CARBON BUDGET BALANCE AND INFLUENCING FACTORS IN THE YELLOW RIVER BASIN OF CHINA

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Abstract. Focusing on the carbon budget balance in the context of global change, this study examines the carbon budget balance in the Yellow River Basin of China in the context of global change, using various methods to explore the driving mechanisms and predict net carbon emissions under different scenarios for 2030. From 2005 to 2020, direct carbon emissions in the Yellow River Basin decreased, carbon sink areas expanded, and net carbon emissions growth slowed down. Carbon emissions are mainly influenced by energy economy, with the effect of natural factors enhancing over time. The forecast results show that carbon emission under the ecological protection scenario in 2030 is 12.63×10^8 t, which is 97.08% of the natural development scenario, and 95.61% of the urban expansion scenario. Therefore, controlling the expansion of construction land and high energy consumption, optimizing land use structure, and strengthening ecological land protection are recommended. The government should enhance low-carbon regulation of national land use and coordinate supporting policies to achieve carbon balance. This study has scientific reference significance for low-carbon and green development in resource-based areas with high energy consumption.
Keywords: *carbon budget, CO_2 emission, geographic detector, primary function-oriented zoning, Yellow River Basin*

Introduction

Since the Industrial Revolution, the widespread use of coal, oil and other fossil fuels has led to substantial greenhouse gas emissions, driving global climate change characterized by rising temperatures and frequent extreme climatic events such as droughts and floods. This has posed significant challenges to human survival and socio-economic development and has also become a global concern (Ploeg and Withagen, 2012; Hussin et al., 2021). The Sixth Assessment Report by the United Nations Intergovernmental Panel on Climate Change (IPCC) highlights that the average global temperature increased by 1.09℃ between 2011 and 2020 compared to the late 19th century, with industrialization being a significant contributing factor (IPCC, 2021; Wang et al., 2023). On June 30, 2015, China submitted the 'Strengthening Action on Climate Change – China's Nationally Determined Contribution to the United Nations, which proposed China's climate change targets for 2030, aiming to reduce CO_2 emission intensity by 60%-65% based on the level in 2005 (Strengthening Action on Climate Change, 2015; Xu et al., 2022). As a key participant in global climate governance, China

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strives to achieve carbon peak around 2030 and carbon neutrality before 2060 (Xi, 2020), reflecting its responsibility and commitment.

The land is the complex syntheses between human activities and ecological environment, serving as the significant carbon source and sink. As an indispensable domain for human survival and development, the anthropogenic activities disrupt the natural carbon cycle, resulting in substantial increase of atmospheric greenhouse gas concentrations (Ma and Wang, 2015; Ran et al., 2023). LULC change is the second largest dedicator to CO_2 emissions following fossil fuel burning, making up 1/3 of global CO_2 emissions from 1850 to 2017 (Zhao et al., 2023). The carbon budget serves as the crucial metric for assessing the carbon flux within different earth system components (Quéré et al., 2018), making it the focus of global climate change research and a significant aspect of low-carbon and green development. Extensive investigations have been conducted on carbon budget accounting (Xia and Yang, 2022; Wang et al., 2023), carbon compensation (Li et al., 2023), influencing factors (Chang et al., 2022) and land use structure (Fan et al., 2018). Jayakrishnan et al. (2022) determined that land use accounted for over 40% of the total CO_2 emissions. By conducting an analysis of spatial disparities in CO_2 emissions within the Amazon basin, Gatti et al. (2021) deduced that deforestation and fire emerged as the primary factors contributing to the escalation of regional CO_2 emissions in the Amazon River Basin. Assis et al. (2022) investigated the impact factors on Amazon forest degradation and predicted the potential effects of future CO_2 emission scenarios on carbon balance. Chinese scholars have examined the carbon budget from diverse perspectives, encompassing scales, objects, content and methodologies. Based on the DMSP-OLS night light data and CO_2 emission statistics, Pan et al. (2021) observed consistent annual increase carbon footprint and carbon deficit in China from 2000 to 2013, and the spatial distribution was low in the south and high in the north. Since 1993, CO_2 emissions from LULC has emerged as the hot topic in China, revealing that factors such as land use type, mode, intensity and structure exert direct or indirect influences on the CO_2 emissions and absorption processes of terrestrial ecosystems and atmosphere (Zhao et al., 2016; Huang et al., 2021). With the development in observation and simulation technology, the carbon budget calculation methodology has evolved from measuring atmospheric CO_2 concentration to employing inversion techniques (Jin et al., 2023). The common carbon accounting inventory of IPCC has been highly recognized for its robust applicability and has been extensively utilized in multi-spatial scale research (Aleinikovas et al., 2018; Zhang et al., 2018; Mi et al., 2019).

The Yellow River Basin is the strategic region and the crucial ecological functional area in China high-quality economic development, playing an indispensable role in attaining CO_2 emission reduction. As the crucial energy hub, the current energy structure of the Yellow River Basin is dominated by fossil fuels, with dense coal chemical industries contributing to increase CO_2 emissions and exert significant pressure on ecological environment. The Yellow River Basin is characterized by high energy consumption, pollution and emissions, with low energy utilization efficiency and severe ecological environment degradation. At present, the socio-economic development across the upper, middle and lower reaches of the Yellow River presents significant disparities and is undergoing profound energy structure and socio-economic transformation, resulting in intensified emission reduction pressure. Land resources play a pivotal role in the ecosystem and serve as a significant driver of CO_2 emissions. The preservation of the carbon balance within the ecosystem, coupled with emission reduction and energy conservation, is intricately linked to fostering. Reducing CO_2 emissions and maintaining

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ecosystem carbon balance are important to high-quality development in the Yellow River Basin.

So as to ensure the ecological security of the Yellow River and its surrounding areas, China has implemented the "major function-oriented zoning plan". Considering landform, climatic conditions, resource endowment, development potential and ecological environment, the Yellow River Basin is categorized into optimized, key, restricted and prohibited development zones (Fan et al., 2010), aiming to achieve sustainable development and ecological civilization construction (Huang and Pan, 2020). The ecologically fragile Yellow River Basin exhibits evident spatial disparities in socio-economic development level, and resource and environmental carrying capacity, with distinct CO_2 emission reduction tasks in vary major function-oriented zones (Fan, 2015). However, the spatial heterogeneity and correlation of carbon budget balance have been overlooked in previous studies, leading to the lack of targeted CO_2 emission reduction measures and compensation mechanisms. Therefore, the study strives to: (1) analyze carbon budget balance by quantifying direct CO_2 emissions, indirect CO_2 emissions and LULC carbon carrying capacity. (2) investigate the effect of social and natural factors on CO_2 emissions by the geographical detector method. (3) project CO_2 emissions trend and put forward low-carbon development countermeasures by setting natural development, urban expansion and ecological protection scenarios. This study will provide crucial scientific references for achieving global carbon budget equilibrium and offer theoretical foundation and support for the Chinese government to design CO_2 emission reduction plans and accomplish high-quality development goals in the Yellow River Basin.

Study area

The Yellow River (31°42'N～45°42'N, 89°35'E～122°17'E, *Fig. 1*) serves as the crucial ecological security barrier and an economically significant region in China, encompassing the total area of $75.24\times10^4 km^2$. It exercises jurisdiction eight provinces and regions: Qinghai, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan and Shandong, which comprises of 91 municipal administrative units along with 739 districts and counties. Referring to the primary function- oriented zoning in 2010 (Fan et al., 2010), the Yellow River Basin is categorized into eight functional zones: National Key Development Prioritized Zone (NKDPZ), Provincial Key Development Prioritized Zone (PKDPZ), National Development Optimized Zone (NDOZ), Provincial Development Optimized Zone (PDOZ), National Major Grain Producing Zone (NMGPZ), Provincial Major Grain Producing Zone (PMGPZ), National Key Ecological Function Zone (NKEFZ), Provincial Key Ecological Function Zone (PKEFZ). The land use is predominantly comprised of grassland and unused land, accounting for 45% and 27% respectively in 2020. The basin is abundant in natural resources, particularly mineral resources, and serves as the primary source for energy consumption and supply in China, also the pivotal region for CO_2 emissions resulting from energy consumption (Yang and Zhen, 2023). In 2020, energy consumption in the Yellow River Basin reached $13.88\times10^8 t$, accounting for 29.9% and 35.1% of total energy consumption and CO_2 emissions, respectively. The abundant fossil energy drives rapid economic development in the Yellow River Basin; but also imposes significant challenges for CO_2 emission reduction. The CO_2 emission reduction in the Yellow River Basin plays the pivotal role in achieving "carbon neutrality" and "carbon peak" of China, which will lead the new social and economic development within the basin.

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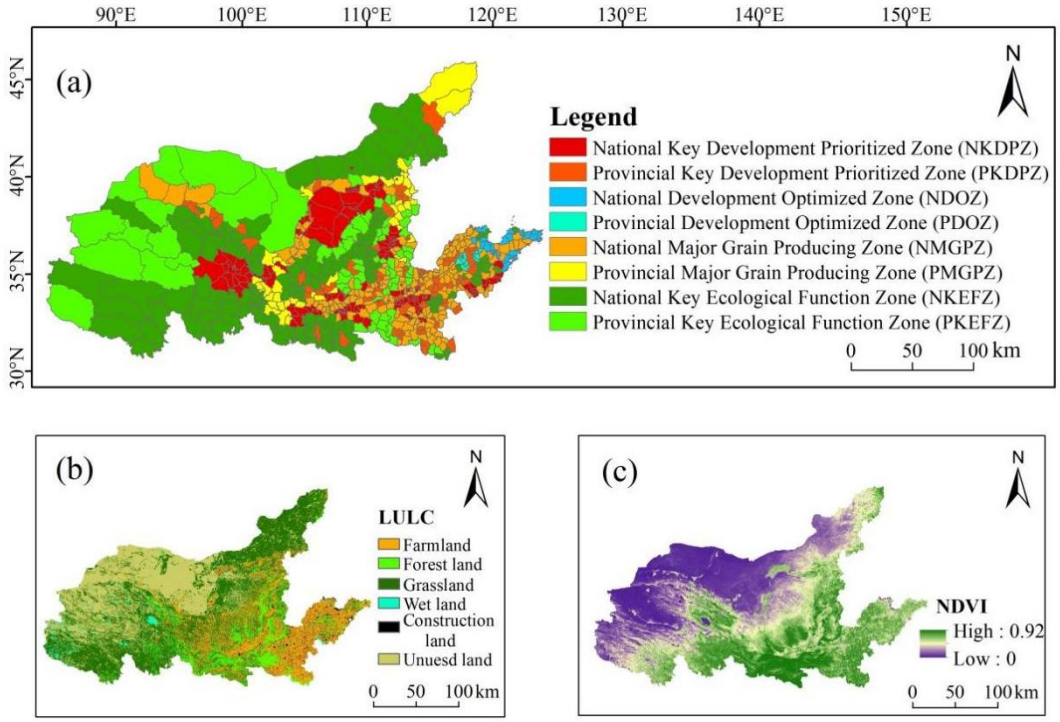

Figure 1. *(a) Primary function-oriented zones of Yellow River Basin (Fan et al., 2010, https://bzdt.ch.mnr.gov.cn/), (b) LULC (Land-use/land-cover, LULC, https://www.resdc.cn/Default.aspx) and (c) NDVI (Normalized Difference Vegetation Index, NDVI, https://www.resdc.cn/Default.aspx) spatial pattern*

Materials and methods

Data sources

The data primarily consist of two categories: remote sensing data and socio-economic data, covering the time span from 2000 to 2020. Remote sensing data include LULC, NDVI and DEM (Digital Elevation Model, DEM). Socio-economic data include major function-oriented zoning, major roads and railways, GDP (Gross domestic product, GDP), population and energy. The data classification is shown in the *Table1*.

Table 1. *Data classification*

Data	Classification	Type	Spatial resolution	Data source
Remote sensing data	LULC	Grid	1km×1km	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences
	NDVI	Grid	1km×1km	
	DEM	Grid	1km×1km	Geospatial data cloud
Socio-economic data	Major function-oriented zoning	Vector	—	China government network
	Main highway	Vector	—	National basic geographic information System
	Main railway	Vector	—	
	GDP	Data table	—	China county Statistical Yearbook and regional statistical Bulletin
	Population	Data table	—	
	Source of energy	Data table	—	China Energy Statistical Yearbook

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Methods

Carbon budget measurement methods

The accounting inventory is developed on the basis of the IPCC National Greenhouse Gas Inventories, and the carbon budget is determined using the following calculation formula:

$$CB = DCE + ICE - CS \quad \text{(Eq.1)}$$

where, *CB* is carbon budget, *DCE* is direct CO_2 emission, *ICE* is indirect CO_2 emission, *CS* is carbon sink (carbon carrying capacity).

DCE refers to the loss of LULC carbon storage, which is counted using the carbon module of InVEST model, including above-ground biological carbon density, underground biological carbon density and soil organic matter carbon pool density.

$$C_{SP} = 3.3968 \times P + 3996.1 \quad \text{(Eq.2)}$$

$$C_{BP} = 6.7981e^{0.00541P} \quad \text{(Eq.3)}$$

$$C_{BT} = 28 \times T + 398 \quad \text{(Eq.4)}$$

where, C_{SP} is the soil carbon density; C_{BP} and C_{BT} are the above-ground and underground biological carbon density, respectively; *P* is the annual precipitation; *T* is the annual average temperature. The annual average temperature and precipitation for China (7.15°C/673.9mm) and Yellow River Basin (6.86°C/362.09mm) are used to calculate the correction coefficient (Giardina and Ryan, 2000; Chen et al., 2007; Alam et al., 2013).

$$K_B = K_{BP} \times K_{BT} = \frac{C'_{BP}}{C''_{BP}} \times \frac{C'_{BT}}{C''_{BT}} \quad \text{(Eq.5)}$$

$$K_S = \frac{C'_{SP}}{C''_{SP}} \quad \text{(Eq.6)}$$

where, K_B and K_S are the correction coefficients of biological and soil carbon density, respectively; K_{BP} and K_{BT} are the correction coefficients of the above-ground and underground biological carbon density, respectively; C'_{BP}, C'_{BT} and C'_{SP} are above-ground biological carbon density, underground biological carbon density and soil carbon density of the Yellow River Basin, respectively; C''_{BP}, C''_{BT} and C''_{SP} are above-ground biological carbon density, underground biological carbon density and soil carbon density of China, respectively. The carbon density of the Yellow River Basin can be calculated by multiplying the carbon density data of China with above correction coefficients (*Table 2*).

ICE is primarily derived from construction land, and industry and the burning of fossil fuels are major emission sources. To calculate indirect CO_2 emissions, nine energy sources are considered, namely coke, coal, kerosene, diesel, crude oil, gasoline, natural gas, fuel oil and electricity. The calculation formula is as follows (Zheng and Wen, 2010; Buendia et al., 2006; Zhou et al., 2019):

$$ICE = \sum_{i=1}^{9} E_{ti} = \sum_{i=1}^{9} (E_{ni} \times \theta_i \times f_i) \quad \text{(Eq.7)}$$

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where, *ICE* represents the total CO_2 emissions from the terminal consumption of fossil fuels; E_{ti} represents the CO_2 emissions from the terminal consumption of Class *i* fossil energy; E_{ni} represents final consumption of all types of fossil energy; θ_i represents the converted criteria coal coefficient of various fossil energy sources; f_i represents the CO_2 emission coefficient of each energy source.

Table 2. *Carbon density in the Yellow River Basin (t hm^{-2})*

Land use	Above-ground biomass	Underground biomass	Soil
Farmland	1.02	14.44	69.75
Forest land	7.58	20.76	90.12
Grassland	6.71	15.48	77.23
Wet land	0	0	11.63
Construction land	0.45	0	64.85
Unused land	0.233	0	26.11

CS refers to the quantity of CO_2 sequestered by regional vegetation. Agricultural production predominantly relies on CO_2 emissions, while cultivated land is not included in the accounting scope of carbon sink. The carbon sink capability of forest land, grassland and water area was quantified in this study. The calculation formula employed is as follows:

$$\mathrm{CS} = \sum_{j=1}^{3} L_j \times \theta_j \quad \text{(Eq.8)}$$

where, L_j is the area of Class *j* land use type; θ_j is the carbon sequestration rate per unit area (Walsh, 2001).

Geographic detector

The Geodetector is the statistical approach utilized for detecting spatial differentiation and identifying the underlying driving factors, enabling the analysis of multifactor interactions across diverse phenomena. Geographic detector possesses the advantages of detecting both quantitative and qualitative data, thereby effectively mitigating the issue of subjective factors influencing multi-factor weights. The method comprises factor detector, risk detector, interaction detector and ecological detector (Wang et al., 2010; Wang and Hu, 2012; Wang and Xu, 2017). The factor detection is employed to discern the spatial disparity of object y. The parameter q ($0 < q < 1$) quantifies the explanatory power of factor x. Interaction detection is utilized to ascertain whether the joint influences of two factors (x_1 and x_2) on y are interrelated or independent. The single factor influence on y is denoted as $q(x_1)$ and $q(x_2)$, while the interaction between the two factors is denoted as $q(x_1 \cap x_2)$. The interaction type and decision basis are presented in *Table 3*.

CA-Markov model

The CA-Markov model integrates the strengths of Markov model time series prediction and CA model spatial simulation (Syphard et al., 2005; Caute and Lawrence, 2017; Zhou et al., 2020). The cellular transformation rule designates the year 2000 as the initial point for land use data, while 2015 serves as the termination year. Both the age

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interval and predicted age are set at 15 years, with the tolerance of 0.15. The Kappa coefficient between measured and simulated land use in 2015 was 0.83, indicating the high reliability. Based on 2015, LULC in 2030 is predicted under different scenarios: (1) Natural development scenario: This scenario is based on the transfer matrix from 2000 to 2015, with land use conversion probability matrix unchanging. (2) Urban expansion scenario: The conversion probability from cultivated land, forest land, grassland and unused land to construction land increased by 5%,1%,2% and 4% in 2030. In the formulation of the suitability map, the most suitable location of industries and mines should be set within 800 m of the main railways and highways. (3) Ecological protection scenario: In accordance with the national ecological policy, the transfer probability of cultivated land to forest land was increased by 5%, and the transfer probability of cultivated land, forest land, grassland and unused land to construction land was reduced by 4%, 2%, 1% and 1%. The water body is considered as restrictive factor, and the conversion to any land category is strictly prohibited.

Table 3. *Factor interaction type and judgment basis*

Judgment basis	Interaction type
$q(x_1 \cap x_2) < \min(q(x_1), q(x_2))$	Reduction of nonlinearity
$q(x_1 \cap x_2) < \max(q(x_1), q(x_2))$	Two-factor enhancement
$\min(q(x_1), q(x_2)) < q(x_1 \cap x_2) < \max(q(x_1), q(x_2))$	Nonlinear attenuation of single factor
$q(x_1 \cap x_2) > q(x_1) + q(x_2)$	Enhancement of nonlinearity
$q(x_1 \cap x_2) = q(x_1) + q(x_2)$	Mutual independence of factors

Results

Spatial and temporal distribution of carbon budget in the Yellow River Basin

Direct CO_2 emissions

The spatial pattern of direct CO_2 emissions in the Yellow River Basin from 2005 to 2020 are depicted in *Fig. 2*. The direct CO_2 emissions in 2005 amounted to 0.18×10^8 t, with 57.61% of the counties being carbon sources. Among them, 78.87% originated from NKDPZ and NKEFZ, which were the primary contributors to direct CO_2 emissions within the Yellow River Basin. The change in LULC mode has resulted in the negative CO_2 emission in PMGPZ, thereby enhancing the ecological carbon sequestration capacity. In 2010, direct CO_2 emissions amounted to -0.09×10^8 t. With the exception of PKDPZ and development optimized zone, all other major function-oriented zones exhibited negative CO_2 emissions, indicating the well-developed carbon storage over the past five years. The direct CO_2 emissions amounted to 0.03×10^8 t in 2015, with approximately 73.37% of the counties being carbon sources. Except for NKDPZ and PKEFZ, CO_2 emissions of other major function-oriented areas exceeded zero. Due to the conversion of the substantial amount of ecological land into construction land, NMGPZ experienced significant increase in CO_2 emissions by 0.02×10^8 t. The CO_2 emissions of NKDPZ and PKEFZ were -2×10^4 t and -5×10^4 t, respectively, indicating the weak carbon sequestration effect. The direct CO_2 emissions increased significantly in 2020, reaching 1.01×10^8 t, and PKEFZ became the highest CO_2 emission zone. Furthermore, approximately 30% of anthropogenic greenhouse gas emissions originate from agricultural land, and 1.2×10^4 km^2 grassland has been transformed to agricultural land resulting in elevated CO_2 emissions of NDOZ.

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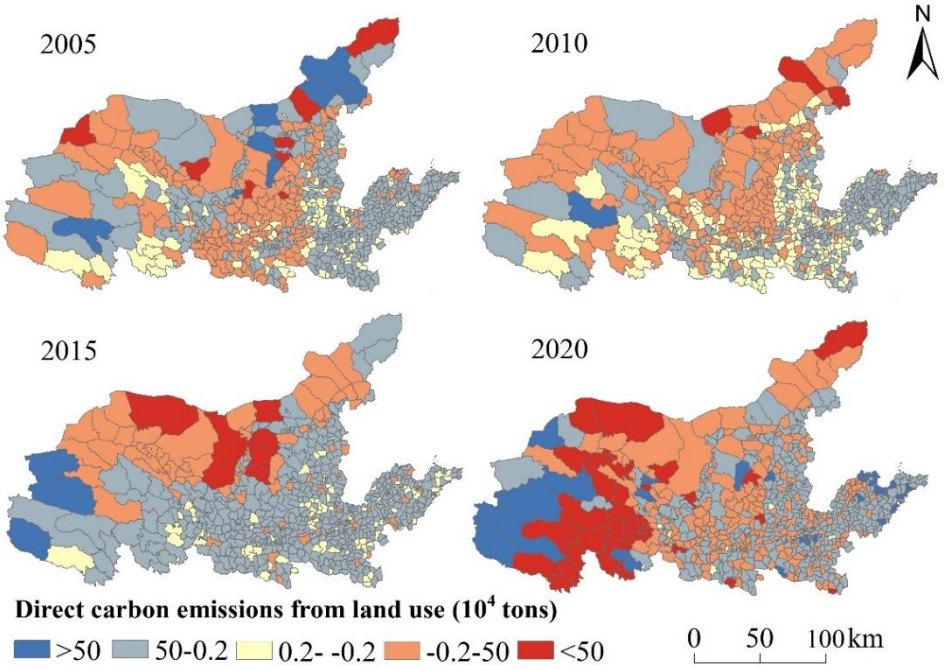

Figure 2. *Spatial distribution of direct CO_2 emissions from land use in 2005, 2010, 2015 and 2020*

Indirect CO_2 emissions

The statistical results of indirect CO_2 emissions in the Yellow River Basin are shown in *Table 4*. In 2005, 2010, 2015 and 2020, the indirect CO_2 emissions in the Yellow River Basin were 6.77, 10.47, 12.81 and 13.74×10^8 t, respectively, showing an obvious upward trend. The change trends vary across different functional areas. The indirect CO_2 emissions of key development prioritized zones, NMGPZ and key ecological function zones exhibited an upward trend, whereas the development optimized zones and PMGPZ both reached the peak in 2015, and then showed slight decline, with reduction rate of 0.01%, 2.36%, and 3.18%, respectively.

Table 4. *Indirect CO_2 emissions and contribution rates of energy consumption in 2005, 2010, 2015 and 2020*

Year	Functional zone	NKDPZ	PKDPZ	NDOZ	PDOZ	NMGPZ	PMGPZ	NKEFZ	PKEFZ
2005	CO_2 emission/10^8 t	1.94	1.17	0.74	0.39	1.61	0.07	0.63	0.22
	Contribution rate/%	28.66	17.24	10.97	5.73	23.78	1.00	9.29	3.32
2010	CO_2 emission/10^8 t	3.36	1.57	1.04	0.59	2.34	0.16	0.84	0.57
	Contribution rate/%	32.08	14.98	9.95	5.66	22.37	1.49	8.01	5.47
2015	CO_2 emission/10^8 t	4.01	1.88	1.44	0.69	2.92	0.19	1.02	0.65
	Contribution rate/%	31.28	14.72	11.23	5.39	22.83	1.54	7.97	5.04
2020	CO_2 emission/10^8 t	4.11	1.89	1.44	0.67	3.67	0.19	1.02	0.73
	Contribution rate/%	4.11	13.80	10.46	4.90	26.68	1.39	7.49	5.35

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The spatial trend of indirect CO_2 emissions in the Yellow River Basin is illustrated in *Fig. 3*. The industrial development in the Yellow River Basin was sluggish in 2005, the number of counties with low CO_2 emissions ($<70\times10^4$ t) was dominant, and the CO_2 emissions in the western were obvious lower than the eastern. The CO_2 emissions in all regions and counties presented varying increase degrees in 2010, especially in central Inner Mongolia and certain parts of Qinghai. The overall CO_2 emissions showed upward trend in 2015, the number of districts and counties with CO_2 emissions surpassing 200×10^4 t increased significantly. Although PDOZ occupied only 0.33%, the CO_2 emissions increased to 5.38%. In 2020, CO_2 emissions from energy consumption reached the maximum, the regions with CO_2 emissions below 10×10^4 t were only distributed in Yushu and Guoluo of NKEFZ. Although CO_2 emissions increased in NKDPZ, PKDPZ and NKEFZ compared to 2015, the CO_2 emission contribution rates have decreased by 1.35%, 0.92% and 0.48%, respectively.

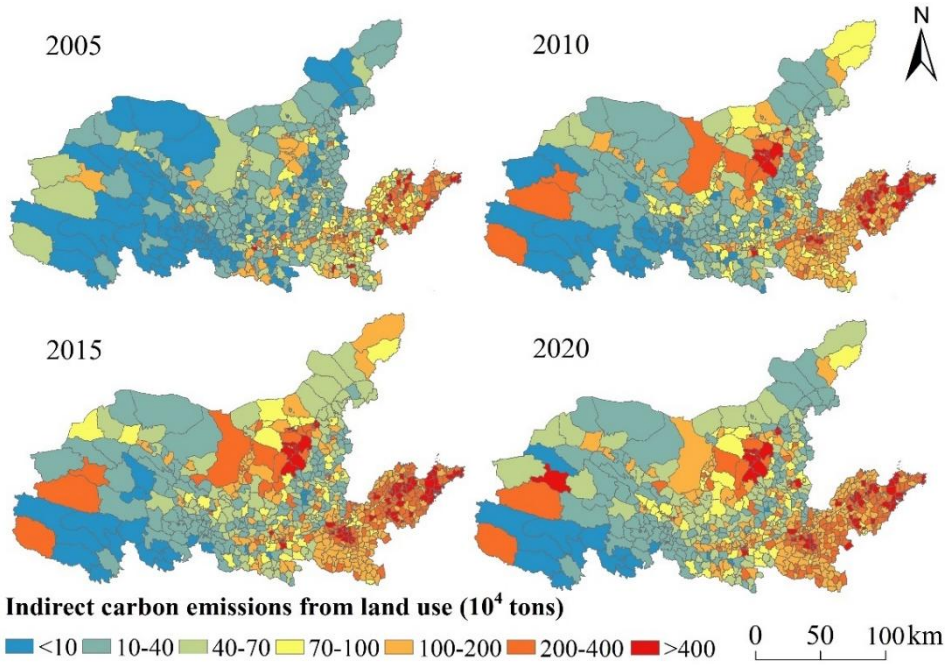

Figure 3. *Spatial distribution of indirect CO_2 emissions from land use in 2005, 2010, 2015 and 2020*

Carbon carrying capacity (carbon sink)

The average annual carbon sequestration in the Yellow River Basin from 2005 to 2020 was 1.85×10^8 t. The carbon sink of water area, grassland, and forest land respectively increases by 15.18%, 4.18% and 2.04%. For different major function-oriented areas, the carbon sink of PMGPZ was basically stable at 0.15×10^8 t from 2005 to 2015, with an accelerated growth rate thereafter. However, the contribution rate of carbon sink slightly declined from 7.97% in 2005 to 7.93% in 2020. NKEFZ is mainly grassland and forest land, exhibiting the highest carbon sequestration effect, with the contribution rate of 46%. PKEFZ and NKDPZ also demonstrated substantial carbon sequestration capabilities, with the average annual carbon sink of 0.38×10^8 t and 0.22×10^8 t, respectively. Over the past two decades, the construction land expansion has encroached upon grassland, resulting

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in the reduction of carbon sequestration capacity and carbon sink contribution. The ecological land area of the optimized development zone accounted for 51.91% of the Yellow River Basin in 2020. However, the carbon sink contribution rate was only 0.98%, suggesting the poor land carbon carrying capacity and minimal carbon absorption effect in NDOZ (*Fig. 4*).

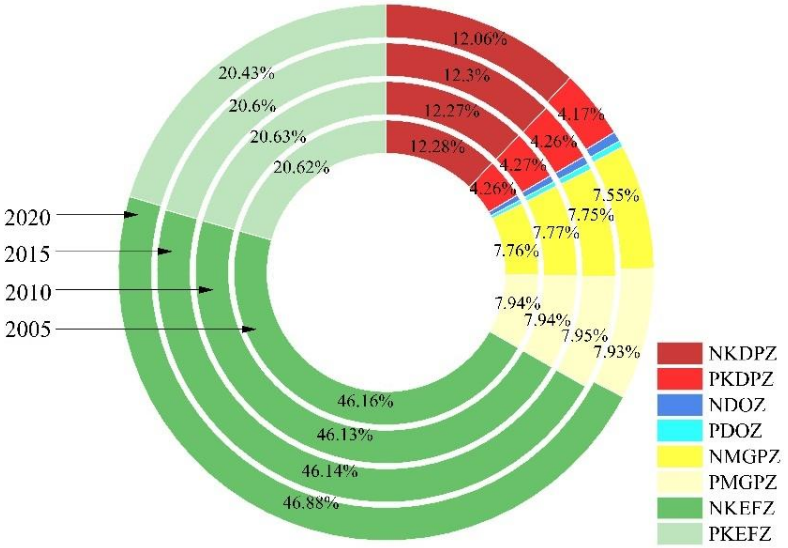

Figure 4. *Contribution rate of carbon sink for each functional zone in 2005, 2010, 2015 and 2020*

Net CO_2 emissions

The net CO_2 emissions in 2005, 2010, 2015 and 2020 were 4.97×10^8 t, 8.61×10^8 t, 10.97×10^8 t and 11.67×10^8 t, respectively. The CO_2 emissions exhibited an upward trend, which slowed down significantly, and the growth rate was only 5.99% during 2015-2020, indicating that CO_2 emissions will peak around 2030 (*Table 5*).

Table 5. *Carbon budget balance in the Yellow River Basin*

Years	Direct CO_2 emission/t	Indirect CO_2 emission/t	CO_2 sink/t	Net CO_2 emission/t
2005	0.04×10^8	6.77×10^8	-1.84×10^8	4.97×10^8
2010	-0.02×10^8	10.47×10^8	-1.84×10^8	8.61×10^8
2015	0.007×10^8	12.81×10^8	-1.84×10^8	10.97×10^8
2020	-0.2×10^8	13.74×10^8	-1.87×10^8	11.67×10^8

In 2005, approximately 28% of districts and counties in the Yellow River Basin exhibited carbon surplus, mainly located in key ecological function zones (70%). 44.83% of districts and counties exhibited low carbon deficit, primarily concentrated in NMGPZ, where the energy consumption structure remains dominated by coal, agricultural land accounts for approximately 50%, and industrial and agricultural activities have increased CO_2 emissions. In 2010, the number of counties experiencing medium, high and extremely high carbon deficits increased. The carbon deficit counties raised 44 in NMGPZ, and the accompanying net CO_2 emissions increased by 0.65×10^8 t. The areas

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with high and extremely high carbon deficits are primarily concentrated in regions characterized by resource exploitation and high energy consumption industries, and CO_2 emissions increase by 0.03×10^8 t in 2005-2010. The growth rate of net CO_2 emissions in the Yellow River Basin significantly decelerated in 2015, declining from 73.19% in 2005-2010 to 27.42% in 2010-2015. The districts and counties in the optimized development zone have no low-carbon deficit and carbon surplus, while the districts and counties with extremely high carbon deficit exceed 50%, which will greatly increase the difficulty of implementing future energy conservation and emission reduction strategies. In 2020, the growth rate of CO_2 emissions decelerated significantly, while net CO_2 emissions reached peak. From 2005 to 2020 (*Fig. 5*), counties in PMGPZ are characterized by low CO_2 emissions, without high and extremely high carbon deficit. The county number exhibiting extremely high deficit status decreased or remained unchanged except for NKDPZ, indicating the positive trend in CO_2 emissions in the Yellow River Basin under the implementation of CO_2 emission reduction policies.

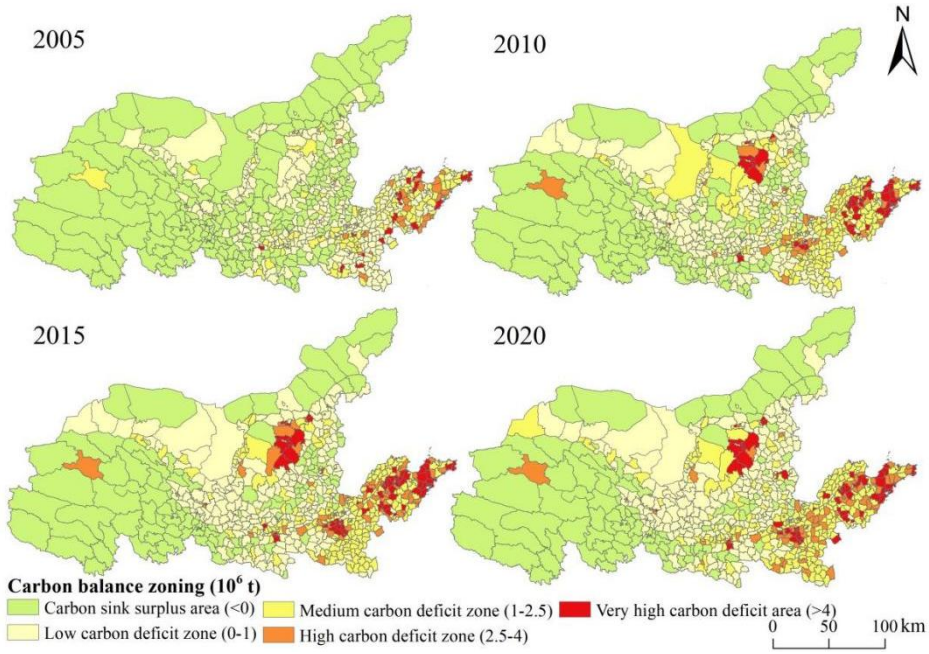

Figure 5. *Carbon balance zoning of the Yellow River Basin in 2005, 2010, 2015 and 2020*

Influencing factors of land use net CO_2 emissions

CO_2 emission is influenced by both natural and human factors. Landscape pattern, vegetation coverage and economic effects of human activities have profound impact on CO_2 emissions in the Yellow River Basin. The main impact factors, including population size (x1), per capita GDP (x2), gross product of secondary industry (x3), energy intensity (x4), energy structure (x5), construction land area (x6), aggregation index (x7) and NDVI (x8), which were selected and classified using discrete processing and the natural breakpoint method, and then were analyzed by geographic detector.

The factor detection shows that the relationship between the interpretation of each factor on net CO_2 emissions in the Yellow River Basin in 2005 is x5＞x2＞x1＞x4＞x6＞x3＞x7＞x8, which is mainly affected by energy structure, followed by per capita GDP and population. Aggregation index and NDVI contributed little to net CO_2 emission. The

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explanatory power of each factor in 2010 was x2＞x5＞x1＞x6＞x4＞x3＞x7＞x8, the impact of per capita GDP was significantly amplified with the q of 0.34, suggesting the interaction between transform and economic development, and economic growth may lead to more CO_2 emissions. The explanatory power of each factor in 2015 was x5＞x1＞x6＞x4＞x8＞x3＞x8＞x7. Energy structure remains the dominant factor; however, the influence of population has been strengthened, with the q reaching 0.34. At the same time, the role of construction land has been significantly augmented concurrently with the expansion of human activities, thereby leading to substantial increase in CO_2 emissions. In 2020, the explanatory power of each factor was x5＞x1＞x2＞x6＞x4＞x8＞x3＞x7, and energy structure and population size are the most important, with q values of 0.29 and 0.14, respectively. Additionally, the significance of GDP of the secondary industry and aggregation index is greater than 0.05, indicating that all factors have comprehensive impact on net CO_2 emissions in 2020, while single factor has weak leading role. Economic factors played predominant role, while natural factors exerted comparatively weaker influence in 2005-2020.

The interaction interpretation of energy structure and construction land is 0.79 in 2005 (*Fig. 6*). The interaction explanation of per capita GDP and population is 0.74, indicating that economic factors play the pivotal role in CO_2 emissions changes. The interaction explanation between population and per capita GDP is of 0.94 in 2010, indicating the substantial influence of human activities on net CO_2 emissions. The interactive interpretation of construction land with energy intensity and energy structure is 0.83 and 0.84, respectively, signifying that the interaction between construction land and energy factors also greatly affect CO_2 emissions. NDVI exhibits limited explanatory power for CO_2 emissions, whereas its interaction with energy structure reaches 0.69, suggesting that vegetation coverage indirectly influences CO_2 emissions. The explanatory power of per capita GDP and population was 0.95 in 2015. Additionally, the interaction between energy structure and construction land exhibited 0.81. Furthermore, the interactive explanatory degrees of population factor, energy intensity and energy structure were 0.66 and 0.72, respectively, suggesting that population, energy intensity, energy structure and construction land played pivotal roles in influencing CO_2 emissions in 2015. The explanatory power of the aggregation index with population, per capita GDP and energy structure exceeded 0.5. However, the individual factor (aggregation index) did not significantly influence CO_2 emissions, which suggests that the fragmentation degree of land landscape patterns indirectly impacts CO_2 emissions. In 2020, the explanatory power of energy structure with construction land, aggregation index and NDVI was 0.87, 0.81 and 0.83, respectively, indicating that the interaction among energy structure, land landscape and vegetation coverage has stronger impact on CO_2 emissions, and the explanatory power of the interaction between natural factors and social factors is significantly stronger than single factors. The primary drivers of CO_2 emissions have shifted between 2005 and 2020, energy economy and human activities were the predominant factors influencing emissions in 2005-2015, while natural factors and energy economic factors became the leading drivers from 2015 to 2020.

Future projections of carbon budget

Under the natural development scenario (*Fig. 7a*), net CO_2 emissions of the Yellow River Basin in 2030 are projected to increase by 1.36×10^8 t compared to 2020. About 30% of the districts and counties exhibit carbon surplus, encompassing over 90% of the

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river basin. The number of districts and counties in low carbon deficit state remained basically stable, while the number of districts and counties in medium decreased significantly, suggesting the reduction of CO_2 emissions in the Yellow River Basin over the next decade. For different major function-oriented zones, the carbon surplus counties of NMGPZ will increase by 15, while the number of low and medium carbon deficit counties will decrease by 7 and 50, respectively. The opposite trend was observed in PKDPZ, where the number of extremely high carbon deficit counties doubled and CO_2 emissions increased by 0.64×10^8 t.

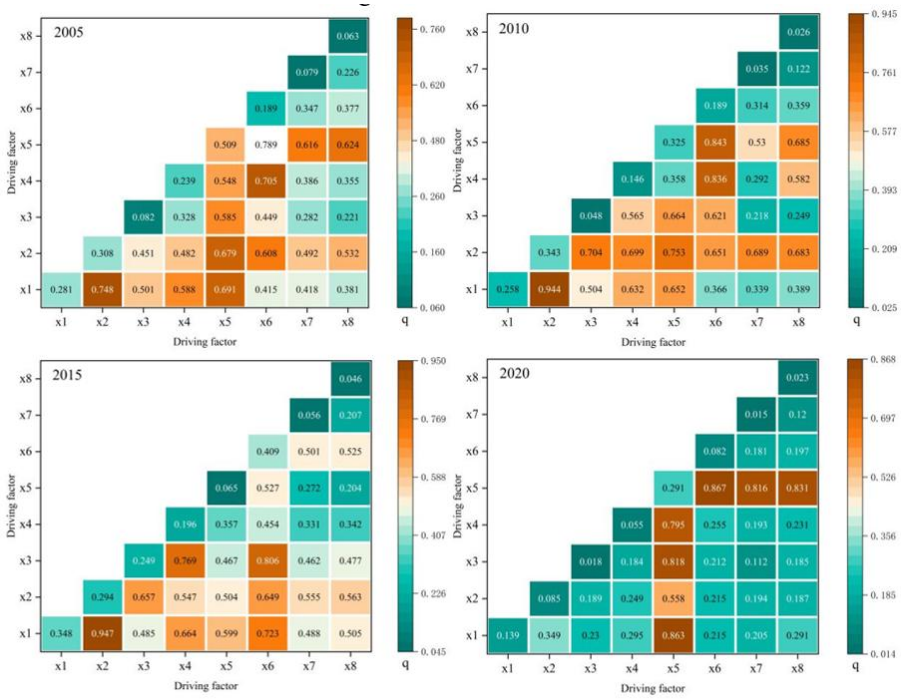

Figure 6. *Interactive detection of influencing factors for CO_2 emissions in the Yellow River Basin*

In the urban expansion scenario (*Fig. 7b*), net CO_2 emissions peak at 13.21×10^8 t in 2030, which is approximately 2.6 times higher than that of 2005, but the growth rate slows down significantly. The number of extremely high carbon deficit counties increased by 18, primarily concentrated in the North China Plain region. In comparison to 2020, CO_2 emissions show consistent decline only in agricultural land, while other functional areas present varying degrees of increase, with the increment of 1.57×10^8 t in NKDPZ. In the context of urban expansion, net CO_2 emissions will peak, and high energy consumption is primarily responsible for indirect CO_2 emissions rise. The major grain producing zones with rapid CO_2 emission growth will be crucial areas in future studies.

Due to the substantial population base, the net CO_2 emission amounts to 12.63×10^8 t in 2030 under the ecological protection scenario (*Fig. 7c*), representing the rise of 0.97×108 tons compared to that of 2020, and the growth rate is consistent with that under the urban expansion scenario, with a significant slowdown. The expansion of carbon sink surplus area will effectively mitigate additional CO_2 emissions. For instance, the carbon sink surplus districts in NKEFZ will increase to 104, grassland serves as the primary land use, with the CO_2 emission reduction of 0.61×10^8 t.

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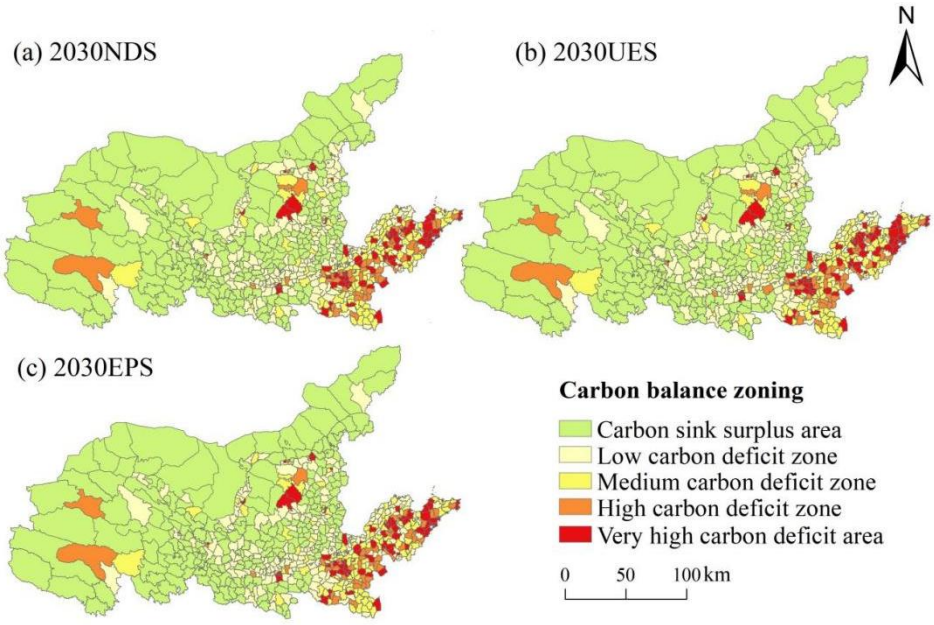

Figure 7. *Carbon balance zoning in the Yellow River Basin under different scenarios (NDS, UES, EPS) in 2030*

Discussion

Recent carbon budget variation in the Yellow River Basin

In response to global warming, the Chinese government had implemented multiple measures to reduce the carbon emissions. Both carbon emission and carbon sequestration from land use in China had shown a significant increasing trend since 1999 (Zhang et al., 2018; Zhou et al., 2019). As a key region for achieving China's carbon reduction goals, the trend of carbon emission and carbon sequestration in the Yellow River Basin in this study was highly consistent with that of China. In the Yellow River Basin, most of the carbon emissions were concentrated in the central urban agglomeration, while carbon sequestration mainly occurred in the peripheral ecological zones (Ma and Liu, 2021; Yang and Zhen, 2023; Wang and Zhen, 2024). Land use change served as an important factor for carbon emissions. Measures such as returning farmland to forests and improving forest management could promote carbon storage in forests. Reclamation led to the conversion of ecological land into farmland. With the reduction of vegetation and soil carbon storage, the carbon storage of ecosystem decreased, which was a carbon emission process (Ma and Wang, 2015). At present, the carbon budget for the upper, middle and lower reaches of the Yellow River presented obvious disparities. In the upstream, effective carbon emission reduction had been achieved in the Qinghai Province and Inner Mongolia Autonomous Region (Zhang et al., 2018), while the carbon emission intensity from land use increased in the Ningxia Hui Autonomous Region, where the pressure of carbon emission reduction was greater (Zheng and Wen, 2020). In the midstream, the carbon emissions from land use increased in both Shaanxi and Shanxi provinces in recent two decades. Construction land was the main source of carbon emissions, while forests was the main carbon sink (Zhao et al., 2023; Wang et al., 2024). In the downstream, both carbon emission and carbon carrying capacity were not matched spatially in the Henan and Shandong Province, where the carbon deficit was serious (Zhao

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2014; Zhang et al., 2018). Most above studies focus on the total carbon emission, which was divided into direct and indirect carbon emission in the current study. The indirect carbon emission had an increasing trend, but the growth rate had decelerated. The direct carbon emission revealed a decreasing trend, hence the effect of natural factors on carbon emission enhancing over time. Further, the functional zone strategy is an important layout of Chinese government to promote regional integration development, constitutes the core strategy to achieve efficient territorial space management. Traditionally, the provincial administrative unit is the policy maker, and the natural zone is the policy implement object. It is difficult to coordinate overall for this strategy, resulting in inefficiency. The targeted policy, implemented in different major function-oriented zoning, is conducive to the optimal allocation of regional resources on carbon emission and sequestration. It provides a new theoretical perspective and scientific basis for accelerating the realization of the carbon budget balance goal.

CO_2 emission reduction countermeasures and suggestions

Significant disparities exist in the temporal and spatial dynamics of CO_2 emissions and influencing factors among the primary function-oriented zones. Therefore, it is imperative to break the restriction of administrative divisions, formulate spatial planning based on the territorial space development pattern, and implement targeted emission reduction measures for different primary function-oriented zones.

The key development prioritized zones in the Yellow River Basin should (1) enforce stringent CO_2 emission standards and industry access criteria, improve energy efficiency, promote industrial structure upgrade, and the development and application of cleaner production technologies; (2) reveal the potential of land utilization, enhance the utilization efficiency of territorial space, strengthen land intensive use, and mitigate excessive urban expansion (Wang et al., 2020); (3) encourage the development of low-carbon and green industrial parks, and facilitate the green transformation of traditional industries; (4) establish carbon reduction targets to effectively control CO_2 emissions growth in key development zones.

For development optimized zones, it is imperative (1) to prioritize ecological environmental protection and ensure continuous enhancement of resource utilization efficiency; (2) to promote industrial upgrading and green sustainable development, foster technological innovation, and mitigate energy consumption and CO_2 emission intensity; (3) to encourage enterprises to embrace low-carbon technologies and clean energy, and support the development of green buildings and low-carbon transportation.

For the major grain producing zones, it is necessary (1) to reasonably regulate urban expansion, restrict agricultural development activities, and avert the degradation of natural ecosystems resulting from industrialization and urbanization; (2) to improve environmental quality through intensify degree increase, cultivated land protection, and mitigating excessive land occupation and resource exploitation; (3) to prioritize agricultural science and technology innovation, elevate the efficiency and technical of cultivated land, and ultimately achieve agricultural modernization (Wu et al., 2021).

The enhancement of ecosystem services should be prioritized for key ecological function zones. By enhancing the quantity and quality of ecological products, expanding green ecological space, and bolstering carbon sequestration capacity, the ecological balance and ecosystem health is ensured. Strictly control large-scale, high-intensity development activities and prohibit the establishment of industries with high pollution and energy consumption. In the future carbon trading market, the area should the

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compensation role of key ecological function zones for ecological construction, restoration and protection should be fully utilized to provide new development opportunities (Wang and Zhen, 2024).

Conclusions

From the viewpoint of primary function-oriented zoning, the study analysed the spatiotemporal differentiation of carbon budget in each functional zone, investigated the influence of natural and social factors on CO_2 emissions using geographic detection techniques, predict the future dynamics of net CO_2 emissions under various scenarios using CA-Markov model, and proposed CO_2 emission reduction measures and suggestions for the Yellow River Basin. The direct CO_2 emissions revealed the declining trend, carbon sink areas increased, carbon carrying capacity enhanced, and the growth rate of CO_2 emissions significantly decelerated. The factor detection indicated that the impact of individual factors on LULC net CO_2 emissions from was generally limited, whereas the influence of energy structure and per capita GDP surpassed that of natural factors. The interaction detection indicates that the net CO_2 emissions are primarily influenced by the interplay of energy economy and human activities in 2005-2015, while the dominant factor shifts to the interaction between natural factors and energy economy in 2015-2020. In order to accomplish "carbon neutrality" and "carbon peaking", it is imperative to further optimize the measures for diverse functional areas in the future and put forward more constructive recommendations. This study has important reality significance for the planning of primary function-oriented zones and the realization of carbon budget balance in the Yellow River Basin, and can also provide scientific reference for the implementation of "carbon neutrality" policy and sustainable development in resource-based areas with high energy consumption worldwide.

Conflict of interest. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Author contributions. Wang Sheng: Conceptualization, Investigation, Project administration, Supervision, Validation, Writing—review & editing. Li Dan: Data curation, Formal analysis, Methodology, Software, Writing—original draft preparation. Li Xiujuan: Conceptualization, Formal analysis, Methodology, Resources, Supervision, Visualization. Li Lingfeng: Writing—original draft preparation, Formal analysis, Methodology. Li Qing: Data curation, Writing—review & editing. Wang Jinfeng: Formal analysis, Investigation, Writing—review & editing.

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