

Article

Continuous Monitoring of Forests in Wetland Ecosystems with Remote Sensing and Probability Sampling

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Abstract: With the drastic reduction in wetland areas, it is essential to conduct an annual monitoring of the biomass or carbon content of wetland ecosystems to support international initiatives and agreements focused on sustainable development, climate change, and carbon equity. Forests in wetland ecosystems play a crucial role in carbon sequestration; however, the monitoring of small, fragmented forest components in wetlands remains insufficient, leading to an underestimation of their ecological and carbon sequestration functions. This study utilizes a model-assisted (MA) estimator, a monitoring procedure that is asymptotically design-unbiased and incorporates remote sensing, to assess the status and trends in the above-ground biomass (AGB) of forest components in wetlands, while also proposing a method of optimizing the sample size to enable continuous monitoring. Based on the population of the forest component of Baiyangdian wetland, major findings indicate that: (1) neglecting the forest component of Baiyangdian wetland will lead to an underestimation of the total aboveground biomass by 224.34 t/ha and 243.64 t/ha in the years 2022 and 2023, respectively; (2) in either year-specific monitoring or interannual change monitoring, the MA estimator is more cost-effective than the expansion estimator, a comparable procedure that relies solely on field observations; (3) the method used to optimize sample size can effectively tackle the cost-related concerns of subsequent continuous monitoring. Overall, the neglect of forest components is inevitably bound to give rise to an underestimation of wetlands, and use of an MA estimator and optimizing the sample size could effectively address the cost issue in continuous monitoring. This holds significant importance when developing management strategies to prevent the further degradation of wetland ecological functions and carbon sink capabilities.

Keywords: wetland forests; model-assisted estimator; optimizing sample size; year-specific monitoring; interannual change monitoring



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1. Introduction

Wetlands are one of the most important and valuable ecosystems on Earth, referred to as the “Earth’s kidneys”. Musonda Mumba, The Secretary General of the Ramsar Convention (TRC), stated the following: “Despite wetlands’ importance, nearly 90 percent of the world’s wetlands have been degraded or lost to date, and we are losing wetlands three times faster than forests. Therefore, there is an urgent need to raise global awareness on wetlands to reverse their rapid loss and to encourage the restoration and conservation of these vital ecosystems”. The Ramsar Convention serves as the only international treaty specifically dedicated to wetlands, requiring the monitoring of the current status and trends of wetlands globally [1]. Wetland biomass can reflect the condition of wetland ecosystems; for example, wetland vegetation biomass is a key indicator of wetland carbon sequestration [2]. Therefore, estimating wetland biomass is of great significance for understanding the carbon cycle of wetland ecosystems, as well as the conservation, strategic planning, and sustainable utilization of wetlands, alongside efforts to combat climate change. The

Ramsar Convention and the United Nations Framework Convention on Climate Change (UNFCCC) mandate continuous inventory estimations, usually carried out annually, at the population or domain level, where domain denotes a subset of the population [3,4].

Wetland is generally categorized into five distinct zones: lake, water, forest, field, and grass. Due to the relatively small proportion and scattered distribution of forest components in wetland, the recent monitoring of wetland forest biomass or carbon stocks and their changes typically involves three approaches: (1) the vast majority of wetland studies generally chose to neglect the forest component for simplicity—for instance, Carnell et al. [5] neglected the wetland forest component while monitoring the carbon storage of wetlands in southeastern Australia, Bu et al. [6] neglected the wetland forest component while monitoring the production potential of carbon storage in arid wetlands, Ningxia Plain, Qian et al. [7] disregarded the wetland forest component while monitoring the carbon storage and spatial distribution pattern of the Jiuduansha wetland in the Yangtze River estuary, etc.; (2) only a small number of researchers, like Vinod et al. [8] and Maziarz et al. [9], utilized an expansion estimator for simple random sampling (SRS) to evaluate biomass or carbon storage and the changes in forest components; (3) only a limited number of researchers, like Thomas et al. [10], utilized auxiliary data obtained from remote sensing imagery to build models for estimating biomass or carbon stock and their changes. The aforementioned methods present significant shortcomings: (1) If the biomass of the forest component is ignored, the total biomass of the wetland must be underestimated. This inaccurate dataset will lead managers to make decisions that are disconnected from the actual situation of the wetland, leading to the continued loss or degradation of wetland ecosystems in future wetland development plans. (2) The traditional design-based estimator is not constrained by assumptions regarding the population structure and distribution of the population, as it relies on the distribution of all potential estimators permitted under rigorous sampling design conditions [11]. However, this estimation method depends on having a sample size that is large enough to fulfill the precision criteria, leading to increased costs, while reducing the sample size may not meet accuracy requirements [12]. (3) Model-based prediction significantly depends on model assumptions [13]. A model that has inadequate assumptions or specifications could introduce bias and lack of precision in the predictions [14]. Moreover, models consist of linear or nonlinear correlations between target variables and auxiliary remote sensing variables; thus, uncertainties in the auxiliary remote sensing data can also impair the monitoring precision [15].

A model-assisted estimator (MA) is a method to improve sampling precision. MA estimators are commonly used in annual forest inventories of large areas, including by Andersen et al. [16], who applied the technique in Alaska, Gregoire et al. [17] and Gobakken et al. [18], who applied it in Hedmark County, Norway, and Saarela et al. [19], who used it in Kuortane, Finland. For interannual change monitoring, Næsset et al. [20] and McRoberts et al. [21] used an indirect MA estimator to calculate forest aboveground biomass (AGB) changes. An MA estimator fully exploits the potential of remote sensing-assisted data in a statistical estimator, integrating synthetic remote sensing data with sample-based field measurements using sampling theory [17]. The validity of the inferences obtained using an MA estimator still relies on the design sample, maintaining design-based asymptotic unbiasedness and consistency [22]. Therefore, regardless of the correctness of the assumed model, MA estimators remain asymptotically design-unbiased; in contrast, inferences based on model estimations without a sampling design do not possess this property [13,23].

MA estimators use model and remote sensing auxiliary information to improve precision [24]. They are expected to produce higher precision using an identical sample size or, equivalently, to achieve similar precision with a smaller sample size [17,25]. In statistical estimation, the sample size utilized in the sampling design is typically an empirical size lacking a theoretical foundation [26]. This empirical sample size often exceeds the necessary requirements for precision. More human resources, physical materials, and financial investments are required to obtain a larger sample size than needed. The elevated costs hinder the ongoing observation of wetlands. Therefore, optimizing the sample size to achieve the accuracy prerequisites stands as a pivotal challenge in the continuous monitoring of wetlands.

Consequently, this study aimed to achieve three main objectives: (1) evaluate the potential underestimation of AGB in the wetland forest component through sampling surveys, emphasizing the risks of neglecting this component; (2) propose and demonstrate a method for optimizing sample size by leveraging previous survey data for subsequent surveys; and (3) assess the effectiveness of MA and expansion estimators in monitoring the wetland forest component, while analyzing the fluctuation patterns of sample sizes in year-specific and interannual change monitoring using different estimation approaches.

2. Materials

2.1. Study Area and Field Data

Baiyangdian wetland, 36,600 ha, located in Xiong'an New Area, is the largest and most representative inland freshwater wetland in North China (115°45'–116°07'E, 38°43'–39°02'N), with very typical wetland features [27–29]. Baiyangdian wetland is situated in the warm-temperate, semi-humid, and continental monsoon climate region characterized by four distinct seasons [30]. It exhibits the distinctive geographical features of being semi-aquatic and semi-arid. Baiyangdian wetland possesses various ecological functions, such as flood prevention, water storage for irrigation, local climate regulation, ecological environment improvement, groundwater replenishment, and biodiversity conservation [31]. Since the establishment of the Xiong'an New Area in 2017, Baiyangdian has emerged as a vital ecological water system supporting the growth of the Xiong'an New Area. Wetlands constitute the largest portion of terrestrial biogenic carbon stocks, regulating the potential release of carbon into the atmosphere [3]. Therefore, Baiyangdian wetland plays a crucial role in natural resources, ecological environment, carbon sequestration, and more.

The study area, i.e., the target population, U , size with $N = 32,330$, is the whole forest component of Baiyangdian wetland (Figure 1). The AGB (t/ha) of the forest at the plot level is the variable of interest (VOI) in this study, aggregated of all aboveground living matter, such as tree stems, stumps, branches, seeds, and leaves. A sample, u , of $n = 111$ square plots selected from the study area by simple random sampling was field-surveyed during the summers of 2022 and 2023. The year 2022 served as the baseline survey, while 2023 represented the second monitoring. Each plot encompassed 30 by 30 m.

2.2. Remotely Sensed Auxiliary Data

The wall-to-wall remote sensing auxiliary data were multispectral images acquired by the Sentinel-2 Multispectral Instrument (MSI). A single scene of each sensor covered the entire study area (Figure 1). The spatial consistency of each remote sensing image was obtained by statistical analysis. The two scenes in this study were acquired on 1 June 2022 and 21 June 2023, synchronizing with the timing of the field surveys. Sentinel-2 data were freely downloaded from the European Space Agency data-sharing website accessed on 1 June 2022 and 21 June 2023 (<https://scihub.copernicus.eu>), and georeferenced to WGS84/UTM Zone 50N. Pre-processing of Sentinel-2 images involved radiometric calibration and atmospheric correction by Sen2cor 2.5.5 and ENVI 5.3.2 remote sensing software, culminating in the transformation of pixel brightness values to reflectance values. To enhance the concordance between the sample plots and the remote sensing data for more precise vegetation characterizations, researchers used the bilinear interpolation method to resample the spatial resolution of the images to ensure it was the same as that of the sample plots.

Remotely sensed auxiliary variables such as the Normalized Difference Water Index (NDWI), Green Chlorophyll Index (CIgreen), Red edge Chlorophyll Index (CIre), Normalized Difference Snow Index (NDSI), Normalized Burn Ratio (NBR) and Haralick textures were calculated for respective datasets, as detailed in Table 1. The R-package “rgdal” was used in data processing [32].

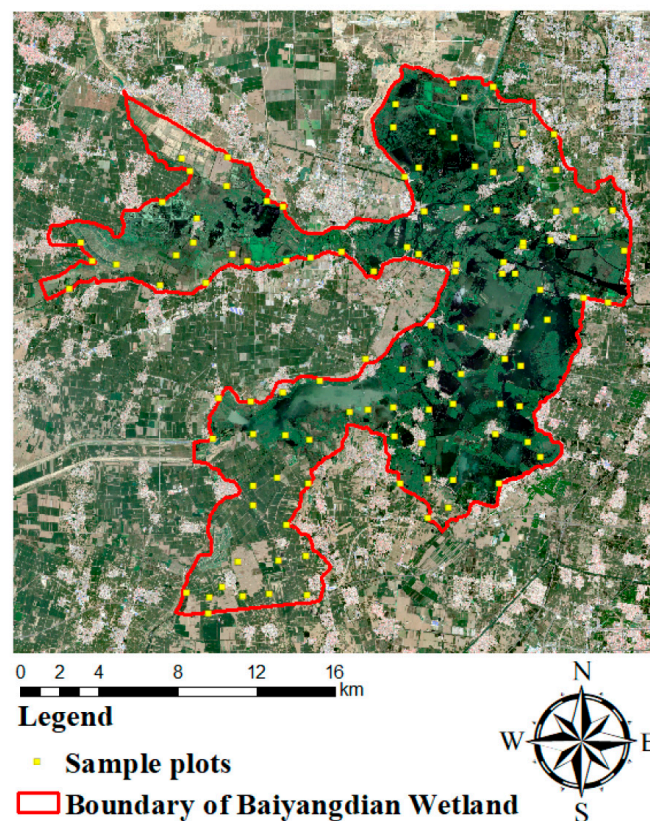


Figure 1. The study area and the sample plots in the whole forest component of Baiyangdian wetland.

Table 1. Summary of the spectral indices. NIR, near-infrared band; SWIR, short-wave infrared band; Green, green band; RedEdge, red edge band (band 5).

Spectral Indices	Formula	References
Normalized Difference Water Index (NDWI)	$(\text{NIR} - \text{SWIR2}) / (\text{NIR} + \text{SWIR})$	Gao [33]
Green Chlorophyll index (C _{green})	$\text{NIR} / \text{Green} - 1$	Gitelson et al. [34]
Red edge Chlorophyll Index (C _{re})	$\text{NIR} / \text{RedEdge} - 1$	Gitelson et al. [34]
Normalized Difference Snow Index (NDSI)	$(\text{Green} - \text{SWIR}) / (\text{Green} + \text{SWIR})$	Hall and Riggs [35]
Normalized Burn Ratio (NBR)	$(\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR})$	Key and Benson [36]

3. Methods

3.1. Overview

We focused on surveying the interannual changes in aboveground forest biomass in the wetland ecosystem. Figure 2 presents the technical itinerary of this study. First, the interannual change between the years 2022 and 2023 was estimated and compared using two estimators, i.e., an expansion estimator and an indirect MA estimator in the context of SRS. Second, a procedure for optimizing sample size was proposed both for year-specific and interannual change monitoring based on the tradeoff between sample size and estimation precision.

The method section is organized in a hierarchical manner. Sections 3.2 and 3.3 introduce the procedures for estimating interannual change and year-specific states. Section 3.4 focuses on the modeling required by previous sections. Section 3.5 introduces sampling precision, a statistic used for comparing different estimators. Finally, Section 3.6 proposes the procedure for optimizing sample size based on the expansion estimator of SRS.

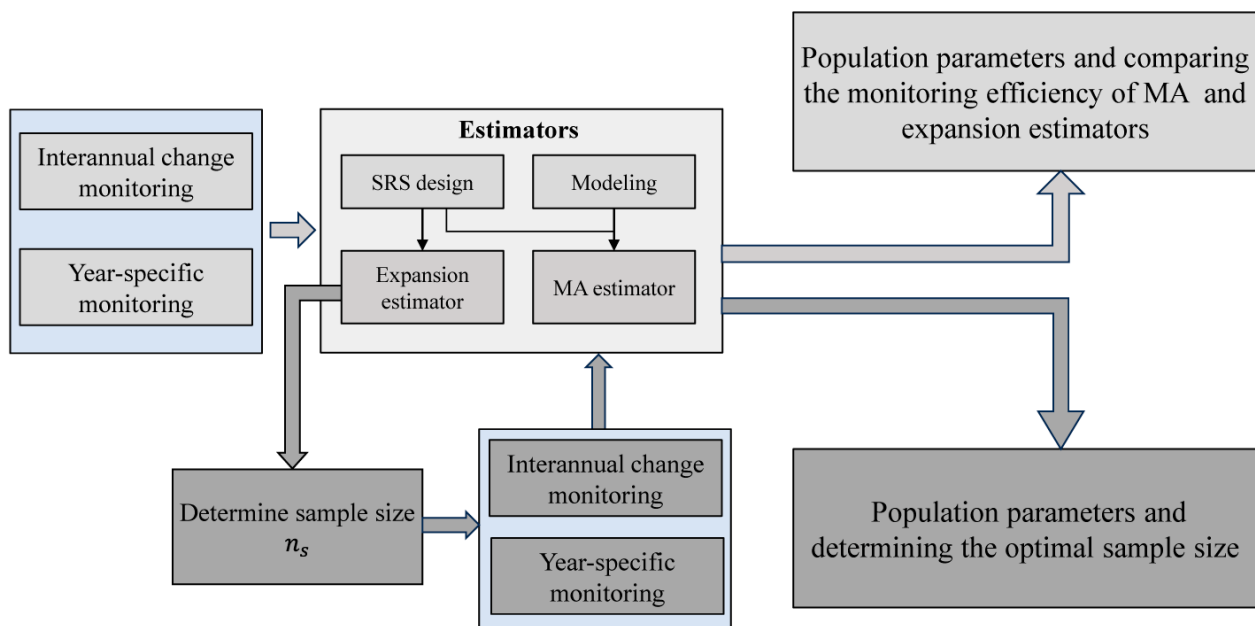


Figure 2. Technical itinerary of this study.

3.2. Interannual Change Monitoring

3.2.1. With Expansion Estimator

Sampling design defines a probability distribution, $p(\bullet)$, over the feasible set of obtainable samples. Different sampling designs result in various estimators, whereas the Horvitz–Thompson (HT) estimator is applicable across all designs [24] (p. 43). With SRS without replacement, the HT estimator reduces to the expansion estimator [11,24,37]:

$$\hat{\Delta}\mu_1 = \frac{1}{n} \sum_{k \in u} \Delta y_k \quad (1)$$

where $\hat{\Delta}\mu_1$ refers to the mean interannual change per hectare for AGB; $\Delta y_k = y_k^{2023} - y_k^{2022}$ is the field-observed interannual change per hectare at the k th sample plot of the field sample, u , of size n ; y_k^{2022} and y_k^{2023} are year-specific AGB observations. An estimator of the variance of $\hat{\Delta}\mu_1$ is

$$\hat{Var}(\hat{\Delta}\mu_1) = \frac{N-n}{N} \cdot \frac{1}{n(n-1)} \sum_{k \in u} (\Delta y_k - \bar{\Delta}y)^2 \quad (2)$$

where $\bar{\Delta}y = \frac{1}{n} \sum_{k \in u} \Delta y_k$ is the observed sample mean of the AGB change; N is the number of population units; the finite-population correction factor, $(N-n)/N$ reduces $\hat{Var}(\hat{\Delta}\mu_1)$, but can be disregarded in instances where the population is substantially larger than the sample size.

This expansion estimator is standard to SRS without replacement and is among the most commonly used in National Forest Inventory programs (NFI) [38,39]. It is simple to use but may not be cost-efficient when meeting a specified precision with a small sample [40,41].

3.2.2. With Indirect Model-Assisted Regression Estimator

The model-assisted estimator is design-based and approximately design-unbiased [24,42]. The primary advantage of the model-assisted regression estimator for SRS is that it can reduce the variance of the estimator of the population parameter by utilizing the relationship between sample observations and their model predictions [22,43].

The element- or plot-level predictions were made with year-specific models for 2022 and 2023 with the modeling detailed in Section 3.4. The element-level interannual change

was calculated as the difference between year-specific predictions. The indirect model-assisted regression estimator, $\hat{\Delta}\hat{\mu}_2$, used these year-specific differences to estimate the mean interannual change for the entire population, which has the following form [24,44,45]:

$$\hat{\Delta}\hat{\mu}_2 = \frac{1}{N} \sum_{k \in U} \hat{\Delta}y_k + \frac{1}{n} \sum_{k \in u} e_k \quad (3)$$

where $\hat{\Delta}y_k = \hat{y}_k^{2023} - \hat{y}_k^{2022}$ is the predicted interannual change per hectare for AGB at the k th element in the population U ; $e_k = \Delta y_k - \hat{\Delta}y_k$ is the residual obtained with the observed sample u . The second term in Equation (3) corrects for systematic bias between model predictions and field observations, ensuring the approximate unbiasedness of this estimator [24] (p. 227). The model is year-specific, denoted as Model-2022, and constructed with field sample data collected in 2022, and likewise for Model-2023. Section 3.4 provides details about modeling.

The variance estimator of $\hat{\Delta}\hat{\mu}_2$ is expressed as follows:

$$\hat{Var}(\hat{\Delta}\hat{\mu}_2) = \frac{N-n}{N} \cdot \frac{\sigma_e^2}{n(n-1)} \quad (4)$$

where $\sigma_e^2 = \sum_{k \in u} \frac{(e_k - \bar{e})^2}{n-1}$ is the residual variance, and $\bar{e} = \frac{1}{n} \sum_{k \in u} e_k$. Apparently, the decrease in $\hat{Var}(\hat{\Delta}\hat{\mu}_2)$ to reduce the uncertainty relies on decreasing σ_e^2 and/or on increasing n , which stands for sample size [44].

3.3. Year-Specific Monitoring

Year-specific estimation is required by the interannual change estimation for calculating the AGB difference between two years. The two estimators above, used for interannual change estimation, i.e., the expansion estimator and model-assisted estimator, are applicable to year-specific estimation as well, with a difference existing in terms of whether the sample data are year-specific or from both years.

3.3.1. With Expansion Estimator

With the SRS design without replacement, an expansion estimator can also be used for year-specific estimation like interannual change estimation, which does not require remote sensing auxiliary information, only the actual observation data of the samples selected by the sampling design. The expansion estimator takes the same form as Equations (1) and (2), but with a different y_k and sample variance $\hat{\sigma}^2$ [24]:

$$\hat{\mu}_3 = \frac{1}{n} \sum_{k \in u} y_k \quad (5)$$

with its variance estimator presented as follows:

$$\hat{Var}(\hat{\mu}_3) = \frac{N-n}{N} \cdot \frac{\hat{\sigma}^2}{n} \quad (6)$$

where y_k is the observed AGB at the k th element; $\hat{\sigma}^2 = \sum_{k \in u} (y_k - \frac{1}{n} \sum_{k \in u} y_k)^2 / (n-1)$ is the sample variance.

3.3.2. With Model-Assisted Estimator

The year-specific model-assisted estimator, similar to the indirect model-assisted estimator for change, incorporates the auxiliary information using model(s) and preserves favorable design properties to improve estimator efficiency [17,23,25,46–48]. The model-assisted estimator for year-specific estimation requires only one model, whether it be Model-2022 or Model-2023, and is expressed in the following form [24]:

$$\hat{\mu}_4 = \frac{1}{N} \sum_{k \in U} \hat{y}_k + \frac{1}{n} \sum_{k \in u} \varepsilon_k \quad (7)$$

where $\hat{y}_k$ is the prediction for element k using a year-specific model fitted with year-specific sample data; $\varepsilon_k = y_k - \hat{y}_k$ is the residual. The estimator, $\hat{\mu}_4$, consists of a synthetic estimate (the first term) and an adjustment term (the second term). The synthetic estimate calculates the mean of the population based only on a model and typically has a small variance. This term may deviate significantly due to bias if the model is mis-specified [24] (p. 411). However, if model is biased regarding the synthetic term, the adjustment term corrects it, thus making the model-assisted estimator approximately unbiased [24] (p. 227).

An estimator of the variance of $\hat{\mu}_4$ is

$$\hat{Var}(\hat{\mu}_4) = \frac{N-n}{N} \cdot \frac{\hat{\sigma}_\varepsilon^2}{n} \quad (8)$$

where $\hat{\sigma}_\varepsilon^2 = \sum_{k \in u} (\varepsilon_k - \frac{1}{n} \sum_{k \in u} \varepsilon_k)^2 / (n-1)$ is the residual variance; the equation is nearly identical to the variance expression in Equation (6), except that $\hat{\sigma}^2$ has been replaced by $\hat{\sigma}_\varepsilon^2$. With a reasonably good model, $\hat{\sigma}_\varepsilon^2$ should be smaller than $\hat{\sigma}^2$, and thus support $\hat{Var}(\hat{\mu}_4) < \hat{Var}(\hat{\mu}_3)$.

3.4. Modeling

Regression models related to the field-observed aboveground biomass and remotely sensed auxiliary variables are a required intermediate component of year-specific and inter-annual change monitoring using a model-assisted estimator. The independent variables were selected parsimoniously from of the pool of Sentinel-2 auxiliary variables using the “bootstrap stepAIC” procedure [49]. Model-2022 and Model-2023 were constructed using year-specific field samples and remote sensing data to make year-specific and interannual change estimations. Both year-specific models have the same general form, $Y = f(X; \beta) + \varepsilon$, which links the dependent variable Y with remotely sensed auxiliary variable X , where β is the model parameter, and ε is a random error term following $N(0, \Omega)$.

The regression Model-2022 describes the relationship between the AGB, y^{2022} ($y^{2022} = [y_1^{2022}, y_2^{2022}, \dots, y_n^{2022}]'$), and the Sentinel-2 independent variables for 2022, x^{2022} ($x^{2022} = [x_{R1}^{2022}, \dots, x_{Rn}^{2022}]' = [1, x_{C1}^{2022}, x_{C2}^{2022}, \dots, x_{Cp}^{2022}]$), where the subscripts “R” and “C” respectively represent row and column vectors, at sample u , with β^{2022} representing a vector of model parameters to be estimated:

$$\text{Model} - 2022 : y^{2022} = f(x^{2022}; \beta^{2022}) + \varepsilon^{2022}, \varepsilon^{2022} \sim N(0, \Omega^{2022}) \quad (9)$$

The regression Model-2023 describes the relationship between the AGB, y^{2023} ($y^{2023} = [y_1^{2023}, y_2^{2023}, \dots, y_n^{2023}]'$), and the independent variables, comprised of remote sensing auxiliary variables from 2023 and fitted values of Model-2022, x^{2023} ($x^{2023} = [x_{R1}^{2023}, \dots, x_{Rn}^{2023}]' = [1, \hat{y}_u^{2022}, x_{C1}^{2023}, x_{C2}^{2023}, \dots, x_{Cq}^{2023}]$), at sample u , with β^{2023} representing a vector of the model parameters that are to be estimated:

$$\text{Model} - 2023 : y^{2023} = f(x^{2023}; \beta^{2023}) + \varepsilon^{2023}, \varepsilon^{2023} \sim N(0, \Omega^{2023}) \quad (10)$$

In this study, Model-2022 and Model-2023 took multivariate linear forms as $y^{2022} = 533.45 - 2013.84 \cdot \text{NDSI.mean} - 452.69 \cdot \text{NBR.homogeneity} - 2.37 \cdot \text{CIgreen.variance} + 4191.05 \cdot \text{CIre.mean}$ and $y^{2023} = 156.72 + 0.77 \cdot \text{X2022pre.y} - 198.06 \cdot \text{NDWI.homogeneity}$ respectively, with four independent variables being selected for Model-2022 and two independent variables for Model-2023.

While spatial autocorrelation is not a concern in this study, heteroscedasticity does exist. To accommodate heteroscedasticity, the model parameters were estimated using weighted least squares (WLS) for which $\hat{\beta} = (\mathbf{X}^T \mathbf{V} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{V} \mathbf{y}$, and $\mathbf{V} = \mathbf{\Omega}^{-1}$ is a diagonal matrix with $v_{kk} = 1/\sigma_k^2$, with k indicating the k th sample unit [50]. The diagonal elements of $\mathbf{V}$ were estimated utilizing the power variance function procedure in accordance with the following form:

$$\text{Var}(\varepsilon_k) = |v_k|^{2t} \quad (11)$$

where v_k is the variance covariate defining the variance function for the k^{th} unit and t represents the parameters estimated using “varPower” function in R-package “nlme” [51].

The root mean square error (RMSE) was used for evaluating the prediction accuracy of the respective models. RMSE and its relative forms are expressed as $\text{RMSE} = \sqrt{\frac{1}{n} \sum_{k=1}^n (y_k - \hat{y}_k)^2}$, and $r\text{RMSE} = \frac{\text{RMSE}}{\bar{y}} \times 100$, where n is the number of sample plot, y_k is the field-measured AGB, $\hat{y}_k$ is the predicted AGB, and $\bar{y} = \frac{1}{n} \sum_{k=1}^n y_k$.

3.5. Sampling Precision

Sampling precision (P) defined as the degree of closeness between the estimate and the unknown parameter, is a crucial metric for assessing the quality of sampling inference [52]. P enables comparisons among estimators by quantifying the sampling error (SE)

$$P = (1 - SE) \times 100\% \quad (12)$$

where $SE = \sqrt{\frac{\hat{\text{Var}}(\hat{\mu})}{\hat{\mu}}}$. P was evaluated to compare the inferential precision achieved from the MA estimator and the expansion estimator across various sample sizes.

3.6. Sample Size Optimization with Monte Carlo

Determining the sample size is an indispensable process in sampling design estimation. Under design-based inference, a small sample size may fail to meet the precision standards required by NFIs [15,53]. Conversely, an excessive sample size may result in higher costs in terms of manpower, resources, and finances. Therefore, it is crucial to find an equilibrium between precision and cost, which allows for the determination of a suitable sample size, particularly for continuous monitoring on an annual basis.

The process of determining the sample size involves establishing the maximum allowable error (d_s) between the population parameter and the estimator of population mean ($\hat{\mu}$) and the level of confidence when d_s is the maximum error. Also, we must obtain the population variance, but this is typically unknown. This study employs the sample variance (σ_{exp}^2) estimated with an expansion estimator based on the baseline inventory in 2022, where the sample size was 111. Due to the relatively large population size N compared to the sample size, the finite population correction factor can be ignored. Given this information, and a Z score determined from the confidence level, the optimal sample size for the expansion estimator can be calculated using the following formula [37] (p. 53):

$$n_s = \frac{Z^2 \sigma_{exp}^2}{d_s^2} \quad (13)$$

As shown in Figure 3, this means that the probability is $(1 - \alpha)$ and that the population parameter is included in the interval $\left[\hat{\mu} - Z_{1-\frac{\alpha}{2}} \sqrt{\frac{\sigma_{exp}^2}{n}}, \hat{\mu} + Z_{1-\frac{\alpha}{2}} \sqrt{\frac{\sigma_{exp}^2}{n}} \right]$. The Z -score representing the upper $\frac{\alpha}{2}$ point in the standard normal distribution is determined by the confidence level. The national forest inventory in China set the confidence level at 95%, corresponding to $Z = 1.96$.

We delved into the relationship between sample size and precision to determine the optimal sample size using Monte Carlo simulation. Using the randomness of repeated sampling to tackle the contingency in the sampling results [54], Monte Carlo simulation

typically involves three steps: (1) drawing n_s sample units from $n = 111$ using simple random sampling; (2) re-estimating point estimators and variance estimators with the resample of size n_s , where, notably, for the MA estimator, it is necessary to refit the model parameters as well; and (3) calculating the means of the above two estimators when iterated 10,000 times [55]. Note that the above optimization procedure for determining a sample size was derived for the expansion estimator. However, if the estimation efficiency is higher for the MA than the expansion estimator, having a smaller sample size for the MA estimator than the one calculated using Equation (13) for the expansion estimator would lead to similar precision. Based on Monte Carlo simulation based on the initial sample of size 111, we further fit an empirical model to predict the sample size for subsequent monitoring using the relationship between sample sizes (n_s) and the precision (P), estimated based on each sample size. This principle works around deriving a sample size optimizer for the MA estimator and generalizes to alternative estimators as well.

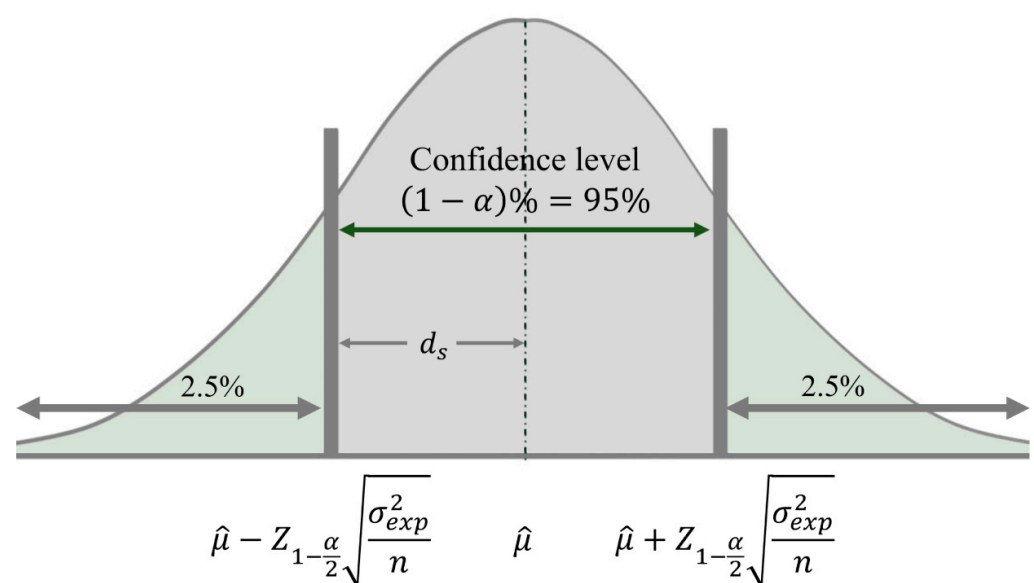


Figure 3. Significance level and confidence level.

4. Results and Discussion

4.1. Model Forms

Model-2022 and Model-2023, constructed with Sentinel-2, are outlined in Table 2. Comparative graphs illustrating the relationship between observations and predictions are presented in Figure 4. Following the parsimony criteria, Model-2022 was established with a minimum of four independent variables, while Model-2023 incorporated only two. In particular, one of the independent variables for Model-2023 is the predicted value from Model-2022, i.e., $X_{2022pre.y}$. It is interesting to note that Model-2023, despite having fewer independent variables, achieves greater predictive accuracy, as indicated by a lower rRMSE, compared to Model-2022 (Table 2). This implies that incorporating the predicted values from Model-2022 into the independent variables of Model-2023 represents a cost-efficient way to improve the efficiency of the continuous monitoring of AGB in wetland ecosystems. The 95% confidence intervals of the MA estimator in 2022 and 2023 are [193.614, 255.246] and [211.444, 275.836].

Furthermore, both Model-2022 and Model-2023 were linear models with model parameters estimated using weighted least squares (WLS) to accommodate heteroscedasticity, implying the statistical significance of the models. Utilizing model-assisted estimation facilitates the creation of a functional model that correlates with Above-Ground Biomass (AGB) and minimizes estimation variance, rather than striving for a “true” model. However, there are also inherent limitations of the linear relationship, such as inconsistency in

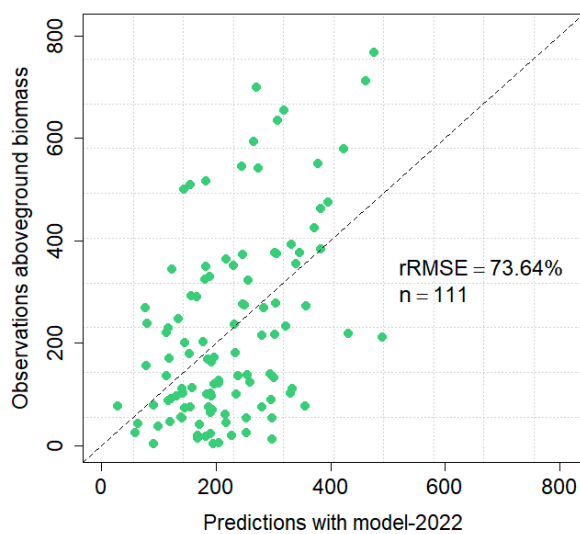
the relationship between the independent and dependent variables, or more complicated conditions. It is essential to ensure the validity of the construction models and match the quality standards of the remote sensing data for prospective forest inventories.

In continuous monitoring, utilizing the previous prediction as the independent variable in the subsequent period (next year) of modeling presents a significant advantage: it optimally utilizes historical data to minimize the number of independent variables, mitigating issues related to multicollinearity. This method also simplifies the independent variable selection process by removing the requirement for remote sensing auxiliary variables and the need to depend exclusively on past data. Consequently, this leads to cost reductions and enhances the accuracy of the model.

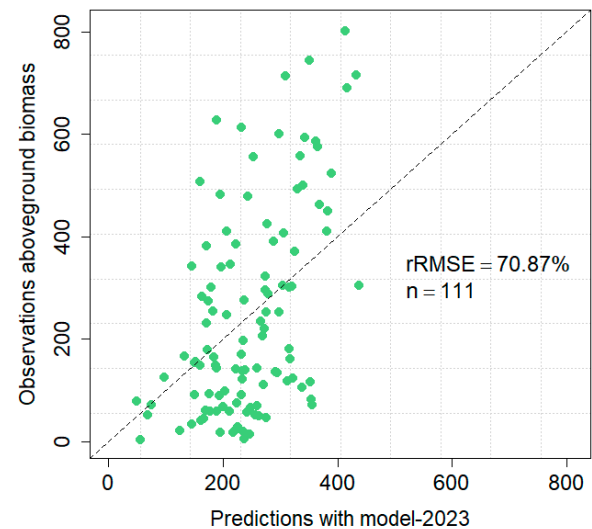
Table 2. Summary of Model-2022 and Model-2023.

Model	RMSE (t/ha)	rRMSE	Independent Variable	Estimate	Standard Error
Model-2022	165.18	73.64	(Intercept)	533.45	273.09
			NDSI.mean	−2013.84	598.60
			NBR.homogeneity	−452.69	131.26
			CIgreen.variance	−2.37	0.71
			CIre.mean	4191.05	833.32
Model-2023	172.58	70.87	(Intercept)	156.72	61.79
			X2022pre.y	0.77	0.15
			NDWI.homogeneity	−198.06	97.42

Statistically significantly different from zero at $\alpha = 0.05$.



(a)



(b)

Figure 4. (a) The graph of observations versus predictions (t/ha) with Model-2022 and (b) the graph of observations versus predictions (t/ha) with Model-2023.

4.2. Year-Specific Monitoring

To provide accurate data assistance for the formulation of the protection and sustainable use of wetland ecosystems plan, this study conducted an investigation and monitoring of the forest component of Baiyangdian wetland. The MA estimator demonstrates enhanced efficiency and cost-effectiveness in calculating AGB by utilizing a model developed using the relationship between the auxiliary variables and the variable of interest (VOI) [56].

A comparison of population parameter estimates derived from the MA and expansion estimators within the framework of SRS is presented in Table 3. Six findings are relevant. First, the population mean computed using the MA estimator closely matches that obtained

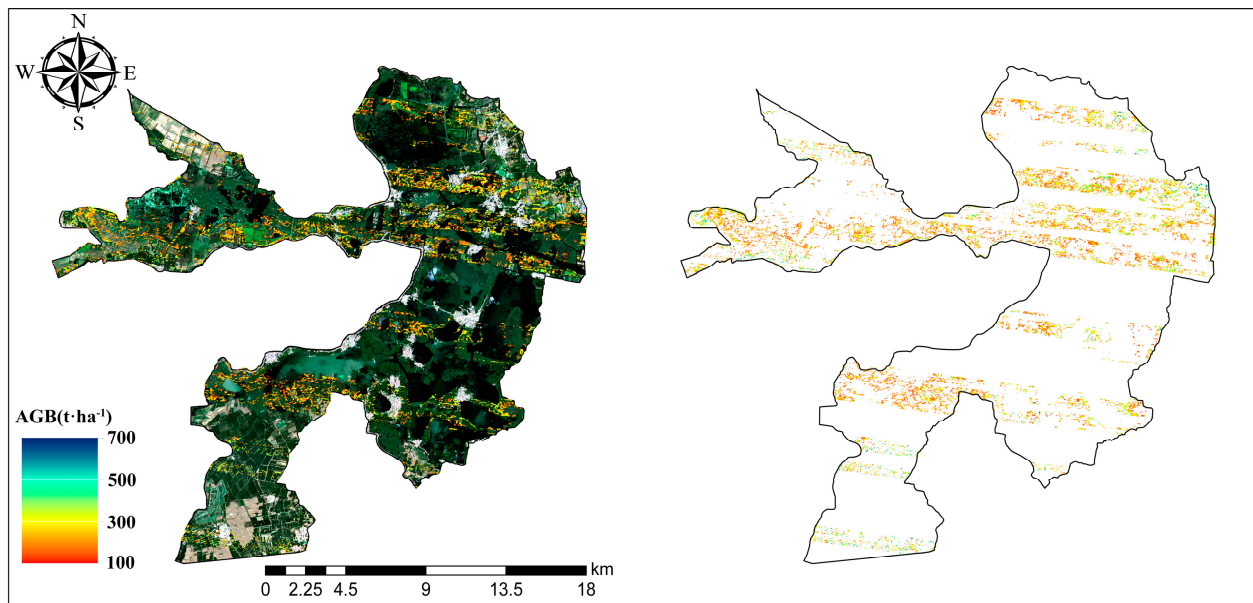
from the expansion estimator, which confirms the approximately unbiased nature of the MA estimator. Additionally, the means estimated in 2023 are higher than those in 2022, indicating the following: (1) there is an increasing trend in the AGB of the forest component of wetland on an annual scale; (2) despite the relatively limited expanse of the forest component of wetland, its exclusion would lead to an underestimation of the total AGB in wetland; (3) the forest component of wetland may have significant potential for future development as a carbon sink [57]; (4) the carbon sink function of the forest component is thus crucial for carbon sequestration and release in wetland ecosystems, where wetlands or water components are generally carbon sources rather than sinks [58–60].

Table 3. Year-specific estimates of the AGB (t/ha) using expansion and MA estimators with 111 sample plots.

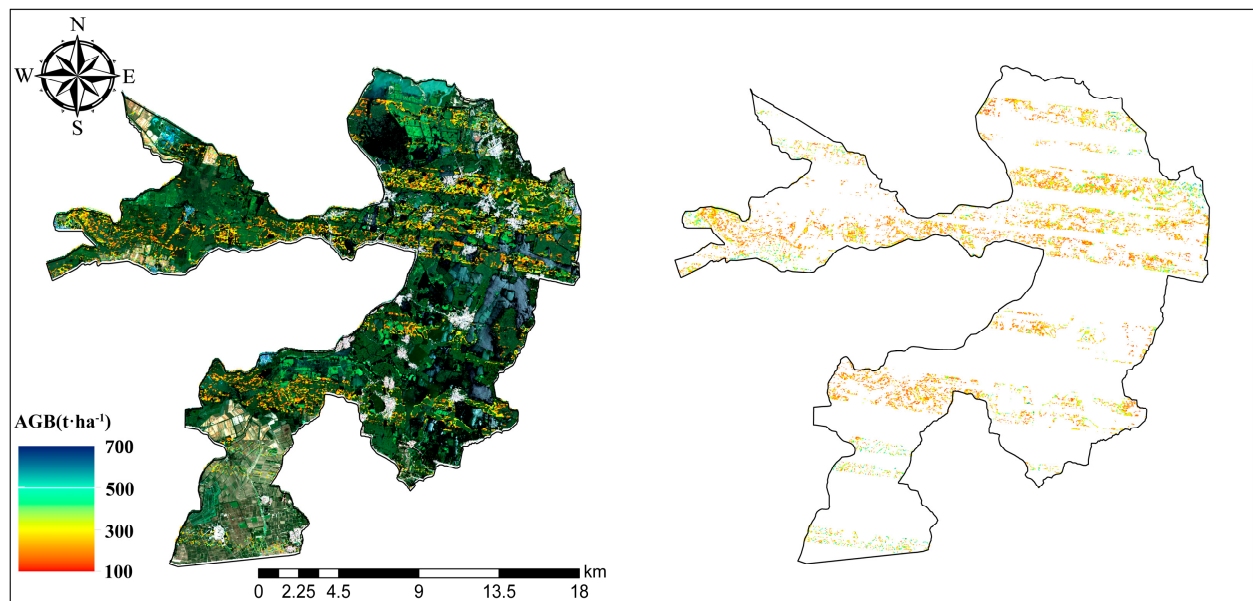
Year	Estimator	Model	$\hat{\mu}$	$\hat{Var}(\hat{\mu})$	P (%)
2022	Expansion estimator	NA	224.31	338.36	91.80
	MA estimator	Model-2022	224.34	247.19	92.99
2023	Expansion estimator	NA	243.51	364.92	92.16
	MA estimator	Model-2023	243.64	269.83	93.26

Second, with the assistance of the remotely sensed data and statistical models, estimates of $\hat{Var}(\hat{\mu})$ derived from the MA estimator were approximately 1.4 times lower than those obtained using the expansion estimator. This suggests superior efficiency due to the capitalization on the variability of residuals of sample units under a reasonable model compared to the variability of observations of sample units. Third, the MA estimator enhances monitoring precision in comparison to the expansion estimator, indicating its appropriateness for lake wetlands characterized by small and fragmented forest areas, such as Baiyangdian. Furthermore, it also proves suitable for continuous forest surveillance in coastal wetlands, swamp wetlands, and artificial wetlands with relatively extensive forest coverage. However, in river wetlands where forest areas are limited, the MA estimator might be affected by small sample bias. Fourth, with a sample size of 111, Table 3 demonstrates that the sampling precision of both the MA estimator and the expansion estimator exceeded 90%, which is the threshold standard of sampling precision for Chinese NFI [61,62]. However, conducting continuous monitoring every year with a sample size of 111 is deemed financially unsustainable. Therefore, it is essential to optimize the sample size in order to tackle the cost concern.

Fifth, by integrating Tables 2 and 3, Model-2023 with an MA estimator exhibited a lower rRMSE and higher sampling precision, suggesting that rRMSE is strongly correlated with sampling precision. This implies the following: (1) rRMSE is useful for analyzing models related to screening and prediction errors; (2) it is advisable to utilize auxiliary variables with a high correlation to the variable of interest as independent variables to reduce rRMSE and uncertainty. Sixth, the MA estimator can be upscaled from the unit level to the population level using model predictions. Consequently, the distribution graphs for the AGB of the entire forest component of Baiyangdian wetland for the years 2022 and 2023 were compiled (Figure 5). These two maps facilitate a more accurate judgment of the spatial distribution of AGB concentration within the forest component.



(a) Predicted AGB for forested areas in June 2022



(b) Predicted AGB for forested areas in June 2023

Figure 5. Year-specific prediction of forest AGB in the Baiyangdian wetland ecosystem with color-Infrared imagery or the vector boundary of Baiyangdian as the background.

4.3. Interannual Change Monitoring

In relatively short time scales, wetland ecosystems undergo alternating successional processes in the water and land directions [63]; conversely, over extended time scales, the traditional successional theory characterizes wetlands as transitional phases progressing from shallow lakes to climax communities of terrestrial forests [3]. From the interannual changes in forest components, a positive estimate indicates that wetland succession is moving towards terrestrial ecosystems, and a negative estimate suggests the opposite. Monitoring the interannual changes in the AGB of the forest component of wetland ecosystems is essential for assessing the trajectory of wetland succession, and it provides a reference for managers when developing management plans that prevent the further degradation of wetland ecosystems.

Table 4 presents a summary of the interannual change estimation for the indirect MA and expansion estimators. Four significant observations can be made. First, both the indirect MA and expansion estimators indicate a positive estimation of the population mean, indicating that the forest component of the wetland is increasing within the succession to improve the carbon sequestration benefits. Recently, the management strategies implemented in Baiyangdian wetland have proven to be effective, with the role of the wetland ecosystem continuously strengthening to bolster carbon sequestration, biodiversity, climate regulation, and other ecological functions.

Table 4. Interannual change estimation with 111 sample plots.

Estimator	$\hat{\Delta\mu}$ (t/ha)	$\hat{Var}(\hat{\Delta\mu})$	P (%)
Expansion estimator	19.21	16.11	79.10
Indirect MA estimator	19.30	15.85	79.38

Second, the difference between the population mean calculated using the indirect MA and the expansion estimators is slightly minor (Table 4). Differences in the estimates are attributed to random variation, because all the estimators in the design-based inference framework are either unbiased or approximately biased [44].

Third, the indirect MA estimator accurately reflects the current status of and trends in wetland forest components, facilitating the assessment of the progress being made towards achieving sustainable development objectives and underscoring the significance of wetlands in fulfilling the United Nations Sustainable Development Goals [1]. Regarding the variance estimator, the indirect MA estimator is computed based on the deviation between the observed sample and the model-predicted outcome, while the expansion estimator is generated from the difference between the observed sample and the sample mean [21]. The expansion estimator yielded a slightly higher variance estimate compared to the indirect MA estimator, which can be attributed to the strong correlation between the AGB and remote sensing auxiliary indices. Hence, the result is consistent with [21], indicating an improvement in the inference efficiency of the indirect MA estimator.

Fourth, within the framework of employing the same 111 sample plots, the indirect MA estimator demonstrates a slightly higher level of precision than the alternative estimator (Table 4). This suggests that the MA estimation method could enhance precision when using a fixed sample size. Conversely, with a fixed sampling precision, the MA estimator demonstrates a greater ability to minimize sample sizes, thereby curtailing expenses, in comparison to the expansion estimator.

4.4. Optimization for Sample Size

The primary obstacle in maintaining continuous monitoring in wetlands is achieving the necessary level of precision while minimizing the sample size. Through conducting Monte Carlo simulation, the impact of sample size on estimates was explored within the framework of the MA estimator and expansion estimator. Samples from a predetermined number of plots, derived from the original set of 111 plots, were randomly selected 10,000 times to derive the anticipated population parameters and variances.

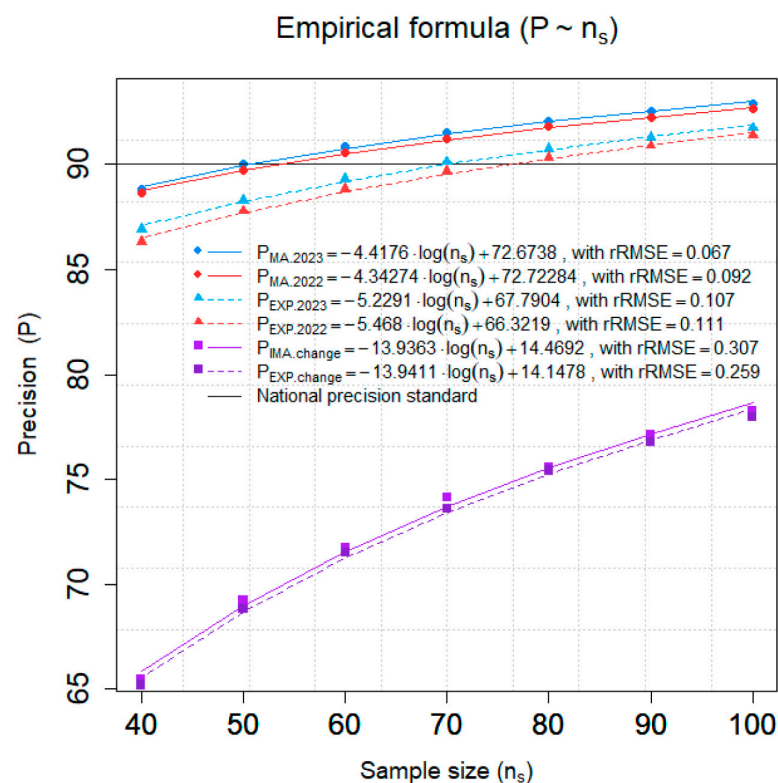
In Tables 5 and 6, the estimates and sampling precisions (P) of year-specific and interannual changes, derived from the MA and expansion estimators, respectively, are presented, considering the differing sample sizes. The empirical formulas of sample size (n_s) and sampling precision, with rRMSE assessing the prediction precision, are displayed in Figure 6. Six findings are relevant. First, in both the year-specific and interannual change estimations, the difference between the population means of the MA and expansion estimators is considerably smaller than the corresponding absolute errors (d_s). This indicates that (1) Model-2022 and Model-2023 have predictive reliability and accuracy in this study and (2) according to (Equation (13)), different sample sizes can be determined by the absolute error in different situations with a given variance estimate in continuous monitoring.

Table 5. Estimates of the AGB (t/ha) for year-specific (2022 and 2023) estimations using MA and expansion estimators with different sample sizes.

n_s	d_s		Expansion Estimator						MA Estimator					
			μ		$Var(\mu)$		$P(\%)$		μ		$Var(\mu)$		$P(\%)$	
	2022	2023	2022	2023	2022	2023	2022	2023	2022	2023	2022	2023	2022	2023
100	37.88	39.34	224.35	243.55	375.96	405.45	91.36	91.73	224.29	243.55	273.41	299.28	92.63	92.90
90	39.93	41.46	224.26	243.52	416.88	450.53	90.89	91.28	224.37	243.46	302.96	331.92	92.24	92.52
80	42.35	43.98	224.30	243.54	470.00	506.56	90.33	90.76	224.25	243.46	338.79	373.16	91.79	92.07
70	45.27	47.02	224.39	243.30	538.57	578.43	89.66	90.12	224.13	243.31	384.77	425.03	91.25	91.53
60	48.90	50.78	224.57	243.52	627.90	676.00	88.84	89.32	224.06	243.49	445.42	493.63	90.58	90.88
50	53.57	55.63	224.50	243.45	752.60	810.73	87.78	88.30	223.86	242.94	528.39	590.10	89.73	90.00
40	59.89	62.20	224.26	243.55	941.20	1015.48	86.32	86.92	224.34	242.44	648.47	732.95	88.65	88.83

Table 6. Estimates of the AGB (t/ha) for interannual changes using MA and expansion estimators with different sample sizes.

n_s	d_s	Expansion Estimator			Indirect MA Estimator		
		$\Delta\mu$	$\hat{Var}(\Delta\mu)$	$P(\%)$	$\Delta\mu$	$\hat{Var}(\Delta\mu)$	P
100	8.25	19.19	17.83	77.99	19.29	17.61	78.25
90	8.70	19.18	19.83	76.79	19.32	19.54	77.13
80	9.23	19.21	22.29	75.43	19.21	22.03	75.57
70	9.86	19.10	25.45	73.59	19.40	25.16	74.14
60	10.65	19.17	29.81	71.52	19.20	29.49	71.72
50	11.67	19.18	35.76	68.82	19.34	35.49	69.20
40	13.05	19.19	44.65	65.19	19.38	44.91	65.43

**Figure 6.** The empirical formulas of sample size (n_s) and sampling precision (P), with $rRMSE$ assessing the prediction precision.

Second, following the computation of sample sizes utilizing the sample size determination formula (Equation (13)), the empirical formulas depicted in Figure 6 were proposed based on the nonlinear correlation between different sample sizes and the corresponding sampling precision under the MA and expansion estimators. These empirical formulas facilitate a more effective and accurate determination of the sample size, meeting the precision criteria. Additionally, they prove to be an essential resource for the continuous monitoring of the forest component of wetlands in terms of optimizing sample size. Third, the curves of each empirical formula, depicted in Figure 5, exhibit a positive correlation; as sample size increases, the speed of the increase in precision transitions from rapid to gradual, ultimately stabilizing at 100% precision. This indicates that the sample size in the sampling design significantly impacts the precision of the inference.

Fourth, the MA estimator retains a higher sampling precision compared to the expansion estimator across various sample sizes. Simultaneously, the discrepancy in precision between the two estimators diminishes gradually as the sample size increases. This demonstrates that (1) the expansion estimator converges slower and (2) the smaller the sample size, the more pronounced the superiority of the MA estimator.

Fifth, the optimal sample size is defined as the sample size required to achieve a sampling precision of 90% or higher. The optimal sample sizes calculated for the MA estimator and expansion estimator indicate a reduction of approximately 50 and 30 sample plots, respectively, when compared to the original sample size of 111. Meanwhile, the MA estimator saved nearly 20 sample plots compared to the expansion estimator. This demonstrates that deciding on the optimal sample size can efficiently reduce monitoring expenses and the MA estimator can decrease the sample size while maintaining the level of precision. Therefore, the MA estimator represents an efficient approach for monitoring the AGB or carbon stock of the forest component of wetland ecosystems, fulfilling the precision requirement for AGB estimates of the forest component of Baiyangdian wetland.

Sixth, the precision of year-specific estimations with the same sample size varies greatly compared to the precision of the interannual change estimations. This discrepancy arises because interannual change data are calculated from the difference between two values, each of which is influenced by observational errors, measurement inaccuracies, and errors in intermediate model predictions. Predicting a change in the response variable may be more challenging than predicting the response variable itself [21]. By utilizing the empirical model, correlating sample size with sampling precision, as illustrated in Figure 6, the optimal sample size for interannual change estimation can be predicted. The optimal sample size for interannual change estimation is approximately four times larger than that for year-specific estimation. This indicates that (1) the sample size set for monitoring interannual change fully meets the requirements for year-specific monitoring; (2) when performing both interannual and annual monitoring, it is crucial to concentrate solely on the sample size needed for interannual variations. However, the cost of interannual change monitoring is excessively high. Therefore, it is essential for interannual change monitoring to improve its precision and reduce expenses by enhancing models or optimizing remote sensing data [21,64].

Sample size optimization is an important issue in forest inventory and monitoring; namely, small sample sizes pose challenges. From a temporal perspective, the methodologies presented in this study facilitate continuous forest monitoring. Spatially, the proposed procedures are reproducible at different wetland ecosystems. Methodologically, it is advisable to develop decent statistical and modeling approaches based on different datasets, and further consider the optimization of design and model parameter estimation. These could enhance the correlation between the sample size and sampling precision in forest monitoring.

4.5. Implication to Wetland Biomass Management

Although occupying only 2% of the Earth's surface, wetlands represent a substantial reservoir, containing 20% of the global organic carbon ecosystem [65,66]. Alarmingly, half

of the world's wetland area has disappeared, with the remaining wetlands facing ongoing degradation [67,68]. How integral the forest component is to wetland health is often overlooked or undervalued. Contrary to wetland, which is partly a carbon source [69,70], the forest component is a carbon sink. That is, although the forest component, functioning as a carbon sink, increases as terrestrial succession proceeds, the degradation of wetland and its function also exists. Hence, it is a key issue for the relevant researchers or decision-makers to investigate the balance between wetland and its forest component and their functions to carry out wetland management and biodiversity conservation. An MA estimator was utilized to monitor the existing status and patterns of the AGB of the forest component of wetland in this study. First, this aids in understanding the value of wetlands and the extent of wetland degradation, thus attracting attention from the pertinent authorities. Second, it can be used as a guide for crafting protective and sustainable usage plans for the remaining wetlands to prevent further loss and degradation, and to restore wetland ecosystems' services and value. Third, this study addresses the gap in AGB assessments of the forest component of Baiyangdian wetland, providing specific methodologies for tracking the current status of and trends in AGB in the forest components of other wetland ecosystems. Additionally, the empirical formula presented in Figure 6 facilitates the optimization of sample size for monitoring the forest component of wetlands.

5. Conclusions and Prospect

This study presents several key conclusions: (1) under the design-based framework, neglecting the forest component of Baiyangdian wetland leads to an underestimation of the total aboveground biomass by 224.34 t/ha in 2022 and 243.64 t/ha in 2023, which results in an underestimation of the wetland's carbon sequestration capacity; (2) compared to the expansion estimator, the MA estimator demonstrates greater effectiveness for year-specific and interannual change monitoring and its advantages are more pronounced with smaller sample sizes during continuous monitoring, as this can reduce the required sample size by approximately 40% compared to the expansion estimator while still achieving NFI precision in China; (3) using prior information to optimize the sample size of subsequent surveys can reduce the cost of continuous wetland monitoring, and interannual change estimation requires a larger sample size than year-specific estimation to fulfill precision requirements; (4) in modeling, utilizing independent variables in the form of predicted values that are readily available from a previous year is crucial for cost-efficiently reducing the rRMSE and uncertainty. Overall, effective estimation techniques are essential for accurately monitoring the forest component of wetlands, and are crucial for maintaining the carbon balance and ensuring the sustainable utilization of wetland ecosystems.

The deficiency of this research is that the original sample size used for interannual change monitoring fails to fulfill the precision requirements. This is because interannual change data are derived from the differences between two values, both of which are influenced by observation, measurement, and errors in intermediate model predictions. Predicting a change in a response variable may be more challenging than predicting the response variable itself, potentially leading to higher costs for interannual change monitoring. Despite these limitations, the study offers valuable preliminary insights and sets the stage for future research. Subsequent studies could boost the precision of investigation and reduce costs by optimizing the model or employing remote sensing auxiliary data with higher precision.

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