Explicit integration of dispersal related metrics improves predictions of SDM in predatory arthropods

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6 Monsimet Jérémy ^{1*}, Devineau Olivier ¹, Pétillon Julien² & Lafage Denis ^{2, 3}

- 7 ¹ Department of Forestry and Wildlife management, Inland Norway University of Applied Sciences,
- 8 Campus Evenstad, Koppang, Norway
- 9 ² UMR CNRS 6553 ECOBIO, Université de Rennes, Rennes, France
- ³ Department of Environmental and Life Sciences/Biology, Karlstad University, Karlstad, Sweden
- 11 *Corresponding author: jeremy.monsimet@inn.no

12 **ABSTRACT**

Fishing spiders (*Dolomedes spp.*) make an interesting model to predict the impact of global 13 changes because they are generalist, opportunistic predators, whose distribution is driven 14 15 mostly by abiotic factors. Yet, the two European species are expected to react differently to forthcoming environmental changes, because of habitat specialization and initial range. We 16 used an original combination of habitat and dispersal data to revisit these predictions under 17 18 various climatic scenarios. We used the future range of suitable habitat, predicted with 19 habitat variables only, as a base layer to further predict the range or reachable habitat by 20 accounting for both dispersal ability and landscape connectivity. Our results confirm the 21 northward shift in range and indicate that the area of co-occurrences should also increase. 22 However, reachable habitat should expand less than suitable habitat, especially when 23 accounting for landscape connectivity. In addition, the potential range expansion was further 24 limited for the red-listed *D. plantarius*, which is more habitat-specialist and has a lower ability 25 to disperse. This study highlights the importance of looking beyond habitat variables to 26 produce more accurate predictions for the future of arthropods populations.

27 **Keywords:** Fishing spiders, Pisauridae, Climate change, Dispersal limitation, Hybrid SDM

28 Introduction

Climate change, which is now threatening all ecosystems worldwide (Bellard et al. 2012), is 29 30 a multi-factor problem that goes beyond raising temperatures only (Pereira et al. 2010, 31 Garcia et al. 2014). Tackling this complexity requires that ecologists obtain realistic predictions of how species distributions will change in response to global change. In recent 32 years, species distribution models (SDMs) proved to be an important tool to for this. SDMs 33 34 are particularly useful to predict geographic distributions by correlating species occupancy 35 to environmental variables (Miller 2010). Applications include conservation planning (Guisan 36 et al. 2013), potential invasion range (Bellard et al. 2013), or forecasting in time (Hijmans 37 and Graham 2006). SDMs were successfully applied to a large variety of terrestrial (see Hao et al. 2019 for a review) and marine organisms (see Melo-Merino et al. 2020 for a review). 38

The accuracy of predictions produced by SDMs varies from algorithm to algorithm, even 39 40 when considering that the MaxENT algorithm is most often used (Qiao et al. 2015). This variation in accuracy can be alleviated with ensemble models, which combine algorithms and 41 produce consensual predictions (Arauja and New 2007, Thuiller 2004). Of course, input data 42 43 also influence the predictions (Thuiller et al. 2019), and while most SDMs use only climatic variables, including other variables such as land-use might improve predictions (Titeux et al. 44 45 2016). In order to make projections in time, it is fundamental to carefully select the right climatic scenario (Thuiller et al. 2019). Right now, the ones produced and updated by the 46 Intergovernmental Panel on Climate Change (IPCC 2007) are the most widely recognized 47 and used climatic scenarios. 48

SDMs assume that the species and its environment are at equilibrium (Guisan and Thuiller 2005), so that all suitable locations are occupied. SDMs also assume that the ecological niche is stable, i.e. that the same factors limit the species in space and time (Richmond et al. 2010). Under these assumptions, SDMs are used to define habitat suitability, which is the

range of physical locations where one species can live (Kearney 2006). However, a properly 53 constructed and calibrated SDM can provide information about the specie's realized niche, 54 ie a combination of habitat with other biotic and abiotic factors (Guisan and Thuiller 2005, 55 56 Soberon and Peterson 2005). The gold standard of SDMs would be fully mechanistic models which were used, for example to study seed dispersal in birds (Merow et al 2011) or 57 population dynamics and evolution of dispersal trait (Bocedi et al. 2017). However, these 58 models are very data-demanding, and simpler hybrid mechanistic-correlative models are 59 often more suitable for less well-studied taxa. In particular these hybrid models allow 60 including active biological processes such as dispersal (Briscoe et al. 2019). Examples 61 include making predictions under full /no dispersal (Thuiller et al. 2009) or using a buffer of 62 dispersal around each presence (Mammola and Isaia 2017). 63

As generalist predators, spiders are relatively independent of a specific prey community, and 64 their assemblage and distribution is mostly influenced by habitat and land use (Lafage et al. 65 2015), which makes them good study cases for SDMs. Fennoscandia is a potential climatic 66 67 refugium for spider populations against the current global warming (Leroy et al. 2014). Refugia can mitigate the effects of climate change by providing suitable conditions for 68 species persistence through time (Keppel and Wardell-Johnson 2012). Dolomedes 69 70 *plantarius* could presumably use Fennoscandia as a refugium, but the ability of the species 71 to effectively spread northward has not been accounted for in previous predictions (Leroy et 72 al. 2013, 2014). Moreover, fishing spiders are threatened by the decrease of range and guality of their wetland and fenland habitats, which are declining globally (Finlayson et al. 73 2019). The other European fishing spider, Dolomedes fimbriatus, also occurs in 74 Fennoscandia. Co-occurrence of both Dolomedes, was considered impossible due to 75 76 different habitat requirements (van Helsdingen 1993). Syntopy is possible though, as the two species can live close to each other (Duffey 2012), for example around the same lake (Ivanov 77

et al. 2017), or in the ecotone habitat between bogs and ponds (Holec 2000). *D. fimbriatus* has a larger ecological niche: the species is more drought and shade tolerant (Duffey 1995), and is less sensitive to water quality (Duffey, 2012). Consequently, *D. fimbriatus* could become a competitor to *D. plantarius* in syntopic sites if global change brings more frequent drought events

Here, we compare the potential range spread of *D. plantarius* and *D. fimbriatus*, and their ability to use Fennoscandia as a refugium. We aim to provide more conservative predictions for Fennoscandia than previously predicted at the European scale by Leroy et al (2013). To do so, we developed hybrid species distribution models including climate and land-use variables, as well as dispersal and landscape connectivity (figure 1). We expected that:

- The distribution of both fishing spiders should expand northward (Parmesan and
 Yohe 2003, Parmesan 2006). A larger expansion is expected under more intense
 climate change.
- 91 2) Since *D. fimbriatus* is a habitat generalist, the range of habitat it can reach should be
 92 larger and occupied faster, than for *D. plantarius* (Hill et al. 1999).
- 3) The area of sympatry between the two species should increase with the range
 expansion of the two species.

95 Methods

96 Occurrence data

97 We downloaded records of presence for both spider species from the GBIF (GBIF: The 98 Global Biodiversity Information Facility 2019) via the rgbif package (citations for R packages 99 are provided in Supplementary material, Appendix 1) in R (R Core Team 2019). The GBIF 100 database gathers volunteer-based naturalist observations (Supplementary material 101 Appendix 2), which often require a quality check. We used the package CoordinateCleaner

(Supplementary material Appendix 1) to remove null or duplicate coordinates, and to flag the 102 records requiring a subjective decision, such as ol records or records located in urban areas, 103 or at the centroid of a county. Urban records were not necessarily false presence, and we 104 105 used aerial photography (ESRI 2009) accessed with packages leaflet and mapedit (Supplementary material Appendix 1) to decide whether to keep these records or not. We 106 107 visually checked, for instance, if a record was not in a recently modified areas in a city. Some records suggesting co-occurrence of the two species were checked in the field during 108 summer 2018 and 2019 (25 locations, including four actually syntopic locations). We retained 109 775 records for Dolomedes fimbriatus and 181 records for Dolomedes plantarius (Figure 2), 110 reflecting the GBIF data available until October 2019 in Fennoscandia. When several records 111 112 fell in the same raster cell, we kept only one.

113 Species distribution modelling

114 Predictor variables

For the climatic component of the ecological niche, we included variables which were biologically relevant for spiders, and not too correlated (Braunisch et al. 2013). Using a correlation coefficient threshold of 0.7 (Dormann et al. 2012), we selected mean and maximum annual temperature, mean diurnal temperature range, mean temperature of the wettest quarter, and annual precipitation, which we extracted from the WorldClim database (Fick and Hijmans 2017) at a spatial resolution of 30 arc-seconds (Supplementary material Appendix 4, Tab. A1).

To predict the future distribution of *Dolomedes* spiders in Fennoscandia, we used IPCC projections for 2050 and 2070, under multi-factors "representative concentration pathways" (RCP) 4.5 and 8.5 (van Vuuren et al. 2011). RCP4.5 corresponds to medium-low greenhouse gas emissions and air pollution, whereas RCP8.5 considers high greenhouse gas emission, medium air pollution, and an increase in carbon dioxide (van Vuuren et al. 2011). we

downloaded these climatic projections from Wordclim (Hijmans et al. 2005) at a spatial
 resolution of 30 arc-seconds.

129 For the habitat component of the ecological niche, we integrated information on ground wetness, which is an important community driver for the semi-aquatic fishing spiders (Lafage 130 et al. 2015, Lafage and Pétillon 2016). We also incorporated forest and grassland density, 131 because the presence of fishing spiders seems to be influenced by the surrounding 132 133 landscape (unpublished data). We downloaded the corresponding geographic layers from the Copernicus Land Monitoring Service at 100-metres resolution (EEA 2018), and upscaled 134 them to 30 arc-seconds resolution to match the bioclimatic data. The forest layer represents 135 the density of the tree cover (from 0 to 100 %) in 2015. The 'Water and Wetness' layer 136 represents the occurrence of wet surfaces from 2009 to 2015, using a water and wetness 137 probability index, indicating the degree of physical wetness, independently of the vegetation 138 cover. Finally, the grassland layer represents the percentage of grassland per pixel. We 139 estimated the change in land use between current and future times with a model which 140 141 harmonises scenarios from different integrated assessment models, namely MESSAGE for RCP8.5 and GCAM for RCP4.5 (Hurtt et al. 2011). 142

143 Calibration area and pseudo-absences

To use presence-absence models with the presence-only GBIF data, we used a random sampling procedure with environmental profiling (RSEP; Senay et al. 2013)- which creates a background of absence records for each algorithm. We generated the pseudo-absences in a different calibration area for each species. *D. plantarius* is a lowland species, so its calibration area was at low altitude <1000m. For *D. fimbriatus*, we excluded areas >1500m.

149 Model validation

Although there are many SDMs, none stands out as better than the others (Qiao et al. 2015).
To improve the predictions, we therefore used an ensemble forecast approach, which

combines several models weighted by their predictive accuracy (Buisson et al. 2010,
Grenouillet et al. 2011).

Following recommendations in Barbet-Massin et al. (2012), we built our ensemble model 154 with 10 runs of gradient boosting models (GBMs), generalized additive models (GAMs) and 155 Maxent. We used 1000 pseudo-absences for the GBMs, and as many pseudo-absences as 156 presences for the GAMs. We used 80% of the data for training the ensemble model and 157 158 testing the single run of model, and 20% for validation. Each model was cross-validated with a 5-fold procedure in package biomod2 (Supplementary material Appendix 1), thus leading 159 to 5 fits for each type of model and each pseudo-absences run. We then evaluated the 160 predictive accuracy of individual models with the true skill statistic (TSS) and the area under 161 the receiving operating curve (AUROC). The TSS metric represents the ratio of hit rate to 162 false alarm rate and varies from -1 to +1 (Allouche et al. 2006). We used a threshold of TSS 163 = 0.4 to include models into the ensemble forecast (Allouche et al. 2006). The AUROC is a 164 measure of "separability", which represents the true positive rates graphically against the 165 166 true negative rates. Following Fawcett (Fawcett 2006), we retained models with AUC>0.7 for the ensemble model. Finally, we converted the probabilities of presence predicted by the 167 ensemble model into a binary presence/absence, with a cut point based on predictions which 168 169 maximized the TSS (Supplementary material Appendix 1). In package biomod2, the relative variable contribution is assessed based on the correlation between the prediction of a model 170 171 including a given variable and the model where this variable was dropped.

We built one model with bioclimatic variables only (model Bioc), and one with bioclimatic and land-use variables (model BLU). We then included dispersal to predict the range of suitable, but unreachable habitat (model Disp). Finally, we accounted for landscape connectivity into model dispCS. The framework is summarized in figure 1 (additional details in Supplementary material Appendix 4, Tab. A1).

177 Including dispersal into SDM

Although they differ in their general dispersal ability, the two species of fishing spider disperse 178 mostly through ballooning and rappelling, where they catch the wind with a thread of silk, 179 and passively fly. Laboratory tests suggested that few individuals exhibit long-distance 180 181 dispersal behaviour on the water surface (unpublished data). We recorded this behaviour only in *Dolomedes fimbriatus* through sailing (when spider raised its body and/or abdomen 182 and/or the legs to catch the wind). However, juveniles of *D. fimbriatus* are generally found in 183 184 the surrounding vegetation rather than on the water (Duffey 2012), which makes aquatic 185 dispersion unlikely.

We modelled dispersal ability via the MigClim package (Supplementary material Appendix 186 1), based on the predicted map of the BLU model. For each species, the MigClim model 187 188 evaluates if suitable cells of the raster could become accessible between current time and 2050/2070. The package uses a dispersal kernel, i.e., a vector of probabilities of dispersal, 189 190 to simulate the dispersal of the species (Supplementary material Appendix 3, Tab. A1). We used an imperviousness map (EEA 2018) to locate areas where the species settlement is 191 highly unlikely. Since both fishing spiders are water-dependent, impervious regions where 192 the soil seals, are barrier to settlement. Part of the MigClim modelling process is random 193 194 (Engler and Guisan 2009), so we replicated each model 30 times and model-averaged the 195 estimates.

In experimental settings, aerial dispersal (ballooning) is usually characterized when the spider is observed tiptoeing in response to a controlled wind. However, not all tiptoeing spiders end up ballooning (Bonte et al. 2009, Lee et al. 2015). The distance covered by aerial dispersal is less than 5 kilometres on average and is not correlated with the duration of the tiptoeing behaviour (Reynolds et al. 2007). We parametrized the MigClim model with values from the literature on aerial dispersal distance in spiders (Thomas et al. 2003, Reynolds et

al. 2007). We weighed these values by the proportion of individuals we observed rappelling in our laboratory experiments (Monsimet et al. in prep), namely, 76.6% of *D. fimbriatus* and 59% *D. plantarius*. For long-distance dispersal, we used the proportion of individuals observed ballooning (*D. fimbriatus*: 14%, *D. plantarius*: 2.9%) for 2019. We considered that the probability of a settlement was similar for both species. Also, we hypothesized that it takes two years for a newly colonized area to produce new propagules, based on the >2year lifespan of spiders in Northern Europe (Duffey 2012).

209 Accounting for landscape connectivity

We used the Circuitscape software (Shah and McRae 2008) to predict the potential dispersal corridors that *Dolomedes* could use to colonize their suitable habitat. Circuit theory estimates multiple pathways based on the resistance and conductance of the landscape (McRae et al. 2008). We used the habitat suitability prediction map from our BLU model to define the resistance map used by Circuitscape. We transformed the estimates of habitat suitability according to recommendations in Keeley (Keeley et al. 2017; see also Supplementary material Appendix 3).

We used a "wall-to-wall" approach (Pelletier et al. 2014, Febbraro et al. 2019) which 217 218 estimates the conductivity of the landscape from South to North, and from West to East. A consensus map was produced by multiplying the resistance layers of different directions. 219 This consensus map was an estimation of the landscape connectivity for the two species. 220 221 The consensus map was binarized by considering conductance higher than mean 222 conductance plus standard deviation as corridors (Febbraro et al. 2019). Areas outside corridors were then considered as a barrier to short-distance dispersal in Migclim. Migclim 223 224 was parametrized as for the model Disp but accounting for the landscape connectivity barrier 225 to make predictions for model DispCS.

226 Range expansion and geographic overlap in time

We compared suitable habitat predicted across species, models, and scenarios. To estimate 227 the range expansion or reduction in the future, we used the biomod2 package in R. We 228 compared the direction of the shift in suitable habitat by calculating the centre of gravity of 229 the suitable range with the SDMTools package (Supplementary material Appendix 1). To 230 231 estimate the overlap of suitable habitat range between species for each time/scenario combination, we used the Schoeners' D overlap metric (Warren et al. 2008), which ranges 232 from 0 for no overlap to 1 for full overlap (Rödder and Engler 2011). We estimated the suitable 233 234 habitat range overlap and not the full niche overlap here. We calculated D with the ENMtools 235 package (Supplementary material Appendix 1).

236 **Results**

237 Modelling and model validation

The predictive performance of both Bioc and BLU models was higher than the threshold with 238 239 either the ROC (>0.7) or the TSS (>0.4) metric (Supplementary material Appendix 4, Tab. A2). The relative contribution of predictors was the same across models and species, with 240 mean annual temperature the most important variable with a contribution higher than 60%. 241 242 For Bioc, mean temperature of the warmest month was also important, with a higher contribution for *D. fimbriatus* than for *D. plantarius* (33% and 11%, respectively). Mean 243 244 temperature of the wettest guarter, annual precipitation and mean diurnal range contributed less than 10% to both models. Forest and ground wetness contributed more than grassland 245 in the BLU models, but their relative contribution was less than 16%. 246

247 Range expansion and geographic overlap in time

The size of the predicted / projected range was similar for both Bioc and BLU models. However, range expansion was predicted to be more restricted when also acccounting for land use (BLU) than when considering only climatic variables (Bioc). Indeed, adding land use variables contracted the suitable habitat at the limit of the range. Suitable range was
also smaller for RCP4.5 than for RCP8.5, with similar patterns in time, except for *D.fimbriatus*where the range was reduced in 2070 compared to current under model BLU (figure 3).

254 Under RCP4.5 scenario, the suitable range was predicted to increase for both species in 2070 with the BLU model (14% for *D. fimbriatus* and 161% for *D. plantarius*). With model 255 Disp, the range should decrease in 2050 for *D. fimbriatus* (20% decrease) and for *D.* 256 257 plantarius (66% decrease: figure 3). Both species should be able to fill the suitable range towards 2070, but both should have a limited spread on the range of suitable habitat under 258 Disp (figure 3 and 4; 14% increase under BLU and 4% under Disp for *D. fimbriatus*; 161% 259 and 16%, respectively, for *D. plantarius*). The range of both species should shrink under 260 DispCS (81% in 2050 and 76% in 2070, compared to current suitable habitat for D. 261 262 *fimbriatus*; 88% and 53%, respectively, for *D. plantarius*).

263 The southern part of the suitable range should shrink, especially in Sweden and, to a lesser extent, in Finland. This range should expand in northern Fennoscandia (figure 4). According 264 265 to model dispCS, tis shift should occur towards the North-Est, with a limited spread in southern Finland (figure 3). Similarly, the range of suitable habitat for *D. plantarius* should 266 267 also increase towards the North-East under model Disp (figure 5). The shift of the centre of 268 gravity is at a higher distance for the models which exclude Dispersal (Bioc and BLU) than model including dispersal (Disp and DispCS). The centre of gravity shifts farther without 269 dispersal (models Bioc and BLU) than with dispersal (models Disp and DispCS). 270

The predicted distribution overlap between species was higher when considering only climatic variables than when accounting for land use at current time (Bioc model). Under the BLU model, the overlap should increase through time and is more important for the scenario SRCRCP8.5 than the 4.5 one (Schoener's D values ranging from 0.55 at current time to 0.62 in 2070 for RCP4.5, it reached 0.68 under 8.5). The overlap should mainly occur at the 276 Southern range of *Dolomedes fimbriatus* distribution (figure 6; Supplementary material 277 Appendix 4, Tab. A4).

278 **Discussion**

Using species distribution models (SDM), we highlighted different range expansions and shifts of two closely related fishing spiders species in Fennoscandia. According to our predictions, the range of suitable habitat should spread for both D. fimbriatus and D. plantarius. Our climatic and habitat models (Bioc and BLU) confirmed the expansion of *D. plantarius* in Fennoscandia predicted by Leroy et al. (2013, 2014). In contrast, our hybrid models including dispersal and landscape connectivity (Disp and DispCS) predicted a more limited expansion.

286 Northward range expansion of both *Dolomedes* species

A northward expansion in Fennoscandia is expected for the two species under both Bioc and 287 288 BLU models. The range of suitable habitat should increase with the intensity of the climate change for *D. plantarius* and for *D. fimbriatus* in 2050. This northward expansion s also 289 predicted in other taxa, as climate change promote an expansion of the range at the colder 290 margin (Parmesan and Yohe 2003, Parmesan 2006). An increase in annual mean 291 292 temperature and in temperature of the warmest month, which are the most important 293 variables for both models, could impact the lifespan of the two spider species, and affect their 294 distribution. Higher temperatures could increase the suitable period to produce juveniles, 295 which could in turn increase the number of juveniles dispersing. The temperature 296 encountered by juveniles also influences the dispersal ability and mode (ie, long vs short 297 distance dispersal; Bonte et al. 2008b). Moreover, latitude and climate affect the time at which the *Dolomedes* reach maturity (Duffey 2012). This could increase the frequency of a 298 299 second brood, which we already observed in September (unpublished data). Such an 300 increase in temperature could, in turn, influence the speed of colonization of new habitats.

301 The inclusion of land use in BLU models shrinks the range of suitable habitat, which confirms 302 results from other, similar studies (Eskildsen et al. 2013)

303 Under the Disp model, suitable habitat should be less reachable for *D. plantarius* than for *D.* 304 *fimbriatus*. The size of the area reached under the Disp model should be smaller than the current area for both species. In 2070, D. fimbriatus should have a range slightly equivalent 305 to the suitable habitat estimated under BLU, whereas it should be smaller for D. plantarius. 306 307 The limited expansion of *D. plantarius* is explained mainly by dispersal ability. Indeed, we observe fewer spiderlings of D. plantarius showing dispersal behaviours, including long-308 309 distance dispersal through ballooning (unpublished data). Non-filling the suitable range is usually explained by either or both past and current limited dispersal, as exemplified by trees 310 species (Svenning and Skov 2004). Some species are trapped in their geographical range, 311 312 species which distribution has not changed since the last glaciation. Under a changing climate, species answer whether through microevolution or adaptive phenotypic plasticity 313 (Radchuk et al. 2019). Some species are not yet able to adjust their phenology and 314 315 physiology to changes induced by climate change. The importance of short-distance dispersal in fishing spiders should nonetheless maintain genetic exchange, or avoid genetic 316 drift, at a smaller scale (Bell et al. 2005). A possible prevalence of this behaviour might also 317 318 reinforce the importance of shorter dispersal as climate change and other factors like the increase of habitat fragmentation decrease long-distance dispersal of spiders (Bonte et al. 319 320 2006).

321 Geographic range overlap and coexistence

The geographic and climatic niche of *D. plantarius* are included in the realised niche of *D. fimbriatus*. The first is a habitat specialist, the last is a generalist species living in a wider variety of environmental conditions over its range. Climate change increases the chance of overlap between these two sister species. However, we did not make predictions at a meso-

or microhabitat scale, which would be too fine for SDMs. Yet, field observations suggest that both Dolomedes species also co-occur at finer spatial scales (Duffey 2012). The discrete nature and propensity to hide and dive of *D. plantarius* (van Helsdingen 1993), together with possible misidentification (Bellvert et al. 2013, Ivanov et al. 2017) might explain the small number of records and of co-occurrences. In North America, closely related species of *Dolomedes* like *D. trition* and *D. vittatus* were reported to co-occur at small spatial scales (Carico 1973).

333 Usually, closely related species co-occur less often than moderately related species 334 (Weinstein et al. 2017). One one hand, an increase in co-occurrence might limit the distribution by segregation at the landscape scale. Indeed, the number of interactions 335 336 between species in the ecosystem increases with climate change (Montova and Raffaelli 337 2010), which generates a spatial separation between generalist and specialist species. Sympatric sister species usually diverge ecologically (Losos 2008), Dolomedes species differ 338 in terms of habitat use (Duffey 2012). D. plantarius needs open habitat with slow-flowing 339 340 water and water all year, while these factors do not seem to restrict D. fimbriatus (unpublished data). On the other hand, spatial segregation might occur at the micro-habitat 341 scale. For instance, a study on *Tetragnatha* spiders showed that one of two co-existing spider 342 343 species builds nursery webs higher in the vegetation when they co-occur (Williams et al. 1995). Finally, an increase in co-occurrence might lead to phenological shift in co-existence 344 345 sites. Our observation in two Swedish locations of *D. fimbriatus* females with juveniles in the nursery while D. plantarius still carried egg sacs could support this. Other closely related wolf 346 spider species (Lycosidae) also show differences in the timing of their breeding season to 347 avoid intraguild predation (Balfour et al. 2003). 348

349 Intrinsic limits of hybrid SDMs

Ideally, a mechanistic model should account for all phases of dispersal, ie, emigration, 350 transfer, settlement, (Travis et al. 2012, 2013). The SDM accounting for dispersal which we 351 used here it not a mechanistic model but is rather based on assumptions concerning the 352 three stages of passive dispersal. Further studies should consider factors which influence 353 354 individuals' dispersal such as food availability (Bonte et al. 2008a), presence of endosymbionts (Goodacre et al. 2009), presence of conspecific in the short-long distance 355 dispersal allocation (De Meester and Bonte 2010), or genetically inherited boldness (Bonte 356 357 and Lens 2007). Since dispersal is not homogeneous within and among species (Clobert et al. 2009), a more realistic model should include information on dispersal and population size 358 for each presence observation. The sampling of all sites is necessary to collect this 359 information. There is a considerable gap between the theory and actual applications of data-360 demanding mechanistic SDMs (Briscoe et al. 2019). Knowing that the most used habitat is 361 not necessarily the most suitable for the fitness of the species (Titeux et al. 2019), we used 362 a hybrid model based on the lack of sufficient data for a full mechanistic model. 363

Less snow cover leads to less insulation, and thus, to colder subnivean habitat, where fishing spiders overwinter (Slatyer et al. 2017). Accounting for thermal niche information is possible with mechanistic models (Ceia-Hasse et al. 2014; Sinervo et al. 2010). However, the current knowledge of eco-physiological responses of fishing spiders to climate change is too scarce to allow fully mechanistic models.

369 **Conservation of fishing spiders**

Fennoscandia may become a climatic refugium for *D. plantarius* as its range in continental Europe is expected to decrease (Leroy et al. 2013, 2014). The stronger the climate is, the more likely Fennoscandia will act as a refugium. The overlap between the two *Dolomedes* species should also increase with the climate change intensity. Arthropods conservation is 374 challenging because of the fine-grain level needed as compared to vertebrates, the low empathy towards invertebrates, and the lowest number of conservation specialists available 375 (Cardoso et al. 2020, Samways et al. 2020). Nonetheless, spiders have already been used 376 377 as bio-indicators (Marc et al. 1999, Prieto-Benítez and Méndez 2011). Our models suggest 378 that the conservation of both species is necessary as the reachable range size should 379 drastically decrease in the future when accounting for dispersal and landscape connectivity. Conservation of preserved sites in a stepping-stones scheme is an alternative for species 380 that are not able to use corridors (Noss and Daly 2006). Maintaining interconnected suitable 381 382 sites in the first five kilometres around sites with known presence should help conserve current sites and promote expansion. With respect to fishing spiders, priority should be given 383 384 to sites in southern Finland and central Sweden, where there is limited connectivity, and the 385 spread of *Dolomedes* species is limited. Since *D. fimbriatus* has higher dispersal abilities, 386 improving the connectivity in the North of the suitable range to make it reachable should improve the future range. 387

This work, together with other studies on *Dolomedes*, could be used to update the now outdated range assessment of *D. plantarius* (World Conservation Monitoring Centre 1996). The species' conservation would benefit from such an update.

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Author contributions

- 395 All authors contributed to the design and implementation of the research. JM analysed the
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- 397 approved of the final version.

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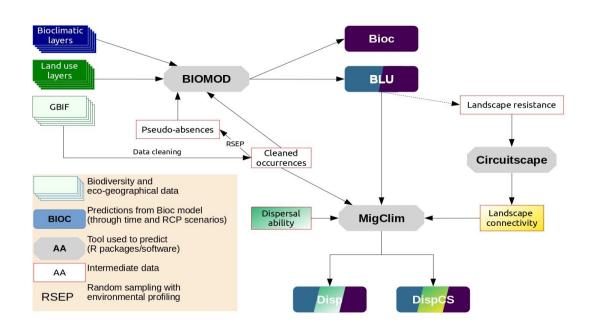
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616 Figures



- 617 Figure 1: Flowchart of the framework used to study the future distribution of the two European
- 618 fishing spiders (Bioc: bioclimatic only model, BLU: bioclimatic and land use model, Disp:
- 619 dispersal model, DispCS: dispersal and landscape connectivity model).

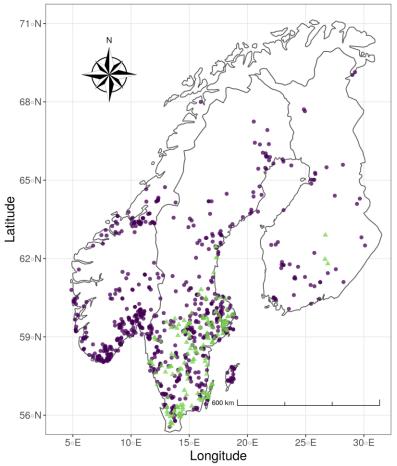


Figure 2: *Dolomedes plantarius* (green triangles) and *Dolomedes fimbriatus* (purple dots)
records in Fennoscandia as of October 2019. Data were extracted from the GBIF database
and supplemented by field samplings.

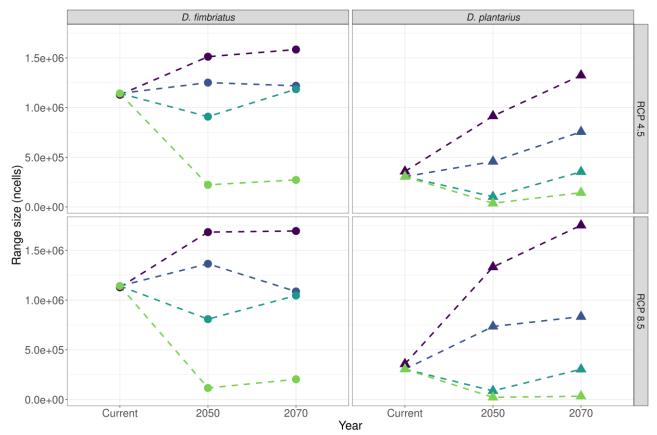
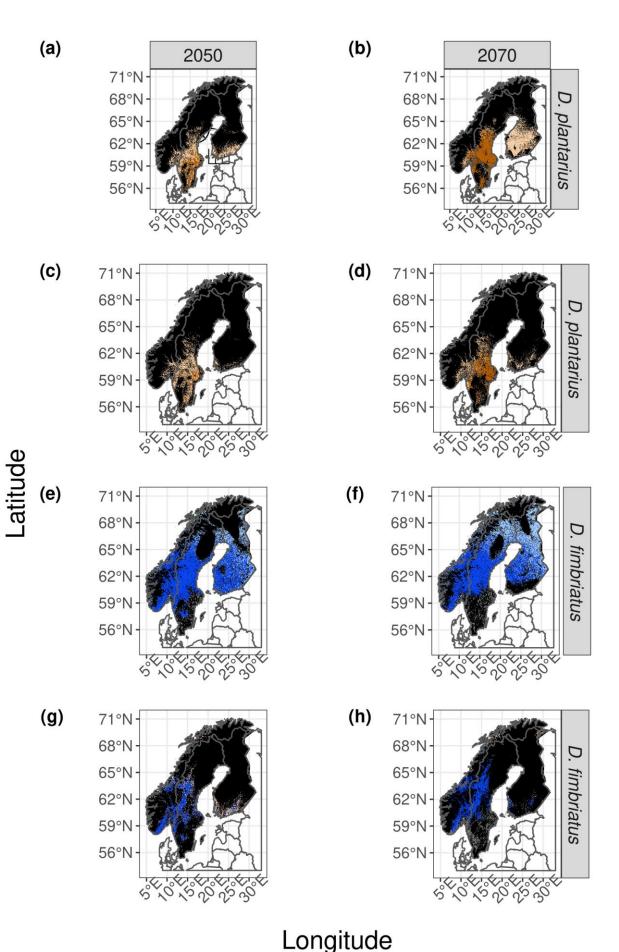


Figure 3: Range size in number of cells of suitable habitat predicted by the different SDMs
in time per species and scenarios. (dark purple: Bioc model: bioclimatic variables only; dark
blue: BLU model, bioclimatic + land use; Turquoise: Disp model with dispersal; green:
DispCS model: dispersal and landscape connectivity).



627 Figure 4: Map of the forecasted suitable habitat with an estimation of the reachable range

- 628 predicted by the dispersion model (Disp) and reachable area from the connectivity model
- 629 (DispCS) under the RCP4.5 scenario (RCP: Representative Concentration Pathway; in dark
- 630 brown the reachable habitat for *D. plantarius* under Disp (a and b) and DispCS (c and d); in
- 631 dark blue the reachable for *D. fimbriatus* under Disp (e and f) and DispCS (g and h); in black:
- 632 unsuitable habitat; in grey: previously occupied habitat lost; in light brown and light blue:
- 633 suitable but non reachable habitat).

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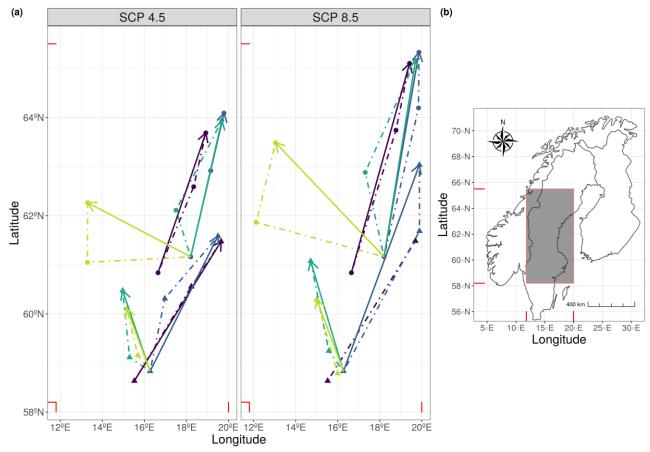


Figure 5: Shift in the centre of gravity of the two species distributions predicted by the four SDMs; solid lines: shift from current to 2070; dashed lines: shift from current time to 2050 and from 2050 to 2070. Dark purple: Bioc model; dark blue: BLU model; turquoise: Disp model; green: DispCS model.

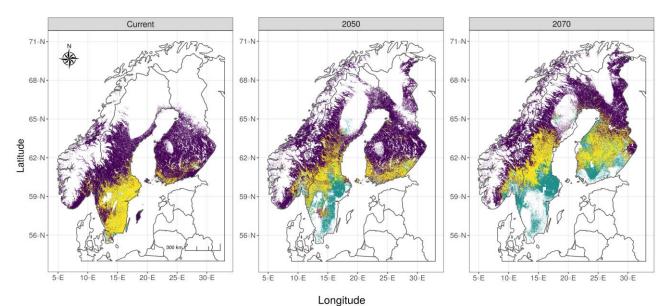


Figure 6: Range overlap predicted by model BLU from current time to 2070 under scenario
RCP4.5. In addition to overlap of suitable range, suitable habitat for each species is
represented.dark purple: suitable habitat for *D. fimbriatus*; green: suitable habitat for *D. plantarius*; yellow: suitable habitat overlapping between the 2 species.