



When is it “good enough?” Comparing datasets for tick-borne disease surveillance and adaptation

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Research Question

Monitoring and surveillance of geographic changes in tick-borne disease incidence over time has been established as an adaptation strategy. To increase capacity for monitoring, also in lower income countries and regions, publicly available tick distribution datasets (containing observation/presence data) are required for modeling future health risks from these vector-borne diseases. Little is known, however, on the respective accuracy of modeling with different datasets, and whether the benefits of more comprehensive data outweigh the potentially higher costs. This study compares three datasets by projecting current and future distributions of *Ixodes ricinus* ticks in Europe. Additionally, this study compares climate change projections from the Fourth and Fifth IPCC Assessment Reports (AR4 and AR5, respectively). A recent study (Levi et al., 2015) suggests that changes in climate may be altering tick life cycles and pathogen transmission.

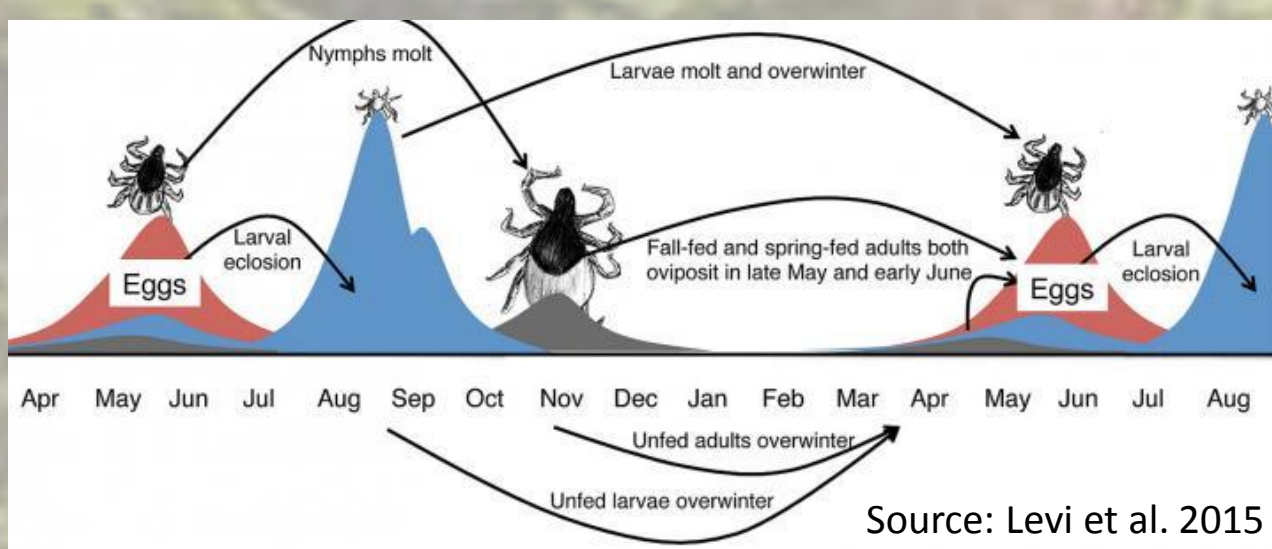


Table 1. Variables used for all modeling, including original sources (www.worldclim.org, www.ccafs-climate.org, and Harmonized World Soils Database (HWSD)).

Variables	Source
Isothermality	WorldClim
Annual Precipitation	WorldClim
Prpc of Wettest Quarter	WorldClim
Prpc of Driest Quarter	WorldClim
Mean Radiation	CCAFS
Soil Type	HWSD

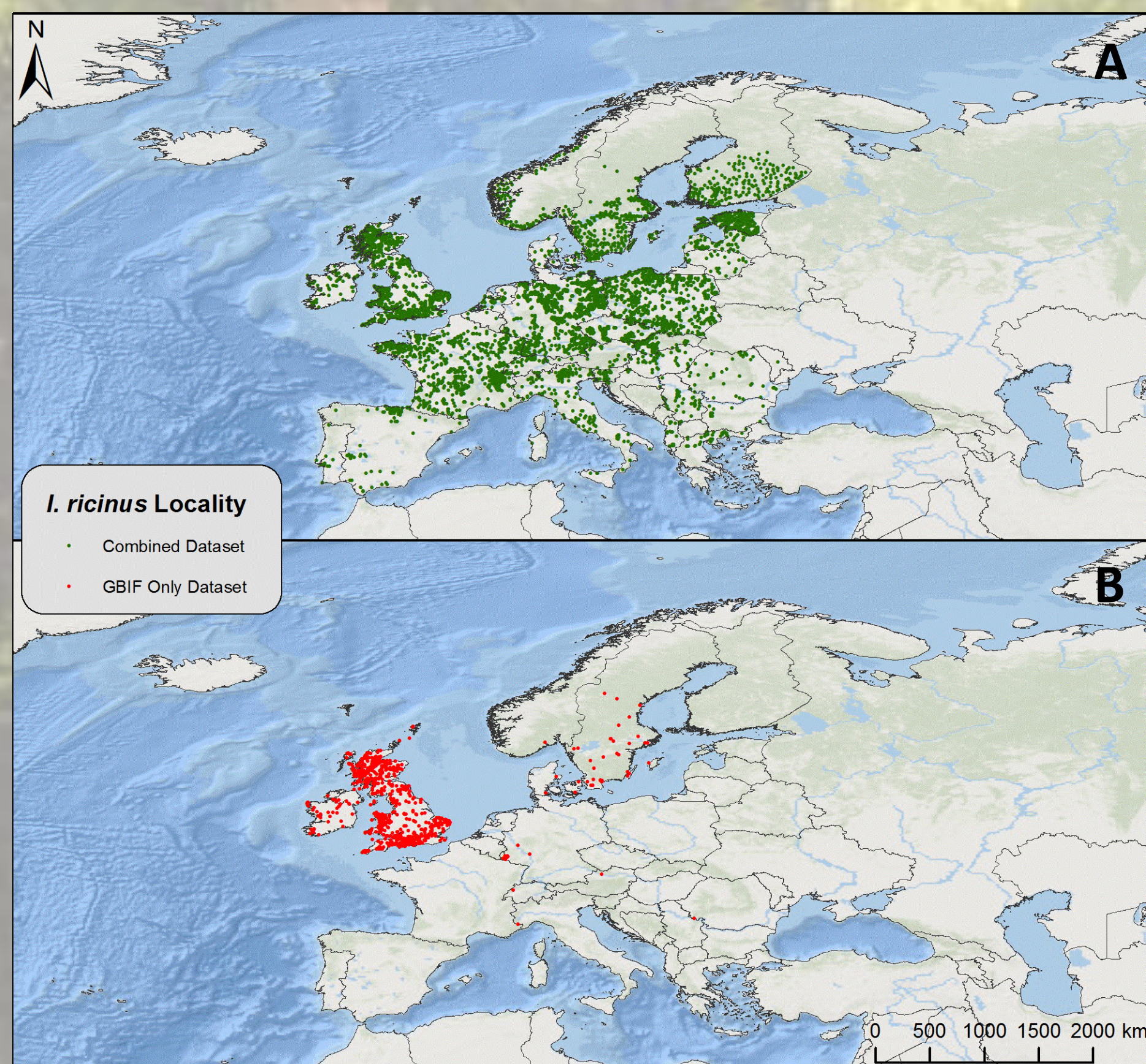


Figure 1. Point locality data for *I. ricinus* ticks after combining GBIF, Rubel et al. (2014), and Estrada-Peña et al. (2013) datasets (A). Point locality data used by Boeckmann & Joyner (2014) for model development (GBIF-only) (B).

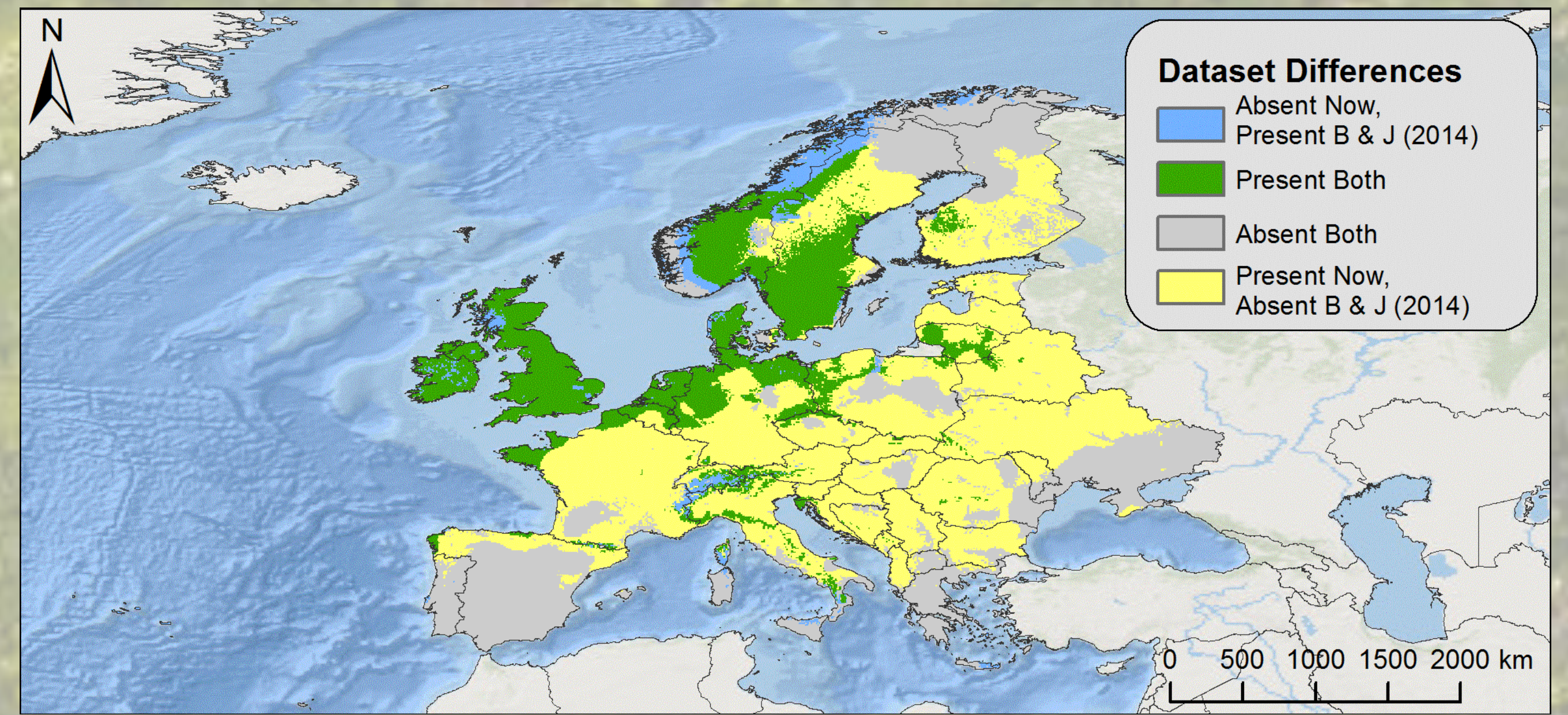


Figure 2. Differences between GARP model using combined dataset and GARP model only using GBIF dataset (“B & J (2014)” = Boeckmann & Joyner 2014).

Methodology

Ecological niche models were created for *I. ricinus* using the Generic Algorithm for Rule-set Prediction (GARP). A total of 8,371 *I. ricinus* georeferenced occurrence locations were compiled from three sources: 2,097 locations came from Global Biodiversity Information Facility (GBIF, 2015, Boeckmann & Joyner, 2014), 1,855 locations came from a new German tick database (Rubel et al., 2014), and 4,419 locations came from a comprehensive European tick database (Estrada-Peña et al., 2013). Current and future *I. ricinus* distribution was modeled using the combined occurrence dataset and environmental variables identical to Boeckmann & Joyner (2014), including the Special Report Emissions Scenarios (SRES) A2 scenario from the IPCC AR4, then a second set of models were created using Representative Concentration Pathway (RCP) 8.5 from the IPCC AR5. Baseline climate data covered the time period 1990–2010 and the future distribution models utilized the CSIRO GCM (A2) and CCSM4 GCM (RCP 8.5) for the time period 2040–2060. Areas of potential expansion and contraction were determined by the level of agreement between the current and future projection models of *I. ricinus*. Finally, results from the various models were compared.

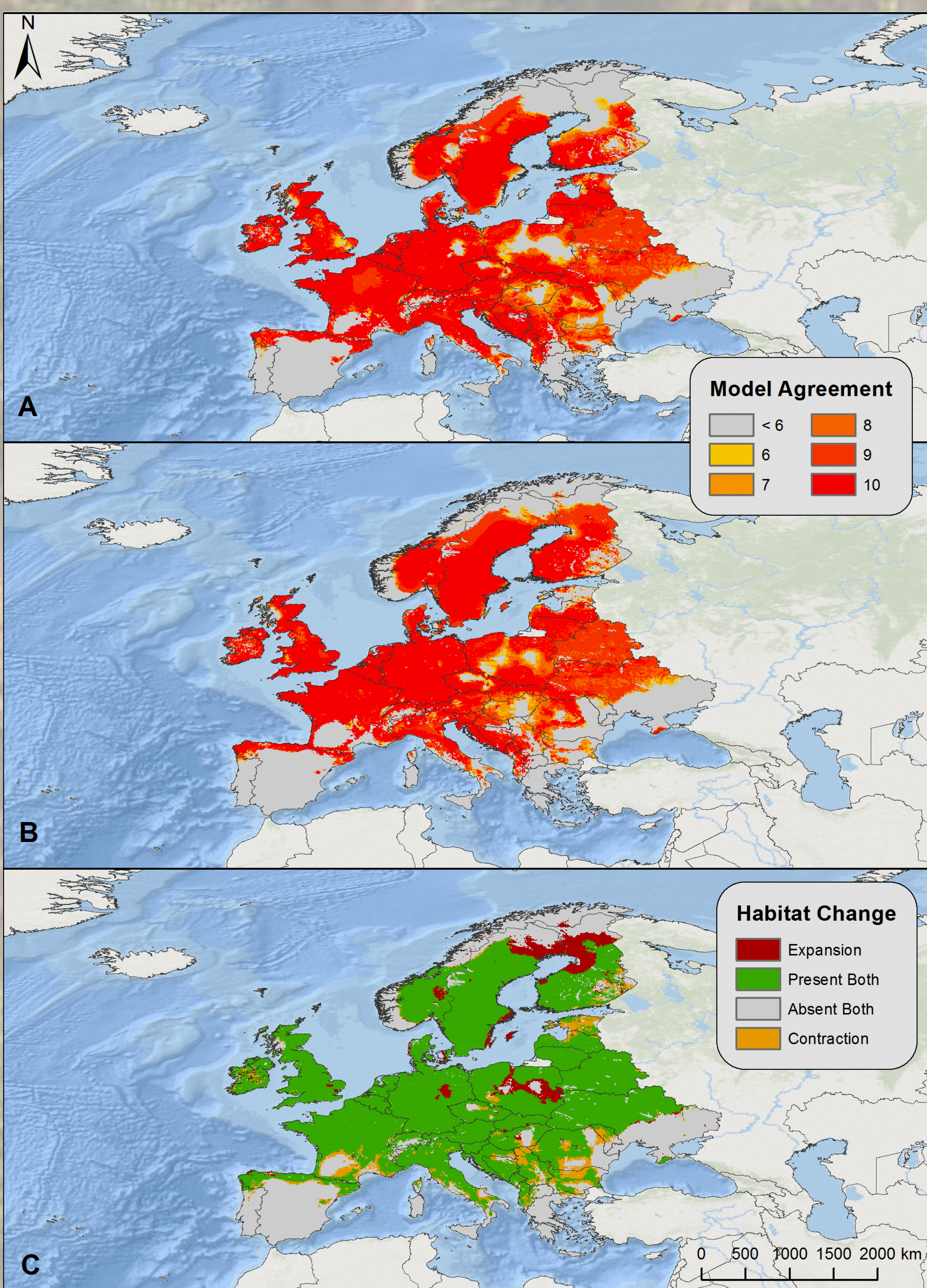


Figure 3. Current (A) and future (B) *I. ricinus* distribution predictions using combined tick locality dataset and the SRES A2 scenario. Projected habitat change (C) is also mapped.

Table 2. Accuracy metrics for current distribution model using combined dataset (Figure 3A).

Metric	Values
Spatially Unique Points	n = 4606
Training Points	n = 3684
Testing Points	n = 922
Total Omission	3.5
Average Omission	13.7
Total Commission	37.55
Average Commission	68.21
AUC	0.74

Table 3. Predicted habitat change using the IPCC AR4 SRES A2 scenario (Figures 3B and 3C).

Habitat Change (A2)	
Expansion	4.93%
Present Both	62.82%
Absent Both	26.96%
Contraction	5.29%

Table 4. Predicted habitat change using the IPCC AR5 RCP 8.5 trajectory (Figures 4A and 4B).

Habitat Change (RCP 8.5)	
Expansion	5.57%
Present Both	64.30%
Absent Both	25.72%
Contraction	4.40%

Table 5. Differences between the SRES A2 scenario and RCP 8.5 trajectory (Figure 4C).

Model Differences	
Absent A2, Present RCP 8.5	3.90%
Present Both	65.94%
Absent Both	27.72%
Present A2, Absent RCP 8.5	2.40%

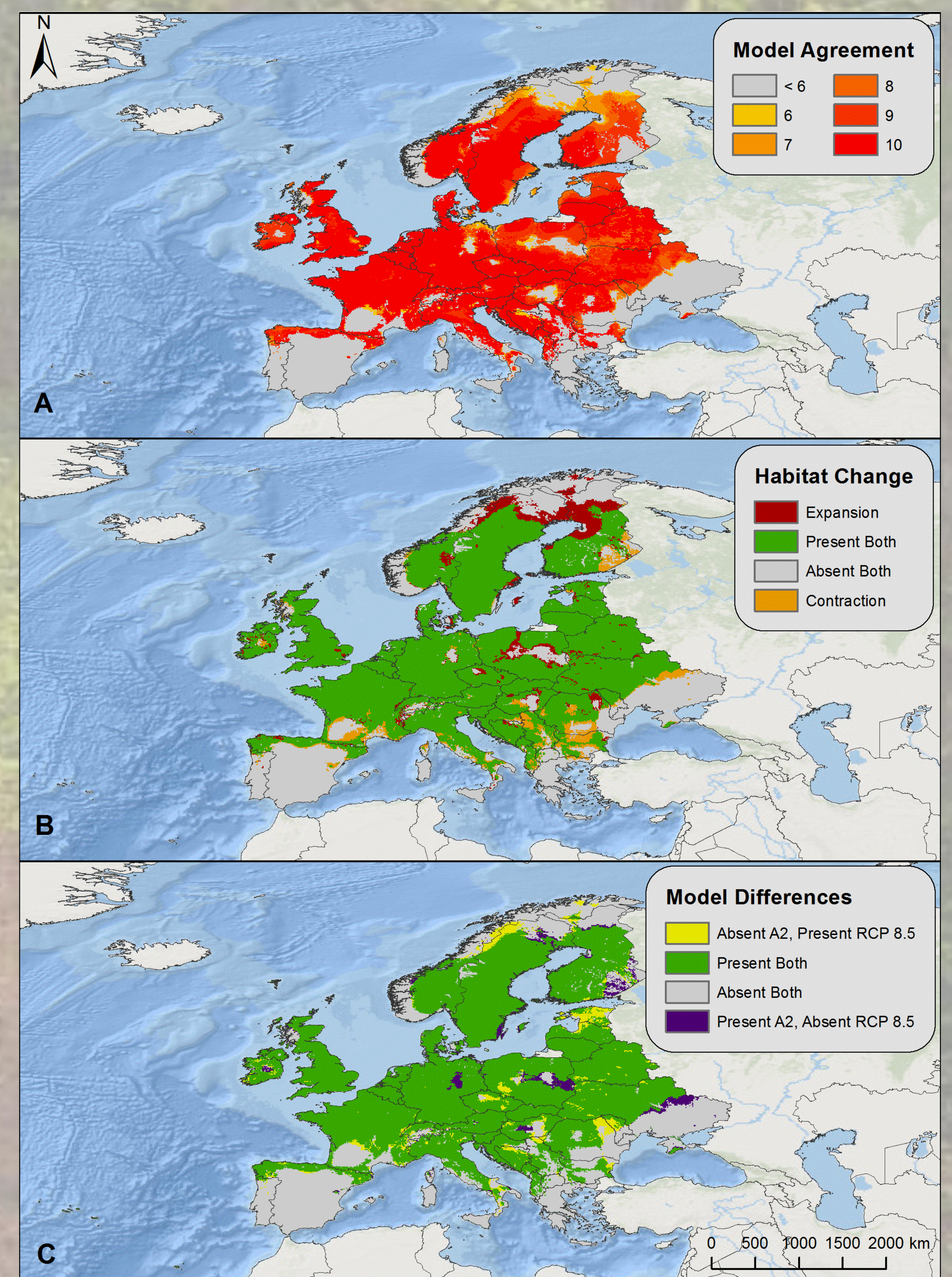


Figure 4. Future (A) *I. ricinus* distribution prediction using the RCP 8.5 trajectory. Projected habitat change (B) and A2/8.5 differences (C) are also mapped.

Significance of the research for practical solutions

Results suggest that while more comprehensive datasets increase the specificity of niche projections, the GARP modeling approach can already provide robust estimates of future niche suitability with fewer data points, although the study area must be limited to the extent of sampled data if it is known that ticks are present in under-sampled locations. GBIF-only models predicted areas of northern Europe accurately, but performed poorly in under-sampled areas of southern Europe. These findings indicate that, depending on the study area, even less exhaustive data can provide useful information for vector-borne disease impact and adaptation analyses and strategies.