Kingston Maurward College

Assessing bird collisions in the United Kingdom: Modelling frequency of bird-strike from road and rail mortality using a Bayesian hierarchical approach

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Contents

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Abstract

Roads are an important way to transport people and goods, but they sometimes have negative impacts on wildlife. One of the leading causes of mortality for several species is identified as road strikes, and the most significant remains bird-vehicle collisions. This study aimed to investigate what species of birds are most affected, and what other factors impact in their susceptibility in road collisions, such as age, sex, season, and type of transports. A total of N=5413 records, and 140 bird species were documented by BTO ringers. For analysis four Bayesian Hierarchical Models were used, with random effects results showing that Barn owls were most affected by collisions. Road mortality presents the highest cause of mortality among species when contrasted with rail mortality. Age and sexual bias was detected across all species, however juveniles and males did appear to be prominent in relation to other age classes. Winter and early spring were the months with most reported casualties and 2016 had lower abundance of mortality across the 10-year period. 75% of birds were found within a week, which may indicate some bias interference from scavenging animals, as true figures could be up to 16 times more. This study discusses some mitigation measures found in current research, that could dramatically reduce numbers of birds affected each year by road mortality.

Introduction

At present there are over 64 million kilometres of roads on the earth, and Great Britain comprises almost 400,000km of asphalt road, which could circulate ten times around the globe (Cooke, Balmford, Johnston, Newton, & Donald, 2020). While roads are important to human society as a means of transport of people and goods, they can have negative impacts on wildlife (Arnold et al., 2019; Johnson, Evans, & Jones, 2017; Meijer, Huijbregts, Schotten, & Schipper, 2018).

Wildlife can suffer adverse effects from roads, for example by direct impacts like collision with transport, or by indirect impacts like the fragmentation of habitats (Schwartz, Williams, Chadwick, Thomas, & Perkins, 2018). In addition, roads contribute to negative effects by noise, pollution, and light (Johnson, Evans, & Jones, 2017).

Roads can be ecological snares for certain species, as an appealing habitat or source of food they may encourage animals to them, only for them to subsequently endure health effects, decreased reproductive success or vehicle-collision as consequence (Cooke, Balmford, Johnston, Newton, & Donald, 2020).

Over the last century, the effects traffic has on the survival of animals has been notable (Møller & Erritzøe, 2017). One of the leading causes of mortality for several species is identified as collisions amongst vehicles and wildlife (Gonzalez-Suarez, Zanchetta Ferreira, & Grilo, 2018). The most considerable remains bird-vehicle collisions, with estimations in some countries of 80-340 million in the United States, 57 million in Europe, and 27 million in England (Husby, 2017; Loss, Will, & Marra, 2015; Møller & Erritzøe, 2017).

Regardless of the considerable amount of investigation into such numbers, insufficient research has investigated the effects of roads on birds, possibly because of misconceptions of flight capabilities that allow them to escape and thereby avoid related effects (Johnson, Evans, & Jones, 2017). Species of birds more profuse alongside roads are usually more often implicated in accidents with vehicles (Madden & Perkins, 2017). Variations in mortality trends might be propelled by alterations in roadkill coverage techniques or driving performance (Madden & Perkins, 2017). Mortality likelihood might also be partially a result of birds' cognitive skills (Møller & Erritzøe, 2017). There is a need to take into consideration all such factors by assessing changes in mortality rate of different bird species during extended periods (Madden & Perkins, 2017).

Avian Senses and Behaviour

Birds constitute an integral part of a complex network in the environment, preserving and supplying several ecological provisions which humans are reliant on for continuous development and success (Johnson, Evans, & Jones, 2017). Birds are ecological facilitators, as they pollinate and disperse important plant species, and they also predate on species that are considered pests across agricultural industry (Johnson, Evans, & Jones, 2017).

The susceptibility of specific species to road traffic is dependent on their behaviour and environment (De Jong, van den Burg, & Liosi, 2018). The information that birds obtain visually from their environment is clearly distinct from that obtained by humans under similar conditions (Martin, 2011). The reason for this is the basic dissimilarities among birds and primates on all degrees of structure of their optical systems, involving physiological optics, retina, visual information they obtain by the brain, and visual areas (Martin, 2011).

Birds' senses display a high level of deviation which seems to be responsive to the cognitive challenges presented, particularly hunting, and thus sensory abilities are perceived as an essential part of every species' ecosystem (Mitkus, Potier, Martin, Duriez, & Kelber, 2018). Birds use vision as their main sensory organism, with many species sharing ultraviolet spectrum (May, Åström, Hamre, & Dahl, 2017). Bird colour vision is resolved by photoreceptor types, therefore some bird's behaviour is driven by UV indications (Lind, Mitkus, Olsson, & Kelber, 2013).

Owls and diurnal birds of prey have bigger eyes when compared to other birds that fly (Mitkus, Potier, Martin, Duriez, & Kelber, 2018). The visual sharpness in a few diurnal birds of prey is a result of their larger eyes, although in contrast to nearly all other species, they are not especially responsive to ultraviolet light (Mitkus, Potier, Martin, Duriez, & Kelber, 2018). Statistical evaluation of every existing visual field information has demonstrated that the binocular fields of non-passerine birds are considerably smaller than passerine species (Mitkus, Potier, Martin, Duriez, & Kelber, 2018).

Dangers to birds of prey, and the way they react visually, mostly derive from predator avoidance, but also strongly from human interaction. They are predisposed to evading predation and collision, for which transportation collisions is the most frequent (Hawk Watch International, 2018). Birds of prey often forage on roads, searching for prey on the edges of roads, even if they effectively catch their prey, they can collide with transportation when attempting to fly off while carrying heavier animals (Hawk Watch International, 2018). When birds of prey are foraging, they fly down with extreme focus, described as tunnel-vision, as they predate on prey, at times flying across roads when they can get hit by vehicles (Hawk Watch International, 2018). Owls are extremely susceptible to road mortality due to their lower hunting flight heights (De Jong, van den Burg, & Liosi, 2018).

Road Design and Infrastructures

Urban development influences migration patterns and wildlife dispersals (Morelli, Beim, Jerzak, Jones, & Tryjanowski, 2014). There is considerable research showing the environmental effects of roads, which turn out to be a major threat to species richness, supporting a significant reduction in bird populations in the vicinity of roads, in particular where traffic is abundant (Selva et al., 2011; Cooke, Balmford, Johnston, Newton, & Donald, 2020). Birds are particularly useful in assessing the effects of anthropogenic disturbance, with road and railway networks already well known as causing adverse effects (for example; sound levels, habitat destruction, obstacle impacts, disturbance and mortality from accidents (Morelli, Beim, Jerzak, Jones, & Tryjanowski, 2014)).

In Great Britain, several bird populations have had a significant reduction over past years, these decreases were associated to many influences, such as: global warming; shifts in land use and farming practices, habitat destruction and fragmentation (Cooke, Balmford, Johnston, Newton, & Donald, 2020). Additionally, roads might have added to these population declines, as traffic quantity has risen by more than 160% in the last sixty years (Cooke, Balmford, Johnston, Newton, & Donald, 2020; Roulin, 2020).

Since 1960, there has been a rise in speed and traffic quantity, and road collision levels are dependent on these two factors (Madden & Perkins, 2017; Orlowski, 2008). Subsequently, according to Orlowski (2008), the English population of House sparrow *Passer domesticus* has decreased by 13% due to road mortality. Other recent studies suggest road accidents to be a primary cause of mortality amongst the decreasing populations of owls in the countryside, such as Barn owl *Tyto alba* and Little owl *Athene noctua* (Orlowski, 2008).

Millions of birds are dying every year from traffic collisions, however, highway schemes usually concentrate on decreasing road collisions with larger mammals due to security and financial motives (Arnold et al., 2019). Presently, ever-increasing new hedgerows are being planted as an integral part of conservation and agricultural programs, which set ideal environments for some species in decline (Orlowski, 2008).

Numerous suggestions on prevention measures of bird road mortality are discussed in various papers; open verges and grassland located close to roads being recommended to grow into shrubs, in order to reduce accessibility to foraged prey such as rodents (Figure 1A) (Barn Owl Trust, 2015; Orlowski, 2008).

Another method can be to make birds fly higher, by placing fences and lines of tall trees closer together (above 3 m) in addition to building walls (Figure 1B and 1C) (Orlowski, 2008). Planning roads with such barriers may help to divert owls and birds of prey as they will fly higher, and therefore could reduce collisions between certain species (Figure 1D) (Ramsden, 2003; Boal & Dykstra, 2018; Roulin, 2020).

Additional mitigation measures include decreasing the quantity and speed of transportation and raising the awareness of drivers. This has been demonstrated to enhance animal numbers in regions with abundant road system, although attempts to employ these shifts have been frequently challenging (Boal & Dykstra, 2018; Selva et al., 2011).

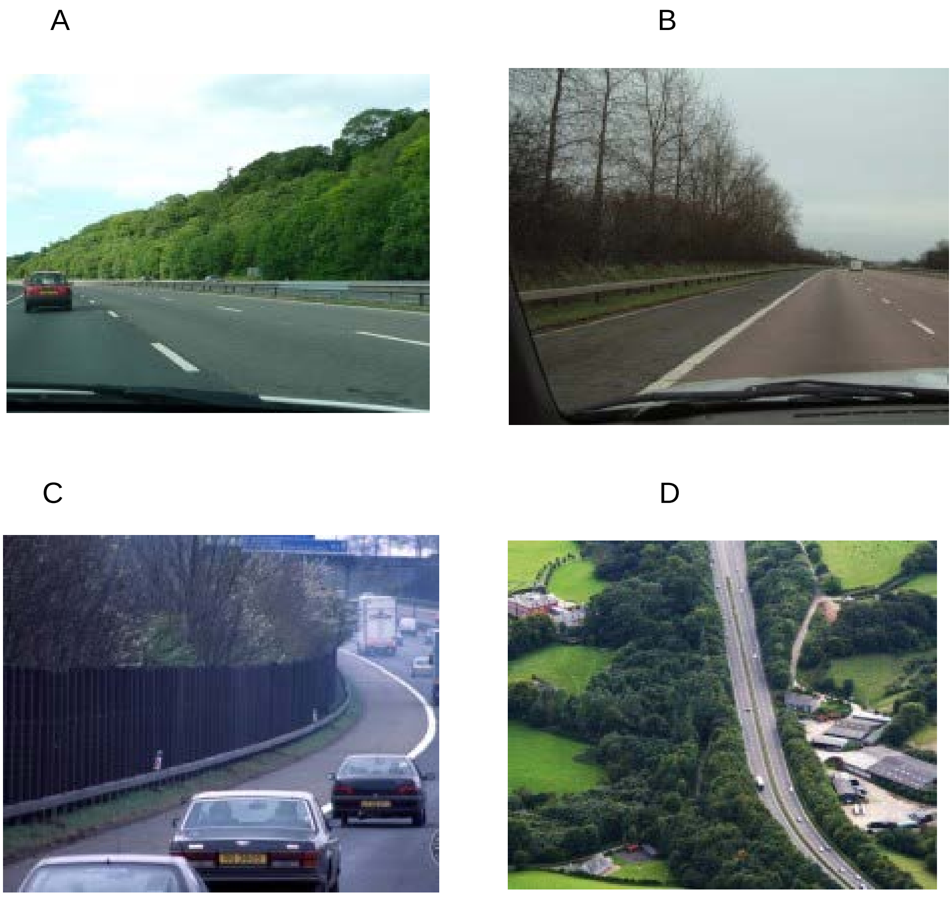

Figure 1. Some mitigation options currently suggested for birds of prey include shielding main roads: (A) edge scrub is an inexpensive alternative, directing birds to fly higher (between 2-5 metres should help to avoid lorries) as well as supporting wildlife and allowing drivers to slow down in the event of colliding; other more costly alternatives consist of (B) tall trees and (C) wall barriers; and (D) a secure area with trees on either side (Barn Owl Trust, 2015).

In summary, there is mounting evidence that road collisions are a major threat to bird populations. This study aimed to evaluate what species are most affected by road mortality and what transportation type has a greater impact. To understand what factors might influence road collisions trends factors such as bird age, bird sex, month, or year of mortality, number and species affected, and conditions the birds were found in were studied. This work sought to investigate relationships between age, sex, month, year, and types of transportation in relation to the abundance (and frequency) of bird collisions.

Methodology

Data used in this study was provided by the British Trust for Ornithology (BTO), comprising records of reported birds in road-collision. The data collected was supplied by ringers throughout Great Britain and Ireland, reporting ringed birds, which may have either a metal ring, metal and colour ring, or less frequently just a colour ring. The BTO Ringing Scheme is funded by a partnership of the British Trust for Ornithology, the Joint Nature Conservation Committee (on behalf of: Natural England, Natural Resources Wales and Scottish Natural Heritage and the Department of the Environment Northern Ireland), The National Parks and Wildlife Service (Ireland) and the ringers themselves.

The data comprised N=5413 records of 140 species involved in road collisions over the past ten years. It also included the types of transports implicated, and other relevant information such as age, sex, month, year, and encounter conditions. Statistical models were used to uncover relationships between species, factors, and collision trends. The factors codes (Age and Finding Condition) are described in – Appendix 1.

Data Analysis

For the statistical analysis four Bayesian hierarchical models with random effects were structured into subsets of broad-based bird guilds; Raptors (Subset 1), Seabirds (Subset 2), Wildfowl (Subset 3), and Garden Birds (Subset 4). Data was converted first using package dplyr (Wickham et al., 2020) piping categorical replicated data rows into numerical integer counts as response variables. Estimation was conducted using Markov Chain Monte Carlo (MCMC) routines in software JAGS version 4.3.0 (Plummer, 2003) through the package runjags (Denwood, 2016) in R version 3.6.3. (R Core Team, 2019).

Models were expressed similarly to a frequentist log-linear model used in lme4 as;

Count ~ Species * Find_Circ + Age + Sex + Month + Year + Find_Cond + (1|Year)

Each model was fitted as;

$$Y_i \sim \text{Poisson}\ (\mu_{ik})$$
$$\log\ (\mu_i) = a + \beta_1 \times \beta_{2\ \ldots} + a_i$$
$$a_i \sim N(0, \sigma^2_{Year})$$

where; k is the over-dispersion parameter, a is intercept, β_1 and further β are fixed effect coefficients, and a_i is the randomized effect (Year).

Models comprised Poisson family distributions running 40000 iterations, 10000 discarded for burn-in, and 4 chains. Priors were set using templates within runjags modest automated uniform gamma distribution detected and set through JAGS (priors = ~ dnorm (0, 10^-6)). Convergence was assessed using MCMC trace plots of iterations retrieved from runjags and inspection of the Gelman-Rubin statistic potential scale reduction factor (psrf) (Gelman et al., 2013).

Model assumptions of mean-variance, log-linearity and potential autocorrelation were explored using residuals vs. fit plots, and a correlation plot function within runjags. MCMC draws from posterior distributions were used for evaluating model component relations. Factor interactions plots were constructed in ggplot2 (Wickham, 2016) to contrast model findings. Summary data was recovered from base-R functions.

Results

Summary results across all data are shown in Table 1. Convergence, and autocorrelation are reported in – Appendix 2. Convergence was complete for all variables in all four subset models 1-4. Autocorrelation levels were acceptable with various levels of only minor correlation across some factors. Models of Subsets 1-4 generated a series of results, much of which demonstrated interesting and diverse variation in response to encountered circumstance (found circumstance) Find_Circ (Road or Rail related mortality) (Appendix 2).

A significant amount of count response species across models did not exhibit a lot of variation in differences (Appendix 2). This is mainly caused by the sparse data across the models or limited sample size (for instance, Subset 2 - Arctic tern *Sterna paradisaea*, N=3). Other species responses were well represented (for example, Subset 1 – Barn owl *Tyto alba*, N=2134; Table 1). Caterpillar bar plots with confidence intervals are shown for all species (Figures 2-4). Species that had interaction and were strongly affected as a result or Road or Rail mortality are those with clear positive or negative difference from the mean zero line and particularly those with confidence intervals that do not have zero crossings.

Few structured hierarchical level predictors (Age, Year, Find_Cond…) exhibited strong interactions. However, in Subset 1 – Raptors were greatly affected and demonstrated an obvious impact of a seasonal effect on mortality frequency for some species (JAN, FEB, MAR, MAY), sexual bias (UNK), and age related influence (UNK). For Subset 1, Barn owls, Kestrels *Falco tinnunculus*, Peregrines *Falco peregrinus*, and Tawny owls *Strix aluco* were clearly affected worst by Roads, a concerning trend (Figure 2). Woodcock *Scolopax rusticola* in Subset 3 were impacted for both Rail and Road mortality (Figure 4). Buzzards *Buteo buteo* had expressed confidence intervals on/just over the zero crossing and presumably with further data would represent a significant impact from Road collisions. Overall, there are clear seasonal effects on one guild (raptors) with casualties on Roads, and a lack of age and sexual identification from specimens of some species (Figure 3).

In all subsets, the species most affected by road collisions (by both Road and Train) were Barn owls and Blackbirds *Turdus merula* (Figure 5). Age bias was shown for all the other species (UNK – 77%) presented as the highest followed by (JUV – 10%) across the age range (Figure 6). Sexual bias was also shown across all species (UNK – 78%), (M – 14%) in comparison with (F – 8%) (Figure 7). In every subset, the month with highest casualties was (JAN) followed by (MAR and APR) (Figure 8), and across years illustrating more range from 2010-2013, while 2016 was the year with lower casualties reported (Figure 9).

The Finding Conditions of all species suggested a higher trend for (FDW – 75%) (Figure 10). Rail related mortality was expressed less across all Subsets and species (Figure 11) and perhaps may benefit from further, separate, investigative modelling for more expression.

SUMMARY DATA								
Factor	**Model Subset 1**		**Model Subset 2**		**Model Subset 3**		**Model Subset 4**	
Species	BarnOwl	2134	HerringGull	138	MuteSwan	171	Blackbird	522
Species	Kestrel	191	Oystercatcher	109	Mallard	53	HouseSparrow	113
Species	TawnyOwl	187	LesserBlack-backedGull	65	CanadaGoose	20	Greenfinch	104
Species	Buzzard	94	Black-headedGull	40	Lapwing	20	Bluetit	103
Species	Sparrowhawk	68	CommonGull	16	Coot	16	Chaffinch	96
Species	RedKite	61	GreatBlack-backedGull	14	Curlew	15	Goldfinch	84
Species	(Other)	109	(Other)	29	(Other)	81	(Other)	760
Age	UNK	2422	UNK	334	DHY	15	UNK	1099
Age	JUV	177	DHY	24	FGH	3	JUV	318
Age	DHY	91	SEC	14	JUV	17	SEC	222
Age	SEC	71	THR	14	SEC	33	DHY	72
Age	FGH	67	JUV	13	THR	8	FGH	66
Age	THR	13	NSTUNK	5	UNK	300	NST	3
Age	(Other)	3	(Other)	7	NA	NA	(Other)	2
Sex	F	196	F	1	F	33	F	204
Sex	M	219	M	5	M	46	M	480
Sex	U	2429	U	405	UNK	297	UNK	1098
Month	JAN	551	JUL	103	0	0	MAY	320
Month	MAR	378	JUN	72	0	0	JUN	272
Month	FEB	358	0	0	0	0	APR	267
Month	APR	244	0	0	0	0	JUL	186
Month	AUG	224	0	0	0	0	MAR	178
Month	SEP	224	0	0	0	0	JAN	150
Month	(Other)	865	(Other)	71	(Other)	124	(Other)	409
Year	2015	358	2013	60	2010	53	2010	221
Year	2010	318	2018	49	2011	44	2011	219
Year	2011	315	2017	43	2015	42	2012	203
Year	2012	309	2014	42	2016	41	2013	187
Year	2018	309	2012	40	2014	37	2017	180
Year	2013	308	2010	39	2012	36	2014	172
Year	(Other)	927	(Other)	138	(Other)	123	(Other)	600
Find_Cond	AWU	106	AWU	21	AWU	11	FDW	1480
Find_Cond	DNF	191	DNF	19	DNF	20	DNI	143
Find_Cond	DNI	246	DNI	29	DNI	23	DNF	73
Find_Cond	DYG	111	DYG	14	DYG	13	DYG	44
Find_Cond	FDW	2020	FDW	254	FDW	275	AWU	15
Find_Cond	FDWDNI	126	FDWDNI	67	FDWDNI	30	FDWDNI	12
Find_Cond	SWU	44	SWU	7	SWU	4	(Other)	15
Find_Circ	Rail	123	Rail	5	Rail	25	Rail	8
Find_Circ	Road	2721	Road	406	Road	351	Road	1774

Table 1. Summary of N bird strike across model subsets: dominant species are shown

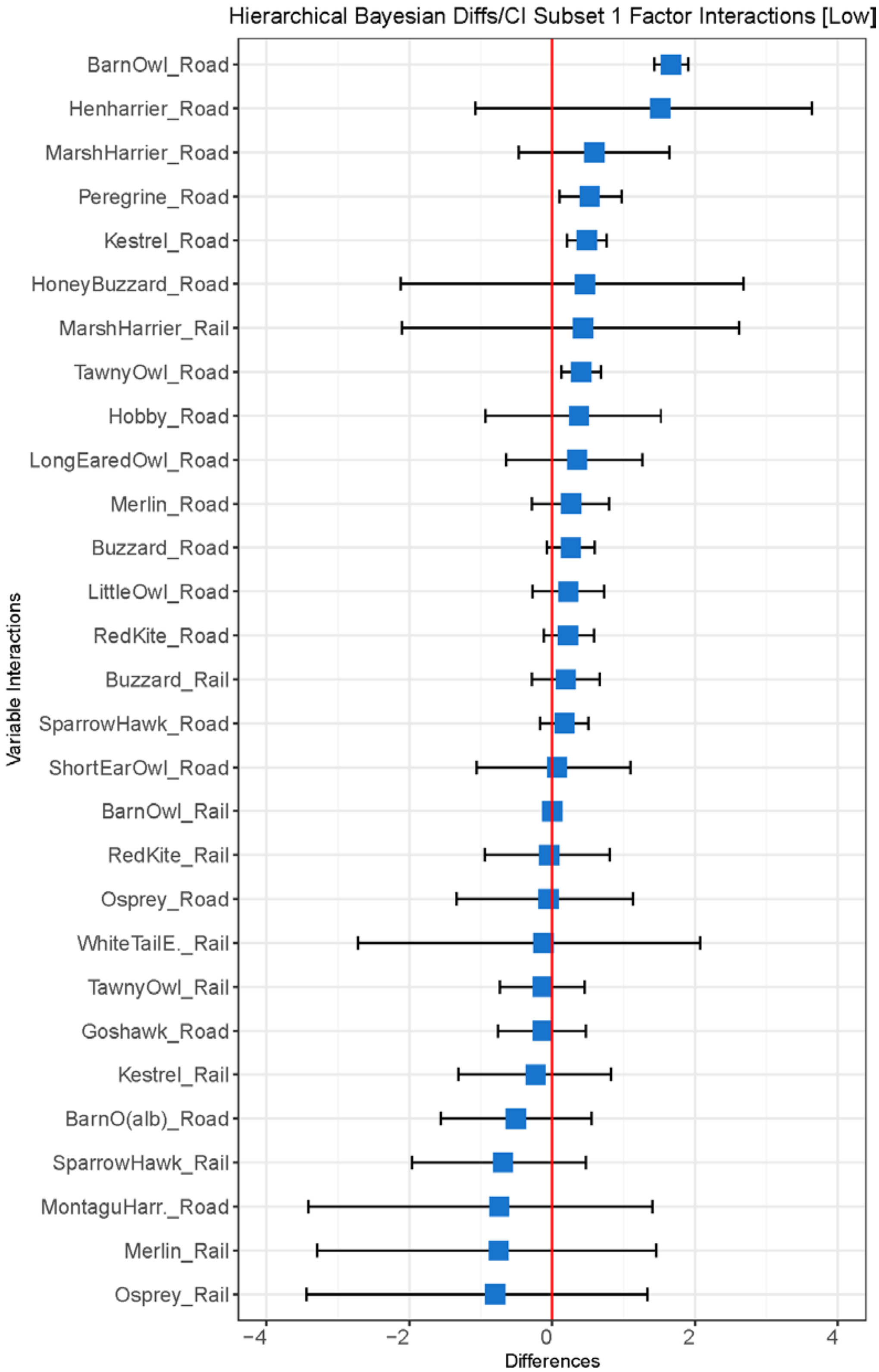

Figure 2. Caterpillar bar plots with credible intervals for Subset 1 species (Note, Barn Owl, Kestrel, Peregrine, Tawny Owl and Buzzard on Roads). Species with CI clear of the zero crossing differences are highly impacted

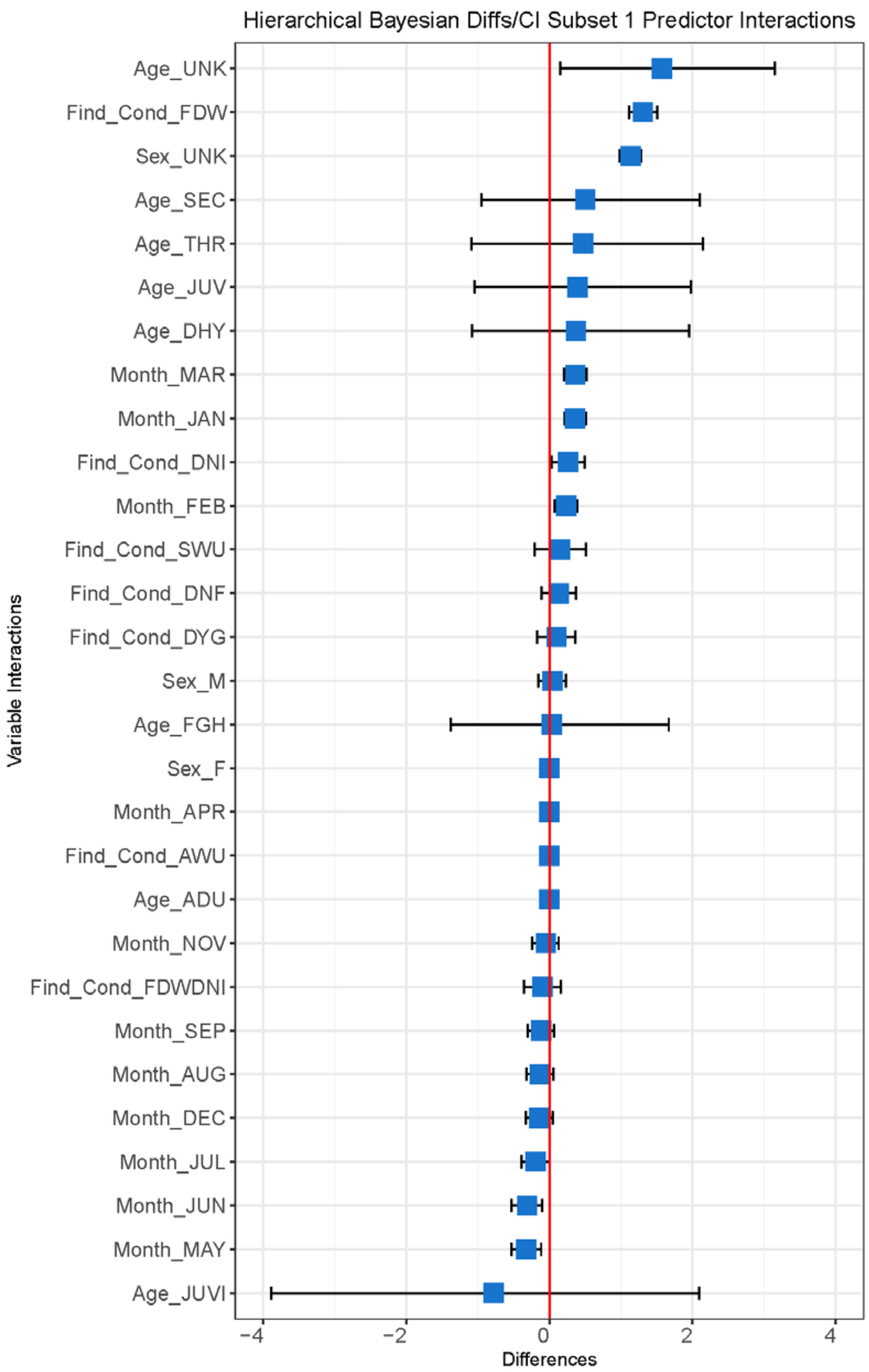

Figure 3. Caterpillar bar plots with credible intervals for Subset 1 predictor levels (Note, Find_Cond_FDW/DNI, Sex UNK, and January, February, March, May and June). Factors with CI clear of the zero crossing differences are influential

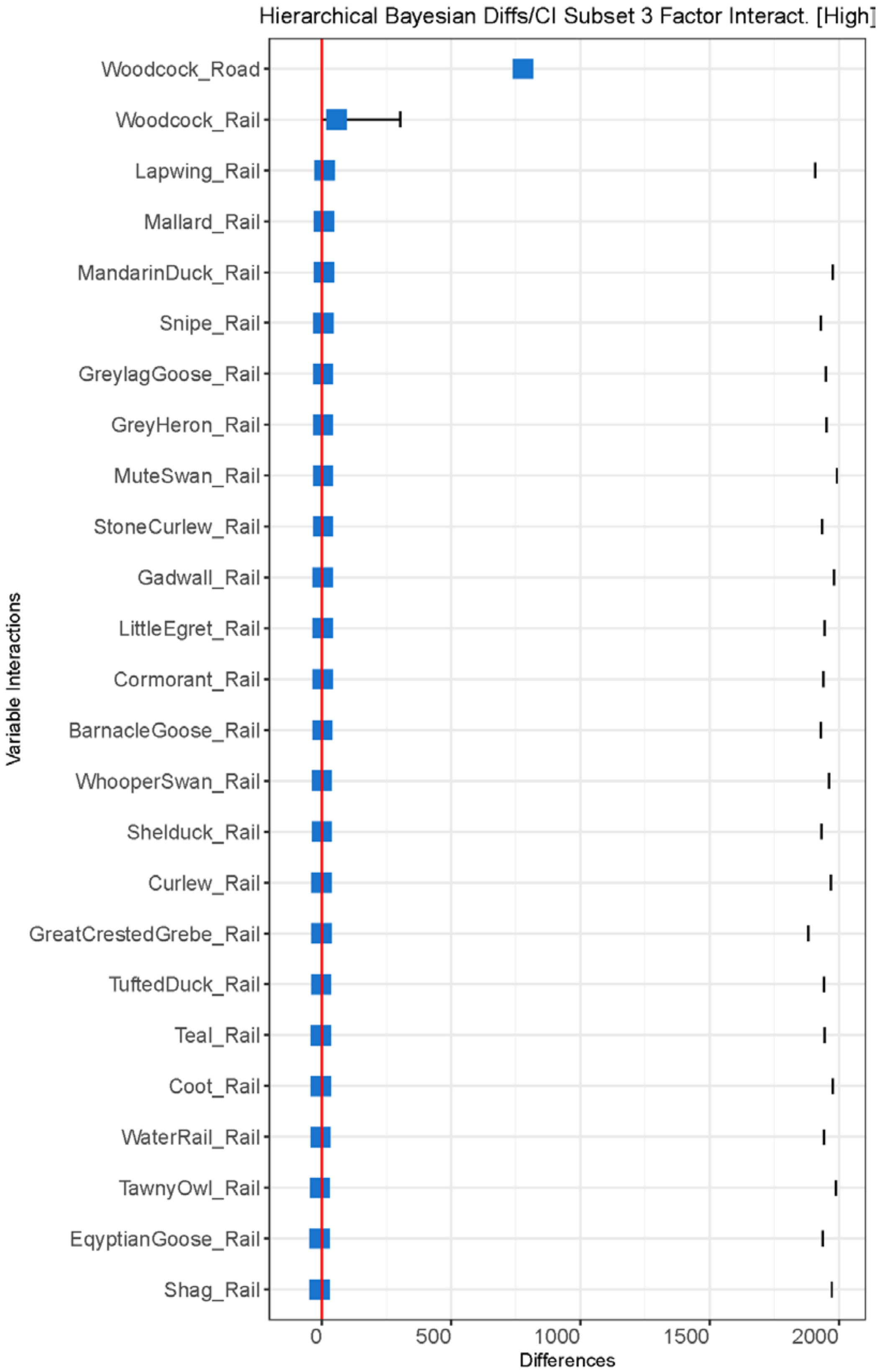

Figure 4. Caterpillar bar plots with credible intervals for Subset 3 species (Note, Woodcock in both Rail and Road). Species with CI clear of the zero crossing are influential. Detached CI's with mean values (blue) on the zero line are non-significant

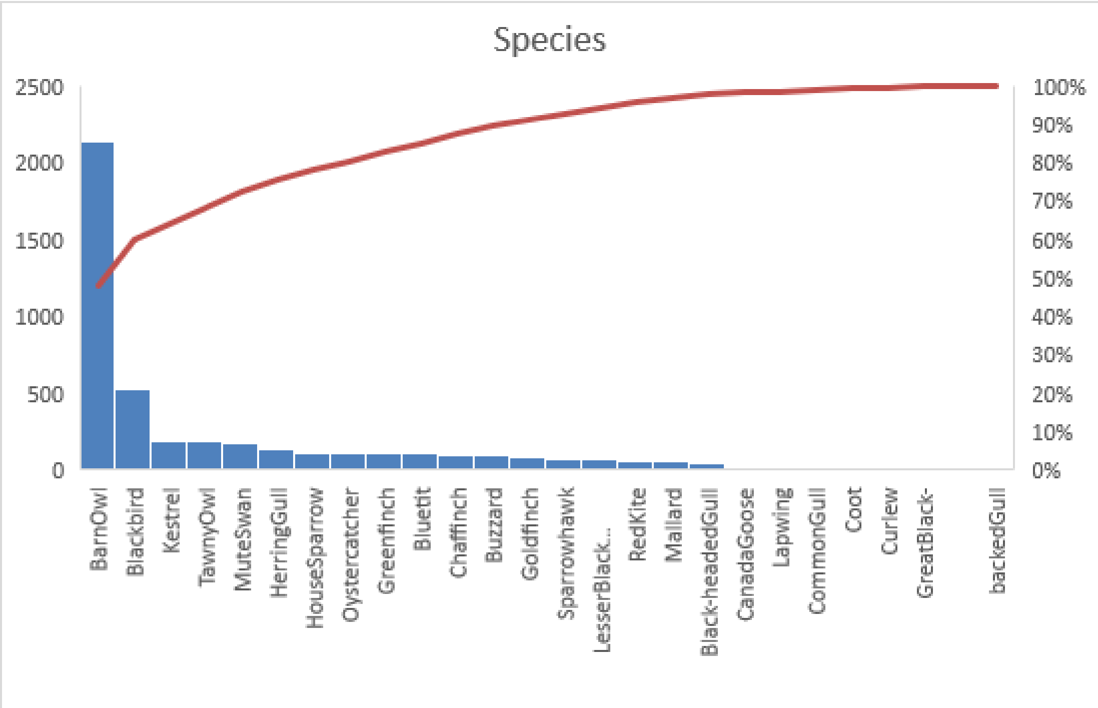

Figure 5. Summary chart showing species highly impacted by road/rail collision - all subsets

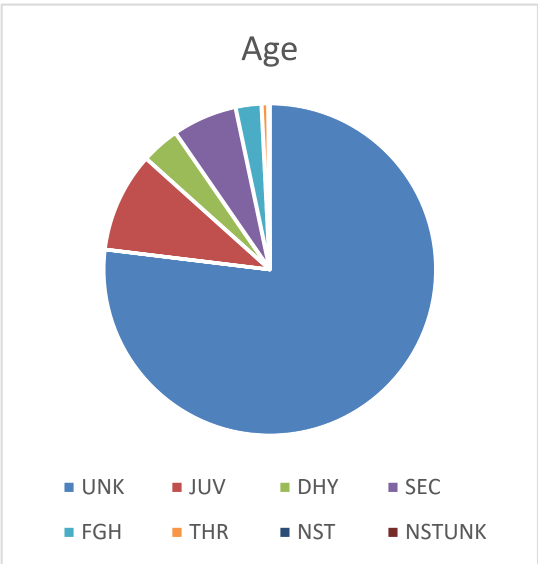

Figure 6. Pie chart describing age range

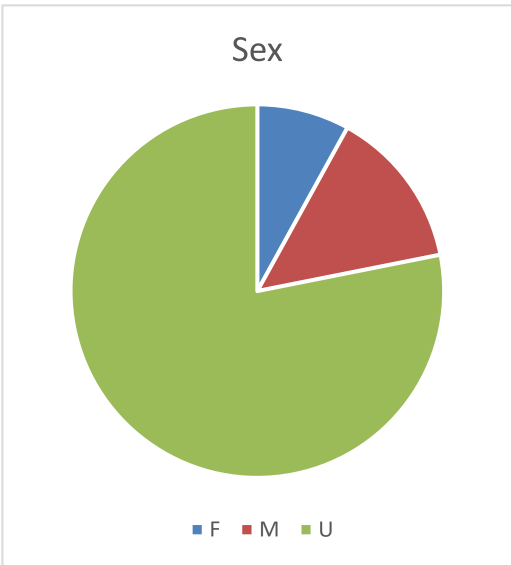

Figure 7. Pie chart showing gender

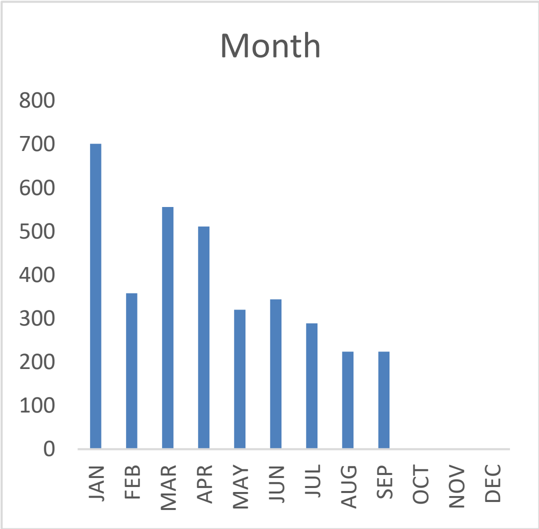

Figure 8. Summary of mortality by months

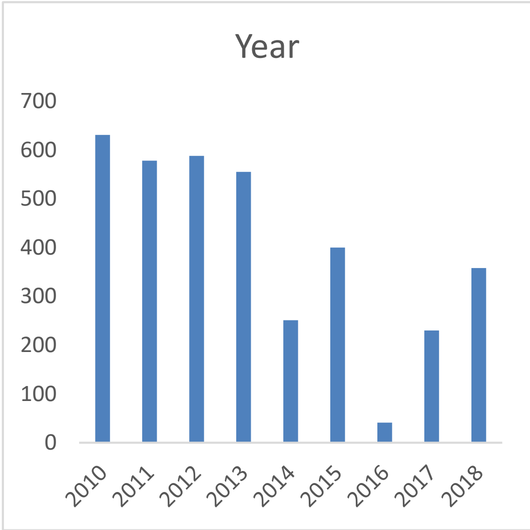

Figure 9. Summary of mortality by years

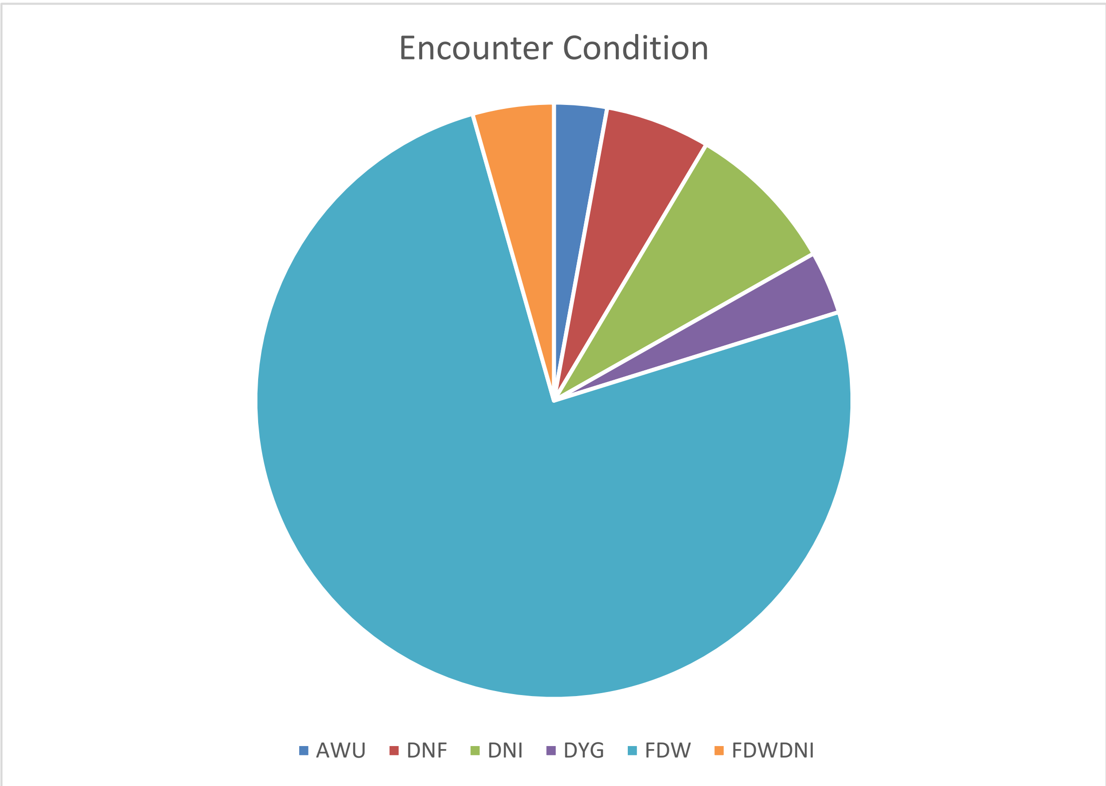

Figure 10. Pie chart showing encounter conditions found

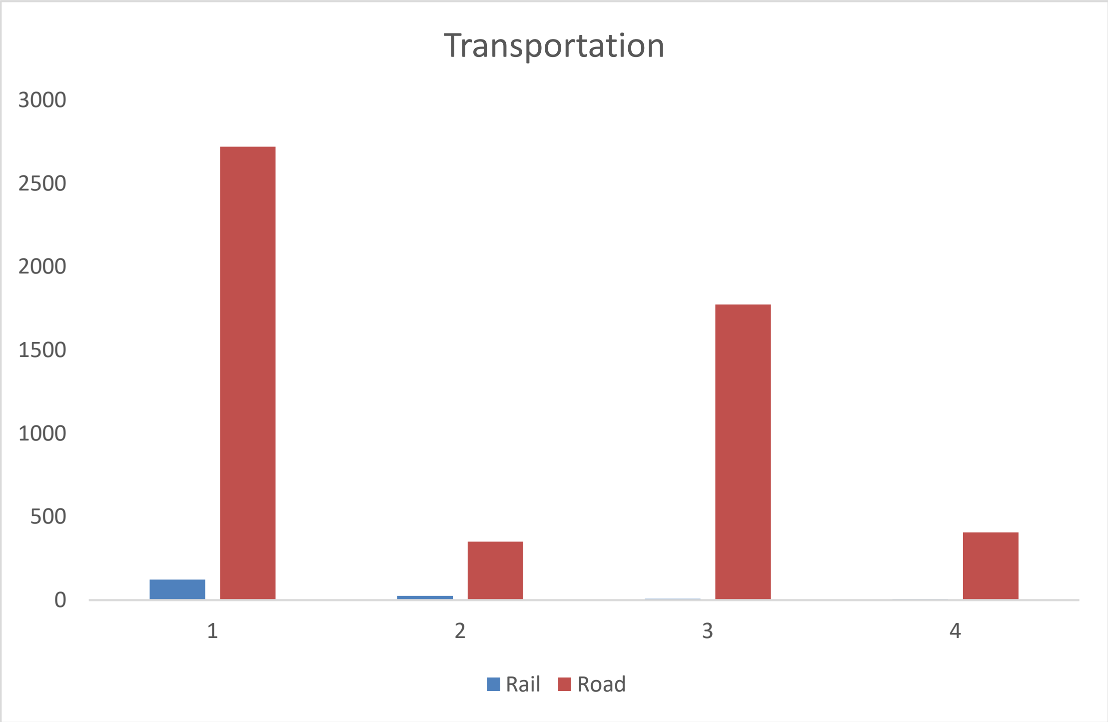

Figure 11. Summary chart of types of transportation influencing bird collision

Discussion

The probability of collisions with transports varies between the groups of birds (Husby, 2017). Across all Subsets (Raptors, Seabirds, Wildfowl and Garden Birds), Raptors were the most impacted by vehicle collisions, followed by Garden Birds. Raptors are very reliant on road environments as they provide them with food (Husby, 2017; Kajzer-Bonk et al., 2019). Barn owls were particularly affected within results of this study, supporting other studies that reached similar conclusions. Barn owls are often implicated in vehicle collisions, which constitutes a persistent pattern and may have an impact on populations of this species (Arnold et al., 2019; Cooke, Balmford, Johnston, Newton, & Donald, 2020). Arnold et al. (2019) has shown that Barn owl transportation collisions are less expressed on roads with shrubs when contrasted with roads with grass on their edges; thus collisions are believed to be a result of the concentrations of small mammals near the edges of roads in various areas.

In this study, it was not statistically possible to make inferences between different sites to understand areas of foraging preference, as spatial data was not provided, however, this could be a potential factor influencing the frequency of Barn owl casualties.

Blackbirds also showed high numbers impacted by transport collisions. They are perhaps not as adversely affected as Barn owls, but are still higher in frequency than all the other species across the Subsets. Roadside surroundings are appealing for this species, for breeding and foraging, and they often perch on trees and use shrubs for hunting nearby roads (Husby, 2017).

The age of almost all the birds reported were biased with more unknown (UNK) reports than known aged assessment. This is understandable given the difficulty of age class assessment for birds killed by impact. Notwithstanding, some UNK reports are followed by JUV, which shows that young birds (juveniles) are greatly impacted when compared to with other age ranges. Road collisions continue to be a significant cause of mortality among young birds, especially after breeding season, as they fledge their nest and disperse away from the place they were born to create their own territory (British Trust of Ornithology, n.d.). Young birds, which have less spatial experience, might be drawn to roadsides by the potential for food resources, which expose them further to transport collisions (Kajzer-Bonk et al., 2019).

Sex ratio was biased (UNK) across all the species. However, males (M) presented more frequency that female birds (F), which might be an artefact within the data as males were more frequently reported. Ecologically, this could be due to males foraging for longer periods of time, especially during the breeding season, whereas females often spend more time in incubation and feeding of offspring (De Jong, van den Burg, & Liosi, 2018).

Seasonal changes may be able to justify the difference in the number of birds reported from roads (Husby, 2017). January presented as the month with highest numbers of casualties, followed by March and April. These results suggest that bird collisions were higher during winter and early spring (breeding season). This could be due to scarcity of prey in winter, and thus the need for birds to forage on roads during this time. Also, higher frequency of reported birds during March and April indicated there was a tendency for more collision during the breeding season. Prey availability could influence trends across years, as there are years with considerably higher numbers. Year 2016 had the lowest casualties. In years that prey was abundant, collisions were greatly decreased (De Jong, van den Burg, & Liosi, 2018).

Mortality was greatest among birds that were found dead within a week, which indicated that birds that are found in a short period of time are more likely to be reported. Studies on bird collisions may be influenced by numerous biases due to prompt scavenging, thus when adjusting for this, mortality rates could be considered up to 16 times higher (Madden & Perkins, 2017; Guinard, Julliard, & Barbraud, 2012). Further, unbiased studies are needed to assess the connection between mortality rates, surrounding environment, and road structure (Guinard, Julliard, & Barbraud, 2012).

Road mortality is clearly dominant in casualties when contrasted with railway transportation, indicating that roads are possibly more appealing to birds than railways. This could be due to road design or abundance of prey. Also, the edges on roads and shrubbery have significant capacity as bird territory (Dover, 2019). Barn owls are drawn to grassy fields because of larger quantities of prey (Arnold et al., 2019; Barn Owl Trust, 2015). To potentially mitigate for this, zones of wild grass could be supplied closer to roads, but only if such areas are screened (Ramsden, 2003).

Meticulous design of roadside flora assemblages is therefore crucial to decrease negative impacts in order for birds and wildlife to benefit (Dover, 2019). To decrease owl road mortality, perhaps a realistic choice of mitigation would be to further implement strategies and management to enhance the quality of farmlands in such a manner that alternative land would be able to support larger numbers of prey (rodents) (Arnold et al., 2019; De Jong, van den Burg, & Liosi, 2018).

The most appropriate practice of bird protection around roads may well be to prevent unintentional invitation of birds toward them (Arnold et al., 2019). Decreasing or removing vegetation, often removing carcasses, so that such areas are not so attractive to foraging birds, or applying road lightning with colours and patterns to try to dissuade birds from being drawn to them (Arnold et al., 2019) are all useful strategies. Ultimately, further investigation is required to understand relationships between location, number and species affected by road collisions.

Conclusion

This study has shown that road mortality among birds is considerably high, across a variety of species, particularly Barn owls. This could be due to their behaviour and foraging opportunities. Also, in winter and early spring mortality frequency is higher possibly due to the lack of prey availability which could encourage birds to forage around roads.

Also, during breeding season, as juvenile birds explore their territory range, and because they are spatially inexperienced, they may forage more frequently on roads. Collisions are more frequent on roads than railways, which suggests that roads pose an attractive environment for birds. This could also be a result reflected in a greate frequency of reporting along roadside environments. Considering most dead birds were found (detected) within a week, scavenging may be taking place naturally, that may not allow for accurate abundance of road or rail mortality reporting.

Road surroundings should be carefully planned and designed, providing increased foraging areas, especially for Barn owls, which are greatly affected by road mortality. This, if applied correctly, could help Barn owls to divert from using these areas. The screening of roads (shrubs, trees, or panels) could help to decrease such road mortality, as birds would have to fly higher and this would subsequently prevent increased bird collisions. Eliminating or modifying grassy road edge areas could decrease accessibility by small mammals, and thus reduce raptors from foraging in these habitats, although this may conflict with other road verge wildlife management, and would need careful consideration and further study.

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Appendices

Appendix 1. Code Definitions

Age Codes

UNK – Unknown

NST – Nestling

JUV – Juvenile

DHY – Definitely hatched (during current year)

FGH – Fully grown (year of hatchling unknown)

ADU – Adult

SEC – Second year

THR – Third year

Encounter Condition

AWU – Alive, Wounded (fate unknown)

DNF – Dead (not fresh)

DNI – Dead (no information)

DYG – Dying

FDW – Freshly dead (within a week)

SWU – Sick, Wounded (fate unknown)

Appendix 2. JAGS Model Results and Convergence Data

	Lower95	Median	Upper95	Mean	SD	Mode	MCerr	MC%ofSD	SSeff	AC.10	psrf
intercept	-131.800	-0.574	135.682	-0.946	65.884	NA	0.342	0.500	37087.000	0.006	1.001
Age_effect[1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Age_effect[2]	-0.355	-0.008	0.344	-0.009	0.178	NA	0.002	1.300	5947.000	0.472	1.000
Age_effect[3]	-0.291	-0.015	0.258	-0.015	0.141	NA	0.002	1.300	5882.000	0.464	1.000
Age_effect[4]	-1.531	-0.153	0.984	-0.202	0.655	NA	0.008	1.300	6025.000	0.467	1.000
Age_effect[5]	-3.038	-0.285	1.733	-0.475	1.284	NA	0.016	1.300	6338.000	0.438	1.001
Age_effect[6]	-0.128	0.169	0.462	0.169	0.151	NA	0.002	1.300	6171.000	0.457	1.001
Age_effect[7]	-3.246	-0.470	1.530	-0.666	1.296	NA	0.017	1.300	6089.000	0.458	1.002
Age_effect[8]	-0.151	0.107	0.360	0.107	0.131	NA	0.002	1.300	6074.000	0.465	1.000
Sex_effect[1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Sex_effect[2]	-0.005	0.159	0.331	0.159	0.086	NA	0.001	1.300	6291.000	0.456	1.000
Sex_effect[3]	-0.030	0.143	0.318	0.143	0.089	NA	0.001	1.300	6284.000	0.455	1.000
Month_effect[1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Month_effect[2]	-0.331	-0.110	0.118	-0.112	0.115	NA	0.001	1.300	6232.000	0.454	1.000
Month_effect[3]	-0.537	-0.227	0.071	-0.229	0.155	NA	0.002	1.300	5980.000	0.472	1.001
Month_effect[4]	-0.383	-0.150	0.084	-0.151	0.119	NA	0.001	1.200	6424.000	0.441	1.001
Month_effect[5]	-0.353	-0.143	0.066	-0.143	0.107	NA	0.001	1.200	6478.000	0.441	1.001
Month_effect[6]	-0.309	-0.112	0.086	-0.113	0.101	NA	0.001	1.200	6571.000	0.432	1.000
Month_effect[7]	-0.206	-0.028	0.144	-0.029	0.090	NA	0.001	1.200	6835.000	0.425	1.001
Month_effect[8]	-0.233	-0.039	0.153	-0.040	0.099	NA	0.001	1.200	6962.000	0.418	1.001
Month_effect[9]	-0.197	-0.030	0.138	-0.031	0.086	NA	0.001	1.200	6750.000	0.431	1.000
Month_effect[10]	-0.512	-0.185	0.135	-0.189	0.166	NA	0.002	1.300	6150.000	0.460	1.000
Month_effect[11]	-0.469	-0.200	0.085	-0.202	0.142	NA	0.002	1.300	6165.000	0.459	1.001
Year_effect[1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Year_effect[2]	-210.161	0.005	187.671	0.209	103.139	NA	0.530	0.500	37885.000	-0.007	1.001
Year_effect[3]	-206.198	-0.034	191.568	0.232	107.188	NA	0.511	0.500	44076.000	0.001	1.001
Year_effect[4]	-198.798	-0.010	199.112	-0.100	105.180	NA	0.465	0.400	51129.000	0.000	1.001
Year_effect[5]	-198.772	-0.014	194.411	0.173	105.261	NA	0.528	0.500	39694.000	0.004	1.001
Year_effect[6]	-196.626	-0.103	201.569	0.178	105.082	NA	0.496	0.500	44892.000	0.002	1.002
Year_effect[7]	-214.513	-0.063	185.070	-0.299	103.598	NA	0.499	0.500	43108.000	-0.002	1.001
Year_effect[8]	-191.160	-0.037	209.052	0.356	105.933	NA	0.560	0.500	35775.000	0.006	1.001
Year_effect[9]	-183.366	-0.053	205.993	0.449	102.552	NA	0.522	0.500	38645.000	-0.010	1.002
Year_effect[10]	-191.482	-0.019	202.171	0.613	103.999	NA	0.495	0.500	44099.000	0.003	1.002
Find_Cd_Eff[1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Find_Cd_Eff[2]	-1.255	-0.103	1.171	-0.068	0.623	NA	0.008	1.300	5725.000	0.489	1.000
Find_Cd_Eff[3]	-1.099	-0.082	1.111	-0.041	0.571	NA	0.008	1.300	5756.000	0.488	1.001
Find_Cd_Eff[4]	-1.044	-0.018	1.154	0.022	0.568	NA	0.008	1.300	5689.000	0.492	1.000
Find_Cd_Eff[5]	-1.154	-0.111	1.123	-0.076	0.585	NA	0.008	1.300	5679.000	0.490	1.001
Find_Cd_Eff[6]	-0.875	0.120	1.288	0.163	0.561	NA	0.007	1.300	5681.000	0.491	1.001
Find_Cd_Eff[7]	-1.217	-0.030	1.278	-0.003	0.636	NA	0.008	1.300	5824.000	0.480	1.001
Find_Cd_Eff[8]	-1.310	-0.079	1.210	-0.053	0.647	NA	0.008	1.300	5801.000	0.489	1.001
Find_Crc_Sp_Eff[1,1]	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
Find_Crc_Sp_Eff[2,1]	-1.420	0.574	3.432	0.796	1.314	NA	0.017	1.300	6238.000	0.461	1.000
Find_Crc_Sp_Eff[1,2]	-1921.228	9.024	2008.803	5.892	1003.002	NA	5.015	0.500	40000.000	-0.004	1.000
Find_Crc_Sp_Eff[2,2]	-1.652	0.336	3.250	0.554	1.321	NA	0.017	1.300	6236.000	0.460	1.000
Find_Crc_Sp_Eff[1,3]	-1871.427	-2.161	2018.515	2.542	994.980	NA	4.997	0.500	39646.000	0.003	1.000
Find_Crc_Sp_Eff[2,3]	-3.295	0.245	4.122	0.262	1.843	NA	0.023	1.300	6176.000	0.463	1.001
Find_Crc_Sp_Eff[1,4]	-1955.837	2.053	1951.431	0.397	995.166	NA	4.976	0.500	40000.000	0.003	1.000
Find_Crc_Sp_Eff[2,4]	-1.638	0.406	3.249	0.626	1.317	NA	0.017	1.300	6176.000	0.462	1.000
Find_Crc_Sp_Eff[1,5]	-1995.650	-2.804	1951.018	-2.451	1005.378	NA	5.027	0.500	40000.000	0.000	1.000
Find_Crc_Sp_Eff[2,5]	-2.624	0.130	3.471	0.253	1.546	NA	0.020	1.300	6032.000	0.469	1.000
Find_Crc_Sp_Eff[1,6]	-1854.890	2.188	2064.552	1.922	995.665	NA	4.913	0.500	41071.000	-0.003	1.000
Find_Crc_Sp_Eff[2,6]	-1.954	0.158	3.151	0.358	1.358	NA	0.017	1.300	6163.000	0.462	1.001
Find_Crc_Sp_Eff[1,7]	-2007.638	-1.788	1938.576	-0.483	1003.943	NA	5.165	0.500	37775.000	0.000	1.000
Find_Crc_Sp_Eff[2,7]	-2.131	0.218	3.199	0.403	1.400	NA	0.018	1.300	6306.000	0.459	1.001
Find_Crc_Sp_Eff[1,8]	-1961.843	10.790	1950.928	8.632	999.621	NA	4.966	0.500	40524.000	0.003	1.000
Find_Crc_Sp_Eff[2,8]	-2.760	0.018	3.287	0.147	1.535	NA	0.020	1.300	5996.000	0.465	1.001
Find_Crc_Sp_Eff[1,9]	-1941.402	1.818	1967.574	3.694	997.814	NA	5.066	0.500	38801.000	-0.004	1.000
Find_Crc_Sp_Eff[2,9]	-1.622	0.358	3.256	0.581	1.316	NA	0.017	1.300	6243.000	0.461	1.000
Find_Crc_Sp_Eff[1,10]	-1972.977	-9.903	1933.391	-6.596	998.118	NA	4.989	0.500	40022.000	-0.003	1.000
Find_Crc_Sp_Eff[2,10]	-1.820	0.298	3.201	0.506	1.341	NA	0.017	1.300	6181.000	0.460	1.000

Find_Crc_Sp_Eff[1,11]	-1893.766	-0.528	2041.210	4.001	1003.814	NA	5.019	0.500	40000.000	0.001	1.000
Find_Crc_Sp_Eff[2,11]	-3.874	-0.249	3.537	-0.234	1.841	NA	0.024	1.300	6076.000	0.457	1.000
Find_Crc_Sp_Eff[1,12]	-2001.927	-2.471	1914.147	-4.009	1000.536	NA	5.056	0.500	39154.000	0.002	1.000
Find_Crc_Sp_Eff[2,12]	-1.986	0.251	3.224	0.450	1.378	NA	0.018	1.300	6044.000	0.467	1.000
Find_Crc_Sp_Eff[1,13]	-1940.582	4.960	1990.863	1.938	1003.438	NA	5.017	0.500	40000.000	0.003	1.000
Find_Crc_Sp_Eff[2,13]	-1.945	0.288	3.391	0.467	1.402	NA	0.018	1.300	6158.000	0.465	1.000
Find_Crc_Sp_Eff[1,14]	-1894.123	-10.672	1997.484	-5.196	995.316	NA	4.970	0.500	40101.000	-0.004	1.000
Find_Crc_Sp_Eff[2,14]	-3.650	0.007	3.760	0.007	1.838	NA	0.023	1.300	6179.000	0.464	1.001
Find_Crc_Sp_Eff[1,15]	-1903.805	-0.463	1993.257	-2.080	997.202	NA	4.961	0.500	40411.000	-0.002	1.000
Find_Crc_Sp_Eff[2,15]	-3.754	-0.016	3.728	-0.033	1.846	NA	0.024	1.300	6141.000	0.464	1.001
Find_Crc_Sp_Eff[1,16]	-1929.840	-4.542	1957.754	-0.953	993.837	NA	4.973	0.500	39941.000	-0.001	1.000
Find_Crc_Sp_Eff[2,16]	-2.162	0.201	3.306	0.386	1.420	NA	0.018	1.300	6360.000	0.466	1.000
Find_Crc_Sp_Eff[1,17]	-1948.730	-5.363	1970.799	3.223	998.430	NA	4.980	0.500	40193.000	0.003	1.000
Find_Crc_Sp_Eff[2,17]	-1.635	0.375	3.258	0.594	1.320	NA	0.017	1.300	6155.000	0.460	1.000
Find_Crc_Sp_Eff[1,18]	-1930.966	7.771	1978.530	7.359	999.124	NA	4.985	0.500	40172.000	0.003	1.000
Find_Crc_Sp_Eff[2,18]	-2.746	0.017	3.346	0.140	1.532	NA	0.019	1.300	6337.000	0.461	1.000
Find_Crc_Sp_Eff[1,19]	-1949.902	1.152	1926.226	1.081	1000.271	NA	5.032	0.500	39508.000	0.001	1.000
Find_Crc_Sp_Eff[2,19]	-2.580	0.213	3.552	0.336	1.549	NA	0.020	1.300	6047.000	0.471	1.000
Find_Crc_Sp_Eff[1,20]	-1966.116	3.104	1965.145	3.935	1001.628	NA	4.993	0.500	40245.000	-0.001	1.000
Find_Crc_Sp_Eff[2,20]	-3.828	-0.212	3.466	-0.194	1.827	NA	0.023	1.300	6184.000	0.450	1.000
Find_Crc_Sp_Eff[1,21]	-1938.722	-1.087	1977.451	-0.724	1001.053	NA	5.025	0.500	39689.000	-0.001	1.000
Find_Crc_Sp_Eff[2,21]	-1.618	0.473	3.425	0.680	1.346	NA	0.017	1.300	6250.000	0.460	1.001
Find_Crc_Sp_Eff[1,22]	-2.584	0.210	3.548	0.345	1.549	NA	0.020	1.300	6044.000	0.471	1.001
Find_Crc_Sp_Eff[2,22]	-1.493	0.511	3.381	0.729	1.318	NA	0.017	1.300	6241.000	0.461	1.000
Find_Crc_Sp_Eff[1,23]	-1939.370	2.482	1961.950	-4.343	999.181	NA	4.972	0.500	40381.000	-0.001	1.000
Find_Crc_Sp_Eff[2,23]	-1.870	0.232	3.180	0.432	1.347	NA	0.017	1.300	6206.000	0.462	1.000
Find_Crc_Sp_Eff[1,24]	-1997.104	-4.137	1931.014	0.268	1005.634	NA	5.001	0.500	40429.000	-0.001	1.000
Find_Crc_Sp_Eff[2,24]	-1.624	0.393	3.265	0.615	1.317	NA	0.017	1.300	6250.000	0.459	1.000
Find_Crc_Sp_Eff[1,25]	-2.448	0.320	3.673	0.450	1.541	NA	0.020	1.300	6064.000	0.472	1.000
Find_Crc_Sp_Eff[2,25]	-1.644	0.369	3.248	0.591	1.317	NA	0.017	1.300	6228.000	0.461	1.000
Find_Crc_Sp_Eff[1,26]	-1944.185	4.641	1939.115	1.566	996.100	NA	4.903	0.500	41272.000	0.000	1.000
Find_Crc_Sp_Eff[2,26]	-1.922	0.254	3.142	0.458	1.348	NA	0.017	1.300	6220.000	0.462	1.000
Find_Crc_Sp_Eff[1,27]	-1977.456	5.400	1934.613	3.782	998.904	NA	4.995	0.500	40000.000	0.000	1.000
Find_Crc_Sp_Eff[2,27]	-2.598	0.116	3.473	0.242	1.539	NA	0.020	1.300	5981.000	0.470	1.001
Find_Crc_Sp_Eff[1,28]	-1993.480	-10.248	1940.684	-6.713	1002.928	NA	5.019	0.500	39923.000	0.001	1.000
Find_Crc_Sp_Eff[2,28]	-2.225	0.186	3.414	0.343	1.457	NA	0.019	1.300	6000.000	0.470	1.000
Find_Crc_Sp_Eff[1,29]	-1981.001	-7.591	1920.703	-5.261	1000.607	NA	5.014	0.500	39827.000	-0.004	1.000
Find_Crc_Sp_Eff[2,29]	-2.640	0.082	3.406	0.212	1.536	NA	0.020	1.300	5938.000	0.465	1.000
Find_Crc_Sp_Eff[1,30]	-1924.315	-0.098	2028.403	-3.386	1001.854	NA	5.020	0.500	39823.000	-0.004	1.000
Find_Crc_Sp_Eff[2,30]	-1.611	0.415	3.261	0.633	1.317	NA	0.017	1.300	6242.000	0.461	1.000
Find_Crc_Sp_Eff[1,31]	-1925.844	11.719	1980.480	8.461	995.903	NA	4.947	0.500	40520.000	0.002	1.000
Find_Crc_Sp_Eff[2,31]	-3.563	0.089	3.884	0.092	1.843	NA	0.023	1.300	6245.000	0.458	1.000
Find_Crc_Sp_Eff[1,32]	-1952.696	-2.899	1950.160	-1.958	996.969	NA	4.985	0.500	40000.000	-0.002	1.000
Find_Crc_Sp_Eff[2,32]	-1.652	0.323	3.271	0.539	1.325	NA	0.017	1.300	6308.000	0.461	1.000
Find_Crc_Sp_Eff[1,33]	-1942.303	-9.542	1952.904	-6.054	997.362	NA	5.068	0.500	38726.000	0.000	1.000
Find_Crc_Sp_Eff[2,33]	-1.868	0.266	3.209	0.473	1.350	NA	0.017	1.300	6174.000	0.459	1.000
Find_Crc_Sp_Eff[1,34]	-1924.564	-2.452	1985.136	-2.092	995.058	NA	5.042	0.500	38949.000	-0.004	1.000
Find_Crc_Sp_Eff[2,34]	-2.213	0.128	3.120	0.316	1.404	NA	0.018	1.300	6183.000	0.462	1.000
Find_Crc_Sp_Eff[1,35]	-1926.235	0.895	2015.354	-2.354	1001.384	NA	5.007	0.500	40000.000	0.001	1.000
Find_Crc_Sp_Eff[2,35]	-4.021	-0.259	3.412	-0.240	1.835	NA	0.023	1.300	6286.000	0.452	1.000
Find_Crc_Sp_Eff[1,36]	-1989.627	-12.694	1924.322	-3.169	1001.178	NA	5.006	0.500	40000.000	0.000	1.000
Find_Crc_Sp_Eff[2,36]	-1.940	0.142	3.164	0.353	1.357	NA	0.017	1.300	6196.000	0.464	1.000
Find_Crc_Sp_Eff[1,37]	-1973.945	-9.381	1945.806	-0.820	1001.703	NA	5.021	0.500	39795.000	0.002	1.000
Find_Crc_Sp_Eff[2,37]	-3.432	0.250	3.935	0.270	1.816	NA	0.023	1.300	6309.000	0.453	1.001
Find_Crc_Sp_Eff[1,38]	-3.828	-0.104	3.576	-0.100	1.830	NA	0.023	1.300	6266.000	0.452	1.000
Find_Crc_Sp_Eff[2,38]	-1.771	0.278	3.184	0.496	1.330	NA	0.017	1.300	6176.000	0.464	1.000
Find_Crc_Sp_Eff[1,39]	-1944.231	-0.721	1966.362	-2.033	999.527	NA	5.076	0.500	38767.000	0.000	1.000
Find_Crc_Sp_Eff[2,39]	-1.807	0.249	3.151	0.465	1.331	NA	0.017	1.300	6225.000	0.463	1.000
Find_Crc_Sp_Eff[1,40]	-1981.750	-4.996	1950.848	-1.155	1005.791	NA	5.047	0.500	39719.000	-0.003	1.000

Find_Crc_Sp_Eff[2,40]	-2.449	0.144	3.231	0.302	1.459	NA	0.019	1.300	6023.000	0.465	1.000
Find_Crc_Sp_Eff[1,41]	- 1942.211	1.451	2002.186	3.385	1000.962	NA	4.966	0.500	40621.000	-0.002	1.000
Find_Crc_Sp_Eff[2,41]	-1.890	0.374	3.374	0.570	1.379	NA	0.017	1.300	6400.000	0.461	1.001
Find_Crc_Sp_Eff[1,42]	- 1938.621	-8.388	2006.991	-7.942	1004.739	NA	4.953	0.500	41142.000	-0.005	1.000
Find_Crc_Sp_Eff[2,42]	-3.883	-0.126	3.555	-0.119	1.851	NA	0.024	1.300	6111.000	0.463	1.000
Find_Crc_Sp_Eff[1,43]	- 1898.066	7.471	2027.935	9.159	1003.963	NA	5.020	0.500	40000.000	-0.003	1.000
Find_Crc_Sp_Eff[2,43]	-3.609	0.262	3.930	0.255	1.869	NA	0.024	1.300	6102.000	0.468	1.000
Find_Crc_Sp_Eff[1,44]	- 2017.590	0.949	1905.200	-5.457	997.554	NA	4.988	0.500	40000.000	-0.003	1.000
Find_Crc_Sp_Eff[2,44]	-2.042	0.159	3.211	0.354	1.388	NA	0.018	1.300	6122.000	0.464	1.000
Find_Crc_Sp_Eff[1,45]	- 1927.979	3.467	1981.923	4.374	996.864	NA	4.936	0.500	40785.000	-0.004	1.000
Find_Crc_Sp_Eff[2,45]	-1.971	0.205	3.196	0.404	1.369	NA	0.017	1.300	6207.000	0.461	1.000
Find_Crc_Sp_Eff[1,46]	- 1980.162	-6.197	1938.959	-7.188	1005.040	NA	5.025	0.500	40000.000	-0.001	1.000
Find_Crc_Sp_Eff[2,46]	-3.810	0.010	3.613	0.023	1.832	NA	0.023	1.200	6434.000	0.451	1.001
Find_Crc_Sp_Eff[1,47]	- 1948.279	-9.447	1950.312	-6.439	997.077	NA	4.985	0.500	40000.000	-0.001	1.000
Find_Crc_Sp_Eff[2,47]	-1.885	0.261	3.220	0.466	1.355	NA	0.017	1.300	6211.000	0.463	1.001
Find_Crc_Sp_Eff[1,48]	- 1968.288	1.232	1948.562	2.849	995.803	NA	4.979	0.500	40000.000	0.002	1.000
Find_Crc_Sp_Eff[2,48]	-2.451	0.111	3.228	0.274	1.458	NA	0.019	1.300	6018.000	0.466	1.001
Find_Crc_Sp_Eff[1,49]	- 1948.632	-0.325	1940.546	0.367	999.217	NA	5.015	0.500	39704.000	0.002	1.000
Find_Crc_Sp_Eff[2,49]	-3.966	-0.148	3.561	-0.139	1.866	NA	0.024	1.300	6100.000	0.472	1.000
Find_Crc_Sp_Eff[1,50]	- 1993.531	-1.962	1965.730	-1.241	1001.495	NA	4.975	0.500	40530.000	0.000	1.000
Find_Crc_Sp_Eff[2,50]	-2.029	0.189	3.213	0.381	1.377	NA	0.018	1.300	6069.000	0.464	1.000
Find_Crc_Sp_Eff[1,51]	- 1976.205	9.286	1939.404	2.853	999.777	NA	4.931	0.500	41103.000	-0.002	1.000
Find_Crc_Sp_Eff[2,51]	-2.123	0.164	3.127	0.359	1.379	NA	0.017	1.300	6228.000	0.459	1.000
Find_Crc_Sp_Eff[1,52]	- 1997.787	-2.092	1919.777	-0.194	1001.844	NA	4.892	0.500	41947.000	0.003	1.000
Find_Crc_Sp_Eff[2,52]	-2.849	-0.092	3.250	0.038	1.541	NA	0.020	1.300	6127.000	0.469	1.001
Find_Crc_Sp_Eff[1,53]	-3.624	-0.080	3.718	-0.054	1.820	NA	0.023	1.300	6236.000	0.453	1.001
Find_Crc_Sp_Eff[2,53]	-1.570	0.427	3.326	0.641	1.319	NA	0.017	1.300	6233.000	0.462	1.000
Find_Crc_Sp_Eff[1,54]	- 1957.534	-5.111	1967.262	-2.637	1002.138	NA	5.011	0.500	40000.000	0.002	1.000
Find_Crc_Sp_Eff[2,54]	-2.739	0.084	3.355	0.202	1.536	NA	0.020	1.300	6134.000	0.466	1.001
Find_Crc_Sp_Eff[1,55]	- 1943.309	7.273	1989.714	6.492	1001.465	NA	5.007	0.500	40000.000	-0.006	1.000
Find_Crc_Sp_Eff[2,55]	-1.942	0.242	3.321	0.440	1.384	NA	0.018	1.300	6230.000	0.466	1.001
Find_Crc_Sp_Eff[1,56]	- 1955.183	-1.717	1972.366	-4.631	1007.831	NA	5.039	0.500	40000.000	-0.002	1.000
Find_Crc_Sp_Eff[2,56]	-2.401	0.089	3.251	0.247	1.454	NA	0.019	1.300	6171.000	0.464	1.000
Find_Crc_Sp_Eff[1,57]	- 1933.372	-1.109	1977.719	0.027	997.912	NA	4.990	0.500	40000.000	-0.004	1.000
Find_Crc_Sp_Eff[2,57]	-2.208	0.329	3.464	0.491	1.463	NA	0.019	1.300	6106.000	0.468	1.000
Find_Crc_Sp_Eff[1,58]	- 1952.565	12.239	1921.451	10.154	996.071	NA	4.980	0.500	40000.000	-0.004	1.000
Find_Crc_Sp_Eff[2,58]	-1.934	0.263	3.204	0.463	1.368	NA	0.017	1.300	6236.000	0.462	1.000
Find_Crc_Sp_Eff[1,59]	- 1929.930	-4.939	1983.539	2.127	1001.737	NA	4.982	0.500	40436.000	-0.001	1.000
Find_Crc_Sp_Eff[2,59]	-1.777	0.258	3.161	0.475	1.327	NA	0.017	1.300	6220.000	0.461	1.000
Find_Crc_Sp_Eff[1,60]	- 1962.548	-0.037	1953.963	-0.067	1000.093	NA	5.008	0.500	39885.000	0.001	1.000
Find_Crc_Sp_Eff[2,60]	-3.751	-0.118	3.574	-0.095	1.811	NA	0.023	1.200	6459.000	0.447	1.000
Find_Crc_Sp_Eff[1,61]	- 1995.076	-1.880	1921.164	-1.599	1001.358	NA	4.983	0.500	40380.000	0.000	1.000
Find_Crc_Sp_Eff[2,61]	-1.810	0.273	3.175	0.478	1.333	NA	0.017	1.300	6303.000	0.463	1.000
Find_Crc_Sp_Eff[1,62]	- 1878.849	13.448	2051.935	16.095	1004.918	NA	5.043	0.500	39714.000	-0.003	1.000
Find_Crc_Sp_Eff[2,62]	-3.887	-0.148	3.582	-0.127	1.839	NA	0.023	1.300	6251.000	0.456	1.000
Find_Crc_Sp_Eff[1,63]	- 1949.447	-13.615	1953.497	-11.470	999.795	NA	4.979	0.500	40327.000	0.002	1.000
Find_Crc_Sp_Eff[2,63]	-1.660	0.310	3.273	0.527	1.326	NA	0.017	1.300	6123.000	0.462	1.000
Find_Crc_Sp_Eff[1,64]	- 2005.581	3.010	1907.637	1.512	993.458	NA	4.967	0.500	40000.000	-0.003	1.000
Find_Crc_Sp_Eff[2,64]	-2.093	0.207	3.341	0.386	1.413	NA	0.018	1.300	6183.000	0.464	1.001
Find_Crc_Sp_Eff[1,65]	- 1974.755	10.359	1942.296	3.260	1000.665	NA	4.943	0.500	40990.000	-0.001	1.000
Find_Crc_Sp_Eff[2,65]	-3.900	-0.124	3.553	-0.122	1.838	NA	0.023	1.300	6383.000	0.459	1.000
Find_Crc_Sp_Eff[1,66]	- 1964.315	2.257	1936.250	-0.756	998.831	NA	4.958	0.500	40591.000	-0.005	1.000
Find_Crc_Sp_Eff[2,66]	-3.917	-0.189	3.508	-0.173	1.834	NA	0.023	1.300	6347.000	0.460	1.001
Find_Crc_Sp_Eff[1,67]	- 1999.746	-14.979	1934.889	-6.395	1001.990	NA	5.010	0.500	40000.000	-0.004	1.000
Find_Crc_Sp_Eff[2,67]	-1.663	0.363	3.277	0.578	1.327	NA	0.017	1.300	6237.000	0.462	1.000
Find_Crc_Sp_Eff[1,68]	- 1917.851	-7.102	1971.822	-6.891	999.337	NA	5.019	0.500	39652.000	0.001	1.000
Find_Crc_Sp_Eff[2,68]	-2.647	0.162	3.432	0.284	1.535	NA	0.019	1.300	6228.000	0.462	1.000
Find_Crc_Sp_Eff[1,69]	- 1958.996	-6.072	1958.841	-3.633	1003.114	NA	4.992	0.500	40373.000	0.000	1.000

Find_Crc_Sp_Eff[2,69]	-2.601	0.147	3.478	0.283	1.538	NA	0.020	1.300	6149.000	0.464	1.000
Find_Crc_Sp_Eff[1,70]	-1916.988	-9.719	2015.235	-4.945	1007.125	NA	5.036	0.500	40000.000	-0.003	1.000
Find_Crc_Sp_Eff[2,70]	-2.663	0.112	3.428	0.249	1.548	NA	0.020	1.300	5870.000	0.474	1.000
Find_Crc_Sp_Eff[1,71]	-1938.938	1.653	1963.933	0.845	994.979	NA	4.975	0.500	40000.000	-0.003	1.000
Find_Crc_Sp_Eff[2,71]	-1.834	0.233	3.168	0.448	1.337	NA	0.017	1.300	6260.000	0.461	1.001
Find_Crc_Sp_Eff[1,72]	-1928.731	-8.374	2026.864	-1.151	1000.867	NA	5.004	0.500	40000.000	0.003	1.000
Find_Crc_Sp_Eff[2,72]	-2.039	0.228	3.307	0.410	1.401	NA	0.018	1.300	6180.000	0.466	1.000
Find_Crc_Sp_Eff[1,73]	-2011.434	1.922	1903.153	-1.555	1000.196	NA	4.973	0.500	40453.000	-0.001	1.000
Find_Crc_Sp_Eff[2,73]	-1.526	0.809	3.928	0.982	1.422	NA	0.017	1.200	6805.000	0.440	1.000
Find_Crc_Sp_Eff[1,74]	-1971.336	1.715	1940.785	-3.044	1001.889	NA	5.014	0.500	39922.000	0.001	1.000
Find_Crc_Sp_Eff[2,74]	-2.673	0.080	3.342	0.200	1.530	NA	0.020	1.300	6158.000	0.467	1.000
Find_Crc_Sp_Eff[1,75]	-1999.038	-0.310	1920.606	-8.525	999.024	NA	4.922	0.500	41204.000	0.003	1.000
Find_Crc_Sp_Eff[2,75]	-1.610	0.423	3.370	0.640	1.337	NA	0.017	1.300	6161.000	0.461	1.000
Find_Crc_Sp_Eff[1,76]	-1939.769	-2.197	1975.990	-1.891	996.624	NA	4.937	0.500	40757.000	0.003	1.000
Find_Crc_Sp_Eff[2,76]	-3.866	-0.089	3.536	-0.097	1.827	NA	0.023	1.300	6140.000	0.463	1.001
Find_Crc_Sp_Eff[1,77]	-1943.313	4.800	1977.698	-3.698	1005.445	NA	5.009	0.500	40296.000	0.004	1.000
Find_Crc_Sp_Eff[2,77]	-1.891	0.231	3.133	0.438	1.342	NA	0.017	1.300	6222.000	0.461	1.000
Find_Crc_Sp_Eff[1,78]	-1936.062	0.283	1950.349	-1.042	993.461	NA	4.893	0.500	41223.000	-0.004	1.000
Find_Crc_Sp_Eff[2,78]	-1.581	0.381	3.352	0.599	1.323	NA	0.017	1.300	6221.000	0.462	1.001
Find_Crc_Sp_Eff[1,79]	-1960.272	-0.272	1953.388	-2.240	997.367	NA	4.983	0.500	40064.000	-0.001	1.000
Find_Crc_Sp_Eff[2,79]	-1.811	0.271	3.142	0.492	1.330	NA	0.017	1.300	6254.000	0.462	1.000
Find_Crc_Sp_Eff[1,80]	-1966.457	-4.191	1956.012	-3.008	996.581	NA	5.024	0.500	39349.000	0.002	1.000
Find_Crc_Sp_Eff[2,80]	-3.609	0.086	3.898	0.075	1.865	NA	0.024	1.300	6039.000	0.465	1.000
Find_Crc_Sp_Eff[1,81]	-3.887	-0.221	3.465	-0.205	1.816	NA	0.023	1.200	6460.000	0.443	1.001
Find_Crc_Sp_Eff[2,81]	-2.006	0.161	3.158	0.368	1.368	NA	0.017	1.300	6144.000	0.467	1.001
Year_precision	0.000	0.162	352.451	63.569	243.708	NA	3.794	1.600	4127.000	0.322	1.004
deviance	3489.075	3519.388	3553.031	3520.103	16.348	NA	0.158	1.000	10642.000	0.249	1.000
resid.sum.sq	397.024	437.198	486.939	439.543	23.811	NA	0.187	0.800	16179.000	0.131	1.000