Title: Survival analysis of wildlife cameras exposed to theft

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Abstract

Setting camera traps along roads is often necessary for ecological research, yet these locations expose cameras to theft leading to substantial data losses. Measures to minimise this risk include placing cameras away from human settlements. However, the effects of this and other measures on camera-trap theft risk are yet to be quantified. Here, we assessed the impact of gates on roads, the frequency of vehicle and human foot traffic, distance to the nearest town, and reduced visibility, on the risk of camera-trap theft, using a four-year, geographically extensive camera-trapping study in Tasmania, Australia. The large dataset covered 564 camera sites operating for 316,372 days (average of 561 camera days per unit), with 112 cumulative thefts. We used Bayesian survival modelling to determine the factors that best explained theft risk. Our results showed a high initial vulnerability to theft that gradually reduced over time, with significant predictors of reduced theft risk being: (i) road sites with lower frequencies of vehicle traffic, (ii) greater distance from the nearest town, (iii) where movement was curtailed by the presence of a gate, and (iv) a temporal trend that likely reflects a selective culling of 'high exposure' sites and increased efforts to hide camera units. The frequency of human foot traffic surprisingly did not significantly elevate theft risk. Our study provides important insights into the factors contributing to a higher risk of camera-trap theft on roads and offers a robust analytical framework to identify these factors for application in diverse social and ecological contexts.

Introduction

Camera traps (CTs) have become an increasingly effective tool in ecological research and for monitoring human activity for park management (Burton *et al.* 2015; Miller *et al.* 2017; Cardona *et al.* 2024). Their applications have included estimating wildlife abundance (e.g., Taylor *et al.* (2022)), population dynamics (e.g., Karanth *et al.* (2006)), and human and wildlife activity patterns (e.g., Miller *et al.* (2017)). While their use continues to increase, the risk of theft of such devices remains one of the major constraints on their effectiveness (Glover-Kapfer *et al.* 2019). Camera-trap theft can lead to substantial costs, and result in significant loss of data, disruption of long-term studies, unequal sampling across study sites and seasons, bias in sampling protocols, and variation in sampling effort (Kukielka *et al.* 2013; Paula *et al.* 2015; Pyšková *et al.* 2018; Meek *et al.* 2019).

Researchers using CTs face the dual challenge of preventing data loss due to theft, while ensuring cameras are appropriately placed for optimal data collection (Cusack *et al.* 2015; Meek *et al.* 2019). The strategy used to determine camera locations, including their placement on or off roads, influences the detection probability of wildlife species and is crucial for obtaining unbiased estimates of species richness, abundance, activity, and subsequent monitoring (Cusack *et al.* 2015; Mann *et al.* 2015; Tanwar *et al.* 2021). While placing CTs at sites away from human presence, such as random forest sites and animal trails, reduces the risk of theft, setting them on man-made features, such as roads, is ideal for monitoring the activity of many species that prefer or are more readily detected on these features, such as carnivorous, cryptic, and introduced species (Cusack *et al.* 2015; Mann *et al.* 2015; Iannarilli *et al.* 2021). Moreover, cameras set on roads can indirectly capture human activity, which can be important information for land management (Miller *et al.* 2017;

Cardona *et al.* 2024). Additionally, in regions difficult to access, these features are often the only feasible locations to deploy CTs (Meek *et al.* 2014). As a result, placing CTs on roads is crucial for enhancing our understanding of predator-prey dynamics, human-wildlife interactions, and visitor behaviour in protected areas. However, the ongoing risk of theft, often forces researchers into a trade-off that leads them to prioritise less-vulnerable but lower-animal-activity locations off roads (e.g., Hossain *et al.* (2016)), impacting the study objectives and outcomes.

As such, over the past decades, diverse strategies to protect CTs deployed on roads from theft have been proposed and attempted in the literature. These include physically securing CTs by mounting them on security posts or locking them to trees with braided steel cables and padlocks (Kelly *et al.* 2008; Meek *et al.* 2012a), as well as deterring and reducing their exposure to thieves by attaching warning messages (Clarin *et al.* 2014; Meek *et al.* 2019) and limiting the duration that CTs remain deployed in the field (e.g., Wegge *et al.* (2004); Glen *et al.* (2013)). Other strategies involve conducting surveys during times of the year or the day when human activity is less frequent at survey sites (e.g., early mornings or off-peak tourism seasons), positioning CTs far from human settlements (e.g., Rovero *et al.* (2009)), and camouflaging cameras with bark and leaves (e.g., Hossain *et al.* (2016); Zahoor *et al.* (2023)). While the effectiveness of measures such as using personal messages and security posts to minimise theft incidents has been tested (Meek *et al.* 2012a; Clarin *et al.* 2014), the effect of factors, such as the distance of the CT to human settlements, on the risk of camera-trap theft remains debated and has not yet been quantified rigorously.

In this study, we analysed a pre-existing data set that includes many theft occurrences from a four-year wildlife monitoring project in diverse regions of Tasmania, Australia. Across the four-year period, a cumulative total of 20% of CTs deployed on a mix of forestry, dirt and gravel roads were stolen (Figure. 1). Using these data, we aimed to investigate the extent to which the proximity of the CT to the nearest town, the frequency of vehicle and human foot traffic at the camera site, the presence of gates on roads, and the researchers' growing expertise in hiding CTs from potential thieves (e.g., improving camouflage and prioritising infra-red flash cameras), influenced the risk of camera-trap theft. By doing so, our goal was to identify factors driving the risk of camera-trap theft and contribute to the development of targeted strategies that enhance the protection of CTs.

Figure 1. Example of a site where a camera trap was stolen during the 4-year camera-trap monitoring project in Tasmania, Australia.

Materials and Methods:

Camera trap dataset and number of stolen cameras

We used data on camera trap (CT) theft occurrences sourced from the Dynamics of Eco-evolutionary Patterns (D.E.E.P) group, University of Tasmania, remote wildlife monitoring program (Vaughan *et al.* 2022; Paton *et al.* 2024). The camera-trap network was distributed across the southeastern, central highlands, northwestern and western regions of Tasmania, Australia (Figure 2). These regions encompass a diversity of vegetation communities, including dry and wet sclerophyll forests, temperate rainforests, low heaths, shrublands, and open buttongrass moorlands, as well as a wide range of land uses such as parks and reserves, production forests (logging), and private lands. The study area is crisscrossed by highways and smaller roads, including numerous dirt or gravel roads commonly used during the day by vehicles and walkers, with nighttime human activity infrequent. These regions cover a broad gradient of development and varying levels of human activity.

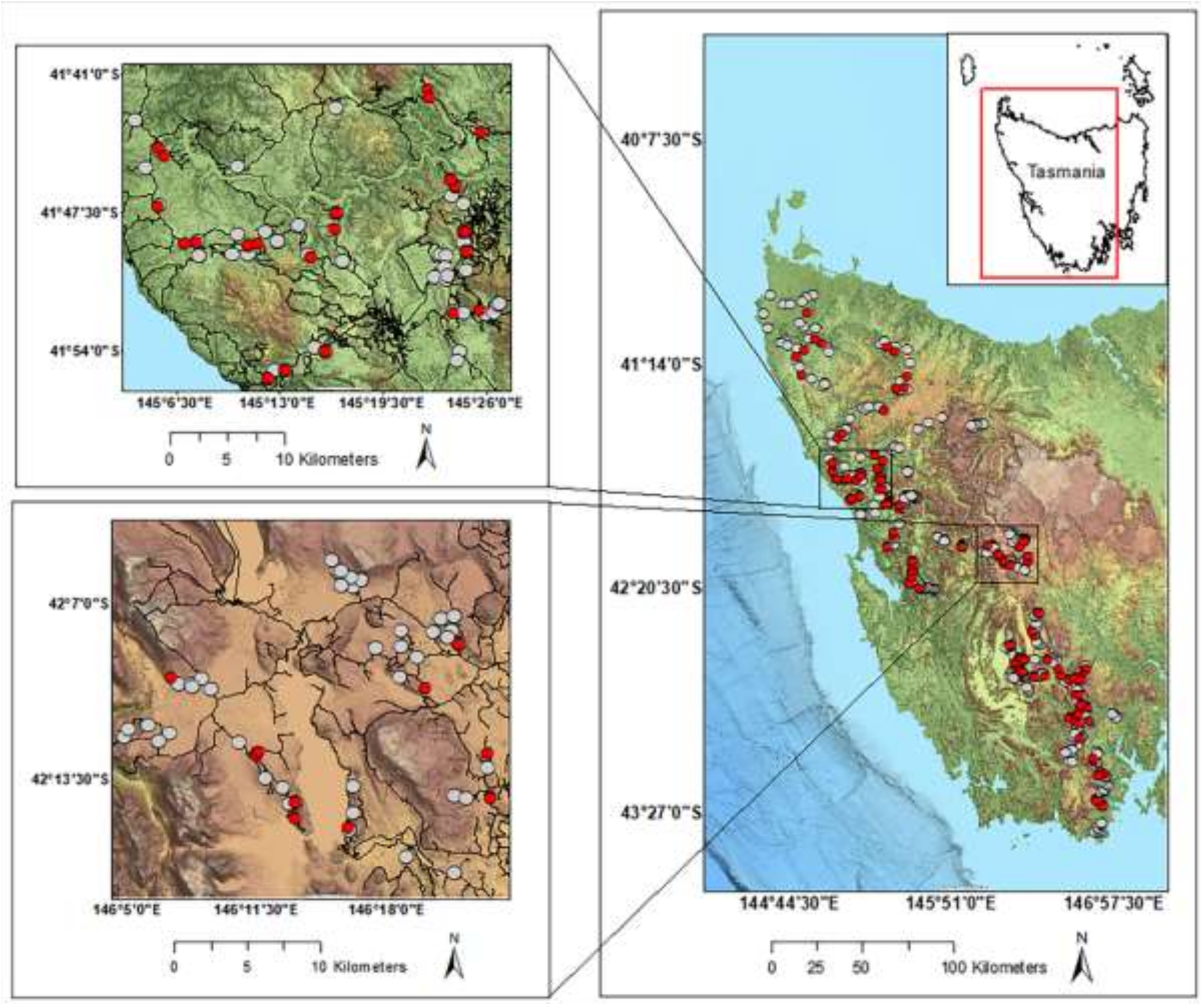

Figure 2. Map of the study area and the location of the camera trap sites. The different colours show whether the camera was stolen (red) or not stolen (grey). The insets show two examples of the camera-network deployments at finer spatial scales.

The monitoring network involved 564 camera sites, using a standard model (Cuddeback X-Change model 1279, which have a changeable flash unit), placed 100 m or greater apart and positioned on a mix of forestry, dirt and gravel roads. The network was operational for a total of 316,372 camera days (minimum estimation, as this does not include those service periods with thefts) between June 2018 to March 2022; 357 CTs were initially deployed in 2018 and an additional 207 CT sites rolled out over 2019 to 2021. The CTs were unbaited, mounted on trees on average 30 cm off the ground adjusted to target medium-large mammal species, and equipped with either an infrared flash or white flash. Infra-red cameras were programmed with 30 s delay for both day and night, while white flash units operated with 30 s delay during the day and one min at night. CTs were serviced every 4-6 months to download images, replace batteries, remove vegetation obstructing the field of view. In cases where a camera was stolen, a new CT was deployed at a new site, typically >250m from the stolen camera's location.

All CTs were camouflaged with vegetation upon their deployment. However, after researchers experienced thefts of CTs deployed during the first year (2018), they intensified their camouflage techniques in subsequent years to better conceal the CTs from view. This enhanced approach included carefully selecting sites with natural vegetation cover, conducting thorough visual inspections from various points before finalising the setup, and regularly replacing the vegetation used for camouflage during the following service checks.

Across the four-year period a total of 112 CTs, or 20% of all those deployed, were eventually stolen (although the lifetime of a given camera at a site varied considerably): 14 cameras in 2018, 38 in 2019, 30 in 2020, 23 in 2021, and seven in 2022 (Figure 2). While the year a CT was stolen was known, the exact date remained unknown, as researchers only discovered a unit was missing during servicing visits meaning a CT could have been stolen at any point since the last service check. Since the exact date a CT was stolen was unknown, we chose to use a Bayesian survival analysis, to investigate the impact of the various predictors on the risk of camera-trap theft. This allowed us to include general interval-censored data under the proportional hazards model and thereby account for uncertainties surrounding the exact moment of camera-trap theft (see Section *Bayesian Survival analysis of camera-trap theft* for details).

Statistical analysis

Model covariates - Predictors of theft.

We tested survival models using five predictors: distance to the nearest town, gates on roads, the frequency of vehicle and human foot traffic at the site, and the researchers' growing expertise in hiding cameras from potential thieves, as detailed below:

a) The distance from each CT site to the nearest town with permanent residents (Appendix S1: Table S1) was calculated as the Great Circle Distance, in kilometres, using Google Earth satellite images. To account for variance heterogeneity, this distance was normalised by subtracting the mean and dividing by the standard deviation (SD) prior to analysis. The presence of a gate on the roads (e.g., forestry gates, National Park gates, and residential gates) was defined as a binary covariate where 0 = no gate, and 1 = presence of a gate.

b) The frequency of vehicle and human foot traffic at the CT site was expressed as an index of relative activity (RA). This index was estimated for each CT site by calculating the number of images of 'vehicles' (e.g., all-terrain vehicles, motorbikes, bicycles, forestry vehicles, and two-wheel drives) and/or 'humans on-foot' (e.g., hikers, joggers, or people with dogs) divided by the number of active trap days at that station (George *et al.* 2006). We added one to this RA to allow the inclusion of zero values (sites with only vehicle or human-foot traffic) and because the researchers at a minimum had visited the sites, and then log-transformed this value before analysis to account for heterogeneity of variances: log (RA + 1). The categorisation into 'vehicle' or 'human on-foot' of the large dataset of images was done using the freely available object detection software MegaDetector (Beery *et al.* 2019; Brook *et al.* 2023). We were not able to calculate the index of RA for CTs stolen within the first four-six months of their deployment which was before their first service check (n=42 cameras), as no data was ever retrieved from these cameras before being stolen. Since using these missing values or excluding these cameras from the subsequent analysis could have impacted the conclusions drawn from the model selection (Donders *et al.* 2006; Nakagawa *et al.* 2011) or result in reduced estimation precision or statistical power (Nakagawa *et al.* 2011), especially because they were likely to be highly vulnerable sites, we imputed the missing values. As the data was Missing Not At Random—since the missing variable (number of images of vehicles and/or humans on-foot) was directly tied to the dependent variable (being stolen) (Nakagawa *et al.* 2011)—we imputed the missing data by generating random values based on a Gaussian probability distribution. The mean was defined as the RA of the closest CT located at least 2 km away, and the standard deviation was set at 10% of the confidence interval. Two cameras did not have a CT at least 2km away and were therefore excluded from the subsequent analysis.

c) The predictor 'deployment expertise' was included to account for potential biases arising from adaptive changes to the deployment strategies used by the researchers to reduce the visibility of CTs. We categorised this predictor into 'initial deployment' referring to the first CTs deployed by researchers during the year 2018, and 'informed deployment' referring to CTs deployed in subsequent years (from 2019 to 2022). In 2018, both the rates and causes of camera-trap theft in these regions of Tasmania were unknown by the researchers, and avoiding theft of such devices was not considered a high priority. However, during the subsequent years (from 2019 to 2022), given the large number of stolen CTs during 2018, researchers increasingly focused on implementing strategies to reduce the visibility of CTs by potential thieves. These strategies included selectively culling sites that were highly exposed and easily discovered by thieves, based on previous incidents of camera-trap theft at those sites; greater emphasis on improving the camouflage of CTs; and the situational prioritisation of CTs with infra-red rather than white-bulb flash.

All the predictors had a Pearson's cross-correlation coefficient $r < 0.7$.

Bayesian Survival analysis of camera-trap theft

All analyses were done using R version 4.2.2 (R Core Team 2020). To investigate the impact of the various predictors on the risk of camera-trap theft we used survival analysis within a Bayesian framework using the package '*rstanarm*' (Brilleman *et al.* 2020). We chose to use Bayesian survival analysis (parametric) because our study incorporates interval-censored data as the exact date a CT was stolen is unknown, but it falls within a known interval—between two consecutive CT service sessions. Although the Cox proportional hazards model has been the most widely used semiparametric regression model in the survival literature, its partial likelihood method is not applicable for interval-censored data under this model (Lin *et al.* 2015; Brilleman *et al.* 2020). As such, a Bayesian approach offers an efficient approach for analysing interval-censored data under the proportional hazards model, and properly accounts for uncertainties surrounding the exact time of camera-trap theft. This model characterised the censored data as a series of intervals $[L_i, R_i]$ for each subject i, where L_i and R_i denote the left and right end of the interval within which the theft of a CT was known to have occurred (Pan *et al.* 2020), specifically between two consecutive service sessions of the CT. For CTs that were not stolen and were removed on a known date, both L and R were set equal, thus representing the exact number of days the camera remained in the field until its removal.

Covariate analysis with model comparison

To check the appropriateness and robustness of the Bayesian survival analysis, we first identified and selected the parametric model that best fit our data. To do this, we compared 14 different models, each comprising a saturated survival model paired with various parametric baseline hazard functions (Weibull, exponential, basis spline and monotone spline, that latter two with different degrees of freedom). To assess how well the assumptions of the best-fitting parametric model aligned with the actual data and identify potential discrepancies, we compared that model's predicted survival function using the *Posterior_survfit* method for '*stansurv*' objects, against Kaplan Meier survival curve estimates using R package 'survival' (Therneau 2020). We visualised results from the Kaplan Meier survival curve estimates using the R package '*survmine*r' (Kassambara *et al.* 2021). Given that the Kaplan-Meier method is only suited for right-censored data, we calculate the median number of days within each time interval and used it an estimate of the censored days (approximate days in the field before the CT was stolen).

Once we selected the best fitting parametric form of the hazard function on the saturated model, we used it to fit and compare all possible simpler linear combinations of the five predictors, resulting in 32 candidate models. For the best-fitting model, we estimated the posterior distribution of the model parameters using a Bayesian estimation via Markov Chain Monte Carlo (MCMC). Variables with 95% credible intervals (CI) not overlapping with 0 were considered to have strong evidence for effects on camera-trap theft. If the 95% CI did not overlap with 0 and the limits were negative, we could be 95% confident that the mean of the intervention group would on average, lie within negative values and present a lower mean compared to the comparison group. Predictions were visualised using the *posterior_survfit* function, which provides survival probability estimates along with their lower (10%) and upper (90%) credible intervals for every possible combination of predictor values at each time point. Predictions were made considering the upper (0.95%) and lower (0.05%) quantile values for continuous covariates and both levels for the categorical (binary) covariates.

For each model we used sufficient iterations to ensure convergence (typically ~ 2,000 iterations) (van de Schoot *et al.* 2021). To establish chain convergence, we used the R-hat diagnostic (R-hat <1.01). Model selection was done using leave-one-out (LOO) cross validation, which assesses the predictive performance of models in a Bayesian setting by estimating the information-theoretic, relative expected Kullback-Leibler discrepancy (Yates *et al.* 2023). The best model was selected based on the expected log predictive density values (scores) and expert knowledge.

Results

Parametric form of the hazard function.

The Weibull model was the best fitting parametric form of the hazard function for our data set followed by the Basis spline model with the highest degree of freedom as internal knots (six degrees of freedom) (Appendix S1: Figure S1). The Weibull model slightly over-estimated the Kaplan-Meier estimates during the initial period of 0 to 900 days and slightly underestimated them in the later period from 900 to 1436 days. The second-best-fitting model implied a higher degree of flexibility closely approaching to the Kaplan-Meier curve. However, this flexibility may lead to overfitting the current dataset which could reduce the model's predictive accuracy on new data (Figure 3).

The Weibull curve modelling the predicted risk of camera trap (CT) theft was characterised by a shape parameter less than 1 ($k = 0.4$), suggesting theft rates of CTs were higher shortly after their deployment, with this rate thereafter decreasing over time (Figure 3).

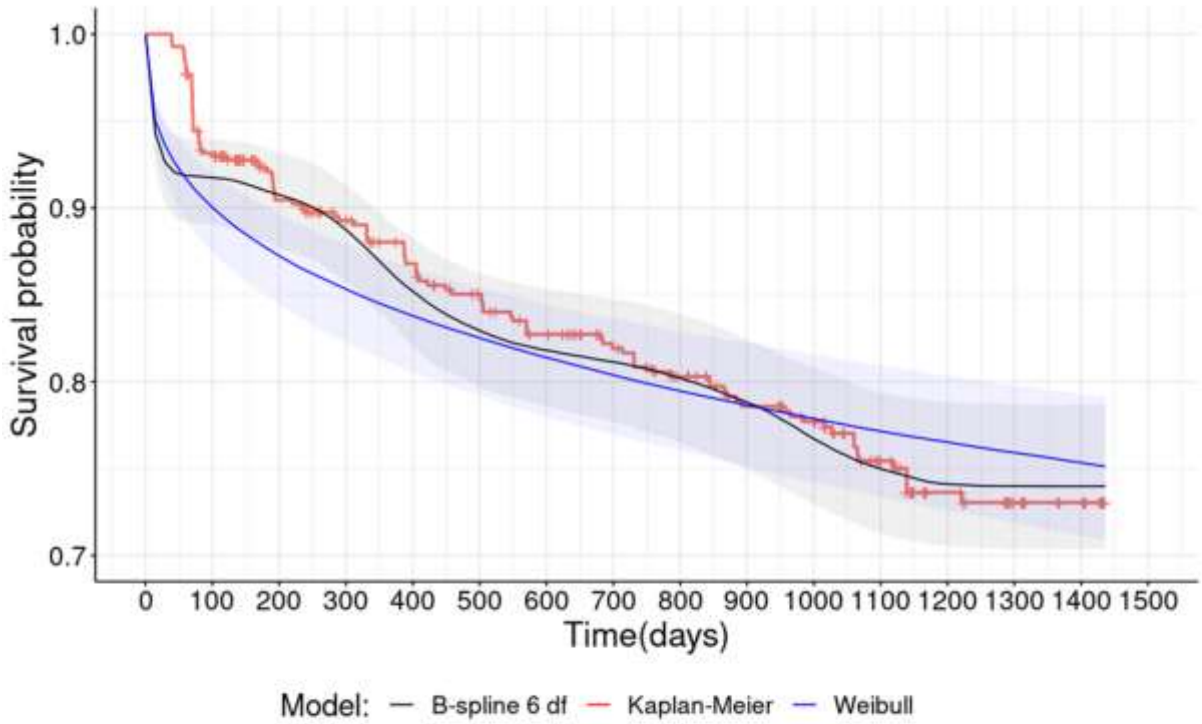

Figure 3. Predicted survival probability of camera traps over time using the best fitted parametric form of the hazard function; Weibull survival model (posterior median and 95% uncertainty limits), the second best fitting parametric form; B-spline survival model with 6 degrees of freedom (df) (posterior median and 95% uncertainty limits), and the non-parametric Kaplan-Meir hazard estimate.

Covariate analysis with model comparison using the Weibull hazard function.

The model containing the predictors ‘deployment expertise’, ‘distance to town’, ‘vehicle relative activity’ (RA) and ‘gate presence’ had the best predictive performance on the survival of CTs (Figure 4). This suggested that human on-foot RA was not as important as the other four covariates in explaining the variance in camera-trap theft in our context. The simpler models, each of which pool estimates for at least one of the covariates, performed poorly relative to the best-performing models (Figure 4, Appendix S1: Table S2).

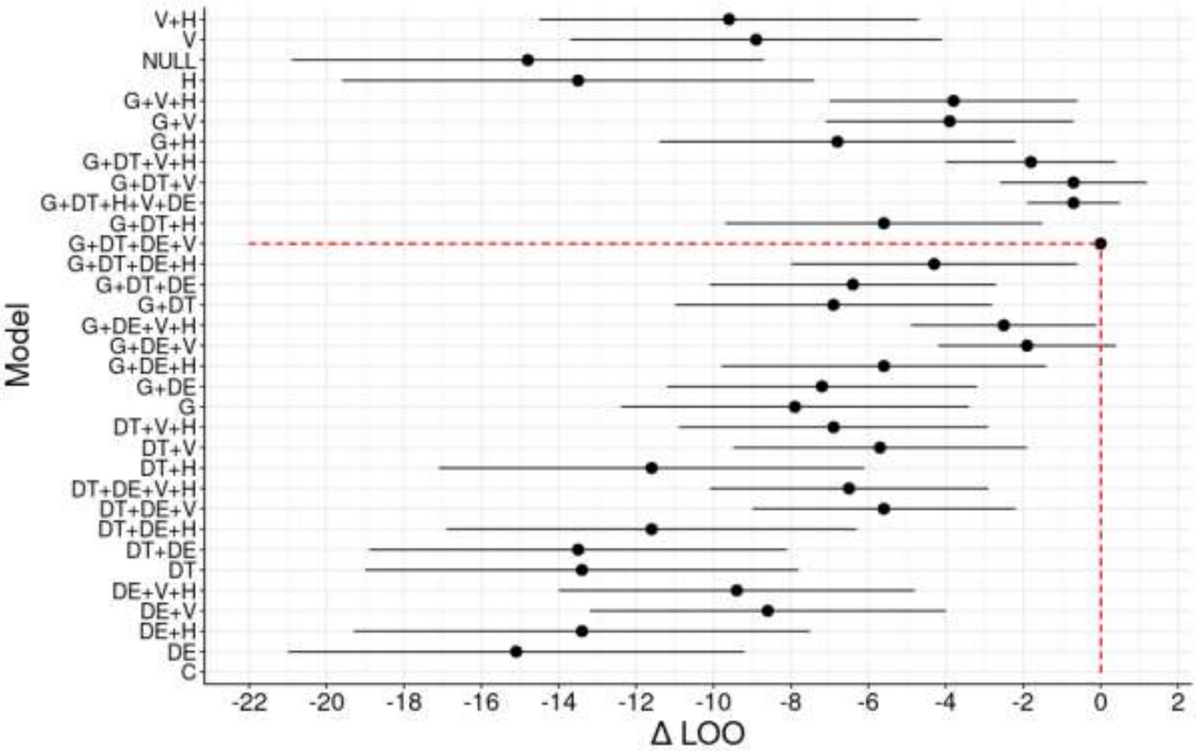

Figure 4. Estimates of model performance using approximate leave-one-out cross-validation. The scores ΔLOOi = LOOi − LOOmin are the differences of the loo estimates of models i = 1, …, 32 and that of lowest LOO value. The error bars depict one-standard error of the ΔLOOi estimates. G = Gate presence, DT = Distance to town, DE = Deployment expertise, H = Human on-foot relative activity, V = vehicle relative activity.

All predictors included in the best-fitting model showed strong evidence for their impact on CT survival probability, as their parameter posterior estimates and 95% Bayesian credible intervals did not overlap with 0 (Figure 5). Distance to town and deployment expertise had the lowest posterior estimates. Increasing distance to town and gate presence lead to a decrease in the hazard function by approximately 25.9% and a 59.3% respectively. Conversely, an increase in one unit of the log-transformed vehicle RA and initial deployment showed evidence of increasing the hazard function by approximately 200.4% and 49.2% respectively.

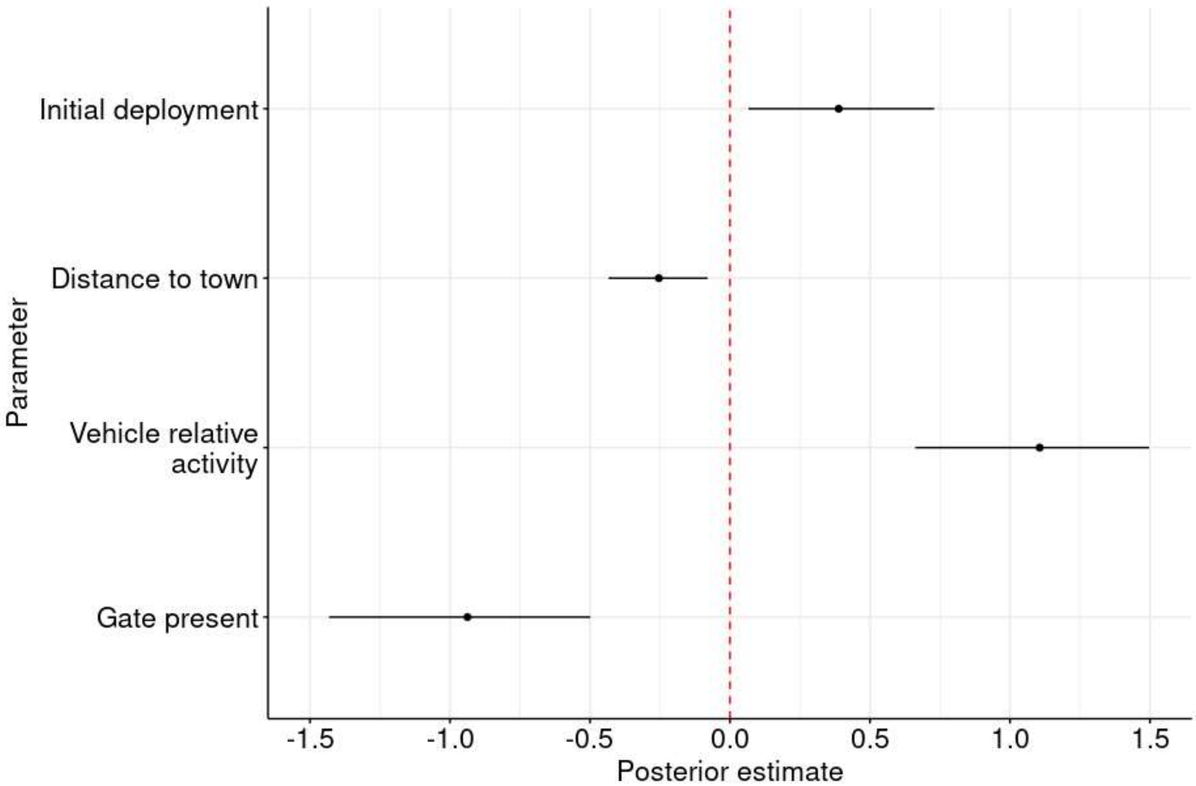

Figure 5. Parameter posterior estimates of predictors included in the best-fitting model (see Figure 4). Horizontal lines indicate 95% Bayesian credible intervals on camera survival probability; the intervals do not overlap with 0 (vertical red line) indicating a strong effect on camera-trap theft.

The predictions of our best model showed that informed deployment, the presence of a gate on the road, a decrease in vehicle RA (lowest 5% quantile = 0.049 images of vehicles per total trap days), and greater distance from the nearest town (highest 95% quantile = 32 km) significantly increased the survival probability of CTs (Figure 6). These CTs were predicted to last 205 times longer without being stolen compared to cameras situated in the worst circumstance: closer to the nearest town (lowest 5% quantile = 5km), on roads without a gate, higher vehicle RA (highest 95% quantile = 0.980 images of vehicles per total trap days), and initially deployed (Figure 6).

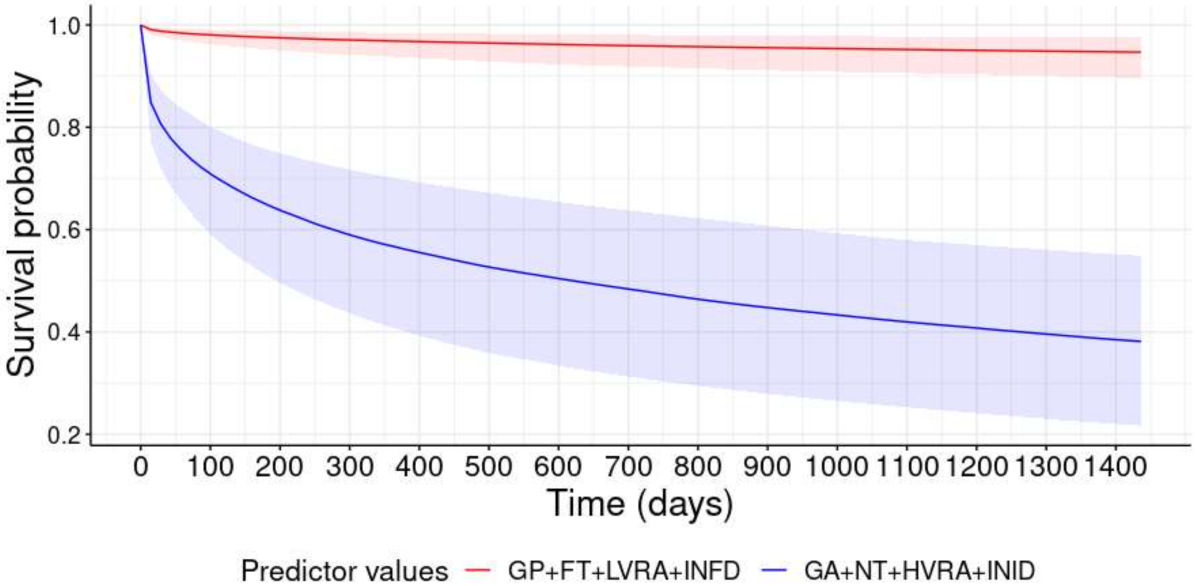

Figure 6. Predicted survival probability of camera traps over time (posterior median and 95% uncertainty limits) under the best- (red) and worst-case (blue) combinations of parameter values. LVRA = lowest vehicle relative activity (5% quantile = 0.049 vehicle images of vehicles per total trap days), HVRA = highest vehicle relative activity (95% quantile = 0.980 of vehicles per total trap days), FT = Furthest distance from the nearest town (95% quantile = 32 km), NT = nearest distance to the nearest town (5% quantile = 5 km), GP = gate on road present, GA = gate on road absent, INFD = informed deployment, INID = initial deployment.

Discussion

In this study, we assessed the impact of a range of factors related to camera trap (CT) placement on the risk of theft of CTs deployed on roads. Interestingly, we found that the frequency of human foot traffic was not a significant factor in camera-trap theft prevention. However, a decrease in the frequency of vehicle traffic, the presence of gates on roads, longer distances to towns, and increasing experience at hiding cameras all showed evidence of significantly decreasing camera-trap theft risk.

Although the exact motivations behind why people steal CTs remains unclear, it is likely that individuals engaging in illegal activities would steal CTs to avoid being identified, and sites with these characteristics in our study were less frequented by such individuals. Gated roads clearly have limited vehicle access, and this will reduce the likelihood of illicit activity such as illegal forest extraction and hunting, as vehicles facilitate rapid ingress and egress from sites, and the transportation of tools (e.g., chainsaws, axes and hunting gear), and recovery of materials associated with such activities (e.g., wood and carcasses) (Clements *et al.* 2014; Woods 2019). In contrast, individuals on foot are generally more likely involved in recreational activities like walking dogs, hiking and jogging. This is consistent with our results, which showed that while the frequency of vehicle traffic was a significant predictor of camera-trap theft, the frequency of human foot traffic was not.

Secondly, locked gates might foster a perception of increased risk among potential offenders of getting caught or facing consequences, as demonstrated in urban settings like alleys (Sidebottom *et al.* 2018). This perception could deter unauthorised individuals, such as motorbikes that can bypass gates, from using these roads for illegal activities. However, the effectiveness of gates in creating a fear of prosecution in remote areas depends on whether managers have the resources to monitor and enforce laws in the area (Abdu 2023). Therefore, in areas lacking adequate monitoring against crime, the presence of a gate on the road might no longer be a strong determinant of the risk of camera-trap theft. Additionally, the frequency of vehicles like motorbikes and bicycles might impact this risk differently compared to other vehicles that cannot bypass gates, such as large four-wheel drives. Advances in machine-learning models for identifying different types of vehicles in CT images, like MegaDetector (Beery *et al.* 2019), could help future studies examine the impacts of specific types of vehicles on camera-trap theft on roads with and without a gate.

Proximity to the nearest town likely attracts more individuals engaged in illegal activities, such as vandals and opportunistic thieves, as these roads require less effort and time to reach. Previous studies have found that forests and farms near towns experience higher instances of illegal forest extraction, vandalism, unauthorised trespassing, and illegal hunting (Barclay *et al.* 2011; Mackenzie *et al.* 2013). However, crime and illegal activity in these areas are not solely determined by their proximity to towns but also by the socioeconomic status, educational levels, and social dynamics of nearby communities, as well as the ecology of the area, such as resource availability and canopy cover (Gerben J. N. Bruinsma 2007; Troy *et al.* 2012; Mackenzie *et al.* 2013; Abdu 2023). Therefore, in areas with, for example, stronger community social cohesion, roads near towns might have low or no levels of illegal activity, potentially leading to no correlation between distance to town and camera-trap theft risk, as suggested in previous studies (Meek *et al.* 2019).

As researchers work within and become familiar with the broad risks associated with a given operational region, they inevitably improved the measures used to hide CTs from potential thieves. Our results showed that this significantly reduced camera-trap theft risk, likely because better-hidden CTs were harder for potential thieves to detect, and because the most vulnerable sites were quickly plundered and thereafter abandoned. These findings emphasise the importance of using strategies such as enhance camouflage and prioritising infra-red flash to mask CTs and minimise their visibility to people. However, the separate impact of camouflaging CTs and using infra-red flash on camera-trap theft risk warrants further investigation. A future study could include a controlled experiment comparing the effects of camouflaged and non-camouflaged CTs on the risk of camera-trap theft using dummy units. Another study could involve collaborating with researchers who deployed both infra-red and white flash CTs on roads with consistent nighttime human activity and experienced theft. Moreover, there are unfortunately trade-offs in these choices. While infra-red flashes are less noticeable to people during nighttime, they produce monochrome images, compared to the bright and coloured images of white-flash cameras (Meek *et al.* 2012b). Infra-red flash images also reduce the detection and identifiability of certain small mammals, as well as species that rely on pelage colour as an identifying characteristic (Meek *et al.* 2015; Burns *et al.* 2018). Another risk – data quality trade-off involves site obscuration: if not arranged correctly, the vegetation used for camouflaging CTs can obstruct the cameras field-of-view, leading to poor image quality, empty frames, or misleading clutter that resembles animals (Moll *et al.* 2020).

Conclusion

The evidence from this study suggests that placing CTs on roads with a gate, at greater distance from the nearest town, and with lower frequencies of vehicle traffic, as well as implementing proactive efforts to hide CTs, reduces theft risk. It is interesting to note that human foot traffic did not significantly elevate this risk in our context, suggesting that the influence of the frequency of human activity on the risk of CT theft depends on the type of activity. To our knowledge, these effects have not been rigorously quantified before, but further data are needed from other social and ecological contexts. Our study offers a robust analytical framework for identifying and testing the factors influencing CT theft risk with application in diverse social and ecological contexts. Moreover, these results indicate that to enhance security of CTs deployed on roads, efforts must go towards multiple anti-theft measures, including strategic placement based on the social and ecological landscape and proactive efforts to hide cameras. If resources are limited or the context of the study area restricts the implementation of some strategies, implementing even a single strategy can still help to reduce CT theft. Nevertheless, we suggest that the implementation of these strategies should be accompanied by careful consideration of the potential trade-offs they might have for data quality and sampling regimes.

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Conflict of interest statement

The authors declare no conflict of interest.

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