**When Risk Maps Mislead: How Model Choice Shapes Mapped Wildlife-Vehicle Collision Risk**

Wildlife–vehicle collision (WVC) risk maps are widely used to identify high-risk areas and inform mitigation priorities, yet maps derived from a single statistical model may convey greater certainty than the modelling process supports. As a result, relying on a single model may hide how sensitive risk estimates are to modelling choices. This study evaluated **model-specification uncertainty** in county-level WVC risk mapping by examining how alternative, empirically supported model formulations affect predicted risk and spatial prioritization across Iowa, USA. WVC counts from 99 counties were modelled using traffic exposure, represented by annual vehicle miles travelled (VMT), and alternative landscape and human-development covariates, including forest cover, forest edge density, impervious surface, and population density. Predictors were transformed where appropriate and standardized prior to modelling. Severe overdispersion in an initial Poisson model motivated the use of negative binomial regression. Four candidate models were evaluated using Akaike's information criterion. Models combining annual VMT with forest cover ($\mathrm{M1}$) and annual VMT with forest edge density ($\mathrm{M2}$) accounted for 99.9% of the total Akaike weight and were retained for subsequent spatial analysis. These models provided alternative representations of forest structure through forest amount and forest configuration. Residuals from both retained models exhibited significant positive spatial autocorrelation ($\mathrm{M1{:}\ Moran's\ I} = 0.193, \mathrm{p} < 0.001;\ \mathrm{M2{:}\ Moran's\ I} = 0.233, \mathrm{p} < 0.001$). Therefore, M1 and M2 were refitted as Bayesian spatial negative binomial models with BYM2 county-level effects. Traffic exposure remained positively associated with WVC counts in both spatial models ($\mathrm{Posterior\ mean}\ \beta = 0.621$). Forest cover ($\beta = 0.189, 95\%\ \mathrm{credible\ interval{:}\ 0.047\text{-}0.331}$) and forest edge density ($\beta = 0.188, 95\%\ \mathrm{credible\ interval{:}\ 0.037\text{-}0.343}$) also showed positive associations. Two-sided Monte Carlo Moran's I tests with 999 permutation indicated no significant residual spatial autocorrelation after spatial modelling ($\mathrm{M1{:}\ Moran's\ I} = -0.091, \mathrm{p} < 0.078;\ \mathrm{M2{:}\ Moran's\ I} = -0.078, \mathrm{p} < 0.224$). Model-specification uncertainty was evaluated by comparing county-level predictions and statewide risk rankings from the two spatial models. The models produced highly concordant rankings (Spearman's ρ = 0.998) and identified the same ten highest-risk counties, demonstrating robust statewide prioritization. Mean between-model prediction disagreement was 2.8%, indicating that most county estimates were relatively stable to model choice. However, this overall agreement concealed localized sensitivity. Fourteen counties differed by at least 5% in predicted WVC counts. The greatest disagreement occurred in Allamakee County, where predictions differed by 17.4% and the county shifted seven positions in statewide ranking, from 33rd to 40th. These findings demonstrate that strong overall agreement between risk maps can coexist with localized model-specification uncertainty. Importantly, the results do not suggest that WVC risk maps are broadly unreliable. Rather, they show that the robustness of mapped risk can vary geographically and with the scale of interpretation. Comparing alternative supported model specifications can reveal where mapped WVC risk estimates are stable and where they are sensitive to model choice. Explicitly communicating this distinction can reduce false impressions of precision and help transportation and wildlife decision-makers interpret risk maps with appropriate confidence. More broadly, the study highlights the value of treating model choice as an explicit component of uncertainty assessment in spatial risk mapping and decision support.