



1 **Moisture Constraints on Realized CO₂-Associated Productivity Gains in** 2 **Xinjiang Drylands**

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19 **Abstract:** Rising atmospheric carbon dioxide (CO₂) can enhance terrestrial productivity, but how CO₂-associated
20 productivity responses are expressed across water-limited ecosystems remains uncertain. Here, we developed a
21 model-based dual-pathway framework comprising an explicit CO₂-associated productivity component and a
22 water-use-efficiency (WUE)-related carbon–water response. Using paired standard CASA and CO₂-CASA
23 simulations, seven-scenario attribution experiments, and complementary carbon–water diagnostics, we evaluated
24 net primary productivity (NPP) changes across Xinjiang, China, during 2001–2020. Baseline CASA reproduced
25 the major spatial and interannual variability of MOD17 NPP. Mean annual NPP in 2018–2020 exceeded that in
26 2001–2003 by 10.24 g C m⁻² yr⁻¹. Under the isolated-component framework, vegetation-state change contributed
27 9.41 g C m⁻² yr⁻¹ (91.9% of the total modeled change), whereas the analytically isolated explicit CO₂ component
28 contributed 1.11 g C m⁻² yr⁻¹ (10.8%) and climate contributed –0.53 g C m⁻² yr⁻¹ (–5.2%). Long-term CO₂–WUE
29 coupling was strongest under intermediate moisture conditions, with class-level associations strongest within
30 100–400 mm and a nonlinear fitted maximum near 200–300 mm. However, first-difference analysis showed little



31 interannual CO₂–WUE association, while April–October precipitation was more closely associated with
32 interannual NPP variability than annual precipitation. Positive productivity trends also persisted after excluding
33 areas potentially influenced by persistent agriculture. Together, these results support a model-based dual-pathway
34 interpretation of CO₂-associated productivity responses while identifying moisture context and temporal scale as
35 key constraints on their expression and interpretation.

36 **Keywords:** CO₂ fertilization; drylands; water-use efficiency; net primary productivity; moisture gradient; scenario
37 attribution

38 1. Introduction

39 Atmospheric CO₂ concentrations have increased substantially since the preindustrial period and are expected
40 to continue rising during this century (IPCC, 2021). Elevated CO₂ can enhance photosynthetic carbon assimilation
41 and vegetation productivity, making the CO₂ fertilization effect an important component of terrestrial carbon-cycle
42 projections (Bazzaz, 1990; Schimel et al., 2015; Keenan et al., 2016). Free-Air CO₂ Enrichment (FACE)
43 experiments have demonstrated increases in photosynthesis and biomass production under elevated CO₂,
44 particularly for C3 vegetation (Ainsworth & Long, 2005; Ainsworth & Rogers, 2007). However, the magnitude of
45 this response varies substantially among ecosystems because vegetation growth is simultaneously constrained by
46 climate, nutrients, and other environmental factors (Terrer et al., 2019). Net primary productivity (NPP),
47 representing the balance between photosynthetic carbon assimilation and autotrophic respiration, is widely used to
48 characterize vegetation productivity (He et al., 2025). Quantifying CO₂-associated changes in NPP therefore
49 provides an important basis for evaluating how rising atmospheric CO₂ is expressed under contrasting
50 environmental conditions.

51 Water availability is particularly important in drylands. Drylands cover a large fraction of the global land
52 surface and contribute disproportionately to the variability of the terrestrial carbon cycle (Poulter et al., 2014;
53 Ahlström et al., 2015; Huang et al., 2016). Although rising CO₂ may increase photosynthetic carbon gain, severe
54 water limitation can constrain the extent to which this response is translated into additional ecosystem productivity.
55 Satellite and modeling studies have also linked rising atmospheric CO₂ with vegetation greening in water-limited
56 regions (Donohue et al., 2013; Piao et al., 2020). Consequently, evaluating dryland CO₂ responses requires not
57 only estimating their overall magnitude but also determining how their expression varies across moisture
58 conditions.

59 Within a regional modeling framework, CO₂-associated productivity change can be examined through two
60 complementary response dimensions. The first is an explicit CO₂-associated productivity component, represented
61 by the additional NPP generated when a prescribed CO₂ response is introduced into the baseline productivity



62 model. The second is a WUE-related carbon–water response, reflecting changes in vegetation productivity relative
63 to water loss. Increasing CO₂ can reduce stomatal conductance and water loss relative to carbon assimilation,
64 potentially increasing water-use efficiency (WUE) (Medlyn et al., 2011, 2015), and observational studies have
65 reported patterns consistent with enhanced WUE and vegetation greening under rising CO₂ in water-limited
66 environments (Donohue et al., 2013; Ukkola et al., 2016; Gonsamo et al., 2021). However, ecosystem-scale WUE
67 can also increase when evapotranspiration declines, particularly under severe water stress. Statistical CO₂–WUE
68 relationships should therefore be interpreted as carbon–water response diagnostics rather than as independent
69 evidence of an immediate physiological CO₂ effect.

70 Interpreting these two response dimensions further requires consideration of both moisture context and
71 temporal scale. A common proportional CO₂ response can generate very different absolute productivity increments
72 depending on background ecosystem productivity (Norby et al., 2005). Distinguishing intrinsic relative sensitivity
73 from the realized absolute productivity gain is therefore essential when interpreting spatial moisture gradients. In
74 addition, precipitation during the vegetation-active period may be more closely associated with interannual
75 productivity variability than total annual precipitation in strongly seasonal drylands (Knapp et al., 2002;
76 Heisler-White et al., 2008; Zeppel et al., 2014). Long-term CO₂–WUE covariation may likewise differ from
77 year-to-year coupling because atmospheric CO₂ changes gradually while vegetation productivity is strongly
78 influenced by short-term climatic variability. Evaluating both spatial moisture gradients and temporal scales is
79 therefore necessary to distinguish persistent carbon–water associations from short-term productivity responses.

80 Xinjiang, northwestern China, provides a suitable regional setting for such analysis because it spans
81 extremely arid basins, mountain ecosystems, grasslands, and relatively mesic environments across a pronounced
82 moisture gradient. At the same time, ecological restoration, land-cover change, agricultural management, and
83 water redistribution have altered vegetation conditions since 2000 (Lu et al., 2018; Li et al., 2021). These human
84 influences may amplify regional productivity trends and potentially confound their interpretation. Testing whether
85 the principal patterns persist under an aridity-index-based dryland definition and after excluding areas potentially
86 influenced by persistent agriculture is therefore important for assessing their robustness.

87 Here, we developed a model-based dual-pathway framework integrating paired standard CASA and
88 CO₂-CASA simulations, seven-scenario attribution experiments, and complementary carbon–water analyses to
89 examine CO₂-associated productivity changes across Xinjiang during 2001–2020. We addressed three questions:
90 (1) What is the magnitude of the explicit modeled CO₂-associated productivity component relative to
91 vegetation-state and climate contributions to long-term NPP change? (2) How does the WUE-related
92 carbon–water response vary across the regional moisture gradient and between long-term and interannual



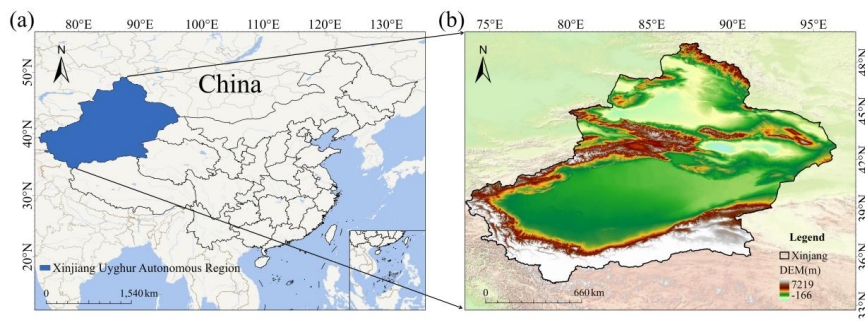
93 timescales? (3) Are the inferred productivity patterns robust to alternative analysis domains, exclusion of areas
94 potentially influenced by persistent agriculture, and uncertainty in the prescribed CO₂-response parameter?
95 Because the prescribed annual CO₂ scalar is spatially uniform, moisture-related spatial differences in the explicit
96 CO₂ component are interpreted as variation in the realized absolute productivity gain rather than as spatial
97 variation in the intrinsic CO₂ response coefficient.

98 **2. Data and methods**

99 **2.1. Study area and dryland delineation**

100 Xinjiang Uygur Autonomous Region, northwestern China, covers approximately 1.66 million km² and has a
101 strongly continental, water-limited climate (Liu et al., 2026; Xu et al., 2026). Annual precipitation ranges
102 from >400 mm in mountainous northern areas to <50 mm in southern basins.

103 Drylands were delineated using Global Aridity Index v3.1 ($AI = P/ET_0$; Zomer et al., 2022), with $AI < 0.65$
104 classified as dryland. After alignment to the 1-km grid, drylands covered 97.7% of Xinjiang. Full-Xinjiang results
105 were retained for regional attribution, while AI-defined drylands and non-agricultural drylands were used for
106 sensitivity analyses. Areas potentially influenced by persistent agriculture were identified from annual MCD12Q1
107 land-cover maps. Grid cells with an agricultural fraction $\geq 25\%$, based on cropland occurrence in at least 3 of the
108 20 study years, were excluded to construct the non-agricultural dryland domain.



109
110 Figure 1 Overview of the study areas: (a) China; (b) Xinjiang Uygur Autonomous Region

111 **2.2. Data sources and pre-processing**

112 This study used multi-source remote sensing data, meteorological data, and ancillary data, all from 2001 to
113 2020, to ensure the integrity of time series analysis as presented in Table 1.

114 **Table 1. Data sources and technical parameters**

Data	Product/Source	Spatial-temporal resolution	Time coverage	Purpose	Preprocessing
NDVI	MOD13A2	1 km, 16-day	2001–2020	FPAR calculation;	MVC composited



	(Collection 6.1)			vegetation greenness and seasonal-cycle characterization	to monthly
LUCC	MCD12Q1 (Collection 6.1)	500 m, annual	2001–2020	Vegetation parameterization; agricultural-influence screening	IGBP reclassified (Table S5)
Air temperature	ERA5-Land (ECMWF)	0.1°, monthly	2001–2020	Temperature stress factor	Resampled to 1 km
Precipitation	ERA5-Land (ECMWF)	0.1°, monthly	2001–2020	Moisture stress; precipitation-gradient and seasonal-window analyses	Resampled to 1 km
Net radiation	ERA5-Land (ECMWF)	0.1°, monthly	2001–2020	ET and W _e calculation	Resampled to 1 km
Total ET	ERA5-Land (ECMWF)	0.1°, monthly	2001–2020	WUE calculation	Resampled to 1 km
CO ₂ concentration	NOAA Mauna Loa	Monthly	2001–2020	CO ₂ fertilization effect	Aggregated to annual mean
MOD17 NPP	MOD17A3HGF (C6.1)	500 m, annual	2001–2020	Baseline CASA validation	Resampled to 1 km
NESDC GPP	China terrestrial GPP dataset	1 km, annual	2001–2020	Supplementary spatial-consistency assessment	Clipped to study area
Xinjiang boundary	RESDC	—	—	Data clipping	—
Aridity index	Global Aridity Index v3.1	30 arc-sec	1970–2000 climatology	Dryland delineation	AI < 0.65; aligned to 1-km grid

2.3. CASA and CO₂-CASA models

2.3.1 Standard CASA model

Standard CASA estimates NPP as the product of absorbed photosynthetically active radiation (APAR) and actual light-use efficiency (ϵ) (Potter et al., 1993; Equation 1). APAR is determined from solar radiation and the fraction of absorbed photosynthetically active radiation (FPAR), which was derived from NDVI (Gower et al., 1999; Equation 2). Actual light-use efficiency is constrained by temperature and moisture stress scalars (Ruimy et al., 1999; Equation 3). Vegetation-type-specific maximum light-use efficiency (LUE_{max}) followed Zhu et al. (2007) and ranged from 0.389 to 0.692 g C MJ⁻¹ (Table S4).

$$NPP(x,t)=APAR(x,t)\times\epsilon(x,t) \quad (1)$$

$$APAR(x,t)=SOL(x,t)\times FPAR(x,t)\times 0.5 \quad (2)$$

$$\epsilon(x,t)=T_{\epsilon 1}(x,t)\times T_{\epsilon 2}(x,t)\times W_{\epsilon}(x,t)\times\epsilon_{\max} \quad (3)$$

2.3.2 CO₂-CASA model



CO₂-CASA extends standard CASA by introducing an annual CO₂ response scalar that acts multiplicatively on light-use efficiency (Equation 4). The reference CO₂ concentration was 369 ppm, corresponding to 2001, and the response parameter δ was set to 0.20 following Ainsworth and Long (2005). All other input data and model parameters were identical between standard CASA and CO₂-CASA. Because the CO₂ scalar varies among years but is spatially uniform within each year, CO₂-CASA preserves nearly the same spatial productivity pattern as standard CASA. Consequently, spatial variation in the absolute CO₂-associated NPP increment primarily reflects spatial variation in baseline CASA productivity rather than spatial variation in the prescribed relative CO₂ response. Sensitivity to δ was evaluated using alternative values of 0.10 and 0.30.

$$\varepsilon = \varepsilon_{base} \times \left[1 + \delta \times \ln \left(\frac{CO_2}{CO_{2,ref}} \right) \right] \quad (4)$$

2.4 Scenario Simulation and Attribution Analysis

Seven simulation scenarios (S1–S7; Table 2) were used to separate modeled NPP changes associated with vegetation state, climate, and atmospheric CO₂. For each scenario, long-term change was calculated as the difference between mean annual NPP in 2018–2020 and 2001–2003, with three-year means used to reduce sensitivity to individual-year anomalies. The total modeled change was defined from S1. Isolated vegetation- and climate-associated components were obtained from the controlled scenarios, whereas the explicit CO₂ component was calculated analytically from the prescribed CO₂ response function (Equations 5–8). Marginal and interaction components were subsequently calculated using Equations 9–14. Because NDVI directly determines FPAR in CASA, the vegetation-state component represents an NDVI-associated model contribution rather than an independently identified physiological driver.

Table 2. Seven-scenario simulation experiment

Scenario	NDVI	Climate (T/P/Rn)	CO ₂ concentration	Physical meaning
S1	Yearly varying	Yearly varying	Yearly varying	Real world
S2	Fixed at 2001	Yearly varying	Yearly varying	Fixed vegetation state
S3	Yearly varying	Fixed at 2001	Yearly varying	Fixed climate
S4	Yearly varying	Yearly varying	Fixed at 2001	Fixed CO ₂
S5	Fixed at 2001	Fixed at 2001	Fixed at 2001	All fixed (baseline)
S6	Yearly varying	Fixed at 2001	Fixed at 2001	Only vegetation varies
S7	Fixed at 2001	Yearly varying	Fixed at 2001	Only climate varies

$$\Delta_{total} = S_1 - S_5 \quad (5)$$

$$\Delta_{veg} = S_6 - S_5 \quad (6)$$

$$\Delta_{clim} = S_7 - S_5 \quad (7)$$

$$\Delta_{co2} = S_{5,base} \times \left[\frac{\beta(t)}{\beta(2001)} - 1 \right] \quad (8)$$

$$\text{Marginal vegetation effect: } (S_1 - S_2) \quad (9)$$



$$\text{Marginal vegetation effect: } (S1 - S3) \quad (10)$$

$$\text{Marginal CO}_2 \text{ effect: } (S1 - S4) \quad (11)$$

$$\text{Vegetation} \times \text{Environment interaction} = (S1 - S2) - \Delta_{\text{veg}} \quad (12)$$

$$\text{Climate} \times \text{Others interaction} = (S1 - S3) - \Delta_{\text{clim}} \quad (13)$$

$$\text{CO}_2 \times \text{Others interaction} = (S1 - S4) - \Delta_{\text{co}_2} \quad (14)$$

where Δ_{total} represents the overall NPP variation relative to the baseline. The terms Δ_{veg} , Δ_{clim} , and Δ_{co_2} denote the isolated pure effects of vegetation, climate, and CO₂, respectively. The interaction terms represent the difference between marginal and isolated components and quantify shared model contributions arising when the target factor varies together with the surrounding environmental conditions.

2.5 Productivity-based Water Use Efficiency

To characterize vegetation productivity relative to water loss, productivity-based water-use efficiency (WUE) was calculated as (Tian et al., 2010):

$$WUE = \frac{NPP}{ET} \quad (15)$$

where NPP is annual NPP simulated by CO₂-CASA and ET is annual evapotranspiration from ERA5-Land. This metric represents modeled productivity per unit water loss rather than a direct physiological measure of leaf-level WUE. Because CO₂-CASA-derived NPP enters the WUE calculation, subsequent CO₂-WUE analyses were interpreted as model-based carbon–water response diagnostics rather than independent validation of a physiological CO₂ effect.

2.6. Statistical Analysis Method

2.6.1 Baseline model validation and CO₂-response characterization

Standard CASA performance was evaluated against MOD17 NPP using Pearson's r , R^2 , RMSE, MAE, and mean bias for spatial and interannual comparisons. Because CO₂-CASA applies a prescribed CO₂ response to the standard CASA framework, its MOD17 comparison was treated as a consistency assessment rather than an independent validation of the CO₂ response mechanism. A controlled experiment with fixed environmental inputs and varying CO₂ concentration was additionally used to characterize the magnitude of the prescribed CO₂ response (Li et al., 2024).

2.6.2 Trend Analysis

Interannual variable trends were fitted using Ordinary Least Squares (OLS) linear regression (Equation 16; Chen et al., 2025). To account for non-normal distributions or outliers, the Theil-Sen slope estimator and Mann-Kendall non-parametric tests were employed as robust supplementary validations (Equation 17; Sen, 1968; Kendall, 1975; Zhang et al., 2026).



$$Y=a+b\times t \quad (16)$$

where Y is the variable value, t is the year, b is the trend slope ($\text{gC}/\text{m}^2/\text{yr}^2$ or $\text{gC}/\text{mm}/\text{yr}^2$), and a is the intercept. Statistical significance of the trend was determined using the t-test ($\alpha = 0.05$).

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^n \text{sgn}(x_j-x_i) \quad (17)$$

where $\text{sgn}(x_j-x_i)$ is the sign function, taking +1 when $x_j>x_i$, -1 when $x_j<x_i$, and 0 when $x_j=x_i$. The sign of the Z value indicates the trend direction, and $|Z| > 1.96$ indicates that the trend is significant at the $\alpha = 0.05$ level.

Regional trend analyses were repeated for full Xinjiang, AI-defined drylands, and non-agricultural drylands to evaluate sensitivity to analysis-domain definition and agricultural influence.

2.6.3 Correlation Analysis vs. Partial Correlation Analysis

To evaluate simple linear relationships, the Pearson correlation coefficient and a standard t-test were employed (Equation 18, Equation 19; Liu et al., 2026). Pearson correlation was used to characterize bivariate linear associations, while first- and second-order partial correlations were used to quantify associations after statistical adjustment for selected climatic covariates (Equations 20–23; Kim, 2015).

$$r=\frac{\sum_i (x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_i (x_i-\bar{x})^2 \times \sum_i (y_i-\bar{y})^2}} \quad (18)$$

$$t=r \times \frac{\sqrt{n-2}}{\sqrt{1-r^2}} \quad (19)$$

$$r_{XY \cdot Z}=(r_{XY}-r_{XZ} \times r_{YZ}) / \sqrt{\left[\left(1-r_{XZ}^2\right)\left(1-r_{YZ}^2\right)\right]} \quad (20)$$

$$r_{XY \cdot Z_1 Z_2}=\left(r_{XY \cdot Z_1}-r_{XZ_2 \cdot Z_1} \times r_{YZ_2 \cdot Z_1}\right) / \sqrt{\left[\left(1-r_{XZ_2 \cdot Z_1}^2\right)\left(1-r_{YZ_2 \cdot Z_1}^2\right)\right]} \quad (21)$$

$$r_{XY \cdot Z_1 Z_2}=\frac{r_{XY \cdot Z_1}-r_{XZ_2 \cdot Z_1} \cdot r_{YZ_2 \cdot Z_1}}{\sqrt{\left(1-r_{XZ_2 \cdot Z_1}^2\right)\left(1-r_{YZ_2 \cdot Z_1}^2\right)}} \quad (22)$$

$$t=r \cdot \sqrt{\frac{n-k-2}{1-r^2}} \quad (23)$$

where x_i and y_i denote individual observed values with $\bar{x}$ and $\bar{y}$ representing their respective series means. For the significance tests and partial correlations, r is the calculated correlation coefficient, n represents the total sample size, and k indicates the number of controlled confounding variables ($k = 1$ when controlling for a single covariate Z , and $k = 2$ when controlling for two covariates Z_1 and Z_2).

2.6.4 First-difference correlation analysis

To distinguish decadal trends from interannual dynamics, first-order differential correlation was applied to year-over-year variations (Equation 24; Dai et al., 2025). A substantial reduction in correlation after differencing



186 suggests that the original association may be partly driven by a shared long-term trend, whereas a persistent
187 relationship is more consistent with interannual covariation.

188 First-difference precipitation–NPP correlations were compared among annual (January–December),
189 antecedent-plus-growing-season (March–October), and vegetation-active-season (April–October) precipitation
190 across five mean annual precipitation classes (<50, 50–100, 100–200, 200–400, and ≥400 mm). First-difference
191 CO₂–WUE partial correlations controlling for precipitation changes were also calculated to test whether long-term
192 CO₂–WUE associations persisted at the interannual scale.

$$r_{\Delta X, \Delta Y} = \frac{\sum_{t=1}^{n-1} (\Delta X_t - \overline{\Delta X})(\Delta Y_t - \overline{\Delta Y})}{\sqrt{\sum_{t=1}^{n-1} (\Delta X_t - \overline{\Delta X})^2 \cdot \sum_{t=1}^{n-1} (\Delta Y_t - \overline{\Delta Y})^2}} \quad (24)$$

193 where X_t and Y_t represent the original variable values in year t , and ΔX_t and ΔY_t denote their respective
194 interannual increments relative to the preceding year. The terms $\overline{\Delta X}$ and $\overline{\Delta Y}$ represent the mean values of these
195 differenced series across the evaluated periods.

196 2.6.5 Generalized additive model fitting

197 To capture nonlinear and non-monotonic relationships without assuming predefined functional forms, we
198 employed Generalized Additive Models (GAMs) (Equation 25; Wood, 2017).

$$g(\mu) = \alpha + \sum_{j=1}^p f_j(x_j) + \varepsilon \quad (25)$$

199 where $g(\mu)$ is the identity link function, α is the intercept, ε is the random error, and $f_j(x_j)$ represents the
200 smooth function (thin plate regression splines) for the j -th predictor, with smoothing parameters automatically
201 optimized via Generalized Cross-Validation (GCV).

202 2.6.6 Exploratory Mediation Analysis

203 To explore the statistical structure of the CO₂–WUE–vegetation relationship, mediation analysis was
204 conducted across precipitation classes using the framework of Imai et al. (2010) (Equation 26). Because the
205 analysis used observational and model-derived variables, it was interpreted as an exploratory pathway diagnostic
206 rather than formal identification of physiological causality.

$$TE = ACME + ADE \quad (26)$$

207 where ACME (Average Causal Mediation Effect) is the indirect effect and ADE (Average Direct Effect) is the
208 direct effect.

209 2.6.7 Pixel-level spatial statistical analysis



For each active pixel, the 20-year interannual trend slope of NPP, and WUE is calculated using least squares linear regression, and the p-value of the t-test is recorded. To enhance the robustness of trend analysis, supplemented by Theil-Sen slope estimates (Sen, 1968) as shown in Equation (27):

$$\beta_{Sen} = \text{median} \left(\frac{x_j - x_i}{j - i} \right), \quad \forall i < j \quad (27)$$

where x_i and x_j represent the respective variable values for years i and j ($i < j$), and median denotes the median value of all computed pairwise slopes across the time series.

The above method constitutes the complete technical framework of this study, as shown in Figure 2. The data flow and logical relationships between the modules are summarized below.

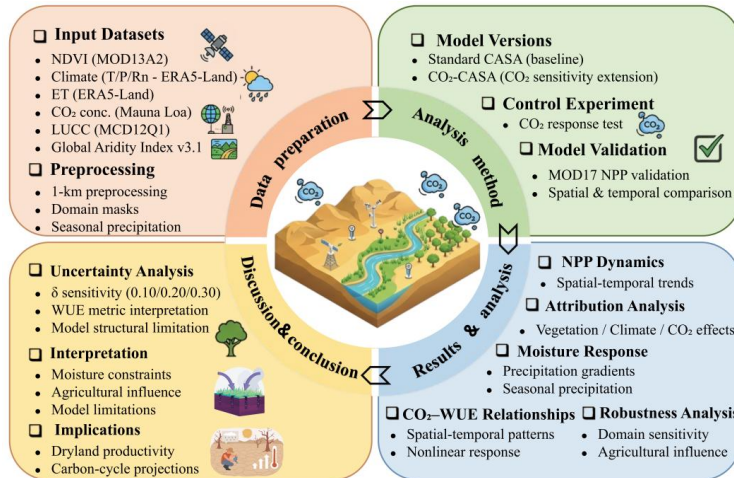


Figure 2 Flowchart of this study

3. Results

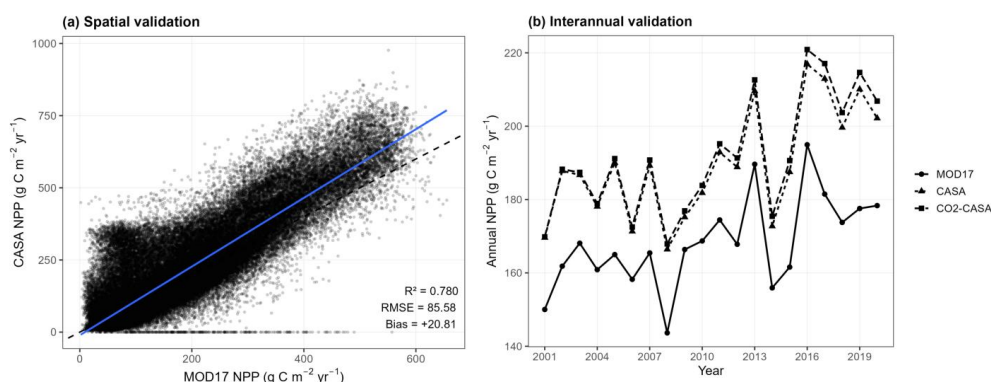
3.1. Baseline model performance and CO₂-response characterization

Standard CASA reproduced the major spatial and interannual variability of MOD17 NPP. Across the dryland domain, spatial agreement reached $r=0.883$ and $R^2=0.780$, with an RMSE of $85.58 \text{ g C m}^{-2} \text{ yr}^{-1}$, an MAE of $60.81 \text{ g C m}^{-2} \text{ yr}^{-1}$, and a positive mean bias of $20.81 \text{ g C m}^{-2} \text{ yr}^{-1}$. Interannual agreement was stronger ($r=0.925$, $R^2=0.856$), although CASA retained a positive bias of $21.29 \text{ g C m}^{-2} \text{ yr}^{-1}$ (Figure 3).

CO₂-CASA retained nearly identical spatial agreement with MOD17 ($R^2=0.780$) and similar temporal agreement ($R^2=0.851$), while showing slightly larger RMSE and bias. MOD17, standard CASA, and CO₂-CASA all exhibited significant positive NPP trends during 2001–2020, with slopes of 1.27 , 1.68 , and $1.92 \text{ g C m}^{-2} \text{ yr}^{-2}$, respectively. In the controlled CO₂-response experiment, increasing atmospheric CO₂ from 369 to 414 ppm while holding other inputs constant increased modeled NPP by 2.30%. Thus, CO₂-CASA preserved the baseline



231 productivity structure while introducing a modest positive CO₂-associated increment. A supplementary
232 comparison with the NESDC GPP product showed broadly consistent spatial productivity patterns (Figure S1,S4).



233
234 Figure 3 Baseline model evaluation: (a) spatial comparison between standard CASA and MOD17 NPP; (b) annual MOD17, standard
235 CASA, and CO₂-CASA NPP during 2001–2020.

236 3.2. Scenario-based decomposition of modeled productivity change

237 3.2.1. Magnitude and temporal dynamics of attribution

238 Based on the seven-scenario simulations, mean annual NPP in 2018–2020 exceeded that in 2001–2003 by
239 10.24 g C m⁻² yr⁻¹. Under the isolated-component framework, vegetation-state change contributed 9.41 g C m⁻²
240 yr⁻¹ (91.9%), whereas the explicit CO₂ model component contributed 1.11 g C m⁻² yr⁻¹ (10.8%) and climate
241 contributed −0.53 g C m⁻² yr⁻¹ (−5.2%). The remaining interaction component was 0.25 g C m⁻² yr⁻¹ (2.4%).

242 When environmental interactions were included, the corresponding marginal effects were 9.68 g C m⁻² yr⁻¹
243 for vegetation (94.5%), 1.39 g C m⁻² yr⁻¹ for CO₂ (13.6%), and −0.57 g C m⁻² yr⁻¹ for climate (−5.6%). The
244 differences between marginal and isolated components were +0.27 g C m⁻² yr⁻¹ for vegetation and +0.28 g C m⁻²
245 yr⁻¹ for CO₂, indicating modest positive interaction components under the observed environmental conditions.
246 Because marginal effects incorporate shared interaction components, their percentage contributions are not
247 additive and therefore do not sum to 100%.

248 Temporally, the isolated vegetation-state component increased significantly over the study period, with a
249 trend of 0.728 g C m⁻² yr⁻² (p<0.001), and was approximately 2.2 times larger in 2020 than in 2002 (Figure 4).
250 The explicit CO₂ component also increased significantly, but with a substantially smaller magnitude, whereas the
251 climate component exhibited pronounced interannual variability and no significant long-term trend (p=0.44).
252 These results identify vegetation-state change as the principal modeled contributor to regional NPP growth,
253 motivating the subsequent analysis of factors associated with NDVI dynamics.

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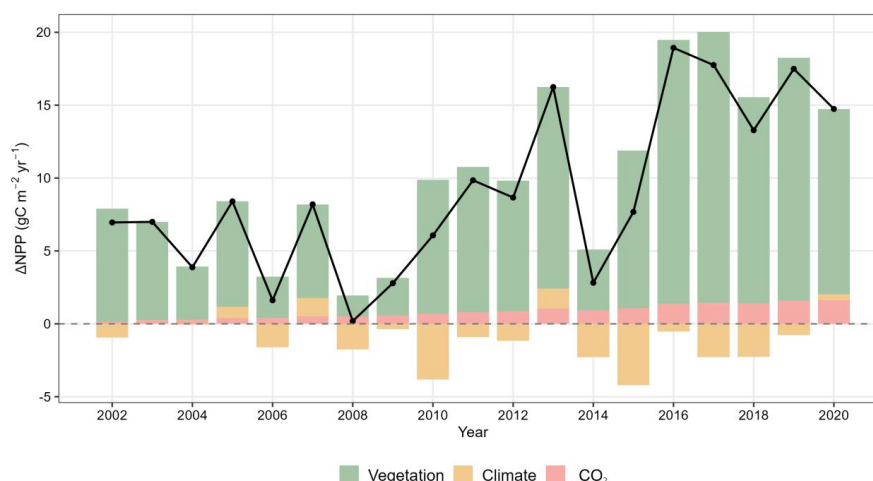


Figure 4 Year-on-year change in contribution by factor

3.2.2 Spatial pattern of attribution results

Pixel-level attribution showed marked spatial heterogeneity in the effects of vegetation, CO₂, and climate (Figure 5). The median vegetation and climate effects were both zero, indicating that regional NPP changes were spatially concentrated rather than uniformly distributed. The 5th–95th percentile ranges were used to characterize the main distributions while reducing the influence of extreme values.

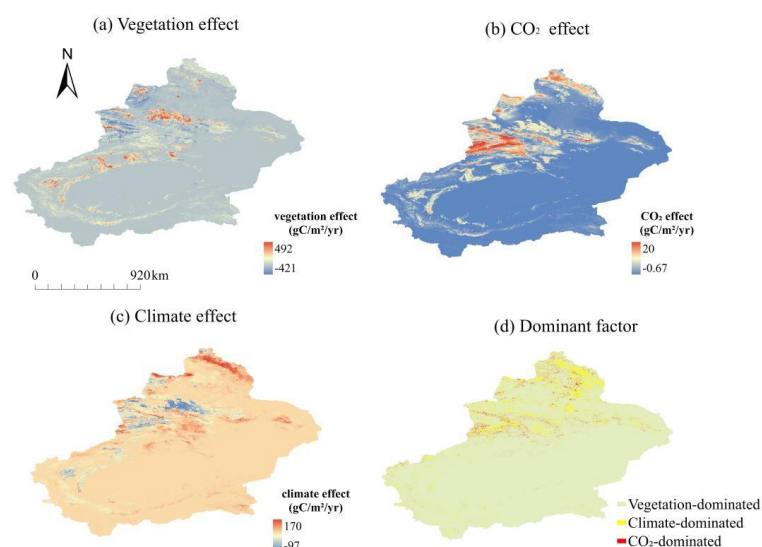
The vegetation effect ranged from -14.6 to $+71.0$ g C m⁻² yr⁻¹ (p05–p95) and was positive in 37.3% of effective pixels, mainly across northern Xinjiang grasslands, the northern Tianshan slopes, and southern oases (Figure 5a). Despite being spatially concentrated, these positive effects accounted for the large regional vegetation contribution identified in the scenario attribution.

The explicit CO₂ component ranged from approximately 0 to $+7.9$ g C m⁻² yr⁻¹ and was positive in 51.4% of pixels (Figure 5b). Because the prescribed CO₂ scalar acts multiplicatively on baseline productivity, larger absolute CO₂-associated increments occurred in high-productivity regions. The climate effect ranged from -10.6 to $+6.8$ g C m⁻² yr⁻¹ (Figure 5c), with positive effects in 25.6% of pixels and negative effects in 27.6%. Their spatial compensation resulted in a slightly negative regional isolated climate component of -0.53 g C m⁻² yr⁻¹ (-5.2%).

Using the factor with the largest absolute isolated component at each pixel, vegetation was classified as the dominant factor in 94.0% of pixels, climate in 5.0%, and CO₂ in 1.0% (Figure 5d). This pixel-level dominance classification differs from the regional contribution estimates reported in Section 3.2.1: the 1.0% CO₂-dominated area indicates only that the explicit CO₂ component was the largest of the three effects in 1.0% of pixels, rather than that CO₂ contributed only 1.0% to regional NPP change. The 1.0% CO₂-dominated area does not represent its



277 regional contribution; CO₂-associated changes expressed through NDVI are included within the vegetation-state
278 component.



279
280 Figure 5 The dominant spatial distribution of different effects: (a) pure vegetation effect; (b) pure CO₂ effect; (c) pure climatic effect;
281 (d) distribution of different master factors

282 3.3. WUE-related carbon–water response diagnostics

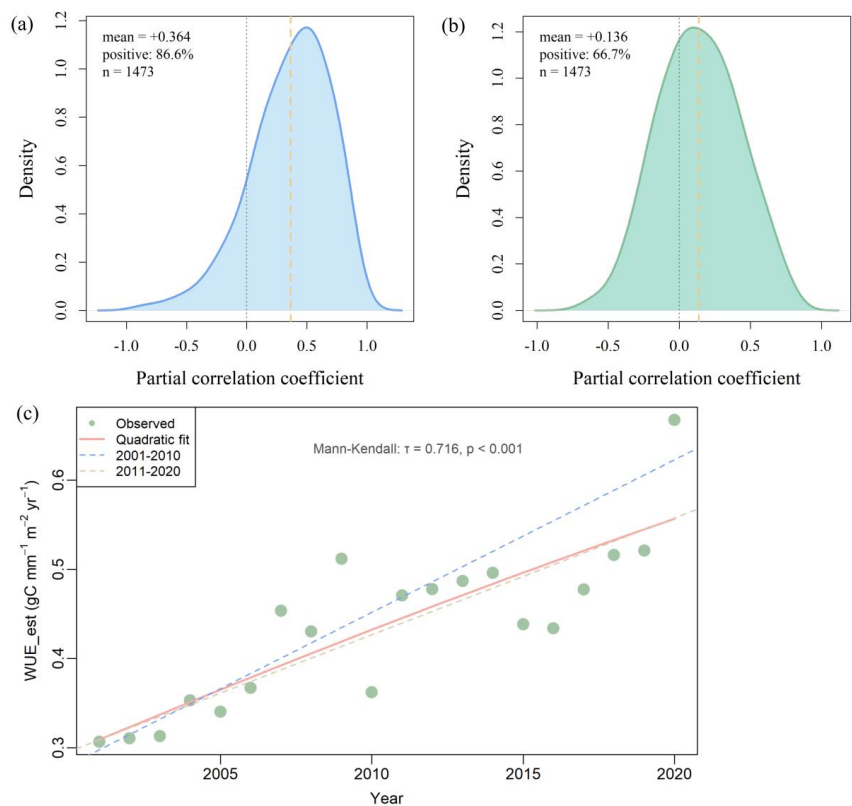
283 Because vegetation-state change dominated the scenario decomposition, we further examined greening
284 within stable land-cover areas and its associations with CO₂ and WUE. Between 2001 and 2020, 96.4% of pixels
285 remained within stable land-cover classes, and these areas accounted for 85.4% of the regional NDVI increase
286 (Table S1).

287 Within 1,473 stable pixels, the mean partial correlation between NDVI and CO₂ after controlling for
288 precipitation was 0.364, compared with 0.136 between NDVI and precipitation after controlling for CO₂; positive
289 correlations occurred in 86.6% and 66.7% of pixels, respectively (Figure 6a,b). At the regional scale, the
290 NDVI–CO₂ partial correlation remained positive after controlling for precipitation ($r=0.772, p=0.0001$) and
291 changed little after additional temperature adjustment (Table S2).

292 Regional productivity-based WUE increased from 0.31 to 0.67 g C m⁻² mm⁻¹ during 2001–2020 (+116%;
293 Mann–Kendall $\tau=0.716, p<0.001$; Figure 6c). Exploratory mediation analysis yielded a positive estimated
294 mediated component in four of five precipitation classes, although it was significant only above 400 mm (Table
295 S3), while pixel-level analyses showed predominantly positive CO₂–WUE relationships. Together, these results
296 identify a WUE-related carbon–water response within the model-based framework.



297



298

299 Figure 6 NDVI verification analysis chart: (a) partial correlation analysis of NDVI and CO₂ after control of precipitation; (b) partial
300 correlation analysis of NDVI and precipitation after control of CO₂; (c) Regional productivity-based WUE during 2001–2020

301 **3.4. Moisture and temporal-scale dependence**

302 **3.4.1. Moisture dependence of CO₂-associated and WUE-related responses**

303 The two modeled response dimensions showed distinct patterns across the regional moisture gradient. The
304 absolute explicit CO₂ component increased from 0.02 g C m⁻² yr⁻¹ in the <50 mm precipitation class to 1.08 g C
305 m⁻² yr⁻¹ in the ≥400 mm class (Table 3; Figure S3). Its relative contribution remained below 3% in precipitation
306 classes below 400 mm and reached 10.6% in the wettest class. Because the prescribed annual CO₂ scalar was
307 spatially uniform, this gradient primarily reflects differences in baseline productivity rather than spatial variation
308 in the prescribed relative CO₂ sensitivity.

309 In contrast, the long-term WUE-related response showed a nonlinear dependence on moisture conditions.
310 After controlling for precipitation, CO₂–WUE partial correlations were positive across all precipitation classes,



with the strongest class-level associations occurring within the 100–400 mm range (Figure 7a). GAM fitting further showed an inverted U-shaped relationship between CO₂–WUE coupling and mean annual precipitation, with the fitted maximum at approximately 223 mm (Figure 7b). Pixel-level analyses supported this pattern, with the 200–400 mm class showing the highest median CO₂–WUE correlation ($r=0.340$) and the largest proportion of positive pixels (84.1%; Table S6; Figure S2).

Thus, the two response dimensions exhibited distinct moisture-dependent expressions: absolute explicit CO₂-associated productivity gains were greater under wetter, more productive conditions, whereas long-term WUE-related coupling was strongest under intermediate moisture conditions.

3.4.2. Temporal-scale dependence and growing-season moisture

The long-term CO₂–WUE association identified above weakened markedly at the interannual scale (Figure 8). After first differencing and controlling for changes in precipitation, the partial correlation between annual changes in CO₂ and WUE approached zero ($r=0.040, p=0.875$). This contrast indicates that the CO₂–WUE relationship was expressed primarily as multi-year to decadal covariation rather than as a consistent year-to-year association.

To characterize the moisture timing most closely associated with interannual productivity variability, first-difference NPP was compared with precipitation aggregated over annual and vegetation-active-season windows. April–October precipitation showed stronger pooled correlations with NPP changes than annual precipitation in both standard CASA ($r=0.645$ vs. 0.540) and CO₂-CASA ($r=0.644$ vs. 0.539), and the April–October window produced the strongest association across all five precipitation classes. Thus, whereas CO₂–WUE covariation was primarily expressed over multi-year to decadal scales, year-to-year productivity variability was more closely synchronized with growing-season moisture.

Table 3. Explicit CO₂ component across precipitation classes

Precipitation interval	ΔTotal (gC/m ² /yr)	explicit CO ₂ component (gC/m ² /yr)	CO ₂ contribution rate (%)
<50 mm	1.11	0.02	1.7
50–100 mm	10.62	0.16	1.5
100–200 mm	12.53	0.26	2.0
200–400 mm	10.77	0.31	2.9
>400 mm	10.14	1.08	10.6

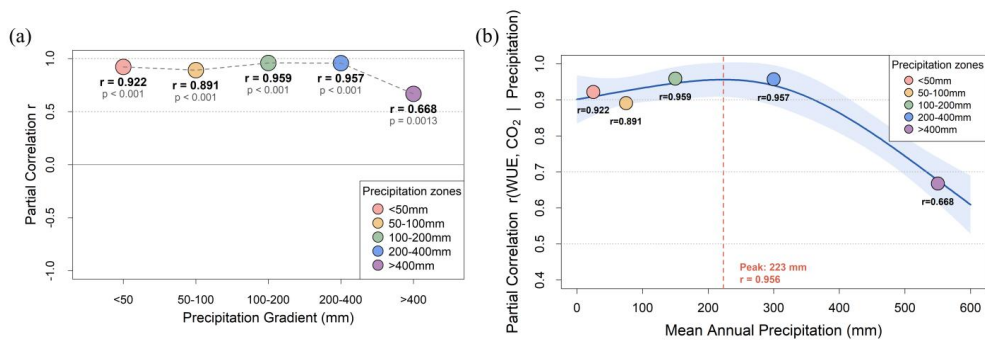


Figure 7. Moisture dependence of long-term CO_2 -WUE coupling: (a) partial correlations between atmospheric CO_2 and productivity-based WUE across precipitation classes after controlling for precipitation; and (b) GAM-fitted relationship between CO_2 -WUE coupling and mean annual precipitation.

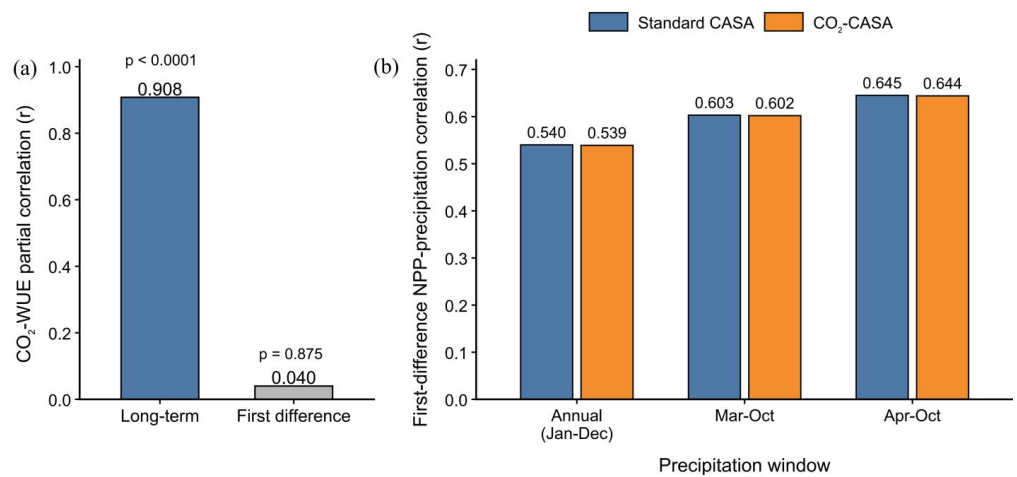


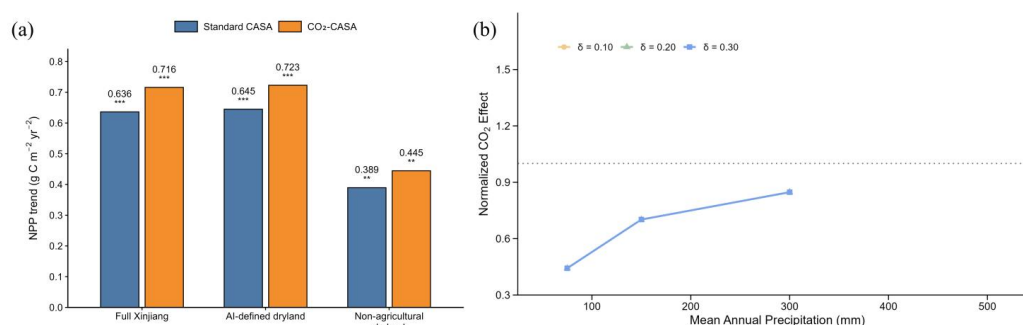
Figure 8. Temporal-scale dependence of carbon-water and productivity responses. (a) Comparison of long-term and first-difference partial correlations between atmospheric CO_2 and productivity-based WUE after accounting for precipitation. (b) Pooled first-difference correlations between NPP and precipitation calculated over annual (January–December), antecedent-plus-growing-season (March–October), and vegetation-active-season (April–October) windows for standard CASA and CO_2 -CASA.

3.5 Robustness across analysis domains

Positive productivity trends persisted across alternative analysis domains. NPP trends were nearly unchanged between full Xinjiang and the aridity-index-defined dryland domain, with standard CASA and CO_2 -CASA slopes of 0.64 and 0.72 $\text{g C m}^{-2} \text{ yr}^{-2}$, respectively. After excluding areas potentially influenced by persistent agriculture, the corresponding trends declined to 0.39 and 0.44 $\text{g C m}^{-2} \text{ yr}^{-2}$ but remained significant ($p < 0.01$; Figure 9a). Thus, the magnitude of the regional productivity trend was sensitive to the inclusion of areas potentially influenced by persistent agriculture, while significant positive trends persisted after their exclusion.



349 Sensitivity tests using $\delta=0.10$, 0.20, and 0.30 changed the magnitude of the explicit CO_2 component but
350 preserved its positive direction (Figure 9b). Together, these analyses show that positive regional productivity
351 trends persisted across alternative spatial domains, while the explicit CO_2 component remained positive across the
352 tested δ values.



353

354 Figure 9. Robustness of modeled productivity responses. (a) Long-term NPP trends from standard CASA and CO₂-CASA across full
355 Xinjiang, the aridity-index-defined dryland domain, and the non-agricultural dryland domain. (b) Sensitivity of the explicit
356 CO₂-associated productivity response to alternative CO₂-response parameters ($\delta=0.10$, 0.20, and 0.30).

357 4. Discussion

358 4.1 Moisture-dependent expressions of CO₂-associated productivity responses

359 Our framework distinguishes complementary model-based dimensions of CO₂-associated productivity
360 responses rather than two additive or independently identified physiological pathways. Scenario attribution
361 identified an analytically isolated explicit CO₂ component that accounted for 10.8% of the modeled NPP increase,
362 whereas vegetation-state change accounted for 91.9% under the isolated-component framework. Separately,
363 productivity-based WUE was used to characterize a complementary carbon–water response dimension. Because
364 NDVI integrates responses to climate, atmospheric CO₂, management, and other environmental changes, the
365 vegetation-state component cannot be interpreted as a WUE-mediated CO₂ contribution.

366 This interpretation remains broadly consistent with experimental and observational evidence that vegetation
367 responses to elevated CO₂ depend strongly on water availability. FACE experiments have demonstrated enhanced
368 photosynthesis and biomass production under elevated CO₂, particularly under relatively favorable environmental
369 conditions (Ainsworth & Long, 2005; Ainsworth & Rogers, 2007). In drylands, persistent water limitation can
370 constrain the extent to which additional carbon assimilation is translated into ecosystem productivity, while
371 satellite-based studies have associated rising atmospheric CO₂ with enhanced vegetation water-use efficiency and
372 greening (Donohue et al., 2013; Gonsamo et al., 2021). These studies provide physiological and observational



context for interpreting the carbon–water relationships identified here, although our model-based diagnostics do not independently resolve those physiological mechanisms.

The moisture gradient in the explicit CO₂ component requires a different interpretation from that of the WUE-related response. Because the prescribed annual CO₂ scalar was spatially uniform, larger absolute CO₂-associated increments in wetter regions do not indicate greater intrinsic CO₂ sensitivity. Instead, the same proportional response produces a larger absolute NPP increment where baseline productivity is higher. The spatial gradient in the explicit component therefore represents moisture-conditioned variation in the realized absolute productivity gain rather than a moisture-dependent CO₂ response coefficient.

The WUE-related response showed a contrasting nonlinear moisture pattern. Class-level and nonlinear analyses consistently indicated stronger long-term CO₂–WUE coupling under intermediate moisture conditions, with the fitted maximum occurring near 223 mm of mean annual precipitation. At the dry end of the gradient, severe water limitation may constrain productivity, while increases in ecosystem-scale WUE can partly reflect reduced evapotranspiration rather than proportional increases in carbon assimilation (Humphrey et al., 2018). Toward wetter conditions, declining water limitation may reduce the relative importance of water-saving responses (Medlyn et al., 2011, 2015). The resulting intermediate-moisture maximum is therefore broadly consistent with conceptual expectations for dryland carbon–water tradeoffs, but the fitted precipitation value should be regarded as a regional empirical feature rather than a universal physiological threshold.

A further constraint is that productivity-based WUE was calculated using CO₂-CASA-derived NPP. Atmospheric CO₂ is therefore structurally represented in the WUE numerator, meaning that subsequent CO₂–WUE correlations and exploratory mediation analyses are not statistically independent tests of a physiological CO₂ effect. These analyses should instead be viewed as internal model-based diagnostics of carbon–water response structure. Their primary value is in identifying how this modeled relationship varies across moisture conditions, rather than in uniquely attributing the relationship to stomatal or other physiological mechanisms.

4.2 Temporal-scale dependence of carbon–water responses

The contrast between long-term and first-difference analyses provides an important constraint on the interpretation of CO₂–WUE coupling. Although atmospheric CO₂ and productivity-based WUE covaried strongly over the 2001–2020 period, their relationship approached zero after first differencing. The long-term association therefore should not be interpreted as a universal year-to-year response to increasing CO₂. Atmospheric CO₂ changed gradually over the study period, whereas annual ecosystem productivity was exposed to much larger short-term climatic variability, allowing strong multi-year covariation to coexist with weak interannual coupling.



The stronger association of first-difference NPP with April–October precipitation further emphasizes the importance of temporal matching between water availability and vegetation activity. In strongly seasonal drylands, precipitation received during the vegetation-active period is more directly synchronized with canopy development and productivity than precipitation accumulated over the full calendar year (Knapp et al., 2002; Heisler-White et al., 2008; Zeppel et al., 2014). This helps explain why annual precipitation was a weaker indicator of interannual productivity variability than growing-season precipitation. The result also reinforces the need to distinguish long-term carbon–water covariation from short-term climatic controls on productivity.

The temporal-scale result also reinforces the need for caution when interpreting ecosystem-scale WUE. Higher WUE does not necessarily imply proportionally greater carbon uptake because it can also arise from reduced water loss, particularly under severe water limitation (Humphrey et al., 2018). WUE should therefore be interpreted jointly with productivity and moisture availability rather than used alone as evidence of greater ecosystem carbon gain.

These scale-dependent patterns also have implications for dryland productivity modeling. Our results do not demonstrate that spatially uniform CO₂-response formulations systematically overestimate dryland responses; rather, they show that prescribed relative CO₂ sensitivity and realized productivity responses should be distinguished when interpreting environmental heterogeneity. Explicit representation of carbon–water processes may therefore help improve regional dryland simulations.

4.3 Robustness and implication

The domain-sensitivity analysis provides additional context for interpreting the regional productivity trend. NPP trends were nearly unchanged when the analysis was restricted from full Xinjiang to aridity-index-defined drylands, whereas exclusion of areas potentially influenced by persistent agriculture substantially reduced their magnitude. Nevertheless, positive trends remained significant. These results indicate that the magnitude of the regional productivity trend was sensitive to the inclusion of potentially agriculture-influenced areas, but such areas did not fully account for its positive direction. Other anthropogenic influences, including ecological restoration, irrigation, water redistribution, and land management, may still be embedded within the vegetation-state component (Lu et al., 2018).

Uncertainty also remains in the prescribed magnitude of the CO₂ response. Sensitivity tests using $\delta=0.10$, 0.20, and 0.30 changed the magnitude of the explicit CO₂ component but preserved its positive direction and broad response pattern. This indicates qualitative robustness within the tested parameter range, although the sensitivity analysis does not independently validate the central value of $\delta=0.20$.



First, CASA is a light-use-efficiency model and does not explicitly represent photosynthetic acclimation, nutrient limitation, stomatal conductance, carbon allocation, or plant hydraulic regulation (Smith & Dukes, 2013). CO₂-CASA should therefore be interpreted as a controlled CO₂-sensitivity extension of the baseline model rather than as an independently calibrated physiological model. The spatially uniform CO₂ scalar cannot resolve intrinsic differences in CO₂ sensitivity among vegetation types or moisture regimes. In addition, observed NDVI already integrates real-world responses to atmospheric CO₂, climate, management, and other environmental influences. Applying an explicit CO₂ scalar to an NDVI-driven CASA simulation may therefore partially overlap with CO₂-associated vegetation changes already represented through the vegetation-state term. Consequently, the explicit CO₂ component should be interpreted as a scenario-based model component rather than as the total causal contribution of atmospheric CO₂.

Second, because productivity-based WUE uses CO₂-CASA-derived NPP in the numerator, atmospheric CO₂ is structurally embedded in the WUE metric. CO₂-WUE correlations and mediation estimates therefore cannot serve as statistically independent physiological tests. Independent GPP and ET observations, eddy-covariance measurements, or process-based stomatal simulations would be required to more directly evaluate the underlying carbon–water mechanisms.

Additional uncertainties arise from spatial autocorrelation, NDVI saturation in densely vegetated areas, ERA5-Land precipitation uncertainty over complex terrain, and incomplete separation of anthropogenic influences. Moreover, the precipitation ranges identified in Xinjiang should be regarded as regional empirical patterns rather than universal ecological thresholds. Testing this framework across other dryland regions, vegetation types, longer records, and independent carbon–water observations will be necessary to evaluate its broader transferability.

5 Conclusions

Using Xinjiang as a regional dryland case study, this study developed a model-based dual-pathway framework integrating paired standard CASA and CO₂-CASA simulations, scenario attribution, and complementary carbon–water diagnostics to examine CO₂-associated productivity responses during 2001–2020. The main conclusions are as follows:

- 1) Vegetation-state change was the dominant modeled component of long-term NPP increase, contributing 9.41 g C m⁻² yr⁻¹ (91.9%) under the isolated-component framework. The analytically isolated explicit CO₂ component was positive but substantially smaller, contributing 1.11 g C m⁻² yr⁻¹ (10.8%), while climate contributed −0.53 g C m⁻² yr⁻¹ (−5.2%). These components represent model-based attribution rather than independent physiological causal effects.



- 465 2) The two model-resolved response dimensions showed distinct expressions across the moisture gradient. The
466 absolute explicit CO₂ component was larger under wetter, more productive conditions, reflecting differences
467 in baseline productivity under a spatially uniform prescribed CO₂ response. In contrast, long-term CO₂–WUE
468 coupling was strongest under intermediate moisture conditions, with class-level associations strongest within
469 100–400 mm and GAM fitting indicating a maximum near 223 mm.
- 470 3) CO₂–WUE coupling was strongly dependent on temporal scale. The long-term association weakened to near
471 zero after first differencing ($r=0.040$, $p=0.875$), indicating that it was expressed primarily at multi-year to
472 decadal rather than year-to-year scales. In contrast, interannual NPP variability was more closely associated
473 with April–October precipitation than with annual precipitation in both CASA formulations, highlighting the
474 importance of growing-season moisture for short-term productivity variability.
- 475 4) The principal productivity patterns were robust to alternative analysis domains and tested CO₂-response
476 parameters. Restricting the analysis to aridity-index-defined drylands produced little change in regional
477 trends, while excluding areas potentially influenced by persistent agriculture reduced trend magnitude but did
478 not eliminate significant productivity increases. Sensitivity tests across $\delta=0.10$ – 0.30 preserved the positive
479 direction of the explicit CO₂ response. These findings emphasize the need to distinguish prescribed relative
480 CO₂ sensitivity from environmentally conditioned productivity responses when interpreting dryland
481 carbon–water dynamics.

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486 **Conflict of Interest**

487 The authors declare there are no conflicts of interest for this manuscript.

488 **Code availability**

489 The CO₂-CASA model implementation and analysis code used in this study, including the model calculations
490 and associated analytical workflows, are openly available through GitHub and permanently archived in Zenodo
491 ([doi:10.5281/zenodo.21887761](https://doi.org/10.5281/zenodo.21887761)).

492 **Data Availability Statement**



493 All primary remote-sensing, meteorological, atmospheric CO₂, and productivity datasets used in this study
494 are publicly available from their original repositories. The MODIS/Terra Vegetation Indices 16-Day L3 Global 1
495 km SIN Grid Version 6.1 (MOD13A2) dataset is available from the NASA Land Processes Distributed Active
496 Archive Center (LP DAAC; Didan, 2021; <https://doi.org/10.5067/MODIS/MOD13A2.061>). Land-cover data were
497 obtained from the MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500 m SIN Grid Version 6.1
498 (MCD12Q1) dataset (Friedl & Sulla-Menashe, 2022; <https://doi.org/10.5067/MODIS/MCD12Q1.061>).

499 Air temperature, precipitation, surface net radiation, and total evapotranspiration were obtained from the
500 ERA5-Land monthly averaged dataset provided by the Copernicus Climate Change Service Climate Data Store
501 (Muñoz Sabater, 2019; <https://doi.org/10.24381/cds.68d2bb30>). Atmospheric CO₂ concentrations were obtained
502 from continuous measurements at Mauna Loa provided by the NOAA Global Monitoring Laboratory
503 (<https://doi.org/10.15138/yaf1-bk21>).

504 The MODIS/Terra Net Primary Production Gap-Filled Yearly L4 Global 500 m SIN Grid Version 6.1
505 (MOD17A3HGF) dataset used for model validation is available from NASA LP DAAC (Running & Zhao, 2021;
506 <https://doi.org/10.5067/MODIS/MOD17A3HGF.061>). The independent gross primary productivity dataset was
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510 Author contribution

511 KM contributed to conceptualization, data curation, formal analysis, and preparation of the original draft. FZ
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