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Review

A Review of Research on Forest Ecosystem Quality Assessment and Prediction Methods

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Abstract: The accurate assessment and prediction of forest ecosystem quality is an important basis for evaluating the effectiveness of regional ecological protection and restoration, establishing a positive feedback mechanism for forest quality improvement and restoration policies, and promoting the construction of an ecological civilization in China. Based on the existing studies at home and abroad, this paper mainly analyzes and summarizes the connotation of forest ecosystem quality, assessment index systems, assessment and prediction methods, and outlooks on the existing problems of imperfect forest ecological quality assessment index systems, preliminary assessment and prediction capabilities, and unknown dynamic responses of forest ecological quality to climate change, etc. Efforts should be made to develop a scientific and standardized assessment index system, produce high-quality forest ecological data products, develop localization of assessment model parameters, and explore forest quality–climate change response mechanisms to provide references for in-depth research to realize the transformation of forest ecosystem quality assessments from historical and status quo assessments to future predictions, and to support the construction of a national ecological civilization.

Keywords: forest ecological quality; assessment index system; assessment and prediction methods

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1. Introduction

Forest ecosystems, as an essential part of green water and green mountains, provide critical ecosystem services [1–3], especially through the roles of a "green water reservoir" for water conservation functions [4,5], a "green carbon pool" for carbon fixation and oxygen release functions [6–8], a "green oxygen bar library" for atmospheric purification functions [9–11], and a "green gene pool" for biodiversity conservation functions [12,13], which are closely related to human welfare. In recent years, to mitigate the severe climate change caused mainly by human activities, the "Kyoto Protocol" has expanded to include forests as an essential initiative to solve the problems of saving energy and emission reduction and to cope with climate change. To this end, many forestry ecological projects have been implemented around the world, such as the "Roosevelt Project" in the United States, the "Great Plan for Transforming Nature" in Russia, the "Three-North Shelterbelt Project," the "Natural Forest Protection and Restoration Project," and the "Gain for Green Project" in China. The implementation of these forestry ecological projects has increased global forest cover to some extent [14–16] but has failed to curb the loss, fragmentation, and degradation of forests caused by human activities [17,18]. Furthermore, a large proportion of natural forests has been replaced by plantations, causing a generally homogeneous forest composition and age structure, low biodiversity, weakened ecological services, and significantly reduced resilience [19]. These are clear indications that the quality of forest ecosystems needs to be urgently improved [3–5]. Therefore, the issue of forest ecological quality has attracted much attention in the current context, and the assessment of its long-term status and future prediction has become a hot topic of research in the fields of forestry and ecology [20–23].

Long-term assessments of forest ecosystem quality are a critical way to understand the dynamic changes of patterns in forest ecosystem quality, which is conducive to quantifying and grasping the spatial and temporal distribution patterns, carbon source/sink characteristics, resistance, and resilience mechanisms of forest ecosystem quality. Furthermore, they can provide support for accurately formulating ecological restoration and regulatory measures, scientifically assessing the effectiveness of ecological engineering protection, efficiently accomplishing the "double carbon target," and responding to climate change. Currently, a series of theoretical and methodological studies on forest ecosystem quality assessments have been carried out at home and abroad [24–26]. Still, the data sources, assessment index systems, and assessment and prediction methods differ due to the differences in research regions, research scales, and research focuses. Based on the existing studies at home and abroad, this paper mainly analyzes and summarizes the connotations of forest ecosystem quality, assessment index systems, assessment and prediction methods, and prospects for the problems of imperfect forest ecological quality assessment index systems, preliminary assessment and prediction capabilities, and unknown dynamic responses of forest ecological quality to climate change. It aims to provide a reference for in-depth research to realize the transformation of forest ecosystem quality assessments from historical and status quo assessments to future predictions and to support the construction of a national ecocivilization which is a new concept and trend in China's era of high-quality development and transcendence of industrial civilization. This requires the synergistic promotion of ecological–economic civilization, ecological–social civilization, and ecological–environmental civilization.

2. Connotation of Forest Ecosystem Quality

Forest ecosystems are integrated ecosystems in which biotic communities (including plants, animals, microorganisms, etc.), mainly trees, interact with the abiotic environment (light, heat, water, air, soil, etc.) and undergo energy conversion and material circulation. A forest ecosystem is rich in species, complex in structure, well-functioning, can improve and maintain the ecological environment, and can provide welfare for human beings [27]. Specifically, forest ecosystems perform ecological functions and services that regulate and sustain ecological security, of which, ecological services refer to the natural environmental conditions and utility that forest ecosystems and ecological processes create and maintain for human survival and development [1,28,29]. The ability of forest ecosystems to perform ecological functions, such as water harvesting, carbon sequestration and oxygen release, biodiversity conservation, and providing ecological services, is an important factor affecting their quality level [30].

In 1992, the term "forest quality" was first introduced by Stolton and was subsequently used in the World Wide Fund for Nature (WWF) report, with Dudley defining its concept at the landscape scale as "the sum of all the functions and values of forests in terms of ecological, social and economic benefits" [31], thus calling attention to the quality of the environment and forests. The term "forest quality" is highly general and abstract and has broad connotations. Scholars at different levels and from different research backgrounds have conducted many exploratory studies on forest subjects at different scales [21,23,32,33]. Still, there is yet to be a widely accepted concept or definition in the academic community. In terms of research subjects and contents, it is both different from and related to topics such as "forest sustainability" and "forest health". "Forest sustainability" emphasizes forest management, i.e., a forest management system that ensures and promotes the sustainable and coordinated development of society, economy, resources, and the environment through the protection, management, and development of forest ecosystems to maintain the health and vitality of forest ecosystems and to meet the demand for forest products and ecological services in the process of socio-economic development.

"Forest health" is derived from "ecosystem health" [34], which is a concept proposed by western countries in response to the problems of single-structure planted forests, a weak ability to control forest pests and diseases, soil and water conservation, etc. Its ideas and concepts were first developed in the United States [35]. It is generally accepted that a healthy forest is one in which the effects of biotic and abiotic factors (e.g., pests, fire, air pollution, invasive alien species, forestry practices, timber harvesting, etc.) on the forest do not threaten the objectives of present or future forest resource management (timber production, forest recreation, wildlife conservation, timber resources, water conservation, etc.) [36,37]. Pathways to understanding forest health include the goal-oriented pathway of the utilitarian view, the ecosystem-oriented pathway of the ecosystem view [38], and an integrated pathway that balances the two [39,40]. "Forest quality" emphasizes the ability of forests to meet the growing ecological, economic, and social needs of humankind as a critically important ecosystem and an irreplaceable development resource; related concepts include "forest resource quality" and "forest ecological quality". The quality of forest resources refers to the sum of the effectiveness of all services provided by forests as a natural resource in a certain area, both in maintaining their own stability and providing social activities such as production and spiritual life to human beings. This depends not only on their own forest characteristics but also on a series of tangible and intangible benefits, such as the ecological environment and social economy brought about by the characteristics of the forest resources and trees. Thus, the connotations of forest ecosystem quality mainly cover three aspects: biological quality, socioeconomic quality, and ecological quality [41]. Forest ecological quality is a comprehensive measure of the ecological services, growth, and self-regulatory functions of forest ecosystems, reflecting the ability of forests to improve the ecological environment and maintain ecological balance [27,30,41]. Due to the abstract nature of the concept, the connotations of forest ecological quality vary for different research objectives, and no unified understanding has been reached yet. Synthesizing existing studies, this paper defines forest ecosystem quality as the quality of the overall or of some components of forest ecosystems on a specific temporal and spatial scale, specifically in terms of their productive service capacity, self-sustainability, resistance to external disturbances, impact on human survival, and sustainable socioeconomic development [42–44]. Constructing an index system that can reflect the ecological quality of forest ecosystems and carrying out forest ecosystem quality assessments are effective ways to grasp the status and development trend of forest ecosystem quality, which help to improve the quality and stability of forest ecosystems.

3. Methods of Forest Ecosystem Quality Assessment

3.1. Assessment Index System

Constructing an assessment index system is the first and key step in a quantitative assessment of forest ecosystem quality, and the selection of the assessment index system is mainly influenced by both the spatial scale of assessment and the ease of obtaining indicators. The current spatial scale involved in forest ecosystem quality assessments includes multiple levels of forest stands and landscapes at regional, national, and global levels, and the corresponding main characterization indicators of forest ecosystem quality mainly include spatial structure, ecological function, green vigor, stability, and health status (Table 1). The means of acquiring assessment index data mainly include traditional ground surveys and multi-source remote sensing image inversion. The former acquires more accurate data, but it requires a lot of time as well as human and material resources and cannot achieve large regional and continuous time-scale inventories [21,23,45–47]. The development of the latter makes up for the shortcomings of traditional estimation methods and can achieve rapid, continuous, and nondestructive estimations of forest ecological parameters at local, regional, and even global scales, which can meet the needs of forest surveys and biophysical parameter detection and provide data sets with different spatial and temporal resolutions for ecological quality assessment and prediction.

Currently, remote sensing images are combined with ground monitoring data to invert key parameters of regional forest ecosystem quality (leaf area index, vegetation cover, productivity, etc.) to achieve spatial gridding of forest quality assessment parameters [48–51], thus realizing long-term, dynamic, and accurate spatial observations of forest ecosystem quality in the study area.

Table 1. Forest ecosystem quality assessment indicators.

Dimensions Involved	Indicator Factors	Applications
Forest structure	Stand origin, community structure, stand age, canopy structure, stand density, tree species composition, depression	[21,23,26,27,46,52]
Ecological function	Water conservation, soil conservation, carbon sequestration and oxygen release, air purification, biodiversity conservation, nutrient sequestration, forest recreation, etc.	[53,54]
Green Vitality	Normalized difference vegetation index (NDVI), stand volume, leaf area index, biomass, forest growth per unit area, litter thickness	[32,55]
Stability	Net primary productivity (NPP) stability, NDVI stability	[54,56]
Site conditions	Elevation, slope direction, slope, slope position, soil thickness, soil fertility, soil erosion degree, etc.	[23,27,57,58]

3.2. Determining the Weight of Indicators

Based on the constructed suitable indicator system, different forest ecosystem quality assessment methods can be used to achieve forest ecosystem quality assessments at different spatial and temporal scales. Since the contribution of each type of indicator characterizing forest ecosystem quality differs, they are given different weights in the assessment process [30]. The correctness and scientificity of indicator weighting determine the reasonableness of forest ecosystem quality assessment results, which is the critical link in the process of forest ecosystem quality assessments. The two main methods of determining indicator weights are subjective weighting methods and objective weighting methods. The former is simple to operate and highly practical, but more subjective due to a heavy reliance on the personal experience of decision-makers, such as analytic hierarchy processes (AHP) [27,45,59,60]. The latter is more objective and avoids the bias brought about by human factors. Still, it will have problems in cases with insufficient sample sizes and does not take into account the variability among evaluation indicators, which may result in inconsistencies between the determined weights and the importance of indicators. Commonly used are the mean-variance integrated analysis [61], principal component analysis [53,59,62], factor analysis [26,63], and the entropy weighting method [54,64,65]. In addition, with the rapid development of artificial intelligence in the fields of data prediction, optimization, evaluation, and classification, machine learning algorithms such as decision trees, support vector machines, regression trees, and neural networks [55] have been applied to the determination of indicator weights. Machine learning algorithms usually have strong self-learning and adaptive capabilities, which can automatically extract rules between input and output data through learning and determine network weights adaptively, greatly reducing the negative impact of subjective weights on assessment results [66].

3.3. Assessment Methods

The selection of suitable forest ecosystem quality assessment methods is the guarantee of scientific and accurate assessment results. In a comprehensive manner, the commonly used methods for forest ecosystem quality assessment at home and abroad mainly include the comprehensive evaluation method, remote sensing assessment method, process modeling method, and machine learning method (Table 2).

Table 2. Comparison of forest ecosystem quality assessment methods.

Methods	Main Features	Input Data	Advantages	Disadvantages
Comprehensive evaluation method	Combination of qualitative and quantitative	Ground monitoring data	Simple method; intuitive evaluation results with high accuracy; high information utilization	The evaluation results may be biased by obscuring some factors that have a greater impact
Remote sensing assessment method	High assessment efficiency; suitable for large-scale forest quality assessment	Ground monitoring data; multi-source remote sensing data	Saves human and material resources; fast evaluation; high evaluation efficiency	Remote sensing images are often affected by satellite type, weather, cloudiness, etc. Remote sensing inversion of forest quality-related indicators needs to be verified by ground monitoring data
Process modeling method	Lateral reflection of forest quality through assessment of forest ecological functions	Ground monitoring data; multi-source remote sensing data	Expression formulas are clear, can capture the intrinsic linkages of ecosystem services, and are highly interpretable	Limitations in input data, model structure, and model parameters make simulation results subject to large uncertainties
Machine learning method	Adept at handling high-dimensional data and non-linear ecological relationships	Ground monitoring data; model simulation data; multi-source remote sensing data	It is self-learning and self-adaptive, greatly reducing the influence of subjective weights on evaluation results; it can couple ecological big data, process models, and use artificial intelligence to invert key parameters or optimize model parameters, thus improving evaluation accuracy	Its data demand is large, over-fitting or under-fitting problems may occur, and the interpretability of simulation results needs to be improved.

3.3.1. Comprehensive Evaluation Method

The comprehensive evaluation method characterizes the quality of forest ecosystems by constructing different indices to reflect their different aspects. It is a combination of qualitative and quantitative analysis and assessment methods, that are widely used in forest ecosystem quality assessment, including the comprehensive index method [67], fuzzy comprehensive evaluation method [68], cluster analysis method [45,62], matter element analysis [27,60,69], and set pair analysis method [27,70], which have different advantages and disadvantages [30]. In the actual assessment process, multiple methods are often combined to avoid the drawbacks of using a single method and to solve the problem in a reasonable way. For example, Xuan Feng et al. (2012) effectively combined the analytic hierarchy process and the fuzzy evaluation method to comprehensively and systematically evaluate and analyze the ecological quality status of Shanxi Province [71]. Feng et al. (2016) assessed the dynamics of provincial forest resource quality in China based on hierarchical analysis and cluster analysis, and the results showed that the implementation of ecological projects such as the Natural Forest Protection and Restoration Project and the Gain for Green Project significantly improved the quality of forest ecosystems at provincial and national levels [45]. Zhang Bo et al. (2022) used a combination of hierarchical analysis and matter element analysis to evaluate the quality of forest resources in Yanchuan County [60].

3.3.2. Remote Sensing Assessment Method

With the development of satellite remote sensing and the advantages of rapid extraction of vegetation information, low cost, and easy estimation based on remote sensing images, remote sensing assessment methods began and are now widely used for forest ecosystem quality change simulations and assessments [43,72–75]. The principle relates to the fact that different substances interact with electromagnetic waves and form spectral absorption and reflection features that reflect information on substance composition and structure at some specific wavelength positions. Such characteristics of matter in response to different wavelength spectra are called spectral characteristics. The spectral characteristics of forest vegetation are an important basis for obtaining their material composition and morphological structure parameters based on remote sensing methods. The spectral characteristics of forest vegetation vary at different growth stages, and, based on this spectral information, key indicators such as aboveground biomass [76], leaf area index [77,78], photosynthetic active radiation [79], net primary productivity [80,81], vegetation index [26], and texture structure index can be inferred. Deep mining of key indicator datasets can obtain forest structure, productivity, ecological function, and stability characteristics and thus assess forest ecosystem quality. For example, Chen Qiang et al. (2015) used MODIS remote sensing data products and basic geographic data, combined with an integrated remote sensing evaluation model of ecosystem quality, to evaluate the quality of ecosystems (forests, grasslands, wetlands, farmlands, and towns) around Dongting Lake in 2001, 2005, and 2010 in terms of productivity, stability, and carrying capacity [44]. In general, remote sensing-based forest ecosystem quality assessment methods greatly save human resources and improve assessment efficiency, but they also have certain limitations. On the one hand, because remote sensing images are often affected by satellite type, weather, cloudiness, etc., and on the other hand, remote sensing inversion of forest quality-related indicators needs to be verified through ground monitoring data. Therefore, most of the current studies integrate multi-source remote sensing and ground monitoring data to obtain the regional forest ecosystem quality.

3.3.3. Process Model Method

Ecological processes are the basis of forest ecological services [82,83]. To date, many ecological process models have been developed to simulate ecosystem carbon and water cycles, and representative models include CLM [84], LPJ [85], CENTURY [86], Biome-BG [87], CEVSA [88,89], InVEST model [90–94], etc. Process models combine explicit expressions of biogeochemistry and biophysics to capture the intrinsic linkages of ecosystem services and can simulate energy exchange and coupled nitrogen–carbon–water cycles between the vegetation, soil, and atmosphere at better spatial and temporal scales. Using the above, the ecological process models can usually quantify the ecological service functions of forest ecosystems [89,95–97], which in turn reflect forest ecosystem quality. However, ecological process models are obtained by simplifying the real world based on certain conditions, and the incompleteness of the attributed data, the limitations of the models themselves, and the lack of knowledge about the processes and control mechanisms of complex ecosystems lead to large uncertainties in different simulation results [98,99]. There are three main sources of uncertainty: the input data, the model structure, and the model parameters [100]. Among them, most of the input data are environmental variables, which depend on observation means and observation errors are difficult to control. The model structure is a simplification of the real physical process, but it is difficult to quantify accurately because the intrinsic mechanism of the ecosystem is very complex. Most of the model parameters follow the initial empirical values, and if the same set of parameters is followed for simulation under different substrates, it will cause large errors [101,102]. Thus, the process model-based assessment of forest ecosystem service functions also needs to utilize more data for model initialization and validation [103,104] and use parameter sensitivity analysis, parameter estimation, and data assimilation to investigate effective model parameters and reduce model simulation errors [105–110]. Remote sensing observations are a good tool for large-scale forest ecosystem monitoring and can provide input and assimilated data for ecosystem model simulations, while process models can help assess forest ecological processes that cannot be directly monitored via remote sensing and can diagnose and predict the effects of environmental changes to overcome the shortcomings of remote sensing technology. Therefore, integrating remote sensing data and process models can help with real-time monitoring and rapid assessment of forest ecosystem quality. The complementarity of remote sensing and process models in studying forest ecosystems has been demonstrated, but effective methods for linking forest ecosystem quality with process models are lacking [111,112] and further research is still needed to explore them.

3.3.4. Machine Learning Method

In recent years, artificial intelligence (AI) has been rapidly developed in the fields of data prediction, optimization, evaluation, and classification. Among various AI techniques, machine learning algorithms have become a valuable tool for processing and analyzing big data. Machine learning has a greater advantage in dealing with nonlinear ecological relationships and can better explain the relationship between biophysical parameters and model parameters, which is a potentially effective method for conducting forest ecosystem quality assessment. Machine learning can be divided into three main types: supervised learning, unsupervised learning, and reinforcement learning [113,114]. The common algorithms mainly include: k-nearest neighbor (KNN), artificial neural network (ANN), random forest (RF), support vector machine (SVM), etc. (Table 3). The advantage of assessing forest ecological quality based on machine learning algorithms lies in two aspects: one is the determination of the weights of each index, and the other is the improvement in assessment accuracy. Machine learning algorithms usually have strong self-learning and self-adaptive capabilities and can automatically extract rules between input and output data through learning and adaptively determine the work weights, which greatly reduces the influence of subjective weights on the evaluation results. For example, Yang Hong et al. (2012) evaluated the ecological quality of the outer Yangtze River estuary by using an artificial neural network method with a seawater quality index, a phytoplankton diversity index, and chlorophyll concentration as evaluation indicators. Li et al. (2021) constructed a back propagation artificial neural network model optimized using a genetic algorithm (GA-BPANN) to evaluate the ecological health of forests in Yunnan Province, which used an artificial neural network to self-correct the weights until the error in the output was reduced to an acceptable level, avoiding the influence of competent factors and performing well in practical applications of regional ecosystem health assessments [55]. The improvement in the accuracy of forest ecosystem quality assessment based on machine learning is due to the advancement of simulation accuracy on the one hand, and on the other hand, mainly lies in coupling big ecological data, process models, and artificial intelligence to carry out inversions of critical parameters or localizations of model parameters to reduce the uncertainty of parameters, which in turn improves the science and accuracy of forest quality. For instance, Zhang et al. (2010) used the Markov chain Monte Carlo (MCMC) method to invert the critical parameters of carbon retention time and carbon retention time based on biometric and vorticity-related data [115]. Richardson et al. (2010) estimated the parameters of the data assimilation linked ecosystem carbon (DALEC) model using vorticity-related flux data, soil respiration, leaf area index, litterfall, and biomass data. They found that the inclusion of soil respiration and biomass data helped parameter estimation and reduced uncertainty in model predictions [116]. Ge et al. (2019) developed a new model data fusion framework using five carbon pools, including litterfall data, leaf area index, net ecosystem productivity, and soil respiration, revealing that the traditional equilibrium state assumption significantly underestimates ecosystem carbon turnover time and carbon sink capacities [117]. Niu et al. (2019) found that greening and warming led to substantially higher transpiration and evapotranspiration in terrestrial ecosystems in China based on surface observations of transpiration and evapotranspiration data and model data fusion methods [118]. In addition, deep learning (DL), as an important branch of machine learning, has significant advantages in solving high-dimensional data [119,120]. Remote sensing image recognition methods based on DL for forest resources have been applied to forest resource surveys, forest vegetation cover statistics, forest pest and disease monitoring, and other fields. Although there is still a gap between remote sensing image analysis based on DL and manual recognition at this stage, with the continuous optimization of DL algorithms, the efficiency of forest ecological quality evaluation can be effectively improved in the future [121].

Table 3. Comparison of standard machine learning algorithms for forest ecosystem quality assessment.

Machine Learning Algorithms	Characteristic	Applications
K-nearest neighbor (KNN)	No parameter estimation; simple and easy to implement; increases the workload and overfitting problem when the sample size is large.	[122,123]
Artificial neural networks (ANN)	Suitable for dealing with multi-factor influence and ambiguous information, no assumptions are required about the data, which can effectively deal with non-linearity, non-normality, and covariance in the data; overfitting can occur.	[26,55,124,125]
Random forest (RF)	It can handle complex, nonlinear ecological relationships and has the advantages of efficient processing of massive data, less human interference, strong resistance to noise, and less likely to produce overfitting; however, it is sensitive to the interrelationship between input variables and will produce bias in the prediction tree, so the importance of variables needs to be measured.	[26,123,126–128]
Support vector machine (SVM)	It can be used in classification and regression analysis to produce higher classification or more accurate estimates in solving small, non-linear, and high-dimensional pattern recognition problems.	[26,123,128]
Deep learning (DL)	Ideal for classifying audio, text, and image data but requires large amounts of data for training.	[127,129]

4. Forest Ecosystem Quality Prediction

To date, many research results have been achieved in forest ecosystem quality assessment, but there are few studies on forest ecological quality prediction. There are three main reasons for this: firstly, forest ecological quality itself is a comprehensive assessment value rather than a measurement value, so it is statistically difficult to define the dependent and independent variables; secondly, the selection of methods and evaluation index systems for calculating forest ecological quality and its evaluation will directly affect the success or failure of prediction models; thirdly, there are many factors affecting forest ecosystem quality, and the calculation volume is often huge.

Most of the current research is on the prediction of forest ecosystem service functions [130] and key parameters of forest quality [127,128,131], with prediction methods including machine learning, neural network methods, Markov prediction methods, and system dynamics simulation. For example, Wang et al. (2022) used two machine learning algorithms, deep learning and random forest, to explore how annual diameter growth varies with forest stand and climate variables [127]. Based on system dynamics theory, Shi et al. (2018) applied Vensim simulation software to evaluate the value of forest ecosystem services provided by the Jilin Forestry Group from 2008 to 2020 under different new afforestation areas and harvesting volumes and to predict the long-term effects under different scenarios, which is very important for the forestry development and strategy formulation of the Jilin Forestry Group [132]. Liu et al. (2019) used a gray prediction model and wavelet neural network to predict the forest area and average annual precipitation in Yunnan Province, and further constructed a comprehensive value model of water and soil ecological service function and water footprint carrying capacity equation to estimate the number of forest water ecological carrying capacity in Yunnan Province, reflecting the degree of influence of forest water and soil ecological service function in Yunnan Province to compensate for local water scarcity [133].

5. Problems and Research Prospects

5.1. Existing Problems

With the rapid development of long-term positioning observation and research networks of forest ecological stations and remote sensing monitoring technology, we have now entered the era of ecological big data. Fully exploiting the implicit information of air–sky–ground integrated forest ecosystem observation data and carrying out regional or national forest ecosystem quality assessments and predictions is an important basis for evaluating the effectiveness of regional ecological protection and restoration, accurately improving the quality and stability of forest ecosystems, and promoting the major strategic needs of ecological civilization construction. At present, the knowledge of forest ecosystem quality and its changes on a national scale is still relatively lacking and insufficient to meet the needs of national forest ecosystem management; moreover, there are still some problems in the assessment and prediction of forest ecosystem quality.

5.1.1. Inadequate Assessment Index System

Forest ecological quality assessment involves scales at the forestry center, county, city, regional, national, global, and other research levels, and their assessment index systems are different for different research scales; moreover, there are problems with insufficient considerations of validity and representativeness of evaluation indexes, resulting in poor comparability of assessment results in different research regions or the same region. In addition, existing assessments of forest ecosystem quality tend to focus on realistic values of indicators characterizing the condition of forest ecosystems, and the magnitude of their values is largely dominated by differences in climatic factors (e.g., precipitation, temperature, total radiation) and geographic background conditions, resulting in low comparability of evaluation results across regions [30,42]. The existence of the above-mentioned problems makes the research results poorly referable and hinders the exchange of scientific and academic activities.

5.1.2. Inadequate Capacity of Forest Ecological Quality Assessment and Prediction

The process of assessing forest ecological quality based on remote sensing technology, process models, and machine learning requires a large amount of accurate and representative ground measurement data for algorithm training and parameter validation, while the current lack of high-quality ground monitoring data sets reduces the inversion accuracy. In addition, forest ecosystem processes are complex, some process mechanisms are not yet clear, and most of the forest ecosystem quality assessment models are introduced from abroad with low model localization, resulting in low accuracy and high uncertainty in forest ecosystem quality assessment and prediction.

5.1.3. Dynamic Response of Forest Ecological Quality to Climate Change Is Unknown

Climate change has become a hot issue of concern in the world today [134], and forest ecosystems play an irreplaceable role in mitigating climate change and restoring the ecological environment [135,136]. Climate change may drive complex changes in the species composition, spatial structure, ecological processes, and functional services of forest ecosystems [137–140], which in turn affect forest ecological quality. The dynamic responses and mechanisms of forest ecosystem quality to climate change need to be further clarified.

5.2. Research Perspectives

In order to effectively solve the problems in forest ecosystem quality assessments, improve the ability of forest ecosystem quality assessments and predictions, and realize the transformation of forest ecological quality assessments from historical and current situation assessments to future predictions, the following discussion on its development prospects is given, mainly including the following three aspects:

1. Develop a scientific and standardized evaluation index system. Therefore, in order to effectively promote the pace of ecological civilization construction in the new era and improve the effectiveness of ecosystem quality management, it is necessary to overcome the above-mentioned problems and to improve the existing ecosystem quality assessment system using screening evaluation indicators and clarifying the assessment criteria of each parameter based on the principles of scientificity, operabil-

ity, comparability, accuracy, and quick sensitivity, so as to reveal the current situation, changes, and restoration potential of its quality in a more realistic way.

2. Produce high-quality forest ecological data products and realize the localization of assessment model parameters. High-quality, ground-based, long-term observation data are the basis of scientific research on forest ecosystems, so we should strengthen long-term, ground-based observation of forests, constantly update and improve the basic data, and obtain real-time and effective sample data. Then, use data assimilation and other methods to integrate multi-source heterogeneous data (ground-based, long-term observation data, remote sensing monitoring data, and model simulation data) to produce high-quality forest ecological data products, realize the localization of assessment model parameters, and improve the accuracy of forest ecosystem quality assessments.
3. Exploring forest quality–climate change response mechanisms. As one of the most important components of the carbon pool of terrestrial ecosystems, forests play an important role in the carbon balance of terrestrial ecosystems and the carbon cycle of surface systems. It is important to understand the response mechanism of forest ecosystem quality to climate change, simulate and predict forest ecosystem quality under future climate change scenarios, and clarify the heterogeneous response of forest ecosystem quality to climate change in advance so as to formulate forest management measures to cope with global climate change and achieve the goal of "carbon neutrality".

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