Wildlife-train collisions: modelling and analysis in space and time

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* 1. Summary

Collisions between and wildlife and vehicles has been widely studied, however, animal mortality from strikes by rail-based networks remains under-represented in the literature. In addition to animal welfare and conservation concerns, costs from train strikes may be considerable and rail authorities have a vested interest to manage the problem.

To assess the risk of collisions, we developed methods to quantify regional train movements in space and time, determine likelihoods of species occurrence, and fit a model to reported collision data. We made predictions of collision rates on the total network based on three management scenarios.

The model fit and predictions were plausible. Speed was the most influential variable followed by presence of kangaroos. Reducing speeds in areas of high predicted kangaroo occurrence during peak animal activity resulted in the greatest reduction in collision rate.

Predictions from the model can help managers decide where, when and how best to mitigate strikes. The model framework is easily adaptable to other species and rail operations and allows managers to assess bias and uncertainty and calibrate/update accordingly.

* 1. Keywords

animal, framework, train, risk, species distribution model, speed, track, crepuscular, WTC

Introduction

Roads and railways support human civilisations by facilitating economic and recreational activities. However, transportation networks may directly or indirectly disrupt ecological systems (Seiler & Helldin, 2006; van der Ree et al, 2015) and their environmental impacts must be managed (Spellerberg, 1998). One of the most visible impacts are animals struck by moving vehicles which directly influence species mortality rates (Forman et al., 2003).

Wildlife-vehicle collisions are a serious problem throughout the western world (Litvaitis & Tash, 2008); spawning a new discipline (road ecology) and inspiring research to develop solutions. For example, deer-vehicle collisions on roads are well-studied in North America (Huijser et al., 2007; Romin & Bissonette, 1996) and Europe (Sáenz-de-Santa-María & Tellería, 2015; Seiler, 2004).Moreover, management of wildlife-vehicle collisions in developing countries will become important as new transportation networks are constructed and existing networks are expanded.

In addition to concerns about animal welfare and conservation status of threatened species, larger animals can directly pose risks to the life of humans (Langley et al., 2006; Rowden et al., 2008). EXAMPLES, EXAMPLES,

Information about the spatial and temporal distribution and magnitude of wildlife-vehicle collisions is useful to managers because it may help more effectively mitigate impacts (Mountrakis & Gunson, 2009). For example, knowing a collision hotspot location along a transportation network for a particular species, such as kangaroos, will assist managers to select and implement the most appropriate form of mitigation (e.g. animal exclusion or change in network activity). Data can also inform statistical modelling which helps to predict the probability of wildlife-vehicle collisions (Gunson et al., 2011).

The majority of wildlife-vehicle collision modelling deals with road networks (van der Ree et al, 2015), yet, the problem extends to other forms of vehicular networks such as air (van Belle et al., 2007) and rail (Wells et al., 1999) operation. Regardless of the mode of transport, the modelling of collisions share some common attributes (Forman et al., 2003). First, the movements or presence of animals are often considered in the models and may include behavioural traits (Roger & Ramp, 2009). Second, vehicle presence or movements can also be considered and may be grouped into a larger category of human behaviour as humans ultimately control speeds and trajectories of vehicles (Ramp & Roger, 2008).

Extensive rail networks with considerable activity exist on every continent in the world, and although broader ecological effects have been discussed (De Santo, 1993; Givoni, 2006) and analysed (Waller & Servheen, 2005), very few studies analyse wildlife-train collisions (see Belant, 1995; Onoyama et al., 1998). Moreover, we only found one published study predicting wildlife-train collisions (Gundersen & Andreassen, 1998). Here, we develop a modelling framework to predict the rate of kangaroo collisions on the regional passenger train network in Victoria. Our methods aim to inform rail operators of potential kangaroo collision risks and can be used to generalise to other species (e.g. wombats) and rail operations (e.g. freight transport).

* 1. Materials and Methods
     1. *Study Area*

We used a 1712-kilometre passenger rail network from regional Victoria, Australia (operated by V/line, a government-owned corporation) in south-east Australia to conduct our study (Figure 1). Trains operate on all sections of the network between the hours of 4am and 2am (following day), with the largest volume occurring Monday through Friday between the hours of 7am and 9am and 4pm and 6pm.

* + 1. *Data Preparation*

To organise our data and modelling, we overlaid a grid of one square kilometre resolution on the rail network (Figure 2). In each grid cell we modelled species occurrences and quantified the train movements and speeds.

Eastern grey kangaroos (Macropus giganteus, Shaw, 1790; "kangaroos" hereafter) are frequently struck animals in regional Victoria and large enough to cause significant damage to trains. V/line provided records of 439 kangaroo collisions spanning a six-year period between 1 January, 2009 and 31 December, 2015. Each record included incident date and time, the name of service line (unique route between two towns), and nearest fraction of a kilometre post (physical sign markers indicating distance along train line). Using geographic information system (GIS) data on the regional rail network, we determined spatial coordinates (GDA94 MGA zone 55 projection) for all collisions from the reported kilometre post and service line.

*Species Occurrence*

Kangaroo occurrence data is sparsely recorded in regional Victoria. To represent exposure risk, we required distributional data across the entire study area and used species distribution modelling to predict relative likelihood of kangaroo occurrence. We emulated methods by Elith et al. (2008) to model and predict occurrence in each grid cell for the whole State of Victoria. The model was trained on data from the online Victorian Biodiversity Atlas (VBA, 2014) and included several environmental variables relating to the biology and behaviour of kangaroos (see Visintin et al, 2016). To reduce the effects of sampling bias, we also included two anthropogenic variables (distance to urban areas and roads) and the spatial coordinates of grid cell centroids as predictors in the model.

*Characteristics of Rail Network*

To determine train movements across space and time, we accessed publicly available locations and times of unique train routes from V/Line general transit feed specification (GTFS) data (Public Transport Victoria, accessed online 3 March, 2016). GTFS is a standard publishing format developed and maintained by a community of public transport agencies for scheduling and spatial data. Since it is publicly available it also allows software developers to write applications for mobile devices that track and report the locations of public transportation (e.g., tramTRACKER). We used a spatial database (Postgres version 9.6; PostGIS version 2.3.0) to process this information and report the average number of trains, the total length of track, and average train speed in each grid cell for each hour of the day where trains occurred.

*Temporal Variation*

To account for temporal variation in collision risk throughout the day, we considered peak periods of train movements in relation to daylight hours. By adding variables that allow a bimodal response of collision rate to hour of day across all seasons, the crepuscular lifestyle of kangaroos (most active at dawn and dusk) is tested. We included three additional variables to the model for this purpose; relative daylight intensity (both linear and quadratic terms) and time between sunrise and sunset.

* + 1. *Statistical Modelling*

We adapted a single-species quantitative risk model (see Visintin et al, 2016) to fit and compare the relationship of kangaroo presence, characteristics of the rail network, and temporal patterns (kangaroo movements during high activity of trains) to collision likelihood. The likelihood that a collision occurs in a given grid cell **i** at hour **j** in month **k** (*pijk = Pr(Yijk=1))*depends on species occurrence **O**, average number of trains **V**, average train speed **S**, relative daylight intensity **L**, duration of daylight **D**, and length of track **K**::

*cloglog(pijk) = β0 + β1 ln(****O****ijk) + β2 ln(****V****ijk) + β3 ln(****S****ijk) + β4 ln(****L****ijk) + β5 ln(****L****ijk)2 + β6 ln(****D****ijk) + ln(****K****ijk)* (1)

Prior to modelling, we centred all explanatory variables by subtracting their means. All predictors exhibited Pearson's product moment correlation coefficients of less than 0.4 using pairwise analysis - indicating low potential effects of multi-collinearity.

We fit the data (n=291120) to a generalised linear model (McCullagh & Nelder, 1989) using maximum likelihood estimation with a binomial distribution and a complementary log-log link on the linear predictor. The complementary log-log link was selected over the more common logit link due to the mathematical theory underpinning our model - risk being measured by the rate of collisions (see Visintin et al., 2016). The model is similar to a proportional hazards model (discrete censored time) often used in survival analysis and epidemiological studies (Cox, 1984).

To assess performance, we cross-validated the model by randomly splitting the data into K=10 partitions. We used nine of these subsets for model fitting and one for assessing model accuracy. For each assessment, we obtained several performance metrics (Cox, 1989; Harrell, 1996; Metz, 1978; Miller, 1991; Somers, 1962) using the function *val.prob* in the R (version 3.3.1) package *rms*. We repeated this procedure for 100 iterations producing a total of 1000 sets of performance metrics and compared them with those from the model fit to all data (Figure 3).

Using the model fit on all data, we predicted the number of expected train-kangaroo collisions in the study area for one year under different management scenarios:

A) no change to operations,

B) moderated train speeds in high kangaroo occurrence areas, and

C) controlled kangaroo occurrence in areas with highest average speed of trains.

Scenario B involved reducing the speeds of trains in grid cells with kangaroo relative occurrence likelihoods of 0.5 or above during the hours of 5am to 9am and 4pm to 8pm. We capped train speeds at 80 km h-1 for these areas (n=42 cells, total unique train trips=275). In scenario C, relative kangaroo occurrence was reduced by approximately half in all grid cells with average train speeds of more than 120 km h-1 (n=154 cells, total track length=121 km) The values were modified for all hours of the day as this management strategy would most likely involve exclusion or reduction in animal populations which operate irrespective of temporal variation.

* 1. Results
  2. Discussion

Model fit...

Train speed...

EGK presence...

Crepuscular activity and temporal patterns...

Detection issues...

Implied management...

Use of existing data...

Reduce animal presence (e.g. deterrents or exclusions) or reduce train threat (e.g. adjust schedules or speeds)...

Costs of management in sensitivity analysis...

* 1. Data Accessibility

Model Dataset - Archived on GitHub

R Code - Archived on GitHub

* 1. Acknowledgements

Sam Parsons, on behalf of V\Line, queried and provided the collision statistics used for the study. Nick Golding consulted on the mathematics and statistics used in the analysis. This project was supported by a University of Melbourne International Research Scholarship and the Australian Research Council Centre of Excellence for Environmental Decisions.

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* 1. Tables

Table 1: Predictor variables used in collision model. Note, prior to modelling all variables were centred by subtracting the means. The collision model includes both the linear and quadratic term of LIGHT.

|  |  |  |
| --- | --- | --- |
| Variable | Description | Units |
| EGK | Relative likelihood of kangaroo occurrence in grid cell | – |
| TRAINS | Train frequency in grid cell | trains h-1 |
| SPEED | Mean train speed in grid cell | km h-1 |
| LIGHT | Relative intensity of ambient light in grid cell based on month | – |
| DAWNORDUSK | Time between dawn and dusk in grid cell based on month | hr |

Table 2: Summary of model fit using all data (n=291120). Highly significant variables are marked with an asterisk.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Beta Coefficient Estimate | Standard Error of Coefficient Estimate | z-value | Pr(>|z|) |
| Intercept | -7.2 | 0.09 | -79.03 | 0.00E+00\* |
| EGK | 0.61 | 0.06 | 10.46 | 0.00E+00\* |
| TRAINS | 0.01 | 0.09 | 0.16 | 8.71E-01 |
| SPEED | 3.62 | 0.31 | 11.53 | 9.29E-31\* |
| LIGHT | -0.65 | 0.11 | -5.82 | 6.02E-09\* |
| DAWNORDUSK | -1.87 | 0.17 | -10.85 | 2.06E-27\* |
| EGK | 0.25 | 0.07 | 3.76 | 1.73E-04\* |

Table 2: Summary of predicted collisions based on different management scenarios. Expected collisions are a total across the entire regional network for a period of one year.

|  |  |  |
| --- | --- | --- |
| Scenario | Description | Expected Total Collisions |
| A | no change to current operations or infrastructure | 404 |
| B | moderated train speeds in high kangaroo occurrence areas during peak travel times | 399 |
| C | controlled kangaroo occurrence in areas with highest average speed of trains | 391 |

* 1. Figures

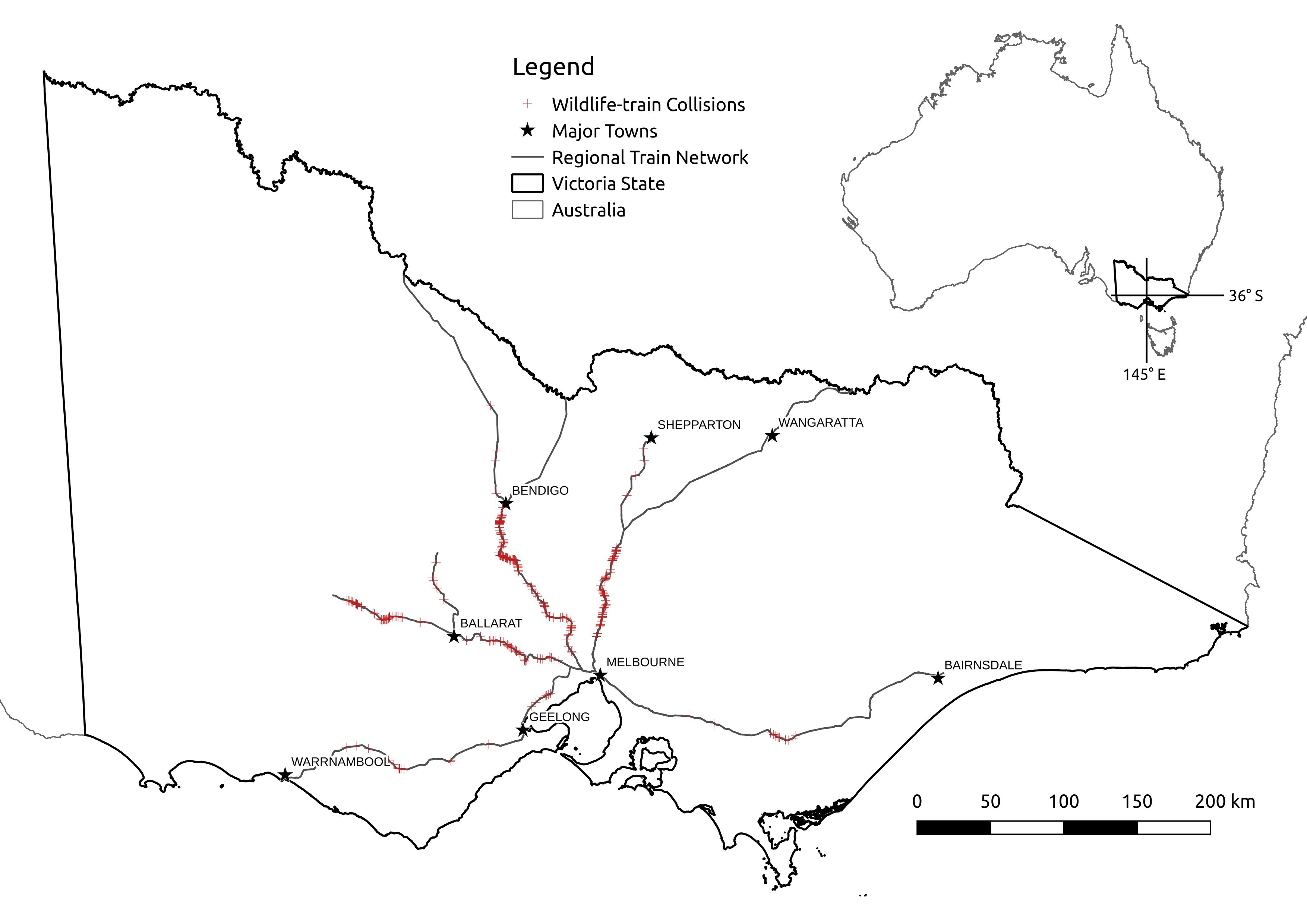
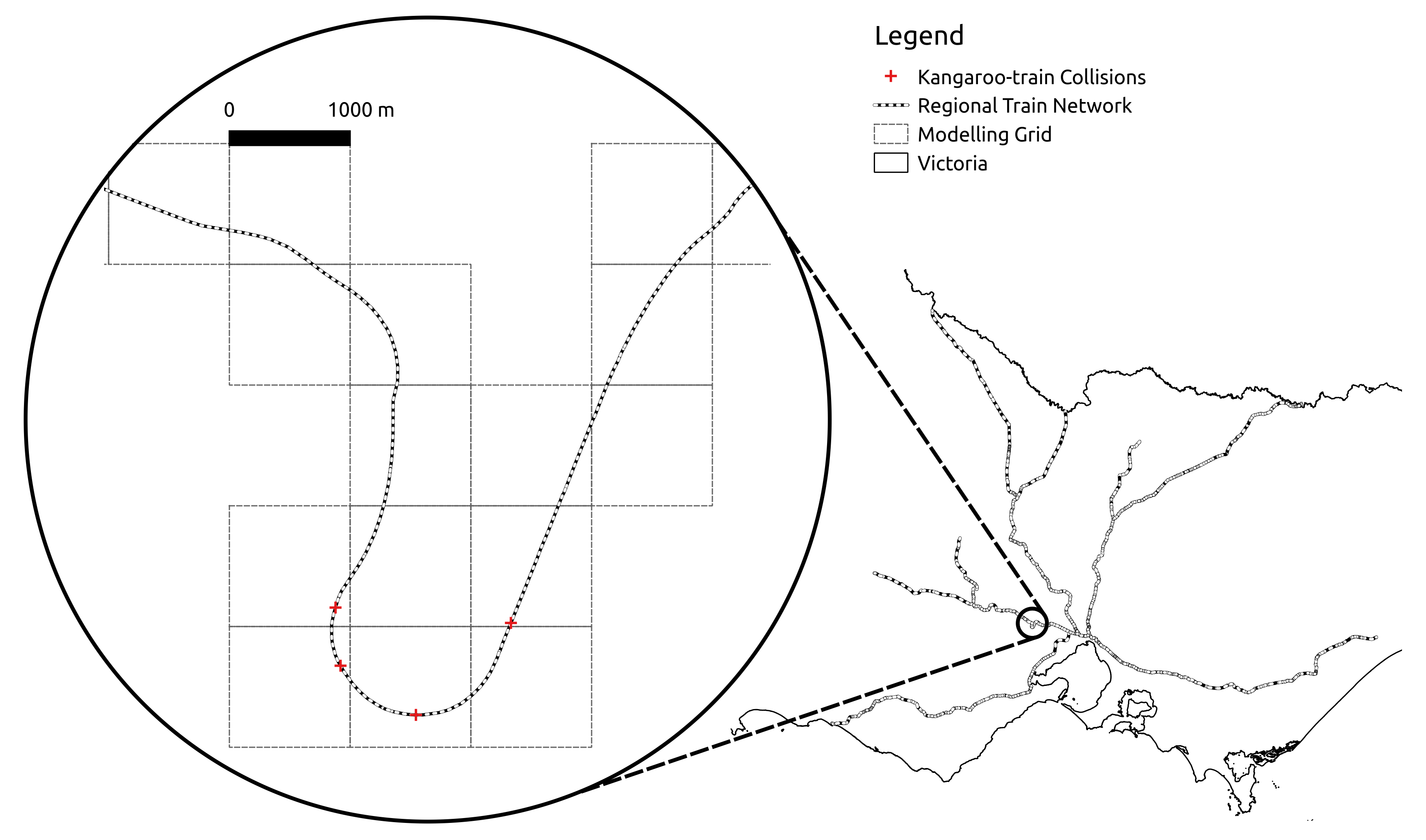
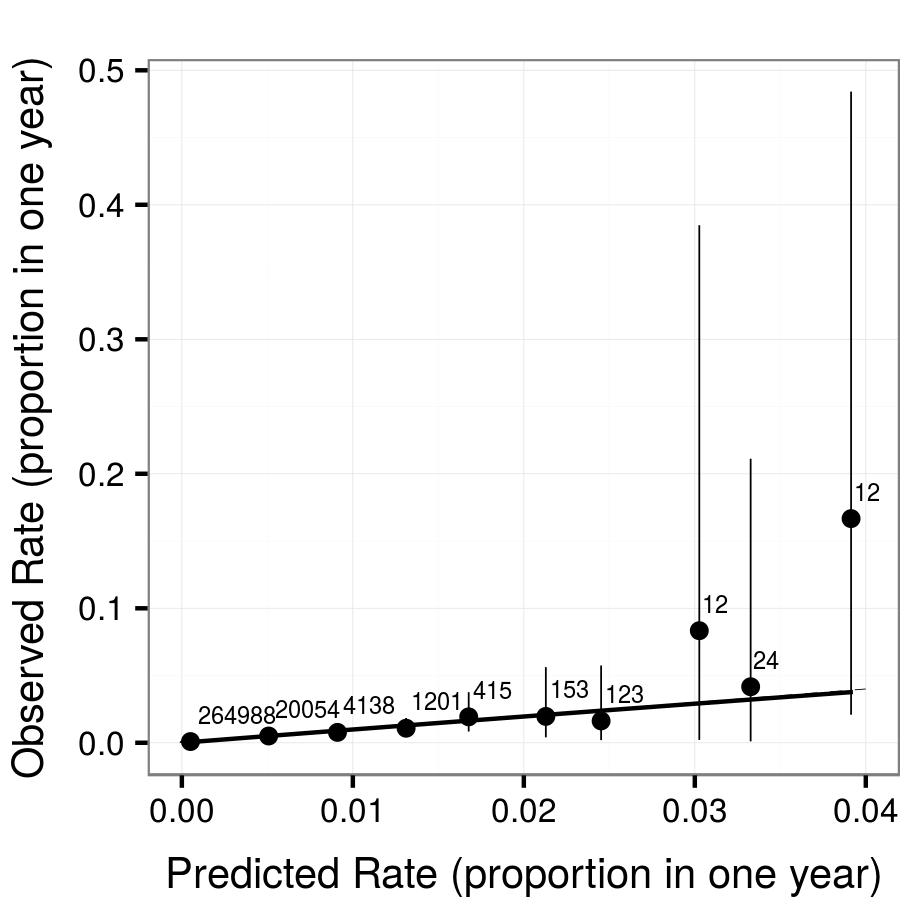
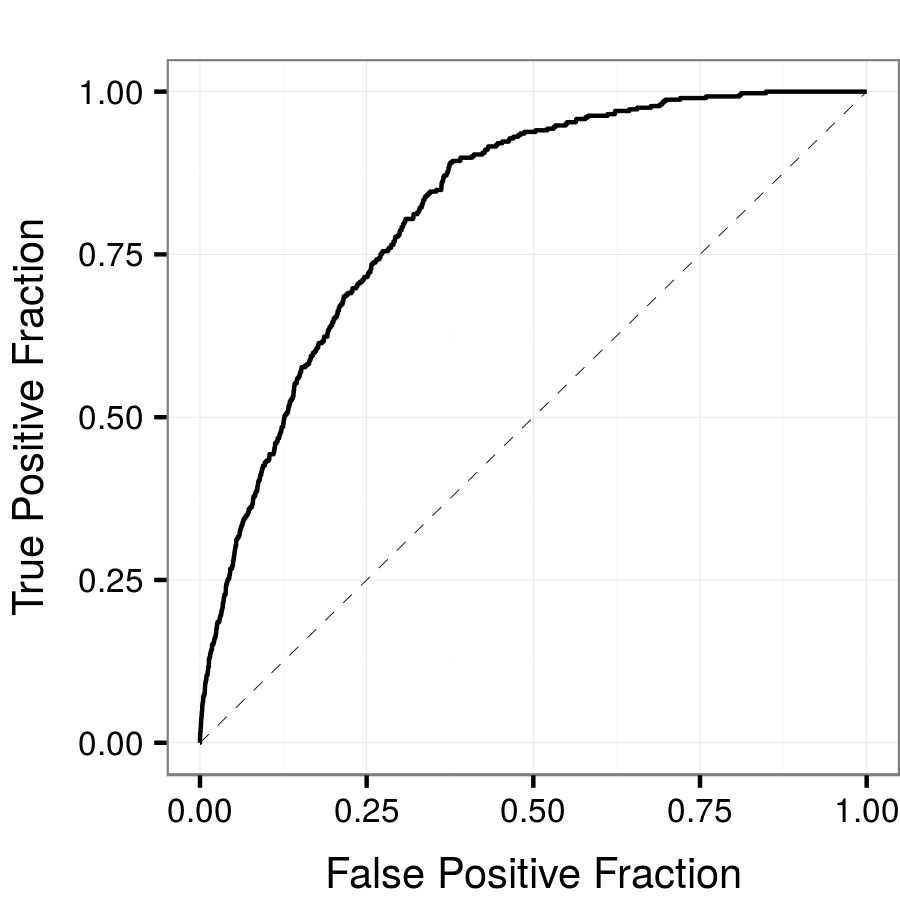
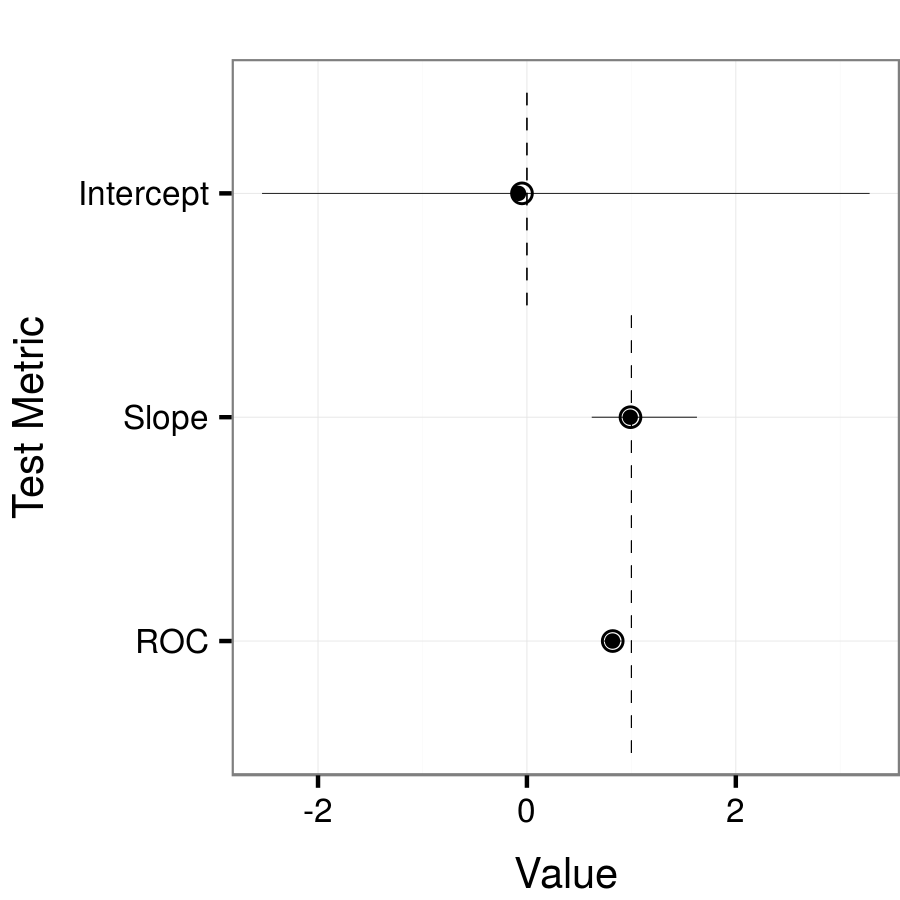
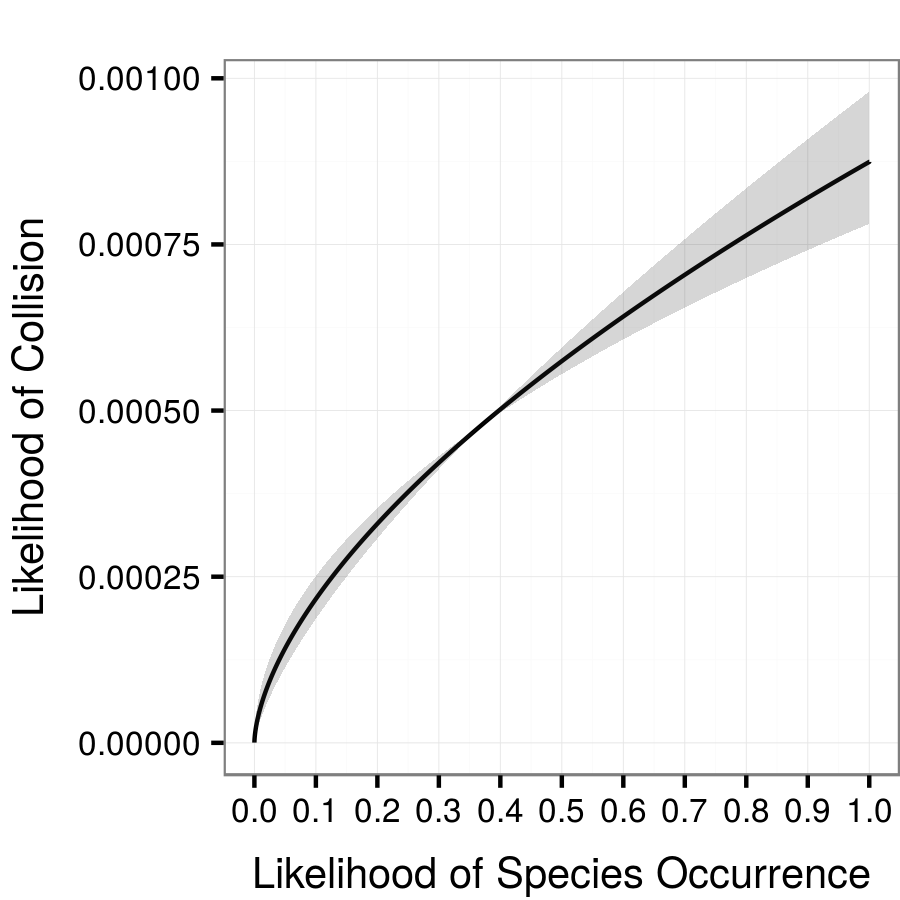


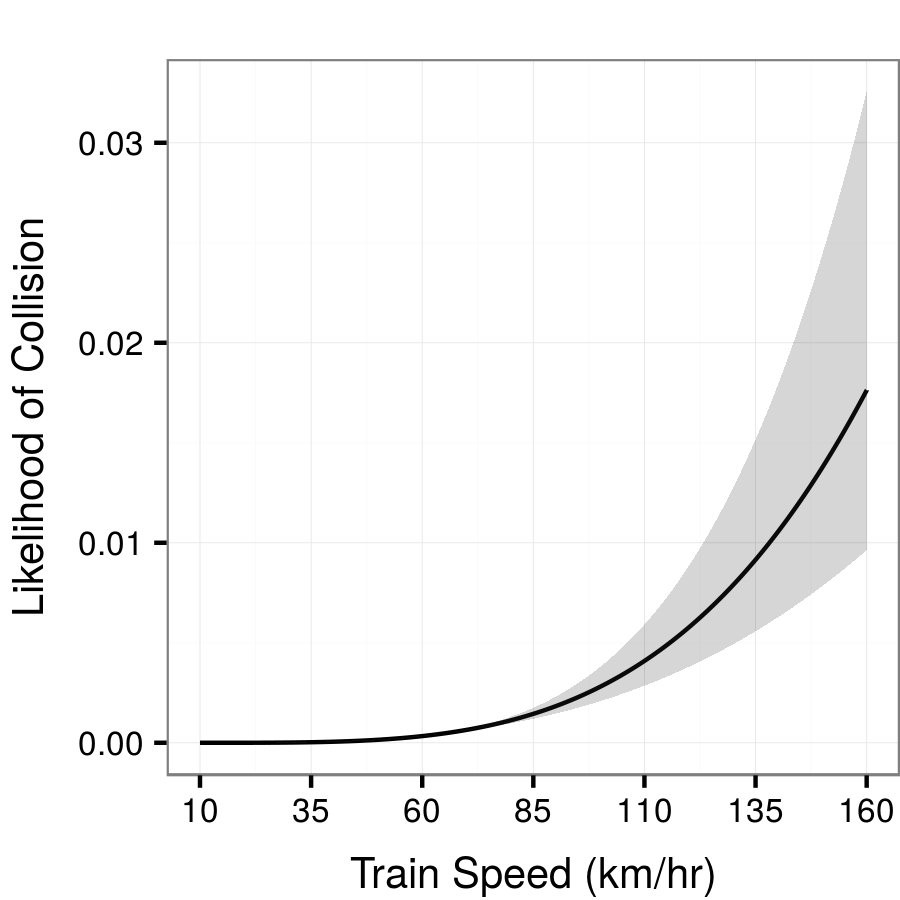
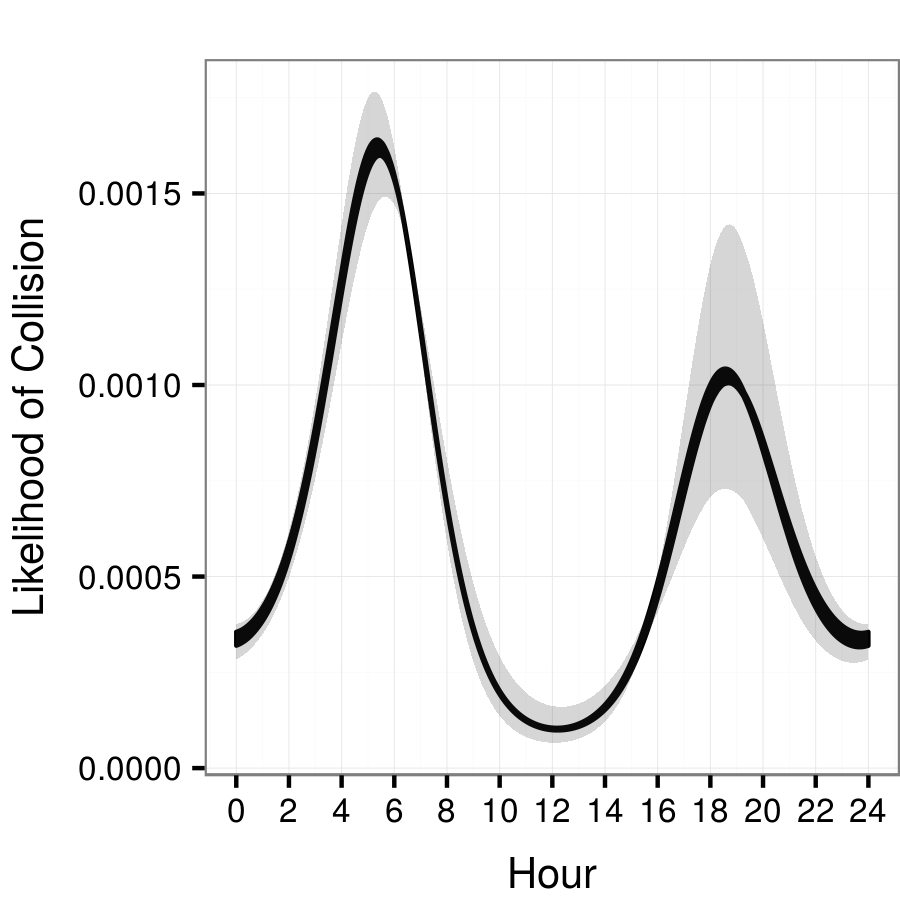
Figure 1: Wildlife-train collisions reported between 2009-2014 in Victoria.



**Figure 2:**  Grid used to organise modelling data (number of cells: 2015; extents: 104000,5741000 x 556000,6084000; projection: GDA94 MGA zone 55)

  **Figure 3:**  **a)** Calibration plot showing rate of observed collisions against predicted rate of collisions. Dots represent the observed rate with 95% confidence intervals at the medians of each bin of predictions (10 total). Labels indicate the total observations in each bin. A regression line is shown between the dependent variable on the predicted values (response-scale) of the model. Perfect calibration is shown by the dashed line (intercept of 0 and slope of 1) **b)** ROC (receiver operating characteristic) curve measuring discrimination ability of model at all threshold values (see Metz, 1978). **c)** Comparison between the collision model fit on full data and on cross-validated subsets. "Intercept" and "Slope" result from regressing the dependent variable on the predicted values and measure calibration (see plot a); "ROC" measures discrimination between collisions and no-collisions (see plot b). For each metric, open circles represent the full data model and solid dots represent mean values - ranges shown as bars - for the cross-validated subsets (n=1000). Dashed lines indicate the expected values for a perfectly calibrated and discriminatory model.

**Figure 4:**  Marginal effects of model predictors on collision likelihood. For each plot, non-target variables are held constant at mean values. Shading indicates 95% confidence intervals.