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Biodiversity Monitoring with Intelligent Sensors: An Integrated Pipeline for Mitigating Animal-Vehicle Collisions

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Abstract

Transports of people and goods contribute to the ongoing 6th mass extinction of species. They impact species viability by reducing the availability of suitable habitat, by limiting connectivity between suitable patches, and by increasing direct mortality due to collisions with vehicles. Not only does it represent a threat for some species conservation capabilities, but animal vehicle collisions (AVC) is also a threat for human safety and security in transport and has a massive cost for transport infrastructure (TI) managers and users. Using the opportunities offered by the increasing number of sensors embedded into TI and the development of their digital twins, we developed a framework aiming at managing AVC by mapping the collision risk between trains and ungulates (roe deer and wild boar) thanks to the deployment of a camera trap network. The proposed framework uses population dynamic simulations to identify collision hotspots and assist with the design of sensors deployment. Once sensors are deployed, the data collected, here photos, are processed through deep learning to detect and identify species at the TI vicinity. Then, the processed data are fed to an abundance model able to map species relative abundance of species around the TI as a proxy of the collision risk. We implement the framework on an actual section of railway in south-western France benefiting from a mitigation and monitoring strategy. The implementation thus highlighted the technical and fundamental requirements to effectively mainstream biodiversity concerns in the TI digital twins. This would contribute to the AVC management in autonomous vehicles thanks to connected TI.

Keywords: Abundance Modelling, Animal Vehicle Collision, Autonomous vehicle, Camera Traps, Computer Vision, Connected Transport Infrastructure, Deep Learning, Digital Twin, Risk Management, Ungulates.

Introduction

Transports of people and goods contribute to the ongoing 6th mass extinction of species (Forman and Alexander 1998, Holderegger and Di Giulio 2010, Haddad et al. 2015, IPBES 2019, Grilo et al. 2021). They impact species viability by three main processes (Teixeira et al. 2020). Transport infrastructure (TI) can have an impact on species: 1) by reducing the availability of suitable habitat for species (Ouédraogo et al. 2020, Kroeger et al. 2021, Fischer et al. 2022, Remon et al. 2022), 2) by limiting the functional connectivity between patches of suitable habitat (Ujvári et al. 2004, Balkenhol and Waits 2009, Safner et al. 2011, Remon et al. 2018, 2022), and 3) by increasing direct animal mortality due to collisions with vehicles (Ceia-Hasse et al. 2018, Testud and Miaud 2018, Lehtonen et al. 2021, Moore et al. 2023).

Not only does it represent a threat for some species conservation capabilities, animal vehicle collisions (AVC) is also a threat for human safety and security in transport when large species are involved. Animal vehicle collisions events also represent a massive cost for TI managers and users due to infrastructure and vehicle repair or compensations for damages (Huijser et al. 2009). For instance, bird strikes represent a 1.2 billion US$ cost annually to the aerial transport sector (Allan 2000) and caused more than 700 human death since 1905 (Avisure 2019, Metz et al. 2020). Moose road-kills along a 61 km railway in central Norway cost 250 000 US$ annually (Jaren et al. 1991).

In Europe, terrestrial AVC often involve large mammals (Grilo et al. 2021) such as moose (*Alces alces*), roe deer (*Capreolus capreolus*), or wild boar (*Sus scrofa*). Animal vehicle collisions also impede conservation programs across the EU particularly concerning large carnivores like grey wolve (*Canis lupus*), brown bear (*Ursus arctos*), or Eurasian lynx (*Lynx lynx*) (Bauduin et al. 2021, Grilo et al. 2021). In addition, large mammal populations tend to increase across the EU. For instance, Ledger et al. (2022) highlighted respectively a 331% and 287% increase of the red deer and roe deer population in the EU.

Thus, solution to ensure traffic safety without enclosing the transport network should be found to limit the barrier effect of transport infrastructure on large mammals without increasing, and rather ultimately reducing, the number of AVC (Grilo et al. 2021, Seiler et al. 2022).

The transport system is in a deep digital transformation with the development and deployment of data-driven TI management (ITF 2021). Thus, an increasing number and diversity of sensors is embedded into TI providing time-continuous information to TI managers ultimately through the TI's digital twin (DT) which is the digital representation of the physical TI (Grieves 2016, Batty 2018, Singh et al. 2021). Indeed, future roads are expected to become able to produce their own energy, be self-monitored thanks to multiple embedded sensors, be carbon neutral and ensure biodiversity gain. Such an autonomous system is expected to also produce multiple services thanks to its digital copy collecting and analysing the sensors' data (Hautière et al. 2012, in press, ITF 2023). To date, collected data are mainly used for TI maintenance or user safety (Moulherat et al. 2022). In addition to the TI management, connected TI are expected to provide information to the vehicle which, in turn, would become more and more autonomous in the near future (Seiler et al. 2022, ITF 2023). In this perspective, sensors embedded in the TI are providing the infrastructure digital model with data collected and analysed for providing relevant information that can feed the TI users including vehicles and therefore drivers (ITF 2021, 2023).

Unfortunately, biodiversity concerns are not yet part of this TI digital environment which nevertheless offers a suitable place for biodiversity-based risk management such as AVC (van Eldik et al. 2020, ITF 2021, 2023, Djema 2022, Moulherat et al. 2022). Indeed, sensor-based animal recognition ability, thanks to artificial intelligence and particularly deep learning, is growing very fast (Tuia et al. 2022) making it possible to automatically detect and recognize the main species involved in AVC in the EU (Aodha et al. 2018, Demertzis et al. 2018, Rigoudy et al. 2022). From a TI management perspective aiming at reducing AVCs, the main current applications are, to date, based only on large mammal detection and aimed at informing drivers of the presence of a big animal. The animal detection can be used to animate dynamic panels or to threaten individuals approaching the TI with a combination of light and sounds with sometimes limited efficiency (Seiler and Olsson 2017). Collecting and analysing species detections (and non-detections) provided by sensors in the TI DT would contribute to improve the AVC management. Indeed, once identified, a collision risk map may be produced by models able to approximate the passage rate of the species involved in AVC around the TI. In this perspective, occupancy or abundance modelling can produce spatial estimates of presence probability or abundance, respectively (Burton et al. 2015, Gilbert et al. 2020, Gimenez et al. 2022, Tuia et al. 2022). Such maps would therefore provide drivers and connected vehicles with relevant context information about the actual risk of species involved in AVC presence.

With the OCAPI initiative, the goal is to enhance the integration of biodiversity-oriented digital facilities into the DT of TI (Moulherat et al. 2021). In this paper, we develop a framework aiming to provide large mammal's presence risk in the TI vicinity based on sensor-based monitoring system. The framework is applied on an actual AVC hotspot between ungulates (roe deer and wild boar) and trains in south-western France benefiting from a mitigation measures program. In this context and based on the monitoring program planned as well as simulation of spatially explicit ungulate's population dynamics implemented in 2021, we simulated ungulates detection stories, mapped their presence risk close to the TI, and tested the model performances to predict the theoretical AVC risk. Then, in 2022-2023, after monitoring for a single year, we applied the theoretical framework to the real situation to test the system for further improvements.

Methods

The methodological framework developed and implemented in this study is composed of 5 major steps (Figure 1). This framework begins with a sensor-based monitoring design phase (step 1 to 3) based on population dynamic simulations of focal species (step 1). The framework then tests the monitoring design expected efficiency in an iterative process (steps 2 and 3). Step 4 of the framework is dedicated to sensor-based data processing, thanks to deep learning, which, in turn, feed abundance models, providing a proxy of the AVC (step 5).

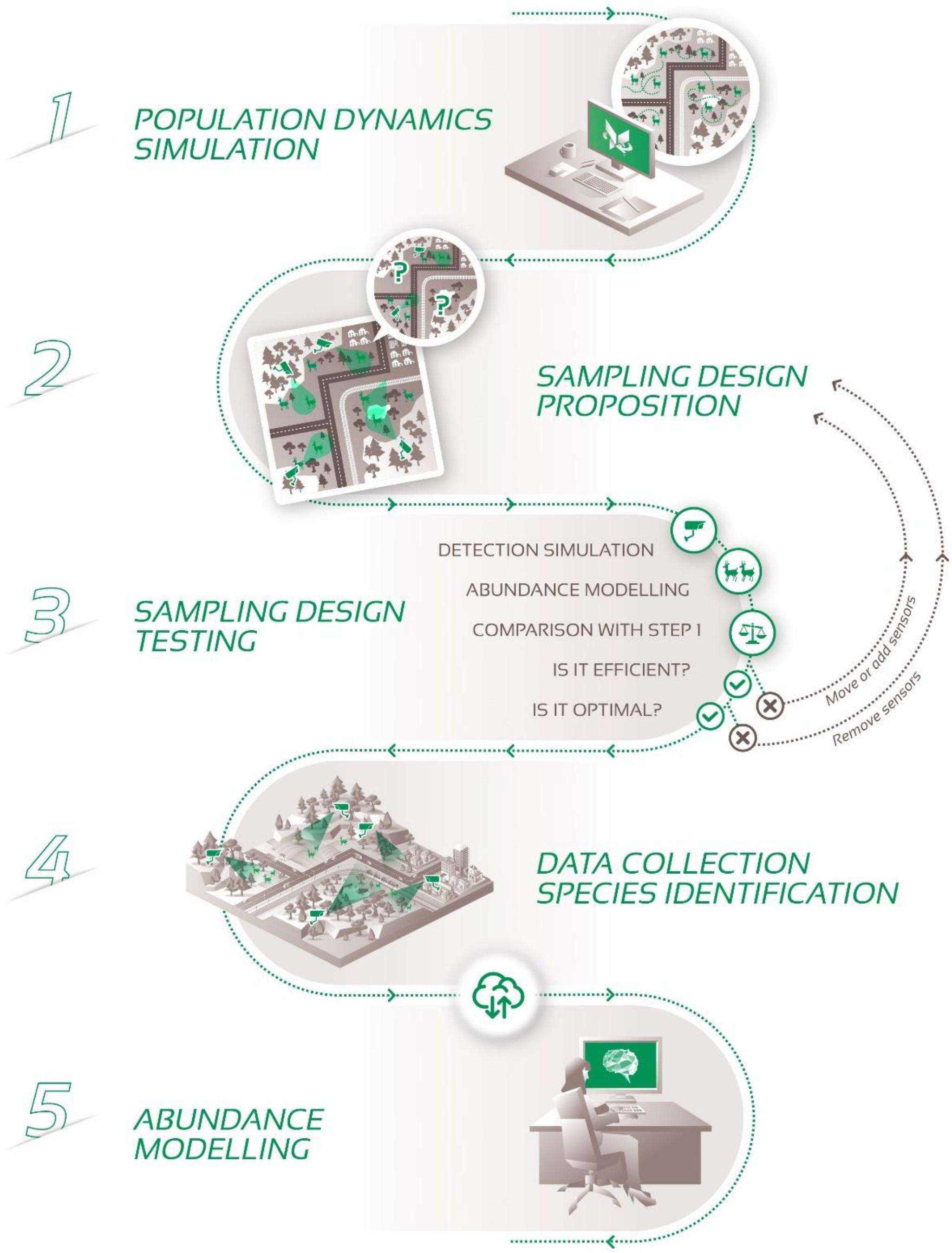

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Figure 1: Framework to deploy sensors along a transport infrastructure to map the animal abundance in the transport infrastructure vicinity in order to manage the animal vehicle collision risk.

Study Site

The study site is a 19.7 km section of the railway joining Toulouse to Agen in south-western France (Figure 2). This section supports about 24 trains daily and was identified by the TI managers for its frequent collisions with large wild mammals (mainly roe deer and wild boar). This site is part of a regional AVC reduction program launched by the French railway network management company (SNCF Réseau) in 2018. The program concerns 5 strategic sites with a high number of AVC, where a statistical analysis of collisions conditions has been performed (Gaillard 2013, Saint-Andrieux et al. 2020) and combined with spatially explicit population dynamic simulations of ungulates to identify the most sensitive places to AVC (Boreau de Roincé et al. 2018). Then, scenarios of mitigation measures have been proposed and their cost-efficiency evaluated based on the expected population functioning after scenarios implementation thanks to new simulations (Zurell et al. 2021, Moulherat et al. 2023). At the same time, a regional camera trap monitoring program following a *Before After Control Impact* (BACI) design (Smith 2002) was designed to evaluate the mitigation measures efficiency. The main mitigation measures planed on the study site are the upgrading of two existing bridges by reshaping the bridges' embankment (sectors 1 and 2, Figure 2) and the fencing of 4 sections of the railway to drive animals to existing or upgraded passages or safer crossing places (sectors 1, 2, 3 and 4, Figure 2). The work concerning the bridges upgrading is planned for 2025.

The study site benefits from a land use map produced by combining data from Corine Land Cover (Büttner et al. 2017), BD TOPO® (IGN 2021), ROUTE 500® (IGN 2020), dedicated fieldwork, and photointerpretation within a 5-km buffer zone around the 19.7 km of the studied railway section. Habitats have been characterised into 26 classes based on the standard EUNIS typology.

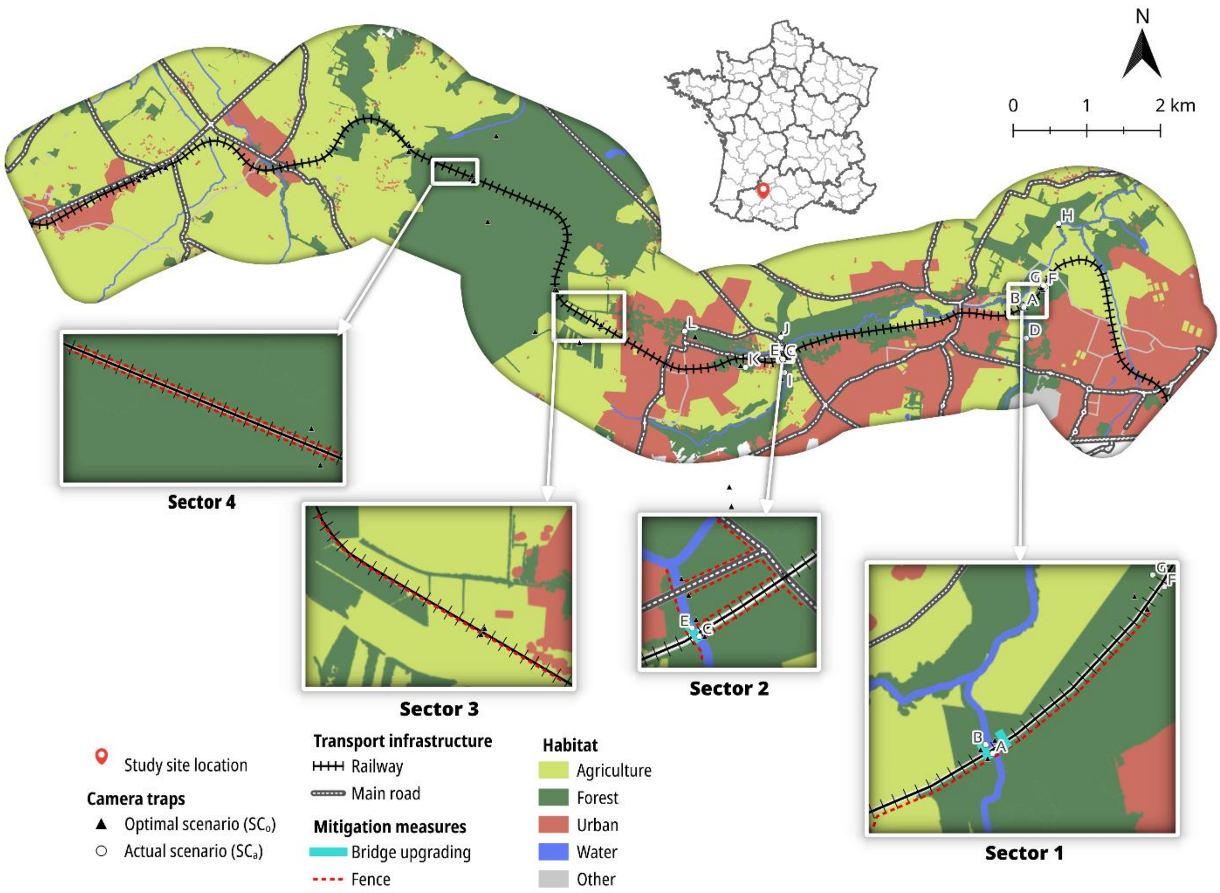

Figure 2: Study site in south-western France focused on 19.7 km of railway where numerous AVC occurred the last 10 years. The land cover is represented using the 5 main habitat typologies as used for the statistical analysis. Camera traps deployed on the field are identified by a letter from A to L.

Ungulate *Population Dynamic Simulation*

As a part of the AVC hotspot identification, we used SimOïko to perform spatially explicit population dynamic simulation of ungulates on the study site. SimOïko is an individual-based spatially explicit model developed to perform population viability analysis based on the MetaConnect model (Moulherat, 2014). In the model, each individual of the simulated population is a unique agent whose virtual life is driven by stochastic processes. For example, survival of an individual depends on the result of a Bernoulli event with probability *p* corresponding to the average survival of the individual age class.

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The model assumes that individuals live in panmictic patches of suitable habitat. In this study, roe deer and wild boar, the AVC target species, are not explicitly modelled. Instead for the sake of simplicity, we used a virtual species representative of a mixture of roe deer and wild boar life history traits (Caro and O'Doherty 1999, Caro et al. 2005, Baguette et al. 2013) hereafter called *ungulate*. Suitable patches for *ungulate* in this landscape are expected to be forests and shrublands.

We modelled the dispersal behaviour of *ungulate* moving between suitable habitat patch using the SimOïko embedded Stochastic Movement Simulator (SMS) algorithm (Palmer et al. , 2011). The SMS algorithm assumes that individuals can perceive their environment to a certain distance and tend to use the "easiest" path within this perceptual range. Thus, the model needs a rugosity map reflecting the ability of individuals to cross the different types of land cover existing within the study site landscape matrix. Thus, for each of the 26 natural habitat types of the study site, a rugosity coefficient is assigned based on expert opinion on *ungulate* moving abilities (Dutta et al. 2022) (see supplementary material for the comprehensive parameterisation of SimOïko). SimOïko's input maps are rasterized using a 5x5 m pixel resolution.

Simulation were initialised with 118 individuals assuming that all the potential suitable patches are occupied at their maximum carrying capacity. The simulation runs for 100 years which is sufficient to ensure the metapopulation dynamic stabilisation for at least the last 50 years (see supplementary material). Therefore, only the results from the last 50 years were used. Simulations were repeated 50 times.

As a result, the model provides the expected number of individuals living in the studied landscape and a map of the cumulative number of animal passage per map pixel during the simulation time (Moulherat 2014).

Monitoring Strategy

To map the abundance of *ungulate* in the TI vicinity using the camera traps deployed for another purpose (e.g. evaluate the mitigation measures efficiency), we mimic the expected monitoring process and analysis to evaluate its effectiveness in an iterative four step process:

1. Propose a location of camera traps scenario.
2. Use the camera trap location scenario and the movement simulation results to simulate detection stories.
3. Analyze the simulated monitoring results with abundance modelling.
4. Compare the movement simulation and the abundance model results in order to control the monitoring program ability to be used for mapping the abundance of *ungulates*. If not, come back to step 1 if some adaptations are possible, else, the ability to actually map the *ungulate*'s abundance is not expected.

Monitoring Program

On the study site, we designed a monitoring program to evaluate the efficiency of 2 bridges upgrades (including fencing) (sectors 1 and 2 Figure 2) and the fencing only of 2 additional sections (sectors 3 and 4 Figure 2) in reducing AVC. Each section benefiting from a mitigation measure is expected to be monitored by a network of minimum 6 cameras. A couple of cameras are recording each side of the railway (entrances of bridges or observed animal's tracks on the field for the fencing projects) to monitor crossing events. Two other cameras are deployed in forests, between 177 and 651 m from the railway, as controls of the *ungulate* activity in the surrounding suitable habitats (Figure 2). Another pair of cameras are placed to survey crossing events in sections not benefiting from mitigation measures as a control of the crossing activity. Additional cameras are added to monitor crossing events in section not benefiting from mitigation measures, but with suspected high crossing frequency or for which simulations results show a possible crossing location deferment. Thus, the total program comprises 38 cameras each deployed for 5 years minimum and hereafter called *Optimal scenario* (SC_o). The monitoring began in August 2022. However, due to TI manager investment abilities, the monitoring could only start for the two bridges upgrading reducing the study site section to 11.7 km long for the framework showcasing (sectors 1 and 2 Figure 2). The continuous deployment of 12 camera traps (Bolyguard, MG984G-36MP 4G) required to monitor these two sections, will be maintained for at least 5 years by the local hunter association and is defined as the *actual scenario* (SC_a).

Both scenarios of camera trap deployment (SC_o and SC_a) were evaluated for their expected ability to provide relevant mapping of *ungulate* abundance close to the TI.

Virtual and Actual Camera-Trap Data Processing

Frequentation Story Simulation of the Virtual Camera Traps

We used the simulated frequentation map to mimic a camera trap survey leading to a frequentation history of 30 recording occasions. Thus, for each sampling occasion, the number of detections in a pixel containing a camera trap is simulated as a random event following a Poisson distribution. The average value of this distribution corresponds to the average number of passages of *ungulates* within the pixel during a single time-step of the population dynamics simulation. In this respect, we divided the average number of passages of dispersing individuals by the proportion of dispersing individuals.

Deep Learning Algorithm Training for Wild Boar and Roe Deer Automatic Detection.

To recognize the main species (here roe deer and wild boar) involved in AVC on the images produced by the monitoring program, we used a deep neural network call YoloV8 (Jocher et al. 2023). This model is known to be fast and accurate for detecting and classifying objects in images. The model finds objects of interest in a picture and creates a bounding box around them. Then the model assigns a category to the bounding box such as a species name in this work. In this perspective, we fine-tuned a YoloV8 pre-trained on the COCO data set (Jocher et al. 2023) with the project data set (Weiss et al. 2016).

The project data set is composed of 40 358 images provided by 41 data providers across France and annotated by 51 experts thanks to the project's collaborative annotation platform (www.ocapi.terroiko.fr). This data set was completed by the images of the COCO data set containing animals or vehicles. Annotations consist in bounding boxes drawn on the pictures and labelled with the name provided by the French national taxonomic referential (Gargominy et al. 2021). The dataset was split randomly into a train (80%) and validation (20%) data set. The train data set contained 262113 boxes from 26 labels including 1307 boxes of wild boar (*Sus scrofa*) and 418 boxes of roe deer (*Capreolus capreolus*). Approximately 5.5% of the images were empty (no animals, nor human or vehicle). Other frequently observed labels included humans, vehicles, foxes, badgers, dogs, cats, horses, chamois, lynx and leporidae, among others. We used an independent data set as test. The test data set is composed of 1174 images containing 212 boxes of roe deer and 24 of wild boar. Thirteen other species with an average of 72.8 boxes (ranging from 1 to 188) per species are present in the test data set.

Frequentation Story of the Deployed Camera Traps

Here we used the photos taken from 29 August 2022 to 16 April 2023 (33 weeks) for 11 sites, and from 24 October 2022 to 16 April 2023 (25 weeks) for the site E to test the framework in real conditions. The local hunter association made simple annotations by identifying the species seen on the pictures (no bounding boxes) using 3 classes labelling system: ungulate (roe deer and wild boar), human/vehicle and other, including any other species and the empty pictures. The data set thus produced is then called the showcase data set. When observations were closer than three minutes apart, only the first observation was kept as the camera-trap was likely triggered several times by the same individual (Rovero and Zimmermann 2016). The observations were discretised into weekly intervals to generate

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the detection history, which records the number of ungulate detections per week and camera trap site.

Abundance Modelling

In this paper, we do not aim to estimate the absolute *ungulate* abundance within the study site, but rather spatially estimate their relative abundance to identify the places with higher collision risks. To do so, we used the N-mixture model proposed by Royle (2004). In this respect, the study area was split into hexagonal cells of 200 m large, leading to 3.5 ha cell's area. The analysis was performed in R version 4.3.0 (R Core Team 2023) using the *pcount* function from the unmarked package (Fiske and Chandler 2011, Kellner et al. 2023).

To test the monitoring design efficiency, we compared the normalised simulated spatial pattern of *ungulate* movements with the normalised abundance predicted by two models using different covariates. The first model (*Mod1*) is built with a single site covariate: the sum of the movements in the cell during all time-steps of all repetitions. The number of sensors per cell is also used as detection covariate in *Mod1*. The second model (*Mod2*) is based on ecological covariate rather than population dynamic simulation output. *Mod2* used several spatial covariates extracted from the land use map:

- The percentage of agriculture, forest, urban and water in each cell.
- The distance between the camera traps and the closest agriculture, forest, railway, road, urban area, water (*for model parameters optimisation*).
- The distance between the cell centroid and the closest agriculture, forest, railway, road, urban area, water (*for prediction over all the map*).

We performed a PCA with the areas of agriculture, forest, urban, water per cell to reduce the number of variables explaining landscape variability in the area while managing the correlation between variables (Gimenez and Barbraud 2017). The two first principal component were kept, representing respectively 84,4% and 12,9% of the variance. The first principal component mainly represents the gradient between forests and urban areas, whereas the second represents the gradient between agricultural areas and the other habitats. We therefore used the cell coordinates on these two axes as synthetic uncorrelated descriptors of the cell habitats characteristics. In the spirit of principal component regression (Graham 2003), the model's covariates were selected on the basis of their predictive capacity, according to the Akaike information criterion (AIC) (Akaike 1974, Burnham et al. 2002), and their ability to represent the variability of the habitats in the study area. For abundance covariates, the distance to each habitat and the two synthetic variables were tested. For detection covariates, the average weekly temperature and the weekly rainfall were tested. We selected the model covariates based on the actual frequentation story. The final model is built of three covariates, the two synthetic covariates from the PCA and the distance to the railway. Only *Mod2*, was used to map the actual abundance of *ungulates*.

Results

Testing the Sampling Design

The simulation process aiming at mimicking the camera trap survey under the SC_0 scenario is composed of 27 sites with 1 to 3 camera per site. The average detection per sampling occasion is of 21.2 occurrences (ranging from 0 to 90 occurrences.

Considering the SC_a scenario, based on 12 sites with a single camera, the average detection per sampling occasion is 11.5 occurrences (ranging from 0 to 29 occurrences). With both scenarios, all sites benefit from at least one detection.

Modelling the Simulated Abundance of Ungulate with Simulated Frequentation Stories

The sampling effectively catches most of the overall simulated movement patterns, both with the expected (SC_0) and actual (SC_a) sampling (Figure 3). Both protocols identify the same potential collision hotspots due to higher ungulate abundance (Figure 3). The *Mod1* model prediction is similar to the population dynamic simulation results under SC_0. However, under SC_a, the global pattern also corresponds to the initially simulated pattern but the lack of cameras in cells mainly composed of forest habitats with very high simulated frequentation over concentrates the abundance prediction in a limited number of cells. With *Mod2*, the global pattern leads to similar most frequented places in the landscape as *Mod1* and the population dynamic results for SC_0 and SC_a. While *Mod1* over concentrates the abundance in a limited number of cells compared to the simulation results, *Mod2* tends to retrieve a similar abundance general pattern but to over spread the abundance around the high abundance cores.

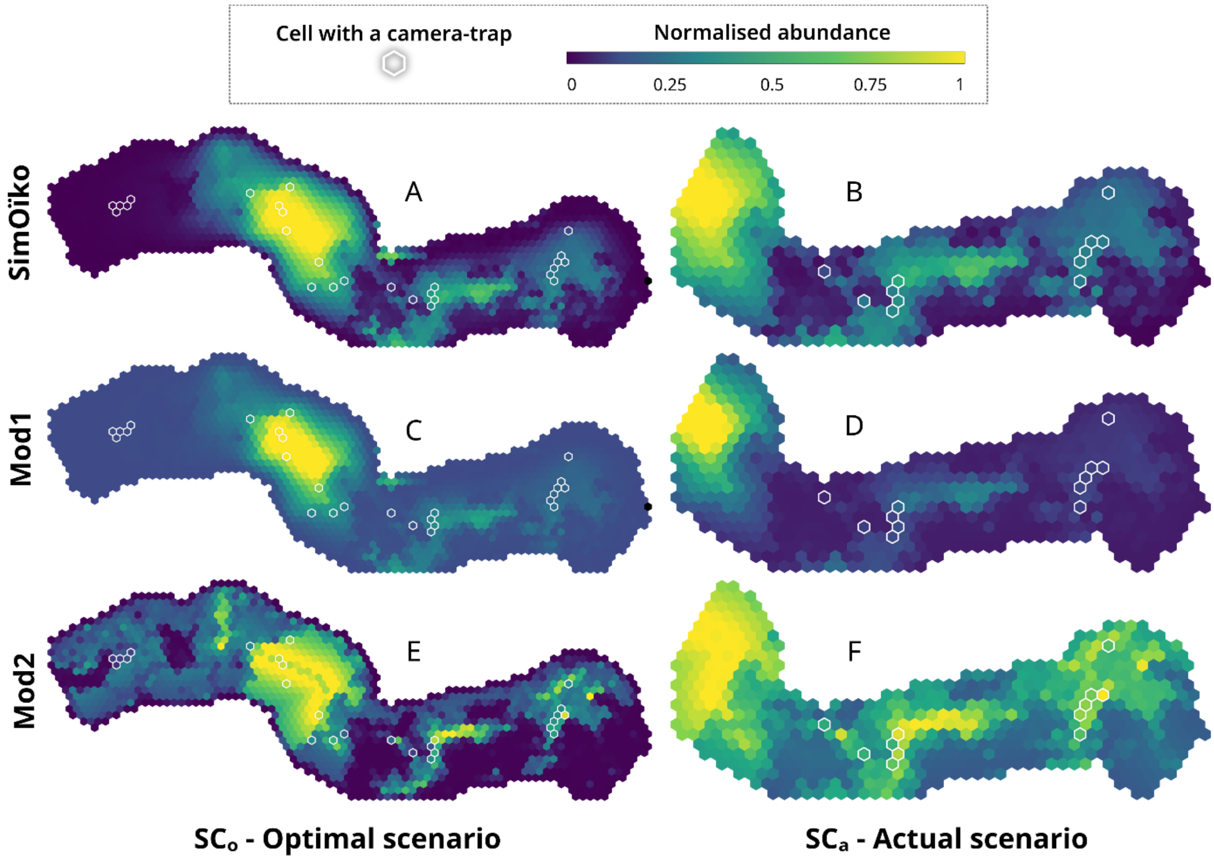

Figure 3: Normalized relative abundance of ungulates per 3.5 ha cell simulated by the population dynamic model (panels A and B), the *Mod1* abundance model (panels C and D) and the *Mod2* model (panels E and F) for SC_0 (panels A, C and E) and SC_a (panels B, D and F). For comparison purposes, the normalisation was performed by normalising each cell of a map by the 97.5 percentile value. Regardless of the abundance modelling scenario, the sampling scenarios are expected to be able to identify relatively the riskiest sectors.

Estimating the Actual Abundance of Ungulates

Automatic Species Recognition

On the OCAPI data set, the mAP@0.5 metric (mean average precision when the intersection over union (IoU) (Padilla et al. 2020), is at least 0.5) of the classification model is 0.78 (Everingham et al. 2010). The confusion matrix is built using the default parameters from YoloV8 (confidence threshold = 0.25, IoU threshold = 0.45). With precisions (Padilla et al. 2020) higher than 90% and recall (Padilla et al. 2020) ranging from about 80% to 97%, the model properly recognizes the targeted species (roe deer and wild boar) (Table 1). Using the model on the test data set, performances to recognize roe deer and wild boar fall down, highlighting the model’s lack of generalization ability (see supplementary material).

Table 1: Classification model performance. The precision reflects the model ability to limit the false positives prediction while the recall corresponds to its capability to avoid false negatives.

	Validation data set			Test data set		
	Number of annotations	Precision (%)	Recall (%)	Number of annotations	Precision (%)	Recall (%)
Roe deer	93	92.47	79.63	212	74.06	83.51
Wild boar	352	93.18	90.11	24	79.17	19.39

Considering the showcase data set, with 80.8% of good classification when an *ungulate* is actually present on the pictures (Figure 5), the model provides useful information to map the AVC risk. For 15.7% of the *ungulate* observation prediction, the picture is actually empty or contains another species (mainly badger confused with wild boar, see supplementary material). Figure 5 also points out the model's ability to identify humans and vehicles as well as other animals and empty pictures.

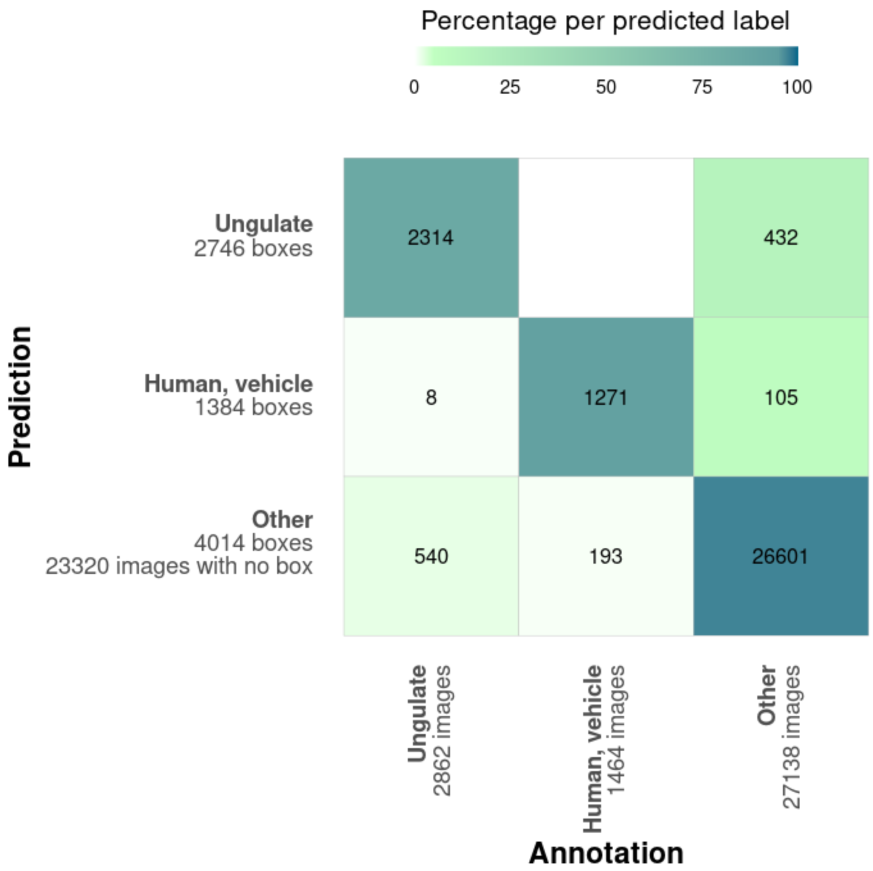

Figure 5: Comparison between prediction made by the model and the actual annotations performed by the local hunter association on the showcase data set. Pictures containing roe deer or wild boar are grouped as ungulates. Similarly, the predicted "Other" class merges boxes with other animals and empty pictures. Thus, the model predictions are presented under a form comparable to the one used by the hunter association. Details of the showcase data set processing results are developed in supplementary material.

Mapping the Actual Abundance of Ungulates

Mod2, implemented on the data issuing from the available 33 weeks monitoring program, results in *ungulates* concentrated along the two rivers crossed by the railway and in the Bouconne forest in the western part of the site (Figure 6).

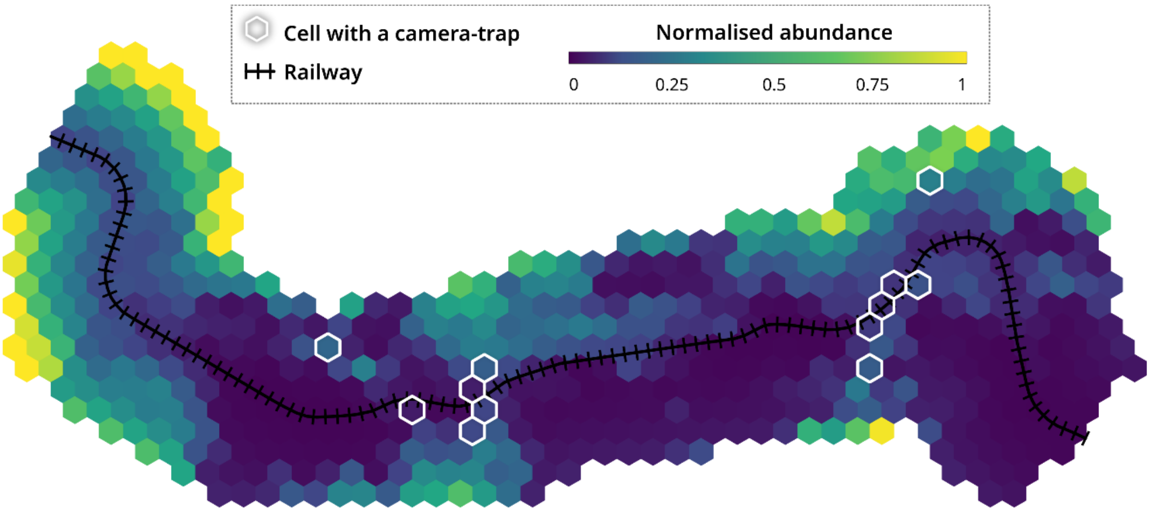

Figure 6: Normalized relative abundance of *ungulates* per 3.5 ha cell estimated by the *Mod2* model. *Ungulates* abundance is used as an AVC risk proxy along the railway section. The higher the abundance, the higher the AVC risk.

Discussion

In this paper, we associated methods from ecology, data science and engineering to develop a 5-steps framework for AVC management on a linear transport infrastructure (Figure 1). Our showcase was developed on a railway section but the framework fits to any type of transport infrastructure. Developing and actually implementing this framework on the field demonstrates that managing the AVC risk thanks to appropriate sensor deployment and data analysis is possible but that many technical as well as fundamental improvements are required before deployment may be possible in future transport infrastructures.

Embedding Biodiversity Relevant Sensors into the Infrastructure

We implemented the framework for an existing TI benefiting from a specific monitoring program. Because biodiversity monitoring is not the central job of TI managers, we can hardly expect that they would deploy a sensor network specific for that purpose. Thus, our framework was developed to be conveniently part of existing network dedicated to other goals (here evaluating the mitigation measures efficiency). However, steps 1 to 3 (the sensor-based the monitoring design phase) may be part of the TI conception phases and particularly contribute to environmental impact assessment. Indeed, population modelling are increasingly used for decision making including environmental impact assessment (Tarabon et al. 2021, Zurell et al. 2021, Boileau et al. 2022, Moulherat et al. 2023) and monitoring programs are expected to be part of the environmental impact assessment in order to control that the mitigation measures are efficient enough to ensure the “no net loss” of biodiversity (European Parliament 2014). Such a framework paves the way for the integration of biodiversity-oriented monitoring systems into the TI and its vicinity in line with proposals done for hydraulic management (Wang et al. 2022) or user safety (Proto et al. 2010).

If using existing cameras around the TI or embedding ones dedicated to biodiversity monitoring may contribute to map the AVC risk, their deployment must be optimised to ensure the system cost efficiency as well as its sustainability (Hautière et al. 2012, in press). In this respect, literature issuing from sensor-based biodiversity monitoring systems provides recommendations (e.g. distance between devices, recording frequencies, etc) (Evans et al. 2019, Kays et al. 2020, Nawaz et al. 2021). Unfortunately, these recommendations are often hardly applicable to the survey of linear structures such as roads, railways or channels. However, based on the three first steps of the proposed framework, scenarios of sensors network deployment can be tested and ultimately optimized by automatically removing or adding devices in the sensor network.

Developing Performant Artificial Intelligence to Recognize Species Involved in AVCs

The recognition algorithm fine-tuned in this work is not general enough to properly perform in operative conditions. The moderate performances of the model are due to multiple factors such as the number of annotated data used to train the model and particularly the lack of pictures taken in operative-like conditions. To improve these performances, we successfully used DeepFaune which was trained on larger data set to recognize our focal species among other French common ones (Rigoudy et al. 2022). Albeit the marginal performance improvement on the data from the showcase, its use in other places of the general monitoring program shows very poor performances for instance when cameras are elevated and animals for which only the back can be seen. To address these current limitations, further recognition algorithms developed to ultimately map AVC should focus on a limited number of relevant species and on the deployment conditions (e.g. sensor orientation, image quality, etc.). In addition, the use of deep learning to recognize species leads to changes in the form of the abundance model inputs (false positives, uncertainty in the recognition, etc.). Further research in the domain of statistical analysis of ecological data may adapt to this new form of input data (Chambert et al. 2018, Tabak et al. 2020) and may help in overcoming the current limited performance of recognition algorithms to ultimately produce an AVC risk map.

From a Static Map of AVC Risk to Real Time Driver Information

As sensors collect data continuously, our framework could possibly be improved by using abundance or occupancy models in continuous-time (Guillera-Arroita et al. 2012, 2012). Continuous-time data discretised do not respect the mathematical hypothesis of classical discrete-time models, as sampling occasions are not temporally independent (Barbour et al. 2013). A continuous-time model would make our framework more objective and reproducible, as the discretisation period is chosen arbitrarily (Rovero and Zimmermann 2016, Schofield et al. 2017, Rushing 2023), as well as the time interval in which

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images are removed because they are likely to be the same individual, and would avoid losing information (Kellner et al. 2022). Continuous-time models have recently been developed for unmarked populations (for example Guillera-Arroita et al. (2011) for occupancy, Guillera-Arroita et al. (2012) for abundance, and even Kellner et al (2022) for co-occurrence), which could be useful for collisions-involved species whose distribution is strongly linked to other species (Hebblewhite 2007, Rioux et al. 2022). This framework would also improve with the development of incremental learning (Zhu et al. 2022), to produce dynamic adaptive maps that could be ultimately sent to connected vehicles.

Mainstreaming Biodiversity in the Digital Twins of Transport Infrastructure

Digital twins are developing regardless of the TI type (e.g. road, railway, airport, etc) and the framework we proposed can be applied to any type of TI with for instance some adaptation for bird detection in a 3D explicit digital environment to manage collisions with planes (Dziak et al. 2022). Similar approaches are also being designed for the development of smart cities and territories (Catalano et al. 2021). Generalizing biodiversity monitoring integration in the interconnected digital twins of the built environment offers a great opportunity to contribute to the survey of biodiversity global trends as a co-benefit of the ongoing digitalisation of landscape management (ANZLIC 2019, Singh et al. 2021, Moulherat et al. 2022).

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