*Risk analysis model*

We treated alive animal records and roadkills as two collections of spatial points, with each point representing the presence of a living animal, , or an animal killed by a vehicle collision, , for a given species at a given location . These data can be modeled using a point process framework (Renner et al. 2015), which characterizes the spatial distribution of events through an intensity function – for and for – that describes the expected number of points per unit area. A fundamental example of such a model is the inhomogeneous Poisson process, which assumes that the intensity is spatially heterogeneous – driven by potential covariates – and that, conditional on the covariates, points are independently distributed (Baddeley et al. 2015). In this study, we move beyond this independence assumption by employing a log-Gaussian Cox process (hereafter denoted as LGCP). This model allows for spatial interactions between points (*e.g.*, attraction or repulsion) unexplained by covariates alone, by incorporating a Gaussian random field (hereafter denoted as GRF) into the intensity function of the point process (Møller et al. 1998).

The intensity of alive individuals results from the true distribution of the given species, i.e. the exposure , and the probability of location to be sampled: . As explained in Section XXX sampling effort was accounted for by descriptors of reported species in the same location, summarized through the PCA component . was modelled using habitat covariates and a spatial random effect. Accordingly, we specified the exposure layer as:

where is the intercept, , …, are the coefficients associated with spatial covariates derived from the principal component analysis on land cover types, and is the coefficient related to the covariate quantifying sampling effort. The parameters and correspond to the range and standard deviation, respectively, of the Matérn covariance function used in the GRF.

Following the risk analysis framework, the intensity of roadkills results from the exposure, , and the danger layer, :

Modelling of the exposure is detailed in equation (1). was modelled using road characteristics as covariates and a spatial random effect. We thus specified the risk model as:

where is the intercept, and , …, are the coefficients associated with speed limits, traffic intensity, distance to watercourses, and distance to vegetation, respectively. In equation (2) exposure was not directly put into the model through an offset to allow for more flexibility between risk and exposure. The associated coefficient thus quantifies the influence of exposure on roadkill occurrences. The parameters and represent the range and standard deviation, respectively, of the Barrier covariance function used in the GRF. This Barrier model constrains spatial correlations to propagate along the road network (Bakka et al. 2019).

*Model implementation*

We implemented the model in INLA version 24.06.27 under R version 4.4.3 (Rue et al. 2009). INLA is a Bayesian inference method based on deterministic Laplace approximations, which contrasts with stochastic simulation-based approaches such as MCMC. This approach enables fast yet accurate estimation, particularly well-suited for spatial models through the SPDE framework (Lindgren et al. 2011). We conducted inference independently for each species. We achieved spatial discretization using a Voronoï mesh composed of cells with a mean area of 3.46 km² (median: 3.38 km²; 95% CI: [2.06 km², 5.33 km²]). The inference workflow was structured as follows:

1. *estimation of the spatial parameters:* estimate the range and standard deviation of the Matérn covariance function for the exposure model;
2. *fitting the E layer:* fit the full exposure model while fixing the parameters of the GRF to the previously estimated values;
3. *posterior sampling:* draw 100 posterior samples of the predicted exposure from the exposure model;
4. *risk model estimation:* for each posterior sample of , fit the corresponding risk model to estimate danger .