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Forecasting Carbon Sequestration Potential in China's Grasslands by a Grey Model with Fractional-Order Accumulation

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Abstract: This study aims to predict the carbon sequestration capacity of Chinese grasslands to address climate change and achieve carbon neutrality goals. Grassland carbon sequestration is a crucial part of the global carbon cycle. However, its capacity is significantly impacted by climate change and human activities, making its dynamic changes complex and challenging to predict. This study adopts a fractional-order accumulation grey model, using 11 provinces in China as samples, to analyze and forecast grassland carbon sequestration. The study finds significant differences in grassland carbon sequestration trends across the sample regions. The carbon sequestration capacity of the grasslands in Xizang (Tibet) and Heilongjiang province is increasing, while it is decreasing in other provinces. The varying prediction results are influenced not only by regional climatic and natural conditions, but also by human interventions such as overgrazing, irrational reclamation, excessive mineral resource exploitation, and increased tourism development. Therefore, more region-specific grassland management and protection strategies should be formulated to enhance the carbon sequestration capacity of grasslands and promote the sustainable development of ecosystems. The significance of this study lies not only in providing scientific guidance for the protection and sustainable management of Chinese grasslands, but also in contributing theoretical and practical insights into global carbon sequestration strategies.

Keywords: grassland; carbon sequestration capacity; grey model; fractional-order accumulation; China

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1. Introduction

To address climate change, 132 countries and regions have started international processes aimed at achieving carbon neutrality, with many nations setting targets to reach this goal [1]. China plans to peak its carbon dioxide emissions by 2030 and aims for carbon neutrality by 2060. One approach to achieving carbon neutrality involves enhancing carbon absorption through ecosystem carbon sinks and industrial carbon sequestration. Ecosystem carbon sinks refer to the processes, activities, or mechanisms by which ecosystems such as forests, grasslands, wetlands, and oceans remove carbon dioxide from the atmosphere. Studies have shown that ecosystem carbon sinks can promote greenhouse gas emission reduction and environmental improvement, thereby mitigating the impacts of climate change on humans and the planet [2–5]. Among them, enhancing terrestrial carbon sinks is considered one of the most mature methods for mitigating climate change [6,7]. Grasslands are the most widely distributed natural vegetation type in the world, covering about 20% of the world's land area [8]. They are crucial ecosystems for material and energy exchange between the land and atmosphere [9,10]. Grasslands play a significant role in the global carbon cycle by maintaining soil and water, purifying the air, preventing wind erosion, and controlling greenhouse gas emissions [11].

Grassland carbon sequestration refers to the process, activities, or mechanisms by which vegetation in grasslands absorbs carbon dioxide from the air through photosynthesis and fixes it in the vegetation or soil, thereby reducing the concentration of carbon dioxide in the atmosphere. Grasslands are important carbon reservoirs, and compared to carbon gain, soils lose carbon more easily and quickly [12]. In the upland grasslands of Northern England, all investigated grasslands were atmospheric carbon sinks, removing 1822–2758 g CO_2-eq m^{-2} $year^{-1}$ [13]. In California, grasslands are more reliable carbon sinks than forests [14]. However, due to human disturbances such as overgrazing and excessive fertilization, the net ecosystem exchange values of grasslands have become negative. Grassland ecosystems are highly sensitive to changes in climatic factors such as precipitation, showing significant seasonal and interannual fluctuations and uncertainties in soil carbon flux, making the assessment of carbon sequestration functions and their driving mechanisms highly uncertain [15]. Therefore, under the "dual carbon" goals, exploring grassland carbon sequestration mechanisms and accurately assessing grassland carbon storage remain critical scientific issues to be addressed. The carbon sequestration capacity of grasslands is crucial for regulating ecosystems and controlling the greenhouse effect. Existing research has also extensively studied grassland carbon sequestration. Early estimates based on the literature data put the global grassland ecosystem carbon storage at approximately 634 Pg C [16,17]. With the development of satellite remote sensing technology and the improvement of global databases, further studies have been conducted on the estimation of global grassland ecosystem carbon storage, with recent estimates showing around 520 Pg C [18]. The carbon storage of Chinese grassland ecosystems ranges between 17.3 and 59.5 Pg C [19–22]. The large differences in research results arise from several factors: First, grassland carbon storage encompasses multiple levels, including above-ground biomass, litter biomass, underground root biomass, and soil organic carbon storage. Second, varying data sources on grassland area and classification lead to differences in above-ground and underground biomass ratios, carbon coefficients, soil estimation thickness, and stratification methods. Consequently, annual data availability is very limited.

The grey model (GM) is a fundamental component of grey system theory, with the GM (1,1) model being its most basic form. To enhance the prediction accuracy of the GM (1,1) model, scholars have made various optimizations and improvements from different perspectives. Wu [23] proposed the fractional-order accumulation grey model (FGM) and argued that introducing fractional order and using particle swarm optimization for the fractional order can reduce the prediction errors of traditional small sample grey models, prioritize new information, and achieve higher prediction accuracy. This model has been applied in various research fields. For example, it has been used to predict gas emissions in the environmental field [24], predict the lifespan of complex equipment in the technical and engineering fields [25], predict natural gas production in the energy field [26], analyze the business environments of the "Belt and Road" countries in the economic management field [27], and predict farmer income in the agricultural field [28]. In recent years, some studies have used the grey model with fractional-order accumulation to predict the carbon sequestration capacity of marine algae and shellfish [29], but few studies have applied it to predicting the carbon sequestration potential of grasslands. Hence, the purpose of this study is to use the provinces of Xizang (Tibet), Qinghai, Neimenggu (Nei Mongol), Xinjiang, Sichuan, Gansu, Shanxi, Ningxia, Hebei, Heilongjiang, and Yunnan as samples, adopting the FGM to analyze and predict the carbon sequestration capacity of grasslands. This work not only allows for a more accurate understanding of the current state of grassland carbon sequestration, but also predicts future trends under different environmental pressures and human activities. The study provides an important scientific basis for formulating effective grassland protection strategies and addressing climate change.

The potential contributions of this study are as follows: First, it employs the FGM to analyze and predict grassland carbon sequestration capacity. Given the multi-level nature of grassland carbon storage and the difficulty of obtaining data for each level, this study uses a grey prediction model suitable for small sample data. By integrating the FGM operator into the traditional GM (1,1) model, it creates a fractional-order GM (1,1) model, significantly enhancing prediction accuracy. This not only broadens the application of the FGM, but also offers a new perspective for predicting grassland carbon sequestration potential. Second, the study's findings provide a solid scientific foundation for policies aimed at boosting grassland carbon sequestration capacity and promoting the sustainable development of grassland ecosystems, thereby supporting the achievement of the "dual carbon" goals.

2. Influence Factors of Grassland Carbon Sequestration

Carbon sequestration in grassland ecosystems is complex, influenced by multiple factors such as vegetation diversity, climate change, and management practices (Figure 1). These factors interact to affect the stability of grassland carbon sequestration.

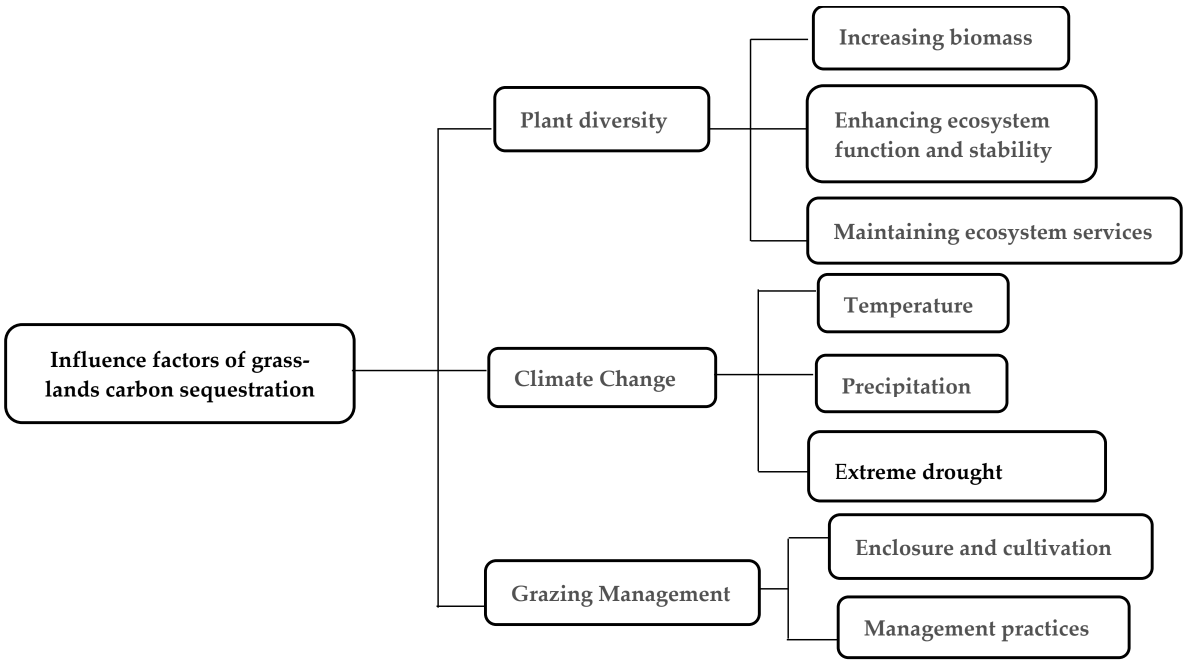

Figure 1. Influence factors of grasslands carbon sequestration.

First, vegetation diversity plays a crucial role in enhancing the carbon sequestration capacity of grasslands. Vegetation diversity not only increases biomass carbon storage, but also enhances the overall functionality and stability of ecosystems, thereby improving grassland carbon sequestration. Increasing vegetation diversity can significantly boost the storage of organic carbon in grassland soils, primarily by increasing carbon input into underground biomass and promoting the contribution of microbial necromass to soil organic carbon [30]. High vegetation diversity is essential for maintaining ecosystem services, including carbon storage [31]. Additionally, vegetation diversity can enhance grassland carbon sequestration by increasing productivity and species asynchrony [32]. Furthermore, there is a positive correlation between vegetation diversity and the carbon storage capacity of grassland ecosystems; as plant species increase, the soil carbon concentration in grassland ecosystems significantly rises [33].

Second, environmental changes, particularly climate change (mainly temperature and precipitation), have a significant impact on the carbon sequestration potential of grasslands [34]. In the context of global warming, rising temperatures accelerate the decomposition of soil organic carbon, reducing soil carbon storage [35]. However, some studies indicate that the loss of soil carbon storage induced by warming is only short-term owing to the limited quantity of active soil carbon pools [36]. The effect of temperature increase on grassland vegetation biomass is also debated [37]. While higher temperatures can enhance the photosynthetic rate of canopy leaves, promoting the synthesis and accumulation of organic matter in grassland plants [38], the warming effect also increases leaf area, leading to higher respiration rates [39], which consumes accumulated organic matter. Precipitation amount and distribution are crucial factors affecting grassland biomass and soil carbon storage [40,41]. Increased precipitation rapidly enhances microbial activity in the soil, leading to a surge in microbial numbers [42]. Precipitation affects soil moisture and nitrogen dynamics in grasslands, influencing water and nutrient availability for plant growth [43], affecting leaf physiological processes and photosynthesis rates [44], and increasing the underground biomass of grassland plants [45]. Extreme climate events affect grassland ecosystems [46]. In the face of extreme drought and wildfire risks, the reliability of grassland carbon sequestration is higher than that of forests because grasslands primarily store carbon underground, while forests store carbon mainly in woody biomass and leaves [14].

Finally, management practices significantly influence the carbon storage capacity of grasslands. Proper grazing management and grassland restoration help maintain vegetation diversity and ecological health, enhancing the carbon storage capacity of grassland ecosystems [47]. Grazing is one of the primary management practices for grasslands, affecting vegetation and soil carbon storage. Grazing behavior causes changes in community characteristics, reducing vegetation biomass and thereby affecting grassland carbon storage [48]. Long-term grazing also affects plant species diversity, such as species richness, vegetation cover, height, density, and biomass [49,50]. Soil carbon density and storage in grasslands change with grazing intensity [51]. Overgrazing increases soil bulk density, reduces soil moisture, and is detrimental to soil carbon input [52]; light grazing promotes microbial activity, affecting soil carbon dynamics and increasing soil carbon density [53]. Grassland soil carbon density shows an increasing trend [54]. Enclosure is one of the most economical and effective measures for grassland vegetation restoration and is a powerful guarantee for grassland ecological management. Enclosure improves vegetation cover and species diversity, promotes vegetation restoration, and increases biomass carbon density in grasslands [55]. However, some studies suggest that prolonged enclosure leads to litter accumulation, which hinders vegetation growth and renewal [56]. Enclosure measures can increase soil carbon density and storage in grasslands [57,58]. This is because enclosure improves the physical properties of grassland soil, increases soil nutrient content, reduces soil bulk density and compaction, and promotes a positive feedback loop between vegetation and soil [59]. Enclosure increases vegetation cover, enhances water infiltration, and reduces soil carbon loss due to erosion [60].

3. Materials

3.1. Research Area

China, one of the largest countries in terms of grassland resources, has a total grassland area of 265 million hectares, with 213 million hectares being natural grasslands, accounting for 80.6% of the total (Third National Land Survey). These natural grasslands are primarily concentrated in the western region and the Tibetan Plateau. The western ten provinces have a combined grassland area of 331 million hectares, representing 84% of the national total. Among them, Neimenggu (Nei Mongol), Xinjiang, Xizang (Tibet), Qinghai, Gansu, and Sichuan have combined grassland areas of 293 million hectares, or about three-quarters of the national grassland area. Xizang (Tibet), Neimenggu (Nei Mongol), Xinjiang, Gansu, and Qinghai are not only traditional pastoral areas, but also important green ecological barriers in northern China. According to the spatial pattern and characteristics of the regions, the State Forestry Administration of China divides the grasslands into five major regions: First is the Mongolia–Ning–Gan Grassland Region, including Neimenggu (Nei Mongol), Gansu, Ningxia, Hebei, and Shanxi, with grasslands accounting for about 30% of the national grassland area. The main landform feature of this region is high plains. Second is the Xinjiang grassland region, which mainly includes Xinjiang Province and is predominantly mountainous grasslands, accounting for over 22% of the national grassland area. Third is the Tibetan Plateau grassland region, including Qinghai and Xizang (Tibet) provinces, which are known for their unique alpine grasslands. Forth is the Southern grassland region, which mainly includes Sichuan and Yunnan provinces, and last is the Northeast grassland region, which mainly includes Heilongjiang, Jilin, and Liaoning provinces. Therefore, this study ultimately selected 11 provinces—Xizang (Tibet), Neimenggu (Nei Mongol), Qinghai, Xinjiang, Sichuan, Gansu, Shanxi, Ningxia, Hebei, Yunnan, and Heilongjiang—as sample areas, fully representing the distribution characteristics of China's grassland ecosystems. Additionally, according to the land cover dataset created by Yang and Huang [61], these 11 provinces each have a grassland area exceeding 10,000 square kilometers, ranking as the top 11 in the nation. The geographical location of the sample areas in China is shown in Figure 2.

Source: Ministry of Natural Resources of the People's Republic of China.

Figure 2. Distribution map of sample provinces.

3.2. Data Sources

There are various methods to calculate carbon storage in grassland ecosystems. Considering data availability and methodological feasibility, this study adopts the carbon density method as utilized by Ni [62] to estimate China's grassland carbon storage. The formula used is as follows: Grassland carbon storage is equal to grassland area times total carbon density per unit area, where total carbon density is equal to vegetation carbon density plus soil carbon density.

The grassland area data are sourced from the annual China Land Cover Dataset (CLCD), developed by Yang and Huang [61]. This dataset, based on 335,709 Landsat images on Google Earth Engine (GEE), provides annual land cover information for China from 1985 to 2022. The dataset is constructed using all the available Landsat data on GEE, creating spatiotemporal features, and applying a random forest classifier to obtain classification results. Furthermore, a post-processing method involving spatiotemporal filtering and logical reasoning is proposed to enhance the spatiotemporal consistency of the CLCD. Finally, based on 5463 visually interpreted samples, the overall accuracy of the CLCD reaches 80%. The grassland area for the sample provinces is shown in Table 1.

Table 1. Grassland area in 11 provinces of China from 2018 to 2022 (km^2).

	Xizang (Tibet)	Neimenggu	Qinghai	Xinjiang	Sichuan	Gansu	Shanxi	Ningxia	Hebei	Yunnan	Heilongjiang
2018	879,376	544,580	457,787	377,747	161,058	157,440	52,493	34,516	32,442	23,850	6472
2019	881,645	546,044	454,948	377,731	160,594	155,182	50,601	34,237	31,557	23,267	5545
2020	881,697	548,986	452,485	374,908	160,026	153,048	49,010	34,161	31,646	22,154	6007
2021	882,649	548,133	452,116	374,722	159,939	152,567	48,260	34,097	31,409	21,884	6155
2022	884,822	542,587	452,023	372,212	158,765	151,216	46,806	33,987	31,138	21,005	6617

Owing to the difficulty in obtaining grassland carbon density data for each province in China, the study references the work of Zhang [20], who divided China's grasslands into seven major grassland regions: the Tibetan Plateau grassland region, the Nei Mongolia Plateau grassland region, the Xinjiang grassland region, the Southern grassland region, the Loess Plateau grassland region, the North China Warm Temperate grassland region, and the Northeast grassland region. This classification is based on the five major grassland regions defined by the Chinese Forestry Administration, with the Mongolia–Ning–Gan grassland region further subdivided into the Nei Mongolia grassland region, the Loess Plateau grassland region, and the North China Warm Temperate grassland region. This seven-region classification better reflects the characteristics of grassland ecosystems across different parts of China. Zhang [20] further calculated the vegetation carbon density, soil carbon density, and total carbon density for these seven major grassland regions using the Terrestrial Ecosystem Model. This calculation utilized meteorological data such as temperature, precipitation, and solar radiation, along with grassland vegetation types, soil texture, altitude, latitude and longitude, and atmospheric CO_2 concentration data. The results are shown in Table 2.

Table 2. Carbon density in seven major grassland regions.

Grassland Region	Vegetation Carbon Density (g C m^{-2})	Soil Carbon Density (kg C m^{-2})	Total Carbon Density (kg C m^{-2})
Tibetan Plateau	1241	21.7	21.7
Neimongolia Plateau	205	7.7	7.9
Xinjiang	409	13.8	14.2
Southern	840	1.3	2.1
Loess Plateau	538	6.0	6.5
North Warm Temperate	1010	7.6	8.6
Northeast	1202	18.3	19.5

Based on this foundation and the geographical locations of the Chinese provinces, Qinghai and Xizang (Tibet) are classified under the Tibetan Plateau grassland region; Neimenggu (Nei Mongol) and Xinjiang are respectively classified as the Nei Mongolia Plateau grassland region and the Xinjiang grassland region; Shanxi is classified under the Loess Plateau grassland region; Hebei is classified under the North China Warm Temperate grassland region; Sichuan and Yunnan are classified under the Southern grassland region; and Heilongjiang is classified under the Northeast grassland region. Most of Ningxia's grasslands are located in the arid zone of central Ningxia, including Wuzhong, Zhongwei, and Yinchuan [63], and thus it is classified under the Loess Plateau Grassland Region. Gansu has a complex terrain, with grasslands primarily distributed across the Gannan Plateau, the Qilian Mountains–Altyn–Tagh mountains, and along the northern desert areas. Given its proximity to both the Nei Mongolia Plateau grassland region and the Tibetan Plateau grassland region, we use the average carbon density of these two regions to represent the grassland carbon density for Gansu Province. The grassland carbon storage for the selected 11 sample provinces is shown in Table 3.

Table 3. Grassland carbon storage in 11 provinces of China from 2018 to 2022 (kg $\times$ 10^{12}).

Year	Xizang (Tibet)	Neimenggu	Qinghai	Xinjiang	Sichuan	Gansu	Shanxi	Ningxia	Hebei	Yunnan	Heilongjiang
2018	19.0824	4.3022	9.9340	5.3640	0.3382	2.3301	0.3412	0.2485	0.2790	0.0501	0.1262
2019	19.1317	4.3137	9.8724	5.3638	0.3372	2.2967	0.3289	0.2465	0.2714	0.0489	0.1081
2020	19.1328	4.3370	9.8189	5.3237	0.3361	2.2654	0.3186	0.2452	0.2721	0.0465	0.1171
2021	19.1535	4.3303	9.8109	5.3210	0.3359	2.2580	0.3137	0.2455	0.2701	0.0460	0.1200
2022	19.2006	4.2864	9.8091	5.2854	0.3334	2.2380	0.3042	0.2447	0.2678	0.0441	0.1290

4. Methods

4.1. Fractional-Order Accumulated Grey Model

The FGM (1,1) was proposed by Wu [23]. It modifies the traditional first-order accumulation to fractional-order accumulation and uses the accumulated data for prediction. This approach weakens the randomness of the original data sequence, reduces the perturbation of the grey prediction model solution, avoids errors in the prediction results of the traditional small sample grey model, and improves the priority of new information to a certain extent, thereby achieving higher prediction accuracy. The modeling process of the FGM (1,1) model is as follows:

Step 1: the original non-negative data sequence is assumed to be

$$X^{(0)} = \left\{ X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n) \right\} \tag{1}$$

And using the equation

$$X^{(r)}(k) = \sum_{i=1}^{k} C_{k-i+r-1}^{k-i} x^{(0)}(i) \tag{2}$$

to obtain the r-order accumulated sequence

$$X^{(r)} = \left\{ X^{(r)}(1), X^{(r)}(2), \cdots, X^{(r)}(n) \right\} \tag{3}$$

the following assumptions are made.

$$C_{r-1}^{0} = 1, C_{k}^{k+i} = 0, C_{k-i+r-1}^{k-i} = \frac{(k-i+r-1)(k-i+r-2)\cdots(r+1)r}{(k-i)!} \tag{4}$$

Then generating the background value sequence $Z^{(r)}$ and calculating the equation

$$Z^{(r)}(k) = 0.5[X^{(r)}(k) + X^{(r)}(k-1)] \tag{5}$$

Step 2: For the r-order accumulated sequence $X^{(r)}$, the whitening differential equation is expressed as:

$$\frac{dX^{(r)}(k)}{dt} + aX^{(r)}(k) = b \tag{6}$$

where a is the development coefficient and b is the grey action quantity. Solving this whitening equation gives the time response function

$$X^{(r)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \tag{7}$$

Step 3: The least squares estimation is used to obtain the following parameter because it can minimize the sum of squared errors.

$$\begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = (B^T B)^{-1} B^T Y \tag{8}$$

where

$$B = \begin{pmatrix} -0.5(X^{(r)}(1) + X^{(r)}(2)) & 1 \\ -0.5(X^{(r)}(2) + X^{(r)}(3)) & 1 \\ \vdots & \vdots \\ -0.5(X^{(r)}(n-1) + X^{(r)}(n)) & 1 \end{pmatrix} Y = \begin{pmatrix} X^{(r)}(2) - X^{(r)}(1) \\ X^{(r)}(3) - X^{(r)}(2) \\ \vdots \\ X^{(r)}(n) - X^{(r)}(n-1) \end{pmatrix} \tag{9}$$

Step 4: $\hat{a}$ and $\hat{b}$ are substituted into the time response function

$$\hat{X}^{(r)}(k+1) = \left[X^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}} \tag{10}$$

where $\hat{x}^{(r)}(k+1)$ is the fitted value at time k + 1, thereby obtaining the sequence

$$\hat{X}^{(r)} = \left\{\hat{X}^{(r)}(1), \hat{X}^{(r)}(2), \cdots, \hat{X}^{(r)}(n), \cdots\right\} \tag{11}$$

Step 5: Equation (11) is performed r-order reduction on $X^{(r)}$ and the following equation is obtained.

$$\hat{X}^{(0)} = \alpha^{(r)}\hat{X}^{(r)} = \left\{\alpha^{(1)}\hat{X}^{(r)(1-r)}(1), \alpha^{(1)}\hat{X}^{(r)(1-r)}(2), \cdots, \alpha^{(1)}\hat{X}^{(r)(1-r)}(n), \alpha^{(1)}\hat{X}^{(r)(1-r)}(n+1), \cdots\right\} \tag{12}$$

where

$$\alpha^{(1)}\hat{X}^{(r)(1-r)}(k) = \hat{X}^{(r)(1-r)}(k) - \hat{X}^{(r)(1-r)}(k-1) \tag{13}$$

Thus, the fitted values of the original data are $\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)$, and the predicted values are $\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \ldots$.

4.2. Particle Swarm Optimization Algorithm

For the FGM, the choice of order *r* significantly impacts prediction accuracy. Different *r* values yield different outcomes. The optimal *r* is chosen to minimize the model's prediction error, typically measured by the mean absolute percentage error (*MAPE*).

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{X}^{(0)}(k) - X^{(0)}(k)}{X^{(0)}(k)}\right| \times 100\% \tag{14}$$

Determining the optimal order r requires extensive and repetitive calculations, which can be challenging to achieve using traditional methods. The particle swarm optimization algorithm provides an effective solution for determining the optimal order *r*.

The particle swarm optimization algorithm is a stochastic optimization technique based on swarms, which was proposed by Kennedy and Eberhart [64]. This algorithm simulates animal social behavior, including that of insects, herds, birds, and fish [65]. The basic principle of the particle swarm optimization algorithm is to find the optimal solution through collaboration and information sharing among individuals within a population. Each individual is referred to as a "particle", and it has only two attributes: velocity and position. Velocity represents the speed of movement, while position represents the direction of movement. The particle swarm optimization algorithm starts with a swarm of randomly initialized particles. The optimal solution is found through iterations. In each iteration, particles update themselves by tracking two "extreme values" (p_{best} and g_{best}). Specifically, each particle searches for the optimal solution independently within the search space and records it as the current personal best (p_{best}). This personal best is then shared with the rest of the particles in the swarm to find the best personal best among all the particles, which is considered the current global best (g_{best}) for the entire swarm. Subsequently, all the particles in the swarm adjust their velocities and positions based on their current personal best and the swarm's shared current global best. In other words, in each iteration, the information from the particles is combined to adjust the velocity in each dimension, which is then used to calculate the particle's new position. The particles continuously change their states in the *D*-dimensional search space until they reach equilibrium or the optimal state. Numerous empirical studies have shown that this algorithm is an effective optimization tool. It has been widely applied in function optimization, neural network training, fuzzy system control, and other fields where genetic algorithms are applied.

The above principle is represented by formulas as follows. We suppose that the particle swarm optimization algorithm involves m particles in a D-dimensional search space, where each particle's position represents a potential solution. The position vector of the *i*-th particle is: $X_i = (x_i{}^1, x_i{}^2, \ldots, x_i{}^D)$, and the velocity vector is $V_i = (v_i{}^1, v_i{}^2, \ldots, v_i{}^D)$. The best position each particle has achieved is its personal best, denoted as p_{best}. The best position found by the entire swarm so far is denoted as g_{best}. In each iteration, the particle's velocity is updated based on its personal best and the global best using the following formula for calculating the particle's velocity change:

$$V_{i+1} = wv_i^d = c_1 r_1 (p_i^d - x_i^d) + c_2 r_2 (p_g^d - x_i^d) \tag{15}$$

where $V_{i\ +1}$ is the updated velocity of the particle, w is the inertia weight, r_1 and r_2 are random numbers in the range [0, 1], c_1 and c_2 are acceleration constants (usually $c_1 = c_2 = 2$), and v_{max} is the maximum velocity limit. In each iteration, each particle's position is updated by adding the velocity vector to the position vector, as determined by the formula:

$$x_{i+1} = x_i + v_i \tag{16}$$

where $x_{i\ +1}$ is the updated position of the particle. The iteration termination condition is determined based on the specific problem, typically when the best position found by the swarm so far meets the preset minimum fitness threshold or the maximum number of iterations is reached.

5. Prediction Results and Discussion

To verify the FGM (1,1) model's accuracy, we first used the traditional GM (1,1) model to predict and employed the MAPE to represent prediction error. The 0.3-order and 1-order fitting results of the total carbon storage for the 11 sample provinces are shown in Table 4. According to the MAPE criterion, a value below 10% indicates "excellent" prediction accuracy. As shown in Table 4, the FGM (1,1) model's MAPE is lower than that of the 1-order GM (1,1) model and is below 10%, proving that the FGM (1,1) model has higher prediction accuracy and can effectively predict grassland carbon storage. The detailed forecast results for the 11 provinces are as follows.

Table 4. Prediction results of total carbon storage in 11 sample provinces.

Year	Actual Value (10^{12} kg)	0.3-Order Fitted Value (10^{12} kg)	1-Order Fitted Value (10^{12} kg)
2018	23.3235	23.3235	23.3235
2019	23.1876	23.1866	23.1863
2020	23.0806	23.1813	23.1815
2021	23.0513	23.0518	23.0526
2022	22.9422	22.9434	22.9437
MAPE (%)		1.74	3.45

5.1. Prediction Results of the Tibetan Plateau Grassland Region

Based on the grassland carbon storage data for Xizang (Tibet) and Qinghai Province from 2018 to 2022, the FGM (1,1) model is used to predict the trend for the next three years, as shown in Figure 3. The results indicate that the grassland carbon sink potential in Xizang (Tibet) is gradually increasing, while the grassland carbon sink capacity in Qinghai is gradually decreasing. The time response functions of the FGM (1,1) models for Xizang (Tibet) and Qinghai are as follows:

$$\hat{x}^{(0.54)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{8.6332e+05}{-0.002}]e^{-0.002k} + \frac{8.6332e+05}{-0.002} \tag{17}$$

$$\hat{x}^{(0.025)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{1.1414e+04}{0.0034}]e^{0.0034k} + \frac{1.1414e+04}{0.0034} \tag{18}$$

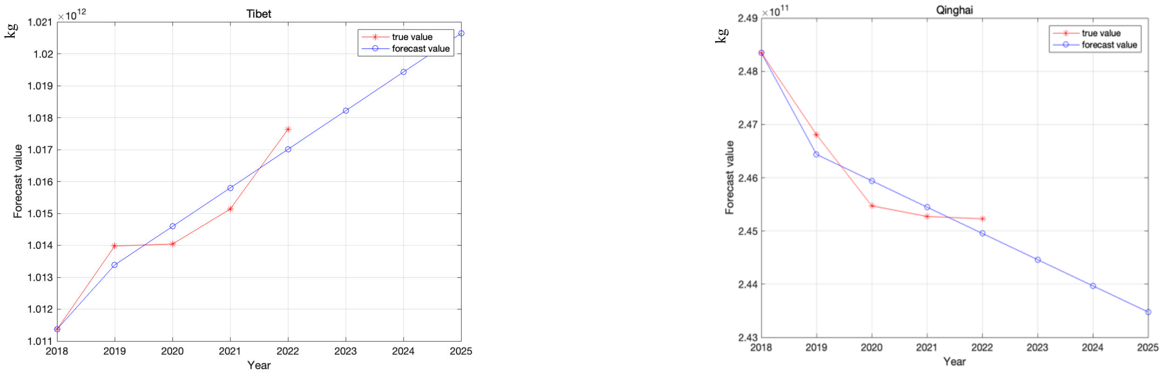

Figure 3. Prediction results for Xizang (Tibet) and Qinghai Province.

The increasing trend of grassland carbon storage in Xizang (Tibet) is related to the active ecological protection policies implemented there. The grasslands in Xizang (Tibet) serve as the "source of rivers" and the "ecological source" for China and the regions of South Asia and Southeast Asia. They are also the "disturber" and "stabilizer" of the climate system in China and the world. Since the 18th National Congress of the Communist Party of China, the Chinese government has attached great importance to the ecological civilization construction in Xizang (Tibet), issuing important instructions and directives on the protection and construction of Xizang (Tibet)'s ecological environment multiple times. In recent years, the government of Xizang (Tibet) has continuously increased its investment in grassland ecological protection and restoration through measures such as the grassland contracting responsibility system, the grassland ecological protection subsidy and reward policy, grassland resource supervision, and the project of restoring grazing land to grassland. These efforts have achieved significant results in grassland ecological protection. The project of restoring grazing land to grassland has restored vegetation through enclosure and reseeding, and management practices such as resting and rotational grazing have maintained plant diversity and soil quality in the grasslands, promoting the health of the grassland ecosystem and increasing its carbon sink potential.

The decreasing trend of grassland carbon storage in Qinghai Province is due to several reasons: First, regarding the characteristics of its grasslands, Qinghai has seven types of grasslands, including alpine meadows, alpine grasslands, and alpine deserts. Alpine meadows, which make up the largest area, are the main type of grassland in Qinghai. The degraded alpine meadows have formed black soil patches that are difficult to manage and pose a serious threat to the grassland ecosystem. Second, human activities such as overgrazing and the output of livestock products have led to a decline in total nitrogen content and a nutrient imbalance, which are major reasons for the degradation of alpine grasslands in Qinghai. Lastly, throughout the government's management process, some departments and local governments in Qinghai have not fully understood the importance of ecological infrastructure construction, leading to the inadequate and ineffective implementation of requirements for the restoration of degraded grasslands. Issues in project planning, acceptance, and post-project management have negatively impacted grassland ecological protection.

5.2. Prediction Results of the Neimongolia–Ningxia–Gansu Grassland Region

As shown in Figure 4, based on the carbon sink capacity data for Neimenggu (Nei Mongol), Gansu, Ningxia, Shanxi, and Hebei from 2018 to 2022, the FGM (1,1) model predicts that the trend will continue to decrease over the next three years, indicating a gradual weakening of the grassland carbon sink capacity in these five provinces. The time response functions of the FGM (1,1) models for Neimenggu (Nei Mongol), Gansu, Ningxia, Shanxi, and Hebei are as follows:

$$\hat{x}^{(0.936)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{1.1745e+04}{3.9908e-04}]e^{3.9908e-04k} + \frac{1.1745e+04}{3.9908e-04} \tag{19}$$

$$\hat{x}^{(0.045)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{1.5436e+05}{0.005}]e^{0.005k} + \frac{1.5436e+05}{0.005} \tag{20}$$

$$\hat{x}^{(0.754)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{3.5441e+04}{0.0041}]e^{0.0041k} + \frac{3.5441e+04}{0.0041} \tag{21}$$

$$\hat{x}^{(0.214)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{5.2830e+04}{0.0209}]e^{0.0209k} + \frac{5.2830e+04}{0.0209} \tag{22}$$

$$\hat{x}^{(0.999)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{2.5062e+03}{0.0154}]e^{0.0154k} + \frac{2.5062e+03}{0.0154} \tag{23}$$

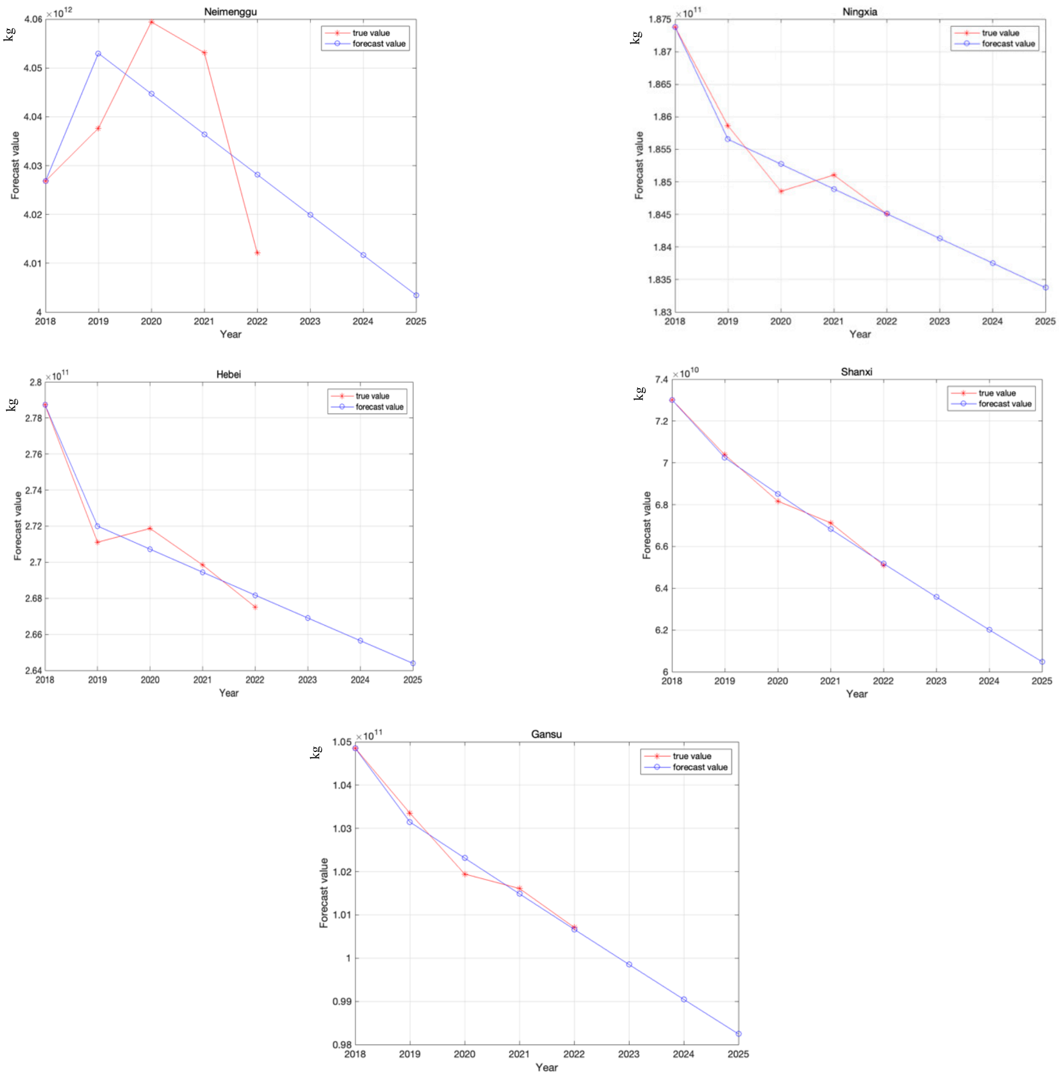

Figure 4. Prediction results for Neimongolia–Ningxia-Gansu grassland region.

The Neimongolia–Ning–Gan grassland region includes Neimenggu (Nei Mongol), Ningxia, Gansu, Shanxi, and Hebei, which can be subdivided into the Inner Mongolia grassland region, the Loess Plateau grassland region, and the North China Warm Temperate grassland region. However, the carbon storage in all these regions shows a declining trend. The reasons for this trend are both common and specific to each province. Common reasons include human activities such as overgrazing, which is a cause of grassland degradation in Neimenggu (Nei Mongol) and southern Gansu. Mining activities have exacerbated the decline in grassland carbon storage in Neimenggu (Nei Mongol), the Qilian Mountains in Gansu, and Shanxi Province. Neimongolia's grassland region is rich in oil and gas resources, the Qilian Mountains have abundant non-ferrous metal resources, and Shanxi Province has substantial coal resources. The unreasonable and excessive mining activities in these areas have led to a series of ecological problems, further accelerating the degradation of grassland resources. The resulting desertification severely affects biodiversity and soil quality. Additionally, unreasonable land use, such as the development of tourism infrastructure, has contributed to grassland degradation in Neimenggu (Nei Mongol), Ningxia, and Hebei. Specific natural factors also play a role, such as Gansu's unique geographical location and complex terrain, which lead to a diverse and changing natural environment. Drought is a significant factor affecting Gansu's ecological environment, with low precipitation, high evaporation, and uneven distribution of rainfall causing seasonal droughts that weaken the grassland ecosystem and increase the risk of degradation.

5.3. Prediction Results and Analysis for the Xinjiang Grassland Region

As shown in Figure 5, based on the carbon sink capacity data for the Xinjiang grassland region from 2018 to 2022, the FGM (1,1) model predicts that the trend will continue to decrease over the next three years, indicating a gradual weakening of the grassland carbon sink capacity in Xinjiang. The time response functions of the FGM (1,1) model for Xinjiang are as follows:

$$\hat{x}^{(0.655)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{3.7982e+05}{0.0031}]e^{0.0031k} + \frac{3.7982e+05}{0.0031} \tag{24}$$

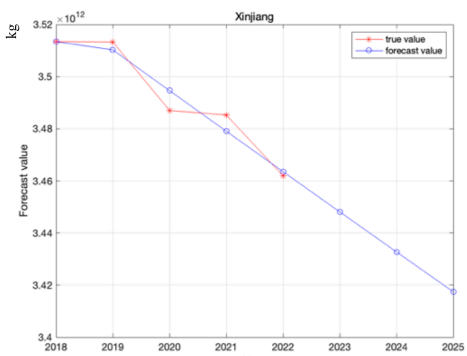

Figure 5. Prediction results for Xinjiang grassland region.

The reasons for the decline in grassland carbon storage in Xinjiang include, firstly, overgrazing and reclamation. Grazing on natural grasslands is a characteristic of Xinjiang's grassland livestock industry. In recent years, the rapid development of the grassland livestock industry has led to an increase in livestock numbers, putting greater pressure on grassland resources. Additionally, with the development of social and economic activities, grasslands have been increasingly developed, with some areas experiencing random reclamation and insufficient management of the relationship between tourism development and grassland ecology, exacerbating desertification and soil erosion. Secondly, improper water resource management is a major factor in the desertification of grasslands in the middle and lower reaches of river basins. In some areas, water resources are over-utilized, and unreasonable upstream water diversion and reclamation have reduced the area of plains water bodies and led to the disappearance of a dominant grass species. Thirdly, with rising temperatures leading to increased drought and desertification, climate change is particularly affecting desert and alpine grasslands in arid and semi-arid regions. Changes in climate have caused the original grassland vegetation to change, gradually reducing the accumulation of organic matter, nutrients, and clay in the soil.

5.4. Prediction Results of the Southern Grassland Region

As shown in Figure 6, based on the grassland carbon sink capacity data for Sichuan and Yunnan from 2018 to 2022, the FGM (1,1) model predicts that the trend will continue to decrease over the next three years, indicating a gradual weakening of the grassland carbon sink capacity in both Sichuan and Yunnan. The time response functions of the FGM (1,1) models for Sichuan and Yunnan are as follows:

$$\hat{x}^{(0.015)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{1.5068e+05}{0.0019}]e^{0.0019k} + \frac{1.5068e+05}{0.0019} \tag{25}$$

$$\hat{x}^{(0.724)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{2.4505e+04}{0.0261}]e^{0.0261k} + \frac{2.4505e+04}{0.0261} \tag{26}$$

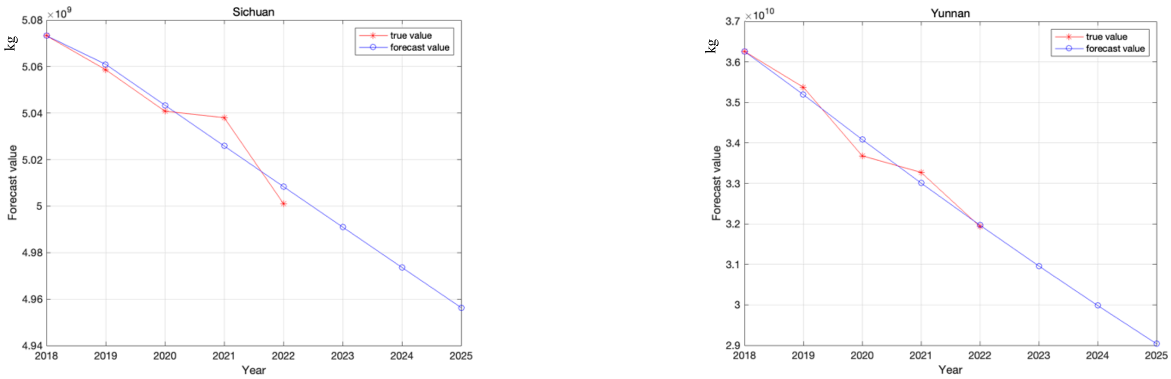

Figure 6. Prediction results for Sichuan and Yunnan Provinces.

The Southern grassland region's natural ecosystems are relatively fragile, with insufficient ecological carrying capacity and environmental capacity. The pressure on ecological protection due to economic development remains significant, and in some areas the issues that have resulted from prioritizing development over protection are becoming increasingly prominent. For example, rapid population growth in pastoral areas has led to a continuous reduction in per capita grassland area. The antagonism between population growth and grassland resource scarcity has become more prominent, resulting in overgrazing, illegal reclamation, and excessive use of grasslands. In addition, the rapid development of tourism in Sichuan and Yunnan in recent years has also negatively impacted the grassland ecosystem. The construction of tourism facilities on grassland areas to meet the personalized needs of tourists not only encroaches on the grassland areas and changes their natural state and use, but also destroys the ecological balance of the grasslands. Construction activities such as land excavation and tree cutting during the building process severely damage natural landscapes, affecting the habitats of wildlife and consequently plant diversity. Furthermore, the increase in tourism activities has led to indirect ecological impacts. The influx of tourists has increased the consumption of local resources, especially water and energy. This excessive consumption has exacerbated environmental pressures on grassland areas, leading to soil quality degradation and vegetation damage, and affecting the health and sustainability of the grassland ecosystem.

5.5. Prediction Results of the Northeast Grassland Region

As shown in Figure 7, based on the grassland carbon sink capacity data for Heilongjiang Province from 2018 to 2022, the FGM (1,1) model predicts that the trend will continue to increase over the next three years, indicating a gradual enhancement of the grassland carbon sink capacity in Heilongjiang Province. The time response function of the FGM (1,1) model for Heilongjiang Province is as follows:

$$\hat{x}^{(0.64)}(\mathrm{k}+1) = [x^{(0)}(1) - \frac{6.2331e+10}{0.0553}]e^{0.0553k} + \frac{6.2331e+10}{0.0553} \tag{27}$$

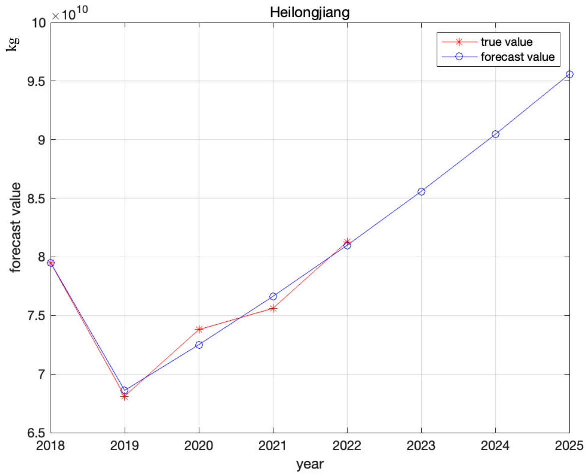

Figure 7. Prediction results for Heilongjiang Province.

The increasing trend in grassland carbon storage in Heilongjiang Province is primarily due to the following reasons: Firstly, compared to the northwestern provinces, Heilongjiang has a superior geographical location with fertile soil and favorable climate conditions. This leads to rich biodiversity, high above-ground biomass, and good overall grassland ecological conditions. The comprehensive vegetation coverage of its grasslands has remained stable at around 80%, with little annual variation. Secondly, through the implementation of grassland grazing bans and the support of national projects such as the new round of grassland ecological protection subsidy and reward policies and the project of restoring grazing land to grassland, Heilongjiang has adopted measures such as enclosure and cultivation, reseeding, and artificial grass planting to protect and restore degraded, desertified, and salinized grasslands. These measures have effectively curbed the deterioration of grassland ecological conditions in the region, significantly improving the grassland ecosystem in some areas.

6. Conclusions

This study uses 11 provinces, including Xizang (Tibet), Qinghai, Neimenggu (Nei Mongol), Xinjiang, Sichuan, Gansu, Shanxi, Ningxia, Hebei, Yunnan, and Heilongjiang, as samples to conduct an in-depth analysis and prediction of China's grassland carbon sink capacity. The results of the FGM indicate significant differences in grassland carbon sink capacity across different regions. Specifically, the grassland carbon sink capacity in Xizang (Tibet) shows a gradual increase, which is attributed to the effective implementation of government ecological protection policies and measures such as restoring grazing land to grassland. Heilongjiang's grassland carbon sink capacity is enhanced owing to its favorable geographical location and climatic conditions. In contrast, other provinces show a declining trend in grassland carbon sink capacity, with both common and unique causes. Common reasons include overgrazing leading to vegetation degradation, climate change accelerating soil carbon decomposition, and land use changes reducing grassland area. Unique factors include ecological system damage from mineral development in Neimenggu (Nei Mongol) and Gansu, increased pressure on grasslands from tourism development in Sichuan and Yunnan, and intensified desertification due to improper water resource management in Xinjiang. This study provides new methods and perspectives for predicting grassland carbon sink capacity and has important theoretical and practical significance for enhancing the sustainable development capacity of grassland ecosystems and achieving carbon neutrality goals. Future research should further explore grassland carbon sink capacity and its dynamic mechanisms under different environmental contexts to better understand and manage grassland ecosystems, thereby promoting the achievement of carbon neutrality goals.

First, ecological protection and restoration should be strengthened. For regions showing an increasing trend in carbon sink capacity, such as Xizang (Tibet), existing ecological protection policies should be continued and strengthened. Effective measures include the grassland contracting responsibility system, the grassland ecological protection subsidy and reward policy, and projects for restoring grazing land to grassland. The government should increase investment to support enclosure, reseeding, and other measures to restore grassland vegetation, further enhancing the health of grassland ecosystems and their carbon sink capacity. Second, grazing and land use should be scientifically managed. In regions with declining carbon sink capacity, such as Qinghai and Xinjiang, scientific grassland management strategies need to be implemented. Grazing intensity should be strictly controlled, and methods of rotational grazing and resting grazing should be promoted to prevent overgrazing and the degradation of grasslands. Additionally, the regulations on land reclamation and tourism development should be strengthened to prevent destructive activities and protect the stability of grassland ecosystems. Third, mineral resource development should be controlled and regulated. For regions like Neimenggu (Nei Mongol) and Gansu, where mineral resource development has led to a decline in grassland carbon sink capacity, the government should formulate and strictly enforce environmental protection measures. Mineral resource development should be combined with ecological protection. Ecological restoration projects to restore damaged grasslands should be implemented to prevent desertification and reduce biodiversity loss, thereby enhancing grassland carbon sink capacity. Fourth, climate change should be addressed: Given the significant impact of climate change on grassland carbon sink capacity, comprehensive measures should be formulated to address this issue. For example, strengthening climate change monitoring, optimizing water resource management, and ensuring sufficient soil moisture in grasslands through water conservancy facilities and water-saving irrigation. Drought-resistant and adaptable plant varieties that enhance grassland resilience and carbon storage capacity should be promoted. These measures will help enhance the stability and carbon sink function of grasslands under extreme climatic conditions.

This study still has certain limitations: First, it only provides evidence of grassland carbon sinks in China; future research can further investigate the carbon sink capacity of grasslands in other environmental contexts. Second, this study only conducted empirical research on provinces with grassland areas exceeding 10,000 square kilometers, without considering provinces with smaller grassland areas. Future research can conduct a more comprehensive study on China's grassland carbon sink capacity.

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