

Temporal variability and environmental drivers of net ecosystem CO₂ exchange in terrestrial ecosystems of the Yellow River Basin

LIN Feng, YANG Ping, FANG Yuju, ZHAO Xuepeng, ZHAO Qiang, SONG Qingfan, JIANG Jiye

2026-08-12

ChinaRxiv

View the original and related papers at
<https://chinaxiv.org/items/chinaxiv-202608.00024>

Source: ChinaXiv. Machine translation. Verify with the original.

Abstract

The Yellow River Basin (YRB), located in the mid-latitude region of China, encompasses diverse ecosystem types and is highly sensitive to climate change. However, the temporal patterns and environmental drivers of net ecosystem CO₂ exchange (NEE) across multiple timescales remain poorly understood. Using eddy covariance observations from the China FLUX network collected between 2003 and 2020, this study investigated the temporal dynamics of NEE and its primary environmental controls in five representative ecosystem types within the YRB and its adjacent 100-km buffer zone: cropland, forest, grassland, shrubland, and wetland ecosystems. The results showed that all five ecosystems exhibited a generally U-shaped diurnal pattern from May to September, characterized by net CO₂ uptake during the daytime and net CO₂ release at night. At the daily scale, cropland displayed a typical bimodal carbon uptake pattern, whereas forest ecosystem exhibited the greatest day-to-day variability in NEE. In contrast, grassland, shrubland, and wetland ecosystems showed relatively smooth daily fluctuations. The net CO₂ source-sink functions derived from NEE differed substantially among ecosystem types. Forest ecosystems acted as the most stable and persistent carbon sinks, whereas croplands exhibited short-term but high-intensity carbon uptake. Wetlands showed pronounced interannual variability, including an extreme net CO₂ release event at the Haibei wetland site in 2007. Grassland and shrubland ecosystems were more susceptible to environmental stress and could shift from net CO₂ sinks to net CO₂ sources during drought years. The environmental controls on NEE exhibited clear time-scale dependence. At the half-hourly scale, photosynthetically active radiation (PAR) was the dominant driver of NEE variability, the influence of temperature increased progressively from the daily to monthly scales. These findings improve the understanding of regional carbon dynamics in the YRB, provide insights into the net CO₂ source-sink status of different ecosystem types, and elucidate the mechanisms regulating ecosystem CO₂ exchange across multiple temporal scales.

Full Text

J Arid Land (2026) 18(8): 1304-1330

doi: 10.1016/j.jaridl.2026.08.002; CSTR: 32276.14.JAL.20260075

Temporal variability and environmental drivers of net ecosystem CO₂ exchange in terrestrial ecosystems of the Yellow River Basin

LIN Feng¹, YANG Ping^{2,3*}, FANG Yuju⁴, ZHAO Xuepeng⁵, ZHAO Qiang¹, SONG Qingfan¹, JIANG Jiyi¹

¹ School of Water Conservancy and Environment, University of Jinan, Jinan

250022, China;

² Culture and Tourism College, University of Jinan, Jinan 250022, China;

³ Institute of Desert Meteorology, China Meteorological Administration, Urumqi 830002, China;

⁴ Jinan Quanjing Middle School, Jinan 250000, China;

⁵ School of Economics and Management, Changji University, Changji 831100, China

Abstract: The Yellow River Basin (YRB), located in the mid-latitude region of China, encompasses diverse ecosystem types and is highly sensitive to climate change. However, the temporal patterns and environmental drivers of net ecosystem CO₂ exchange (NEE) across multiple time scales remain poorly understood. Using eddy covariance observations from the ChinaFLUX network collected between 2003 and 2020, this study investigated the temporal dynamics of NEE and its primary environmental controls in five representative ecosystem types within the YRB and its adjacent 100-km buffer zone: cropland, forest, grassland, shrubland, and wetland ecosystems. The results showed that all five ecosystems exhibited a generally U-shaped diurnal pattern from May to September, characterized by net CO₂ uptake during the daytime and net CO₂ release at night. At the daily scale, cropland displayed a typical bimodal carbon uptake pattern, whereas forest ecosystem exhibited the greatest day-to-day variability in NEE. In contrast, grassland, shrubland, and wetland ecosystems showed relatively smooth daily fluctuations. The net CO₂ source-sink functions derived from NEE differed substantially among ecosystem types. Forest ecosystems acted as the most stable and persistent carbon sinks, whereas croplands exhibited short-term but high-intensity carbon uptake. Wetlands showed pronounced interannual variability, including an extreme net CO₂ release event at the Haibei wetland site in 2007. Grassland and shrubland ecosystems were more susceptible to environmental stress and could shift from net CO₂ sinks to net CO₂ sources during drought years. The environmental controls on NEE exhibited clear time-scale dependence. At the half-hourly scale, photosynthetically active radiation (PAR) was the dominant driver of NEE variability, the influence of temperature increased progressively from the daily to monthly scales. These findings improve the understanding of regional carbon dynamics in the YRB, provide insights into the net CO₂ source-sink status of different ecosystem types, and elucidate the mechanisms regulating ecosystem CO₂ exchange across multiple temporal scales.

Keywords: Yellow River Basin (YRB); eddy covariance; net ecosystem CO₂ exchange (NEE); Random Forest (RF); temporal variability; ecosystem types

Citation: LIN Feng, YANG Ping, FANG Yuju, ZHAO Xuepeng, ZHAO Qiang, SONG Qingfan, JIANG Jiyi. 2026. Temporal variability and environmental drivers of net ecosystem CO₂ exchange in terrestrial ecosystems of the Yellow River Basin. *Journal of Arid Land*, 18(8): 1304-1330. <https://doi.org/10.1016/j.jaridl.2026.08.002>; <https://cstr.cn/32276.14.JAL.20260075>

*Corresponding author: YANG Ping (E-mail: shc_yangp@ujn.edu.cn)

Received 2026-02-13; revised 2026-06-26; accepted 2026-07-27

© 2026 Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, and Science Press. Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

<http://jal.xjegi.com/>; <https://www.keaipublishing.com/en/journals/journal-of-arid-land/>

This version posted 2026-08-12.

1 Introduction

Against the backdrop of intensifying global warming, the continued increase in atmospheric carbon dioxide (CO_2) concentrations has become a key factor affecting the stability of the Earth system (IPCC, 2021). As an important component of the global carbon cycle, terrestrial ecosystems absorb CO_2 through photosynthesis and release CO_2 through ecosystem respiration, thereby playing a pivotal role in regulating the global carbon budget (Ren and Cai, 2025). Even small imbalances between these processes can alter atmospheric CO_2 concentrations and subsequently influence climate regulation and ecosystem feedback mechanisms (Baldocchi, 2008). Therefore, net ecosystem CO_2 exchange (NEE), which quantifies the balance between ecosystem carbon uptake and release, has become a key indicator for determining whether terrestrial ecosystems function as net CO_2 sinks or sources over a given time scale. NEE is therefore widely used in studies of the global carbon cycle and in assessments of carbon neutrality pathways (Baldocchi, 2008; Chen et al., 2025).

Assessing the carbon sequestration potential of terrestrial ecosystems has become a central objective of global change research. Existing studies have focused primarily on forest ecosystems characterized by favorable hydrothermal conditions and high productivity (Pan et al., 2011; Harris et al., 2021) and on intensively managed croplands (Zhang et al., 2020). These ecosystems generally exhibit strong and relatively stable carbon sink functions and provide important climate-regulating ecosystem services (Smith et al., 2008; Mitsch et al., 2013). However, the persistent “missing carbon sink” problem in global carbon budget assessments suggests that the understanding of carbon source-sink dynamics and carbon sequestration potential in terrestrial ecosystems, particularly in mid-latitude regions, remains incomplete (Houghton et al., 2018; Ciais et al., 2019; Friedlingstein et al., 2023).

From a mechanistic perspective, the strength and stability of terrestrial carbon sinks vary substantially among ecosystem types and are regulated by complex nonlinear interactions between vegetation physiological processes and abiotic factors such as radiation, temperature, and water availability (Baldocchi, 2008; Lasslop et al., 2010). Mid-latitude regions encompass both temperate and sub-

tropical climate zones and are characterized by diverse ecosystem types, pronounced climatic gradients, and intensive human activities. As a result, carbon flux responses to environmental drivers are often highly complex and scale dependent (Zhang et al., 2023d; Bai et al., 2024). At hourly to daily time scales, NEE is typically most sensitive to variations in photosynthetically active radiation (PAR) and air temperature (T_a). In contrast, at monthly to annual time scales, water availability and its associated land-atmosphere feedbacks frequently become the dominant constraints on ecosystem carbon uptake, particularly in arid and semi-arid areas (Huxman et al., 2004; Poulter et al., 2014; Ahlström et al., 2015; Humphrey et al., 2021). Moreover, elevated vapor pressure deficit (VPD) can induce stomatal closure and reduce evapotranspiration, thereby suppressing carbon assimilation, altering water-use efficiency, and increasing the vulnerability of carbon sinks to environmental stress (Novick et al., 2016; Grossiord et al., 2020). Therefore, identifying the dominant controls on NEE across different temporal scales and quantifying their relative contributions are essential for reducing uncertainties in regional carbon budget estimates and improving carbon sink assessments in mid-latitude marginal monsoon and arid-semi-arid transition regions.

The Yellow River Basin (YRB) is located in the core mid-latitude region of China and lies along the northwestern fringe of the East Asian monsoon system, making it highly sensitive to changes in temperature and moisture conditions (Bai et al., 2024). The basin spans a wide range of geomorphic units, extending from the Qinghai-Xizang Plateau through the Inner Mongolia Plateau and the Loess Plateau to the North China Plain. This geographical gradient creates substantial variation in elevation, climate, and vegetation characteristics (Zhang et al., 2021d). Recent studies have demonstrated that the YRB possesses considerable carbon sequestration potential. Large-scale ecological restoration projects on the Loess Plateau have significantly increased regional biomass carbon stocks (Feng et al., 2016; Fu et al., 2017). Alpine meadows on the Qinghai-Xizang Plateau function as carbon sinks during the growing season (Kato et al., 2004; Piao et al., 2009), while

intensively managed croplands on the North China Plain (Bao et al., 2014; Wang et al., 2015c) and coastal wetlands in the Yellow River Delta (Chu et al., 2016; Tang et al., 2018) also exhibit substantial carbon uptake during specific periods. Nevertheless, long-term eddy covariance observations and comparative analyses across multiple ecosystem types within the YRB remain limited, hindering a comprehensive understanding of regional carbon source-sink dynamics and their underlying regulatory mechanisms.

To address this knowledge gap, this study integrated eddy covariance observations collected between 2003 and 2020 from five representative ecosystem types in the YRB, including forests, croplands, grasslands, shrublands, and wetlands. The objectives are to (1) characterize the temporal variability of NEE across multiple time scales, (2) identify the dominant environmental drivers regulating NEE at different temporal scales, and (3) quantify the relative contributions

Fig. 1 Location of the selected eddy covariance sites and the spatial distribution of major land-cover types within the Yellow River Basin (YRB) and its adjacent 100-km buffer zone.

Figure 1: Fig. 1 Location of the selected eddy covariance sites and the spatial distribution of major land-cover types within the Yellow River Basin (YRB) and its adjacent 100-km buffer zone.

of key environmental factors to NEE variability. The findings are expected to improve our understanding of carbon cycling processes in mid-latitude terrestrial ecosystems and provide a scientific basis for accurately assessing carbon sequestration potential and enhancing the reliability of regional carbon sink accounting in semi-arid areas.

2 Materials and methods

2.1 Study area

The YRB is located in the mid-latitude region of China (32°10′–41°50′N, 95°53′–119°05′E). The Yellow River has a total length of approximately 5464 km and drains an area of about 8×10^5 km². The basin is characterized by a west-to-east decreasing elevation gradient. Originating in the Bayan Har Mountains on the Qinghai-Xizang Plateau, the river flows successively through the Qinghai-Xizang Plateau, the Inner Mongolia Plateau, the Loess Plateau, and the Huang-Huai-Hai Plain before discharging into the Bohai Sea. Owing to its complex topography and pronounced climatic gradients, the basin supports a wide range of ecosystem types, including forests, grasslands, croplands, shrublands, and wetlands (Fig. 1). To improve ecosystem representation, eddy covariance sites within the YRB and its adjacent 100-km buffer zone were included in this study.

Fig. 1 Location of the selected eddy covariance sites and the spatial distribution of major land-cover types within the Yellow River Basin (YRB) and its adjacent 100-km buffer zone.

2.2 Data sources

The data used in this study were obtained from the National Ecosystem Science Data Center, National Science & Technology Infrastructure of China (<http://www.nesdc.org.cn>), and the National Qinghai-Xizang Plateau/Third Pole Environment Data Center (<http://data.tpdc.ac.cn>). The dataset includes observations from 15 eddy covariance flux sites located within the YRB and its adjacent 100-km buffer zone. Sites located outside the basin boundary were included to improve

ecosystem coverage and enhance site representativeness, as their climatic conditions and vegetation characteristics are comparable to those of the peripheral areas of the basin.

The bibliographic references and data links/does for all observation site are summarized in Table 1. The dataset comprises two categories of variables across five ecosystem types: carbon flux variables and environmental variables. NEE was selected as the primary carbon flux variable. Environmental variables included T_a ($^{\circ}\text{C}$), soil temperature (T_s ; $^{\circ}\text{C}$), relative humidity (RH; %), PAR ($\mu\text{mol}/(\text{m}^2 \cdot \text{s})$), precipitation (mm), wind speed (WS; m/s), VPD (kPa), and soil volumetric water content (SWC; m^3/m^3).

Table 1 Basic information for the observation sites

Site	Ecosystem type	Observation period	Longitude ($^{\circ}\text{E}$)	Latitude ($^{\circ}\text{N}$)	Data reference	Link/doi
Changwu	Cropland	2005–2009	107.68	35.24	Wang et al. (2024)	https://doi.org/10.57760/sciencedb.171
Luancheng	Cropland	Oct 2013–Sep 2017	114.41	37.53	Liu et al. (2023a)	https://doi.org/10.57760/sciencedb.000
Shouyang	Cropland	2012–2014	113.20	37.50	Mei et al. (2023)	https://doi.org/10.57760/sciencedb.073
Yingke	Cropland	2008–2011	100.41	38.85	Wang et al. (2024)	https://doi.org/10.11888/Terre.tpd.30
Yucheng	Cropland	2003–2010	116.57	36.82	Zhao et al. (2021)	https://doi.org/10.11922/sciencedb.j00
Arou	Grassland	2009–2011	100.46	38.04	Wang et al. (2024)	https://doi.org/10.11888/Terre.tpd.30
Damao	Grassland	2015–2018	110.32	41.64	Song et al. (2023)	https://doi.org/10.57760/sciencedb.000
Haibei meadow	Grassland	2015–2020	101.31	37.61	Zhang et al. (2023b)	https://doi.org/10.57760/sciencedb.067
Sanjiangyuan	Grassland	2012–2016	100.55	34.35	He et al. (2023)	https://doi.org/10.57760/sciencedb.000
Haibei shrub	Shrubland	2003–2013, 2016–2018, and 2020	101.33	37.66	Zhang et al. (2021b, 2023a)	https://doi.org/10.12199/nescd.ecodb.005 https://doi.org/10.57760/sciencedb.067
Guantan	Forest	2008–May 2012	100.25	38.53	Wang et al. (2024)	https://doi.org/10.11888/Terre.tpd.30
Baotianma	Forest	2017–2018	111.93	33.49	Niu et al. (2023)	https://doi.org/10.57760/sciencedb.j00

Site	Ecosystem type	Observation period	Longitude (°E)	Latitude (°N)	Data reference	Link/doi
Xiaolangdi	Forest	2011–2020	112.46	35.02	Huang et al. (2023)	https://doi.org/10.57760/sciencedb.eco
Haibei	Wetland	2004–2009	101.32	37.60	Zhang et al. (2021a)	https://doi.org/10.11922/sciencedb.101
Hongyuan	Wetland	Jun 2015–2020	102.65	33.10	Chen et al. (2023)	https://doi.org/10.57760/sciencedb.000

2.3 Data processing

2.3.1 NEE data processing and Random Forest model construction

This study used standardized flux products publicly released by ChinaFLUX and related national ecosystem science data platforms. The data from each eddy covariance site had already undergone raw flux calculation, quality control, nighttime low-turbulence filtering, gap-filling, and other standard processing procedures conducted by the data providers according to ChinaFLUX or equivalent protocols. Therefore, the original 10-Hz high-frequency measurements were not reprocessed. Instead, the processed data products provided by the data platforms were directly used for subsequent analyses.

To improve transparency and reproducibility, Table 2 summarizes the data processing methods reported in the corresponding data publications for each site. According to these descriptions, flux corrections and quality-control procedures generally included raw-data outlier removal, sonic virtual temperature correction, coordinate rotation (primarily double-rotation or two-dimensional coordinate rotation), detrending or block averaging, Webb–Pearman–Leuning (WPL) density correction, frequency-response or spectral correction, stationarity testing, integral turbulence characteristic testing, exclusion of measurements collected during rainfall events, nighttime friction

velocity (u^*) filtering, removal of anomalous flux values, and energy balance closure evaluation (Webb et al., 1980; Foken and Wichura, 1996; Mauder and Foken, 2004).

Table 2 Summary of net ecosystem carbon dioxide (CO_2) exchange (NEE) quality-control procedures, friction velocity (u^*) filtering, and gap-filling methods for each observation site

Site	Flux process- ing soft- ware/method	u^* thresh- hold	Valid data after QC (%)	Short- gap filling	Long- gap filling	Reference
Changwu	-	-	-	LI	-	Wang et al. (2024)
Luancheng	-	-	66.0	MDS (<30 d)	NLR	Liu et al. (2023a)
Shouyang	-	-	-	-	-	Mei et al. (2023)
Yingke	REddyProc	-	-	MDS	RF	Wang et al. (2025b)
Yucheng	ChinaFLUX stan- dard method	-	39.1-50.4	-	ChinaFLUX stan- dard method	Zhao et al. (2021)
Arou	REddyProc	-	-	MDS	RF	Wang et al. (2025b)
Damao	ChinaFLUX stan- dard method	0.10 m/s	34.0-61.6	LI (<2 h)	MDS	Song et al. (2023)
Haibei meadow	EddyPro v. 7.0.6	0.15 m/s	34.7-46.5	-	BRT	Zhang et al. (2023b)
Sanjiangyu	ChinaFLUX stan- dard method	-	-	LI (<2 h)	LI and NLR	He et al. (2023)
Haibei shrub	EddyPro v. 7.0.6	0.15 m/s	38.1-48.3	LI (<2 h)	NLR and BRT	Zhang et al. (2021b)
Guantan	REddyProc	-	-	MDS	RF	Wang et al. (2025b)
Baotianman	LoggerNet; Ed- dyPro 6.0.0	0.20 m/s	52.0 and 61.0	-	MDS and MDV	Niu et al. (2023)

Site	Flux process- ing soft- ware/method	u^* thresh- hold	Valid data after QC (%)	Short- gap filling	Long- gap filling	Reference
Xiaolangdi -		0.15 m/s in 2016; 0.26 m/s in 2017; and not reported for the remain- ing years	45.1-67.9	MDS (<15 d)	ANN and MDV	Huang et al. (2023)
Haibei	ChinaFLUX stan- dard method		34.1-48.9	LI (<2 h)	NLR	Zhang et al. (2021a)
Hongyuan	MATLAB -		31.8-39.3	LI (<2 h)	NLR	Chen et al. (2023)

Note: LI, linear interpolation; MDS, marginal distribution sampling; MDV, mean diurnal variation; NLR, nonlinear regression; ANN, artificial neural network; BRT, boosted regression trees; RF, Random Forest. REddyProc was primarily used for post-processing half-hourly flux data. Valid data after quality control (QC) refers to the final proportion of valid half-hourly NEE observations reported in the corresponding data publications. If specific information on u^* thresholds, valid data proportions, or gap-filling methods was not reported in the original publications, these items are indicated as “-” in the table, and no additional assumptions were made in this study.

Methods used to identify outliers and low-quality data varied among sites and primarily included standard-deviation threshold methods, moving-window approaches, and physically based threshold screening. u^* filtering was applied at all sites, with the reported u^* thresholds for several sites ranging from approximately 0.10 to 0.26 m/s. Following quality control and u^* filtering, the proportion of valid observations ranged approximately from 31.8% to 67.9%.

For gap-filling, short gaps were generally filled using linear interpolation, whereas longer gaps were filled using methods such as mean diurnal variation (MDV), marginal distribution sampling (MDS), nonlinear regression (NLR), boosted regression trees (BRT), RF, or artificial neural networks (ANN). These

methods typically employed environmental variables, including PAR (or solar radiation), T_a , T_s , VPD, SWC, and WS, as predictors to improve the continuity of NEE time series and reduce uncertainties in annual carbon budget estimates (Papale et al., 2006; Moffat et al., 2007).

RF is an ensemble machine-learning algorithm based on multiple decision trees (Breiman, 2001). The method generates multiple training datasets through bootstrap resampling, randomly selects a

subset of predictors at each splitting node, and combines predictions from all decision trees to produce the final output. RF can effectively characterize complex nonlinear relationships between predictor and response variables while reducing the risk of overfitting associated with individual decision trees. Therefore, it has been widely applied to investigate and predict relationships between ecosystem carbon fluxes and environmental drivers. Because ecosystem NEE is jointly regulated by radiation, temperature, moisture conditions, vegetation physiological processes, and other interacting factors, its responses to environmental variations are often highly nonlinear. RF is therefore particularly suitable for capturing these complex relationships. In addition, variable-importance metrics derived from RF models can be used to quantify the relative contributions of different environmental factors to NEE variability, thereby providing insights into potential driving mechanisms.

In this study, RF regression models were developed using quality-controlled and gap-filled NEE data together with synchronous environmental observations to identify the dominant environmental controls on NEE across different temporal scales. NEE was treated as the response variable, while T_a , T_s , PAR, VPD, RH, WS, precipitation, and SWC were used as predictor variables. To ensure consistency among variables, we standardized all predictors and response variables using Z-score normalization prior to model training.

The RF models were implemented using the Python scikit-learn library (Pedregosa et al., 2011). The model parameters were set as follows: `n_estimators=1000`, `max_features=5`, and `min_samples_leaf=5`. After model fitting, normalized impurity-based feature importance was used to quantify the relative importance of environmental predictors associated with NEE variability. These importance values reflect model-derived statistical associations and should not be interpreted as independent causal effects. Pearson correlation analysis was used to assess the relationships between NEE and individual environmental variables at the half-hourly, daily, and monthly scales using paired valid observations, with statistical significance evaluated at $P < 0.05$ and $P < 0.01$ levels. During April–October 2016–2017, the daily relationships of NEE with T_a and PAR were further evaluated using Pearson and Spearman correlation coefficients together with linear and quadratic regressions; model performance was evaluated using R^2 and root mean square error (RMSE). For the half-hourly analysis, daytime NEE–PAR relationships under $\text{PAR} \geq 10 \mu\text{mol}/(\text{m}^2 \cdot \text{s})$ were fitted using a rectangular hyperbolic model, whereas nighttime NEE– T_a relationships under $\text{PAR} < 10 \mu\text{mol}/(\text{m}^2 \cdot \text{s})$ were

fitted using an exponential model.

2.3.2 Calculation of VPD

Saturation vapor pressure was not directly measured; it was calculated from air temperature using the Tetens empirical equation (Campbell and Norman, 1998; Yuan et al., 2021):

$$e_s = 0.6108 \exp \left(\frac{17.27T_a}{T_a + 237.3} \right), \quad (1)$$

where T_a is air temperature ($^{\circ}\text{C}$); and e_s is the saturation vapor pressure (kPa).

Actual vapor pressure e_a (kPa) was calculated from RH (%) as follows:

$$e_a = e_s \left(\frac{\text{RH}}{100} \right). \quad (2)$$

Finally, VPD (kPa) was calculated as:

$$\text{VPD} = e_s - e_a. \quad (3)$$

3 Results

3.1 Temporal variability of NEE

3.1.1 Diurnal variability of NEE

Marked differences were observed among cropland, forest, grassland, shrubland, and wetland ecosystems in the diurnal patterns, carbon sink strength, and duration of CO_2 uptake reflected by

NEE. From May to September, all five ecosystem types exhibited a characteristic U-shaped diurnal pattern, with net CO_2 uptake during the daytime and net CO_2 release at night from 2003 to 2020 (Fig. 2). During this period, NEE exhibited the largest diurnal amplitudes, with values ranging approximately from -1.60 to $0.35 \text{ mg CO}_2/(\text{m}^2 \cdot \text{s})$. Both the maximum CO_2 uptake and the maximum CO_2 release were observed in the cropland ecosystem. In the remaining months, diurnal NEE variation was relatively weak, and the amplitudes of the diurnal cycles were substantially smaller.

Among the five ecosystem types, cropland exhibited the most pronounced diurnal variation in NEE. The U-shaped pattern was particularly evident in April, May, August, and September, indicating strong daytime CO_2 uptake and large diurnal amplitudes. In August, the minimum NEE approached $-1.60 \text{ mg CO}_2/(\text{m}^2 \cdot \text{s})$, reflecting a short-term but highly intensity carbon sink. The forest ecosystem maintained net CO_2 uptake over a longer period and displayed

a clear diurnal pattern from April to October. However, its overall variation was more moderate, with NEE generally ranging from -0.80 to $0.30 \text{ mg CO}_2/(\text{m}^2 \cdot \text{s})$.

Pronounced diurnal variation in grassland and wetland ecosystems was mainly observed from June to September. In particular, the wetland ecosystem exhibited strong daytime CO_2 uptake during July and August, although the magnitude of uptake varied substantially from month to month. The shrubland ecosystem showed relatively smooth NEE dynamics. Although it also exhibited a U-shaped pattern from May to September, its overall amplitude was smaller than those observed in the cropland and forest ecosystems.

3.1.2 Intra-annual variability of daily NEE

At the daily scale, the five ecosystem types exhibited distinct intra-annual patterns and magnitudes of NEE variability from 2003 to 2020 (Fig. 3). The cropland ecosystem displayed a characteristic bimodal pattern of carbon uptake. The first uptake peak occurred around May, reaching approximately $-4.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$, followed by a pronounced CO_2 release peak around mid-June, with values up to $3.5 \text{ g C}/(\text{m}^2 \cdot \text{d})$. This release period was primarily associated with bare-soil exposure and tillage disturbance during the transition from winter wheat harvest to summer maize planting. A second uptake peak occurred in August, reaching approximately $-7.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$, reflecting the strong photosynthetic activity of summer maize during its peak growing season.

The forest ecosystem exhibited the greatest day-to-day variability among all ecosystem types. Daily NEE decreased rapidly after May and reached its maximum CO_2 uptake in July, with values of approximately $-10.5 \text{ g C}/(\text{m}^2 \cdot \text{d})$. This pronounced variability may be attributed to the higher leaf area index, biomass, and canopy photosynthetic capacity of forests, which can amplify the effects of short-term fluctuations in daily radiation, VPD, and diffuse radiation on ecosystem carbon exchange (Duursma et al., 2009; Liu et al., 2022; de Pue et al., 2023).

In contrast, grassland and shrubland ecosystems showed relatively smooth seasonal fluctuations, with most carbon uptake occurring between June and September. The maximum CO_2 uptake in shrubland (approximately $-3.4 \text{ g C}/(\text{m}^2 \cdot \text{d})$) exceeded that of grassland (approximately $-1.4 \text{ g C}/(\text{m}^2 \cdot \text{d})$). However, the day-to-day variability of shrubland remained considerably lower than that of forest ecosystems. The pattern is likely attributable to the generally lower leaf area index, reduced productivity potential, and persistent water limitation characteristic of semi-arid shrublands, which constrain ecosystem responses to short-term meteorological fluctuations (Jia et al., 2014).

The wetland ecosystem showed substantial CO_2 release during March and April, reaching approximately $1.5 \text{ g C}/(\text{m}^2 \cdot \text{d})$, before gradually shifting to net CO_2 uptake after late May. Maximum uptake occurred during July and August, with values of approximately $-2.5 \text{ g C}/(\text{m}^2 \cdot \text{d})$. Compared with forests, wetlands

Fig. 2 Monthly mean diurnal cycles of net ecosystem carbon dioxide exchange (NEE) in cropland, forest, grassland, shrubland, and wetland ecosystems across the YRB.

Figure 2: Fig. 2 Monthly mean diurnal cycles of net ecosystem carbon dioxide exchange (NEE) in cropland, forest, grassland, shrubland, and wetland ecosystems across the YRB.

showed lower day-to-day variability, likely because persistently high soil moisture and the buffering effects of water-level fluctuations reduced the influence of short-term meteorological variability on NEE. As a result, wetland carbon exchange appears to be more strongly regulated by seasonal hydrothermal conditions and freeze-thaw processes than by short-term weather fluctuations (Wei et al., 2022).

3.1.3 Monthly variability of NEE in terrestrial ecosystems of the YRB

At the monthly scale, NEE showed pronounced seasonal variation across all five ecosystem types

Fig. 2 Monthly mean diurnal cycles of net ecosystem carbon dioxide (CO_2) exchange (NEE) in cropland, forest, grassland, shrubland, and wetland ecosystems across the YRB. (a), January; (b), February; (c), March; (d), April; (e), May; (f), June; (g), July; (h), August; (i), September; (j), October; (k), November; (l), December. Negative NEE values indicate net ecosystem CO_2 uptake, whereas positive values indicate net CO_2 release.

from 2003 to 2020 (Fig. 4). As vegetation activity increased during the growing season, each ecosystem gradually transitioned from net CO_2 release to net CO_2 uptake and reached peak carbon uptake during summer. Forest, grassland, shrubland, and wetland ecosystems all functioned as net carbon sinks from June to August, whereas the cropland ecosystem experienced a brief period of net carbon release in June before reaching its strongest carbon sink intensity in August.

The cropland ecosystem showed a distinct bimodal seasonal pattern. The first period of carbon uptake occurred during April and May, followed by a transition to a net carbon source in June and a second period of strong carbon uptake from July to September, peaking in August. This pattern was closely associated with the cropping systems and management practices at the cropland sites. Sites such as Changwu, Luancheng, and Yucheng are primarily located in the middle and lower reaches of the YRB and within the agricultural region of the North China Plain, where winter wheat–summer maize rotation is the dominant cropping system. During June, winter wheat reaches maturity and is harvested, resulting in temporary bare-soil exposure, enhanced residue decomposition, and tillage disturbance, while summer maize remains in the sowing or seeding

Fig. 3

Figure 3: Fig. 3

Fig. 4. Monthly totals of NEE in five terrestrial ecosystem types across the YRB. Panels: (a) Cropland; (b) Forest; (c) Grassland; (d) Shrubland; (e) Wetland. The y-axis is NEE ($\text{g C}/(\text{m}^2 \cdot \text{month})$); the x-axis is Month, from Jan to Dec.

Figure 4: Fig. 4. Monthly totals of NEE in five terrestrial ecosystem types across the YRB. Panels: (a) Cropland; (b) Forest; (c) Grassland; (d) Shrubland; (e) Wetland. The y-axis is NEE ($\text{g C}/(\text{m}^2 \cdot \text{month})$); the x-axis is Month, from Jan to Dec.

Fig. 3 Intra-annual dynamics of daily NEE in five terrestrial ecosystem types across the YRB study area. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland. The dashed horizontal line denotes $\text{NEE}=0.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$; negative NEE values indicate net ecosystem CO_2 uptake, whereas positive values indicate net CO_2 release.

stage with relatively low photosynthetic capacity. Therefore, cropland functions as a temporary carbon source during this period. In July and August, summer maize enters its rapid growth stage, photosynthetic activity increases substantially, and the ecosystem shifts back to a strong carbon sink.

The forest ecosystem exhibited a longer and more stable carbon sink period. NEE decreased after April and maintained strong net CO_2 uptake from May to August, indicating that the greater biomass and longer canopy duration of forests support sustained and stable carbon sequestration. Grassland and shrubland ecosystems showed similar seasonal patterns, functioning as net carbon sinks from June to September. However, their carbon uptake intensities were generally lower than those of forests and croplands. The stronger summer carbon uptake observed in shrublands compared with grasslands may be related to higher vegetation cover and greater water-use efficiency.

The wetland ecosystem functioned as a carbon sink from May to August and reached its maximum uptake intensity in July. However, it rapidly shifted back to a carbon source after September, indicating that monthly-scale carbon exchange in wetlands is jointly regulated by vegetation phenology, hydrological conditions, and organic matter decomposition processes.

Fig. 4 Monthly totals of NEE in five terrestrial ecosystem types across the YRB. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland. The horizontal line at $\text{NEE}=0 \text{ g C}/(\text{m}^2 \cdot \text{month})$ indicates the balance between net CO_2 uptake and net CO_2 release. Negative NEE values indicate net ecosystem CO_2 uptake, whereas positive values indicate net CO_2 release.

Fig. 5

Figure 5: Fig. 5

3.1.4 Interannual variability of NEE in terrestrial ecosystems of the YRB

The annual net CO₂ budgets of the different ecosystem types in the YRB exhibited pronounced interannual variability from 2003 to 2020 (Fig. 5). Cropland and forest ecosystems consistently functioned as strong and stable net CO₂ sinks throughout the observation period. Specifically, the maximum annual net CO₂ uptake by cropland occurred at the Yingke site in 2011 ($-960.25 \text{ g C}/(\text{m}^2 \cdot \text{a})$), while forest ecosystems reached their strongest net CO₂ uptake at the Guantan site in 2011 ($-886.08 \text{ g C}/(\text{m}^2 \cdot \text{a})$). Even for the weakest annual net CO₂ uptake records (the Changwu cropland site in 2007 and the Xiaolangdi forest site in 2013), annual NEE remained negative, indicating persistent net carbon uptake despite considerable interannual fluctuations in sink strength.

In contrast, shrubland and grassland ecosystems generally functioned as relatively weak carbon sinks. Shrubland showed limited interannual variability and consistently maintained net CO₂ uptake throughout the study period. Grassland, however, showed lower stability. Although most grassland site-year records indicated net CO₂ uptake, the strongest uptake was observed at Arou in 2011 ($-351.66 \text{ g C}/(\text{m}^2 \cdot \text{a})$), whereas net CO₂ release occurred at Damao during 2015–2017 and at Sanjiangyuan in 2016.

The wetland ecosystem exhibited the strongest interannual variability among all ecosystem types. At the Haibei wetland site, substantial net CO₂ release occurred between 2004 and 2008,

Fig. 5 Interannual variations in NEE at selected eddy covariance sites within the YRB. Negative NEE values indicate net ecosystem CO₂ uptake, whereas positive values indicate net CO₂ release.

with the largest release recorded in 2007 ($1027.97 \text{ g C}/(\text{m}^2 \cdot \text{a})$). Flux partitioning analysis indicated that this anomalous carbon loss was associated with both enhanced ecosystem respiration and reduced gross primary productivity (GPP), with the increase in ecosystem respiration contributing more strongly to the observed net CO₂ release (Table S1).

3.2 Environmental controls on NEE in terrestrial ecosystems of the YRB

3.2.1 Relationships between environmental factors and NEE across different time scales

At the half-hourly scale, correlations between environmental variables and NEE were generally weak, although most correlation coefficients were statistically

significant (Fig. 6a). This finding suggests that ecosystem CO_2 exchange showed detectable instantaneous responses to changes in environmental conditions. Among all variables, PAR was significantly negatively correlated with NEE across all five ecosystem types, indicating that it was the most consistent environmental driver at this temporal scale. T_a and T_s also generally showed significant negative correlations with NEE, with particularly strong relationships observed in shrubland ecosystems. RH was typically weakly and positively correlated with NEE, whereas VPD showed significant negative correlations in all ecosystem types. In contrast, SWC, WS, and precipitation generally showed weak correlations with NEE, although significant relationships were detected in all ecosystem types. Overall, these results suggest that short-term fluctuations in NEE were primarily regulated by the combined effects of radiation, temperature, and atmospheric moisture conditions.

At the daily scale, the correlations between environmental factors and NEE became stronger and more consistent, highlighting the increasing importance of temperature regulation (Fig. 6b). Both T_a and T_s were significantly negatively correlated with NEE in all ecosystem types, with the strongest relationships observed in forests. PAR remained significantly negatively correlated with NEE in all ecosystems except grassland. Meanwhile, RH showed significant negative correlations with NEE in all ecosystem types, indicating that higher atmospheric humidity generally favored net CO_2 uptake at the daily scale. The effects of precipitation and WS became more pronounced than those observed

at the half-hourly scale, although substantial ecosystem-specific differences remained. Precipitation showed a weak positive correlation with NEE in cropland ecosystems, whereas significant negative correlations were observed in grassland, shrubland, and wetland ecosystems. WS generally exhibited weak positive correlations with NEE across all ecosystem types.

At the monthly scale, correlations between environmental variables and NEE more clearly reflected cumulative environmental effects, and the explanatory power of temperature reached its maximum (Fig. 6c). T_a and T_s were generally significantly negatively correlated with NEE, with the strongest relationships observed in forest and shrubland ecosystems. These results indicate that temperature was a key regulator of seasonal NEE dynamics. RH remained negatively correlated with NEE at the monthly scale, whereas the influence of PAR weakened and remained significant only in some ecosystems. In contrast, precipitation exhibited significant negative correlations with NEE across all five ecosystem types, suggesting that increased precipitation generally enhances ecosystem CO_2 uptake at the monthly scale. The long-term influence of VPD was primarily evident in shrubland and wetland ecosystems. Overall, correlation analysis revealed a pronounced scale dependence in the environmental regulation of NEE. Short-term variations were mainly driven by instantaneous environmental factors, particularly PAR, whereas medium- and long-term variations were increasingly governed by the combined effects of temperature and moisture conditions.

Fig. 7

Figure 6: Fig. 7

Fig. 6 Pearson's correlation coefficient (r) values between NEE and environmental variables across ecosystem types at the half-hourly (a), daily (b), and monthly (c) scales. PAR, photosynthetically active radiation; RH, relative humidity; SWC, soil water content; T_a , air temperature; T_s , soil temperature; VPD, vapor pressure deficit; WS, wind speed; *, significance at $P < 0.05$ level; **, significance at $P < 0.01$ level. "-" indicates that the correlation coefficient was not calculated because of insufficient valid data.

3.2.2 Relative contributions of environmental factors to NEE across different time scales

The relative contributions of environmental factors to NEE varied substantially among temporal scales (Fig. 7). At the half-hourly scale, PAR was the dominant predictor in most ecosystem types, particularly in forests and croplands, where it exhibited the highest feature importance. This result indicates that ecosystem CO_2 exchange at short time scales is primarily controlled by photosynthetic light responses and is highly sensitive to instantaneous fluctuations in radiation.

At the daily scale, PAR remained an important driver in cropland ecosystem; however, the importance of temperature variables (T_a and T_s) increased markedly, especially in grassland and wetland ecosystems. This shift suggests that cumulative thermal effects become increasingly important in regulating daily carbon exchange dynamics.

At the monthly scale, temperature variables emerged as the dominant contributors to NEE variability. Shrubland, wetland, forest, and grassland ecosystems showed particularly high relative importance of T_a at this temporal scale, highlighting the dominant influence of seasonal thermal conditions on long-term ecosystem carbon exchange.

A comparison between the RF feature-importance results and the correlation analysis showed strong consistency. Environmental variables identified as highly important by the RF model generally corresponded to those exhibiting strong and statistically significant correlations with

Fig. 7 Relative importance rankings of environmental factors influencing NEE at the half-hourly (a), daily (b), and monthly (c) scales.

NEE. This agreement between two independent analytical approaches enhances confidence in the inferred environmental controls on ecosystem carbon exchange.

Overall, the relative contribution of temperature variables, particularly T_a , increased progressively with increasing temporal scale and reached its maximum at the monthly scale. In contrast, PAR exerted its strongest influence at the half-hourly and daily scales. These findings demonstrate clear scale-dependent

differences in the mechanisms regulating ecosystem CO_2 exchange: short-term fluctuations are primarily driven by rapid changes in light availability, whereas long-term seasonal dynamics are mainly governed by variations in thermal conditions.

3.2.3 Seasonal variability of meteorological factors during representative period (2016-2017)

To further compare ecosystem responses to environmental conditions under a common climatic background, we selected the period 2016-2017 as a representative period for examining the seasonal dynamics of meteorological factors across the five ecosystem types in the YRB. This period was selected because observations were available for at least one site in each ecosystem type during this overlapping period.

PAR and T_a showed pronounced seasonal patterns, increasing synchronously during the warm season and decreasing during the cold season (Fig. 8). These variables provide the primary radiative and thermal conditions underlying seasonal fluctuations in NEE. The seasonal peaks of PAR and T_a were particularly pronounced in cropland and grassland ecosystems.

RH and VPD also exhibited seasonal variation but generally varied in opposite directions throughout the year. VPD increased while RH decreased during the warm season, whereas the opposite pattern occurred during the cold season. This inverse relationship suggests that atmospheric moisture conditions may play an important role in regulating ecosystem carbon exchange, particularly under high-VPD conditions during the growing season.

Precipitation and SWC displayed consistent seasonal wet-dry transition patterns. Variations in SWC generally corresponded to precipitation events, reflecting the response of soil moisture to rainfall inputs. Clear differences among ecosystem types were observed. Forest and wetland ecosystems maintained relatively high SWC values with comparatively small seasonal fluctuations, whereas grassland and shrubland ecosystems experienced lower SWC during dry periods and exhibited greater sensitivity to precipitation pulses.

In contrast, WS showed weaker seasonal regularity than PAR, T_a , RH, VPD, precipitation, and SWC. This finding suggests WS primarily acted as a background environmental factor rather than a dominant driver of seasonal NEE variability.

3.2.4 Responses of NEE to PAR and T_a at daily and half-hourly scales during the representative period (2016-2017)

To characterize ecosystem responses to key environmental drivers during the representative period, we first examined the relationships between NEE and T_a and between NEE and PAR using daily observations from April to October, when vegetation activity and ecosystem carbon exchange were most active (Fig. 9).

Fig. 8 Temporal variations in environmental variables across five ecosystem types during 2016-2017. (a-d), cropland; (e-h), forest; (i-l), grassland; (m-p), shrubland; (q-t), wetland. For ease of comparison, variables with closely related environmental meanings were paired as follows: PAR- T_a for radiative and thermal conditions, RH-VPD for atmospheric moisture conditions, and precipitation-SWC for water input and soil-moisture response; T_s and WS were displayed together as the remaining variables. PAR, T_a , RH, VPD, SWC, T_s , and WS are the 7-day centered moving averages, while precipitation is shown as a 7-day cumulative value. Gaps or absent curves indicate periods or variables with insufficient valid observations.

The results revealed substantial differences among ecosystem types in their responses to temperature and radiation at the daily scale. Overall, the relationship between NEE and T_a exhibited strong ecosystem-specific characteristics. In cropland, the relationship was relatively weak, and NEE showed no clear response to changes in T_a . In contrast, forest, grassland, shrubland, and wetland ecosystems generally exhibited negative relationships between NEE and T_a , indicating enhanced CO_2 uptake with increasing temperature. Among these ecosystems, shrubland showed the strongest temperature response. The quadratic regression results suggest pronounced nonlinear temperature responses in shrubland and wetland ecosystems, while forest and grassland ecosystems also exhibited temperature sensitivity, although with lower response magnitudes.

NEE generally showed a decreasing trend with increasing PAR in most ecosystem types, indicating that increasing radiation generally enhanced net ecosystem CO_2 uptake. Forest and cropland ecosystems exhibited the strongest responses to PAR, followed by wetland and grassland ecosystems, whereas shrubland showed a comparatively weaker response. In most cases, quadratic regression provided a better fit than linear regression, suggesting that the daily-scale response of NEE to PAR exhibited nonlinear saturation characteristics.

To further investigate the underlying mechanisms of ecosystem carbon exchange, we examined the relationships between NEE and PAR and between NEE and T_a at the half-hourly scale using growing-season observations from 2016-2017 under daytime ($\text{PAR} \geq 10 \mu\text{mol}/(\text{m}^2 \cdot \text{s})$) and nighttime ($\text{PAR} < 10 \mu\text{mol}/(\text{m}^2 \cdot \text{s})$) conditions, respectively (Figs. 10 and 11). This separation was adopted because daytime NEE primarily reflects photosynthetic responses to radiation, whereas nighttime NEE mainly represents ecosystem respiration and its temperature dependence.

The results showed that daytime half-hourly NEE exhibited pronounced nonlinear responses to PAR across all five ecosystem types (Fig. 10). Specifically, NEE decreased rapidly with increasing PAR and gradually approached an asymptote at higher radiation levels, displaying a typical light-saturation response. Among the ecosystem types, cropland and forest showed the largest response amplitudes, followed by wetland and shrubland, while grassland showed the weakest response. These findings indicate that PAR exerted strong control over daytime carbon uptake at the half-hourly scale.

Fig. 9

Figure 7: Fig. 9

Fig. 10 Daytime half-hourly relationships between NEE and PAR during the 2016–2017 growing seasons. Panels: (a) Cropland; (b) Forest; (c) Grassland; (d) Shrubland; (e) Wetland. Scatter points represent 30-min daytime NEE observations; red curves indicate rectangular hyperbola fits.

Figure 8: Fig. 10 Daytime half-hourly relationships between NEE and PAR during the 2016–2017 growing seasons. Panels: (a) Cropland; (b) Forest; (c) Grassland; (d) Shrubland; (e) Wetland. Scatter points represent 30-min daytime NEE observations; red curves indicate rectangular hyperbola fits.

Fig. 9 Relationships between daily NEE and T_a (a, c, e, g, and i) and between daily NEE and PAR (b, d, f, h, and j) across five ecosystem types. Shaded areas denote the 95% confidence intervals.

In contrast, nighttime half-hourly NEE generally exhibited positive exponential relationships with T_a (Fig. 11). As T_a increased, nighttime NEE increased correspondingly, indicating enhanced respiration-driven CO_2 release. The temperature sensitivity of nighttime NEE varied among ecosystem types, with stronger responses observed in wetland and shrubland ecosystems and weaker responses in forest and grassland ecosystems.

Overall, the results from the representative period demonstrated clear process differentiation in ecosystem carbon exchange at the half-hourly scale. Daytime NEE showed a pronounced light-saturation response to PAR, whereas nighttime NEE showed a positive exponential response to T_a .

Fig. 10 Daytime half-hourly relationships between NEE and PAR during the 2016–2017 growing seasons. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland.

Fig. 11 Nighttime half-hourly relationships between NEE and T_a during the 2016–2017 growing seasons. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland.

Figure 11. Nighttime half-hourly relationships between NEE and T_a during the 2016–2017 growing seasons. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland.

Figure 9: Figure 11. Nighttime half-hourly relationships between NEE and T_a during the 2016–2017 growing seasons. (a), cropland; (b), forest; (c), grassland; (d), shrubland; (e), wetland.

4 Discussion

4.1 Variability of NEE in terrestrial ecosystems of the YRB

This study revealed distinct patterns of NEE variability across multiple temporal scales in cropland, forest, grassland, shrubland, and wetland ecosystems of the YRB. At the diurnal scale, all five ecosystem types exhibited a characteristic U-shaped pattern from May to September, with net CO₂ release at night and net CO₂ uptake during the daytime. This pattern is consistent with observations reported for coastal wetlands in the Yellow River Delta (Chu et al., 2016), spring wheat ecosystems in the Heihe River Basin (Sun et al., 2016), and grasslands in the central Tianshan region (Zhang

et al., 2023c). However, substantial seasonal differences were evident. From April to October, daytime carbon uptake remained strong and nighttime CO₂ release was relatively weak. In contrast, from November to the following March, the U-shaped pattern weakened considerably and nighttime CO₂ release increased. This seasonal transition is likely associated with reduced photosynthetic activity caused by low-temperature stress and vegetation dormancy (Yan et al., 2023).

Clear differences among ecosystem types were also observed. Due to the early spring regrowth of crops such as winter wheat and the influence of agricultural management practices, including irrigation and fertilization (Liu et al., 2023b), cropland ecosystems generally exhibited enhanced diurnal fluctuations earlier than the other ecosystem types and showed larger diurnal amplitudes during the same period.

At the daily scale, differences in the timing, duration, and intensity of the net carbon uptake period among ecosystem types reflected the combined influences of vegetation structure, phenology, and hydrothermal constraints. Cropland exhibited the latest onset of net carbon uptake, beginning after approximately day 130 of the year. However, the uptake rate increased rapidly thereafter, forming a strong carbon sink during the peak growing season, with daily NEE values approaching $-5.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$. This strong uptake is largely attributable to management practices, such as fertilization, that enhance ecosystem productivity (Zhang et al., 2021c). Nevertheless, cropland also exhibited the shortest carbon uptake period and rapidly transitioned to a carbon source following autumn harvest (around day 270), reflecting the typical seasonal growth cycle of annual crops (Du and Liu, 2013; Zhang et al., 2021c).

Forest ecosystems exhibited the longest and strongest carbon uptake period. Net carbon uptake began earliest (around day 90) and ended latest (around day 300), resulting in a carbon uptake season lasting more than 200 days (Baldocchi et al., 2005; Yan et al., 2023; Qiao et al., 2025). During the peak growing season, daily NEE approached $-10.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$, reflecting the high photosynthetic productivity of forest ecosystems. Forest also exhibited greater day-to-day variability in NEE, suggesting that forest carbon fluxes are highly responsive to

short-term fluctuations in radiation and temperature.

Grassland and shrubland ecosystems exhibited similar phenological patterns, with net carbon uptake generally beginning around day 120 and ending around days 270–280. These similarities reflect the common hydrothermal constraints characteristic of semi-arid environments. However, the peak carbon uptake of shrubland (approximately $-3.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$) was generally greater than that of grassland (approximately $-1.5 \text{ g C}/(\text{m}^2 \cdot \text{d})$), consistent with the higher biomass and productivity of shrubland vegetation.

Wetland ecosystems exhibited more complex daily-scale dynamics, often displaying double-peak or multi-peak patterns during the growing season, with peak uptake rates of approximately $-2.0 \text{ g C}/(\text{m}^2 \cdot \text{d})$. This behavior suggests that, in addition to radiation and temperature, wetland carbon exchange is strongly influenced by hydrological conditions. Water-level fluctuations regulate photosynthesis in aquatic and hygrophytic vegetation and alter ecosystem respiration by modifying soil redox conditions. Consequently, wetland carbon exchange represents the integrated outcome of complex interactions among hydrological, biological, and climatic processes.

At the monthly scale, all ecosystem types exhibited a characteristic seasonal cycle of net carbon uptake during spring and summer and net carbon release during autumn and winter (Fig. 4). This pattern is primarily driven by seasonal variations in radiation and temperature and is consistent with observations from temperate ecosystems worldwide. Nevertheless, substantial differences among ecosystem types were observed in the timing, magnitude, and duration of their carbon sink functions.

Forest ecosystems exhibited the longest carbon uptake period (approximately 6–7 months) and the strongest uptake peak, which can be attributed to their greater biomass and larger leaf area index. Cropland ecosystems displayed a carbon uptake pattern characterized by rapid onset, high intensity, and relatively short duration. In the present study, the multi-year mean NEE of cropland exceeded that of forest ecosystems in absolute magnitude, indicating that cropland can function as a strong net CO_2 sink under intensive agricultural management in the YRB. This finding is

consistent with observations from winter wheat–summer maize rotation systems in the North China Plain and irrigated croplands in northwestern China (Wang et al., 2012; Tao et al., 2022).

The strong carbon uptake capacity of cropland is largely attributable to enhanced GPP resulting from multiple-cropping systems, irrigation, fertilization, and the cultivation of high-yield crop varieties. However, a large negative NEE does not necessarily imply long-term carbon sequestration because harvested biomass removes substantial amounts of fixed carbon from the ecosystem, thereby reducing the long-term carbon storage potential of croplands (Zhang et al., 2020). In contrast, although forests exhibited lower annual NEE values than croplands, their longer carbon residence times and lower levels of human

disturbance enable them to provide a more stable and persistent contribution to regional carbon storage (Zhu et al., 2022; Pan et al., 2024).

Grassland and shrubland ecosystems showed similar seasonal dynamics, although shrublands generally exhibited greater carbon uptake than grasslands. Notably, while wetlands also followed the general pattern of acting as carbon sinks during summer and carbon sources during winter, their carbon exchange dynamics were more strongly controlled by hydrological conditions, resulting in greater temporal complexity. Furthermore, wetlands functioned as a net carbon source when averaged across all study years (Table 3), suggesting that the carbon sink function of alpine wetlands may be vulnerable to persistent climatic stress.

Table 3 Comparison of CO₂ fluxes among different terrestrial ecosystems

Ecosystem type	Study area	Time scale	CO ₂ emission/uptake (g C/m ²)	Reference
Cropland	Wheat fields in the North China Plain	Growing season	−437.90	Zhang et al. (2020)
Cropland	Jinzhou agroecosystem site, Liaoning Province, China	Annual mean	−270.00 ± 31.00	Zhang et al. (2021c)
Cropland	Yellow River Basin (YRB)	Annual mean	−447.28	This study
Forest	Qilian Mountains	Annual	−545.99	Du et al. (2022)
Forest	Field poplar forest in Hongze Lake	Growing season	−1758.10	Xu et al. (2018)
Forest	YRB	Annual mean	−350.04	This study
Grassland	Horqin sandy grassland	Growing season	−139.83	Niu et al. (2018)
Grassland	Xilinhote grassland	Annual	−120.00	Wang et al. (2015b)
Grassland	YRB	Annual mean	−25.98	This study

Ecosystem type	Study area	Time scale	CO ₂ emission/uptake (g C/m ²)	Reference
Shrubland	East scrub meadow in Qilian Mountains	Growing season	−662.98	Gao et al. (2022)
Shrubland	Yanchi Research Station, Ningxia Hui Autonomous Region, China	Annual	−77.00	Jia et al. (2014)
Shrubland	YRB	Annual mean	−85.76	This study
Wetland	Chongming Dongtan Coastal Reclamation Wetland	Growing season	−1033.20	Wang et al. (2015a)
Wetland	Liaohe Delta	Annual mean	−556.00	Jia et al. (2017)
Wetland	YRB	Annual mean	286.28	This study

Note: Time-scale terminology follows the original publications. “Annual”denotes an annual total; “Annual mean” denotes the multi-year mean of annual values.

According to the partitioning results for ecosystem respiration (R_{eco}) and GPP derived from observations at the Haibei wetland site during 2004-2009 (Table S1), the extreme CO₂ release observed in 2007 resulted from the combined effects of enhanced R_{eco} and reduced GPP, with the increase in R_{eco} contributing more substantially to the net carbon loss. Previous studies have demonstrated that carbon emissions from alpine wetlands and peatlands are highly sensitive to changes in water level. Lower water levels increase oxygen exposure within peat layers and accelerate organic matter decomposition, whereas rewetting can significantly suppress ecosystem respiration (Zhao et al., 2010; Cui et al., 2017). Studies conducted on peatlands of the Qinghai-Xizang Plateau further suggest that declining water levels under warming and drying conditions

can accelerate decomposition processes and weaken ecosystem carbon sequestration capacity (Zhang et al., 2024; Yang et al., 2025). Therefore, the extreme carbon release observed in 2007 should be interpreted as an anomalous event driven primarily by enhanced respiration under warm and dry conditions rather

than as a typical characteristic of alpine wetland carbon exchange.

The annual net CO₂ budgets of all ecosystem types exhibited substantial interannual variability (Fig. 5), highlighting the sensitivity of ecosystem carbon cycling to climate variability and other disturbances, including land management practices and extreme climatic events. In this study, the mean annual NEE values of forest and cropland ecosystems were -350.04 and -447.28 g C/(m² · a), respectively, which are comparable to values reported for rotational croplands in the North China Plain (-437.90 g C/m²). These results indicate that although these ecosystems may function as carbon sources during the non-growing season, strong photosynthetic carbon uptake during the growing season is sufficient to maintain net annual carbon sequestration.

Even forests, which are generally regarded as stable carbon sinks, exhibited substantial interannual variability in carbon uptake capacity and may approach carbon neutrality or even function as weak carbon sources in some years due to drought, pest outbreaks, diseases, or changes in stand age structure. Grassland and shrubland ecosystems functioned as relatively weak carbon sinks at the interannual scale, with mean annual NEE values of -25.98 and -85.76 g C/(m² · a), respectively. Their carbon budgets are particularly sensitive to interannual precipitation variability (Yang et al., 2022), and prolonged drought conditions may reverse their carbon sink function.

Several limitations should be acknowledged. First, the limited number of observation sites and their uneven spatial distribution among ecosystem types may affect the representativeness of basin-scale carbon budget estimates. Second, cropland was treated as a single ecosystem category without explicitly distinguishing among cropping systems, irrigation regimes, or management practices, potentially masking important regional differences in carbon exchange. Third, differences among sites in data availability, valid data proportions, gap-filling approaches, and reporting standards may introduce uncertainty into annual NEE estimates and cross-site comparisons. Finally, because eddy covariance measurements quantify NEE rather than the complete ecosystem carbon balance, the terms “carbon sink” and “carbon source” used in this study refer specifically to NEE-based net CO₂ exchange during the observation period and should not be interpreted as indicators of total ecosystem carbon balance.

4.2 Scale dependence and regulatory mechanisms of environmental controls on ecosystem NEE in the YRB

RF-derived feature importance was used to identify the key environmental predictors of NEE. Because predictor variables may exhibit collinearity, these importance values should be interpreted as model-based measures of relative contribution rather than independent causal effects.

At the half-hourly scale, PAR was identified as the primary driver of NEE variability. This result is consistent with the instantaneous nature of photosynthesis

as a light-driven biochemical process. At sub-daily time scales, photon flux density directly regulates the photosynthetic electron transport chain and provides the energy required for carbon assimilation, thereby exerting strong control over instantaneous ecosystem carbon uptake rates (Xia et al., 2024). However, as the temporal scale increased from half-hourly to daily and monthly intervals, the explanatory power of temperature variables (T_a and T_s) gradually exceeded that of PAR and became the dominant environmental control.

This shift reflects scale-dependent differences in the mechanisms regulating ecosystem carbon exchange. Although light provides the energy source for photosynthesis, temperature determines the potential capacity for carbon uptake over longer time scales by influencing enzymatic activity, growing-season length, and vegetation phenology. Through its effects on leaf development and canopy duration, temperature regulates the temporal window during which ecosystems can function as carbon sinks. Previous studies conducted in the YRB and across the Northern Hemisphere have similarly demonstrated that climate warming-induced phenological changes are among the key factors explaining interannual variability in carbon sequestration across mid- and high-latitude regions (Gu et al., 2022; Bai et al., 2024).

In addition, Li et al. (2022) reported that nighttime temperature exerts a significant cumulative effect on monthly ecosystem respiration, providing further evidence that temperature increasingly influences ecosystem carbon budgets through its control of respiratory carbon losses. This transition from short-term photosynthetic regulation to long-term thermal and phenological control highlights the importance of adopting a multi-temporal-scale perspective when assessing regional carbon budgets.

The half-hourly observations collected during 2016–2017 further supported these findings. Under daytime conditions, the NEE–PAR relationship exhibited a pronounced nonlinear negative response characterized by an initial rapid decline followed by gradual saturation. This pattern is consistent with the well-established light-response curve of ecosystem photosynthesis and indicates that radiation directly controls net carbon uptake at short time scales. However, as PAR increased beyond a certain threshold, the marginal increase in carbon uptake diminished, reflecting the saturation of photosynthetic capacity. These process-based results provide additional support for the conclusion that PAR is the dominant driver of half-hourly NEE variability.

Although warm-season conditions provide abundant light and thermal resources, this study found that ecosystem responses to increasing temperature and radiation were not linear. Instead, NEE frequently approached saturation or even declined beyond certain thresholds. This nonlinear behavior can largely be attributed to the influence of VPD (Grossiord et al., 2020; Lu et al., 2022). While SWC is traditionally considered the primary limiting factor in semi-arid ecosystems, our results, consistent with those of Zhang et al. (2022) and Sun et al. (2024), suggest that VPD exerts a more immediate and direct constraint on NEE at the daily scale.

From a physiological perspective, when VPD exceeds the tolerance threshold of vegetation, stomata partially or completely close to reduce water loss and prevent hydraulic failure. This response can substantially limit photosynthetic carbon assimilation even when soil moisture remains adequate, resulting in a pronounced decline in net ecosystem carbon uptake (Koehler et al., 2023). Under ongoing climate warming, the increasing mismatch between available light and thermal resources and effective water availability has emerged as an important mechanism contributing to the weakening of carbon sink strength in grassland and shrubland ecosystems. As a consequence, these ecosystems may temporarily function as carbon sources during periods of peak growing-season drought stress (Yang et al., 2022).

Under nighttime conditions, the $NEE-T_a$ relationship generally exhibited a positive exponential pattern, indicating that respiration-driven carbon release increased with rising T_a . However, the magnitude of this temperature response differed among ecosystem types, suggesting that the influence of temperature on nighttime carbon exchange is jointly regulated by vegetation functional characteristics and local hydrothermal conditions. These findings further demonstrate the clear process-level differentiation at the half-hourly scale: daytime carbon exchange is primarily controlled by radiation-driven photosynthesis, whereas nighttime carbon exchange is dominated by the temperature sensitivity of ecosystem respiration.

Further analysis indicated that differences in carbon sink stability among ecosystem types under similar climatic conditions are largely attributable to variations in biological structure and human management. Forest ecosystems maintained relatively stable carbon sink functions even during drought years, consistent with the findings of Kühnhammer et al. (2023). This resilience is primarily associated with the deep rooting systems of trees, which enable access to deeper soil water reserves and help sustain transpiration and photosynthesis under conditions of surface soil drying and elevated VPD.

In contrast, grassland and shrubland ecosystems are generally dominated by shallow-rooted vegetation and therefore depend more strongly on precipitation-driven soil moisture pulses. Consequently, their carbon exchange is more sensitive to short-term fluctuations in water availability, resulting in greater variability in NEE (Zhang et al., 2023c).

Cropland ecosystems exhibit a distinctly different response pattern. Irrigation and fertilization effectively alleviate water and nutrient limitations, thereby reducing the direct influence of climatic variability on ecosystem productivity. As a result, croplands display rapid and high-intensity carbon

uptake, a characteristic commonly observed in intensively managed agricultural systems of the North China Plain (Zhang et al., 2022).

Wetland ecosystems exhibit another unique regulatory mechanism. Both excessively high-water levels and severe drought conditions can suppress net CO_2 uptake, consistent with findings from coastal and inland wetlands (Zhao et al.,

2023; Wang et al., 2025a). These studies suggest the existence of an optimal hydrological range for wetland carbon sequestration. Excessively high-water levels may limit oxygen transport to plant roots through aerenchyma tissues and inhibit photosynthetic activity, whereas excessively low water levels can stimulate soil organic matter decomposition and increase respiratory carbon losses. This strong dependence on hydrological conditions contributes to the pronounced interannual variability and uncertainty observed in wetland carbon budgets.

5 Conclusions

Based on eddy covariance observations collected between 2003 and 2020, this study investigated the multiscale temporal dynamics of NEE and its environmental controls across five representative ecosystem types in the YRB, including cropland, forest, grassland, shrubland, and wetland ecosystems.

NEE exhibited pronounced temporal variability and substantial differences among ecosystem types. At the diurnal scale, all ecosystems displayed a characteristic U-shaped pattern from May to September, characterized by net CO_2 uptake during the daytime and net CO_2 release at night. At the daily scale, cropland exhibited a typical bimodal pattern of carbon uptake associated with crop phenology and agricultural management, whereas forest ecosystems showed the greatest day-to-day variability in NEE. The remaining ecosystem types exhibited comparatively smoother seasonal fluctuations.

The magnitude, duration, and stability of NEE-based net CO_2 uptake differed markedly among ecosystem types. Forest ecosystems maintained the most persistent and stable carbon sink fluctuations, while croplands exhibited shorter but more intensive periods of carbon uptake. Wetlands showed the strongest interannual variability, including an anomalously large net CO_2 release event at the Haibei wetland site in 2007, which was primarily associated with enhanced ecosystem respiration. Grassland and shrubland were more vulnerable to environmental stress and could temporarily shift from net CO_2 release under drought conditions.

The dominant environmental controls on NEE varied substantially across temporal scales. PAR was the primary driver of instantaneous NEE variability at the half-hourly scale, reflecting the direct regulation of photosynthetic processes by light availability. In contrast, temperature became increasingly important at daily and monthly scales through its influence on vegetation activity, phenology, and ecosystem respiration. These findings demonstrate the strong temporal-scale dependence of NEE regulation and highlight the influence of considering both ecosystem-specific characteristics and temporal scale when evaluating regional carbon dynamics.

Nevertheless, several sources of uncertainty remain. These include the uneven spatial distribution of flux observation sites, limited ecosystem representation, and the treatment of cropland as a single ecosystem category without explicitly accounting for differences in cropping systems and management practices.

Future studies should incorporate additional long-term flux observations, finer classifications of vegetation and agricultural management types, and the integration of eddy covariance measurements with remote sensing products and process-based models. Such efforts will help improve the accuracy and reliability of basin-scale assessments of ecosystem carbon exchange and carbon sequestration potential.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the Shandong Provincial Natural Science Foundation (ZR2024QD207, ZR2024ME171), the China Postdoctoral Science Foundation (2025MD774146), the Special Funds for Basic Scientific Research Business Expenses at Central-level Public Welfare Scientific Research Institutes (IDM2024001), the New Talent Research Project University of Jinan (XJ2024011901), and the Science and Technology Development Fund of the Chinese Academy of Meteorological Sciences (2021KJ034).

The datasets used in this study were provided by the National Ecosystem Science Data Center, National Science & Technology Infrastructure of China (<http://www.nesdc.org.cn>) and the National Qinghai-Xizang Plateau/Third Pole Environment Data Center (<http://data.tpdac.ac.cn>). We sincerely thank these data platforms and the data contributors for their valuable support.

Author contributions

Conceptualization: LIN Feng; Investigation: LIN Feng, FANG Yuju, ZHAO Xuepeng, SONG Qingfan, JIANG Jiye; Writing - original draft preparation: LIN Feng; Writing - review & editing: LIN Feng, YANG Ping, FANG Yuju, ZHAO Xuepeng, ZHAO Qiang, SONG Qingfan, JIANG Jiye; Supervision: YANG Ping, ZHAO Qiang. All authors approved the manuscript.

References

- Ahlström A, Raupach M R, Schurgers G, et al. 2015. The dominant role of semi-arid ecosystems in the trend and variability of the land CO₂ sink. *Science*, 348(6237): 895–899.
- Bai Y, Zhu Y Q, Liu Y Z, et al. 2024. Vegetation greening and its response to a warmer and wetter climate in the Yellow River Basin from 2000 to 2020. *Remote Sensing*, 16(5): 790, doi: 10.3390/rs16050790.

- Baldocchi D. 2008. 'Breathing' of the terrestrial biosphere: lessons learned from a global network of carbon dioxide flux measurement systems. *Australian Journal of Botany*, 56(1): 1-26.
- Baldocchi D D, Black T A, Curtis P S, et al. 2005. Predicting the onset of net carbon uptake by deciduous forests with soil temperature and climate data: a synthesis of FLUXNET data. *International Journal of Biometeorology*, 49: 377-387.
- Bao X Y, Wen X F, Sun X M, et al. 2014. Interannual variation in carbon sequestration depends mainly on the carbon uptake period in two croplands on the North China Plain. *PLoS ONE*, 9(10): e110021, doi: 10.1371/journal.pone.0110021.
- Breiman L. 2001. Random forests. *Machine Learning*, 45: 5-32.
- Campbell G S, Norman J M. 1998. *An Introduction to Environmental Biophysics* (2nd ed.). New York: Springer, 40-43.
- Chen W N, Wang S, Niu S L. 2023. A dataset of carbon, water and heat fluxes of Zoige alpine meadow from 2015 to 2020. *China Scientific Data*, 8(2): 70-77. (in Chinese)
- Chen Z Q, Wu L, Chen N C, et al. 2025. Modeling terrestrial net ecosystem exchange based on deep learning in China. *Remote Sensing*, 17(1): 92, doi: 10.3390/rs17010092.
- Chu X J, Han G X, Zhu S Y, et al. 2016. Effect of environmental and biotic factors on net ecosystem CO₂ exchange over a coastal wetland in the Yellow River Delta. *Chinese Journal of Applied Ecology*, 27(7): 2091-2100. (in Chinese)
- Ciais P, Tan J, Wang X, et al. 2019. Five decades of northern land carbon uptake revealed by the interhemispheric CO₂ gradient. *Nature*, 568: 221-225.
- Cui L J, Kang X M, Li W, et al. 2017. Rewetting decreases carbon emissions from the Zoige alpine peatland on the Tibetan Plateau. *Sustainability*, 9(6): 948, doi: 10.3390/su9060948.
- de Pue J, Wieneke S, Bastos A, et al. 2023. Temporal variability of observed and simulated gross primary productivity, modulated by vegetation state and hydrometeorological drivers. *Biogeosciences*, 20: 4795-4818.
- Du Q, Liu H Z. 2013. Seven years of carbon dioxide exchange over a degraded grassland and a cropland with maize ecosystems in a semiarid area of China. *Agriculture, Ecosystems and Environment*, 173: 1-12.
- Du Y G, Pei W W, Zhou H K, et al. 2022. Net ecosystem exchange of carbon dioxide fluxes and its driving mechanism in the forests on the Tibetan Plateau. *Biochemical Systematics and Ecology*, 103: 104451, doi: 10.1016/j.bse.2022.104451.

- Duursma R A, Kolari P, Perämäki M, et al. 2009. Contributions of climate, leaf area index and leaf physiology to variation in gross primary production of six coniferous forests across Europe: a model-based analysis. *Tree Physiology*, 29(5): 621–639.
- Feng X M, Fu B J, Piao S L, et al. 2016. Revegetation in China's Loess Plateau is approaching sustainable water resource limits. *Nature Climate Change*, 6: 1019–1022.
- Foken T, Wichura B. 1996. Tools for quality assessment of surface-based flux measurements. *Agricultural and Forest Meteorology*, 78(1–2): 83–105.
- Friedlingstein P, O' Sullivan M, Jones M W, et al. 2023. Global carbon budget 2023. *Earth System Science Data*, 15(12): 5301–5369.
- Fu B J, Wang S, Liu Y, et al. 2017. Hydrogeomorphic ecosystem responses to natural and anthropogenic changes in the Loess Plateau of China. *Annual Review of Earth and Planetary Sciences*, 45: 223–243.
- Gao Y F, Yi L B, Zhang F W, et al. 2022. The relationship between CO₂ flux and vegetation leaf area index of four alpine grassland types in Qilian Mountains. *Chinese Journal of Grassland*, 44(5): 1–8. (in Chinese)
- Grossiord C, Buckley T N, Cernusak L A, et al. 2020. Plant responses to rising vapor pressure deficit. *New Phytologist*, 226(6): 1550–1566.
- Gu H S, Qiao Y X, Xi Z X, et al. 2022. Warming-induced increase in carbon uptake is linked to earlier spring phenology in temperate and boreal forests. *Nature Communications*, 13: 3698, doi: 10.1038/s41467-022-31496-w.
- Harris N L, Gibbs D A, Baccini A, et al. 2021. Global maps of twenty-first century forest carbon fluxes. *Nature Climate Change*, 11: 234–240.
- He F Q, Li Q, Chen D D, et al. 2023. A dataset of carbon, water and heat fluxes over an *Elymus nutans* artificial grassland in the Sanjiangyuan Area (2012–2016). *China Scientific Data*, 8(4), doi: 10.11922/11-6035.csd.2023.0056.zh. (in Chinese)
- Houghton R A, Baccini A, Walker W S. 2018. Where is the residual terrestrial carbon sink? *Global Change Biology*, 24(8): 3277–3279.
- Huang H, Zhou Y, Zhang J S, et al. 2023. A dataset of carbon and water flux observations in a *Quercus variabilis* plantation in Xiaolangdi (2016–2017). *China Scientific Data*, 8(4), doi: 10.11922/11-6035.csd.2023.0082.zh. (in Chinese)
- Humphrey V, Berg A, Ciais P, et al. 2021. Soil moisture-atmosphere feedback dominates land carbon uptake variability. *Nature*, 592: 65–69.
- Huxman T E, Smith M D, Fay P A, et al. 2004. Convergence across biomes to a common rain-use efficiency. *Nature*, 429(6992): 651–654.
- IPCC (Intergovernmental Panel on Climate Change). 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the

Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge and New York: Cambridge University Press, 4-5.

Jia Q Y, Yu W Y, Zhou L, et al. 2017. Atmospheric and surface-condition effects on CO₂ exchange in the Liaohe Delta wetland, China. *Water*, 9(10): 806, doi: 10.3390/w9100806.

Jia X, Zha T S, Wu B, et al. 2014. Biophysical controls on net ecosystem CO₂ exchange over a semiarid shrubland in Northwest China. *Biogeosciences*, 11(17): 4679-4693.

Kato T, Tang Y H, Gu S, et al. 2004. Carbon dioxide exchange between the atmosphere and an alpine meadow ecosystem on the Qinghai-Tibetan Plateau, China. *Agricultural and Forest Meteorology*, 124(1-2): 121-134.

Koehler T, Wankmüller F J P, Sadok W, et al. 2023. Transpiration response to soil drying versus increasing vapor pressure deficit in crops: physical and physiological mechanisms and key plant traits. *Journal of Experimental Botany*, 74(16): 4789-4807.

Kühnhammer K, van Haren J, Kübert A, et al. 2023. Deep roots mitigate drought impacts on tropical trees despite limited quantitative contribution to transpiration. *Science of The Total Environment*, 893: 164763, doi: 10.1016/j.scitotenv.2023.164763.

Lasslop G, Reichstein M, Papale D, et al. 2010. Separation of net ecosystem exchange into assimilation and respiration using a light response curve approach: critical issues and global evaluation. *Global Change Biology*, 16(1): 187-208.

Li N, Shao J J, Zhou G Y, et al. 2022. Improving estimations of ecosystem respiration with asymmetric daytime and nighttime temperature sensitivity and relative humidity. *Agricultural and Forest Meteorology*, 312: 108709, doi: 10.1016/j.agrformet.2021.108709.

Liu F, Shen Y J, Cao J S, et al. 2023a. A dataset of water, heat, and carbon fluxes over the winter wheat-summer maize croplands in Luancheng during 2013-2017. *China Scientific Data*, 8(2), doi: 10.11922/11-6035.csd.2023.0031.zh. (in Chinese)

Liu P R, Tong X J, Zhang J S, et al. 2022. Effect of diffuse fraction on gross primary productivity and light use efficiency in a warm-temperate mixed plantation. *Frontiers in Plant Science*, 13: 966125, doi: 10.3389/fpls.2022.966125.

Liu X Y, Li X H, Gao L X, et al. 2023b. Early-season and refined mapping of winter wheat based on phenology algorithms—a case of Shandong, China. *Frontiers in Plant Science*, 14: 1016890, doi: 10.3389/fpls.2023.1016890.

Lu H B, Qin Z C, Lin S R, et al. 2022. Large influence of atmospheric vapor pressure deficit on ecosystem production efficiency. *Nature Communications*, 13: 1653, doi: 10.1038/s41467-022-29009-w.

- Mauder M, Foken T. 2004. Documentation and Instruction Manual of the Eddy Covariance Software Package TK2. Arbeitsergebnisse, No. 26. Bayreuth: University of Bayreuth, Department of Micrometeorology, 8–24.
- Mei X R, Gao X, Sun D B, et al. 2023. An observation dataset of carbon fluxes of a rainfed spring maize cropland in Shouyang, Shan Xi (2012~2014). Science Data Bank, doi: 10.57760/sciencedb.07304. (in Chinese)
- Mitsch W J, Bernal B, Nahlik A M, et al. 2013. Wetlands, carbon, and climate change. *Landscape Ecology*, 28: 583–597.
- Moffat A M, Papale D, Reichstein M, et al. 2007. Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes. *Agricultural and Forest Meteorology*, 147(3–4): 209–232.
- Niu X D, Sun P S, Tao S R, et al. 2023. A dataset of carbon and water fluxes in a natural oak forest of Baotianman in Henan Province (2017–2018). *China Scientific Data*, doi: 10.11922/11-6035.csd.2023.0124.zh. (in Chinese)
- Niu Y Y, Li Y Q, Wang X Y, et al. 2018. Characteristics of annual variation in net carbon dioxide flux in a sandy grassland ecosystem during dry years. *Acta Prataculturae Sinica*, 27(1): 215–221. (in Chinese)
- Novick K A, Ficklin D L, Stoy P C, et al. 2016. The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. *Nature Climate Change*, 6: 1023–1027.
- Pan Y D, Birdsey R A, Fang J Y, et al. 2011. A large and persistent carbon sink in the world's forests. *Science*, 333(6045): 988–993.
- Pan Y D, Birdsey R A, Phillips O L, et al. 2024. The enduring world forest carbon sink. *Nature*, 631: 563–569.
- Papale D, Reichstein M, Aubinet M, et al. 2006. Towards a standardized processing of net ecosystem exchange measured with eddy covariance technique: algorithms and uncertainty estimation. *Biogeosciences*, 3(4): 571–583.
- Pedregosa F, Varoquaux G, Gramfort A, et al. 2011. Scikit-learn: machine learning in Python. *Journal of Machine Learning Research*, 12: 2825–2830.
- Piao S L, Fang J Y, Ciais P, et al. 2009. The carbon balance of terrestrial ecosystems in China. *Nature*, 458: 1009–1013.
- Poulter B, Frank D, Ciais P, et al. 2014. Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature*, 509: 600–603.
- Qiao B Y, Sheng L L, Chen K L, et al. 2025. Net ecosystem exchanges of spruce forest carbon dioxide fluxes in two consecutive years in Qilian Mountains. *Applied Sciences*, 15(12): 6845, doi: 10.3390/app15126845.
- Ren T J, Cai A D. 2025. Global patterns and drivers of soil dissolved organic carbon concentrations. *Earth System Science Data*, 17(6): 2873–2885.

- Smith P, Martino D, Cai Z C, et al. 2008. Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 363(1492): 789–813.
- Song J X, Zhou L, Zhou G S, et al. 2023. A dataset of carbon and water fluxes of the temperate desert steppe in Damao Banner, Inner Mongolia (2015–2018). *China Scientific Data*, 8(2), doi: 10.11922/11-6035.csd.2023.0021.zh. (in Chinese)
- Sun S C, Shao M A, Gao H B. 2016. Energy and CO₂ exchanges and influencing factors in spring wheat ecosystem along the Heihe River, northwestern China. *Journal of Earth System Science*, 125(8): 1667–1679.
- Sun X P, Xiao Y, Wang J H, et al. 2024. The respective effects of vapor pressure deficit and soil moisture on ecosystem productivity in Southwest China. *Remote Sensing*, 16(8): 1316, doi: 10.3390/rs16081316.
- Tang X L, Zhao X, Bai Y F, et al. 2018. Carbon pools in China's terrestrial ecosystems: new estimates based on an intensive field survey. *Proceedings of the National Academy of Sciences of the United States of America*, 115(16): 4021–4026.
- Tao F L, Li Y B, Chen Y, et al. 2022. Daily, seasonal and inter-annual variations in CO₂ fluxes and carbon budget in a winter-wheat and summer-maize rotation system in the North China Plain. *Agricultural and Forest Meteorology*, 324: 109098, doi: 10.1016/j.agrformet.2022.109098.
- Wang J T, Zhong Q C, Ou Q, et al. 2015a. Characteristic of CO₂ flux in the coastal reclaimed wetland of Chongming Dongtan during the growing season. *Resources and Environment in the Yangtze Basin*, 24(3): 416–425. (in Chinese)
- Wang L J, Zhao M L, Nie M, et al. 2025a. Thresholds of wetland carbon sink regulation by water level. *Environmental Science & Technology*, 59(27): 13811–13819.
- Wang W Y, Guo J X, Wang Y S, et al. 2015b. Observing characteristics of CO₂ flux and its influencing factors over Xilinhote grassland. *Journal of the Meteorological Sciences*, 35(1): 100–107. (in Chinese)
- Wang X F, Ma M G, Huang G H, et al. 2012. Vegetation primary production estimation at maize and alpine meadow over the Heihe River Basin, China. *International Journal of Applied Earth Observation and Geoinformation*, 17: 94–101.
- Wang X F, Che T, Xiao J F, et al. 2025b. A post-processed carbon flux dataset for 34 eddy covariance flux sites across the Heihe River Basin, China. *Earth System Science Data*, 17(4): 1329–1346.
- Wang Y Y, Hu C S, Dong W X, et al. 2015c. Carbon budget of a winter-wheat and summer-maize rotation cropland in the North China Plain. *Agriculture, Ecosystems and Environment*, 206: 33–45.

- Wang Z Q, Fang F R, Zhou L, et al. 2024. A dataset of meteorological observations at the National Field Scientific Observation and Research Station of Farmland Ecosystem in Changwu County, Shaanxi Province (2005–2019). *China Scientific Data*, 9(3), doi: 10.11922/11-6035.csd.2024.0053.zh. (in Chinese)
- Webb E K, Pearman G I, Leuning R. 1980. Correction of flux measurements for density effects due to heat and water vapour transfer. *Quarterly Journal of the Royal Meteorological Society*, 106(447): 85–100.
- Wei J Q, Li X Y, Liu L, et al. 2022. Radiation, soil water content, and temperature effects on carbon cycling in an alpine swamp meadow of the northeastern Qinghai-Tibetan Plateau. *Biogeosciences*, 19(3): 861–875.
- Xia H Y, Jiang H L, Zhang C H, et al. 2024. Light saturation and temperature jointly dominate the diurnal variation of net ecosystem exchange in grassland ecosystems. *Ecological Indicators*, 168: 112737, doi: 10.1016/j.ecolind.2024.112737.
- Xu Y F, Ji H, Han J G, et al. 2018. Variation of net ecosystem carbon flux in growing season and its driving factors in a poplar plantation from Hung-tse Lake wetland. *Chinese Journal of Ecology*, 37(2): 322–331. (in Chinese)
- Yan Y J, Zhou L, Zhou G S, et al. 2023. Extreme temperature events reduced carbon uptake of a boreal forest ecosystem in Northeast China: evidence from an 11-year eddy covariance observation. *Frontiers in Plant Science*, 14: 1119670, doi: 10.3389/fpls.2023.1119670.
- Yang P, Wang N A, Zhao L Q, et al. 2022. Responses of grassland ecosystem carbon fluxes to precipitation and their environmental factors in the Badain Jaran Desert. *Environmental Science and Pollution Research*, 29: 75805–75821.
- Yang T W, Sun J J, Li Y F, et al. 2025. Impact of climate-induced water-table drawdown on carbon and nitrogen sequestration in a *Kobresia*-dominated peatland on the central Qinghai-Tibetan Plateau. *Communications Earth & Environment*, 6: 188, doi: 10.1038/s43247-025-02168-6.
- Yuan R R, Huang X L, Hao L. 2021. Spatio-temporal variation of vapor pressure deficit and impact factors in China in the past 40 years. *Climatic and Environmental Research*, 26(4): 413–424. (in Chinese)
- Zhang F W, Li H Q, Zhao L, et al. 2021a. An observation dataset of carbon, water and heat fluxes in an alpine wetland in Haibei (2004–2009). *China Scientific Data*, 6(1), doi: 10.11922/csdata.2020.0033.zh. (in Chinese)
- Zhang F W, Li H Q, Zhao L, et al. 2021b. An observation dataset of carbon, water and heat fluxes over an alpine shrubland in Haibei (2003–2010). *China Scientific Data*, 6(1), doi: 10.11922/csdata.2020.0034.zh. (in Chinese)

- Zhang F W, Li H Q, Zhang L M, et al. 2023a. A dataset of the observations of carbon, water and heat fluxes over an alpine shrubland in Haibei (2011–2020). *China Scientific Data*, 8(2), doi: 10.11922/11-6035.csd.2023.0013.zh. (in Chinese)
- Zhang F W, Si M K, Guo X W, et al. 2023b. A dataset of the observations of carbon, water and heat fluxes over an alpine meadow in Haibei (2015–2020). *China Scientific Data*, 8(2), doi: 10.11922/11-6035.csd.2023.0012.zh. (in Chinese)
- Zhang H, Zhao T H, Lü S D, et al. 2021c. Interannual variability in net ecosystem carbon production in a rain-fed maize ecosystem and its climatic and biotic controls during 2005–2018. *PLoS One*, 16(5): e0237684, doi: 10.1371/journal.pone.0237684.
- Zhang J, Chen H, Wang M, et al. 2024. An optimized water table depth detected for mitigating global warming potential of greenhouse gas emissions in wetland of Qinghai-Tibetan Plateau. *iScience*, 27(2): 108856, doi: 10.1016/j.isci.2024.108856.
- Zhang K, Wang Y, Mamtimin A, et al. 2023c. Temporal and spatial variations in carbon flux and their influencing mechanisms on the Middle Tien Shan region grassland ecosystem, China. *Remote Sensing*, 15(16): 4091, doi: 10.3390/rs15164091.
- Zhang Q, Lei H M, Yang D W, et al. 2020. Decadal variation in CO₂ fluxes and its budget in a wheat and maize rotation cropland over the North China Plain. *Biogeosciences*, 17(8): 2245–2262.
- Zhang W G, Tian J J, Zhang X H, et al. 2023d. Which land cover product provides the most accurate land use land cover map of the Yellow River Basin? *Frontiers in Ecology and Evolution*, 11: 1275054, doi: 10.3389/fevo.2023.1275054.
- Zhang X J, Wang G Q, Xue B L, et al. 2021d. Dynamic landscapes and the driving forces in the Yellow River Delta wetland region in the past four decades. *Science of The Total Environment*, 787: 147644, doi: 10.1016/j.scitotenv.2021.147644.
- Zhang Y C, Guo X N, Pei H W, et al. 2022. Evapotranspiration and carbon exchange of the main agroecosystems and their responses to agricultural land use change in North China Plain. *Agriculture, Ecosystems & Environment*, 338: 108103, doi: 10.1016/j.agee.2022.108103.
- Zhao F H, Li F D, Zhan C S, et al. 2021. A carbon and water fluxes dataset of the farmland ecosystem of winter wheat and summer maize in Yucheng (2003–2010). *China Scientific Data*, 6(2), doi: 10.11922/csd.2020.0044.zh. (in Chinese)
- Zhao L, Li J, Xu S, et al. 2010. Seasonal variations in carbon dioxide exchange in an alpine wetland meadow on the Qinghai-Tibetan Plateau. *Biogeosciences*, 7(4): 1207–1221.

Zhao M L, Li P G, Song W M, et al. 2023. Inundation depth stimulates plant-mediated CH₄ emissions by increasing ecosystem carbon uptake and plant height in an estuarine wetland. *Functional Ecology*, 37(3): 536–550.

Zhu X J, Fan R X, Chen Z, et al. 2022. Eddy covariance-based differences in net ecosystem productivity values and spatial patterns between naturally regenerating forests and planted forests in China. *Scientific Reports*, 12: 20556, doi: 10.1038/s41598-022-25025-4.

Appendix

Table S1 Annual net ecosystem CO₂ exchange (NEE) and its partitioned components at the Haibei wetland site during 2004–2009

Year	NEE (g C/(m ² · a))	R_{eco} (g C/(m ² · a))	GPP (g C/(m ² · a))
2004	431.91	1969.94	1538.03
2005	279.68	2088.97	1809.30
2006	610.55	2198.73	1585.17
2007	1027.97	2490.73	1462.34
2008	442.12	2081.46	1639.34
2009	−65.27	2057.68	2122.95

Note: R_{eco} , ecosystem respiration; GPP, gross primary productivity. R_{eco} and GPP were obtained directly from the original partitioned flux dataset. The relationship among the variables is $\text{NEE} = R_{\text{eco}} - \text{GPP}$. Positive NEE values indicate net CO₂ release to the atmosphere, whereas negative NEE values indicate net ecosystem CO₂ uptake.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv. Machine translation. Verify with the original.