LIFE SAFE-CROSSING: PREVENTING ANIMAL-VEHICLE COLLISIONS

ACTION A6. Set-up of a geographic database of the roadkills and development of a hybrid app that provides real time feedback to users

Action report December 2020

LIFE SAFE CROSSING
PREVENTING ANIMAL-VEHICLE COLLISIONS

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LIFE SAFE-CROSSING

PREVENTING ANIMAL-VEHICLE COLLISIONS

ACTION A6. Road mortality risk models, and crossing roads probability models.

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Responsible partner: AGRISTUDIO s.r.l.

Authors: Matteo, Falco[1], Antonucci, Antonio[2]; de Las Heras, Matías[3]; Di Domenico, Giovanna[2]; Fabrizio, Mauro[2]; Fedorca, Ancuta[4]; Fedorca, Mihai[4]; Iliopoulos, Yorgos[5]; Ionescu, Georgeta[4]; Jurj, Ramon[4]; Latini, Roberta[6]; López, Marcos[3]; Mertzanis, Yorgos[5]; Psaralexi, Maria[5,7]; Scillitani, Laura[6]; Salcedo, Francisco-Javier[8] & Voumvoulaki, Niki[9].

[1] University of Rome "La Sapienza"

[2] Parco Nazionale della Majella (Italy)

[3] Agencia de Medio Ambiente y Agua (Spain)

[4] National Institute for Research and Development in Forestry 'Marin Drăcea' (Romania)

[5] CALLISTO Wildlife and Nature Conservation Society (Greece)

[6] Parco Nazionale d'Abruzzo Lazio e Molise (Italy)

[7] Aristotle University of Thessaloniki (School of Biology, Department of Ecology)

[8] Consejería de Agricultura, Ganadería, Pesca y Desarrollo Sostenible de la Junta de Andalucía (Spain)

[9] EGNATIA ODOS S.A (Greece)

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1. INTRODUCTION

1.1. General presentation and aims of the action

The main objective of this action is to identify roads sections with highest probability of road mortality for the wildlife in the different project areas. Analysis was performed for each area, and focused on two large carnivore target species, the brown bear (*Ursus arctos*) in Greece and Romania and its relict population surviving in Italy (*Ursus arctos marsicanus*), and the Iberian lynx (*Lynx pardinus*) in Spain. In Italy and Greece we also analyzed data regarding other mammal species.

The specific objectives of this analysis are:

- modelling road mortality risk, using animal vehicle collision (AVC) data
- modelling the relative probability of road-crossing, using telemetry data

The first analysis (AVC models) was developed contrasting the characteristics of the environmental surrounding each AVC-point with those available over the roads of the project area; the latter (crossing models) was developed using crossing points derived by global position system (GPS) telemetry data, and contrasting the landscape conditions between crossing and non-crossing points over the roads. To reach this aim, a Maximum Entropy model (MaxEnt, Phillips et al. 2006) was developed to provide spatially-explicit predictions about the risk of road mortality and road crossing. In this context, MaxEnt projections was used to build continuous maps for each project area and target species, determining the degree of risk of roadkill (AVC mortality risk maps), and which sections are more likely to be crossed by the target species (crossing-road risk maps).

2. STUDY AREAS AND DATA

2.1. Defining study areas

The six areas of interest, located in four European countries, are: Florina and Kastoria provinces (FK-GR) in Greece, Abruzzo-Lazio-Molise national Park (PNALM-IT) and Majella National Park (PNM-IT) in Italy, Curbura Carpatilor (CC-RO) in Romania, and Doñana National Park (PND-SP) and Sierra Morena (SM-SP) in Spain. For predicting the probability of AVC mortality risk and crossing probability, the definition of the extent of the study area becomes fundamental because linked to the concept of what is considered available for safe-crossing. Accordingly, study area has been defined as all the paved roads (hereafter, “road-network”) included within the 100% minimum convex polygon (MCP100%) built respectively on AVC and GPS-telemetry data, and corresponds to the area used for the model calibration. In addition, a buffer was built around the MCP100% to account for road sections available for animals that occur outside the MCP’s boundaries, using the radius derived by the average home range of brown bears in Greece (Kanellopoulos et al. 2006), Italy (Maiorano et al. 2019) and Romania (Pop et al. 2018), and lynxes in Spain (Ferreras et al. 1997; Lopez-Bao et al. 2010).

2.2. AVCs and crossing-points data

GPS-telemetry data used in the analysis coming from 79 radio collared brown bears tracked along a time period of 14 years, from 2005 to 2019: 32 tracked in Romania, 23 in Greece and 24 in Italy (23 Marsican brown bears in PNALM and 1 in PNM). Crossing points were determined by the intersections between the lines derived by animal trajectory and road segments, produced in the Action A3 (see Action A3 report for a more detailed description). GPS-locations used for detecting a crossing point included only consecutive fixes with a time lag of maximum1 hour.

Overall, AVC data used in the analysis consisted in 515 collisions involving the target species (brown bear and Iberian lynx), wild ungulates and other wild carnivores. Specifically, AVC data are composed by 57 brown bear and 27 mesocarnivore’s roadkills in Greece, 27 brown bear’s roadkills in Romania, and 120 lynx roadkills in Spain (both Doñana and Sierra Morena records); in the Italian cases of study, AVC data include a sample size of brown bear roadkills (N=7, both PNALM and PNM records), and a large sample size of ungulates and other carnivore species (n=278, in both PNALM and PNM). GPS telemetry data as well as AVC data used to develop the models are the same data analyzed in the frame of Action A3.

Since that different species could reflect different behavioral response to the various habitat components before crossing (and being potentially killed), the dataset used for modeling AVC mammal's species is divided into four species group or ecological guild, which are large carnivores (i.e., wolf and brown bear; N=45), small and meso-carnivores (i.e., badger, fox, marten, and wild cat; N=43), deer (i.e., red deer and roe deer; N=104) and wild boar (N=82). Each ecological guild is modeled separately, and then, all final models are also averaged to provide a single "global AVC mortality risk" model.

3. METHODS

3.1. Variables preparation and selection

A set of environmental, orographic and anthropogenic variables were considered to model the probability risk of AVC and road crossing (Table 1), because the distribution of collisions and crossing points can be linked to the attraction exercised by a specific habitat (Barrientos and Bolonio, 2009; D'Amico et al. 2015).

Environmental variables were obtained by the combination of land use classes (Corine Land Cover, CLC) and forest type high-resolution layers derived by the Copernicus projects (https://land.copernicus.eu/pan-european), at a nominal scale ranging from 1:10,000 to 1:5,000. We combined the original land cover categories into four classes: forests (including broadleaf, mixed and coniferous forest), open fields (including pastures, meadows, and alpine prairies), shrublands (ecotonal and transitional vegetation), and agriculture. Because of the great extension of cultivated lands within the Spanish landscape, for this project area, the category agriculture was divided into three separately classes: intensive agriculture, heterogeneous agriculture and fruit trees agriculture.

To account for orographic complexity, a digital elevation model (DEM) was used to compute four orographic variable predictors, like altitude and slope, the latter calculated as both mean and standard deviation, and a measure of terrain roughness called vector roughness index (VRM; ArcMap v. 10.2, ESRI).

Anthropogenic variables included the Euclidean distances measured from the closest settlement edge and viaduct (or bridge and tunnel), and the roads density within a buffer calculated by different radii (or grain sizes, see *Optimized multigrain analysis*). Density of roads were calculated for both paved and unpaved roads accessible by vehicles. Because traffic volume data are not available for the entire road-network, category of roads were used as proxy for traffic volume: primary roads (i.e., high traffic volume) include all the main paved roads that directly connect the main human settlements in the study area, secondary roads (i.e., medium traffic volume) include all the secondary paved roads (and few unpaved roads but accessible by vehicles) that enter in the main roads, while tertiary roads (i.e., absence of local traffic) include all unpaved roads not accessible by vehicles (Table 1); the latter category (tertiary roads) was included in the final set of variable predictors for giving a further picture of environmental composition of the surrounding landscape. In addition, the presence of unpaved roads accessible only by foot close to the paved roads could be use by animal for better moving across the landscape, therefore representing an attractive resource for crossing and, potentially, to be killed by vehicle.

All variables were calculated or re-sampled with a common origin and 25x25 m cell size resolution, corresponding to the lowest spatial resolution of the variables (i.e., DEM). In addition, a grain optimization procedure developed by Laforge et al. (2015) was used to test different grain sizes and identify the optimal grain size (*sensu* Holland et al. 2004) for each environmental variable see *Optimized multigrain analysis*). Accordingly, for all variables excepted the distances (e.g., distance from human settlements), we used a circular moving window of different continuous radii and we ran a map-algebra focal function (i.e., Spatial Analyst tools in ArcMap, ESRI) over the study areas, i.e., road-network; then, at each pixel we calculated the mean (and standard deviation) value within the moving window, creating a new set of variables, reflecting alternative grain sizes of habitat components perception. In line with the previous action (A3) of the project, 400 m was set as minimum grain size of perception, while the mean radius of the home range of the brown bear (in Italy, Greece, and Romania) and Iberian lynx (in Spain); intermediate grain sizes were chosen to reflect a continuous scale of increments of 500m.

Table 1 – Set of habitat variables selected for the AVC and crossing models.

Type	Layer	Description (code)	Source	Cell-size resolution (m)
Environmental	Intensive agriculture (%)	Non-irrigated arable land (211), permanently irrigated land (212), rice fields (213), annual crops associated with permanent crops (241)	European Corine Land Cover (CLC2012)	20x20
	Fruit trees agriculture (%)	Vineyards (221), fruit trees and berry plantations (222), olive groves (223)	European Corine Land Cover (CLC2012)	20x20
	Heterogeneous agriculture (%)	Complex cultivation patterns (242), land principally occupied by agriculture, with significant % of natural vegetation (243)	European Corine Land Cover (CLC2012)	20x20
	Forest (%)	Broadleaf (311), mixed (313), and coniferous forest [included agro-forestry areas (244)	European Corine Land Cover (CLC2012)	20x20
	Shrublands (%)	Sclerophyllous vegetation (323), Transitional woodland-shrub (324)	European Corine Land Cover (CLC2012)	20x20
	Grasslands (%)	-	GRASS layer Copernicus	20x20
	No-vegetated open areas (%)	Pastures (231), moors and heathland (322), beaches, dunes, sands (331), bare rocks (332), sparsely vegetated areas (333), burnt areas (334)	European Corine Land Cover (CLC2012)	20x20
	Tree cover density (%)	Canopy cover of forested areas	Canopy Cover Copernicus	20x20
Anthropogenic	Primary roads density (Km/Km2)	All primary paved roads accessible by vehicles: motorway, trunk, primary roads	Openstreetmap (OSM)/Atlas DeAgostini	-
	Secondary roads density (Km/Km2)	All secondary paved (and potentially unpaved) roads accessible by vehicles: secondary roads, tertiary roads, and unclassified roads	Openstreetmap (OSM)/Atlas DeAgostini	-
	Unpaved roads density	All unpaved roads inaccessible by vehicles: bridleway, cycleway, footway, path	Openstreetmap (OSM)/Atlas DeAgostini	
	Distance from viaducts and tunnels	Viaducts, bridges, and tunnels	Openstreetmap (OSM)/Atlas DeAgostini	
	Distance from human settlements (Km)	Human settlements	European settlements map (ESM2012)	10x10
Orographic	Altitude (m)	Terrain elevation (DEM)	European DEM	25x25
	Slope (°)	Terrain slope	Derived by DEM	25x25
	VRM	Vector Roughness Measure	Derived by DEM	25x25

3.2. Optimized multi-grain analysis

Each variable was standardized by subtracting the mean value from each observation and dividing by its standard deviation to allow comparison of covariates' effects and to improve model convergence (Zuur et al. 2009). Then, the optimized multi-grain analysis (Laforge et al. 2015) was used to identify the optimal grain size for each environmental variable. Accordingly, effect of changing the grain size of one variable at the time was evaluated to determine its most parsimonious spatial scale, conditionally on the other covariates. For one variable at the time, all models with (i.e., global model) and without (i.e., quasi-global model) the focal variable measured at each grain size were compared, using the sample-size corrected by Akaike's Information Criterion (AIC_c; Burnham and Anderson, 2002); that is (Laforge et al. 2015):

$$\Delta AIC_c variable(x) = AIC_{c\ global\ model} - AIC_{c\ global\ model-variable(x)}$$

By plotting grain size versus ΔAICc, the most parsimonious scale (i.e., minimum ΔAICc values) for that variable was identified, and subsequently this grain size was used to enter the variable into the final multi-grain models. If the effect of a variable had a different sign at different grain sizes (i.e., reflecting different selection processes), both grain sizes were retained for the final model (results are visible in the Appendix section).

At each gran size, variables collinearity was examined first using the pairwise Pearson's correlation (r>|0.7|; Dormann et al. 2013), and then, testing the multicollinearity among the remaining uncorrelated variables using the variance inflation factor (VIF>5).

3.3. Model development: calibration, projection and evaluation

MaxEnt algorithm was used to model both probability of crossing and AVC mortality risk. MaxEnt predictions are commonly used for modelling species distributions, basing on presence-only or presence-absence data. In this analysis, AVC records and crossing-points data (i.e., presences) were used within a presence-only modeling design, where availability (i.e., background points, also called pseudo-absence) was randomly sampled within the road network, using 10,000 background points. To avoid the over fitting of the test data, we use 0.1 as the regularization number (Phillips et al. 2004). Models were evaluated using a repeated split cross validation and iterations were fixed as 500. Eighty percent of the locations were used for model fitting and 10% for model evaluation. The mean area under the receiver operating characteristic curve (AUC) was used to evaluate model performance, and AUC values > 0.75 are considered as suitable for conservation planning (Elith et al. 2006; Lobo et al. 2008). Variable importance was calculated as the percent contribution of each variable to the final model based on a permutation approach (i.e., Jackknife method; Phillips et al. 2006), and response curves for variables were provided from the model calibration to show direction, strength and statistical significance of each model predictor. This modeling procedure was repeated for each study area and species (or group of species). All the results and projections (maps) of AVC and crossing models derived by the final averaged model, calculated by the mean values among all replicates.

To detect road sections with the highest probability of crossing or roadkill (hereafter, “crossing hotspot” and “AVC hotspot”), the continuous probability was discretized into binary maps, distinguishing the AVC (and crossing) hotspot (coded as 1) and non-hotspot road sections (coded as 0). To do this, a cut-off threshold was selected to binarize the continuous maps, derived by the maximization of the sensitivity (i.e., true positive rate = proportion of actual positives that are correctly identified as such) and specificity (i.e., true-negative rate = the proportion of actual negatives that are correctly identified as such) values.

4. RESULTS

4.1. AVC and crossing risk maps (Greece)

The final set of uncorrelated predictor variables were the following: agriculture (Agri), tree cover density (TCD), grasslands (Grass), shrublands (Shrubs), distance to primary paved roads (Road1), distance to secondary paved roads (Road2), distance to unpaved roads (Road3), distance to human settlements (DisHS), distance to viaducts, bridges, and tunnels (DisViad), and altitude (DEM).

For the target species (brown bear), anthropogenic variables largely contributed to explain the probability of both AVC and crossing risk, mainly density of secondary roads (30.6% in the AVC model) and primary roads (19.8% and 27% in the AVC and crossing models respectively). In addition, whereas in the AVC model agriculture (23.7%) and distance to human settlements (9.5%) gave a large contribution, at the contrary tertiary roads (23.8%) and tree cover density (17.1%) increased their importance in the crossing model. For mesocarnivores, more than the 80% of variables contribution to AVC model was reached by only one single variable, that is the density of primary roads.

AVC models provided high performance power (AUC), respectively 0.83 and 0.95 for brown bear and mesocarnivores. Similarly, brown bear’s crossing model performance was high (0.87).

Figure 1 –AVC probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in Greece.

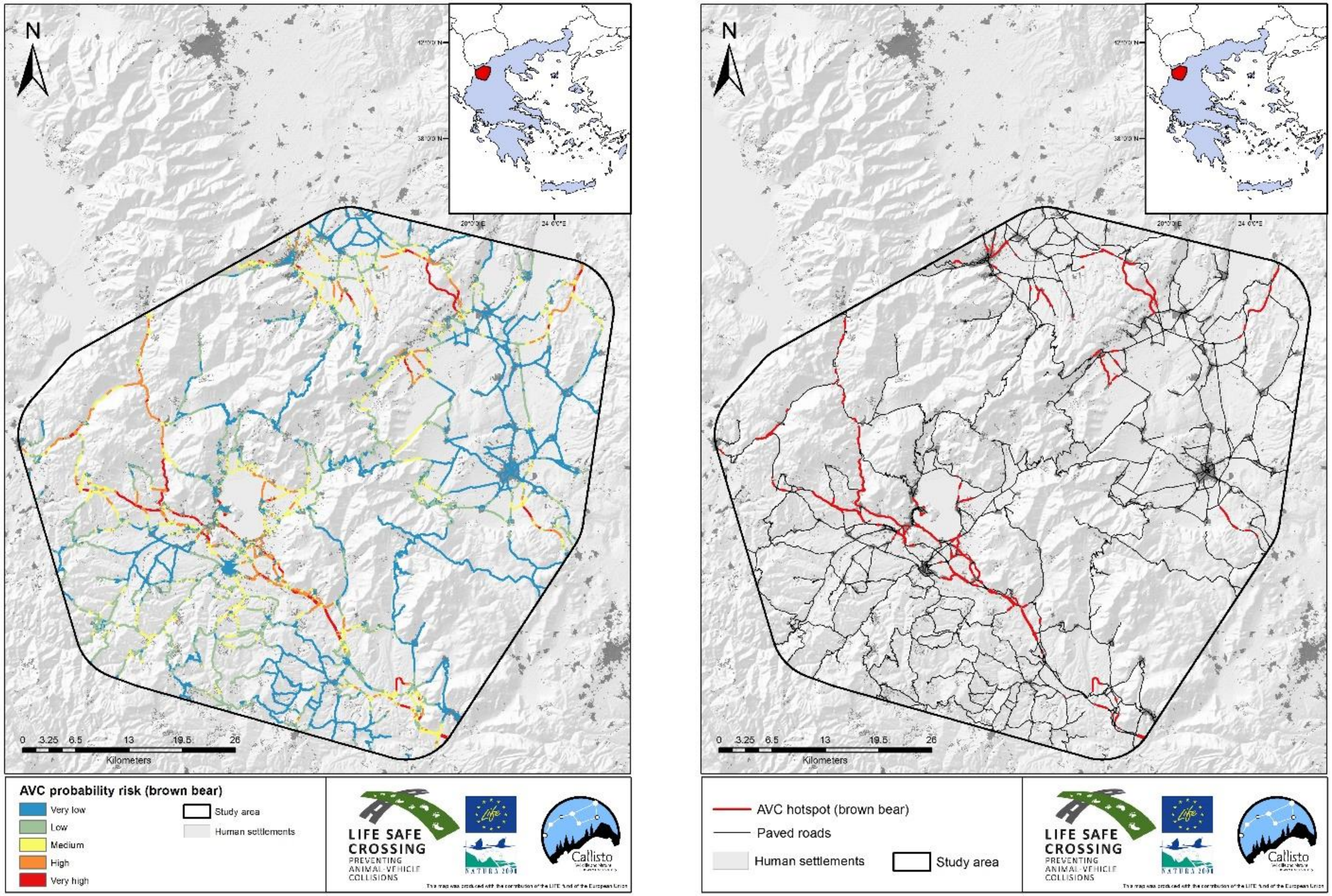


Figure 2 – Crossing probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in Greece.

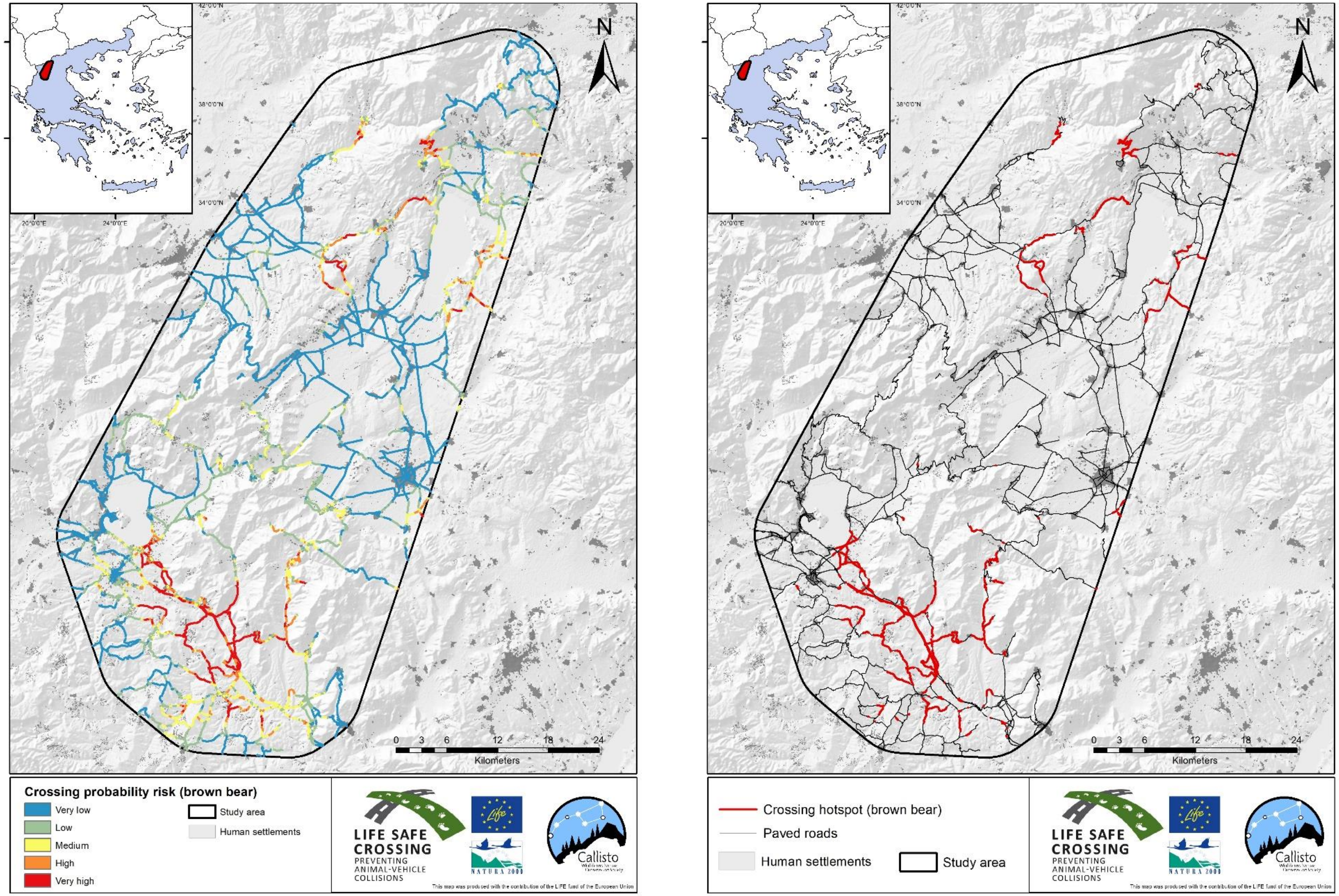
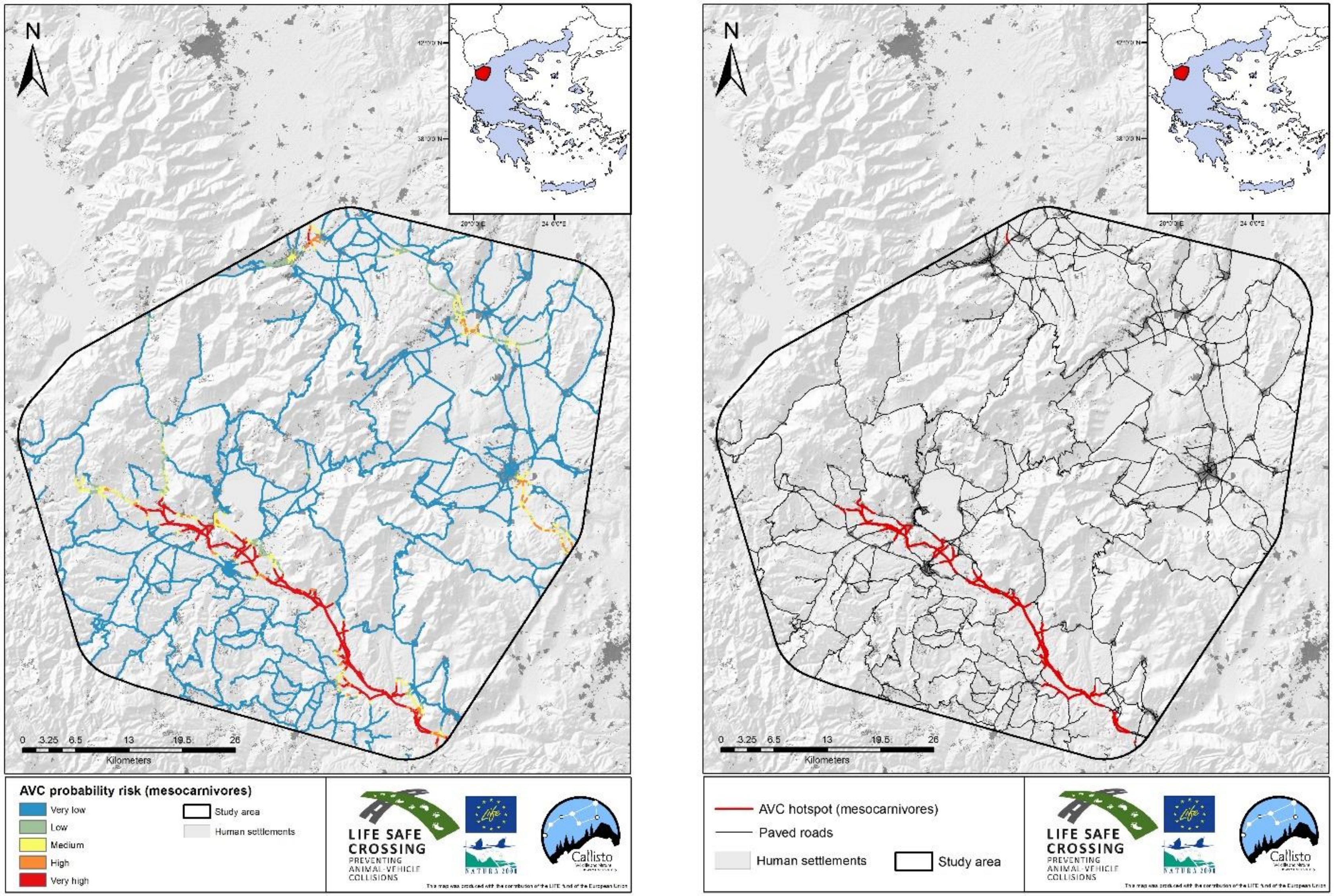


Figure 3 – AVC probability risk maps for mesocarnivores divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in Greece.



The final set of uncorrelated predictor variables were the following: agriculture (Agri), tree cover density (TCD), grasslands (Grass; only for crossing model), shrublands (Shrubs), distance to primary paved roads (Road1), distance to secondary paved roads (Road2), distance to unpaved roads (Road3), distance to human settlements (DisHS), and distance to viaducts, bridges, and tunnels (DisViad).

The variables that gave the main contribution for predicting AVC risk were agriculture (43.3%), tertiary roads (12.8%), and distance from human settlements (12.6%) for the target species (brown bear and wolf), secondary roads (53.1%), tertiary roads (12.4%), primary roads (10.5%), and TCD (9.5%) for deer, secondary roads (49.4%), agriculture (25.2%), tertiary roads (15.7%) for wild boar. In addition, the variables that mainly explained brown bear's crossing risk were secondary roads (41.7%), VRM (28.2%), and primary roads (11.4%).

AVC models provided high performance power (AUC), ranging from 0.75 (target) to 0.82 and 0.87 for deer and wild boar respectively; similarly, brown bear's crossing model provided a high performance score (0.87).

Figure 4 – AVC probability risk maps for brown bear and wolf divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNALM (Italy).

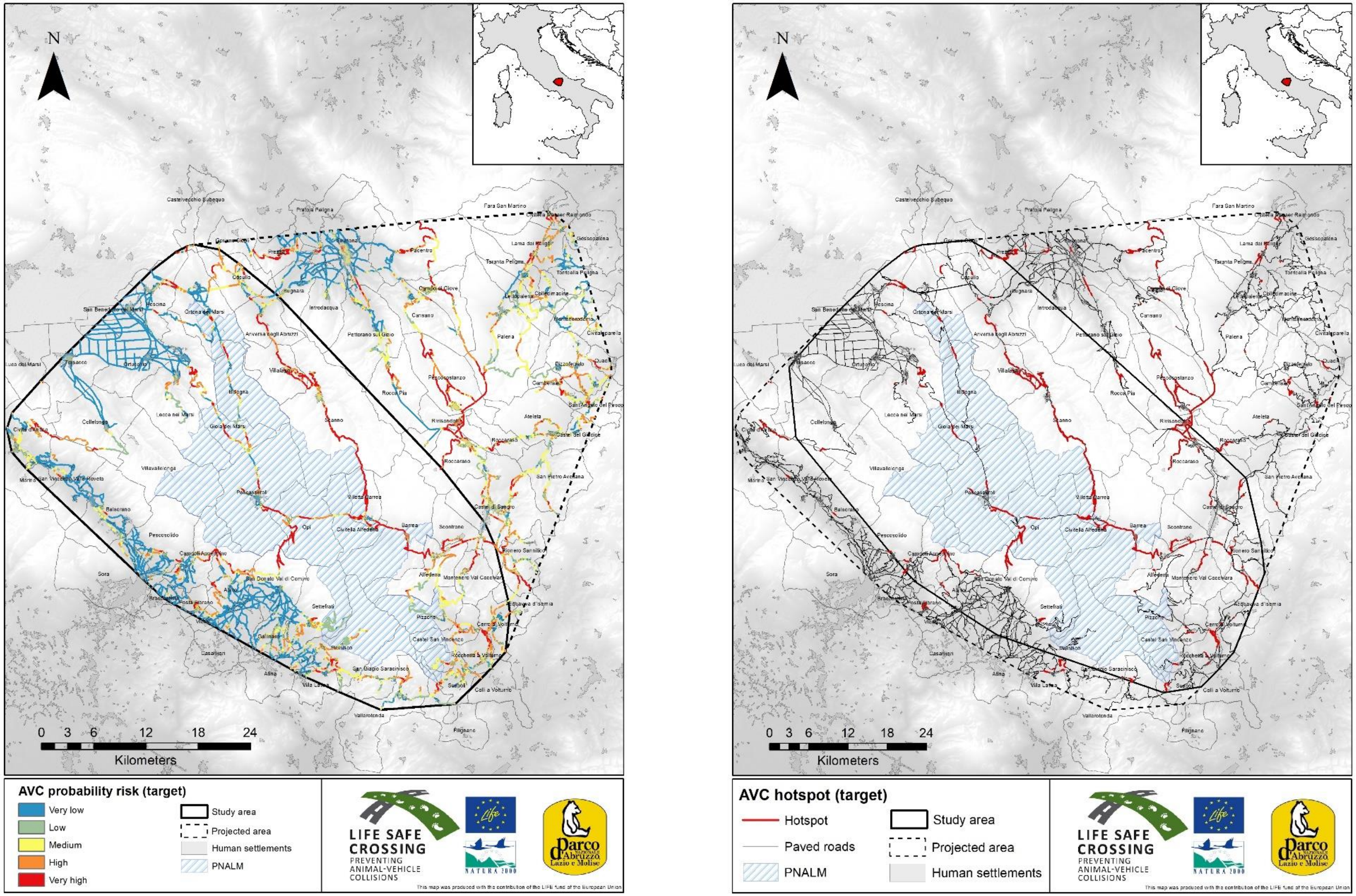


Figure 5 – AVC probability risk maps for deer divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNALM (Italy).

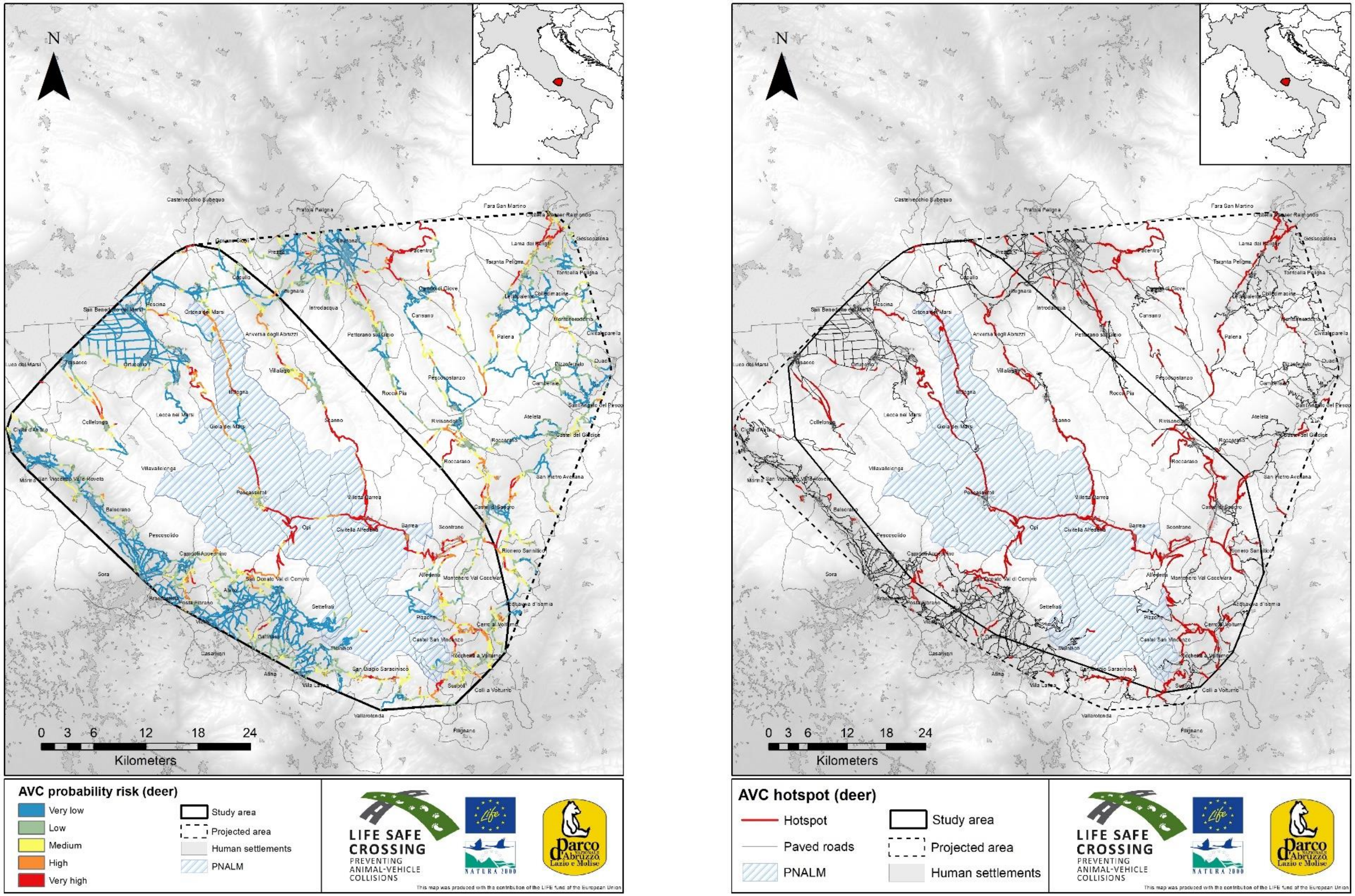


Figure 6 – AVC probability risk maps for wild boar divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNALM (Italy).

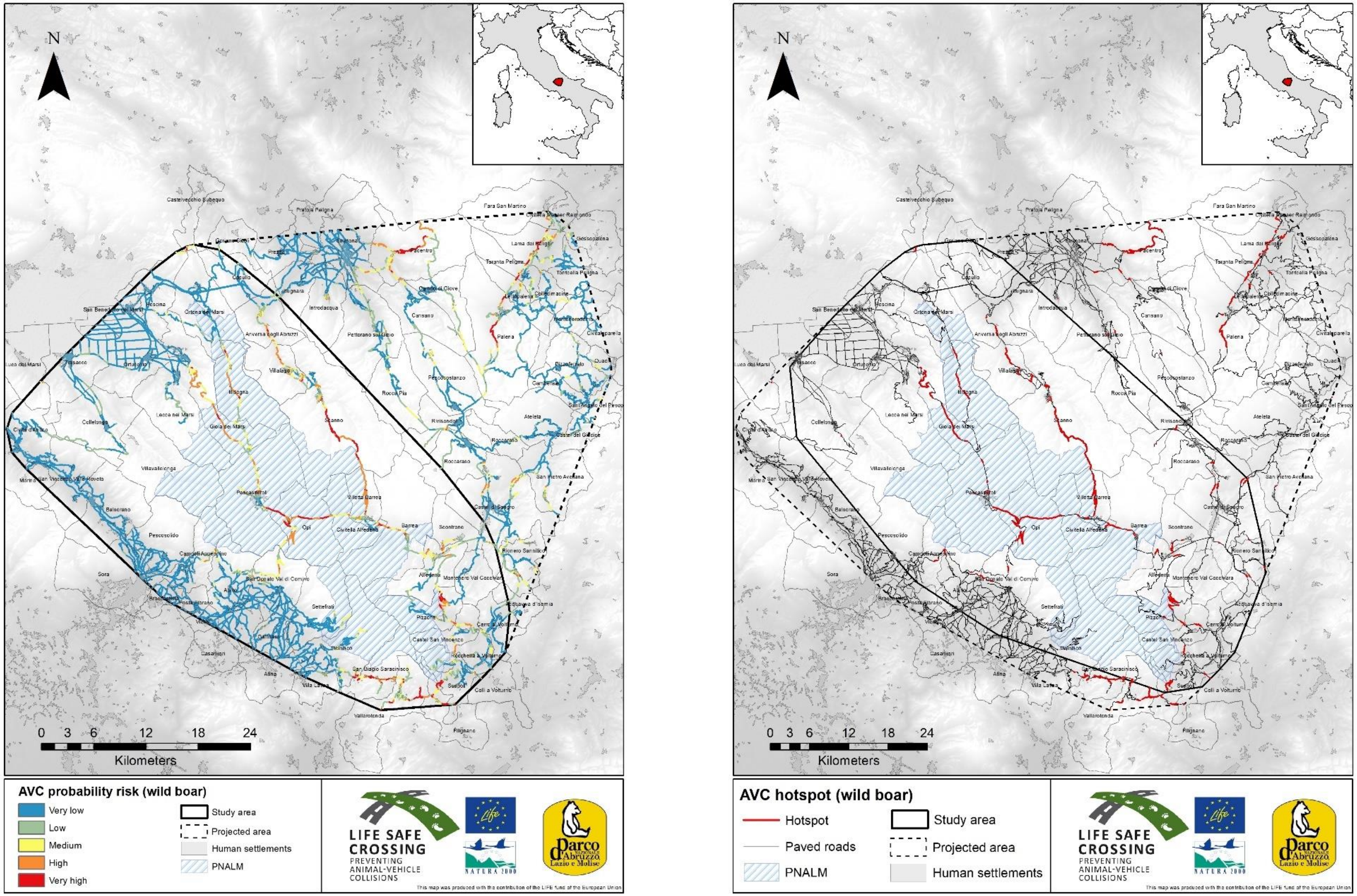
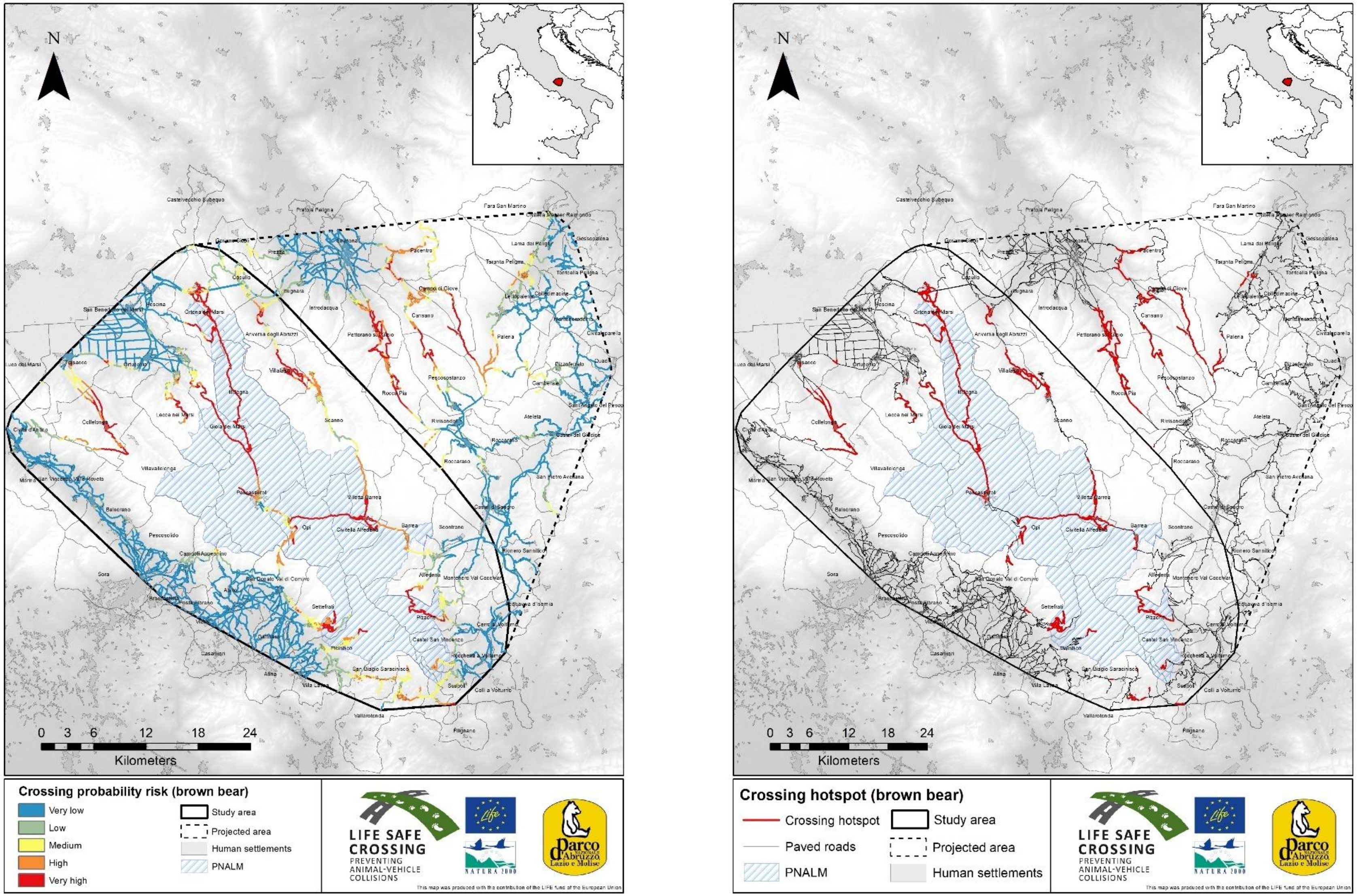


Figure 7 – Crossing probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNALM (Italy).

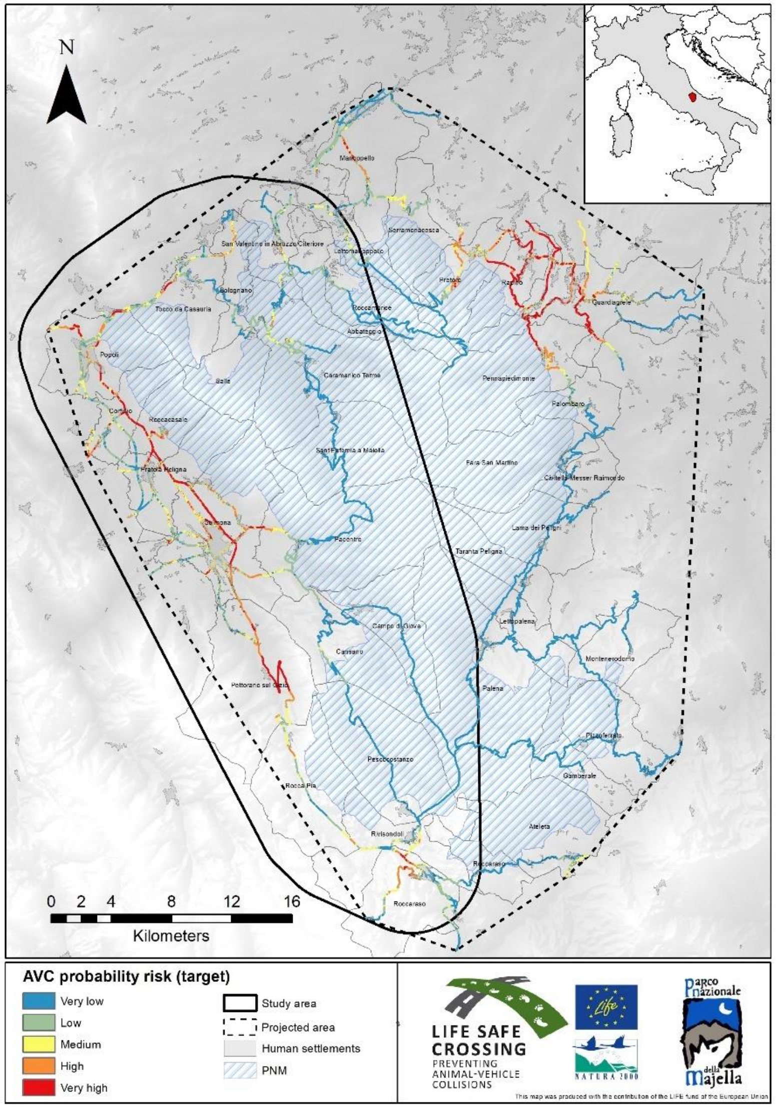


The final set of uncorrelated predictor variables were the following: agriculture (Agri), tree cover density (TCD), grasslands (Grass; only for crossing model), shrublands (Shrubs), distance to primary paved roads (Road1), distance to secondary paved roads (Road2), distance to unpaved roads (Road3), distance to human settlements (DisHS), and distance to viaducts, bridges, and tunnels (DisViad).

The variables that gave the main contribution for predicting AVC risk were agriculture (24.2%), secondary roads (21.7%), and distance to viaduct, bridge and tunnel (19.2%) for the target species (brown bear and wolf), primary roads (26.3%), agriculture (24.5%), TCD (12.7%), and shrublands (10.2%) for deer, agriculture (32.8%), TCD (22.5%), distance from settlements (18.2%), distance from viaducts, bridges and tunnels (12.6%) for wild boar, and secondary roads (31.8%), agriculture (24.8%), distance from settlements (11.9%), distance from viaducts, bridge and tunnels (9.2%) for mesocarnivores. In addition, the variables that mainly explained brown bear’s crossing risk were VRM (28.2%), distance to viaducts, bridges and tunnel (28.1%), shrublands (10.5%), and primary roads (9.5%).

AVC models provided high performance power (AUC), ranging from 0.77 (deer) to 0.78 (wild boar), 0.81 (target) and 0.89 (mesocarnivores); also, brown bear’s crossing model provided a high performance score (0.91).

Figure 8 – AVC probability risk maps for brown bear and wolf divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNM (Italy).



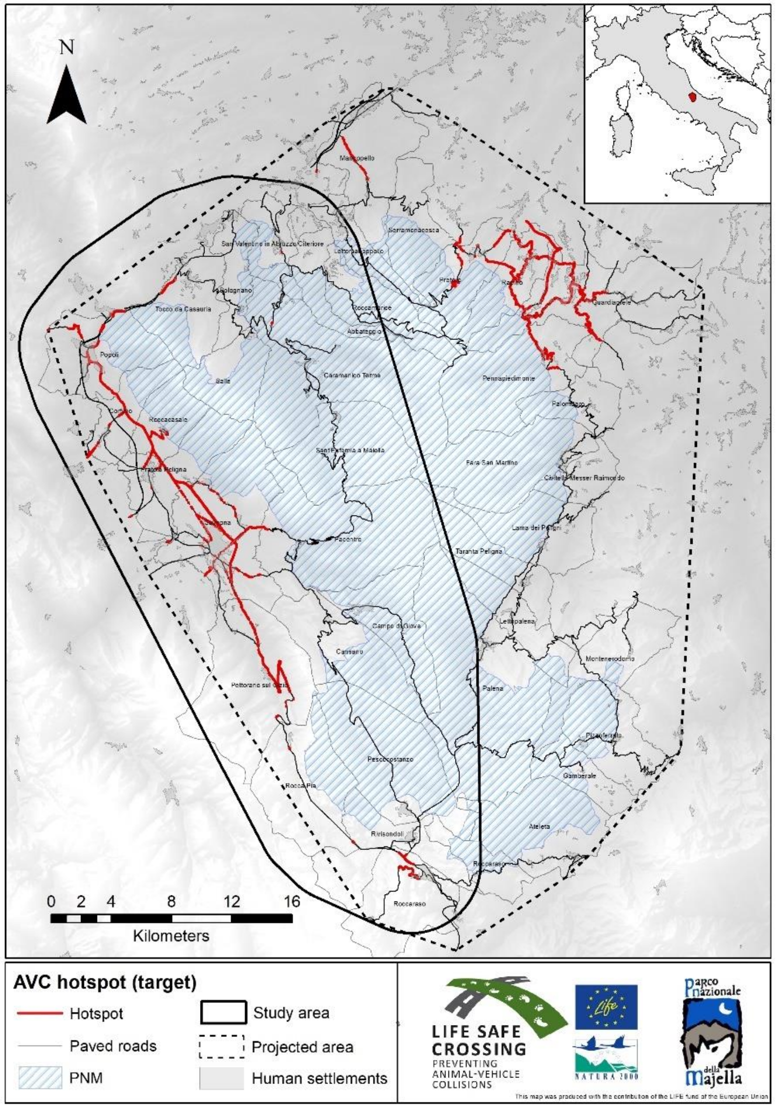
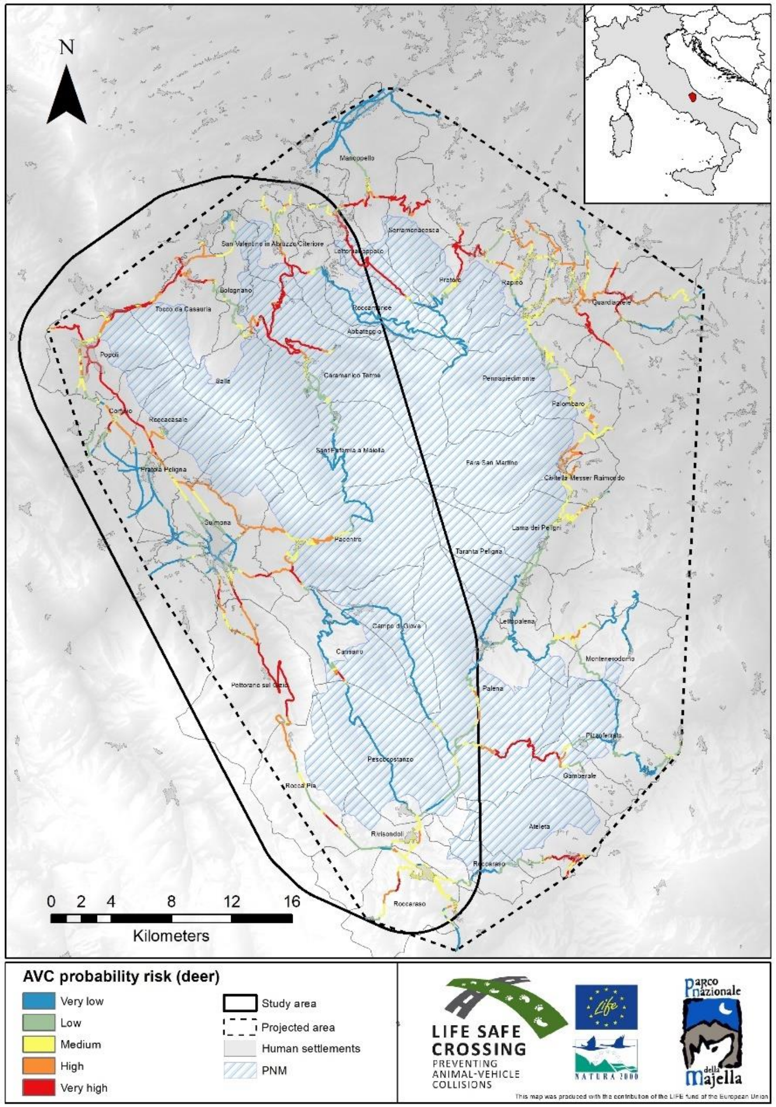


Figure 9 – AVC probability risk maps for deer divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNM (Italy).



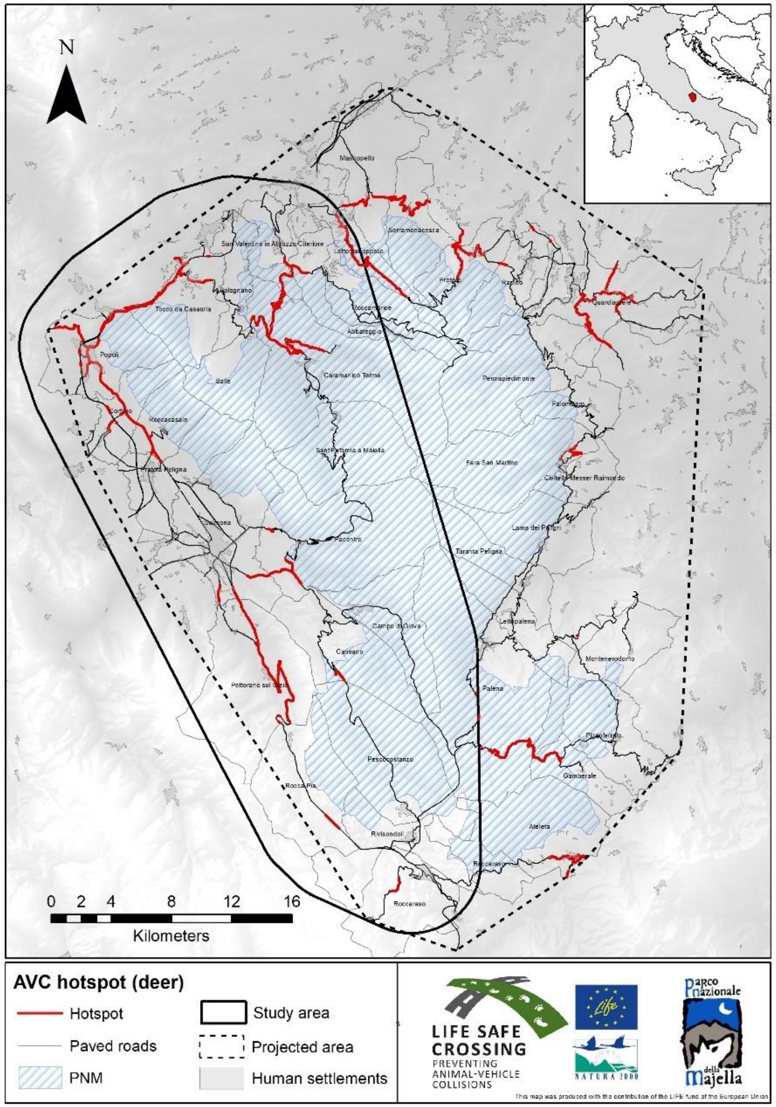
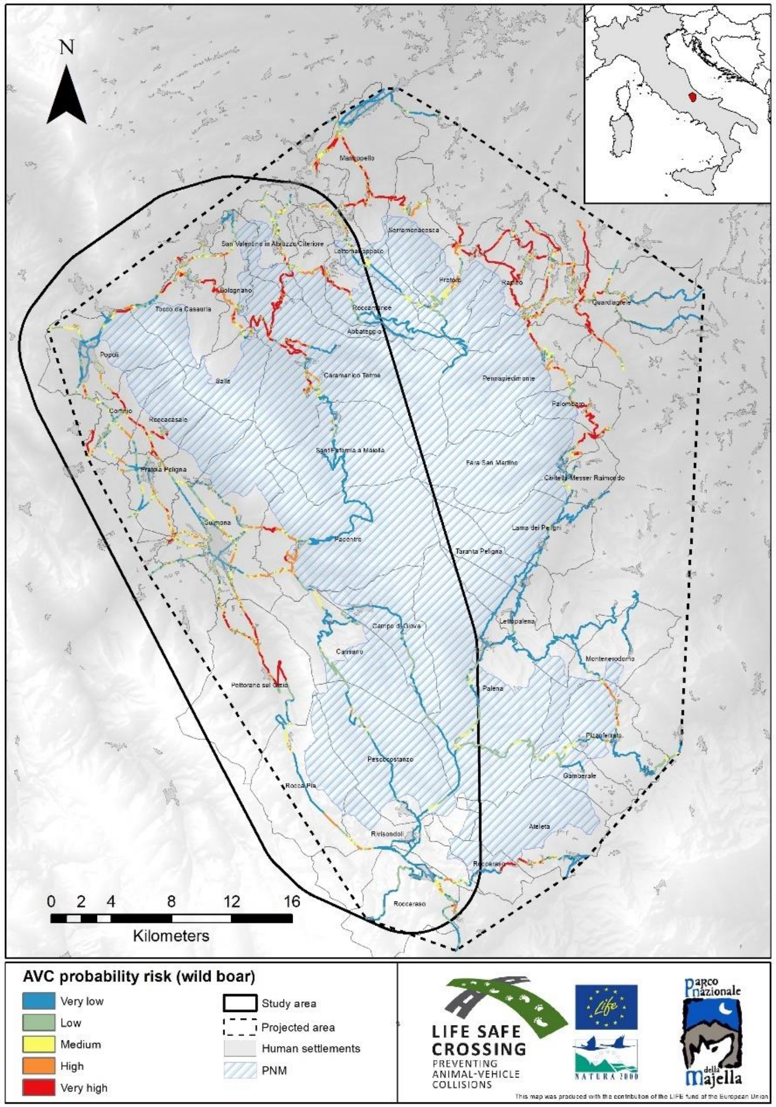


Figure 10 – AVC probability risk maps for wild boar divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNM (Italy).



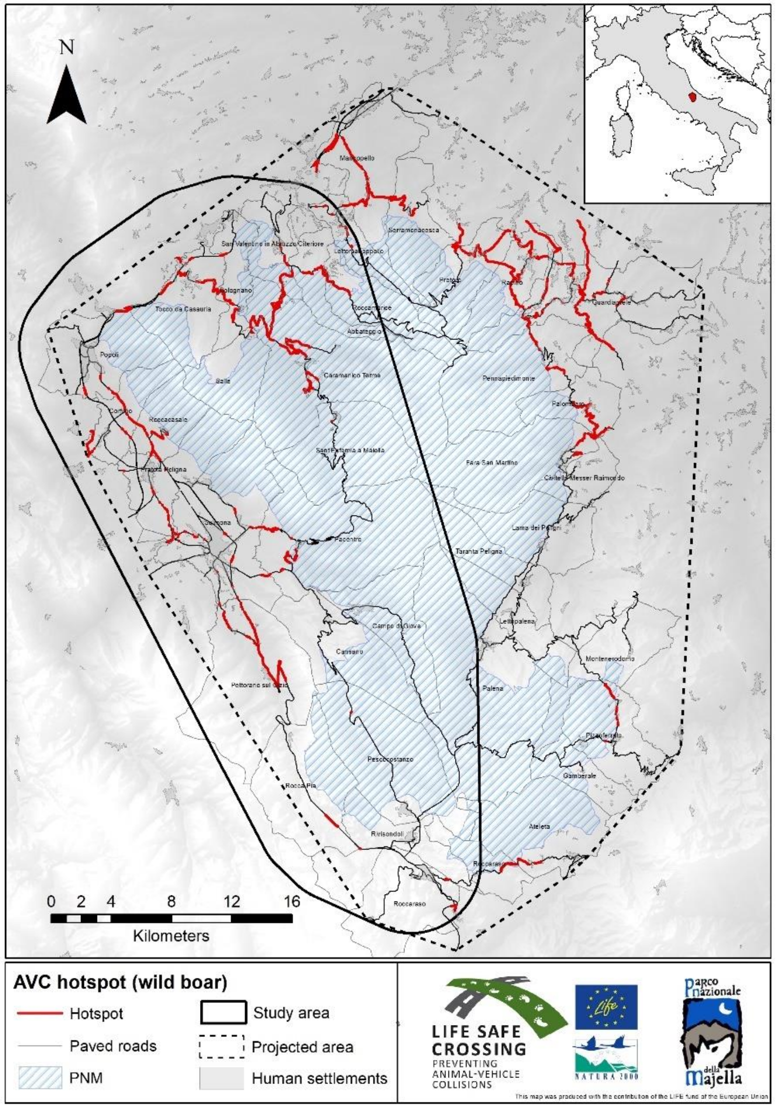
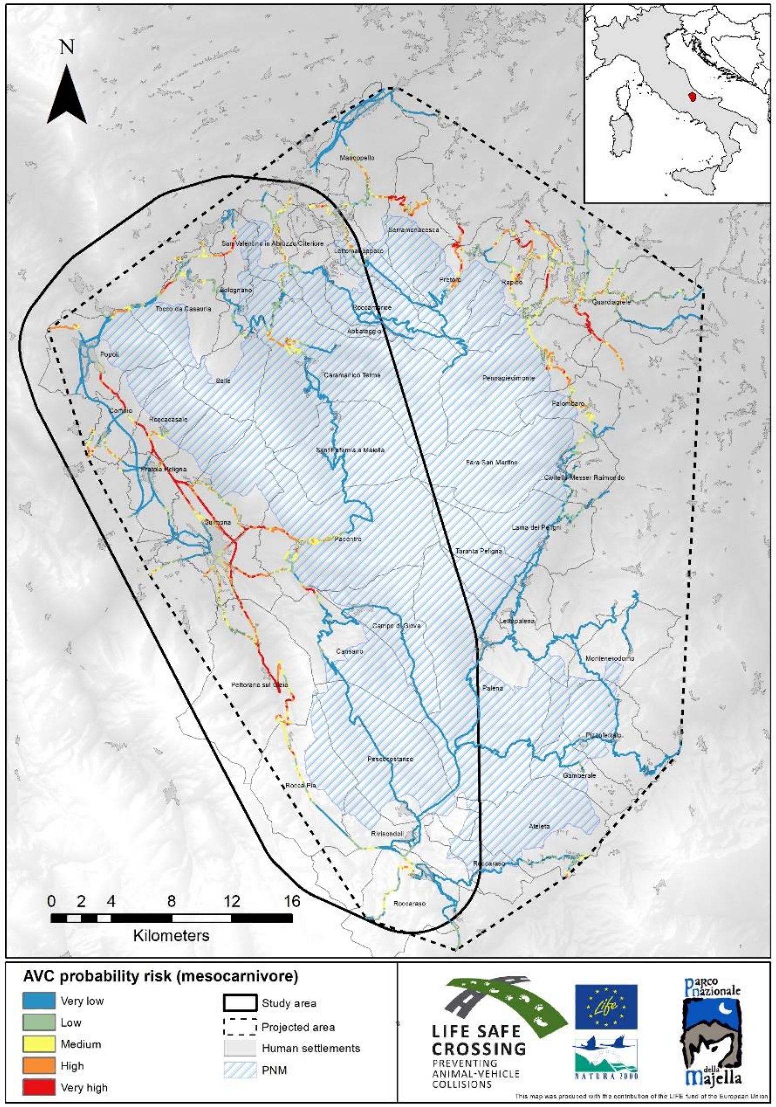


Figure 11 – AVC probability risk maps for mesocarnivores divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections and species, in the PNM (Italy).



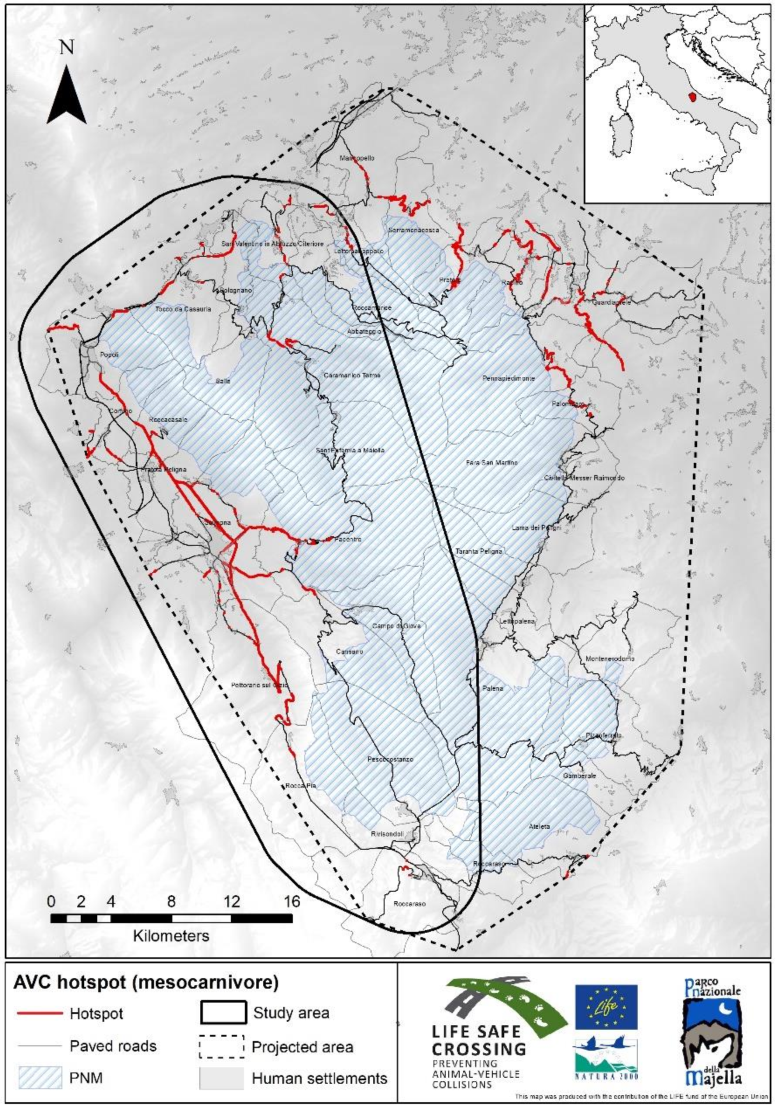
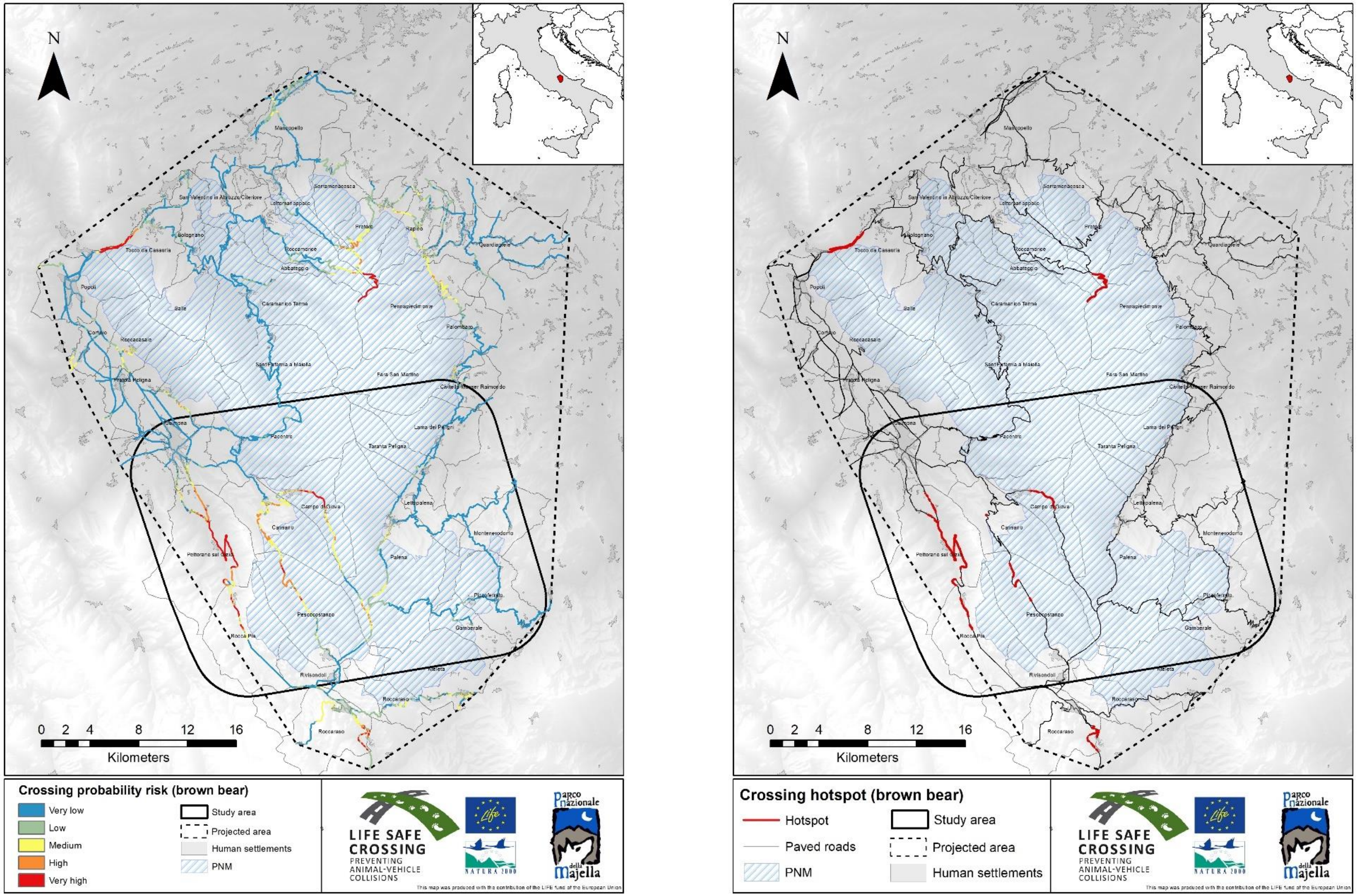


Figure 12 – Crossing probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the PNM (Italy).

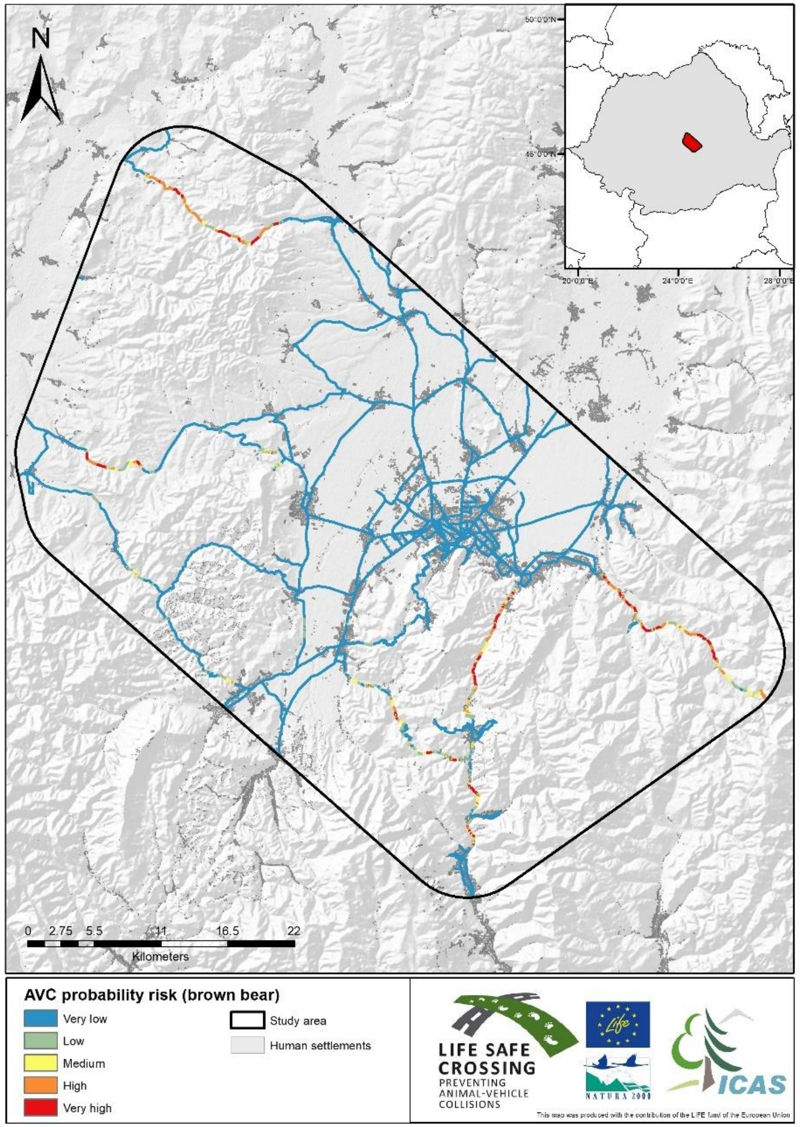


The final set of uncorrelated predictor variables were the following: tree cover density (TCD), grasslands (Grass; only for crossing model), shrublands (Shrubs), distance to primary paved roads (Road1), distance to secondary paved roads (Road2), distance to human settlements (DisHS), and distance to viaducts, bridges, and tunnels (DisViad).

For the target species (brown bear), the variables that gave the main contribution for predicting AVC risk were TCD (45.7%) and secondary roads (39.2%). In addition, the variables that mainly explained brown bear's crossing risk were TCD (42.5%), shrublands (20.3%), and secondary roads (20.2%).

AVC and crossing models provided high performance power (AUC), respectively 0.95 and 0.92.

Figure 13 – AVC probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in Romania.



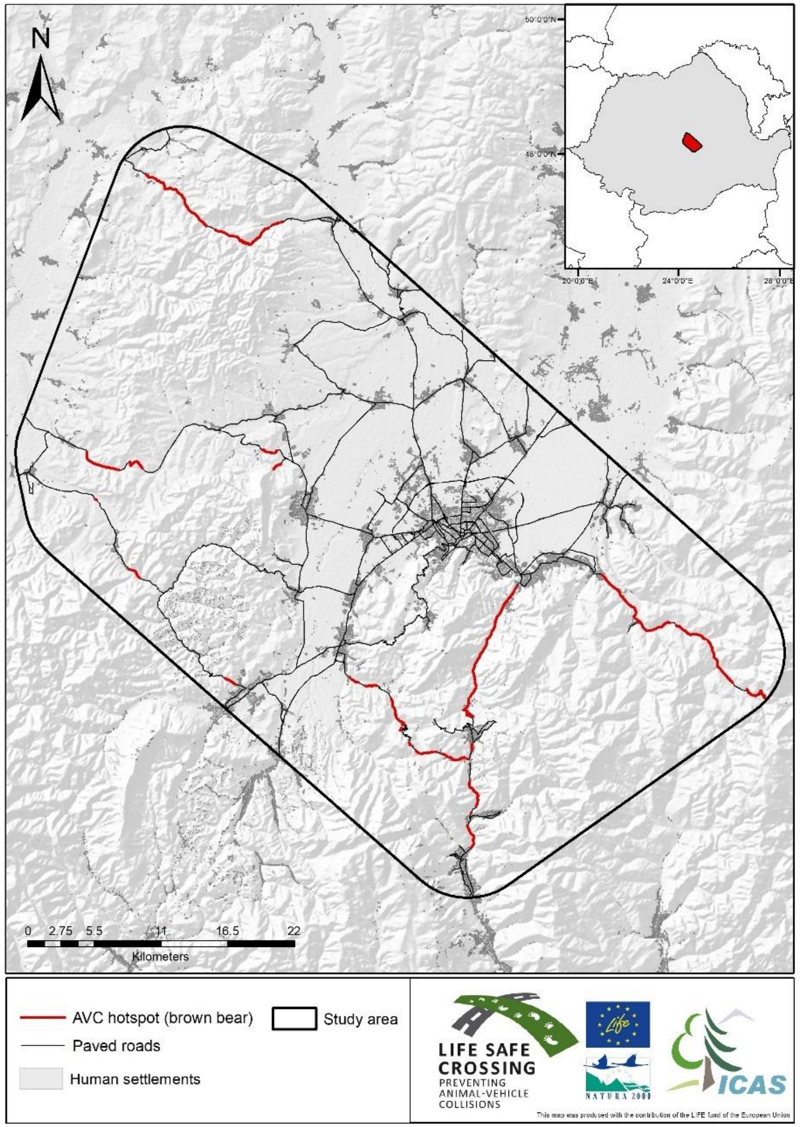
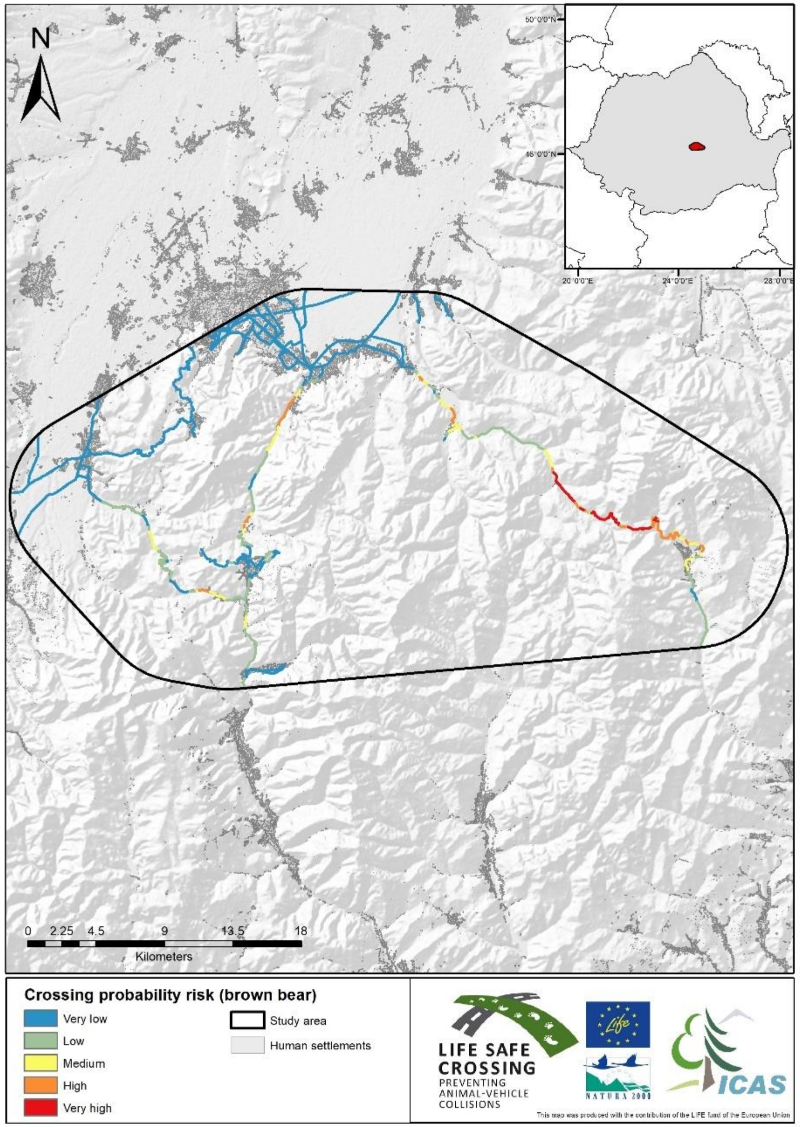
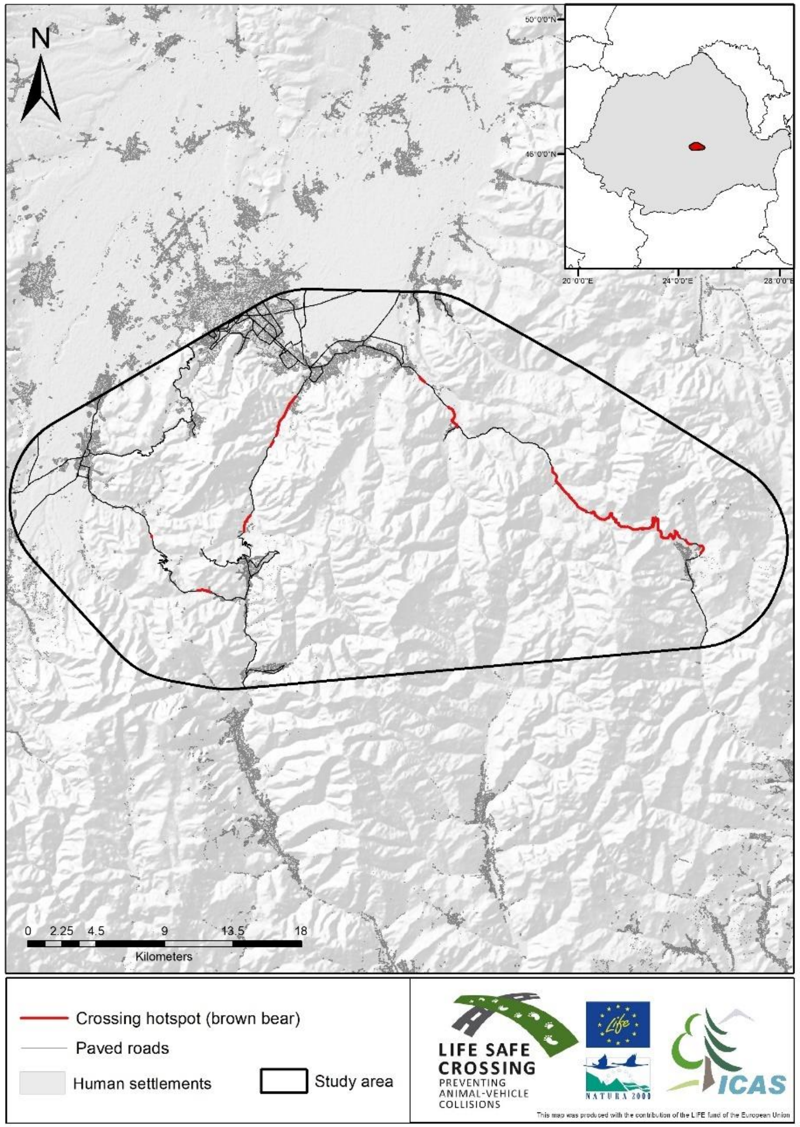


Figure 14 – Crossing probability risk maps for brown bear divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in Romania.





The final set of uncorrelated predictor variables were the following: intensive agriculture (AgriInt), heterogeneous agriculture (AgriHet), trees fruit agriculture (AgriFruit), overstorey tree cover density (TCD), forest cover (Forest; only for the Sierra Morena study area), grasslands (Grass), shrublands (Shrubs), distance to primary paved roads (Road1), distance to secondary paved roads (Road2), distance to unpaved roads (Road3), distance to human settlements (DisHS), distance to viaducts, bridges, and tunnels (DisViad), altitude (DEM), and terrain slope (Slope).

For the target species (Iberian lynx), the variables that gave the main contribution for predicting AVC risk were tertiary roads (34.1%), secondary roads (16.4%), intensive agriculture (11.8%), and distance from viaducts, bridges and tunnels (8.8%) in the Doñana study area, and TCD (22.3%), primary roads (13.2%), secondary roads (10.4%), and DEM (9.1%) in the Sierra Morena study area.

AVC models projected in both study areas (Doñana and Sierra Morena) provided high performance power (AUC), respectively 0.75 and 0.82.

Figure 15 – AVC probability risk maps for lynx divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the Doñana National Park (Spain).

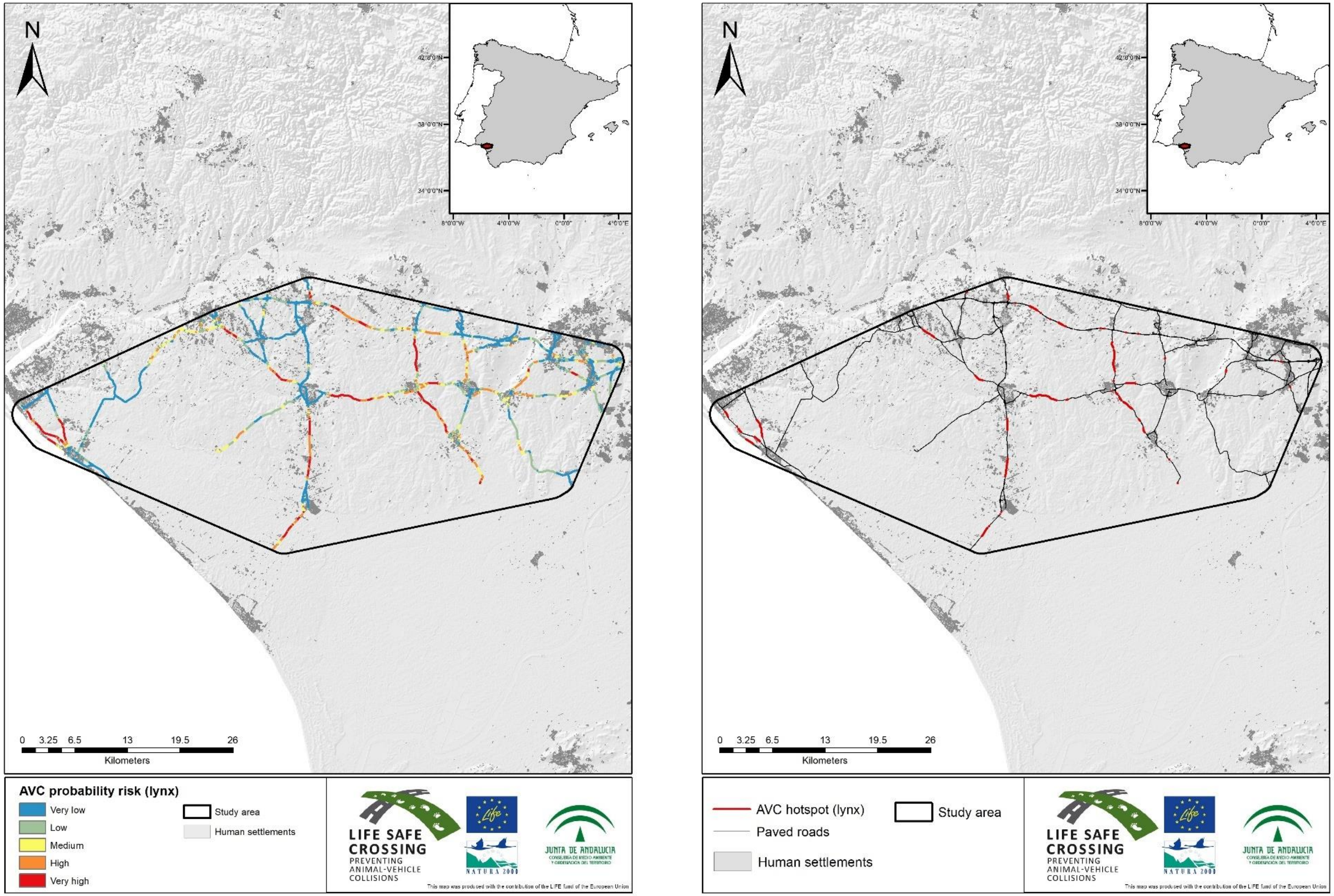
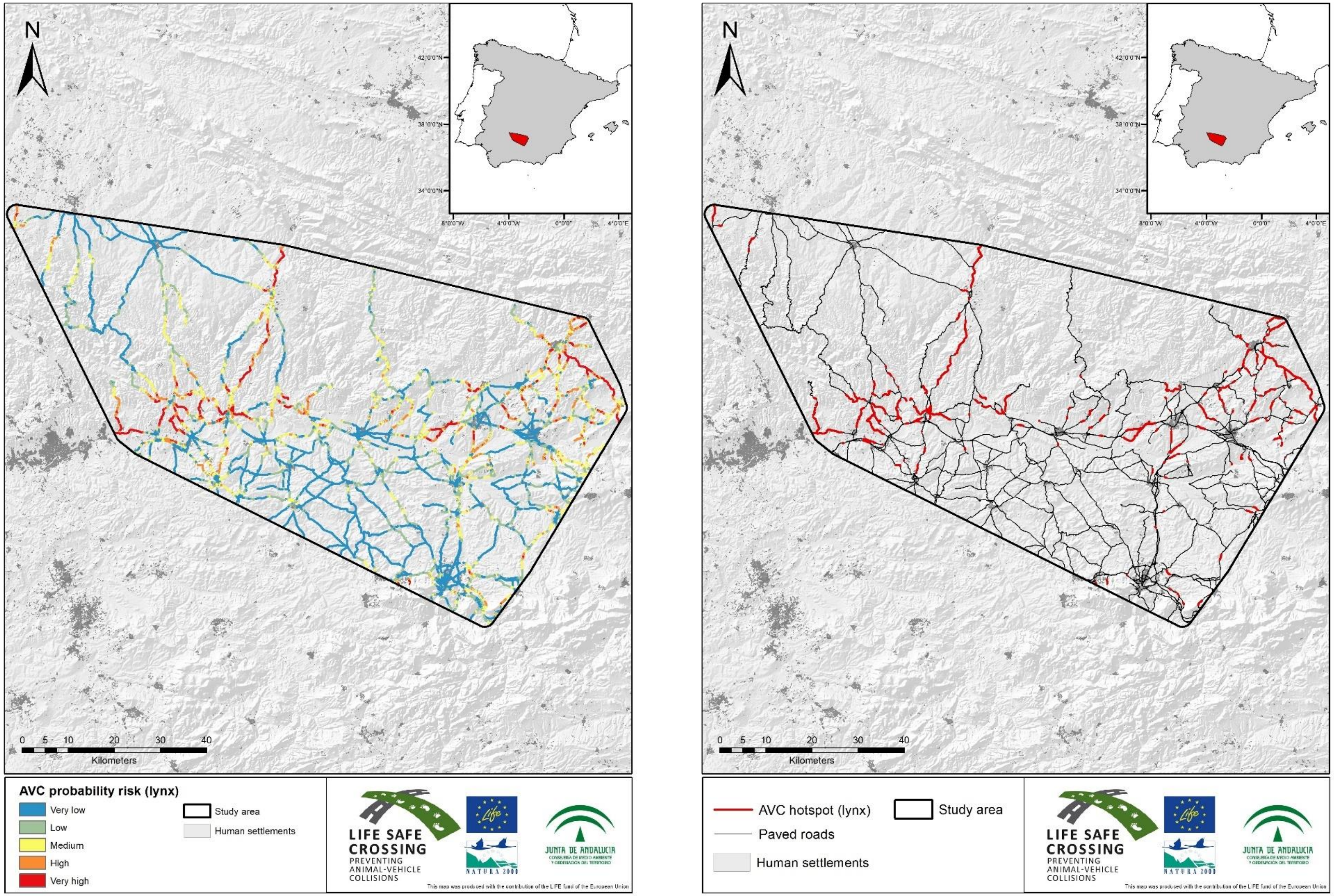


Figure 16 – AVC probability risk maps for lynx divided in 5 classes of risk (very-low, low, medium, high, very-high), and their respective hotspot road sections, in the Sierra Morena (Spain).



5. GENERAL CONSIDERATIONS

All the models developed showed a significant power. The range was within 0.75 (Iberian lynx in the Doñana National Park, Spain) and 0.95 (equally, mesocarnivores in Greece, and brown bear in Romania) for AVC and 0.92 (brown bear in Romania) and 0.87 (equally, brown bear in the PNALM study area, i.e. Italy, and in Greece) for crossing.

The results obtained and the maps produced can represent an important management tool to define and prioritize the future management interventions to mitigate the effects of vehicular traffic on Carnivore conservation in a human-dominated context.

Surely, it is also important to underline the limits of the model mainly related to the availability of information. Accordingly, previous studies have found that road-kills involving carnivores can depend on population density, species biology (e.g., seasonal and circadian effects), habitat and landscape structure, road and traffic characteristics (Clevenger et al. 2003; Grilo et al. 2009; Find'o et al. 2019; Garrote et al. 2018). In these analysis, whereas anthropogenic components and landscape structures were accounted for predicting the risk of AVC and crossing, others road–related features that shown to affect road-kills were not available, for instance vehicle speed (Jaarsma et al. 2006), traffic volume (Clarke et al. 1998), and type of nearby passages (Clevenger et al. 2003; Malo et al. 2004). In addition, due to the reduced number of brown bear's road-kills collected in the Italian study areas (i.e., PNALM and PNM), it was necessary combine brown bears and wolves AVC data, limiting the models to predict large carnivores AVC probability risk.

To conclude we can say that the results obtained are important from a methodological point of view because they are based on a common and standard approach for the different countries involved in the project.

The MaxEnt models, projected maps (in both shapefile and raster format), and all ancillary results of this action have been provided to all the partners, in order to be used in their management activities also after the project end.

In the last year of the project, the data collected during the project implementation will be used to validate AVC models.

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APPENDIX

Table S1 – Optimal grain size(s) for each variable used in the final AVC models, in Greece. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	AVC models	
	target	mesocarnivore
Agri	6470	6470
Shrubs	2000	3500
Grass	5000	3500
TCD	5000	2000
DEM	5000	400
Road1	1500	1500
Road2	400	3500
Road3	6470	400
DistViad	-	-
DistHS	-	-

Table S2 – Optimal grain size(s) for each variable used in the final crossing models, in Greece. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	Crossing model
	target
Agri	400/6470
Shrubs	400
Grass	400/6470
TCD	400
DEM	400
Road1	5000
Road2	400/6470
Road3	5000
DistViad	-
DistHS	-

Table S3 – Optimal grain size(s) for each variable used in the final AVC models, in Italy. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	**AVC model (PNALM)**			**AVC model (PNM)**			
	target	**deer**	**wild boar**	**target**	**deer**	**wild boar**	**mesocarnivore**
Agri	400	4000	1000	2500	2000	400	2500
Shrubs	4650	400/4000	1000	3500	2000	4650	1500
Grass	-	-	-	-	-	-	-
TCD	4650	400	1000/4000	400	3500	400	4650
VRM	4650	1000	2000	1000	3000	1500	400
Road1	2000	3500	2500	4650	1500	4650	4650
Road2	400	400	1000	1000	3500	400/4650	400
Road3	400	1500	2500	4650	3500	4650	2500
DistViad	-	-	-	-	-	-	-
DistHS	-	-	-	-	-	-	-

Table S4 – Optimal grain size(s) for each variable used in the final crossing models, in Italy. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	**Crossing model (PNALM)**	**Crossing model (PNM)**
	target	**target**
Agri	4650	400
Shrubs	2000	4650
Grass	4650	400
TCD	4650	1000
VRM	4650	4650
Road1	1500	4650
Road2	1000	1500
Road3	1500	2500
DistViad	-	-
DistHS	-	-

Table S5 – Optimal grain size(s) for each variable used in the final AVC models, in Romania. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	AVC model
	target
Shrubs	5880
Grass	400
TCD	1500
Road1	1000
Road2	1000
DistViad	-
DistHS	-

Table S6 – Optimal grain size(s) for each variable used in the final crossing models, in Romania. Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	Crossing model
	target
Shrubs	3500
Grass	1000
TCD	1500
Road1	2000
Road2	1500
DistViad	-
DistHS	-

Table S7 – Optimal grain size(s) for each variable used in the final AVC models, in Spain (Doñana National Park and Sierra Morena). Multi-grain variables were tested for multicollinearity, including all variables with r<|0.7| and VIF<5.

Variables	**AVC model**	
	Donana	**Morena**
AgrHet	2080	400
AgrInt	1000	1000
AgrTree	1000	1000
Forest	-	1000
Shrubs	1500	400
Grass	400	400
TCD	1000	400
DEM	1000	2080
Slp	2080	2080
Road1	400	2080
Road2	400	1000
Road3	2080	1500
DistViad	-	-
DistHS	-	-