Comment on “Forest microclimate dynamics drive plant responses to warming”

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Methods

All analyses were conducted on the “all species” (n = 2,943 observations) and “common species” (n = 2,846 observations) datasets provided by Zellweger *et al.* (1-2). The two datasets led to similar statistical results and conclusions. For the sake of simplicity, only the results derived from the “all species” dataset are shown in this Technical Comment.

Here, we investigated the underlying microclimate determinants of “microclimatic debt” and “thermophilization” observed in understory plant communities. These variables were both computed from the 95th percentiles of the floristic temperature distribution between the baseline survey and resurvey, divided by the time interval between the two surveys (see methods of Zellweger *et al.* (1)). Variations in the “microclimatic debt” and “thermophilization” were analyzed considering the effects of local and global components of microclimate which depicted trends in temperature buffering due to canopy cover change and global maximum temperatures, respectively, during the growing season (1).

We conducted an explicit comparison of the effects of local and global drivers of microclimate on the microclimatic debt and thermophilization observed in understory plant communities. That is, we refined the linear mixed-effect models (LMM) framework as in Zellweger *et al.* as follows: thermophilization or microdebt = $\text{macroTC}_{\text{[the global component of microclimate]}} + \Delta\text{Tbuff}_{\text{[the local component of microclimate]}} + \text{macroTC}*\Delta\text{Tbuff}_{\text{[the interaction between global and local components of microclimate]}}$ + (1|region). This model assumes that change in macroclimate temperature (macroTC), change in temperature buffering (ΔTbuff) and the two-term interaction likely explain the microclimatic debt (microdebt) or the community thermophilization. Here, change in microclimate conditions is not considered as an explicative variable because microclimate conditions is computed as the sum of macroTC and ΔTbuff. Instead, we accounted directly for ΔTbuff in the model in order to disentangle the effect of local and global components of microclimate on plant communities’ reshuffling. Explicative variables were transformed to z-scores to compare the magnitude of their respective effects. We checked for colinearity between macroTC and ΔTbuff, and found that both variables were independent ($R^2 < 0.01$). We fitted LMMs explaining the plant communities’ thermophilization and the microclimatic debt separately, using the restricted maximum likelihood parameter estimate to ensure a robust estimate of coefficients (3). We calculated both the mean effect and the proportion of variation explained by each fixed variable, as well as their respective 95% confidence intervals through a bootstrap approach (n = 10,000 iterations). The significance of each variable was determined from the bootstrap distributions for the two alternative hypotheses of a mean coefficient estimate being greater or lower than zero (i.e. the null hypothesis). To assess the goodness-of-fit of the models, we also computed the mean marginal (i.e. variance explained by the fixed effects) and conditional (i.e. variance explained by both the fixed and random effects) R^2 values, as well as their respective 95% confidence interval from the set of bootstrap iteration.

All statistical analyses were performed in R (version 3.6.3; 4) using the *lme4* (3), *optimx* (5) and *merTools* (6) packages to fit LMM and to run bootstraps, as well as the *MuMIn* package (7) to compute marginal and conditional R^2 values. The *variancePartition* package (8) was used to compute the

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proportion of variation explained by each factor in the LMMs. R code supporting analyses are openly available (9).

References

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