Land cover and management effects of ecosystem resistance to drought stress

Xiao, C., Zaehle, S., Yang, H., Wigneron, J.-P., Schmullius, C., and Bastos, A. *Earth Syst. Dynam. Discuss*

Response to Reviewer #1

R1C1: Thank you to the authors for your comprehensive responses and the additional analyses, which have successfully addressed many of my initial concerns. I have a few remaining thoughts on aspects of the manuscript that could be clarified further.

Thank you for the constructive comments and detailed suggestions.

R1C2: I was particularly impressed with the findings presented in Figure 5. Your large-scale remote-sensing based analysis has yielded some really intriguing results. One point that still wasn't entirely clear to me, however, is your use of the term "similar background climate." I understand that you employed a multiple linear regression model to control for temperature and precipitation, but missing the consideration of climate seasonality when using the annual mean. Even regions with the same mean climate can differ significantly for the coldest and warmest months. In addition, a consideration of radiation variability could strengthen the model, especially for high-latitude regions where both primary and secondary forests are present (important for interpreting Fig. 5a). Your Figure R4 already hints at the weak relationship between T2m and drought duration in boreal regions, suggesting that radiation could be an important factor there.

(i) Thank you for suggesting taking climate seasonality into consideration when we define a similar climate background. When we define the climate space, there is a trade-off between the number of available pixels for comparison and the details of our climate space. Since we have a limited area with significant drought resistance due to the short time series of L-VOD, the noise in the L-VOD data or areas where droughts do not strongly influence the vegetation growth in 2010-2020, we used only climatological mean temperature and precipitation to define our climate space.

We added the following sentences in Lines 545-550 in Section 4.5:

… *Even though we controlled for similar climate backgrounds by aggregating pixels based on their long-term temperature and precipitation averages, there are other climate effects that were not considered in our statistical analysis, for example, the interannual variability of precipitation and climate seasonality of temperature. With only limited areas exhibiting significant drought resistance α, and given the need to ensure a large enough* *number of pixels for comparison in a similar climate space, it remains challenging to disentangle the potential confounding effects of all the climate variables and their variabilities.*

(ii) In the boreal regions, radiation is an important limitation factor for vegetation growth (Seddon et al., 2016). However, the surface incoming shortwave radiation strongly correlates with the yearly total precipitation (Figure R1a), yearly mean temperature (Fig. R1b), and soil moisture drought duration on land (Fig. R1c).

Precipitation is closely related to cloud cover, which directly influences the incoming solar radiation at the land surface. The air temperature at 2 m increases due to a higher energy input when surface incoming solar radiation is higher. Droughts are associated with clear-sky conditions that favor more incoming solar radiation (O et al., 2022).

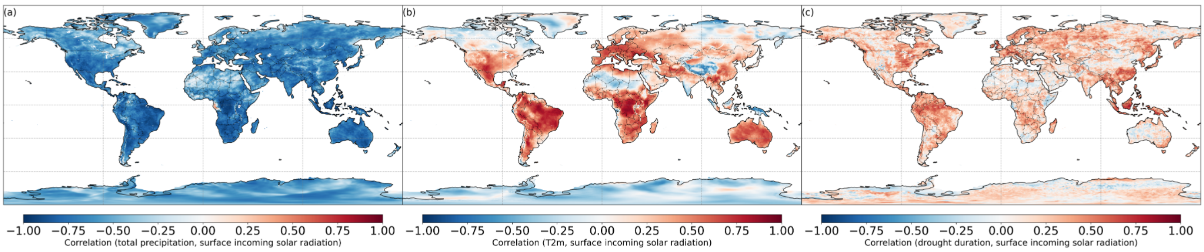

Figure R1. Temporal correlation between yearly mean surface incoming solar radiation and (a) yearly total precipitation (b) yearly mean temperature at 2 m and (c) drought duration (months per year) in 1979-2020.

To avoid the influence of collinearity on vegetation sensitivity to temperature and drought duration, and since we only have ten years of data for the regression with L-VOD, we decided not to incorporate radiation into our linear regression model. Nevertheless, we acknowledge that the trade-off between drought and radiation can partly explain some of the patterns of high drought resistance that we find in energy-limited areas, e.g. in high latitudes.

Therefore, we evaluate how our results change when controlling for radiation by adding surface incoming solar radiation as an additional predictor. Fig. R2 shows that adjusted R^2 increased by 0.04 on average from L-VOD. The median of the adjusted R^2 difference is -0.03. Adjusted R^2 does not increase in most areas except for the boreal eastern Siberia. In the region north of 60° N, the averaged adjusted R^2 increased by 0.126. Drought resistance shows an average difference of -0.009 month^{-1} and a median difference of -0.001 month^{-1}. Temperature sensitivity shows an average difference of -0.003 and a median difference of 0.001. For EVI and kNDVI, adjusted R^2 increased by 0.05 and 0.084 on average. The median of the adjusted R^2 difference is -0.02 and 0.003. The adjusted R^2 increases in southern South America, southern Australia, central North America, and central Eurasia regions, where surface incoming solar radiation is highly correlated with temperature at 2 m, which can lead to problems in interpreting the coefficient of temperature. In the region north of 60° N, the averaged adjusted R^2 only increased by 0.012 and 0.014.

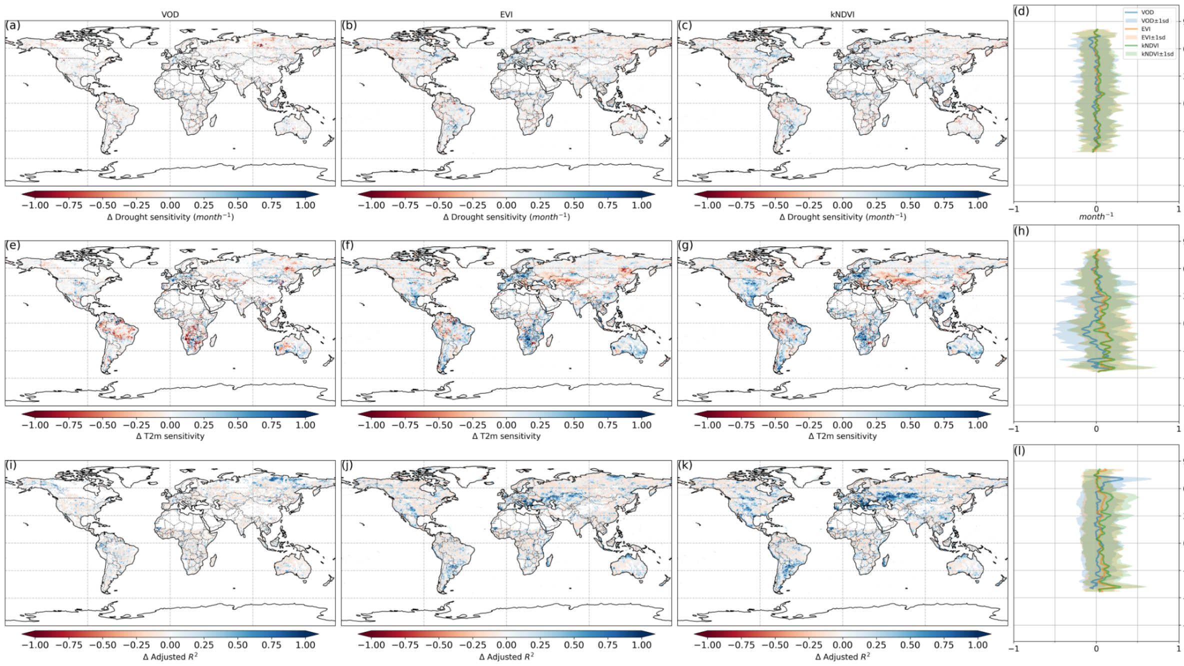

Figure R2. Difference between linear regression model with/without surface incoming solar radiation as an additional predictor for ecosystem resistance to drought duration α from L-VOD, EVI, and kNDVI (a, b, c). Similar for temperature sensitivity β (e, f, g) and adjusted R^2 (i, j, k). The averages for different latitudes and their standard deviations are shown on the right (d, h, l).

We then compare (Fig. R3) how the values of α and β change. For significant drought resistance and temperature sensitivity coefficients (P-value < 0.05), which we have used for further statistical analysis of land cover and management effects, the results are similar to regression without radiation or with radiation in predictors. The correlation between α (without radiation) and α (with radiation) is close to 1 (Fig. R3a-c). Similar results are found for β (Fig. R3d-f).

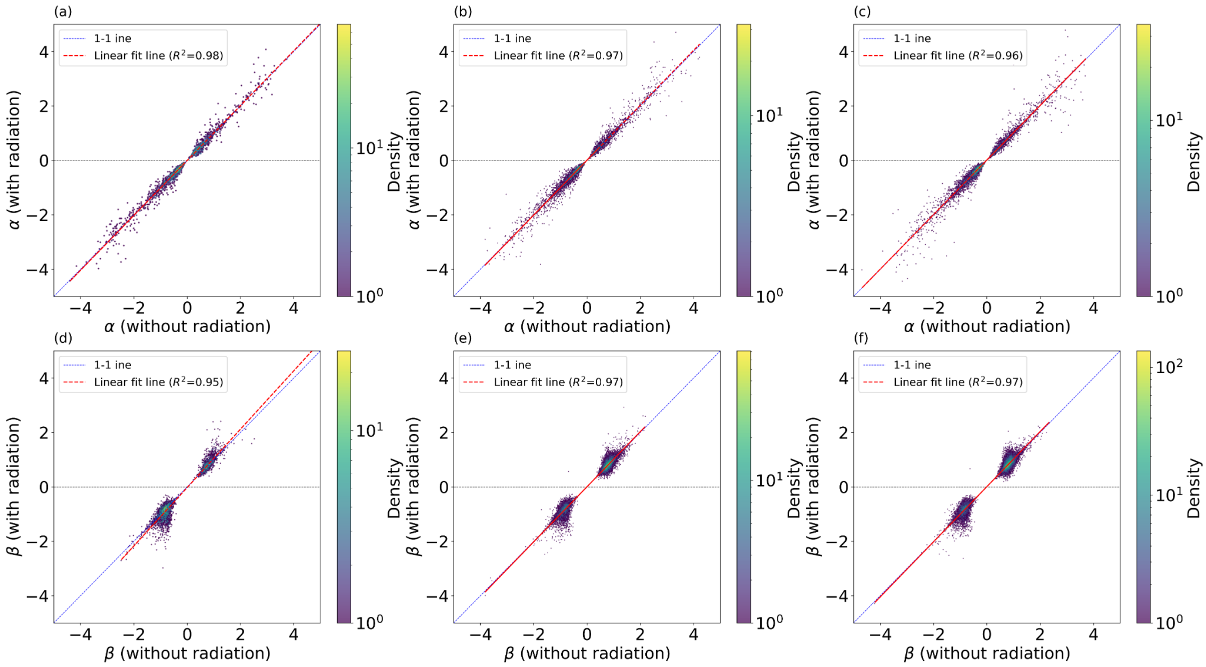

Figure R3. Difference between estimated significant drought resistance α (a-c) and temperature sensitivity β (d-f) (P-value < 0.05) with/without surface incoming solar radiation as an additional predictor.

We further evaluate how the effect of land cover on drought resistance changes if we consider radiation as an additional predictor for the pixels with increased adjusted R^2. Fig. R4 shows that the similar significant α and β do not change our main conclusion. Dominant forests are more resistant than dominant crops to drought stress. Although there are still some changes in the significance test between groups: the significance of the contrast between α in >75% forests and >75% crops calculated from EVI becomes non-significant.

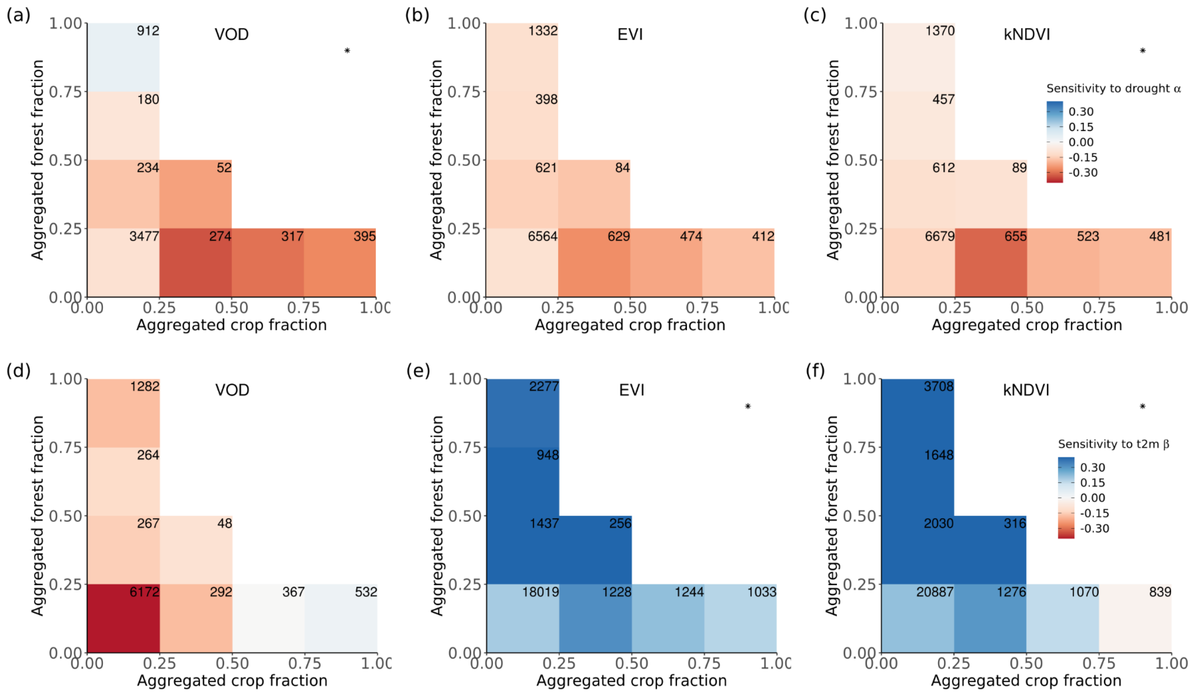

Figure R4. Ecosystem resistance to drought and temperature after including surface incoming solar radiation as an additional predictor only for areas where adjusted R^2 increases, binned for different levels of the aggregated forest and cropland fraction classes from the three land cover products (a) L-VOD, (b) EVI and (c) kNDVI for drought resistance coefficients α and (d-f) for temperature resistance coefficients β. Only significant coefficients α in the linear model (P-value < 0.05) are included and groups with less than 20 pixels are excluded. The number in each bin is the number of pixels in this category. Only pixels with no change in 25% bins of the four dominant vegetation categories (forests, shrublands, grasslands, and croplands) are analyzed. The star on the upper right corner indicates significantly higher resistance in forest > 75% than crop > 75% at the 0.05 significance level from the unpaired two-sample Wilcoxon test.

Finally, we evaluate whether adding radiation as an additional predictor influences our conclusion that primary forests are more resistant to drought than secondary forests (Fig. R5). Primary forests are still more resistant to drought stress than secondary forests and the difference is most obvious in L-VOD, although there are still some changes in the significance test between groups: a higher resistance α in primary forests than in secondary forests change from non-significant to significant in kNDVI.

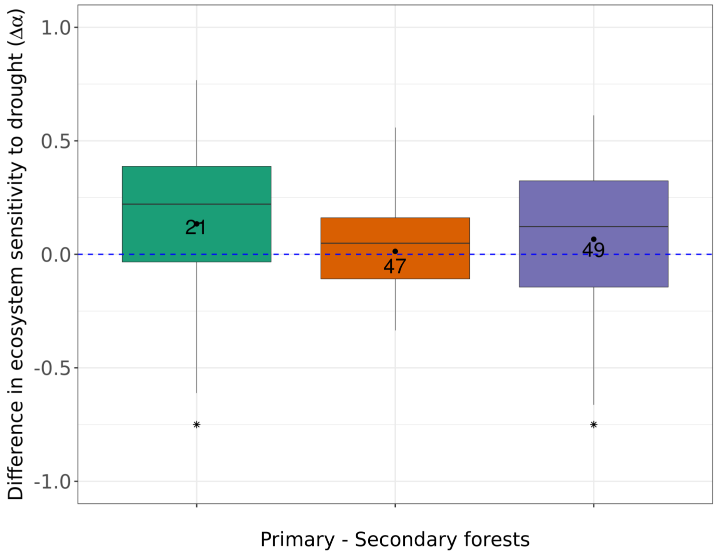

Figure R5. Similar to Figure 5a in the original manuscript, but including the effects of surface incoming solar radiation only for areas where adjusted R^2 increases.

Considering the risk of overfitting for our small samples and the strong correlation between radiation and temperature as well as drought duration, we decided to keep the original predictors, temperature and drought duration to investigate the ecosystem resistance to drought stress.

We added the following explanation of the choice of predictors in Lines 227-232:

We note that radiation plays an important role in the energy-limited boreal region. However, surface incoming solar radiation strongly correlates with temperature and drought duration. The air temperature at 2 m increases due to a higher energy input when surface incoming solar radiation is higher. Droughts are associated with clear-sky and sunnier conditions that favor more incoming solar radiation (O et al., 2022). To avoid the influence of collinearity on estimated vegetation sensitivity to temperature and drought duration, and given that only ten years of data are available, we did not incorporate radiation into our linear regression model.

And reference in Lines 895-896:

O, S., Bastos, A., Reichstein, M., Li, W., Denissen, J., Graefen, H., and Orth, R.: The Role of Climate and Vegetation in Regulating Drought–Heat Extremes, J Climate, 35, 5677–5685, https://doi.org/10.1175/JCLI-D-21-0675.1, 2022.

We have discussed the potential effect of radiation in boreal regions in Lines 430-432 in our submitted manuscript before:

For boreal regions, the soil is generally humid, so that drought defined as the 10th percentile of the corresponding distribution likely still provides critical water storage for vegetation. The potential environmental limitations to vegetation growth in these areas are temperature and radiation rather than water availability (Boisvenue and Running, 2006).

R1C3: I also appreciated your comparative analysis of alpha based on the growing season versus the whole year. However, I don't agree that "the calculated drought resistance is the same" as you stated in your reply. I am actually a bit surprised by the resulting goodness of fit (now showing an explained 36% variation of the original alpha) when only focusing on parts of the northern hemisphere. I would expect even more deviation could occur when including the southern hemisphere, given the strong effects of elevation on the growing season there. I suggest an explicit discussion of the potential impacts of the choice of aggregation period as the growing season on the analysis. Any insights into this would be fascinating and valuable.

We apologize for the unclear statement that *'the calculated drought resistance is the same'*. In our reply, we tried to describe different situations when drought resistance was significantly changed when calculating drought duration only for the growing season, instead of the whole year. In this statement, we tried to express that there exist some pixels where the whole year drought duration is exactly the same as the growing drought duration, so that the calculated drought resistance α in those pixels does not change. However, in our reply, we also described other situations when absolute values of α_{gs} become higher or α_{year} is above 1 but α_{gs} becomes close to 0 (See Reply (i) to Comment R1C4 of our previous replies "... *In 75 pixels, the absolute values of α_{year} decrease from values above 1 to values below 0.1 of α_{gs} as shown by the values close to the zero line in Fig. R3*..."). In general, indeed the conclusion is that they are not the same.

We have shown in our reply to the previous R1C4 that there is a good correlation (0.8) between the calculated alpha based on whole-year drought duration (α_{year}) and growing-season drought duration (α_{gs}) in the Northern Hemisphere extratropics. That is, α_{gs} explains 64% of the variance of α_{year}. Only 8.6% of the pixels changed their signs of α between the two calculations. We also applied the same analysis for the globe using the phenology data from MODIS MCD12Q2 and defined the growing season with the long-term mean green-up day and dormancy day of the year. The results are shown in Fig. R6 and Fig. R7 shown below.

At the global scale, α_{gs} shows a spatial correlation of 0.66 with α_{year} (Fig. R8a). The average difference is -0.003 month^{-1}. If filtered only to significant α (P-value < 0.05), the spatial correlation between α_{gs} and α_{year} is 0.92 (Fig. R8b). Similar to what we found in the Northern Hemisphere extratropics, the spatial contrast of negative values and positive values of α_{gs} and α_{year} are still similar. The value of α switched signs between the two calculations only for 0.1% of those pixels where α_{gs} and α_{year} are both significant. 83.0% of the pixels where both α_{gs} and α_{year} are significant increase their absolute values due to a shorter drought duration when considering only the growing season drought. Temperature sensitivity β_{year} and β_{gs} show stronger correlation of 0.94 (Fig. R8c-d). Overall, our main results for the differences between forests and crops, and the effects of land management practices still hold. Similar results are found in EVI and kNDVI (not shown for conciseness).

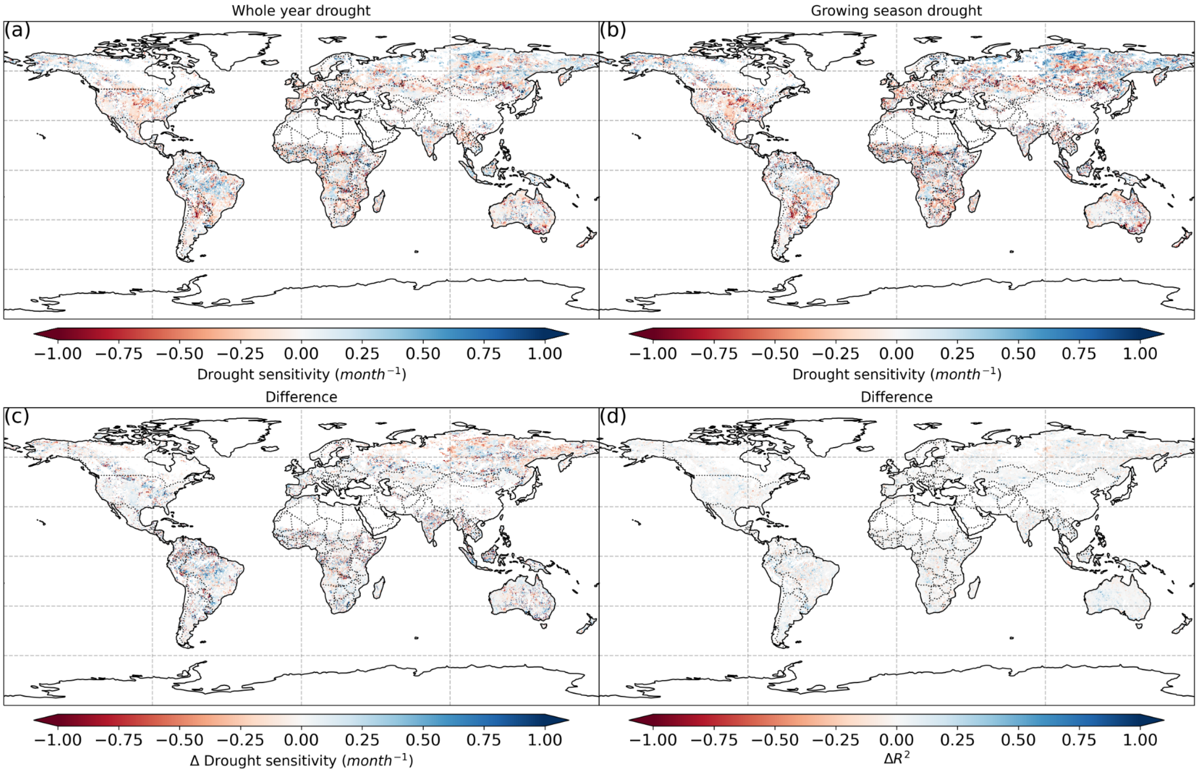

Figure R6. Comparison between the linear regression model with the whole year drought or growing season drought duration for ecosystem resistance to drought duration α_{year} (a) and α_{gs} (b) from L-VOD. The differences in α and R^2 (model with whole year drought minus growing season are shown in (c, d).

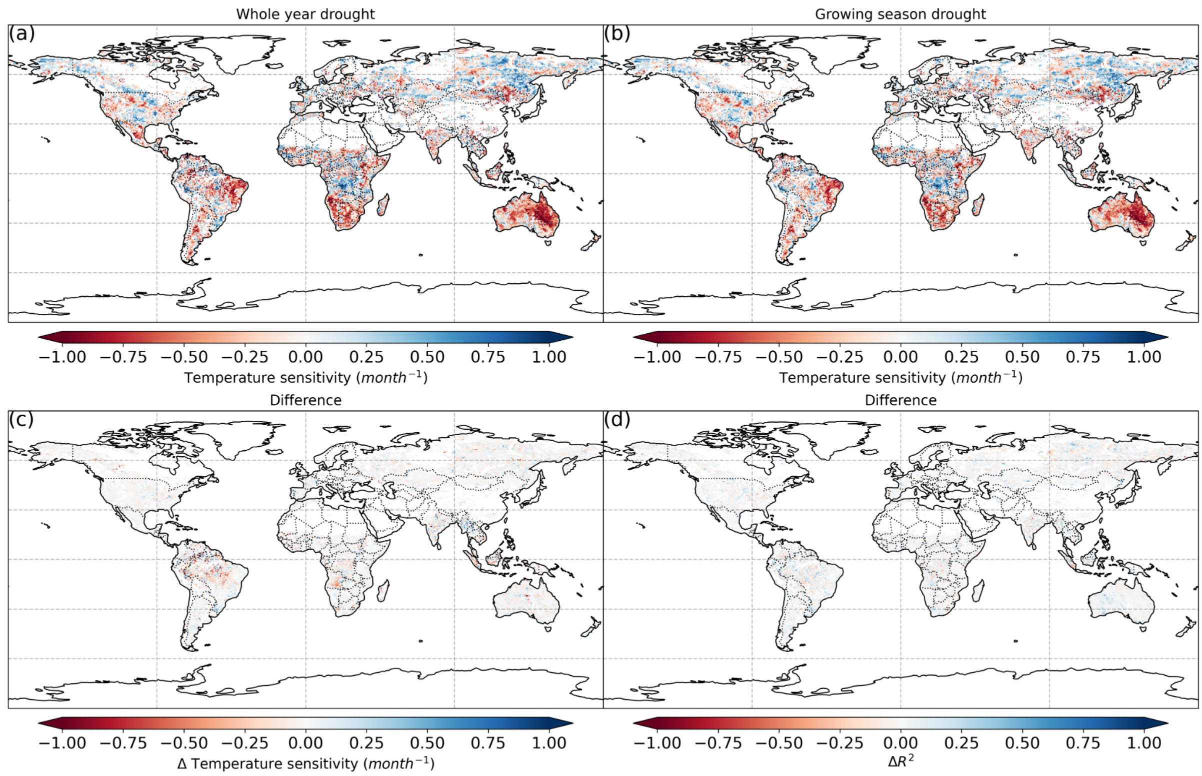

Figure R7. Comparison between the linear regression model with the whole year drought or growing season drought duration for temperature sensitivity β (a, b) from L-VOD. The differences in β and R^2 (model with whole year drought minus growing season) are shown in (c, d).

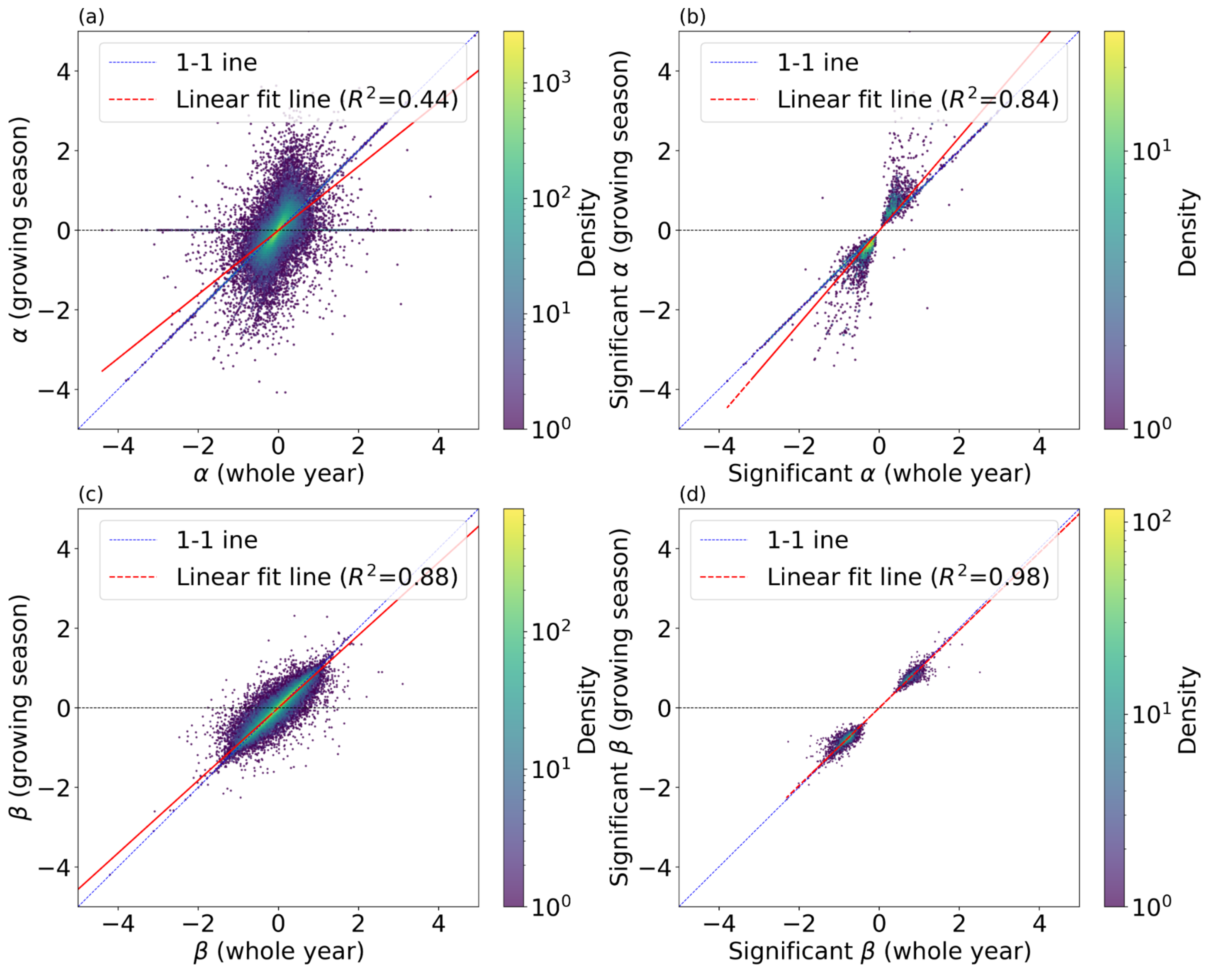

Figure R8. Comparison between ecosystem resistance to the whole year drought duration and growing season drought duration. (a) For drought resistance α; (b) For significant drought resistance α (P-value < 0.05); (c) For temperature sensitivity β; (d) For significant temperature sensitivity β (P-value < 0.05).

We added the following sentences in Lines 434-436 accordingly:

We also evaluated whether limiting drought duration to the growing season of each year. The resulting α and β values over pixels where the coefficients are significant (P-value < 0.05) are strongly correlated to α and β calculated based on whole-year drought duration and results still hold.

R1C4: In summary, I find the study to be filled with novel insights and am excited about its contributions. Further clarification is needed for more compelling findings and could make the work even more impactful.

Thank you again for the insightful comments and suggestions. We added some sentences to our main text in our reply to R1C2 and R1C3 for clarification and we also pasted them here:

We added the following sentences in Lines 545-550 in Section 4.5:

… Even though we controlled for similar climate backgrounds by aggregating pixels based on their long-term temperature and precipitation averages, there are other climate effects that were not considered in our statistical analysis, for example, the interannual variability of precipitation and climate seasonality of temperature. With only limited areas exhibiting significant drought resistance α, and given the need to ensure a large enough number of pixels for comparison in a similar climate space, it remains challenging to disentangle the potential confounding effects of all the climate variables and their variabilities.

We added the following explanation of the choice of predictors in Lines 227-232:

We note that radiation plays an important role in the energy-limited boreal region. However, surface incoming solar radiation strongly correlates with temperature and drought duration. The air temperature at 2 m increases due to a higher energy input when surface incoming solar radiation is higher. Droughts are associated with clear-sky and sunnier conditions that favor more incoming solar radiation (O et al., 2022). To avoid the influence of collinearity on estimated vegetation sensitivity to temperature and drought duration, and given that only ten years of data are available, we did not incorporate radiation into our linear regression model.

And reference in Lines 895-896:

O, S., Bastos, A., Reichstein, M., Li, W., Denissen, J., Graefen, H., and Orth, R.: The Role of Climate and Vegetation in Regulating Drought–Heat Extremes, J Climate, 35, 5677–5685, https://doi.org/10.1175/JCLI-D-21-0675.1, 2022.

We added the following sentences in Lines 434-436 accordingly:

We also evaluated whether limiting drought duration to the growing season of each year. The resulting α and β values over pixels where the coefficients are significant (P-value < 0.05) are strongly correlated to α and β calculated based on whole-year drought duration and results still hold.

Reference

O, S., Bastos, A., Reichstein, M., Li, W., Denissen, J., Graefen, H., and Orth, R.: The Role of Climate and Vegetation in Regulating Drought–Heat Extremes, J Climate, 35, 5677–5685, https://doi.org/10.1175/JCLI-D-21-0675.1, 2022.

Seddon, A. W. R., Macias-Fauria, M., Long, P. R., Benz, D., and Willis, K. J.: Sensitivity of global terrestrial ecosystems to climate variability, Nature, 531, 229–232, https://doi.org/10.1038/nature16986, 2016.

Land cover and management effects of ecosystem resistance to drought stress

Xiao, C., Zaehle, S., Yang, H., Wigneron, J.-P., Schmullius, C., and Bastos, A. *Earth Syst. Dynam. Discuss*

Response to Reviewer #2

R2C1: I thank the authors for their efforts in revision. Most of my concerns are resolved. However, I still have some questions.
1) As mentioned by Reviewer 1, do you have estimates of the explanatory power of regression (2) for each pixel? Which region do your regressions explain very well? As I stated in the last round, apart from drought months and temperature, other factors can be important for biomass/productivity interannual variability, especially in croplands with human management. I would suggest the authors only focus on regions where your regressions can work very well or drought months are very important.
In addition, the authors at least need to acknowledge that the model might be not able to perfectly disentangle drought and temperature effects given the strong collinearity between them shown in Figure R4.

Thanks for the suggestions, they helped to clarify the results and better organize the methods. We estimated the explanatory power of regression with R^2 and the results are shown in Fig. R9. We also added it in our Appendix A as Fig. A7. Our regression explains well in some areas in eastern South America, southern Africa, eastern Australia, and some boreal regions where the R^2 is higher than 0.5. At the global scale, approximately 15%, 23%, and 27% of the pixels exhibit an R^2 exceeding 0.5 when derived from L-VOD, EVI, and kNDVI, respectively.

We added the following sentences in Lines 312-314 to describe the spatial distribution of R^2:

Our model performs better in some areas in eastern South America, southern Africa, eastern Australia, and some boreal regions, where the R^2 is higher than 0.5 (Figure A7). At the global scale, approximately 15%, 23%, and 27% of the pixels exhibit an R^2 exceeding 0.5 when derived from L-VOD, EVI, and kNDVI, respectively.

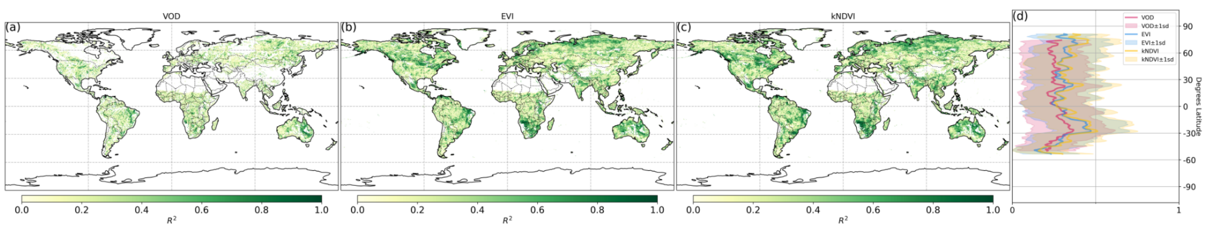

Figure R9. Spatial map of R^2 for (a) L-VOD, (b) EVI, (c) kNDVI. The averages for different latitudes and their standard deviations are shown on the right (d).

We agree with the reviewer that other factors beyond drought duration and temperature can be important. To address this, we consider only pixels where the drought duration or temperature significantly influences the L-VOD, kNDVI, or EVI at a significance level of 5% in subsequent analyses where we investigate the effect of land cover and land management practices (Fig. 3c, 4, 5).

We agree with the reviewer that the model might not be able to perfectly disentangle the drought and temperature effects given the strong collinearity in some tropical regions (Fig. R10). We added Fig. R10 in supplementary as new Fig. A8. and added the following sentences in Lines 552-554 (Section 4.5):

Drought duration shows a high correlation with yearly mean temperature in some regions in northern Amazon, Southern Africa and South Asia (Figure A8), so the multiple linear regression model might not perfectly disentangle their effects in these areas. We avoid these issues by analyzing those pixels with significant values of α and β (P-value < 0.05).

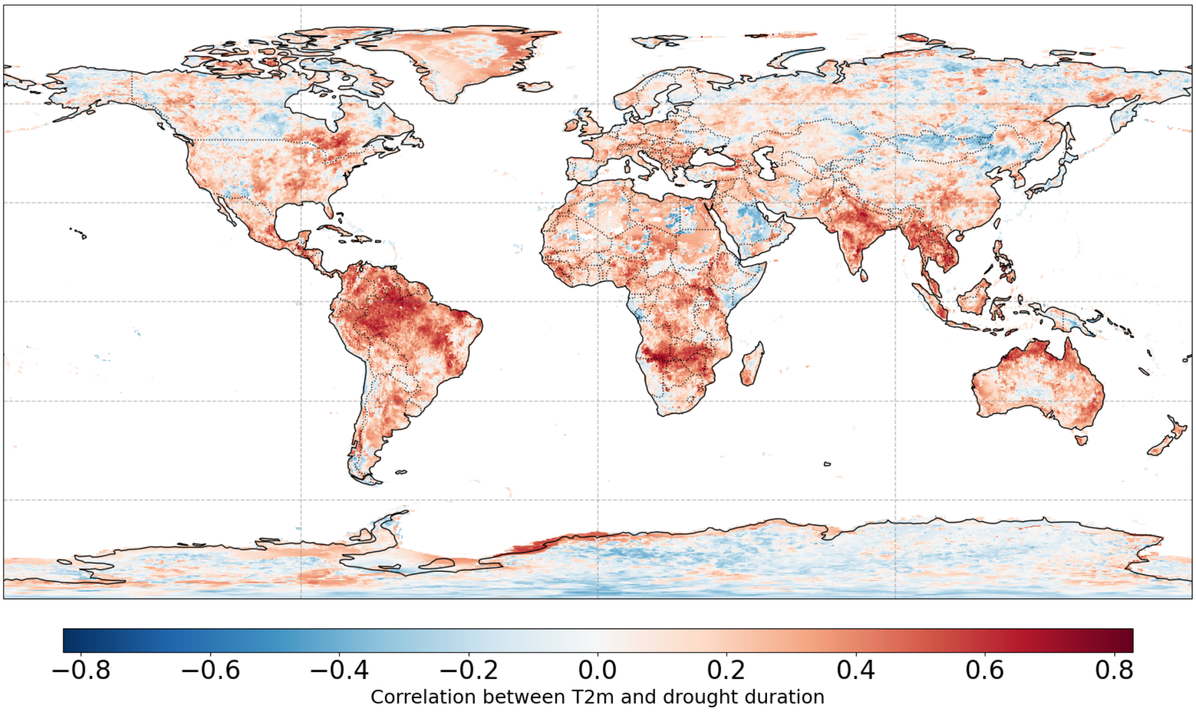

Figure R10. Temporal correlation between yearly mean temperature and drought duration (months per year) in 1979-2020.

Following the reviewer's remark, we now consider the effects of crop and forest wood harvest (based on LUH2 v2h) on drought resistance. However, the crop harvest fraction provided by

LUH2 v2h is homogeneous over the globe (Fig. R11), so that such information does not aid our analysis.

Forest wood harvest in LUH2 v2h is smaller than 1% of the respective forest area for more than 90% of vegetated pixels (vegetation cover ≥ 5%) (Fig. R12). Therefore, we tested that the effect on our main results is residual (not shown). However, this information allows us to compare drought resistance for different wood harvest intensities in forests, analogous to our analysis of crop irrigation. We found that forest-dominated pixels with more intense harvest activity (wood harvest intensity ≥ 10%) tend to be less resistant to drought than forest-dominated pixels with virtually no harvest (< 1% forests are harvested) (Fig. R13).

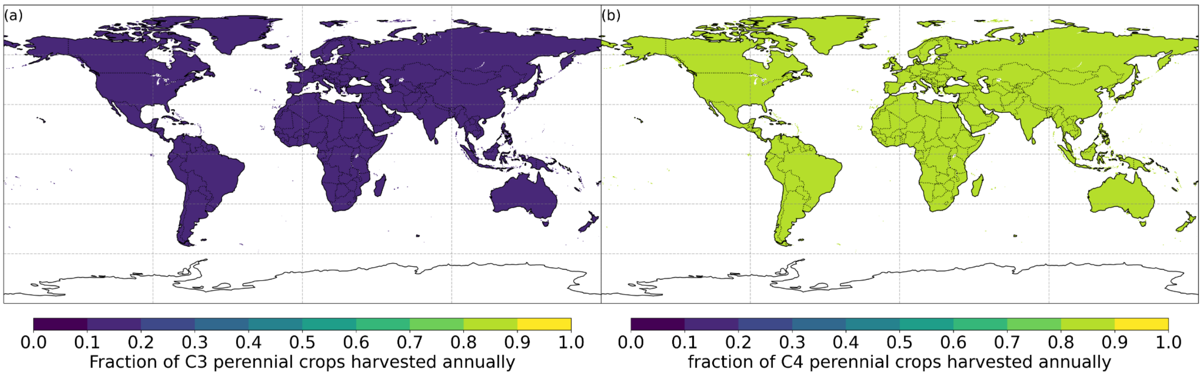

Figure R11. Averaged fraction of crop harvest annually for (a) C3 perennial crops, (b) C4 perennial crops in 2010-2020.

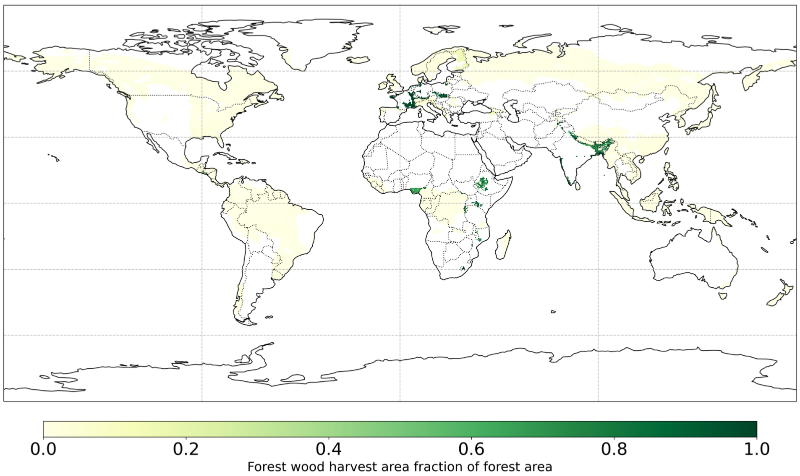

Figure R12. Averaged wood harvest fraction of forest area annually in 2010-2020.

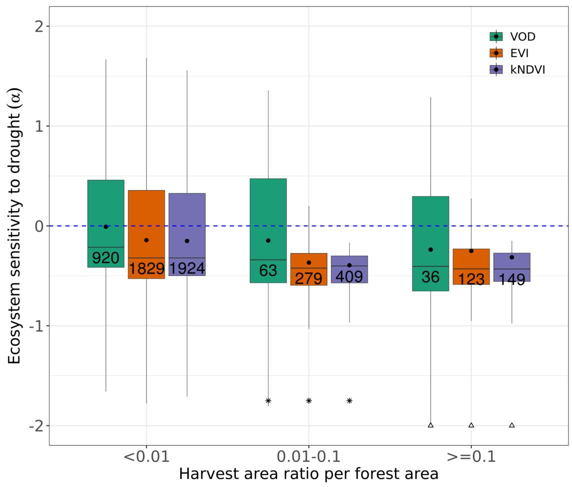

Figure R13. Ecosystem resistance to droughts for different forest wood harvest area ratio of forest area. Only significant coefficients α in the linear model (P-value < 0.05) are included. Stars indicate that the median value of a given category is greater than the median of the previous category and triangles indicate the median of this category is greater than the median of the first category at the 0.05 significance level from the unpaired two-sample Wilcoxon test. The number in each box is the number of bins/pixels in this category. Only pixels with > 50% forest cover in 2011-2020 were selected.

We added the analysis method in Lines 190-192:

... It also provides wood harvest area as a fraction of the total grid cell area. We converted this to the fraction of wood harvest from forests (described below as forest wood harvest intensity) by dividing the wood harvest area by the forest area fraction of the total grid cell area. We limit this analysis to pixels with > 50% forest cover.

We changed the "We finally investigated the ecosystem resistance α for different irrigation levels (Figure 5c)." in Line 308 to:

We also investigated the ecosystem resistance α for different irrigation levels (Figure 5c).

We added Fig.R13 as Fig.5d in our manuscript and the following sentences in results in Lines 404-407:

We finally explored the potential role of forest wood harvest intensity (Figure 5d). All three satellite products agree on a significant decrease of drought resistance (α) with increased forest wood harvest intensity, from a median of -0.21 month^{-1} under < 1% harvest area ratio, to -0.34 month^{-1} under 1-10% wood harvest intensity, and -0.40 month^{-1} for >10% harvest intensity, based on L-VOD. Results from EVI and kNDVI are consistent with those of L-VOD.

We also added the following sentence to our discussion section 4.3 in Lines 503-510:

Our results indicate that forests with higher harvest intensities tend to be less resistant to drought globally. In-situ studies in different biomes show that forest management can influence forest resistance to disturbances such as drought (Silva Junior et al., 2020; Fawcett et al., 2022). This could be linked to the more complex structure of dense forests, whose below canopy microclimate might help to buffer forest stands from macroclimatic temperature extremes, e.g., in temperate broadleaved and mixed forest biome (Sanczuk et al., 2023). Forest thinning, depending on its intensity, has also been reported to result in lower drought resistance and resilience in older mature forests in north temperate forest ecosystems. This might be due to trees reaching larger sizes during stand development, which in turn increases water demand during droughts (D'Amato et al., 2013).

We also added a sentence in Line 32:

Forest harvest decreases the drought resistance of forests.

We added the new references in Lines 745, 773, 929, and 950:

D'Amato, A. W., Bradford, J. B., Fraver, S., and Palik, B. J.: Effects of thinning on drought vulnerability and climate response in north temperate forest ecosystems, Ecol Appl, 23, 1735–1742, https://doi.org/10.1890/13-0677.1, 2013.

Fawcett, D., Sitch, S., Ciais, P., Wigneron, J. P., Silva-Junior, C. H. L., Heinrich, V., Vancutsem, C., Achard, F., Bastos, A., Yang, H., Li, X., Albergel, C., Friedlingstein, P., and Aragão, L. E. O. C.: Declining Amazon biomass due to deforestation and subsequent degradation losses exceeding gains, Global Change Biology, n/a, https://doi.org/10.1111/gcb.16513, 2022.

Sanczuk, P., De Pauw, K., De Lombaerde, E., Luoto, M., Meeussen, C., Govaert, S., Vanneste, T., Depauw, L., Brunet, J., Cousins, S. A. O., Gasperini, C., Hedwall, P.-O., Iacopetti, G., Lenoir, J., Plue, J., Selvi, F., Spicher, F., Uria-Diez, J., Verheyen, K., Vangansbeke, P., and De Frenne, P.: Microclimate and forest density drive plant population dynamics under climate change, Nat Clim Change, 1–8, https://doi.org/10.1038/s41558-023-01744-y, 2023.

Silva Junior, C. H. L., Aragão, L. E. O. C., Anderson, L. O., Fonseca, M. G., Shimabukuro, Y. E., Vancutsem, C., Achard, F., Beuchle, R., Numata, I., Silva, C. A., Maeda, E. E., Longo, M., and Saatchi, S. S.: Persistent collapse of biomass in Amazonian forest edges following deforestation leads to unaccounted carbon losses, Sci Adv, 6, eaaz8360, https://doi.org/10.1126/sciadv.aaz8360, 2020.

Finally, based on these results, we have decided to analyze the forest age effect on drought resistance only for primary tropical evergreen broadleaf forests (EBF), rather than tropical EBF as in the previous version of the manuscript. This is because we have already shown a significant difference between the primary and secondary forests (reproduced Fig. 5b as Fig. R14 here) and the age structure of secondary forests is expected to be influenced by management practices. The result is similar to the previous, with an increased average in drought resistance α with increasing forest age. The median of α is significantly higher in forests aged 100-300 years and older than 300 years. Therefore we modified the sentences in Lines 266-269 to:

…, we selected pixels with dominant tropical evergreen broadleaf forests, >50% forest fraction to avoid confounding effects of management over secondary forests. We then selected only pixels belonging to the primary forests we defined above and grouped the forest ages into three groups [0, 100), [100, 300) and ≥ 300 years.

We changed previous Lines 390-396 to:

We further tested the effect of forest ages in modulating the ecosystem resistance in the tropical primary evergreen broadleaf forest. Based on L-VOD, forests older than 100 years are substantially more resistant to drought than forests younger than 100 years. The median of α for forests younger than 100 years is -0.549 month^{-1}, while the median values of α for forests aged 100-300 years and older than 300 years are 0.455 month^{-1} and 0.360 month^{-1} respectively. We also find a significant (P-value < 0.05) increase of α in kNDVI between forests aged 100-300 years and older than 300 years, but the effect is not as large as in L-VOD and we found no significant differences based on EVI. These results indicate that VOD is more sensitive to water volume and biomass than reflectance indices in general.

We changed "In tropical evergreen broadleaf forests" in Line 30 to:

In tropical primary evergreen broadleaf forests…

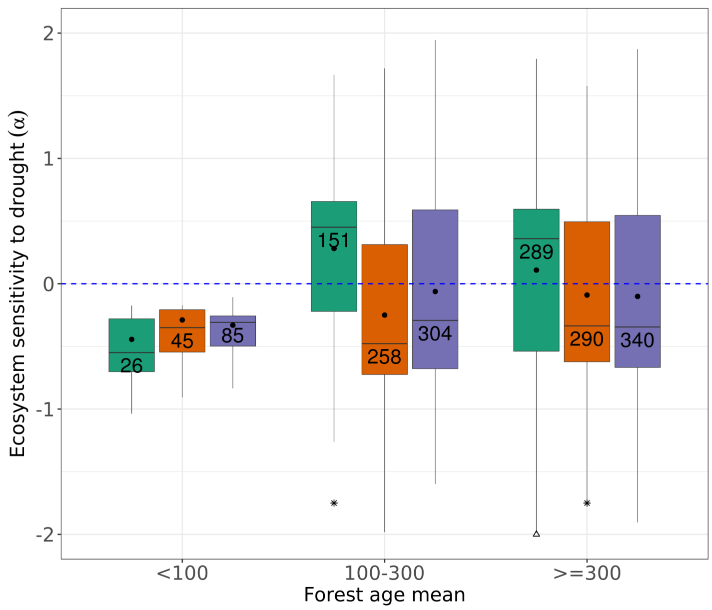

Figure R14. Ecosystem resistance to droughts for different forest ages in the tropical primary EBF. Only significant coefficients α in the linear model (P-value < 0.05) are included. Stars indicate the median value of this category is greater than the median of the previous category and triangles indicate the median of this category is greater than the median of the first category at the 0.05 significance level from the unpaired two-sample Wilcoxon test. The number in each box is the number of bins/pixels in this category.

Finally, in the discussion, we refer to other factors that might influence the relationships we find in Lines 556-564:

Other factors related to land management, e.g., different crop rotations or harvest intensities, also play an important role in changing the vegetation biomass or greenness, especially in croplands, and might influence drought resistance and temperature sensitivity. The LUH2 v2h dataset provides additional information about crop and wood harvest practices. Crop harvest in LUH2v2 is spatially homogeneous so that it cannot be used to evaluate spatial differences in drought and temperature sensitivity over croplands. Forest wood harvest in LUH2 v2h is smaller than 1% of the respective forest area for more than 90% of vegetated pixels (vegetation cover ≥ 5%). Therefore, we tested that the effect on our main results for primary forests and forest age is residual. For a more detailed analysis of other management practices, higher-resolution data on vegetation and management would be needed.

R2C2: 2) Figure 2: The color is not reader-friendly. It looks like very limited areas show significant drought resistance at a 10% significance level? Could you add a statistical analysis on this? Can you mask regions that show insignificant values using the color of white instead?

We agree with the reviewer that there are only limited areas showing significant drought resistance at a 10% significance level. To constrain the uncertainty, we only used the pixels showing significant drought resistance at a 5% significance level for all the statistical analyses.

Thanks for suggesting a statistical analysis of the significance and uncertainty of drought resistance. We added a more detailed description about the percentage of the pixels showing significant drought resistance at 10% and 5% significance levels in Lines 286-290 (Section 3.1):

In our analysis, we observe that 12% of pixels show significant drought resistance at a 10% significance level (6%, 6%, and 7% at a 5% significance level) from L-VOD, EVI, and kNDVI. We only used the significant drought resistance at a 5% significance level to investigate the impacts of land cover and land management, ensuring that the vegetation growth is impacted by drought conditions.

We also added more descriptions on the percentage of the pixels showing significant temperature sensitivity at 10% and 5% significance levels in Lines 300-303 (Section 3.1):

15%, 26%, and 31% of pixels show significant temperature sensitivity at a 10% significance level (9%, 17%, and 21% at a 5% significance level) from L-VOD, EVI, and kNDVI. We only used these pixels to investigate the land cover and land management effects to make sure that the vegetation growth is relevant to temperature.

Thanks for suggesting a better color scheme to visualize the drought resistance pattern. We also checked whether our color scheme is color-blind friendly. We now modified Figure 2 (reproduced here as Fig. R15) using white color to mask the insignificant values and a new color palette in Figure 2d, h and changed the color range for α from -1-1 to -0.5-0.5. We changed the figure caption in Lines 308-310 to:

The pixels with non-significant α and β at a 10% significance level are masked with white color. The full-page figures where pixels with non-significant α and β at a 5% significance level are masked with white color are provided in the supplementary Figure S1-S3 for better visualization.

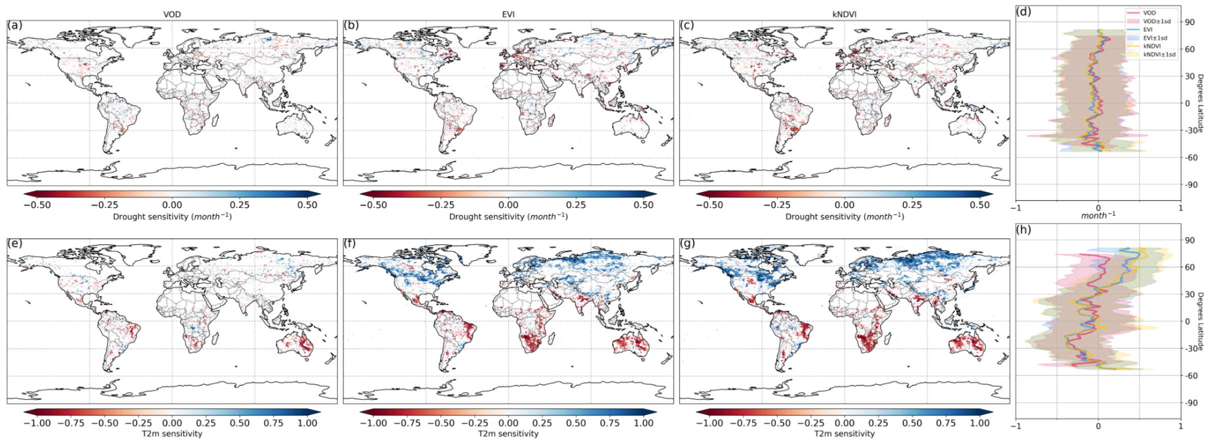

Figure R15. Ecosystem resistance to drought duration and temperature sensitivity. Spatial map of drought resistance α for (a) L-VOD, (b) EVI, (c) kNDVI. Same for temperature sensitivity β (e, f, g). The averages for different latitudes and their standard deviations are shown on the right (d, h). The pixels with non-significant α and β at a 10% significance level are masked with white color. The full-page figures where pixels with non-significant α and β at a 5% significance level are masked with white color are provided in the supplementary Fig. S1-S3 for better visualization.

We also changed the color palette for Fig. A6 and Fig. B1 and reproduced them here as Fig. R16 and Fig. R17:

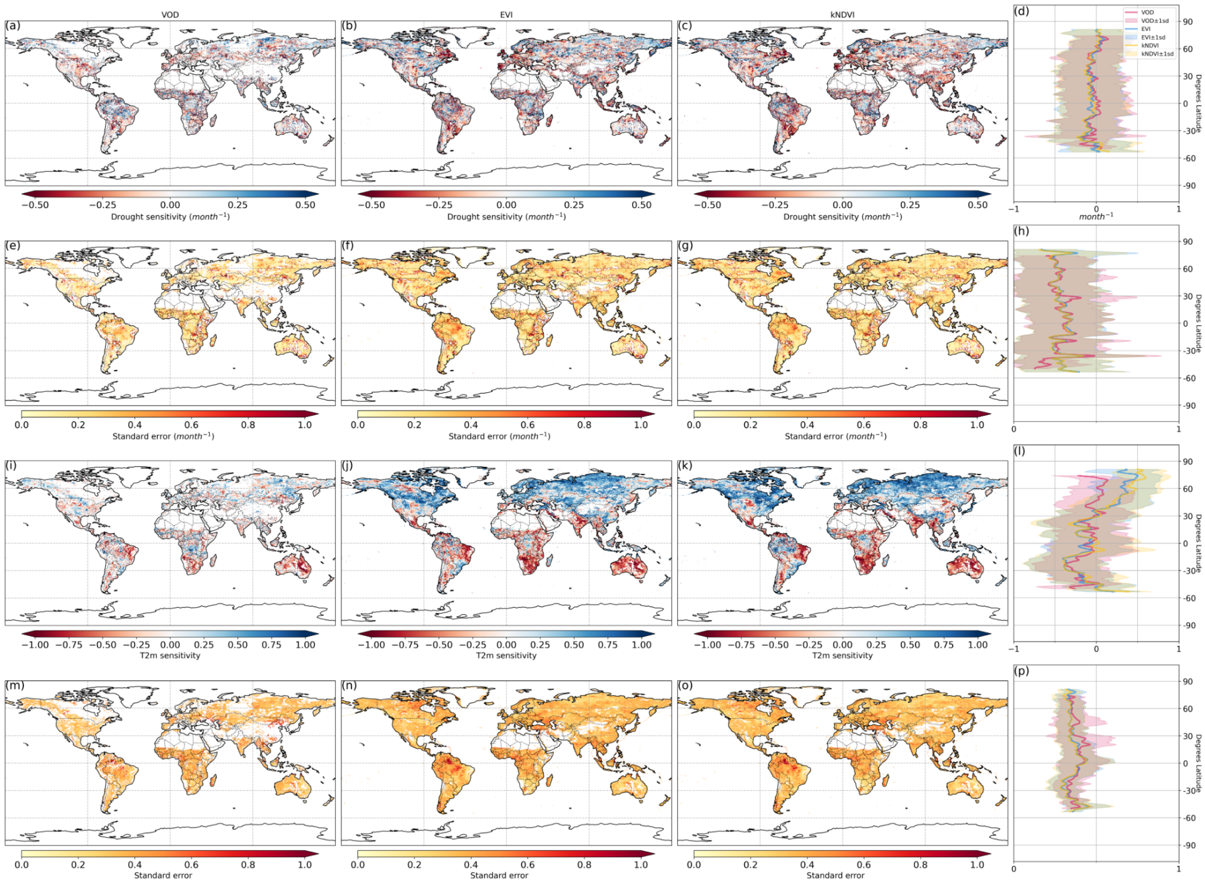

Figure R16. Ecosystem resistance to drought duration and its standard error. Spatial map of drought coefficients α for (a) L-VOD, (b) EVI, (c) kNDVI and their standard error (e, f, g). Same for temperature coefficients β (i, j, k) and their standard error (m, n, o). The averages for different latitudes and their standard deviations are shown on the right (d, h, l, p).

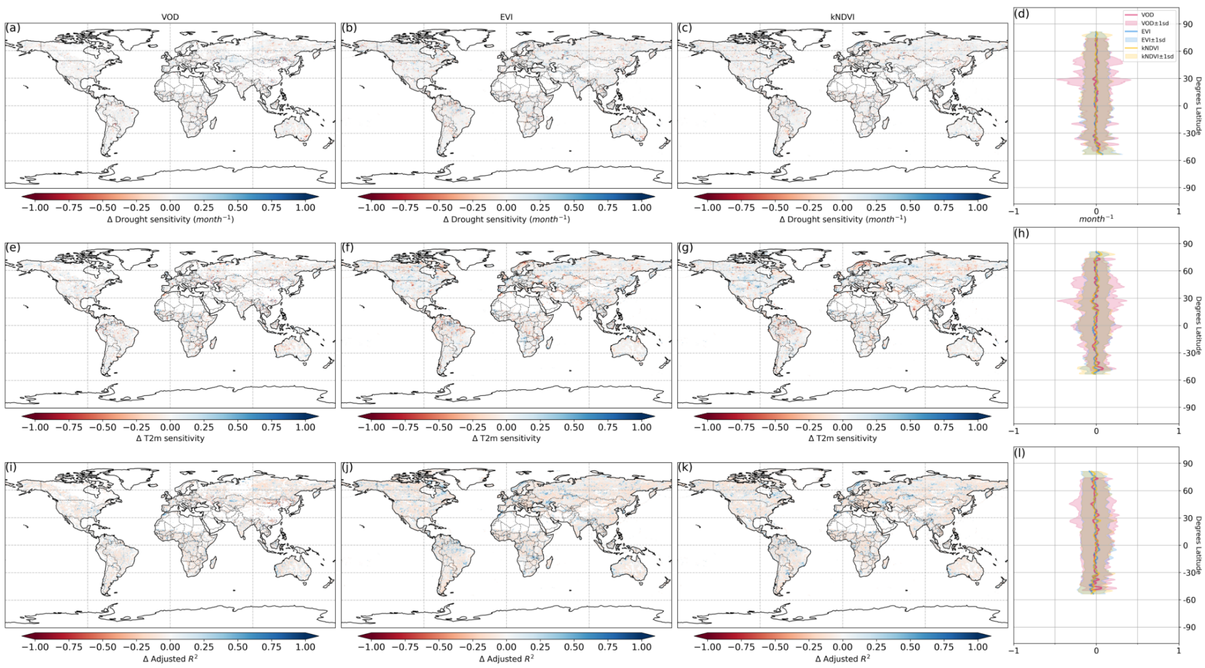

Figure R17. Difference between linear regression model with/without memory term (model with φ minus model without φ) for ecosystem resistance to drought duration α from L-VOD, EVI and kNDVI (a, b, c). Similar for temperature sensitivity β (e, f, g) and adjusted R^2 (i, j, k). The averages for different latitudes and their standard deviations are shown on the right (d, h, l).

R2C3: 3) Figure 3: Here you used the significance level of 5%. Any reason?

Thank you for pointing it out. We used a significance level of 5% in Figure 3 and all the subsequent statistical analyses. As discussed in R1C2, there are only limited areas showing significant drought resistance. We applied a less strict significance level of 10% in Figure 2 to better visualize the spatial pattern of drought resistance. However, for all subsequent statistical analyses, we used a significance level of 5% for a more robust analysis of the relevance of land use and management by reducing the fraction of false positives. Nevertheless, we acknowledge that there is an inconsistency between the map in Figure 2 and the subsequent figures. Therefore, we will add full-page figures in the supplement with the pixels selected for subsequent analysis (see at the end of the replies Fig. R18-20 as Fig. S1-3 in our supplementary).

R2C4: I suggest the authors revise the paper. I'm happy to review it again.

Thanks again for the constructive comments and suggestions during the review process.

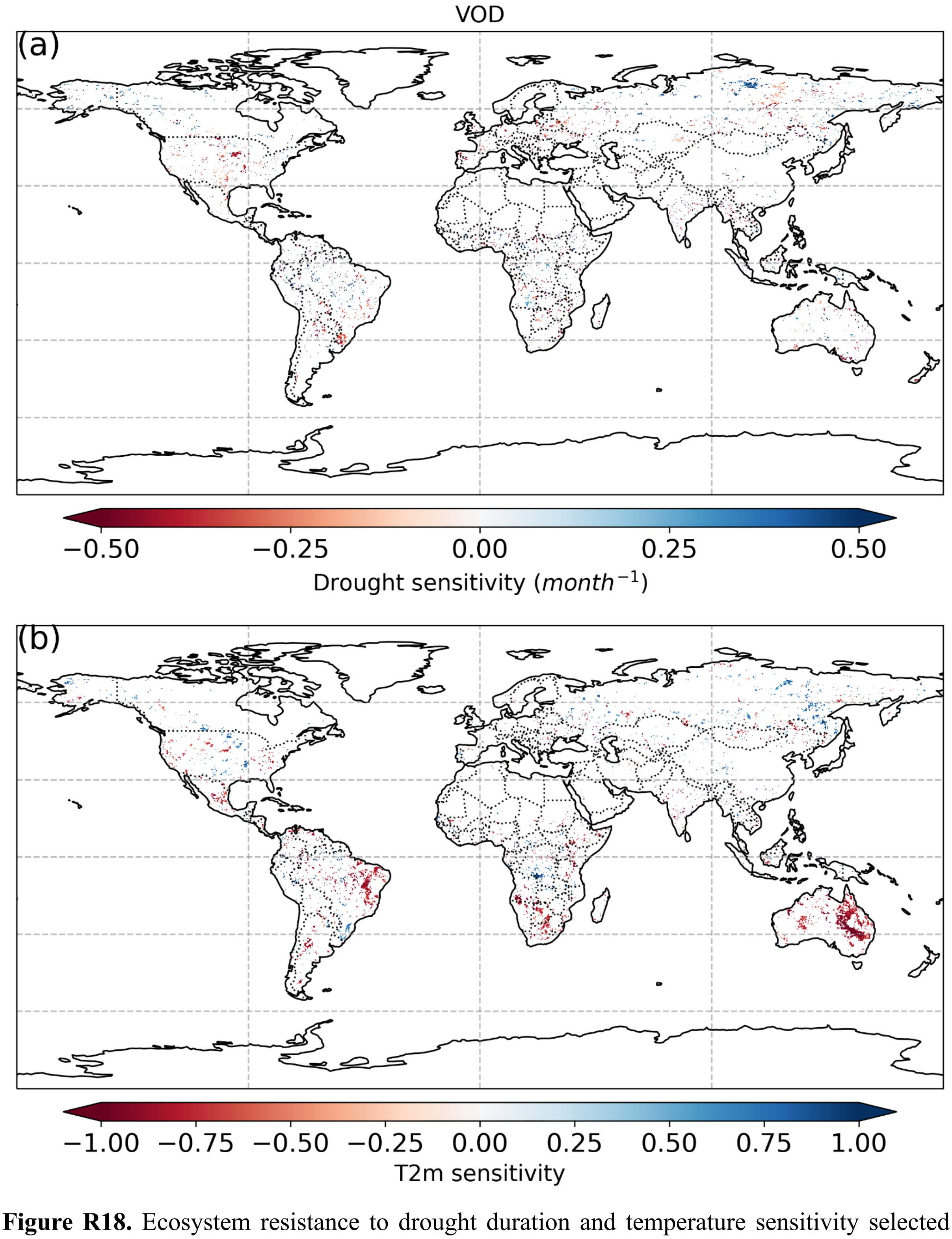

Figure R18. Ecosystem resistance to drought duration and temperature sensitivity selected for our analysis of land cover and management effects (P-value < 0.05). Spatial map of (a) drought resistance α and (b) temperature sensitivity β for L-VOD.

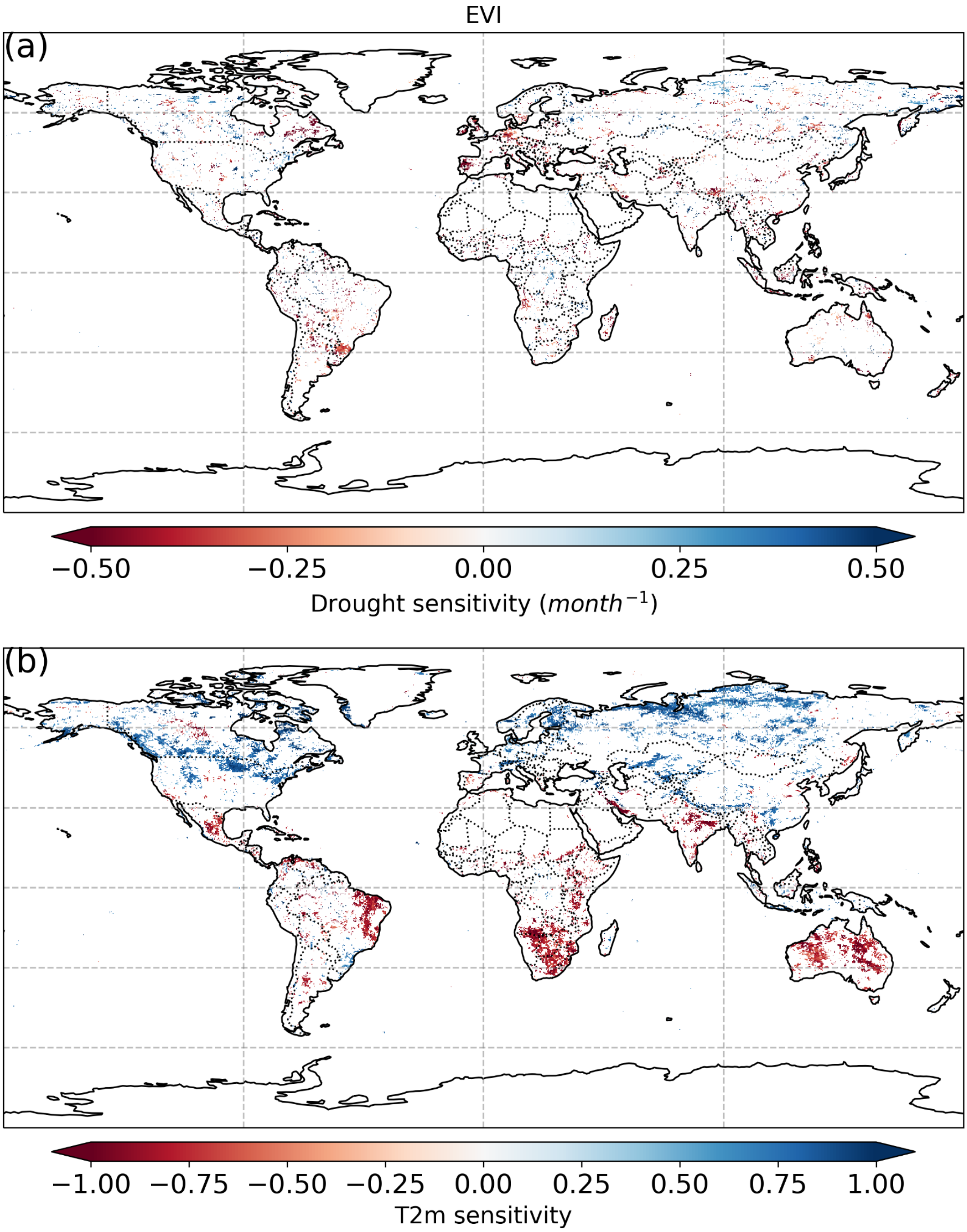

Figure R19. Ecosystem resistance to drought duration and temperature sensitivity selected for our analysis of land cover and management effects (P-value < 0.05). Spatial map of (a) drought resistance α and (b) temperature sensitivity β for EVI.

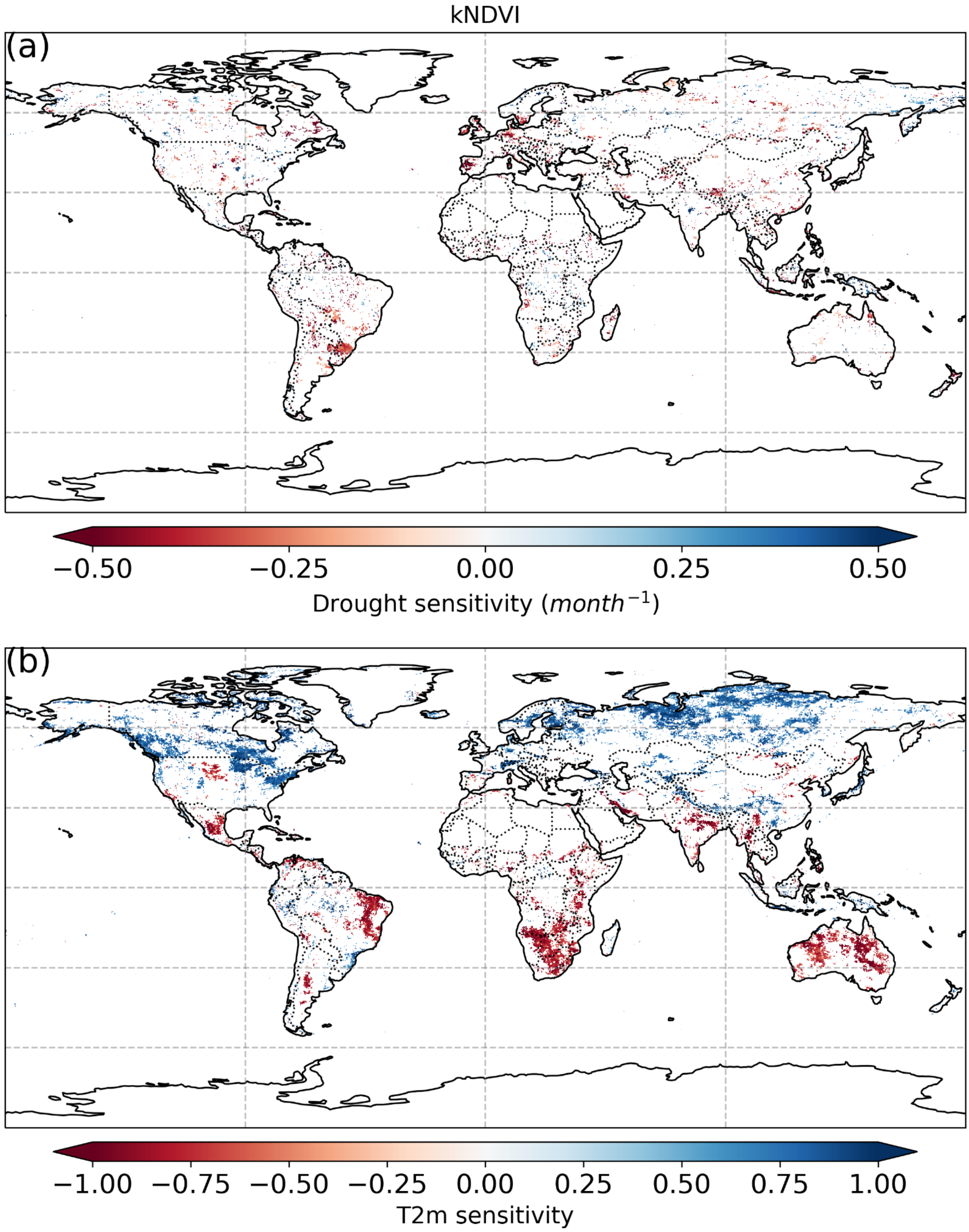

Figure R20. Ecosystem resistance to drought duration and temperature sensitivity selected for our analysis of land cover and management effects (P-value < 0.05). Spatial map of (a) drought resistance α and (b) temperature sensitivity β for kNDVI.

Reference

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