Carbon Research

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# Estimation methods of wetland carbon sink and factors influencing wetland carbon cycle: a review

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**Abstract**

In the global ecosystem, wetlands are vital carbon sinks, playing a crucial role in absorbing greenhouse gases such as carbon dioxide and mitigating global warming. Accurate estimation of wetland carbon content is essential for research on wetland carbon sinks. However, the carbon cycle of wetlands is complex, and the carbon sinking of wetlands is affected by climate, topography, water level conditions, vegetation types, soil types, and other factors. This has caused significant challenges in the estimation of wetland carbon sinks. In current studies, most research has focused on the impact of individual factors on wetland carbon sinks, often ignoring the interaction between various factors, which further leads to uncertainty in wetland carbon measurements. This paper aims to elucidate the process of the wetland carbon cycle, summarize the factors affecting wetland carbon sinks, and explore the interplay between various factors and their influence on wetland carbon sinks, aiming to provide theoretical support for the study of wetland carbon sinks. Additionally, this paper reviews the advantages and disadvantages of current wetland carbon measurement methods, proposes research directions for combining machine learning methods, identifies existing difficulties in current wetland carbon measurement, and offers suggestions to serve as a reference for future wetland carbon sink estimation and wetland management.

**Highlights**

- The potential and significance of wetland carbon sinks are explained.
- The advantages and disadvantages of current wetland carbon measurement techniques are summarized.
- The prospective method for integrating machine learning into integrated wetland carbon measurement is proposed.

**Keywords** Wetland carbon sink, Carbon sequestration, Carbon measurement, Machine learning, Carbon dioxide, Carbon cycle

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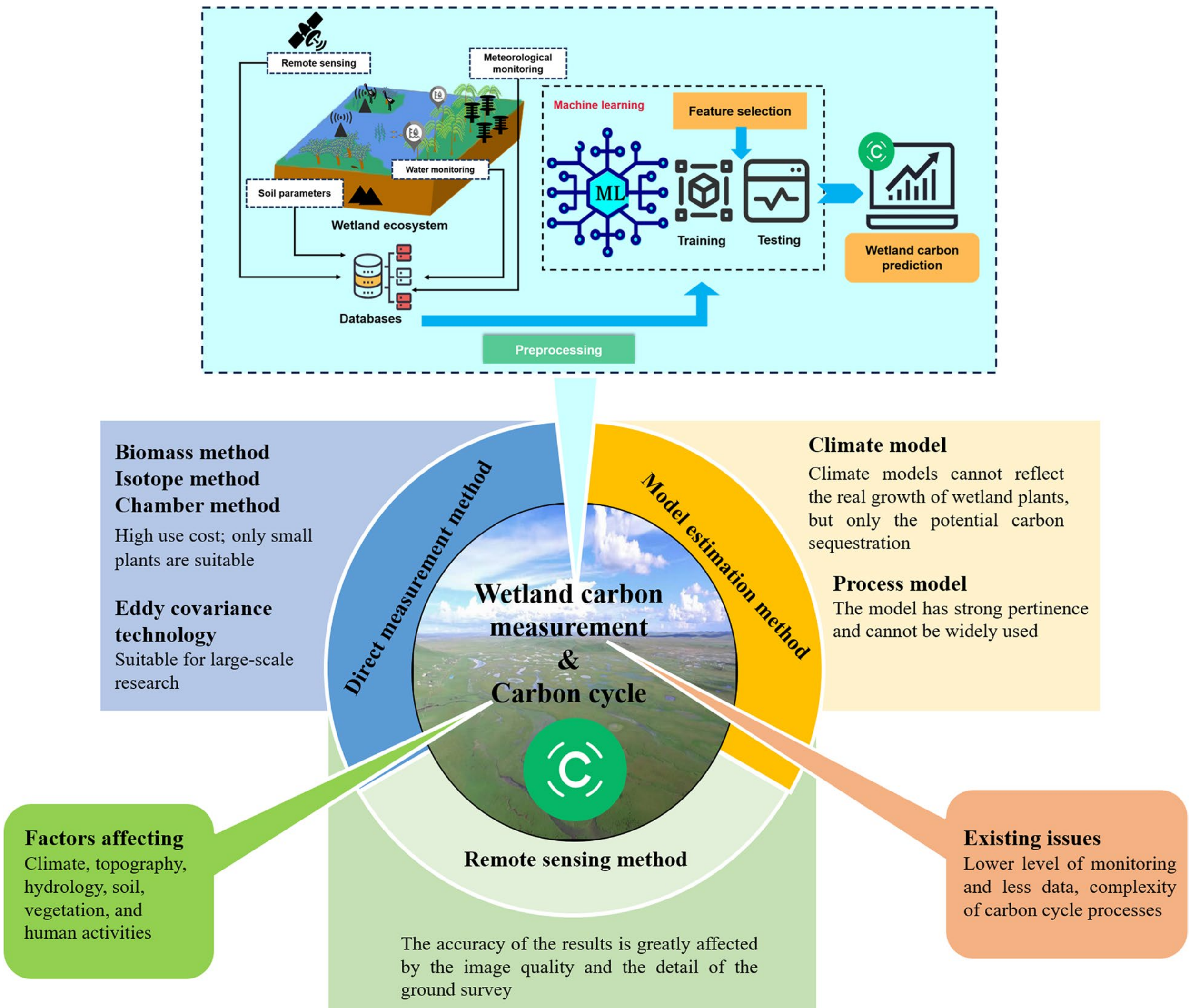
**Graphical Abstract**




## 1 Introduction

Wetlands are among the soils with the most abundant carbon content in the world, and they are also among the soils with the highest carbon storage per unit area in all terrestrial ecosystems (Zhang et al. 2024). The wetland ecosystem is formed by the interaction between water and land (Li et al. 2022a, b, c; Li et al. 2022a, b, c). Wetlands slow down the decomposition rate due to their anoxic soil conditions, resulting in the accumulation of a large amount of organic carbon (Nahlik and Fennessy 2016). Therefore, wetlands have become important carbon sinks in the atmosphere and have a profound impact on reducing greenhouse gases (Callaway et al. 2012; Taillardat et al. 2020). However, current research on estimating wetland carbon sinks is still in the initial stage of development, and the carbon cycle process of wetlands is complex, with many factors affecting wetland carbon sinks. Therefore, estimating wetland carbon sinks remains a challenge.

To clarify the carbon sequestration capacity of wetlands, researchers conducted carbon measurements to assess their potential as carbon sinks (Luis et al. 2014; Wang et al. 2020; Yu et al. 2022). Currently, carbon measurement methods for wetlands are roughly divided into three categories: direct measurement method, model estimation method, and remote sensing method (Li et al. 2020). The direct measurement method is used to directly measure the carbon flux between water, vegetation, soil, and gas. It is usually used for small-scale measurement or for verifying large-scale or regional-scale estimation results (Alexandrov et al. 2002). However, it is somewhat destructive to vegetation, and the limited data obtained make large-scale measurements challenging (Li et al. 2022a, b, c). In the model estimation method, the Thornthwaite Memorial model, which is proposed based on the relationship between average evaporation, temperature, precipitation, and vegetation, is widely used in climate models (Zhang et al. 2022a, b). However, climate models cannot reflect the actual growth status of plants and can only represent the potential net primary productivity (NPP) of vegetation (Zhou et al. 2013). The regional scale process models mainly include BEPS (Koju et al. 2020), Biome-BGC (Li et al. 2020), CENTURY and others. This kind of model is composed of several sub-models according to the carbon cycle process and mechanism of wetland (Zhang et al. 2002). These models consider the influence of soil, hydrology, and vegetation on the carbon cycle of wetlands, especially the biogeochemical processes such as changes in water levels, soil characteristics, hydrological conditions affecting soil temperature, carbon fixation by herbaceous and bryophytes, and the impact of aerobic conditions on decomposition (Li et al. 2006). Each sub-model collaborates with one another to complete the estimation. While the process model's reliability is high, its complexity is also high (McGuire et al. 1997; Li et al. 2023a, b, c). Converting parameters at grid points to different scales is relatively challenging in regional and global estimation processes, affecting their large-scale utilization (Friend et al. 1997). The remote sensing method primarily utilizes satellite data on large-scale photosynthetically active radiation, photosynthetically active radiation absorption rate, vegetation index, and light energy utilization rate to estimate net ecosystem productivity (GPP) and NPP, thereby reflecting the impact of large-scale climate change on NPP. Currently, data sources such as NOAA-AVHRR, SPOT, TM, MODIS, aerial remote sensing, and microwave remote sensing are widely utilized in estimating GPP and NPP through remote sensing techniques (Zhao et al. 2010). However, due to variations in research methodologies and spatial and temporal scales, the applicability and generalization of results and predictions remain challenging, necessitating extensive measured data for validation (Valentini et al. 2000). While these methods partially fulfill wetland carbon measurement requirements, they still exhibit limitations that impede widespread adoption. Moreover, given the intricate nature of wetland carbon cycles and their susceptibility to numerous factors, accurate wetland carbon measurement forms the cornerstone of wetland carbon sink research. It holds significant importance in wetland carbon monitoring, protection, and enhancing carbon sequestration efforts. Consequently, the development of more effective wetland carbon measurement methods remains imperative.

The wetland carbon cycle and flux dynamics are influenced by various external factors, including wetland type, soil properties, vegetation, geographical location, human disturbance, and meteorological conditions such as temperature and precipitation (Nag et al. 2017; Zhao et al. 2023). These factors contribute to the complexity of wetland carbon measurement. For instance, different wetland types exhibit varied capacities for carbon absorption, transformation, and storage, leading to uncertainty regarding their role as carbon sources or sinks (Wang et al. 2022b, a; Zhang et al. 2024). A six-year study conducted on peatlands in Northern Ireland revealed that the collective emissions of $CH_4$ and dissolved organic carbon surpassed $CO_2$ sequestration for over two years (Koehler et al. 2011). Additionally, during warm or dry summers, northern peatlands transition to atmospheric carbon sources, with fluctuations in wetland carbon sequestration primarily attributed to annual variations in hydrological conditions (Waddington and Roulet 2000; Li et al. 2023a, b, c). Sanderman et al. (2013) examined the uncertainty in soil carbon accounting stemming from unresolved soil erosion. In southeastern Australia, the dynamics of soil redistribution introduce uncertainty into carbon assessment (Chappell et al. 2012). The soil carbon pool is a crucial component of the wetland carbon pool, primarily influenced by three main factors: the microenvironmental conditions affecting decomposition (hydrology, temperature, pH, and Eh), the nature of the substrate, and decomposition time. Wetland vegetation influences the carbon cycle through stomatal regulation, with carbon fixation influenced by factors such as vegetation type, canopy $CO_2$ concentration, seasonal fluctuations in moisture, and water level changes. Notably, vegetation residues often undergo conversion into peat due to water limitation and strong reducibility (Albuquerque and Mozeto 1997). Wetland vegetation biomass undergoes rapid changes during growth, with root biomass indirectly estimated from aboveground biomass, introducing additional uncertainty to carbon measurement (Fahey et al. 2010). Water's capacity to store $CO_2$ is primarily influenced by climate, nutrient levels (N, P, Fe) (Ziheng et al. 2021), water acidification, eutrophication, increased solar ultraviolet radiation, and adjacent ecosystems, while carbon release from water is primarily due to runoff from lakes, mineralization, degradation, and human activity such as fishing (Carminati et al. 2016; Li et al. 2022a, b, c). Human disturbance alters the balance of carbon sources and sinks in wetlands, leading to increased greenhouse gas emissions (Li et al. 2022, 2022a, b, c; Peters et al. 2012). Additionally, climate, topography, and hydrological conditions, among other factors, not only influence the wetland carbon cycle but also interact with each other, making it challenging to identify the key driving factors affecting wetland carbon sinks.

Recently, global attention to natural carbon sinks has increased. However, research on natural carbon sink estimation mainly focuses on forests, grasslands, and oceans, with few studies on wetland carbon sink estimation. Currently, the methods for estimating wetland carbon sinks in the existing literature are relatively scattered, and the summary of the influencing factors of wetland carbon sinks is not comprehensive enough. Additionally, the influencing factors of wetland carbon sequestration capacity tend to focus on the description of independent factors and lack consideration of interaction and correlation between factors from a systematic perspective. This paper reviews and discusses the influencing factors of the wetland cycle and wetland carbon sink and the correlation between various factors, summarizes the advantages and disadvantages of existing wetland carbon measurement methods, and addresses the difficulties of current wetland carbon measurement. Finally, by combining emerging technologies, this paper prospectively explores the development of wetland carbon measurement methods, in order to provide a theoretical basis for establishing a more credible, accurate and effective wetland carbon sink calculation method and improving the carbon sequestration capacity of wetlands.

## 2 Influencing factors of carbon cycle and carbon sink in wetland

### 2.1 Wetland carbon cycle

The significance of carbon sinks in terrestrial ecosystems is determined by the dynamics of the ecosystem's carbon cycle. The ecosystem carbon cycle involves the exchange of $CO_2$-based carbon between ecosystems and their surroundings (Wang et al. 2021). Ecosystems can be categorized as either carbon sources or sinks based on their carbon balance: carbon sources indicate that emissions exceed absorption, while carbon sinks indicate that total absorption exceeds emissions. The dynamic changes in the ecosystem carbon cycle will influence the magnitude of the ecosystem's carbon source and sink, thereby regulating the concentration of $CO_2$ in the atmosphere and the trajectory of global warming (Friedlingstein et al. 2006; Matthews and Keith 2007; Williams et al. 2019). As illustrated in Fig. 1, the wetland carbon cycle comprises two components: aerobic and anaerobic. It involves photosynthesis and respiration under aerobic conditions, and primarily $CH_4$ production under anaerobic conditions. Vegetation utilizes $CO_2$ during photosynthesis to synthesize organic matter. The respiration of wetlands involves the conversion of carbohydrates into $CO_2$. In wetlands, organic carbon is converted into compounds, including $CO_2$ and $CH_4$, stored in plants, dead plant matter, microorganisms, or peat. Under anaerobic conditions, $CH_4$ is also generated and released into the atmosphere. Moreover, the movement of soluble and particulate organic carbon with water enhances the wetland's role in the broader carbon cycle. Protecting wetlands is crucial for the atmospheric carbon cycle since a substantial portion of the soil carbon pool is stored within them. When plant productivity exceeds decomposition, net soil carbon accumulation occurs. This process eventually leads to the formation of deep peat deposits, which can accumulate for thousands of years. However, wetland conditions are crucial for carbon accumulation and storage. For instance, wetland drainage introduces oxygen into the soil, thereby accelerating the decomposition of organic matter. Consequently, organic carbon, nitrogen, and other nutrients in the soil are rapidly lost (Liu et al. 2017). Therefore, protecting wetlands helps to reduce greenhouse gas emissions.

### 2.2 Factors influencing wetland carbon sinks

The carbon sequestration capacity of wetlands is influenced by the uptake and emission of greenhouse gases in the carbon cycle process. This process is regulated by numerous factors, including climate, topography, hydrology, soils, vegetation, and human activities. Moreover, there are interactions between these factors. As a result, the amount of carbon captured and released by wetlands may vary significantly. When estimating the carbon sequestration potential of wetlands, it is essential to consider the impact of various factors on their carbon storage (Table 1).

Climate change has been identified as a significant threat to wetlands (Stewart et al. 2013). It can impact wetland ecosystems by increasing temperatures and altering hydrological patterns (Erwin 2009). Climate change can influence wetlands through direct and indirect effects such as rising temperatures, changes in rainfall intensity and frequency, droughts, floods, and storm frequency (Ray et al. 2016). As a result of climate change, the decomposition rate of wetlands exceeds the production rate, potentially causing wetlands to transition from sinks to carbon sources, emitting $CO_2$ and $CH_4$ into the atmosphere (Laiho 2006; Flanagan and Syed 2011). For example, peatlands are natural wetlands characterized by peat accumulation, containing a large amount of organic matter. Peatlands account for about 3–4% of the world's land area and contain 400–500 Pg C, equivalent to half of the carbon in the atmosphere (Gorham 1991). For thousands of years, peatlands have served as a persistent carbon sink, which is an important function for peatlands to mitigate climate change (Dise 2009). Peat decomposition

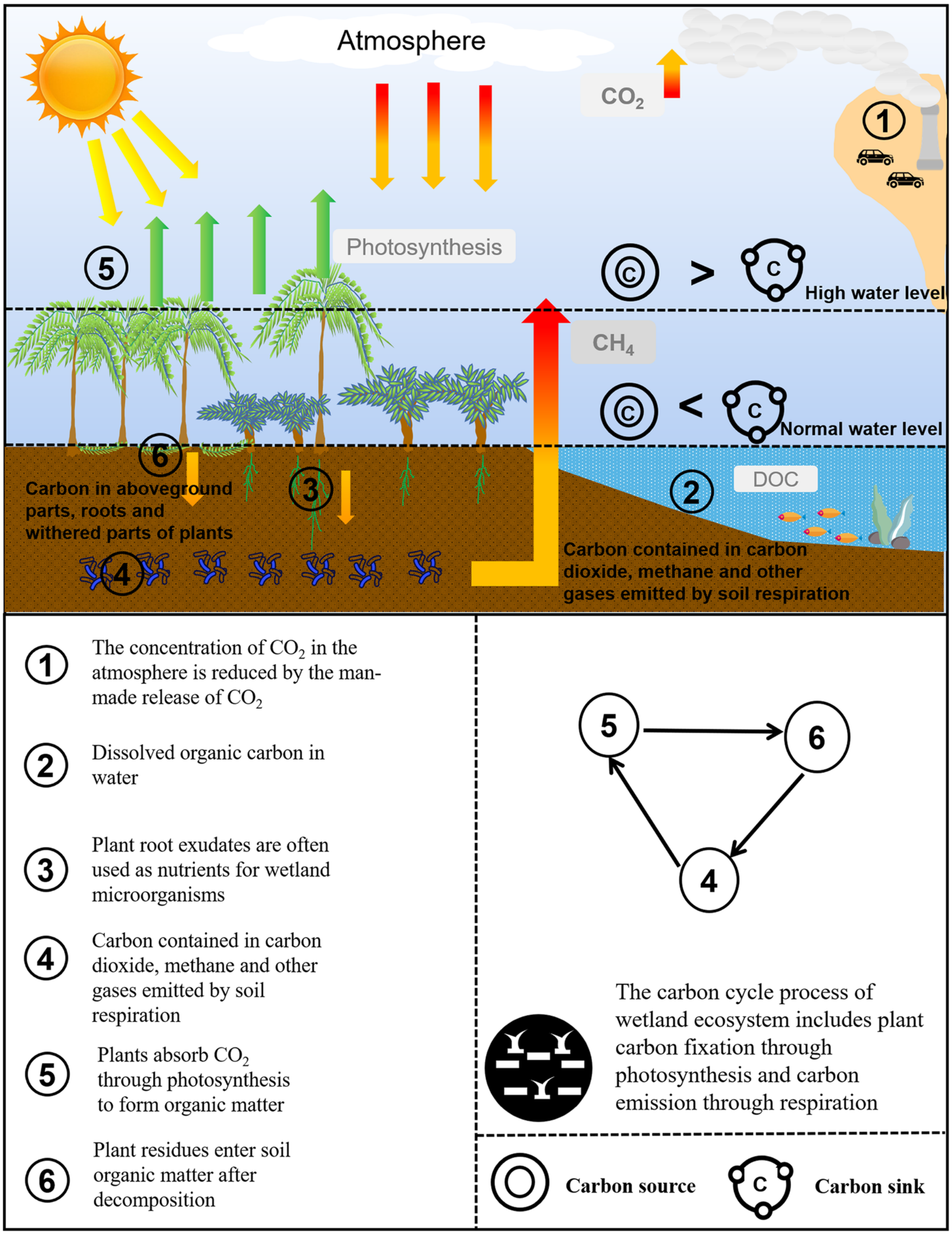



**Fig. 1** Wetland carbon cycle

is a highly complex process that depends on various parameters such as temperature, humidity, aeration, plant composition, and microbial community. These factors interact and change over time and with depth. Among all these variables, temperature and water use efficiency play pivotal roles in peat decomposition (Gong et al. 2020). Climate change leads to higher temperatures, lower water levels, and peat drought, resulting in a higher peat decomposition rate. Another consequence of peat decomposition is that microorganisms exhibit a higher respiration rate for the decomposed organic matter, leading to the release of carbon into the atmosphere. Furthermore, since low primary productivity ($CO_2$ captured by photosynthesis) cannot offset the release of carbon dioxide, carbon sequestration will be limited (Lund et al. 2012; Aronson et al. 2013). However, if the

**Table 1** The influence factors of wetland carbon sink and its influence degree

| Influencing factors | Degree |
|---|---|
| Temperature | Elevated temperatures increase transpiration, decrease soil moisture, condense hydrolysis cycles, and accelerate wetland drying. |
| Precipitation | Precipitation can determine net primary productivity of vegetation. |
| Water levels | Fluctuations in wetland water levels due to seasonal wetting and drying can affect carbon dioxide and methane emissions. |
| Sea level rise | The vegetation composition of coastal wetlands is changed. |
| Soil | Different global wetland types have different rates of carbon accumulation or decomposition, different soil organic carbon densities, and different carbon sequestration capacities. |
| Vegetation | Vegetation converts atmospheric carbon dioxide into organic matter through photosynthesis and stores it in the organic structure of vegetation. Root exudates provide nutrients to wetland microorganisms and influence carbon sequestration and emission processes in wetlands. |
| Wetland type | Wetland types affect vegetation and carbon-fixing microbial communities. |
| Human activity | Overgrazing, agricultural reclamation and urban development can disrupt the ecological balance, reduce the number of animals and plants, decrease ecosystem productivity, and increase carbon loss in wetlands. |

increase in temperature is accompanied by an increase in precipitation, primary productivity may increase, and peatlands can maintain their vital role as natural carbon sinks for mitigating climate change (Backstrand et al. 2010; Vitt et al. 2000). Changes in precipitation and temperature impact inland wetlands. The sea level rise caused by climate change will impact coastal wetlands (Mitsch and Hernandez 2013). Sea level rise caused by climate warming may alter the vegetation composition of coastal wetlands and impact ecosystem functions, including photosynthetic activity, biomass production, litter decomposability, and nutrient cycling, thereby affecting the carbon sequestration rate of coastal wetlands (Mitsch and Hernandez 2013; Zhou et al. 2023).

The carbon sequestration function of wetland vegetation involves converting atmospheric $CO_2$ into organic matter via photosynthesis and storing it within the vegetation's organic structure (Pal et al. 2017). Root exudates provide nutrients for wetland microorganisms, influencing the processes of carbon absorption and emission in wetlands (Hoffman et al. 1998; Zhao et al. 2022; Bai et al. 2023). Vegetation is the main source of ecosystem carbon sequestration. The difference in carbon sequestration capacity of different wetland ecosystems is controlled by hydrological factors and depends on vegetation types (Lolu et al. 2019). For example, sedge meadows and reed marshes are carbon sinks on an interannual time scale. However, in the flood season, due to the different degree of inundation, the sedge meadow changed from a carbon sink to a carbon source. The effect of flood on the carbon sink function of reed marshes depends on the water level. The carbon sink function of reeds was enhanced under the inhibition of moderate floods, but weakened during the flood season due to extremely high water levels (Wang et al. 2024). Collecting and accurately estimating below-ground biomass data for wetland vegetation poses challenges. To estimate the carbon stock of wetland vegetation litter, litter is harvested from sample plots, its biomass measured, and then converted using a carbon content factor. Decomposition rates of dead litter vary across wetland ecosystems. Therefore, the contribution of dead litter to the total carbon stock differs and must be estimated based on specific conditions (Dayathilake et al. 2020).

Soil represents the largest land-based carbon pool, playing a pivotal role in the global carbon cycle (Chapin et al. 2009; Hansen and Nestlerode 2014). Wetland soils typically have a high organic carbon density, with various wetland types collectively storing approximately 30% of terrestrial carbon (Yoo et al. 2022). Various global wetland types display different rates of carbon accumulation or decomposition, diverse soil organic carbon densities, and distinct carbon sequestration capabilities (Zamora et al. 2022; Li et al. 2023a, b, c). For instance, isolated wetlands exhibit low soil bulk density yet high carbon concentration (Perez-Rojas et al. 2019; McClellan et al. 2017); whereas river wetlands possess higher volume density but lower carbon concentration (Dong et al. 2020).

The wetland ecosystem is characterized by its hydrological conditions. Variations in wetland water levels due to seasonal fluctuations between dry and wet periods can influence emissions of carbon dioxide and methane (Guo et al. 2023). Changes in water conditions, particularly disruptions in wetland ponding and drainage measures, can significantly influence organic carbon accumulation. These changes might have a profound impact on both wetland ecosystems and the global carbon cycle (Zhang et al. 2022a, b).

The carbon storage in wetlands is also significantly influenced by wetland types (Ma et al. 2022). For example, lake basins generally encompass swamps, rivers, and lake wetlands. The interaction between topography

**Table 2** Comparison of wetland carbon measurement methods

| Method | Advantage | Limitations | Scope of application |
|---|---|---|---|
| **Isotope method** | The isotope method can be used for in-situ determination to avoid interference, and the test results are more accurate. | High use cost. | Only small vegetation is suitable. |
| **Chamber method** | Simple operation, low cost, convenient and fast, repeatable operation and continuous observation. | There will be box effect and uncertainty in the result. | It is applicable to the gas exchange flux between vegetation / atmosphere or soil / atmosphere. |
| **Biomass method** | Biomass method is direct, simple and easy to operate. | Closely related to a variety of factors, such as soil type and climate conditions, the measurement results are not accurate enough. | It is only widely used in small-scale biomass estimation. |
| **Eddy covariance technique** | Wetland ecosystems can be studied as a whole. | It is easily affected by the environment, and the required equipment is expensive, the operation is difficult, and the test cycle is relatively long. | Suitable for large-scale research. |
| **Model simulation method** | The productivity and carbon storage of wetland ecosystems are estimated by considering environmental factors through mathematical model. | The model has strong pertinence and cannot be widely used. | It is not only a necessary means to study the carbon cycle of large-scale wetland ecosystems, but also an important means to predict the long-term change of soil carbon. |
| **Remote sensing technique** | It provides a new possibility for long-term quantitative observation of large-scale and high-resolution ecosystem changes. | The accuracy of the results is greatly affected by the image quality and the detail of the ground survey. | It is suitable for studying the change of vegetation carbon pool in a large scale. |

and water leads to the difference of vegetation distribution among different types of wetlands (Xu et al. 2021). Emergent plants are widely distributed in marsh wetlands with relatively shallow water levels. The well-developed roots of emergent plants can secrete root exudates and increase the organic carbon content in sediments (Fang et al. 2019). River and lake wetlands with high water level generally cannot support the growth of emergent plants. River wetlands are ecosystems composed of flowing water bodies, while lake wetlands are static ecosystems characterized by slow water flow or relatively static water bodies. Due to the low water flow rate, a large amount of particulate matter and organic matter is often deposited at the bottom of lakes (Zhang et al. 2017). Therefore, differences in plant growth and water flow status in different types of wetlands will significantly affect the content of organic matter in sediments, potentially resulting in variations in the structure and activity of carbon-fixing microbial communities in these wetlands (Fang et al. 2020). As a crucial component of wetland carbon sequestration, autotrophic microorganisms account for 8–27% of the organic carbon pools in wetlands. Microorganisms drive the carbon cycle of wetland soils through catabolism and anabolism. Studies have found that the carbon dioxide sequestration potential of microorganisms depends on the type of wetland (Zhang et al. 2023).

Human activities amplify the effects of natural factors, resulting in significant changes in wetlands. Primary human activities impacting wetlands include overgrazing, agricultural reclamation, and urban development. These activities degrade the ecological balance, reduce flora and fauna, diminish ecosystem productivity, and contribute to wetland carbon loss. Over the past few centuries, peatlands have emitted 160 to 250 Tg C $yr^{-1}$ into the atmosphere due to drainage or reclamation (Bridgham et al. 2007).

## 3 Carbon measurement methods of wetlands

Measuring wetland carbon is essential for estimating carbon sinks (Tadic et al. 2021). Whether studying vegetation or soil carbon sinks in wetlands, measuring environmental variables is crucial before assessing the capacity of the carbon sink. Protecting wetland ecosystems, promoting carbon sequestration, and reducing global emissions are of paramount importance. Various methods, based on distinct principles and tools, are used in wetland carbon measurements, each with its pros and cons. Wetland environmental conditions add uncertainty to carbon measurements. Each carbon measurement method discussed in this paper possesses distinct advantages and limitations ( Table 2).

### 3.1 Direct measurement method

The direct measurement method quantifies the carbon flux between water, vegetation, soil, and atmosphere. The direct measurement method quantifies the carbon flux between water, vegetation, soil, and atmosphere. The biomass method estimates the aboveground biomass per unit area by sampling specific plots and analyzing the vegetation within (Brix et al. 2001; Edwards et al. 2006). For example, the biomass of tree species in Finnish forest peat bogs was estimated using established biomass equations (Minkkinen et al. 2002). However, vegetation growth is a dynamic process closely related to various factors such as soil type and climate conditions. Therefore, the measurement results using biomass method are not accurate enough and are only widely used for small-scale biomass estimation (Bayley and Guimond 2009). The isotope method employs tracers and decay laws of isotopes to study soil age and carbon sources (Beach et al. 2011). Carbon isotope methods have been used by researchers to study carbon exchange between wetlands and the atmosphere (Krüger et al. 2002). The isotope method can be used for in-situ determination to avoid interference, and the test results are more accurate, but it is only suitable for small vegetation and the cost of use is high. The chamber method estimates net carbon exchange, but its accuracy can be compromised due to environmental changes (Ohlsson et al. 2005; Villa and Bernal 2018). Both static and dynamic factors will seriously change the spatial variability of observed gases due to the enclosure effect, the living environment covered by vegetation will change, and the soil environment will be disturbed, resulting in the change of trace gas concentration gradient, pressure gradient, turbulence pulsations, and gas flow, which makes the measurement results difficult to reflect the actual situation (Davidson et al. 2002). Eddy covariance measurement evaluates wetland ecosystems holistically, though it has limitations based on environmental conditions (Glenn et al. 2006). The eddy covariance technique was utilized by researchers to measure methane emissions from temperate wetlands (Kowalska et al. 2013). However, the carbon flux of eddy covariance measurements is affected by wind direction, atmospheric stability, roughness below, and probe mounting height, and requires a flat and homogeneous environment, expensive equipment, difficult operation, longer test cycles, and increased test costs.

### 3.2 Model estimation method

Simulation models offer statistical tools for estimating productivity and carbon stocks in wetland ecosystems. Currently, the commonly used models include process models, climate models, etc.

Climate models estimate carbon sequestration based on correlations with meteorological factors, representing potential rather than actual carbon sequestration. However, climate models cannot reflect the real growth of wetland vegetation, but only the potential carbon sequestration. The process models measure the carbon sequestration potential of wetlands by studying the growth mechanism and environmental factors of vegetation. The DNDC model is usually used for this purpose (Li et al. 2007). The model is a classical wetland process model, which comprehensively considers the control of soil, hydrology, and vegetation on the wetland carbon cycle, especially the biogeochemical processes such as water level change, the impact of soil characteristics, the impact of hydrological conditions on soil temperature, carbon fixation of herbs and bryophytes, and the impact of aerobic conditions on decomposition (Zhang et al. 2002). Numerous models address the wetland ecosystem's carbon cycle, with peatland models like those by Frolking et al. (2001) and Heinemeyer et al. (2010) being especially prevalent, the CLIMBER2 -LPJ model, the McGill wetland model simulating peatland NPP and GPP, the peat decomposition model, the peat core formation and distribution model, the SEMITEC model and the peat age series model MILLENIA. While theoretical models are mechanistically clear, their broad application is limited by data needs and scaling challenges.

### 3.3 Remote sensing method

The advent of remote sensing technology has enabled long-term, quantitative observations of ecosystem changes at both large scales and high resolutions. Researchers have started to integrate remote sensing technology with ecosystems to develop models based on satellite data. Notably, the CASA remote-sensing-driven ecosystem model and the PIXGRO model, which integrate remote sensing data, have demonstrated significant potential for simultaneous studies of carbon and water vapor fluxes (Adiku et al. 2006; Boegh and Soegaard 2004). Furthermore, the synergy of GIS, remote sensing technology, and ecological modeling can assess carbon dynamics across various spatial scales (Lal 2002), including determining spatial and temporal changes in wetland systems (Irdemez and Eymirli 2021), evaluating the sensitivity of wetlands to climate change (Ouyang et al. 2014), and monitoring methane emission fluxes from peat wetlands (Zhang et al. 2020). The net primary productivity of vegetation is the portion of $CO_2$ fixed by photosynthesis to organic matter per unit time and unit area and the remaining portion after deducting respiration, which is a direct reflection of the carbon sequestration efficiency of vegetation (Liao et al. 2022; Shen et al. 2022). The vegetation index was obtained using remote sensing images, and the net primary productivity of vegetation was calculated based on the vegetation index, and then the carbon sequestration potential was calculated using wetland area change parameters (Huang et al. 2022; Wang et al. 2022b, a). While remote sensing technology is apt for studying large-scale vegetation carbon pool changes, the accuracy of its results is contingent upon image quality and the granularity of ground investigations.

## 4 Existing issues and future outlook

### 4.1 Existing issues

Due to the carbon cycle of the wetland occurring primarily within soil, water, and vegetation, which is controlled by many factors such as wetland types and elements, there are great differences in decomposition rate and transformation products, resulting in more complex heterogeneity of wetland carbon spatial distribution, which has caused many problems and difficulties for wetland carbon measurement (Zheng et al. 2013; Spangler et al. 2021).

Additionally, due to the rapid change of wetlands and the poor accessibility of ground investigation, even using modern remote sensing technology, it is impossible to obtain the real-time distribution of wetlands, especially the accurate temporal and spatial dynamics of flooded areas (Nghiem et al. 2017; Chen et al. 2022). The scientific definition and boundary determination of wetlands are constantly controversial (Yin and Lu 2006), and the control factors and mechanism of the wetland carbon cycle and the threshold of carbon source or sink pattern transformation are not clear (Braun et al. 2019; Fortuniak et al. 2021), and the current wetland carbon sink estimation research considers the influence of independent factors, with less consideration given to the interaction between various factors, so the key driving factors may be ignored. The degree of detailed monitoring of wetlands is low; wetland soils, and organic carbon data from water bodies are lacking and obsolete; all these factors cause great uncertainty in wetland carbon measurement.

### 4.2 Future outlook

In order to achieve more accurate and reliable wetland carbon measurement, new approaches need to be opened up. Machine learning can deal with the complex relationship between input parameters and target variables (Zhong et al. 2021; Xu et al. 2022). Different from other methods, the machine learning model does not assume the relationship between functions in the process of estimating NPP, but optimizes the estimation of NPP through continuous learning. This method will not artificially set the effective interval when optimizing the model parameters, which is more objective. In addition, machine learning can effectively solve complex,

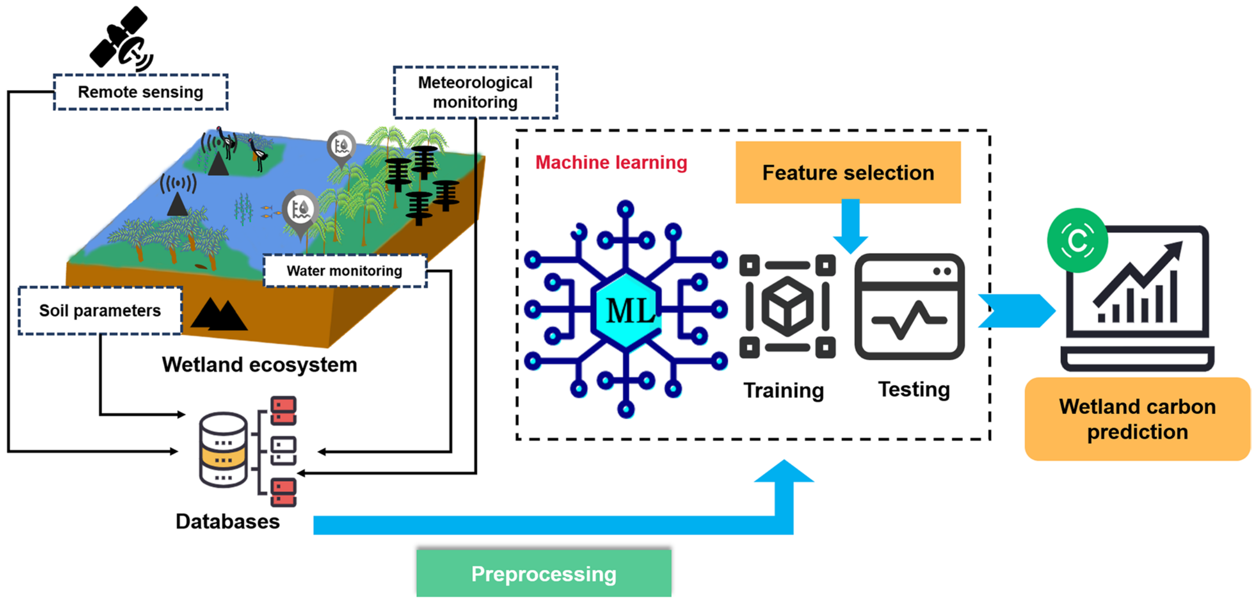



**Fig. 2** Application of machine learning in wetlands

nonlinear, and knowledge-independent problems. Therefore, it has the characteristics of high prediction performance, good heterogeneity, short calculation time, and ease of use (Gong et al. 2019).

At present, machine learning has been successfully used in the prediction and dimensionality reduction of high-dimensional input data sets in the fields of environment, agriculture, and so on (Morgan and Jacobs 2020). For example, Hamrani et al. (2020) used three types of machine learning models to predict the emission potential of greenhouse gases in farmland and proved that the prediction performance of the deep learning model Long Short-Term Memory (LSTM) neural network in agriculture is better than that of classical machine learning models (random forest [RF], support vector machine [SVM], and least absolute shrinkage and selection operator (LASSO)). In the study of forest ecosystem carbon, Ahirwal et al. (2021) used machine learning models (Adaboost, Bagging, RF, and Extreme Gradient Boosting (XGBoost)) to test the importance of various environmental variables in predicting biomass and soil carbon. Wang et al. (2023) used six machine learning methods to predict the primary productivity of grassland ecosystems and compared them with reference data to demonstrate the applicability of machine learning in predicting grassland primary productivity. Furthermore, machine learning is also used to fill the gap in the methane flux observed by eddy covariance. The performance of the decision tree algorithm is slightly better than that of the artificial neural network, but the artificial neural network also shows comparable performance (Irvin et al. 2021).

Therefore, it is a feasible method to establish a wetland carbon sink estimation model through machine learning. It can not only quickly and accurately estimate the wetland carbon sink, but also screen out the key factors according to the importance of the influencing factors of wetland carbon sink. The process is shown in Fig. 2. The machine learning data set is constructed by using the measured data of soil, vegetation, water, meteorology, and remote sensing data. The key driving factors of wetland carbon sink are screened through the training and testing process of machine learning to predict and estimate the wetland carbon sink. Machine learning can open up new ideas for future wetland carbon sink estimation (Bu et al. 2019; Belloli et al. 2022), but in order to further improve the effectiveness and accuracy of wetland carbon measurement, the following efforts need to be made:

(1) The relationship between wetland carbon sink capacity and key variables such as water level and temperature should be emphasized. The wetland carbon cycle is intricate. Leveraging the relationship between key factors during model construction can simplify the models and enhance their precision.
(2) Observations of specific ecosystems and carbon cycle elements, such as wetland soil carbon pool dynamics and soluble organic carbon leaching losses, should be intensified. Previous ecological monitoring lacked depth in these areas; hence,

a comprehensive evaluation of the carbon sinks in wetland ecosystems is essential.

(3) Enhancing the study and monitoring of wetland ecosystems, and harnessing the rapid, large-scale, and real-time capabilities of remote sensing, can aid in exploring carbon remote sensing estimation methods tailored for various wetland types. The carbon monitoring networks for different wetland types will be progressively enhanced. There will be a focused effort on building flux towers, integrating wireless sensors, and enhancing remote transmission capabilities. Additionally, remote sensing and GIS technology will be employed to maintain a continuously updated database on wetland distribution and areas. Model development hinges not only on a deep understanding of ecosystem processes and mechanisms but also requires robust ground survey data and remote sensing information for validation. This will facilitate the refinement of modeling processes, optimization of parameters, and heightened prediction accuracy for future carbon sinks.

## 5 Conclusion

In this review, we comprehensively analyzed and summarized the estimation methods of wetland carbon sink and the factors influencing wetland carbon cycle.

(1) The factors influencing wetland carbon cycle were analyzed, including climate change, hydrological conditions and human activities. The complex interactions between these factors make it more challenging to accurately understand the changes in wetland carbon cycle.

(2) Although wetland carbon sinks can be estimated by existing methods, there are still some challenges, such as the limitations of application scope and model parameters.

(3) To better understand the dynamic changes of the wetland carbon cycle, it is recommended to enhance the construction of a long-term monitoring and observation network. In addition, interdisciplinary cooperation and comprehensive utilization of various technical means of machine learning will also be important directions for future research to address the challenges facing the wetland carbon cycle.

In summary, through in-depth study of wetland carbon sink estimation methods and factors affecting wetland carbon cycle, we can better understand the role of wetlands in the global carbon cycle and provide a scientific basis for future wetland protection and carbon management.

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**Authors' contributions**
All authors contributed to the study design. Conceptualization, preparation of the original manuscript, writing review and editing were performed by Lixin Li. First draft preparation, writing review and editing were performed by Haibo Xu. The manuscript was reviewed and edited by Xiongwei Liang, Qian Zhang, Zhaoshun Zhan, and Jie Xing. All authors read and approved the final manuscript.

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**Availability of data and materials**
No data was used for the research described in the article.

## Declarations

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

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