major burrows within their home range (ranging between 5 and 25 ha), distinguishable by their size (Triggs, 1988). High burrow density can be used as a reflection of good wombat habitat, while burrow occupancy rates are a surrogate for estimation of population size.

Although historically considered abundant, few data exist of actual densities and current distribution. The evidence that does exist suggests that the distribution of the common wombat has contracted since European arrival, particularly in western Victoria, southern Queensland and northern South Australia (Triggs, 1988; McIlroy, 1995; Buchan & Goldney, 1998). The common wombat is impacted upon by a range of threatening processes, including road-kill, habitat loss, predation, disease and culling (Triggs, 1988; Roger *et al.*, 2007). This contraction is alarming as species decline is often first recognized at range extremes (Baldi, 1999; Lehman *et al.*, 2006). Much of the current distribution of the common wombat lies in fragmented or disturbed areas (Buchan & Goldney, 1998); environments that are often characterized by roads. Their adaptability and preference for human-modified habitats has maintained perceptions of their commonality. Common wombats are edge specialists, preferring patchy habitats with a mix of open and closed forest in proximity to watercourses or drainage lines (Roger *et al.*, 2007). This seeming preference, determined by landscape structure, puts them in direct contact with anthropogenic disturbance.

The persistence of the common wombat is a concern as there are only three extant species of wombat, two of which are threatened. The common ancestors of wombats were once a diverse and dominant group, with many forms larger than the current extant species (Woolnough & Steele, 2001). Today, the southern hairy-nosed wombat *Lasiorhinus latifrons* is restricted to small fragmented areas concentrated along the Nullarbor Plain in South Australia, and is listed as vulnerable, while the northern hairy-nosed wombat *Lasiorhinus krefftii* is listed as critically endangered with fewer than 115 individuals located in central Queensland (Banks *et al.*, 2003).

In this paper we provide an example of the benefits of incorporating spatially explicit information of habitat use in the modelling of animal-vehicle collisions. To do this we chose a road for which a fatality model for common wombats had previously been constructed and where habitat suitability modelling had also been conducted for this species. This enabled us to make a comparative assessment of the increase in value of incorporating habitat use variables in the fatality model. We discuss the importance of our results for management and encourage conservation managers to utilize models that include



**Figure 1** The study area is along the Snowy Mountains Highway, adjacent to Blowering Reservoir. White areas are cleared, light grey areas are forested.

spatially explicit information on species distributions that are at an appropriate scale to the fatality locations being modelled.

## METHODS

### Study area

The study was conducted on the Blowering foreshores between the townships of Tumut (35°19' S, 148°14' E) and Talbingo (35°34' S, 148°18' E) in Kosciuszko National Park, southern New South Wales, Australia (Fig. 1). The study area of 30 km<sup>2</sup> is bound in the west by the Blowering Reservoir while the east is characterized by native forest and grassy south-west facing slopes of what was once remnant pasture. The study area is dominated by cleared

land, moist and dry forest, blackberry thickets *Rubus fruticosus*, patches of bracken fern *Pteridium esculentum* and briar bushes *Rosa rubiginosa*. Slope areas are dominated by shrubs *Leptospermum* spp. and patches of trees *Eucalyptus* spp. (Jaremovic & Croft, 1991). The area has a temperate climate, with cool wet winters and warm summers, and an average yearly rainfall of 900 mm (Australian Bureau of Meteorology records for Tumut Plains). The common wombat shares the open grassy foraging areas with native and introduced herbivores; namely the eastern grey kangaroo *Macropus giganteus*, the emu *Dromaius novaehollandiae* and the European rabbit *Oryctolagus cuniculus*. The windy and single-laned Snowy Mountains Highway (speed limit 100 km h<sup>-1</sup>) runs through the site fragmenting the foreshore area from the slopes and is a known hotspot for animal–vehicle collisions. An average of 247 cars travel this section of highway each day with peak volumes occurring between 9 : 00 and 18 : 00 hours (Ramp *et al.*, 2005). Traffic volume remains relatively constant throughout the year.

### Data collection

Fatalities of common wombats along the 40 km segment of the Snowy Mountains Highway between Tumut and Talbingo were recorded between 1998 and 2005. Beginning in March of 2002, fatalities were recorded using a hand-held global positioning system (GPS) device (Garmin II Plus) following Ramp *et al.* (2005). The road was travelled twice daily 5 days per week with carcasses removed from the roadside after recording to avoid double counting. Only fatalities (post-March 2002) were used for modelling as prior to this fatalities were not spatially referenced.

Habitat use was determined by recording the location of common wombat burrows in the study area (Roger *et al.*, 2007). Burrow location has been used to represent habitat use in other species such as the muskrat *Ondatra zibethicus* (Nadeau *et al.*, 1995). Similarly, variations of wombat density have been shown to be correlated with the placement of the burrow within a landscape (Downes *et al.*, 1997), primarily because wombats construct burrows in relation to physiographic features of the landscape. Burrow surveys were conducted in June and July 2005 by systematically surveying the entire study area on foot, following Rishworth *et al.* (1995). Transects running east–west were traversed by four observers spaced lengthwise 15–30 m apart (depending on the visibility of terrain). Each transect ran from the border of the reservoir for an average distance of 1600 m. Approximately 120 transects per observer were traversed in total, covering an area of 30 km<sup>2</sup>. Burrow locations were recorded using a GPS and scored as either abandoned or occupied based on the criteria for major burrows described by McIlroy (1973). Maximum height and width of burrow entrances were also recorded. Entrances greater than 2100 cm<sup>2</sup> were scored as occupied, and visible signs of occupation were also used; such as tracks and presence of scat. When in doubt, small sticks were placed across burrow entrances and checked the following morning for sign of displacement. A raster layer of burrow location data (both occupied and abandoned burrows) was then created in ArcGIS 9.1 (Environmental Systems Research Institute 2006).

## Model development

### Dependent variables

Common wombat fatalities were compiled using ArcGIS 9.1. An equal number of absence points were randomly generated on the highway using Hawth's Analysis Tools add-on for ArcGIS (Beyer, 2004). Although common wombat fatalities were recorded over the entire 40 km length of the highway, only fatalities recorded on the 15 km length within the study area were used in the analysis in order to match the 30 km<sup>2</sup> area surveyed for burrows. A total of 208 presence–absence data points were used in the analysis.

### Predictor variables

Selected variables were based on a previously developed habitat suitability model that used burrow location to predict habitat use by wombats (Roger *et al.*, 2007). Predictors selected for use in the modelling process included: distance to drainage lines (not including the Blowering Reservoir), forest cover, distance to blackberry bush, slope, normalized difference vegetation index (NDVI), distance to the nearest burrow, burrow occupation and abandonment clustering (Getis-Ord  $G_i^*$  statistic) and hillshade. All environmental variables were stored as raster layers within ArcGIS with a resolution of 25 m.

Vegetation community data were obtained from 30 m LANDSAT data and used to calculate the proportion of forest cover surrounding each wombat fatality. A circular sampling area based on the average home range of a common wombat (Skerratt *et al.*, 2004) was generated assuming the radius of a circle was equal to the diameter (320 m). The area covered by all forest communities in the study area (moist forest, disturbed forest, severely disturbed forest, moist forest tending to dry and dry forest) was aggregated into a proportion of area covered by forest following Ramp *et al.* (2005).

Raster layers of distance from wombat fatality to the nearest river or watercourse (m), the nearest blackberry bush (m) and the nearest burrow (m) were generated using the Euclidian distance function in ArcGIS Spatial Analyst. A raster layer of slope (degrees) was derived from a 20 m resolution Digital Elevation Model (DEM). Hillshade was used as an alternative to aspect because aspect is a circular variable and does not behave well in correlative studies (Beers *et al.*, 1966). Hillshade, generated using the Raster Surface toolbox in ArcGIS, was used to provide a proxy for relative radiation load.

An NDVI image at 15 m resolution (acquired 26 December 2000) was used as an index of greenness within the study area. NDVI values were created by the Australian Bureau of Meteorology from visible and near infrared reflectance measurements ( $NDVI = (NIR - VIS)/(NIR + VIS)$ ), where NIR is the near infrared light reflected by the vegetation and VIS the visible light reflected by the vegetation (Pettorelli *et al.*, 2006). Negative NDVI values correspond to an absence of vegetation, while higher values are associated with greater density and greenness of the plant canopy (Justice *et al.*, 1985). The NDVI values were then converted into

a habitat complexity index (NDVI-SD) by taking the standard deviation of values within a 200-m radius. Focal statistics within ArcGIS was used to resample the 15 m advanced spaceborne thermal emission and reflection radiometer (ASTER) cell sizes to conform to the 25 m used for the remainder of the data. In the NDVI-SD index higher values represent mixed forest and grassland, while lower values represent pure forest and grassland.

To model burrow clusters in the landscape, clusters of occupied and abandoned wombat burrows were analysed using the Getis–Ord  $G_i^*$  spatial clustering statistic (Getis & Ord, 1992; Ord & Getis, 1995). The  $G_i^*$  statistic can detect spatial clusters despite negative tests for global spatial autocorrelation (Swenson & Howard, 2005). It measures the degree of spatial clustering of a sample based on how different it is from the mean of the data set. The statistic is a Z-score with a mean of zero and a standard deviation of 1. In our case, a positive  $G_i^*$  value represents a cluster of occupied burrows, while a negative  $G_i^*$  value represents a cluster of abandoned burrows. The extent to which a  $G_i^*$  value is greater or less than the mean represents the strength of the spatial clustering in the sample, with values greater in magnitude than  $\pm 2$  approximately at the 95% significance level (Laffan, 2006). The  $G_i^*$  statistic was calculated following Laffan (2006), calculations are based on Euclidean distance using circular radii from 125 m to 12,500 m at 125 m increments and aggregated into a single layer using the radius with the greatest magnitude. The Z-score represents the statistical significance of clustering for a specified distance.

#### Fatality model

A binary logistic regression model was constructed using wombat fatality presences and randomly generated absences. Generalized additive models (GAMs) were constructed for each possible combination of predictors in R (R Development Core Team, 2005). All predictor variables were checked for collinearity before use. Predictor variables were normalized by transformation in order to stabilize variances. The logarithmic transformation was applied to the distance to blackberry, river and burrow variables, while the square-root transformation was applied to the forest, slope and hillshade variables. The relationship between each predictor and the dependent variable was assessed to choose the appropriate degrees of freedom for each predictor based on realistic ecological relationships. Plausibility of response shapes was used to discern the relationship between variables. Relationships were either left linear or splined with 2, 3 or 4 degrees of freedom.

#### Model selection

Eight variables were considered for inclusion in the fatality model, for a total of 256 candidate models. This is a 'model selection' problem, which we addressed by finding the model that best predicted new observations using a cross-validation approach known as the bootstrap .632 rule. This has been shown to be appropriate for model selection when the underlying parameter distributions are unknown (Hastie *et al.*, 2001), or

when robustness of underlying model assumptions is desired. A penalty-based approach such as Akaike Information Criterion (AIC) does not share such properties. Bootstrapping was used because it has been shown to improve cross-validation, particularly when using the .632 rule (Efron, 1983; Efron & Tibshirani, 1997).

To evaluate performance in predicting new observations, two loss functions were employed: misclassification error rate and deviance. Misclassification error rate is a natural and readily interpreted measure of predictive performance, whereas deviance is a measure of predictive success that has theoretical rather than pragmatic origins. In particular, cross-validation approaches using the deviance function have been shown to estimate the same quantity as AIC (Efron, 2004), although using a data-driven approach rather than a parametric, large sample argument.

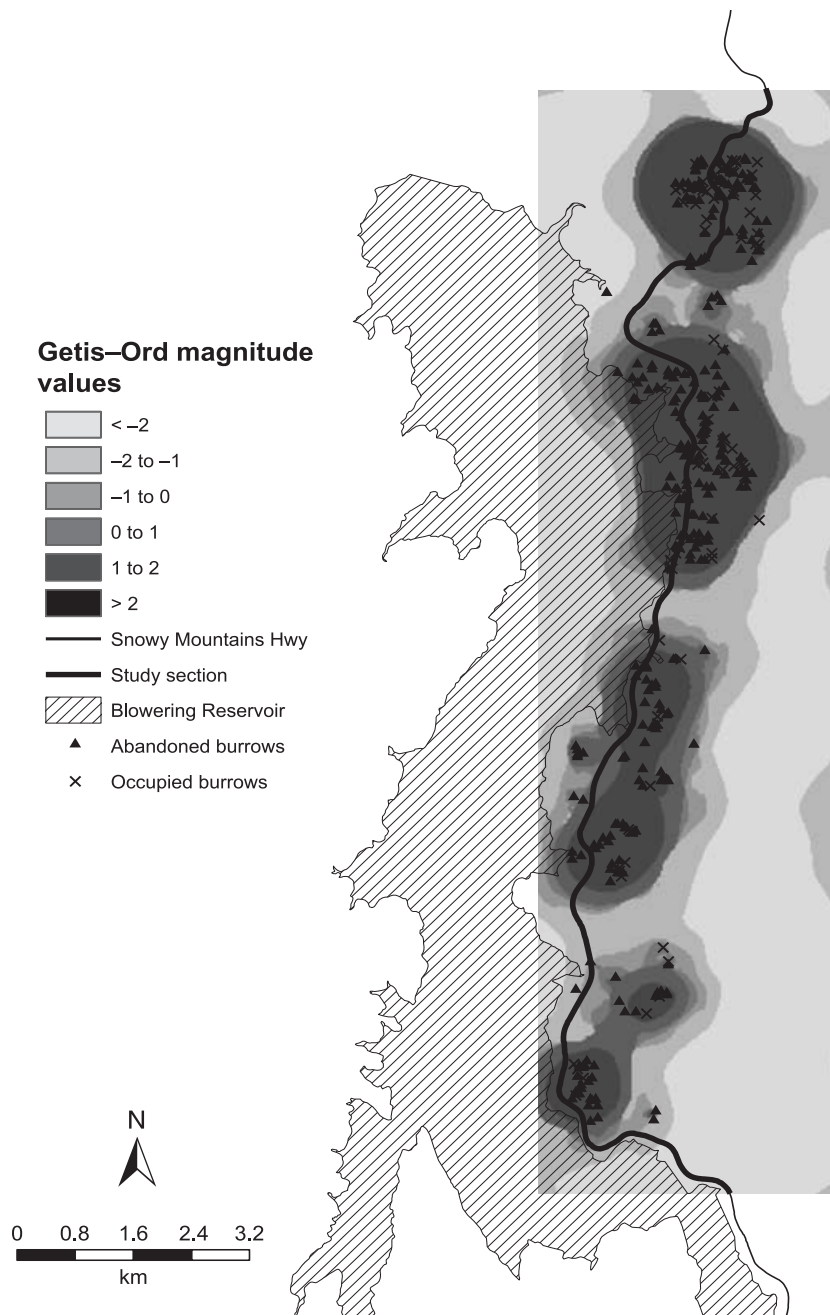
Use of the misclassification error rate requires a threshold value to classify the predicted probability as presence or absence. Rather than choosing an arbitrary threshold, a receiver operating characteristic (ROC) curve was used to find the threshold that best discriminates between the sensitivity (probability that a wombat fatality is correctly predicted) and 1 minus specificity (a false positive prediction) (Ferrier *et al.*, 2002). For the deviance loss function, the deviance per observation was calculated rather than the total deviance, so that it was comparable across re-samples in which the validation data sets had different sizes.

Following Ramp *et al.* (2005), the final model was selected by comparing all models subsets for the eight predictors and employing the one standard error (SE) rule (Hastie *et al.*, 2001) to select the best model set. That is, the final model was the most parsimonious model within 1 SE of the model with best predictive performance. Using this approach ensures a model with good predictive performance that is small, hence readily interpretable. Final model selection was based on comparing the best models (within both loss function groups) that contained the fewest number of predictor variables. Due to reviewer concerns, model selection was repeated using AIC, which resulted in similar results in terms of model rankings to use of the bootstrap .632 rule, as applied to the deviance criterion.

Hierarchical partitioning was used to lend additional support to the model selection process (MacNally, 2000; Brambilla *et al.*, 2006). A goodness-of-fit measure for the entire hierarchy of models using all combinations of predictor variables was calculated using maximum likelihood. The contribution of each predictor to variability in the full model was identified and compared to results from the bootstrapping process.

## RESULTS

A total of 81 occupied and 297 abandoned burrows were identified in the 30 km<sup>2</sup> of the study area. Burrows were not evenly distributed throughout the landscape and were clearly clumped into occupied and abandoned clusters (Fig. 2). A total of 209 wombat fatalities were recorded over the 40 km length of highway between 1998 and 2005 (Fig. 3). For the 15 km

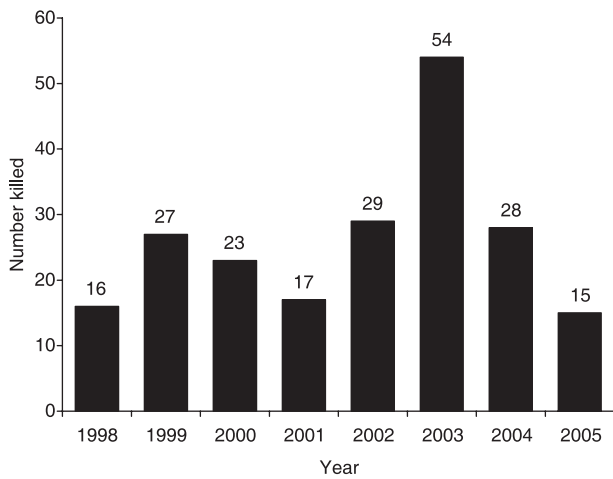


**Figure 2** The  $G_i^*$  values grouped into magnitude classes, values range between <math>< -2</math> and > 2. Occupied and abandoned burrows are overlaid. Also displayed are the Blowering Reservoir and the Snowy Mountains Highway.

road length used in this study, 104 were recorded between March 2002 and December 2005. The number of fatalities varied among years, with a mean number of  $23.2 \pm 5.18$  per year between the period of 1998 and 2005 for the 40 km stretch of highway. For the 15 km length used in the analysis, a mean number of  $27.3 \pm 7.12$  per year between 2002 and 2005 were recorded (or 0.005 wombat kills per day per km). Fatalities were not evenly distributed along the highway, and were clearly clumped (Ramp *et al.*, 2005).

**Fatality model**

The misclassification error rate and deviance loss functions identified 50 and 202 models, respectively, within 1 SE of the best model (Table 1). Discrimination among predictors using the deviance loss function was relatively poor compared to misclassification error. NDVI-SD and the  $G_i^*$  statistic were selected in 100% of models in the best model set using misclassification error. There was good agreement on the final model among the



**Figure 3** Number of common wombats killed along a 40 km length of the Snowy Mountains Highway between Tumut and Talbingo (1998–2005).

three methods of model selection, selecting NDVI-SD, distance to blackberries, the proportion of forest cover, distance to the nearest burrow and the  $G_i^*$  statistic (Table 2).

The final model explained 61.9% of the deviance (Table 3), (AUC 0.887), misclassification error 0.1856. NDVI-SD explained 45% of the variation in the model and was positively correlated with fatality probability, tapering off at higher NDVI-SD values (Fig. 4). The probability of a fatality was higher closer to blackberry bushes, explaining 29% of the variation in the model. The  $G_i^*$  statistic, representing occupied and abandoned burrow clusters, explained 18% of the model variation and was nega-

tively correlated with the probability of a fatality. Distance to the nearest burrow and the proportion of forest were included in the final model but explained less model variation. The probability of a fatality decreased with increasing burrow distance, while generally decreasing as forest cover increased until cover was greater than 80%.

**DISCUSSION**

Incorporating common wombat habitat use considerably improved the predictive capacity of road fatality modelling. Despite the exclusion of variables describing road characteristics and temporal variability, our model explained 61.9% of the deviance. In comparison, the model presented by Ramp *et al.* (2005) only explained 11% of the deviance. Ramp *et al.* (2005) had considered variables based on species ecology (such as species home range) when generating possible predictors, however, their selection was not founded on proven relationships between the species of interest and habitat use. Our model also benefited from two additional years of fatality point data.

The variables included in the final model were all indicative of habitat use by wombats. Wombats preferentially forage in habitats with a mixed forest canopy cover and with abundant and high quality grass (Evans *et al.*, 2006). The positive relationship with NDVI-SD suggests that wombats have a higher probability of being killed when foraging in their preferred habitats. Similarly, the probability of a fatality decreased with increasing distance from blackberry bushes. Despite being an invasive plant species, common wombats have adapted to the abundance of this thorny shrub, using it for shelter as their burrows are often located

**Table 1** Model results for road fatality probability. Table presents the number of models within 1 standard error (SE) of the best model and the proportion of models containing the variable within 1 SE of the best model for each criterion.

Model	Loss function	Total no. of models	Predictor variables								Median no. of variables
			bl	f	s	riv	h	n	bu	g	
Predicting fatalities	Misclassification error rate	50	0.62	0.60	0.56	0.48	0.50	1.0	0.56	1.0	6
	Deviance	202	0.56	0.51	0.51	0.52	0.50	0.63	0.56	0.58	6

Symbols for predictor variables occurring in model set are distance to blackberry (bl), percent forest cover (f), slope (s), distance to river (riv), hillshade (H), normalized difference vegetation index-standard deviation (SD) (n), distance to burrow (bu) and  $G_i^*$  statistic (g).

**Table 2** Variable coefficients and Z-scores for the predicting wombat fatality model.

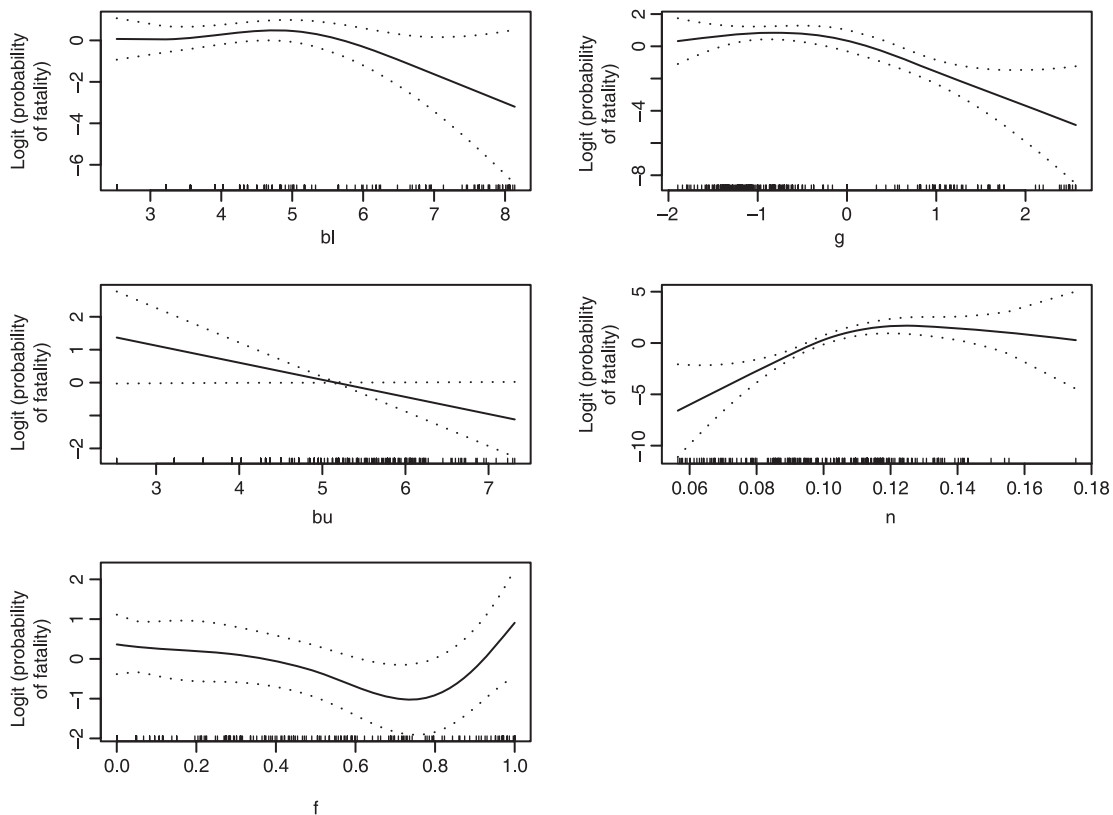
Model	Variable	d.f.	Coefficient	Independent contribution	Chi-squared	P
Predicting fatalities	Intercept		-3.072			
	Blackberry	2	-0.114	29.0374	7.7253	0.005
	Burrow	1	-0.519	5.7326	0.0098	0.018
	NDVI-SD	3	57.077	45.1481	15.9365	< 0.001
	$G_i^*$ statistic	1	-1.009	18.7980	8.9496	0.003
	Forest	3	-0.533	1.2836	10.0467	0.007

The independent contribution of each variable was determined through hierarchical partitioning is presented as a percentage of the total explained variance.

**Table 3** Comparison of the deviance explained by our final model and Ramp *et al.* (2005) using the complete data set with degrees of freedom (d.f.) along with the area under the curve (AUC).

Model	Final model	Null	Residual	% Deviance explained	AUC
Predicting fatalities	f + bu + g + n + bl	286.1	108.9	61.9	0.887
Current model		(d.f. = 206)	(d.f. = 194)		
Predicting fatalities	S + SIN + SOI + T + W + E	777.2	691.9	11.0	0.778
Ramp <i>et al.</i> (2005)		(d.f. = 2135)	(d.f. = 2129)		

Symbols for predictor variables occurring in model set are distance to blackberry bush (bl), percent forest cover (f), distance to burrow (bu), normalized difference vegetation index-SD (n) and  $G_i^*$  statistic (g). Symbols for predictor variables for Ramp *et al.* (2005) are slope (S), sinuosity (SIN), southern oscillation index (SOI), distance to nearest town (T), distance to water (W), and elevation (E).



**Figure 4** Partial plots of the relationship between the probability of a fatality and the predictor variables included in the final model. The x-axis represents the range of values for each environmental variable ((f) percent forest cover, (bl) distance to blackberry, (bu) distance to burrow, (g)  $G_i^*$  statistic and (n) normalized difference vegetation index-standard deviation)). Probabilities on the y-axis are plotted in transformed ‘logit’ space, so that they can be interpreted in the same way as linear regressions. Dashed lines represent 95% confidence intervals around the fitted response shape.

directly beneath the dense bushes. As is typical for invasive weeds, blackberries often occur in abundance along roadsides. The implication of this finding for managers is clear: reducing the density of this weed along roadsides will likely reduce the likelihood of wombat road fatalities. Consideration, however, should be given to the potential effect that this loss of habitat may have on population persistence, despite the likely reduction in mortality due to collisions with vehicles.

Both variables included to specifically represent habitat use were present in the final model. Distance to the nearest burrow was used to reflect environments where wombat density is likely

to be higher. The probability of a fatality decreased as distance from burrows increased, vindicating the use of this measure of habitat use. Also included was the  $G_i^*$  statistic. More than just an indication of burrow density, this statistic provided information on clusters of occupied or abandoned burrows in the landscape. Fatality probability was highest in areas within close proximity to abandoned clusters, while the probability of a fatality was lower where burrows clusters were occupied. Road fatalities are by far the highest source of mortality in the region for common wombats. Hence, areas with high fatality rates may deplete the local population, resulting in a greater proportion of abandoned

burrows. Vacated burrows are likely repopulated by migrating animals from source populations over time (E. Roger, S.W. Laffan and D. Ramp, unpublished data). Evidence for this theory can also be found in the large variation in annual numbers of wombats killed on the road (Fig. 3), and is likely a reflection of changes in wombat density in the area, rather than changes in traffic volume or speed. An alternative for explaining why fatality probability was highest in proximity to abandoned burrow clusters is that wombats are killed travelling to areas with abandoned burrow clusters to forage as the territory is unoccupied. It remains to be tested whether the location of abandoned and occupied burrow clusters in the landscape changes and over what temporal scale.

### Implications for fatality modelling

Seldom do studies explicitly and *a priori* assert the relevance of predictors (Austin, 2002). The current trend in predictive fatality modelling is to take an exploratory or data-mining approach to the selection of predictor variables, with most predictors describing the road and road environment. Often predictors are not carefully selected and their inclusion can lead to arbitrary fitting of predictor-dependent variable relationships. The number of possible predictor variables used in predictive modelling papers range from 10 in Ramp *et al.* (2005) and Clevenger *et al.* (2003) to as many as 28 in Malo *et al.* (2004). Instead, fatality models can be greatly improved by reducing the amount of possible predictors and utilizing knowledge of species use of habitat. These data are often difficult to come by but the improvement on their inclusion suggests that greater emphasis should be placed on their attainment. Austin (2007) notes that species responses depend on the nature of environmental predictors and associated ecological processes and that use of existing knowledge to choose potential predictor variables is paramount. Likewise, as occupancy patterns of many species within landscapes vary according to the composition and configuration of land cover (Swihart *et al.*, 2006), the scale of species habitat use should be reflective of the scale of the fatalities being modelled. Caution should be given before extrapolating values across broader landscapes for these reasons.

A number of studies have used a variety of predictor variables to develop predictive fatality models (Finder *et al.*, 1999; Clevenger *et al.*, 2003; Nielsen *et al.*, 2003; Malo *et al.*, 2004; Saeki & Macdonald, 2004; Jaeger *et al.*, 2005; Ramp *et al.*, 2005; Seiler, 2005; Jaarsma *et al.*, 2006). Many have highlighted the importance of considering multiple spatial scales and landscape level as well as road attributes in the analyses (Lode, 2000; Clevenger *et al.*, 2003; Malo *et al.*, 2004; Saeki & Macdonald, 2004; Taylor & Goldingay, 2004), but few have stressed the importance of incorporating species patterns of habitat use as an important predictor.

Evidence for the importance of animal density and movement patterns influencing proximity to roads exists for a wide range of species (Kramer-Schadt *et al.*, 2004; McDonald & St Clair, 2004; Alexander *et al.*, 2005; Clevenger & Waltho, 2005; Barnum *et al.*, 2007). In modelling the effect of road traffic on amphibian species, Carr & Fahrig (2001) incorporated pond variables into

their models of traffic density. The relationship between stream length and frog dispersal was thought to be a major factor in understanding frog road-related mortality. Seiler (2005), along with measures of landscape and road and traffic data, incorporated a measure of moose density/abundance (although this variable was not spatially explicit) in the modelling process. This information was based on hunting records, but its inclusion was only used to explore whether controlling moose density could be used as a measure of reducing moose fatalities. Seiler (2005) noted that better knowledge of moose abundance and the occurrence of preferred forage may have improved the predictive power of the models. Both Jaeger *et al.* (2005) and Jaarsma *et al.* (2006) considered species-specific characteristics, but only in reference to crossing behaviour or characteristics that may make species more susceptible to collisions with vehicles. Use of species-specific habitat use in fatality models has, to date, received minimal attention.

As a large, wide-ranging herbivore, the common wombat as a study species has wide applicability for highlighting the importance of incorporating habitat use in fatality models. Despite common wombats being territorial in nature, such high site fidelity is not necessary for species-specific measures of habitat use to be important in fatality models. Other indirect methods of habitat use can be used to model target species (e.g. nests, tree hollows and tracks) that coupled with habitat use variables can improve the performance of fatality models.

The demand for solutions to decrease animal–vehicle collisions is driving the development of predictive fatality models. Improved predictive modelling can be achieved by incorporating variables that describe species distributions in the landscape and careful *a priori* consideration of which predictor variables should be modelled. Ideally, selection of predictors should be based on knowledge of the species being modelled and that are correlated with species distributions. If mitigation of animal–vehicle collisions is to be successful, we suggest that monitoring of species occurrence and movement within the landscape is vital for the development of accurate, reliable and robust models of fatality hotspots. Failure to do so reduces the ability to understand the role of habitat characteristics in determining species distributions and the susceptibility of fauna to collisions with vehicles.

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