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Revision notes: We sincerely thank the Editor and the editorial office for their time and effort in handling our manuscript, coordinating the review process, and identifying suitable reviewers. We are also very grateful to both reviewers for their careful reading, constructive comments, and valuable suggestions. These comments have helped us identify several weaknesses in the previous version and have provided important guidance for improving the scientific rigor, methodological clarity, and overall quality of the manuscript. We have revised the manuscript carefully according to the Editor's and reviewers' suggestions. The revised portions have been marked in red in the revised manuscript. Below, we provide a point-by-point response to all comments and summarize the corresponding changes made in the manuscript.

Responses to the reviewer's comments

Response to Reviewer #1

Comment 1: Lines 27–29: The climatic-gradient thresholds are reported inconsistently. In the Abstract, the arid-zone threshold is given as 1.31 kPa, whereas in Section 4.1 and the Conclusion (Line 468) it is given as 1.67–1.68 kPa. The same discrepancy applies to the temperate zone (0.68 kPa in the Abstract; 1.67–1.68 kPa referred to in Section 4.3, Line 407). The authors must reconcile these values, clarify whether the Abstract reports the GAM-derived or piecewise-derived threshold, and ensure consistency throughout.

Response: Thank you for pointing out this important inconsistency. We agree that the threshold values were not clearly and consistently reported in the previous version, which could cause confusion about the aridity-based grouping scheme and the threshold-detection method.

In the revised manuscript, we have reconciled these values by adopting a single and consistent aridity-index-based classification framework throughout the Abstract, Methods, Results, Discussion, and Conclusion. Global land areas are now divided into four aridity zones: arid, semi-arid, semi-humid, and humid regions. We no longer mix the previous climate-zone grouping with the aridity-based grouping when reporting VPD thresholds. Accordingly, the earlier inconsistent values, including 1.31 kPa, 0.68 kPa, and 1.67-1.68 kPa, have been removed from the manuscript.

We also clarified the method used to derive the reported thresholds. In the revised analysis, we compared three nonlinear models, including the one-breakpoint piecewise regression, the two-breakpoint piecewise regression, and the generalized additive model (GAM). The one-breakpoint piecewise model was selected for the main threshold interpretation because the two-breakpoint model did not substantially improve model fit based on ΔAICc values, while the GAM-derived transition points were broadly consistent with the one-breakpoint thresholds. Therefore, thresholds reported in the main text now refer to the one-breakpoint piecewise model, whereas the GAM and two-breakpoint results are presented as supplementary evidence for model comparison and robustness evaluation.

Under this revised framework, the threshold values are reported consistently as follows: arid zone, 1.90 kPa; semi-arid zone, 1.46 kPa; semi-humid zone, 0.49 kPa; and humid zone, 0.47 kPa. These values are now used consistently in the Abstract, Section 4.1, Section 4.3, Figure 4 caption, and the Conclusion. We further revised the wording to describe these values as dominant transition points in the observed VPD-E relationship, rather than exact or universal ecological thresholds, because the estimated thresholds may still depend on model choice and data uncertainty.

These revisions resolve the inconsistency identified by the reviewer and ensure that the aridity-based grouping scheme, threshold-detection method, and reported threshold values are internally consistent throughout the manuscript.

Revised text in the Abstract:

The VPD–E relationship exhibits a pronounced aridity-dependent threshold, which decreases progressively from arid (1.90 kPa) and semi-arid (1.46 kPa) regions to semi-humid (0.49 kPa) and humid (0.47 kPa) regions.

Revised text in the Methods (Section 2.2.4):

We used piecewise linear regression and generalized additive models (GAM) to examine the nonlinear relationship between VPD and E and to identify possible threshold behavior. Piecewise linear regression is useful when the relationship between two variables changes across different intervals of the predictor, because it can estimate both the breakpoint location and the slopes on each side of the breakpoint (Yu et al., 2024). GAMs are flexible regression models that can describe nonlinear relationships by fitting smooth functions to the predictor without imposing a fixed functional form (Brunner and Naveau, 2023).

Revised text in the Results (Section 3.4):

The estimated thresholds showed a clear aridity gradient. The dominant transition point was highest in the arid zone (1.90 kPa), followed by the semi-arid zone (1.46 kPa). The thresholds were much lower in the semi-humid zone (0.49 kPa) and humid zone (0.47 kPa). These results show that the VPD–E relationship reached its main transition at higher VPD in dry regions but at lower VPD in wetter regions. Therefore, the thresholds reported here should be interpreted as dominant transition points in the observed nonlinear relationship, not as fixed ecological limits. The model comparison among the one-breakpoint model, two-breakpoint model, and GAM was used as a robustness check for the threshold estimates.

Revised text in the Fig. 4 caption:

Figure 4. Aridity-dependent thresholds in the nonlinear response of terrestrial evapotranspiration to vapor pressure deficit. a-d, One-breakpoint piecewise fits between VPD and E for the arid, semi-arid, humid, and semi-humid AI-based aridity zones, respectively. Points show annual

area-weighted means, coloured by sample density. Solid lines indicate fitted relationships and dashed vertical lines indicate the estimated VPD thresholds. The AI-based aridity zones based on the AI index are shown in the supplementary Figure 5.

Comment 2: Section 2.2.2: The "space-for-time" moving-window approach to compute $dE/dVPD$ is borrowed from land-use-change literature, where the logic is well-established for discrete cover transitions. Applying it here to derive VPD sensitivity assumes that spatial VPD gradients at 5×5 km are driven solely by biophysical feedbacks, rather than by mesoscale atmospheric dynamics. Please provide justification for this assumption for the global domain, especially in complex terrain or coastline-adjacent pixels. Furthermore, the authors should discuss the robustness of this assumption and, if possible, offer a cross-validation against pixel-level temporal regression ($dE/dVPD$ from time series at each pixel).

Response: We agree that the moving-window approach requires a clearer explanation and a more cautious interpretation. In the revised manuscript, we have therefore substantially revised Section 2.2.2 to clarify the spatial scale, assumptions, screening criteria, and limitations of the method.

First, we clarified that the analysis was not conducted using a 5×5 km window. All variables were harmonized to a common 0.1° grid, and the moving window was defined as a 5×5 grid-cell neighborhood, corresponding to a $0.5^\circ \times 0.5^\circ$ local window centered on each target pixel. This revision removes the ambiguity caused by the previous “ 5×5 km” wording and makes the spatial scale consistent with the gridded VPD and E datasets used in the analysis.

Second, we revised the interpretation of $dE/dVPD$. We now define it as a spatially derived apparent local sensitivity of E to VPD, rather than as a fully isolated causal effect. We removed the over-strong implication that VPD is the sole driver of spatial E variation. Instead, we state that the method estimates the E–VPD relationship under local neighborhood constraints and that the result should be interpreted cautiously because local VPD gradients may still be affected by mesoscale atmospheric dynamics, topography, land-sea contrasts, and other unresolved surface

heterogeneity.

Third, we added explicit within-window screening criteria to reduce the influence of heterogeneous surface conditions. Candidate pixels were retained only when they shared the same dominant MODIS land-cover type as the target pixel, when the difference in dominant-type fractional cover was less than 10%, and when the elevation difference from the target pixel was less than 100 m. These criteria were introduced to reduce the influence of abrupt land-cover differences and topographic gradients, particularly in heterogeneous regions.

Fourth, because a moving-window estimate cannot fully remove all confounding effects, we added additional robustness support using independent datasets and complementary pixel-scale analysis. Specifically, we introduced an independent VPD dataset derived from CRU TS v4.09 temperature and vapor pressure, and an independent evapotranspiration dataset from P-LSHv2, to evaluate whether the main ERA5-Land- and GLEAM-based results depend strongly on a single data source. In addition, the revised manuscript includes pixel-scale detrended partial correlation analysis between VPD and evapotranspiration components after controlling for precipitation and soil moisture. Although this partial correlation analysis is not a direct replacement for the moving-window $dE/dVPD$ estimate, it provides an independent temporal perspective on the VPD–evapotranspiration relationship.

We also acknowledge the reviewer’s suggestion regarding pixel-level temporal regression. Because temporal regression and spatial moving-window regression estimate different quantities and are affected by different confounding factors, we did not present temporal regression as a direct one-to-one validation of the spatial sensitivity estimate. Instead, we revised the text to avoid overclaiming causality and interpreted $dE/dVPD$ together with partial correlation analysis, SEM pathways, and independent dataset checks. These revisions make the assumptions, robustness, and limitations of the moving-window approach clearer.

Revised text in the Methods (Section 2.2.2):

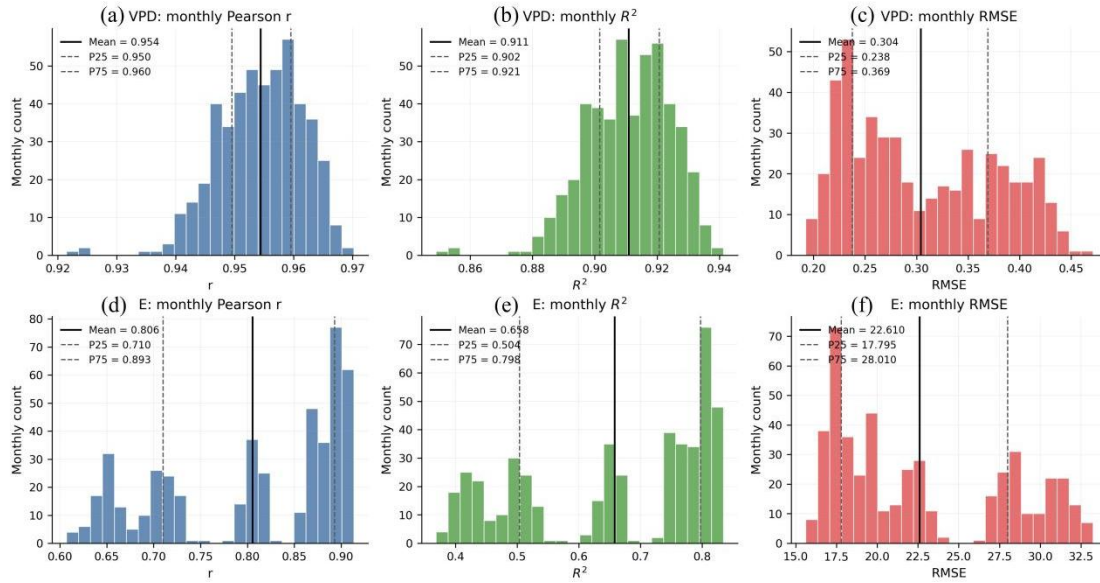
Due to the complex bidirectional interactions between local background climate and varying E conditions across different scales, this study adopts a moving window

strategy inspired by the “space-for-time” approach to calculate the sensitivity of E to VPD ($dE/dVPD$) (Y. Li et al., 2023). The core assumption of this approach is that the target pixel and qualified neighboring pixels share broadly similar background climatic and surface conditions within a local window. Therefore, spatial differences in E and VPD among these screened pixels can be used to estimate the apparent local sensitivity of E to VPD (Li et al., 2024). This estimate should not be interpreted as a fully isolated causal effect of VPD, because local VPD gradients may still be influenced by mesoscale atmospheric dynamics, topography, land-sea contrasts, and other unresolved surface heterogeneity. To reduce these confounding effects, candidate pixels were retained only when they shared the same dominant MODIS land-cover type as the target pixel, differed by <10% in dominant-type fractional cover, and had an elevation difference of <100 m from the target pixel.

This study applies a spatial moving-window strategy to estimate $dE/dVPD$ values (Zhao and Feng, 2024). All analyses were conducted on a common 0.1° grid, corresponding to the native spatial resolution of both the ERA5-Land VPD data and the GLEAM evaporation data used in this study. For each target pixel, candidate comparison samples were selected from surrounding pixels within a 5×5 grid-cell moving window, i.e., a neighborhood of $0.5^\circ \times 0.5^\circ$ centered on the target pixel. To reduce the influence of surface heterogeneity, only pixels sharing the same dominant land-cover type as the target pixel were retained, and the difference in dominant land-cover fraction was required to be less than 10% according to the MODIS MCD12C1 land-cover product. In addition, pixels with an elevation difference greater than 100 m from the target pixel were excluded to minimize topographic effects. The sensitivity for each target pixel was then estimated from the relationship between E differences and VPD differences between all qualified neighboring pixels and the target pixel. In this procedure, the nonparametric Theil-Sen slope estimator was used to reduce the influence of skewed sample distributions and outliers.

$$slope = median \left(\frac{y_i - y_j}{x_i - x_j} \right) \quad (6)$$

Here x and y indicate the E and VPD differences; i and j are the geolocations of samples within the moving window. The unit of $dE/dVPD$ is mm hPa^{-1} . Positive values indicate that E tends to be higher in locations with higher VPD within the local window, whereas negative values indicate that E tends to be lower in locations with higher VPD. The Theil-Sen slope estimator adopts the median value of a range of possible slopes and is therefore insensitive to statistical outliers.



Supplementary Figure 1. Validation of the reliability of the VPD and E datasets. a-c, spatial distributions of the correlation coefficient (r), coefficient of determination (R^2), and root mean square error (RMSE) between the two VPD datasets. d-f, spatial distributions of r , R^2 , and RMSE between the two E datasets.

Comment 3: Line 164: The moving-window size is stated as " 5×5 km based on previous studies," but no citation is provided, and the dataset native spatial resolutions (ERA5 ~ 31 km, GLEAM ~ 25 km, MODIS MCD12C1 ~ 5.5 km) are substantially coarser than 5 km. This creates a fundamental mismatch: in practice, a 5×5 km window over ERA5 or GLEAM data contains a single pixel. The authors need to explicitly state the actual grid resolution at which the analysis was conducted and reconcile it with the stated window size.

Response: We thank the reviewer for pointing out this important ambiguity. We agree that the original wording " 5×5 km" was inaccurate and could cause a

fundamental misunderstanding of the spatial implementation of the moving-window method. In the revised manuscript, we have corrected this description.

The analysis was not conducted using a 5×5 km window. Instead, all variables used in the dE/dVPD analysis were harmonized to a common 0.1° grid. The moving window was therefore implemented as a 5×5 grid-cell neighborhood, corresponding to a $0.5^\circ \times 0.5^\circ$ local window centered on each target pixel. We have revised Section 2.2.2 to explicitly state this actual analysis resolution and the corresponding moving-window definition. We also clarified how candidate pixels were selected within this 5×5 grid-cell window. To reduce surface heterogeneity, candidate pixels were retained only when they shared the same dominant MODIS land-cover type as the target pixel. The difference in dominant land-cover fraction was required to be less than 10%, and pixels with elevation differences greater than 100 m from the target pixel were excluded. The MODIS MCD12C1 land-cover information was used to define the dominant land-cover type and its fraction on the common 0.1° analysis grid.

These revisions correct the erroneous “ 5×5 km” statement, reconcile the moving-window description with the actual spatial resolution of the analysis, and make the methodological implementation clearer.

Revised text in the Methods (Section 2.2.2):

This study applies a spatial moving-window strategy to estimate dE/dVPD values (Zhao and Feng, 2024). All analyses were conducted on a common 0.1° grid, corresponding to the native spatial resolution of both the ERA5-Land VPD data and the GLEAM evaporation data used in this study. For each target pixel, candidate comparison samples were selected from surrounding pixels within a 5×5 grid-cell moving window, i.e., a neighborhood of $0.5^\circ \times 0.5^\circ$ centered on the target pixel. To reduce the influence of surface heterogeneity, only pixels sharing the same dominant land-cover type as the target pixel were retained, and the difference in dominant land-cover fraction was required to be less than 10% according to the MODIS MCD12C1 land-cover product. In addition, pixels with an elevation difference greater than 100 m from the target pixel were excluded to minimize topographic effects. The

sensitivity for each target pixel was then estimated by regressing the differences in E and VPD between all qualified neighboring pixels and the target pixel. In this procedure, the nonparametric Theil-Sen slope estimator was used to reduce the influence of skewed sample distributions and outliers.

Comment 4: Line 270: The global mean sensitivity of $293.27 \pm 62.28 \text{ mm} \cdot \text{hPa}^{-1} \cdot \text{yr}^{-1}$ is a central quantitative result, yet the units are unconventional. Sensitivity ($dE/dVPD$) is dimensionally $[\text{mm} / \text{hPa}]$, not $[\text{mm} \cdot \text{hPa}^{-1} \cdot \text{yr}^{-1}]$. The inclusion of yr^{-1} suggests this may be derived from annual trend magnitudes rather than a pure partial derivative. Unless I have misunderstood the definition of what quantity this represents, e.g., is it a sensitivity coefficient, a trend-normalised ratio, or a regression slope?

Response: We agree that the unit should be clarified. In the revised manuscript, $dE/dVPD$ is defined as a moving-window-based apparent local sensitivity of E to VPD. It was estimated from spatial differences in E and VPD between each target pixel and its qualified neighboring pixels within a local window. Therefore, its unit is mm hPa^{-1} . It is not a trend rate, and it should not include yr^{-1} .

We have removed yr^{-1} from the unit throughout the manuscript. We also revised the wording in the Methods and Results to make clear that $dE/dVPD$ represents an apparent local sensitivity under neighborhood constraints, rather than a temporal trend-normalized ratio or a fully isolated causal effect of VPD. Positive values indicate that E tends to be higher in locations with higher VPD within the local window, while negative values indicate that E tends to be lower in locations with higher VPD.

Revised text in the Results (Section 3.2):

3.2 Global Terrestrial E Response to VPD

The apparent sensitivity of terrestrial E to VPD showed pronounced but spatially heterogeneous patterns at the global scale (Fig. 2a). Overall, 60.71% of land areas exhibited positive apparent sensitivity to VPD, with a global mean sensitivity of $293.27 \pm 62.28 \text{ mm hPa}^{-1}$ (mean $\pm$ spatial standard deviation). Here, $dE/dVPD$

denotes the moving-window-based apparent local sensitivity of E to VPD, rather than a regression-based interannual response. Spatially, negative sensitivity was concentrated mainly in arid and cold regions, whereas positive sensitivity dominated in relatively warm and humid regions (Fig. 2a). The climatic dependence of $dE/dVPD$ is shown in Fig. 2b. Negative or weak sensitivity occurred mainly under dry climate conditions, especially in warm and low-precipitation bins, whereas positive sensitivity became more widespread in wetter bins and in many cool-to-temperate bins. Overall, the apparent VPD–E relationship varied strongly along temperature and precipitation gradients, but the pattern did not indicate a simple response to temperature alone.

Across land-use types, we grouped the 16 original land-cover categories into four major classes: forest, grassland and wetland, cropland, and non-vegetated land (Fig. 2c; Supplementary Fig. 2). All classes generally showed positive apparent sensitivity to VPD, but with clear differences in magnitude. Forests showed the strongest sensitivity ($405.34 \text{ mm hPa}^{-1}$), followed by grasslands and wetlands ($342.26 \text{ mm hPa}^{-1}$) and barren areas ($200.40 \text{ mm hPa}^{-1}$), whereas croplands showed the weakest sensitivity ($78.12 \text{ mm hPa}^{-1}$). The latitudinal profiles further show that positive sensitivity was generally greater in forests and grasslands/wetlands than in croplands and barren regions. Taken together, these results indicate that higher local VPD tended to be associated with higher E in densely vegetated regions under the moving-window estimate, while this apparent relationship was weaker in sparsely vegetated or managed cropland areas.

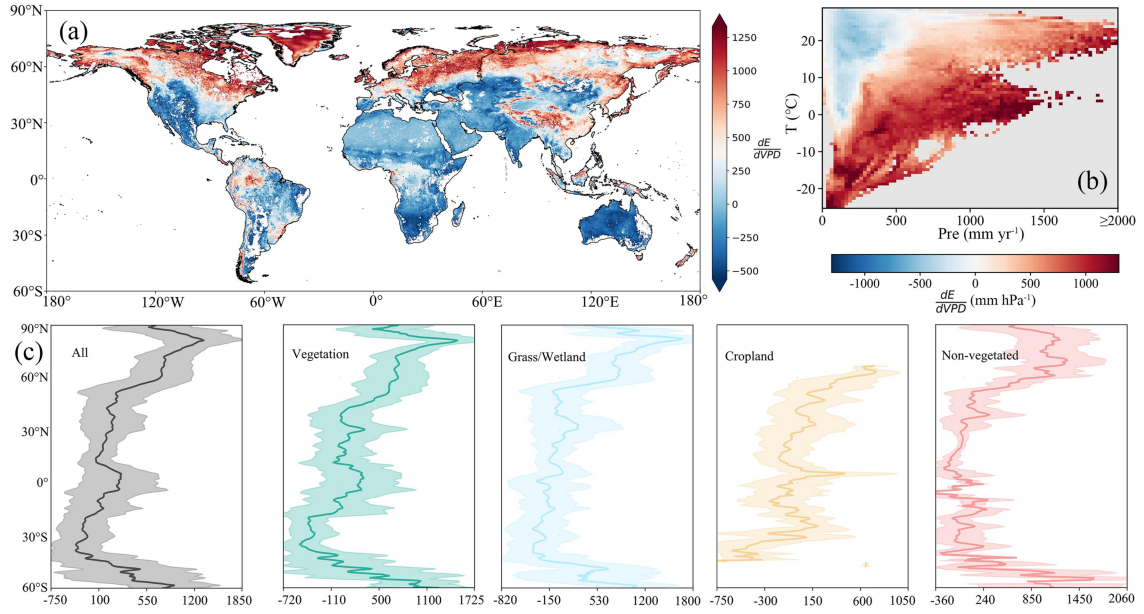


Figure 2. Apparent sensitivity of terrestrial evapotranspiration (E) to vapor pressure deficit (VPD) during 1981-2020. (a) Spatial distribution of the sensitivity coefficient $dE/dVPD$. Red colors indicate positive apparent sensitivity, and blue colors indicate negative apparent sensitivity. (b) Variation in $dE/dVPD$ across climate gradients. The x-axis represents mean annual precipitation during 1981-2020, and the y-axis represents mean annual air temperature during 1981-2020. Each climate bin contains valid land pixels within a given T-Pre range, and the color shows the area-weighted mean $dE/dVPD$. Values with precipitation greater than 2000 mm yr⁻¹ were included in the last precipitation bin. (c) Latitudinal distribution of $dE/dVPD$ across different land-use classes, with shaded areas representing the standard deviation within each latitude band. The unit of $dE/dVPD$ is mm hPa⁻¹.

Comment 5: Lines 296-303: The statement that "VPD rose abruptly in 1998 (0.034 hPa yr⁻¹)" reports a trend rate, not an abrupt change, and the phrasing conflates trend magnitude with event-driven anomaly. Additionally, Figure 3b shows VPD peaking at 7.839 hPa in 2010, the connection between the 1998 El Niño and the 2010 peak is not straightforward and warrants more rigorous treatment, potentially with ENSO-index partial correlation.

Response: We agree that the previous wording was not appropriate. The value reported in the earlier version represented a trend rate and should not have been

described as an abrupt change. We also agree that the VPD peak in 2010 should not be linked to the 1998 El Niño without a separate event-attribution analysis or ENSO-index-based test.

We have revised Section 3.3. We removed the statement that VPD “rose abruptly” and removed the unsupported interpretation related to the 1998 El Niño. The revised section now focuses on detrended anomalies and pixel-scale partial correlations between VPD and evapotranspiration components. We now describe only the observed interannual variability in the detrended anomaly series. We also report the spatial partial correlations between VPD and E_t after controlling for SM_{rz} and Pre, and between VPD and E_b after controlling for SM_s and Pre.

Revised text in the Results (Section 3.3):

3.3 Global Patterns of the Relationships Between VPD and E_t and E_b

VPD and total E both showed clear interannual variability during 1981–2020 (Fig. 3a, b). At the global scale, the detrended anomaly series showed broadly consistent interannual variations, especially after 2000. E_t showed relatively coherent interannual variations, whereas E_b exhibited stronger fluctuations (Fig. 3d, f).

After controlling for SM_{rz} and Pre, VPD showed a mainly positive partial correlation with E_t across global land areas (Fig. 3c). Positive partial correlations accounted for 65.79% of valid pixels. This positive pattern was widespread across the Northern Hemisphere, including large parts of North America, Europe, and northern Asia. Positive correlations also appeared in parts of East Asia, South America, and the tropics. In contrast, negative correlations were limited and spatially scattered. The spatial pattern therefore indicates that, after the effects of water supply were reduced, VPD remained positively linked with E_t over most land regions, and this link was especially widespread in northern extratropical regions. After controlling for SM_s and Pre, VPD showed a weaker relationship with E_b and the spatial pattern was more mixed (Fig. 3e). Negative partial correlations accounted for 59.09% of valid pixels. Negative correlations were concentrated mainly in dry and water-limited regions, including most of Australia, southern Africa, and parts of central Asia. Some negative patches also appeared in other low-latitude and subtropical regions. Positive

correlations were still present, but they covered a smaller area and were distributed more unevenly. These positive areas were mainly found in parts of Europe and East Asia, with some additional scattered patches elsewhere.

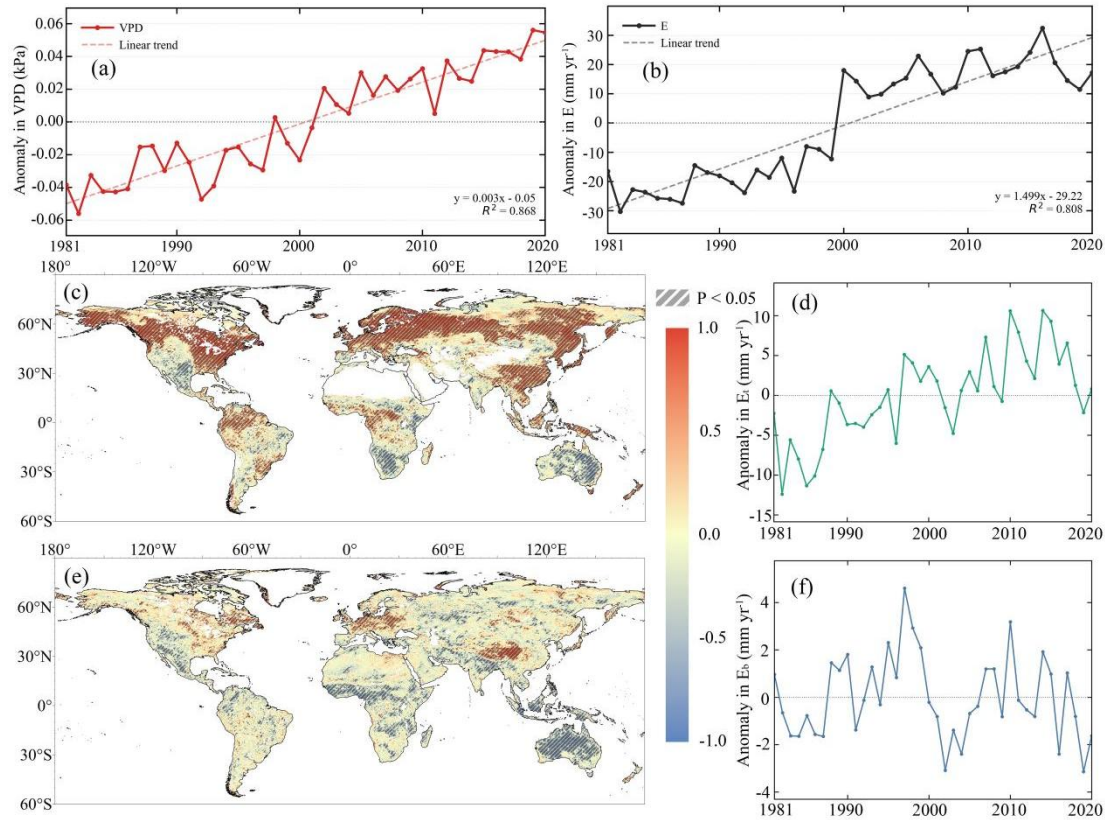


Figure 3. Interannual variability of global mean annual anomalies of VPD and evapotranspiration components and spatial partial correlations between VPD and evapotranspiration components during 1981–2020. (a) Global mean annual anomaly of vapor pressure deficit (VPD). The dashed line indicates the linear trend. (b) Global mean annual anomaly of total evapotranspiration (E). The dashed line indicates the linear trend. (c) Spatial distribution of partial correlation coefficients between VPD and transpiration (E_t) after controlling for root-zone soil moisture (SM_{rz}) and precipitation (Pre); the partial correlation was calculated using detrended annual series, and hatched areas indicate statistically significant correlations at $p < 0.05$. (d) Global mean annual anomaly of transpiration (E_t) over valid land pixels. (e) Spatial distribution of partial correlation coefficients between VPD and bare-soil evaporation (E_b) after controlling for surface soil moisture (SM_s) and Pre; the partial correlation was calculated using detrended annual series, and hatched areas indicate statistically significant correlations at $p < 0.05$. (f) Global mean annual anomaly of bare-soil evaporation (E_b) over valid land pixels.

Comment 6: Lines 362-364: The SEM model is stated to explain 77% of the variance in E, and this is presented as a single global metric. However, SEM was presumably fitted globally on spatially aggregated, or grid-cell mean data. The authors should clarify the unit of analysis (pixel-level, regional mean, or annual global mean) and include model fit statistics (Fisher's C, AIC) in the main text rather than only referencing Figure 5.

Response: We agree that the SEM analysis in the previous version was not described clearly enough. In particular, the previous text could give the impression that the SEM result was derived from a single global model and that the reported R^2 value represented a universal global diagnostic. This was not sufficiently cautious. We have therefore substantially redesigned and clarified the SEM analysis in the revised manuscript.

First, the revised SEM is no longer a single global annual model. Instead, we fitted separate SEMs for four aridity-index-based zones: arid, semi-arid, semi-humid, and humid regions. For each zone, all variables were first spatially averaged to obtain monthly regional time series. Therefore, the unit of analysis is the monthly regional-mean anomaly within each aridity zone, not individual pixels and not annual global means. To reduce the influence of the seasonal cycle, we removed the 1982–2020 climatological monthly mean from each monthly time series and then standardized the deseasonalized anomalies using z-scores. This revision makes the SEM framework more consistent with the scale at which the pathways are interpreted.

Second, we revised the SEM structure. The revised SEM includes E, VPD, SMrz, LAI, T, Pre, and SR. This structure was designed to examine the linked statistical pathways among atmospheric moisture demand, root-zone soil water supply, vegetation state, energy conditions, and evapotranspiration. We also revised the interpretation of the SEM results. The pathways are now described as aridity-zone-scale statistical pathways, rather than pixel-level causal effects.

Third, we explicitly evaluated model diagnostics and model structure. We first fitted a restricted SEM that did not include the residual statistical association between

VPD and LAI. For these restricted SEMs, Fisher's C and AIC were used to evaluate model fit and model parsimony. The directed-separation tests indicated that a residual association between VPD and LAI remained after controlling for SMrz, T, Pre, and SR. We therefore retained this association in the final SEM, but we interpreted it only as a statistical control pathway, not as direct physiological evidence that elevated VPD promotes LAI development.

After this residual association was retained, the final full SEMs became saturated models. In a saturated SEM, all relevant independence claims implied by the model structure are already accounted for, and there are no remaining independence claims for Fisher's C tests. Therefore, Fisher's C is not an appropriate goodness-of-fit statistic for the final full SEMs. Reporting Fisher's C for the final saturated SEMs in the main text would therefore be statistically misleading. For this reason, we used Fisher's C only for the restricted SEMs, and we based the final interpretation on standardized path coefficients, R^2 values, direct and indirect effect decomposition, and AIC comparison between the restricted and full SEMs.

We have added Supplementary Table S1 to provide the complete model diagnostic information, including the comparison between the restricted and full SEMs. We did not place the full diagnostic table in the main text because it contains multiple diagnostics for two model structures across four aridity zones, and because Fisher's C is only applicable to the restricted models but not to the final saturated models. Including the full table in the main text would make the Results section unnecessarily technical and could distract from the main ecohydrological interpretation. Instead, the revised main text now clearly states the unit of analysis, the use of Fisher's C and AIC for the restricted SEMs, the reason why Fisher's C is not reported for the final saturated SEMs, and the basis used for interpreting the final SEM results. The complete numerical diagnostics are provided in Supplementary Table S1 for transparency.

Revised text in the Methods (Section 2.2.5):

2.2.5 Quantifying the Influence of VPD on E Under Multi-Factor Coupling Using Structural Equation Modeling (SEM)

To elucidate the direct and indirect pathways of VPD on E under the coupling effects of multiple factors, this study used SEM to quantify the path relationships among atmospheric moisture demand, water supply, vegetation state, energy availability, and evapotranspiration. SEM, as a multivariate statistical path analysis tool, is widely utilized in ecohydrological systems to identify and disentangle complex inter-variable relationships, enabling simultaneous estimation of direct effects of multiple independent variables on a dependent variable, indirect effects mediated through intervening variables, and total effects (Guo et al., 2025). Here, SEM was used to test whether the observed VPD–E relationships were consistent with coupled ecohydrological pathways.

The variables included E, VPD, SMrz, LAI, T, Pre, and SR. For each aridity zone, all variables were first spatially averaged to obtain monthly regional time series. Therefore, the unit of analysis was the monthly regional-mean anomaly within each climate zone. The model data were based on multi-source remote sensing and reanalysis products from 1982 to 2020. To reduce confounding from the seasonal cycle, we removed the 1982–2020 climatological monthly mean from each monthly time series and then standardized the deseasonalized anomalies using z-scores. Separate SEMs were fitted for arid, semi-arid, semi-humid, and humid regions to account for the climatic dependence of VPD–E relationships.

During the model construction process, T, Pre, and SR were treated as exogenous climatic drivers because they directly regulate atmospheric moisture demand. SMrz was included as an intermediate water-supply variable influenced by atmospheric dryness and background climatic conditions. LAI was included as a vegetation-state variable jointly associated with atmospheric moisture demand, soil-water availability, and climatic controls. E was specified as the final response variable, jointly regulated by atmospheric moisture demand, root-zone soil moisture, vegetation state, temperature, precipitation, and surface solar radiation. Correlations among the exogenous climatic variables, including T, Pre, and SR, were allowed in the SEM to account for their covariation.

A restricted SEM excluding the direct statistical association between VPD and

LAI was first tested. Directed-separation tests indicated that a residual association between VPD and LAI remained after controlling for SMrz, T, Pre, and SR. Therefore, this association was retained in the final SEM. However, it was interpreted as a statistical control pathway rather than direct evidence that elevated VPD physiologically promotes LAI development. We used the “piecewiseSEM” package to build the path model and extracted standardized path coefficients (Std.Estimate) using the “coefs” function. Indirect effects were calculated by multiplying standardized coefficients along each mediation pathway, and total effects were obtained by summing direct and indirect effects. Model diagnostics and model comparison between the restricted and full SEMs are summarized in Supplementary Table S1. Fisher’s C and AIC were used to diagnose the restricted SEMs. After retaining the residual VPD-LAI association, the final full SEMs became saturated models and therefore had no remaining independence claims for Fisher’s C tests. Accordingly, the final SEM interpretation was based on standardized path coefficients, R^2 values, effect decomposition, and AIC comparison between the restricted and full SEMs.

Comment 7: Lines 375-378: The finding that LAI increases markedly under high VPD (standardised coefficient = 0.90) but has only a weak direct effect on Et (standardised coefficient = 0.07) is counterintuitive and deserves deeper mechanistic discussion. A strong VPD–LAI relationship with near-zero LAI–Et effect suggests that either collinearity in the SEM is absorbing the LAI pathway into the VPD direct effect, or that the LAI variable used (GIMMS V1.2 monthly) does not resolve the sub-seasonal dynamics at which VPD–stomatal coupling operates. Please, make sure to address this explicitly.

Response: We agree with the reviewer that the previous interpretation of the VPD–LAI pathway was not sufficiently cautious. In the previous version, the SEM was fitted as a single global model, and this could have mixed broad climate gradients, seasonal vegetation changes, and local ecohydrological processes. This model structure could therefore lead to an overinterpretation of the VPD–LAI path.

In the revised manuscript, we no longer use the earlier single global SEM result

in which VPD showed a strong positive association with LAI and LAI had a weak direct effect on E. Instead, we fitted aridity-zone-specific SEMs using monthly deseasonalized standardized anomalies. We also included additional control variables, including T, Pre, SR, SM_{rz}, LAI, VPD, and E. This revised design reduces the influence of the seasonal cycle and broad spatial climate gradients.

We also revised the interpretation of the VPD–LAI pathway. We first tested a restricted SEM that excluded the direct statistical association between VPD and LAI. Directed-separation tests indicated that a residual VPD–LAI association remained after controlling for SM_{rz}, T, Pre, and SR. We therefore retained this association in the final SEM. However, we now interpret it only as a statistical control pathway, not as direct physiological evidence that elevated VPD promotes LAI development.

We further revised the Discussion to state that the positive remaining relationship between VPD and LAI in wetter regions likely reflects residual co-variation among atmospheric dryness, radiation, temperature, and vegetation activity after soil water and climate factors are controlled. This revision directly addresses the reviewer’s concern that the previous VPD–LAI path may have reflected climate gradients, seasonal vegetation activity, or collinearity rather than a direct mechanism.

Revised text in the Methods (Section 2.2.5):

The variables included E, VPD, SM_{rz}, LAI, T, Pre, and SR. For each aridity zone, all variables were first spatially averaged to obtain monthly regional time series. Therefore, the unit of analysis was the monthly regional-mean anomaly within each climate zone. The model data were based on multi-source remote sensing and reanalysis products from 1982 to 2020. To reduce confounding from the seasonal cycle, we removed the 1982–2020 climatological monthly mean from each monthly time series and then standardized the deseasonalized anomalies using z-scores. Separate SEMs were fitted for arid, semi-arid, semi-humid, and humid regions to account for the climatic dependence of VPD–E relationships.

During the model construction process, T, Pre, and SR were treated as exogenous climatic drivers because they directly regulate atmospheric moisture demand. SM_{rz}

was included as an intermediate water-supply variable influenced by atmospheric dryness and background climatic conditions. LAI was included as a vegetation-state variable jointly associated with atmospheric moisture demand, soil-water availability, and climatic controls. E was specified as the final response variable, jointly regulated by atmospheric moisture demand, root-zone soil moisture, vegetation state, temperature, precipitation, and surface solar radiation. Correlations among the exogenous climatic variables, including T, Pre, and SR, were allowed in the SEM to account for their covariation.

Revised text in the Discussion (Section 4.2):

However, the positive remaining relation between VPD and LAI in wetter regions should not be read as evidence that higher VPD directly promotes vegetation growth (Yuan et al., 2019). It more likely reflects remaining co-variation among atmospheric dryness, radiation, temperature, and vegetation activity after soil water and climate factors are controlled (Zhang et al., 2021). Overall, VPD regulation of E is climate dependent. Its main mechanism lies in the joint effects of higher atmospheric water demand, limited soil water supply, canopy state, and energy conditions.

Comment 8: Lines 406-410: In the discussion of the SM–atmospheric water vapor feedback under high VPD in arid regions, the mechanism is described qualitatively without connecting it to the quantitative results established earlier (e.g., the SEM path coefficients or the $dE/dVPD$ spatial distribution). The discussion would be very interesting if the authors could map the regions where VPD already exceeds the 1.67-1.68 kPa threshold (as identified in Section 4.1) onto the negative-sensitivity regions shown in Figure 2a to demonstrate that the feedback mechanism is already active.

Response: We have revised Section 4.3 to link the interpretation more directly to the spatial $dE/dVPD$ pattern, the updated threshold analysis, and the climate-zone-specific SEM results.

We no longer use the earlier threshold value of 1.67–1.68 kPa. The threshold

analysis has been revised under a consistent AI-based aridity framework. The dominant transition points are now reported as 1.90 kPa for arid regions, 1.46 kPa for semi-arid regions, 0.49 kPa for semi-humid regions, and 0.47 kPa for humid regions. Therefore, we did not add a map based on the old 1.67–1.68 kPa threshold, because this value is no longer used in the revised manuscript.

Instead, we revised the discussion to connect the updated thresholds with the negative $dE/dVPD$ areas shown in Fig. 2a. We also linked this interpretation with the SEM results, where VPD was negatively related to SM_{rz} across all AI-based aridity zones, especially in semi-arid and semi-humid regions. These results suggest that high VPD can strengthen water-supply limitation and then suppress E in dry regions. This revision makes the feedback interpretation more closely tied to the quantitative results presented earlier in the manuscript.

Revised text in the Discussion (Section 4.3):

4.3 Implications of land–atmosphere Feedback Under Future VPD Increase Scenarios

The projected increase in VPD is expected to further alter land–atmosphere coupling by modulating terrestrial E, with consequent impacts on regional to global water cycling (Yuan et al., 2019). In the AI-based AI-based aridity zones, the threshold analysis shows clear differences in how E may respond under future VPD increase. In the arid and semi-arid regions, the one-breakpoint thresholds are high (1.90 and 1.46 kPa, respectively). This interpretation is consistent with the negative $dE/dVPD$ areas shown in Fig. 2a and with the climate-zone-specific SEM results, where VPD was negatively related to SM_{rz} across all AI-based aridity zones, especially in semi-arid and semi-humid regions. These results suggest that high VPD may strengthen water-supply limitation in dry regions and then suppress E.

In the humid and semi-humid regions, the thresholds are much lower (0.47 and 0.49 kPa, respectively). This result suggests that ecosystems in wetter regions may reach the response transition under much lower VPD. These regions may therefore shift earlier as atmospheric dryness continues to increase, even though E can still rise with VPD over part of the observed range (Fig. 2a). This contrast suggests that future VPD increase may affect humid and semi-humid regions earlier, while dry regions

may shift toward stronger E suppression after water limitation becomes dominant. Such differences may increase ecosystem vulnerability and disturb water and carbon cycling, especially in forests and water-limited agricultural systems (Will et al., 2013; Gentine et al., 2019).

Collectively, the sustained rise in VPD is likely to intensify land–atmosphere feedbacks and increase uncertainties in global water and carbon cycling (Gentine et al., 2019). Climate models and risk assessments should therefore better represent the threshold differences among arid, semi-arid, semi-humid, and humid regions. These threshold differences also imply that adaptation measures should be region-specific. Semi-humid and humid regions may need earlier warning because of their lower thresholds, while arid regions require stronger water-management measures under chronic water limitation. Targeted water resource management and ecological conservation measures are therefore needed to strengthen ecosystem resilience and reduce the ecological risks associated with rising VPD.

Comment 9: Lines 431-436: The acknowledgement that ERA5 overestimates SM in arid regions (Kokkalis et al., 2024) is important, but its consequence is underplayed. For example, given that the SEM assigns the VPD–SM path a standardized coefficient of -0.84, the strongest single path in the entire model, a systematic positive bias in SM would directly attenuate this coefficient, inflating the apparent direct effect of VPD on E. This has a directionally predictable effect on the ms's central conclusions and should be discussed with explicit reference to the SEM coefficients.

Response: In the previous version, we referred to an old SEM coefficient from the global annual model. This has been removed because the revised manuscript now uses aridity-zone-specific SEMs based on monthly deseasonalized standardized anomalies.

In the revised manuscript, we explain that ERA5-Land may overestimate soil moisture in arid regions, which can affect the inferred VPD–SM_{rz}–E coupling. This issue is relevant to our SEM because VPD was negatively related to SM_{rz} across all

AI-based aridity zones. If soil moisture is biased in dry regions, the estimated strength of the SM_{rz}-mediated pathway may also be affected. In this case, part of the VPD effect on E may be attributed differently between the direct VPD–E path and the indirect pathway through SM_{rz}.

We also expanded the uncertainty discussion for global E products. We now state that available E products differ in long-term means, temporal trends, spatial patterns, and component partitioning. These differences may affect both the estimated magnitude and the inferred pathway structure of VPD regulation on E. Therefore, the quantitative results should be interpreted with caution.

Revised text in the Discussion (Section 4.4):

Data uncertainty remains an important limitation in this study. First, our analysis relies on ERA5-Land reanalysis and global E products. Although ERA5-Land provides broadly consistent land-surface variables, it may still contain uncertainties in soil moisture, especially in arid regions. This uncertainty can affect the inferred VPD–SM_{rz}–E coupling. This issue is relevant to our SEM because VPD was negatively related to SM_{rz} across all AI-based aridity zones. If soil moisture is biased in dry regions, the estimated strength of the SM_{rz}-mediated pathway may also be affected. In this case, part of the VPD effect on E may be attributed differently between the direct VPD–E path and the indirect pathway through SM_{rz}.

Comment 10: Lines 444-449: The authors acknowledge that piecewise regression assumes a single breakpoint. Yet in the Conclusion (Lines 466-469), a full table of single-threshold values per climate zone is presented as a primary finding. The authors should either present evidence that the VPD–E response in each zone is indeed well described by a single breakpoint (e.g., by showing that a two-breakpoint model does not significantly improve fit) or explicitly qualify the reported thresholds as approximations of the dominant transition, avoiding overstatement of their precision.

Response: We agree that the threshold values should not be overstated as exact ecological limits. In the revised manuscript, we now describe the thresholds as

dominant transition points in the observed VPD–E relationship.

We revised the Methods and Results to make the model comparison clearer. We compared the one-breakpoint piecewise model, the two-breakpoint piecewise model, and the GAM. Model performance was assessed using R^2 , RMSE, and AICc. $\Delta AICc$ was used to evaluate whether the two-breakpoint model improved the fit relative to the one-breakpoint model. The two-breakpoint model did not show a clear improvement across the four aridity zones, while the GAM curves showed similar nonlinear transition behavior. Therefore, the one-breakpoint model was used for the main threshold estimates, and the GAM and two-breakpoint results were used as robustness checks.

We also revised the Results, Discussion, and Conclusion to avoid overstatement. The reported thresholds are now interpreted as approximate dominant transition points, not fixed ecological boundaries.

Revised text in the Methods (Section 2.2.4):

2.2.4 Threshold Detection Using Piecewise Linear Regression and GAM

We used piecewise linear regression and generalized additive models (GAM) to examine the nonlinear relationship between VPD and E and to identify possible threshold behavior. Piecewise linear regression is useful when the relationship between two variables changes across different intervals of the predictor, because it can estimate both the breakpoint location and the slopes on each side of the breakpoint (Yu et al., 2024). GAMs are flexible regression models that can describe nonlinear relationships by fitting smooth functions to the predictor without imposing a fixed functional form (Brunner and Naveau, 2023).

We first removed extreme values to reduce the influence of outliers. For both VPD and E, values below the 1st percentile and above the 99th percentile were excluded. We then analyzed the VPD–E relationship at the global scale and within different climate dryness classes to assess regional differences in nonlinearity and threshold behavior. For the piecewise regression analysis, we treated VPD as the

independent variable and E as the dependent variable. We tested both a one-breakpoint model and a two-breakpoint model. The one-breakpoint model can be written as:

$$y = \begin{cases} k_1x + b_1, & x \leq x_0 \\ k_2(x - x_0) + k_1x_0 + b_1, & x > x_0 \end{cases} \quad (8)$$

where x is VPD, y is E, x_0 is the breakpoint, k_1 and k_2 are the slopes before and after the breakpoint, and b_1 is the intercept. The two-breakpoint model extends this form by allowing two turning points and three linear segments. This model was used to test whether the VPD–E relationship contains more than one transition point. We also fitted a GAM to the same data:

$$y = \beta_0 + f(x) + \varepsilon \quad (9)$$

where $f(x)$ is a smooth spline function of VPD, β_0 is the intercept, and ε is the residual error. We used the GAM to provide an independent description of the nonlinear VPD–E relationship and to check whether the threshold-like behavior inferred from the piecewise models was robust.

We compared model performance using the coefficient of determination (R^2), root mean square error (RMSE), and corrected Akaike information criterion (AICc) (Qiu et al., 2025). $\Delta AICc$ was used to evaluate whether the two-breakpoint model improved the fit relative to the one-breakpoint model. We then used the comparison among the one-breakpoint model, the two-breakpoint model, and the GAM to determine whether a single threshold was sufficient to describe the VPD–E relationship, or whether a more complex nonlinear form was needed. The GAM curve was also used as a reference to evaluate the stability of the breakpoint inferred from the piecewise regression.

Revised text in the Results (Section 3.4):

3.4 Threshold Effects and the Universality of Nonlinearity

The nonlinear relationship between VPD and E varied clearly across AI-based aridity zones (Fig. 4). We compared the one-breakpoint piecewise model, the

two-breakpoint piecewise model, and the GAM to identify the dominant transition points in the VPD–E relationship. The one-breakpoint model was used for the main threshold estimates because the two-breakpoint model did not show a clear improvement in model fit across the four aridity zones, based on ΔAICc values (Supplementary Figs. 3 and 4). The GAM curves also showed similar nonlinear transition behavior, which supports the stability of the one-breakpoint estimates.

The estimated thresholds showed a clear aridity gradient. The dominant transition point was highest in the arid zone (1.90 kPa), followed by the semi-arid zone (1.46 kPa). The thresholds were much lower in the semi-humid zone (0.49 kPa) and humid zone (0.47 kPa). These results show that the VPD–E relationship reached its main transition at higher VPD in dry regions but at lower VPD in wetter regions. Therefore, the thresholds reported here should be interpreted as dominant transition points in the observed nonlinear relationship, not as fixed ecological limits. The model comparison among the one-breakpoint model, two-breakpoint model, and GAM was used as a robustness check for the threshold estimates.

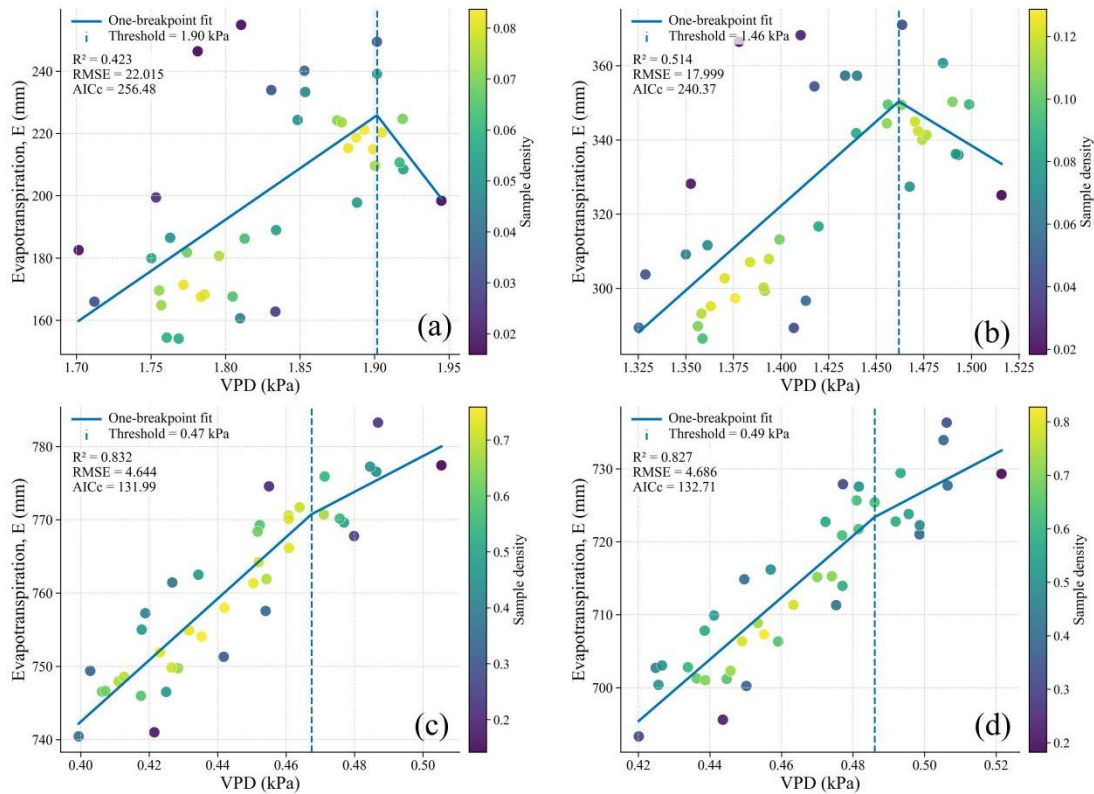
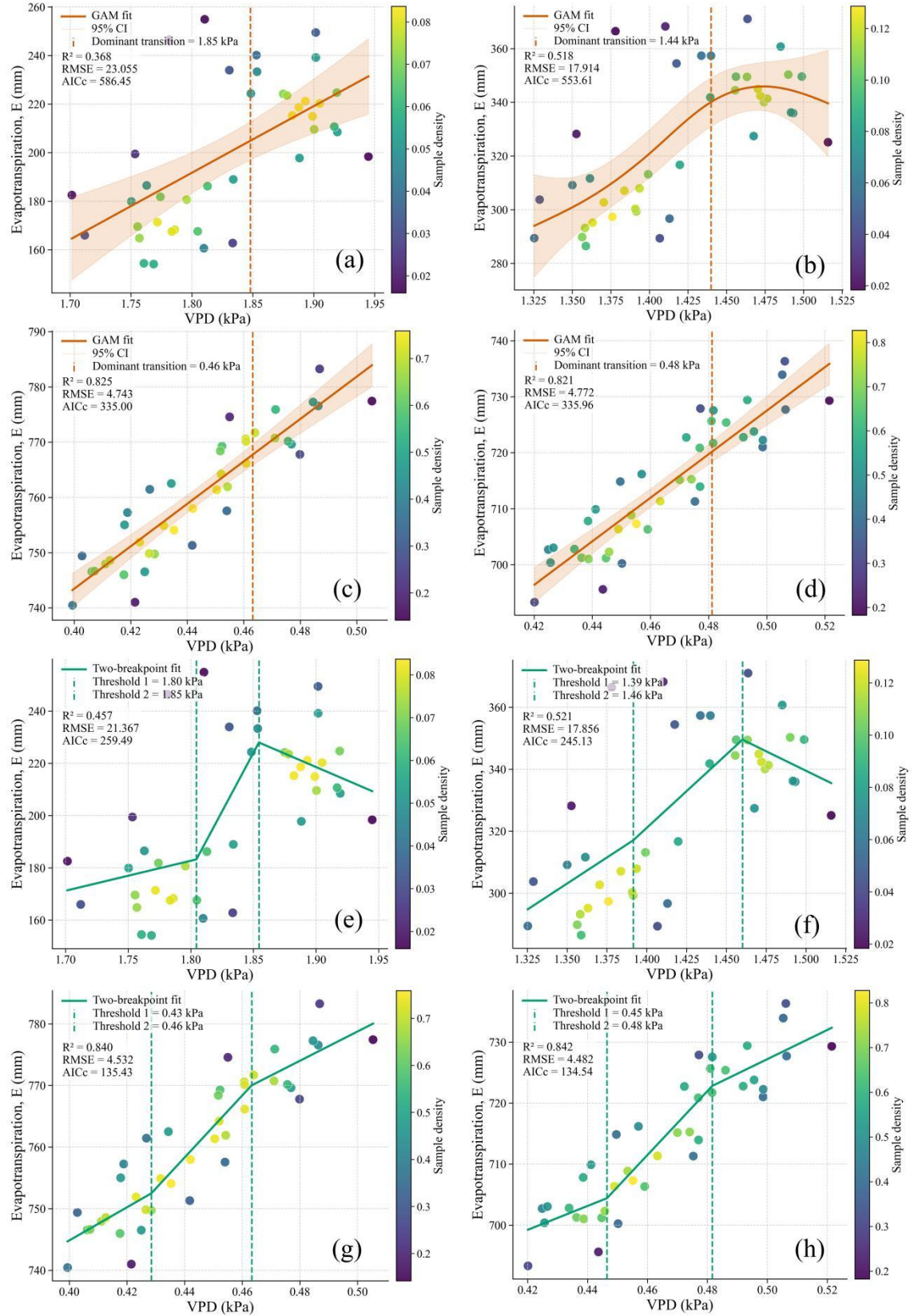


Figure 4. Aridity-dependent thresholds in the nonlinear response of terrestrial evapotranspiration to vapor pressure deficit. a–d, One-breakpoint piecewise fits between VPD and E for the arid,

semi-arid, humid, and semi-humid aridity zones, respectively. Points show annual area-weighted means, coloured by sample density. Solid lines indicate fitted relationships, and dashed vertical lines indicate the estimated VPD transition points. The AI-based aridity zones are shown in Supplementary Fig. 5.



Supplementary Figure 3. Nonlinear threshold responses of terrestrial evapotranspiration to vapor pressure deficit across AI-based aridity zones. Panels a–d show the GAM-based nonlinear responses of terrestrial evapotranspiration (E) to vapor pressure deficit (VPD) in the arid, semi-arid, humid, and semi-humid AI-based aridity zones, respectively. Panels e–h show the corresponding two-breakpoint piecewise fits for the same four AI-based aridity zones in the same order. In each panel, points represent annual area-weighted mean observations for the corresponding climate zone, with color indicating sample density. Solid curves denote the fitted nonlinear relationships, and shaded areas in the GAM panels indicate the 95% confidence intervals of the fitted responses. Vertical dashed lines indicate the estimated threshold locations, defined as the dominant transition point for the GAM and as the two fitted breakpoints for the two-breakpoint piecewise model. Together, these results illustrate the aridity-zone-dependent nonlinear response of E to VPD and provide a robustness check for the threshold estimates reported in the main text.

Response to Reviewer #2

Comment 1: The abstract should better distinguish established knowledge from the novel contribution of this study. Statements that VPD affects evapotranspiration, that soil moisture limitation constrains E in arid regions, and that transpiration is an important pathway are broadly consistent with existing understanding. The main potential contribution of this work is the global quantification of VPD–E sensitivity, regional heterogeneity, and apparent VPD thresholds. The abstract should emphasize this quantitative contribution rather than presenting well-known mechanisms as new findings.

Response: Thank you for this constructive comment. We agree that the previous Abstract did not clearly separate established knowledge from the main contribution of this study. The effects of VPD on evapotranspiration, soil moisture limitation, and transpiration are already known from previous studies. We therefore revised the Abstract to emphasize the quantitative contribution of this work.

The revised Abstract now focuses on three main findings. First, we report the global apparent sensitivity of E to VPD, including the proportion of land areas with positive sensitivity and the global mean sensitivity. Second, we report the component-level difference between transpiration and bare-soil evaporation after controlling for precipitation and soil moisture. Third, we report the aridity-dependent transition points in the apparent VPD–E relationship. We also added the climate-zone-specific SEM result to show that VPD regulates E through linked atmospheric, soil-water, vegetation, and energy pathways.

Revised text in the Abstract:

Abstract: Vapor pressure deficit (VPD) has been widely recognized as a key driver of uncertainty in future global evapotranspiration (E) trends. Accurately characterizing the spatiotemporal dynamics of VPD and elucidating its influence on terrestrial E are critical for understanding land–atmosphere water and energy feedback processes under climate warming. However, previous studies have largely focused on the physiological regulation of plant transpiration (E_t) at the leaf or canopy scale, leaving the quantitative understanding of VPD–E interactions at the global scale incomplete.

By integrating multi-source remote sensing products and reanalysis datasets, this study quantitatively evaluates the role of VPD in regulating global terrestrial E variability. The main findings are as follows: (1) Approximately 60.71% of global land area exhibits positive apparent sensitivity of E to VPD, with a global mean sensitivity of $293.27 \pm 62.28 \text{ mm hPa}^{-1}$, and stronger responses observed in warm and humid regions. (2) VPD is positively correlated with E_t overall, particularly in mid-to-high latitudes of the Northern Hemisphere, whereas its correlation with bare soil evaporation (E_b) is weaker and tends to be negative in water-limited regions. (3) The VPD–E relationship exhibits a pronounced aridity-dependent threshold, which decreases progressively from arid (1.90 kPa) and semi-arid (1.46 kPa) regions to semi-humid (0.49 kPa) and humid (0.47 kPa) regions. Further path analysis reveals that VPD regulates E through interconnected pathways involving atmospheric demand, soil moisture, vegetation physiology, and energy supply, with an overall negative net effect on E. This study clarifies the dominant pathways and regional heterogeneity of VPD–E interactions at the global scale, providing quantitative constraints for predicting the response of the terrestrial water cycle to increasing atmospheric aridity.

Comment 2: The space-for-time moving-window approach is not sufficiently explained. This method can be useful for estimating the local apparent sensitivity of E to VPD, but it relies on strong assumptions: neighbouring pixels must share similar climate, soil, vegetation, topography, and management conditions, and spatial VPD gradients must be a reasonable proxy for temporal VPD changes. The manuscript should clarify how “similar background climate” was defined and whether differences in soil moisture, radiation, elevation, vegetation structure, and land management were controlled.

Response: We agree that the moving-window method required a clearer explanation, especially regarding its assumptions and the definition of comparable background conditions. We have revised Section 2.2.2 to make the method more transparent and to avoid overinterpreting the estimated sensitivity.

In the revised manuscript, we clarify that the moving-window method was used to estimate the apparent local sensitivity of E to VPD, rather than a fully isolated causal effect. We now state that the core assumption is that the target pixel and qualified neighboring pixels share broadly similar background climatic and surface conditions within a local window. We also explain that the estimated $dE/dVPD$ should be interpreted as an apparent local sensitivity because local VPD gradients may still be affected by mesoscale atmospheric dynamics, topography, land-sea contrasts, and other unresolved surface heterogeneity.

We further clarified how the comparable neighboring pixels were selected. All variables were analyzed on a common 0.1° grid. For each target pixel, candidate pixels were selected within a 5×5 grid-cell moving window, corresponding to a $0.5^\circ \times 0.5^\circ$ neighborhood. To reduce the effects of surface heterogeneity, only pixels with the same dominant MODIS land-cover type were retained. The difference in dominant land-cover fraction was required to be less than 10%, and pixels with an elevation difference greater than 100 m from the target pixel were excluded. These criteria were used to make the local comparison pixels more comparable in terms of land-cover background and topographic setting.

We also revised the description of the sensitivity calculation. The manuscript now states that $dE/dVPD$ was estimated from the relationship between E differences and VPD differences between the target pixel and all qualified neighboring pixels. The Theil-Sen slope estimator was used to reduce the influence of skewed samples and outliers. We also added the unit of $dE/dVPD$ and clarified the interpretation of positive and negative values.

These revisions clarify the assumptions, screening criteria, spatial scale, and interpretation of the moving-window method. They also make clear that the resulting $dE/dVPD$ should be treated as an apparent local sensitivity under neighborhood constraints, rather than as a strict causal effect of VPD.

Revised text in the Methods (Section 2.2.2):

2.2.2 Estimation of E Sensitivity to VPD

Due to the complex bidirectional interactions between local background climate

and varying E conditions across different scales, this study adopts a moving window strategy inspired by the “space-for-time” approach to calculate the sensitivity of E to VPD ($dE/dVPD$) (Y. Li et al., 2023). The core assumption of this approach is that the target pixel and qualified neighboring pixels share broadly similar background climatic and surface conditions within a local window. Therefore, spatial differences in E and VPD among these screened pixels can be used to estimate the apparent local sensitivity of E to VPD (Li et al., 2024). This estimate should not be interpreted as a fully isolated causal effect of VPD, because local VPD gradients may still be influenced by mesoscale atmospheric dynamics, topography, land-sea contrasts, and other unresolved surface heterogeneity. To reduce these confounding effects, candidate pixels were retained only when they shared the same dominant MODIS land-cover type as the target pixel, differed by <10% in dominant-type fractional cover, and had an elevation difference of <100 m from the target pixel.

This study applies a spatial moving-window strategy to estimate $dE/dVPD$ values (Zhao and Feng, 2024). All analyses were conducted on a common 0.1° grid, corresponding to the native spatial resolution of both the ERA5-Land VPD data and the GLEAM evaporation data used in this study. For each target pixel, candidate comparison samples were selected from surrounding pixels within a 5×5 grid-cell moving window, i.e., a neighborhood of $0.5^\circ \times 0.5^\circ$ centered on the target pixel. To reduce the influence of surface heterogeneity, only pixels sharing the same dominant land-cover type as the target pixel were retained, and the difference in dominant land-cover fraction was required to be less than 10% according to the MODIS MCD12C1 land-cover product. In addition, pixels with an elevation difference greater than 100 m from the target pixel were excluded to minimize topographic effects. The sensitivity for each target pixel was then estimated from the relationship between E differences and VPD differences between all qualified neighboring pixels and the target pixel. In this procedure, the nonparametric Theil-Sen slope estimator was used to reduce the influence of skewed sample distributions and outliers.

$$slope = median \left(\frac{y_i - y_j}{x_i - x_j} \right) \quad (6)$$

Here x and y indicate the E and VPD differences; i and j are the geolocations of samples within the moving window. The unit of $dE/dVPD$ is mm hPa^{-1} . Positive values indicate that E tends to be higher in locations with higher VPD within the local window, whereas negative values indicate that E tends to be lower in locations with higher VPD. The Theil-Sen slope estimator adopts the median value of a range of possible slopes and is therefore insensitive to statistical outliers.

Comment 3: The spatial scale of the moving window needs to be explained. The authors mention using a 5×5 km window, but this seems quite small relative to the spatial resolution of the input datasets. The manuscript should clarify the final resolution of the analysis and the resampling procedure for each dataset. Sensitivity tests with different window sizes are recommended to demonstrate the robustness of the results.

Response: In the original manuscript, the window size was incorrectly described as “ 5×5 km”. This was a wording error. The moving window used in our analysis was not a 5×5 km window, but a 5×5 grid-cell window on the common 0.1° grid.

We have revised Section 2.2.2 to clarify the final spatial resolution and the actual window size. All variables used in the moving-window calculation were harmonized to a common 0.1° grid. This resolution is consistent with the ERA5-Land VPD data and the GLEAM evapotranspiration data used as the main datasets in this study. For each target pixel, neighboring pixels were selected within a 5×5 grid-cell moving window. This corresponds to a $0.5^\circ \times 0.5^\circ$ local neighborhood centered on the target pixel, rather than a 5×5 km area.

We also clarified the screening procedure for candidate neighboring pixels. Only pixels with the same dominant MODIS land-cover type as the target pixel were retained. The difference in dominant land-cover fraction was required to be less than 10%, and pixels with an elevation difference greater than 100 m from the target pixel were excluded. These criteria were used to reduce the influence of land-cover and topographic differences within the local window.

We acknowledge that testing different window sizes would be useful for further evaluating the robustness of the moving-window estimate. In this revision, we focused on correcting the scale description and clarifying the data harmonization and screening criteria, because the main issue in the previous manuscript was the inaccurate description of the spatial window. We now make clear that $dE/dVPD$ represents a moving-window-based apparent local sensitivity under neighborhood constraints, rather than a strict causal effect or a direct temporal sensitivity.

Revised text in the Methods (Section 2.2.2):

This study applies a spatial moving-window strategy to estimate $dE/dVPD$ values (Zhao and Feng, 2024). All analyses were conducted on a common 0.1° grid, corresponding to the native spatial resolution of both the ERA5-Land VPD data and the GLEAM evaporation data used in this study. For each target pixel, candidate comparison samples were selected from surrounding pixels within a 5×5 grid-cell moving window, i.e., a neighborhood of $0.5^\circ \times 0.5^\circ$ centered on the target pixel. To reduce the influence of surface heterogeneity, only pixels sharing the same dominant land-cover type as the target pixel were retained, and the difference in dominant land-cover fraction was required to be less than 10% according to the MODIS MCD12C1 land-cover product. In addition, pixels with an elevation difference greater than 100 m from the target pixel were excluded to minimize topographic effects.

Comment 4: The abstract states that E increases with rising VPD over 60.7% of the land surface, whereas Section 3.1 states that E decreases in areas where VPD increases, suggesting that atmospheric drying has an inhibitory effect. Section 3.2 then reports that 60.71% of land areas show positive sensitivity. This description is confusing and should be clarified.

Response: We agree that the previous wording was confusing because it mixed two different analyses. Section 3.1 describes the long-term spatial trends of VPD and E during 1981–2020. Section 3.2 reports the moving-window-based apparent local sensitivity of E to VPD. These two analyses describe different quantities and should not be interpreted as the same result.

We revised the Abstract and Results to make this distinction clear. In the Abstract and Section 3.2, we now state that 60.71% of global land areas showed positive apparent sensitivity of E to VPD. In Section 3.1, we describe the spatial overlap between long-term VPD and E trends, rather than treating this pattern as direct evidence of VPD sensitivity. We also revised the wording to avoid over-causal interpretation.

Revised text in the Results (Section 3.1):

By contrast, the trend in terrestrial E was more spatially variable and weaker in overall coherence (Fig. 1d-f). Increases in E were mainly observed in East Asia, northern Europe, and some high-latitude regions, whereas declines were concentrated in Africa, central South America, southwestern North America, and eastern Australia (Fig.1d). The corresponding monthly and anomaly series indicate strong seasonal variability but only a modest long-term increase in global mean E (Fig. 1e, f). Compared with VPD, the E anomaly series showed larger year-to-year fluctuations, especially after 2000 (Fig. 1f). Taken together, areas with rapid VPD increases often coincided with declining E, particularly in water-limited regions. This pattern describes the spatial overlap between long-term VPD and E trends. In contrast, at higher latitudes, where VPD increased only weakly, E generally increased.

Comment 5: Figure 1 is difficult to interpret. The colorbars in panels (a) and (b) should clearly indicate the variable, unit, and sign convention. The text states that significant increases in VPD cover 76.22% of the land surface, but the figure does not clearly distinguish significant from non-significant trends. Hatching, stippling, or a separate significance panel should be added. I also suggest revising the colorbars so that decreases and increases are clearly represented by blue and red, respectively, with zero set as the midpoint.

Response: We have revised Figure 1 to improve its readability. In the revised figure, the trend maps are shown in panels a and d. The colorbars now indicate the variables and units. We also revised the color scheme so that blue indicates decreasing trends, red indicates increasing trends, and zero is set as the midpoint of the colorbar.

We added hatching to show areas where the trends are statistically significant at $p < 0.05$. This makes the significant and non-significant regions easier to distinguish. The figure insets now show the percentage of valid land pixels with positive and negative trends. These percentages describe the direction of the Sen's slope, not the percentage of significant trends. We also revised the manuscript text to avoid confusing positive trend area with significant trend area.

Revised text in the Figure (Section 3.1):

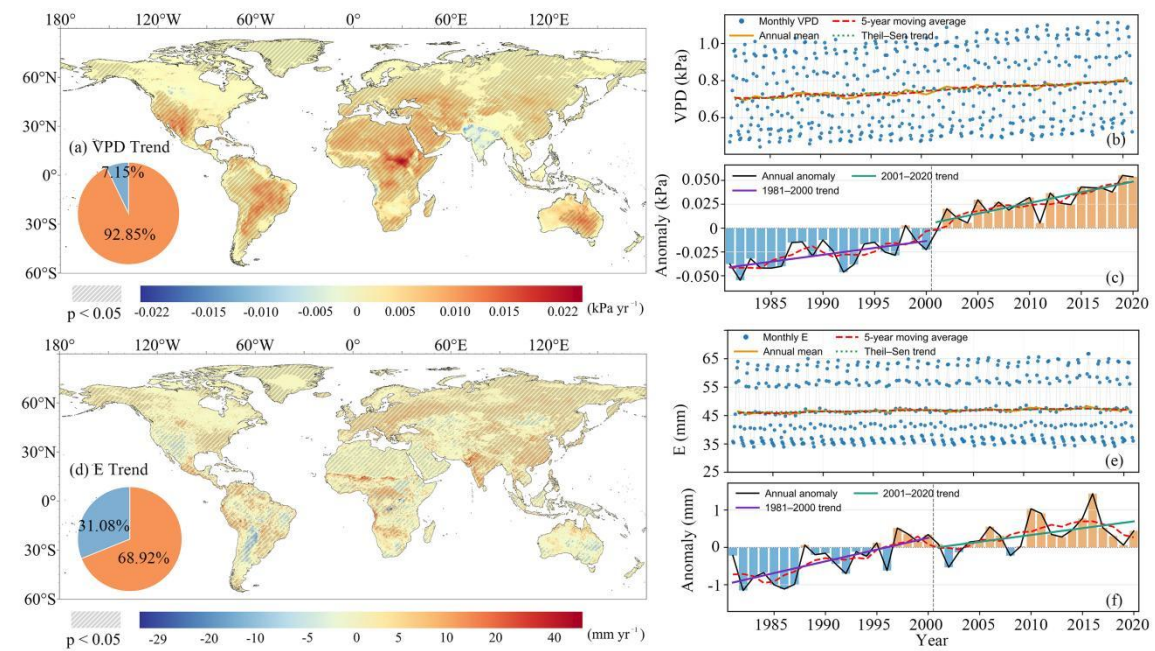


Figure 1. Spatiotemporal changes in terrestrial VPD and E during 1981-2020. a, Sen's slope of VPD. Red colors indicate increasing trends, and blue colors indicate decreasing trends. Hatched areas indicate trends significant at $P < 0.05$. The inset shows the percentage of valid land pixels with positive and negative VPD trends. b, monthly global mean VPD, with annual mean, 5-year moving average and Theil-Sen trend. c, annual VPD anomalies relative to 1981-2020, with the 5-year moving average and piecewise linear trends for 1981-2000 and 2001-2020. d, Sen's slope of terrestrial E. Red colors indicate increasing trends, and blue colors indicate decreasing trends. Hatched areas indicate trends significant at $P < 0.05$. The inset shows the percentage of valid land pixels with positive and negative E trends. e, monthly global mean E, with annual mean, 5-year moving average and Theil-Sen trend. f, annual E anomalies relative to 1981-2020, with the 5-year moving average and piecewise

linear trends for 1981–2000 and 2001–2020. In the insets, orange indicates positive trends and blue indicates negative trends.

Comment 6: Figure 2b is particularly confusing. A large fraction of samples appears to fall between approximately -7 and -28 °C. While such temperatures may occur in high-latitude or high-elevation regions, their dominance raises concerns that cold, ice-covered, tundra, or very low-E regions may be overrepresented. The precipitation range also appears too low if it represents annual precipitation; humid and tropical regions commonly exceed 300 mm yr⁻¹. The authors should clarify whether the axes show annual means or monthly values, whether each point represents a grid cell or a grid cell–month sample, whether area weighting was applied, and whether permanent ice/snow, barren, or very low-LAI regions were excluded.

Response: We agree that the previous Figure 2b was confusing. The precipitation range was too narrow, and the sample definition was not clearly explained. We have revised Figure 2b and its caption to make the climate-gradient analysis clearer.

In the revised Figure 2b, the x-axis represents mean annual precipitation during 1981–2020, and the y-axis represents mean annual air temperature during 1981–2020. The precipitation data were converted to mean annual precipitation before binning. We also expanded the precipitation range from the previous 0–300 mm yr⁻¹ to 0–2000 mm yr⁻¹. Pixels with precipitation greater than 2000 mm yr⁻¹ were included in the last precipitation bin. This revision avoids excluding humid and tropical regions from the climate-gradient analysis.

We also clarified the sample definition. Each sample in Figure 2b represents one valid land pixel, not a grid cell–month sample. For each temperature–precipitation bin, the color represents the area-weighted mean dE/dVPD. Area weighting was applied using latitude-based weights to reduce the overrepresentation of high-latitude pixels. In the revised analysis, 5,650,488 valid land pixels were included. Pixels between -28 °C and -7 °C accounted for about 17.2% of the valid pixels, so this temperature range did not dominate the revised binning.

We did not apply an additional low-LAI filter in this revision. Barren land was also not removed, because it was retained as a separate land-use class in Figure 2c. To avoid overstatement, we now describe the samples in Figure 2b as valid land pixels and clarify the binning procedure in the figure caption. We also revised the text in Section 3.2 to focus on the climatic dependence of $dE/dVPD$, rather than implying that cold or low-E regions dominated the result.

Revised text in the Results (Section 3.2):

The climatic dependence of $dE/dVPD$ is shown in Fig. 2b. Negative or weak sensitivity occurred mainly under dry climate conditions, especially in warm and low-precipitation bins, whereas positive sensitivity became more widespread in wetter bins and in many cool-to-temperate bins. Overall, the apparent VPD–E relationship varied strongly along temperature and precipitation gradients, but the pattern did not indicate a simple response to temperature alone.

Revised Figure 2:

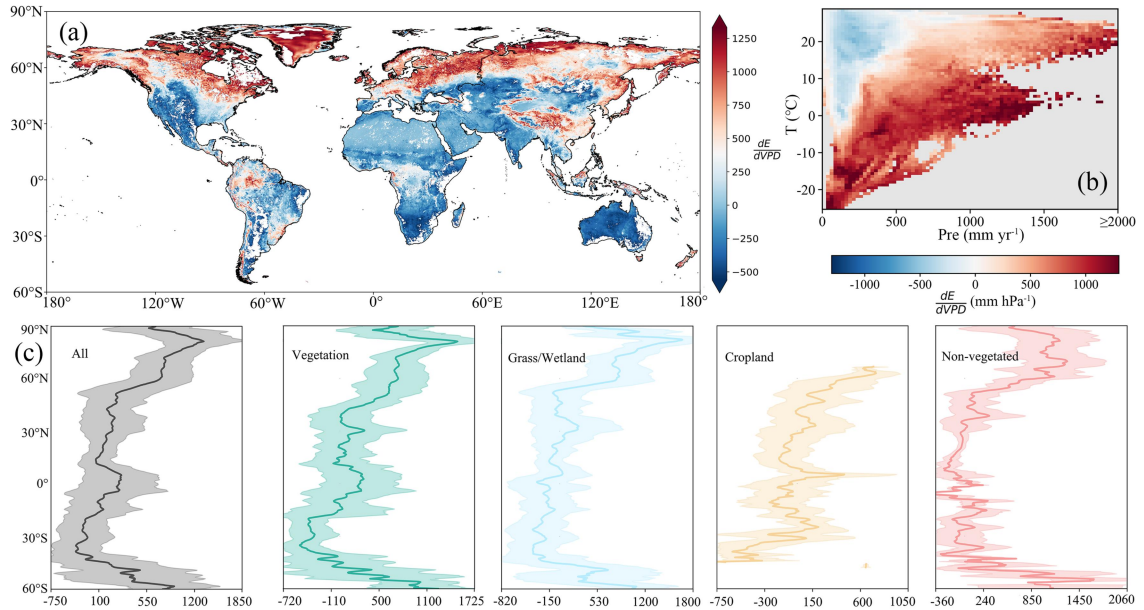


Figure 2. Apparent sensitivity of terrestrial evapotranspiration (E) to vapor pressure deficit (VPD) during 1981-2020. (a) Spatial distribution of the sensitivity coefficient $dE/dVPD$. Red colors indicate positive apparent sensitivity, and blue colors indicate negative apparent sensitivity. (b) Variation in $dE/dVPD$ across climate gradients. The x-axis represents mean annual precipitation during 1981-2020, and the y-axis

represents mean annual air temperature during 1981–2020. Each climate bin contains valid land pixels within a given T-Pre range, and the color shows the area-weighted mean $dE/dVPD$. Values with precipitation greater than 2000 mm yr⁻¹ were included in the last precipitation bin. (c) Latitudinal distribution of $dE/dVPD$ across different land-use classes, with shaded areas representing the standard deviation within each latitude band. The unit of $dE/dVPD$ is mm hPa⁻¹.

Comment 7: Some explanations in the Results section, particularly lines 284–287, are not fully supported. In addition, the threshold results are unclear. Line 333 mentions that the arid-zone threshold is about 1.31 kPa, lines 337–338 refer to “temperate zones” with values of 1.67–1.68 kPa, and lines 406–409 again mention “arid regions” with values of 1.67–1.68 kPa. These inconsistencies should be corrected.

Response: We agree that the previous version contained two issues: some explanations in the Results section were too interpretive, and the threshold values were not reported consistently across the manuscript.

First, we revised the Results section to avoid unsupported mechanistic wording. In the previous version, the text around Lines 284–287 interpreted the land-use differences as evidence that higher VPD was more likely to stimulate E in densely vegetated regions. We agree that this statement was too strong for the Results section. In the revised Section 3.2, we now describe only the observed patterns in apparent sensitivity across land-use classes. We also changed the wording to emphasize association under the moving-window estimate rather than a direct causal stimulation. The revised text now states that forests showed the strongest sensitivity, followed by grasslands and wetlands, barren areas, and croplands, and that higher local VPD tended to be associated with higher E in densely vegetated regions under the moving-window estimate.

Second, we corrected the inconsistent threshold values throughout the manuscript. The previous manuscript mixed different classification schemes, including Köppen–Geiger AI-based aridity zones and aridity-based classes. This led

to inconsistent values, such as the arid-zone threshold of 1.31 kPa, the temperate-zone threshold of 1.67–1.68 kPa, and the later description of 1.67–1.68 kPa as an arid-region threshold. We have removed these inconsistent values from the revised manuscript.

In the revised manuscript, we use one consistent framework based on AI-based aridity zones. The threshold results are now reported as follows: arid zone, 1.90 kPa; semi-arid zone, 1.46 kPa; semi-humid zone, 0.49 kPa; and humid zone, 0.47 kPa. These values are reported consistently in the Abstract, Results, Discussion, and Conclusion.

We also revised the structure of the manuscript to make the threshold results clearer. A new Results subsection, Section 3.4 “Threshold Effects and the Universality of Nonlinearity,” now presents the nonlinear VPD–E thresholds directly. In this section, we compare the one-breakpoint piecewise model, the two-breakpoint piecewise model, and the GAM. The one-breakpoint model was used for the main threshold estimates because the two-breakpoint model did not show a clear improvement in model fit across the four aridity zones based on ΔAICc values. The GAM curves showed similar nonlinear transition behavior, supporting the stability of the one-breakpoint estimates.

Finally, we revised the Discussion to avoid repeating inconsistent threshold values and to focus on the ecohydrological meaning of the aridity-dependent thresholds. The revised Section 4.1 now interprets the thresholds as dominant transition points in the observed VPD–E relationship, rather than as fixed ecological limits. This revision prevents overinterpretation and makes the threshold analysis internally consistent.

Revised text in the Discussion (Section 4.1):

4.1 Ecohydrological Meaning of Aridity-Dependent VPD Thresholds

The aridity-dependent thresholds suggest that the VPD – E relationship is jointly shaped by atmospheric demand and land water supply. VPD can enhance E by increasing atmospheric water demand, but this effect depends on whether enough water is available for evaporation and transpiration. When soil water becomes limited,

higher VPD may no longer increase E. Instead, it may strengthen atmospheric drying and reduce available water.

In arid and semi-arid regions, the higher thresholds indicate that the main transition in the VPD-E relationship occurs only under stronger atmospheric demand. This pattern is consistent with the fact that E in drylands is often limited by water supply before atmospheric demand becomes dominant. Therefore, dry regions may show weak or negative E responses to VPD when water limitation increases. Previous studies also showed that dryland aridity changes are controlled by multiple interacting factors, including precipitation, soil moisture, vegetation activity, and atmospheric demand, rather than by VPD alone (Lian et al., 2021). In humid and semi-humid regions, the lower thresholds indicate that the VPD-E relationship can shift at lower VPD levels. These regions usually have more available water, so E can respond more directly to atmospheric demand. However, this response may weaken after the transition point because vegetation regulation and declining near-surface moisture can limit further water loss. Vegetation responses to climate also vary across hydroclimatic conditions, especially in humid, warm, and forested ecosystems (Gao et al., 2024). Thus, the thresholds identified here should be viewed as dominant transition points in the observed VPD-E relationship, not as fixed ecological limits. Their values may vary with vegetation type, soil water storage, climate background, and data product.

Comment 8: Piecewise regression and GAM are major components of the study, yet their results are mainly presented and interpreted in the Discussion. The Results section should include a clear subsection on nonlinear VPD thresholds, including model fits, threshold estimates, uncertainty ranges, and differences between methods. The Discussion should then focus on the ecohydrological interpretation of these thresholds.

Response: Thank you for this constructive suggestion. We agree that the nonlinear threshold analysis is an important part of the study and should be presented as a main result, rather than being embedded mainly in the Discussion. We have therefore

reorganized the manuscript to make the role of the piecewise regression and GAM analyses clearer.

The main revision is that we moved the threshold analysis into a new Results subsection, Section 3.4, entitled “Threshold Effects and the Universality of Nonlinearity.” This subsection now reports the nonlinear VPD–E relationship across AI-based aridity zones. It describes the comparison among the one-breakpoint piecewise model, the two-breakpoint piecewise model, and the GAM. The one-breakpoint model was retained for the main threshold estimates because the two-breakpoint model did not show a clear improvement in model fit across the four aridity zones, based on ΔAICc values. The GAM curves showed similar nonlinear transition behavior and were used as an independent check of the stability of the threshold estimates.

The revised Results section also reports the threshold estimates using a single aridity-based framework. The dominant transition point was highest in the arid zone (1.90 kPa), followed by the semi-arid zone (1.46 kPa), while much lower thresholds were found in the semi-humid zone (0.49 kPa) and humid zone (0.47 kPa). This presentation makes the threshold pattern clearer and avoids mixing different classification systems.

Regarding uncertainty, we clarified the interpretation of the threshold estimates. We did not calculate formal bootstrap confidence intervals, so we did not add unsupported numerical confidence ranges. Instead, we used the consistency among the one-breakpoint model, two-breakpoint model, and GAM as a model-based robustness check. We also state that the thresholds should be interpreted as dominant transition points in the observed nonlinear VPD–E relationship, rather than as fixed ecological limits.

Following this reorganization, the Discussion no longer mainly reports model-fitting results. We added a new Section 4.1, “Ecohydrological Meaning of Aridity-Dependent VPD Thresholds,” to interpret the threshold pattern from an ecohydrological perspective. This section focuses on how atmospheric demand and land water supply may jointly shape the higher thresholds in arid and semi-arid

regions and the lower thresholds in humid and semi-humid regions. Thus, the revised manuscript now separates the statistical threshold results from their ecohydrological interpretation.

Revised text in the Results (Section 3.4):

3.4 Threshold Effects and the Universality of Nonlinearity

The nonlinear relationship between VPD and E varied clearly across AI-based aridity zones (Fig. 4). We compared the one-breakpoint piecewise model, the two-breakpoint piecewise model, and the GAM to identify the dominant transition points in the VPD–E relationship. The one-breakpoint model was used for the main threshold estimates because the two-breakpoint model did not show a clear improvement in model fit across the four aridity zones, based on ΔAICc values (Supplementary Figs. 3 and 4). The GAM curves also showed similar nonlinear transition behavior, which supports the stability of the one-breakpoint estimates.

The estimated thresholds showed a clear aridity gradient. The dominant transition point was highest in the arid zone (1.90 kPa), followed by the semi-arid zone (1.46 kPa). The thresholds were much lower in the semi-humid zone (0.49 kPa) and humid zone (0.47 kPa). These results show that the VPD–E relationship reached its main transition at higher VPD in dry regions but at lower VPD in wetter regions. Therefore, the thresholds reported here should be interpreted as dominant transition points in the observed nonlinear relationship, not as fixed ecological limits. The model comparison among the one-breakpoint model, two-breakpoint model, and GAM was used as a robustness check for the threshold estimates.

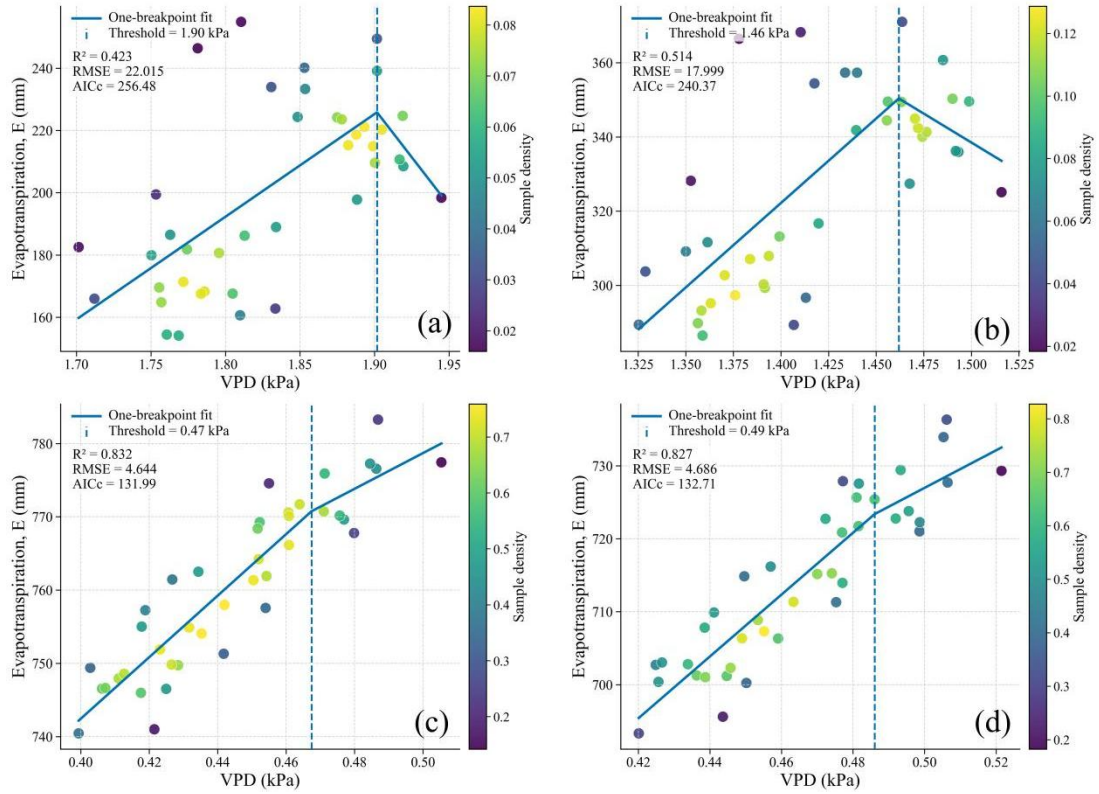


Figure 4. Aridity-dependent thresholds in the nonlinear response of terrestrial evapotranspiration to vapor pressure deficit. a-d, One-breakpoint piecewise fits between VPD and E for the arid, semi-arid, humid, and semi-humid AI-based aridity zones, respectively. Points show annual area-weighted means, coloured by sample density. Solid lines indicate fitted relationships and dashed vertical lines indicate the estimated VPD thresholds. The AI-based aridity zones based on the AI index are shown in the supplementary Figure 5.

Revised text in the Discussion (Section 4.1):

4.1 Ecohydrological Meaning of Aridity-Dependent VPD Thresholds

The aridity-dependent thresholds suggest that the VPD – E relationship is jointly shaped by atmospheric demand and land water supply. VPD can enhance E by increasing atmospheric water demand, but this effect depends on whether enough water is available for evaporation and transpiration. When soil water becomes limited, higher VPD may no longer increase E. Instead, it may strengthen atmospheric drying and reduce available water.

In arid and semi-arid regions, the higher thresholds indicate that the main

transition in the VPD-E relationship occurs only under stronger atmospheric demand. This pattern is consistent with the fact that E in drylands is often limited by water supply before atmospheric demand becomes dominant. Therefore, dry regions may show weak or negative E responses to VPD when water limitation increases. Previous studies also showed that dryland aridity changes are controlled by multiple interacting factors, including precipitation, soil moisture, vegetation activity, and atmospheric demand, rather than by VPD alone (Lian et al., 2021). In humid and semi-humid regions, the lower thresholds indicate that the VPD-E relationship can shift at lower VPD levels. These regions usually have more available water, so E can respond more directly to atmospheric demand. However, this response may weaken after the transition point because vegetation regulation and declining near-surface moisture can limit further water loss. Vegetation responses to climate also vary across hydroclimatic conditions, especially in humid, warm, and forested ecosystems (Gao et al., 2024). Thus, the thresholds identified here should be viewed as dominant transition points in the observed VPD-E relationship, not as fixed ecological limits. Their values may vary with vegetation type, soil water storage, climate background, and data product.

Comment 9: The SEM analysis needs clearer reasoning and explanation. As I understand it, the model suggests that changes in VPD can explain 66% of the variation in LAI. I am skeptical that this reflects a direct effect of VPD on LAI; it may instead reflect spatial climate gradients or seasonal changes. High VPD does not necessarily promote leaf area development; it usually imposes atmospheric water stress. This pathway may simply indicate that warmer, more productive regions have both higher VPD and higher LAI. The authors should test the SEM using deseasonalized anomalies, climate-zone-specific models, and additional control variables such as radiation, soil moisture, vegetation type, and growing-season length. Also, what do the red lines in Figure 5 represent?

Response: We thank the reviewer for this important comment. We agree that the original SEM description was not clear enough, especially for the interpretation of the

VPD–LAI pathway. We also agree that a positive VPD–LAI path should not be interpreted as evidence that higher VPD directly promotes leaf area development. High VPD usually represents atmospheric water stress, and its relationship with LAI may be affected by climate background, radiation, soil water conditions, and seasonal vegetation activity.

To address this concern, we revised the SEM analysis and its explanation in the manuscript. First, we changed the SEM from a single global model to aridity-zone-specific SEMs for arid, semi-arid, semi-humid, and humid regions. This reduced the influence of broad spatial climate gradients. Second, we used monthly deseasonalized standardized anomalies for the SEM analysis. Specifically, we removed the 1982–2020 climatological monthly mean from each monthly time series and then standardized the deseasonalized anomalies using z-scores. This step was used to reduce the influence of the seasonal cycle. Third, we included additional climatic and ecohydrological controls in the SEM, including air temperature (T), precipitation (Pre), surface solar radiation (SR), root-zone soil moisture (SMrz), LAI, VPD, and E. In this revised structure, SR represents the radiation control, and SMrz represents the water-supply control.

We also clarified the interpretation of the VPD–LAI path. In the revised SEM, a restricted model excluding the direct statistical association between VPD and LAI was first tested. Directed-separation tests showed that a residual VPD–LAI association remained after controlling for SMrz, T, Pre, and SR. Therefore, this association was retained in the final SEM. However, we now explicitly interpret it as a statistical control pathway, not as direct physiological evidence that elevated VPD promotes LAI development. We also clarified in the Discussion that the positive remaining relationship between VPD and LAI in wetter regions is more likely to reflect residual co-variation among atmospheric dryness, radiation, temperature, and vegetation activity after soil water and climatic factors are controlled.

We also clarify that the R^2 value shown for LAI does not mean that VPD alone explains that proportion of LAI variation. The R^2 value represents the variance explained by all predictors in the LAI submodel, including VPD, SMrz, T, Pre, and

SR. Therefore, it should not be read as the explanatory power of the single VPD–LAI pathway.

Regarding vegetation type and growing-season length, we did not include them as separate monthly predictors in the SEM because the revised SEM was fitted to monthly regional-mean deseasonalized anomalies within each climate zone. Vegetation type and growing-season length mainly describe spatial or seasonal background differences rather than monthly anomaly dynamics in this SEM framework. We reduced their potential influence by using climate-zone-specific models and by removing the climatological monthly cycle. In addition, land-cover information was used in the moving-window sensitivity analysis to reduce surface heterogeneity.

Finally, we clarified the meaning of the line colors in Figure 5. Red arrows indicate negative standardized path coefficients, while black arrows indicate positive standardized path coefficients. Solid arrows indicate significant pathways, and dashed arrows indicate non-significant pathways.

Revised text in the Discussion (Section 4.2):

4.2 Mechanisms of VPD Regulation of E Under Multi-Factor Coupling

The climate-zone-specific SEM results show that VPD affects terrestrial E through linked atmospheric, soil-water, vegetation, and energy pathways. This effect does not only represent higher atmospheric water demand. It also depends on soil water supply, canopy state, and energy conditions. The SEM structure was built from known ecohydrological processes. The estimated paths were generally consistent with this process basis. VPD was negatively related to SM_{tz} in all AI-based aridity zones, with standardized coefficients of -0.25 , -0.61 , -0.66 , and -0.53 in arid, semi-arid, semi-humid, and humid regions, respectively (Fig. 5a-d). SM_{tz} and LAI were generally positively related to E. These results suggest that soil water supply and canopy condition are important links between atmospheric drying and actual evapotranspiration. The SEM results should still be read as climate-zone-scale statistical pathways. They do not prove pixel-level causal effects. The restricted and full SEM comparison also supported the retention of the residual VPD-LAI

association in the final model (Supplementary Table S1).

The direct effect of VPD on E differed clearly among AI-based aridity zones. The effect was strongest and negative in arid regions (standardized coefficient = -0.79 ; Fig. 5a). It was also strongly negative in semi-arid regions (standardized coefficient = -0.55 ; Fig. 5b). The effect became weak and non-significant in semi-humid regions (standardized coefficient = -0.06 ; Fig. 5c). The effect was weaker but still negative in humid regions (standardized coefficient = -0.23 ; Fig. 5d). This pattern suggests that the remaining direct VPD path mainly reflects atmospheric drying stress and stomatal regulation after T, Pre, SR, SM_{rz} , and LAI are included in the model. This path should not be read only as the effect of higher evaporative demand (M. Wang et al., 2025). In water-limited regions, higher VPD can increase atmospheric water demand and also increase plant and soil water stress. These combined effects can reduce actual E when soil water is limited. Previous studies also reported that E responses to VPD depend on soil moisture, plant water regulation, and background dryness (Massmann et al., 2019; Zhang et al., 2023).

The effect decomposition further supports this climate-dependent mechanism (Supplementary Fig. 6). The total effect of VPD on E was negative in all AI-based aridity zones. The negative effect was strongest in arid and semi-arid regions (standardized total effect = -0.96 and -0.69). The effect was much weaker in semi-humid and humid regions (standardized total effect = -0.06 and -0.14). The overall indirect effect of VPD on E also varied among AI-based aridity zones. It was negative in arid, semi-arid, and semi-humid regions (standardized indirect effect = -0.17 , -0.14 , and -0.01), but it became positive in humid regions (standardized indirect effect = 0.08). This positive indirect effect in humid regions likely reflects compensation from LAI-related and energy-related pathways. LAI had positive effects on E in all AI-based aridity zones, especially in semi-humid and humid regions (standardized coefficient = 0.50 and 0.38 ; Fig. 5c,d). However, the positive remaining relation between VPD and LAI in wetter regions should not be read as evidence that higher VPD directly promotes vegetation growth (Yuan et al., 2019). It more likely reflects remaining co-variation among atmospheric dryness, radiation, temperature,

and vegetation activity after soil water and climate factors are controlled (Zhang et al., 2021). Overall, VPD regulation of E is climate dependent. Its main mechanism lies in the joint effects of higher atmospheric water demand, limited soil water supply, canopy state, and energy conditions.

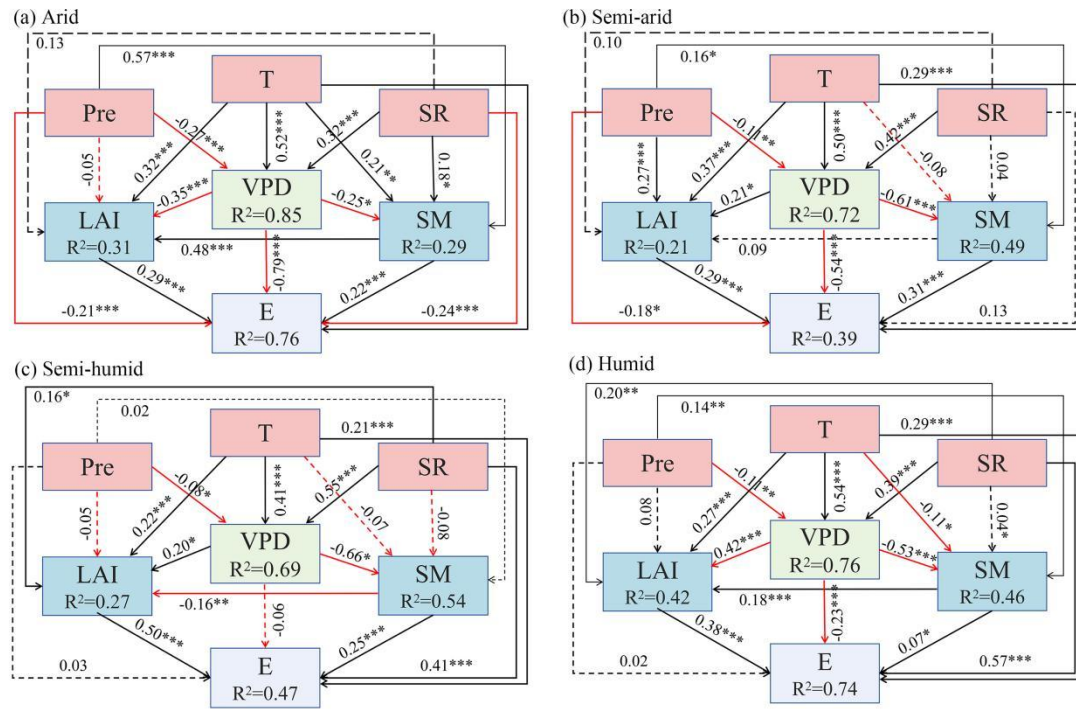
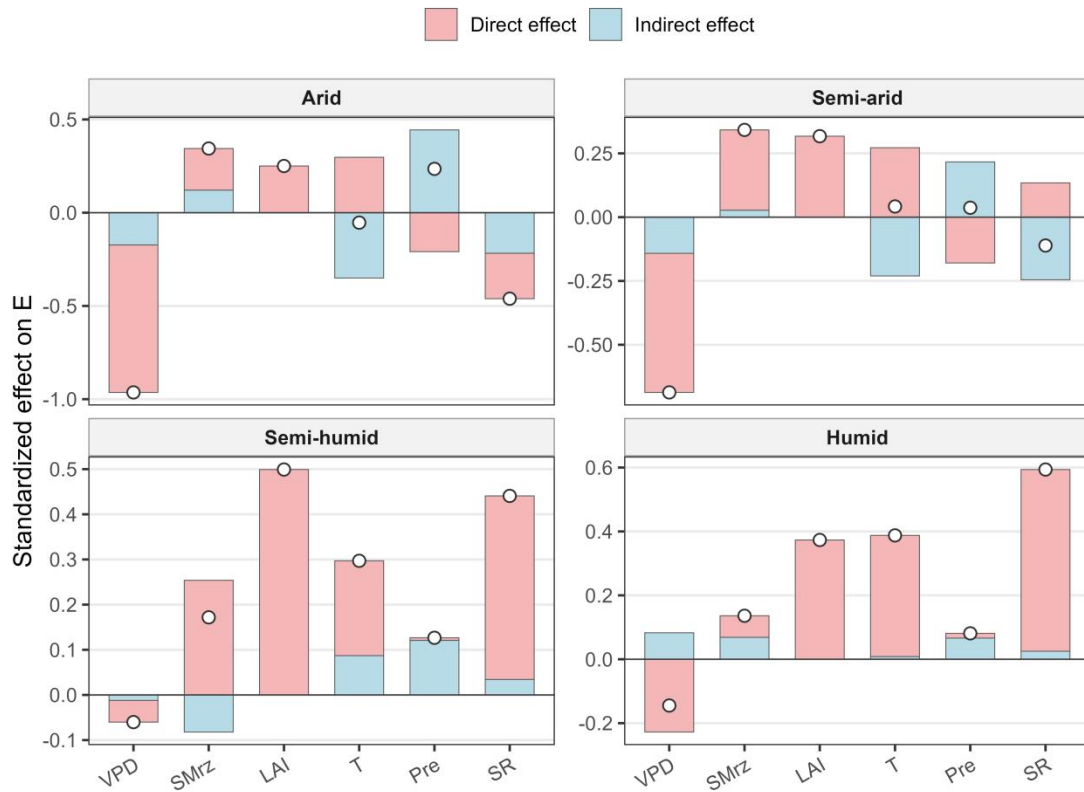


Figure 5. Climate-zone-specific structural equation models showing the pathways linking VPD and E under different hydroclimatic conditions. Panels show the SEM results for (a) arid, (b) semi-arid, (c) semi-humid, and (d) humid regions. Numbers on arrows indicate standardized path coefficients. Red and black arrows denote negative and positive path coefficients, respectively.

Solid and dashed arrows indicate significant and non-significant pathways, respectively.

Significance levels are denoted as $p < 0.05$, $p < 0.01$, and $p < 0.001$. R² values inside the boxes indicate the proportion of variance explained for each endogenous variable. Pre, precipitation; T, air temperature; SR, surface solar radiation; VPD, vapor pressure deficit; LAI, leaf area index; SM, root-zone soil moisture; E, evapotranspiration. The residual association between VPD and LAI was retained as a statistical control pathway and should not be interpreted as direct physiological evidence that elevated VPD promotes LAI development.



Supplementary Fig. 6. Decomposition of direct, indirect, and total effects on evapotranspiration across AI-based aridity zones. The figure shows the standardized effects of each predictor on E in the full aridity-zone-specific SEMs. Panels show results for (a) arid, (b) semi-arid, (c) semi-humid, and (d) humid regions. Pink bars represent direct effects, and blue bars represent indirect effects mediated through other variables in the SEM. White circles represent total effects, calculated as the sum of direct and indirect effects. The y-axis shows the standardized effect on E. VPD, vapor pressure deficit; SMrz, root-zone soil moisture; LAI, leaf area index; T, air temperature; Pre, precipitation; SR, surface solar radiation; E, evapotranspiration.

Additional revisions

In addition to the revisions made in response to the specific comments of the two reviewers, we also made several additional revisions to improve the rigor, clarity, and internal consistency of the manuscript. These changes were not linked to a single reviewer comment, but they were necessary for making the revised manuscript more focused and easier to understand.

First, we removed the analysis of canopy interception from Section 3.3. The main reason is that the mechanisms linking VPD to transpiration and bare-soil evaporation are relatively well established, whereas the influence of VPD on canopy interception is less direct and more difficult to interpret mechanistically. Canopy

interception is mainly controlled by canopy structure, precipitation amount, and rainfall intensity. Therefore, a statistical relationship between VPD and interception may not necessarily indicate a clear physical mechanism. To avoid overinterpretation, we focused Section 3.3 on transpiration and bare-soil evaporation, for which the physical and ecohydrological interpretations are more robust. Second, we detrended the data used in Section 3.3 before conducting the partial correlation analysis. This revision allows the results to better reflect interannual covariation rather than shared long-term trends. We also added significance markers in Figure 3 to indicate correlations significant at $p < 0.05$. Third, we improved the description of Figure 2. We added the units of the variables shown in the figure and revised the figure caption to clarify the meaning of the axes and the unit of $dE/dVPD$. These changes make the climate-gradient analysis easier to interpret and reduce ambiguity about whether the variables represent annual or monthly quantities. Fourth, we removed some overly specific regional descriptions from the Results section, such as references to southern China and the eastern United States. These regional examples were not essential for the main argument and could distract from the global-scale patterns. We therefore revised the text to use broader and more cautious regional descriptions, such as northern extratropical regions, East Asia, Europe, and water-limited regions. This change helps avoid overinterpretation of local patterns while keeping the focus on the global spatial heterogeneity of the VPD–E relationship. Fifth, we added the official citation for ERA5-Land to improve the completeness of the data-source description. Finally, we added supplementary maps showing the spatial distributions of land-cover types and AI-based AI-based aridity zones. These maps provide useful background information for interpreting the spatial heterogeneity of the VPD–E relationship.