

Supplementary Material for

Drought thresholds shape divergent responses in ecosystem water use efficiency

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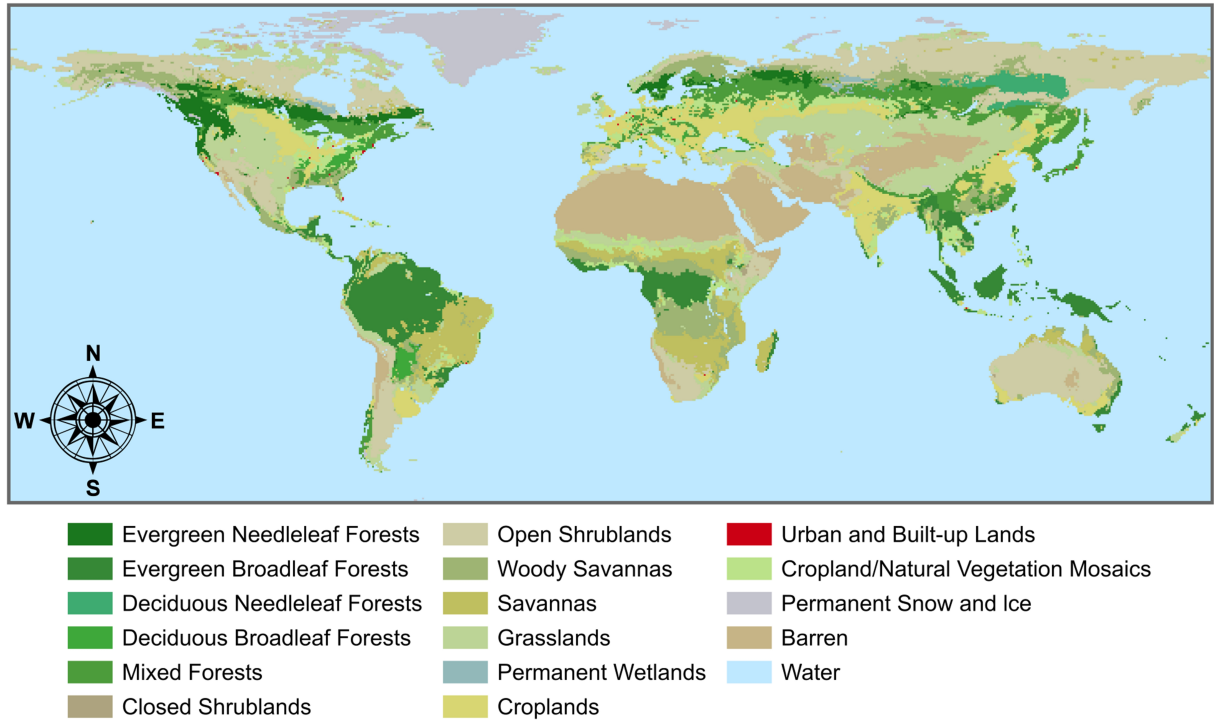


Figure S1.

Land cover and land use types derived from the MCD12Q1 IGBP product. Vegetation types are abbreviated as DBF (deciduous broadleaf forest), EBF (evergreen broadleaf forest), DNF (deciduous needleleaf forest), ENF (evergreen needleleaf forest), MF (mixed forest), GRA (grassland), SAV (savanna), SHR (shrubland), and CRO (cropland).

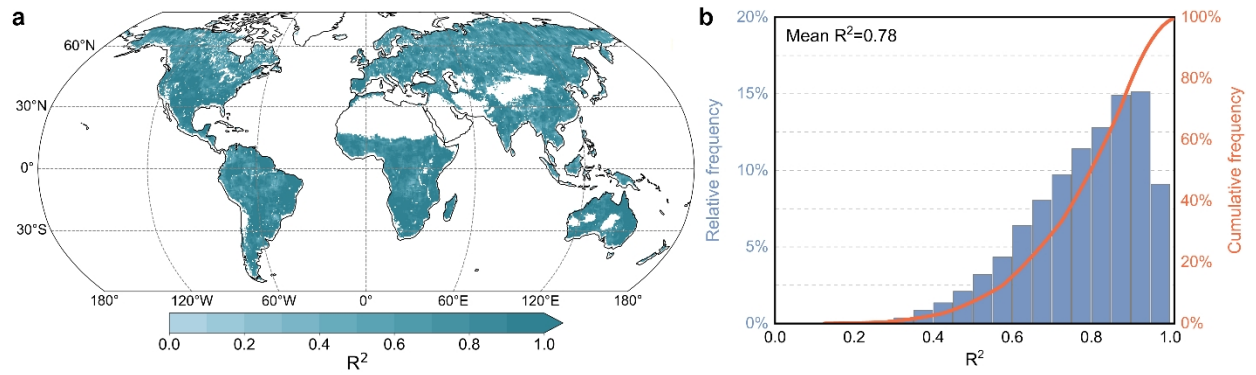


Figure S2.

Performance of the optimal model used for response pattern classification. (a) Spatial distribution of R^2 values for the optimal-fit models (either GAM or piecewise linear regression) across the globe. (b) Histogram and cumulative frequency distribution of global R^2 values. The global mean R^2 is 0.78.

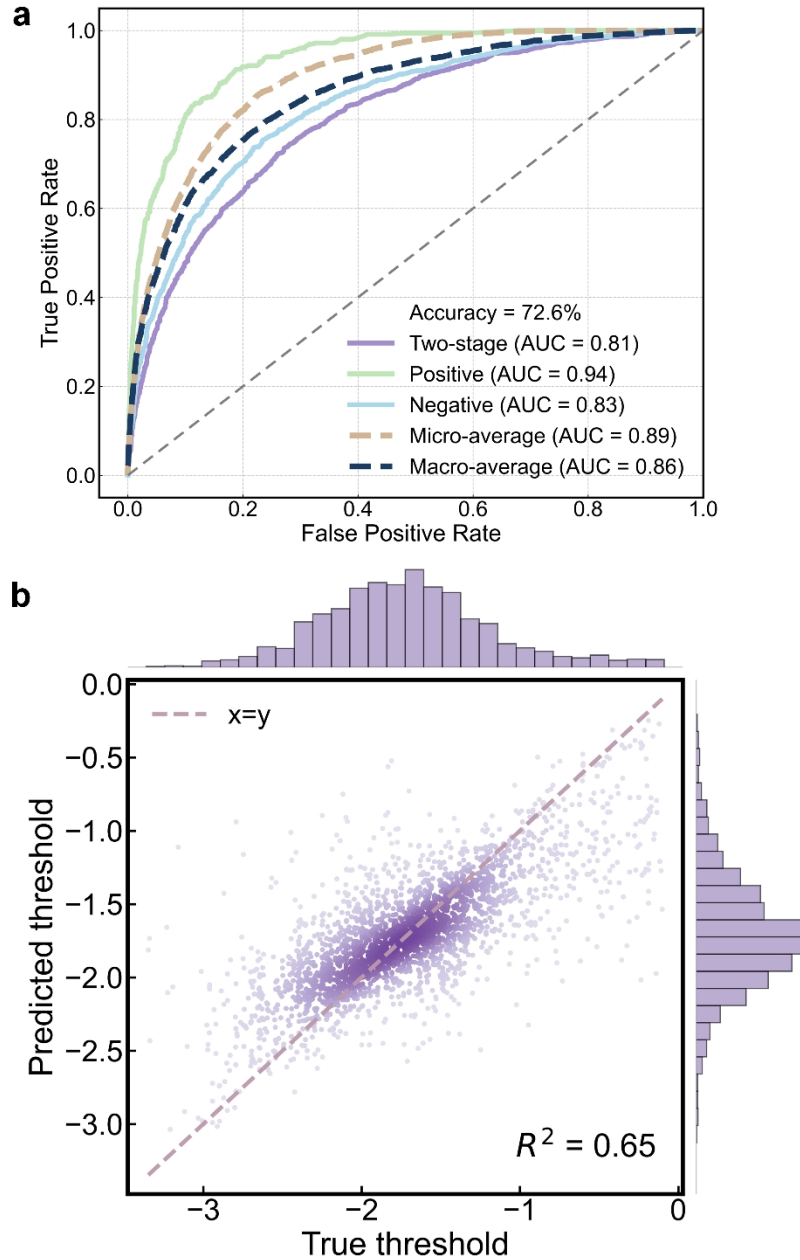


Figure S3.

Performance of the final Deep Forest models. (a) Performance of the Deep Forest classification model for identifying WUE response pattern types. The Receiver Operating Characteristic (ROC) curves indicate model performance, with curves closer to the top-left corner and higher Area Under the Curve (AUC) values representing better classification performance. The model achieved an accuracy of 72.6%. (b) Performance of the Deep Forest regression model for predicting the threshold values of the two-stage response pattern. The scatter points represent the corresponding predicted and true thresholds, and the dark purple area indicates the high point density. The marginal

histograms show the frequency distributions of observed and predicted thresholds. The coefficient of determination (R^2) reached 0.65.

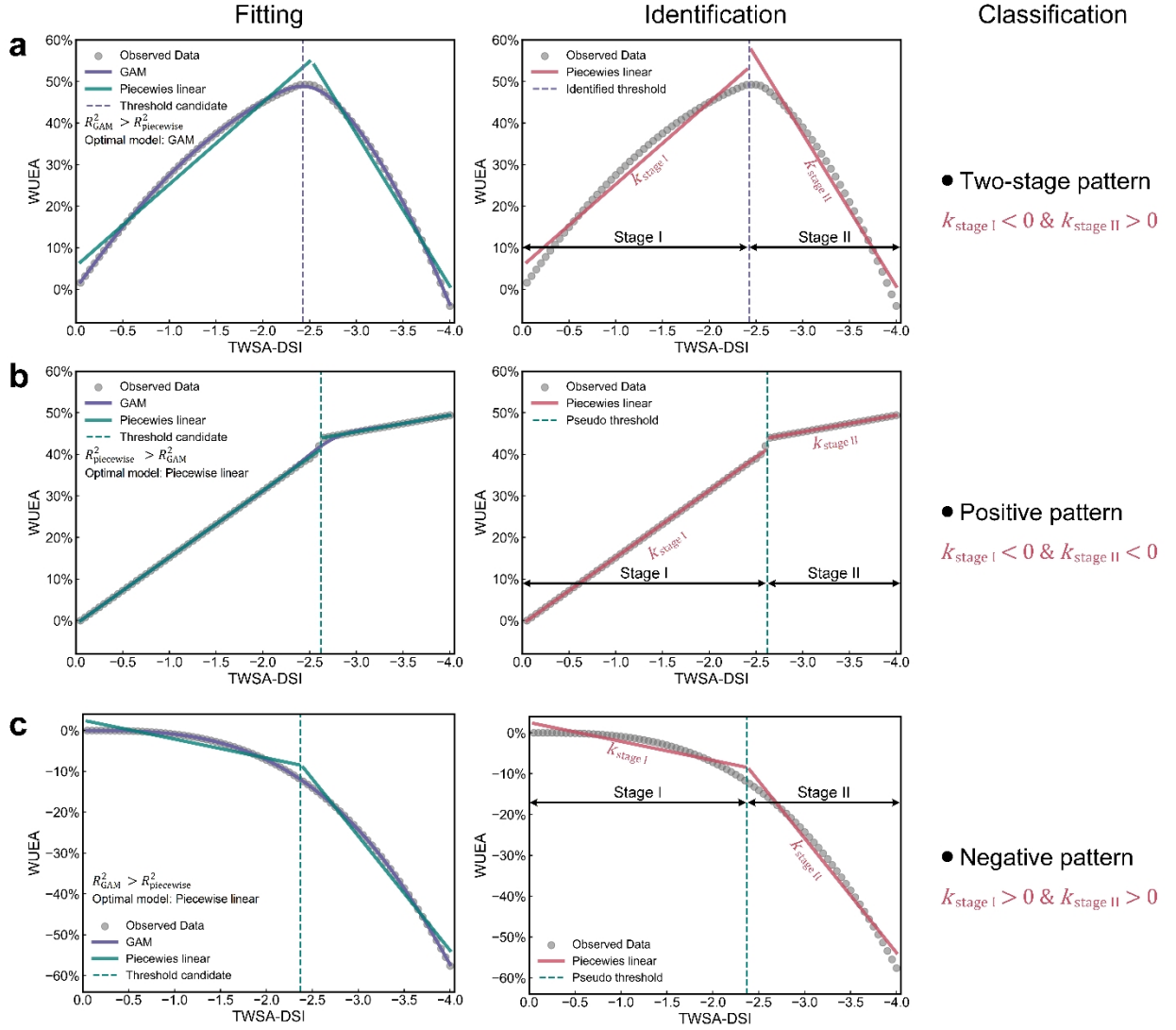


Figure S4.

Response pattern classification and threshold identification framework. The framework consists of three main steps: Fitting, Identification, and Classification. Panels (a–c) illustrate the process for identifying two-stage, positive, and negative response patterns, respectively. In the Fitting step, the optimal-fit model (either piecewise linear or GAM) is selected based on the model performance. The Identification step divides the WUE response into two stages according to the threshold candidate from the optimal-fit model and computing slopes on either side of the threshold. Finally, the Classification step assigns each response to one of the three categories based on the sign combination of the stage-specific slopes.

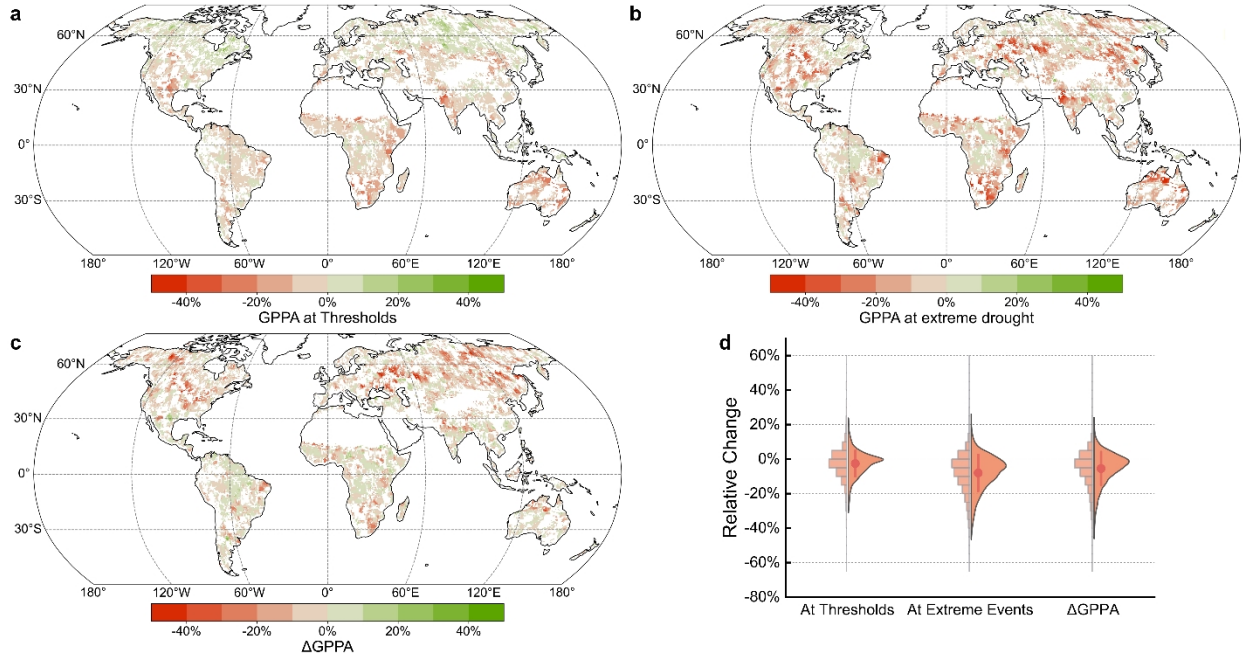


Figure S5.

Spatial and statistical distribution of GPPA in the two-stage response pattern. (a) Global distribution of GPPA at the threshold point. (b) Global distribution of GPPA during the most extreme drought conditions. (c) Spatial distribution of Δ GPPA, defined as the difference between (b) and (a). (d) Statistical distributions of GPPA at the threshold point, GPPA under the most extreme drought, and their difference (Δ GPPA). In the violin plots, dots represent the mean values, and whiskers indicate one standard deviation.

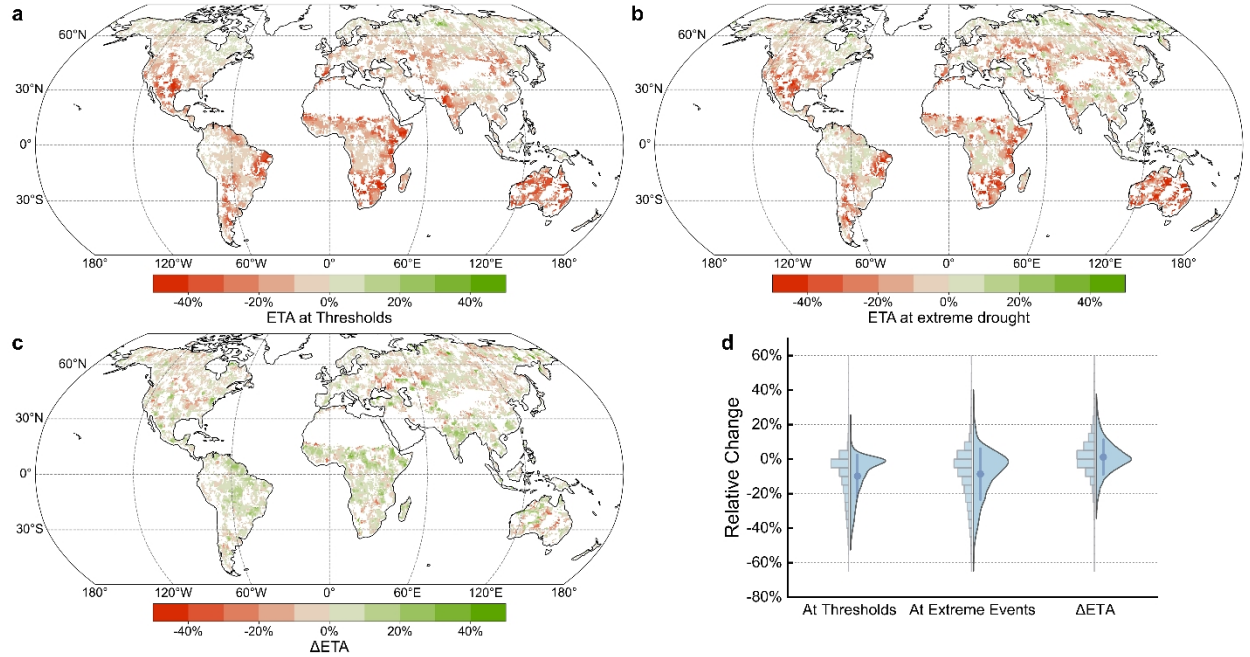


Figure S6.

Spatial and statistical distribution of ETA in the two-stage response pattern. (a) Global distribution of ETA at the threshold point. (b) Global distribution of ETA during the most extreme drought conditions. (c) Spatial distribution of ΔETA , defined as the difference between (b) and (a). (d) Statistical distributions of ETA at the threshold point, ETA under the most extreme drought, and their difference (ΔETA). In the violin plots, dots represent the mean values, and whiskers indicate one standard deviation.

Table S1.

Classification standards for wetness (W)/dryness (D) levels based on TWSA-DSI.

Category	Wet/Dry Level	TWSA-DSI
W4	Exceptionally wet	(2.0, $+\infty$)
W3	Extremely wet	(1.60, 2.0]
W2	Very wet	(1.30, 1.60]
W1	Moderately wet	(0.80, 1.30]
W0	Slightly wet	(0.50, 0.80]
WD	Near normal	(-0.50, 0.50]
D0	Abnormally dry	(-0.80, -0.50]
D1	Moderate drought	(-1.30, -0.80]
D2	Severe drought	(-1.60, -1.30]
D3	Extreme drought	(-2.0, -1.60]
D4	Exceptional drought	($-\infty$, -2.0]

Table S2.

Input variables used in the Deep Forest model: abbreviations, types, units, and data sources.

Variable	Abbreviation	Type	Units	Source
Albedo	Alb	Climatic	Unitless	(Muñoz-Sabater, 2019)
Air pressure	AP		kPa	
Net shortwave radiation	Rad		W	
Precipitation	Pre		mm	
Wind speed	WS		m/s	
Temperature	Tem		°C	
CO ₂ concentration	CO ₂		ppm	(Cheng et al., 2022)
Vapor pressure deficit	VPD		kPa	(Abatzoglou et al., 2018)
Potential evapotranspiration	PET		mm	(Martens et al., 2017; Miralles et al., 2011)
Aridity index	AI		Unitless	$= PET / Precipitation$
Land cover type	LCT	Vegetative	Unitless	(Friedl and Sulla-Menashe, 2019)
leaf area index	LAI		Unitless	(Cao et al., 2023)
Normalized difference vegetation index	NDVI		Unitless	(Li et al., 2023)
Rooting depth	RD		m	(Yang et al., 2016)
Leaf water potential at 50% of xylem conductance	LWP		MPa	(Liu et al., 2021)
Vegetation capacitance	VC		mm/MPa	
Slope parameter in the Medlyn's stomatal conductance model	SP		kPa ^{0.5}	
Maximum xylem conductance	MXC		mm/hr/MPa	
Ratio between the leaf water potential at 50% of stomatal conductance and	RLS		Unitless	

that at 50% of xylem conductance				
Bulk density	Bulk	Soil	cg/cm ³	(Poggio et al., 2021)
Cation Exchange Capacity	CEC		mmol(c)/kg	
Coarse fragments	Coarse		cm ³ /dm ³	
Proportion of clay particles	Clay		g/kg	
Proportion of sand particles	Sand		g/kg	
Proportion of silt particles	Silt		g/kg	
Total nitrogen	TN		cg/kg	
Organic carbon density	OCD		hg/m ³	
Soil pH	pH		pH*10	
Soil organic carbon content	SOC		dg/kg	
Total phosphorus	TP		mg/kg	(He et al., 2021)

Table S3.

Proportion of vegetated land area showing increases or decreases in WUE, GPP and ET under the two-stage WUE response pattern.

	At thresholds		At the most extreme events	
	Increase	Decrease	Increase	Decrease
WUE	94.4%	5.6%	42.9%	57.1%
GPP	36.8%	63.2%	21.5%	78.5%
ET	18.3%	81.7%	28.2%	71.8%

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