## Land-cover and management modulation of ecosystem resistance to drought stress

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

**Response to Reviewer #1**

**R1C1: This study examines vegetation sensitivity to droughts and heat on a global scale using several satellite-derived proxies of vegetation conditions, including L-VOD, EVI, and kNDVI. To estimate vegetation sensitivity, the authors propose an autoregressive model that incorporates annual drought frequency, annual thermal condition, and the previous year's vegetation states. By comparing the sensitivities to drought and heat across different land cover types, including primary and secondary forests, the authors identify distinct differences in vegetation sensitivities, which they term ecosystem resistance. The study highlights the role of forest cover and land management in shaping the ecosystem resistance to droughts and suggests the advantages of using L-VOD in monitoring vegetation dynamics for dense forests. The research addresses relevant scientific questions within the scope of ESD and provides a novel perspective that considers land cover differences, particularly with respect to the effects of land management practices such as forest management and irrigation. The scientific methods and assumptions are clearly outlined, and the results are well-presented.**

We thank the reviewer for the overall positive evaluation of our study and for the valuable insights. Below we offer a detailed point-by-point response to the comments.

**R1C2: One main concern about this study is the ambitious claim of "management modulation" of ecosystem resistance, which may not be straightforward to conclude. The results are based on linear autoregression models, and the management effects are derived from comparing primary and secondary forests that span multiple climate zones. It is possible that the differences observed between primary and secondary forests (e.g., Fig. 5a) are due to climate differences rather than forest management. For example, NEU and EEU, which are both dominated by secondary forests (Fig. 1; Fig. 3a), have contrasting alpha values (Fig. 3b) and different Köppen climate classifications. To better isolate the primary-secondary forest differences and see the effects of forest management, it would be helpful to exclude variations related to other drivers or to group Fig. 1 based on climate zones. Otherwise, the current conclusion that "primary forests, typically associated with higher biodiversity, tend to show stronger resistance to droughts than secondary forests" could be misleading, as the differences may simply be related to ecosystem types shaped by climate rather than forest management.**

We agree with the reviewer that a direct causal relationship cannot be fully evaluated by our analysis. We propose to change the word 'modulation' to 'effects' in our title and main text. See more details in our reply to R1C3.

**R1C3: The current title of the study seems ambitious when using the word "modulation." It may be more appropriate to use a different word, such as "differences," to accurately reflect the findings of the study. The word "modulation" suggests a strong causal relationship, but what we see here are simply differences between primary and secondary forests.**

We agree with the reviewer that the term 'modulation' may imply a strong direct causal relationship. Instead, we have changed the title to "Land-cover and management effects on ecosystem resistance to drought stress". We used 'effects' to indicate that we have taken into account some effects from climate background, such as Koeppen climate classification, long-term temperature, and precipitation average, and we have provided possible explanations for the effects.

We would like to highlight that in the original manuscript, we have controlled for climate factors, namely climatological temperature and precipitation for comparison between primary and secondary forests. We only compared the pixels dominated by primary and secondary forests in a similar climate background defined by long-term mean temperature and precipitation. We had provided more details in the submitted manuscript Section 2.5 Lines 208-216. We acknowledge that we need to refer to the method again when analyzing our results. We would like to clarify this point by adding one sentence in our results section 3.3 now in Lines 350-352:

*It should be noted that to minimize the potential effects of the fact that primary and secondary forests are distributed differently across climate zones, we compare pairs of pixels with primary and secondary forests under similar temperature and precipitation climatological conditions bins as described in section 2.5.*

Following this approach, we detected a significant difference between primary and secondary forests as shown in Fig. 5a both in the submitted and updated versions without the AR1 term.

We have also accounted for the climate effects by comparing drought resistance for different forest and crop fractions in tropical, temperate, and boreal climate zones from Koeppen climate zones as shown in Fig. A4, Fig. A5, and discussed now in Lines 411-415.

In the submitted manuscript, we already tried to reduce the confounding effects due to climate by comparing only pixels with different forest ages in the tropics. We have limited the forest type effects by comparing only tropical evergreen broadleaf forests of different ages because only this forest type contains sufficient pixels spanning from 0 to 300 years old for a robust comparison. We realize that this is not clear in our methods, and now add the following sentences to Lines 253-254:

*To minimize the potential climate confounding effects on the dependence of α on forest age, we limited our comparison in the tropics due to limited pixels with >=300 years old trees for other regions.*

Furthermore, to explain these effects, we have discussed some possible mechanisms to explain the stronger drought resistance in primary forests in Section 4.3, but we acknowledge that more explanation and supporting evidence are needed. We have added more discussion to Section 4.3, now in Lines 438-448:

*Primary forests also show higher hydraulic diversity than secondary forests, which buffers impacts in ecosystem flux during dry periods across temperate and boreal forests (Anderegg et al., 2018). Secondary forests in the Brazilian Amazon are vulnerable to drought stress with a lower carbon balance and growth rates, and they only reached 56% of the tree diversity in the nearest primary forests (Elias et al., 2020). In Amazon forests, forest greening in degraded forests disturbed by fire has been found to be more dependent on water resources than in mature forests (Roux et al., 2022). The new forest edges in much more fragmented degraded forest landscapes increase canopy desiccation, tree mortality, and fire frequency (Briant et al., 2010; Broadbent et al., 2008), especially during drought events (Roux et al., 2022). In boreal forest ecosystems in Sweden, primary forests have been found to be less affected by drought compared to secondary forests (Wolf et al., 2023). Primary forests also likely harbor older trees, which also show higher resistance to drought (Fig. 5b). Besides, primary forests might have a more extensive rooting system with higher availability of soil water. However, it remains difficult to disentangle the above factors for the complex ecosystem due to limited data.*

We also changed ‘modulation’ in Lines 20-21 to:

*We analyze how ecosystem resistance varies with land cover across the globe and investigate the potential effects of forest management and crop irrigation.*

Lines 431:

***4.3 Effects of land management and forest age on ecosystem resistance***

Lines 450:

*Apart from the effect of land cover due to different sensitivity to drought stress for different vegetation types, ...*

Line 500:

*The effects of specific land cover and land management on drought resistance are thus important for these regions in the future.*

**Comments on the analytical methods**

**R1C4: I have several questions regarding the linear autoregressive model used in this study. First, how is it ensured that the droughts used in the first term occur within or before the growing season and affect vegetation growth? Second, is there a justification for using yearly mean temperature instead of yearly maximum temperature in the second term? It would be helpful to either provide relevant references or explain the advantages of using annual mean temperature (e.g., smaller prediction errors compared to using yearly maximum). Third, the third term in the model is incorporated to consider vegetation memory effects, but the study does not present any results related to this coefficient. It would be helpful to briefly mention any relevant findings even if they are not significant. Additionally, it's worth questioning the inclusion of this term in the model if it does not contribute to reducing the overall prediction error. Fourth, for better readability, it would be helpful to mention the "c" term in section 2.4 of the study.**

Thanks for the constructive comments on our analysis methods. We address the four points below, (i) drought in the growing season; (ii) temperature predictor; (iii) AR1 term; (iv) description for the intercept term c.

(i) First, we acknowledge that drought months might not exactly overlap with the growing season. We analyzed yearly maximum L-VOD, which normally happens in the growing season and yearly mean EVI, kNDVI which reflect the vegetation conditions during the whole year but are mostly affected by growing season values.

Drought occurring before the growing season will be reflected in the yearly mean EVI and kNDVI. Intense drought happening prior to the growing season is also likely to have legacy effects on vegetation growth during the growing season (e.g. Buermann et al., 2018; Bastos et al., 2020). Therefore, the sub-annual effects of drought prior to or during the growing season are expected to be reflected in the yearly maximum L-VOD. Disturbance prior to the growing season also directly leads to decreased yearly maximum values during the growing season. Droughts occurring after the growing season, however, would not have any effect on the yearly maximum L-VOD as estimated here. They would affect mean annual EVI and kNDVI but should have a small contribution since the impact would be expressed during the senescent period. We do not consider explicitly interannual legacy effects from droughts, but we have performed a sensitivity analysis on the effects of interannual long-term memory effects, which did not affect the results (now moved to Appendix B).

To evaluate whether the non-growing season drought might influence the results, we selected only drought months occurring during the growing season (April to September) in the Northern Hemisphere extratropics, where vegetation shows clear seasonality. The results are shown in Fig. R1. The spatial pattern of negative and positive values of drought resistance is not significantly changed, with $\alpha$ calculated from growing season drought ($\alpha_{gs}$) and $\alpha$ calculated from the whole year drought ($\alpha_{year}$) showing a spatial correlation of 0.80 (Fig. R1a, b, c). The averaged difference in the multiple linear regression model $R^2$ is 0.003 and the median is 0. The absolute values of $\alpha_{gs}$ become higher in some areas because of the shorter drought duration when considering only the growing season drought (Fig. R3). In 75 pixels, the absolute values of $\alpha_{year}$ decrease from values above 1 to values below 0.1 of $\alpha_{gs}$ as shown by the values close to the zero line in Fig. R3. The values of $\alpha_{gs}$ in those 75 pixels are all insignificant ($P$-value $\geq 0.05$). The reason for such differences could be partly due to a much smaller annual variance of drought duration in the growing season in these few pixels (N = 75) for 2010-2020 (0.96 in growing season drought duration, 2.89 in the whole year drought duration), which leads to higher standard errors and unreliable estimates of $\alpha_{gs}$. When the drought duration within the growing season exactly matches the whole year drought duration, the calculated drought resistance is the same (close to the 1:1 line in Fig. R3). Overall, our main results for the differences between forest and crops, and effects of land management practices still hold. The spatial patterns of temperature sensitivity for L-VOD are also similar, with a spatial correlation of 0.96 (Fig. R2). Similar results are found in EVI and kNDVI (not shown).

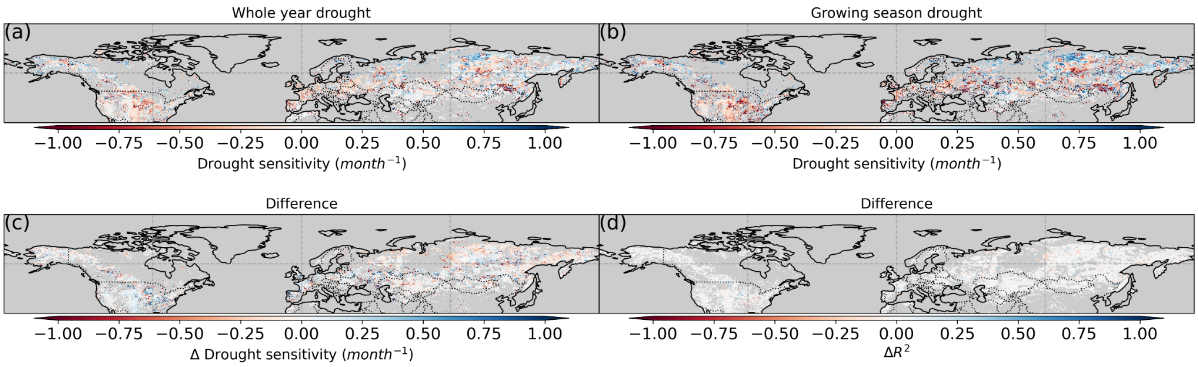


**Figure R1.** Comparisons between the linear autoregressive model with the whole year drought or growing season drought duration for ecosystem resistance to drought duration $\alpha_{year}$ (a) and $\alpha_{gs}$ (b) from L-VOD. The differences in $\alpha$ and $R^2$ (model with whole year drought minus growing season are shown in (c, d).

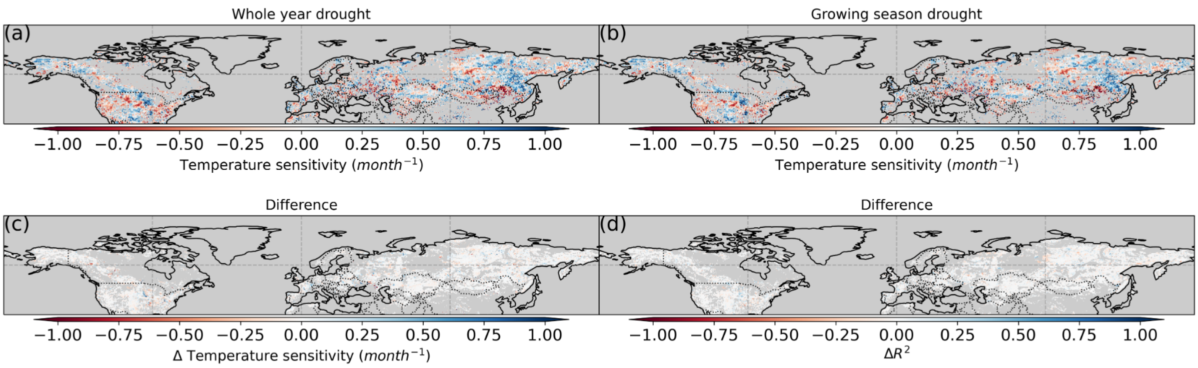

**Figure R2.** Comparisons between the linear autoregressive model with the whole year drought or growing season drought duration for temperature sensitivity $\beta$ (a, b) from L-VOD. The differences in $\beta$ and $R^2$ (model with whole year drought minus growing season) are shown in (c, d).

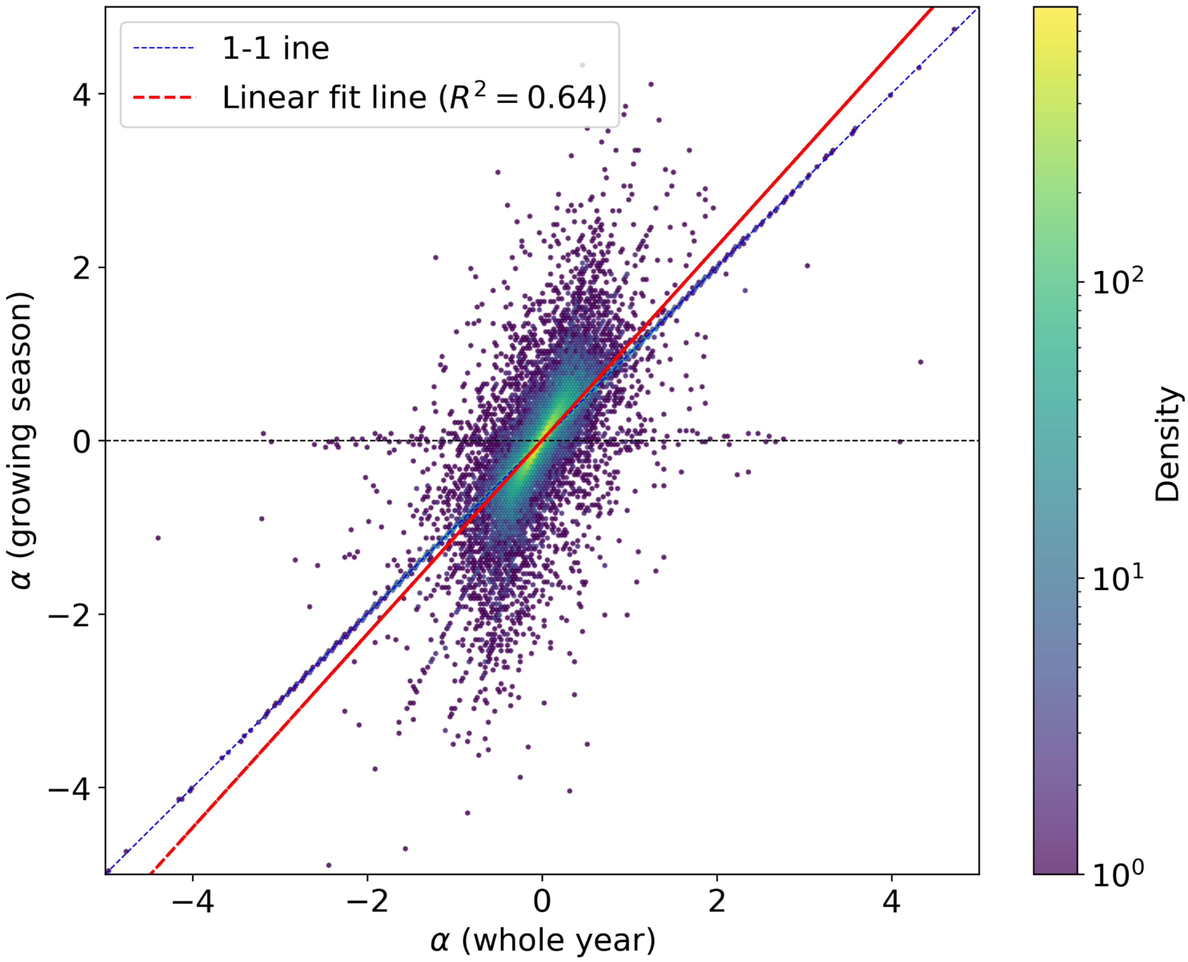


**Figure R3.** The comparison between ecosystem resistance to the whole year drought duration and growing season drought duration.

(ii) Second, we agree that there is an inconsistency between the yearly mean temperature and the discussion about heat stress. We include yearly mean temperature in our linear regression model due to the following two arguments:
First, yearly mean temperature strongly correlates with drought duration (months per year) in 1979-2020 (Fig. R4). This is especially marked for tropical and semi-arid regions, with correlations between the two variables over 0.6. Therefore, if a simple linear regression model with drought duration as the only predictor would be used, the coefficients would implicitly include the effects of mean annual temperature variations. To estimate drought resistance more reliably, one needs to control for temperature, justifying the use of a more complex model.

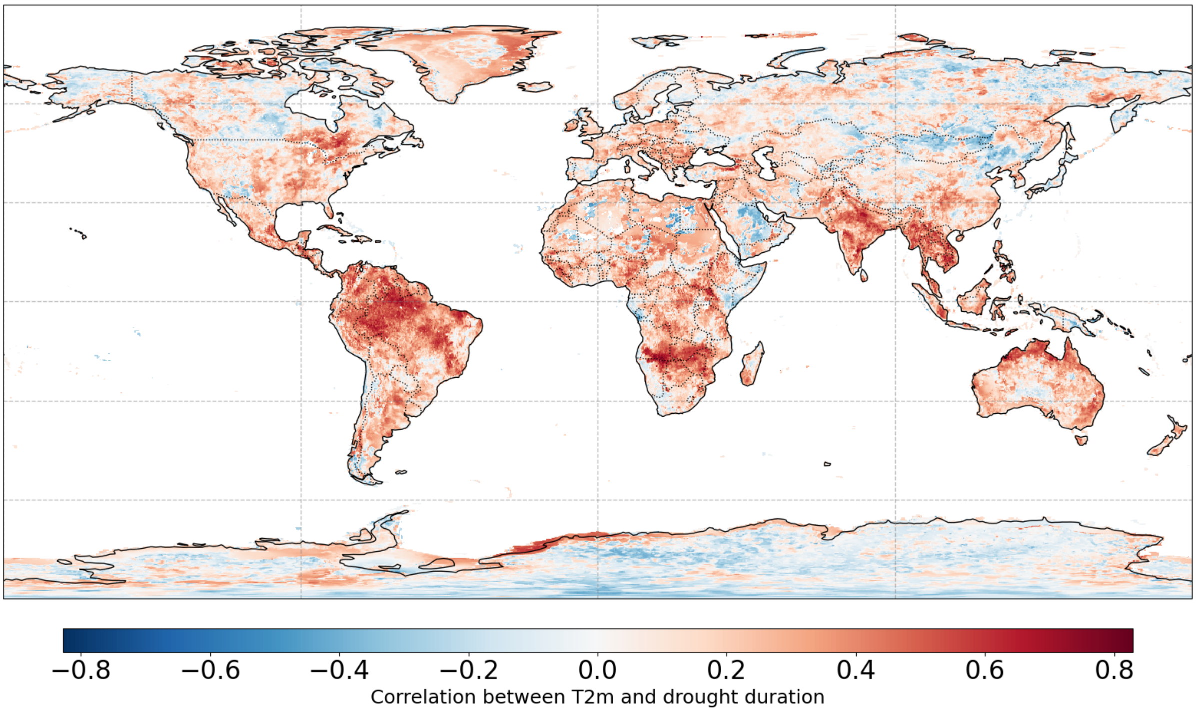


**Figure R4.** Temporal correlation between yearly mean temperature and drought duration (months per year) in 1979-2020.

Second, after controlling for temperature, the adjusted $R^2$ of the model increases by more than 0.1 in 26% and 40%, and 44% of the pixels for L-VOD, EVI, and kNDVI. This justifies fitting a model with two degrees of freedom, versus a simple linear regression.

Based on the above arguments, we have now changed it to "temperature sensitivity".

We changed the sentence in Line 224 now to:

*Similarly, we used β as a metric for the ecosystem sensitivity to temperature anomalies.*

Line 227 to:

*α and β were evaluated for each pixel.*

(iii) Third, we added the AR1 term to consider the memory effects at an annual scale, which is the dependence of a vegetation state (i.e. L-VOD, EVI, kNDVI) anomaly on the previous year's anomaly.  The AR1 term expresses the speed of the vegetation to return to its normal state following any perturbation (i.e. not necessarily drought-related). This term is often associated with ecosystem resilience in an environment driven by climate factors dominantly (De Keersmaecker et al., 2016). This term can also be interpreted as biological memory (Liu et al., 2019), which may reflect intrinsic ecosystem feedback such as biomass accumulation or loss (Barron-Gafford et al. 2014) as well as effects of other environmental and climate drivers or nonlinear responses not explicitly considered in linear models such as the one used here (Liu et al., 2019). Based on flux tower data, biological memory has been found to contribute to increased $R^2$ on daily net ecosystem exchange (NEE) prediction (Cranko Page et al., 2022) and to vary with the above internal feedbacks, especially disturbances and human activities (Liu et al., 2019). Therefore, we initially applied the linear autoregressive model Eq. (2) shown in Line 184 in the submitted manuscript.

However, such memory effects might differ when we consider the different vegetation indices at annual scales. To evaluate whether the AR1 term carries additional information to the variability in our target variables, we compared the adjusted $R^2$ of the model with and without the AR1 term. Generally, the adjusted R2 increases when we include the AR1 term. The spatial distribution of the differences in drought resistance $\alpha$, temperature sensitivity $\beta$, and adjusted $R^2$ is shown in Fig. R5.

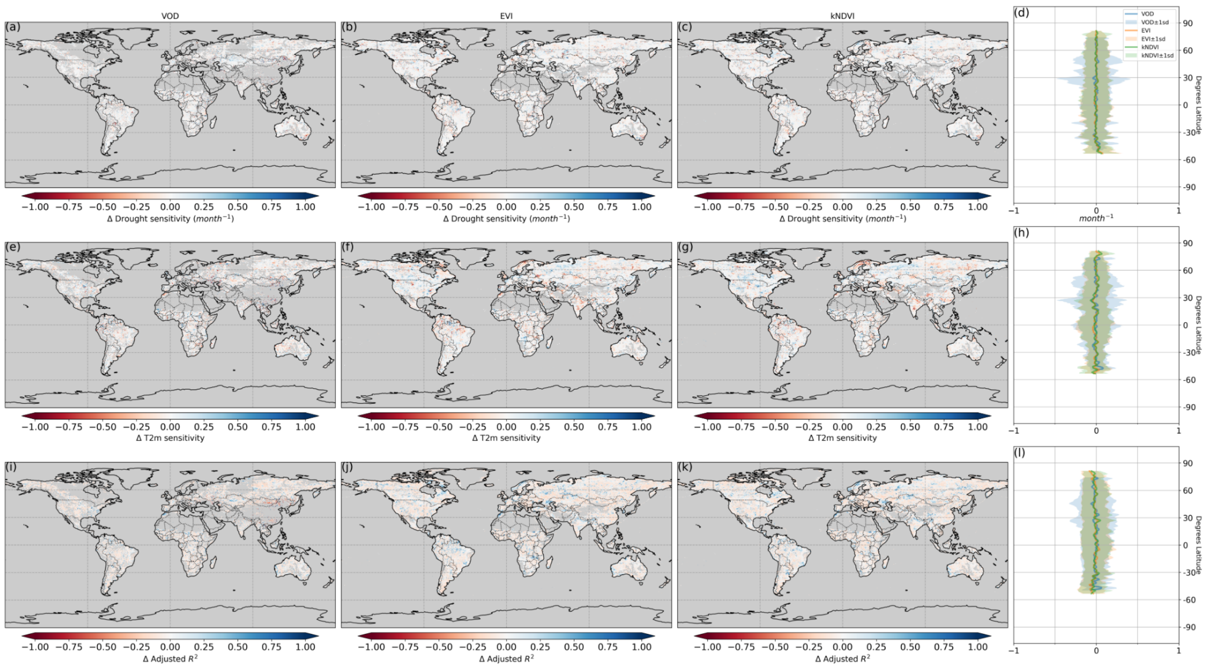


**Figure R5.** Difference between linear regression model with/without memory term (model with $\varphi$ minus model without $\varphi$) for ecosystem resistance to drought duration $\alpha$ from L-VOD, EVI and kNDVI (a, b, c). Similar for temperature sensitivity $\beta$ (e, f, g) and adjusted $R^2$ (i, j, k). The averages for different latitudes and their standard deviations are shown on the right (d, h, l).

The overview of the differences is shown in Table R1. The average values of the difference in $\alpha$ ($\Delta\alpha$) and $\beta$ ($\Delta\beta$) are close to 0. The spatial correlation between $\alpha$ and $\beta$ calculated with/without memory term $\varphi$ is 0.88 or higher. The averaged Δadjusted $R^2$ are all close to 0 and sometimes even negative, which means that introducing the memory term does not contribute to explaining more variance of yearly vegetation state in 2011-2020.

Table R1. Overview of the differences in coefficients and adjusted $R^2$, and spatial correlation of $\alpha$ and $\beta$ between models with/without memory term $\varphi$

| | L-VOD | EVI | kNDVI |
|---|---|---|---|
| Mean $\Delta\alpha$ ($month^{-1}$) | 0.0002 | -0.0013 | -0.0021 |
| Mean $\Delta\beta$ | -0.0064 | -0.0049 | -0.0023 |
| Mean $\Delta$adjusted $R^2$ | -0.017 | -0.012 | -0.014 |
| Spatial correlation ($\alpha$) | 0.88 | 0.93 | 0.93 |
| Spatial correlation ($\beta$) | 0.90 | 0.95 | 0.96 |

Because the drought resistance and temperature sensitivity are similar and we only have a 10-year long time series, to avoid overfitting, we have decided to remove the memory term in new Eq (2), now in Lines 201-202:

*To calculate the ecosystem resistance to drought, we applied a linear model for each pixel following Eq. (2):*

$$Y_{anom}\left(t\right) = \alpha N\left(t\right) + \beta T_{anom}\left(t\right) + c + \epsilon\left(t\right) \tag{2}$$

and removed the description for $\varphi$ in Lines 225 now from:

"*The third term of the equation corresponding to the previous year's vegetation anomalies could be associated with the recovery rate to the average state or persistent impact during the next year. Thus, φ can represent vegetation memory, which has previously been proposed to be associated with long-term resilience to any type of perturbation. α is in the unit of* $month^{-1}$ *but β and φ have no unit due to standardization.*"

to:

*α is in the unit of* $month^{-1}$ *but β has no unit due to standardization.*

and we discussed the reason to choose to use a more simple model in Lines 211-218 and Appendix B:

*We also analyzed the linear autoregressive model as Eq. (4):*

$$Y_{anom}\left(t\right) = \alpha N\left(t\right) + \beta T_{anom}\left(t\right) + \varphi Y_{anom}\left(t-1\right) + c + \epsilon\left(t\right) \tag{4}$$

*in which we also considered the memory effect with the AR1 term, which has been demonstrated to be fundamental to understanding the daily carbon metabolism of terrestrial ecosystems (Liu et al., 2019; Cranko Page et al., 2022) and ecosystem resilience of monthly*

*NDVI (De Keersmaecker et al., 2016). We evaluated if interannual memory effects influence drought sensitivity, temperature sensitivity, and adjusted $R^2$, but the additional predictor does not carry new information for annual L-VOD, EVI, and kNDVI anomalies. The drought sensitivity and temperature sensitivity are similar and adjusted $R^2$ does not increase in general (Appendix B), so we used the most parsimonious model Eq. (2).*

and we have changed the sentence describing the method in our abstract in Lines 19-20 to:

*We apply a linear model accounting for drought and temperature effects to characterize ecosystem resistance by their sensitivity to drought duration and temperature anomalies.*

We also changed the caption for Fig. 3 in Line 305-308 now to:

*(b) Distribution of ecosystem resistance α to drought for different reference sub-regions, the number in each box is the number of pixels in this category. Only regions with averages that are statistically different from zero are shown (two-sided Student t-test; P-value<0.05); (c) Distribution of ecosystem resistance to drought α for different dominant IGBP vegetation classes. Only significant α from the linear model is selected (P-value<0.05) are selected.*

Similarly, we substitute the "linear AR1 model" with the "linear model" in our main text and figure captions.

We have moved the discussion about the AR1 term, Fig. R5 and Table R1 in Appendix B.

We have also updated all results and figures based on the new Eq. (2). The main results and conclusions of the original study do not change.

There are some small changes in our results:

Lines 261-262:

*At the global scale, α based on Eq. (2) are negative in 55% of pixels with valid values from L-VOD, 56% from EVI, and 59% from kNDVI (Figure A6a-A6c, Figure 3a).*

Lines 265-267:

*but in Southeast Asia, EVI shows the lowest drought resistance with a median of -0.12 month$^{-1}$ in disagreement with L-VOD which has a median of 0.03 month$^{-1}$. kNDVI shows the same sign as EVI, with a median of -0.05 month$^{-1}$. In the Amazon, there are around 15% and 18% more pixels showing negative resistance from EVI and kNDVI than L-VOD.*

Lines 288-291:

*32 regions coloured red or blue in Fig. 3a have mean values of α significantly different from zero, as determined by the two-tailed Student t-test (P-value < 0.05). The* *median values of α range from -0.20 to 0.07 month$^{-1}$ across regions, and the average values from -0.25 to 0.08 month$^{-1}$. Among these regions, 25 regions show significant negative mean α.*

Lines 295:

*In the tropics, SAS, CAF, WAF, and NAU, which have lower forest cover show negative mean α, …*

Lines 297-300:

*α based on L-VOD are higher in evergreen needleleaf forests (ENF), shrublands (SH) and evergreen broadleaf forests (EBF), but lower in cropland (C), deciduous needleleaf forests (DNF), and crop/natural vegetation mosaic (CNVM) (Figure 3c). kNDVI and EVI agree on the lower resistance in C and CNVM and high resistance in SH, ENF, and mixed forests (MF) (Figure A3).*

Lines 313-317:

*Pixels dominated by forests are significantly (P-value < 0.05; indicated by stars) more resistant to droughts than those where cropland predominates (Figure 4a-c). α increases with increased forest fraction, from a mean value of -0.07 month$^{-1}$ (0-25% forest cover) to 0.07 month$^{-1}$ (75-100% forest cover), and decreases with increased cropland fraction, from -0.07 month$^{-1}$ for 0-25% crop cover to -0.30 month$^{-1}$ for 75-100% crop cover.*

Lines 354-358:

*The median of the difference between primary and secondary forests ($\Delta\alpha$) is 0.382 month$^{-1}$ and is significantly greater than 0 based on the one-sample Wilcoxon test (P-value < 0.05). However, we did not detect such a large difference between EVI and kNDVI, whose medians of $\Delta\alpha$ between forest types are -0.040 month$^{-1}$ and 0.052 month$^{-1}$, but given the large spread of the distribution, their medians are not significantly greater than 0 based on the one-sample Wilcoxon test (P-value > 0.05).*

Lines 362-365:

*The median of α for forests younger than 100 years is -0.458 month$^{-1}$ but the medians of α of forests from 100 to 300 years and forests older than 300 years are 0.429 month$^{-1}$ and 0.361 month$^{-1}$ respectively. We also find a significant (P-value < 0.05) increase of α in kNDVI between forests younger than 100 years and older than 300 years, but the effect is not as large as in L-VOD.*

Lines 368-372:

*We finally investigated the ecosystem resistance α for different irrigation levels (Figure 5c). The result shows an increasing resistance for L-VOD with the irrigation levels, with the median of α for L-VOD increasing from -0.342 month$^{-1}$ to 0.023 month$^{-1}$ between less than 10% actually irrigated cropland and more than 50% actually irrigated cropland (P-value < 0.05). For kNDVI and EVI, the change in the median of α is negligible but we still* *found a higher percentage of pixels with close to zero or positive resistance for higher irrigation fractions.*

(iv) Fourth, we have added the description describing the term “c” in Line 206 now, thank you for the suggestion.

> *... c is the intercept term and $\epsilon$ is the residual term...*

**R1C5: One concern I have is about the explanatory power of each regression over each grid point, given that only 10 values are available for the regression. This could touch a pragmatic lower bound for sample size, and it is therefore important to ensure that the derived coefficients are significant and that their spatial patterns are indicated. For example, in Fig. 2, it would be helpful to show the significance of the derived coefficients along with their spatial patterns. This would allow readers to better assess the reliability of the results and understand the degree of confidence that can be placed in the findings.**

Thanks for suggesting showing the significant coefficients explicitly. To address this concern, we propose a new version of Fig. 2 to overlap the original maps with stippling and grey shade where results are NOT significant at a 10% significance level (reproduced below as Fig. R6). We also moved the original Fig. 2 to Appendix A as Fig.A6 to show the overall spatial distribution of drought resistance and temperature sensitivity and the standard error, which we described in our main text to indicate uncertainty now in Lines 269-270 and 280-281.

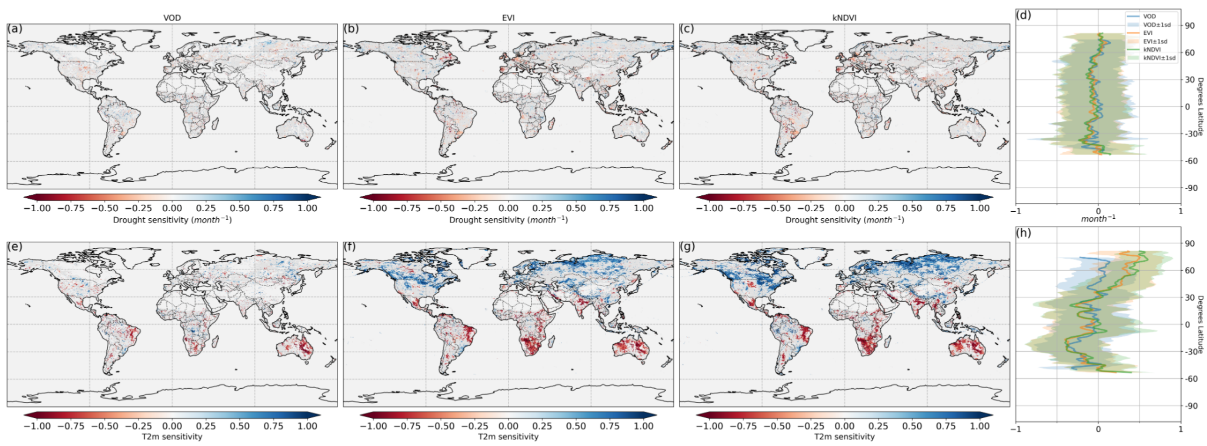


**Figure R6.** Ecosystem resistance to drought duration and temperature sensitivity. Spatial map of drought resistance $\alpha$ for (a) L-VOD, (b) EVI, (c) kNDVI. Same for temperature sensitivity $\beta$ (e, f, g). The averages for different latitudes and their standard deviations are shown on the right (d, h). The pixels with NON-significant $\alpha$ and $\beta$ at a 10% significance level are marked with stippling and plotted with a light grey shade to better show the significant results.

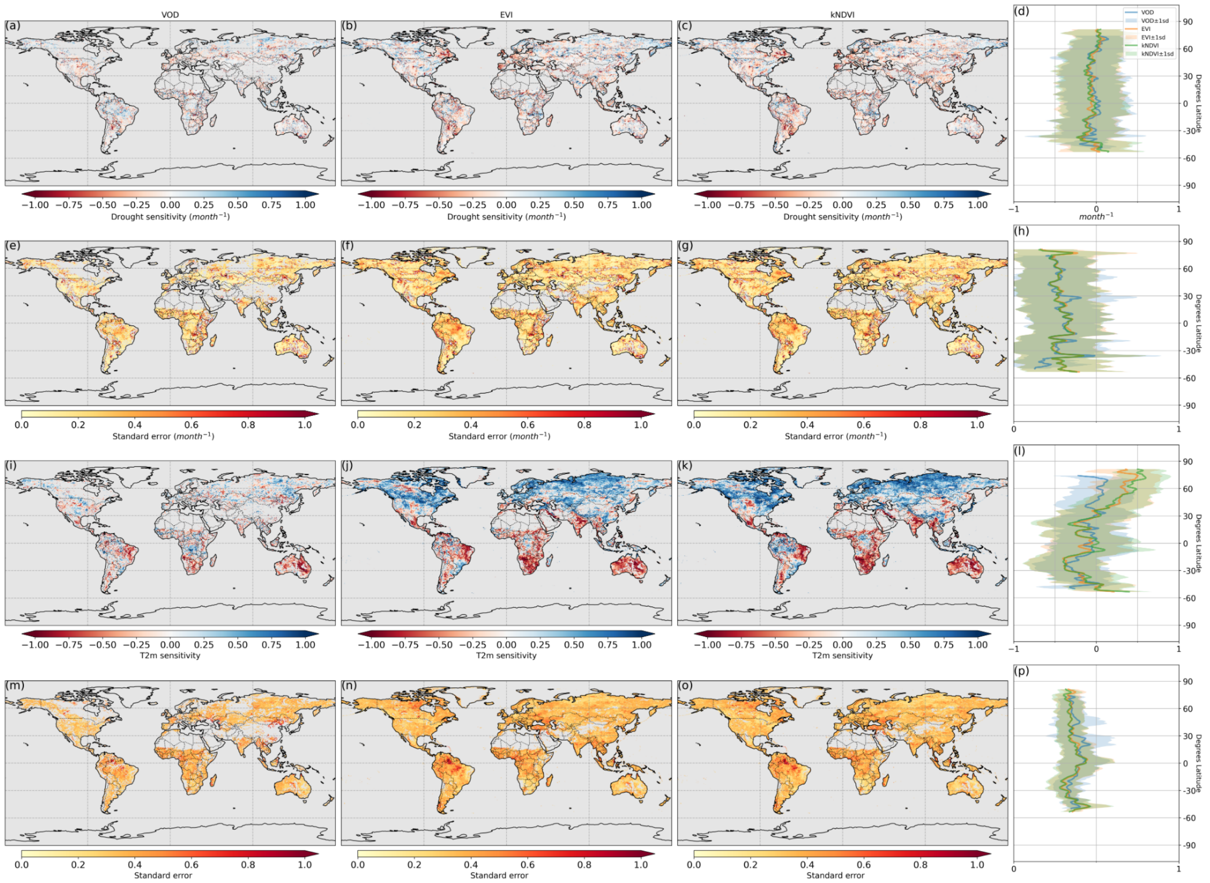


**Figure A6.** Ecosystem resistance to drought duration and its standard error. Spatial map of drought resistance $\alpha$ for (a) L-VOD, (b) EVI, (c) kNDVI and their standard error (e, f, g). Same for temperature sensitivity $\beta$ (i, j, k) and their standard error (m, n, o). The averages for different latitudes and their standard deviations are shown on the right (d, h, l, p).

**Ln 150: Are the land cover classification considering temporal changes? For example, land cover A for year 1 but becomes land cover B for year 2, what would be the eventual land cover for analysis?**

Thanks for pointing this out. Indeed, we have considered the temporal changes of land cover over 2010-2020 by only analyzing those pixels without dominant land cover classification changes for Fig. 3a, c. We realize that we failed to explain this, and now add the following sentences to Section 2.5 Line 232-233:

*We only analyzed those pixels without changes in the dominant IGBP vegetation cover class during the period 2010-2020.*

For Fig. 4, we selected only those pixels without forest, crop, and grass changes at a 25% interval level over 2010-2020. This was described in Section 2.3 Lines 202-203 previously. This information is now added to the figure caption as well in Line 337:

*Only pixels with no change in the 25% bins of the four dominant biomes (forests, shrublands, grasslands, and croplands) are analyzed.*

For Fig. 5, we realized that we failed to explain this, and now add the following sentences to Section 2.5 Line 233-236:

*We only analyzed those pixels with less than 10% changes in primary and secondary forest, tropical evergreen broadleaf forests, and crop cover fraction in 2010-2020. We used 10% to avoid abrupt and substantial changes in vegetation cover that might directly modulate the biomass variations and therefore affect our regression.*

We change the following sentence in Line 241 to better define the dominant primary forests and secondary forests:

'*First, the grid cells were filtered by > 50% forest fraction and those containing LUH2 v2h forest management information were categorized according to ERA5 temperature and total precipitation long-term averages.*' to

*First, we define primary forests as those pixels with > 50% forest fraction and primary forests dominate > 50% of the forest fraction, similar for secondary forests where secondary forests dominate > 50% of the forest fraction in 2010-2020. These pixels were then categorized according to ERA5 temperature and total precipitation long-term averages.*

For forest ages and crop irrigation, we add the following sentence in Line 252:

*We only selected pixels with over 50% forest fraction in 2011-2020 and no variation in the dominant vegetation type (tropical evergreen broadleaf forests).*

and in Lines 254:

*We only compare pixels where crop fraction is > 50% in 2011-2020 for irrigation effects.*

and figure caption as well in Line 380-381:

*Only pixels with unchanged dominant primary and secondary forest, tropical EBF, and crop cover in 2011-2020 were selected, as defined in Section 2.5.*

We add the description about how we determine the significance of the difference between two bins in our method Section 2.5 in Lines 257-258 now:

*For the comparison between two groups, we applied the unpaired two-sample Wilcoxon test to test whether there is a significant difference between their medians (P-value < 0.05).*

We then make our results more concise without explicitly showing the test method we use:
In Lines 363-365:

*We also find a significant (P-value < 0.05) increase of α in kNDVI between forests younger than 100 years and older than 300 years, but the effect is not as large as in L-VOD.*

In Lines 371:

*...significantly (P-value < 0.05)...*

**Ln 188: It is not clear how the anomalies were standardized.**

We used the standard score of the anomalies and have now added a mathematical equation to better clarify our standardization methods (now Eq. 3) in Line 208:

$$\frac{X-\mu}{\sigma} \tag{3}$$

**Other comments**

**Ln 26: Up on the improved analysis of primary-secondary forest differences in alpha, this sentence "L-VOD indicates that primary forests tend to be more resistant to drought events than secondary forests" may need to be rephrased.**

We have rephrased the sentence in Lines 25-26 to:

*L-VOD indicates that primary forests tend to be more resistant to drought events than secondary forests <u>when controlling for the differences in background climate, but ...</u>*

**Ln 27: "EVI and kNDVI saturation in dense forests.", do you mean for the biomass estimates? Note that EVI is designed to be less susceptible to saturation over dense forest areas (Huete et al., 2002: 10.1016/S0034-4257(02)00096-2).**

We agree with the reviewer that EVI is designed to be less susceptible to saturation than NDVI over forest areas for green vegetation and forest cover. However, reflectance-based indices still reflect mostly the top of canopy density/cover. For aboveground biomass estimates, optical indices (i.e. NDVI or EVI) have been found to saturate in dense vegetation at moderate L-VOD values (Li et al., 2021).

**Ln 39: any reference for the concept "ecosystem resistance"?**

Yes, Gessler et al. (2020) extensively reviewed the concept of resistance in their study. We have restructured the sentence in Lines 39-43 to be:

*..., i.e., the ecosystem resistance (Gessler et al., 2020; Ingrisch and Bahn, 2018) and recovery trajectory following the disturbance (Schwalm et al., 2017; Wigneron et al., 2020; Wu et al., 2022; Yao et al., 2023). Ecosystem resistance is defined as the concurrent impact of a disturbance on response parameters. However, event-specific resistance may differ under different drought conditions. We applied a long-term resistance definition as the vegetation sensitivity to drought duration over multiple years, making it consistent for spatial comparison.*

**Ln 40: Studies related to vegetation recovery and legacy effects have been increasing recently, more latest references are needed for supporting the sentence "recovery trajectory following the disturbance".**

We have added more recent references in Line 40:

*... the recovery trajectory following the disturbance (Schwalm et al., 2017; Wigneron et al., 2020; Wu et al., 2022; Yao et al., 2023)*

**Ln 41: "The mitigation of climate extreme events and maintenance of land carbon sink are highly dependent on the resistance of ecosystems and their changes under land use and land cover change.": Looks a bit abrupt to come to this sentence, some transition may be needed. Also, please provide references for this sentence.**

Thanks for pointing out the abrupt transition. We have restructured this part and added the following sentences to Lines 43-48:

*... Therefore, gaining a thorough understanding of the global patterns of ecosystem resistance and identifying the potential drivers behind their spatial variations is crucial for comprehending the impact of drought events on the land carbon sink. Potential drivers include climate background, plant species, biodiversity, tree height and ages and land use and land management. Land use and land management can potentially affect ecosystem resistance through changes in species composition, biodiversity and stand structure.*

**Ln 55-56: "Taller tropical forests … because …. ": note that the influence of tree height on the response of tropical forests to drought and subsequent non-drought growth remains controversial. The deep roots of the tropical forest may also play a critical role, check the studies Brando, 2018: https://doi.org/10.1038/s41561-018-0147-z and Giardina et al., 2018: https://doi.org/10.1038/s41561-018-0133-5.**

Thanks for pointing out and suggesting additional literature. We have rephrased this sentence in Lines 62-67 for clarity:

*Taller tropical forests have been shown to be more vulnerable to vapor pressure deficit (VPD) fluctuations during drought periods because of smaller xylem-transport safety margins, in studies based on Ku-band VOD (Liu et al., 2021) and SIF (Giardina et al., 2018). However, the opposite has been found when analyzing resistance to precipitation variability (Giardina et al., 2018) and terrestrial water storage anomalies (Liu et al., 2021), with taller* *trees being associated with higher resistance to soil-moisture deficit, based on the same vegetation proxies. However, some satellite products are less capable of detecting vegetation dynamics in dense forests.*

**Ln 58: "kNDVI is better correlated …", compared to which indices?**

We have rephrased this sentence in Lines 68-70 for clarity.

*kNDVI is better correlated with key vegetation parameters, such as leaf area index (LAI), gross primary productivity (GPP), and sun-induced chlorophyll fluorescence (SIF) compared to NDVI.*

**Ln 63: DVGMs or DGVMs?**

Corrected to DGVMs.

**Ln: 64-66: "DVGMs and upscaled FLUXCOM GPP have suggested that GPP anomalies are less negative or even positive for pixels including …": less negative than what? The entire sentence is a bit difficult to understand, good to rephrase it or divide it into several short sentences.**

Thanks for pointing this out. We have rephrased this sentence in Lines 74-79:

*For example in Europe, both DGVMs and upscaled FLUXCOM GPP have suggested that GPP anomalies under low soil moisture conditions are less negative, or even positive, in pixels with more than 80% forest cover than in those pixels with lower forest cover. On the contrary, pixels with higher crop cover show stronger negative impacts on GPP anomalies compared to the pixels with low crop coverage in drought and heat events that occurred in 2003, 2010 and 2018 in Europe (Bastos et al., 2020). Over the globe, FLUXCOM GPP shows a reduced sensitivity to depleted soil moisture with increased tree cover (Walther et al., 2019).*

**Ln 66: "However, ecosystem fluxes are not directly observable at the ecosystem scale." the definition of an ecosystem is quite broad and may be good to indicate what the ecosystem scale is referring to here.**

Thanks for pointing this out. We have already changed the sentence in Lines 79-80 to:

*However, ecosystem fluxes are not directly observable at a regional scale beyond the footprint of flux towers (a few hundred meters).*

**Ln 72-74: "For example, modifying forest density and structure by high-intensity overstory removal was tested in conifer-broadleaf mixed forests in Central Europe and considerably increased their growth resilience to droughts and decreased drought-induced mortality by two-thirds (Zamora-Pereira et al., 2021).": It could be helpful to indicate the findings mentioned here are based on a stand-alone forest gap model.**

Thanks, we agree. We have rephrased this sentence in Lines 85-87 to:

*For example, based on a stand-alone forest gap model, modifying forest density and structure by high-intensity overstory removal in conifer-broadleaf mixed forests in Central Europe considerably increased their growth resilience to droughts and decreased drought-induced mortality by two-thirds (Zamora-Pereira et al., 2021).*

**Ln 101: "VOD has been used 100 as a proxy for biomass", I guess you meant "aboveground" biomass.**

We have rephrased it to aboveground biomass.

**Ln 162: Table 3 can not be found.**

We apologize for the missing table. We have now included it in the main text after Line 181.

**Table 3. Overview of the classification for the four biomes for land cover products.**

| Biomes | MCD12Q1 | Land Cover CCI | LUH2 v2h |
|---|---|---|---|
| Forests | Evergreen Needleleaf Forests, Evergreen Broadleaf Forests, Deciduous Needleleaf Forests, Deciduous Broadleaf Forests, Mixed Forests | Tree Broadleaf Evergreen, Tree Broadleaf Deciduous, Tree Needleleaf Evergreen, Tree Needleleaf Deciduous | Forested primary land, Potentially forested secondary land |
| Shrublands | Closed Shrublands, Open Shrublands, Woody Savannas, Savannas | Shrub Broadleaf Evergreen, Shrub Broadleaf Deciduous, Shrub Needleleaf Evergreen, Shrub Needleleaf Deciduous | |
| Grasslands | Grasslands | Natural Grass | Managed pasture, Rangeland |

| | | | |
|---|---|---|---|
| Croplands | Croplands, Cropland/Natural Vegetation Mosaics | Crops | C3 annual crops, C3 perennial crops, C4 annual crops, C4 perennial crops, C3 nitrogen-fixing crops |

**Ln 180: Figure 1, what does the white area represent?**

The white area represents either (1) areas that are not dominated by primary or secondary forests, which are defined by pixels with > 50% forest fraction and > 50% of the forest fraction dominated by primary or secondary forests in 2011-2020, (2) where the irrigation ratio is zero or (3) where the minimum cropland fraction in MODIS is less than 50% in 2011-2020.

To make it consistent with our analysis of the effect of irrigation on drought resistance, we have modified Fig. 1 and changed the irrigation area ratio of cropland for minimum MODIS cropland > 25% to > 50% in 2011-2020 (Fig. R7).

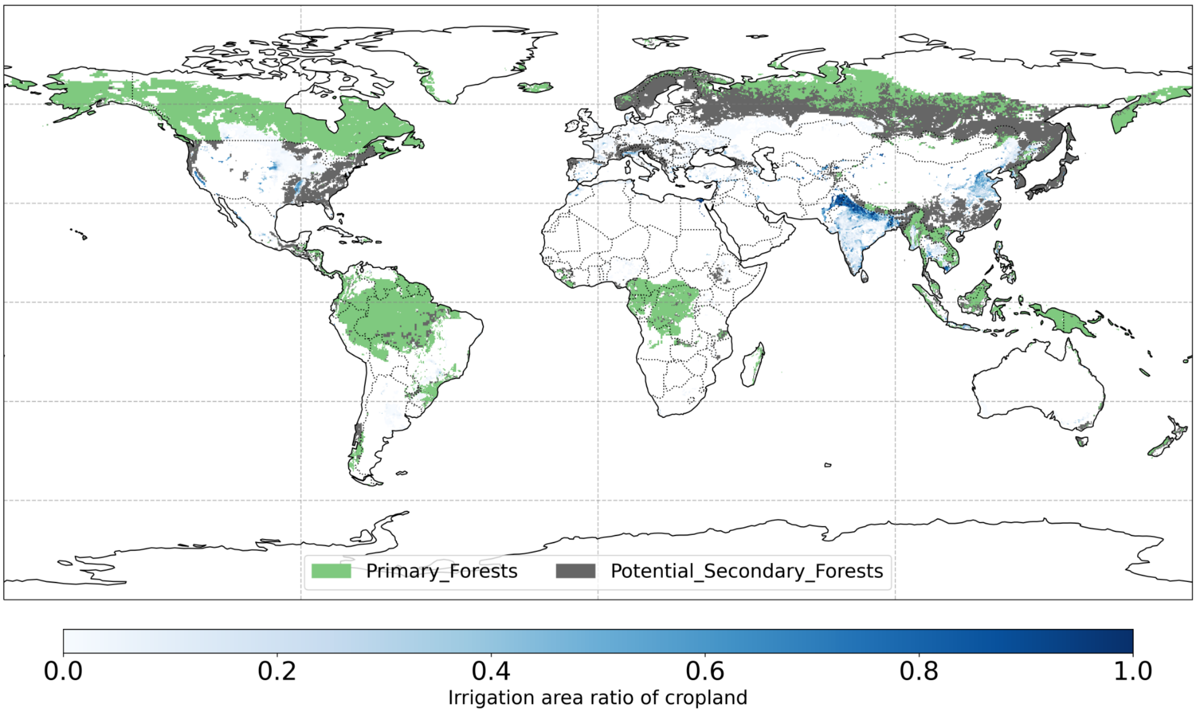


**Figure R7.** Global map of forest management types in LUH2v2 and irrigation area ratio of cropland for minimum MODIS cropland > 50% in 2011-2020.

We have also changed the sentence in Lines 255-257 now to:

"*We compared the crop irrigation ratio between bins < 10%, 10% to 50% and ≥ 50% for pixels with >50% cropland fraction, which is dominated by cropland in India and North America (Figure 1).*"
to:

*We compared the crop irrigation ratio between bins < 10%, 10% to 50% and ≥ 50% for pixels with >50% cropland fraction, which is dominated by cropland in India (Figure 1).*

**Ln 228-229: "L-VOD is positive in Amazon, central Africa and Southeast Asia regions", difficult to see central Africa and Southeast Asia are positive, are they significant?**

We agree with the reviewer that in central Africa, the pattern is not clear. In the Southeast Asia region, L-VOD showed that pixels with positive drought resistance cover 53.7% of the total vegetated area (MODIS vegetation cover > 0.05) with a significantly positive mean from Student's t-test, as shown in Fig. 3b. We have rephrased the sentence in Line 265:

*..., where drought resistance based on L-VOD is positive in Amazon and Southeast Asia regions, ...*

**Ln 236: clearer compared to what? I can see clearer patterns than those from alpha, but for beta, L-VOD is not as clear as EVI or kNDVI.**

We apologize for the unclear statement. Here the patterns of beta are clearer compared to alpha for all three indices. We have rephrased the sentence in Line 273 to:

*The temperature sensitivity shows a clearer spatial pattern than the resistance to drought duration.*

**Ln 247: Figure 2, double check the unit of temperature coefficients, if it is needed for x axis for (i) and (p)?**

We have removed the wrong unit labels of temperature coefficients in Fig. 2i, 2p (now Fig. A6i, A6p).

**Ln 264: what does the black text in Fig. 3a represent, no regression is applied, or zero coefficients?**

The black text represents that the mean of the distribution of $\alpha$ is not significantly different from zero. We have restructured the caption in Lines 303-305 for clarity:

*… Blue represents significant positive mean of α and red represents significant negative mean of resistance, black indicates regions whose means of the distribution are not significantly different from zero (P-value < 0.05); …*

## Reference

Anderegg, W. R. L., Schwalm, C., Biondi, F., Camarero, J. J., Koch, G., Litvak, M., Ogle, K., Shaw, J. D., Shevliakova, E., Williams, A. P., Wolf, A., Ziaco, E., and Pacala, S.: Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models, Science, 349, 528–532, https://doi.org/10.1126/science.aab1833, 2015.

Anderegg, W. R. L., Konings, A. G., Trugman, A. T., Yu, K., Bowling, D. R., Gabbitas, R., Karp, D. S., Pacala, S., Sperry, J. S., Sulman, B. N., and Zenes, N.: Hydraulic diversity of forests regulates ecosystem resilience during drought, Nature, 561, 538–541, https://doi.org/10.1038/s41586-018-0539-7, 2018.

Barron-Gafford, G. A., Cable, J. M., Bentley, L. P., Scott, R. L., Huxman, T. E., Jenerette, G. D., and Ogle, K.: Quantifying the timescales over which exogenous and endogenous conditions affect soil respiration, New Phytol, 202, 442–454, https://doi.org/10.1111/nph.12675, 2014.

Bastos, A., Ciais, P., Friedlingstein, P., Sitch, S., Pongratz, J., Fan, L., Wigneron, J. P., Weber, U., Reichstein, M., Fu, Z., Anthoni, P., Arneth, A., Haverd, V., Jain, A. K., Joetzjer, E., Knauer, J., Lienert, S., Loughran, T., McGuire, P. C., Tian, H., Viovy, N., and Zaehle, S.: Direct and seasonal legacy effects of the 2018 heat wave and drought on European ecosystem productivity, Science Advances, 6, eaba2724, https://doi.org/10.1126/sciadv.aba2724, 2020a.

Bastos, A., Fu, Z., Ciais, P., Friedlingstein, P., Sitch, S., Pongratz, J., Weber, U., Reichstein, M., Anthoni, P., Arneth, A., Haverd, V., Jain, A., Joetzjer, E., Knauer, J., Lienert, S., Loughran, T., McGuire, P. C., Obermeier, W., Padrón, R. S., Shi, H., Tian, H., Viovy, N., and Zaehle, S.: Impacts of extreme summers on European ecosystems: a comparative analysis of 2003, 2010 and 2018, Phil. Trans. R. Soc. B, 375, 20190507, https://doi.org/10.1098/rstb.2019.0507, 2020b.

Briant, G., Gond, V., and Laurance, S. G. W.: Habitat fragmentation and the desiccation of forest canopies: A case study from eastern Amazonia, Biol Conserv, 143, 2763–2769, https://doi.org/10.1016/j.biocon.2010.07.024, 2010.

Broadbent, E. N., Asner, G. P., Keller, M., Knapp, D. E., Oliveira, P. J. C., and Silva, J. N.: Forest fragmentation and edge effects from deforestation and selective logging in the Brazilian Amazon, Biol Conserv, 141, 1745–1757, https://doi.org/10.1016/j.biocon.2008.04.024, 2008.

Buermann, W., Forkel, M., O'Sullivan, M., Sitch, S., Friedlingstein, P., Haverd, V., Jain, A. K., Kato, E., Kautz, M., Lienert, S., Lombardozzi, D., Nabel, J. E. M. S., Tian, H., Wiltshire, A. J., Zhu, D., Smith, W. K., and Richardson, A. D.: Widespread seasonal compensation effects of spring warming on northern plant productivity, Nature, 562, 110–114, https://doi.org/10.1038/s41586-018-0555-7, 2018.

Cranko Page, J., De Kauwe, M. G., Abramowitz, G., Cleverly, J., Hinko-Najera, N., Hovenden, M. J., Liu, Y., Pitman, A. J., and Ogle, K.: Examining the role of environmental memory in the predictability of carbon and water fluxes across Australian ecosystems, Biogeosciences, 19, 1913–1932, https://doi.org/10.5194/bg-19-1913-2022, 2022.

De Keersmaecker, W., van Rooijen, N., Lhermitte, S., Tits, L., Schaminée, J., Coppin, P., Honnay, O., and Somers, B.: Species-rich semi-natural grasslands have a higher resistance but a lower resilience than intensively managed agricultural grasslands in response to climate anomalies, Journal of Applied Ecology, 53, 430–439, https://doi.org/10.1111/1365-2664.12595, 2016.

Elias, F., Ferreira, J., Lennox, G. D., Berenguer, E., Ferreira, S., Schwartz, G., Melo, L. de O., Reis Júnior, D. N., Nascimento, R. O., Ferreira, F. N., Espirito-Santo, F., Smith, C. C., and Barlow, J.: Assessing the growth and climate sensitivity of secondary forests in highly deforested Amazonian landscapes, Ecology, 101, e02954, https://doi.org/10.1002/ecy.2954, 2020.

Gessler, A., Bottero, A., Marshall, J., and Arend, M.: The way back: recovery of trees from drought and its implication for acclimation, New Phytol, 228, 1704–1709, https://doi.org/10.1111/nph.16703, 2020.

Giardina, F., Konings, A. G., Kennedy, D., Alemohammad, S. H., Oliveira, R. S., Uriarte, M., and Gentine, P.: Tall Amazonian forests are less sensitive to precipitation variability, Nat Geosci, 11, 405–409, https://doi.org/10.1038/s41561-018-0133-5, 2018.

Ingrisch, J. and Bahn, M.: Towards a Comparable Quantification of Resilience, Trends in Ecology & Evolution, 33, 251–259, https://doi.org/10.1016/j.tree.2018.01.013, 2018.

Konings, A. G., Rao, K., and Steele-Dunne, S. C.: Macro to micro: microwave remote sensing of plant water content for physiology and ecology, New Phytologist, 223, 1166–1172, https://doi.org/10.1111/nph.15808, 2019.

Li, X., Wigneron, J.-P., Frappart, F., Fan, L., Ciais, P., Fensholt, R., Entekhabi, D., Brandt, M., Konings, A. G., Liu, X., Wang, M., Al-Yaari, A., and Moisy, C.: Global-scale assessment and inter-comparison of recently developed/reprocessed microwave satellite vegetation optical depth products, Remote Sensing of Environment, 253, 112208, https://doi.org/10.1016/j.rse.2020.112208, 2021.

Liu, L., Chen, X., Ciais, P., Yuan, W., Maignan, F., Wu, J., Piao, S., Wang, Y.-P., Wigneron, J.-P., Fan, L., Gentine, P., Yang, X., Gong, F., Liu, H., Wang, C., Tang, X., Yang, H., Ye, Q., He, B., Shang, J., and Su, Y.: Tropical tall forests are more sensitive and vulnerable to drought than short forests, Global Change Biology, n/a, https://doi.org/10.1111/gcb.16017, 2021.

Liu, Y., Schwalm, C. R., Samuels-Crow, K. E., and Ogle, K.: Ecological memory of daily carbon exchange across the globe and its importance in drylands, Ecol Lett, 22, 1806–1816, https://doi.org/10.1111/ele.13363, 2019.

Qin, Y., Xiao, X., Wigneron, J.-P., Ciais, P., Brandt, M., Fan, L., Li, X., Crowell, S., Wu, X., Doughty, R., Zhang, Y., Liu, F., Sitch, S., and Moore, B.: Carbon loss from forest degradation exceeds that from deforestation in the Brazilian Amazon, Nat. Clim. Chang., 11, 442–448, https://doi.org/10.1038/s41558-021-01026-5, 2021.

Roux, R. L., Wagner, F., Blanc, L., Betbeder, J., Gond, V., Dessard, H., Funatzu, B., Bourgoin, C., Cornu, G., Herault, B., Montfort, F., Sist, P., Begue, A., Dubreuil, V., Laurent, F., Messner, F., Hasan, A. F., and Arvor, D.: How wildfires increase sensitivity of Amazon forests to droughts, Environ Res Lett, 17, 044031, https://doi.org/10.1088/1748-9326/ac5b3d, 2022.

Schwalm, C. R., Anderegg, W. R. L., Michalak, A. M., Fisher, J. B., Biondi, F., Koch, G., Litvak, M., Ogle, K., Shaw, J. D., Wolf, A., Huntzinger, D. N., Schaefer, K., Cook, R., Wei, Y., Fang, Y., Hayes, D., Huang, M., Jain, A., and Tian, H.: Global patterns of drought recovery, Nature, 548, 202–205, https://doi.org/10.1038/nature23021, 2017.

Walther, S., Duveiller, G., Jung, M., Guanter, L., Cescatti, A., and Camps-Valls, G.: Satellite Observations of the Contrasting Response of Trees and Grasses to Variations in Water Availability, Geophysical Research Letters, 46, 1429–1440, https://doi.org/10.1029/2018GL080535, 2019.

Wigneron, J.-P., Fan, L., Ciais, P., Bastos, A., Brandt, M., Chave, J., Saatchi, S., Baccini, A., and Fensholt, R.: Tropical forests did not recover from the strong 2015–2016 El Niño event, Science Advances, 6, eaay4603, https://doi.org/10.1126/sciadv.aay4603, 2020.

Wolf, J., Asch, J., Tian, F., Georgiou, K., and Ahlström, A.: Canopy responses of Swedish primary and secondary forests to the 2018 drought, Environ Res Lett, 18, 064044, https://doi.org/10.1088/1748-9326/acd6a8, 2023.

Wu, C., Peng, J., Ciais, P., Peñuelas, J., Wang, H., Beguería, S., Andrew Black, T., Jassal, R. S., Zhang, X., Yuan, W., Liang, E., Wang, X., Hua, H., Liu, R., Ju, W., Fu, Y. H., and Ge, Q.: Increased drought effects on the phenology of autumn leaf senescence, Nat Clim Change, 12, 943–949, https://doi.org/10.1038/s41558-022-01464-9, 2022.

Yao, Y., Liu, Y., Zhou, S., Song, J., and Fu, B.: Soil moisture determines the recovery time of ecosystems from drought, Global Change Biol, 29, 3562–3574, https://doi.org/10.1111/gcb.16620, 2023.

Zamora-Pereira, J. C., Yousefpour, R., Cailleret, M., Bugmann, H., and Hanewinkel, M.: Magnitude and timing of density reduction are key for the resilience to severe drought in conifer-broadleaf mixed forests in Central Europe, Ann Forest Sci, 78, 68, https://doi.org/10.1007/s13595-021-01085-w, 2021.