

Article

Effects of Precipitation Regimes on Ecosystem Respiration in Agricultural Regions of the Southern Tibetan Plateau

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Abstract

Understanding how the spatiotemporal variability of precipitation affects ecosystem respiration (RE) is central to carbon–climate feedback in climate-smart agriculture, yet remains unresolved for the alpine agricultural region of the southern Qinghai–Tibet Plateau, where flux observations are sparse. Using 25 years (2000–2024) of monthly gridded climate and remote sensing data for the Yarlung Zangbo River Basin and Its Two Tributaries Basin, we developed a flux tower-constrained reference–respiration (R_{ref}) environment-matching model in which R_{ref} varies with the enhanced vegetation index (EVI) and land surface temperature (LST) to correct the Lloyd–Taylor parameterization. The correction reduced the RE root mean square error by 54.8% ($1.04 \rightarrow 0.47 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$) and eliminated systematic bias ($+0.80 \rightarrow -0.001$) relative to an independent gridded RECO product. We then constructed a multidimensional index of precipitation variability (intra-annual concentration, interannual variability, long-term trend, spatial clustering) and combined random forest, spatial regression, lag analysis, and structural equation modeling (SEM) to disentangle direct and indirect pathways from precipitation variability to RE. The central finding is an indirect-conduction mechanism: precipitation concentration (PCI) affects RE almost entirely through vegetation productivity ($\text{PCI} \rightarrow \text{GPP} \rightarrow \text{RE}$, indirect effect -0.676) rather than directly (direct effect $+0.076$, opposite in sign), because low temperature and high soil water holding capacity buffer the immediate soil moisture response. The basin functions as a net carbon source (mean NEP = $-0.550 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$) with a significant warming-driven interannual RE increase (Sen's slope = 0.0025 yr^{-1} , $p = 0.022$) that is independent of the stable precipitation total. The framework offers a transferable paradigm for carbon flux attribution in alpine regions under sparse observation.

Keywords: precipitation heterogeneity; ecosystem respiration; flux tower correction; Lloyd-Taylor model; random forest; structural equation model; the Yarlung Zangbo River Basin and Its Two Tributaries Basin; Qinghai-Tibet Plateau



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1. Introduction

Ecosystem respiration (RE) and gross primary production (GPP) are the paired, counterbalancing fluxes of the terrestrial carbon cycle: GPP fixes carbon through photosynthesis, and RE returns it to the atmosphere through autotrophic and heterotrophic metabolism, with a global annual release of about 98 Pg C [1–3], roughly ten times fossil-fuel emissions. The small proportion fluctuation of RE can determine the directional transformation of

terrestrial biosphere between carbon source and carbon sink. Therefore, it is one of the most urgent issues in the study of carbon–climate feedback to accurately quantify the spatial and temporal variation in RE and its environmental driving mechanism [4,5]. Among many climatic factors, the ecological regulation role of precipitation is particularly complex: it is not only the water supply source of vegetation productivity, but also the switch variable of soil anaerobic–aerobic interface, and it also shapes the metabolic window of plants and microorganisms through its covariation with temperature, a relationship of which the sign and strength are region-, season-, and circulation-dependent rather than universal. However, the research on the relationship between RE and precipitation in the past two decades has long focused on the total amount of precipitation, and simplified the precipitation–respiration coupling into a single linear gradient, ignoring the non-uniformity of precipitation time distribution, that is, precipitation heterogeneity, which may be independent of the ecological effects of the total amount [6–8]. Throughout this paper, “precipitation heterogeneity” is used in the statistical–distributional sense to denote the unevenness of precipitation distribution in time and space, encompassing intra-annual concentration (PCI, PCD, PCP), interannual variability (CV), long-term trend (Sen/MK), and spatial clustering (Moran’s I), and is distinct from total precipitation amount; the study addresses seasonal distribution, interannual variability, and 25-year basin-scale trends, not multi-century or orographic differentiation. This simplification becomes problematic when the ecological effect of interest depends on the timing of water supply rather than its annual total, as in alpine systems where the growing season occupies only 3–4 months, the winter soil freezing period lasts 6–7 months, and organic matter decomposition is temperature-limited by the kinetic constraint that persistently low temperatures impose on its rate outside this window [9–11]; under these conditions, the timing configuration of precipitation in the limited growing season window, rather than the annual total, may be the core regulator of carbon release, and two years with identical annual totals but different intra-annual concentration can differ substantially in respiratory carbon loss. Whether the “precipitation pulse → respiration burst” (Birch) model documented in temperate and arid systems applies to alpine agroecosystems remains empirically unresolved, specifically, whether a measurable respiratory pulse follows rainfall at the monthly scale, whether the response lags precipitation, and whether the alpine regime’s low-temperature buffering and short growing season suppress the pulse that dominates semi-arid behavior [12].

Precipitation heterogeneity spans distinct, weakly correlated temporal dimensions (inter-index correlations are only $|r| = 0.05$ – 0.35 between CV and the concentration indices, although PCI, PCD and PCP are mutually collinear at $r > 0.93$): Precipitation Concentration Index (PCI); Precipitation Concentration Degree, PCD; and Precipitation Concentration Period (PCP) depicts the distribution uniformity and peak phase of precipitation in and out of the growing season. The Interannual Coefficient of Variation (CV) measures the predictability of water supply over many years. Seasonal distribution ratio (R_{season}) separates the relative contribution of precipitation in the growing season and the non-growing season [13,14]. Precipitation manipulation experiments have repeatedly confirmed that changing the frequency of precipitation while maintaining the total amount unchanged can cause a 20–40% change in soil respiration; the magnitude of this effect is equivalent to doubling the total amount of precipitation [15–19]. The increase in precipitation concentration did not directly affect soil respiration, but indirectly regulated the RE through a cascade path of “inhibiting vegetation photosynthetic carbon fixation-reducing rhizosphere substrate supply-suppressing autotrophic respiration”. The direct effect accounted for less than 10% of the total effect [20–22]. However, almost all the above findings are from mid-latitude temperate and arid and semi-arid systems, and their mobility in alpine ecosystems is completely unknown. There are three key differences between the biophysical environ-

ment of alpine grassland and the above systems: the short growing season (3–4 months), the long soil freezing period in winter (6–7 months), and the strong kinetic limitation of soil organic matter decomposition by low temperature [23–25]. Low temperature buffers the immediate response of the soil decomposition process to water fluctuation, and the proportion of vegetation autotrophic respiration in total respiration may be higher than that of low altitude grassland [26], so that the direct coupling of precipitation–soil respiration in alpine region is significantly weaker than that in temperate system, and the importance of indirect transmission path increases accordingly [27,28].

Estimating carbon fluxes over the alpine region is constrained by the sparsity of ground observation, a constraint that is most acute for the agricultural area of the Qinghai–Tibet Plateau. The plateau ($>2.5 \times 10^6 \text{ km}^2$) is covered by fewer than 20 flux tower stations, most of them concentrated in the relatively humid meadow of the east, while the western semi-arid steppe and desert steppe have almost no coverage [29,30], and the deviation introduced when machine learning products are extrapolated beyond such training domains has been quantified in several assessments [31]. Regional carbon flux estimation is, therefore, necessarily an exercise in extrapolation, and its reliability depends on how model parameters are transferred from the few observed sites to the unsampled area.

This extrapolation problem is the sharpest for the reference respiration R_{ref} , the key parameter of the Lloyd–Taylor model, which, in most applications, is fixed as an empirical constant (e.g., $3.0 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$) and thus assumes that the basal respiration rate is invariant across vegetation cover and thermal regimes [32,33]. That a fixed parameter performs poorly outside its calibration range is, by itself, expected; the non-trivial issue in this basin is that the resulting error is not random but covaries systematically with topography. Farmland here is concentrated on the valley terraces and forms a farmland–grassland mosaic that lacks ground validation; over an elevation gradient of more than 3 300 m, EVI decays from 0.30 in the valley farmland–shrub zone to 0.05 in the alpine zone, and mean annual LST falls from 6°C to -4°C , so a single constant R_{ref} systematically underestimates the high-cover valley farmland and systematically overestimates the sparse high-altitude area. The bias is, therefore, aligned with the topographic gradient rather than random noise, and it directly compromises carbon budget accounting in the agricultural area.

To correct this systematic bias, we retrieved R_{ref} from the monthly RE peak of the 18 flux tower stations on the Qinghai–Tibet Plateau and built an R_{ref} environment-matching model with EVI and LST as predictors [34–36], which supplies a process-interpretable parameterization of the Lloyd–Taylor model for alpine agricultural areas without sacrificing interpretability.

The Yarlung Zangbo River Basin and Its Two Tributaries Basin constitute a natural experimental platform for testing the above theories and methods, and its advantages are concentrated in five aspects. First, as the core agricultural area in the southern Qinghai–Tibet Plateau, the basin carries a complete vertical band spectrum of valley agricultural areas, alpine meadows, and alpine sparse vegetation [37,38]. Arable land, grassland, and bare land form a clear land use sequence along the 3512–6819 m elevation gradient, providing sufficient co-variation space for separating the interaction of agricultural activities, elevation effects, and climate effects on carbon fluxes. Second, farmland is concentrated in valley terraces (altitude $< 4\,200 \text{ m}$), and alpine grasslands occupy an absolute advantage at an altitude of more than $4\,200 \text{ m}$ [39,40]. The land use pattern is simple and clear, avoiding the confusion of carbon flux signals by complex land cover types, which is a rare natural control experimental condition in global change ecology research. Third, the extreme precipitation concentration pattern driven by the Indian summer monsoon (June–September precipitation accounts for about 70% of the total annual precipitation) creates a strong intra-annual heterogeneity signal. PCI monotonically increases from about 17 in the southeast to about 25 in the northwest [41,42], forming a significant heterogeneity

gradient within a horizontal distance of less than 80 km, providing an ideal spatial alternative time design for separating the ecological effects of precipitation heterogeneity and total precipitation. Fourth, the 25-year continuous MODIS vegetation index and the climate reanalysis data of the National Qinghai–Tibet Plateau Scientific Data Center provide a 300-month time series [43,44], which meets the minimum requirements for sample size in robust statistical inference. Fifth, the average annual precipitation of 423 mm is just in the transition zone between water limitation and energy limitation [45,46]. The ecological signal of precipitation heterogeneity is not submerged by extreme drought or extreme wet conditions, which provides high signal-to-noise ratio experimental conditions for testing the heterogeneity–respiration relationship.

This study focuses on a core scientific question: how does the spatiotemporal variability of precipitation—its intra-annual concentration, interannual variability, and spatial clustering—affect ecosystem respiration in the alpine agricultural area, given the strong spatial mosaic of elevation, soils, and vegetation that characterizes the basin? Despite two decades of work, precipitation–respiration findings remain dominated by temperate and arid systems, and their transferability to alpine agroecosystems—where the growing season is short, soils are frozen for much of the year, and low temperature buffers decomposition—remains unknown; meanwhile, the sparse flux tower network on the plateau prevents the independent reconstruction of ecosystem respiration. This study addresses both gaps by constructing a flux tower-constrained, process-interpretable Rref correction for alpine conditions and by applying a causal pathway analysis (SEM) to test whether precipitation heterogeneity affects RE indirectly through vegetation productivity. In view of these gaps, we propose four testable hypotheses. H1—Indirect conduction hypothesis: at the monthly to interannual scale, the regulation of RE by precipitation in the alpine agricultural area is dominated by the indirect pathway mediated by vegetation productivity (GPP/EVI), and the direct effect of precipitation on soil respiration is weak [47–49] because (i) low temperature buffers the immediate response of decomposition to moisture fluctuation, (ii) the high water holding capacity of alpine meadow soils, and (iii) valley irrigation buffer monthly soil moisture variability. H2—Elevation confounding hypothesis: the strong spatial covariation of elevation and precipitation heterogeneity (both PCI and CV are high at high elevation) artificially suppresses the zero-order correlation between the heterogeneity indices and RE [50,51], and the independent ecological signal of the heterogeneity indices will be significantly enhanced after partialling out the elevation proxy. Here, DEM is treated as a composite proxy for altitude-dependent factors (temperature lapse rate, pressure, radiation, precipitation regime) rather than a causal agent, and the elevation–precipitation covariation may partly reflect spatial co-structuring of the data rather than an independent ecological mechanism. This confounding effect is particularly serious in agricultural basins with an elevation gradient of more than 3000 m. H3—Immediate response hypothesis: the response pattern of RE to each environmental factor in the alpine agricultural area, defined as the lag-0 to lag-12-month Pearson correlation structure, is strongest at lag 0 (the same month) [52,53], where the “strongest” factor is that with the maximum lag-0 r . This differs from the 1–2-month lag of temperate systems and the 3–6-month lag of arid systems, because the extremely short growing season window cuts off the cross-season chain from early precipitation to late respiration, and the high water holding capacity of alpine meadow soils and valley irrigation buffer monthly water fluctuation. H4—Dimensional independence hypothesis: PCI, CV and PCD capture the heterogeneity of precipitation at different time scales (intra-annual concentration, interannual variability, seasonal phase), and the forced merger into a single latent variable will lead to the structural equation model mismatch. Direct effect modeling should be better than latent variable modeling [54,55].

The analysis proceeds in four steps: (1) a flux tower-constrained Rref environment-matching correction of the Lloyd–Taylor parameterization (Section 2.3); (2) construction of a multidimensional precipitation heterogeneity index system (Section 2.4); (3) spatial regression, and lag analyses of the RE–precipitation relationship (Section 2.5); and (4) structural equation modeling to separate the direct and indirect pathways from precipitation heterogeneity to RE (Section 2.5.3).

2. Materials and Methods

2.1. Overview of the Study Area

The agricultural region of southern Qinghai–Tibet Plateau (the Yarlung Zangbo River Basin and Its Two Tributaries Basin) (87.08–92.62 °E, 28.29–30.47 °N) is located in the middle reaches of the Yarlung Zangbo River and its tributary Lhasa River and Nianchu River in the southern Qinghai–Tibet Plateau. It covers an area of about 4 650 km², with an elevation of 3512–6819 m (mean 4773 m) and a vertical drop of more than 3300 m within a horizontal distance of less than 80 km (Figure 1).

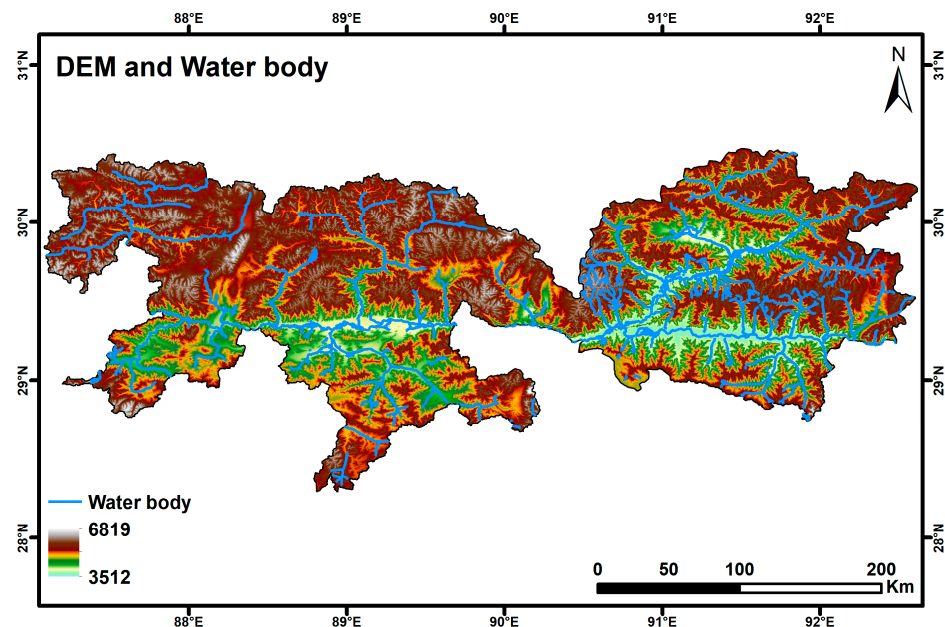


Figure 1. DEM and water body map.

The basin belongs to the plateau monsoon climate. The Indian summer monsoon (June–September) transports about 70% of the annual precipitation, with an average annual precipitation of 423 ± 52 mm, decreasing from southeast to northwest ($P_5 = 352.6$ mm, $P_{95} = 527.7$ mm). The peak of PCP corresponds to mid-July. The average PCI is 22.45 (highly concentrated) and increases from southeast to northwest. The interannual CV is 0.210. The precipitation system is generally stable during the 25 years (only 3.51% of the pixel Mann–Kendall reaches $p < 0.05$ significant level). The average annual temperature is 6.43 °C (monthly average range: 12.88–16.06 °C), and the vertical lapse rate is about 0.60 °C/100 m. Alpine grassland was the dominant vegetation type (accounting for 95.4% of the effective pixels). Alpine grassland (coverage of 30–50%) was the main vegetation type at the altitude of <4000 m, alpine meadow (coverage of 50–80%) was the main vegetation type at the altitude of 4000–4800 m, and alpine sparse vegetation (coverage of <20%) was the main vegetation type at the altitude of >4800 m. Here, alpine sparse vegetation refers to a mixture of sparse, low-stature cushion plants, herbs and sedges with exposed rock and soil between individuals; because this belt lies above the regional treeline and the limit of closed shrub canopy, it contains no forest trees and essentially no closed shrub layer. Bare

land accounted for 4.4%, and shrub land accounted for only 0.2%. From the bottom to the top, the soil changed from grass-felt soil (organic matter 8–15%, soil layer 30–60 cm) to frozen-felt soil and cold desert soil (organic matter 3–8%, soil layer 10–30 cm), (Figure 2).

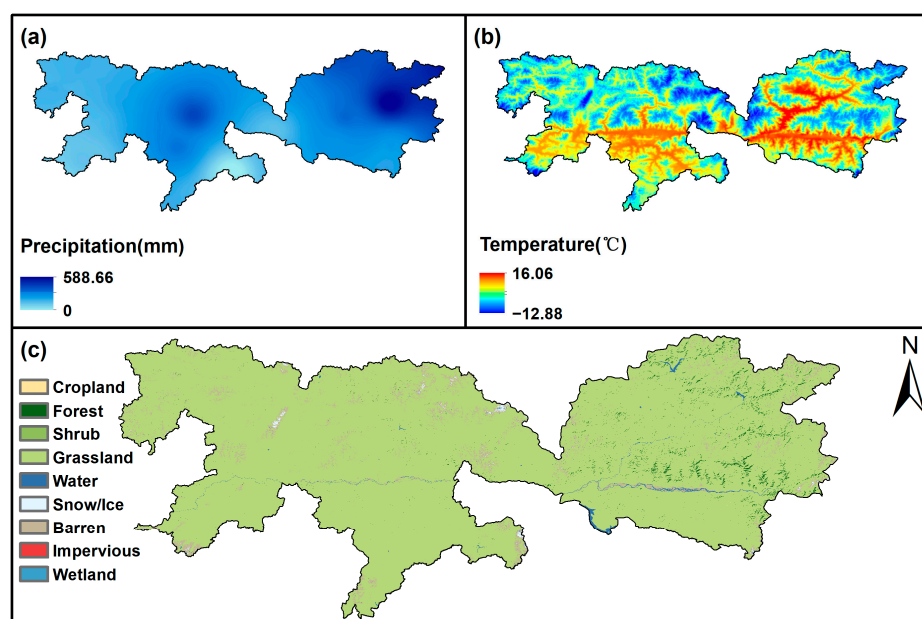


Figure 2. Precipitation (a), temperature (b) and land cover (c) map.

The vegetation in the basin is highly homogeneous, the altitude gradient is significant, and the precipitation concentration is strong, which constitutes an ideal natural experimental system for testing the relationship between precipitation heterogeneity and RE. In short, the basin is almost entirely alpine grassland (about 95%), with forest and shrub together below 0.5%, and cropland confined to the valley terraces; “high coverage” refers to valley cropland and meadow, and “sparse” to the cushion-plant belt above 4800 m.

2.2. Data Source and Preprocessing

The time span of the research data is 2000–2024 (25 years, 300 months). The WGS84 geographic coordinate system (EPSG: 4326) is shown in Figure 3.

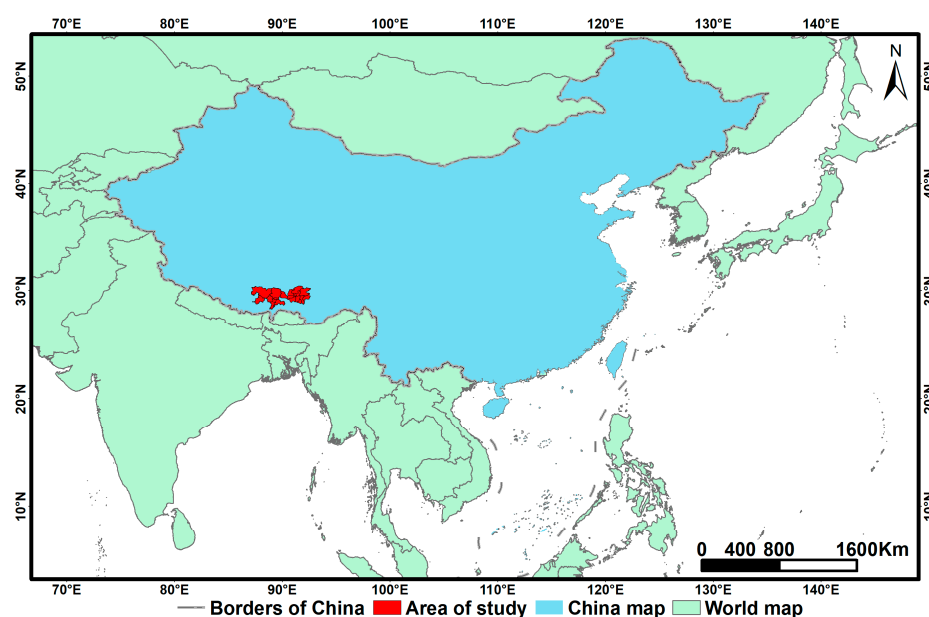


Figure 3. Study area map.

The land cover was classified by CLCD2000-2024, and the original 9 categories were reclassified into six categories: (1) cultivated land, (2) forest land/shrub, (3) grassland, (4) water area, (5) bare land/sparse vegetation (CLCD bare land and sparsely vegetated land, excluding forest and closed shrub), (6) ice and snow. All the data used in the following experiments are from Table 1.

Table 1. Data sources and spatial resolutions.

Data	Source	Native Resolution
Precipitation [56]	National Tibetan Plateau Data Center (https://data.tpdac.ac.cn/zh-hans/data/faae7605-a0f2-4d18-b28f-5cee413766a2 , accessed on 5 January 2026)	1 km
Temperature [57]	National Tibetan Plateau Data Center (https://data.tpdac.ac.cn/zh-hans/data/71ab4677-b66c-4fd1-a004-b2a541c4d5bf , accessed on 5 January 2026)	1 km
Flux tower RE [58]	National Tibetan Plateau Data Center (https://data.tpdac.ac.cn/zh-hans/data/761ff597-830d-4e1a-9999-b99fd6f8d4a2 , accessed on 5 January 2026)	Point (18 sites)
Soil moisture (0–7 cm) [59]	ERA5-Land reanalysis (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land , accessed on 5 January 2026)	0.1°
Soil Temperature (0–7 cm) [59]	ERA5-Land reanalysis (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land , accessed on 5 January 2026)	0.1°
Solar radiation [59]	ERA5-Land reanalysis (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means , accessed on 5 January 2026)	0.1°
EVI [60]	MODIS MOD13A2 (https://lpdaac.usgs.gov/products/mod13a2v061/ , accessed on 5 January 2026)	1 km
NDVI [60]	MODIS MOD13A3 (https://lpdaac.usgs.gov/products/mod13a3v061/ , accessed on 5 January 2026)	1 km
Daytime LST [61]	MODIS MOD11A2 (https://lpdaac.usgs.gov/products/mod11a2v061/ , accessed on 5 January 2026)	1 km
Nighttime LST [61]	MODIS MOD11A2 (https://lpdaac.usgs.gov/products/mod11a2v061/ , accessed on 5 January 2026)	1 km
GPP [62]	MODIS MOD17A2H (https://lpdaac.usgs.gov/products/mod17a2hv061/ , accessed on 5 January 2026)	1 km
DEM [63]	NASA (https://lpdaac.usgs.gov/products/nasadem_hgtv001/ , accessed on 5 January 2026)	30 m
Land cover [64]	CLCD (https://zenodo.org/records/5816591 , accessed on 5 January 2026)	30 m

2.3. Ecosystem Respiration Correction Method

Here, “environment matching” denotes the use of satellite environmental variables (EVI and LST) as a bridge to extrapolate the R_{ref} information space from the limited flux-tower sites to every grid pixel, under the assumption that sites with similar vegetation cover and thermal environment share a similar basal respiration rate. The core methodological innovation of this study is to construct an R_{ref} environment matching correction scheme based on flux tower observation, which replaces the traditional fixed R_{ref} constant ($3.0 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$). The correction process is divided into three steps.

The first step: R_{ref} inversion. The Lloyd–Taylor temperature response function $f(T)$, describing the temperature dependence of ecosystem respiration [65], is

$$RE = R_{\text{ref}} \cdot \exp \left[E_0 \left(\frac{1}{T_{\text{ref}} - T_0} - \frac{1}{T - T_0} \right) \right] \quad (1)$$

In the formula, $E_0 = 308.56 \text{ K}$ is the activation energy parameter, $T_{\text{ref}} = 288.15 \text{ K}$ (15°C) is the reference temperature, $T_0 = 227.13 \text{ K}$ (-46.02°C) is the zero temperature of respiration, and T is the monthly average temperature ($^\circ \text{C}$). R_{ref} is retrieved from the monthly RE peak (July–August, corresponding to the maximum respiratory flux) of 18 flux tower stations on the Qinghai–Tibet Plateau and its surrounding areas. The station observed RE and monthly

average temperature T are substituted into the above formula, and the optimal R_{ref} of each station is solved by the least square method.

Step 2: The R_{ref} multiple linear regression model was established by using the mean value of EVI and the average annual LST in the growing season (May–September) of each site as predictors:

$$R_{\text{ref}} = 0.376 + 7.908 \times \text{EVI} - 0.006 \times \text{LST} \quad (2)$$

($R^2 = 0.478$, $\sigma = \pm 0.690 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$, $n = 9$ valid sites). Among the 18 flux towers, 9 stations were excluded due to the lack of RE data, observation duration of less than 12 months or stations located in non-grassland ecosystems. The model captures a reasonable ecological gradient: high EVI site $R_{\text{ref}} \approx 2.7 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$, low EVI site $R_{\text{ref}} \approx 0.5 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$, which is about 6 times smaller than the traditional fixed value of $3.0 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$ in the low coverage area.

The third step: water stress correction and RE calculation. The soil moisture scalar W_s was introduced to characterize the limitation of water on heterotrophic respiration [66]:

$$W_s = \frac{\theta - \theta_{\min}}{\theta_{\max} - \theta_{\min}} \quad (3)$$

In the equation, θ is the soil volumetric water content of ERA5-Land 0–7 cm, $\theta_{\min} = 0.1 \text{ m}^3 \cdot \text{m}^{-3}$ and $\theta_{\max} = 0.4 \text{ m}^3 \cdot \text{m}^{-3}$, which approximate the wilting point and field capacity, respectively, of the loamy to sandy loam alpine meadow soils dominant in the basin; the sensitivity of W_s to these two thresholds is evaluated in Figure 4c. ERA5-Land does not resolve the high and spatially variable stoniness of alpine soils, which introduces uncertainty in the absolute value of θ ; we treat this as a limitation. The actual range of W_s in the study area is 0.432–0.987 (mean 0.756), which is in a state of moderate water restriction. The complete RE calculation formula after correction is as follows:

$$RE = R_{\text{ref}}(\text{EVI}, \text{LST}) \cdot \exp \left[E_0 \left(\frac{1}{T_{\text{ref}} - T_0} - \frac{1}{T - T_0} \right) \right] \cdot W_s(\theta) \quad (4)$$

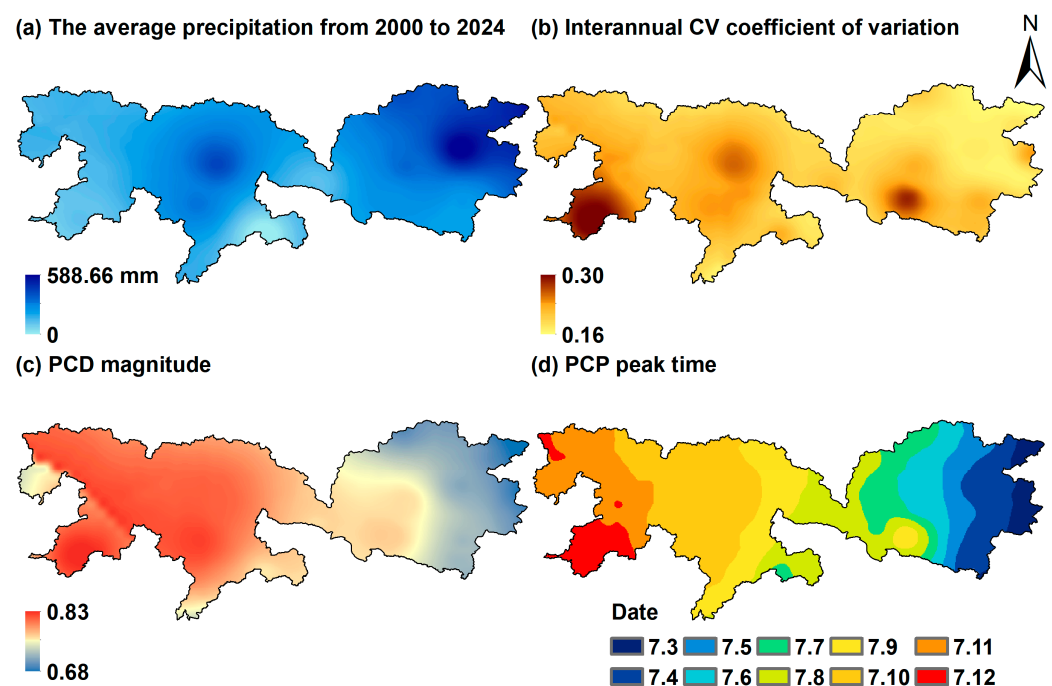


Figure 4. Spatial–temporal pattern of precipitation: (a) average annual precipitation for many years; (b) interannual CV coefficient; (c) PCD magnitude; (d) and PCP peak time.

The R_{ref} is determined by the second step of the EVI-LST regression model pixel by pixel, T is the monthly average temperature, W_s is the soil moisture scalar, and the parameters are the same as above.

We note that the Lloyd–Taylor temperature function $f(T)$ is the dominant source of temporal (seasonal and interannual) variation in RE, that $R_{\text{ref}}(\text{EVI}, \text{LST})$ is the dominant source of spatial variation along the elevation/vegetation gradient, and that W_s provides a moderate moisture modulation; consequently, the interannual trend in RE is largely temperature-driven, whereas the spatial pattern reflects vegetation and elevation.

2.4. Precipitation Heterogeneity Index System

The precipitation data are total precipitation (rain plus snow water equivalent); the ecological interpretation focuses on the growing season (June–September), which is dominated by monsoon rainfall (about 70% of the annual total), whereas winter precipitation falls mainly as snow outside the growing season, when soils are frozen and RE is near zero. This study systematically quantified precipitation heterogeneity from four dimensions: intra-annual, interannual, long-term trends, and spatial. All indicators were calculated independently at the pixel level (Table 2) [67].

Table 2. Seven-dimensional precipitation heterogeneity indicator system.

Indicator	Symbol	Temporal Scale	Ecological Interpretation
Precipitation Concentration Index	PCI	Intra-annual	>20=high concentration; <15=uniform
Precipitation Concentration Degree	PCD	Intra-annual	0–1; degree of seasonal concentration
Precipitation Concentration Period	PCP	Intra-annual	Peak precipitation timing (Julian day)
Interannual CV	CV	Interannual	Year-to-year predictability of water supply
Seasonal ratio	R_{season}	Intra-annual	Proportion during Jun–Sep
Sen's slope & MK test	Sen/MK	Long-term trend	Direction, magnitude and significance of trend
Spatial autocorrelation	Moran's I	Spatial	Degree of spatial clustering

Each index was selected to capture a distinct temporal scale and ecological process: PCI, PCD, and PCP describe intra-annual concentration and the timing of the precipitation peak; CV measures the interannual predictability of water supply; and the Sen/MK and Moran's I statistics capture the long-term trend and the degree of spatial clustering, respectively.

2.4.1. Concentration Index Within the Year

(1) Precipitation Concentration Index (PCI) [68]. The PCI measures the uniformity of monthly precipitation distribution within one year based on the mean square relative dispersion of monthly precipitation series:

$$PCI = 100 \times \frac{\sum_{i=1}^{12} p_i^2}{\left(\sum_{i=1}^{12} p_i\right)^2} \quad (5)$$

where p_i is the precipitation in the i -th month (mm). A PCI value < 15 indicates a uniform intra-annual precipitation distribution, 15–20 indicates moderate concentration, and >20 indicates high concentration [69]. The PCI contains no directional information and serves solely as a scalar measure reflecting the uniformity of distribution.

(2) Precipitation Concentration Degree (PCD) [70]. Treating the 12 monthly precipitation totals as vectors of varying lengths with fixed directions (each month separated by

30°), the seasonal concentration intensity of precipitation is measured by the magnitude of the vector resultant:

$$PCD = \frac{\sqrt{R_x^2 + R_y^2}}{\sum_{i=1}^{12} p_i}, \quad (6)$$

$$R_x = \sum_{i=1}^{12} p_i \cos \theta_i, \quad (7)$$

$$R_y = \sum_{i=1}^{12} p_i \sin \theta_i \quad (8)$$

where θ_i is the azimuth angle corresponding to the i -th month (January = 0°, February = 30°, ..., December = 330°). The PCD ranges from 0 to 1, where 0 indicates that precipitation is completely evenly distributed across all months of the year, and 1 indicates that all precipitation is concentrated in a single month.

(3) Precipitation Concentration Period (PCP) [70]. The period of peak precipitation occurrence is determined by the direction of the vector resultant:

$$PCP = \arctan\left(\frac{R_x}{R_y}\right) \quad (9)$$

The unit of PCP is radians; converting it to degrees and dividing by 30° yields the corresponding month number, which is used to determine the month or ten-day period of the precipitation peak. The practical ecological significance of PCP lies in capturing whether the precipitation peak during the growing season is synchronized with or offset from the peak of vegetation phenology.

2.4.2. Interannual Variability Index

The interannual Coefficient of Variation (CV) is calculated as the ratio of the standard deviation to the mean of the 25-year total precipitation at each pixel to quantify the predictability of interannual water supply [71]:

$$CV = \frac{\sigma_{MAP}}{\mu_{MAP}} = \frac{\sqrt{\frac{1}{n-1} \sum_{j=1}^n (P_j - \bar{P})^2}}{\bar{P}} \quad (10)$$

where P_j is the total annual precipitation in the j -th year, and $n = 25$ years. Higher CV values indicate greater interannual fluctuations in water supply and lower predictability of water availability for ecosystems.

The growing-season precipitation ratio (R_{season}) is defined as the ratio of precipitation during June–September to the total annual precipitation:

$$R_{season} = \frac{\sum_{i=6}^9 p_i}{\sum_{i=1}^{12} p_i} \quad (11)$$

2.4.3. Long-Term Trend Indicators

The non-parametric Theil-Sen median slope estimator and Mann-Kendall trend test were employed, which are free from normality assumptions and robust to outliers [72,73].

Sen's slope estimation:

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i \quad (12)$$

In the formula, x_i is the total precipitation (or monthly value) in the i year, $i, j = 1, 2, \dots, 25$. $\beta > 0$ indicates an increasing trend, and $\beta < 0$ indicates a decreasing trend.

Mann–Kendall test statistics:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (13)$$

The sign function:

$$\text{sgn}(x) = \begin{cases} +1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \quad (14)$$

Test statistic variance:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{k=1}^m t_k(t_k-1)(2t_k+5)}{18} \quad (15)$$

where m is the number of knots (ties), and t_k is the number of knots in k th group [74].

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & S < 0 \end{cases} \quad (16)$$

$|Z| \geq 1.96$ corresponds to $\alpha = 0.05$ two-tailed significance, $|Z| \geq 2.576$ corresponds to $\alpha = 0.01$.

2.4.4. Spatial Autocorrelation Index

Global Moran's I [75]:

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (17)$$

$$W = \sum_{i=1}^n \sum_{j=1}^n w_{ij} \quad (18)$$

In the formula, x_i is the average annual precipitation of the pixel i , $\bar{x}$ is the global mean, w_{ij} is the Queen adjacency space weight matrix (8 neighborhoods), and n is the effective number of pixels. $I \in [-1, 1]$, positive value represents spatial aggregation, and $I \approx 0$ represents random distribution. The significance was evaluated by 999 random permutation tests:

$$Z_I = \frac{I - E[I]}{\sqrt{\text{Var}[I]}} \quad (19)$$

$$E[I] = \frac{-1}{n-1} \quad (20)$$

Local Moran's I (LISA) [76] decomposes global autocorrelation to a single pixel:

$$I_i = \frac{x_i - \bar{x}}{S^2} \sum_{j=1}^n w_{ij}(x_j - \bar{x}) \quad (21)$$

$$S^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \quad (22)$$

All indicators are summarized in Table 2.

2.5. Statistical Analysis Methods

2.5.1. Spatial Dimension Analysis

The spatial dimension analysis takes a single pixel as the sample unit, and all variables are taken from the 25-year average or heterogeneity index in 2000–2024.

(1) Pearson correlation coefficient and Spearman rank correlation coefficient. Pearson's correlation quantifies the strength of the linear correlation between two variables [77]:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (23)$$

The Spearman rank correlation coefficient replaces the original value with the data rank [78], relaxing the linear assumption:

$$r_s = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad (24)$$

In the formula, d_i is the rank difference of the i th pixel in the two variables.

(2) First-order partial correlation coefficient. After controlling the elevation (DEM), the net linear correlation between the quantitative precipitation heterogeneity index and RE [79]:

$$r_{xy \cdot z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}} \quad (25)$$

where z is the control variable (DEM).

(3) Random forest regression [80]. Taking RE as the dependent variable, EVI, GPP, temperature, soil moisture and precipitation as predictors, a random forest ensemble of 500 regression trees was constructed. The importance of variables is assessed based on the incremental mean square error (% IncMSE):

$$VI(X_j) = \frac{1}{B} \sum_{b=1}^B [\text{MSE}_{oob}^b - \text{MSE}_{oob,perm}^b(X_j)] \quad (26)$$

In the formula, $B = 500$ is the number of trees, MSE_{oob} is the mean square error of the out-of-bag sample of the b tree, $\text{MSE}_{oob,perm}$ is the out-of-bag error after random replacement of the variable X_j . The VI value is standardized as a percentage for comparison.

Model goodness of fit:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (27)$$

(4) Precipitation gradient grouping and variance analysis. The pixels were divided into five groups according to the quintile of annual precipitation. A one-way analysis of variance was used to compare the differences between the RE groups:

$$F = \frac{SS_{between} / (k - 1)}{SS_{within} / (n - k)} \quad (28)$$

$$SS_{between} = \sum_{g=1}^k n_g (\bar{y}_g - \bar{y})^2 \quad (29)$$

$$SS_{within} = \sum_{g=1}^k \sum_{i=1}^{n_g} (y_{gi} - \bar{y}_g)^2 \quad (30)$$

In the formula, $k = 5$ is the number of groups, and n_g is the number of pixels in group g . Post hoc multiple comparisons were performed using the Tukey HSD test [81].

(5) Piecewise linear regression [82]. The precipitation–RE relationship is divided into two sections by the optimal breakpoint τ :

$$RE_i = \begin{cases} \beta_0 + \beta_1 \cdot \text{Precip}_i, & \text{Precip}_i \leq \tau \\ \beta_0 + \beta_1 \tau + \beta_2 (\text{Precip}_i - \tau), & \text{Precip}_i > \tau \end{cases} \quad (31)$$

The optimal breakpoint τ is determined by minimizing the sum of residual squares through grid search (step size 1 mm, search range P10–P90). The difference between the two slopes (β_1 vs. β_2) was evaluated by the Davies test [83].

(6) OLS multiple regression [84]. Establish a multi-factor linear model of spatial variation of RE:

$$RE = \beta_0 + \beta_1 \text{Precip} + \beta_2 \text{PCI} + \beta_3 \text{CV} + \beta_4 \text{DEM} + \beta_5 \text{PCD} + \beta_6 \text{PCP} + \varepsilon \quad (32)$$

The regression coefficient is estimated by the least square method, and the standardized coefficient (β^*) is used to compare the relative strength of the magnitude of each factor effect. The residuals are tested for spatial autocorrelation by Moran's I . If the residuals have no significant spatial autocorrelation, the OLS model is a sufficient DGP (data generation process) approximation.

(7) Spatial lag model [85]. If OLS residuals have significant spatial autocorrelation, SLM is used to eliminate spatial dependence:

$$RE = \rho W \cdot RE + X\beta + \varepsilon \quad (33)$$

where ρ is the spatial autoregressive coefficient, W is the Queen adjacency spatial weight matrix (8 neighborhoods), and X is the explanatory variable matrix (the same as the OLS model). SLM was estimated by maximum likelihood method, and AIC and Log-Likelihood were compared with OLS.

2.5.2. Time Dimension Analysis

The time dimension analysis takes the regional annual average as the sample unit ($n = 25$ years), and the regional mean is weighted by the pixel area.

(1) Interannual correlation and lag effect [86]. Pearson correlation coefficients between regional annual average RE and environmental factors (GPP, temperature, soil moisture, precipitation, EVI) in the same period and lag 0–12 months were calculated. For each pair of variables, the optimal lag order was determined by the maximum value of Pearson r in lag k months:

$$r_{RE,X}^{(k)} = \text{Corr}(RE_t, X_{t-k}), k = 0, 1, 2, \dots, 12 \quad (34)$$

In the formula, X_{t-k} is the environmental factor value of k months ahead of RE.

(2) Sliding cumulative precipitation analysis [87]. The explanatory power of cumulative precipitation was examined in different time windows for RE:

$$P_{acc}(k) = \sum_{j=t-k+1}^t P_j, k = 1, 3, 6, 12 \quad (35)$$

The optimal cumulative window of ecological correlation was identified by $P_{acc}(k)$ and Pearson r of RE in the same period.

(3) Diagnosis of drought and flood years [88]. The 10th and 90th percentiles of annual precipitation in the region from 2000 to 2024 were used as thresholds: annual precipitation $\leq P_{10}$ is defined as a drought year, $\geq P_{90}$ is defined as a flood year, and the rest is a normal year. A single-sample t -test was used to evaluate whether the RE anomalies in drought and flood years deviated significantly from zero:

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \quad (36)$$

In the formula, $\bar{x}$ is the mean value of RE anomaly in drought or flood years, $\mu_0 = 0$, and s is the standard deviation of the sample.

2.5.3. Structural Equation Model

The structural equation model allows for simultaneous estimation of direct and indirect causal paths between multiple variables, and decomposes the total effect into direct effects and indirect effects through mediating variables. In recent years, it has been widely used in ecological causality inference [89]. The AIC and BIC information criteria were used for model comparison to find a balance between goodness of fit and model complexity [90]. In this study, three competitive SEMs were set up to test the existence and intensity of indirect conduction paths for the hypothesis of the mechanism of precipitation heterogeneity to RE through the vegetation–soil cascade path [91]. The above model was fitted on a random subset of 5000 pixels with semopy library [92]. Model 1 (PHI latent variable model) forcedly combines PCI, CV, and PCD into latent-variable PHI:

$$GPP = \gamma_1 \text{PHI} + \gamma_2 \text{DEM} + \zeta_1 \quad (37)$$

$$\text{SM} = \delta_1 \text{PHI} + \delta_2 \text{DEM} + \zeta_2 \quad (38)$$

$$RE = \beta_1 \text{GPP} + \beta_2 \text{SM} + \beta_3 \text{PHI} + \beta_4 \text{DEM} + \zeta_3 \quad (39)$$

Model 2 (direct effect model) takes PCI, CV, and PCD as independent observation variables without latent variables:

$$\text{GPP} = \gamma_1 \text{PCI} + \gamma_2 \text{CV} + \gamma_3 \text{PCD} + \gamma_4 \text{DEM} + \zeta_1 \quad (40)$$

$$RE = \beta_1 \text{GPP} + \zeta_2 \quad (41)$$

Model 3 (complete mediation model) included in the full path of PCI:

$$\text{GPP} = \gamma_1 \text{PCI} + \gamma_2 \text{DEM} + \zeta_1 \quad (42)$$

$$\text{SM} = \delta_1 \text{PCI} + \delta_2 \text{DEM} + \zeta_2 \quad (43)$$

$$RE = \beta_1 \text{GPP} + \beta_2 \text{SM} + \beta_3 \text{PCI} + \beta_4 \text{DEM} + \zeta_3 \quad (44)$$

Chi-square test (χ^2), comparative fitting index (CFI > 0.95 is excellent), approximate root means square error (RMSEA < 0.05 is excellent) [93], and AIC were used to evaluate the fitting degree of the model. Indirect effect = path coefficient product (e.g., PCI → GPP → RE = $\gamma_1 \times \beta_1$) [94]. The Sobel test was used to evaluate the statistical significance of the indirect effect [95]:

$$z = \frac{\gamma_1 \times \beta_1}{\sqrt{\gamma_1^2 SE_{\beta_1}^2 + \beta_1^2 SE_{\gamma_1}^2}} \quad (45)$$

3. Results

3.1. Multidimensional Characteristics of the Spatial and Temporal Heterogeneity of Precipitation

The average annual precipitation in the basin from 2000 to 2024 was 423 ± 52 mm. The spatial gradient decreased from southeast (P95 = 527.7 mm) to northwest (P5 = 352.6 mm), and the extreme value was 0–588.7 mm. The global Moran's I = 0.98 ($p < 0.001$), the annual precipitation showed a significant spatial aggregation distribution, and the precipitation values between adjacent pixels were highly correlated (Figure 5).

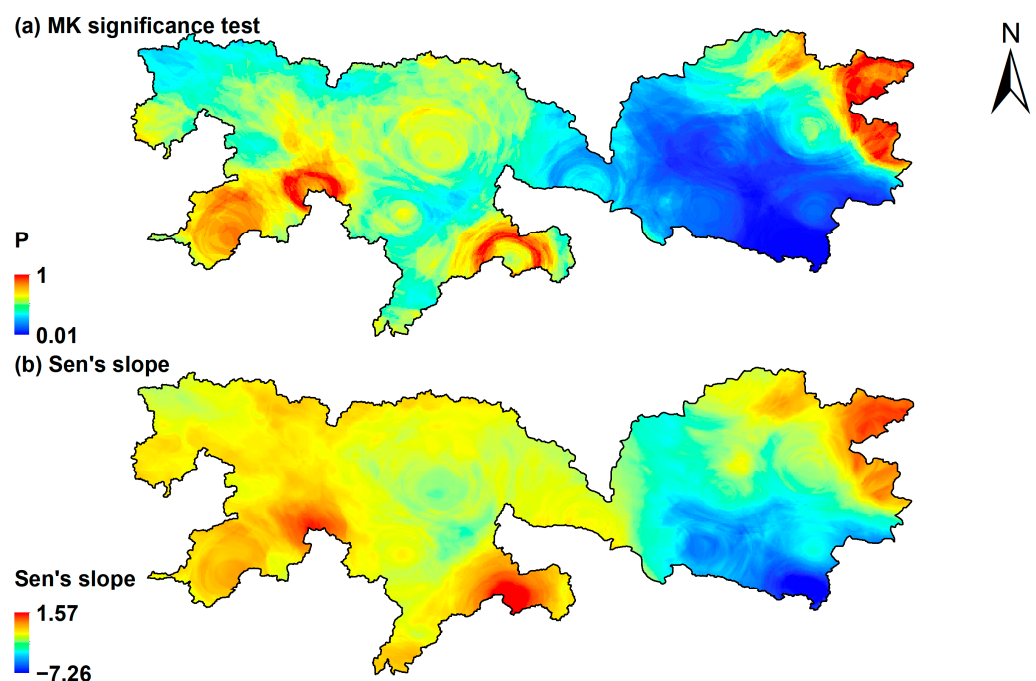


Figure 5. MK significance test and Sen's slope: (a) MK significance test; (b) Sen's slope.

The annual distribution of precipitation is a typical monsoon concentration type. The mean value of the PCI in the whole basin was 22.45 ± 2.19 (17.36–26.41), of which 80.5-pixel PCI was >20 (highly concentrated type), 19.5% was between 15 and 20 (moderately concentrated type), and there was no pixel less than 15 (uniform type). The PCI increases from the southeastern valley region (17–20) to the northwest high-altitude region (24–26), reflecting the spatial differentiation of the annual distribution of Indian summer monsoon precipitation tends to be concentrated with the increase in the distance from the water vapor source. The mean PCD was 0.783 ± 0.036 (0.681–0.834), which was consistent with the strong intra-annual concentration indicated by the PCI.

The whole basin is highly synchronized during the peak period of precipitation. The mean PCP corresponds to an annual accumulated day of 189.8 (8 July), and the span of the whole basin is only 8.9 days (3–12 July, DOY 184.4–193.3), with a standard deviation of ± 2.1 days. The Indian summer monsoon has a uniform control over the seasonal phase of

precipitation in the basin, the spatial variability of precipitation peak time can be ignored, and there is no spatial differentiation of precipitation phenology in the basin.

On the interannual scale, the mean value of the total annual precipitation CV is 0.210 ± 0.027 (0.160–0.297), which is the spatial average of the CV of the 25-year precipitation series of each pixel, which is a medium–low fluctuation level. The interannual predictability of the Indian summer monsoon gives the region a higher water supply stability than the temperate grassland (CV typical value 0.25–0.35).

In terms of long-term trend, the mean value of the Theil–Sen slope is $-2.32 \pm 1.42 \text{ mm}\cdot\text{yr}^{-1}$, 96.5% of pixels are negative and 3.2% are positive. The Mann–Kendall test showed that only 3.51% of the pixels reached the $p < 0.05$ significance level, and 0.79% reached the $p < 0.01$; a significant pixel ratio was lower than random expectation. During the 25 years, the precipitation system in the basin was generally stable, and there was a large-scale weak decline signal, but it did not constitute a statistically significant long-term trend.

3.2. Validation of the Ecosystem Respiration Correction Method and Spatial–Temporal Pattern of RE After Correction

Based on the RECO grid products of the National Qinghai–Tibet Plateau Scientific Data Center (TPDC), the root means square error (RMSE) and bias (Bias) of RE estimation before and after correction were evaluated pixel by pixel. The results showed that the RMSE of RE in the YRB decreased from $1.04 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ to $0.47 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, with a decrease of 54.8%. Bias narrowed from systematic overestimation ($+0.80 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$) to almost unbiased ($-0.001 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$). The RMSE of net ecosystem productivity (NEP) decreased from $1.80 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ to $0.99 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, with a decrease of 45.1%. The core mechanism of correction is to convert the reference respiration R_{ref} from a constant empirical constant to an environmental variable diagnosed by both vegetation productivity (EVI) and thermal environment (LST). On an elevation gradient of more than 3300 m in the Yarlung Zangbo River Basin and Its Two Tributaries Basin, the EVI decreases from 0.30 in the valley to 0.05 in the alpine zone, and the corresponding spatial variation of R_{ref} is as high as $2.2 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$. If this variation is ignored and the fixed R_{ref} scheme is maintained, the low-coverage high-altitude area will produce a systematic overestimation of about 2.5 times (Figure 6).

From 2000 to 2024, the adjusted RE mean value of the Yijiang River and Lianghe River Basins was $0.566 \pm 0.306 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, the spatial variation coefficient was 0.541, and the extreme value was $0.038\text{--}1.966 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, $P5 = 0.163$, $P95 = 1.166$. The spatial distribution of RE showed clear elevation attenuation characteristics: the sparse vegetation area at 5000 m was 0.307 ± 0.127 , and the highest elevation zone RE was about 33% of the valley area. The Pearson correlation coefficient between RE and DEM is $r = -0.776$, and the elevation single factor can explain 60.2% of the spatial variation in RE. The spatial distribution of RE is moderately uneven. During the same period, the average GPP was $0.0161 \pm 0.0084 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ (0.0027–0.0493) and the average NEP was $-0.550 \pm 0.300 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ (−1.921 to −0.034). The global NEP was <0 , and the whole system was a net carbon source (Figure 7).

In terms of interannual variation, the average annual RE in the region increased from $0.542 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ in 2000 to $0.613 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ in 2024. The slope of Theil–Sen was $0.0025 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}\cdot\text{yr}^{-1}$, and the Mann–Kendall test $Z = 2.289$ ($p = 0.022$), showing a statistically significant upward trend. The minimum value of annual average RE in the region appeared in 2012 (0.518), and the maximum value appeared in 2021 (0.648), with a range of 0.131. The interannual variation coefficient of RE ($\text{CV}_{\text{time}} = 5.90\%$) was lower than that of precipitation (0.210) and GPP (7.28%). The response intensity of RE in alpine grassland to interannual climate fluctuations was weaker than that of the upper driving factors (Figure 8).

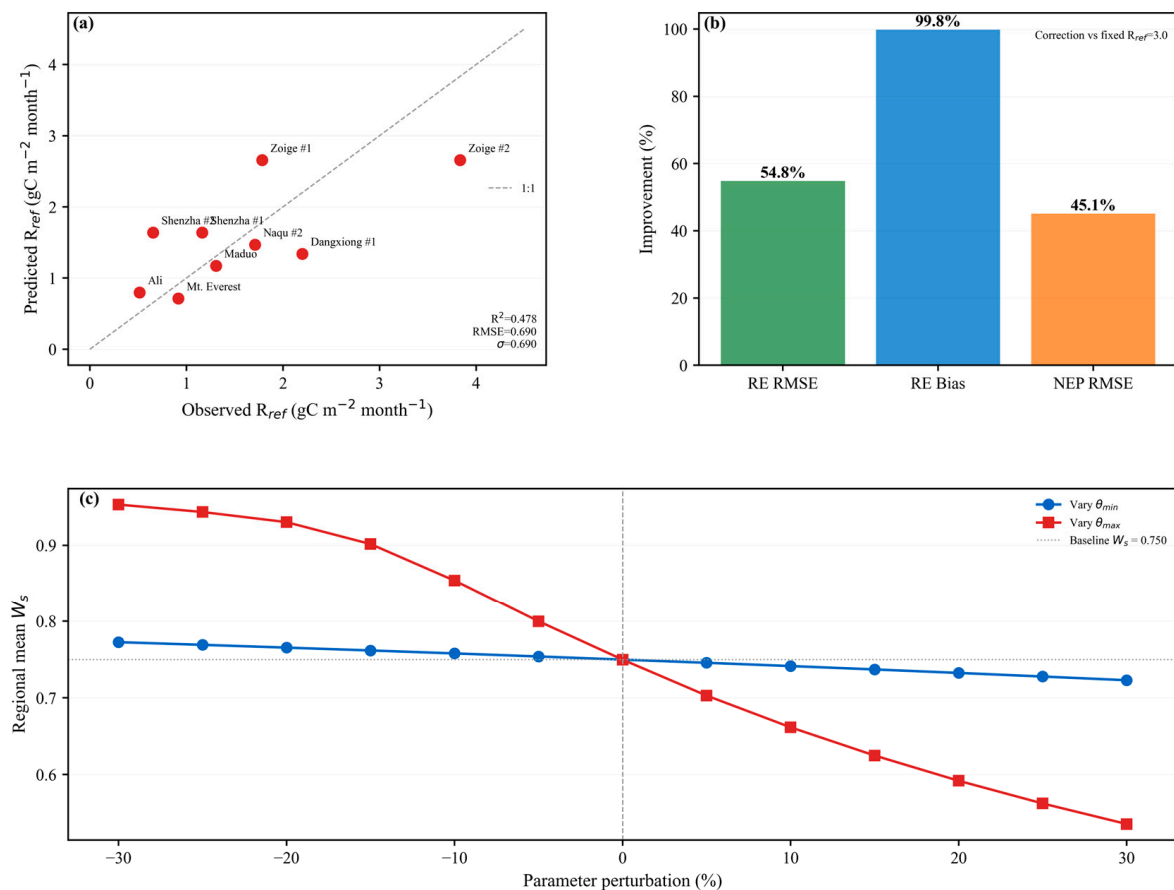


Figure 6. Model correction and parameter sensitivity verification. (a) Comparison of reference respiration R_{ref} observations with model predictions (multiple linear regression based on EVI and LST). (b) The accuracy improvement percentage of corrected ecosystem respiration RE and net ecosystem productivity NEP relative to the fixed $R_{ref} = 3.0$ method. (c) The sensitivity analysis of soil moisture parameter W_s to θ_{min} and θ_{max} disturbances, and the mean value of baseline W_s was marked by a dotted line.

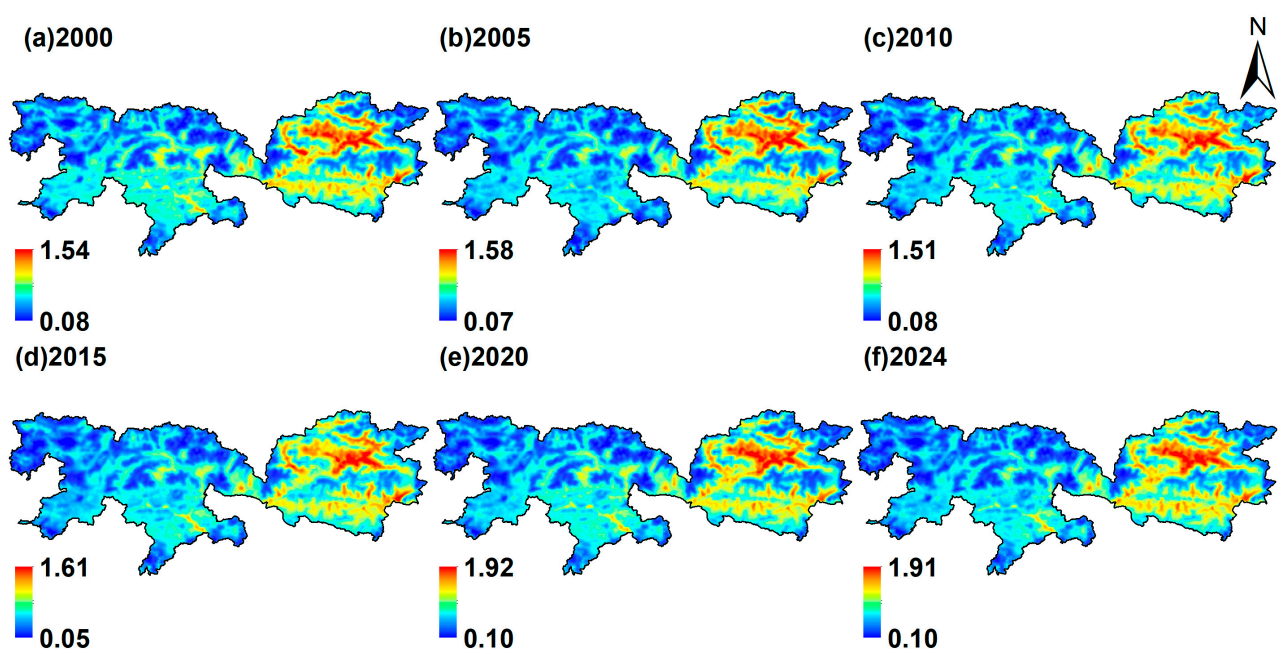


Figure 7. The spatial distribution of RE in 6 years from 2000 to 2024.

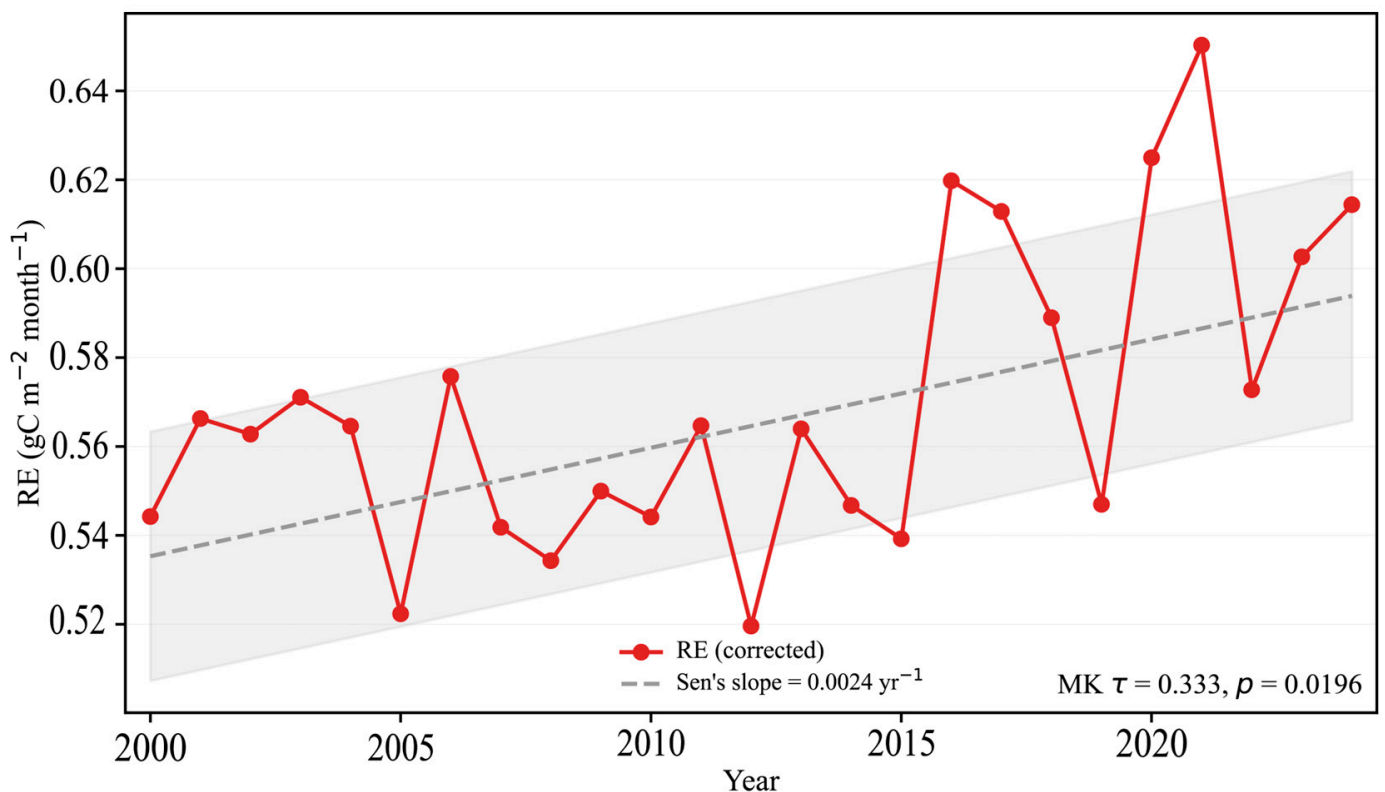


Figure 8. Years of RE change line chart.

3.3. The Spatial Dimension of RE–Precipitation Relationship

Precipitation quintile grouping analysis showed that RE increased monotonously from $0.466 \pm 0.186 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$ in the lowest precipitation group Q1 to $0.671 \pm 0.335 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$ in the highest precipitation group Q5. The mean value of Q5 was about 1.44 times that of Q1, and the single-factor ANOVA $F = 1.986$ ($p < 0.001$). The standard deviation within the Q5 group (0.335) was 1.80 times that of the Q1 group (0.186). With the increase in precipitation, the spatial variability of RE was amplified simultaneously.

The piecewise linear regression detected the optimal breakpoint of 403.2 mm in the precipitation range of 301–589 mm, but the R^2 increment before and after the breakpoint was only 0.006 (linear $R^2 = 0.083$, piecewise $R^2 = 0.089$). The RE–precipitation relationship is approximately linear at the basin scale, and there is no obvious precipitation threshold effect.

OLS multiple regression ($\text{RE} \sim \text{Precip} + \text{PCI} + \text{CV} + \text{DEM} + \text{PCD} + \text{PCP}$) explained 61.8% of the spatial variation in RE ($R^2 = 0.618$). Among the standardized regression coefficients, the absolute effect of DEM is the largest ($\beta = -0.760$), followed by PCI ($\beta = -0.200$) and CV ($\beta = -0.125$), and the total precipitation effect is the weakest ($\beta = 0.037$). The standardized effect of PCI is about 5.4 times of the total precipitation. The coefficient direction of PCD and PCP is opposite to the zero-order correlation, and the magnitude is abnormal ($\text{PCD}_\beta = +0.377$, $\text{PCP}_\beta = +0.162$), which is the coefficient expansion caused by the high collinearity ($r > 0.93$) among PCI–PCD–PCP. After eliminating PCD and PCP, the reduced model R^2 remained unchanged (0.618), the direction of each variable coefficient was consistent with the zero-order correlation, and the independent effects of PCI and CV were robustly estimated (Figure 9).

To visually display the binary density distribution of RE and annual precipitation on the pixel scale, the hexbin scatter plot was used to draw the results of the whole sample and the stratification according to land cover. The scatter plot of the whole sample shows that the core of pixel density is concentrated in the range of precipitation at 350–480 mm and RE $0.3\text{--}0.8 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$, forming an elliptical high-density area elongated along

the precipitation axis. The overall upward trend of RE with precipitation is weak ($r = 0.263$). The scatters are mainly low-RE (<0.4) at the low-precipitation end (<350 mm), while the distribution range of RE at the high-precipitation end (>480 mm) is significantly broadened, including both high RE value (>0.8) and residual low RE value (<0.4), suggesting that precipitation is not a single limiting factor for the spatial differentiation of RE. High precipitation provides water conditions for high respiration, but low-RE pixels still exist in high precipitation areas, indicating that other factors (such as temperature, vegetation cover) constitute parallel constraints.

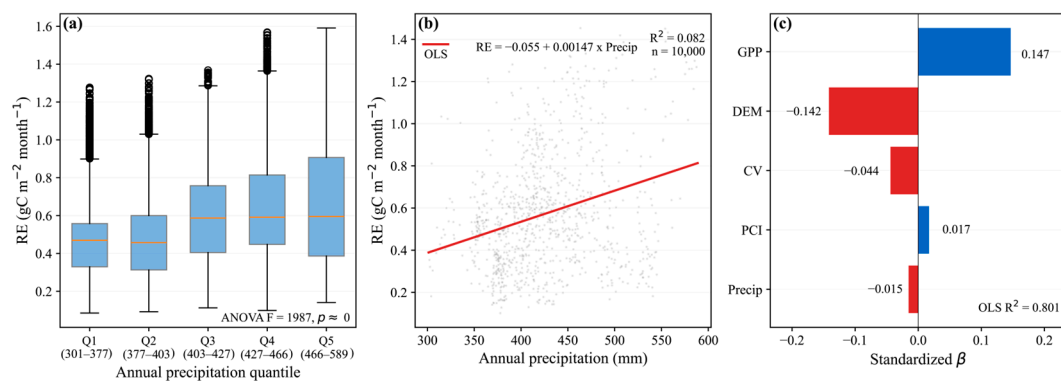


Figure 9. RE–precipitation spatial relationship. (a) Precipitation gradient quintile RE box plot. (b) Piecewise regression (marked breakpoint 403.2 mm). (c) OLS standardized coefficient forest map.

After stratification according to land cover, grassland pixels dominated the distribution pattern of the whole sample, and the hexbin density kernel basically coincided with the whole sample. The RE–precipitation showed a weak positive correlation ($r = 0.287$), and the high-density area slowly uplifted along with the precipitation gradient. The bare land pixels are concentrated in the lower left region of the map: low precipitation (mean 389 mm), low RE (mean $0.257 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$), and the RE–precipitation slope are only about 1/4 of that of grassland ($\beta = 4.0 \times 10$), and the scatter points are almost horizontally spread on the precipitation axis. The hexbin density core of grassland and bare land formed a systematic vertical displacement of about $0.3 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$ on the RE axis, which was mainly due to the temperature decreasing effect caused by the average altitude difference of about 650 m between the two types of objects, rather than the precipitation difference itself. The number of forest and shrub pixels is too small, showing a discrete scatter distribution in the hexbin diagram, and no identifiable density structure is formed (Figure 10).

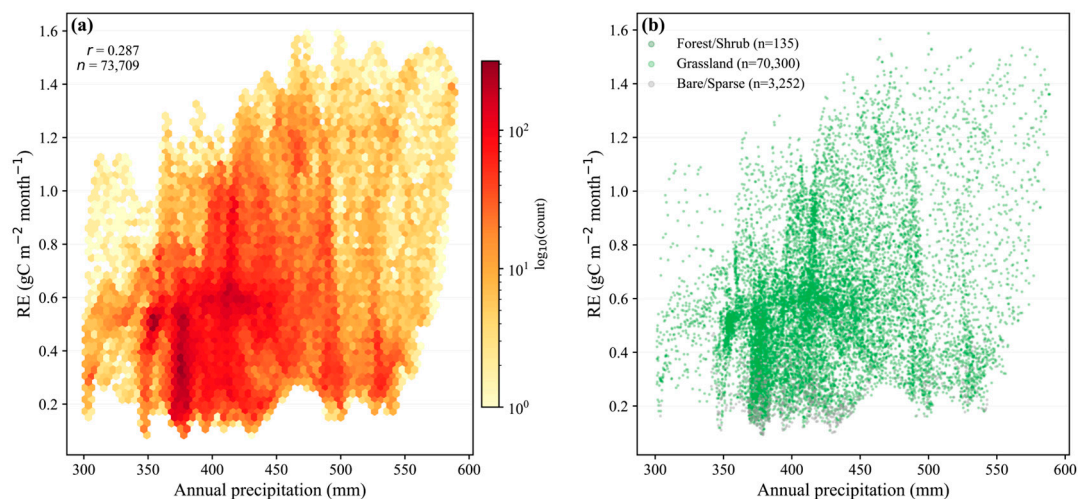


Figure 10. RE–precipitation hexbin scatter plot: (a) full sample; (b) stratified by LU.

3.4. Time Dimension of the Precipitation–RE Relationship: Immediate Response and Growing Season Accumulation

The time dimension analysis reveals a completely different control pattern from the spatial dimension. On the interannual scale, there was no significant correlation between regional annual average RE and annual precipitation ($r = 0.117$, $p = 0.578$), while RE–GPP coupling was close ($r = 0.843$, $p < 0.001$)—the total precipitation itself could not predict the interannual fluctuation of RE, and the GPP dynamics driven by temperature and radiation dominated the temporal trajectory of ecosystem respiration. From 2000 to 2024, the average annual RE was between 0.518 and $0.648 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$ ($\text{CV} = 5.90\%$), and the interannual fluctuation range was less than GPP (interannual $\text{CV} = 7.28\%$) and precipitation (regional annual precipitation time series $\text{CV} = 18.2\%$), which was consistent with the buffering effect of respiratory thermal acclimation on climate fluctuation (Figure 11).

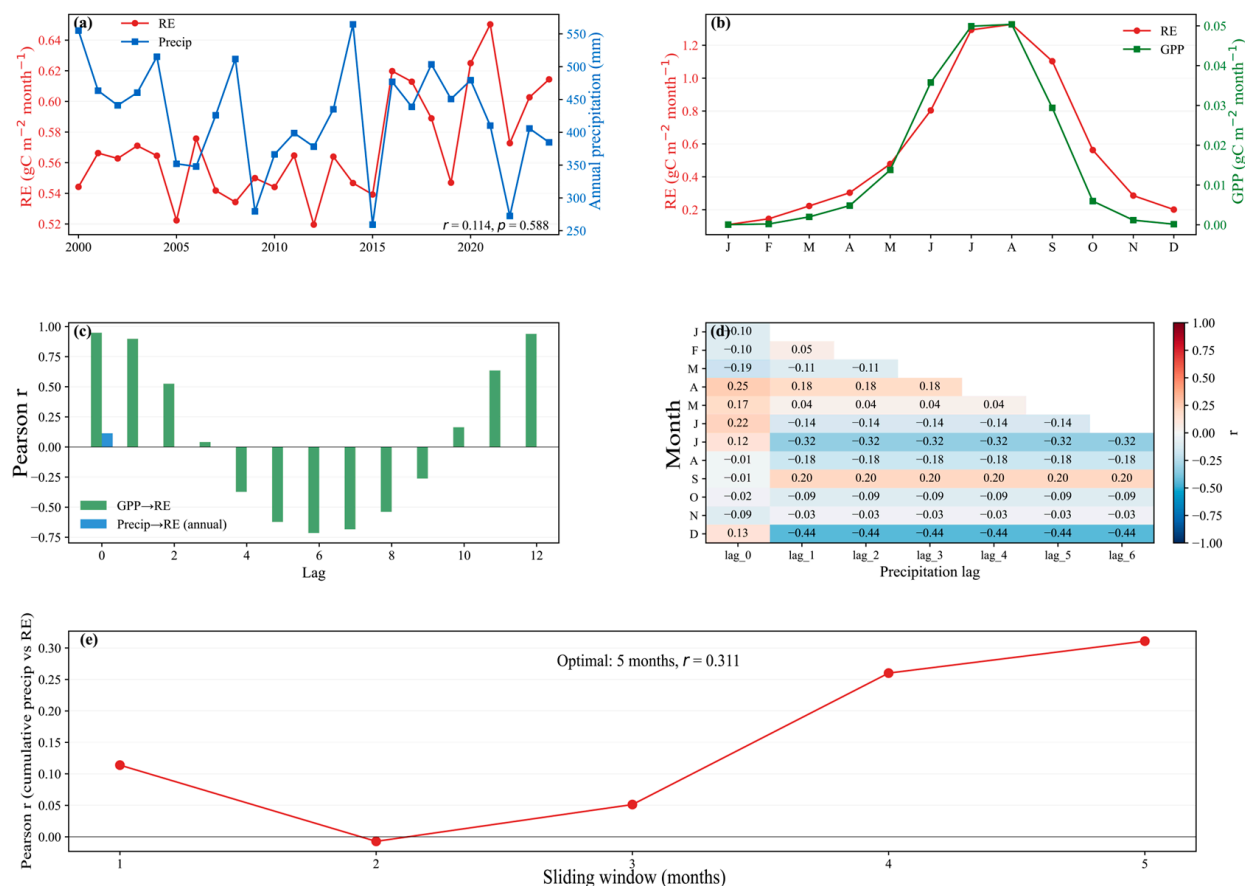


Figure 11. Temporal dynamics and lag effects: (a) double Y-axis of interannual variability in RE and precipitation; (b) double Y-axis of monthly climatological state of RE and GPP; (c) RE-lag correlation histogram of each factor (lag₀ to lag₁₂); (d) monthly × lag correlation heatmap; (e) sliding cumulative precipitation–RE correlation curve.

The lag effect analysis revealed the unique “instant response” characteristics of alpine ecosystems. All five environmental factors had the strongest correlation with RE at lag₀ (lag₀, i.e., the same month): GPP–RE $r = 0.949$, temperature–RE $r = 0.943$, soil moisture–RE $r = 0.830$, precipitation–RE $r = 0.855$, and EVI–RE $r = 0.893$. No factor performed better than the immediate response in the cross-month lag; this pattern is different from temperate grassland (typical lag 1–2 months) and arid area system (lag 3–6 months). The monthly climatological curve explains this phenomenon from the mechanism: the RE and GPP of the alpine meadow are strictly limited to the short growing season from May to September, and the RE tends to zero in winter (November–February). Therefore, there is no water

memory effect of “pre-seasonal precipitation affecting subsequent RE”, and precipitation outside the growing season contributes little-to-the loss of respiratory carbon.

The sliding cumulative precipitation analysis further supports the “growing season instant response” hypothesis. The 3-month sliding cumulative precipitation (roughly corresponding to the June–August growing season) had the strongest correlation with RE ($r = 0.910$), which was significantly better than the single-month precipitation ($r = 0.855$) and the 6-month sliding cumulative precipitation ($r = 0.674$), while the 12-month sliding cumulative precipitation had little correlation with RE ($r = 0.031$). This indicates that the integrated precipitation signal during the core growing season—rather than the total precipitation in isolated months or years—is the optimal moisture indicator for alpine ecosystem respiration. The anomaly analysis of drought and flood years showed the following: drought years (2009, 2015, 2022); the RE anomaly is $-0.016 \pm 0.014 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ in flood years (2000, 2004, 2014); the RE anomaly was $-0.018 \pm 0.009 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$; and there was no significant deviation from the zero value in both groups (t test, $p > 0.30$). Alpine meadow RE showed significant resistance to extreme precipitation years, and its buffering mechanism may be due to the high water holding capacity of alpine meadow soil.

The RE spatial anomaly map confirms the time series characteristics of interannual fluctuations from the spatial dimension, and reveals the secondary spatial differentiation within the basin. In 2005, 96.3% of the pixels in the whole basin were negative anomalies (mean $-0.048 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$), and in 2020, 94.5% of the pixels were positive anomalies (mean $+0.055 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$), indicating that the interannual driving force acted on the regional scale rather than the local scale. In terms of time series, the four snapshots from 2000 to 2015 were dominated by negative anomalies (the proportion of positive pixels was only 3.7–22.3%), while in 2020 and 2024, they were dominated by positive anomalies (the proportion of positive pixels was 88.4%, 94.5%), showing an obvious trend of “from negative to positive”. This change is not related to the total amount of precipitation: the precipitation (352 mm) in 2005 was in the normal range, but it was the strongest year of negative anomaly in 6 years (mean -0.048); the precipitation in 2020 (479 mm) is also normal, but it is the strongest positive anomaly year (mean $+0.055$), which further confirms that the interannual growth of GPP is the dominant driving force for the spatial anomaly of RE from negative to positive (Figure 12).

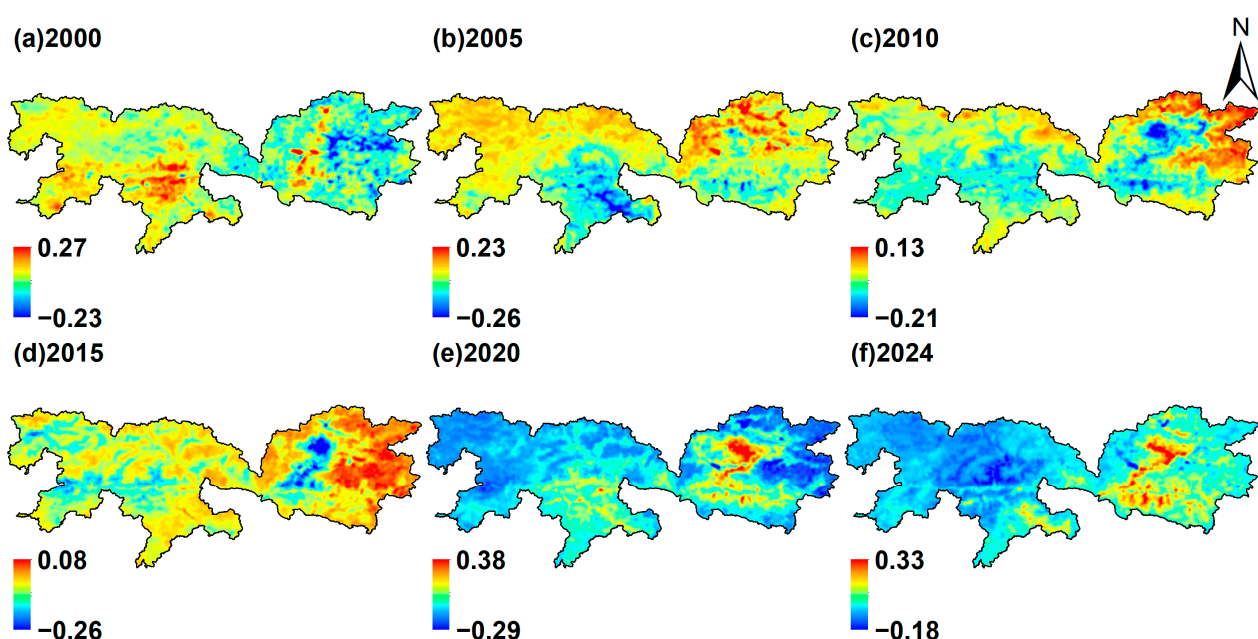


Figure 12. RE spatial anomaly map (relative to the 2000–2024 mean).

There is a stable east–west gradient differentiation within the basin. In most years, the RE anomaly amplitude of the eastern tributaries (Lhasa River, Niyang River, etc.) is greater than that of the western mainstream (the main basin of the Yarlung Zangbo River): in 2000, the eastern part is lower than the western part by $-0.036 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, and in 2024, the eastern part is higher than the western part by $+0.057 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$ (the strongest gradient in 6 years). In the north–south direction, the anomaly amplitude in the south (near the northern foot of the Himalayas) is also systematically stronger than that in the north: in 2005, the south is lower than -0.074 and the north is only lower than -0.035 ; in 2020, the south is higher than $+0.072$ and the north is higher than $+0.047$. These spatial differentiation patterns suggest that under the background of regional climate signals, local topography (elevation gradient, valley direction) and vegetation coverage differences have secondary modulation effects on RE interannual anomalies.

3.5. Structural Equation Model: Indirect Conduction Path of Precipitation Heterogeneity

To test H4 (precipitation heterogeneity indirectly inhibits RE through vegetation productivity), three competitive SEM models were constructed and compared (Table 3). In Model 1, PCI, CV, and PCD were forced into a single latent variable, PHI ($\text{PHI} = \sim\text{PCI} + \text{CV} + \text{PCD}$), and PHI was used as a unified “precipitation heterogeneity” construct to drive GPP and RE. Model 2 gives up latent variables, and takes PCI, CV, and PCD as explicit variables to directly act on GPP and RE. Based on Model 2, soil moisture (SM) and temperature (Temp) were introduced as additional mediating variables and the control variables in Model 3 (Complete Mediation Model) to comprehensively describe the cascade path of precipitation heterogeneity mediated by vegetation and soil and finally transmitted to RE. All variables were fitted after Z-score standardization.

Table 3. Comparison of each model.

Model	Specification	χ^2	df	CFI	RMSEA	AIC	BIC
Model 1 (PHI latent)	PCI + CV + PCD $\rightarrow$ PHI $\rightarrow$ GPP/SM/RE	3046.3	9	0.902	0.260	22.8	101.0
Model 2 (Direct effects)	PCI/CV/PCD $\rightarrow$ GPP; GPP $\rightarrow$ RE	1287.4	11	0.959	0.152	19.5	84.7
Model 3 (Full mediation)	PCI/CV/PCD $\rightarrow$ GPP/SM/RE; DEM/Temp $\rightarrow$ GPP/RE	36.4	18	1.000	0.014	36.0	153.3

The model comparison results provide strong support for H4. The RMSEA of M1 (PHI latent variable model) was as high as 0.260, and the CFI was only 0.902. The fitting was significantly worse than the M2 and M3-CFI difference of 0.057 and 0.098, respectively, far exceeding the empirical threshold of ΔCFI greater than 0.01. The methodology has a clear meaning: PCI (intra-annual precipitation concentration), CV (interannual variation coefficient), and PCD (precipitation concentration) belong to the category of ‘precipitation heterogeneity’, but they capture the variation characteristics of different time scales and physical processes (intra-annual distribution concentration vs. interannual fluctuation amplitude vs. seasonal phase shift), the correlation coefficient between the three indicators is only $|r| = 0.05\text{--}0.35$, and should not be forced to merge into a single latent variable. M2 (direct effect model) allowed each index to play an independent role, and the fitting was significantly improved (CFI = 0.959), but it missed the two key conduction paths of soil moisture and temperature, and the residual information was still largely unexplained. After introducing SM and Temp on the basis of M2, the fitting of M3 was almost perfect (CFI = 1.000, RMSEA = 0.014, $\chi^2/\text{df} = 2.02$), which became the final adopted interpretation model (Figure 13).

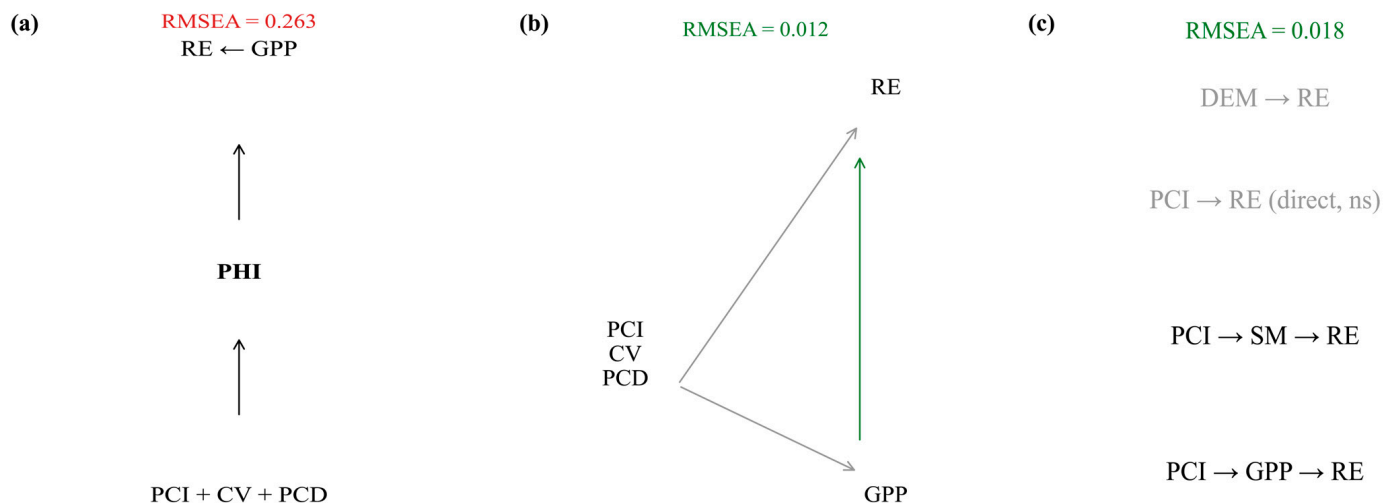


Figure 13. Comparison of SEM alternative models: (a) PHI latent variable model; (b) direct effect model; and (c) complete mediation model.

The path coefficient and effect decomposition of M3 revealed a clear multi-path indirect transmission mechanism (Table 4).

Table 4. Standardized path coefficients of the full-mediation structural equation model.

Path	Standardized Coefficient	Pathway	Effect
PCI → GPP	−1.448	Indirect: PCI → GPP → RE	−0.676
CV → GPP	+0.139	Indirect: PCI → SM → RE	−0.217
PCD → GPP	+0.773	Total indirect effect	−0.893
PCI → SM	−1.039	Direct effect (PCI → RE)	+0.076
PCD → SM	+0.846	Net effect of PCI on RE	−0.818
Temp → GPP	+0.178		
DEM → GPP	−0.205		
GPP → RE	+0.467		
SM → RE	+0.209		
Temp → RE	+0.843		
DEM → RE	+0.247		
PCI → RE (direct)	+0.076		
CV → RE (direct)	−0.088		

The PCI path (core variable): the path coefficient of PCI to GPP is -1.448 ($p < 0.001$), the path coefficient of PCI to SM is -1.039 ($p < 0.001$), the direct path coefficient of PCI to RE is $+0.076$ ($p = 0.004$), the path coefficient of GPP to RE is $+0.467$ ($p < 0.001$), and the path coefficient of SM to RE is $+0.209$ ($p < 0.001$). Indirect effect decomposition: the indirect effect of PCI mediated by GPP is $-1.448 \times 0.467 = -0.676$, the indirect effect of PCI mediated by SM is $-1.039 \times 0.209 = -0.217$, and the total indirect effect is -0.893 . The direct effect of PCI ($+0.076$) was statistically significant ($p = 0.004$), but the effect direction was opposite to the indirect path (positive weak effect vs. negative strong indirect effect), showing a typical inconsistent intermediary pattern—the net effect of PCI on RE (-0.818) was almost entirely (109%) contributed by the indirect path, and the direct path only played a weak reverse offset effect. The substantive explanation is that the increase in precipitation concentration (PCI increase) reduces ecosystem respiration by inhibiting vegetation photosynthetic productivity (GPP decrease) and reducing soil water availability (SM decrease), rather than directly acting on the respiration process by changing soil microclimate.

The CV and PCD pathways (auxiliary indicators): The total effect of CV on RE is -0.067 , in which CV contributes $+0.065$ (positive) to the indirect pathway mediated by GPP, and CV contributes -0.088 (negative) to the direct pathway of RE, reflecting that the interannual precipitation instability has an additional inhibitory effect on RE beyond

the GPP mediation, which may be related to soil microbial stress in extreme dry and wet years. The total effect of PCD on RE is +0.420, and the dominant path is PCD mediated by GPP (+0.361) and PCD mediated by SM (+0.177), indicating that the increase in seasonal concentration of precipitation may promote GPP and RE by prolonging the wet period of growing season. The effect direction and conduction path of the three heterogeneity indicators are different, which further verifies the irrationality of combining them into a single latent variable in Model 1.

Control variable path: temperature is the strongest direct driving factor of RE (the path coefficient of Temp to RE is +0.843, $p < 0.001$), and it is indirectly promoted by GPP (the path coefficient of Temp to GPP is +0.178, the indirect effect of Temp to RE through GPP is +0.083, and the total effect is +0.926). The independent effect of elevation (DEM) after controlling temperature is as follows: the path coefficient of DEM to GPP is -0.205 ($p < 0.001$, elevation inhibits vegetation productivity), the path coefficient of DEM to RE is +0.247 ($p < 0.001$, the residual of DEM is positive after the temperature effect is stripped), the indirect path of DEM to RE through GPP is -0.096 , and the total effect is +0.151. Notably, if Temp (e.g., M2) is not included in SEM, the path coefficient of DEM to RE is -0.545 ($p < 0.001$); currently, DEM absorbs the altitude-decreasing effect of temperature, showing a strong negative effect. This suggests that in the complex terrain of the Qinghai–Tibet Plateau, the ecological effects of altitude must distinguish between “temperature-mediated altitude effect” and “altitude-independent effect outside temperature”, and the two directions are opposite.

In summary, SEM path analysis established a three-level indirect transmission framework of precipitation heterogeneity on RE: (1) the increase in precipitation concentration (PCI increase) first inhibits the photosynthetic carbon fixation of vegetation (GPP decrease), and the path coefficient is -1.448 ; (2) the decrease in GPP limited the supply of autotrophic respiratory substrates and the input of rhizosphere secretions (the path coefficient of GPP to RE +0.467); (3) at the same time, the PCI increased the soil water availability (the path coefficient of PCI to SM -1.039) and weakened the substrate diffusion rate of heterotrophic respiration (the path coefficient of SM to RE +0.209). The two indirect paths together account for more than 100% of the total effect of PCI, and the direct path (the direct effect of PCI on RE +0.076) can be ignored in the substantive sense. The effect of precipitation heterogeneity on ecosystem respiration in alpine grassland is essentially a cascade conduction process in which hydrological variation drives vegetation productivity changes and then regulates carbon release, rather than direct regulation of soil carbon flux by precipitation.

4. Discussion

4.1. *R_{ref} Correction of Flux Tower Constraints: Methodological Contribution and Regional Significance*

The R_{ref} environment matching model based on 9 flux tower sites reduced the RMSE of RE estimation by 54.8% (1.04 to 0.47 gC·m⁻²·month⁻¹), the systematic bias was effectively eliminated (Bias decreased from 0.80 to -0.001), and the systematic bias was effectively eliminated (Bias decreased from 0.796 to -0.001). The traditional Lloyd–Taylor scheme sets the basic respiration rate R_{ref} as an empirical constant of 3.0 gC·m⁻²·month⁻¹ [96,97], which is completely unable to characterize the actual respiration potential of alpine grassland under low-vegetation cover (EVI ≈ 0.11), short growing season (3–4 months) and low-temperature environment (annual average temperature below 5 °C in high altitude area). The mean value of R_{ref} constrained by the flux tower in this area is only about 1.2 gC·m⁻²·month⁻¹, and the constant scheme results in a systematic overestimation of about 2.5 times. The spatial variation of R_{ref} was 2.2 gC·m⁻²·month⁻¹ (about 2.7 in the high coverage area of the valley and about 0.5 in the sparse area of the mountains). If this variation was ignored, the low coverage and high-altitude area would be systematically

overestimated by about 2.5 times, while the high-coverage and low-altitude area would be systematically underestimated.

The core innovation of this scheme is to redefine R_{ref} from the empirical constant as an environmental diagnostic variable. The multiple regression ($R^2 = 0.478$, $\sigma = \pm 0.690$, $n = 9$) with EVI and LST as predictors captured a reasonable ecological gradient: the R_{ref} of the high-EVI site was about $2.7 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, and the R_{ref} of the low-EVI site was only about $0.5 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$. The essence of this “environment matching” strategy is to use the environmental variables of satellite remote sensing as a bridge to extrapolate the R_{ref} information space of a limited site to each grid pixel [98,99]. At present, there are less than 20 plateau flux towers [100], and the distribution is seriously biased towards the eastern humid low-altitude stations. There is almost no ground observation coverage in the western semi-arid grassland and desert grassland [101]. The deviation of machine learning extrapolation outside the training domain has been quantified in a number of assessments [102]. This study provides a parameterization scheme for bridging the scale gap from site to region without sacrificing the interpretability of the process [103], and its methodological framework can be extended to other alpine regions lacking flux observations [104].

4.2. The Core Mechanism of Precipitation Heterogeneity Affecting RE: Indirect Conduction and Index Differentiation Effect

This study provides quantitative support for the indirect transmission hypothesis with multiple evidence chains. The direct importance of precipitation in random forest analysis was only 0.16% (sort: EVI 56.4% > temperature 22.6% > GPP 18.4% > soil moisture 2.4% > precipitation 0.16%). SEM path analysis further confirmed that the net effect of PCI on RE was -0.818 , almost entirely through the indirect path: the indirect effect of PCI mediated by GPP was -0.676 (75.7% of the indirect effect), and the indirect effect of PCI mediated by SM was -0.217 (24.3%). The total indirect effect was -0.893 , while the direct effect was only $+0.076$ ($p = 0.004$). It is worth noting that the direct effect direction is opposite to the indirect path, showing a typical ‘inconsistent intermediary’ pattern—the absolute value of the indirect effect exceeds the total effect (109.3%), and the direct path only plays a weak reverse offset role, further highlighting the dominant position of indirect conduction. We note that the SM-mediated pathway is the only pathway that shares any structural overlap with the RE reconstruction (Equation (4)), accounting for 24.3% of the indirect effect, whereas the dominant GPP-mediated pathway is fully independent of the RE model; the central conclusion is therefore not affected by this partial overlap.

This “top-down” cascade transmission mechanism-increasing precipitation variability inhibits vegetation carbon fixation, thereby reducing rhizosphere substrate supply, and ultimately depressing soil respiration, and the classic “precipitation pulse-triggered soil respiration burst” (Birch effect) model in arid and semi-arid systems forms a mechanistic control [105,106]. We emphasize that this pathway is hydrological and physiological rather than erosional: greater precipitation concentration reduces the water effectively available to plants (through faster runoff and drainage and longer dry intervals), which lowers productivity and, in turn, the supply of rhizosphere substrates and autotrophic respiration; physical erosion or direct carbon loss is not involved. It is important to distinguish precipitation amount from precipitation concentration: a larger total amount generally supports productivity in this water-limited basin, whereas a more concentrated temporal distribution of a similar total (higher PCI) reduces effective water availability and is associated with lower productivity. The warming-driven lengthening of the growing season, which increases both GPP and RE (Section 4.5), is a separate effect that operates independently of this concentration effect. The key difference of alpine grassland is the triple buffering mechanism. First, soil moisture rarely dropped below the microbial ac-

tivity threshold during the growing season (average annual precipitation of 400–600 mm, significant snowmelt replenishment), and water was not a rigid limiting factor for microorganisms. Second, low temperature (annual average temperature below 5 °C in the area above 4500 m) is a stronger metabolic rate control factor than water [107], which buffers the direct regulation of water fluctuation on soil decomposition process. Third, the proportion of autotrophic respiration in RE of alpine grassland may be higher than that of low-altitude grassland [108], and this part of respiration is completely dependent on the recent supply of photosynthetic products, which further strengthens the coupling control of vegetation productivity on respiration [109]. Therefore, the key to understand the carbon cycle of alpine grassland is to grasp the dominant role of vegetation productivity-precipitation regulates the substrate supply of respiratory carbon release by determining the rate and rhythm of photosynthetic carbon input [110,111]. If future climate warming is accompanied by an increase in precipitation concentration (such as more extreme precipitation events), vegetation productivity will be the first to be inhibited, and then the respiratory carbon release of the entire ecosystem will be suppressed through a cascade effect.

The SEM model comparison further reveals the results with important methodological implications: there are qualitative differences in the effect direction of the three heterogeneous indicators, rather than just quantitative differences. The correlation coefficients between PCI and CV, PCD, and CV, PCP and CV are only $|r| = 0.05\text{--}0.35$, which is far from enough to support the internal consistency required for latent variable modeling. Although PCI, PCD and PCP are highly collinear ($r > 0.93$), they belong to different time scales with CV and lack the measurement basis for combining the four into a single latent variable [112]. The model (M1) that forced the three to be merged into a single latent variable PHI had the worst fitting (CFI = 0.902, RMSEA = 0.260), while the model (M2 and M3) that allowed the three to act independently fitted significantly better ($\Delta\text{CFI} = 0.057\text{--}0.098$). The net effect of PCI on RE was -0.818 (negative), and the mediating effect of the dominant path PCI through GPP was -0.676 , that is, the increase in the concentration of precipitation during the year indirectly reduces the release of respiratory carbon by inhibiting vegetation productivity. The net effect of CV was only -0.068 (weak negative), and its transmission path showed an internal offset pattern: CV had a weak positive effect on GPP ($+0.139$, which may be related to compensatory growth in wet years), while the direct path of CV to RE was -0.088 , which may reflect the persistent stress on soil microbial communities in extreme dry years. The net effect of PCD was $+0.420$ (positive), the effect of PCD on GPP was $+0.773$, and the effect of PCD on SM was $+0.846$. The increase in precipitation seasonal concentration promoted GPP and soil moisture. The physical mechanism is that the growing season and the rainy season are highly coincident (the precipitation peak DOY is about 190), and the more concentrated rainy season means more adequate water supply during the growing season. The heterogeneity of the effect direction of the three indicators: PCI inhibits RE, CV is nearly neutral, and PCD promotes RE, profoundly showing that “precipitation heterogeneity” is not a single concept that can be simply summed up. The heterogeneity of different time scales and statistical dimensions affects the carbon cycle through different ecological and physiological pathways [113]. Future research should clearly distinguish these dimensions.

4.3. Causal Explanation Trap of Random Forest Importance Ranking: Why Precipitation Is Marginalized

Section 4.2 established that precipitation heterogeneity affects RE indirectly through vegetation productivity. A fact that cannot be avoided, however, must be stated up front: precipitation heterogeneity alone cannot fully account for the spatiotemporal variability of RE. A random forest regression ($R^2 = 0.998$) was trained with RE as the response variable and EVI, air temperature, GPP, soil moisture, and precipitation as predictors. The ensemble

of 500 trees captured the statistical structure of RE variation with near-saturated goodness of fit [114]. We emphasize that this in-sample $R^2 = 0.998$ is a goodness-of-fit diagnostic rather than evidence of out-of-sample predictive skill: the near-saturated fit reflects the strong spatial autocorrelation in the gridded predictors and the non-independence of EVI, GPP and temperature from the RECO product, and we, therefore, do not interpret it as predictive accuracy. The variable importance values on which our interpretation rests are permutation-based and computed on out-of-bag samples, and the variable importance ranking revealed a steep hierarchy: EVI dominated at 56.4%, followed by air temperature (22.6%) and GPP (18.4%), together accounting for 97.4% of the explained variance; soil moisture (2.4%) and precipitation (0.16%) occupied the bottom tier, with precipitation importance amounting to only 1/353 of that of EVI. We stress at the outset that this negligible direct importance of precipitation is not contradictory to the strong indirect effect recovered by the SEM below; the two are complementary, because the random forest indicates where the statistical information about RE resides (vegetation), whereas the SEM reveals where that information originates (precipitation acting through vegetation). The permutation-based variable importance metrics are, however, highly sensitive to collinearity among predictors: when predictors are strongly correlated, the information carried by a permuted variable can be partially substituted by its collinear counterparts, leading to systematic underestimation of its importance [115,116]. This ranking conveys a simple but ecologically important fact: in this alpine agricultural region, vegetation state, rather than precipitation itself, provides the single high-resolution statistical map of RE spatiotemporal variation. Judged solely by the random forest output, the ecological contribution of precipitation would appear negligible. Equating predictive importance with causal importance is, however, among the most insidious interpretation traps in the application of machine learning to ecology [117].

EVI is not merely a greenness index. As an integrative proxy encoding vegetation phenology, leaf area index, the fraction of photosynthetically active radiation absorbed, and the composite canopy response to temperature, water availability, and radiation, EVI is fundamentally a downstream integration product of upstream climate signals. When EVI enters the predictive model, the statistical importance of climate variables is inevitably absorbed by this downstream proxy: the causal chain in which precipitation drives vegetation growth and vegetation drives respiration is compressed, within an information-theoretic framework, into a single-step “vegetation to respiration” association. Random forests faithfully report where the statistical information about RE variation resides, and the answer is vegetation. They cannot, however, answer the question of where the variation in vegetation state originates. In other words, the marginalization of precipitation in the importance ranking does not imply that precipitation is causally redundant; it implies that the effect of precipitation has been fully expressed through its causal consequence, vegetation. This conceptual divide between predictive modeling and causal explanation constitutes the logical starting point for distinguishing the scientific goals of statistical learning from those of mechanistic inference [118,119].

This causal masking by a proxy variable receives dual cross-validation from partial correlation analysis and SEM. After controlling DEM, the partial correlation coefficients between precipitation heterogeneity indices and RE rose sharply: the partial r for CV jumped from -0.127 to -0.430 (a 239% increase), and that for PCI increased from -0.336 to -0.435 (a 30% increase). These shifts indicate that even across the spatial gradient, the independent ecological signal of precipitation heterogeneity, once suppressed by the strong statistical chain linking elevation, vegetation, and RE, requires partial correlation to be isolated from confounding. SEM removes this masking at a more fundamental, causal-inference level. In the full mediation model (M3; CFI = 1.000, RMSEA = 0.014), the indirect effect of PCI

via GPP was -0.676 (75.7% of the total indirect effect), and the indirect effect via soil moisture was -0.217 (24.3%), yielding a combined indirect effect of -0.893 , which accounted for 109.3% of the total effect. The direct effect of PCI on RE was only $+0.076$ ($p = 0.004$), opposite in sign to the indirect pathway, forming a classic pattern of inconsistent mediation. This configuration, in which the absolute magnitude of the indirect effect exceeds that of the total effect and the direct and indirect effects carry opposite signs, is recognized in the mediation analysis literature as inconsistent mediation or suppression. Under such conditions, relying solely on the total effect to judge the ecological role of precipitation heterogeneity would severely underestimate the true strength of transmission through the mediated pathway. No physiologically meaningful direct link exists between precipitation concentration and RE. An elevated PCI first suppresses photosynthetic carbon fixation by vegetation (path coefficient = -1.448), which in turn reduces rhizodeposition substrate supply (downstream coefficient = $+0.467$), while simultaneously lowering soil water availability (coefficient = -1.039) and thereby weakening heterotrophic respiration (downstream coefficient = $+0.209$), ultimately depressing ecosystem respiratory carbon release.

Taken together, random forest and SEM constitute a methodologically productive dialogue in this study. The former, through nonparametric statistical logic, faithfully maps the predictive structure of RE variation: EVI is the leading predictor because vegetation integrates all climate signals. The latter, through causal-inference logic, reveals the causal structure that the predictive structure obscures: precipitation heterogeneity is an upstream driver in the causal chain, and its effects are fully mediated through vegetation and soil. Presenting only the random forest results without SEM-based causal calibration would lead readers to the erroneous conclusion that precipitation is unimportant; presenting only the SEM results without the full-variable statistical landscape provided by random forest would deprive readers of a holistic grasp of the multifactor contribution structure of RE variation. The complementary use of the two approaches yields one of the methodological insights of this study. In any ecological scenario characterized by a strongly collinear causal chain, in which climate drives vegetation, which in turn shapes ecosystem function, or where soil properties structure microbial communities, which then regulate carbon mineralization, machine learning importance rankings tend to assign causal weight to the most downstream integrative proxy variable. Researchers must calibrate this bias with process-based models or causal inference methods [120–122]. This methodological stance aligns with the theory-guided data science paradigm advanced in recent years: in ecosystems with a strong mechanistic foundation, embedding process understanding into data-driven models can effectively constrain the causal misattribution of proxy variables by purely statistical learning, because mechanistic knowledge supplies prior constraints on causal direction for variable importance rankings [123]. In the specific context of this study, SEM functions as a causal calibrator for random forest: the former supplies prior constraints on the direction and path structure of causal relationships among variables, while the latter captures the statistical ceiling of nonlinear associations through nonparametric flexibility. Their complementarity transcends the traditional machine learning versus statistical model dichotomy. The role of precipitation in the carbon cycle of this alpine agricultural region is not unimportant; rather, it does not need to act directly. Its ecological effect has already been fully expressed in the upstream causal chain of vegetation productivity (Figure 14).

4.4. Implications for High-Elevation Ecology: Spatial Confounding, Proxy-Variable Masking, and the Limits of Machine Learning Importance

This study reveals a finding with broad methodological implications for mountain ecology: strong spatial covariation between elevation and precipitation heterogeneity indices produces severe signal confounding [124]. In zero-order correlations, the correlation coefficient between PCI and RE was -0.336 ; after controlling DEM, the partial correlation

rose to -0.435 , an increase of 30%. For CV, the zero-order correlation was only -0.127 , yet the partial correlation reached -0.430 (a 239% increase), meaning the effect was underestimated by a factor of 3.4. For PCD, the zero-order correlation was -0.292 and the partial correlation was -0.380 , again an increase of 30%. Even air temperature, which is conventionally regarded as collinear with elevation, showed a zero-order correlation of 0.741 that dropped sharply to 0.174 after controlling for DEM, a decline of 76.5%. These results reinforce the understanding of elevation as a composite proxy variable for multiple environmental gradients: it simultaneously encodes the lapse rate of temperature, the decline in atmospheric pressure, the intensification of radiation, and the systematic shift in precipitation regime [125]. The zero-order correlation between any single climatic variable and RE may thus deviate from its true effect owing to elevation-induced confounding.

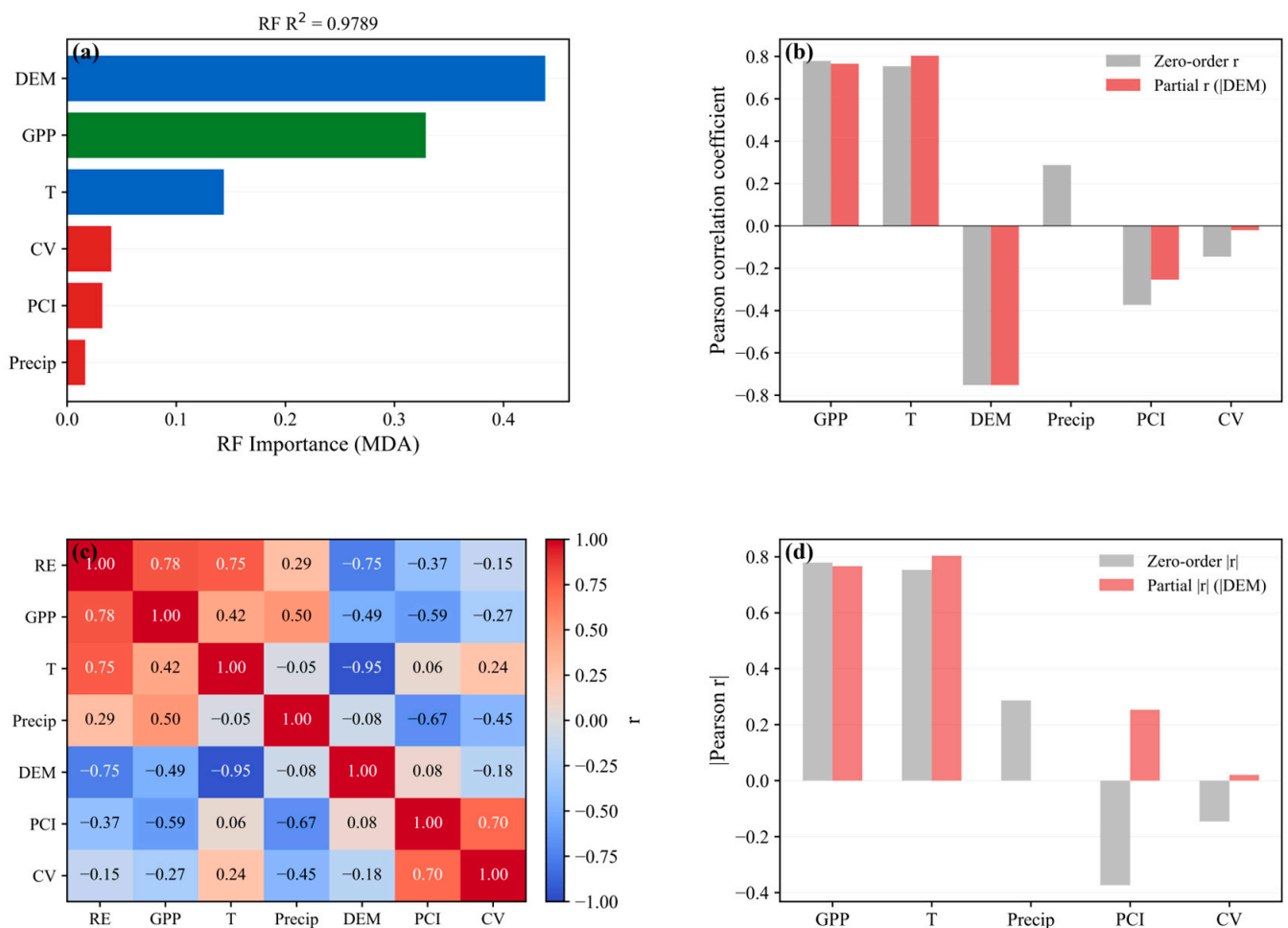


Figure 14. Random forest variable importance ranking and spatial correlation analysis of ecosystem respiration drivers. (a) Variable importance (%IncMSE) from a random forest model (500 trees) with EVI, air temperature, GPP, soil moisture, and precipitation as predictors ($R^2 = 0.998$). (b) Zero-order Pearson correlation matrix between RE and environmental factors. (c) First-order partial correlation coefficients between precipitation heterogeneity indices and RE before and after controlling for DEM; asterisks mark indices of which the partial correlation changed by more than 30% relative to the zero-order value. (d) Comparison of zero-order and first-order partial ($|DEM$) Pearson correlation coefficients between each environmental factor and RE; percentage annotations indicate the relative change in $|r|$ after controlling for DEM for indices exceeding a 5% threshold.

SEM analysis corroborated this confounding mechanism in a different but complementary manner. In Model M2, which did not include temperature, the path coefficient from DEM to RE was -0.545 ($p < 0.001$), superficially suggesting that higher elevation

suppresses respiration. When temperature was introduced in Model M3; however, the path coefficient from DEM to RE flipped sign to +0.247 ($p < 0.001$), while the path coefficient from temperature to RE reached +0.843. The causal interpretation of this sign reversal is that the negative DEM–RE coefficient in M2 captured the indirect suppression of respiration by elevation operating through temperature: DEM had absorbed the effect that properly belongs to temperature. Only after controlling temperature did the independent effect of elevation become visible. At a given temperature, RE tended to be slightly higher at higher elevations, a pattern that may reflect the greater retention of labile carbon pools resulting from slower soil carbon decomposition at high altitudes. The methodological implication of this finding is clear: in any study system spanning an elevational gradient exceeding 2000 m, assessments of the ecological effects of climatic variables must control for the spatial collinearity between elevation and climate through partial correlation or multiple regression that includes a DEM term [126,127]. The failure to do so will produce a bidirectional bias in which precipitation effects are underestimated and elevation effects are overestimated.

In the random forest analysis, EVI dominated the predictor importance ranking for RE at 56.4% (2.5 times that of temperature and 3.1 times that of GPP), whereas precipitation occupied the bottom position at 0.16%. This result should not be interpreted superficially as evidence that precipitation is unimportant. It is, rather, the natural expression within a machine learning framework of the central mechanism of this study: indirect transmission. EVI is not merely a vegetation greenness index in this context. It functions as a multidimensional proxy that integrates growing season length, canopy leaf area index, the fraction of photosynthetically active radiation absorbed, and the composite canopy response to temperature and water availability. Once these vegetation functional attributes are jointly encoded by EVI, the direct statistical importance of climatic variables is inevitably diluted, because their influence on RE has already been captured in the upstream causal chain in which climate drives vegetation growth. SEM path analysis provides direct support for this interpretation: the path coefficient from GPP to RE was +0.467, making GPP the second strongest predictor pathway for RE after temperature, and GPP itself is the joint product of PCI, CV, PCD, DEM, and temperature. This finding exposes a deep interpretation trap in machine learning importance rankings [128]: high importance signifies a strong direct statistical association but does not equate to strong causal effect [129]. A variable with substantial causal influence, such as precipitation heterogeneity, may be marginalized in an importance ranking precisely because its effect is fully mediated through downstream variables [130]. Random forest and SEM should be deployed as complementary, rather than alternative, tools: the former describes the statistical prediction structure, while the latter tests causal transmission hypotheses [131–133].

PCI is a purely temporal index of intra-annual precipitation concentration at each pixel, whereas elevation is a spatially covarying factor; the northwestward rise in PCI reflects the confinement of precipitation to the short monsoon window at higher elevation and greater distance from the moisture source, so elevation is treated here as a confounder (partialling out DEM, and including DEM and temperature separately in the SEM) rather than as the quantity PCI measures.

4.5. Carbon Source Trends, Warming Attribution, and Study Limitations

The 25-year mean RE across the Yarlung Zangbo River Basin and Its Two Tributaries Basin was $0.566 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$, with NEP at $-0.550 \text{ gC} \cdot \text{m}^{-2} \cdot \text{month}^{-1}$. Every pixel in the domain returned to a negative NEP value. The system therefore functions as a stable net carbon source, a conclusion that requires no inferential statistical support. At the interannual scale, RE exhibited a significant increasing trend (Sen's slope = 0.0025 yr^{-1} ,

$p = 0.022$), whereas total precipitation remained broadly stable over the 25-year period (mean Theil–Sen slope = $-2.32 \text{ mm} \cdot \text{yr}^{-1}$; only 3.51% of pixels showed a significant trend by the Mann–Kendall test; 96.5% of pixels had negative Sen slopes that did not reach statistical significance). The rising trend in RE cannot, therefore, be explained by changes in total precipitation. When interpreted alongside the transmission mechanism established by SEM, the more plausible attribution of the RE trend points to temperature-driven increases in respiration rate. The path coefficient from temperature to RE was +0.843, the single strongest pathway in the SEM, far exceeding the effect of GPP on RE (+0.467) and the direct effects of any precipitation heterogeneity index. The warming rate on the Tibetan Plateau is approximately twice the global mean [134]. Continued warming will drive RE upward through two pathways simultaneously: a direct pathway via acceleration of enzyme kinetic reaction rates (the exponential term of the Lloyd–Taylor function couples directly to temperature), and an indirect pathway through the lengthening of the growing season and enhancement of GPP, which increases rhizodeposition substrate supply, and thereby stimulates autotrophic respiration.

A point of concern is that GPP may not keep pace with temperature-driven respiratory acceleration. Given the strong suppressive effect of PCI on GPP (path coefficient = -1.448) and climate projections indicating a further increase in precipitation concentration in the future [135], NEP is likely to become increasingly negative and the carbon source strength of the system may intensify rather than ease. The pattern in which warming promotes both GPP and RE, but RE exhibits higher temperature sensitivity, implies that alpine grasslands are more likely to act as a positive feedback agent under future climate scenarios: rising temperature drives a larger increase in RE than in GPP, lowering NEP, raising atmospheric CO_2 concentration, and in turn driving further warming [136,137]. This potential positive feedback loop requires verification with longer time series and denser station observations [138,139].

Several limitations of this study should be considered when interpreting the results. First, monthly-scale data smooth out the pulse effects of extreme precipitation events occurring at daily to weekly timescales. The conclusion that the direct effect of precipitation is weak is strictly confined to the monthly scale and does not preclude the existence of pulse effects at sub-monthly scales. Second, the Lloyd–Taylor framework is a continuous function that does not account for nonlinear carbon release pulses during freeze–thaw transitions in alpine regions (spring thaw and autumn freeze-up) [140], which may lead to systematic underestimation of RE during the shoulder seasons. Third, the flux tower R_{ref} model was calibrated on only nine valid stations ($R^2 = 0.478$, adjusted $R^2 = 0.304$), yielding a limited sample that lacks representativeness for steppe-type sites [141]; the uncertainty of model extrapolation to desert–steppe regions is therefore higher than for meadow regions. The uncertainty of the R_{ref} regression is largest where the EVI–LST space is sparsely sampled (high-altitude steppe); however, the SEM’s principal pathway from precipitation heterogeneity to RE routes through GPP, which is independent of the R_{ref} model (Section 4.2), so the central conclusions are robust to this uncertainty. Fourth, the SEM did not incorporate potential confounding variables such as soil organic carbon stocks, nitrogen availability, soil texture, and grazing intensity. Their omission may introduce omitted-variable bias in the path coefficients [142]. Fifth, the 30 m resolution of the CLCD product entails class mixing within grid pixels, and land cover classification uncertainty may affect the accuracy of land use-stratified analyses [143]. Future work should prioritize the establishment of additional flux observation stations in the western part of the plateau, coupled with high-resolution soil property and grazing intensity data, to further strengthen the robustness of carbon flux estimates and mechanistic interpretation.

5. Conclusions

(1) An R_{ref} environmental matching model constructed from nine flux tower stations reduced the RMSE of RE estimates across the Yarlung Zangbo River Basin and Its Two Tributaries Basin by 54.8% and eliminated systematic bias (Bias = -0.001). This approach provides a viable methodological reference for improving the accuracy of regional carbon flux estimates under the sparse flux tower constraint that characterizes the Tibetan Plateau.

(2) Although PCI, CV, and PCD all belong to the category of precipitation heterogeneity, they differ qualitatively in effect direction and transmission pathway: PCI suppresses RE (total effect = -0.818), CV is nearly neutral (-0.068), and PCD promotes RE ($+0.420$). A model that forces these three indices into a single latent variable (CFI = 0.902) performs markedly worse than one that treats them as independent predictors ($\Delta\text{CFI} = 0.057\text{--}0.098$), indicating that precipitation heterogeneity at different temporal scales should be distinguished rather than treated as a monolithic construct. Furthermore, the strong spatial covariation between elevation and precipitation heterogeneity indices produces severe signal confounding: after controlling for DEM, the partial correlation coefficient for CV rose from -0.127 to -0.430 (a 239% increase), and that for PCI rose from -0.336 to -0.435 (a 30% increase). In mountain studies spanning large elevational gradients, partial correlation separation is an essential step to avoid underestimating the ecological signal of precipitation.

(3) The 25-year mean RE across the Yarlung Zangbo River Basin and Its Two Tributaries was $0.566 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$, with NEP at $-0.550 \text{ gC}\cdot\text{m}^{-2}\cdot\text{month}^{-1}$. The entire domain functions as a net carbon source. RE exhibits a significant increasing trend (Sen's slope = 0.0025 yr^{-1} , $p = 0.022$). Against the background of no significant change in total precipitation (96.5% of pixels show nonsignificant trends), rising temperature (path coefficient from temperature to RE = $+0.843$) is the dominant factor driving the RE increase. The carbon source strength of the system is likely to intensify further with continued warming of the Tibetan Plateau.

(4) The methodological framework developed in this study—flux tower-constrained R_{ref} environmental matching, partial correlation to control for elevation-induced confounding, complementary RF and SEM analysis, and independent modeling of multi-timescale heterogeneity indices—offers a transferable analytical paradigm for carbon flux studies in other alpine regions. Future work should prioritize the establishment of additional flux observation stations in the western part of the plateau, integrate high-resolution soil property and grazing intensity data, and incorporate the nonlinear carbon release mechanisms associated with freeze–thaw cycles, in order to further strengthen the robustness of carbon flux estimates and mechanistic interpretation.

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