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Analysis of spatiotemporal evolution characteristics and driving factors of carbon storage in Dongting Lake Wetland, China

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Abstract: Lake wetlands play a crucial role as global carbon sinks, significantly contributing to carbon storage and ecological balance. This study estimates the quarterly carbon storage in the Dongting Lake wetland for the years 2010, 2015, and 2020, using MODIS remote sensing imagery and the InVEST model. A Structural Equation Model (SEM) was then employed to analyze the driving factors behind changes in carbon storage. Results show that intra-annual carbon storage increases and then decreases, with maximum level in the third quarter (average of 34.242 Tg) and a minimum one in the first quarter (average of 21.435 Tg). From 2010 to 2020, inter-annual carbon storage variations initially exhibited an increasing trend before decreasing, with the peak annual average carbon storage reaching 32.230 Tg in 2015. Notably, the coefficient of variation for intra-annual carbon storage increased from 8.5% in 2010 to 25.8% in 2020. Key driving factors that influence carbon storage changes include surface solar radiation, temperature, and water level, with carbon storage positively correlated with surface solar radiation and temperature, and negatively correlated with water level. These findings reveal the spatiotemporal evolution characteristics of carbon storage in the Dongting Lake wetland, offering scientific guidance for wetland conservation and regional climate adaptation policies.

Keywords: Lake wetland; Carbon storage; Dynamic evolution; Climate-hydrological drivers; Dongting Lake

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Introduction

Wetlands are among the ecologically valuable ecosystems worldwide, playing a crucial role in preserving species diversity, maintaining ecological balance, conserving water sources, regulating climate, and preventing soil erosion (Dar et al. 2021). Despite covering only 6% to 9% of the Earth's land area, wetlands store approximately 35% of the global terrestrial carbon pool (Deng et al. 2022), making them one of the most significant carbon reservoirs. Rich in undecomposed Dissolved Organic Carbon (DOC), wetland soils possess the highest carbon density of any terrestrial ecosystem (Stern et al. 2007) and play a crucial role in global carbon cycle and climate regulation (Liu, 2004; Gorham, 1991). However, increasing global climate change intensifies and unsustainable human exploitation have led to large-scale degradation and loss of wetland ecosystems (Debanshi and Pal, 2020; Lin et al. 2021). Such degradation can trigger the release of stored carbon as of CO_2 and CH_4, Potentially transforming wetlands from carbon sinks to carbon sources if release rates exceed absorption rates (Liu et al. 2019).

Carbon storage, defined as the amount of carbon retained in an ecosystem (Post et al. 1982), reflects an ecosystem's ability to sequester carbon. Developing rapid and high-precision models for estimating wetland carbon storage, assessing its spatiotemporal dynamics, and predicting future wetland landscapes and carbon storage are of great significance for stabilizing and enhancing wetland carbon sequestration. These efforts not only support

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China's strategic goals of "carbon peak" and "carbon neutrality" but also contribute to global climate change mitigation and ecological environment protection (An et al. 2022). Methods for estimating carbon storage include field measurement (Donato et al. 2011), ecosystem carbon flux monitoring (Zhang et al. 2019), and model-based estimation approaches (Tong et al. 2016). Traditional field measurements, which involve selecting sample plots to estimate total biomass, work well for small-scale sites but face challenges when applied to medium- or large-scale areas. Ecosystem carbon flux monitoring methods, on the other hand, estimate ecosystem carbon storage by obtaining soil profile carbon density data and combining it with soil structure analysis. Both approaches are costly and limited by the availability of field data, making them unsuitable for reconstructing past conditions or predicting future trends (Sun and Li, 2017). Recent advancements in remote sensing technology have significantly improved image resolution, facilitating more efficient image acquisition and processing. Utilizing remote sensing imagery allows for dynamic assessment of wetland carbon storage variations. This approach, characterized by simple input requirements, flexible parameter settings, higher accuracy, and broader applicability (Babbar et al. 2021; Iverson et al. 1993; Patil et al. 2015; Chirici et al. 2007), has become a widely adopted method in wetland carbon storage research. For example, Ni (2013) provided accurate estimations of carbon storage in China's terrestrial ecosystems using remote sensing technology, setting an important benchmark for global carbon pool research. An et al. (2022) used remote sensing data to estimate carbon storage in the Dongting Lake area from 1995 to 2020 and to predict future land use and carbon storage from 2030 to 2050. Similarly, Mo et al. (2023) assessed the impact of land-use changes on forest carbon storage by combining remote sensing data with modern computational methods. Gu et al. (2024) dynamically predicted carbon storage of Pinus kesiya var. langbianensis forests using remote sensing and model optimization, providing a scientific basis for forest carbon sink management. Li et al. (2024a) further predicted the spatial distribution of future carbon storage in the Bosten Lake Basin of China by integrating remote sensing imagery with the InVEST and PLUS models. The InVEST model, which is applicable worldwide, requires minimal input data and provides visualized outputs, making it well-suited for multi-scale assessments of carbon sequestration functions of wetland ecosystems when integrated with remote sensing data such as land use and vegetation cover from satellite images.

As one of the largest freshwater lake wetlands in southern China, Dongting Lake Wetland—characterised by its diverse environments of lakes, marshes, and wetland meadows marshes plays a vital role in carbon absorption and storage. Its connection to the Yangtze River system, unique geographical location and climatic conditions make it an ideal case for studying carbon storage in lake wetlands. Moreover, the wetland is significantly influenced by human activities and climate change, making real-time monitoring and precise calculation of carbon storage essential for effective management and conservation.

This study utilizes MODIS remote sensing imagery from all four quarters of 2010, 2015, and 2020 in the Dongting Lake area. The land cover in the study area was classified using the Classification And Regression Tree (CART) decision tree method in ENVI, and the InVEST model's carbon storage module was applied to calculate wetland carbon storage. The results were analyzed alongside data on water level fluctuations, temperature, precipitation, and solar radiation to elucidate the spatiotemporal dynamics of carbon storage in the lake wetland and support ecological planning and carbon neutrality goals in the region.

1 Materials and methods

1.1 Study area

The Dongting Lake Wetland acts as a key ecological barrier in the middle and lower reaches of the Yangtze River, playing a vital role in safeguarding China's grain-producing regions. The study area experiences a subtropical monsoon climate, characterized by moderate temperatures and abundant sunshine. The average annual precipitation is approximately 1,400 mm, with most rainfall occurring in June and July. The mean annual temperature is approximately 17°C, with around 1,600 hours of sunshine per year and a total annual radiation of roughly 430 kJ/cm^2 (Committee, 2016). In recent years, due to global climate change and human activities, the Dongting Lake Wetland has been gradually shrinking. Consequently, in-depth research on its carbon storage dynamics is essential to explore its spatiotemporal patterns. Fig. 1 illustrates the study region.

1.2 Data sources

Due to the limited availability of 30 m × 30 m Landsat images with acceptable cloud cover in the study area. MODIS images were selected for analysis. The data were obtained from USGS Earth Explorer (https://earthexplorer.usgs.gov). A total of 12 MODIS MOD13Q1 images, covering all four quarters of 2010, 2015, and 2020, were used. Each image has a spatial resolution of 250 m × 250 m and a temporal resolution of 16 days. Preprocessing of the MODIS images involved projection transformation (WGS84/UTM Zone 49N) and clipping using ENVI 5.6 software.

Meteorological data comprised of total surface solar radiation, average daily temperature, and average daily precipitation for each quarter of the respective years, were obtained from the National Science and Technology Resources Sharing Service Platform—National Earth System Science Data Center (http://www.geodata.cn). Hydrological data for the study area were obtained from the Hydrological Yearbook of the Yangtze River Basin.

1.3 Research methods

The CART decision tree algorithm, combined with visual interpretation and field surveys was used to classify Land Use/Land Cover (LU/LC) for each quarter of 2010, 2015, and 2020 in the study area. The resulting classification images were aggregated, converted to vector format, and then retransformed into raster format. The raster datasets, representing land cover types and corresponding carbon density were subsequently input into the InVEST model to estimate carbon storage for each quarter of the selected years. This methodology allowed us to investigate seasonal and annual variations in carbon storage in the Dongting Lake Wetland, analyze the impacts of water level, temperature, precipitation, and Solar Radiation (SR) on its spatiotemporal dynamics, and explore the underlying driving mechanisms. The specific implementation steps are shown in Fig. 2.

1.3.1 LU/LC classification method: Classification and Regression Tree (CART)

The CART (Classification and Regression Trees) algorithm is a recursive partitioning method that iteratively divides a dataset into smaller subsets until a predefined stopping condition is met (Das et al. 2020). At each step, the algorithm selects an optimal feature and best split point to maximize the sample purity within each subset and to effectively separate different classes. This is achieved by calculating the Gini index, which quantifies the probability that two randomly selected samples from the dataset belong to different classes. For a classification problem with K classes, the Gini

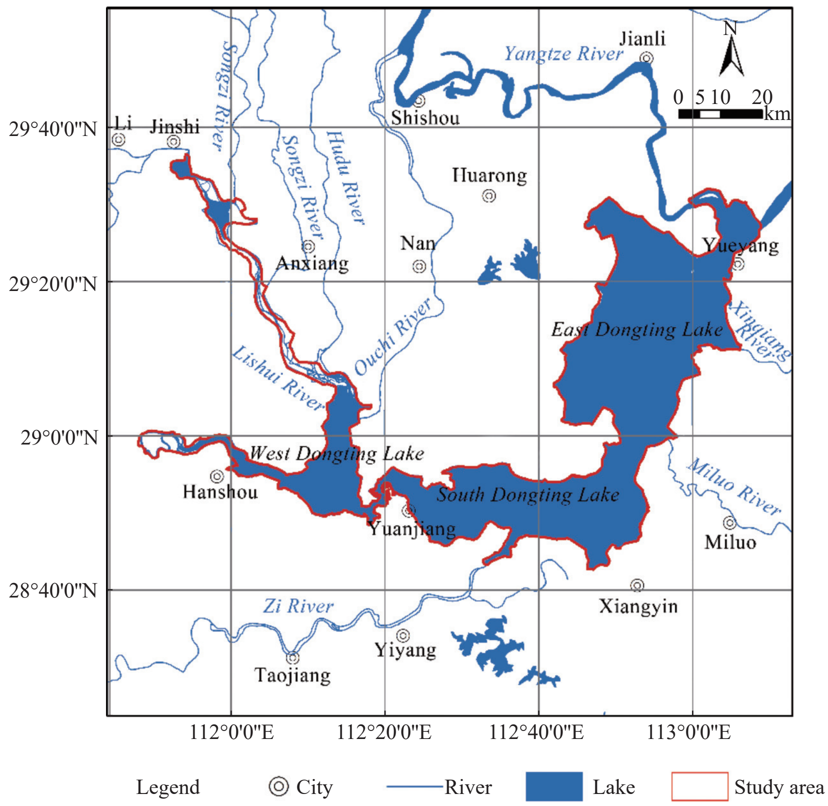

Fig. 1 Schematic diagram of the location of the research area

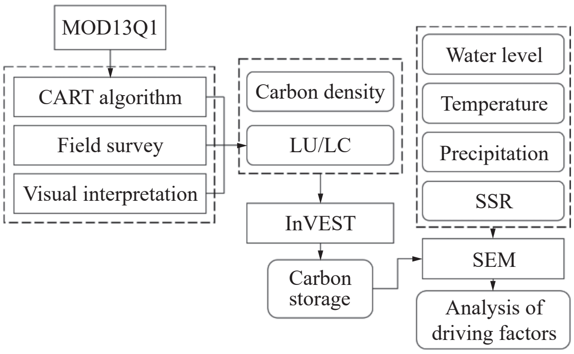

Fig. 2 Flowchart for wetland carbon storage calculation and driving factor analysis

index for a feature A is calculated as:

$$Gini(A) = 1 - \sum_{i=1}^{K} p(i|A)^2 \tag{1}$$

Where: $p(i|A)$ represents the probability of a sample belonging to the i^{th} class given feature A.

During each split, the CART algorithm evaluates all features and their possible split points, selecting the one that yields in the greatest reduction in the overall Gini index. This process is recursively applied until the stopping condition is met, constructing a complete decision tree model. Based on the "Land Use Status Classification" standard (GB/T 21010—2017), and the current land use status of the study area, land cover was classified into five categories: Water bodies, tidal flats, sedge marshes, reed marshes, and woodlands. The LU/LC data were derived from MODIS MOD13Q1 imagery by employing the CART algorithm and sample data. The accuracy of the classification results was assessed using Kappa coefficient, which measures the consistency between the classification results and actual land surface conditions. The Kappa coefficient is calculated as:

$$\text{Kappa} = (P_A - P_E)/(1 - P_E) \tag{2}$$

Where: P_A represents the observed agreement probability, and P_E is the expected agreement probability.

The CART algorithm was applied to map the distribution of different land cover types for each quarter 2010, 2015, and 2020 in the study area. The classification overall accuracy exceeded 87% and the Kappa coefficient was above 83% for each dataset, indicating that the land use data derived from remote sensing images are reliable for subsequent carbon storage estimation.

1.3.2 Carbon storage calculation method: InVEST Model

The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model was developed by the Natural Capital Project at Stanford University, in collaboration with the Nature Conservancy (TNC), and the World Wildlife Fund (WWF). It was designed to assess changes in the quantity and value of ecosystem services through spatial analysis. Using its carbon storage module, the model calculates carbon storage based on land cover distribution data and carbon density data for each cover type (De'ath and Fabricius, 2000). Known for its broad applicability and high reliability (Ding et al. 2023), the InVEST model incorporates the following carbon storage components for different land use/land cover types, as detailed in Table 1.

The formula for calculating total carbon storage is:

$$C_{\text{tot}} = C_{\text{above}} + C_{below} + C_{\text{soil}} + C_{\text{dead}} \tag{3}$$

$$C_{\text{tot}i} = (C_{\text{above}i} + C_{\text{below}i} + C_{\text{soil}i} + C_{\text{dead}i}) \times A_i \tag{4}$$

Where: C_{tot} represents the total carbon storage, C_{above} represents the surface biomass carbon storage, C_{below} represents the underground biomass carbon storage, C_{soil} represents the soil's organic carbon storage. C_{dead} represents the litter carbon storage, i is the average carbon density of each land cover type, and A_i is the area of the land cover type.

Extensive surveys on carbon density in the Dongting Lake area have been conducted by previous researchers (Zhou et al. 2024; An et al. 2022). This study primarily relies on the research findings of An et al. (2022) to define the carbon density values of different land cover types in the study area, as shown in Table 2.

Table 2 The carbon density of various cover types in the research area (unit: Mg C/km^2) (Cited from An et al. 2022)

Table 1 Carbon storage sources of land use/cover types

Carbon storage types	Sources of carbon storage
Surface biomass carbon storage	All living vegetation above the ground surface
Underground biomass carbon storage	Underground living root systems
Soil organic carbon storage	Organic carbon in mineral and organic soils
Litter carbon storage	Litter, standing or fallen deadwood

Types	C_{above}	C_{below}	C_{soil}	C_{dead}
Water	0	0	0	0
Mudflat	1	1	0.99	0
Sedge marsh	0.82	0.87	89	1
Reed marsh	6	6	20	0
Woodland	64.2	118	207.3	3.5

1.3.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was employed to analyze the meteorological and hydrological factors that drive changes in carbon storage within the wetland critical zone. SEM is a tool that integrates causal modeling with multivariate statistical analysis and is capable of exploring the relationships between independent and dependent variables in complex systems. In this study, surface solar radiation, temperature, precipitation, and water level were designated as independent variables, while carbon storage served as the dependent one. The model was developed using SmartPLS software to analyze the impact of these natural driving factors on carbon storage changes.

1.3.4 Correlation coefficient

To examine the relationships among land cover types, meteorological factors, hydrological conditions, and carbon storage, the Pearson Correlation Coefficient was used to quantify the linear correlation between these variables. The coefficient, which ranges from −1 to +1, is a widely used statistical measure that quantifies the strength and direction of a linear relationship between two continuous variables. The Pearson Correlation Coefficient is calculated using the following formula:

$$r_{xy}=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{5}$$

Where: r_{xy} is the Pearson correlation coefficient between variables x and y; x_i and y_i are the i^{th} observed values of the two variables; $\bar{x}$ and $\bar{y}$ are the mean values of variables x and y, respectively; and n is the total number of samples. The correlation analysis aids in understanding the contribution of different influencing factors to the fluctuation in carbon storage, providing essential data for ecosystem management and informed decision-making.

2 Results and analysis

2.1 Spatiotemporal characteristics of land cover changes

Fig. 3 shows significant spatiotemporal variations in land cover types in the Dongting Lake Wetland across both seasonal and annual timescales. Water bodies are predominantly located in the central and northern parts of the, while tidal flats occur sporadically along the edges of water bodies. Sedge and reed marshes are the dominant land cover types, extensively distributed around the lakes and in the southern regions. Woodlands mainly occur on the wetland periphery and in some elevated areas.

In 2015, the lake water area slightly decreased compared to 2010 but remained concentrated in the central lake region. In contrast, the areas of sedge and reed marshes expanded, particularly in the southern part of the lake, while tidal flats exhibited a minor overall increase, and distribution remained largely stable. By 2020, the lake water area had further decreased, while the sedge marshes expanded, especially along the lake margins. Reed marshes coverage increased significantly, peak in the first quarter of 2020, while woodlands remained relatively stable with minor reductions in some areas. Overall, from 2010 to 2020, water body areas decreased annually and tidal flats fluctuated with a slight overall decrease. Meanwhile, the areas of sedge and reed marshes expanded notably towards the lake margins, particularly in the first and fourth quarters of each year. In comparison, changes in the woodland area were relatively minor. These findings indicate that wetland ecosystem distribution patterns are significantly responsive to seasonal hydrological fluctuations, climate change, and human activities.

2.2 Spatiotemporal characteristics of carbon storage

The spatiotemporal distribution of carbon storage for each quarter in 2010, 2015, and 2020 was derived using the InVEST model. As shown in Fig. 4 shows, carbon storage exhibits highly spatial heterogeneity. Compared to 2010, the connectivity of high-carbon-density areas decreased in some regions, while spatial heterogeneity increased in 2015 and 2020. High-carbon-density zones were primarily concentrated in woodlands, with average coverage areas of 570.52 km^2 in the second and 732.37 km^2 third quarters, respectively, compared to 377.79 km^2 in the first and 526.13 km^2 fourth quarters. Consequently, the proportion of high-carbon-density areas was significantly larger in the

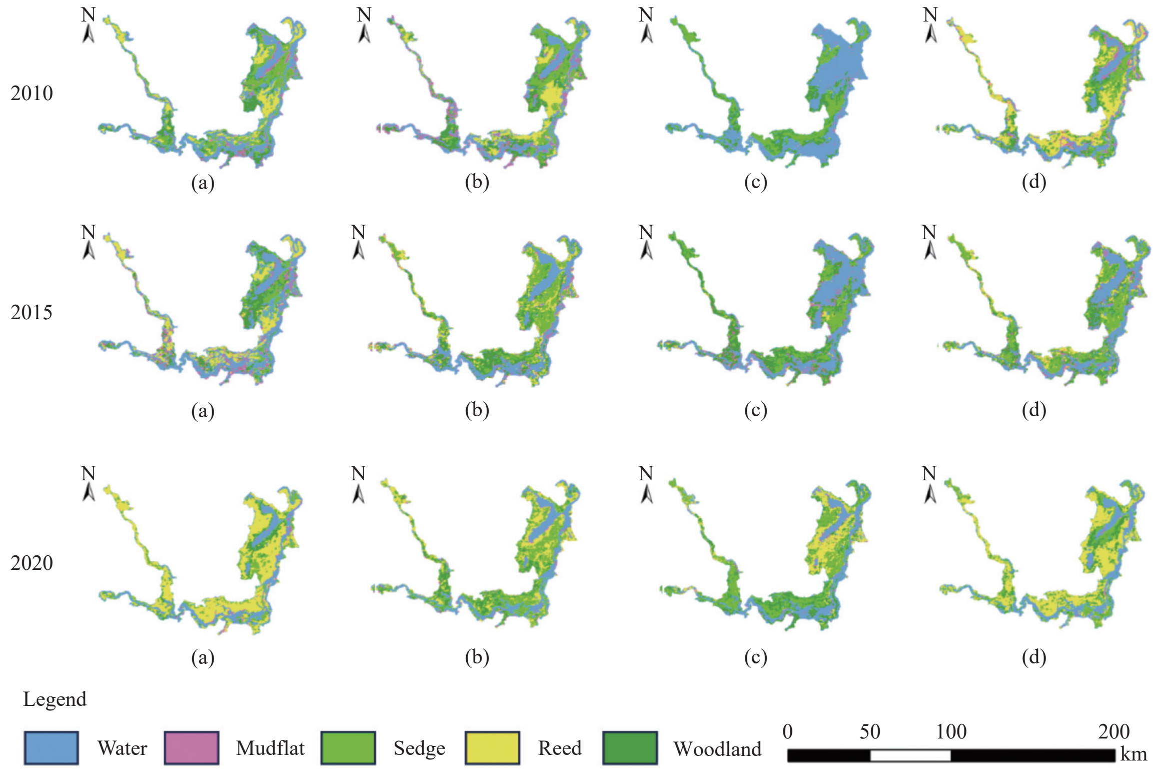

Fig. 3 Spatial and temporal distribution of land cover in the research area

(a, b, c, and d correspond to the first, second, third, and fourth quarters of the corresponding year, respectively)

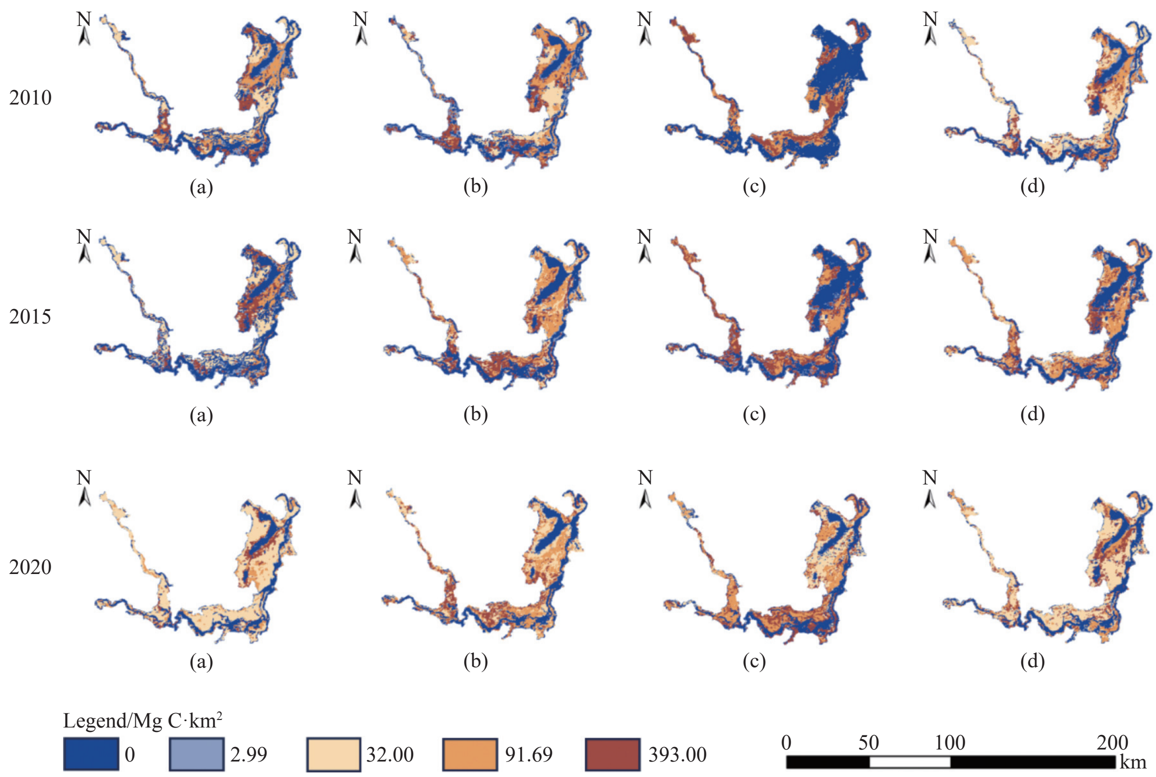

Fig. 4 Spatial and temporal distribution map of land cover in the research area

second and third quarters than in the first and fourth quarters.

Fig. 5 indicates that the carbon storage is lowest in the first quarter of each year, with an average value of 21.433 Tg. This is attributed to the dry season, and low temperatures that restrict vegetation growth. In the second quarter, as vegetation growth reaches its peak, the average carbon storage value rises to 30.244 Tg, an increase of 8.811 Tg over the first quarter, reflecting enhanced carbon sequestration. The third quarter records the highest average carbon storage at 34.242 Tg, coinciding with peak photosynthesis activity and maximal carbon sink function during this period. In the fourth quarter, carbon storage declines to an average of 27.960 Tg, which is still higher than in the first quarter, reflecting the commencement of wetland vegetation dormancy.

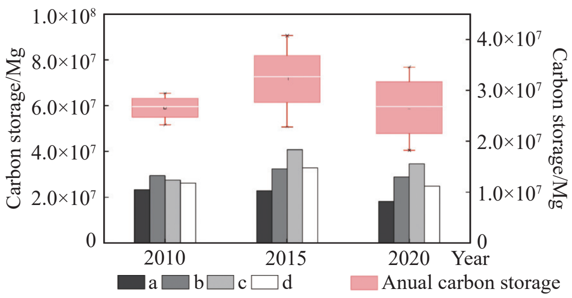

Fig. 5 Quarterly and annual carbon storage in the research area

Notes: The carbon storage values of the bar chart correspond to the left y-axis, while the carbon storage values of the box plot correspond to the right y-axis.

Examining annual trends, the average annual carbon storage was 26.576 Tg in 2010, peaked at 32.230 Tg in 2015, and then dropped to 26.604 Tg in 2020, showing an initial increase followed by a decline. In 2010, carbon storage fluctuated minimally among quarters, ranging from 23.25 Tg to 29.444 Tg, with a coefficient of variation of 8.5%, suggesting a relatively stable natural environment and human activities. However, in 2015 and 2020, seasonal variations were more pronounced, with coefficients of variation of 22.8% and 25.8%, respectively, indicating that natural environment and human activities had a greater impact. Moreover, the overall carbon storage in 2020 decreased by 17.5% compared to 2015, suggesting a decline in carbon sequestration capacity and a trend towards wetland degradation.

2.3 Analysis of factors influencing carbon storage

Numerous studies have demonstrated that temperature, precipitation, water level, and solar radiation are critical factors influencing wetland carbon storage (Jia et al. 2016; van Groenigen et al. 2005; Li et al. 2024b; Xie et al. 2011; Ren et al. 2016). Higher temperatures can boost ecosystem primary productivity and increase wetland carbon storage (Jia et al. 2016), although they also accelerate accelerate soil organic matter decomposition, leading to greater CO_2 and CH_4 emissions (van Groenigen et al. 2005). Increased solar radiation enhances photosynthetic efficiency, fostering plant growth and, consequently, carbon sequestration (Zhang et al. 2023). Moreover, fluctuations in precipitation and water level may alter soil moisture, affecting microbial community structures and directly influencing carbon inputs, decomposition processes, and the stability of lacustrine wetlands (Li et al. 2024b; Laiho, 2006).

Fig. 6 illustrates the seasonal variations in meteorological and hydrological factors. The study area, characterized by a tropical to subtropical monsoon climate, experiences concurrent high rainfall and temperatures. The highest values of these factors occur in the third quarter. For instance, in the third quarter of 2015, the highest temperature and solar radiation reached 27.9°C and 676.1 kJ/cm^2, respectively, while in the third quarter of 2010, the highest precipitation and water levels were recorded 11.53 mm and 28.71 m. In contrast, the lowest values occur in the first quarter. For example, in the first quarter of 2010, the lowest temperature, solar radiation, and water level were 5.9°C, 252.4 kJ/cm^2, and 20.56 m, respectively. The lowest precipitation was 0.86 mm in the first quarter 2015. These distinct seasonal patterns underscore how extreme values in specific quarters impact wetland carbon storage dynamics.

To examine the impact of meteorological and hydrological factors on carbon storage, a Structural Equation Model (SEM) was developed using monitoring data for each influencing factor along with corresponding changes in wetland area and carbon storage density. In this model, the coefficient of determination (R^2) can be used to represent the proportion of the dependent variable's variation that is explained by the independent variables. The formula for calculating R^2 is:

$$R^2 = 1 - \frac{\delta^2}{\sigma^2} \tag{6}$$

Where: δ^2 represents the residual variance of the dependent variable, and σ^2 is the total variance of the independent variable.

The resulting R^2 values for temperature and carbon storage were 0.718 and 0.849, respectively, indicating that the model effectively explains the impact of Surface Solar Radiation (SSR) on

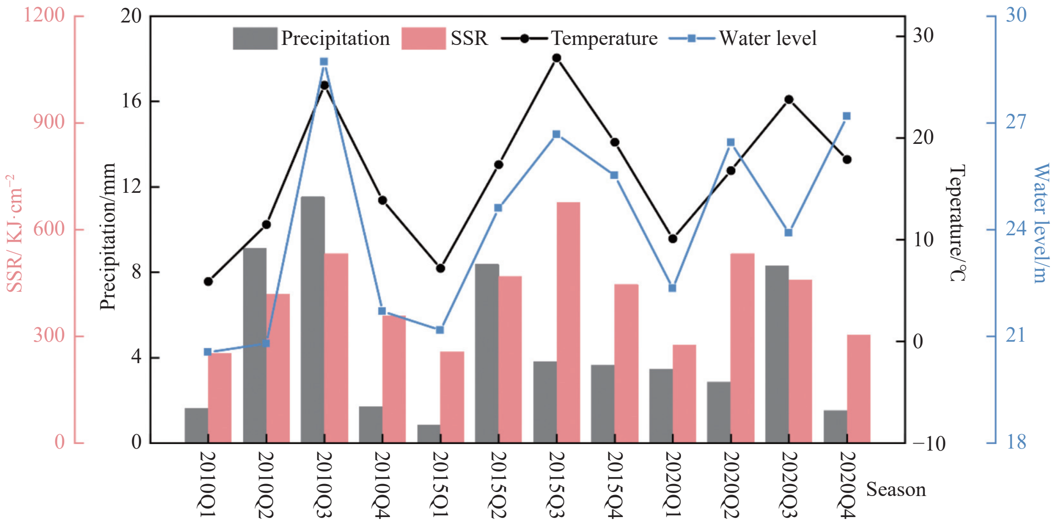

Fig. 6 Seasonal variation of meteorological and hydrological factors

temperature and the combined effects of meteorological and hydrological factors on carbon storage, as shown in Fig. 7. Specifically, SSR has a direct positive effect on carbon storage (+0.663) and an indirect positive effect through its positive influence on temperature (+0.847). Temperature, in turn, positively effects on carbon storage (+0.773), while water level has a negative effect (−0.598). Precipitation has a weak negative effect on carbon storage (−0.159).

To further analyze the driving factors of carbon storage changes across quarters, this study calculated the Pearson correlation coefficients between the areas of different land cover types, meteorological factors, hydrological factors, and carbon storage. The results as shown in Fig. 8.

During the transition from the first to the second quarter, surface solar radiation and temperature exhibited a strong positive correlation with carbon storage. Increased solar radiation and rising temperatures provided abundant energy and favourable conditions for the growth of wetland vegetation, which in turn significantly enhanced photosynthesis and bolstered the wetland's carbon sequestration capacity. Water levels and precipitation also showed a moderate positive correlated, as appropriate water levels and moderate precipitation support vegetation growth and carbon accumulation before flooding occurs. The correlation between water bodies and tidal flat areas with carbon storage was weak, likely due to their lower carbon densities. Woodland and sedge marshes showed a strong positive correlation with carbon storage, especially for woodlands where the correlation coefficient exceeded 0.95, indicating that an increase in the area covered by these types enhances carbon sequestration. However, reed marshes showed a strong negative correlation with carbon storage, as their expansion during this period appeared to encroach on woodland and sedge marshes, thereby reducing overall carbon storage.

During the transition from the second to the third quarter, surface solar radiation and tempera-

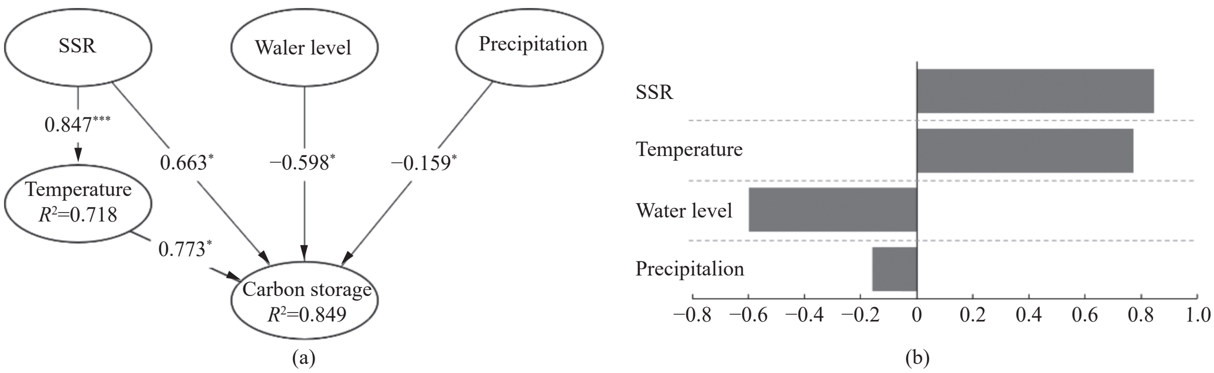

Fig. 7 SEM of driving factors and carbon storage

Notes: The arrows in (a) represent path coefficients, with * indicating P<0.1, ** indicating P<0.05, *** indicating P<0.001, and other paths having P>0.05; (b) illustrates the magnitude of influence of each independent variable on carbon storage.

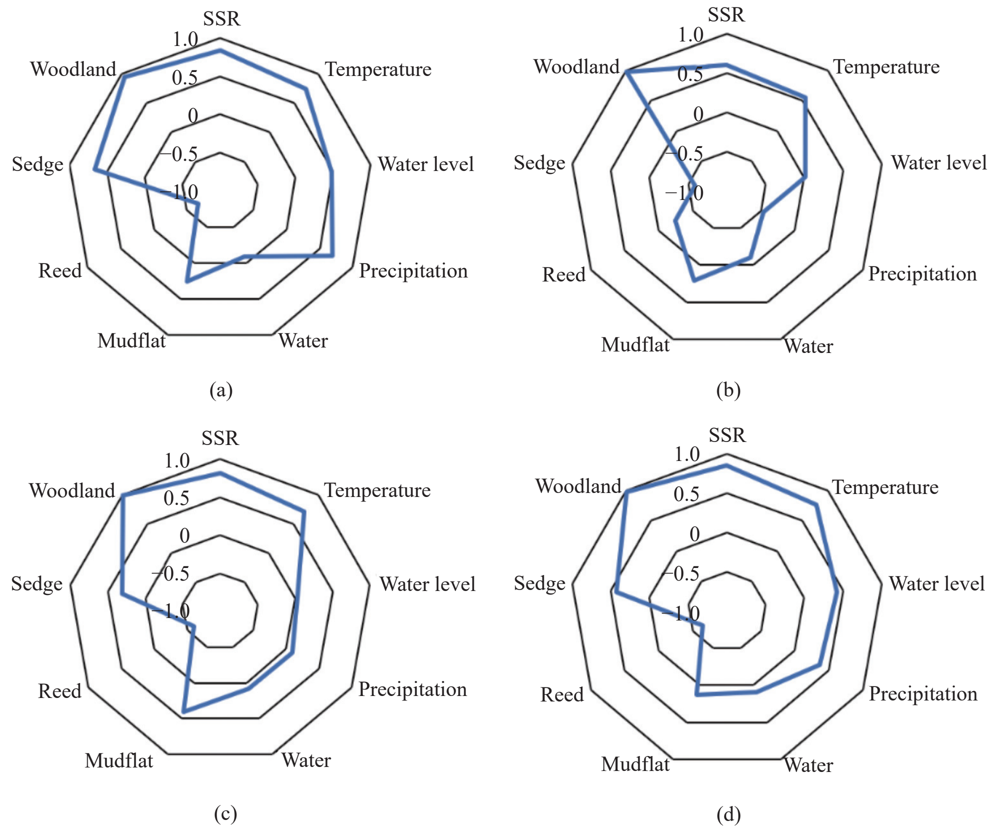

Fig. 8 Pearson correlation coefficient of driving factors and carbon storage

Notes: (a), (b), and (c) represent the first to second quarters, the second to third quarters, and the third to fourth quarters, respectively; (d) represents the 12 quarters of 2010, 2015, and 2020.

ture remained positively correlated with carbon storage, but the correlation diminished, suggesting diminishing marginal benefits for carbon sequestration. The correlation between water level and carbon storage was extremely low, while precipitation was negatively correlated; heavy rainfall during this period may cause flooding, which damage wetland vegetation and release stored carbon. Water bodies and tidal flats continued to show a weak correlation, whereas woodland maintained a very high positive correlation with carbon storage. Meanwhile, area covered by sedge marshes and reed marshes exhibited negative correlations, likely due to competitive interactions with woodland vegetation.

During the transition from the third to the fourth quarter, the positive correlation of surface solar radiation and temperature with carbon storage strengthened, further enhancing their beneficial impact. At this stage, water level and precipitation had only weak correlation with carbon storage, indicating that they were not the main driving factors of changes. The impact of water body area on carbon storage remained at an extremely low level, while the area of tidal flats showed a modest positive correlation as dropping water levels exposed more tidal flats, allowing for organic matter accumulation. Woodland, as a stable source of carbon storage, maintained a high level of positive correlation with carbon storage, whereas sedge marshes and reed marshes exhibited positive and negative correlations with carbon storage, respectively.

In summary, an analysis of the quarterly data from 2010, 2015, and 2020 revealed that different driving factors impact wetland carbon storage in various ways. Surface solar radiation and temperature consistently maintain a significant positive correlation, serving as primary drivers for carbon sequestration. Water levels show a weak positive correlation, particularly during the first-to-second quarter transition. Precipitation has a complex role: Moderate rainfall supports vegetation growth, but excessive rainfall may hinder carbon sequestration.

3 Discussion

The carbon storage changes in the study area from 2010 to 2020 showed an initial increase followed by a decline, a trend generally consistent with findings of other studies in this region (An et al. 2022; Luo and Wang, 2024). Luo and Wang (2024) applied the InVEST model and the optimal parameter geographic detector to explore the univariate and interactive effects of of various factors on carbon storage spatial differentiation in the Dongting Lake ecological economic zone from 1990 to 2020, identifying habitat quality as the primary driving factor. Similarly, An et al. (2022) calculated carbon storage for the Dongting Lake ecological economic zone across multiple years (1995, 2000, 2005, 2010, 2015, and 2020) and used a geographically weighted regression model combined with socioeconomic, elevation, and meteorological data to predict carbon storage trend for 2030, 2040, and 2050. Hou et al. (2024) investigated long-term carbon storage changes over the past 300 years using historical reconstruction data and remote sensing imagery, analyzing the impact of land use and land use patterns on carbon storage. Their findings suggest that increasing the proportion of farmland and construction land leads to a decrease in carbon storage, whereas forest land has the opposite effect. Additionally, they found that the spatial regularity of farmland, construction land, and forest land enhances carbon storage, while the regularity of grassland is positively correlated with carbon sequestration capacity. This suggests that regular landscape arrangements may reduce ecosystem heterogeneity, limit species diversity, and lower ecosystem complexity, thus affecting carbon storage capacity. While most studies on carbon storage have focused on interannual changes, this study analyzed both interannual and quarterly variations. The results indicate that carbon storage peaks in the third quarter and reaches its lowest levels in the first quarter, providing some reference for exploring the patterns of carbon storage variation within a year.

The study revealed that among hydrological and meteorological factors, temperature had the most significant influence on seasonal variations in carbon storage. In the third quarter of each year, despite a substantial increase in water body area due to rising water levels and a corresponding decrease in total vegetation coverage, the positive effect of vegetation entering its peak growing season exceeds the negative impact of higher water levels. As a result, carbon storage typically reaches its annual maximum during this period. However, an exception was observed in 2010, when carbon storage did not peak in the third quarter. Further analysis indicated that an exceptionally large seasonal rise in water levels that year led to an expansion of the water bodies. In this case, the negative impact of rising water levels on carbon sequestration capacity outweighed the positive effect of seasonal vegetation growth, preventing carbon storage from reaching its expected peak. It was also found that land use changes had varying correlations with carbon storage. The areas covered by water bodies and tidal flats exhibited a weak correlation with carbon storage, while reed marshes showed negative correlations. This is because reeds often reach their peak growing season as sedge marshes and woodlands begin to degrade, replacing these higher carbon density vegetation types. Consequently, the expansion of reed marshes statistically corresponds to a decline in carbon storage. In contrast, sedge marshes showed a moderate positive correlation with carbon storage, maintaining a relatively stable carbon sequestration capacity. Woodlands consistently showed a strong positive correlation with carbon storage throughout the year, highlighting their critical role in carbon sequestration, which is consistent with the findings of Ji et al. (2020).

It is important to note that the carbon sequestration process in wetland ecosystems is highly complex, with spatial and temporal variations influenced by multiple factors across different scales and dimensions. In addition to natural factors, social factors related to human activities may also have a significant impact on carbon storage, especially land use change (Chen et al. 2015). Firstly, ecosystem restoration measures, such as the conversion of farmland to forest program, the comprehensive management project of rocky desertification, and the natural forest protection project, contribute to increase carbon storage (Tong et al. 2018; Hu et al. 2022). Conversely, urbanization practices, such as converting forests and grasslands to croplands, or further transforming croplands into industrial/urban areas, reduce humus inputs to soils. Furthermore, agricultural intensification disrupts soil organic matter stabilization and accelerates humus mineralization, thereby reducing carbon storage (Li et al. 2022) Secondly, the discharge of harmful pollutants, including heavy metals, can inhibit plant growth and development (Zhang et al. 2019), leading to a decrease in carbon storage. In addition, the basic necessities of human life, such as clothing, food, housing, and transportation, all form carbon sources (Liddle, 2014). As a result, the increase in population density often correlates with the decrease in ecosystem carbon storage (Yang et al. 2023). Addressing these anthropogenic influences remains a critical area for future research.

The resolution of remote sensing imagery and the choice of interpretation methods have a certain impact on the accuracy of wetland land cover classification, which poses challenges for wetland remote sensing studies. The integration of advanced image processing algorithms and multi-source data fusion techniques can significantly improve classification accuracy. Models such as the STARFM (Gao et al. 2006), the ESTARFM (Zhu et al. 2010), and STAFFN (Chen et al. 2018) effectively fuse the high-frequency temporal information of MODIS images with the high spatial resolution data of Landsat images, yielding remote sensing data with improved spatiotemporal accuracy. Future research could incorporate emerging technologies and methodologies to generate high-precision, long-term time-series images, providing more reliable data for analyzing spatiotemporal variations in carbon storage.

4 Conclusions

This study systematically analyzed the spatiotemporal variations and driving factors of carbon storage in the Dongting Lake Wetland by integrating MODIS remote sensing imagery, the InVEST model, meteorological and hydrological data, and structural equation modeling across different seasons for the years 2010, 2015, and 2020. The findings reveal significant seasonal and interannual fluctuations in carbon storage. The key conclusions drawn from the study are as follows:

(1) Seasonal variations of carbon storage: Carbon storage in the wetland follows a distinct seasonal pattern. In the first quarter, limited surface solar radiation and low temperature restrict vegetation growth, resulting in the lowest carbon storage. In contrast, the third quarter marks the peak growth period of wetland vegetation, with enhanced photosynthesis significantly boostingcarbon sequestration, resulting in the highest annual carbon storage. The second and fourth quarters exhibit intermediate levels, with the second-highest and second-lowest carbon storage, respectively.

(2) Interannual trend in carbon storage: From 2010 to 2020, the average annual carbon storage initially increased before declining. The highest recorded value occurred in 2015, reaching 322.30 Tg. The amplitude of intra-annual fluctuations has intensified, with the coefficient of variation growing from 8.5% in 2010 to 25.8% in 2020. This trend suggests that seasonal variability in wetland carbon storage has become more pronounced in recent years.

(3) Influence of meteorological and hydrological factors: Temperature plays a significant role in seasonal variations in carbon storage, while surface solar radiation directly enhances carbon storage and also indirectly influences it through temperature increases. Precipitation and water level fluctuations exhibit negatively impact, particularly during seasonal rise in water levels which expand water bodies and inhibit wetland vegetation growth, ultimately reducing carbon storage. Appropriate regulation of water levels in the Dongting Lake Wetland is therefore crucial for maintaining carbon sequestration potential.

(4) Impact of human activities and management implications: In addition to natural factors, carbon storage dynamics are significantly influenced by human activities, particularly land use changes. Future conservation efforts should prioritize wetland ecosystems protection and restoration, regulate water level fluctuations, enhance carbon sink functions, and minimize carbon source emissions. These strategies will support the sustainable development of wetland ecological functions contribute to long-term carbon sequestration.

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