

## **Global environmental drivers of local abundance-mass scaling in soil communities**

Ana Carolina Antunes<sup>1,2</sup>, Benoit Gauzens<sup>1,2</sup>, Ulrich Brose<sup>1,2</sup>, Anton M. Potapov<sup>6</sup>, Malte Jochum<sup>3,4</sup>, Luca Santini<sup>5</sup>, Nico Eisenhauer<sup>3,4</sup>, Olga Ferlian<sup>3,4</sup>, Simone Cesarz<sup>3,4</sup>, Stefan Scheu<sup>6,7</sup>, Myriam R. Hirt<sup>1,2</sup>

<sup>1</sup> Institute of Biodiversity, Friedrich Schiller University Jena, Jena, Germany

<sup>2</sup> EcoNetLab, German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Puschstrasse 4, 04103, Leipzig, Germany

<sup>3</sup> Experimental Interaction Ecology, German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Puschstrasse 4, 04103, Leipzig, Germany

<sup>4</sup> Institute of Biology, Leipzig University, Puschstrasse 4, 04103, Leipzig, Germany

<sup>5</sup> Department of Biology and Biotechnologies “Charles Darwin”, Sapienza University of Rome, Rome, Italy

<sup>6</sup> Johann Friedrich Blumenbach Institute of Zoology and Anthropology, University of Goettingen, Goettingen, Germany

<sup>7</sup> Centre of Biodiversity and Sustainable Land Use, Büsgenweg 1, 37077 Göttingen, Germany

Corresponding Author:

Ana Carolina Antunes<sup>1,2</sup>

iDiv, Puschstrasse 4, Leipzig, Saxony, Zip 04103, Germany

Email address: ana\_carolina.antunes@idiv.de

## Supporting Information – S1

Table S1: description of sampling methods in each site

Site Location	Group	Sampling method	Number of plots	Area per plot m <sup>2</sup>	Soil core	Sampling date	Body mass estimation
USA, Canada	Macrofauna	litter sieving, hand sorting	80	0.5	NA	2016 - 2017	length-mass regressions from Wardhaugh 2013, Sohlström et al. 2018
USA, Canada	Mesofauna	1 soil core, heat-extraction	80	0.00196	5cm diameter, 10 cm depth	2016 - 2017	length–mass regressions for specific taxa from Mercer et al. 2001
Germany	Macrofauna	2 soil cores, heat-extraction	48		20cm diameter, two samples per plot	2008 - 2011	measured or estimated with mass-length regressions from Ehnes et al. 2014
Germany	Macrofauna	litter sieving, mustard extraction	48	0.25	NA	2008 - 2011	measured or estimated with mass-length regressions from Ehnes et al. 2014
Germany	Mesofauna	2 soil cores, heat-extraction	48		5cm diameter, two samples per plot	2008 - 2011	measured or estimated with mass-length regressions from Ehnes et al. 2014
Indonesia	Mesofauna	2 soil cores, heat-extraction	32	0.0256	litter + 5cm depth	2013	length-mass regressions were used for Collembola: dry weight (Peterson 1975)
Indonesia	Macrofauna	litter sieving, heat-extraction	32	3	NA	2012	length-body mass regressions were used to estimate spp body mass (Sohlström et al. 2018)

## **Supporting Information – S2**

### *Additional environmental variables descriptors*

In order to explore the effect of additional environmental and edaphic variables on our analysis, we extracted the human footprint index based on data on human pressures at 1 km<sup>2</sup> resolution (from 1993 and 2009) (Venter et al. 2016). Current global scale land-change classifications were extracted from van Asselen and Verburg (2012) at a 5-arcminute resolution (Table S2). Original land-use maps were converted to numerical data, following Pouzols et al. (2014) and Eitelberg (2018), with values imputation for the missing categories (Table 1 - S2). Other environmental variables were available from the respective projects for each community: litter layer was measured (cm) and weighted (g/m<sup>2</sup>); carbon and nitrogen content were measured in the soil (dry weight), and used to calculate C: N ratio. We used the georeferences of the communities' location and study years in a 0.05 degrees unit to extract NDVI (from 2000 to 2018) (MOD13C2 Series – Didan, 2015).

Table S2: Current global scale land-change classifications were extracted from Van Asselen & Verburg (2012) and Eitelberg (2018)

<b>Land System</b>	<b>Pouzols et al. (2014)</b>	<b>Eitelberg (2018)</b>	<b>Imputation</b>	<b>Final intensity value</b>
Cropland; extensive, few livestock	0.4	0.4		0.4
Cropland; extensive, bovines, goats & sheep		0.4		0.4
Cropland; extensive, pigs & poultry			0.45	0.45
Cropland; medium intensive, few livestock	0.3	0.3		0.3
Cropland; medium intensive, bovines, goats & sheep		0.3		0.3
Cropland; medium intensive, pigs & poultry			0.35	0.35
Cropland; intensive, few livestock	0.2	0.2		0.2
Cropland; intensive, bovines, goats & sheep		0.2		0.2
Cropland; intensive, pigs & poultry			0.25	0.25
Mosaic cropland and grassland; bovines, goats & sheep		0.8		0.8
Mosaic cropland and grassland; pigs & poultry			0.85	0.85
Mosaic cropland (ext.) and grassland; few livestock	0.7	0.7		0.7
Mosaic cropland (med. int.) and grassland; few livestock	0.6	0.6		0.6
Mosaic cropland (int.) and grassland; few livestock	0.5	0.5		0.5
Mosaic cropland and forest; pigs & poultry			0.55	0.55
Mosaic cropland (ext.) and forest; few livestock	0.7	0.7		0.7
Mosaic cropland (med. int.) and forest; few livestock	0.6	0.6		0.6
Mosaic cropland (int.) and forest; few livestock	0.5	0.5		0.5
Dense forest	1	1		1
Open forest, few livestock	0.9	0.9		0.9
Open forest, pigs & poultry			0.95	0.95
Mosaic grassland and forest	1	1		1
Mosaic grassland and bare	1	1		1
Grassland, natural	1	1		1
Grassland, few livestock	0.9	0.9		0.9
Grassland, bovines, goats & sheep		0.9		0.9

Bare	0.1	1	1
Bare, few livestock	0.9	0.9	0.9
Peri-urban & villages	0.1	0.1	0.1
Urban	0.1	0	0

---

### Supporting Information – S3

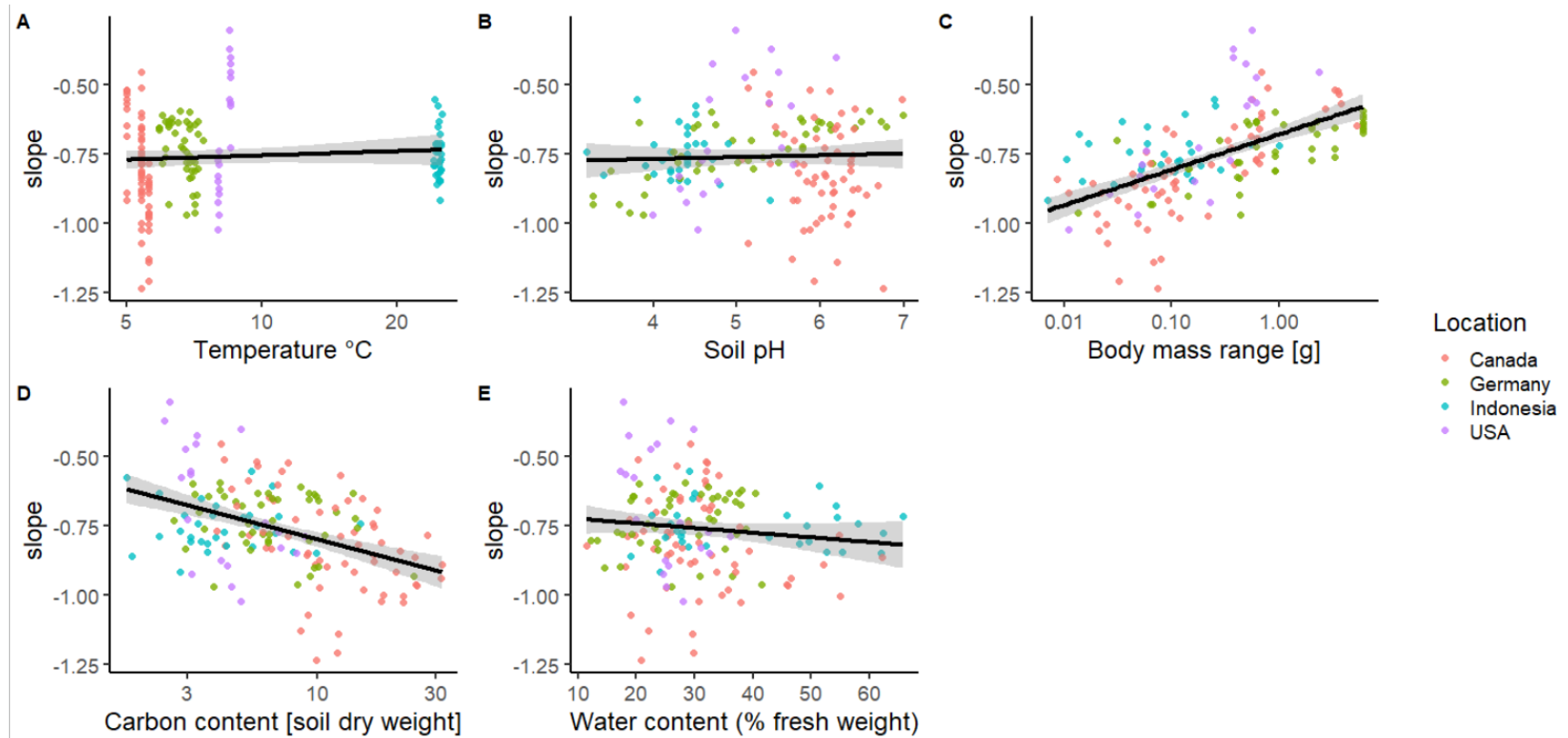
To evaluate if additional environmental variables affect body mass-abundance relationships across local communities, we used Linear Mixed Effects Models that relate the previously evaluated slopes of the body mass-abundance relationship for each soil animal community to the local community's body mass range and environmental variables (soil temperature, precipitation, land-use intensity, soil pH, human footprint index, the carbon content in the soil, litter layer mass and depth, C: N rate in the soil, water content in the soil). Based on a correlation analysis of all environmental variables, we removed NDVI from the model due to its high correlation with soil temperature. The mixed-modeling approach was used to account for potential spatial autocorrelation by using the `corGaus` function from `nlme` package (Pinheiro et al. 2020), which required the use of a randomly parameterized dummy variable as a random effect (note that the `corGaus` function is only available for mixed-effects models that require a random effect variable). Each of the independent variables was added as a linear term, without interactions. We started with the full model comprising all independent variables and selected the best-fitting model by the 'dredge' function of the `MuMIn` package (Barton 2022), using the Bayesian information criterion (BIC) for model comparison ( $\Delta\text{BIC} < 2$ ).

The two most supported models ( $\Delta\text{BIC} < 2$ ) were used to generate model-averaged estimates of the parameters using the 'model.avg' function from the `MuMIn` package. Model-averaged estimates from the top models ( $\Delta\text{BIC} < 2$ ) included the body-mass range, water content in the soil, soil carbon content and temperature. This final model reveals linear increases in the slope with increasing body-mass range, soil temperature and water content and decreases with increasing soil carbon content (Table 1 - S3). The general relationships between the slopes and the variables selected in the final model were illustrated in Figure 1 (S3).

Table S3: Summary of the parameter estimates of the final Mixed-Effect Model (conditional average) for slope prediction. Estimates, standard errors and p-value for the Z-statistic are indicated.

<b>Predictors</b>	<b>Estimates</b>	<b>Std. Error</b>	<b>Pr(&gt; z )</b>
(Intercept)	-0.63931	0.15688	$4.72 \times 10^{-5}$
log body mass range	0.10926	0.01452	$< 2 \times 10^{-16}$
log carbon content	-0.16443	0.03951	$3.61 \times 10^{-5}$
log soil temperature	0.13989	0.05617	0.0135
soil pH	0.03220	0.01321	0.0156

Figure S3: Relationships between the slopes of the body mass-abundance relationship in the communities in each location (colored symbols) with **A.** mean soil temperature ( $\log_{10}$ ), ( $y = -0.81 + 0.051x$ ,  $R^2 = 0.0063$ ), **B.** soil pH, ( $y = -0.79 + 0.0066x$ ,  $R^2 = 0.0015$ ), **C.** body mass range of the communities ( $\log_{10}$ ), ( $y = -0.68 + 0.13x$ ,  $R^2 = 0.35$ ), **D.** soil carbon content ( $\log_{10}$ ), ( $y = -0.56 - 0.24x$ ,  $R^2 = 0.18$ ) and **E.** water content in the soil (% fresh weight), ( $y = -0.71 - 0.0017x$ ,  $R^2 = 0.0014$ ).





## Supporting Information – S4

To describe general body mass-abundance relationships across communities, we fitted a linear model pooling the abundance and mass data of the species for all sites. We ran a linear regression of the dependence of each species  $\log_{10}$  abundance on the  $\log_{10}$  body mass and edaphic variables (soil temperature, precipitation, land-use intensity, soil pH, human footprint index, the carbon content in the soil, litter layer mass and depth, C: N rate in the soil, water content in the soil). Based on a correlation analysis of all environmental variables, we removed NDVI from the model due to its high correlation with soil temperature. Each of the independent variables was added as a linear term, without interactions. We started with the full model comprising all independent variables and selected the best-fitting model by the 'dredge' function of the `MuMIn` package (Barton 2022), using the Bayesian information criterion (BIC) for model comparison ( $\Delta\text{BIC} < 2$ ).

The two most supported models ( $\Delta\text{BIC} < 2$ ) were used to generate model-averaged estimates of the parameters using the 'model.avg' function from the `MuMIn` package. Model-averaged estimates from the top models ( $\Delta\text{BIC} < 2$ ) included body mass, human footprint index, land-use intensity, litter layer depth, soil temperature, soil pH and water content in the soil). This final model reveals linear increases in the species abundance with increasing human footprint index and land-use intensity and decreases with increasing species body mass, litter layer depth, soil temperature, soil pH and water content in the soil (Table 2 - S2). Our model can be used in future predictions to assess the abundance of soil species for large-scale projections.

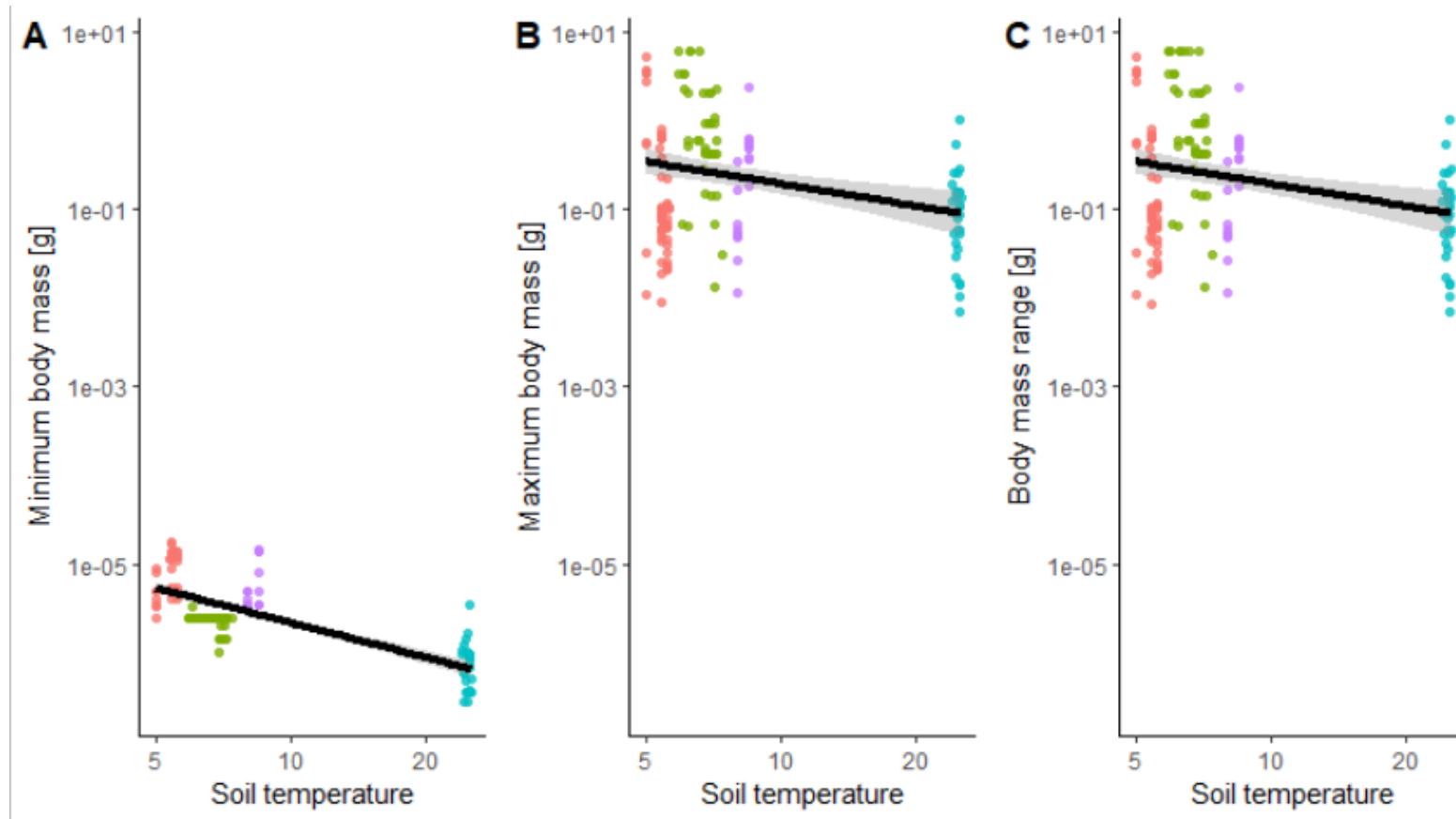
Table S4: Summary of the parameter estimates of the final Mixed-Effect Model for species abundances prediction. Estimates, standard errors and p-value for the Z-statistic are indicated.

Predictors	Estimates	Std Error	Pr(> z )
(Intercept)	1.882579	0.124495	< 2 x 10 <sup>-16</sup>
human footprint index	0.006876	0.001473	3.07 x 10 <sup>-6</sup>
land-use intensity	0.246828	0.038845	< 2 x 10 <sup>-16</sup>
litter layer depth	-0.020904	0.006052	0.000553
log soil temperature	-2.818322	0.050278	< 2 x 10 <sup>-16</sup>
log body mass	-0.743859	0.006296	< 2 x 10 <sup>-16</sup>
soil pH	-0.090023	0.011250	< 2 x 10 <sup>-16</sup>
log water content	-0.162260	0.058978	0.005945

## Supporting Information – S5

To evaluate how the body-mass range of the communities varies along the gradient of temperature, we ran linear regressions of the dependence of **A.**  $\log_{10}$  minimum body mass (g), **B.**  $\log_{10}$  maximum body mass (g) and **C.**  $\log_{10}$  body-mass range (g) (difference between maximum and minimum body masses) on soil temperature ( $^{\circ}\text{C}$ ) for each of the 155 communities using the `lm` function in R (R Core Team, 2020).

Figure S5: Relationships between the soil temperature ( $\log_{10}$ ) in each location (colored symbols) with **A.** minimum body mass ( $\log_{10}$ ) ( $y = -4.4 - 1.3x$ ,  $R^2 = 0.63$ ) **B.** maximum body mass ( $\log_{10}$ ) ( $y = 0.12 - 0.83x$ ,  $R^2 = 0.078$ ) and **C.** body mass range ( $\log_{10}$ ) ( $y = 0.12 - 0.83x$ ,  $R^2 = 0.078$ ) in each community.



## References

Barton, K. 2022. MuMIn: Multi-Model Inference. R package version 1.46.0. <https://CRAN.R-project.org/package=MuMIn>

Didan, K. 2015. MOD13C2 MODIS/Terra Vegetation Indices Monthly L3 Global 0.05Deg CMG V006. NASA EOSDIS Land Processes DAAC 10:415.

Ehnes, R. B. et al. 2014. Lack of energetic equivalence in forest soil invertebrates. - *Ecology* 95: 527–537.

Eitelberg, D. A. 2018. An Exploration of Human-Environment Interactions that Shape the Earth ' s Surface.

Mercer, R. D. et al. 2001. Invertebrate body sizes from Marion island. - *Antarct. Sci.* 13: 135–143.

Peterson. 1975 DryWeightetc.-*Pedobiol.*1975.pdf. in press.

Pouzols, F. M. et al. 2014. Global protected area expansion is compromised by projected land-use and parochialism. - *Nature* 516: 383–386.

Sohlström, E. H. et al. 2018. Applying generalized allometric regressions to predict live body mass of tropical and temperate arthropods. - *Ecol. Evol.* 8: 12737–12749.

van Asselen, S. and Verburg, P. H. 2012. A Land System representation for global assessments and land-use modeling. - *Glob. Chang. Biol.* 18: 3125–3148.

Venter, O. et al. 2016. Global terrestrial Human Footprint maps for 1993 and 2009. - Sci. Data 3: 1–10.

Wardhaugh, C. W. 2013. Estimation of biomass from body length and width for tropical rainforest canopy invertebrates. - Aust. J. Entomol. 52: 291–298.