

Author's response to RC2

(Letters C & R denote comment and reply, respectively)

General comment

The manuscript addresses an important ecohydrological question by examining how hydro-lithological variation and inferred bedrock-water storage may regulate seasonal forest responses to climatic water deficit (CWD) in the Qinling Mountains. The comparison of structural and functional vegetation indicators is potentially valuable, and the attempt to quantify the role of subsurface water storage is particularly interesting. However, I have substantial concerns about the construction and interpretation of the counterfactual bedrock-water analysis, as well as about the interpretation of the regression coefficient β_1 as drought sensitivity. These issues affect several of the manuscript's central conclusions.

Response: We sincerely thank the reviewer for the careful evaluation of our manuscript. Your constructive comments and suggestions, especially those concerning conceptual and statistical issues, have been very helpful in improving our work. In response, we have substantially revised the analytical framework and narrowed the corresponding ecological claims. Our major revisions are summarised below:

(1) We have removed the CWDe-based counterfactual analysis, because neither its algebraic construction nor the comparison between CWD- and CWDe-based coefficients could identify vegetation responses in the absence of bedrock-water access. S_{deep} is now analysed as a model-derived water-balance residual, and its relationship with vegetation responsiveness is interpreted as a statistical association. Please see our replies to C1–C3.

(2) We have revised the definition and interpretation of vegetation responsiveness. We have replaced the original CWD-based coefficient with β_{SPEI} , estimated using SPEI. It is now interpreted as statistical vegetation responsiveness to meteorological moisture anomalies. We have also removed unsupported interpretations concerning energy–water limitation and added

sensitivity analyses using alternative SPEI timescales and dry-only observations. Please see our reply to C4.

(3) We have added uncertainty assessment for the retained analyses using spatial-block-bootstrap resampling. Confidence intervals are reported for the principal hydro-lithological group estimates and their pairwise contrasts. Uncertainty is also quantified for climatic-background associations and for both components of the S_{deep} analysis: occurrence and conditional magnitude. Please see our reply to C5.

Together, these revisions address the concerns on the counterfactual interpretation of the bedrock-water analysis, the definition of vegetation responsiveness and statistical uncertainty. The Discussion and Conclusion have also been revised accordingly.

Point-by-point response

C1: The authors first define ordinary climatic water deficit as $\text{CWD} = \text{PET} - \text{ET}$ (L131–135). To estimate monthly bedrock-water use, the authors assume that when ET exceeds the water supplied by precipitation plus the water remaining in the soil, the missing amount is assigned to bedrock water (Eq. 2). To create a counterfactual scenario without a bedrock subsidy, they define $\text{CWD}_e = \text{CWD} + S_{\text{bedrock}}$ and rerun the regression using CWD_e instead of CWD. They then conclude that the difference between the resulting coefficients quantifies the extent to which bedrock water buffers vegetation responses (L254–263). I see two major issues here. First, to simplify Eq. (2), let A denote the available shallow-water supply represented by the inner term in Eq. (2). In months for which $S_{\text{bedrock}} > 0$, Eq. (2) reduces to $\text{ET} - A$. Since CWD_e is defined as $\text{CWD} + S_{\text{bedrock}}$, and since CWD is defined as $\text{PET} - \text{ET}$, Eq. (4) essentially becomes $\text{CWD}_e = (\text{PET} - \text{ET}) + (\text{ET} - A)$. Thus, in months with $S_{\text{bedrock}} > 0$, the ET term cancels algebraically and CWD_e becomes $\text{PET} - A$, i.e. a deficit index based on PET relative to estimated shallow-water availability. To me, this reads more like an alternative water-deficit metric than a counterfactual representing the absence of bedrock-water access.

Response: We agree with the reviewer’s algebraic derivation and its conceptual implication. When the modelled residual is positive, adding it to CWD cancels the actual-ET term, so CWDe reduces to a deficit defined by potential evapotranspiration relative to modelled shallow-water availability. CWDe therefore cannot be interpreted as a counterfactual condition in which bedrock-water access is removed. We have consequently removed the CWDe-based counterfactual analysis, the comparison between CWD- and CWDe-based coefficients, and the associated interpretation of their difference as a quantitative measure of bedrock-water buffering.

In the revised analysis, meteorological drought is characterised using SPEI. The underlying monthly climatic water balance is defined as $D_{i,t} = P_{i,t} - PET_{i,t}$, which is accumulated over the selected timescale and converted to SPEI. SPEI is then used in the vegetation responsiveness model (Eq. 3). S_{deep} is analysed separately as a model-derived water-balance residual, and its statistical association with vegetation responsiveness is evaluated independently of the SPEI calculation. The revised analysis is presented in Figs. 3–6, with indicator-specific occurrence and conditional-magnitude results in Tables S9–S10 and water-balance sensitivity in Table S11.

Representative revised text: Lines 208 to 219: ‘Meteorological drought was characterised using the standardised precipitation evapotranspiration index (SPEI). For pixel i and month t , the monthly climatic water balance was calculated as

$$D_{i,t} = P_{i,t} - PET_{i,t} \quad (2)$$

The climatic water balance was accumulated over 1, 3 and 6 months and converted to SPEI using the log-logistic distribution in the SPEI framework (Vicente-Serrano et al., 2010; Pang et al., 2025; Wang et al., 2026). Calculations used the 2000–2023 climate record, with at least 240 valid monthly observations required per pixel. SPEI-3 was the primary index; SPEI-1 and SPEI-6 assessed accumulation-timescale sensitivity. Positive and negative SPEI values represent wetter- and drier-than-normal conditions, respectively. The primary regression therefore describes responsiveness along a dry-to-wet hydroclimatic gradient. A separate dry-only analysis was restricted to $SPEI < 0$.

Representative revised text: Lines 238 to 248: ‘A continuous monthly water balance was used to estimate the portion of ET not accounted for by precipitation and soil available water. The accounting scheme first uses monthly precipitation to offset ET, then draws any remaining deficit from simulated shallow-soil storage; any unresolved deficit is assigned to S_{deep} . Similar deficit-based approaches have been used to infer water supply beyond the represented soil store when shallow storage is insufficient to meet ET demand (Dralle et al., 2021; McCormick et al., 2021; Ehlert et al., 2024; Qiu et al., 2026). The non-negative residual, S_{deep} , is termed inferred bedrock-water subsidy. An important limitation is that positive S_{deep} is generated only when precipitation and simulated shallow-soil storage are insufficient to meet the represented ET demand. However, plants may access below-soil water even when shallow-soil water remains available, particularly in ecosystems with shallow soils or deep-rooted vegetation (Ding et al., 2021).’

References:

Dralle, D. N., Hahm, W. J., Chadwick, K. D., McCormick, E., and Rempe, D. M. (2021). Technical note: Accounting for snow in the estimation of root zone water storage capacity from precipitation and evapotranspiration fluxes. *Hydrology and Earth System Sciences*, 25, 2861–2867. <https://doi.org/10.5194/hess-25-2861-2021>.

McCormick, E. L., Dralle, D. N., Hahm, W. J., Tune, A. K., Schmidt, L. M., Chadwick, K. D., and Rempe, D. M. (2021). Widespread woody plant use of water stored in bedrock. *Nature*, 597, 225–229. <https://doi.org/10.1038/s41586-021-03761-3>.

Ehlert, R. S., Hahm, W. J., Dralle, D. N., Rempe, D. M., and Allen, D. M. (2024). Bedrock controls on water and energy partitioning. *Water Resources Research*, 60, e2023WR036719. <https://doi.org/10.1029/2023WR036719>.

Qiu, Y., Zhang, F., Gao, L., He, Z., Xiong, H., Peng, L., Wang, Z., Cui, H., Su, C., Zhang, D., Zhou, S., Ma, C., and Zhou, A. (2026). Uncovering the dynamic role of bedrock-stored water in

ecosystem evapotranspiration. Journal of Hydrology, 668, 134987.
<https://doi.org/10.1016/j.jhydrol.2026.134987>.

C2: Second, the vegetation response variable in the two regression models remains unchanged. Therefore, the dependent variable still represents the actual observed vegetation response, including any effect of bedrock-water access. I do not understand how replacing CWD with CWDe while keeping the same observed vegetation response identifies how vegetation itself would have responded in the absence of bedrock water. The change in the regression slopes demonstrates that the same vegetation observations relate differently to two definitions of water deficit, but that does not by itself identify the causal buffering effect of bedrock water. Yet, the authors use this comparison to infer buffering (L397–404), amplification and structural overshoot” (L406–410, L418–430), and even a shift from energy to water limitation (L414–417).

Response: We agree with the reviewer that the former CWD–CWDe comparison cannot identify how vegetation would have responded in the absence of bedrock-water access because the same observed vegetation response was used in both regressions. The resulting slope difference therefore cannot be interpreted as a counterfactual or causal estimate of bedrock-water buffering. The associated interpretations of buffering, amplification, structural overshoot and a shift from energy to water limitation therefore exceeded what the analysis could support. We have accordingly removed these interpretations from the revised manuscript. In the revised analysis, vegetation responsiveness is estimated from the observed vegetation–SPEI relationship, and its association with inferred S_{deep} is evaluated separately through occurrence and conditional-magnitude analyses. These analyses estimate statistical associations and do not represent hypothetical vegetation responses in the absence of bedrock-water access. The summer HG2 occurrence association is therefore described only as consistent with a buffering interpretation. The lack of a consistent conditional-magnitude association provides no support for a magnitude-dependent buffering relationship. The occurrence and conditional-magnitude associations are shown in Figs. 5 and 6; corresponding indicator-specific results are reported in

Tables S9–S10, with parameter and environmental robustness evaluated in Tables S11–S12.

Representative revised text: Lines 312 to 333: ‘We next related $\beta_{i,s}$ to the occurrence and conditional magnitude of the inferred bedrock-water subsidy. Because positive S_{deep} occurred in 1.4% or less of forest pixels in autumn, the primary residual models were restricted to spring and summer, with autumn treated as exploratory. For the occurrence component, we fitted the following equation:

$$\beta_{i,s} = \alpha_{G_{i,s}}^{(0)} + \theta_{G_{i,s}} O_{i,s} + \mathbf{C}_{i,s}^T \boldsymbol{\gamma} + \varepsilon_{i,s} \quad (11)$$

where $\theta_{G_{i,s}}$ denotes the occurrence association for the hydro-lithological group of pixel i and season s . The covariate vector $\mathbf{C}_{i,s}$ contains long-term seasonal precipitation, temperature and elevation, together with forest type as a categorical covariate. Within each hydro-lithological group and season, the occurrence association was defined as the adjusted difference between pixels with positive and zero residuals

$$\Delta_{\text{occ},g,s} = \hat{\beta}_{g,s}^{(O=1)} - \hat{\beta}_{g,s}^{(O=0)} = \hat{\theta}_{g,s} \quad (12)$$

where g denotes a specific hydro-lithological group. Conditional magnitude was evaluated only for pixels with $S_{\text{deep}} > 0$:

$$\beta_{i,s} = \alpha_{G_{i,s}}^{(M)} + \kappa_{G_{i,s}} M_{i,s} + \mathbf{C}_{i,s}^T \boldsymbol{\gamma} + \varepsilon_{i,s} \quad (13)$$

where $\kappa_{G_{i,s}}$ denotes the conditional-magnitude slope corresponding to the hydro-lithological group of pixel i and season s . For a specific hydro-lithological group g and season s , the corresponding conditional-magnitude slope is denoted $\kappa_{g,s}$. This coefficient represents the change in β_{SPEI} per one-unit increase in $M_{i,s}$, corresponding to a one-standard-deviation increase in $\ln(1 + S_{\text{deep},i,s})$ among positive pixels within that season. For interpretation, fitted relationships were displayed against residual magnitude on its original scale. A reduction in the absolute magnitude of β_{SPEI} was interpreted as weaker vegetation–drought coupling. These associations were not interpreted as causal effects of bedrock-water uptake.’

Representative revised text: Lines 489 to 498: ‘The occurrence association with GPP showed a

clear seasonal contrast (Fig. 6). The occurrence contrast, defined as the adjusted difference in GPP–SPEI responsiveness between pixels with positive S_{deep} and zero S_{deep} (Eq. 12), was negative in summer across all three hydro-lithological groups. The contrast was -0.0347 in HG2 (95% spatial-block-bootstrap CI, -0.0653 to -0.0026), compared with -0.0248 (-0.0567 to 0.0087) in HG1 and -0.0057 (-0.0307 to 0.0193) in HG3. Thus, in HG2, pixels with positive S_{deep} had an adjusted GPP–SPEI coefficient 0.0347 lower than pixels with zero S_{deep} . Because summer GPP–SPEI responsiveness was positive, this shift towards zero indicates weaker dependence of GPP on meteorological wet–dry anomalies where positive S_{deep} occurred, consistent with a buffering interpretation.’

Representative revised text: Lines 517 to 527: ‘The conditional-magnitude analysis did not reproduce the occurrence association. Among pixels with positive S_{deep} , summer conditional-magnitude slopes for GPP responsiveness were 0.0070 in HG1, -0.0089 in HG2 and 0.0221 in HG3, with only the HG3 confidence interval excluding zero. In HG2, the negative slope was small and uncertain, indicating that the weaker GPP–SPEI coupling associated with S_{deep} occurrence did not strengthen systematically as S_{deep} increased. Thus, the results support an occurrence-based association in HG2, but not a magnitude-dependent buffering relationship. Spring conditional-magnitude slopes differed among groups and showed no consistent pattern. Across indicators, summer S_{deep} occurrence in HG2 was associated with GPP responsiveness closer to zero but with NDVI and EVI responsiveness farther from zero. Full occurrence and conditional-magnitude results for the other indicators and seasons are reported in Tables S8–S10.’

Representative revised text: Lines 589 to 594: ‘Overall, the high summer GPP responsiveness of HG2 was robust to drought definition, forest type, elevation and clustering resolution. The HG2 occurrence association was directionally stable across water-balance parameterisations but not uniformly supported across environmental strata, whereas the conditional-magnitude association was not robust. These results describe regional associations rather than causal effects of

hydro-lithological properties or bedrock-water uptake.'

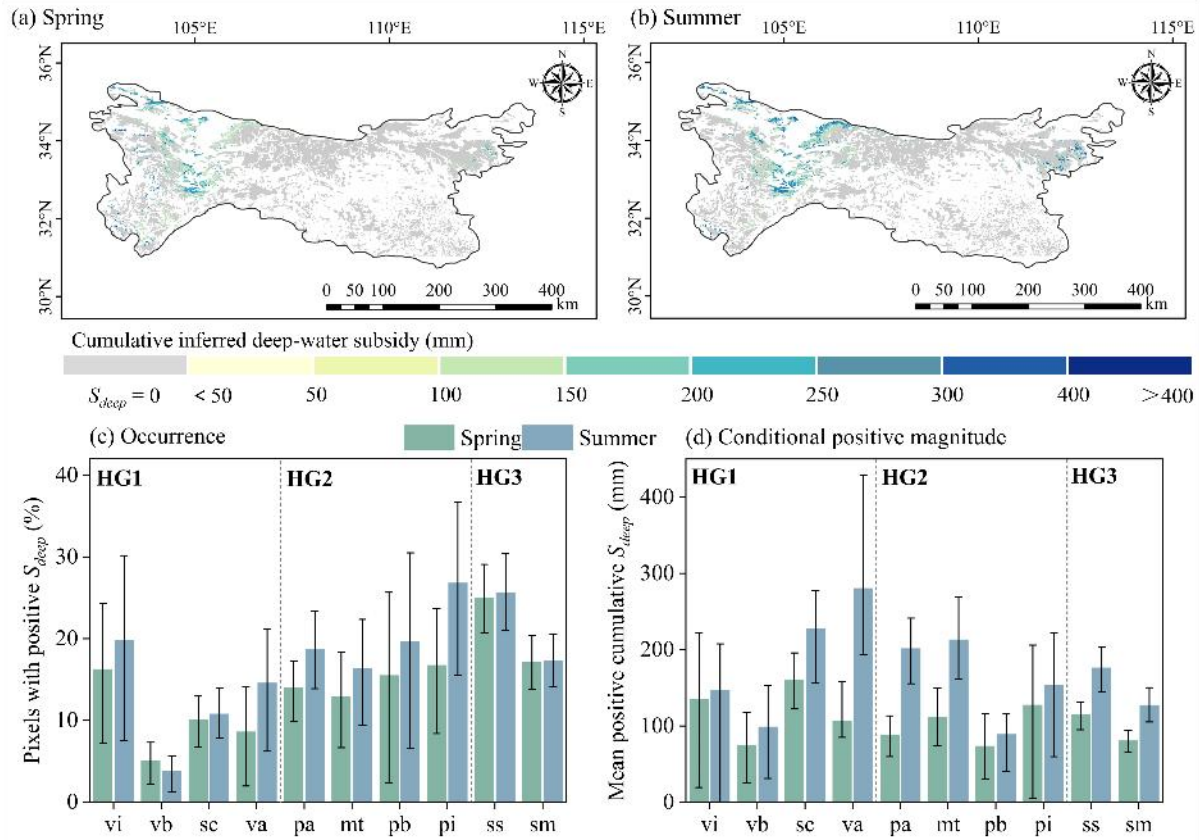


Figure 5. Spatial occurrence and conditional magnitude of the inferred bedrock-water subsidy. Spatial distributions of cumulative inferred bedrock-water subsidy (S_{deep}) are shown for (a) spring and (b) summer over 2000–2023. Grey pixels indicate no positive inferred subsidy, whereas coloured pixels show positive cumulative S_{deep} . (c) Percentage of forest pixels with positive seasonal S_{deep} within individual lithological classes, grouped by hydro-lithological setting. (d) Mean cumulative S_{deep} among positive pixels. Bars distinguish spring and summer conditions, and error bars show spatial-block-bootstrap 95% CI. Occurrence represents the spatial presence of positive inferred subsidy during the study period.

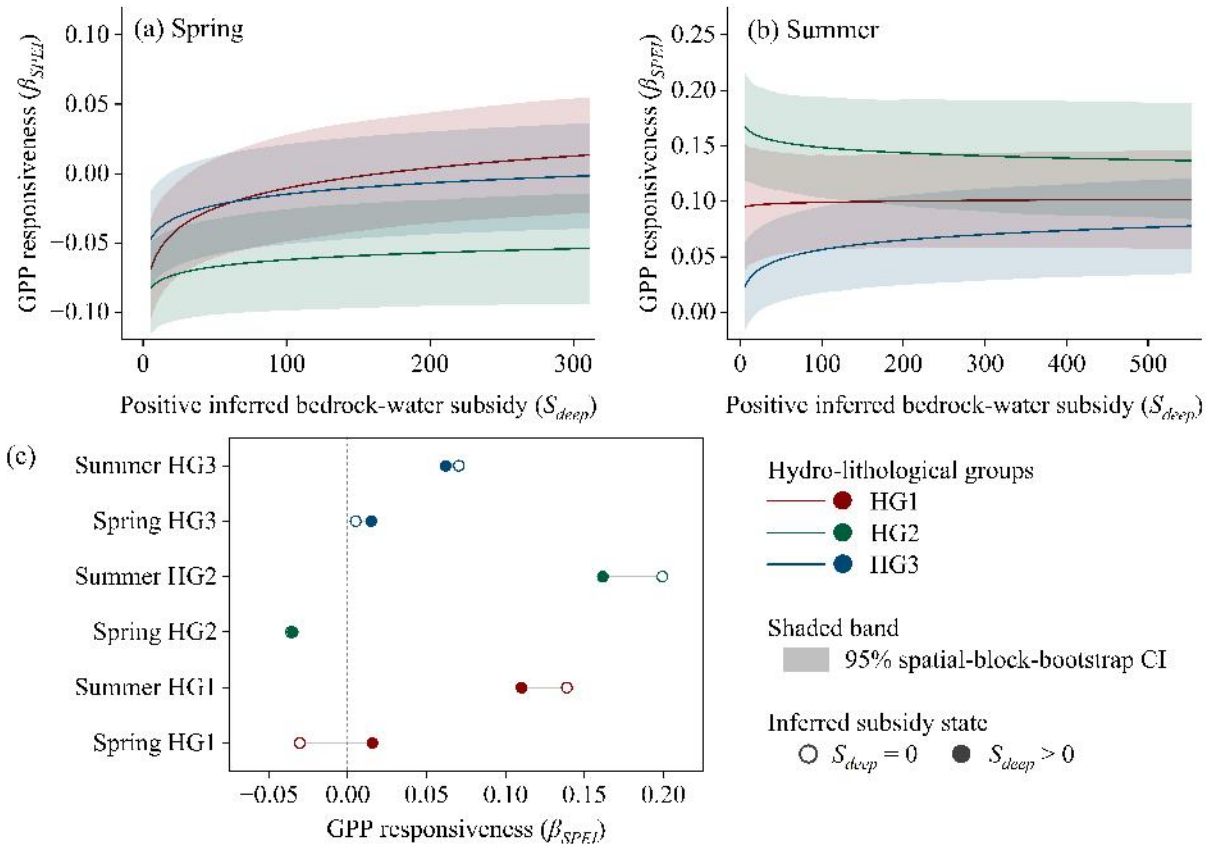


Figure 6. Associations of inferred bedrock-water subsidy occurrence and conditional magnitude with GPP responsiveness. Conditional relationships between positive S_{deep} ($S_{deep} > 0$) and GPP responsiveness to SPEI-3 (β_{SPEI}) are shown for (a) spring and (b) summer. Curves represent hydro-lithological-group-specific relationships estimated from the conditional-magnitude model and fitted only among pixels with positive seasonal S_{deep} . Shaded bands indicate spatial-block-bootstrap 95% confidence intervals. (c) Adjusted GPP responsiveness for pixels with zero and positive seasonal S_{deep} in spring and summer. Open and filled symbols indicate $S_{deep} = 0$ and $S_{deep} > 0$, respectively. Differences between these states represent the occurrence association. For positive β_{SPEI} values, negative shifts towards zero under positive S_{deep} are interpreted as buffering-consistent associations.

200 **Table S9.** Occurrence associations of inferred bedrock-water subsidy with NDVI, EVI and SIF responsiveness.

Indicator	Season	Δ_{occ} (95% CI)		
		HG1	HG2	HG3
NDVI	Spring	-0.015 (-0.027, -0.003)	-0.019 (-0.028, -0.011)	-0.016 (-0.024, -0.008)
EVI		-0.036 (-0.046, -0.025)	-0.017 (-0.024, -0.011)	-0.022 (-0.029, -0.015)
SIF		-0.008 (-0.016, -0.001)	-0.010 (-0.017, -0.001)	-0.017 (-0.022, -0.012)
NDVI	Summer	0.011 (-0.022, 0.041)	-0.042 (-0.072, -0.010)	0.018 (-0.004, 0.040)
EVI		-0.008 (-0.033, 0.015)	-0.072 (-0.094, -0.049)	-0.016 (-0.033, 0.003)
SIF		-0.001 (-0.011, 0.010)	-0.028 (-0.039, -0.018)	-0.005 (-0.010, 0.000)

201 Note: GPP occurrence results are reported in the main text. Δ_{occ} is the adjusted difference $\beta_{SPEI}(S_{deep} > 0) - \beta_{SPEI}(S_{deep} = 0)$. Negative values indicate
 202 lower β_{SPEI} in positive-residual pixels. Confidence intervals are 95% percentile intervals from 1,000 spatial-block-bootstrap replicates. Bold values
 203 indicate intervals that exclude zero before rounding.

204 **Table S10.** Conditional-magnitude associations of inferred bedrock-water subsidy with NDVI, EVI and SIF responsiveness.

Indicator	Season	Conditional-magnitude slope (95% CI)		
		HG1	HG2	HG3
NDVI	Spring	0.0108 (0.0043, 0.0171)	−0.0016 (−0.0083, 0.0065)	0.0075 (0.0022, 0.0122)
EVI		−0.0079 (−0.0159, −0.0008)	−0.0007 (−0.0058, 0.0039)	−0.0010 (−0.0053, 0.0029)
SIF		−0.0022 (−0.0055, 0.0014)	−0.0129 (−0.0159, −0.0086)	0.0018 (−0.0013, 0.0048)
NDVI	Summer	0.0218 (0.0036, 0.0357)	0.0320 (0.0163, 0.0443)	0.0036 (−0.0074, 0.0137)
EVI		0.0143 (−0.0002, 0.0270)	0.0075 (−0.0053, 0.0205)	−0.0023 (−0.0110, 0.0061)
SIF		−0.0059 (−0.0106, −0.0010)	−0.0010 (−0.0057, 0.0036)	−0.0061 (−0.0086, −0.0035)

205 *Note: GPP conditional-magnitude results are reported in the main text. Slopes are estimated among pixels with $S_{deep} > 0$ and represent the change in*
 206 *β_{SPEI} per one-standard-deviation increase in $\ln(1 + S_{deep})$, standardised within each season using common scaling across hydro-lithological groups.*
 207 *Confidence intervals are 95% percentile intervals from 1,000 spatial-block-bootstrap replicates. Bold values indicate intervals that exclude zero. These*
 208 *slopes are statistical associations, not dose-response estimates of bedrock-water use.*

C3: In addition, the methods state that all response and predictor variables are standardized to zero mean and unit variance after differencing (L203–207). If CWD and CWDe are therefore standardized separately in their respective models, their variances and covariance structures with the other predictors will differ, so a quantitative comparison between the resulting standardized coefficients requires further justification.

Response: Because CWD and CWDe are standardised separately in the original analysis, a one-standard-deviation change in each predictor does not represent the same raw-scale change, and their covariance structures with the other model terms also differ. The resulting standardised coefficients therefore do not provide a valid basis for the quantitative comparison used in the original analysis. Thus, the entire CWD–CWDe comparison and all interpretations based on the coefficient difference have been removed from the revised manuscript, as described in our responses to C1 and C2. In the revised analysis, vegetation responsiveness is estimated using a single drought metric, SPEI. For the conditional-magnitude analysis of S_{deep} , positive values are log-transformed and standardised within each season using a common mean and standard deviation across all hydro-lithological groups, so the group-specific slopes within a season refer to the same standardised predictor scale. The revised analysis therefore no longer relies on quantitative comparisons between separately standardised alternative drought metrics. The common scaling used for the conditional-magnitude analysis is documented in Appendix C and Table S10.

Representative revised text: Lines 277 to 286: ‘Conditional magnitude was evaluated only for pixels with $S_{\text{deep}} > 0$, separating residual magnitude from its spatial prevalence. For modelling,

positive seasonal values were log-transformed and standardised within each season using a common mean and standard deviation across all hydro-lithological groups

$$M_{i,s} = \frac{\ln(1+S_{deep,i,s})-\mu_s}{\sigma_s} \quad (8)$$

where μ_s and σ_s are the season-specific mean and standard deviation of $\ln(1 + S_{deep})$, respectively, across all positive pixels and all hydro-lithological groups. These scaling parameters were fixed at their original-sample values during bootstrap resampling. M was used in the conditional-magnitude models, while untransformed positive values, expressed in millimetres, were used for descriptive means, medians and interquartile ranges.'

Representative revised text: Lines 328 to 330: *'This coefficient represents the change in β_{SPEI} per one-unit increase in $M_{i,s}$, corresponding to a one-standard-deviation increase in $\ln(1 + S_{deep,i,s})$ among positive pixels within that season.'*

C4: Independently of these issues, I also have difficulty with the interpretation of β_1 as drought sensitivity. The methods explicitly state that negative β_1 indicates declining vegetation activity with increasing CWD, whereas positive β_1 indicates increasing vegetation activity (L210–215). The manuscript further suggests that the frequently positive functional response may occur because higher CWD coincides with clearer skies and greater incoming radiation (L283–286). This would mean that a larger positive β_1 cannot straightforwardly be interpreted as greater drought vulnerability, as it may partly reflect covariation between CWD and energy availability. This makes statements such as “greenness-based metrics may overlook substantial drought impacts” in the abstract (L23–25) difficult to support from the coefficient magnitude alone. The authors should therefore explicitly separate energy- and moisture-driven covariation, for example through models incorporating incoming radiation and/or VPD, or through an alternative

sensitivity analysis. The manuscript also needs to distinguish throughout between "responsiveness to CWD" and adverse "drought vulnerability."

Response: We agree that the original regression coefficient cannot be interpreted as a direct measure of drought vulnerability because its sign and magnitude may reflect covariation between hydroclimatic conditions and other atmospheric controls. We have therefore removed the statement that greenness-based metrics ‘may overlook substantial drought impacts’ and the related interpretation based on coefficient magnitude alone. Because incoming radiation and VPD are not available for a direct energy–moisture separation, we have instead add sensitivity analyses to assess whether the principal hydro-lithological group pattern is robust to drought timescale and the exclusion of relatively wet observations. Vegetation responsiveness was re-estimated using SPEI-1, SPEI-3, SPEI-6 and, separately, using only meteorologically dry observations ($\text{SPEI} < 0$). The principal summer GPP pattern persists across these analyses, with HG2 remaining the most responsive group, although coefficient magnitude and, for some indicators, sign vary among specifications. We explicitly acknowledge that neither the SPEI-based analysis nor these sensitivity tests isolate moisture effects from covarying radiation, VPD or temperature. Accordingly, the coefficient is now denoted by β_{SPEI} and interpreted throughout as statistical vegetation responsiveness to meteorological moisture anomalies. The replacement of CWD with SPEI is described in our response to C1. The drought-timescale and dry-only sensitivity results are reported in Tables S6–S7 and summarised in Appendix B.

Representative revised text: Lines 232 to 236: ‘The sign of β_{SPEI} indicates the direction of vegetation–SPEI coupling: Positive values correspond to higher vegetation activity under wetter anomalies, whereas negative values correspond to higher activity under drier anomalies. Among

274 *positive coefficients, larger values indicate stronger positive vegetation–SPEI coupling. We refer*
275 *to this signed coefficient as vegetation responsiveness.’*

276 ***Representative revised text:*** *Lines 597 to 599: ‘SPEI-based regressions do not isolate moisture*
277 *effects from covarying meteorological variables such as radiation, vapour pressure deficit (VPD)*
278 *and temperature.’*

279 **Table S6.** Sensitivity of seasonal vegetation responsiveness to SPEI accumulation timescale.

<i>Indicator</i>	<i>Season</i>	<i>HG1</i>	<i>HG2</i>	<i>HG3</i>
<i>NDVI</i>	<i>Spring</i>	<i>−0.058 / −0.094 / −0.071</i>	<i>−0.056 / −0.091 / −0.072</i>	<i>−0.051 / −0.091 / −0.068</i>
	<i>Summer</i>	<i>−0.084 / −0.046 / −0.059</i>	<i>−0.090 / −0.026 / −0.051</i>	<i>−0.059 / −0.014 / −0.024</i>
	<i>Autumn</i>	<i>−0.039 / 0.017 / 0.021</i>	<i>−0.043 / −0.002 / 0.002</i>	<i>−0.038 / 0.034 / 0.026</i>
<i>EVI</i>	<i>Spring</i>	<i>−0.020 / −0.034 / −0.034</i>	<i>−0.016 / −0.036 / −0.042</i>	<i>−0.010 / −0.021 / −0.014</i>
	<i>Summer</i>	<i>−0.106 / −0.081 / −0.051</i>	<i>−0.120 / −0.068 / −0.048</i>	<i>−0.091 / −0.076 / −0.050</i>
	<i>Autumn</i>	<i>−0.029 / −0.007 / 0.048</i>	<i>−0.017 / 0.003 / 0.066</i>	<i>−0.040 / 0.002 / 0.030</i>
<i>GPP</i>	<i>Spring</i>	<i>−0.031 / −0.024 / −0.008</i>	<i>−0.021 / −0.018 / −0.008</i>	<i>−0.018 / −0.003 / 0.005</i>
	<i>Summer</i>	<i>0.045 / 0.137 / 0.104</i>	<i>0.147 / 0.207 / 0.157</i>	<i>−0.049 / 0.061 / 0.031</i>
	<i>Autumn</i>	<i>−0.066 / −0.011 / 0.006</i>	<i>−0.071 / −0.020 / −0.008</i>	<i>−0.037 / 0.013 / 0.019</i>
<i>SIF</i>	<i>Spring</i>	<i>−0.017 / −0.012 / −0.017</i>	<i>0.000 / 0.005 / −0.010</i>	<i>−0.025 / −0.022 / −0.022</i>
	<i>Summer</i>	<i>−0.070 / 0.011 / −0.030</i>	<i>−0.071 / 0.016 / −0.023</i>	<i>−0.049 / 0.012 / −0.015</i>
	<i>Autumn</i>	<i>−0.019 / 0.006 / 0.016</i>	<i>−0.041 / −0.024 / −0.015</i>	<i>0.003 / 0.015 / 0.008</i>

280 *Note: Within each hydro-lithological group cell, values are adjusted responsiveness estimates (β_{SPEI}) for SPEI-1/SPEI-3/SPEI-6, respectively. The SPEI*
281 *accumulation timescale was changed at the pixel-level responsiveness stage, while the remaining model specification was held constant.*

282 **Table S7.** Full-sample versus dry-only summer vegetation responsiveness to SPEI-3.

Indicator	Full-sample β_{SPEI} (95% CI)			Dry-only β_{SPEI} (95% CI)			Pixel r
	HG1	HG2	HG3	HG1	HG2	HG3	
NDVI	-0.046 (-0.062, -0.031)	-0.026 (-0.043, -0.010)	-0.014 (-0.027, -0.003)	-0.012 (-0.022, -0.002)	-0.014 (-0.025, -0.004)	0.015 (0.007, 0.022)	0.511
EVI	-0.081 (-0.095, -0.067)	-0.068 (-0.081, -0.054)	-0.076 (-0.087, -0.064)	-0.032 (-0.041, -0.021)	-0.051 (-0.064, -0.041)	-0.015 (-0.024, -0.006)	0.434
GPP	0.137 (0.117, 0.156)	0.207 (0.190, 0.222)	0.061 (0.041, 0.079)	0.135 (0.124, 0.147)	0.167 (0.156, 0.178)	0.125 (0.116, 0.133)	0.730
SIF	0.011 (0.005, 0.018)	0.016 (0.008, 0.025)	0.012 (0.009, 0.016)	-0.040 (-0.054, -0.028)	-0.103 (-0.117, -0.084)	0.036 (0.024, 0.045)	-0.140

283 *Note: Values are adjusted summer responsiveness estimates (β_{SPEI}) with percentile 95% confidence intervals from 1,000 spatial-block-bootstrap*
284 *replicates. The dry-only analysis re-estimated the pixel-level coefficients using only observations with SPEI < 0 before refitting the second-stage*
285 *models. Pixel r is the pixel-level correlation between full-sample and dry-only coefficients for each vegetation indicator. Bold values indicate intervals*
286 *that exclude zero.*

C5: Finally, the key results are presented without uncertainty quantification, e.g. for the estimated contrasts in β , the marginal effects in Table 1, and especially the reported sensitivity changes between the original and counterfactual models. For example, changes in structural sensitivity from 0.026 to 0.022 and from 0.016 to 0.012 are interpreted as evidence of bedrock-water buffering (L397–401), while elsewhere changes are expressed as relative differences ranging from 0.7% to 24.2% (L418–424). Confidence intervals, or preferably resampling-based uncertainty estimates, are needed to establish whether these differences are distinguishable from estimation uncertainty. Given how small some of the absolute changes in effect size are, I would expect at least some uncertainty intervals to overlap. Any uncertainty analysis should also account for spatial autocorrelation among grid cells rather than treating spatial observations as independent.

Response: We agree that uncertainty is not adequately quantified for several key results in the original manuscript. We have therefore added percentile 95% confidence intervals based on 1,000 spatial-block-bootstrap replicates for the retained principal regression estimates, contrasts and associations. Hydro-lithological group differences in vegetation responsiveness are evaluated directly from the bootstrap distribution of the pairwise contrast, providing a formal assessment of between-group differences. Uncertainty is also quantified for the climatic-background associations and for the occurrence and conditional-magnitude components of the S_{deep} analysis. The bootstrap resamples contiguous 20×20 -cell spatial blocks instead of individual pixels to account for spatial dependence among grid cells. As explained in our responses to C1–C3, the CWD–CWDe coefficient comparisons have been removed because they are no longer considered quantitatively interpretable. The former marginal-effect presentation in Table 1 has also been removed, and the climatic-background results are now presented as group-specific associations with spatial-block-bootstrap uncertainty in Fig. 4. Principal adjusted estimates and their confidence intervals are shown in Fig. 3, direct hydro-lithological group contrasts are presented in Fig. S3, climatic-background uncertainty is given in Fig. 4, and S_{deep} uncertainty is displayed in Fig. 6 and Tables S9–S12.

Representative revised text: Lines 335 to 340: ‘Spatial dependence was addressed using a block bootstrap. The 0.01° analysis grid was partitioned into contiguous 20×20 -cell blocks (approximately 0.2° per side) that were then sampled with replacement. All observations and seasonal records within each sampled block were retained together. Percentile 95% confidence intervals were obtained from the 2.5th and 97.5th percentiles of the bootstrap distributions. Differences among hydro-lithological groups were evaluated directly from bootstrap distributions of pairwise contrasts.’

Representative revised text: Lines 341 to 342: ‘All principal group comparisons, climatic-background analyses, two-part residual analyses and robustness analyses used 1,000 spatial-block-bootstrap replicates.’

Representative revised text: Lines 375 to 382: ‘Hydro-lithological differences in vegetation responsiveness to SPEI (β_{SPEI}) were most pronounced for summer GPP (Figs. 3 and S2). After adjustment for elevation and forest type, summer GPP responsiveness to SPEI-3 was 0.137 (95% spatial-block-bootstrap CI, 0.117 to 0.156) in HG1, 0.207 (0.190 to 0.222) in HG2 and 0.061 (0.041 to 0.079) in HG3. All three confidence intervals excluded zero, indicating positive summer GPP–SPEI coupling across the hydro-lithological groups, with the highest adjusted estimate in HG2 and the lowest in HG3. Direct hydro-lithological group contrasts for all indicators and seasons are shown in Fig. S3.’

Supplementary Information (Fig. S3): ‘Figure S3. Direct pairwise hydro-lithological group contrasts in adjusted seasonal vegetation responsiveness to SPEI-3. Panels show (a) NDVI, (b) EVI, (c) GPP and (d) SIF for spring, summer and autumn. Each contrast is calculated as the first listed hydro-lithological group minus the second within the same model. Points show estimated contrasts, and horizontal bars show percentile 95% confidence intervals from the spatial-block bootstrap. Intervals that exclude zero indicate support for a difference between the corresponding hydro-lithological groups under the specified model.’

Figure 4 caption: ‘Black dots indicate estimates whose spatial-block-bootstrap 95% confidence

intervals exclude zero. Cells without dots have confidence intervals that include zero.'

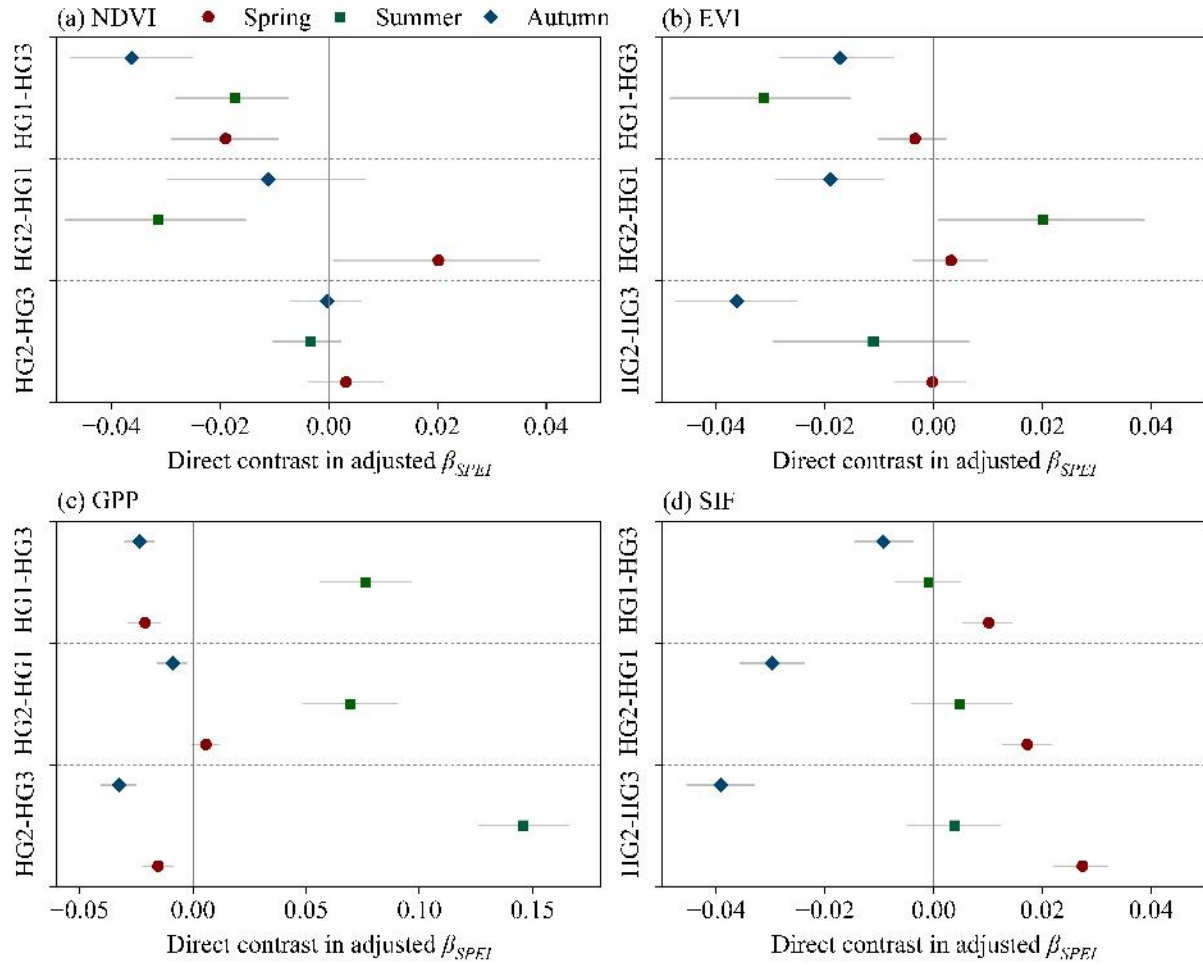


Figure S3. Direct pairwise hydro-lithological group contrasts in adjusted seasonal vegetation responsiveness to SPEI-3. Panels show (a) NDVI, (b) EVI, (c) GPP and (d) SIF for spring, summer and autumn. Each contrast is calculated as the first listed hydro-lithological group minus the second within the same model. Points show estimated contrasts, and horizontal bars show percentile 95% confidence intervals from the spatial-block bootstrap. Intervals that exclude zero indicate support for a difference between the corresponding hydro-lithological groups under the specified model.

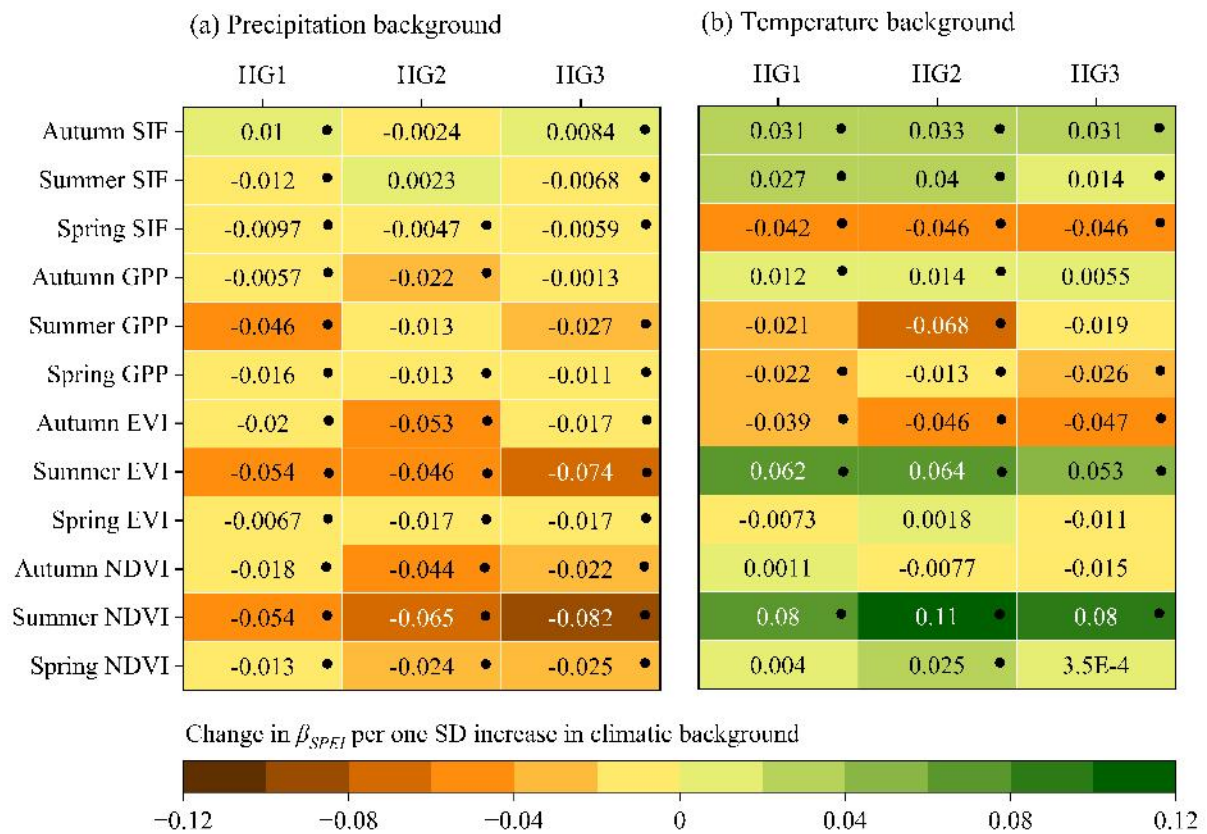


Figure 4. Climatic-background associations with vegetation responsiveness across hydro-lithological groups. Heatmaps show group-specific associations between long-term climatic background and seasonal vegetation responsiveness to SPEI-3 (β_{SPEI}) for (a) precipitation and (b) temperature. Each cell gives the estimated change in β_{SPEI} per one-standard-deviation increase in the corresponding climatic-background variable after mutual adjustment for precipitation and temperature and adjustment for elevation and forest type. Positive and negative values indicate increases and decreases in the signed β_{SPEI} coefficient, respectively. Black dots indicate estimates whose spatial-block-bootstrap 95% confidence intervals exclude zero. Cells without dots have confidence intervals that include zero.

Concluding general comment

Overall, I think the manuscript addresses a worthwhile question and contains potentially useful analyses, but the central mechanistic and causal conclusions currently go beyond what the statistical comparison appears to identify. In particular, the authors should reconsider the interpretation of CWDe as a counterfactual without bedrock-water access, distinguish statistical responsiveness to CWD from adverse drought vulnerability, and provide uncertainty estimates for the reported coefficient differences and marginal effects. Addressing these points would be required to connect between the statistical results and the manuscript's ecological conclusions.

Response: We thank the reviewer for this constructive summary. We agree that the original manuscript drew stronger mechanistic and causal interpretations from the statistical results than the analyses can support. In response, we have made three major revisions: (i) removing the CWDe-based counterfactual analysis and its causal buffering interpretation; (ii) reinterpreting the vegetation-response coefficient as statistical responsiveness to SPEI-defined meteorological drought; and (iii) adding spatial-block-bootstrap uncertainty estimates for the retained contrasts and associations. We have also revised the Discussion and Conclusion accordingly to align the ecological interpretation with the statistical evidence.