Session S6: Impactos climáticos

Quantifying the role of climate and the environment on Lyme disease risk

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Introduction

Lyme disease is a tick-borne disease widely distributed in the Northern Hemisphere affecting approximately 65,000 people per year[1]. It is caused by bacteria of the complex *Borrelia burgdorferi* s.l., which is transmitted in Europe by *Ixodes ricinus* ticks[1]. In Germany, roughly 34.3 million euros are destined per year to treat patients with long term clinical manifestations of *Borrelia* infections[2]. Climatic and environmental conditions are key drivers of tick developmental rates and feeding habits, as well as of human exposure. As a result, warmer months are associated with the Lyme disease season[3]. In the context of a changing climate, shifts in the onset of the tick season are already being observed, indicating the relevance of climate patterns on disease risk[4]. In this study, we aim to quantify the role of climate on the number of Lyme disease cases reported to the German surveillance system.

Data

We used confirmed Lyme disease cases per NUTS2 district reported to the German surveillance system in nine of the 16 Federal States. Time series of cases differed between Federal States, with the longest period ranging from 2001 to 2021[5]. Population projections by NUTS2 district were extracted from the German Statistics office for the entire study period[6].

We used monthly values of mean, maximum and minimum temperature, wind speed, relative humidity and accumulated precipitation, extracted from the E-OBS repository[7]. Based on the literature, we chose suitable land cover classes from the CORINE's 2018 dataset and derived the overall environmental suitability for *Ixodes ricinus* ticks per district[8].

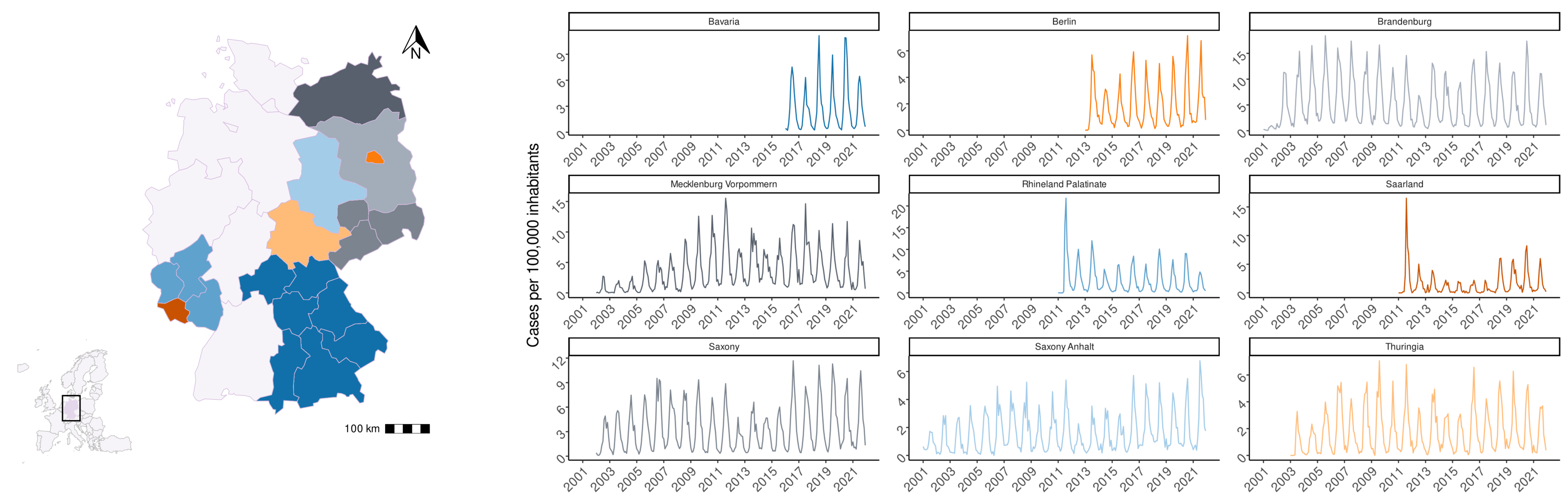

Figure 1. Lyme disease cases in Germany. NUTS2 districts with compulsory notification of LD by 2021 (left), and time series of the incidence per 100,000 individuals grouped by Federal State (right).

Modelling Framework

We used a Bayesian spatiotemporal hierarchical mixed-model framework to compute the effects of environmental and climatic variables on monthly LD risk in Germany between 2001 and 2021. Assuming LD case counts per district '*i*' and month '*t*', y_{it}, followed a negative binomial distribution, we defined the mean risk μ_{it} using the linear predictor,

$$\log(\mu_{it}) = \alpha + \log(p_{i\,a(t)}) + \Sigma\beta_k x_{kit} + \delta_{m(t)} + \upsilon_{i\,a(t)} + u_{i\,a(t)}$$

where α is the intercept, $p_{i\,a(t)}$ is the annual population size per district, $\Sigma\beta_k x_{kit}$ is a combination of *k* environmental and climatic covariates with regression coefficients β, $\delta_{m(t)}$ and $\gamma_{a(t)}$ are a series of monthly and yearly random effects, respectively, and $\upsilon_{i\,a(t)}$ and $u_{i\,a(t)}$ are year-specific spatially structured and unstructured random effects. We then used a range of goodness of fit statistics to select the candidate models with the highest performance compared to a reference model, containing random effects only.

Results

Between 2001 and 2021 there were a total of 162,851 confirmed Lyme disease cases in Germany. Highest incidence rates were observed in predominantly rural areas, such as Brandenburg, Mecklenburg-Vorpommern and Saxony.

The highest increase in goodness of fit was observed when incorporating coniferous forests, humidity, wind speed, accumulated precipitation and maximum temperature (final model). Looking at the seasonal random effects, the final model showed a small shift of their marginal effects towards zero (Figure 2).

The inclusion of environmental and climatic variables changed the pattern of the spatially structured random effects. The areas in the map shaded in gold indicate that the inclusion of climate helped to account for the spatial dependency and variation in Lyme cases. Pink-shaded areas indicate the influence of unmeasured processes (e.g., deer population, access to health care, etc.).

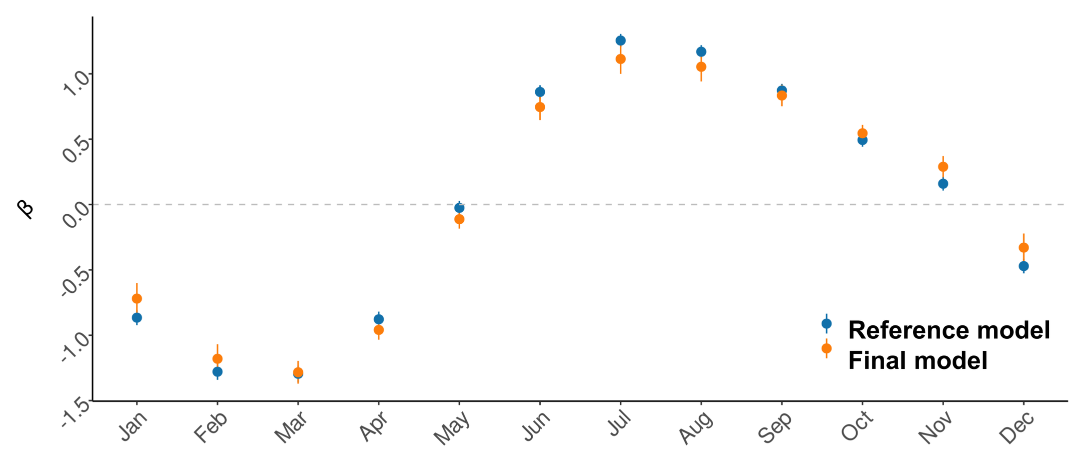

Figure 2. Seasonal random effects

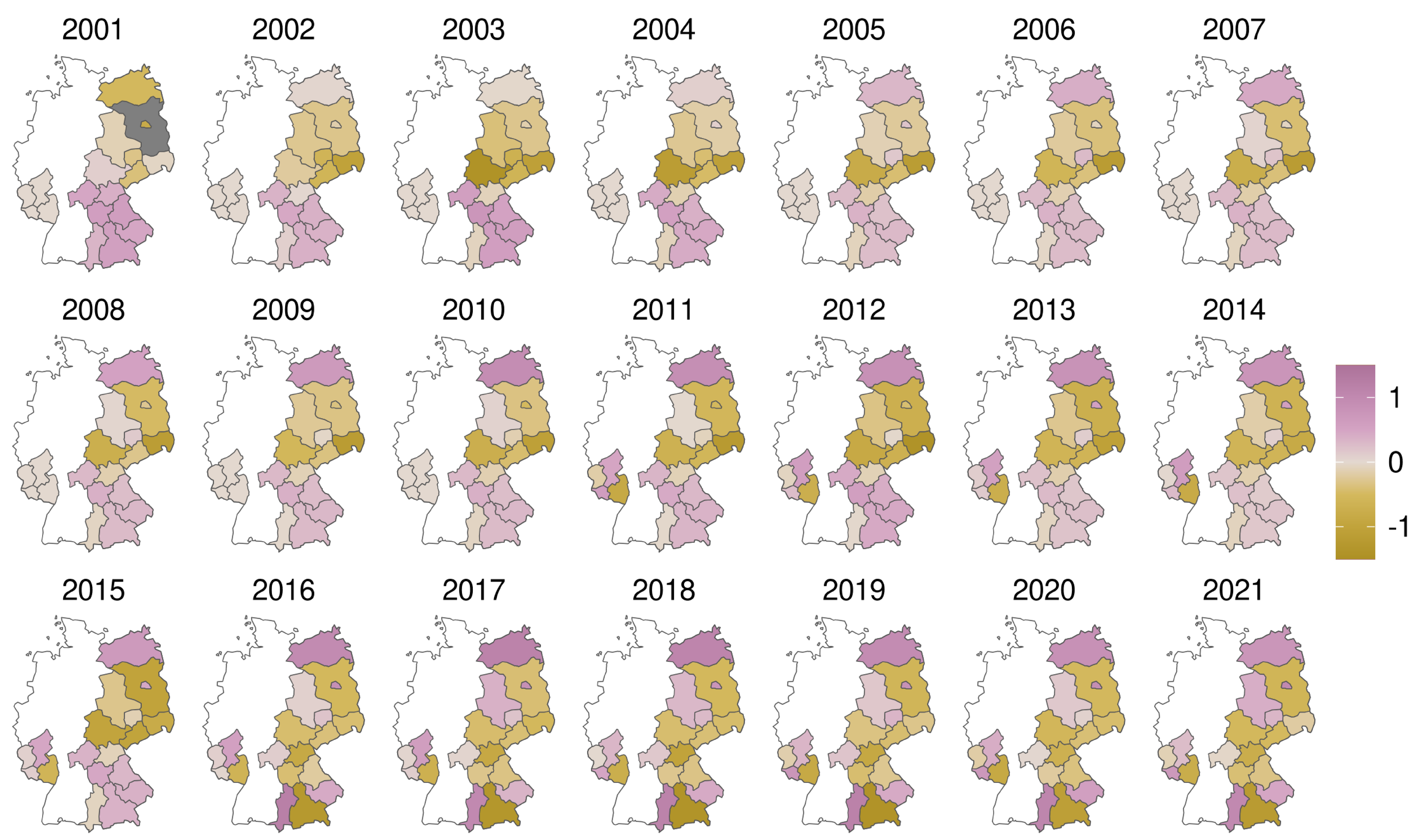

Figure 3. Year-specific spatially structured random effects (2001-2021). Each map shows the standardized difference between the reference model, i.e. with random effects only, and the final model, i.e. including random effects and explanatory variables. Positive values (pink-shaded areas) indicate that the explanatory variables increased the mean effect of the spatially structured random effects. Negative values (gold-shaded areas) indicate where the explanatory variables helped account for the spatial variation. Zero indicates no change between models.

Preliminary conclusion

- These results indicate that surveillance data can be used to quantify the influence of eco-climatic processes on Lyme disease risk.
- Delays in reporting pathways and selection bias might influence the ability of the models to accurately estimate the climate sensitivity of Lyme disease risk.
- This study highlights how climate products can be coupled with health services to better understand transmission dynamics and influence decision making in the public health sector.

Next steps

- Further work will involve including additional variables, such as deer habitat suitability and elevation.
- Model exploration so far assumes a linear and immediate effect of climatic drivers on disease risk. Next steps involve expanding the range of covariables and exploring the role of lagged effects on disease risk, as well as non-linear associations.
- In case of a strong climate signal, projections will be computed with combinations of RCP and SSP scenarios.

References

1. Lindgren & Jaenson. 2006. Lyme borreliosis in Europe: influences of climate and climate change, epidemiology, ecology, and adaptation measures. WHO
2. Müller et al. 2012. Evaluating frequency, diagnostic quality and cost of Lyme borreliosis testing in Germany: a retrospective model analysis. Clin & Dev Imm 13
3. Ehrmann et al. 2017. Environmental drivers of Ixodes Ricinus abundance in forest fragments of rural European landscapes. BMC Ecol 17:31
4. Fernández-Ruiz & Estrada-Peña. Could climate trends disrupt the contact rates between Ixodes Ricinus (Acari, Ixodidae) and the reservoirs of Borrelia burgdorferi s.l.? PLoS ONE 15 (5)
5. Robert Koch Institute: SurvStat@RKI 2.0, https://survstat.rki.de. Access 11/2021.
6. Statistisches Bundesamt (Destatis). 2022.
7. Cornes et al. 2017. An ensemble version of the E-OBS temperature and precipitation datasets. J Geophys Res Atmos 123
8. European Union, Copernicos Land Monitoring Service 2022, European Environment Agency (EEA)

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