

➤ Spatial analysis of wildlife roadkill risk from opportunistic data

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Why roadkill risk mapping at regional scale?

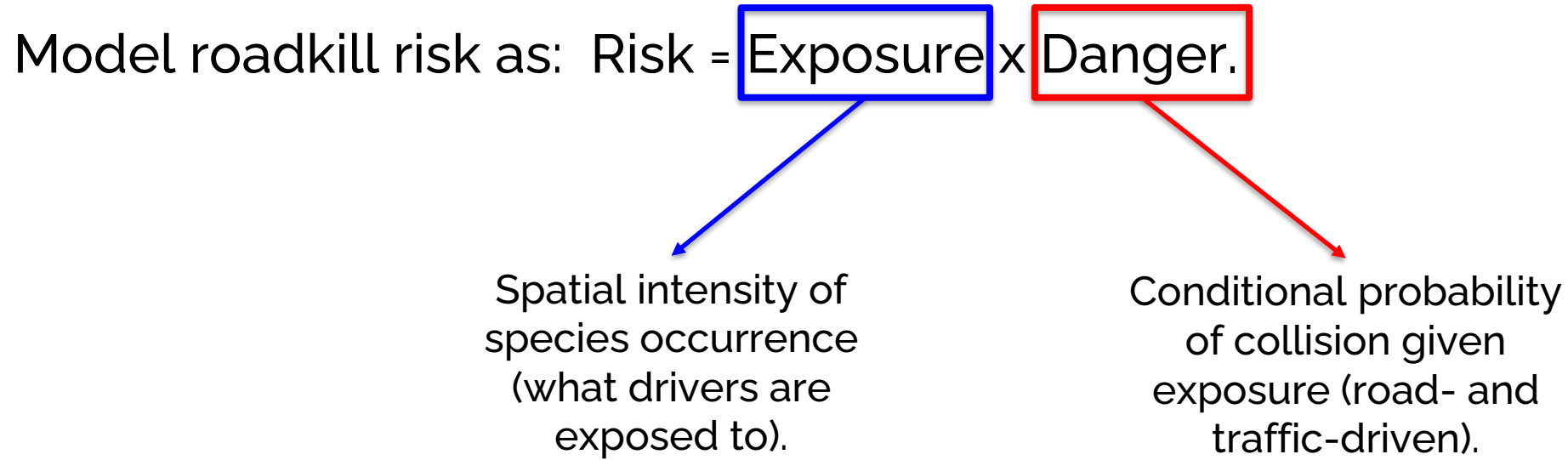
Why it matters (impact & planning)

- Roadkills impact road safety, wildlife demography and ecological connectivity.
- Mitigation exists (fencing, ecopassages, speed management) but is costly.
- So decisions require spatial prioritisation at regional scale.

Why it's challenging (data & modelling)

- No standardised surveys at regional extent
→ leverage opportunistic and practitioner data.
- But these data are strongly biased (effort, accessibility, detectability).
- Covariates can be coarse
→ need explicit multi-layer spatial statistical structure.

Why roadkill risk mapping at regional scale?



Can opportunistic data yield useful predictive maps at regional scale?

Can we separate exposure from danger, and identify their drivers?

Which road sections remain unexplained and require targeted investigation?

Selected species

Ten mammal species:

- well known both by naturalists and road patrollers
- sufficiently large body sizes to expect detection of killed individuals during non-dedicated patrols.



Red fox (*Vulpes vulpes*)



Wild boar (*Sus scrofa*)



Roe deer
(*Capreolus capreolus*)



European badger
(*Meles meles*)



Pine marten (*Martes martes*),
house marten (*Martes foina*),
least weasel (*Mustela nivalis*)
and stoat (*Mustela erminea*)
grouped as **small mustelids**



Red deer (*Cervus elaphus*)



European hare
(*Lepus europaeus*)



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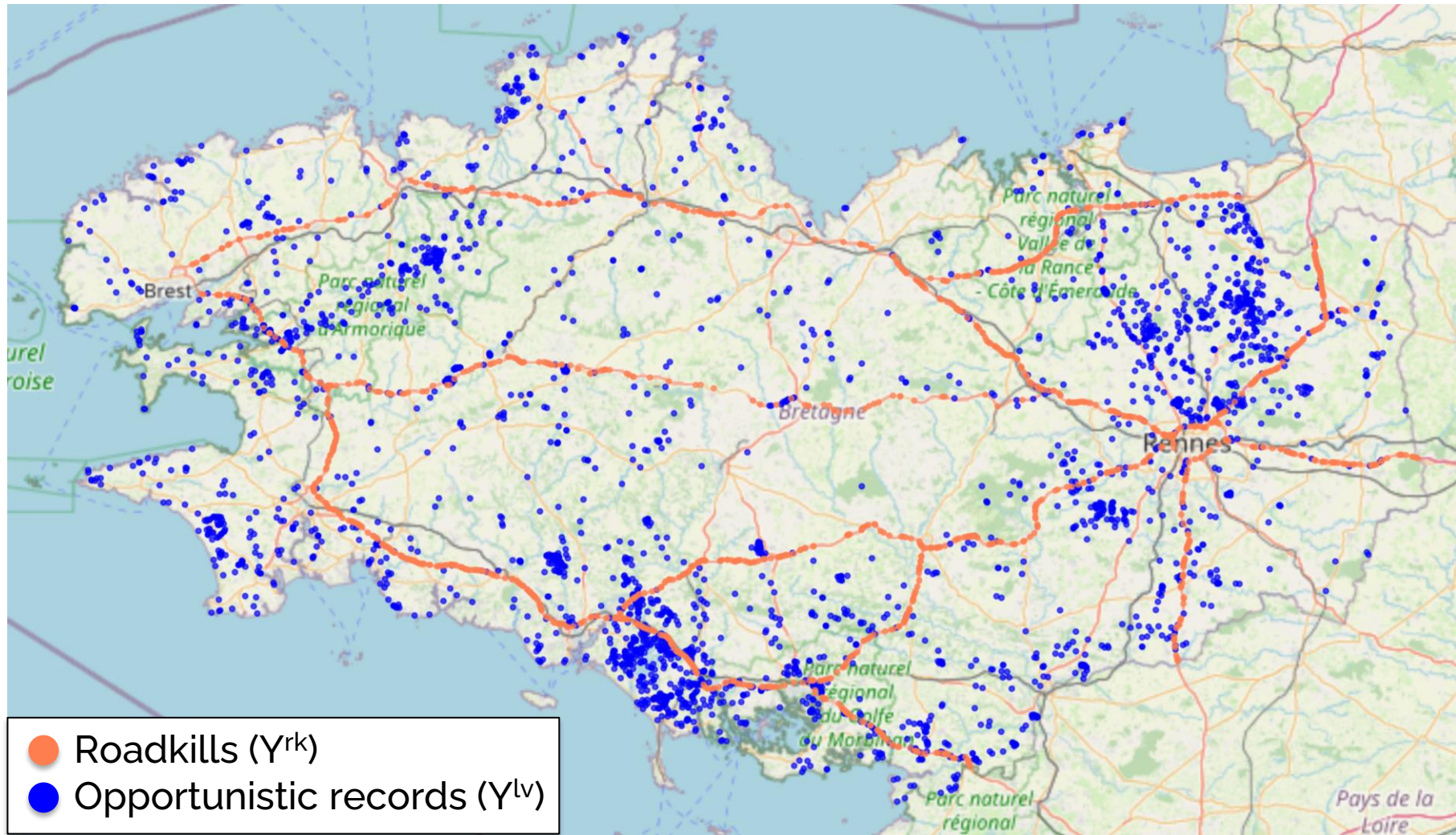
Opportunistic records and patrols



Agir pour
la biodiversité



Une voix pour la nature



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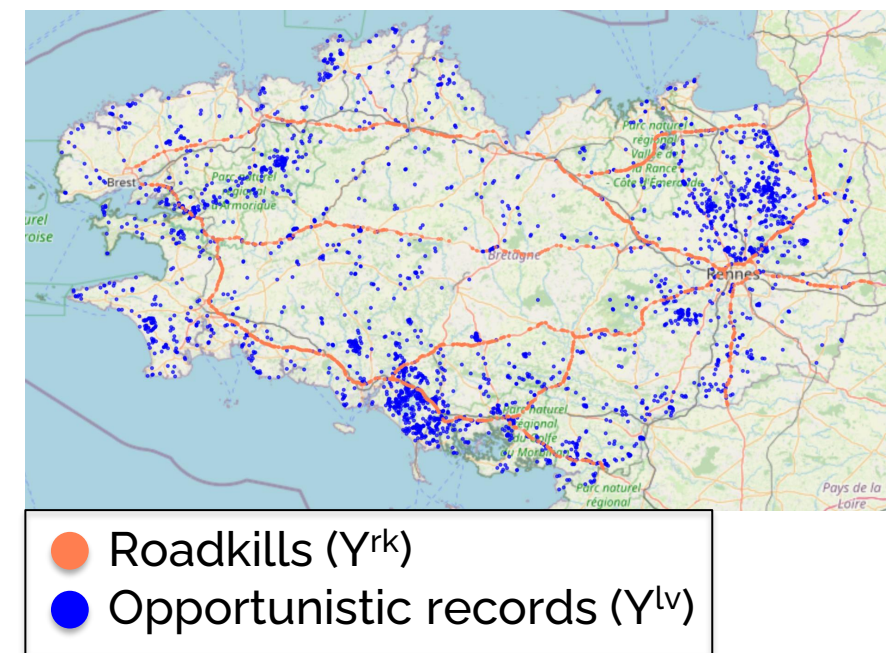
Model: exposure

$$\text{Risk} \quad \text{Exposure} \quad \text{Danger}$$

$$\Lambda_i^R(s) = \Lambda_i^E(s) \times \Lambda_i^D(s)$$

$$\begin{cases} Y_i^{\text{lv}}(s) | \Lambda_i^{\text{lv}}(s) \sim \text{LGCP}(\Lambda_i^{\text{lv}}(s)) \\ \Lambda_i^{\text{lv}}(s) = \Lambda_i^E(s) \times p_i(s) \end{cases}$$

$$\begin{cases} \log(\Lambda_i^{\text{lv}}(s)) = \alpha_0 + \sum_{k=1}^4 \alpha_k \text{PC}_k(s) + W(s) + \alpha_5 \text{SAMPLING}(s) \\ W \sim \text{GRF}(\rho^{\text{lv}}, \sigma^{\text{lv}}) \end{cases}$$



1. Total number of records
2. Number of dates with records
3. Number of species recorded
4. Number of observers

Model: danger and risk

Risk

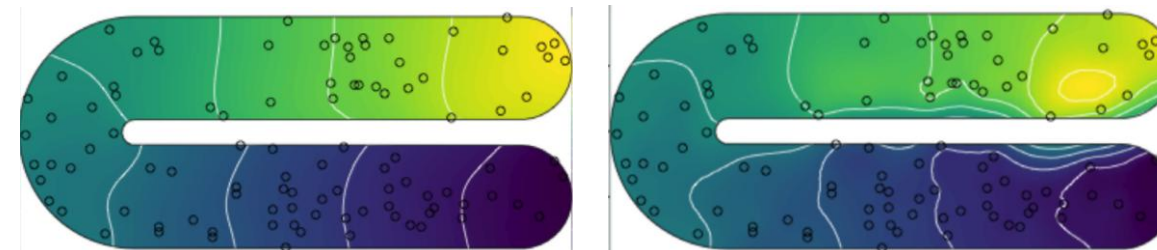
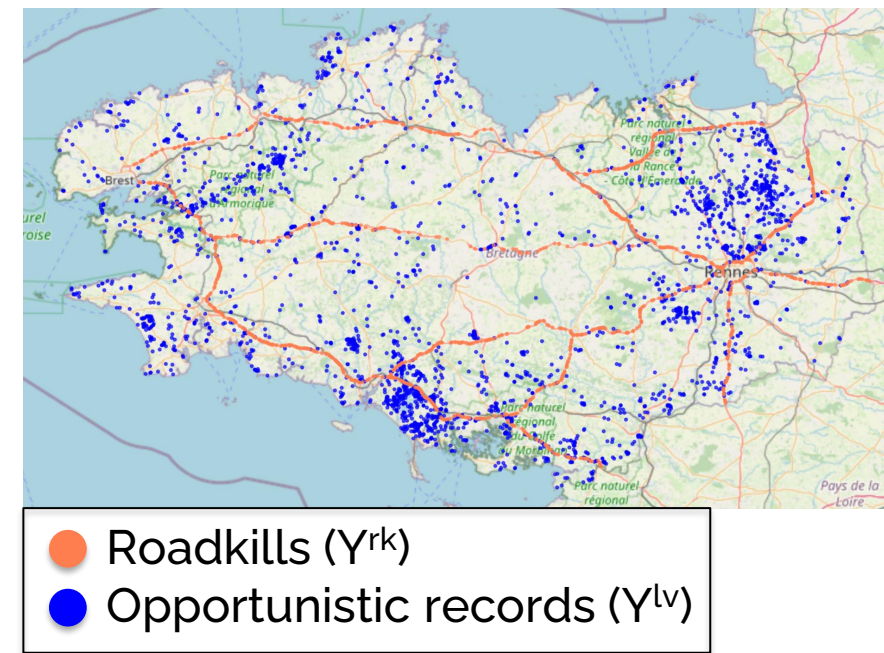
Exposure

Danger

$$\Lambda_i^R(s) = \Lambda_i^E(s) \times \Lambda_i^D(s)$$

$$\begin{cases} Y_i^{\text{rk}}(s) | \Lambda_i^R(s) \sim \text{LGCP}(\Lambda_i^R(s)) \\ \Lambda_i^R(s) = \Lambda_i^E(s) \times \Lambda_i^D(s) \end{cases}$$

$$\begin{cases} \log(\Lambda_i^R(s)) = \beta_5 \Lambda_i^E(s) + \beta_0 + \sum_{k=1}^4 \beta_k \text{COV}_k(s) + Z(s) \\ Z \sim \text{GRF}(\rho^{\text{rk}}, \sigma^{\text{rk}}) \end{cases}$$

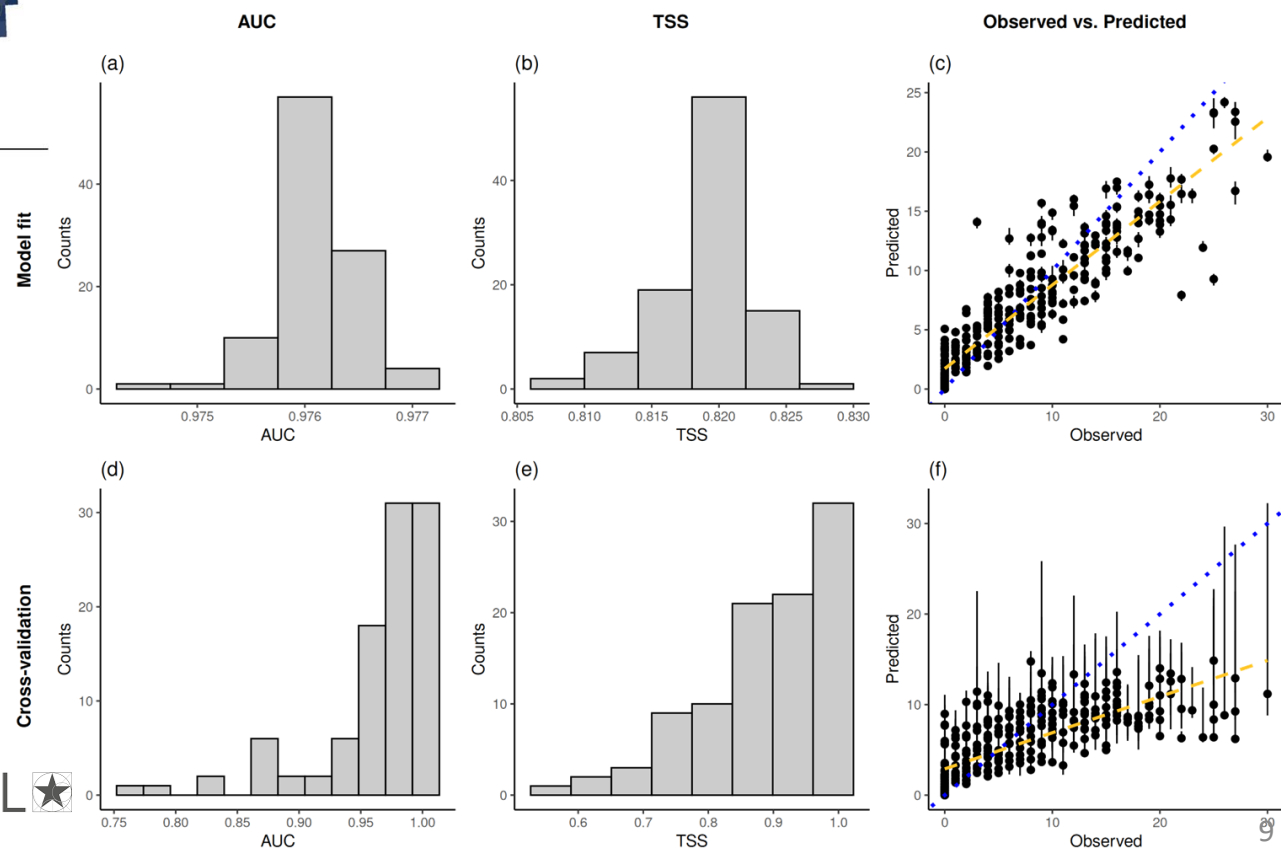
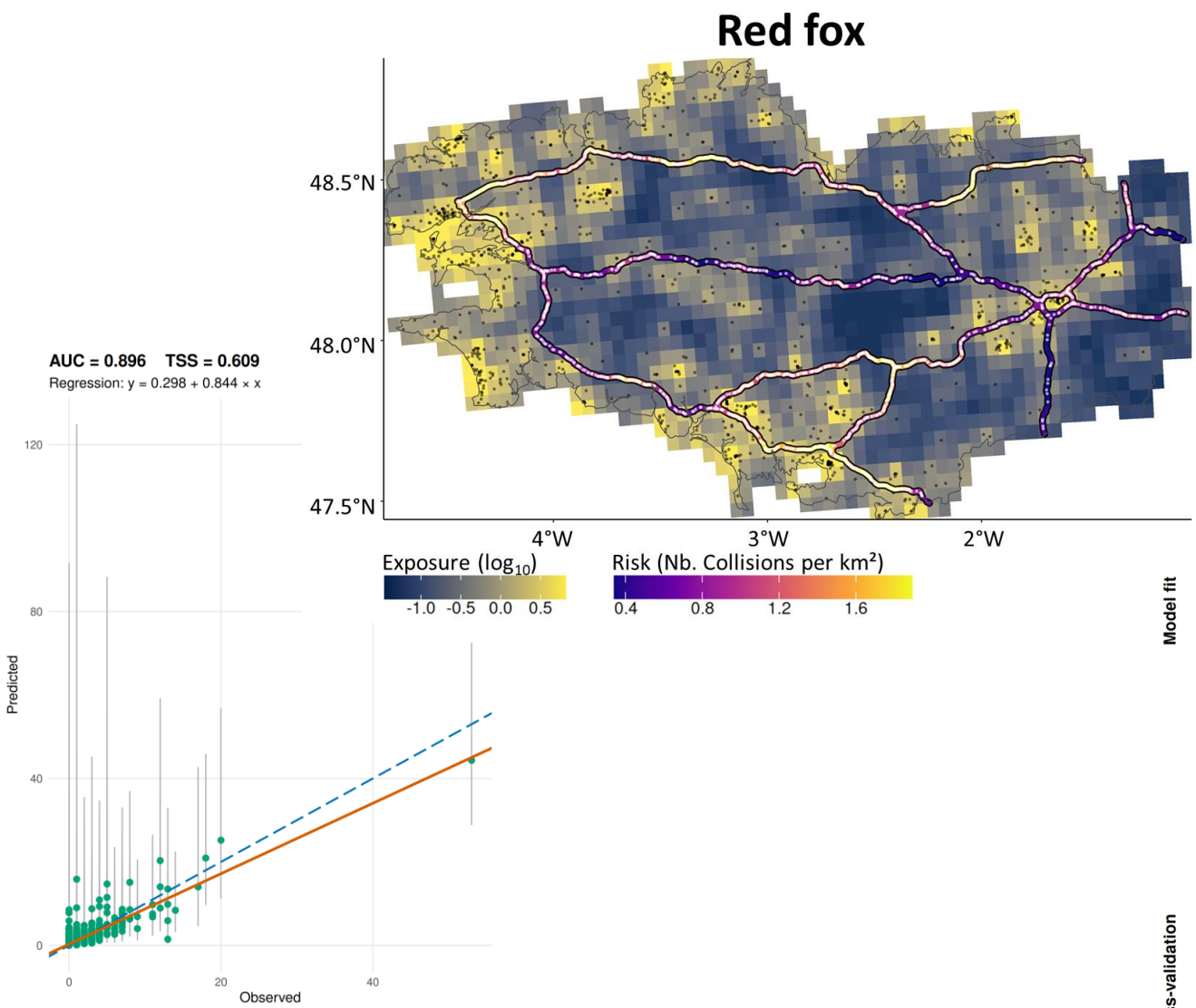


Barrier vs. stationary spatial Gaussian fields

Inference and implementation

- Bayesian inference with **INLA-SPDE** (computationally efficient for regional-scale spatial random fields).
- **Barrier model** to limit unrealistic spatial correlation across non connected road segments.
- **Predictors**: land-cover gradients, distances to key habitats, road category, traffic, mean speed.
- **Model checking**: in-sample fit + spatial cross-validation (random holdout of road segments, ~10% of data).

Model: validation and prediction



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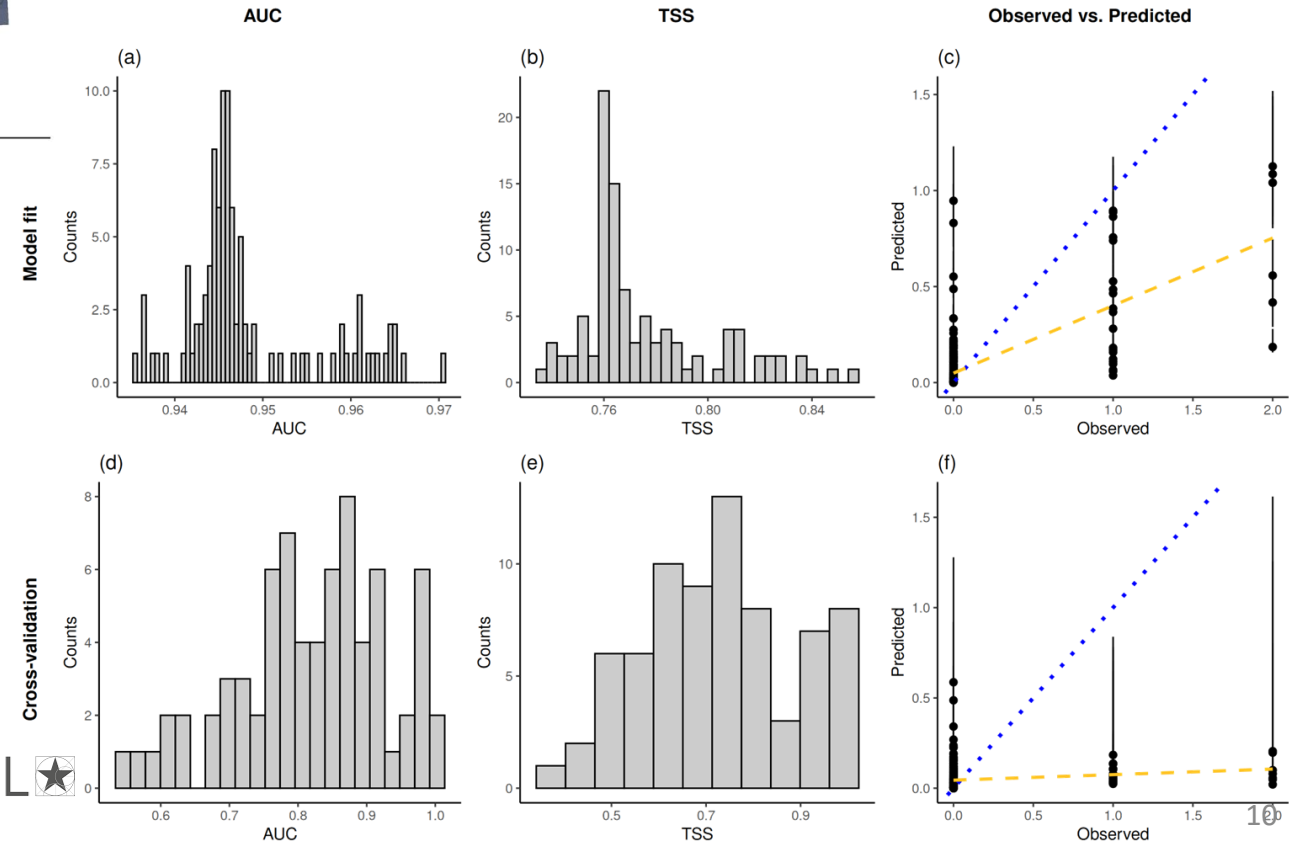
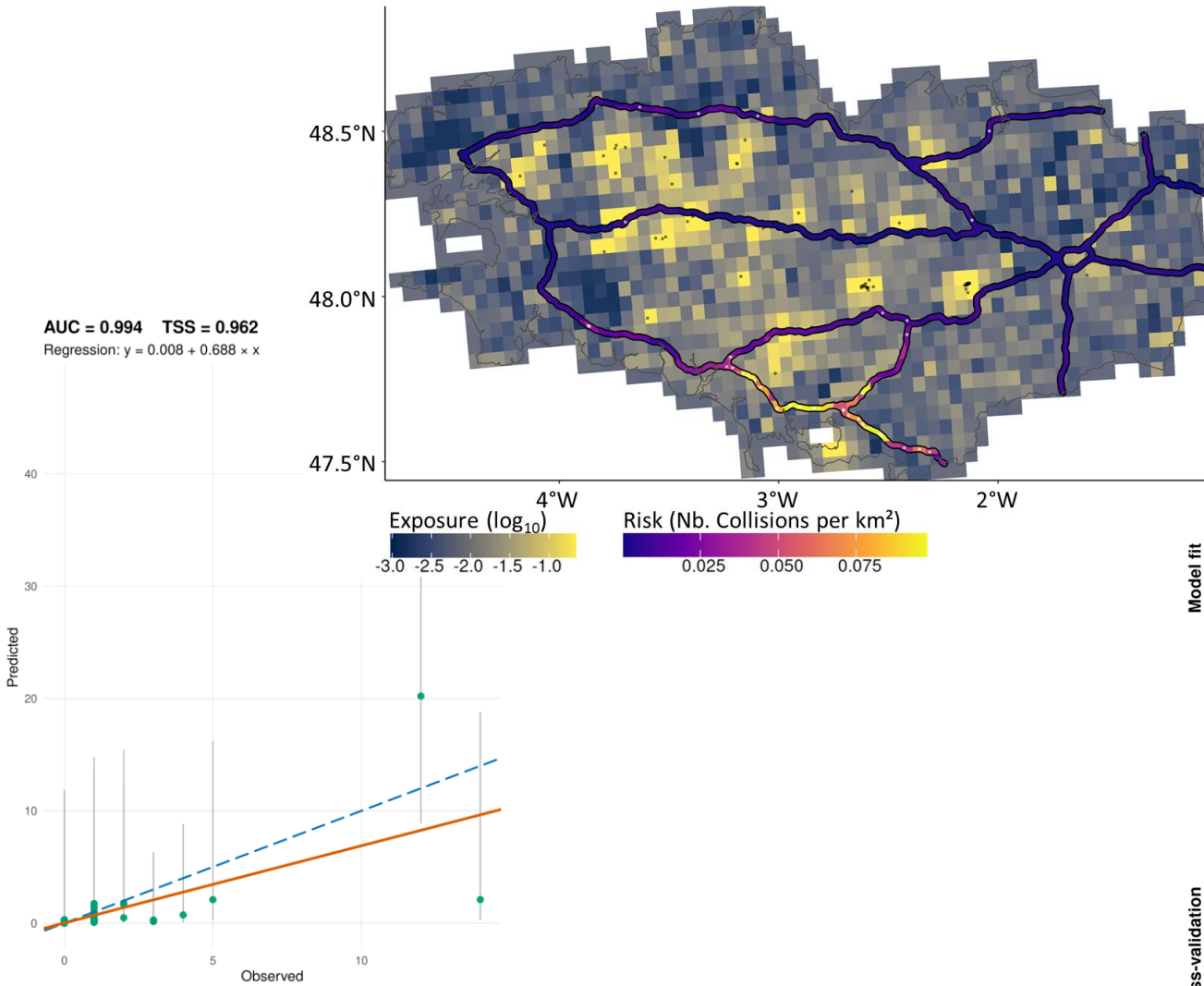
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Model: validation and prediction

Red deer



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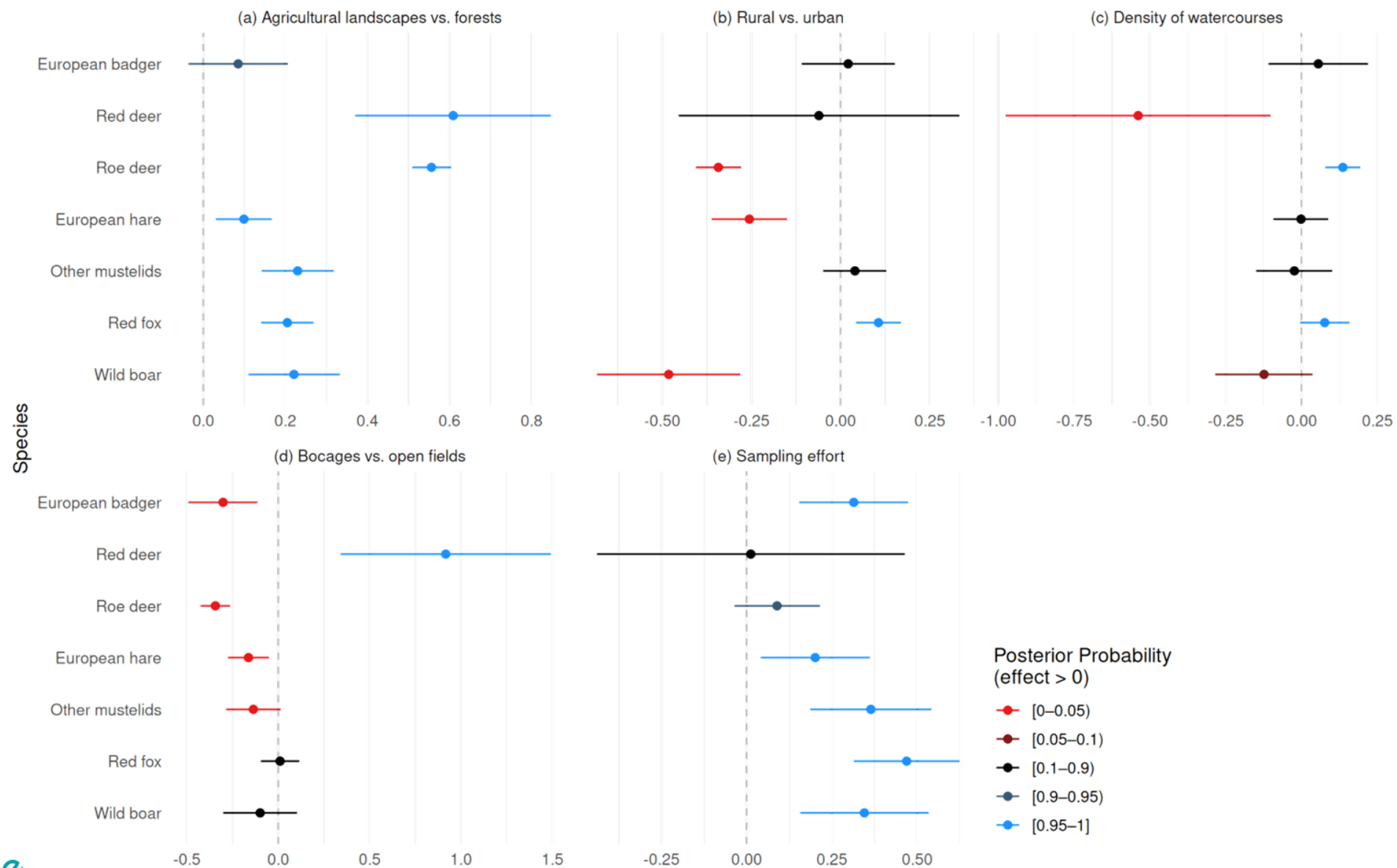


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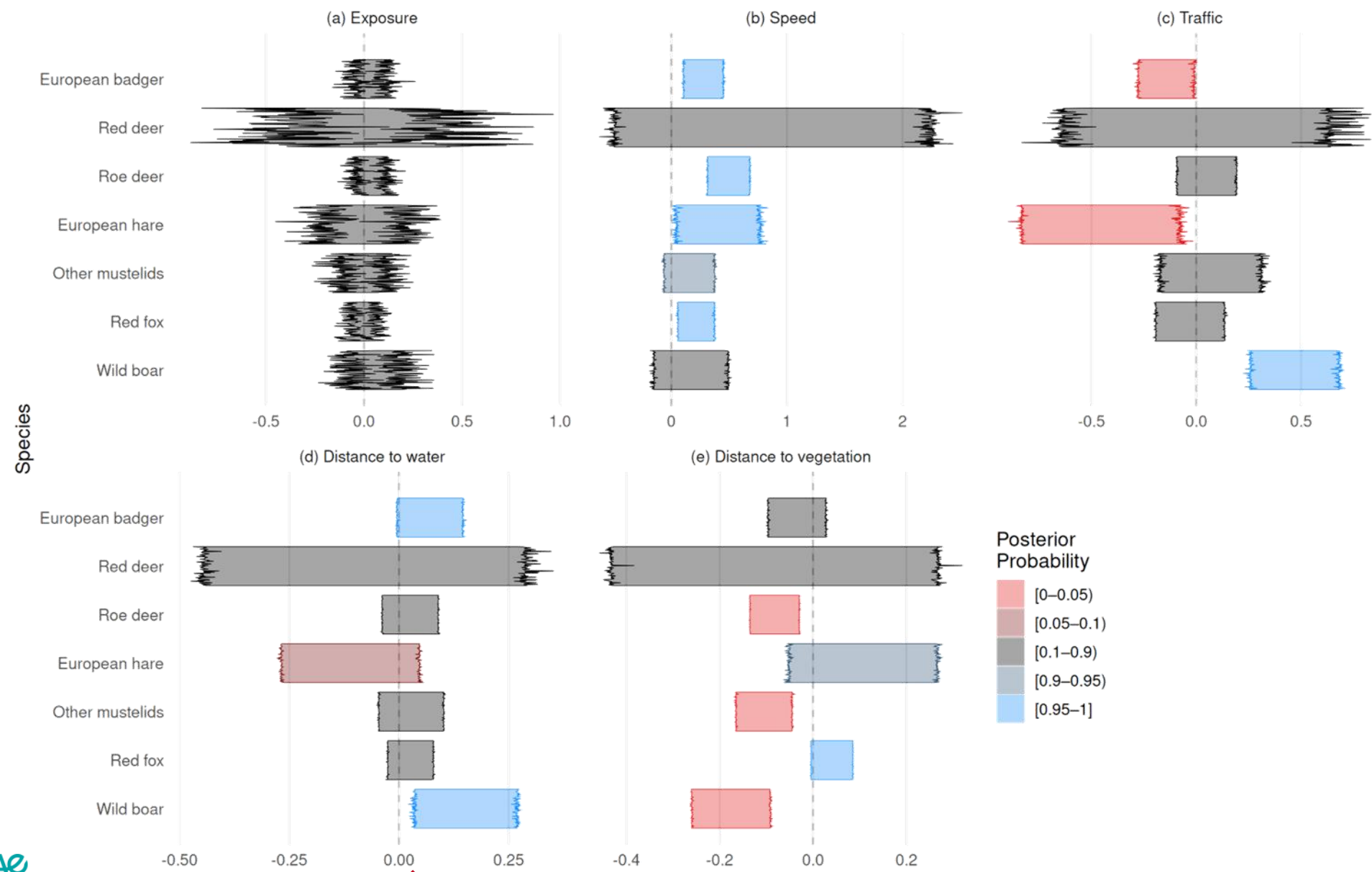
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Results: effect of covariates on species distribution (exposure)



Results: effect of covariates on roadkills (risk)



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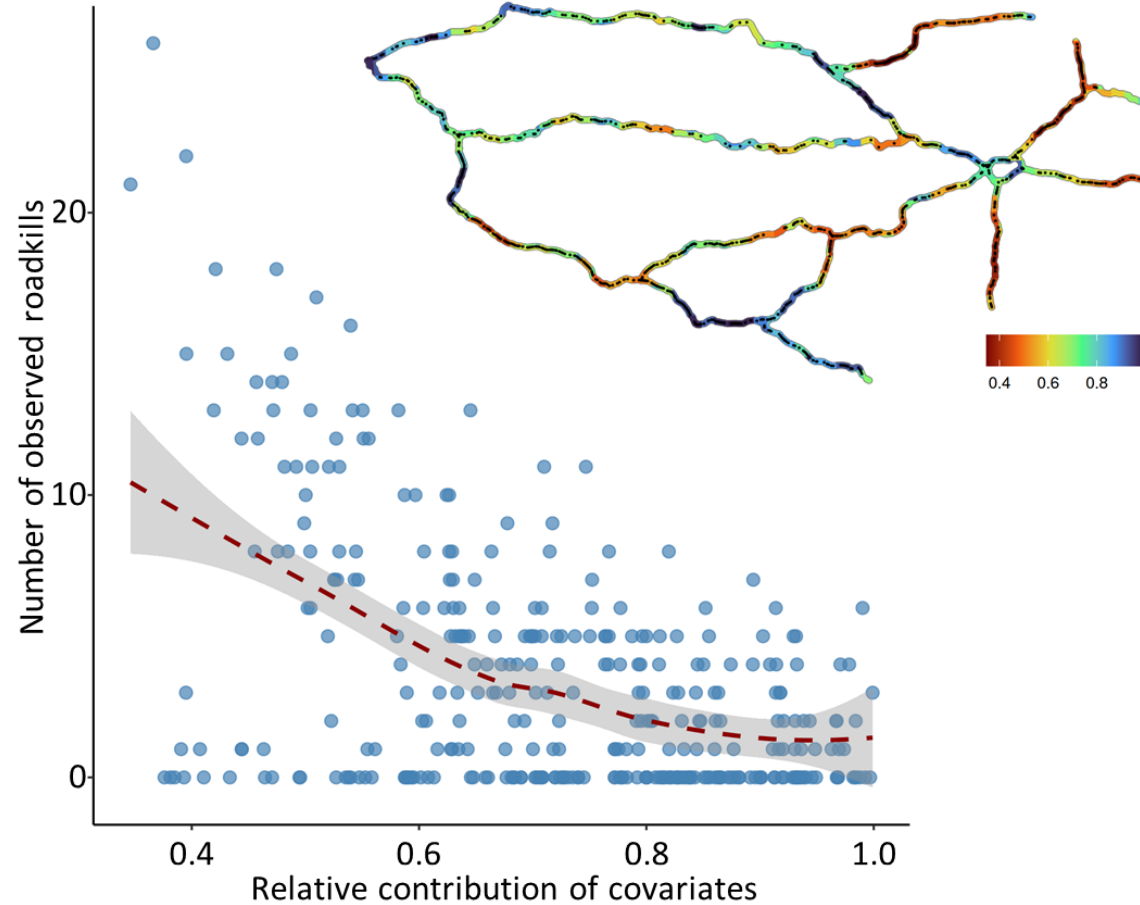
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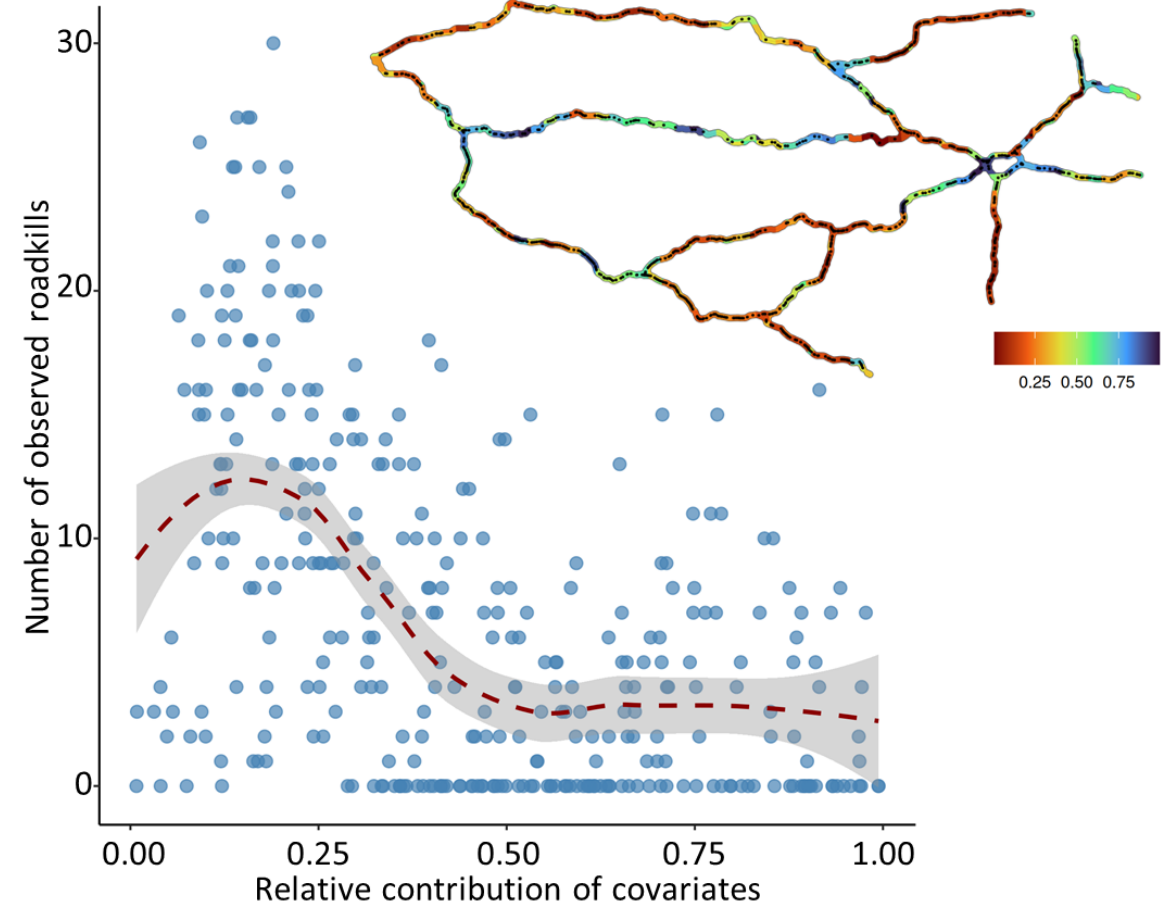
Estimate (x)

Results: where do coarse predictors fail?

Other mustelids



Red fox



$$\log(\Lambda_i^R(s)) = \beta_5 \Lambda_i^E(s) + \beta_0 + \sum_{k=1}^4 \beta_k \text{COV}_k(s) + Z(s)$$

Conclusion and perspectives

Practical outcomes

- Use **exposure × danger** maps to rank road sections for mitigation (fencing, crossings, speed reduction)
→ prioritisation of road sections under explicit uncertainty.
- Residual hotspots define priority sites for on-the-ground diagnostics and targeted surveys.

Modelling outcomes

- Decomposing risk disentangles distribution-driven exposure from road-driven danger.
- Predictors capture regional gradients, while residual hotspots highlight where to invest in targeted data
→ add fine-scale road covariates and embed small standardised datasets to quantify bias.

Opportunistic and semi-protocolled datasets can support biologically sensible regional roadkill risk maps.

Thank you ! 😊



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