Sveriges lantbruksuniversitet
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Identifying blackspots of wildlife collisions on the Swedish railroad

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Abstract

The number of wildlife collisions on the Swedish railroads is increasing at a rate unmatched by the development of wildlife populations and expansion of the railroad traffic. It is therefore essential to identify areas where the yearly risk of collisions is great (blackspots), to be able to allocate mitigating efforts in areas where they are most essential and effective. The aim of this report was to develop a method to identify blackspots for roe deer and moose collisions on railroads. Incidents are reported by segments, which are partitioned sections of the railroads. I defined a segment as a blackspot when it had continuously high number of incidents. Four different sets of blackspots were created. Segments were defined as blackspots if they were 10 or 13 years above the 60th percentile of the national distribution of incidents per km, or 10 or 13 years above the 70th percentile. The segments within these four sets where then ranked. To evaluate the different sets, I performed separate logistic regression for each set of defined blackspots where the dependent variables were the blackspots (1) and segments below the 50th percentile for all years (0). To further analyse the difference of the sets, receiver operating characteristics (ROC) - curves were calculated for each final model which is a statistical tool used to assess a logistic model's ability to differentiate between, in this case, blackspots and low-frequency segments. For both species, 13 years above the 70th percentile resulted in models with the greatest ability to discriminate between blackspots and low-frequency segments and held the highest number of incidents per total length of railroads. Future analysis of which percentile to use and how many years the segment should be above that percentile is needed. However, I have developed a method to identify the segments that are in the biggest need of mitigating efforts. The strength of my approach to identify blackspots is that it can be adjusted to different needs and purposes, and is flexible to suit many different goals.

Keywords: blackspots, train-wildlife collisions, roe deer, moose

Populärvetenskaplig sammanfattning

Antalet kollisioner med vilt ökar längs Sveriges järnvägar vilket bland annat orsakar ekonomiska förluster till följd av reparation av tåg och tågräls. Det orsakar även psykologiska besvär för lokförare som inte har möjlighet att bromsa, samt förlust av jaktbara arter och onödigt lidande bland vilt. Samhället står därför inför utmaningen att minska dessa kollisioner genom att identifiera de områden där åtgärder kommer att vara mest effektiva. Områden där viltkollisioner ofta förekommer med höga frekvenser kan kallas för *blackspots*. Syftet med denna rapport är att identifiera viktiga aspekter för definiering av blackspots såväl som att skapa en metod som kan ta vara på dessa aspekter längs med järnväg.

Trafikverkets databas OFELIA innehåller bl.a. incidenter med vilt som förväntas störa tågtrafiken längs järnvägar. För åren 2001 till 2016 sammanställde jag antalet incidenter per tågsträcka och art. Totalt rapporterades 62 786 incidenter fördelade på 38 däggdjurs-arter. De vanligaste arterna inblandade i kollisioner var rådjur och älg följt av ren, tamdjur, hjort (kronhjort och dovhjort) och vildsvin. Antalet incidenter såväl som antalet sträckor som det rapporterats incidenter på har stadigt ökat under den aktuella tidsperioden.

Blackspots för rådjur och älg definierades genom att välja ut de sträckor som under flest antal år haft en särskilt hög olycksbelastning sett till antal olyckor per km per år i Sverige. Mer i detalj valde jag fyra olika kombinationer av blackspots, 10 eller 13 år över 60 percentilen av det årliga antalet olyckor per km för alla sträckor, eller 10 eller 13 år över 70 percentilen. Dessa kombinationer utvärderades sedan med hjälp av en logistisk regression där blackspots jämfördes med sträckor med få olyckor för att se hur väl blackspotsen kunde identifiera miljövariabler som leder till en ökad mängd kollisioner. De definierade blackspotsen rankades sedan utefter ett set av kriterier för att kunna belysa de sträckor där det största behovet av åtgärder finns. För att se hur väl modellerna kunde skilja mellan blackspots och kontroll, alltså sträckor med få olyckor, användes ett statistiskt verktyg kallat Receiver Operating Characteristics (ROC).

Genom att välja ut de sträckor som låg minst 13 år över 70 percentilen identifierades de sträckor som hade högst antal kollisioner per km. Denna studie har pekar ut ett set av tågsträckor med ett upprepat högt antal kollisioner där motverkande åtgärder bör koncentreras. Studien har även belyst vikten av att fokusera på vilka kriterier som ska inkluderas vid definition av blackspots. Genom att automatisera de steg som genomförts i denna studie finns goda förutsättningar för att snabbt kunna identifiera framtida konfliktsträckor mellan tågtrafik och djur i Sverige.

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1 Introduction

Four thousand trains are in movement on Swedish railroads every day (Trafikverket, 2016a). On average, there are about 30 ungulates per every 10 km^2 in Sweden, and roughly one individual every 577 meter (Älgskadefondsföreningen, 2010). When driving 90 km/h a train would therefore pass one individual every 23 second. Not surprisingly, about 3000 collisions with wildlife and train are reported each year (Seiler et al., 2011). The railroad and its traffic affects wildlife in various ways; death by collision, barrier affect, removal of habitat (Baofa et al., 2006; KušTa et al., 2014; van der Ree et al., 2015) as well as humans; costs caused by damage, search for injured animals, decrease of available game, stress for train drivers (Grey, 2015; Seiler et al., 2011; Storaas et al., 2005).

In Scandinavia, train-wildlife collisions (TWC) are increasing in numbers unmatched by changes in wildlife populations, infrastructure or traffic (Rolandsen et al., 2015; Seiler et al., 2011; Trafikverket, 2011). Even so, collisions with wildlife on railroad-systems receive very little attention compared to vehicle-wildlife collisions on roads (Popp and Boyle, 2017). According to a news article of the Swedish Television one collision with moose is estimated to cost up to 1 million SEK, and a way of delineating areas where mitigating efforts may be most cost-effective is increasingly important as collisions are increasing in number (svt, 2017).

Blackspots can be defined as segments of infrastructure where TWC occur more frequent than elsewhere (Infrastructure, 2014; Shilling and Waetjen, 2015). Blackspots can be used to assign segments where different actions can be tested for their ability to decrease incidents with wildlife, such as wildlife crossings, fencing, electronic systems to deter animals, playing of recorded natural wildlife alarming etc. (Babińska-Werka et al., 2015; van der Ree et al., 2015). Different methods to identify aggregations of collisions have been employed, such as KDE (kernel density estimation), KDE+ (modified kernel density estimation which identifies significant clusters), kriging (estimates a surface from the given points of collisions) and Getis Ord, Gi* (identifies cluster of high and low values) (Bíl et al., 2013; Ramp et al., 2005; Shilling and Waetjen, 2015; Snow et al., 2005; Thakali et al., 2015). These methods produce a set of segments that can be denoted blackspots. In some cases, blackspots are analysed further regarding spatial and temporal trends to further aid recommendations to mitigate the risk of collisions. However, these methods use wildlife collisions registered with coordinates or distances from a reference point along roads. TWCs in Sweden are reported at stations or by segments of varying lengths.

There is a need to identify segments with reoccurring high numbers of TWCs to be able to decide where implemented mitigating efforts might have the largest ecological and economic benefit. The aim of this project was therefore to develop an identification system for blackspots regarding train-wildlife incidents. 1) What criteria can be used for setting a limit and at what limit is a segment a blackspot; 2) How sensitive is the set limit?

2 Method

2.1 Railroad network

My study is based on major railroads that are managed by the Swedish Transport Administration (STA) (figure 1). In total, there are 14 000 km of railroads which are operated by STA of which 80% are electrified and about a third are double-tracked (Trafikverket, 2016b). A major part of the railroads are repeatedly cleared of trees at a distance of about 20 meter at either side of the track to prevent damage from falling trees (Trafikverket, 2017a). Few railroads are fenced against wildlife, but fences to prevent human suicides are expanding and may eventually also affect TWC in urban areas (Trafikverket, 2017b).

Figure 1. The Swedish railroad operated by STA (Trafikverket, 2016b)

2.2 Database of incidents

Train drivers are obliged to report incidents that may cause problems to train traffic to a train dispatcher at the STA where they are compiled in a database (OFELIA). Such incidents include, among others, collisions with and observations of dead, injured or otherwise trapped or troubled wild and domestic animals on the railroad. Incidents are positioned with reference to one but mostly to two adjacent train stations (start and end-point of a railroad segment). I used OFELIA records on animal-related incidents from the years 2001-2016.

Data from 2001 to 2012 had previously been processed for analysis (Seiler et al., 2011). I complemented with data from 2013 to 2016. Due to the nature of the OFELIA database, the available records needed to be cleaned and validated in several steps before they could be used in further analysis. Information on species and type of incident is often not coded but explained in descriptive text. To extract relevant data from these reports, I used queries in R (R Core Team, 2016) and Rstudio (Rstudio, 2012) and sorted records with respect to species and type of incident.

2.2.1 Sorting of stations and segments

The database contains information about station and segments for each reported incident. The driver usually provides information regarding the station from which the train most recently departed, and the nearest or one of the upcoming stations the train will pass. If a segment is not defined by two neighboring stations, it would stretch over several consecutive stations and thus contain several smaller segments. To avoid overlapping segments, several segments were either altered or removed. For example, if an incident were reported between station A and D, that segment would be given an ID of A-D (figure 2). Thus, ignoring the intermediate stations B and C, where other incidents may have been reported for segments such as A-B, A-C and B-C. To decide whether to combine all reports in the longest segment A-D or to ignore and remove the longest one, I compared the sum of incidents of the different segments. For example, in a case where A-B had 20 incidents, B-C had 10 and A-C had 2, I would keep A-B and B-C since they contain the largest number of incidents. If A-C would have had 40 incidents, and therefore a larger sum than of 20+10, A-B and B-C would have been merged into A-C. With this procedure, I removed 200 segments from further analysis including 417 incidents (0.7%), and merged 178 segments into longer composite segments. The *Inlandsbanan* railroad was removed from the final set of segments since it is trafficked by only two rather slow trains per day and is not part of the regular rail network. Various (often very short) private railroads were neither included in the analyses.

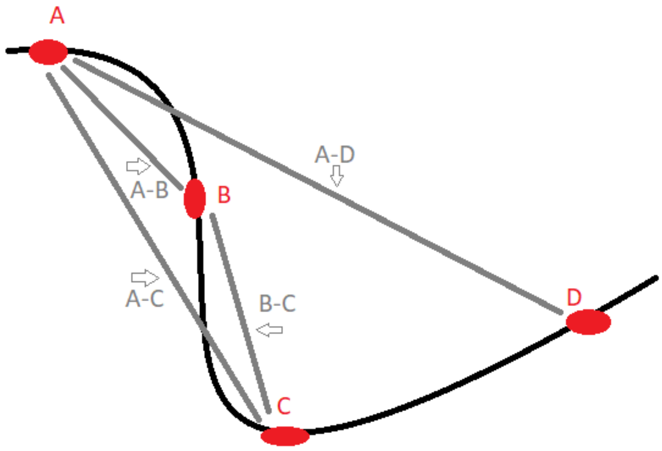

Figure 2. In the database OFELIA, the driver usually provides information regarding the station from which the train most recently departed, and the nearest or one of the upcoming stations the train will pass when reporting an incident. If a segment is not defined by two neighboring stations, it would stretch over several consecutive stations and thus contain several smaller segments. To avoid overlapping segments, several segments were either altered or removed. This figure shows an example of this mentioned overlap where red dots are stations, grey lines are segments with the given ID in grey letters. The black line represents the actual railroad.

2.3 Identifying blackspots

2.3.1 Limit for blackspot identification

Out of the 38 species reported in OFELIA, roe deer (*Capreolus capreolus*) and moose (*Alces alces*) represented the largest part, as reported earlier (Seiler et al., 2011). Only these two species were therefore selected for further analysis of blackspots. From the reported cases, I calculated incident frequencies per species, km and year for each of the defined railway segments.

I considered a segment being a blackspot if the incident frequencies were above a specified limit during a specified number of years. Segments without any reported incidents during the entire time series were removed from analysis to since the lack of incidents could be due to several reasons such as being outside of the geographical range of the species. This resulted in 909 segments with roe deer incidents and 876 segments with moose incidents. The lower limit in TWC frequency was set to the 60th or 70th percentiles of the distribution of all incidents nationwide. A challenge was to identify sufficiently many blackspots to allow for logistic regression analyses, while avoiding identifying too many segments for the results being applicable in practise. This was done by assessing the number of segments included with different percentiles and years above that percentile (figure 3). The number of years above the limit was set to either a minimum of 10 years (60% of the available time-series) or 13 years (80% of the available time-series). This resulted in four different classifications of blackspots for each of roe deer and moose, 10 or 13 years above the 60th percentile as well as 10 or 13 years above the 70th percentile. Each set of blackspots was given a unique name to differentiate between the 8 different sets. The first letter indicates species (R=roe deer, M=moose), the first two numbers represent the number of years above the limit, 10 or 13, followed by two numbers representing the 60th or 70th percentiles. For example, R1060 is roe deer, where the limit is at least 10 years above the set limit of the 60th percentile.

I also identified segments that had a low frequency of incidents as a control to be able to evaluate explanatory variables in a logistic regression. I choose a limit of below the 50^{th} percentile for all years as non-blackspots.

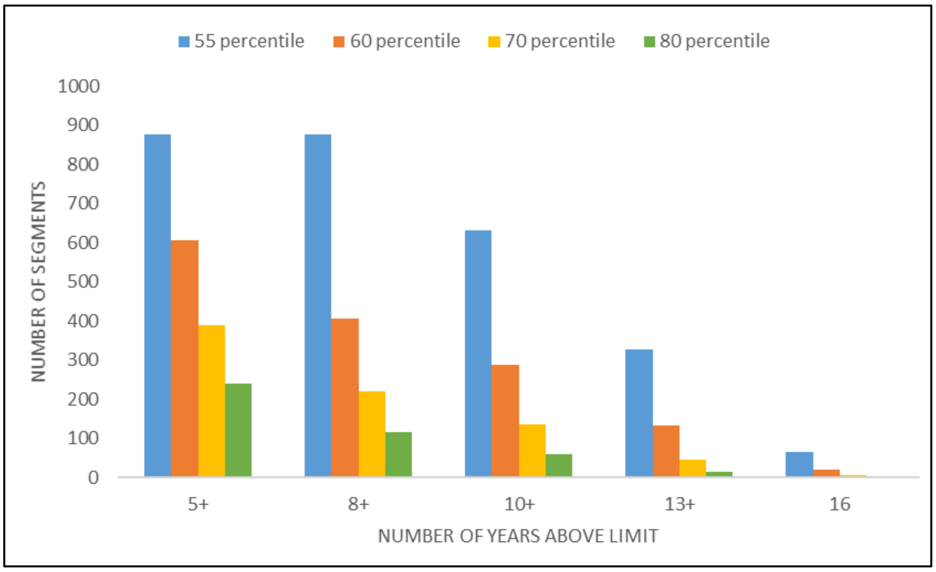

Figure 3. The number of railroad-segments generated dependent on the set limit (55, 60, 70 and 80^{th} percentile of the yearly number of incidents) and number of years above the limit (5, 8, 10, 13 and 16 years above the limit) for moose from the year 2001 to 2016.

After the four sets of blackspots had been identified I ranked the segments defined as blackspots according to a combined index of the:

- average number of incidents per km and year,
- maximum value of number of incidents per km for a year,
- number of years with incidents and
- number of years above the limit used for that set

2.4 Evaluating blackspots

I wanted to study the effect of the four different limits on the predictability of blackspots using a set of explanatory variables. I used logistic regression analysis where the dependent binary variable was the defined blackspots (as 1) and the defined low-frequency segments as controls (as 0). The explanatory variables (table 1) were chosen based on previous research on ecology of roe deer and moose (Morellet et al., 2013; Seiler et al., 2011; Storaas et al., 2005). All explanatory variables were quantified in ArcGIS within either a 2 000 m buffer (for landscape variables such as habitat composition) or a 200 m buffer (for factors influencing animal movement and behaviour in immediate vicinity to the railroad). Snow data was extrapolated from downloaded information on snow depth from 368 SMHI stations (SMHI, 2017).

Table 1*: Overview of the chosen explanatory variables for the logistic regression for comparison of blackspots to low-frequency segments for roe deer and moose. Each explanatory variable is associated with an expected effect based on earlier studies and ecology of the species. Range, average and standard deviation of the variables are based on the extrapolated data from ArcGIS for the segments used in the analysis.*

Variable	Unit for analysis	Distance from rail-road	Source	Expected effect (Moose/Roe deer)	Range	Average	Standard deviation
Roads	Length (km)/km rail	200 m	Lantmäteriet	(+/+)	0 – 56.19 km	11.9 km	7.21 km
Watercourses	Length (km)/km rail	2000 m	Lantmäteriet	(+/+)	0 - 191 km	41.4 km	26.9 km
Water surface	Coverage (arcsin%)	2000 m	Lantmäteriet	(+/+)	0 – 29.60 km^2	4.20 km^2	4.60 km^2
Power lines	Length (km)/km rail	2000 m	Lantmäteriet	(+/+)	0 - 129.9 km	14.4 km	11.5 km
Forest	Coverage (arcsin%)	2000 m	Lantmäteriet	(+/-)	0 – 194.83 km^2	25.70 km^2	19.9 km^2
Open land	Coverage (arcsin%)	2000 m	Lantmäteriet	(-/+)	0 – 61.36 km^2	12.2 km^2	10.4 km^2
Fen	Coverage (arcsin%)	2000 m	Lantmäteriet	(+/-)	0 – 81.73 km^2	3.48 km^2	6.44 km^2
Urban centers	Coverage (arcsin%)	2000 m	Lantmäteriet	(-/+)	0 – 32.66 km^2	6.15 km^2	5.93 km^2
Snow	Average depth (m)/km rail	2000 m	SMHI	(+/-)	0 – 0.321 m	0.0947 m	0.0692 m
Trains per day	Count	200 m	STA	(both/both)	0 – 997 trains/day	59.3 trains/day	78.3 trains/day
Felling	Number of years with felling	2000 m	Skogsstyrelsen	(+/no effect)	0 – 17.56 km^2	3.02 km^2	2.80 km^2
Level crossing	Count / km rail	200 m	STA	(-/-)	0 – 120	18.9	335
Over/under crossing	Count / km rail	200 m	STA	(+/+)	0 – 39	4.12	5.40
Powerline crossing	Count / km rail	200 m	Lantmäteriet	(+/+)	0 – 18	1.96	2.55

I initially evaluated the Spearman's correlation matrix in R to avoid multicollinearity between explanatory variables. If a pair of explanatory variables held a correlation value above 0.65, one of the variables were removed based on correlation with other explanatory variables as well as the believed importance for the species. The variance influence factor (VIF) for the explanatory variables in different models were calculated in order to identify additional variables that needed to be removed due to collinearity (Montgomery et al., 2012). The variable with the highest VIF-value was removed, and this process was repeated until all remaining explanatory variables had VIF-values below two (Zuur et al., 2010).

The remaining variables were defined as the full model, and model selection was performed with the aid of the dredge function in MuMIn, a package in R (Barton, 2016). All possible combinations of the explanatory variables in the full model were combined and ranked according to AICc. The variables present in all models with a difference in AICc<2 to the highest ranking model (lowest AICc) were included in the final model (Burnham et al., 2002).

A receiver operating characteristic plot (ROC) with the associated area under the curve (AUC) was calculated for each of the eight final models to evaluate the power of the four different sets in discriminating between blackspots and controls, i.e., segments with less than 50^{th} percentile of incidents, (Fellows, 2012). ROC plots the ratio of correctly identified blackspots to all true blackspots, i.e., the true positive rate (TPR, i.e., the ratio of correctly identified blackspots to all true blackspots) in relation to the false positive rate (FPR, i.e., the ratio of controls incorrectly classified as blackspots to all controls) for different probability thresholds to define the blackspots (different probabilities of a segment being a blackspot, where 50% is commonly used for a confusion matrix) (Park et al., 2004). A high AUC-value indicates a model which is good at separating blackspots from controls, with a value of 0.8 being an excellent discriminator (Hosmer et al., 2013; Park et al., 2004). However, the same AUC can still be quite different with regards to the ability to discriminate with different cut-off thresholds since the same size of area does not indicate the same shape. The shape of the area is important as it says a lot about the model's ability to identify blackspots and low-frequency segments individually. It is therefore important to combine the AUC-value with a visual analysis.

3 Results

3.1 Descriptive statistics

There were 62 786 incidents with 38 species registered from 2001 to 2016 on 1328 segments with a total length of 10 492 km. The average length of a segment was 10.53 km with a standard deviation of 7.87 km. The longest segment was 62.33 km, and the shortest was 1 km. The highest number of incidents was noted in 2010, with 5 591 wildlife incidents. For ungulates, the overall trend is increasing for both numbers of incidents as well as the numbers of segments (table 2, figure 4 and 5). Roe deer and moose were the most common species involved in incidents, representing 35.5 % and 26.8 % respectively. The five most common ungulates (roe deer, moose, reindeer, deer (fallow deer and red deer), and wild boar) stand for 84.2% of all reported incidents, with a total of 52 844 incidents. A clear majority of incidents with ungulates were collisions (90%), followed by animals observed on track (5%), animals detected as carcasses (3%), other (1%) and injured animals (<1%).

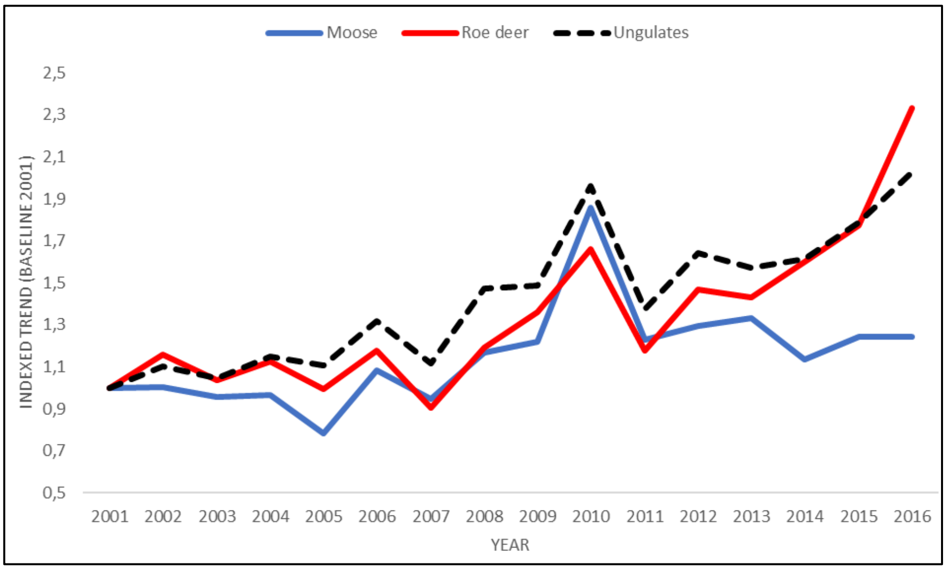

Figure 4. The indexed trend of number of incidents with moose, roe deer and ungulates on the railroad in Sweden from year 2001 to 2016 with the baseline for the index at 2001.

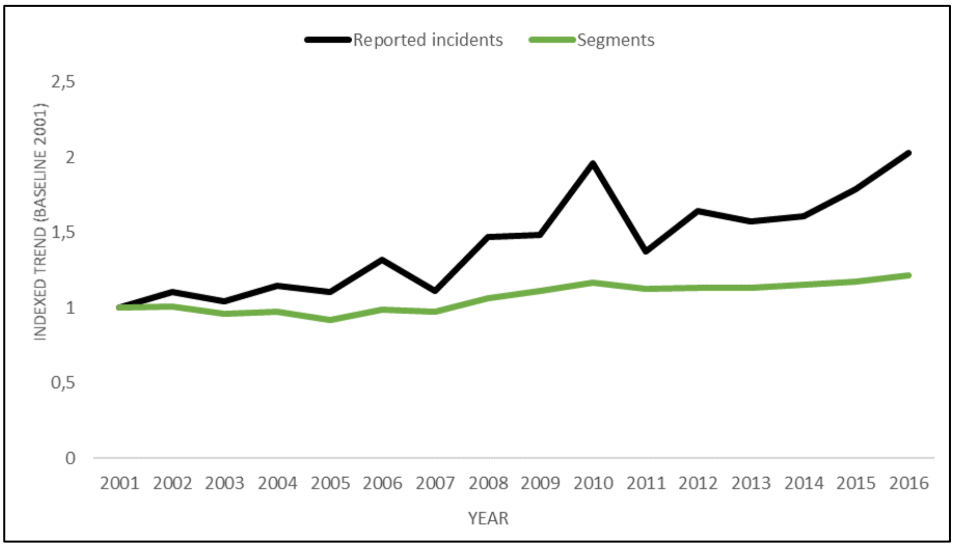

Figure 5. Indexed trends of the number of reported incidents with ungulates from 2001 to 2016 and the number of railroad-segments reported on by year from 2001 to 2016 with the baseline for the index at 2001. An increase can be observed for both indexes, where the number of reported incidents has a steeper slope.

Table 2. *The number of animal-related incidents registered in OFELIA by species from year 2001 to 2016 where the total number of incidents is sorted in ascending order. OFELIA is a database where all incidents which can possibly affect the train traffic in Sweden are reported.*

Species	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Grand Total
Roe deer	1006	1137	1025	1146	967	1166	929	1212	1402	1807	1326	1566	1522	1725	1939	2426	22301
Moose	879	898	843	861	683	948	852	1036	1107	1733	1178	1196	1223	1076	1155	1188	16856
Reindeer	304	347	386	510	682	660	628	884	637	796	553	734	615	698	783	704	9921
Domesticated animal	471	456	461	416	392	447	436	503	489	643	610	291	46	46	10	5	5722
Deer	48	52	53	60	61	109	67	103	120	175	183	196	172	222	206	255	2082
Wild boar	10	16	24	18	30	38	43	74	132	146	110	165	177	179	245	277	1684
Raptor	29	37	34	33	49	52	67	83	83	131	108	175	130	185	229	218	1643
Unknown	32	11	15	23	20	38	27	31	48	63	86	163	164	160	118	159	1158
Small game	17	16	27	21	18	25	34	33	35	55	33	36	80	78	105	114	727
Bird	20	22	22	17	17	21	28	19	37	22	26	45	39	50	43	50	478
Bear	1	5	5	5	8	1	11	5	7	9	9	5	4	10	3	6	94
Lynx	3	4	2	4	4	5	9	6	7	5	4	5	3	9	5	6	81
Wolf	0	1	2	1	1	1	1	2	2	5	3	2	1	3	3	3	31
Mouflon	0	0	1	1	0	0	0	0	1	1	0	0	0	0	2	2	8
Grand Total	2820	3002	2900	3116	2932	3511	3132	3991	4107	5591	4229	4579	4176	4441	4846	5413	62786

3.2 Defined blackspots

The number of segments identified as blackspots decreased with a higher sat limit of selection criteria. For roe deer, 276 (R1060), 163 (R1070), 140 (R1360) and 67 (R1370) segments were defined as blackspots with a total length of 2 712 km, 1 574 km, 1 469 km, and 671 km respectively (table 3). For moose, 288 (M1060), 134 (M1070), 132 (M1360) and 46 (M1370) segments were defined as blackspots with a total length of 3 247 km, 1 477 km, 1 508 km, and 539 km respectively (table 3).

There was a large variation in the average number of incidents among the blackspots identified as top ten for roe deer (table 4), but the average number of incidents varied little for the top ten blackspots for moose (table 5).

Table 3. *Final generated sets of blackspots for roe deer and moose dependent on the set limit and number of years above the set limit (column 1). The letter represents the species, the two first numbers represents the number of years above the set limit and the two latter numbers represents the limit (percentile of distribution of incidents for each year).*

Set of blackspots	Number of segments	Average number of incident per km and year	Total length in km (percent of total)	Incident counts (percent of total)	Incident count/Total length
R1060	276	0.30	2712 (25%)	12579 (70%)	4.63
R1070	163	0.37	1574 (15%)	8987 (50%)	5.60
R1360	140	0.38	1469 (14%)	8432 (47%)	5.63
R1370	67	0.50	671 (6%)	4982 (28%)	7.42
M1060	288	0.20	3247 (31%)	10092 (72%)	3.10
M1070	134	0.26	1477 (14%)	5998 (42%)	4.06
M1360	132	0.25	1508 (14%)	6039 (43%)	4.04
M1370	46	0.32	539 (5%)	2815 (20%)	5.22

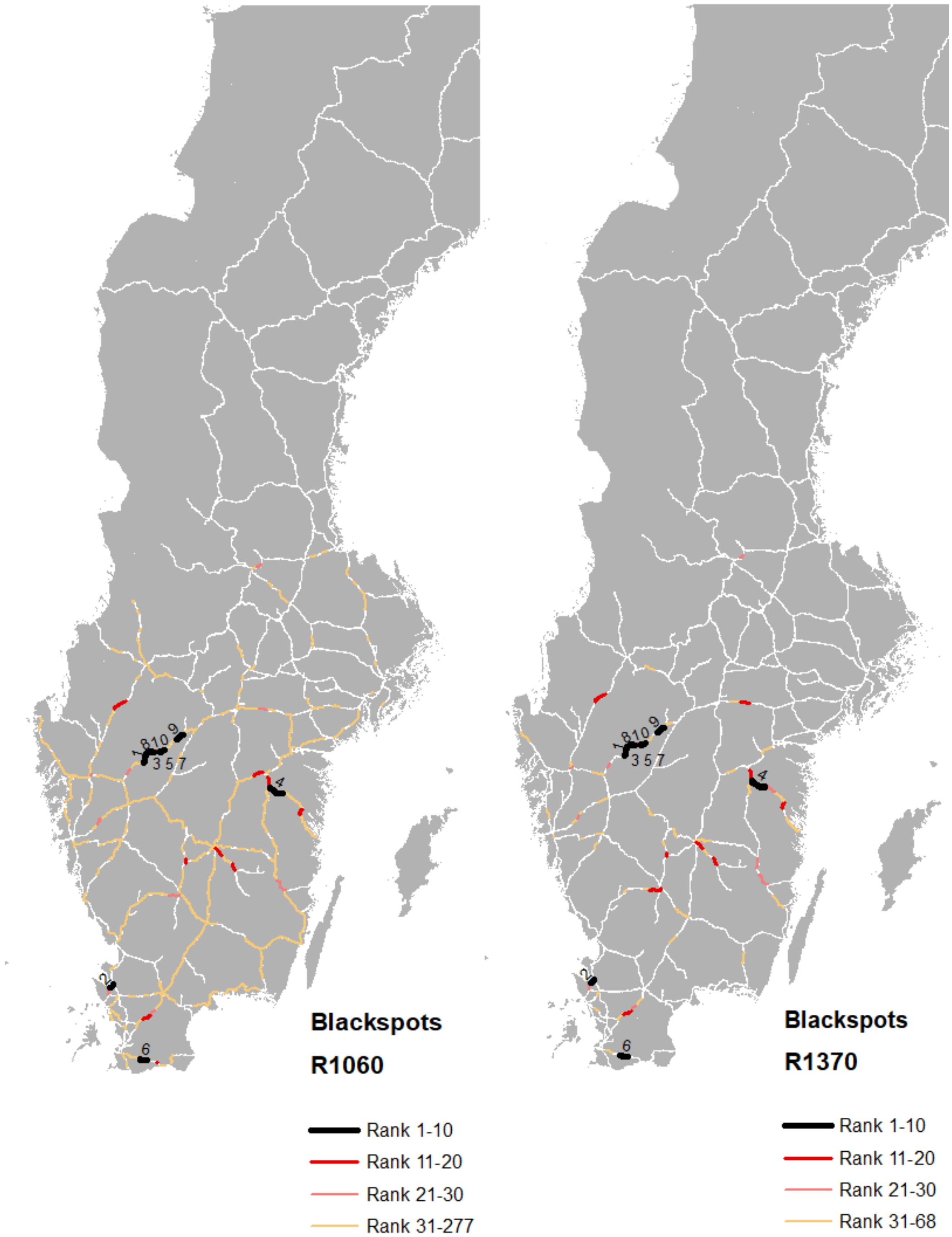

Figure 6. Segments identified as blackspot by 10 years above the 60th percentile of the distribution of incidents each year (R1060), and 13 years above the 70th percentile (R1370) for roe deer, where colour indicates ranking. The ranking was decided by the average number of incidents, maximum number of incidents reported for a year, the number of years with incidents and number of years above the set percentile. The top ten blackspots are marked in black with a number representing the order.

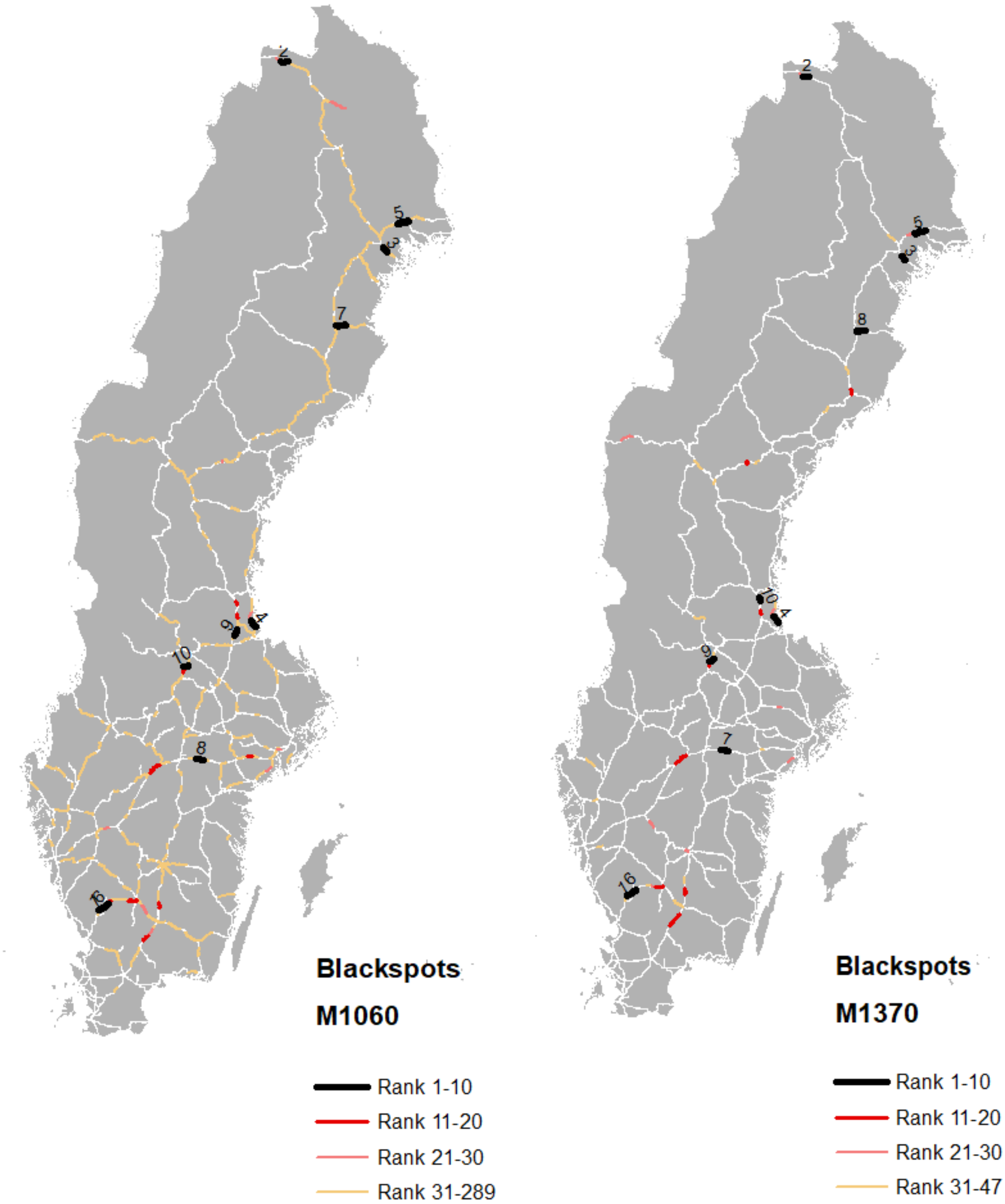

Figure 7. Segments identified as blackspot by 10 years above the 60th percentile of the distribution of incidents each year (M1060), and 13 years above the 70th percentile (M1370) for moose, where colour indicates ranking. The ranking was decided by the average number of incidents, maximum number of incidents reported for a year, the number of years with incidents and number of years above the set percentile. The top ten blackspots are marked in black with a number representing the order.

Table 4. *Top ten blackspots for roe deer on the Swedish railroad (R1370)*

Segment	Name of segment	Average (incident/km and year)	Number of years with incidents	Number of years above limit	Ranking	Length (km)
BMB-TRM	Blomberg - Trolmen	1.26	16	16	1	6.36
VH-Ä	Vegeholm - Ängelholm	1.07	16	16	2	5.86
RBK-TRM	Råbäck – Trolmen	0.94	15	15	3	2.46
BSÄ-ÅVG	Bjärkaby-Säby – Viresjö	0.96	16	16	4	18.6
FHM-HLK	Forshem - Hällekis	0.80	16	16	5	3.81
LMM-SRP	Lemmeström - Skurup	0.88	16	16	6	8.83
BMB-KLL	Blomberg - Källby	0.75	14	14	7	3.58
HLK-RBK	Hällekis - Råbäck	0.77	14	14	8	4.08
HSR-LYD	Hasslerör - Lyrestad	0.67	16	16	9	9.68
LNÅ-ÄSR	Lugnås - Äskekärr	0.68	16	16	10	6.00

Table 5. *Top ten blackspots for moose on the Swedish railroad (M1370)*

Segment	Name of segment	Average (incident/km and year)	Number of years with incidents	Number of years above limit	Ranking	Length (km)
KID-LRD	Kinnared – Landeryd	0.44	16	14	1	11.6
AK-SOA	Abisko östra – Stordalen	0.52	16	16	2	10.5
SBY-SVT	Norra Sunderbyn – Sävast	0.45	16	16	3	8.54
HFJ-TDJ	Hamrångefjärden – Trödje	0.48	16	16	4	12.5
AVS-MJV	Avafors – Morjärv	0.43	16	15	5	23.7
LRD-SPH	Landeryd – Skeppshult	0.49	16	16	6	8.11
HGÖ-KM	Högsjö – Kilsmo	0.49	16	16	7	11.0
BST-FFS	Bastuträsk – Finnforsfallet	0.42	16	13	8	15.5
RHM-ULY	Rämshyttan - Ulvshyttan	0.40	16	15	9	8.93
HDN-RBO	Holmsveden - Röstbo	0.44	15	15	10	6.96

3.3 Regression analysis of blackspots

AUC increased for both species with a higher set limit (table 6 and 7). The number of included explanatory variables was the same in all roe deer models, while it decreased in the moose models as the set limit increased. Snow was the only explanatory variable included in all final models for roe deer. In moose, fen, forest, over/under crossing, powerline, and road were included in all final models (table 6 and 7).

Table 6. *Final set of explanatory variables included in the four different sets of blackspots for roe deer. An explanatory variable was included if it occurred in all models closer than two to the model with the lowest AICc. Variables in bold were included in all final models for all different sets of blackspots (snow).*

Model	Included factors	Significance	Estimate	Std. Error	AICc – AICc of highest ranked model	AUC
R1060	**Snow**	***	-39.9	4.80	327.72 – 326.5	0.8066
	Train	.	-0.140	0.0750		
R1070	**Snow**	***	-42.3	5.91	257.6 – 257.6	0.8280
	Road	.	-0.678	0.346		
R1360	**Snow**	***	-45.8	6.75	233.8 – 232.9	0.8295
	Train	*	-0.220	0.0980		
R1370	**Snow**	***	-43.8	7.76	167 – 166.1	0.8535
	Urban centres	**	-3.76	1.33		

Table 7. *Final set of explanatory variables included in the logistic regression models for the four different sets of blackspots for moose. An explanatory variable was included if it occurred in all models' closer than two to the model with the lowest AICc, the final model was therefore not always the model with the lowest AICc. Variables in bold were included in all final models for all four sets of blackspots (fen, forest, over/under crossing, powerlines, roads).*

Model	Included factors	Significance	Estimate	Std. Error	AICc – AICc of highest ranked model	AUC
M1060	**fen**	**	10.7	3.38	443.2 – 443.1	0.8645
	forest	***	4.40	0.641		
	Over/under crossing	***	-0.95	0.166		
	powerline crossing	*	-1.20	0.494		
	powerline	***	0.44	0.131		
	road	***	-1.75	0.287		
	train	**	-0.415	0.137		
M1070	**fen**	***	15.1	4.02	297.9 – 297.9	0.8840
	forest	***	3.76	0.790		
	Over/under crossing	***	-0.785	0.200		
	powerline	*	0.366	0.143		
	road	**	-1.19	0.408		
	snow	*	5.57	2.59		
	urban centres	*	-3.61	1.75		
M1360	**fen**	***	13.3	3.99	287.5 – 286.3	0.8892
	forest	***	3.79	0.732		
	Over/under crossing	***	-1.00	0.217		
	powerline	.	0.274	0.152		
	road	***	-2.14	0.378		
	train	.	-0.29	0.161		
M1370	**fen**	***	13.3	3.99	287.0 – 285.8	0.8888
	forest	***	3.77	0.732		
	Over/under crossing	***	-1.00	0.217		
	powerline	.	0.275	0.151		
	road	***	-2.13	0.377		
	train	.	-0.290	0.161		

The AUC increased with a higher sat limit for both roe deer and moose (table 6 and 7). All models for both species were better at separating defined low-frequency segments than blackspots which can be seen by observing the black line in figure 8 to 15, where closeness to the upper axis rather than the left indicates a model which is good at discriminating with a high TPR (true positive rate, the number of blackspots correctly classified as blackspots/all blackspots at different probability thresholds). When the TPR was low the models for roe deer were no better than a random discriminator. This indicates that the model's ability to discriminate between the two outcomes with a high probability threshold were weak, and it is first with a low probability threshold that the model is a good discriminator.

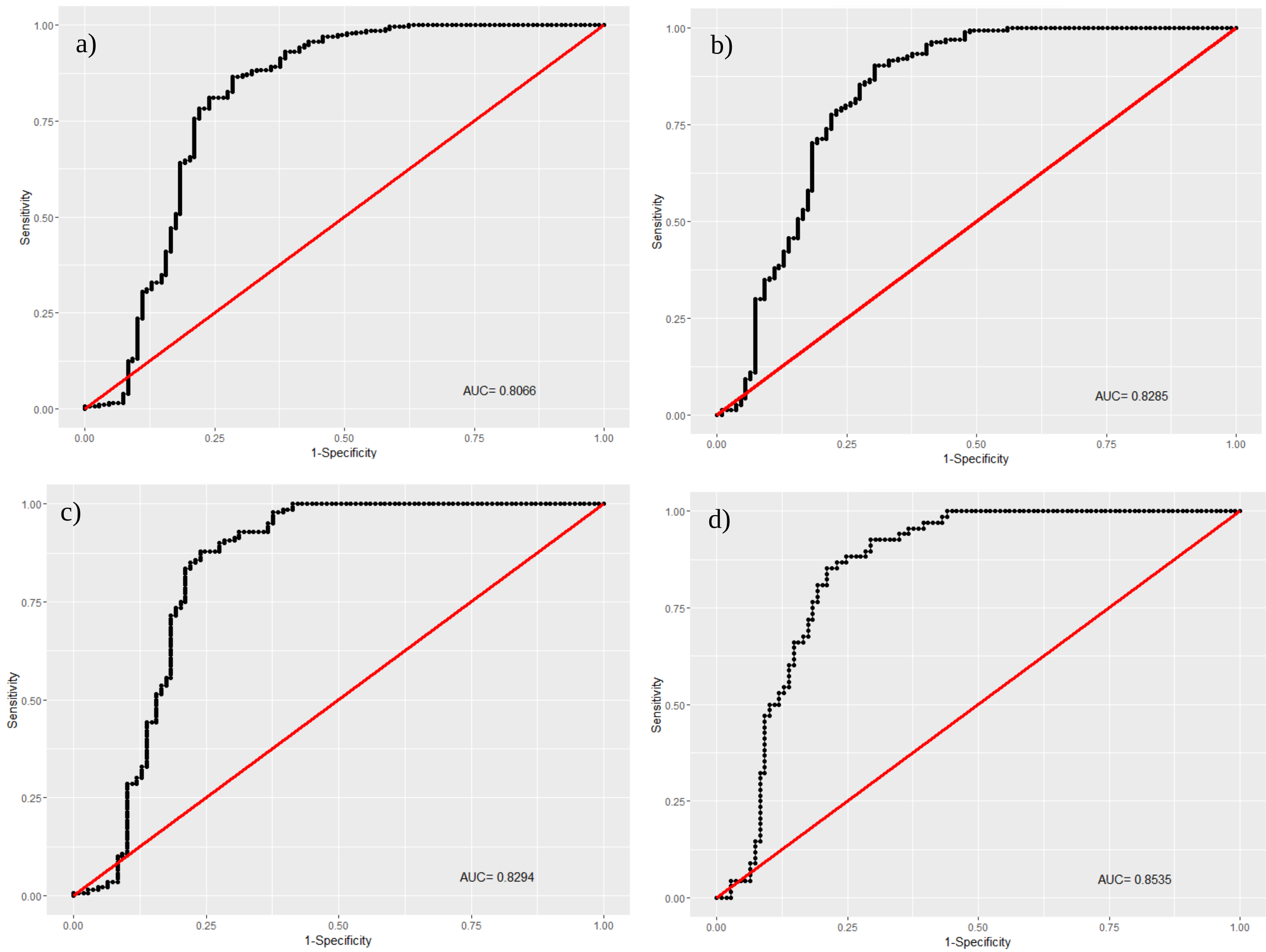

Figure 8. ROC (Receiver operating characteristics) plots for model R1060 (a), R1070 (b), R1360 (c), and R1370 (d) where the black line shows the relation between TPR (true positive rate, sensitivity) and FPR (false positive rate, 1-Specificity). When the black line is close to the red line the model is no better than a random discriminator to differentiate between blackspot and controls, low-frequency segments. The closer the black line is to the upper and left axis, the better it is at discriminating between the two outcomes. The AUC value indicates how good the model is at discriminating between the different outcomes, were 0,8 is abbreviated as very good.

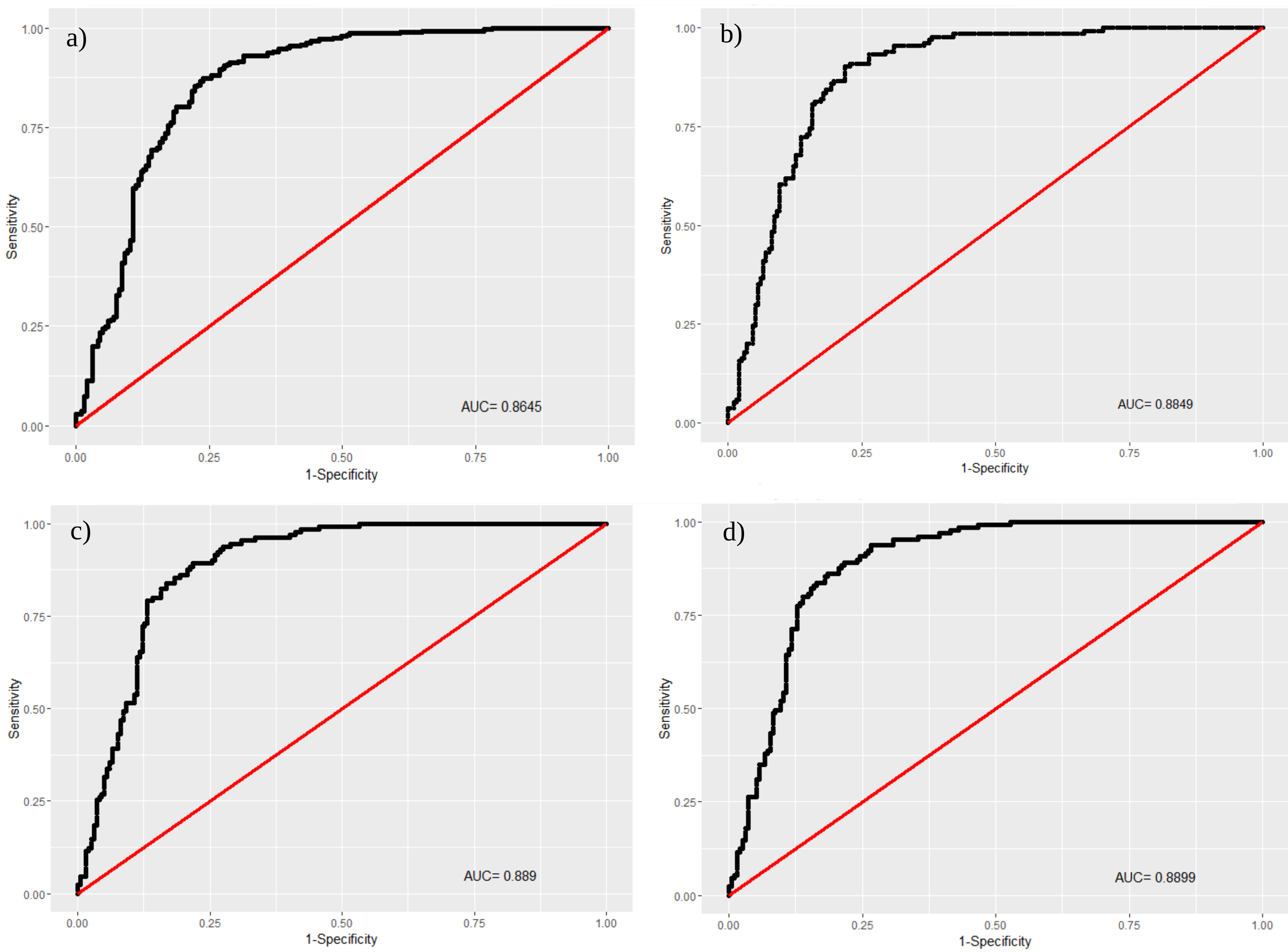

Figure 9. ROC (Receiver operating characteristics) plots for model M1060 (a), M1070 (b), M1360 (c), and M1370 (d) where the black line shows the relation between TPR (true positive rate, sensitivity) and FPR (false positive rate, 1-Specificity). When the black line is close to the red line the model is no better than a random discriminator to differentiate between blackspot and controls, low-frequency segments. The closer the black line is to the upper and left axis, the better it is at discriminating between the two outcomes. The AUC value indicates how good the model is at discriminating between the different outcomes, were 0,8 is abbreviated as very good.

4 Discussion

I have in this report developed a method to identify blackspots on the Swedish railroad, highlighting the railroad segments which repeatedly had a high frequency of incidents for a major part of the studied time-series. For both species analysed in this report, the ability to differ blackspots from low-frequency segments increased with a higher set limit (regarding set percentile of the yearly distribution of the number of incidents as well as number of years above the percentile). However, which limit to choose is also a practical question and should be decided in cooperation with STA and other interested parties. I recommend the highest limit, 1370, as it was the best at differing blackspots from low-frequency segments and identified a set with the highest average number of incidents per km and the highest quota of number of incidents/total length.

The identified blackspots for roe deer are mostly in south of Sweden, as compared to moose where blackspots were found across the entire country. This reflects the geographical distribution of the two species (Svenska Jägareförbundet, 2016, 2015). The top ten blackspots for moose are in similar geographical areas between all four sets, but both position and the given rank differed between the different limits. This marks the importance of the appropriate choice of ranking criteria as it can have large impact on the final choice of segments.

Previous methods to identify blackspots of wildlife collisions on roads are based on spatial points and cluster analyses, and this is not possible for this data. Instead we used an index of reoccurring high number of incidents as a measure of intensity to define blackspots. This index is based on the relative intensity of incidents for all segments in a year. The method developed in this report is easily repeated, the challenge is setting a limit to identify a desirable number of blackspots. One should be aware that these blackspots do not have a rigorous definition about which measurements to incorporate which gives them a flexibility. One of the difficulties of this and similar studies is therefore identifying which criteria should be used to delineate and rank blackspots. In the end, the needed criteria will differ depending on who is asking the question. The flexibility is therefore important, and equally important is the reason for including different criteria.

The AUC-value increases with a higher set percentile for defining blackspots, and a higher set limit increases the model's ability to differentiate between blackspot and defined low-frequency segments. The shape of the curves of the ROC-plots also indicate that the models are increasingly better at separating defined blackspot from low-frequency segments. The top three sets of blackspots for moose have similar AUC-values. This indicates that the explanatory variables couldn't get better at discriminating between the two different outcomes even when choosing a higher limit. An alternative way of identifying blackspots would therefore be based on the position where the AUC levels out. Further studies could investigate the AUC for a larger number of sets of blackspots, ranging from 0 years above the limit up to all available years to assess where the AUC-value levels out and eventually decline. An important factor to incorporate in such a study is the difference in number of blackspots, as running a model on too few dependent variables will give uncertain results (Peduzzi et al., 1996). This suggested method relies on the assumption that a major part of the explanatory variables that truly impact the probability of a blackspot have been identified. Otherwise, the AUC will not truly level out at a limit which indicates the "true" blackspots.

Interpreting the included explanatory variables should be done with caution as the available data extrapolated from ArcGIS as well as the reported incidents often had low resolution regarding geographical precision. Few explanatory variables were included in the final models for roe deer. This could be an effect of both the low resolution and the possibility that I have not succeeded in incorporating the explanatory variables which are important for roe deer. Snow was the only variable included in all final models. Many of the segments defined to have low-frequency of incidents for roe deer were in the northern half of Sweden. I therefore believe that the relationship with snow shows the increase of snow with increasing latitude rather than an impact on the probability of a blackspot. For future analysis, the explanatory variables could also include more categories of open land, such as agricultural habitat, which is known to increase the presence of roe deer (Brown, 2012). It would also be interesting to include the difference in population size depending on geographical location in the analysis.

The final explanatory variables for moose are similar to those identified in previous reports (Rolandsen et al., 2015; Seiler et al., 2011). Fen had the highest parameter estimate which indicates its importance for presence of moose, which is similar to earlier research (Kuijper et al., 2016). The negative effect of powerlines as well as of roads is in opposite to what I expected. For roads, a possible explanation is that the presence of roads in close vicinity to railroads could work as a deterring mechanism for moose rather than funnelling them up on the railroad. The presence of powerlines could be an indicator of more human settlements, decreasing the probability of moose in the area (Torres et al., 2011). However, it could also indicate that the powerlines are attractive to moose and therefore they spend less time in close vicinity to the railroad. Powerlines are sometimes used to plant species that moose prefer as forage (Bergqvist and Bergström, n.d.; Henningsson, 2013; Sveriges Radio, 2003). Powerlines, or rather the powerline segments, might therefore even work as a mitigating effort for TWCs.

Earlier studies have used predictive modelling to understand where incidents occur at a higher rate (Gundersen and Andreassen, 1998; KušTa et al., 2014). Predictive modelling is an important tool as it can suggest mechanisms that can explain the occurrence of blackspots. This allows an understanding of how blackspots will develop with changes in the landscape as well as climate change.

As the TWCs are reported on segments and not with coordinates, there will be some difficulties when positioning mitigation measures to reduce TWCs. Preferably, the reporting system should be updated so that there is a higher geographical precision of where the TWCs occur and with a higher accuracy regarding the species and type of incident reported in the database. Since the number of years included in the database will continue to grow the appropriate number of years above the limit will have to be revised.

4.1 Conclusion

I have developed a method to identify blackspots with repeatedly high numbers of incidents. By automating the process, it could offer a tool for different interested parties. The decision of which limit to use and what measures to include for the ranking might require more elaboration, but the main way of thinking and important questions to answer when dealing with repeatedly high numbers of incidents on railroads have been identified.

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