

Author's response to RC1

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

General comment

This manuscript focuses on how bedrock water storage regulates seasonal forest sensitivity to climatic water deficit in the Qinling Mountains. The topic has certain scientific significance and is relevant to ecohydrology and critical-zone hydrology. The authors combine multiple remote-sensing vegetation indicators, meteorological data, hydro-lithological classification, ridge regression, and a water-balance framework. However, the manuscript still has several important problems, including insufficient validation of bedrock water estimation, some overinterpretation of statistical results, and limited readability of several figures. Therefore, I recommend major revision.

Response:

We sincerely thank the reviewer for the careful evaluation of our manuscript. In response to the constructive comments and suggestions, we have substantially revised the manuscript point by point. In particular, we have made three major revisions:

(1) We have improved the analytical framework for quantifying vegetation responsiveness by replacing the original ET-based drought metric with SPEI, analysing NDVI, EVI, GPP and SIF separately, and clarifying the use of fixed seasonal windows across the elevation gradient. Please see our replies to C1, C2, C4 and C5.

(2) We have strengthened the hydro-lithological and bedrock-water analyses by replacing the original threshold-based regionalisation with a data-driven hydro-lithological classification, clarifying the definition and limitations of the inferred S_{deep} , separating its occurrence from conditional magnitude, and adding sensitivity and robustness analyses. Please see our replies to C6, C7 and C8.

(3) We have refined the mechanistic interpretation to better align with the evidence and improved

the presentation of the results, particularly by clarifying the climatic-background associations and enhancing figure readability. Please see our replies to C9 and C10.

These revisions address your concerns regarding the analytical framework, the reliability and interpretation of the inferred bedrock-water metric, as well as the scope and presentation of the conclusions.

Point-by-point response

C1: Introduction: The introduction discusses several topics at the same time, including lithology, seasonal drought sensitivity, differences between structural and functional vegetation indicators, and bedrock water use. However, the core scientific question is still not sufficiently concise.

Response: We have reorganised the original Introduction around the central question of seasonal forest responsiveness to hydroclimatic variability across hydro-lithological settings in the Qinling Mountains. The revised Introduction presents seasonal and indicator-specific vegetation responses as the primary focus of the study, with analyses of climatic background and inferred bedrock-water subsidy serving as complementary explanatory components. In line with this framework, the final paragraph of the Introduction now presents the study objectives more concisely. This revised structure is reflected in the Results sequence from indicator-specific patterns across hydro-lithological settings (Figs. 3 and S3), through climatic-background associations (Fig. 4), to the secondary inferred-subsidy analysis (Figs. 5–6), with robustness checks summarised in Appendix B (Tables S5–S7; Fig. S4).

Revised manuscript text: Lines 93 to 112: *‘Here, we investigate how hydro-lithological settings structure seasonal vegetation responsiveness to hydroclimatic variability across the Qinling Mountains, a monsoon-dominated mountain system with pronounced geological, climatic and elevational heterogeneity. We address three linked questions: whether vegetation responsiveness to SPEI differs among hydro-lithological settings characterised by contrasting combinations of shallow-soil storage and mapped regolith hydraulic properties, whether this responsiveness varies*

with long-term precipitation and temperature backgrounds, and whether it is associated with the occurrence and conditional magnitude of a model-derived inferred bedrock-water subsidy that may indicate bedrock-water supply. To address these questions, we quantify the pixel-level seasonal responsiveness of NDVI, EVI, GPP and SIF to SPEI, compare it among hydro-lithological groups after accounting for elevation and forest type, examine its associations with the long-term climatic background, and evaluate its associations with the inferred bedrock-water subsidy. Together, these analyses distinguish broad hydro-lithological patterning in vegetation responsiveness from the more conditional association with possible bedrock-water supply.”

C2: Lines 105–110 and Lines 219–220: The Qinling Mountains are highly heterogeneous in geology and topography, with elevation ranging from low foothills to high mountains above 5200 m. However, the statistical analysis uniformly defines the growing season as March to November and divides it into spring, summer, and autumn. It is unclear whether this fixed seasonal division is appropriate for such a mountainous region.

Response: We agree that fixed calendar seasons cannot be assumed to represent identical phenological stages across the elevation gradient of the Qinling Mountains. We have therefore clarified that we use March–May, June–August, and September–November as common calendar windows for regional comparison and do not imply uniform phenological stages across the study area. To assess whether the principal summer GPP pattern persists across elevation, we have added an elevation-stratified robustness analysis and refitted the summer models within low-, middle- and high-elevation strata. Although summer GPP responsiveness varies with elevation, HG2 shows the highest summer GPP–SPEI coefficient across all three strata. We have accordingly limited our interpretation to the persistence of relative hydro-lithological differences in vegetation responsiveness across elevation strata. Phenological equivalence among sites is not assumed. The elevation-stratified evidence is presented in Fig. S4 and summarised in Appendix B.

Revised manuscript text: Lines 159 to 165: *‘Spring, summer and autumn were defined as March–May, June–August and September–November, respectively. Fixed calendar windows ensured*

consistent regional comparisons but do not imply identical phenological stages across elevations. Elevation-stratified analyses test whether the principal summer pattern persists across topographic settings, without directly isolating phenological effects.'

Lines 348 to 355: 'Elevation robustness was assessed by dividing the retained forest domain into low-, middle- and high-elevation classes using the 33.3rd and 66.7th percentiles of elevation. The principal summer GPP analyses were repeated within each class, with confidence intervals estimated using 1,000 spatial-block-bootstrap replicates (Fig. S4).'

Lines 558 to 561: 'Responsiveness also declined from low to high elevation across all hydro-lithological groups (Fig. S4). HG1 and HG3 became negative at high elevation, whereas HG2 remained weakly positive.'

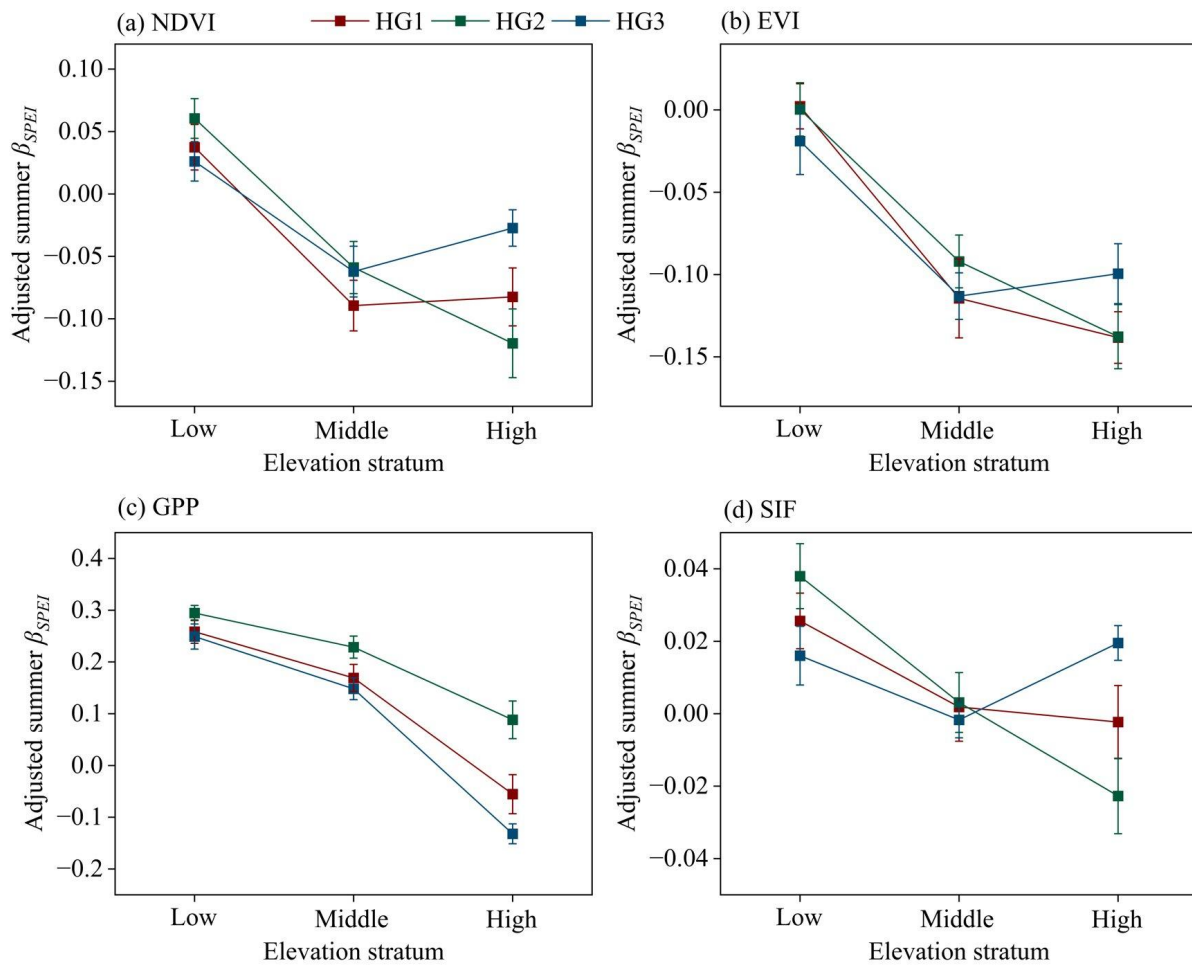


Figure S4. *Elevation-stratified summer vegetation responsiveness to SPEI-3 across hydro-lithological groups. Panels show (a) NDVI, (b) EVI, (c) GPP and (d) SIF for HG1–HG3 across*

low- (66–1,230 m), middle- (1,231–1,916 m) and high- (1,917–4,686 m) elevation strata. The strata correspond to the lower, middle and upper thirds of the retained elevation distribution. Points are adjusted β_{SPEI} estimates from models fitted within each elevation stratum, and error bars show percentile 95% confidence intervals from 1,000 spatial-block-bootstrap replicates.

C3: Line 106: “5,202m” has a formatting error.

Response: Thank you for identifying this formatting error. We have corrected it in the revised manuscript.

C4: Lines 121–130 and Lines 287–291: The manuscript classifies NDVI and EVI as structural indicators, and GPP and SIF as functional indicators. However, the functional indicators are not always consistent with each other. Directly using an ensemble mean may weaken or mask differences among individual indicators.

Response: We agree that combining NDVI and EVI or GPP and SIF into ensemble means may obscure indicator-specific responses, because GPP and SIF do not show fully consistent responses. We have therefore removed the structural and functional ensemble means from the revised analysis. All pixel-level responsiveness estimates, hydro-lithological group comparisons, climatic-background associations, inferred bedrock-water subsidy analyses and robustness tests are now conducted separately for NDVI, EVI, GPP and SIF. The revised results show that the indicators are not interchangeable: The clearest hydro-lithological differentiation occurs for summer GPP, whereas SIF shows weaker differentiation among hydro-lithological groups. We have therefore retained canopy greenness and photosynthetic function as descriptive categories, with each indicator evaluated separately according to its ecological meaning. Indicator-specific spatial patterns and direct hydro-lithological group contrasts are shown in Figs. S2–S3, and the dry-only analysis in Table S7 further demonstrates that the four indicators are not interchangeable.

Revised manuscript text: Lines 136 to 139: *‘NDVI and EVI were treated as canopy-greenness indicators, while GPP and SIF represented distinct aspects of photosynthetic function. Each*

indicator was analysed separately, without using structural or functional ensemble means for inference.'

Lines 395 to 402: 'The differentiation was also indicator-dependent. NDVI and EVI showed consistently negative summer responsiveness to SPEI, with smaller hydro-lithological group differences than those observed for GPP (Figs. 3 and S3). Negative greenness–SPEI coefficients should not be interpreted as evidence that drought improves canopy condition. SIF showed positive summer responsiveness but similarly limited group differentiation.'

C5: Line 135: CWD is defined as $PET - ET$ – Since ET itself is also affected by vegetation activity, using CWD to explain NDVI, EVI, GPP, and SIF may be problematic.

Response: We agree that using $PET - ET$ as the drought predictor raises a methodological concern, because actual ET is itself partly influenced by vegetation activity, which can introduce circularity when estimating vegetation responsiveness using CWD. We have therefore replaced the original CWD framework with the standardised precipitation evapotranspiration index (SPEI), which is calculated from precipitation and potential evapotranspiration. The new drought index does not include actual ET and therefore avoids the direct coupling between the drought metric and concurrent vegetation activity. SPEI has also been used to evaluate vegetation responsiveness to drought across multiple accumulation timescales in recent forest and ecohydrological studies (Vicente-Serrano et al., 2010; Pang et al., 2025; Wang et al., 2026). All pixel-level vegetation responsiveness estimates have been recalculated, and the subsequent hydro-lithological, climatic-background and robustness analyses have been repeated using SPEI. SPEI-3 is used as the primary drought metric, while SPEI-1 and SPEI-6, together with a dry-only analysis restricted to $SPEI < 0$, are included to assess sensitivity to drought timescale and sampling domain. The separate water-balance calculation of inferred S_{deep} uses actual ET, which is not included in the drought predictor. Accordingly, we have interpreted β_{SPEI} as vegetation responsiveness to meteorological moisture anomalies, not as drought vulnerability, resistance or resilience. Sensitivity to SPEI timescale and dry-only sampling is reported in Tables S6–S7 and Appendix B.

Revised manuscript text: Lines 207 to 214: ‘Meteorological drought is 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 is 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 $SPEI < 0$.’

Lines 229 to 231: ‘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 positive coefficients, larger values indicate stronger positive vegetation–SPEI coupling. We refer to this signed coefficient as vegetation responsiveness.’

References:

- Pang, J., Xu, H., Xu, Y., et al. (2025). Flash droughts threaten global managed forests. *Nature Communications*, 16, 11027. <https://doi.org/10.1038/s41467-025-66021-2>
- Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I.: A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index, *J. Climate*, 23, 1696–1718, <https://doi.org/10.1175/2009JCLI2909.1>, 2010.
- Wang, Z., Wu, R., Liu, Y., et al. (2026). Declining Sensitivity and Increasing Resistance Time of Ecosystem Water Use Efficiency to Meteorological Drought. *Hydrology and Earth System Sciences*,

30, 4985–5004. <https://doi.org/10.5194/hess-30-4985-2026>

C6: Line 240: Bedrock water in this study is not directly observed, but inferred from a water-balance equation. The reliability of this calculation remains uncertain because no references or regional-scale/site-scale validation is provided.

Response: We agree that the interpretation of the inferred bedrock-water subsidy requires methodological support and a clearer discussion of its validation limitations. We have therefore added references to previous deficit-based water-balance approaches (Dralle et al., 2021; McCormick et al., 2021; Ehlert et al., 2024; Qiu et al., 2026). These approaches use precipitation, evapotranspiration and soil–water storage to infer water supply beyond the represented soil store when shallow storage is insufficient to meet ET demand. We have also clarified an important structural limitation of the approach: 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 water stored below the soil profile even when shallow-soil water remains available, particularly in ecosystems with shallow soils or deep-rooted vegetation (Ding et al., 2021). Thus, $S_{deep} = 0$ should not be interpreted as indicating no below-soil water contribution, whereas positive S_{deep} does not quantify the total below-soil water contribution to vegetation water use. Independent depth-resolved observations are not available across the study region; therefore, S_{deep} cannot be directly validated as bedrock-water storage or plant uptake. To evaluate sensitivity to the principal water-balance assumptions, we have rerun the complete monthly balance with AWC scaled by 0.8 and 1.2 and with initial storage set to 0.5 or 0.75 AWC. The resulting summer S_{deep} fields are highly consistent with the baseline estimate with spatial correlations ranging from 0.948 to 1.000, and the negative direction of the summer occurrence association in HG2 persists across all tested parameterisations. These sensitivity analyses support robustness to the tested assumptions. Accordingly, the revised manuscript treats S_{deep} as a model-derived residual and explicitly limits its interpretation. The water-balance sensitivity analysis is documented in Appendix D and Table S11, while additional elevation- and forest-type-stratified analyses are reported in Table S12.

Revised manuscript text: Lines 232 to 243: ‘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).’

Lines 281 to 289: ‘Sensitivity analyses varied one water-balance assumption at a time. AWC was scaled to 0.8 or 1.2 of the baseline value, with initial storage adjusted accordingly. Additional scenarios retained the baseline AWC but initialised storage at 0.5 or 0.75 AWC. The complete monthly water balance was recalculated for each scenario before refitting the association models (Table S11).’

Lines 571 to 577: ‘The HG2 occurrence association retained a negative direction across all tested water-balance parameterisations. Summer occurrence contrasts ranged from approximately -0.024 to -0.047 , with 95% confidence intervals excluding zero in four of the five scenarios (Table S11). The $\text{AWC} \times 0.8$ scenario remained negative, but its 95% confidence interval included zero. By contrast, the HG2 conditional-magnitude slope remained weak, and all corresponding confidence intervals included zero.’

Lines 596 to 599: ‘Neither the mapped hydraulic properties nor the inferred bedrock-water subsidy resolves actual water sources, root access or subsurface flow paths. Direct validation requires depth-resolved soil and rock moisture measurements, isotope or sap-flow observations, and information on roots and subsurface structure.’

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>.

Ding, Y., Nie, Y., Chen, H., Wang, K., and Querejeta, J. I. (2021). Water uptake depth is coordinated with leaf water potential, water-use efficiency and drought vulnerability in karst vegetation. New Phytologist, 229, 1339–1353. <https://doi.org/10.1111/nph.16971>.

1 **Table S11.** Sensitivity of summer GPP occurrence and conditional-magnitude associations to alternative water-balance parameterisations.

Scenario	r	Δ_{occ} (95% CI)			Magnitude slope (95% CI)		
		HG1	HG2	HG3	HG1	HG2	HG3
Baseline	1.000	-0.0248 (-0.0567, 0.0087)	-0.0347 (-0.0653, -0.0026)	-0.0057 (-0.0307, 0.0193)	0.0070 (-0.0115, 0.0236)	-0.0089 (-0.0252, 0.0084)	0.0221 (0.0111, 0.0321)
AWC $\times$ 0.8	0.948	0.0023 (-0.0265, 0.0323)	-0.0236 (-0.0519, 0.0020)	-0.0151 (-0.0380, 0.0079)	-0.0050 (-0.0211, 0.0122)	-0.0110 (-0.0281, 0.0054)	0.0292 (0.0181, 0.0404)
AWC $\times$ 1.2	0.968	-0.0337 (-0.0694, 0.0026)	-0.0473 (-0.0834, -0.0112)	-0.0017 (-0.0272, 0.0249)	0.0111 (-0.0079, 0.0258)	-0.0050 (-0.0265, 0.0163)	0.0091 (-0.0010, 0.0197)
Initial storage = 0.5 AWC	0.998	-0.0258 (-0.0567, 0.0092)	-0.0363 (-0.0699, -0.0060)	-0.0098 (-0.0353, 0.0153)	0.0061 (-0.0117, 0.0241)	-0.0112 (-0.0296, 0.0094)	0.0224 (0.0102, 0.0334)
Initial storage = 0.75 AWC	1.000	-0.0248 (-0.0569, 0.0114)	-0.0350 (-0.0660, -0.0047)	-0.0059 (-0.0285, 0.0177)	0.0068 (-0.0099, 0.0243)	-0.0094 (-0.0256, 0.0095)	0.0215 (0.0106, 0.0326)

2 Note. Each scenario changes one water-balance assumption relative to the baseline. r is the spatial correlation between scenario-specific and baseline

3 summer S_{deep} fields. Δ_{occ} compares positive- and zero- S_{deep} states, whereas conditional-magnitude slopes are estimated among positive pixels only.

4 Confidence intervals are percentile 95% intervals from 1,000 spatial-block-bootstrap replicates. Bold values indicate intervals that exclude zero.

C7: Line 245: $S_{\text{bedrock,cum}}$ is described as cumulative plant available water capacity in bedrock or bedrock water storage capacity. However, according to the calculation process, it is closer to the cumulative inferred bedrock water use or deep-water subsidy during 2000–2023. Directly equating it with bedrock water storage capacity may not be accurate.

Response: We agree that the original term “bedrock-water storage capacity” exceeded what could be inferred from the water-balance calculation. As described in our response to C6, the revised manuscript now defines S_{deep} as an inferred, model-derived water-balance residual. We have removed the term ‘bedrock-water storage capacity’ throughout the manuscript. Seasonal S_{deep} is obtained by summing the corresponding monthly non-negative residuals over 2000–2023, so it represents a cumulative residual over the study period. Because these seasonal cumulative values are strongly zero-inflated, we further distinguish their spatial occurrence from their conditional magnitude among pixels with positive S_{deep} . The terminology and interpretation have been revised accordingly. The definition and methodological limitations of S_{deep} have also been clarified in the revised Methods section. The occurrence/conditional-magnitude framework and supporting seasonal summaries are documented in Appendix C and Tables S8–S10.

Revised manuscript text: Lines 261 to 276: ‘Monthly residuals were summed over all corresponding calendar months during 2000–2023 to obtain cumulative seasonal S_{deep} . Because cumulative seasonal S_{deep} contained many zero values, we separated its analysis into spatial occurrence and conditional magnitude. Occurrence was defined as

$$O_{i,s} = I \left(S_{\text{deep},i,s} > 0 \right) \quad (7)$$

where $O_{i,s}$ equals one when cumulative seasonal S_{deep} is positive, and zero otherwise. Because monthly residuals are non-negative, a positive cumulative seasonal S_{deep} indicates that a pixel had at least one positive monthly residual within that calendar season over 2000–2023. Occurrence therefore represents spatial presence over the study period and does not quantify event frequency or water-source switching. Group-level occurrence was summarised as the proportion of pixels with $O_{i,s} = 1$.

C8: Lines 266–271: The study area is divided into three hydro-lithological regions, namely HS-HR, LS-HR, and LS-LR. In particular, LS-LR occupies most of the study area and may contain more complex variations in elevation, climate, vegetation type, and lithology. It is therefore questionable whether comparisons based only on the mean values of the three regions are sufficient.

Response: We agree that the original threshold-based classification and comparisons based only on group means could obscure substantial environmental heterogeneity within the Qinling Mountains. We have therefore replaced the original HS-HR, LS-HR and LS-LR scheme with a data-driven hydro-lithological classification based on lithology-level values of shallow-soil available water capacity, regolith porosity and intrinsic permeability. Candidate three-, four- and five-group solutions are evaluated using classification diagnostics, including silhouette width, forest-domain representation, lithological-class composition and bootstrap stability. On the basis of these diagnostics, the three-group solution is retained as the primary classification. The revised analysis also no longer relies on unadjusted group means: Vegetation responsiveness is compared using pixel-level models that account for elevation and forest type, while long-term precipitation and temperature are examined separately as climatic-background associations. Spatial uncertainty is quantified using block-bootstrap confidence intervals and direct pairwise group contrasts. To further assess heterogeneity within the retained classification, we have added alternative four- and five-group solutions, lithology-level analyses and continuous-property models. These analyses reveal additional within-group variation, particularly outside HG2, while the relatively high summer GPP responsiveness of HG2 persists across clustering resolutions. We have therefore interpreted the three hydro-lithological groups as broad regional configurations. Supporting classification diagnostics and robustness checks are reported in Tables S1–S4, while direct pairwise hydro-lithological contrasts are shown in Fig. S3.

Revised manuscript text: Lines 171 to 183: ‘Lithological classes were grouped according to their soil and regolith properties to distinguish contrasting hydro-lithological settings. Clustering was performed at the lithological-class level rather than at the individual-pixel level. For each

lithological class, we calculated the median soil available water capacity (AWC), regolith porosity and log10-transformed intrinsic permeability ($\log_{10} k$) across all retained forest pixels. These lithology-level values were standardised to zero mean and unit variance so that the three descriptors contributed on a common scale. We then calculated Euclidean distances among lithological classes on the basis of the three standardised descriptors and applied Ward.D2 hierarchical clustering. Candidate solutions with three, four and five groups are evaluated using average silhouette width, forest-domain representation, the number of lithological classes in each group and bootstrap stability. Classification diagnostics and group membership are reported in Tables S1–S2.

Lines 190 to 197: ‘On the basis of these diagnostics, the three-group solution is retained, and each forest pixel inherited the group assigned to its lithological class (Fig. 2; Table S1). The groups therefore represent contrasting combinations of mapped soil storage and regolith hydraulic properties. Because AWC, porosity and permeability were used to define the groups, they were not simultaneously included as covariates in the principal group models; separate continuous-property models were used as exploratory checks.’

Lines 295 to 297: ‘Adjusted group-by-season means and pairwise group contrasts were obtained from the fitted model after accounting for elevation and forest type.’

Lines 563 to 570: ‘HG2 remained the most responsive group under the four- and five-group classifications (Table S3). Increasing the number of groups mainly resolved additional hydraulic heterogeneity outside HG2. Under $k = 5$, the original HG3 separated into lithological subsets with contrasting summer GPP responses. The persistence of HG2 across $k = 3–5$ indicates that its high summer GPP responsiveness was not sensitive to the selected clustering resolution; finer classifications mainly resolved additional heterogeneity within the original HG3.’

Table S2. Silhouette width, bootstrap stability and minimum group representation of candidate hydro-lithological classifications.

<i>k</i>	<i>Average silhouette width</i>	<i>Mean ARI</i>	<i>10th-percentile ARI</i>	<i>Minimum lithologies per group</i>	<i>Minimum forest area (%)</i>
3	0.451	1.000	1.000	2	22.26
4	0.446	0.977	0.800	1	0.75
5	0.355	0.891	0.697	1	0.75

Note: Average silhouette width summarises within-cluster cohesion relative to between-cluster separation for each reference clustering solution. ARI quantifies agreement between each bootstrap classification and its corresponding reference classification. ARI values are derived from 1,000 within-lithology bootstrap realisations. The 10th-percentile ARI represents lower-tail clustering stability, whereas the minimum number of lithological classes per group and minimum forest area describe group balance.

89 **Table S3.** *Adjusted summer GPP responsiveness to SPEI-3 under alternative clustering resolutions.*

<i>k</i>	<i>Cluster</i>	<i>Corresponding k = 3 group</i>	<i>β_{SPEI} (95% CI)</i>	<i>Forest area (%)</i>	<i>No. of lithologies</i>
3	HG1	HG1	0.137 (0.117, 0.156)	22.26	4
	HG2	HG2	0.207 (0.190, 0.222)	28.94	4
	HG3	HG3	0.061 (0.041, 0.079)	48.80	2
4	HG1	HG1	0.137 (0.117, 0.156)	22.26	4
	HG2	HG2	0.207 (0.190, 0.221)	28.19	3
	HG3	HG3	0.061 (0.041, 0.079)	48.80	2
	HG4	HG2	0.192 (0.134, 0.235)	0.75	1
5	HG1	HG1	0.137 (0.117, 0.156)	22.26	4
	HG2	HG2	0.207 (0.191, 0.222)	28.19	3
	HG3	HG3	0.007 (−0.018, 0.032)	20.41	1
	HG4	HG2	0.192 (0.134, 0.235)	0.75	1
	HG5	HG3	0.099 (0.078, 0.118)	28.39	1

90 *Note. Values are adjusted hydro-lithological-group-specific means from second-stage models fitted*
91 *separately for each clustering resolution, with elevation and forest type included as covariates.*
92 *Confidence intervals are 95% percentile intervals obtained from 1,000 spatial-block-bootstrap*
93 *replicates. The ‘Corresponding k = 3 group’ column maps clusters in the finer solutions to the k =*
94 *3 reference classification. Forest area is the percentage of the final retained forest domain, and the*
95 *number of lithologies is the number of lithological classes assigned to each cluster. Bold values*
96 *indicate intervals that exclude zero.*

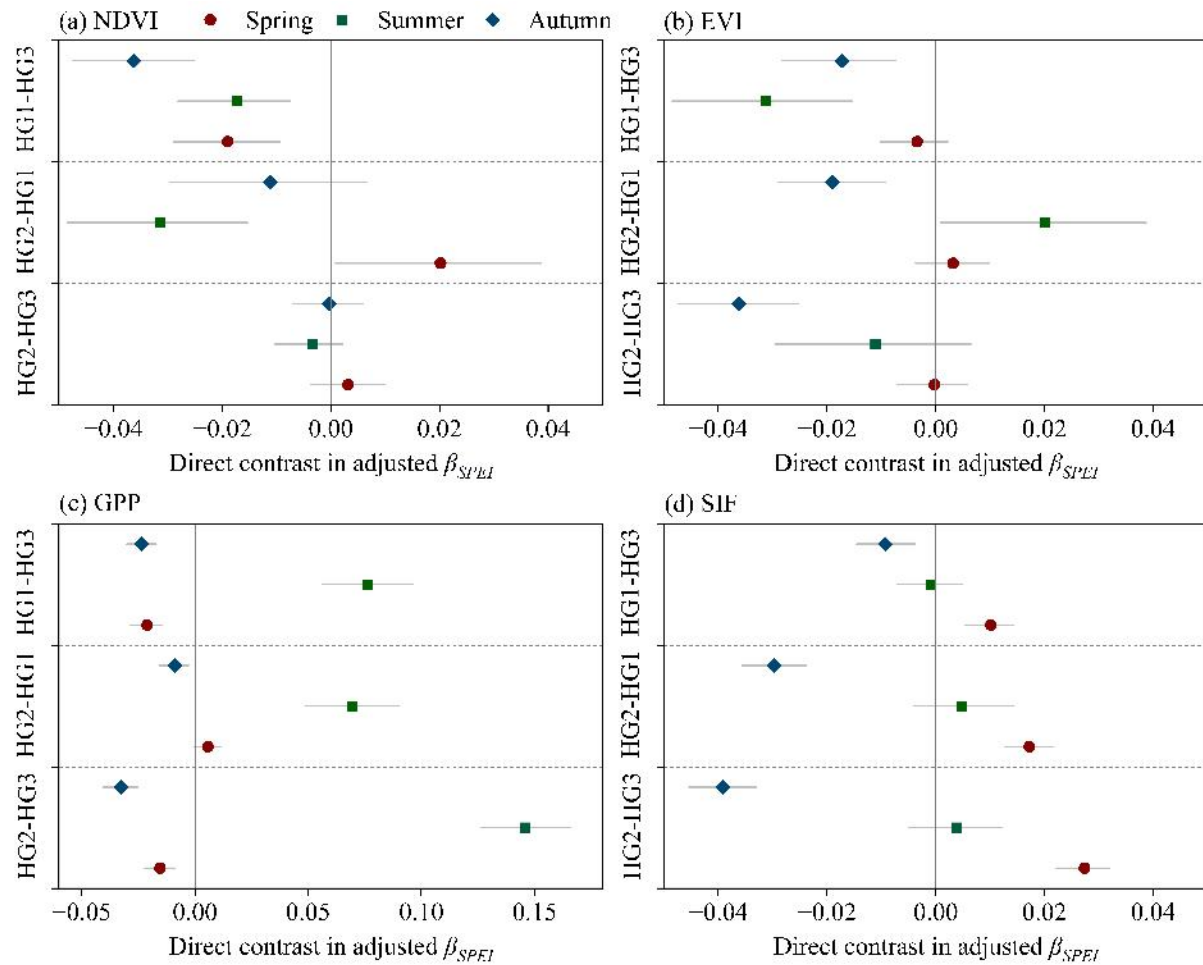


Figure S3. Direct pairwise hydro-lithological group contrasts in adjusted seasonal vegetation responsiveness to SPEI-3. Panels show (a) NDVI, (b) EVI, (c) GPP and (d) SIF for spring, summer and autumn. Each contrast is calculated as the first listed hydro-lithological group minus the second within the 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.

C9: Lines 343–349: The manuscript reports that summer and autumn precipitation are negatively correlated with vegetation greenness and functional activity, and explains this pattern by transient anoxia, nutrient leaching, and reduced incoming radiation. However, these variables are not included in the current model.

Response: We agree that the original Discussion attributes the observed climatic associations to

mechanisms that are not represented in the analysis. We have therefore removed the specific explanations involving transient anoxia, nutrient leaching and reduced incoming radiation, and revised both the interpretation and presentation of the climatic-background analysis. In the revised manuscript, long-term precipitation and temperature are treated only as spatial climatic-background variables associated with variation in vegetation responsiveness to SPEI. A negative precipitation-background coefficient therefore indicates that the signed vegetation–SPEI responsiveness coefficient decreases toward wetter locations. We have also reported the contrasting patterns among indicators explicitly and restricted mechanistic interpretation to processes that are consistent with, but not directly resolved by, the analysis. Unmeasured factors such as radiation, vapour pressure deficit, rooting depth and subsurface flow remain unresolved. The limitations related to the interpretation and validation of the inferred bedrock-water subsidy are addressed separately in our response to C6 and the corresponding manuscript revisions. The revised climatic-background associations and their spatial-block-bootstrap support are summarised in Fig. 4.

Revised manuscript text: Lines 300 to 307: ‘Here, $b_{G_{i,s}}^P$ and $b_{G_{i,s}}^T$ denote the hydro-lithological-group-specific precipitation- and temperature-background slopes, respectively. These slopes describe spatial associations between long-term climatic background and vegetation responsiveness.’

Lines 429 to 434: ‘Summer GPP responsiveness declined with increasing precipitation background, with slopes of -0.046 in HG1, -0.013 in HG2 and -0.027 in HG3; only the HG2 confidence interval included zero. Because summer GPP–SPEI coefficients were positive, these negative slopes indicate that wetter long-term conditions were associated with weaker dependence of GPP on short-term meteorological moisture anomalies.’

C10: Figure 9: Figure 9 has poor readability, and it is difficult to identify useful information from the figure.

Response: We have removed the original Figure 9 in our revised manuscript. We have added two

135 new figures that clearly separate the presentation of the spatial patterns of inferred S_{deep} from its
136 associations with GPP responsiveness. The spatial pattern and association results are now presented
137 in revised Figs. 5 and 6, respectively.

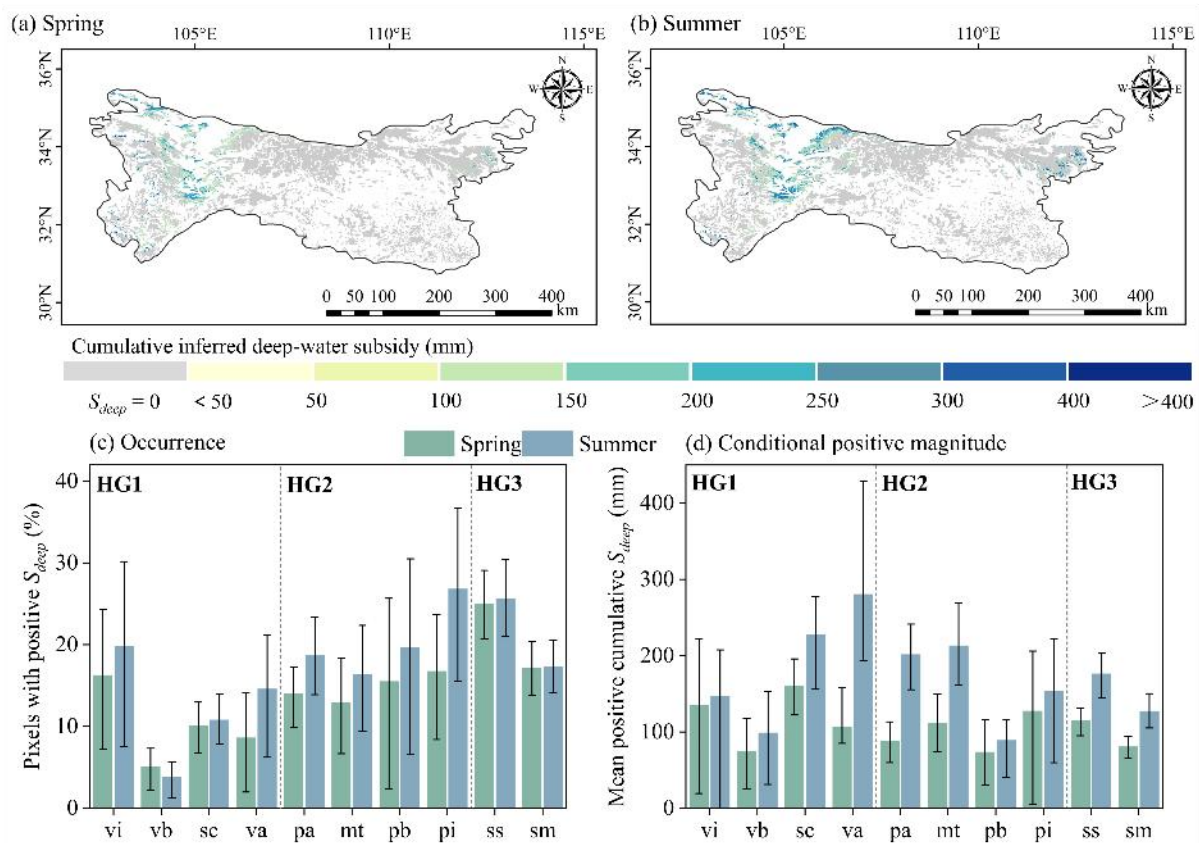


Figure 5. Spatial occurrence and conditional magnitude of the inferred bedrock-water subsidy. Spatial distributions of cumulative inferred bedrock-water subsidy (S_{deep}) are shown for (a) spring and (b) summer over 2000–2023. Grey pixels indicate no positive inferred subsidy, whereas coloured pixels 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.

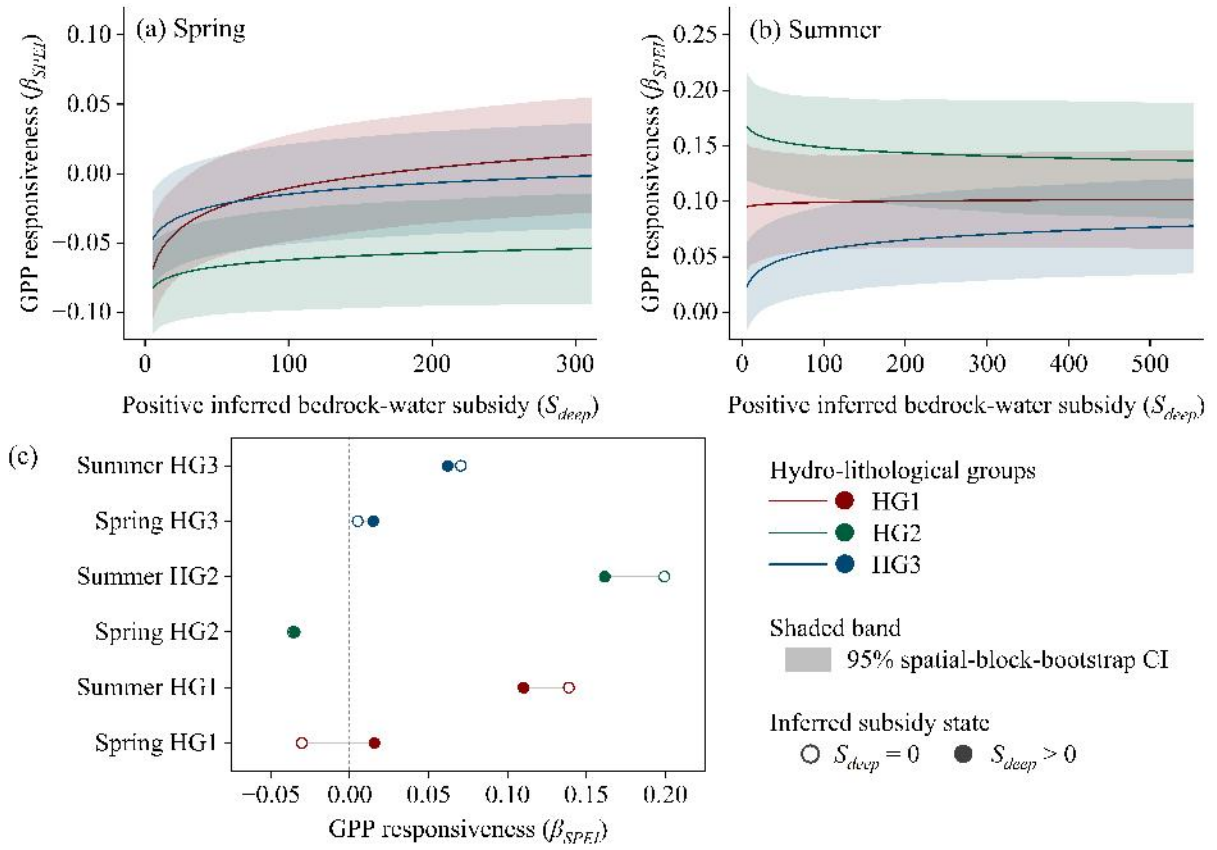


Figure 6. Associations of inferred bedrock-water subsidy occurrence and conditional magnitude with GPP responsiveness. Conditional relationships between positive S_{deep} ($S_{deep} > 0$) and GPP responsiveness to SPEI-3 (β_{SPEI}) are shown for (a) spring and (b) summer. Curves represent hydro-lithological-group-specific 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.