Sustainable Forestry (2021) Volume 4 Issue 2
doi:10.24294/sf.v4i2.1606

ORIGINAL RESEARCH ARTICLE

Research progress of forest ecological quality assessment methods

Haoshuang Han[1,2], Rongrong Wan[1,2*]

[1] *Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China.*

[2] *University of Chinese Academy of Sciences, Beijing 100049, China. E-mail: rrwan@niglas.ac.cn*

ABSTRACT

Forests have ecological functions in water conservation, climate regulation, environmental purification, soil and water conservation, biodiversity protection and so on. Carrying out forest ecological quality assessment is of great significance to understand the global carbon cycle, energy cycle and climate change. Based on the introduction of the concept and research methods of forest ecological quality, this paper analyzes and summarizes the evaluation of forest ecological quality from three comprehensive indicators: forest biomass, forest productivity and forest structure. This paper focuses on the construction of evaluation index system, the acquisition of evaluation data and the estimation of key ecological parameters, discusses the main problems existing in the current forest ecological quality evaluation, and looks forward to its development prospects, including the unified standardization of evaluation indexes, high-quality data, the impact of forest living environment, the acquisition of forest level from multi-source remote sensing data, the application of vertical structural parameters and the interaction between forest ecological quality and ecological function.

Keywords: Forest Ecological Quality; Biomass; Productivity; Forest Structure; Remote Sensing Technique

ARTICLE INFO

Received: 28 April 2021
Accepted: 21 June 2021
Available online: 1 July 2021

1. Introduction

Forest ecosystem is a key factor affecting the quality of the ecological environment, and plays a vital role in maintaining the global carbon balance and mitigating the greenhouse effect[1]. The strategy of reducing greenhouse gas emissions caused by deforestation and forest degradation to increase carbon stocks (REDD+) emphasizes the role of forests as carbon sinks, and the Kyoto agreement has also listed forests as an important measure to solve the problems of energy conservation, emission reduction and climate change[2]. In recent years, a large number of natural forests have been replaced by artificial forests, and the tree species and age structure of forests are generally single and young, resulting in the reduction of species diversity and the weakening of ecological functions. However, the protection measures carried out by various countries have failed to effectively curb the loss of forests, and the ecological quality of forests has been significantly degraded[3-5]. In this context, the problem of forest ecological quality has attracted much attention, and its evaluation has become a research hotspot of scholars at home and abroad.

The monitoring and evaluation of forest ecological quality is of great significance to quantitatively grasp the carbon source/sink characteristics, temporal and spatial distribution and dynamic changes of forest ecosystem, and also provide a basis for the evaluation of forest natural resources assets and the formulation of forestry management measures. It is an important way to understand the forest ecological quality, which will promote the improvement of forest ecological quality. Due to the differences in forest biophysical characteristics and environmental conditions on the space-time scale, domestic and foreign scholars evaluate the forest ecological quality in different research areas, different emphases and different scales, and their data acquisition methods, evaluation index systems and evaluation methods are also different[6-8]. Based on the existing research at home and abroad, this paper puts forward the key ecological parameters that characterize the forest ecological quality, systematically combs the evaluation methods of each ecological parameter, and makes prospects for the evaluation indicators, high-quality data, forest environmental impact factors, remote sensing means, etc., in order to provide reference for the in-depth study of forest ecological quality evaluation.

2. Connotation of forest ecological quality

Forest is a biological community mainly composed of woody plants, which has the characteristics of rich species, complex structure, strong stability and perfect functions. It can improve and maintain the ecological environment and provide necessary biological resources for human beings[9]. The forest ecosystem, which is composed of forests, other organisms and the environment, has ecological functions and ecological services to regulate and maintain ecological security. Among them, forest ecological services are the natural environmental conditions formed and maintained by the forest ecosystem and its ecological process, and the utility provided directly or indirectly for human beings[10,11]. Forest ecological function and ecological service capacity are important factors affecting its quality level.

In 1992, Stolton first proposed the term "forest quality", and then, together with Dudley *et al*., defined its concept in the World Wide Fund for Nature (WWF) report as "the sum of all functions and values of forests in terms of ecological, social and economic benefits"[3]. Forest ecological quality reflects the connotation of forest quality from an ecological perspective, a comprehensive measure of forest ecological functions and ecological services, growth conditions and self-reg- ulation functions, and reflects the ability of forests to improve the ecological environment and maintain ecological balance[4,9]. Due to the abstraction of the concept, the connotation of forest ecological quality will be different for different research objectives, and a unified understanding has not been reached at present. Based on the existing research, this paper defines the forest ecological quality as that the forest has a variety of ecological functions such as water conservation, climate regulation, air purification, carbon fixation and oxygen release, nutrient accumulation, biodiversity maintenance, etc., provides human beings with natural living conditions, biological resources, intangible value and other ecological services, and reflects the stability, elasticity and resilience under the stress of biological and abiotic factors.

3. Overview of forest ecological quality assessment research

3.1 Evaluation index system

Scholars usually choose easily accessible indicators to evaluate the ecological quality of forests

Table 1. Forest ecological quality evaluation indicators

Involved level	Index factor	Application
Forest biomass	Biomass per unit area, net biomass per unit area, stock per unit area, etc	[12–15]
Forest structure	Stand origin, community structure, forest age, canopy structure, density, tree species, canopy density, etc	[9,12–15]
Forest productivity	Volume increment, biomass increment, forest growth per unit area, etc	[8,9,14,15]
Forest health	Healthy forest area ratio, forest vitality, forest disaster (disease, pest, fire, etc.) area ratio, dry loss rate, etc	[9,14,15]
Ecological service function	Water conservation, soil conservation, carbon fixation and oxygen release, biodiversity, etc	[9,12,15]
Site conditions	Altitude, slope direction, gradient, slope position, soil layer thickness, soil organic matter, etc	[8,12]

in terms of biophysical properties, site conditions and growth conditions (**Table 1**). Generally speaking, the main characterization parameters of forest ecological quality include forest structure, forest biomass, forest productivity, forest ecological service efficiency, health status and so on. Due to the diversity and complexity of forest in terms of geographical environment, species and spatial scale, the selection of evaluation indicators will face many problems, such as a large number, high correlation between factors, and difficult data acquisition.

3.2 Sources of evaluation data

The spatial scales involved in forest ecological quality assessment include forest farms, regions, and even the world. The differences of spatial scales affect the way of obtaining observation data. The traditional method to obtain the key parameters representing the forest ecological quality is mainly the sample survey. The data obtained by this method is more accurate, but it requires a lot of time, manpower and material resources, and it is unable to realize the inventory of large areas and duration time scales[14,16]. The development of remote sensing technology makes up for the shortcomings of traditional estimation methods, which can realize the rapid, continuous and nondestructive estimation of forest ecological parameters at local, regional and even global scales, meet the needs of forest investigation and biophysical parameter detection, and provide data sets with different spatial resolutions and time series for ecological quality assessment (**Table 2**). At present, the research on the dynamic change inversion of forest biomass, productivity and carbon storage at the regional level more combines remote sensing images with regional and national forest inventory data to generate the spatial distribution map of forest status[2,17-21], so as to realize the long-term, dynamic and fine spatial observation of forest ecological quality in the study area.

Table 2. Application characteristics of different remote sensing sensors in forest resource observation

Sensor	Characteristic	Application
Optical remote sensing	The spectral information is rich, and the forest level parameters can be obtained; however, it is easily affected by the atmosphere. For dense, multi-layer and complex canopy, there are problems of mixed pixels and easy saturation, and it is not sensitive to forest spatial structure information.	[22,23]
Microwave remote sensing	All weather, all day imaging, less atmospheric interference, can react with forest trunks to obtain forest vertical status parameters; however, due to the influence of terrain and surface roughness, there is also a problem of saturation.	[24,25]
Lidar	It can overcome the problem of easy saturation and obtain the vertical structure of forest; however, its high cost makes it difficult to obtain a wide range of image data, and it has not been widely used at present.	[26,27]
Multi source remote sensing	Multi-source remote sensing can avoid the limitations of a single data source and improve the accuracy of vegetation interpretation and inversion; however, there are problems in data source quality and fusion method selection.	[22,28]

3.3 Research methods of forest ecological quality

3.3.1 Determination of index weight

The evaluation of forest ecological quality can be achieved by building a suitable index system. Various indicators have different contributions to the evaluation results, so they need to be given different weights. The weight determination methods mainly include subjective weighting method and objective weighting method. The former has simple operation, high reliability and practicability, but it largely depends on the personal experience of decision makers, with strong subjectivity, such as analytic hierarchy process[9,14]; the latter is more objective, avoiding the deviation caused by human factors, but there will be the problem of insufficient sample size, and without considering the differences between evaluation indicators, there may be inconsistencies between the determined weight and the importance of indicators. The commonly used methods are mean square deviation comprehensive analysis[12], principal component analysis[13], factor analysis[8,15], entropy weight method[29,30].

3.3.2 Research methods

The selection of research methods is the key link to evaluate the forest ecological quality scientifically and accurately. Generally speaking, the research methods of forest ecological quality mainly include investigation method, remote sensing evaluation method, model method, single evaluation method, comprehensive evaluation method, etc. Regional and national forest surveys are the basis for obtaining forest carbon reserves, health status and ecological service functions. Long-term monitoring can obtain the dynamic changes of forest ecological quality. In addition, with the development and application of ecological models and 3S technology, more new methods are used to simulate and evaluate the change of forest ecological quality. For example, invest model can quantify the service function of forest ecosystem; the application of GIS and remote sensing technology in forest ecological quality assessment has also attracted much attention[14,31].

The indicator species method is a representative method in the single evaluation. By determining the key species, endemic species, endangered species or environmentally sensitive species in the forest ecology, its quantity, productivity, biomass, structure and function and other indicators are obtained, so as to establish a model to describe the health status of the forest ecology and reflect the level of forest ecological quality on the side[32,33]. Comprehensive evaluation method is a method used more in the evaluation of forest ecological quality, that is, using multiple evaluation indicators to evaluate the research object in many aspects. The commonly used methods are shown in **Table 3**. In the actual process, many methods are often integrated to avoid the disadvantages of a single method and solve problems reasonably[29,30].

Table 3. Comparison of index system method for forest ecological quality assessment

Evaluation method	Advantage	Inferiority	Application
Composite index method	The method is simple, the evaluation result is intuitive, the accuracy is high, and the information utilization rate is high.	It may cover up some evaluation factors with great influence, resulting in deviation of evaluation results.	[31]
Fuzzy comprehensive evaluation method	Turn factors with unclear boundaries and difficult to quantify into quantitative indicators; the evaluation effect is better for complex problems with multiple factors, multiple levels and fuzzy concepts.	The membership degree of fuzzy algorithm is subjective, and the model cannot be self-verified.	[33,34]
Cluster analysis	The algorithm is intuitive, easy to implement and occupies less memory.	The selection of classification number and initial class center location is highly subjective; it is not friendly to data with complex shapes.	[14]
Matter element analysis	Using matter-element transformation, structural transformation and other methods to solve incompatible problems, it is suitable for multi-factor evaluation.	The uncertainty of evaluation criteria and the definition of classical domain and node domain need to be further studied.	[9,30]
Set pair analysis	Solving the problem of certainty and uncertainty can deal with incomplete information.	There is still room for improvement in dealing with indicators of different contributions.	[9,35]

Table 4. Application of forest ecological parameter inversion model

Model	Features	Application
Multiple linear regression	The independent variable and dependent variable are required to have a linear relationship. This method is limited for non-linear ecological relationships or a small number of variables that cannot explain the variance of dependent variables.	[37,38]
Stepwise multivariate linearity	The iterative method is used to eliminate the factors with weak correlation and obtain the optimal fitting model, which requires the linear relationship between the prediction variables and dependent variables, and collinear and over fitting problems will occur when there are too many prediction variables.	[39]
KNN	There is no parameter estimation and it is simple, but in the case of large sample size, the workload will be increased and the problem of over fitting will occur.	[40]
ANN	It is suitable for dealing with the influence of multiple factors and the situation with fuzzy information, without making assumptions on the data, and can effectively deal with the nonlinear, non normal and collinear problems between the data; but there will be fitting.	[41–43]
RF	It can deal with complex and nonlinear ecological relationships, and has the advantages of efficient processing of massive data, less human interference, strong anti noise ability, and not easy to produce over fitting; however, it is very sensitive to the relationship between input variables, which will lead to the deviation of the prediction tree, so it is necessary to measure the importance of variables.	[8,44,45]
SVM	It can be used for classification and regression analysis, and can produce higher classification or more accurate estimation in solving small sample, nonlinear and high-dimensional pattern recognition problems.	[8]

3.3.3 Parameter inversion model method

The selection of forest ecological parameter inversion model directly affects the accuracy and reliability of the results[21]. Model methods mainly include two categories: parametric methods and nonparametric Machine Learning Algorithm (MLA). Compared with linear model, MLA has some advantages: it can deal with nonlinear ecological relations; it can fit the inversion model from the limited training data; it can solve classification problems that are difficult to distinguish[36]. MLA includes k-nearest neighbor (KNN), artificial neural network (ANN), random forest (RF), support vector machine (SVM), etc. (**Table 4**).

4. Study on key parameters of forest ecological quality evaluation

Forest biomass and productivity are two widely used indicators of forest research[12,17]. Forest biomass is one of the important parameters for monitoring forest carbon storage, forest fire, land use change, global climate change, etc., which can be used to reveal the process laws of forest ecosystem energy balance and material cycle[2,46,47]. Forest productivity can also describe the ecological function of forests in terms of accumulation of organic matter, which is of great significance to the level of forest ecological quality[8]. In addition, forest structure reflects the characteristics of forest evolution mode and growth state in the process of forest dynamic change, and becomes an important factor in monitoring and managing forest ecosystem, which helps human beings understand the current situation, dynamic changes and development trends of forests[48]. According to the principles of scientificity, comprehensiveness, relative independence, feasibility, representativeness and generalization, we believe that forest biomass, forest productivity and forest structure can comprehensively measure forest characteristics, growth status and ecological functions, which are the three key parameters to evaluate forest ecological quality.

4.1 Remote sensing estimation of forest biomass

Forest biomass consists of aboveground and underground parts. Most studies often use standard root shoot ratio to calculate Belowground Biomass (BGB) from Aboveground Biomass (AGB)[2,49,50]. Relatively speaking, forest AGB assessment is intuitive and feasible, and scholars at home and abroad have studied it more at present.

There are many methods for estimating forest AGB, which can be divided into non remote sensing methods and remote sensing methods. Non remote sensing methods mainly include measurement methods, model estimation methods, stock conversion methods, etc. These methods are suitable for small-scale biomass research; the estimation of large-scale forest biomass needs the help of remote sensing, that is, by establishing a linear or nonlinear model between the image spectral information and the biomass at the sampling point, the forest biomass can be retrieved.

4.1.1 Remote sensing characteristic parameters

Different vegetation and the same kind of vegetation have different shapes and characteristics of reflection spectrum curve in different growth stages, so as to reflect vegetation information, and vegetation biomass is related to different elements of vegetation or a certain characteristic state[22]. For complex vegetation remote sensing, vegetation index has better sensitivity and anti-interference than single band estimation of biomass, and can be used to remove changes caused by canopy geometry, soil background, illumination angle and atmospheric conditions[51]. Widely used vegetation indexes include Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), etc. With the development of relevant research, domestic and foreign scholars have proposed some modified vegetation indexes (Soil-adjusted Vegetation Index (SAVI), Transformed Soil-adjusted Vegetation Index (TSAVI), Modified Soil-adjusted Vegetation Index (MSAVI), etc.) to weak soil background and atmospheric impact, so as to enhance vegetation information (**Table 5**).

Table 5. Characteristics of common vegetation index in biomass estimation

Vegetation index	Advantage	Inferiority	Application
RVI	RVI is a sensitive indicator parameter of green plants and has a good correlation with biomass.	When the vegetation coverage is higher than 50%, RVI has high resolution, but it is affected by atmospheric conditions; when the vegetation coverage is less than 50%, the RVI resolution decreases.	[22,55]
NDVI	It enhances the reflection contrast between vegetation and soil, effectively highlights vegetation, and is more suitable for vegetation monitoring with medium coverage or in the middle stage of development.	It is easy to be saturated in the high vegetation coverage area; under the condition of low vegetation coverage, it is sensitive to soil brightness.	[22,56,57]
DVI	It performs well in the case of low vegetation coverage, and can better identify vegetation and water bodies, which is conducive to the monitoring of vegetation environment.	When the vegetation cover is dense, it is extremely sensitive to the change of soil background.	[22,58]
SAVI, TSAVI, MSAVI	The soil adjustment coefficient is introduced to correct the sensitivity of NDVI to soil background.	Some vegetation signals may be lost, making the vegetation index low.	[59–62]
Enhanced Vegetation Index (EVI)	The blue band is added to enhance the vegetation signal, improve the sensitivity to high biomass areas, and correct the effects of soil background and aerosol scattering.	It is mostly used in areas with dense vegetation.	[22,63]
Greenness Vegetation Index (GVI)	The influence of soil background value on plant spectrum is excluded or weakened.	GVI is susceptible to solar radiation, atmospheric radiation, environmental radiation and other external conditions.	[22,58]
Perpendicular Vegetation Index (PVI)	It is less affected by soil background, and its ability to resist atmospheric effects is also significantly better than other vegetation indexes.	As the leaf area index increases, it will become very sensitive to the soil background.	[52,64]

Texture is one of the important features used to identify objects or regions of interest in the image[52]. The texture features of vegetation have great potential for distinguishing vegetation types, more effectively reflecting remote sensing image ground object information and adjusting inversion models[6,53,54].

4.1.2 Overview of forest AGB remote sensing inversion research

Scholars use different remote sensing data sources in the process of forest biomass estimation in order to achieve better inversion results. The types of remote sensing data mainly include passive optical remote sensing, active or passive microwave remote sensing and lidar remote sensing.

Optical remote sensing is one of the common methods to obtain forest biomass information, which can accurately obtain forest canopy information and extract vegetation parameters to estimate forest biomass[39,64]. Liu estimated the forest biomass of Chongqing by using the vegetation index, tassel transform component and principal component variable information of TM data[18]. Zhou generates vegetation index (SVIs) and texture factors through high-resolution optical remote sensing images, and then combines terrain factors and field sampling data to quantify the biomass on Robinia pseudoacacia plantation[65]. Considering that the accuracy of NDVI estimation of biomass in a single season is insufficient and there is a problem of saturation, Zhu *et al*. used NDVI values of Landsat images in different seasons to perform forest AGB inversion[39].

Microwave (such as synthetic aperture radar) can penetrate the canopy and interact directly with the main body of forest biomass—leaves, trunks and branches. The ability of microwave remote sensing makes it a practical method for accurate estimation of forest biomass. On the other hand, the combination of lidar data and ground measured data can obtain a more effective distribution map of forest carbon resources and forest aboveground biomass[27].

Multi source remote sensing data can make up for the lack of a single data source and improve the accuracy of biomass inversion. Common multi-source data combination modes include: optical remote sensing sets with different spatial and spectral resolutions; optical remote sensing and SAR data of different polarization modes; optical remote sensing and lidar remote sensing. Xu *et al*. used

Landsat-8 OLI image and GF-2 image as data sources, and used single band, vegetation index and other spectral information as well as fixed sample land data of forest resources survey to estimate forest biomass in Jishui County, Jiangxi Province[66]. Li *et al*. used fully polarized C-band SAR data and Landsat-5 TM optical data to build a remote sensing information model to quantitatively retrieve the forest biomass of natural secondary forests in the greater Hinggan Mountains[67]; Wang *et al*. fused Synthetic Aperture Radar (SAR, Sentinel-1) and optical remote sensing (Landsat-8, Sentinel-2) data to evaluate grassland biomass[68], which is still suitable for forest biomass estimation; Minh *et al*. estimated the forest biomass of Madagascar using the tree cover data generated by ALOS PALSAR and optical remote sensing[25]. Tang obtained ecological parameters such as forest canopy height and canopy density based on LiDAR and multispectral remote sensing data, and then established a forest AGB inversion model using multiple linear regression and BP neural network model[43]; Li *et al*. estimated the AGB of temperate forests through stratified sampling and geostatistical modeling, combined with airborne lidar data, SPOT images and field sampling data[69]; Chi *et al*. integrated GLAS data and Landsat/ETM+ data, and then carried out forest AGB estimation research[70].

4.2 Estimation of forest productivity

Vegetation productivity refers to the rate at which green plants accumulate or fix organic matter, mainly including Gross Primary Productivity (GPP) and Net Primary Productivity (NPP)[71]. Among them, forest NPP represents the remaining part after removing the organic matter consumed by plant autotrophic respiration from GPP, reflecting the intensity of forest carbon sink[71,72].

4.2.1 Influencing factors of NPP spatio-temporal pattern

The dominant factors that produce the temporal and spatial differences of forest NPP are different, mainly including environmental factors, forest age and forest disturbance.

The influence of climate (such as temperature, precipitation, light) on NPP is achieved by changing the length of the growing season and the rate of photosynthesis. Abundant rain and heat conditions have a significant impact on plant productivity. Fang *et al*. studied the NPP changes of Changbaishan pine and cypress on a long time scale and found that the lowest temperature in April and the precipitation in June and July are the main reasons for the NPP changes[73]. Other studies have found that the increase of temperature will stimulate the autotrophic respiration of plants, and different water and heat combinations have an important impact on the temporal and spatial differentiation of NPP in the study area[74,75]. Extreme climate (drought, extreme high temperature or low temperature, etc.) also have a profound impact on terrestrial ecosystems[73,76]. In addition, the increase of carbon dioxide concentration between green plant cells can improve the photosynthetic efficiency of vegetation and increase forest productivity; nitrogen deposition affects the absorption and utilization of nitrogen by vegetation, thus affecting the photosynthesis of vegetation. In addition, topography, soil and tree species will also affect the temporal and spatial pattern of NPP.

The relationship between forest age and NPP has attracted more and more attention, which is of great significance to improve the accuracy of NPP estimation. The photosynthetic utilization rate of young trees is higher, which improves the absorption of carbon by stems, branches and thick roots, and NPP increases rapidly; NPP of trees reached the maximum in the medium term; in the later stage, as the growth of aboveground biomass decreases, and NPP is mainly composed of leaf and fine root turnover organic matter, NPP will decline to a relatively stable state[77,78].

Human activities (such as logging), forest fires, forest diseases and insect pests and other disturbances can directly release carbon to the atmosphere and accelerate the respiratory process, which has a strong impact on the carbon cycle, and may even be the leading factor causing the mutation of forest ecosystem in a special period of time[79]. Disturbance activities can also change the age structure and tree species composition of forests, resulting in temporal and spatial differences in forest NPP[77].

4.2.2 Overview of forest NPP estimation research

Forest NPP can be composed of organic matter and litter accumulated in roots (thick roots, fine roots), stems and branches, food consumption, volatile organic matter, unobserved litter and dead tree organic matter[77,80].

The research on forest NPP has been carried out since the last century, and the commonly used research methods such as direct harvesting method and carbon flux observation method are suitable for the observation of forest NPP in a small range. With the development of remote sensing technology, using remote sensing images and forest inventory data to estimate forest NPP in a large area has become a hot spot. For example, using MODIS NPP data and downscaling methods to carry out multi-scale NPP research[81]; NPP was estimated using NDVI significantly correlated with leaf area index[82]. Summarize the NPP research models commonly used by scholars, mainly including empirical/statistical models, remote sensing models and process mechanism models (**Table 6**).

Table 6. Three main NPP estimation models

Model	Advantage	Shortcoming	Representative model	Application
Empirical/statistical model	Meteorological data are easy to obtain and the model is simple.	The actual surface vegetation types are ignored, reflecting a trend or potential NPP.	Miami model, Chikugo model; Comprehensive model, etc.	[83,84]
Remote sensing model	Use remote sensing technology to obtain relevant parameters.	The quality of remote sensing image affects the accuracy of the model; Input parameters of different forest types lack calibration.	CASA, GLO-PED model, InTECc model, etc.	[85,86]
Process mechanism model	Considering the ecological mechanism of vegetation, the estimation result is more accurate, which is usually applied to the productivity simulation of small areas.	There are many parameters, the model is more complex, it is difficult to correct, and some parameters are difficult to obtain, so it is difficult to promote.	BIOME-BGC model, etc.	[87]

In addition, the method of estimating forest NPP through the correlation between NPP and forest biomass has also been widely used and practiced[73,77,78,80,88,89]. Some studies have shown that some NPP estimation models lack consideration of forest age, and the spatial distribution of forest carbon sources/sinks is more dependent on forest age than environmental factors[72,80].

4.3 Remote sensing inversion of forest structural parameters

The forest structure reflects the structural elements of trees and the connection mode of their attributes. The structural parameters that reflect the forest status mainly include: tree height, diameter, forest age, tree species composition, canopy height, canopy density, forest origin, etc.[90].

Remote sensing technology is an effective way to extract forest structural parameters. Li *et al*. comprehensively use remote sensing data, terrain factors, land cover, and forest inventory data to retrieve the average age of forest stands in Jiangxi Province, and then analyze the impact of forest age on forest NPP[72]. Hansen *et al*. used regression tree algorithm combined with Landsat-7 and Landsat-8 comprehensive data to draw the tree height distribution map of sub Saharan region, with high inversion accuracy[91]. Qiu and Liao used glas waveform parameters to estimate the discrete forest maximum tree height, canopy height, forest canopy density, etc., and assisted GLAS in retrieving forest parameters on a regional scale with optical images and ground data[20,92].

LiDAR can accurately obtain forest vertical parameters (such as tree height), but its coverage in the horizontal direction is limited; optical remote sensing can obtain a wide range of forest canopy horizontal parameters, but it is relatively insensitive to the change of vertical height. Therefore, there are more and more studies on the combination of LiDAR and optical remote sensing to obtain forest structural parameters. Hudak *et al*. combined LiDAR, ETM data and five statistical methods to estimate canopy height[26]. Jin *et al*. used the small-scale vegetation canopy height extracted by LiDAR as the ground truth value data to train the

RF model, so as to realize the inversion of large-scale vegetation canopy height[93].

5. Existing problems and research prospects

5.1 Existing problems

Due to the multi-level, complexity, unity, dynamic change and other characteristics of forest, its ecological quality assessment may cover all aspects, which determines that there will be many problems in the assessment process.

5.1.1 Selection of evaluation indicators

The evaluation indicators of forest ecological quality are screened only by theory or experience, and insufficient consideration is given to the effectiveness and representativeness of the evaluation indicators, which may lead to the lack of comparability of research cases in different research areas or even the same region, so that the research results cannot be effectively used and referenced, and hinder the exchange of scientific research and academic activities.

5.1.2 High quality data problems

In the process of retrieving forest ecological parameters using remote sensing technology, accurate and representative ground measurement data are needed for algorithm training and product verification, so high-quality sample data set is the premise of forest ecological quality estimation. Generally speaking, the verification data obtained from field sampling and vorticity related flux observation are of high accuracy, but such methods take a long time and have a small application area, and the data cannot be synchronized, which reduces the inversion accuracy. In addition, the estimation of forest biophysical parameters is more based on model simulation. Different models will have differences in parameters, thresholds, operation conditions and accuracy, which increases the uncertainty factors. For example, the forest biomass of the sample plot cannot be measured directly, and some ecological parameters (such as tree height, DBH, and forest age) are needed to assist in the calculation. Different studies use different regression models to calculate the ground point biomass, even for the same region, the results will be different.

5.1.3 Environmental impact

The level of forest ecological quality is closely related to its living environment. Environmental factors such as soil, climate, atmospheric composition, hydrological conditions, terrain and interference factors such as biological activities and natural disasters will affect the forest. However, few studies have evaluated the relative impact of environmental factors and interference factors at the same time, resulting in insufficient analysis of the impact mechanism of forest ecological quality.

5.1.4 Remote sensing means application issues

Remote sensing is a feasible method to obtain regional forest ecological parameters and quantitatively assess the ecological quality of forests, but most studies choose easily accessible horizontal forest structure parameters and do not consider enough vertical forest structure factors to comprehensively assess the ecological quality of forests with complex structure characteristics.

5.2 Development prospect

According to the problems existing in the evaluation of forest ecological quality, the following discussions and prospects are made for its development prospects.

First of all, forest ecological quality assessment needs to develop a standardized and unified index system. Reasonable evaluation indexes will improve the accuracy and objectivity of the assessment. The selection of each index should follow the principles of scientificity, representativeness and comprehensiveness to avoid problems such as unclear meaning, index duplication and strong correlation. For example, when it is forest land, “vegetation coverage” and “canopy density” have certain repeatability. Under different regions, different tree species and different site conditions, the threshold value of the evaluation index can be adjusted according to local conditions to improve the promotion ability, so that the research results of scholars can be mutually verified and used for reference, and promote academic exchanges.

Secondly, high-level forest ecological quality estimation requires long-term dynamic observation, so strengthen the long-term network monitoring and management of ground forests, constantly update and improve the basic data, so as to obtain real-time and effective sample data. Integrating multi-source remote sensing data, sample survey data, field sampling data, machine learning models and other data and methods to estimate forest biophysical parameters to quantify forest ecological quality, this research idea can reduce the uncertainty of a single model, improve the estimation accuracy, and realize forest assessment at different scales. In addition, carrying out forest multi-scale research is not limited to the pixel scale of remote sensing data, but also using object-oriented methods for forest ecological parameter estimation and multi-scale transformation, so as to improve the accuracy and generalization ability of the estimation model.

Thirdly, environmental factors (climate, terrain, soil, etc.), interference factors (drought, flood, pest, fire, etc.) and human activities should be considered in the process of forest ecological quality assessment. These factors will cause forest changes, resulting in differences in ecological quality levels. In addition, the parameters of the same species with different age structures and the heterogeneous species with the same age structure are different. Considering the age and species structure of tree species when quantifying the evaluation parameters can improve the accuracy of inversion results and promote the refinement and systematization of forest resources mapping.

Finally, multi-source remote sensing data is expected to improve the inversion accuracy of large-scale forest biophysical parameters, mainly by fusing the bands of different remote sensing platforms and sensors with different spectra and resolutions, so as to give full play to the advantages of a variety of remote sensing images and obtain more accurate and comprehensive forest horizontal and vertical structure ecological parameters. In addition, the expansion of research scale and the diversification of data sources have increased the amount of data, and the use of appropriate and efficient computing methods is also worth exploring and studying.

It is worth mentioning that the quality of forest ecological quality will affect the exertion of forest ecological functions and benefits. With the deepening of forest development and utilization, its ecological functions will be damaged or even changed, which is bound to have an impact on the level of forest ecological quality. Therefore, the research on the relationship between forest ecological functions and their ecological quality should be paid attention to in the next work.

Conflict of interest

The authors declared no conflict of interest.

References

1. Achard F, Eva HD, Stibig HJ, *et al*. Determination of deforestation rates of the world's humid tropical forests. Science 2002; 297(5583): 999–1002.
2. Chave J, Davies SJ, Phillips OL, *et al*. Ground data are essential for biomass remote sensing missions. Surveys in Geophysics 2019; 40(4): 863–880.
3. Dudley N, Schlaepfer R, Jackson W, *et al*. Forest quality: Assessing forests at a landscape scale. London: Routledge; 2012.
4. Shi C, Wang L. Connotation of forest resources quality. Issues of Forestry Economics 2007; 27(3): 221–224.
5. Bull GQ, Boedhihartono AK, Buenoueno G, *et al*. Global forest discourses must connect with local forest realities. International Forestry Review 2018; 20(2): 160–166.
6. Sarker LR, Nichol JE. Improved forest biomass estimates using ALOS AVNIR-2 texture indices. Remote Sensing of Environment 2011; 115(4): 968–977.
7. Riedler B, Pernkopf L, Strasser T, *et al*. A composite indicator for assessing habitat quality of riparian forests derived from earth observation data. International Journal of Applied Earth Observation and Geoinformation 2015; 37(9): 114–123.
8. Zhao Q, Yu S, Zhao F, *et al*. Comparison of machine learning algorithms for forest parameter estimations and application for forest quality assessments. Forest Ecology and Management 2019; 434(12): 224–234.
9. Wu G. The study on indicator system and evaluation method of forest resources quality at county-level [PhD thesis]. Beijing: Beijing Forestry University; 2010. p. 111.
10. Zhao T, Ouyang Z, Zheng H, *et al*. Forest ecosystem services and their valuation in China. Journal of Natural Resources 2004; 19(4): 480–491.
11. Feng J, Ding L, Wang J, *et al*. Case-based evaluation of forest ecosystem service function in China. Chinese Journal of Applied Ecology 2016; 27(5): 13750–1382.
12. Guo X. Multi-scale assessments on ecological quality of urban forest in Shanghai [PhD thesis].

Shanghai: East China Normal University; 2017. p. 191.
13. He D. The evaluation of forest ecological quality in Liling of Hunan Province [PhD thesis]. Hunan: Central South University of Forestry and Technology; 2017. p. 116.
14. Feng J, Wang J, Yao S, *et al*. Dynamic assessment of forest resources quality at the provincial level using AHP and cluster analysis. Computers and Electronics in Agriculture 2016; 124(4): 184–193.
15. Du Z, Gan S, Hu J. Comprehensive evaluation of forest resources quality in China. Central South Forest Inventory and Planning 2018; 37(3): 1–5.
16. Li H, Lei Y, Zeng W. Forest carbon storage in China estimated using forestry inventory data. Scientia Silvae Sinicae 2011; 47(7): 7–12.
17. Zhao M, Zhou G. Estimation of biomass and net primary productivity of major planted forests in China based on forest inventory data. Forest Ecology and Management 2005; 207(3): 295–313.
18. Liu Q, Ouyang Z, Li A, *et al*. Study on spatial differentiation characteristics of forest vegetation biomass and carbon stock in Chongqing city. Research of Soil and Water Conservation 2016; 23(06): 221–226, 381.
19. Du H, Cui R, Zhou G, *et al*. The responses of Moso bamboo (Phyllostachys heterocycla var. Pubescens) forest aboveground biomass to Landsat TM spectral reflectance and NDVI. Acta Ecological Sinica 2010; 30(5): 257–263.
20. Qiu S. The research of regional forest above ground biomass inversion combining ICESat-GLAS waveform and HJ-1A hyperspectral imageries [PhD thesis]. Harbin: Northeast Forestry University; 2016. p. 128.
21. Zhang C, Denka S, Cooper H, *et al*. Quantification of sawgrass marsh aboveground biomass in the coastal Everglades using object-based ensemble analysis and Landsat data. Remote Sensing of Environment 2018; 204(10): 366–379.
22. Zhao Y. Yaogan yingyong fenxiyuanli yu fangfa (Chinese) [Principles and methods of remote sensing application analysis]. Beijing: Science Press; 2013: 36–163.
23. Zhang L, Shao Z, Diao C. Synergistic retrieval model of forest biomass using the integration of optical and microwave remote sensing. Journal of Applied Remote Sensing 2015; 9(1): 18.
24. Chen E. Development of forest biomass estimation using SAR data. World Forestry Research 1999; 12(6): 18–23.
25. Minh DHT, Ndikumana E, Vieilledent G, *et al*. Potential value of combining ALOS PALSAR and Landsat-derived tree cover data for forest biomass retrieval in Madagascar. Remote Sensing of Environment 2018; 213(4): 206–214.
26. Hudak AT, Lefsky MA, Cohen WB, *et al*. Integration of lidar and Landsat ETM+ data for estimating and mapping forest canopy height. Remote sensing of Environment 2002; 82(2/3): 397–416.
27. Chen Q, Mcroberts RE, Wang C, *et al*. Forest aboveground biomass mapping and estimation across multiple spatial scales using model-based inference. Remote Sensing of Environment 2016; 184(7): 350–360.
28. Wang P, Wan R, Yang G. Advance in classification and biomass estimation of plants in westlands based on multi-source remote sensing data. Wetland Science 2017; 15(1): 117–127.
29. Liu T, Kong Y, Wu Y, *et al*. Provincial forest ecological security evaluation in China based on the entropy weight of the fuzzy matter-element model. Acta Ecologica Sinica 2017; 37(15): 4946–4955.
30. Yu J, Fang L, Cang D, *et al*. Evaluation of land eco-security in Wanjiang district based on entropy weight and matter element model. Transactions of the Chinese Society of Agricultural Engineering 2012; 28(5): 267–273.
31. Xie Y, Gong J, Qi S, *et al*. Assessment and spatial variation of biodiversity in the Bailong River Watershed of the Gansu Province. Acta Ecologica Sinica 2017; 37(19): 6448–6456.
32. Wang Y, Wu H, Xu H. Biological and ecological bases of using insect as a bio-indicator to asses forest health. Chinese Journal of Applied Ecology 2008; 19(7): 1625–1630.
33. Zhou J, Wan R. Advances in methods of wetland ecosystem health evaluation. Ecological Science 2018; 37(6): 209–216.
34. Wu Y, Li Y, Zhang L, *et al*. Assessment of lakes ecosystem health based on objective and subjective weighting combined with fuzzy comprehensive evaluation. Journal of Lake Sciences 2017; 29(5): 1091–1102.
35. Tan F, Zhang M, Li H, *et al*. Assessment on coordinative ability of sustainable development in Beijing-Tianjin-Hebei region based on set pair analysis. Acta Ecologica Sinica 2014; 34(11): 3090–3098.
36. Cooner AJ, Shao Y, Campbell JB. Detection of urban damage using remote sensing and machine learning algorithms: Revisiting the 2010 Haiti earthquake. Remote Sensing 2016; 8(10): 851–868.
37. Crowther TW, Glick HB, Covey KR, *et al*. Mapping tree density at a global scale. Nature 2015; 525(7568): 201–205.
38. Were K, Bui DT. A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape. Ecological Indicators 2015; 52(12): 394–403.
39. Zhu X, Liu D. Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS Journal of Photogrammetry and Remote Sensing 2015; 102(8): 222–231.
40. Rodrigues-Veiga P, Quegan S, Carreiras J, *et al*. Forest biomass retrieval approaches from earth observation in different biomes. International Journal of Applied Earth Observation and Geoinformation 2019; 77(12): 53–68.
41. Wang Y, Lu C, Zuo C. Coal mine safety production forewarning based on improved BP neural network. International Journal of Mining Science and Tech-

nology 2015; 25(2): 319–324.
42. Ma D, Zhou T, Chen J, *et al*. Supercritical water heat transfer coefficient prediction analysis based on BP neural network. Nuclear Engineering and Design 2017; 320(06): 400–408.
43. Tang X. Estimation of forest aboveground biomass by integrating ICESat/GLAS waveform and TM Data [PhD thesis]. Harbin: University of Chinese Academy of Sciences; 2013. p. 1–127.
44. Dube T, Mutanga O. Evaluating the utility of the medium-spatial resolution Landsat 8 multispectral sensor in quantifying aboveground biomass in umgeni catchment, South Africa. ISPRS Journal of Photogrammetry and Remote Sensing 2015; 101(11): 36–46.
45. Srinet R, Nandy S, Patel NR. Estimating leaf area index and light extinction coefficient using Random Forest regression algorithm in a tropical moist deciduous forest, India. Ecological Informatics 2019; 52(5): 94–102.
46. Houghton RA, Hall F, Goetz SJ. Importance of biomass in the global carbon cycle. Journal of Geophysical Research: Biogeosciences 2009; 114: 1–13.
47. Le Toan T, Quegan S, Davidson MWJ, *et al*. The biomass mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. Remote Sensing of Environment 2011; 115(11): 2850–2860.
48. Hui G. Studies on the application of stand spatial structure parameters based on the relationship of neighborhood trees. Journal of Beijing Forestry University 2013; 10(4): 1–8.
49. Paul KI, Larmour J, Specht A, *et al*. Testing the generality of below-ground biomass allometry across plant functional types. Forest Ecology and Management 2019; 432(8): 102–114.
50. Paul KI, Roxburgh SH, Chave J, *et al*. Testing the generality of above-ground biomass allometry across plant functional types at the continent scale. Global Change Biology 2016; 22(6): 2106–2124.
51. Frampton WJ, Dash J, Watmough G, *et al*. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. ISPRS Journal of Photogrammetry and Remote Sensing 2013; 82(4): 83–92.
52. Haralick RM. Statistical and structural approaches to texture. Proceedings of the IEEE 1979; 67(5): 786–804.
53. Eckert S. Improved forest biomass and carbon estimations using texture measures from worldview-2 satellite data. Remote Sensing 2012; 4(4): 810–829.
54. Zhao P, Lu D, Wang G, *et al*. Forest aboveground biomass estimation in Zhejiang Province using the integration of Landsat TM and ALOS PALSAR data. International Journal of Applied Earth Observation and Geoinformation 2016; 53(8): 1–15.
55. Jordan CF. Derivation of leaf-area index from quality of light on the forest floor. Ecology 1969; 50(4): 663–666.
56. Wang Z, Liu C, Alfredo H. From AVHRR-NDVI to MODIS-EVI: Advances in vegetatoion index research. Acta Ecologica Sinica 2003; 23(5): 979–987.
57. Zhang X, Wu B. A temporal transformation method of fractional vegetation cover derived from high and moderate resolution remote sensing data. Acta Ecologica Sinica 2015; 35(4): 1155–1164.
58. Tucker CJ. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing and Environment 1979; 8(2): 127–150.
59. Huete AR. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment 1988; 25(3): 295–309.
60. Baret F, Guyot G. Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sensing of Environment 1991; 35(2/3): 161–173.
61. Qi J, Chehbouni A, Huete AR, *et al*. A modified soil adjusted vegetation index (MSAVI). Remote Sensing of Environment 1994; 48(2): 119–126.
62. Venancio LP, Mantovani EC. Forecasting corn yield at the farm level in Brazil based on the FAO-66 approach and soil-adjusted vegetation index (SAVI). Agricultural Water Management 2019; 225(20): 1–16.
63. Huete AR, Didan K, Miura T, *et al*. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 2002; 83(1/2): 195–213.
64. Richardson AJ, Wiegand CL. Distinguishing vegetation from soil background information. Photogram-metric Engineering and Remote Sensing 1977; 43(12): 1541–1552.
65. Zhou J, Zhao Z, Zhao Q, *et al*. Quantification of aboveground forest biomass using Quickbird imagery, topographic variables, and field data. Journal of Applied Remote Sensing 2013; 7(1): 073484.
66. Xu H, Pan P, Ning J, *et al*. Remote sensing estimation of forest aboveground biomass based on multiple linear regression and neural network model. Journal of Northeast Forestry University 2018; 46(1): 63–67.
67. Li M, Wang B, Fan W, *et al*. Simulation of forest net primary production and the effects of fire disturbance in Northeast China. Chinese Journal of Plant Ecology 2015; 39(4): 322–332.
68. Wang J, Xiao X, Baigain R, *et al*. Estimating leaf area index and aboveground biomass of grazing pastures using Sentinel-1, Sentinel-2 and Landsat images. ISPRS Journal of Photogrammetry and Remote Sensing 2019; 154(6): 189–201.
69. Li W, Niu Z, Liang X, *et al*. Geostatistical modeling using lidar-derived prior knowledge with SPOT-6 data to estimate temperate forest canopy cover and above-ground biomass via stratified random sampling. International Journal of Applied Earth Observation and Geoinformation 2015; 41(4): 88–98.
70. Chi H, Huang J, Qiu J, *et al*. Estimation of forest aboveground biomass using ICESat/GLAS data and Landsat/ETM+ imagery. Science of Surveying and Mapping 2018; 43(4): 9–16.
71. Yuan W, Cai W, Liu D, *et al*. Satellite-based vegetation production models of terrestrial ecosystem: An

overview. Advances in Earth Science 2014; 29(5): 541–550.
72. Li D, Zhang C, Ju W, *et al*. Forest net primary productivity dynamics and driving forces in Jiangxi Province, China. Chinese Journal of Plant Ecology 2016; 40(7): 643–657.
73. Fang O, Wang Y, Shao X. The effect of climate on the net primary productivity (NPP) of Pinus koraiensis in the Changbai Mountains over the past 50 years. Trees 2016; 30(1): 281–294.
74. Kruse J, Rrnnenberg H, Adams MA. Three physiological parameters capture variation in leaf respiration of Eucalyptus grandis, as elicited by short-term changes in ambient temperature, and differing nitrogen supply. Plant, Cell & Environment 2018; 41(6): 1369–1382.
75. Pan H, Huang P, Xu J. The spatial and temporal pattern evolution of vegetation NPP and its driving forces in the middle-lower areas of Min River based on geographical detector analyses. Acta Ecologica Sinica 2019; 39(20): 1–11.
76. Piao S, Zhang X, Chen A, *et al*. The impacts of climate extremes on the terrestrial carbon cycle: A review. Science China Earth Sciences 2019; 62(10): 1551–1563.
77. Yu Y, Chen J, Yang X, *et al*. Influence of site index on the relationship between forest net primary productivity and stand age. PloS One 2017; 12(5): 1–20.
78. Wu W, Yao S, Xu Z. Study on NPP of main forest types based on national forest inventory data in Jiangxi Province, China. Journal of Nanjing Forestry University (Natural Sciences Edition) 2019; 43(5): 193–198.
79. Riutta T, Malhi Y, Kho LK, *et al*. Logging disturbance shifts net primary productivity and its allocation in Bornean tropical forests. Global Change Biology 2018; 24(7): 2913–2928.
80. Wang B, Liu M, Zhang B. Dynamics of net production of Chinese forest vegetation based on forest inventory data. Forestry Resources Management 2009; (1): 35–43.
81. Cheng F, Liu S, Zhang Y, *et al*. Effects of land-use change on net primary productivity in Beijing based on the MODIS series. Acta Ecologica Sinica 2017; 37(18): 5924–5934.
82. Zheng Y, Zhou G. A forest vegetation NPP model based on NDVI. Chinese Journal of Plant Ecology 2000; 24(1): 9–12.
83. Lieth H. Modeling the primary productivity of the world. Nature and Resources 1972; 8(2): 5–10.
84. Zhou G, Zhang X. A natural vegetation NPP model. Chinese Journal of Plant Ecology 1995; 19(3): 193–200.
85. Chen X, Zeng Y. Spatial and temporal variability of the net primary production (NPP) and its relationship with climatic factors in subtropical mountainous and hilly regions of China: A case study of Hunan province. Acta Geographica Sinica 2016; 71(1): 35–48.
86. Yan H, Wang S, Billesbach D, *et al*. Improved global simulations of gross primary product based on a new definition of water stress factor and a separate treatment of C3 and C4 plants. Ecological Modelling 2015; 297(11): 42–59.
87. Behera SK, Tripathi P, Behera MD, *et al*. Modeling net primary productivity of tropical deciduous forests in North India using bio-geochemical model. Biodiversity and Conservation 2019; 28(8/9): 1–17.
88. Fang J, Liu G, Xu S. Biomass and net production of forest vegetation in China. Acta Ecologica Sinica 1996; 16(5): 497–508.
89. Zhou G, Wang Y, Jiang Y, *et al*. Estimating biomass and net primary production from forest inventory data: A case study of China's Larix forests. Forest Ecology and Management 2002; 169(1/2): 149–157.
90. Shen G, Zhai M. Senlin peiyuxue (Chinese) [Forest cultivation]. Beijing: China Forestry Press; 2011.
91. Hansen MC, Potapoy PV, Goetz SJ, *et al*. Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data. Remote Sensing of Environment 2016; 185(2): 221–232.
92. Liao K, Qi S, Wang C, *et al*. Estimation of forest aboveground biomass and canopy height in Jiangxi province using GLAS and landsat TM images. Remote Sensing Technology and Application 2018; 33(4): 713–720.
93. Jin S, Su Y, Gao S, *et al*. The transferability of random forest in canopy height estimation from multi-Source remote sensing data. Remote Sensing 2018; 10(8): 1008–1183.